Applying extreme value theory to a gridded dataset - a method for estimating extreme areal precipitation in Norway

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Abstract

(UPDATE WHEN FINISHED!!!) To obtain estimates of extreme areal precipitation in Norway, the Norwegian Meteorological Institute currently applies a statistical method that combines measured point precipitation, empirical growth factors, and areal reduction factors. We here suggest performing statistical analysis directly on areal 24-hour precipitation from a gridded dataset covering the period 1957-today. Grid-based methods provide increased objectivity and consistency, and enables estimation in ungauged catchments. The proposed method fits the Generalized Extreme Value (GEV) distribution to areal precipitation series.

1 Introduction

Estimates of extreme precipitation are decisive for planning and design of important infrastructure, such as reservoir dams, water control systems, urban runoff and transport lines. The accuracy of extreme precipitation estimates is therefore crucial in both economic and safety aspects. Precipitation in regions with varied topography, like Norway, is influenced by contributions from large-scale frontal systems, subject to orographic effects through forced lifting of air masses, and convective small-scale systems. The relatively sparse station network also adds to the complexity. Extreme precipitation estimates are usually presented as values with low frequency of occurrence or long return periods. For dam design and flood estimation in Norway, the probable maximum precipitation (PMP) is applied along with the 500 or 1000 year return levels, depending on the risk (*NVE*, 2011). Authorities for roads, railways, and urban planning are more concerned with short-term and intense precipitation with return periods of 5 to several hundred years.

For most purposes, there is a need for integrated precipitation over an area, introducing a number of challenges because precipitation is associated with large spatial variability. As stated by *Skaugen* et al. (1996), extreme areal precipitation will be a sum of variables, partially from the parent distribution and partially from the distribution of its extremes. *Skaugen* et al. (1996) also describes how the central limit theorem applies when the point process is spatially independent, implying that the distribution of areal precipitation converges to a Gaussian. Consequently, the parent distribution converges to a Gaussian as the area increases and spatial correlation is reduced. Simultaneously, the extremes of the same distribution converge to a Generalized Extreme Value (GEV) distribution of Type I. This is in accordance with *Leadbetter* et al. (1980) who state that "if X_n is an independent and identically distributed (i.i.d.) (standard) normal sequence of random variables, then the asymptotic distribution of $M_n = max(X_1, ..., X_n)$ is of Type I". We here present a method for estimating extreme areal precipitation in large and small catchments on the Norwegian mainland, and relate our analysis to the theory introduced above.

According to *Hanssen-Bauer* et al. (2009) an increase in annual precipitation is observed in the entire country throughout the last century, particularly since the end of the 1970s. In addition, the frequency and intensity of extreme precipitation events are projected to increase (*Hanssen-Bauer* et al., 2009; *Seneviratne* et al., 2012). The intensity of rainfall-induced floods are thus expected to increase and higher temperatures probably lead to a shift towards earlier spring floods and increased possibility for floods during late autumn and winter (*Wilson* et al., 2010; *Hanssen-Bauer* et al., 2009; *Hisdal* et al., 2006). Due to these observed and projected changes, existing design criteria for infrastructure should be revised. *Svensson & Jones* (2010) found that there is no obvious preferred method for estimating extreme areal precipitation, but that most countries use some kind of regionalization to transfer information from one location to another.

The Norwegian Meteorological Institute (MET Norway) has a national responsibility for providing estimates of extreme areal precipitation estimates in Norway. The present approach (*Førland & Kristoffersen*, 1989; **?**) is a modified version of a method developed by the National Environment Research Council (NERC) in Great Britain in 1975 (*NERC*, 1975). The method is based on point measurements at meteorological stations and empirical "growth factors", and is here referred to as the station-based growth factor method (SB-gf). Estimation is time-consuming as it implies several manual steps, including subjective measures which influences the result significantly. The latter leads to a certain lack of consistency.

We therefore propose a new method, hereby referred to as the grid-based GEV method (GB-GEV), for estimating extreme areal precipitation based on gridded daily precipitation data with 1 km resolution and the GEV distribution. Fine-scale grids have the advantage of providing spatially continuous datasets and an improved basis for estimates in ungauged catchments. Additionally, downscaled climate projections exist on a similar grid, which enables estimation of extreme precipitation for future climate conditions. SB-gf and GB-GEV are presented in the flowchart in Fig. 1 and terminologies are further explained below. In sections 2 and 3 we describe the two methods, and analyze the GEV shape parameter for Norwway. Section 4 provides results from the method comparison and a discussion, followed by conclusions and recommendations in section 5.

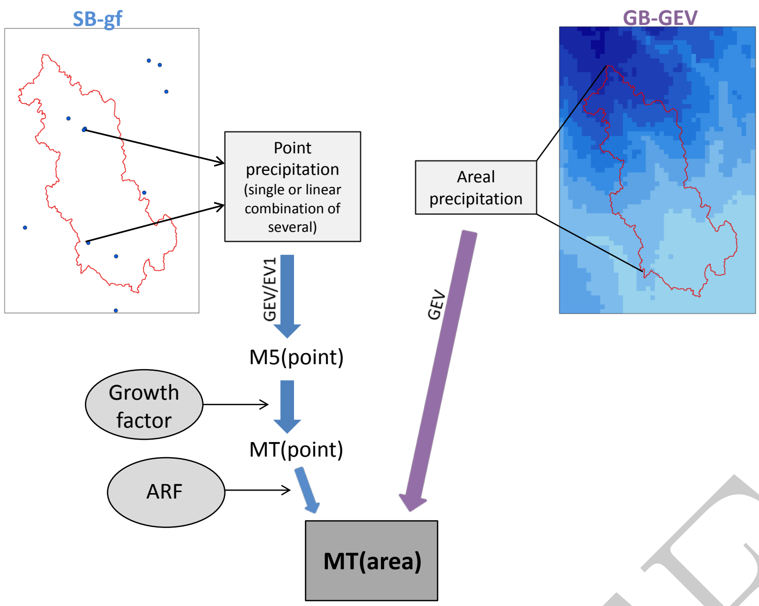

Figure 1: Flowchart of the two methods for estimating extreme precipitation; SB-gf and GB-GEV.

Definitions:
PN: Normal annual precipitation [mm] (average for the period 1961-1990)
T: Return period [years]
MT: Precipitation with a T year return period [mm] (e.g. M5: Precipitation with a 5 year return period)
MT (n hr): Precipitation of n hours duration with a T year return period (e.g. M5(24hr): Precipitation of 24 hours duration with a 5 year return period)
PMP: Probable maximum precipitation [mm], defined as the theoretical maximum precipitation for a given duration under modern meteorological conditions (*WMO*, 2009)
ARF: Areal reduction factor (*NERC*, 1975; *Bell*, 1976)
SB-gf: Station-based growth factor method (*NERC*, 1975; *Førland & Kristoffersen*, 1989; **?**)
GB-GEV: Grid-based Generalized Extreme Value (GEV) method

2 SB-gf

In the UK Flood Studies Report (*NERC*, 1975) a comprehensive statistical analysis was performed on a large rainfall dataset. Empirical growth factors were developed, describing MT as a function of M5, also called the index value. M5 for a ‘representative point” within the area is estimated by the Gumbel-method (*Gumbel*, 2004), equivalent to fitting a GEV type I distribution, and MT is computed in the following way

$$MT = M5e^{C[ln(T-0.5)-1.5]} \tag{1}$$

The factor C is determined empirically as a function of M5, and varies geographically. Analysis performed by *Førland* (1987) suggest that values defined for Scotland and Northern Ireland are most suitable for Norwegian conditions. For 24-hour precipitation with M5 between 25 and 350 mm, C may be approximated by

$$C \sim 0.3584 - 0.0473ln(M5) \tag{2}$$

Growth factors are used along with standardized ARFs, coverting point values to areal values, and together they constitute the method we here call SB-gf.

The implementation of growth factors from the UK (*NERC*, 1975) at MET Norway more than 30 years ago was motivated by its relatively simple execution at the time, the large amounts of data, and the extensive statistical analysis behind. Because computer power has increased considerably, the use of empirical growth factors may not be the optimal approach today. In addition, growth factors were originally developed for point precipitation and applying it on areal precipitation might violate the statistical assumptions on which it was based.

3 GB-GEV

3.1 Gridded precipitation

Gridded estimates of daily precipitation for the Norwegian mainland are available at MET Norway for the period 1957 until today (www.seNorge.no). These are obtained from observations at approximately 400 precipitation stations, interpolated to a 1x1 km^2 grid (*Tveito* et al., 2005; *Mohr*, 2009; *Jansson* et al., 2007). Irregular triangular networks (TINs) are applied in the interpolation; an elevation TIN based on the altitude at the meteorological stations and a precipitation TIN based on measured precipitation. A terrain adjustment is performed, assuming that precipitation increases by 10% per 100 m up to 1000 masl and by 5% above that (*Førland*, 1979, 1984). The gridded dataset is used operationally in e.g. flood forecasting in Norway.

Uncertainties associated with the gridded dataset are mainly related to the interpolation procedure, which in areas with rough topography is particularly challenging. Precipitation enhancement with elevation is based on a simple model known to be highly inaccurate in some cases. For instance, *Engeset* et al. (2004); *Saloranta* (2012) found that the vertical precipitation gradient is exaggerated, leading to overestimation in high elevations and underestimation in some low elevated areas. In regions with a limited amount of stations (mountains and northern regions), the influence of single stations is large and may cause biases in the grid-based results.

3.2 The GEV distribution

The GEV distribution describe the three possible types of extreme value distributions for block maxima of any variable (*Coles*, 2001). We have that the cumulative distribution of the block maxima converges to a GEV distribution G(x) as the record length approaches infinity. The three-parameter GEV distribution is of the form

$$G(x) = exp\{-[1 + \xi(\frac{z-\mu}{\sigma})]^{-\frac{1}{\xi}}\} \tag{3}$$

where μ = location, σ = scale, and ξ = shape. Depending on ξ, the GEV distribution converge into one of three types (defined according to the convention used in *Coles* (2001)); Type I/Gumbel/EV1 ($\xi = 0$), Type II/Fréchet/EV2($\xi > 0$), and Type III/Weibull/EV3($\xi < 0$).
Over the years GEV has become an established and widely used model, for precipitation extremes included, and a large variety of analysis tools are developed. *Coles & Tawn* (1996) claim this to be valid also for areal precipitation.

3.3 Estimation of areal extremes

We want to improve the methodology for estimating extreme areal precipitation by moving from point precipitation from meteorological stations (station-based) to areal precipitation from the gridded dataset (grid-based), and from growth factors to the GEV distribution. As areal time series are applied, ARFs become redundant. We fit the GEV distribution to annual maximum areal 24-hour precipitation in each catchment. The method of "maximum likelihood estimation" (MLE) is primarily used to estimate the GEV parameters. An immediate advantage of GEV over growth factors is the possibility for an uncertainty measure in terms of confidence intervals.

It is common practice to use PMP-estimates in the design of critical constructions like e.g. reservoir dams. PMP is supposed to represent a precipitation amount with a return period of infinity. However, discussions in the literature point to great disagreement on whether there exists an upper limit to precipitation, and both ethical and technical issues are associated with the concept (*Benson*, 1973; *Koutsoyiannis*, 2004a). Statistical methods represent great uncertainties for long return periods, and the evolvement of numerical weather models introduces the possibility of perhaps more physically based PMP-estimates (*Cotton* et al., 2003; *WMO*, 2009). With these considerations we have in this study not attempted a new statistical method for PMP-estimation, however, we suggest that a thorough analysis of model-based estimation methods is carried out in the future.

3.4 The GEV ξ-parameter

Estimation of the GEV ξ-parameter is very uncertain, especially for short time series which is often the case with meteorological variables. At the same time ξ is essential in extrapolating to longer return periods. Here we refer to ξ for point and areal precipitation as ξ_p and ξ_a, respectively.

3.4.1 Point precipitation

According to several studies, extreme 24-hour precipitation at a point follows a Type II distribution (heavy upper tail; ξ_p>0) (*Wilks*, 1993; *Koutsoyiannis & Baloutsos*, 2000; *Katz* et al., 2002; *Coles* et al., 2003; *Coles & Pericchi*, 2003; *Koutsoyiannis*, 2004a). This distribution also represents the lowest risk for engineering structures as design values are higher than for Type I and Type III. (*Buishand*, 1989; *Coles & Tawn*, 1990; *Buishand*, 1991; *Coles & Tawn*, 1996; *Koutsoyiannis*, 1999, 2004b). *Wilson & Toumi* (2005) give evidence for a universal ξ_p and are supported by *Veneziano* et al. (2009) who suggest a near-universal ξ_p only depending on duration. *Koutsoyiannis* (2004b) studied ξ_p using several methods of estimation, and a ξ_p of 0.15 is indicated as appropriate for mid-latitude areas of the Northern Hemisphere. *Wilson & Toumi* (2005) found a mean ξ_p estimate of 0.10 when fitting a GEV distribution to long daily precipitation records from the UK. *Veneziano* et al. (2009) suggests that a constraint on ξ using theoretical arguments is necessary.

In Fig. 2a we present MLE-estimates of ξ_p in single 1x1 km^2 grid-cells for the period 1957-2012. Negative ξ_p are seen mostly in coastal areas, while continental parts are dominated by positive values. Due to large uncertainties in parameter estimation we performed the same estimation using "weighted least squares" (WLS) (*Koutsoyiannis*, 2004b). WLS gives higher importance to the largest values with weights equal to the empirical quantiles, and was shown by *Koutsoyiannis* (2004b) to be a better fit to empirical values. WLS-estimates (not shown) give a wider range of values, but keep the same spatial pattern. We also estimated ξ_p from measurements at 569 observational sites (cf. Fig. 5), and the distribution from both datasets are plotted in Fig. 3. The distribution from the observational dataset is scaled for plotting purposes. A near Gaussian distribution of ξ_p around 0.02-0.03 is evident. To assess the regional variability of ξ_p, we selected 18 series with more than 100 records (cf. Fig. 5) and applied Pearson's Chi-square test with α-level of 0.05 to test independence between ξ_p at paired sites. ξ_p for 6 sites in the continental southeast and 6 sites in the southwest show no significant variation within the separate regions. Applying the station-year method to create a combined series from the respective 6 sites, we find an estimated ξ_p of 0.04 in the southwest and 0.07 in the southeast. As we combine the 12 sites, in addition to 6 sites in other parts of the country, significant regional variation is evident, suggesting that a constant ξ_p is not appropriate in Norway.

It is essential to realize that GEV and other mathematical distributions are simply models that represent an estimated reality. The complexity of nature, however, introduces a number of reasons why our observational series and associated estimates do not strictly follow the theoretical framework. In addition to sampling effects related to short time series and uncertainty associated with non-accurate estimation methods, some of the deviance between observations and theory might be explained by the different weather systems producing extreme precipitation in Norway. Comparing Figs. 2a and 2b reveals that negative ξ_p-estimates are mostly found in areas characterized by higher annual precipitation. In these areas the highest daily precipitation values are dominated by stratiform systems in the prevailing westerlies, and the precipitation intensity is enhanced by orographic effects across the Norwegian mountain range. However, in most areas with positive ξ_p, high-intensity precipitation may occur during frontal systems from the SE-E sector, as well as for heavy convective summer showers. The positive ξ_p may thus be explained by these regions being exposed to mixed-type precipitation systems;- isolated convective showers, stratiform frontal systems or embedded convective cells within frontal systems.

In Fig. 4 we further analyse the relationship between ξ_p and PN, confirming the above statement that ξ_p decreases with increasing PN. A linear regression shows that this relationship becomes stronger for longer record lengths.

Papalexiou & Koutsoyiannis (2012) also found that ξ_p-estimates depend on the record length, and show a tendency to a larger ξ_p for longer series. To investigate a possible dependence in Norway we plot ξ_p at the 569 observational sites against record length (Fig. 5). We estimate ξ_p using both MLE and and WLS. We divided the 569 series into different lengths to increase the amount of data, and computed the median, 5th and 95th quantiles for all lengths for which at least 5 series were available. We find a very weak trend in ξ_p with record length, but the variability is strongly reduced and ξ_p-estimates seem to converge towards a slightly positive value. WLS-estimates are somewhat higher than MLE-estimates for all record lengths, and has a wider range of values as mentioned above. 62% of WLS-estimates are positive, while only 57% of MLE-estimates are positive. However, the difference between estimates at single sites seems quite random, and since WLE has trouble converging at times we choose to stay with MLE. (KAN GI MER UTDYPENDE ARGUMENTER FOR AA FORTSETTE MED MLE OM NODVENDIG. ESTIMERING AV USIKKERHET ER EN STOR OPPGAVE, SIDEN VI ANTAGELIGVIS MAA BRUKE BOOTSTRAPPING.)

We have shown that ξ_p varies between regions in Norway, and that this variability can be related to PN. We also observe that record length influence the ξ_p-estimates and that the accuracy most likely incresases significantly with longer series. The relatively short time series of 55 years available from the gridded dataset imposes great uncertainties and we therefore propose to restrict ξ_p according to findings in Figs. 4 and 5. Fig. 4 suggests a start value of 0.15 for very arid regions and a decrease of $\tilde{0}.08$ per 1000 mm increase in PN, which corresponds well with the range for longer series in Fig. 5. The start value of 0.15 also agrees well with other studies. Acoording to theory ξ_p varies smoothly in space and literature has shown that it is constant over larger regions, thus we can determine ξ_p through the average PN in a catchment.

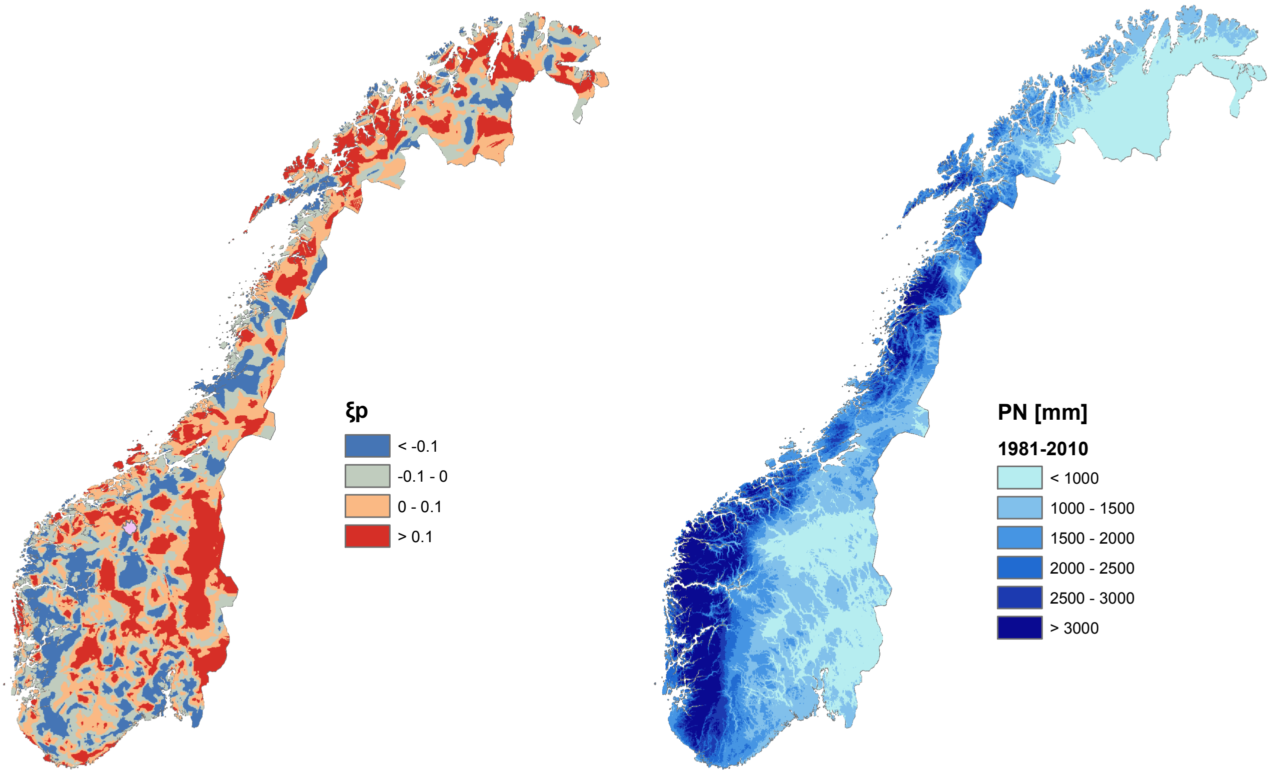

Figure 2: a) Estimated ξ_p. b) Mean annual precipitation for the period 1981-2010.

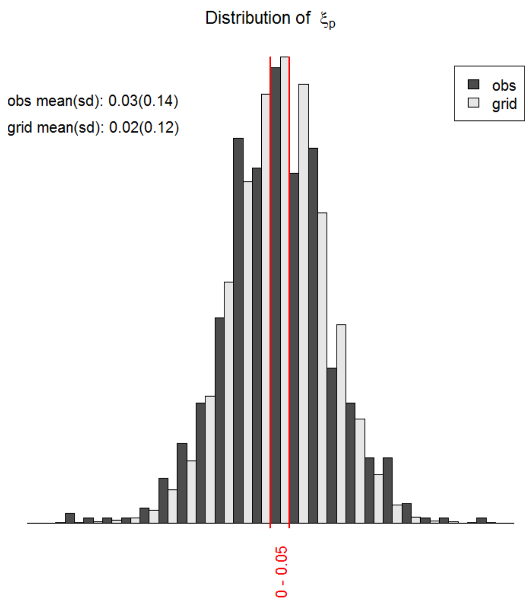

Figure 3

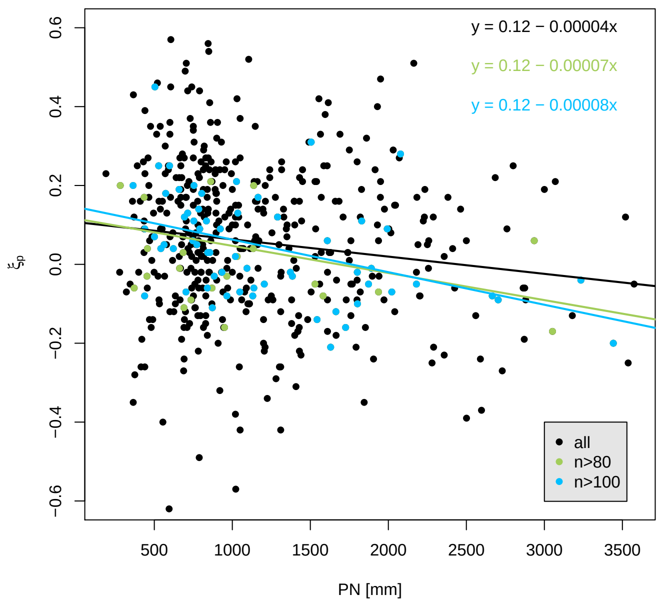

Figure 4

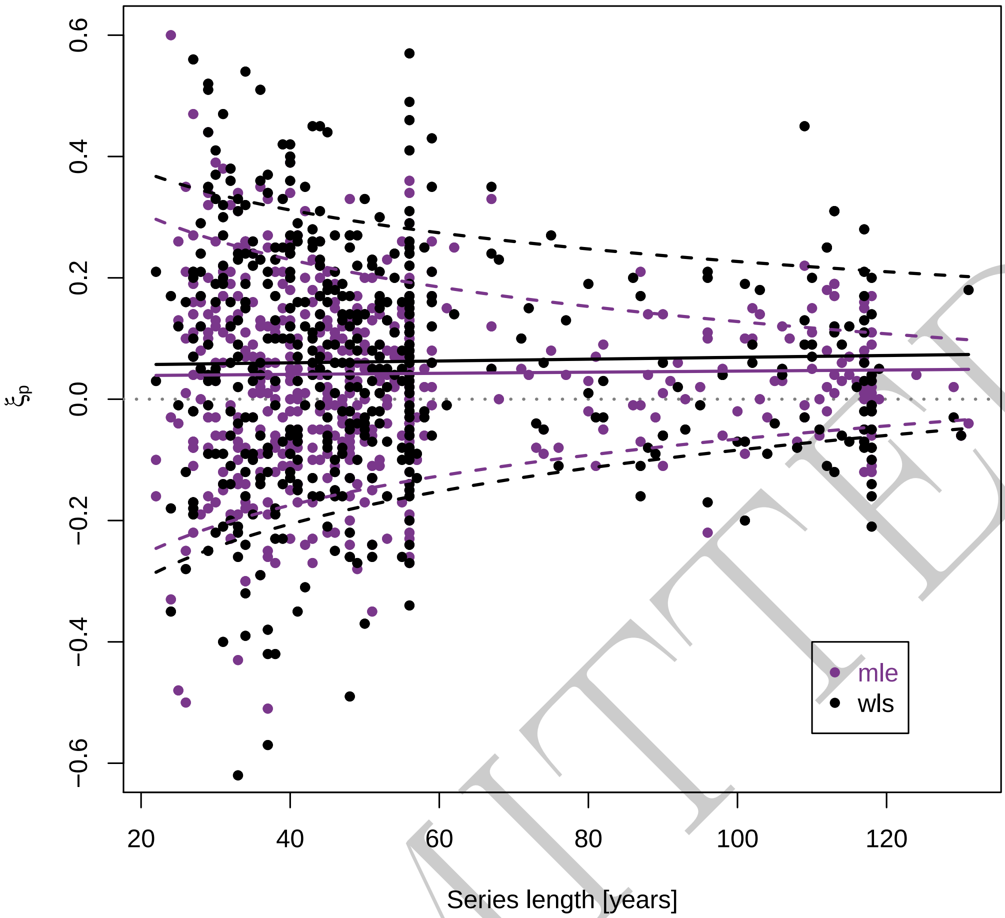

Figure 5

3.4.2 Areal precipitation

As mentioned earlier, areal precipitation has a different frequency distribution than point precipitation, also with regards to extremes. The distribution of extreme areal precipitation is not well studied, mostly because areal precipitation is not a directly measurable variable. As spatial correlation decreases with increasing area it is reasonable to expect the parent distribution to converge towards a Gaussian due to the central limit theorem, as explained in the introduction. The domain of attraction of a Gaussian upper tail is the GEV Type I distribution. Thus, according to mathematical theory, areal precipitation extremes converge towards a GEV type I. This should apply regardless of the distribution of point precipitation within the same area.

Overeem et al. (2010) studied ξ_a from weather radar in the Netherlands. Goodness of fit tests were used to show that the GEV distribution fits adequately to areal precipitation data, although the convergence is slower and the need for longer data series is even more crucial. *Overeem* et al. (2010) found that ξ_a decreases with increasing area, moving from a GEV Type II towards a GEV Type I, and suggest that this may be attributed to the nature of spatial dependence of precipitation.

We argued in the last section that the range of extremes, and thus the ξ-parameter, will vary according to dominating precipitation systems. Another aspect for areal precipitation is that different processes will create a different population of extremes depending on the size of the catchment. For further analysis we selected 17 catchments in Norway, varying in size from 105 to 5693 km^2. The catchments were selected according to availability of SB-gf estimates and to represent different parts of the country. They are presented in Table 1 and in Fig. 6.

We compared ξ_a and the mean ξ_p in all catchments, using the gridded dataset. There is a tendency to larger difference between ξ_p and ξ_a in larger catchments, as a result of reduced spatial correlation. Fig. 7 reveals a weak pattern indicating that ξ_a is reduced compared to ξ_p when $\xi_p > 0$, and increased when $\xi_p < 0$. This supports our theoretical hypothesis that extreme areal precipitation converges towards a GEV Type I distribution as the area increases and spatial correlation approaches zero, regardless of the extremal distribution in a point. Several catchments depart from this pattern, however, which might be explained by poor representation of spatial correlation in the gridded dataset. No assumption on spatial correlation is included in the gridding procedure, thus in areas with a sparse station network the correlation to distant stations from which the triangulation is made is likely to be exaggerated.

HVORDAN BESTEMME SHAPE(AREAL) FRA SHAPE(PUNKT)? (HVIS VI BESTEMMER OSS FOR AA MODELLERE SHAPE OG IKKE ESTIMERE DIREKTE...) PAA SAMME MAATE SOM I FORSTE VERSJON??? HITTIL ER SHAPE(AREAL) = SHAPE(PUNKT) - BESTEMT MED GJENNOMSNITTLIG PN I VASSDRAGET: SHAPE = 0.15 - 0.00008*PN

Catchment	**Size [km^2]**	**Median elevation**	**PN [mm]**	**Reference**
1. Teksdal	105/107	177	1300/1555 (+19.6%)	*Førland* (1997)
2. Lauvsnes	114/107	209	1350/1380 (+2.2%)	*Isaksen* (2006)
3. Aursunda	118/119	260	1300/1398 (+7.5%)	*Mamen* (2009)
4. Svartevatn	210/204	1046	2050/2748 (+34.0%)	*Førland* (1991b)
5. Roskreppfjord	282/266	1050	1450/1887 (+30.1%)	*Førland* (1991b)
6. Vekteren	308/293	610	1250/1118 (-10.6%)	*Førland* (1991a)
7. Siljan	490/492	220	1050/1157 (+10.2%)	*Førland* (1986b)
8. Aursjøen	487/496	1280	760/829 (+9.1%)	*Hanssen-Bauer* (1992)
9. Jølstra	570/573	680	2200/3130 (+42.3%)	*Førland* (1986a)
10. Namsvatn	696/701	750	1300/1151 (+11.5%)	*Førland* (1991a)
11. Soneren	701/754	540	900/989 (+9.9%)	*Hanssen-Bauer* (1991)
12. Sira	1720/1554	693	2020/2529 (+25.2%)	*Førland* (1991b)
13. Røssvatn	1500/1941	580	1200/1536 (+28.0%)	*Førland* (1988)
14. Røssåga	1800/1941	580	2000/1536 (-23.2%)	*Mamen* (2011b)
15. Barduelva	2366/2107	671	575/892 (+55.1%)	*Førland* (1990)
16. Arendal	4200/4006	520	1150/1290 (+12.2%)	*Mamen* (2011a)
17. Virdnejavrre	5693/5805	435	450/434 (-3.6%)	*Førland* (1994)

Table 1: Catchments sorted after increasing size. Median elevation is taken from the digital elevation model with 1 km resolution applied in the gridded dataset. Values used in SB-gf are shown first, followed by values used in GB-GEV. The percentage difference between PN used in SB-gf and PN used in GB-GEV is given in parentheses.

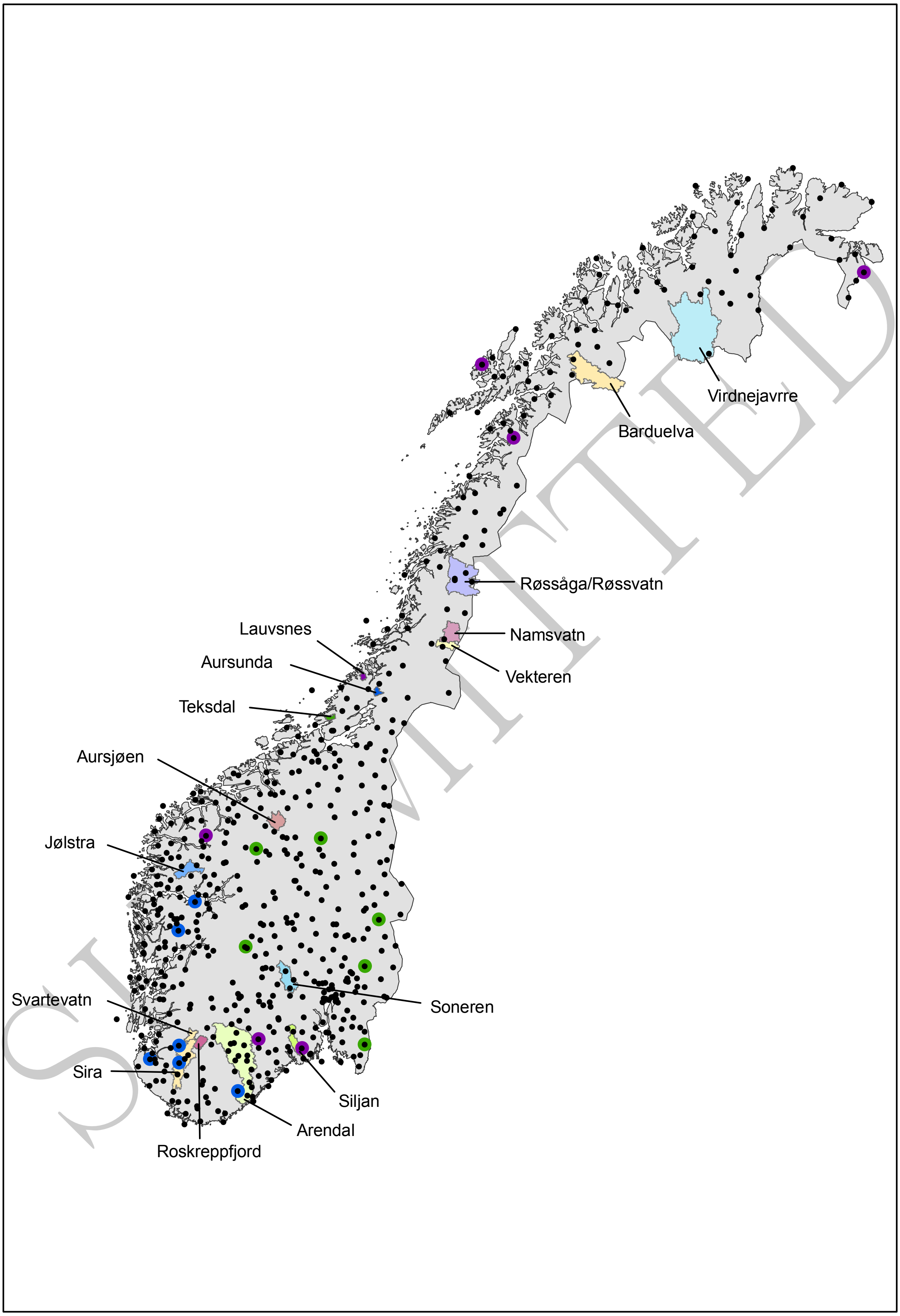

Figure 6: Catchments and observational sites. Red indicates sites with long (>100 years) observational series.

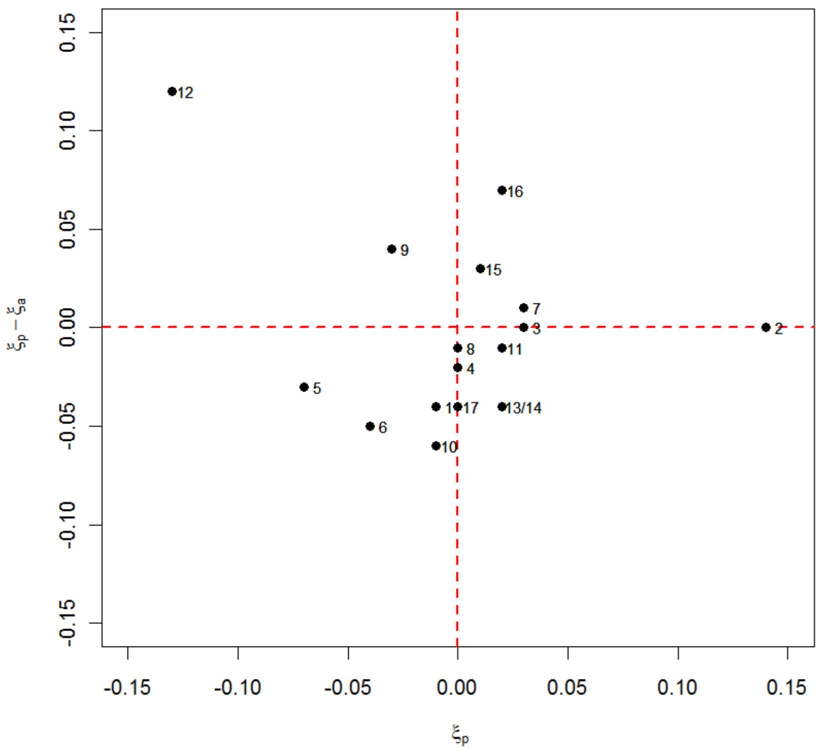

Figure 7: Mean ξ_p against ξ_p in the catchments (indicated by number, cf.Table 1).

4 Method comparison and discussion

We compare estimates from GB-GEV, both estimated and modelled ξ_a, to SB-gf estimates in the 17 catchments, making use of previously determined SB-gf estimates computed at MET Norway on different occations (cf. Table. 1). Percentage differences for M100, M500, and M1000 are shown in Fig. 8. GB-GEV estimates lie within a 25% deviation from SB-gf estimates in most catchments. In the wetter catchments where PN used in the two methods differ significantly, GB-GEV estimates are somewhat higher than SB-gf estimates, especially for M100. The largest deviation is seen in Svartevatn, where GB-GEV estimates are 40-60% higher. A natural explanation for this is the added elevation gradient in the gridded dataset, which in wet areas such as Svartevatn, will likely generate serious overestimation since the elevation gradient is defined as a percentage. It is also likely that SB-gf underestimates the return levels as the only available observations nearby are located in lower elevations. The growth factors in SG-gf seem to correspond to a somewhat higher positive ξ compared to the estimated ξ_a in GB-GEV. Consequently, in the case of GB-GEV $>$ SB-gf for shorter return periods, the longer return periods might correspond quite well. While in the opposite case the difference will grow further with longer return periods.

Figs. 9- 12 show examples of estimates from four catchments; Soneren, Siljan, Aursunda and Barduelva. Empirical values are also shown. The 95% and 99% confidence intervals for estimates with modelled ξ_a are included, indicating the model uncertainty. For longer return periods all estimates stay within the confidence intervals of GB-GEV (Mod.ξ_a) estimates in all catchments. Assessing model performance is a difficult task, especially since empirical values only reach a MT equal to the record length while we are mostly interested in the longer MTs. We note that the few higher values follow an unstable path corresponding to an ambiguous distribution. A MT-plot of emprirical values from a very long series will also follow and unstable path and the sign and magnitude of ξ will depend on which part of the plot one considers. (SHOW THIS WITH STATION-YEAR SERIES? CAN ALSO SHOW THAT WLS DOES NOT GIVE BETTER FIT THAN MLE???)

Uncertainties in the gridded dataset are likely to influence our estimates, particularly in high-elevated regions. This is partly due to lack of observations which further complicates the interpolation. Another aspect is the vertical precipitation gradient, known to overestimate precipitation in higher elevations. The latter, being defined as a percentage, produces an even greater overestimation of extreme values. On the other hand, extremes in any interpolated dataset are often underestimated due to smoothing, and the relatively sparse station network results in many large precipitation amounts not being measured as small convective cells may travel between observation sites rather than across. In catchments located on the borders between different precipitation regimes, the spatial coherence might be reduced both due to the nature of different precipitation systems and the heterogeneous effect of the precipitation gradient. An important part of computing extreme areal precipitation estimates is to be aware of these effects and, while anticipating improved datasets, consider additional estimation methods in the more uncertain regions.

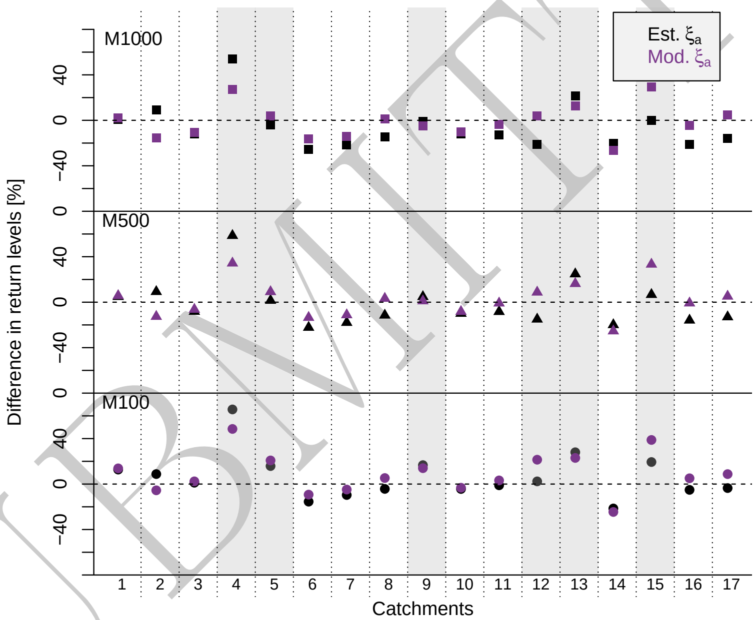

Figure 8: Percentage difference in M100 (circle), M500 (triangle), and M1000 (square) between SB-gf and GB-GEV estimates (MLE in black and WLS in blue). Grey background indicates catchments with large difference in PN used in the two methods.

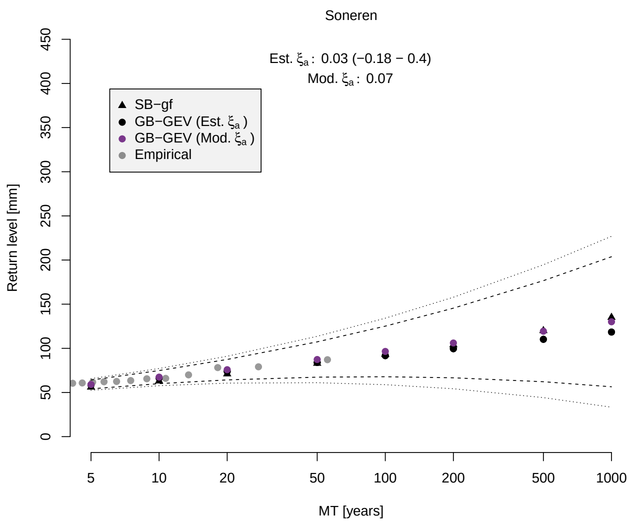

Figure 9

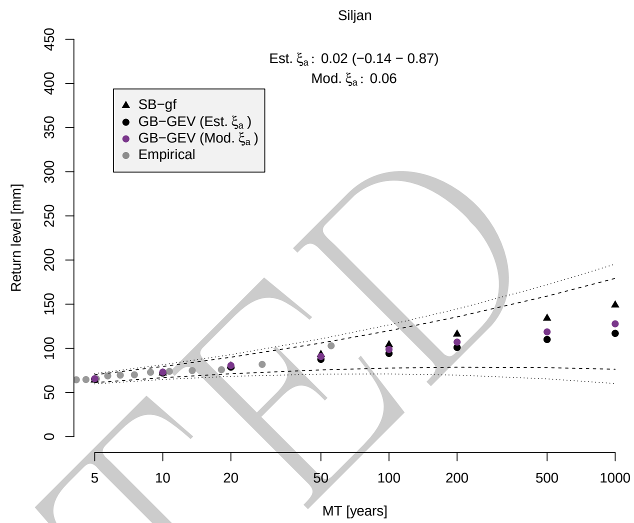

Figure 10

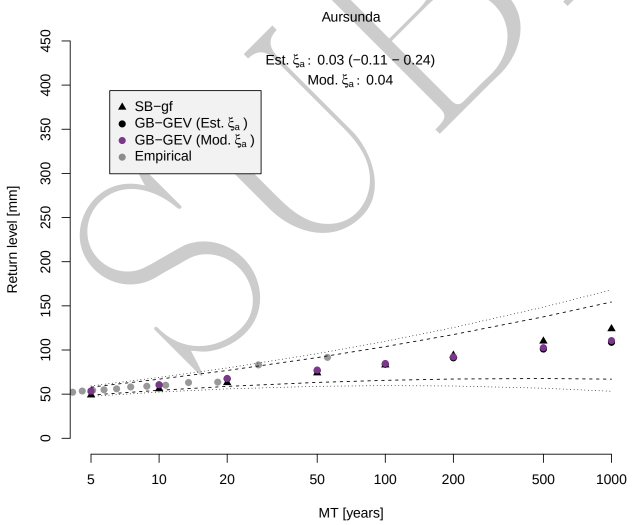

Figure 11

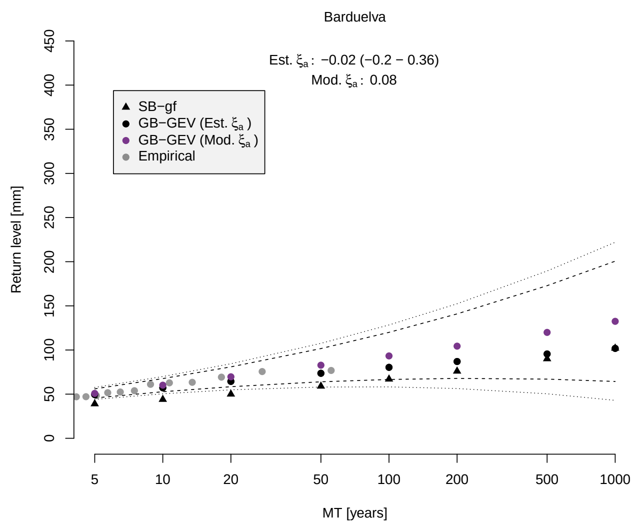

Figure 12

5 Conclusions and Recommendations (UPDATE WHEN FINISHED!!!)

We propose a new grid-based method, GB-GEV, for estimating extreme areal precipitation in Norway. Estimates from GB-GEV are compared to estimates from the existing method at MET Norway, SB-gf. Due to large uncertainties it is difficult to indicate which estimates are better. However, there are relevant and decisive differences between the methods.

- Grid-based methods are less manual and time-consuming compared to the station-based method, as well as objective and consistent in terms of input data. In addition, estimates in ungauged catchments, although rather uncertain, are easier to obtain. Estimates are dependent on the quality of the gridded dataset, thus we emphasize the importance of further development, such as dealing with the known issue of overestimation in high-elevated areas.
- GB-GEV estimates are generally lower than SB-gf estimates, but lie within a 25% deviation in most catchments. For longer return periods SB-gf estimates stay within the confidence intervals of GB-GEV estimates in all catchments.
- Estimating the GEV ξ-parameter is a not trivial. ξ seem to vary spatially depending on dominating precipitations systems, and for areal extremes the catchments size also plays a role due to spatial correlation...

With the large uncertainties associated with any estimation of extreme precipitation, there lies an advantage in using different estimation methods. The authors recognize that GB-GEV estimates are as good as the gridded dataset allows. This means that in areas with few observations and complex topography the estimates become unreliable. Still, GB-GEV estimates will become more accurate as gridded products improve in the future, and the suggested methodology will provide more objective and geographically consistant results than the SB-gf method.

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