Representation of 100-year design rainfall uncertainty in catchment-scale flood modeling: A MCMC bayesian approach

By Saba Mirza Alipour, Kolbjørn Engeland and Joao Leal

Saba Mirza Alipour is a Ph.D research fellow at Department of Engineering and Science, University of Agder.
Kolbjørn England is a researcher at Norwegian Water Resources and Energy Directorate (NVE).
Joao Leal is a professor at Department of Engineering and Science, University of Agder.

Sammendrag

Representasjon av usikkerhet i 100-års nedbøren for flommodellering på nedbørfelt-skala: En MCMC tilnærming. Usikkerheter knyttet til estimering av nedbørsmengder er en av de viktigste kildene til usikkerhet i flommodellering. Representasjon av disse usikkerhetene kan være utfordrende på grunn av ufullstendige historiske data, klimaendringer og værets stokastiske natur. I denne studien ble det brukt en Bayesiansk tilnærming med forkunnskaper om formparameteren for å tilpasse den generelle ekstremverdi (GEV) -fordelingen til årlige maksimalverdier for døgnnedbør. Metoden ble brukt for forskjellige datasett (stasjonsbaserte data, feltbaserte data og griddede data). Til slutt ble det valgt et konfidensintervall for 100-års nedbøren for hele nedbørfeltet. Resultatene illustrerer en betydelig forskjell i de beregnede konfidensintervallene avhengig av om man gjør en lokal analyse med stasjonsbaserte data, eller en analyse på nedbørfelt-skala med feltbaserte data eller griddede data. Funnene viser også at konfidensintervallene kan endres betydelig avhengig av den valgte perioden for analysene. Ingen signifikante trender i ekstremnedbør ble identifisert.

Summary

Uncertainties associated with the estimation of design rainfall is one of the major sources of uncertainty in flood modelling. Representation of these uncertainties can be challenging due to the incomplete historical data, climate change effect and the stochastic nature of the weather. In this study, a Bayesian inference with prior knowledge about the shape parameter was applied to fit the Generalised Extreme Value (GEV) distribution for annual maximum rainfall data. The method was used for different data sets (station-based data, catchment-based data, and gridded data) and finally, a range was selected as a 100-year design rainfall as the catchment precipitation. The results illustrate a considerable difference in the calculated ranges resulting from local scale analyses (station-based data) and catchment scale analysis (catchment-based and gridded data). The findings also show that the confidence intervals of the quantiles can considerably change depending on the selected period for the analyses. No significant trends in extreme precipitation were found.

Introduction

Estimation of design rainfall over a catchment area is an important task in engineering practice related to water resources and flood management. However, due to the complex and chaotic nature of weather and precipitation generating processes, there is a considerable degree of uncertainty in the design rainfall estimates. This uncertainty will, in subsequent steps, contribute to uncertainty in design flood estimates, flood zone mapping and flood risk assessments. Assessing uncertainty in design rainfall estimates is therefore an important task. Uncertainty sources for design rainfall estimates are the limited sample size, the aggregation of design rainfall from point measurements to the catchment scale, and climate variability and trends. The sample uncertainty is explained by the limited sample size, i.e., we need to estimate a design rainfall of 200 years return period based on much less than 200 years of data. The estimated design precipitation will therefore, in many cases, be higher than any observed precipitation. The actual areal precipitation is unknown since the precipitation is measured in gauges. The uncertainty in estimated areal rainfall depends on the spatial variability of the precipitation events that generate the extreme events. Convective precipitation with a high spatial variability dominates in small catchments whereas stratiform precipitation dominates in larger catchments. Relatively small catchments far away from precipitation gauges have therefore the largest uncertainty in design rainfall estimates. The design rainfall for a catchment area will be smaller than the design rainfall for a point. Therefore, in engineering, area reduction factors (ARFs) are used to adjust design values from point measurements to the catchment area. Climate trends and changes introduce an additional challenge since the basic assumption of stationarity is no longer fulfilled resulting in a design rainfall that is time dependent.

A large and growing body of literature has investigated different approaches and methods to estimate design rainfall. The most widely used methods is based on fitting a probability distribution to annual maxima data. Extreme Value theory shows that the Generalized Extreme Value (GEV) distribution is the asymptotic distribution for maxima extracted from sufficient large blocks of data (Fisher and Tippett, 1928, Coles, 2001). The GEV distribution is therefore a good approximation for the maxima of long, but finite, sequences of random variables, such as annual rainfall maxima (Pelosi et al., 2020). In addition to the basic form of GEV distribution, the GEV model is applied in other forms such as mixed GEV distribution to account for different flood generating processes (e.g., Kedem et al., 1990, Yoon et al., 2013) and nonstationary GEV distribution (e.g., Cunderlik and Burn, 2003, Leclerc and Ouarda, 2007, Agilan and Umamahesh, 2017). As mentioned before, the nonstationary GEV models are applied to non-stationary time series (i.e., series with statistical properties varying in time due to changes in the dynamic system) to reflect the effect of long-term climate change on a phenomenon. In the nonstationary case, the parameters of the model are expressed as a function of time t and possibly other covariates as well (Coles, 2001). Different examples of nonstationary GEV models can be found in the works conducted by Khaliq et al. (2006), Cannon (2010), Um et al. (2017) and Ouarda and Charron (2019). One important and influencing part in GEV modeling process is the length of time series. Ideally the longer time series are selected to fit the GEV distribution and for the shorter records ISO standard ISO 19901-1 recommends to not use return periods more than a factor of four beyond the length of the data set (e.g., for the data covering a period of 30 years, the longest return periods that should be investigated is 120 years) (Vanem, 2015). However, DeGaetano and Castellano (2018) showed that the use of long, nonstationary precipitation records has the potential to yield precipitation-frequency estimates that are not representative of the current (or future) extreme rainfall climatology.

When estimating design rainfall, we need to estimate the parameters of the GEV distribution so that it gives the best possible fit to the observed data. Typical estimators are ordinary moments (OM), L-moments (LM), Maximum likelihood (ML), generalized maximum likelihood (GML)) and Bayesian approaches. A comparative study of performance of different estimators can be found in the works presented by Martins and Stedinger (2000) and Kobierska et al. (2018). In most applications the l-moments, GML or Bayesian approaches are recommended since they are robust with respect to outliers and either explicitly or implicitly apply constraints on the shape parameter. Bayesian approach is now widely used for inference (e.g., Yan and Moradkhani, 2016, Lima et al., 2018, Lutz et al., 2020). Some important advantages of the Bayesian methods are (i) the possibility to set prior information (i.e., on the shape parameter) (ii) the uncertainty in design flood estimates can easily be extracted and (iii) it is easy to introduce and make inference for non-stationary models. Many studies have proposed the Bayesian framework as a satisfactory method to estimate confidence intervals for flood quantiles (e.g., Martins and Stedinger, 2000, Renard et al., 2006, Lima et al., 2016, Lima et al., 2018). The Bayesian approach is also recommended by the Norwegian meteorological institute (Lutz et al., 2020).

Estimation of design rainfall over an area/catchment, is one of the subjects that has received considerable attention in recent years. This issue is particularly important for rainfall-runoff modeling of extreme hydrometeorological events. There is a large volume of published studies describing methods to transfer local/station measurements to larger scales such as catchment scale. Among the proposed methods, Area Reduction Factors (ARFs), are widely used to convert estimates of extreme point rainfall to estimates of extreme area-averaged rainfall (Wright et al., 2014). The design precipitation for a catchment area will decrease with increasing catchment area due to the spatial averaging of precipitation and the transition from convective to stratiform precipitation as the most relevant extreme precipitation generating process. The target duration of extreme precipitation will also depend on catchment size. In Svensson and Jones (2010), different methods for estimating the ARF were critically reviewed. They reported that there is no obvious preferred method for estimating extreme areal precipitation.. Dyrrdal (2012) provided a summary of existing methodology applied by the Norwegian Meteorological Institute (MET Norway) for estimating extreme precipitation in station sites and catchments in Norway. She found that exciting methods are laborious and outdated, and proposed a grid-based methodology as an alternative to using ARFs. An example of grid based methodology where the annual maximum area rainfall is extracted from gridded precipitation data is applied in Dyrrdal et al. (2016). They conclude that using a grid-based approach is efficient, and more objective than station-based methods combined with ARFs. However, the grid-based estimates are generally lower than the station-based estimates that use ARFs.

In this study we want to demonstrate how the choice of approach affects the design precipitation estimates for one catchment in southern Norway. The main goal of this study is to estimate 100-year rainfall for a catchment with several precipitation stations inside or in the proximity (described in next section) with the associated uncertainty using both stations based and grid-based approaches. We compared estimates using three different approaches i) use annual maxima for each station (experiment 1), ii) the estimates from the previous step are combined to establish a mixture distribution (experiment 2) and iii) use annual maxima from catchment average precipitation extracted from gridded precipitation data (experiment 3). In (i) and (ii) ARF were used to get the catchment design rainfall. For all approaches, a Bayesian methodology was used to estimate the design rainfall and the associated uncertainty.

In addition to the proposed procedure, this paper aims to highlight the importance of time series length by comparing the estimated design rainfalls for different periods in the same station.

Study area

The study catchment is upstream the gauging station Flaksvatn in Tovdalselva river, located in Agder province (Norway) (Fig. 1). The catchment area is 1867 km^2. The mean annual precipitation in the catchment is approximately 1260 mm, with most of the rainfall occurring between October and March (about 60%) (Data collected from http://nevina.nve.no/). On 02.10. 2017, an extreme flood event occurred in the downstream parts of the river and inundated Birkeland city that is located beside this river. This event was the highest ever recorded flood in this river. The information of this event, measured at Flaksvatn station and Senumstad station (Fig. 1), is presented in Table 1.

Data

Annual maximum daily rainfall data recorded from 6 stations operated by the Norwegian meteorological institute were collected from SeKlima.met.no. Information about the stations is listed in Table 2 and their locations on the map are displayed in Fig. 2. Two stations, namely Herefoss and Rislå have been relocated (about 500 m and 700 m respectively) and are now operating as Herefoss and Senumstad stations. (The Meteorological institute has established

Table 1. Summary of the recorded data of the flood event in the study area. Discharge and precipitation data belong to Flaksvatn and Senumsatd stations, respectively. The max discharge 30.09 and 01.10 were observed at 23:00, whereas the 02.10, the discharge culminated at 09:00

Date	Rainfall (mm)	Max Water level (m)	Max Discharge (m^3.s^{-1})
30.09.2017	45.1	21.40	501.3
01.10.2017	173.1	24.57	1062
02.10.2017	63.6	25.56	1195

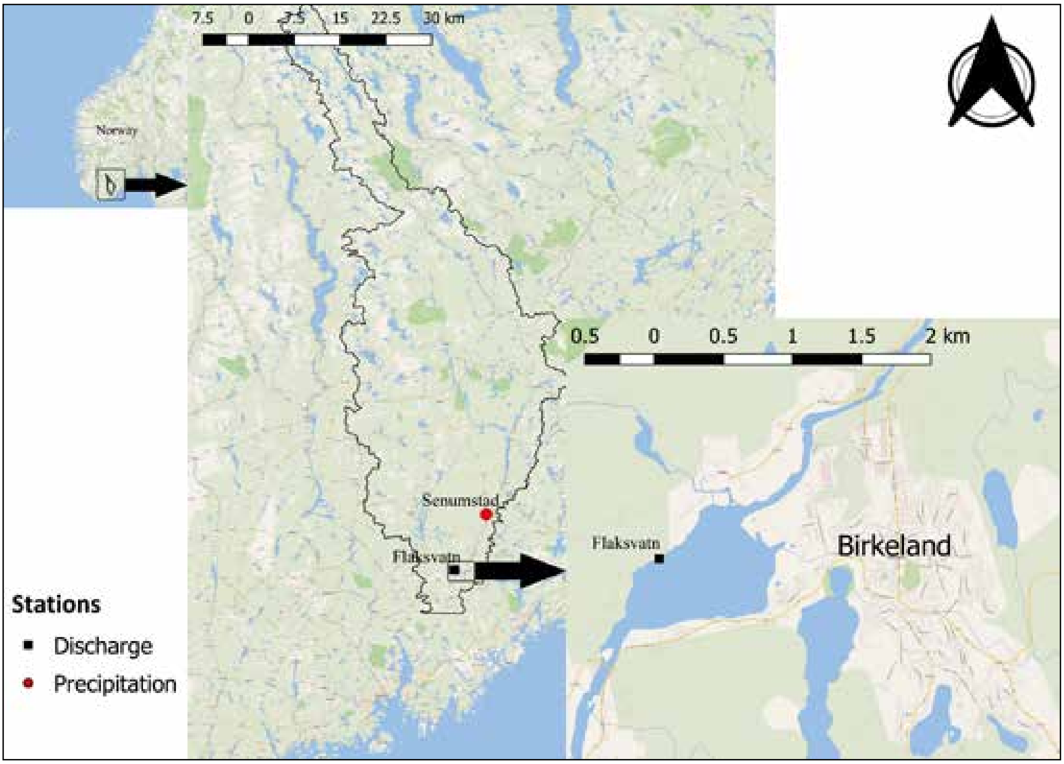


Figure 1. Tovdal river catchment and the study area

Table 2. Operation periods and length of the recorded timeseries for the stations of the catchment

Station	Operation period	Time series length (years)
Dovland	From Sep 1958	54
Herefoss	From Jul 1895	123
Kjevik	From Jun 1939	75
Mykland	From Jul 1895	126
Senumstad-Rislå	From Sep 1958	54
Tovdal	From Jul 1895	95

homogenized time series that merge the observations from before and after the relocation). Among the stations presented in Table 2, Mykland station was removed from the study because of missing data in the daily rainfall records.

In Norway, estimates of daily precipitation on a 1x1 km grid, presented by MET Norway, can be found in www.seNorge.no. The gridded data are based on interpolation of observations at approximately 400 precipitation stations (Dyrrdal et al., 2016). We used the gridded data to extract daily precipitation averaged for the

Figure 2.The locations of stations

catchment upstream the streamflow station at Flaksvatn (Fig. 1). Subsequently the annual maximum rainfall data for the years from 1961 to 2019 were extracted.

Methods

In this study, we used the annual maximum precipitation data and therefore assumed that the data follows the generalized extreme value (GEV) distribution (Jenkinson, 1955):

$$F(x|\mu,\sigma,\xi) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \quad \text{Eq. 1}$$

where x is annual maximum rainfall, μ is the location parameter, σ is the scale parameter and ξ is the shape parameter.

The challenge of statistical inference is to estimate the parameter vector $\theta=[\mu,\sigma,\xi]$ so that the GEV distribution has the best fit to the data x. In this study we used Bayesian inference.

Bayesian inference is based on the Bayes' theorem (Bayes, 1763) and states that the posterior probability $P(\theta|x)$ of the parameters θ given the data depends on the likelihood of the parameters given data $L(\theta|x)$ and the prior knowledge of the parameters $P(\theta)$:

$$\frac{L(\boldsymbol{\theta}|x)P(\boldsymbol{\theta})}{P(x)} \quad \text{Eq. 2}$$

the likelihood function is specified as the product of the probability density function (pdf) of the GEV distribution evaluated at all observations. $P(x)$ is or marginal probability of x and acts as a normalizing constant. Since $P(x)$ is a constant, Eq. 2 can be written as:

$$P(\boldsymbol{\theta}|x) \propto L(x|\boldsymbol{\theta})P(\boldsymbol{\theta}) \quad \text{Eq. 3}$$

Table 3. The prediction intervals (5% and 95% CI) for 100-year flood quantiles.

ID	100-year design rainfall (mm/day)			ARF effect (*0.88) Climate factor (*1.2) Time resolution (*1.13) (mm/day) (ARF is not used for Experiment 3)		
Experiment 1	**ML**	**0.05**	**0.95**	**ML**	**0.05**	**0.95**
Dovland	120	102	162	144	122	194
Herefoss	120	109	141	143	130	168
Kjevik	114	99	145	136	118	174
Senumstad	147	128	198	175	152	236
Tovdal	124	108	154	148	129	184
Experiment 2						
Catchment	123	116	136	147	138	162
Experiment 3						
Grid data	104	92	134	141	125	182

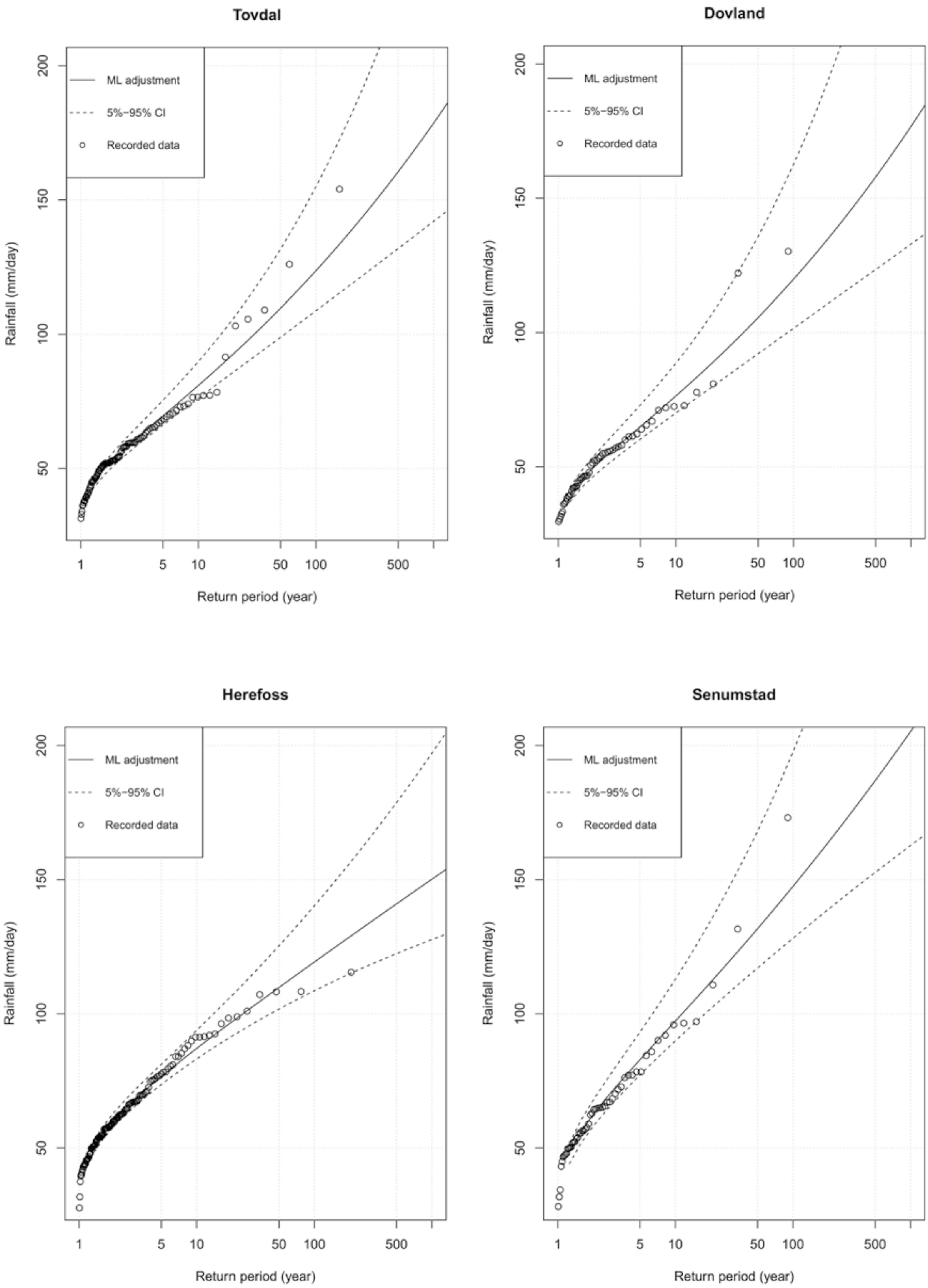
In this study we selected the prior distribution for the GEV parameters, based on the recommendations in Martins and Stedinger, 2000 and Lutz et al., 2020. Accordingly, we used uninformative prior distributions for location (μ) and scale (σ) and beta distribution for shape parameter ($\xi \sim B(p=6, q=9)$) which is defined on the interval [–0.5, 0.5].

We used a Markov Chain Monte Carlo (MCMC) algorithm to estimate the posterior probability distribution of the parameter set θ. We used the algorithm implemented in the R-package nsRFA (Viglione et al., 2020), where a Metropolis Hastings algorithm is implemented, and carried out 50,000 iterations to obtain a sample of the posterior distribution of the GEV parameters θ. This posterior sample of GEV parameters was subsequently used by the GEV distribution to provide a predictive distribution of the design rainfall (i.e., in our case the 100-year rainfall where the cumulative GEV distribution equals 0.99) in the form of a sample. From this sample the 90% prediction interval for the design rainfall was calculated.

To transfer the climate change effects and possible future changes, the design rainfall values are multiplied by climate factors. The climate factors are calculated based on return period, rainfall duration, geographical location, reference period, scenario period and climate models (global/regional) (Hanssen-Bauer et al., 2009). In this study the defined rainfall interval is multiplied by a climate factor equal to 1.2. The factor is selected based on the values reported by Hanssen-Bauer et al. (2009), for the case study region (Agder) under high emissions scenario (RCP8.5) (Table 3). In order to achieve design values that represent 24 hour duration and not a calendar day, we multiplied all estimates by 1.13 as recommended by the Norwegian meteorological institute (https://klimaservicesenter.no/kss/vrdata/ivf-veiledning). Further, we needed to convert point (station) rainfall estimates to catchment-averaged estimates for experiment 1 and 2 where station data were used. We used area reduction factor recommended by the Norwegian meteorological institute (https://klimaservicesenter.no/kss/laermer/kraftig-nedbor). For daily precipitation in a catchment of 1867 km^2, the ARF value is 0.88.

Results and discussion

Following the approaches described in the previous section, the design rainfall ranges (or prediction intervals) were estimated using Bayesian MCMC and results are presented in Table 3 and Figs. 3 and 4, displays the 100-year design rainfall value with the associated prediction intervals for each experiment.


Tovdal
ML adjustment
5%−95% CI
Recorded data
Rainfall (mm/day)
Return period (year)
Dovland
ML adjustment
5%−95% CI
Recorded data
Rainfall (mm/day)
Return period (year)
Herefoss
ML adjustment
5%−95% CI
Recorded data
Rainfall (mm/day)
Return period (year)
Senumstad
ML adjustment
5%−95% CI
Recorded data
Rainfall (mm/day)
Return period (year)

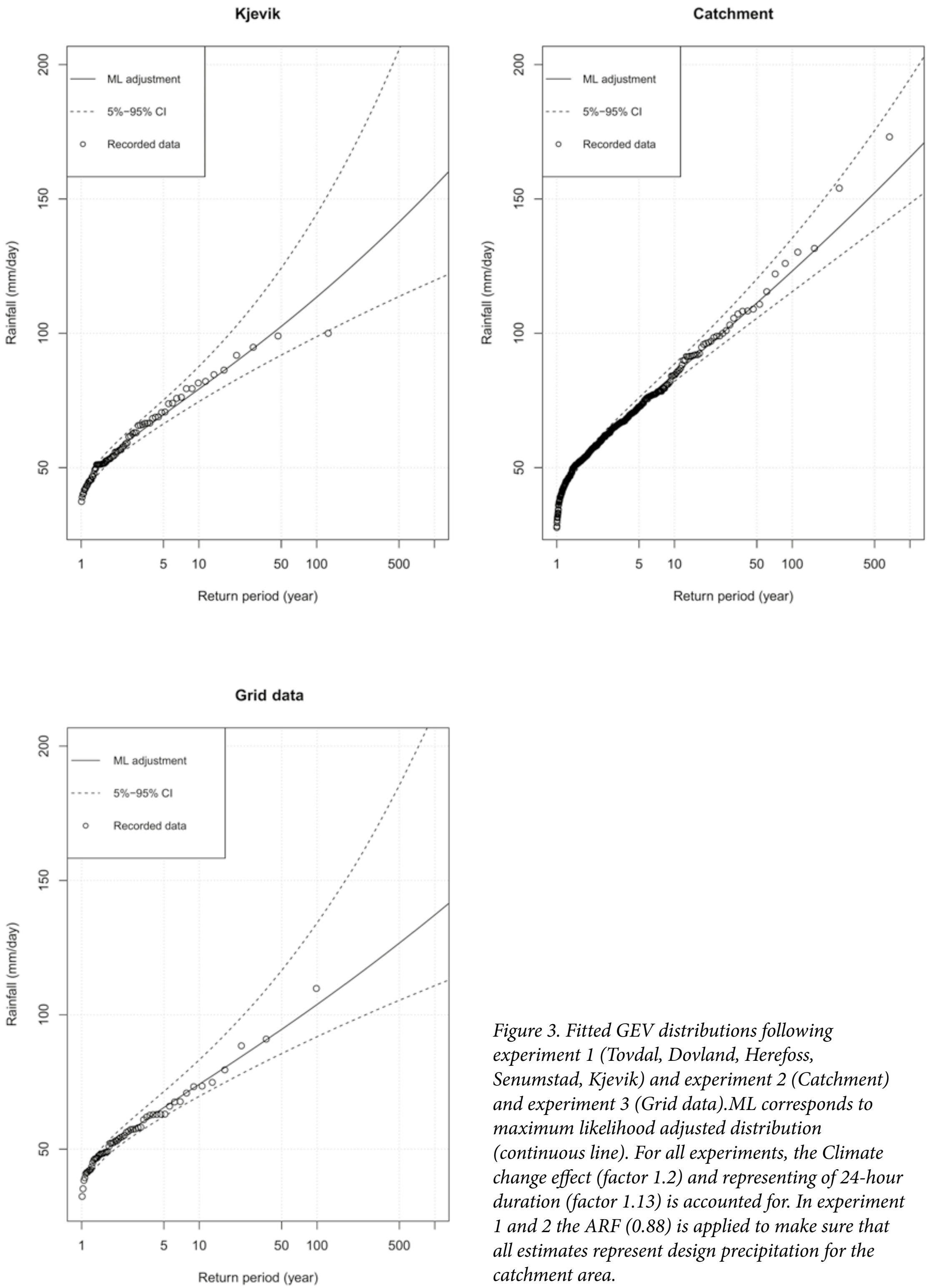


Figure 3. Fitted GEV distributions following experiment 1 (Tovdal, Dovland, Herefoss, Senumstad, Kjevik) and experiment 2 (Catchment) and experiment 3 (Grid data).ML corresponds to maximum likelihood adjusted distribution (continuous line). For all experiments, the Climate change effect (factor 1.2) and representing of 24-hour duration (factor 1.13) is accounted for. In experiment 1 and 2 the ARF (0.88) is applied to make sure that all estimates represent design precipitation for the catchment area.

For experiment 1, we see from Table 3 and Fig. 4 that the highest design rainfall value (ML) and its confidence intervals is estimated for Senumstad station, and the lowest values are obtained for Kjevik (lowest ML and 5% CI) and Herefoss (lowest 95% CI). From the table it can be seen that the data from the stations Tovdal, Kjevik and Dovland results in rather similar ranges.

Comparing the ranges obtained from experiment 1 and 2, it can be seen that the second experiment (catchment) leads to more narrow prediction intervals whereas the ML estimate is practically similar to the estimated design precipitation at the Tovdal station and slightly smaller than the average of the design rainfall estimated at each station.

Using the gridded data in experiment 3 (Grid data) results in slightly smaller ML estimates than the values obtained from experiment 1 and 2. The only exception can be seen for Senumstad station, which is considerably higher than the Grid-based ML value, and Kjevik which corresponds to smaller ML value. Likewise, the 5% CI value for the grid-based estimate is lower than the other stations except for Dovland and

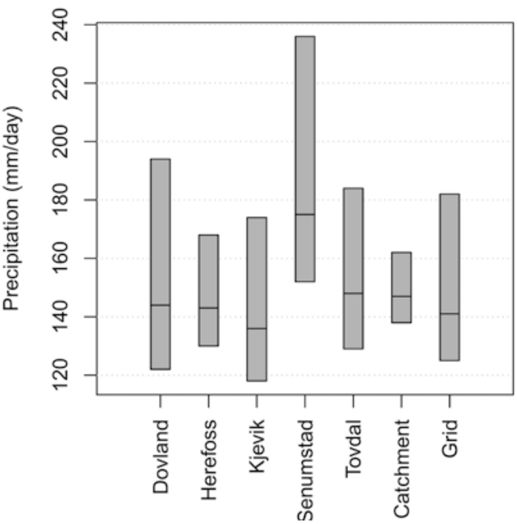


Figure 4. Comparing the estimated 100-year design rainfall values resulted from experiment 1 (Dovland, Herefoss, Kjevik, Senumstad and Tovdal), experiment 2 (Catchment), and experiment 3 with grid data.

Kjevik, whereas the 95% CI value is below the values obtained from Dovland, Senumstad and Tovdal.

The results from experiment 1 shows that using data from only one precipitation station when estimating a design rainfall for a large catchment might be challenging since the selected station might not be representative for the whole catchment. In this study, Senumstad provides the highest estimates (147 mm) whereas Kjevik provides the lowest estimate (114 mm). Using several precipitation stations inside and close to the catchment, allows us to provide more robust estimates.

The estimates from Herefoss, Dovland, Kjevik, Tovdal and SeNorge are not significantly different, and the estimates are practically similar. This shows that for this particular catchment, the gridded data are useful for estimating design rainfall, and we avoid the use of ARFs and the need to select one particular precipitation station. Since we in this study do not want to under-estimate the uncertainty, we selected to use the estimates from Dovland station. However, we recognize, that in areas with a larger spatial variability in precipitation, the use of one single station would be even more challenging.

One important issue that should be considered in time series analyses, is the selection of the length of the time series. To investigate the effect of time series period on the estimated design rainfall, various time spans that consist of the most recent 30, 40, 50, 60, 70,80, 90 and 100 years of data were used to estimate the 100-year design rainfall and the results are displayed in Fig. 5 for each of the stations. According to the results, the changes in the modified ML estimates are not significantly different (Fig. 5 (a)). Unlike the ML line, the variation in upper bound (0.95 CI) is considerable when moving from shorter to longer periods. A decreasing trend can be observed in 0.95 CI values by increasing the data length. However, there are exceptions such as in Kjevik (70 years), Tovdal (90 years) and Senumstad (50 years). The variation of 0.95 CI line can to a large degree be attributed to the uncertainty in the estimated shape parameter which depends on the length of data.

According to Fig. 5, using the longer time spans narrows down the estimated interval or in other words results in smaller uncertainties. This is a direct effect of the increasing sample size that decreases the sample uncertainty. In extreme value analysis, there is a strong tradition for using the maximum possible amount of data when estimating design values to reduce estimation uncertainties. However, in the presence of changes in the climate, using long time series might result in biased estimates. Detecting trends in extremes is challenging since strong variability from year-to-year masks possible trends. To investigate the presence of trends in location and scale parameters, the nonstationary GEV models were developed and tested for each of the stations (location and scale parameters as time varying parameters) and no significant trends were found, neither in the location nor the scale parameters. A stationary model was therefore used for this catchment.

Conclusions

In this study, a Bayesian inference is used along with prior knowledge about the shape parameter to fit the Generalised Extreme Value (GEV) distribution for annual maximum rainfall data. The method was used for three experiments. Firstly, the method was applied for each station. Secondly, the estimated posteriors of the stations were merged into one sample and the design rainfall range was identified. Thirdly, the catchment average precipitation from SeNorge was used in the estimations. The results of the experiments were compared with each other. Furthermore, the effect of selecting different periods to estimate the quantiles intervals were assessed. The main results of this paper are as follows:

- Using precipitation data from only one station to estimate design rainfall might result in biased estimates. Hence, it is better to use several stations within or close to the target catchment.
- Using one sample involving all the posteriors (experiment 2, catchment-based scenario)

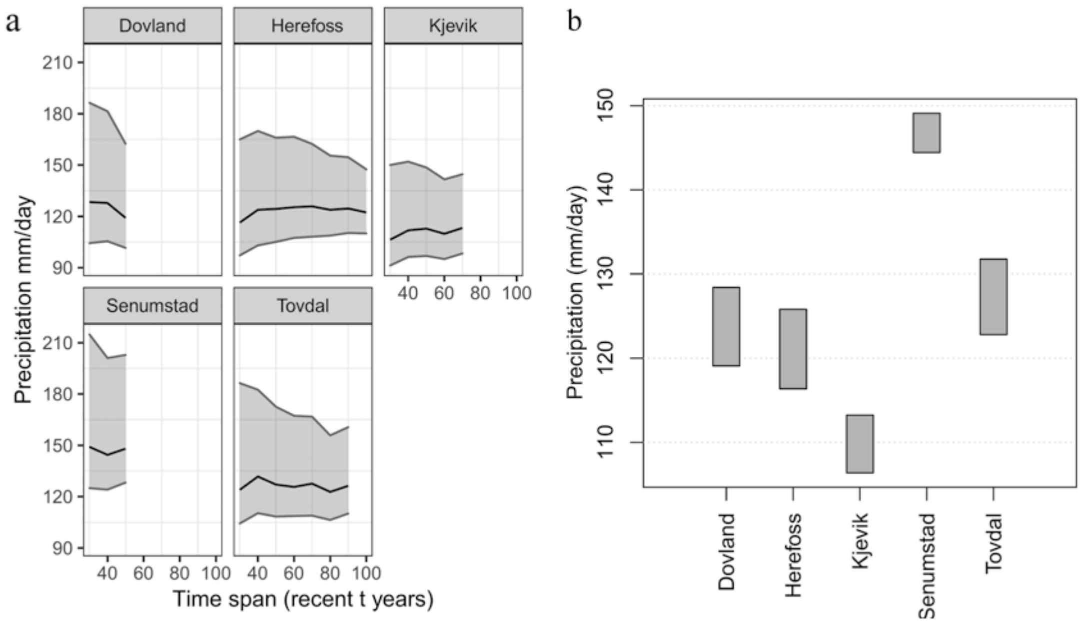


Figure 5. a. The effect of time series length on the estimated 100-year design rainfall (the middle black line presents the ML values, and the upper and lower lines display the 95% and 5% CI). b. the variation ranges for ML values displayed in panel a.

may narrow down the estimated design rainfall interval but it may result into small predictive uncertainty and therefore fail to cover possible extreme events.
- Using gridded precipitation data gave similar results to using station-based data combined with area reduction factor.
- The length of the time series and the number of years that are representing the extremes is a trade-off between having sufficient data to reduce sampling uncertainty and avoiding possible non-stationarities in the extremes. For this study, the stationarity assumption was fulfilled.

The estimated 100-year precipitation based on the data from Dovland was selected to be used to represent the uncertainty in design precipitation and will be used for further analysis of flood zones. We believe that the prediction range is in particular useful for risk-assessments and could also be used to provide safety factor that reflects the knowledge (and uncertainty) in our estimates and are therefore more tailored to each application.

References

Agilan, V., Umamahesh, N., 2017. What are the best covariates for developing non-stationary rainfall intensity-duration-frequency relationship? Advances in Water Resources, 101: 11-22.

Bayes, T., 1763. LII. An essay towards solving a problem in the doctrine of chances. By the late Rev. Mr. Bayes, FRS communicated by Mr. Price, in a letter to John Canton, AMFR S. Philosophical transactions of the Royal Society of London(53): 370-418.

Cannon, A.J., 2010. A flexible nonlinear modelling framework for nonstationary generalized extreme value analysis in hydroclimatology. Hydrological Processes: An International Journal, 24(6): 673-685.

Coles, S., 2001. Extremes of non-stationary sequences, An introduction to statistical modeling of extreme values. Springer, pp. 105-123.

Cunderlik, J.M., Burn, D.H., 2003. Non-stationary pooled flood frequency analysis. Journal of Hydrology, 276(1-4): 210-223.

DeGaetano, A.T., Castellano, C., 2018. Selecting time series length to moderate the impact of nonstationarity in extreme rainfall analyses. Journal of Applied Meteorology and Climatology, 57(10): 2285-2296.

Dyrrdal, A.V., 2012. Estimation of extreme precipitation in Norway and a summary of the state-of-the-art. Meteorologisk institutt. met. no rapport, 8: 19.

Dyrrdal, A.V., Skaugen, T., Stordal, F., Førland, E.J., 2016. Estimating extreme areal precipitation in Norway from a gridded dataset. Hydrological Sciences Journal, 61(3): 483-494.

Fisher, R.A., Tippett, L.H.C., 1928. Limiting forms of the frequency distribution of the largest or smallest member of a sample, Mathematical proceedings of the Cambridge philosophical society. Cambridge University Press, pp. 180-190.

Hanssen-Bauer, I., Drange, H., Førland, E., Roald, L., Børsheim, K., Hisdal, H., Lawrence, D., Nesje, A., Sandven, S., Sorteberg, A., 2009. Climate in Norway 2100. Background information to NOU Climate adaptation (In Norwegian: Klima i Norge 2100. Bakgrunnsmateriale til NOU Klimatilplassing), Oslo: Norsk klimasenter.

Jenkinson, A.F., 1955. The frequency distribution of the annual maximum (or minimum) values of meteorological elements. Quarterly Journal of the Royal Meteorological Society, 81(348): 158-171.

Kedem, B., Chiu, L.S., Karni, Z., 1990. An analysis of the threshold method for measuring area-average rainfall. Journal of Applied Meteorology and Climatology, 29(1): 3-20.

Khaliq, M.N., Ouarda, T.B., Ondo, J.-C., Gachon, P., Bobée, B., 2006. Frequency analysis of a sequence of dependent and/or non-stationary hydro-meteorological observations: A review. Journal of hydrology, 329(3-4): 534-552.

Kobierska, F., Engeland, K., Thorarinsdottir, T., 2018. Evaluation of design flood estimates–a case study for Norway. Hydrology Research, 49(2): 450-465.

Leclerc, M., Ouarda, T.B., 2007. Non-stationary regional flood frequency analysis at ungauged sites. Journal of hydrology, 343(3-4): 254-265.

Lima, C.H., Kwon, H.-H., Kim, Y.-T., 2018. A local-regional scaling-invariant Bayesian GEV model for estimating rainfall IDF curves in a future climate. Journal of Hydrology, 566: 73-88.

Lima, C.H., Lall, U., Troy, T., Devineni, N., 2016. A hierarchical Bayesian GEV model for improving local and regional flood quantile estimates. Journal of Hydrology, 541: 816-823.

Lutz, J., Grinde, L., Dyrrdal, A.V., 2020. Estimating Rainfall Design Values for the City of Oslo, Norway—Comparison of Methods and Quantification of Uncertainty. Water, 12(6): 1735. DOI: https://doi.org/10.3390/w12061735

Martins, E.S., Stedinger, J.R., 2000. Generalized maximum-likelihood generalized extreme-value quantile estimators for hydrologic data. Water Resources Research, 36(3): 737-744.

Ouarda, T.B., Charron, C., 2019. Changes in the distribution of hydro-climatic extremes in a non-stationary framework. Scientific reports, 9(1): 1-8.

Pelosi, A., Furcolo, P., Rossi, F., Villani, P., 2020. The characterization of extraordinary extreme events (EEEs) for the assessment of design rainfall depths with high return periods. Hydrological Processes, 34(11): 2543-2559.

Renard, B., Lang, M., Bois, P., 2006. Statistical analysis of extreme events in a non-stationary context via a Bayesian framework: case study with peak-over-threshold data. Stochastic environmental research and risk assessment, 21(2): 97-112.

Svensson, C., Jones, D.A., 2010. Review of methods for deriving areal reduction factors. Journal of Flood Risk Management, 3(3): 232-245.

Um, M.-J., Kim, Y., Markus, M., Wuebbles, D.J., 2017. Modeling nonstationary extreme value distributions with nonlinear functions: an application using multiple precipitation projections for US cities. Journal of Hydrology, 552: 396-406.

Vanem, E., 2015. Uncertainties in extreme value modelling of wave data in a climate change perspective. Journal of Ocean Engineering and Marine Energy, 1(4): 339-359.

Viglione, A., Hosking, J.R., Laio, F., Miller, A., Gaume, E., Payrastre, O., Salinas, J.L., N'guyen, C.C., Halbert, K., Viglione, M.A., 2020. Package 'nsRFA'. Non-supervised Regional Frequency Analysis. CRAN Repository, Version 0.7-15.

Wright, D.B., Smith, J.A., Baeck, M.L., 2014. Critical examination of area reduction factors. Journal of Hydrologic Engineering, 19(4): 769-776.

Yan, H., Moradkhani, H., 2016. Toward more robust extreme flood prediction by Bayesian hierarchical and multimodeling. Natural Hazards, 81(1): 203-225.

Yoon, P., Kim, T.-W., Yoo, C., 2013. Rainfall frequency analysis using a mixed GEV distribution: a case study for annual maximum rainfalls in South Korea. Stochastic Environmental Research and Risk Assessment, 27(5): 1143-1153.