Estimating extreme precipitation on different spatial and temporal scales in Norway

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Oslo, October 2015

Anita Verpe Dyrrdal

Contents

1 Introduction

1.1 Motivation

A major trigger of floods and landslides in Norway is intense and/or prolonged rainfall in large river systems particularly in combination with snow melt. Norwegian Water Resources and Energy directorate (NVE) has estimated the average annual cost of flood damage in Norway per 2009 to be about 200 million NOK (€23.3 million). Damages on the Norwegian transport network are in the order of 100 million NOK/year (€11.7 million/year) (*Bjordal & Helle*, 2011; *Bråthen*, 2008). Over-design of infrastructure can represent unnecessary expenses, whereas under-design can lead to losses associated with damage and in the worst case, loss of life. Estimates of extreme precipitation are frequently used in flood estimation and are decisive for planning and design of important infrastructure, such as reservoir dams, water control systems, urban runoff and transport lines. Hence the accuracy of extreme precipitation estimates is crucial both in terms of economy and safety.

The relationship between extreme precipitation and floods and landslides in Norway has been studied in several papers (*Sandersen* et al., 1996; *Førland* et al., 2007; *Jaedicke* et al., 2008; *Nadim* et al., 2009; *Hanssen-Bauer* et al., 2009; *NVE*, 2011). Rainfall over several consecutive days can result in floods over larger areas, and snowmelt during spring is often a major contributor. Such floods are usually seen in large-scale catchments in Norway, many of them which are located in the southeast, and often cause great damages to infrastructure, agriculture, and private property. In a worst case scenario, large-scale floods can lead to dam failure and hence enormous damages and possible loss of lives. Heavy rainfall over shorter durations, commonly associated with a severe thunderstorm, can trigger rapid flooding, or flash floods. This often occurs during summer. In urban areas where natural drainage system is lacking and the man-made system is insufficient, such rapid flooding is referred to as urban flooding. According to *Doswell* et al. (1996) flash floods are a result of high to extremely high rainfall rates from convective events, whereas river floods are associated with rainfall events over days and perhaps months. Common consequences of flash floods include damages to buildings, infrastructure and the disruption of traffic flow. A more indirect effect of extreme precipitation is different types of landslides, which in turn can lead to closure of transport lines and/or disturbances in telecommunications, power, and water supply to local communities. *Sandersen* et al. (1996) and *Nadim* et al. (2009), among others, state that debris flows in Norway are often triggered at times of heavy rainfall, causing high soil saturations and positive pore pressures.

In a global perspective, there are several sectors that are or can be negatively affected by climate extremes, including precipitation extremes. *Seneviratne* et al. (2012) mention transportation, infrastructure, water, tourism, agriculture, food security, forestry, and health. In Europe, flooding is the most frequent natural disaster (*EEA*, 2008; *Seneviratne* et al., 2012), and economic losses from floods have increased considerably over previous decades (*Lugeri* et al., 2010). According to *Barredo* (2009) a larger exposure of people and economic assets, explained by socioeconomic development, urbanization, and construction in flood-prone areas, is probably the major cause of increasing economic losses.

An accumulating body of scientific evidence show that global temperatures are rising due to anthropogenic emissions of greenhouse gases (*IPCC*, 2013). According to the well-established Clausius-Clapeyron relationship, this temperature rise allows for an increased moisture content in the atmosphere, and hence more precipitation. The latest report from the Intergovernmental Panel on Climate Change (IPCC) states that precipitation has increased since 1901 in mid-latitude land areas of the Northern Hemisphere. In Norway, observations show that the frequency of moderate to strong precipitation has generally increased in the recent decades (*Hanssen-Bauer* et al., 2009; *Dyrrdal* et al., 2012).

Fig. 1 from *Dyrrdal* et al. (2012) shows mainly positive trends in the frequency of precipitation events exceeding 10 mm/day, during the period 1957-2010.

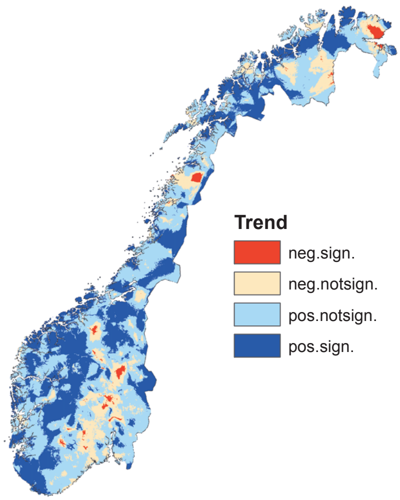

Figure 1: Trend in number of daily precipitation events exceeding 10 mm, for the period 1957-2010. Blue indicates positive trends, red indicates negative trends (dark color = statistically significant at the 95% confidence level, light color = not significant). The figure is retrieved from *Dyrrdal* et al. (2012), Fig.S4.

The observed tendency is expected to continue into the future. As illustrated in Fig. 2 from *Seneviratne* et al. (2012), extreme precipitation events over most of the mid-latitude land masses will very likely become more intense and more frequent by the end of this century (*IPCC*, 2013). According to *Hisdal* et al. (2006); *Hanssen-Bauer* et al. (2009); *Wilson* et al. (2010), the intensity of rainfall-induced floods is expected to increase and higher temperatures probably lead to a shift towards earlier spring floods and increased probability for floods during late autumn and winter. Due to these observed and projected changes, existing design criteria for infrastructure should be revised.

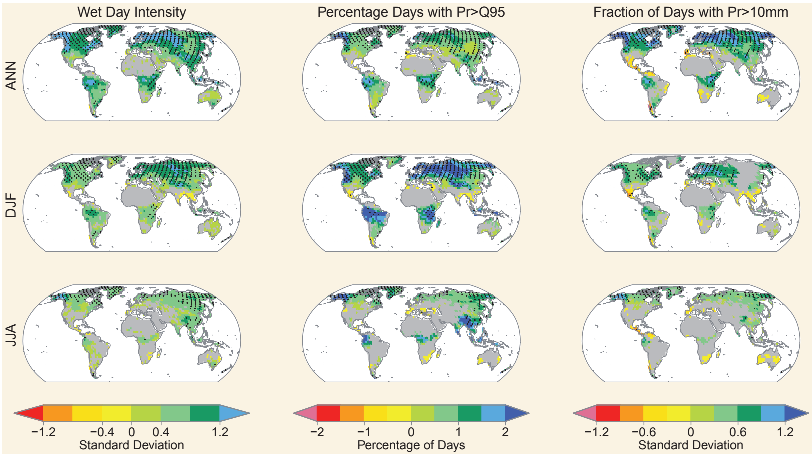

Figure 2: "Projected annual and seasonal changes in three indices for daily precipitation (Pr) for 2081-2100 with respect to 1980-1999, based on 17 GCMs contributing to the CMIP3. Left column: wet-day intensity; middle column: percentage of days with precipitation above the 95% quantile of daily wet day precipitation for that day of the year, calculated from the 1961-1990 reference period; right column: fraction of days with precipitation higher than 10 mm. The changes are computed for the annual time scale (top row) and two seasons (DJF, middle row, and JJA, bottom row) as the fractions/percentages in the 2081-2100 period (based on simulations under emission scenario SRES A2) minus the fractions/percentages of the 1980-1999 period (from corresponding simulations for the 20th century). Changes in wet-day intensity ans in the fraction of days with Pr ¿ 10 mm are expressed in units of standard deviations, derived from detrended per year annual or seasonal estimates, respectively, from the three 20-year periods 1980-1999, 2046-2065, and 2081-2100 pooled together. Changes in percentages of days with precipitation above the 95% quantile are given directly as differences in percentage points. Color shading is only applied for areas where at least 66% (i.e., 12 out of 17) of the GCMs agree on the sign of the change; stippling is applied for regions where at least 90% (i.e., 16 out of 17) of the GCMs agree on the sign of the change.“. The figure and the caption are adapted from *Seneviratne* et al. (2012), Fig.3-6. GCM = General Circulation Model, CMIP3 = the third "Coupled Model Intercomparison Project“ ANN = annual, DJF = December-January-February season, JJA = June-July-August season.

Extreme precipitation estimates are typically obtained through the fitting of data points to the tail of a theoretical probability distribution, or an extreme value distribution. Due to the lack of observations of extreme events, data transfer or regional frequency analysis (RFA) (e.g. *Hosking & Wallis*, 1993; *Overeem* et al., 2009; *Svensson & Jones*, 2010b) is commonly applied to increase the precision of rainfall frequency estimates by pooling of data from several sites. Further details on extreme value theory and RFA are provided in Section 2.1.1. For design purposes there is a constant demand for multi spatial- and temporal scale estimates. The lack of sub-daily precipitation measurements often makes it more appropriate to rely on the scaling of daily precipitation. *Paulat* et al. (2008) and *Wüest* et al. (2010) took advantage of temporal information from weather radar to disaggregate precipitation into a gridded hourly dataset for Germany and Switzerland, respectively. A similar approach was taken by *Vormoor & Skaugen* (2013) to disaggregate daily precipitation into 3-hourly precipitation in Norway, as further described in Section 3.3.2. Radar and gridded datasets are also valuable for studying the integrated precipitation over a catchment, important in e.g. flood estimation (see Section 2.1.2).

In recent years, studies of extreme precipitation have become numerous and advanced statistical tools have evolved. Rapid advances in computer science give tremendous opportunities and facilitate simulation-based techniques such as the popular Markov Chain Monte Carlo (MCMC) (*Gilks* et al., 1996), which again has led to an increase in the use of Bayesian methods (e.g. *Box & Tiao*, 2011). The technical development also encourage the modeling of multivariate extremes or spatial modeling of univariate extremes that can be achieved through statistical tools such as copulas, max-stable random fields, and latent variable approaches (*Davison* et al., 2012, see Section 2.1.3). The latter is commonly applied within a hierarchical modeling framework. According to *Zhang & Singh* (2007) the advantage of the copula method is that no assumption is needed for the rainfall variables to be independent or Gaussian or have the same type of marginal distributions. They examined how four Archimedean copulas represented the dependency between total depth, duration, and peak intensity of hourly precipitation in Louisiana, USA, and found that copula-based distributions fit the observations better than a bivariate normal distribution. *Kao & Govindaraju* (2007) adopted the same procedure in a large region in Indiana, USA, using hourly precipitation data of 50-55 year lengths from 53 rain gauges. They argue that the method can be translated to other geographical areas. *Grimaldi & Serinaldi* (2006) tested several three-dimensional copula models on half-hourly extreme precipitation at 10 rain gauges in Italy, showing it is possible to estimate, in a probabilistic way, peak and total depth values to be used in design hyetograph analysis. *Smith & Stephenson* (2009) applied an extension of the Gaussian max-stable process to model annual maximum rainfall from five sites in South-West England, and used a pairwise likelihood within a Bayesian analysis to estimate the model parameters. *Cooley* et al. (2007) were the first to apply a Bayesian Hierarchical Model (BHM), as an alternative to RFA, to estimate the parameters of an extreme value distribution of daily precipitation in Colorado, US. Similar to an RFA analysis, a BHM pools the data but uses a geostatistical approach to more naturally model the datas spatial nature (*Cooley*, 2009). *Sang & Gelfand* (2009) applied a BHM to study extreme precipitation events from a gridded dataset in the Cape Floristic Region of South Africa, while *Sang & Gelfand* (2010) used an extended version of the same model, including a Gaussian spatial copula model, to study annual maximum rainfall in South Africa. *Ghosh & Mallick* (2011) proposed a spatio-temporal BHM to model extreme precipitation events in the US.

Climate information on local scales is an important requirement in many climate change impact applications. This thesis contributes to such applications through the development of new methods for estimating precipitation design values; for current climate conditions on different temporal scales, and for catchments and at any point in mainland-Norway, via high-resolution maps. Additionally, the author makes a first necessary effort towards estimating design values for future climate conditions, through the evaluation of the most recent climate model experiments.

1.2 Aims and objectives

The aim of this thesis is to improve estimated values of extreme precipitation for design purposes in Norway. This is done through the development of new methods for estimating extreme precipitation for both daily and sub-daily durations, and for points and catchments. Specifically, the author aims to create maps of return levels on a fine-scale grid, covering entire mainland-Norway. An assessment of the quality of sub-daily precipitation extremes in regional climate model simulations is also of interest. A secondary aim is to increase the knowledge of the spatial distribution of extreme precipitation in Norway.

Specific objectives include:

1. Develop a new methodology for estimating extreme areal precipitation in catchments in Norway, based on updated data and modern statistical methods. Compare new methodology to the existing methodology at the Norwegian Meteorological institute (MET Norway). Return periods of 500 and 1000 years are of main interest here.

2. Develop a method for estimating extreme sub-daily precipitation at any point in Norway. Create fine-scale maps of sub-daily return levels. Return periods from 5 to 200 years are of main interest here.

3. Evaluate extreme sub-daily precipitation from the most recent regional climate model simulations over Norway.

The thesis work consists of three scientific papers (in Appendix) addressing the above-mentioned research questions; two which have been peer-reviewed and accepted for publication (Paper I and Paper II), and one that was submitted in March 2015 (Paper III). Objective 1 was addressed in paper I (*Dyrrdal* et al., 2014a), objective 2 was addressed in Paper II (*Dyrrdal* et al., 2014b), and objective 3 was addressed in Paper III (*Dyrrdal & Stordal*, 2015).

The remaining part of the thesis is organized as follows: The scientific background and methods are presented in Section 2, where the author elaborates on the theory and relevant earlier work. Section 3 describes the datasets applied and the regional setting, and in Section 4 the findings in the three papers are summarized and discussed. The work is brought together into a general perspective and contributions to the national climate services are assessed. Finally, Section 5 provides conclusions and indications of future research.

2 Methodology

This chapter provides an introduction to the scientific theory and methods further pursued in the three papers. An overview of the state-of-the-art on the research field is also given, including studies that represent important background for this thesis.

2.1 Precipitation frequency estimation

The purpose of precipitation frequency estimation is to analyze past measurements in order to estimate future occurrence probabilities. Studying extremes is challenging simply because of its very nature; few occurrences. This means the records of extremes are short and large uncertainties are introduced when extrapolating to longer return periods. Methods for precipitation frequency estimation at a point include statistical extreme value theory, as well as increasing the amount of data through spatial data pooling or lowering the threshold for what is considered extreme (*Svensson & Jones*, 2010b). Different countries choose different statistical distributions, fitting techniques, and input data. But according to *Svensson & Jones* (2010b) most countries use some way of incorporating information from nearby sites when estimating precipitation frequencies. This borrowing of strength across measuring sites is referred to as regionalization. Sources of uncertainty in frequency analysis include choice of analytical approach and statistical model, and estimation of model parameters (*WMO*, 2009a). The problem that often arises with meteorological series is the limited amount of measurements, both spatially and temporally, which complicates the selection of statistical model and the estimation of its parameters.

Extreme value theory provides a framework to model the tail of probability distributions, enabling extrapolation of extremes. The two most common extreme value distributions include the Generalized Extreme Value (GEV) distribution (*Fisher & Tippett*, 1928; *Jenkinson*, 1955), and the Generalized Pareto (GP) distribution (*Pickands*, 1975; *Cooley* et al., 2007). The GEV model makes use of the statistical behavior of $M_n = \max\{X_1, \ldots, X_n\}$, where $X_1 \ldots, X_n$ are independent and identically distributed random variables. The extremal types theorem states that the normalized distribution of M_n converges to a GEV distribution G(x) as $n \to \infty$ (*Fisher & Tippett*, 1928; *Jenkinson*, 1955). Therefore, the GEV distribution is commonly used to model block maxima such as the annual maxima. This approach is popular due to its simple structure and relatively low demand of data. An attractive property of the GEV distribution is max-stability (*Coles*, 2001), meaning that the component-wise maximum of n independent random variables from the distribution has that same distribution. If the complete data series is available, extreme value theory states that exceedences over a sufficiently high threshold approximately follows a GP distribution. Due to limited data, particularly on sub-daily scales, and difficulties associated with threshold selection, GEV is chosen as the primary estimation model in the current thesis.

The precipitation amount of an extreme event is often computed as T-years return levels. A return level is defined as the precipitation amount that is exceeded by the annual maximum in any particular year with probability $\frac{1}{T}$, or in other words, the amount that on average occurs every T years (*Coles*, 2001). The average interval between each occurrence is referred to as return period T, or recurrence interval; hence the longer the return period, the more extreme. In the dam safety regulations for Norway (*NVE*, 2011) it is stated that dams, depending on the danger potential, should handle a design inflow with a 500-1000 year return period, and in some cases the Probable Maximum Precipitation (PMP). PMP is defined as the greatest accumulation of precipitation for a given duration meteorologically possible for a design watershed or a given storm area at a particular location at a particular time of year (*WMO*, 2009b), and represents a return period of infinity. The concept of PMP has been criticised by hydrologists as it assumes a physical upper bound of precipitation amount, while extreme value theory indicates that this bound does not necessarily exist. E.g. *Papalexiou & Koutsoyiannis* (2006) found no evidence for an upper bound of dew point or precipitation when estimating PMP at four stations in the Netherlands and one in Greece, using the moisture maximization method. They also found that the method gives highly uncertain estimates and is very sensitive to the available data. Authorities for roads, railways, and urban planning are more concerned with sub-daily intense precipitation with return periods of 5 to 200 years. Estimation of events with low probability or long return period is challenging as only few obervations of such extremes are available, thus extrapolation is necessary.

2.1.1 Generalized Extreme Value (GEV) distribution

The current study has mainly applied the GEV distribution, which describe the three possible types of extreme value distributions for block maxima of any variable, regardless of the underlying distribution (*Coles*, 2001). Many studies have shown that the GEV distribution fits well to extreme point precipitation, including *Bonnin* et al. (2006) (United States), *Alila* (1999) (Canada) and *Kyselý & Picek* (2007) (Check Republic). *Alexandersson* et al. (2001) found that GEV fits very well to a combined data set of about 2300 observations of daily precipitation from a reasonably homogeneous area on the border of Norway and Sweden. They also showed that GEV is superior to the simpler two-parameter Gumbel distribution. *Coles & Tawn* (1996) claim the GEV distribution to be valid also for areal precipitation. *Overeem* et al. (2010) demonstrated that GEV can be fitted to areal precipitation series from weather radar in the Netherlands, although the convergence to a GEV distribution is slower than for point precipitation and the need for long time series is even more crucial.

The three-parameter GEV distribution is of the form

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

where μ is location, σ is scale, and ξ is shape. Depending on ξ, the GEV distribution converges 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 in extreme value statistics, and a large variety of analysis tools are developed.

One drawback with the GEV model is the assumed stationarity, which is usually not accurate for climate data. There exists extensions to the GEV method that deal with non-stationarity in terms of systematic changes in time such as trends, shifts or seasonality (*Coles*, 2001; *Renard* et al., 2013; *Cheng* et al., 2014). Past changes in precipitation amount in Norway are not spatially homogeneous and vary with time period (*Hanssen-Bauer* et al., 2009; *Alfnes & Førland*, 2006). Detecting robust trends in extremes of relatively short records is problematic, thus the stationary GEV model is used in this study. The assumption of independence is fairly well met when dealing with large blocks such as annual maxima. We must keep in mind, though, that the GEV is an asymptotic model which provides no information on the distribution of the underlying population.

Throughout this work the author has applied Maximum Likelihood Estimation (MLE) (*Smith*, 1985; *Coles*, 2001), along with Bayesian inference in Paper II, to estimate the three GEV parameters. MLE chooses the model that gives the highest probability to the observed data, through a likelihood function. To evaluate the extreme value model, one usually compares to the empirical distribution of the observations. Other frequently used parameter estimation methods include the method of moments (*Pearson*, 1894; *Madsen* et al., n.d.), L-moments (*Hosking*, 1990), and probability weighted moments (*Hosking* et al., 1985), but also Bayesian methods have arrived in the recent years (e.g. *Coles &*

Tawn, 1996; *Cooley* et al., 2007; *Gaetan & Grigoletto*, 2007; *Sang & Gelfand*, 2009).

The shape parameter, ξ, is difficult to estimate and is highly sensitive to outliers, but is also the parameter of greatest importance for long return periods. Fig. 3 shows return levels and probability density functions for a fictitious site, where the blue long-stippled curve represents a positive ξ, the green short-stippled curve represents $\xi = 0$, while the red solid curve represents a negative ξ. For $\xi > 0$ (blue curve) the precipitation amount can reach infinity. This is also true for $\xi = 0$ (green curve), although at a slower rate. For $\xi < 0$ (red curve) precipitation amounts approaches an upper limit as return periods become large.

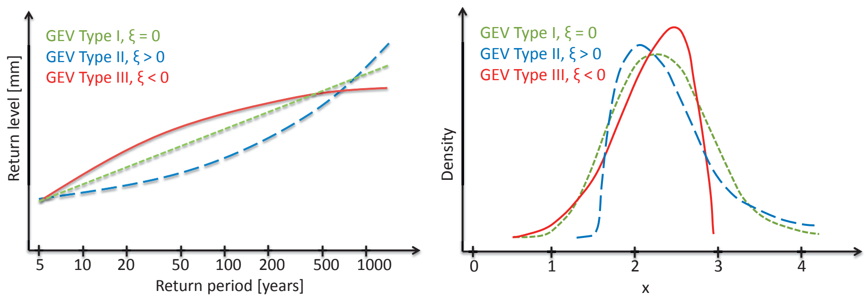

Figure 3: Example of return level plot (left) and probability density functions (right) for the three GEV distributions.

Many studies claim that extreme daily precipitation at a point follows a GEV Type II distribution ($\xi > 0$) (*Wilks*, 1993; *Koutsoyiannis & Baloutsos*, 2000; *Katz* et al., 2002; *Coles* et al., 2003; *Coles & Pericchi*, 2003; *Koutsoyiannis*, 2004a; *Serinaldi & Kilsby*, 2014). This distribution also represents the lowest risk for engineering structures as design values are higher than for GEV Type I and Type III. *Koutsoyiannis* (2004b) indicated a ξ value of 0.15 as appropriate for daily precipitation in mid-latitude areas of the Northern Hemisphere, and *Wilson & Toumi* (2005) suggest a universal ξ of around 0.10. Further, *Papalexiou & Koutsoyiannis* (2013) found that ξ is strongly affected by record length and when corrected for this, the parameter varies within a narrow range which values depend on geographical location. *Veneziano* et al. (2009) suggest that a constraint on ξ using theoretical arguments is necessary. One alternative to avoid unreasonable ξ values, due to limited data and/or inaccurate estimation methods, is proposed by *Martins & Stedinger* (2000). They modified the GEV likelihood function to include a Bayesian prior distribution on ξ, and steer its value into a realistic range. Another approach is to use the Gumbel distribution, which sets ξ to zero. This can be dangerous, as it most likely underestimates precipitation return levels in many parts of the world, and can have serious implications for important infrastructure that rely on such estimates.

When employing the GEV model on single data series, the uncertainty of the estimates can be relatively large (see Section 2.1.1). Regional frequency analysis (RFA) (e.g. *Hosking & Wallis*, 1993; *Overeem* et al., 2009) is commonly used to increase the accuracy of estimates, as stated in Section 1, by combining observations from nearby rain gauges within a region and assuming regionally homogeneous parameters. In ungauged catchments, a data transfer scheme is often applied to transfer information from a nearby and hydrologically similar site (*Kjeldsen & Jones*, 2010). Such a proceedure can significantly increase the data basis if a suitable site exists. The most common RFA approach is referred to as the index-flood method, which identifies a homogeneous region by e.g. assuming a constant ξ parameter and dispersion coefficient $\frac{\sigma}{\mu}$ over the region of interest (*Gellens*, 2002; *Fowler & Kilsby*, 2003; *Overeem* et al., 2009). In a second step an index variable is defined and used to scale the data and obtain a common frequency distribution (*Svensson & Jones*, 2010b). Limitations associated with RFA include a border effect when regions are defined, and inter-site dependence which is found to increase the variance of the estimator (e.g. *Matalas & Langbein*, 1962; *Stedinger*, 1983; *Hosking & Wallis*, 1988). To deal with the issue of inter-site correlation *Wang* et al. (2014) incorporated spatial dependence into an index-flood model and showed significantly increased accuracy in return level estimates in

Switzerland, compared to the L-moment method. In orographic regions, like Norway, RFA can be particularly challenging due to the large spatial variation of precipitation and the difficulty in defining homogenious regions (e.g. *Førland & Kristoffersen*, 1989).

2.1.2 Areal extremes

Areal precipitation is often of greater interest than point precipitation, however challenges arise because areal precipitation is not directly measurable and varies non-uniformly in space. *Skaugen* et al. (1996) states that the areal precipitation will be a sum of variables, partially from the parent distribution and partially from the distribution of its extremes. Many studies confirm that precipitation spatial variability should be taken into account when estimating areal precipitation (*Obled* et al., 1994; *Arnaud* et al., 2002; *Schuurmans & Bierkens*, 2006), however, little attention has been given the examination of the extreme value distribution for precipitation over catchments. Although initially meant for weather forecasting, radar has become a unique tool for studying the distribution of areal precipitation, its relationship to point precipitation and for estimation of extremes (e.g. *Durrans* et al., 2002). The Netherlands is a leading country in the use of weather radar in extreme precipitation analyses; *Overeem* et al. (2009) and *Overeem* et al. (2010) studied the GEV parameters of areal precipitation in the Netherlands using radar, showing that μ increases and ξ decreases with increasing area. In Norway, accumulated precipitation from radar exists for the last few years, but is as per today of limited accuracy mainly due to a considerably rougher terrain compared to the Netherlands.

To convert extreme precipitation values in a point to represent a larger area, areal reduction factors (ARF) (*NERC*, 1975; *Bell*, 1976) are traditionally used. ARFs attempt to empirically describe the spatial correlation structure of precipitation through the ratio between area-averaged precipitation intensity and the point precipitation intensity for a certain duration and return period, as follows

$$ARF(D,T,A) = \frac{I(D,T,A)}{I(D,T,0)} \tag{2}$$

where D is duration, T is years, A is area size, and I is intensity. Two traditional empirical methods for deriving ARFs are described in *Bell* (1976); the "storm-centered" approach where the region over which the areal precipitation is estimated differs from storm to storm, and the "fixed-area" approach where this region is fixed. Storm-centered ARFs are computed from the ratio between the maximum areal precipitation for a given duration and region and the maximum point precipitation for the same duration and within the same region, using individual precipitation events. Storm-centered methods are mainly applied for estimating PMP (*Omolayo*, 1993). Fixed-area ARFs are computed from the ratio between the mean annual maximum areal precipitation for a given duration and region and the mean annual maximum point precipitation for the same duration and for a number of points within the same region. According to e.g. *Svensson & Jones* (2010a) ARFs are found to vary with predominant weather type, season, return period and estimation method.

Observation-based and model-based gridded products on high temporal and spatial resolutions have evolved over the recent years. Amongst them are the national datasets described in *Tveito* et al. (2005) (Norway), *Brunetti* et al. (2012) (North Eastern Italy), *Paulat* et al. (2008) (Germany) and *Wüest* et al. (2010) (Switzerland). On European scales E-OBS (*Haylock* et al., 2008) is frequently used, and on global scales one can mention *Saha* et al. (2010) (NOAA/NCEP), *Rienecker* et al. (2011) (NASA), and the widely used ERA-interim (*Dee* et al., 2011) (ECMWF). *Isotta* et al. (2015) indicate regional model-based assimilation as a promising technique for representing extreme events. The above-mentioned gridded datasets provide the opportunity to study areal precipitation without the use of ARFs, as attempted in Paper I (see Section 4). Here areal precipitation is extracted from an interpolated dataset of daily precipitation, and an extreme value analysis is performed directly on the areal time series.

2.1.3 Spatial extremes

Extreme precipitation in regions with varied topography, like Norway, exhibits large spatial variations. As well as being exposed to several types of weather systems depending on region, topography strongly controls the rainfall distribution on local scales. This orographic effect tends to give a general increase in mean precipitation with elevation, but over very high mountains the precipitation may increase up to a certain height and then decrease (e.g. *Smith*, 1979). The spatial complexity of precipitation in Norway is far from captured by a relatively sparse station network, and the short observational series is not representative for a realistic range of extremes. Furthermore, precipitation is a non-stationary variable in time. This calls for spatial modeling of extremes to form spatially continuous maps of e.g. return levels, where we can extract the return level of interest for any point, represented by grid cells.

A number of advanced analysis tools for spatial extremes has evolved internationally in the recent years. They include "copula" (*Nelsen*, 1999; *Gudendorf & Segers*, 2010), spatial "max-stable processes" (*de Haan & Ferreira*, 2006), and "latent variable" models (*Banerjee* et al., 2004). Copula means "link" and is a multivariate probability distribution that, by using separate marginal and joint dependence models, can describe complicated dependence structures. Max-stable models basically extends multivariate extreme value theory to an infinite dimension (*Smith & Stephenson*, 2009). Max-stable models are important in applications as they appear as limiting distributions for the maximum of a large collection of appropriately normalized independent random variables. The GEV distribution is the only univariate distribution that is max-stable.

A latent variable can be understood as a factor that must exist and must affect the value of the observed variable, but which cannot be directly measured. According to *Davison* et al. (2012), a latent variable approach is able to model the marginal behavior of precipitation, such as return levels, while copulas and max-stable models are necessary to capture the joint distribution of extremes. This is further explained in Section 4.1 and in Paper II, where a latent variable approach is applied within a Bayesian Hierarchical Model (BHM) to estimate return levels of hourly precipitation (see Section 4). The modeling in a BHM involves multiple layers or sub-models: The data layer, where observations are dealt with, the process layer, where covariates are introduced, and the prior layer, where Bayesian priors are assigned to the model parameters. The latter means that all uncertain quantities are considered as random parameters, with prior probability distributions that are updated through information from data and Bayes' theorem (*Tebaldi* et al., 2004). Bayes' theorem describes the probability of event A given event B, and is written as follows

$$p(A \mid B) = \frac{p(B \mid A)\, p(A)}{p(B)} \tag{3}$$

This formulation is very useful in modeling systems with a complicated manner of interactions such as hierarchical models. Bayesian methods enables straightforwards incorporation of latent variables and estimation of the relevant quantities with associated uncertainty.

2.1.4 Current method for precipitation frequency estimation in Norway

Today, MET Norway apply the method described in *Førland* (1983, 1984b, 1992); *Førland & Kristoffersen* (1989) to estimate extreme precipitation in points and catchments. The method, here referred to as SB-gf (station-based growth factor method), was developed from the UK Flood Studies Report (*NERC*, 1975), where a comprehensive statistical analysis was performed on a large rainfall dataset. Empirical growth factors were developed, describing precipitation with a T year return period (MT) as a function of M5 (precipitation with a 5 year return period), also called the index value. The ratio MT/M5 is referred to as growth factor. M5 for a "representative point" within the area is estimated by the Gumbel-method (*Gumbel*, 2004), a GEV distribution with a shape parameter (ξ) equal to zero. MT is computed as follows:

$$MT = M5e^{C(ln(T-0.5)-1.5)} \tag{4}$$

The factor C is determined empirically and varies geographically as a function of M5. Values defined for Scotland and Northern Ireland were found suitable for Norwegian conditions (*Førland*, 1987).

In SB-gf, growth factors are used along with standardized ARFs to convert point values to areal values. 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 and the extensive statistical analysis on a substantial dataset. SB-gf include several subjective measures, and since computer performance has improved along with observational datasets in Norway, SB-gf may not be the optimal approach today. In addition, growth factors were originally developed for point precipitation and the application on areal precipitation might violate the statistical assumptions on which they were based.

Return levels for sub-daily durations are estimated using empirically-derived scaling factors on MT obtained from the above procedure (*Førland*, 1987, 1992).

2.2 Future climate scenarios

To investigate probable future changes in climate variables the best available tool is climate model simulations. Output from coarse-resolution general circulation models (GCMs), also known as global climate models, are fitted to regional or local scales through one of two downscaling methods; dynamical downscaling through regional climate models (RCM) or empirical statistical downscaling (ESD) (*Flato* et al., 2013).

RCMs typically have a horizontal resolution of about 10-50 km (as opposed to 100-250 km in GCMs), and give a better representation of mountains, coastlines, and small scale physical and dynamical processes. They use atmospheric driving data derived from GCM simulations or analyses of observations (reanalysis) (*Di Luca* et al., 2013), referred to as lateral boundary conditions (LBCs). Reanalysis-driven simulations are a common reference when evaluating the RCM performance through a comparison to observations. *Dickinson* et al. (1989) and *Giorgi* (1990) were the first to use RCMs for climate applications, and now such models are widely employed. *Xue* et al. (2014) performed a review of the RCM downscaling abilities. They found that significant improvement can be achieved by properly adjusting convective parameterizations for the dynamic region and resolution used. Factors they found crucial include adequate LBCs and proper domain setting, convective schemes, land surface parameterizations, initializations, and numerical schemes.

Flato et al. (2013) state that there is *high confidence* that downscaling improves the simulation of spatial climate details in regions with highly variable topography, and for mesoscale phenomena and extremes. RCMs simulate moderate precipitation events well, and can accurately capture the spatial and temporal characteristics of intense daily precipitation events. However, they tend to overestimate the precipitation frequency and underestimate the intensity of heavy precipitation (*Fowler* et al., 2007; *Boberg* et al., 2009; *Kjellström* et al., 2010; *Crétat* et al., 2014). According to *Giorgi & Marinucci* (1996) and *Laprise* et al. (1998) the choice of RCM resolution can modulate the effects of physical forcings and parameterization.

Christensen et al. (1998) showed that very high resolutions are required for the mountain chains in Norway and Sweden to be sufficiently well resolved and give a realistic simulation of the surface hydrology. High-resolution RCMs have been shown to contribute realistic details by the representation of fine-scale surface forcings and resolving some mesoscale processes (*Racherla* et al., 2012). They have been found to improve daily precipitation extremes relative to GCMs, and there is evidence that they also improve sub-daily values (e.g. *Maraun* et al., 2010; *Tripathi & Dominguez*, 2013). *Heikkilä* et al. (2010) found that high resolution is important in complex terrains, and that both orographic precipitation and extremes in Norway were largely improved in a 10-km resolution model compared to a 30-km resolution version of the same model.

The Intergovernmental Panel on Climate Change (IPCC) published a Special Report on Extremes (SREX) in 2012 (*Seneviratne* et al., 2012; *IPCC*, 2012). They state that it is *likely* that the frequency of heavy precipitation will increase in the 21st century over many areas of the globe. In the most recent IPCC Report on Climate Change (*IPCC*, 2013) they go further in stating that extreme precipitation events over most of the mid-latitude land masses will *very likely* become more intense and more frequent by the end of this century. However, the general conclusions of the IPCC is that climate models continue to perform less well for precipitation than for temperature, much due to the difficulty in simulating clouds. *IPCC* (2013) further claims that models may underestimate the projected increase in future extreme precipitation. Despite the challenges in simulating extreme precipitation, new RCM simulations on improved spatial and temporal resolutions are produced.

To account for the uncertainty in RCM simulations that arise from different model formulations and setups, it is now common to analyze results from several RCMs run on the same domain and with the same resolution. Such multi-RCM matrix is referred to as an ensemble (e.g *Druyan* et al., 2010; *Mearns* et al., 2012; *Kim* et al., 2013). *Xue* et al. (2014) claim that a careful selection of ensemble members with high dynamic downscaling ability is crucial.

Since the process of convection occurs on very small scales, climate models with their relatively coarse resolution have not been able to resolve convection explicitly, but rely on parameterization schemes. Such schemes commonly lead to misrepresentation of the diurnal cycle of convective precipitation, underestimation of dry days and overestimation of low-precipitation event frequency, and the underestimation of hourly precipitation intensities (*Prein* et al., 2015). To meet these issues, climate models have over the past few years developed a new group of high-resolution models referred to as convective-permitting climate models (*Kendon* et al., 2012; *Ban* et al., 2014; *Prein* et al., 2015).

3 Study region and data

In addition to the statistical tools presented in Section 2, different types of data was utilized to obtain the objectives in Section 1.2. The study region and datasets used in the analyses are presented in the following section.

3.1 Precipitation climate in Norway

The precipitation climate in Norway varies spatially and is highly affected by the complex topography. As seen in Fig. 4, there is a strong west-east gradient in mean annual precipitation, with decreasing amounts as we move eastwards across the mountain range. Precipitation types in Norway falls in three categories: frontal, orographic and convective (*Roe*, 2005). Most of the precipitation is frontal, caused by large-scale cyclone activity in the North Atlantic (*Heikkilä* et al., 2010). Frontal or stratiform precipitation systems extend over a horizontal area on the order of ∼100 km, while the vertical velocity of the updraft is only on the order of ∼10 cm/s. In contrast, convective precipitation systems are associated with strong latent-heat-driven vertical motion on the order of ∼10 m/s on horizontal scales of a few kilometres (e.g. *Houze*, 1993; *IPCC*, 2001). Convection arises from thermal stratification of the atmosphere when it becomes unstable or conditionally unstable (e.g. *Andrews*, 2010; *Wallace & Hobbs*, 2006), thus the vertical profiles of temperature and moisture play key roles. Atmospheric instability typically forms from heating at the surface, cooling in upper levels, or advection of different air masses at different heights. In many cases, convective and stratiform precipitation interact or occur together. Orographic precipitation can be separated into three independent mechanisms according to *Smith* (1979); Large-scale upslope precipitation caused by vertical lifting of air as it passes over rising terrain, small-scale enhancement or redistribution of precipitation over small hills, or formation of convective clouds in a conditionally unstable airmass due to solar heating of the mountain slope. Orographic and frontal precipitation dominate the climate along the western coast of the country which receives most precipitation in autumn and winter. The broad mountain range to the east strongly controls the precipitation with the highest amounts occurring near or slightly upwind of the steepest surface slope (*Nordø & GJortnæs*, 1966; *Andersen*, 1972). While for more narrow mountain ranges in Norway the maximum precipitation falls at the mountain top or on the lee side (*Andersen*, 1972).

Although the western coast receives the largest amounts of total annual precipitation, typically exceeding 2000 mm/year, hourly precipitation levels are not very high. Finnmark in the far north and Østlandet in the southeast are somewhat sheltered from the large frontal systems which mainly come from the west, thus the total annual precipitation is relatively low. In these regions, however, intense precipitation is dominated by convective summer showers, generating high sub-daily rainfall amounts particularly in the warmer south. As a consequence of the above-mentioned features, there are important differences in the spatial structure of daily and hourly precipitation extremes in Norway. Daily extremes are higher in western regions of South-Norway where frontal precipitation dominates and annual maxima usually occur in autumn. Shorter-duration extremes associated with convective events dominate along the southern coast, and annual maxima usually occur in summer.

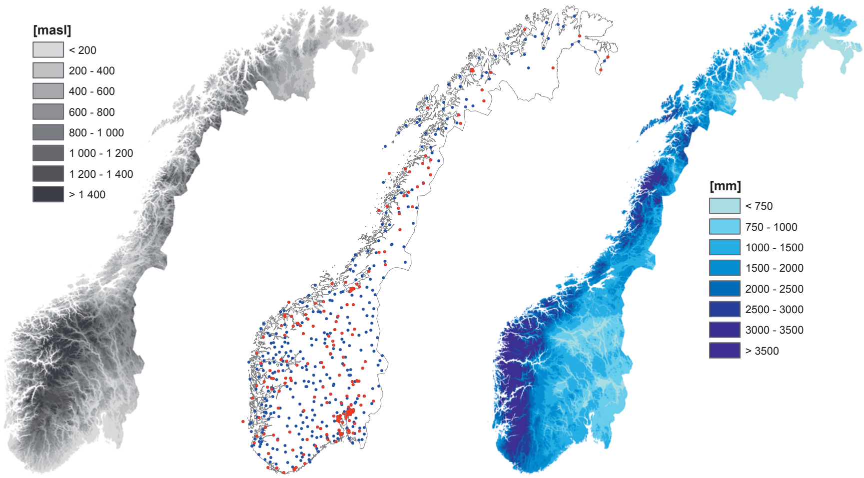

Figure 4: Left: Topography from a 100 m resolution demographic model. Middle: Meteorological stations measuring daily (blue) and hourly (red) precipitation. Right: Mean annual precipitation for the period 1957-2012.

3.2 Observations

The meteorological network measuring daily precipitation in Norway consists of more than 550 stations per January 2015, around 200 of which also measure hourly precipitation (see Fig. 4). The number of stations has varied substantially over the years, resulting in relatively few long observational series. The spatial distribution of stations is somewhat inhomogeneous, as a large number of the stations are located in lower elevations in southern parts of the country.

Three types of rain gauges are used to measure precipitation in Norway. Regular stations operate with a simple bucket that is emptied manually by an observer, and the total emptied amount is usually registered once a day. Automated stations have either tipping bucket or weight pluviometer, with a temporal resolution down to 1 minute. The first tipping bucket stations were established in the spring of 1967 and the first weight pluviometer stations in December 1991. All measurements are quality-controlled prior to being made public according to a free data policy at MET Norway (http://met.no/English/Data_Policy_and_Data_Services/).

3.3 Gridded datasets

3.3.1 Daily precipitation

MET Norway produces gridded datasets of daily temperature and precipitation for the period 1957-present, with a 1x1 km^2 resolution (*Tveito* et al., 2005; *Mohr*, 2009; *Jansson* et al., 2007). Temperature grids are based on measurements at over 200 locations interpolated through residual kriging, where the deterministic component is described by terrain and geographic position. Daily (06-06 UTC) precipitation results from an interpolation of all available precipitation measurements, using Triangulated Irregular Networks (TINs). Prior to the interpolation, measurements are adjusted for systematic gauge undercatch due to aerodynamic effects and wetting, according to *Førland* et al. (1996). A precipitation TIN based on measured precipitation and an elevation TIN based on the altitude at the meteorological stations are created. Furthermore, a terrain adjustment is performed on the precipitation grid based on the assumption that precipitation increases by 10% per 100 m up to 1000 m above sea level (masl) and 5% above that (*Førland*, 1979, 1984a). Two versions of the precipitation grid exist; one where observations are corrected for systematic gauge undercatch due to aerodynamic effects and wetting (*Førland* et al., 1996) (used in Paper III), and one without this correction (used in Paper I). The gridded datasets are used operationally in e.g. flood forecasting and to create snow maps in Norway (*Engeset* et al., 2004a,b).

Uncertainties associated with the daily gridded datasets are mainly related to the interpolation procedure, which in areas with rough topography is particularly challenging. Additionally, precipitation enhancement with elevation and correction for gauge undercatch are based on a simple models known to be highly inaccurate in some cases. For instance, *Engeset* et al. (2004b); *Saloranta* (2012) found that the vertical precipitation gradient is exaggerated, leading to overestimation in high elevations and underestimation in some lowly 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.

3.3.2 3-hourly precipitation

Vormoor & Skaugen (2013) estimated 3-hour precipitation on a similar grid as described above, for the period September 1957 to December 2010. They disaggregated the daily precipitation values into 3-hourly values, taking the diurnal cycle of precipitation from a 0.1°-resolution hourly hindcast described in *Reistad* et al. (2011). The hindcast was generated from dynamical downscaling of 1) ERA-40 atmospheric reanalysis (1957-2002) (*Uppala* et al., 2005) and 2) operational analyses from The European Centre for Medium-Range Weather Forecasts (ECMWF) (*Haakenstad* et al., 2012). The downscaling was performed using a hydrostatic numerical weather prediction (NWP) model, the High-Resolution Limited-Area Model (HIRLAM) version 6.4.2 (*Undén* et al., 2002), with 0.1° horizontal resolution and 40 vertical levels. Evaluation of the 3-hour precipitation grid suggests it should be favored over alternative datasets, although deviations from observations can be relatively large.

3.4 Fine-scale RCM precipitation

The most recent ensemble of regionally downscaled climate simulations are produced within CORDEX (COordinated Regional climate Downscaling EXperiment) (*Giorgi* et al., 2009), which aim is to provide downscaled climate information for improved regional adaptation and impact assessment. EURO-CORDEX (*Jacob* et al., 2014) is the European branch of the project, with 29 participating groups. RCM simulations are conducted on two spatial scales; 0.44° (EUR-44) and 0.11° (EUR-11), the latter corresponding to about 12 km. The EUR-11 dataset include simulations for the following periods: 1989-2008 (hindcast, driven by ERA-interim reanalysis (*Dee* et al., 2011)), 1951-2005 (control run, driven by a GCM), 2006-2100 (scenario run, driven by a GCM). Data are stored at every 3 hours, which represents an increase in temporal resolution compared to most RCM simulations. Thus, EUR-11 provides the first large ensemble of modeled precipitation on a relatively fine spatial and temporal scale. Fine-scale simulations are advantageous in areas of complex topography, like Norway (*Heikkilä* et al., 2010).

Paper III presents an evaluation of both 3-hourly and daily precipitation from the following EUR-11 RCM simulations for the hindcast period 1989-2008: RACMO 2.2, HIRHAM 5, RCA 4, RegCM 4.2, WRF 3.3.1 (two different configurations), and CCLM 4.8.17.

An issue associated with all gridded datasets is areal smoothing, which especially affects extremes. E.g. *Wibig* et al. (2014) and *Isotta* et al. (2014) state that areal averaging increases the number of wet days and moderate precipitation amounts, but decreases the highest daily precipitation amounts. *Isotta* et al. (2015) also found that two European regional reanalyses underestimate the frequency of heavy precipitation. The degree of smoothing depends on station density, the spatial correlation of extremes (related to the horizontal extension of the precipitation events), and obviously on the grid resolution. To evaluate climate model output, one usually relies on station observations, reanalyses datasets or interpolated datasets, such as those described in Section 3.3 above. Climate model output is regarded as "true" areal averages (*Chen & Knutson*, 2008; *Hofstra* et al., 2010), but the misrepresentation of areal average in the evaluation dataset should be assessed. *Haylock* et al. (2008) argue that one of the main reasons affecting the behaviour of extremes in gridded data is related to the interpolation methodology. According to *Hofstra* et al. (2010) this misrepresentation in interpolated datasets is due to variable station density and often sparse station network, and includes the following effects: 1. Exaggerated variance in the case of several stations within the same grid cell, 2. Over-smoothing of variance in the case of large distances between stations, 3. Extremes are more affected than the mean (also found in *Gervais* et al. (2014)). In the gridded datasets of Section 3.3 the effects are not uniform in space, but the two latter effects are most prominent. Station observations can be converted to areal averages by means of ARFs (see Section 2.1.2), as done in e.g. *Tripathi & Dominguez* (2013).

4 Presentation of findings

The research described in this thesis is presented in three papers. Paper I, entitled "Estimating extreme areal precipitation in Norway from a gridded dataset" was accepted for publication in Hydrological Sciences Journal in May 2014, and published online in July 2014. Paper II, entitled "Bayesian hierarchical modeling of extreme hourly precipitation in Norway" was accepted for publication in Environmetrics in July 2014, and published online in August 2014. Paper III, entitled "Evaluation of fine-scale extreme precipitation from EURO-CORDEX RCM simulations over Norway" was submitted for peer-review in International Journal of Climatology in March 2015.

All three papers focus on extreme precipitation over the mainland Norway, on different spatial and temporal scales as described below:

- Paper I: 1x1 km^2 - any area of interest, daily
- Paper II: 1x1 km^2, hourly
- Paper III: $0.11°$, 3-hourly and daily

The first two papers deal with past and present climate, with the aim of producing return level estimates using a combination of measured precipitation at meteorological stations and statistical tools. The third paper deals with projections of future climate from regional climate models, and is mainly an evaluation of the performance of these models to simulate short-duration precipitation on a relatively fine spatial scale. The GEV distribution fitted to annual maxima to estimate return levels is applied in all three papers.

The motivation and research approach in each paper is briefly introduced below, along with main findings and implications for national climate services.

4.1 Estimating point and areal precipitation extremes

MET Norway is responsible for providing return level estimates in Norway, mainly for use in flood estimation, dam safety, and transport infrastructure design. This requires methods for estimating both point (station or grid cell) and areal (catchment) precipitation design values. The current methods in Norway (Section 2.1.4) was developed more than 30 years ago (e.g. *Førland & Kristoffersen*, 1989), and there is a need for new methodology based on updated data and statistical tools.

Areal precipitation extremes are estimated in Paper I, where we make use of already existing gridded products at MET Norway, specifically daily precipitation from 1957-present on a 1x1 km^2 grid (see Section 3.3). We extract the integrated precipitation over a catchment and fit a GEV distribution to the areal time series, in order to compute return levels for the specific catchment. Obvious advantages of this method is avoiding the use of rather uncertain ARFs, and obtaining a measure of estimate uncertainty. Fig. 5 presents the procedures of the current method, referred to as SB-gf, and the proposed method GB-GEV. Return level estimates from the two methods were compared in Fig. 6, showing that GB-GEV estimates are generally lower than SB-gf estimates, but lie within a 25% deviation in most catchments. The accuracy of the GB-GEV estimates is obviously determined by the quality of the gridded dataset used as input, and will consequently gain by the constant improvement of these (Section 2.1.2). The problem of smoothing, which affects the extremes in particular, is likely to be reduced in future datasets, for instance through regional model-based assimilation tools (e.g. *Isotta* et al., 2015). For daily time scales, the rather simple procedure described in Paper I contributes to a more efficient and objective estimation of catchment return levels in Norway. The study is to our knowledge unique as to apply the GEV distribution on areal precipitation, besides *Overeem* et al. (2010) who fit GEV to areal radar precipitation. The author recognizes, however, that the methodological advances brought forward in Paper I are mainly associated with application, rather than statistics. From a meteorological perspective, Paper I contributes to the understanding of the spatial distribution of extremes in Norway and the underlying mechanisms, and represent a first step towards a model for the GEV shape parameter as further elaborated in the next section.

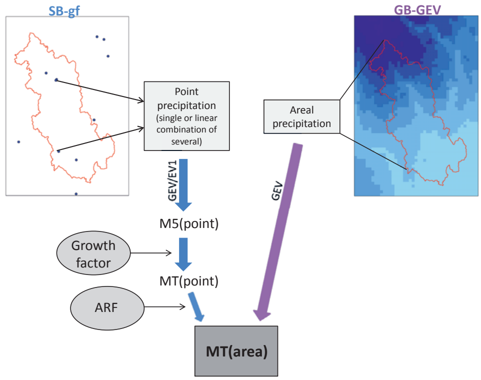

Figure 5: Flowchart of the existing (SB-gf; 2.1.4) and proposed method (GB-GEV; Paper I) for estimating extreme areal precipitation.

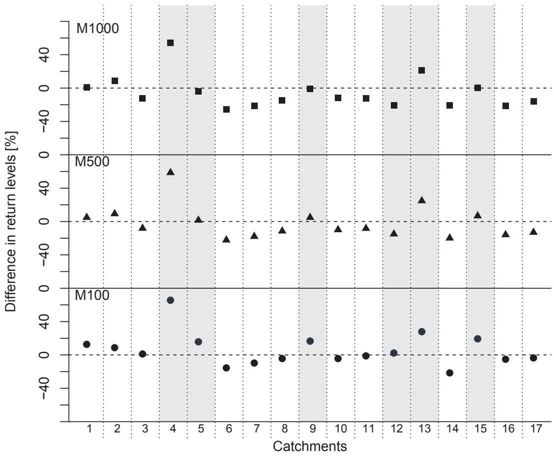

Figure 6: Percentage difference in M100 (circle), M500 (triangle), and M1000 (square) between SB-gf and GB-GEV estimates at 17 Norwegian catchments. Grey background indicates catchments with large difference in annual precipitation used in the two methods.

The BHM model presented in Paper II is a type of latent variable approach, which we believe is among the best methods to estimate the spatial distribution of marginal properties, such as return levels. This is supported by both *Davison* et al. (2012) and *Apputhurai & Stephenson* (2013), and means that while our model is able to capture climatological information at a given site, the total precipitation at this site at a specific time (the weather) would most likely be underestimated. This is because one assumes that, conditioned on the underlying process, extremes will arise independently at different sites (*Davison* et al., 2012). Such assumption is clearly not realistic for adjacent locations. We create fine-scale return level maps for hourly precipitation in Norway through fitting the GEV distribution to observational series of hourly precipitation, and link the GEV parameters to geographical and meteorological variables (covariates). Next, the model spatially interpolates the GEV parameters via their relationship to covariates on a 1x1 km^2 grid. A Gaussian field is used to allow for local adaptivity and accommodate for over-dispersion. In other words, the covariates account for the deterministic component, while the Gaussian field accounts for the spatial random effect (the stochastic component). If the link between observations and the covariates is weak, the model will borrow strength from a nearby site and the random effect will be large. A Bayesian Model Averaging (BMA) approach evaluates all possible combinations of covariates and constructs a weighted average (derived from the posterior probabilities) over all of them. Thus, directly assessing model uncertainty which has long been a shortcoming in return level estimation in Norway. Estimation of model parameters is easily performed via Markov Chain Monte Carlo (MCMC). The model, hereby referred to as the BMA model, is freely available as an R-package on http://cran.r-project.org/web/packages/spatial.gev.bma.

Out of sample assessments show that our model is able to reproduce the heterogeneity in observed return levels. In Fig. 7 the 20-year return level estimated by the BMA model is compared to direct station MLE estimates, revealing strong agreement. Amongst the eight covariates tested (four geographical and four meteorological), mean summer precipitation and temperature, along with latitude, longitude, mean annual precipitation and elevation feature the highest inclusion probabilities in the model for the GEV μ parameter.

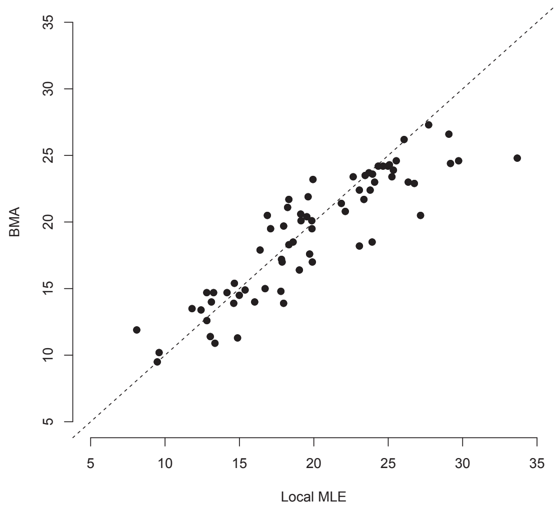

Figure 7: Scatterplot of modeled M20 for hourly precipitation at the 69 locations estimated by the BMA approach versus a local MLE fit to observations. Axis labels are in mm.

To our knowledge, this is the first attempt to produce such fine-scale return level maps of hourly precipitation in Norway and also the first use of a BHM in an area of such large spatial variability in precipitation. The paper thus represents the state-of-the-art in the field of spatial modeling of extreme precipitation. Of similar studies the author can mention *Geirsson* et al. (2015) who recently modeled annual maximum 24-hour precipitation in Iceland, implementing stochastic partial differential equations (SPDE) to spatially model GEV μ and σ. They did however not make use of BMA. The return level maps created in Paper II have a wide range of applications, and the model is flexible in terms of region, type of covariates, and variable of interest. Please note that the statistical methodology and technical developments presented in Paper II was mainly lead by the second author.

The two methods in Paper I and Paper II fulfill many requirements of climate services in Norway, with regards to precipitation design values. They provide objective and spatially coherent estimates and substitute outdated statistical tools and data. The BMA model represents one of the most novel approaches within spatial modeling of extremes, and is a promising tool for further advancement and increased accuracy of Norwegian design values. To withstand the expected increase in extreme precipitation frequency and intensity, however, it would be necessary to incorporate a climate change factor into the design values. This subject is addressed in Paper III, and summarized in Section 4.3.

4.2 The GEV shape parameter in Norway

Throughout the work on Paper I, we discovered some interesting features when applying extreme value theory in such a spatially varying precipitation climate. Thus, a large part of the paper deals with an analysis of the value and spatial distribution of the GEV shape parameter, ξ, in Norway. We show that this important, but hard to estimate, parameter varies across Norway according to dominating precipitation systems.
Unlike several studies suggesting a positive and near-constant ξ value over larger regions (e.g. *Koutsoyiannis*, 2004b; *Veneziano* et al., 2009; *Wilson & Toumi*, 2005), we find that ξ is generally positive in the southeast and negative in the southwest of Norway. One explanation to this particular pattern might be a larger range of precipitation amounts in the southeast due to the exposure of mixed-type precipitation systems, while in the southwest extremes are usually produced by frontal systems. We also show, as found in *Papalexiou & Koutsoyiannis* (2013), that ξ tends to narrow its range as the record length increases. Since parameter

estimation methods can give unreasonable ξ values, we propose to restrict the parameter according to empirical evidence, for instance through the frequency distribution shown in Fig. 8. One possible solution would be to implement a Bayesian prior distribution specifically for Norway according to the empirical values, similar to (*Martins & Stedinger*, 2000, see Section 2.1.1). The restriction requires a more extensive analysis of the ξ point value in different parts of the country, and also how this value changes with increasing catchment size. Such analysis was beyond the scope of our paper.

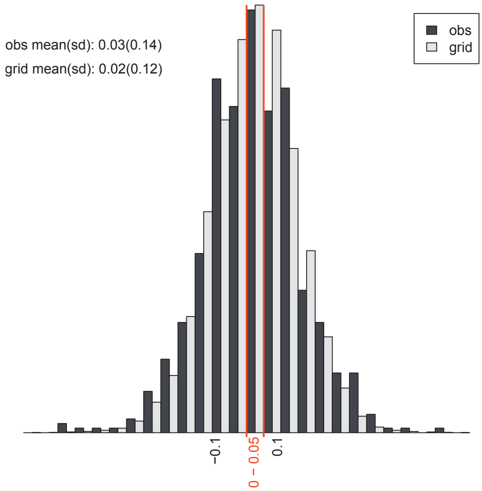

Figure 8: Frequency distribution of ξ estimated from observations (dark grey) and the daily gridded dataset (Section 3.3.1) (light grey). Red interval indicates the mean.

Due to the limited number of sub-daily observations, only a few studies on ξ on such shorter duration precipitation exist. However, similar to a decrease with increasing area (e.g. *Overeem* et al., 2010), ξ is likely to decrease with increasing duration. This is confirmed in e.g. *Overeem* et al. (2010) and *Van de Vyver* (2012). In Paper II ξ and the two other GEV parameters are modeled through their relationship to gridded covariates, as described in the section below. The resulting return levels are compared to return levels estimated from three modified versions of the model, including one that prescribes ξ to a value of 0.15 for the entire country. The three models that allow ξ to vary appear to offer estimates that are more consistent across Norway, but no covariate seem to capture the spatial distribution of ξ in a satisfactory manner leading to considerable uncertainty in its estimates. The most influential covariates, however, are latitude and longitude. The actual values of ξ are reasonable with a posterior mean of ξ 0.11, although with a substantially wide 95% confidence interval of -0.65 to 0.87.

Although paper III focuses on seasonal maxima to evaluate the extremes in RCM simulations (see Section 4.3), return level estimates are briefly assessed. Experience from analyses in Paper I inspired the use of a Bayesian prior on ξ, and the modified MLE-approach of *Martins & Stedinger* (2000) mentioned above was adopted to estimate return levels from simulations and observations.

4.3 Fine-scale RCM simulations of summer precipitation extremes

Future climate change, with likely implications for Norway being increased precipitation (see Section 1.1), require preventative actions in the planning and design of infrastructure. Climate model simulations give essential information in the design process of infrastructure built to last several decades into the future. One way to account for possible future changes in design values is in Norway referred to as "climate factors", and is defined as the factor we need to multiply current design values with to get an estimate of future design values. This procedure does not require bias correction of climate model simulations, as the simulated change between historical periods and future periods is utilized. Climate factors can be used directly on estimates provided by the methods in Paper I and Paper II. To obtain more accurate precipitation amounts for future climate, however, bias correction to match the observed precipitation statistics would be required. As the initial step towards analyzing possible future changes in sub-daily extremes in Norway, we have in Paper III evaluated 3-hourly and daily summer precipitation from seven different simulations over the mainland-Norway, included in the EUR-11 ensemble described in Section 3.4. The limitation to summer season relates to the availability of sub-daily observations and is justified in Section 3.1, stating that the highest short-duration extremes usually occur in summer. The success of covariates related to summer temperature and precipitation in the BMA model (Section 4.1; Paper II) also confirms this statement. Still, the representativeness of this study is somewhat biased towards regions dominated by extreme short-duration summer precipitation. Although a few studies have analyzed the EUR-11 dataset, including *Kotlarski* et al. (2014) who evaluated daily temperature and precipitation over Europe, the sub-daily simulations have not yet been given the same attention.

Our focus in Paper III was on extreme summer precipitation in terms of seasonal maxima, quantiles and return levels, but we also analyzed the frequency of wet events and total summer precipitation. We compared EUR-11 simulations to two types of datasets; The daily and 3-hourly observation-based gridded data described in Section 3.3, and measurements at 19 meteorological stations around the country (see Fig. 4). We find slightly different results depending on reference dataset and temporal scale, but most models are able to reproduce the spatial distribution and extreme values relatively well. Fig. 9 is a quantile-quantile plot of 3-hourly summer precipitation from 19 observational sites (x-axis) and the nearest EUR-11 grid cells. The seven simulations are noted by their institute or community of origin. Lower quantiles are well represented, and some simulations are able to reach close to the highest observed quantiles.

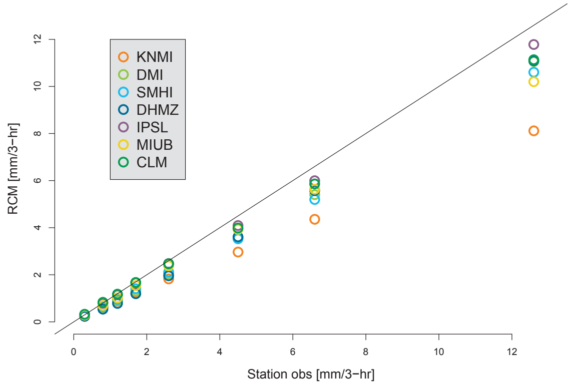

Figure 9: The 0.25, 0.5, 0.6, 0.7, 0.8, 0.9, 0.95, and 0.99 quantiles for 3-hr summer precipitation at 19 stations and the seven EUR-11 RCMs

Regarding wet day frequency all models show a positive bias, and an overall positive bias is also seen for 3-hour events. This overestimation is a common issue in regional climate models. We identify two models with larger deviances compared to the reference data and the other models, one giving low precipitation intensities (KNMI), while the other largely overestimates the frequency of wet events and hence total summer precipitation (DHMZ). In addition to model deficiencies in terms of poor representation of convection and orographic enhancement, possible causes of detected biases might involve incompatible properties between model and reference data. This includes different or missing adjustment for gauge undercatch between the datasets.

We find it likely that the high spatial resolution of 0.11° improves the simulations of extreme precipitation in Norway, especially in areas of orographic enhancement as shown by (e.g. *Heikkilä* et al., 2010). In addition to reproducing more accurate precipitation values, the increased spatial resolution is beneficial as a tool for local climate adaptation. Although the study does not bring forward any methodological advanced in terms of evaluation or statistical tools, we believe to be the first to evaluate 3-hourly precipitation over Norway from the EUR-11 ensemble. The results thus represents an important feedback to the RCM community on the ability of their models to reproduce extreme precipitation levels, as well as the possibility and requirements for implementing these simulated levels into national climate services.

5 Conclusions and future perspectives

Results in the current thesis contributes to the understanding of extreme precipitation in Norway, in terms of mechanisms, spatial distribution and level of design values. The main contribution, however, is towards the methodology for estimating such design values in Norway. New statistical methods for estimating daily precipitation extremes over catchments, and hourly extremes in any point on a fine-scale map have been developed. These methods can easily be implemented as part of the national climate service provided by MET Norway, as requirements of accurate design values on smaller spatial and temporal scales becomes increasingly important. In the light of climate change, expected future design values must be explored. The last part of the thesis therefore concentrates on assessing the most recent climate model simulations in terms of their ability to reproduce observed precipitation levels in Norway. The work in this thesis has had a large focus on requirements from practitioners and end-users, thus the applicability of results are crucial.

This thesis has demonstrated the complex spatial structure of extreme precipitation in Norway, which is shown to differ between temporal scales. In contrast to more orographically homogeneous countries like The Netherlands, where advanced radar products allow for good quality areal precipitation assessments, we still need to rely on derived products from in situ observations. In Paper I we make use of an observation-based gridded dataset to fulfill the demand for more objective and efficient estimation of design values for areal precipitation. GB-GEV can easily be applied to other gridded products, for instance projections of future precipitation. The GEV shape parameter had a key role in Paper I, as it varies across Norway according to the type of precipitation systems that produce extremes in different regions. Our results contradict with several studies of the shape parameter over larger spatial scales, claiming that the parameter should be (nearly) constant and strictly positive. The author realizes however, as also shown in our paper, that the estimation of the shape parameter is affected by record length and the the range of values narrows with longer time series. Consequently, the shape parameter should be restricted according to empirical evidence.

On sub-daily scales observations are limited and practitioners in Norway have relied on empirical-statistical relationships to derive sub-daily design values from daily precipitation. As hourly time series have become longer and more numerous, the possibility to model spatial extremes arises. In Paper II we successfully apply a Bayesian Hierarchical Model to reproduce return levels of hourly precipitation in Norway, through the use of relevant covariates on a fine-scale grid and Bayesian Model Averaging. Effective covariates seem to be variables describing convective conditions, such as summer temperature and precipitation, in addition to mean annual precipitation and geographical variables (latitude, longitude, and elevation). This paper represents the state-of-the-art within spatial modeling of extremes.

Adjusting design values based on historic and current climate information according to expected future changes is crucial, thus as an important first step towards producing precipitation return level maps for future climate in Norway, the state-of-the-art within climate model simulations from EURO-CORDEX have been evaluated in Paper III. These can now provide precipitation values on relatively fine spatial and temporal scales, more specifically 0.11° horizontal resolution and 3-hourly temporal resolution. The simulations are to a large degree able to reproduce precipitation extremes on daily and sub-daily scales over Norway. Biases are relatively small, with a few exceptions. Bias correction is probably necessary in a next step, but our results are promising in the aspects of using EUR-11 simulations to assess possible future changes in extreme precipitation.

The research presented herein represents first attempts at addressing extreme precipitation design values by use of the GEV distribution in Norway on a detailed level. Nevertheless, many tasks remain for implementation and future analyses that can challenge or strengthen our findings. In particular, we would like to explore recent developments on non-stationary GEV methods, study the effect of topography on the extreme value distribution, and possibly separate extremes coming from different weather types. As mentioned in Section 2.1.1 and in Paper I, the author would like to restrict the shape parameter through a Bayesian prior distribution. One possible approach would be to create an empirical distribution using good-quality observational data, either for the country as a whole, or regional distributions. Ideally, a separation between stratiform and convective extremes should be made. A new and improved gridded dataset for daily precipitation is currently being developed at MET Norway, covering the same period 1957-present. The new dataset is created by spatial interpolation based on Bayesian methods, and information is propagated from the coarser to the finer scales by means of an iterative Optimal Interpolation (OI) procedure (*Lussana & Tveito*, 2014, not published). Similar datasets on sub-daily scales, and combination datasets based on observations, radar, reanalysis and numerical models are also planned for. Since GEV-GB depend strongly on input data, it is likely that using these coming datasets will improve the estimates of areal extreme precipitation.

For extreme precipitation estimates at a point there is a need for regionalization, possibly through pooling of data over homogeneous regions. The BMA-model would be a good contribution for such a task, providing knowledge on the spatial distribution of the GEV parameters. Although we are pleased with the performance of the BMA model for our purposes, a number of improvements concerning algorithm and scientific basis are suggested in Paper II. To better address the different weather regimes, it may be useful to split the country into regions and perhaps seasons. Covariates that more appropriately describe the spatial distribution of hourly extremes can be implemented, and the limiting assumption of stationarity in the covariates should be addressed by letting regression coefficients vary in space. A comparison of BMA model estimates and direct GEV estimates on grid precipitation for different durations would be an interesting exercise. Ultimately, the goal is to implement the BMA-model into the operational services at MET Norway.

Suitable bias-correction methods for selected EUR-11 simulations, according to the results in Paper III, should be developed in order to analyze changes in precipitation design values between the historical control run and projections of future climate. A thorough examination of possible changes in 3-hourly precipitation extremes in Norway are yet not available, and would answer to an important demand. However, firstly we would like to perform a similar evaluation as in Paper III using the new gridded datasets for daily precipitation and disaggregated 3-hour values. For a better comparison and more robust conclusions it would be useful to include assessments on the quantitative levels of uncertainty associates with each dataset. When available, high-resolution convection-permitting ensemble simulations for Norway should be investigated.

The field of extreme precipitation has evolved substantially over the past few years, and the author believes that increased national research efforts would be worthwhile, especially from a climate change adaptation perspective.

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Appendix

Paper I

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Estimating extreme areal precipitation in Norway from a gridded dataset

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Abstract 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 from 1957 to the present. 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 in order to estimate precipitation return levels required for design values for flooding and dam safety. The study includes an investigation of the spatial variation of extreme precipitation in Norway, reflected through the GEV shape parameter. Our results suggest that this parameter varies spatially according to dominating precipitation systems and, most probably, to the degree of orographic enhancement.

Key words extreme precipitation; Norway; areal precipitation; GEV; precipitation; gridded data

Estimation des précipitations extrême sur le territoire Norvégien à partir de données représentées sur grille

Résumé A l’heure actuelle, pour obtenir une estimation de la répartition en surface des précipitations extrêmes sur le territoire Norvégien, l’institut météorologique en Norvège utilise une méthode statistique basée sur la combinaison de la mesure locale, d’un facteur de croissance empirique et d’une méthode d’abattement des pluies de surface. Nous proposons, ici, une nouvelle méthode basée sur une analyse statistique appliquée non pas sur la la mesure locale mais plutôt sur les données de précipitations journalières représentées sur une grille et couvrant la période allant de 1957 jusqu’à nos jours. L’utilisation de ces dernières a montré un potentiel croissant ces dernières années et permettent, en particulier, l’estimation des précipitations pour des bassins non jaugés. La méthode que nous proposons applique la loi des extrêmes généralises directement aux précipitations surfaciques pour en déduire, par la suite, les temps de retour des événements pluvieux en question. Ces derniers sont nécessaires pour la plus part des études d’impacts hydrologiques et des ouvrages de protections contre les crues tels que les barrages. La méthode proposée a été appliquée sur les précipitations extrêmes dérivées a partir de données représentées sur une grille régulière couvrant le territoire Norvégien. Nous avons étudié, en particulier, la distribution spatiale du paramètre de forme de la loi des extrêmes généralisées. Les résultats montrent que ce paramètre varie dans l’espace en fonction des systèmes précipitant dominants et que les barrières orographiques tels que les montagnes jouent aussi un rôle déterminant.

Mots clefs précipitation extrême ; Norvège ; précipitation surfacique ; GEV ; précipitation ; données représentée sur grille

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. Extreme precipitation in regions with varied topography, like Norway, is caused by convective small-scale systems as well as larger scale frontal systems, subject to orographic enhancement (Roe 2005). The relatively sparse station network also adds to the complexity. Estimates of extreme precipitation are usually presented as values with low frequency 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 danger potential (NVE 2011). Authorities for roads, railways, and urban planning are more concerned with short-term and intense precipitation with return periods of 5 to 200 years. For design purposes there is a constant demand for higher temporal resolution, still the lack of sub-daily precipitation measurements often makes it more appropriate to rely on the scaling of daily precipitation.

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 as the area increases and spatial correlation is reduced. Simultaneously, the extremes of the same distribution will converge to one of three types of the Generalized Extreme Value (GEV) distribution. In the current study we explore the spatial distribution of extreme precipitation in points and areas in Norway, and present a method for estimating extreme areal precipitation in Norwegian catchments.

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. Further, 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 flood 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 (Hisdal *et al*. 2006, Hanssen-Bauer *et al*. 2009, Wilson *et al.* 2010). Due to these observed and projected changes, existing design criteria for infrastructure should be revised. Svensson and 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 and Kristoffersen 1989, Førland 1992) 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 use empirical growth factors to derive estimates of longer return periods. The method 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 also leads to a lack of consistency.

We therefore propose a new method for estimating extreme areal precipitation statistics based on daily precipitation interpolated on a 1x1 km2 grid (Tveito *et al*. 2005, Jansson *et al*. 2007, Mohr 2009) and the GEV distribution. The proposed method is hereby referred to as the grid-based GEV method (GB-GEV). An immediate benefit of GEV over growth factors is the possibility for a direct uncertainty measure in terms of confidence intervals. Fine-scale grids have the advantage of providing spatially continuous datasets and a simplified 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. To our knowledge, we are the first to use finescale grids directly in the estimation of areal precipitation return levels. In Section 2 we describe the development of the alternative method, including an investigation of the GEV shape parameter in Norway. Section 3 provides results from the method comparison and a discussion, followed by conclusions in Section 4.

2 FROM STATION-BASED TO GRID-BASED ESTIMATES

In this section we briefly describe the existing station-based method for estimating extreme areal precipitation, and then show the basic principles of the proposed grid-based method. The two methods, SB-gf and GB-GEV, are presented in Fig. 1 and terminologies are further explained in the text.

2.1 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 precipitation with a T year return period (MT) as a function of M5 (precipitation with a 5 year return period), also called the index value. The ratio MT/M5 is referred to as growth factor. 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

$$\mathrm{M\,T} = \mathrm{M5}e^{\mathrm{C}(\ln(\mathrm{T}\,-0.5)-1.5)} \tag{1}$$

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

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

Growth factors are used along with standardized areal reduction factors (ARF) (NERC 1975, Bell 1976), converting 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.

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 directly, ARFs then become redundant.

2.2 Precipitation grid

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 on a 1x1 km2 grid (Tveito *et al*. 2005, Jansson *et al*. 2007, Mohr 2009). The operational period of the different precipitation stations vary, so does the collection of measurements applied in the interpolation from day to day. Triangulated irregular 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 meters above sea level (m a.s.l.) and by 5% per 100 m above that. 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) and 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.

2.3 The GEV distribution

The GEV distribution, introduced by Jenkinson (1955), describes the three possible types of extreme value distributions for block maxima of any variable (Coles 2001). The 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 is location, σ is scale, and ξ is shape. Depending on ξ, the GEV distribution converges 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 in extreme value statistics, and a large variety of analysis tools are developed. Coles & Tawn (1996) claim the GEV distribution to be valid also for areal precipitation.

Large uncertainty is associated with the estimation of the GEV ξ parameter, representing a challenge when fitting the GEV model. The uncertainty increases for short time series which is often the case with meteorological variables. The complex topography and climate in Norway also introduce inhomogeneities and a mixture of precipitation processes in different parts of the country further complicates the estimation of ξ. Still, ξ is essential in extrapolating to longer return periods important for design. The challenge associated with the estimation of ξ motivates a more thorough analysis of the nature and spatial distribution of this parameter in Norway. Here we refer to ξ for point and areal precipitation as ξ_p and ξ_a, respectively.

2.4 The GEV parameter ξ_p in Norway

According to several studies, extreme 24-hour precipitation at a point follows a Type II distribution (heavy upper tail; $\xi_p > 0$) (Wilks 1993, Koutsoyiannis and Baloutsos 2000, Katz *et* *al*. 2002, Coles *et al*. 2003, Coles and 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. Wilson and 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 and 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) suggest that a constraint on ξp using theoretical arguments is necessary.

To study the spatial distribution of ξ_p in Norway, we use the method of "maximum likelihood estimation" (MLE) (Prescott and Walden 1980). Figure 2(a) presents estimates of ξ_p in single 1x1 km^2 grid-cells for the period 1957–2012. We performed the same analysis using the method of "weighted least squares" (WLS) (Koutsoyiannis 2004b), with weights equal to the empirical quantiles. This method grants higher importance to the largest values, and was shown by Koutsoyiannis (2004b) to be a better fit to empirical values. The spatial distribution of WLS estimates is similar to that of MLE estimates, thus not shown here. Negative ξ_p are seen mostly in coastal areas, while continental parts are dominated by positive values, showing the same spatial pattern seen in the actual observations. In Fig. 3 the empirical distribution from the gridded dataset and observations at 569 sites (cf. Fig. 6) is shown, revealing a near Gaussian distribution of ξ_p with a mean of 0.020.03. The Gaussian distribution of ξ_p is in accordance with previous findings by e.g. Papalexiou and Koutsoyiannis (2013).

We further assess the regional variability of ξ_p, by selecting 18 series with more than 100 years of measurements (cf. Fig. 6) and apply Pearson's Chi-square test (Pearson 1900) with α-level of 0.05 to test spatial homogeneity between ξ_p at paired sites. ξ_p for 6 sites in the continental Southeast and 6 sites in the Southwest shows no significant variation within the separate regions. As we combine the 12 sites, in addition to 6 sites in other parts of the country, significant inhomogeneity is evident, suggesting that a constant and strictly positive ξ_p is not appropriate for Norway.

It is essential to realize that GEV and other mathematical distributions are simply models that are supposed to mimic the main features of nature. The complexity of nature and its measurements, however, introduces a number of reasons why our observational series and associated estimates do not strictly follow the theoretical framework of e.g. the GEV model. 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 processes producing extreme precipitation in Norway. Comparing Fig. 2(a) and (c) reveals that negative ξ_p estimates are mostly found in areas characterized by higher annual precipitation. In these areas the largest daily precipitation values are mainly produced by stratiform systems in the prevailing westerlies, and the precipitation intensity is enhanced by orographic effects across the Norwegian mountain range. A possible explanation for negative values of ξ_p may be the rather uniform exposure of precipitation types, and that orographic enhancement modifies the extreme value distribution. Some clues on the latter can be obtained from literature. Blumen (1990) and Yu and Cheng (2013) found that the extent and degree of orographic enhancement depends closely on local topographic geometry, and Yu and Cheng (2008, 2013) found that there are complicated microphysical interactions between the orographic part and the background precipitation from the low pressure system. In addition, Yu and Cheng (2013) suggest that the magnitude of orographic enhancement is not proportional to the background precipitation alone, but to the product of the background precipitation and the wind speed of the oncoming flow. According to Caroletti and Barstad (2010) precipitation in western Norway is dominated by forced uplift, and they show that for stations at some distance from the coast the background precipitation is much smaller than orographic precipitation during extreme events. It follows that orographic effects influence the distribution of extreme precipitation in these areas. Furthermore, since the mountain range responsible for the forced uplift is static, it is not unreasonable to assume a limit for the orographic effects and hence an upper bound (negative ξ_p) for extreme precipitation. In most areas with positive ξ_p, however, orographic effects are minimal and high-intensity precipitation may occur during frontal systems from the Southeast-East sector, and during heavy convective summer showers. These regions thus experience a wider range of precipitation amounts as they are heavier 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 the normal (averaged over the period 1961–1990) annual precipitation (PN), which can be seen as a proxy for the type of dominating precipitation processes. The above statement that ξ_p decreases with increasing PN is confirmed, and a linear regression shows that this relationship becomes stronger for longer record lengths. For record lengths exceeding 80 and 100 years the fitted slopes are statistically significant at the 0.001 level.

Papalexiou and Koutsoyiannis (2013) also found that ξ_p estimates depend on the record length, and show a tendency to higher ξ_p for longer series. To investigate a possible dependence in Norway we estimate ξ_p at the 569 observation sites, using both MLE and WLS, and plot the result against record length (Fig. 5). We divided the 569 series into different lengths to increase the number of series, and computed the median, 5th and 95th quantiles for all lengths for which at least 5 series were available. We find a weak non-significant positive trend in ξ_p with record length. 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 random, and since WLE does not change the general picture we choose to stay with MLE as our estimation method throughout this study.

2.5 The GEV parameter ξ_a in Norway

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 a result of reduced spatial correlation with increasing area, we have that the parent distribution converges towards a Gaussian due to the central limit theorem. Simultaneously, we expect the extremes of the same distribution to converge towards a GEV type I (ξ_a = 0), which is the domain of attraction of a Gaussian upper tail. This is in accordance with Leadbetter *et al*. (1980) who state that "if Xn is an independent and identically distributed (i.i.d.) (standard) normal sequence of random variables, then the asymptotic distribution of Mn = max(X_1, ..., X_n) is of Type I".

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. In the current section we investigate the behavior of ξ_a in Norway using the gridded dataset.

We argued in the previous section that the range of extremes, and thus the ξ_p parameter, varies according to dominating precipitation systems and orographic effects. Another aspect for areal precipitation is that different processes and degree of spatial correlation 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.

If the extremes converge towards a GEV Type I in larger areas, ξ_a would be smaller than ξ_p in areas where ξ_p is positive, and vice versa. This is however not seen in Fig. 7, where we plot the mean ξ_p against ξ_a in the catchments. But we note a small tendency to larger differences (deviation from the diagonal) in larger catchments.

To minimize the effects of inhomogeneity, we select two areas; Southeast and Southwest (cf. Fig. 2) that are relatively homogeneous in terms of ξ_p. Positive ξ_p values dominate the Southeast, while negative dominate the Southwest. Within the areas we select 25 points and estimate ξ_a for increasingly larger areas around the points. Figure 8 reveals a scale-break around 1500 km^2 in both areas, and a second scale-break around 6000 km^2 in the Southeast. These can probably be attributed to the geographical extent of different precipitation systems that produce extremes in the two areas, and confirm that we are dealing with a mixture of different extreme value distributions that complicates our study. The two scale-breaks in the Southeast indicate that a greater variety of precipitation types occur here, as suggested in Section 2.4, and that these precipitation types produce extremes from different distributions. After the last scale-break we note that ξ_a decreases, reflecting the reduced spatial correlation as the area increases. In accordance with Overeem *et al.* (2010), extremes converge from a GEV type II towards a GEV Type I distribution in the Southeast. In the Southwest, however, the Type III distribution is further strengthened. The latter may indicate that in areas of negative ξ_p the assumptions for the central limit theorem, such as the observations being i.i.d., are not met. A reason for this might be that orographic enhancements have a non-linear and spatially intermittent effect, and hence contaminate the extreme value distribution. These findings have to be considered preliminary, and due to the strong gradients in the Norwegian precipitation climate along with possible misrepresentation of spatial correlation in the gridded dataset, a more thorough investigation of ξ_a is necessary.

2.6 GB-GEV

Our analyses indicate a connection between relevant precipitation indices and the spatial distribution of the GEV ξ parameter in Norway. We recognize, however, that further work is needed to present a model for ξ_a according to empirical evidence. As a result, we here choose to estimate ξ_a directly. The proposed method, GB-GEV, thus includes fitting the GEV distribution to annual maximum areal 24-hour precipitation extracted from the precipitation grid, using MLE to estimate the three GEV parameters.

It is common practice to use estimates of probable maximum precipitation (PMP), which represent a precipitation amount with a return period of infinity, in the design of critical constructions like e.g. reservoir dams. Great uncertainties are associated with the estimation of long return periods, and the evolvement of numerical weather (NWP) 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 NWP-based estimation methods is carried out in the future.

3 METHOD COMPARISON AND DISCUSSION

We compare return level estimates from GB-GEV and SB-gf in the 17 catchments, making use of previously determined SB-gf estimates computed at MET Norway on different occasions (cf. Table. 1). Percentage differences for M100, M500, and M1000 are shown in Fig. 9. GB-GEV estimates lie within a 25% deviation of 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 (see Fig. 10). The largest deviation is seen in Svartevatn, where GB-GEV estimates are 40–60% higher. A natural explanation for this is the elevation gradient for precipitation used in the gridded dataset, which in wet areas such as Svartevatn, is likely to generate serious overestimation since the elevation gradient is defined as a percentage. The growth factors in SB-gf seem to correspond to a somewhat higher positive ξa compared to the estimated ξa 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.

Figure 11 shows examples of estimates from four catchments; Soneren, Siljan, Aursunda and Roskreppfjord, including empirical values. As these are grid-based empirical values, and thus biased towards GB-GEV, they can not be applied to determine the better model. The 95% and 99% confidence intervals, indicating the uncertainty in the GB-GEV estimates, are shown in the figure. It must be emphasized that this confidence interval only reflects the uncertainty in the estimation of the GEV parameters, while additional and unquantifiable uncertainty is associated with the gridded dataset. For longer return periods SB-gf stays within the confidence intervals of GB-GEV in all catchments, except at Sira where SB-gf moves slightly above the upper confidence level for M1000.

Uncertainties in the gridded dataset are likely to influence our estimates, particularly in high elevated and ungauged regions. 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 the 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 events 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 alternative estimation methods in the more uncertain regions.

A more comprehensive study of different precipitation types and their spatial distribution would be an interesting focus for future work. Numerical weather models or statistical pattern recognition (Skaugen 1997) can for instance be used to separate frontal from convective precipitation, which could further confirm the effect of precipitation types on the negative shape parameters seen in the Southwest. An analysis of the orographic effect on spatial correlation also remains a subject of future research.

4 CONCLUSIONS

We propose a new grid-based method, GB-GEV, for estimating extreme areal precipitation in Norway. To the best of our knowledge we are the first to use fine-scale grids for this purpose, and to investigate the behavior of the GEV ξ parameter in Norway. Estimates from GB-GEV are compared to estimates from the existing method at MET Norway, SB-gf. Due to large uncertainties and short time series, as well as the absence of areal precipitation measurements, it is difficult to indicate which estimates are better. However, there are relevant and decisive differences between the methods. Our findings can be summarized as follows:

- Grid-based methods are less manual and time-consuming compared to the station-based method, as well as more objective and consistent in terms of input data. In addition, estimates in ungauged catchments are easier to obtain.

- GB-GEV estimates are generally lower than SB-gf estimates, but lie within a 25% deviation in most catchments.
- We have shown that ξ_p varies spatially in Norway, seemingly depending on dominating precipitations systems and orographic enhancement. For areal extremes the catchment size plays an additional role due to the degree of spatial correlation. We also observe that record length influences the ξ_p estimates and that the accuracy most likely increases with longer series. Our results suggest that ξ_a should be modeled according to empirical evidence, however, a more extensive analysis and perhaps additional data sources are required before concluding on a suitable model.

The authors recognize that GB-GEV estimates are dependent on the quality of the gridded dataset. This means that estimates are less robust in areas with few observations and complex topography. Still, GB-GEV estimates will become more accurate as gridded products improve in the future, and the suggested methodology provides more objective and geographically consistent results than the SB-gf method. GB-GEV can also be applied in estimating extreme precipitation from future climate projections.

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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. PN is normal annual precipitation. For size and PN we show values used in SB-gf 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.

Catchment	Size (km²)	Elevation (m a.s.l.)	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)

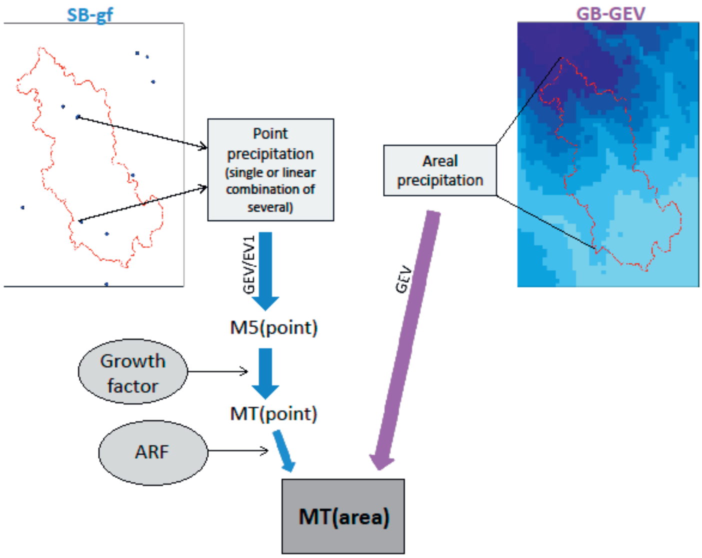

Fig. 1 Flowchart of the two methods for estimating extreme areal precipitation; SB-gf and GB-GEV.

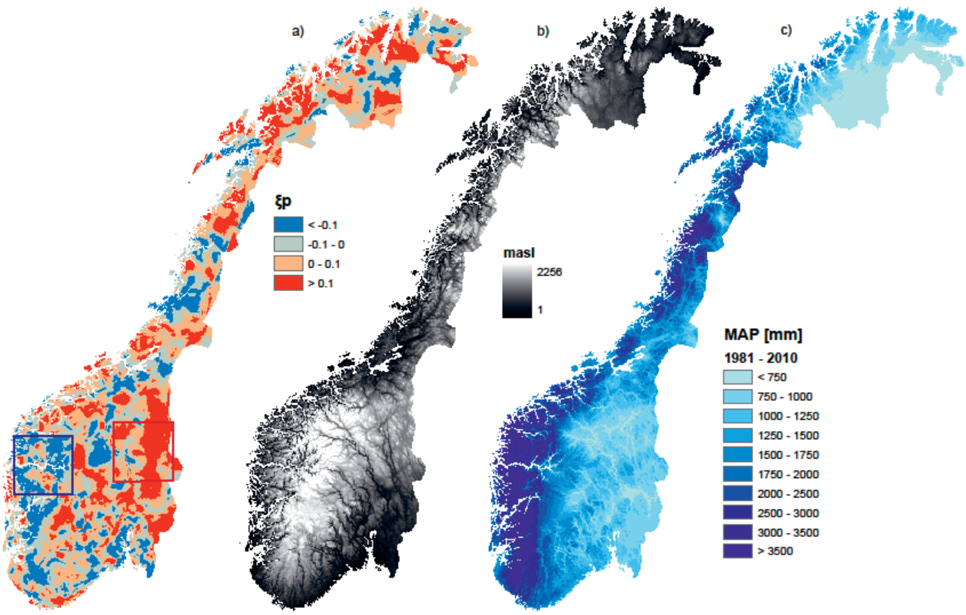

Fig. 2 (a) ξ_p estimated from the gridded dataset. The two squares represent areas with mainly positive (red) and negative (blue) ξ_p and are used in the further analysis. (b) Topography in Norway. (c) Mean annual precipitation for the period 1981-2010.

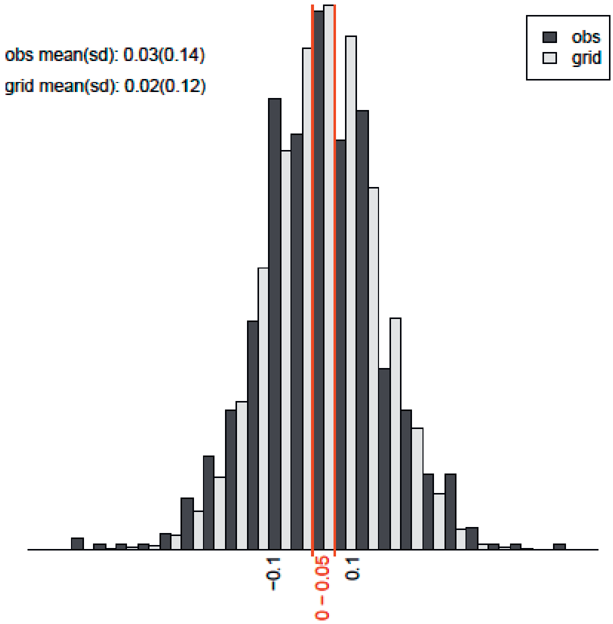

Fig. 3 Frequency distribution of ξ_p estimated from observations (dark grey) and the gridded dataset (light grey). Red interval indicates the mean.

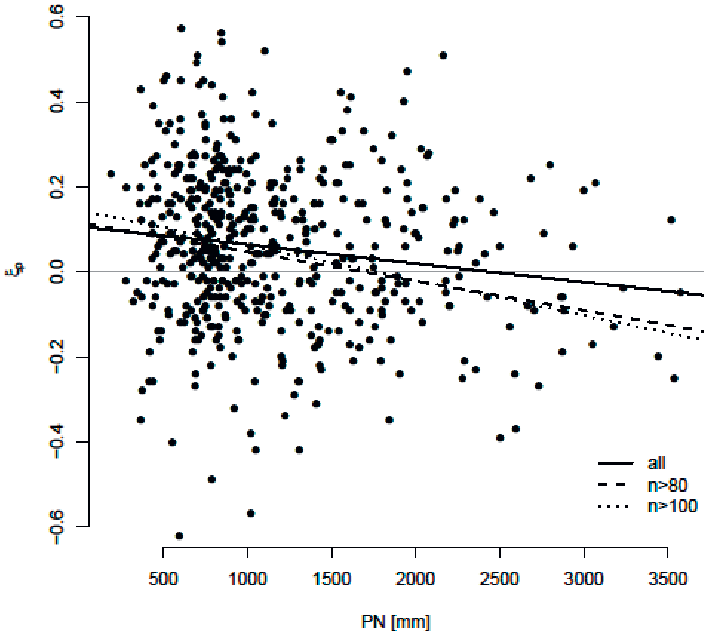

Fig. 4 ξ_p estimated from observations against normal annual precipitation. Linear regression lines for: all series (solid), series of length > 80 years (dashed), and series of length > 100 years (stippled). The grey horizontal line indicates $\xi_p = 0$.

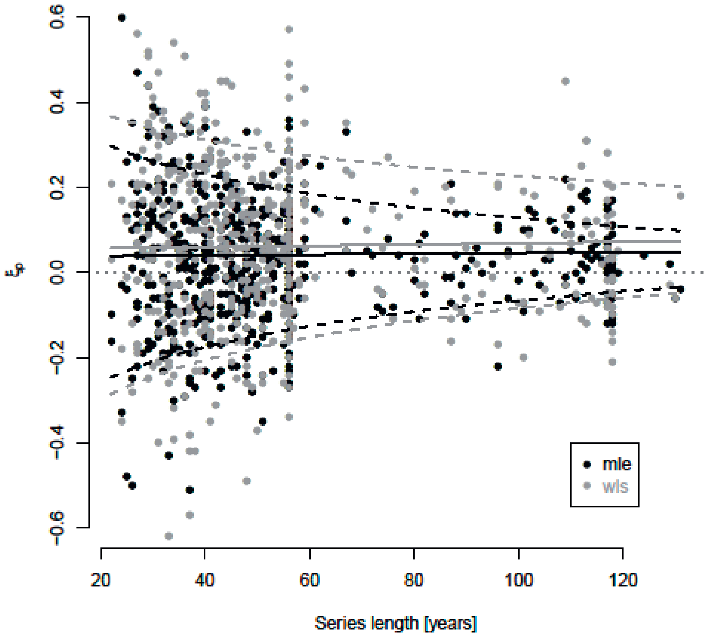

Fig. 5 ξp estimated from observations against time series length.

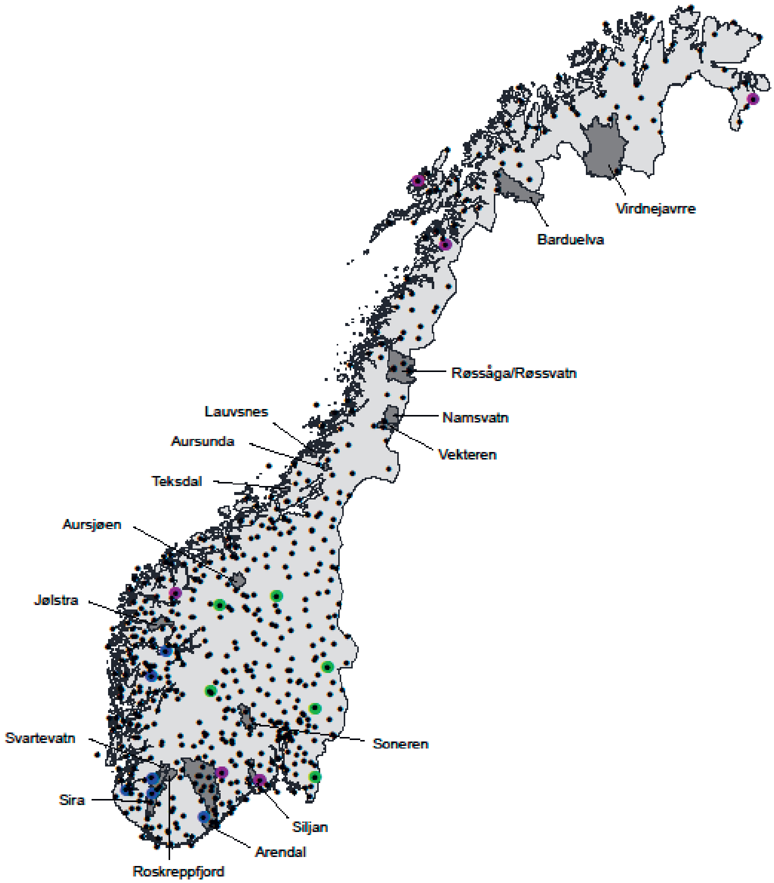

Fig. 6 Catchments and observation sites. Colored sites indicate long (>100 years) observational series separated into regions.

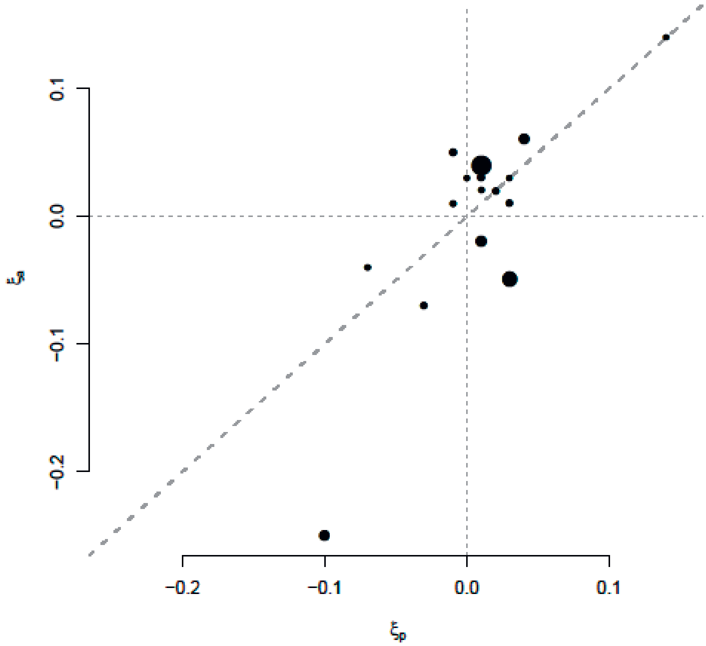

Fig. 7 Mean ξ_p against ξ_a in the catchments. The size of the dots indicates catchment size. The thick grey dashed line indicates the diagonal ($\xi_a = \xi_p$) and the thin grey dashed lines indicate $\xi_p = 0$ and $\xi_a = 0$.

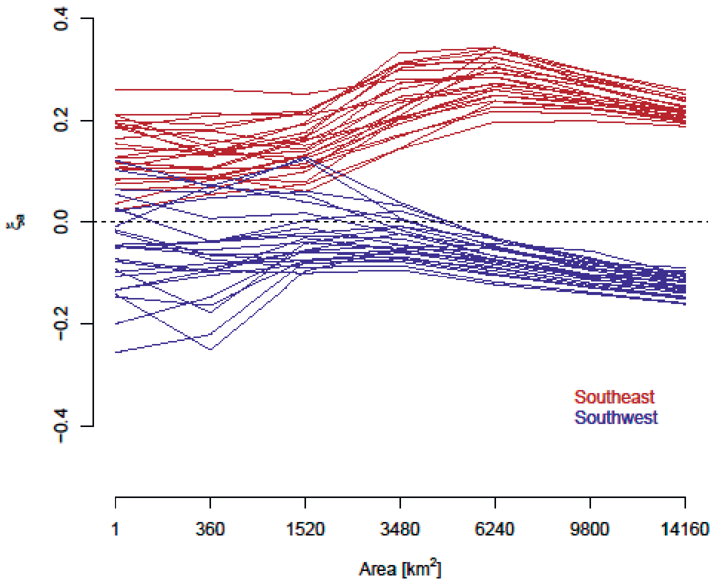

Fig. 8 ξ_a estimated from the gridded dataset, against area size in the Southeast (red) and the Southwest (blue) of Norway.

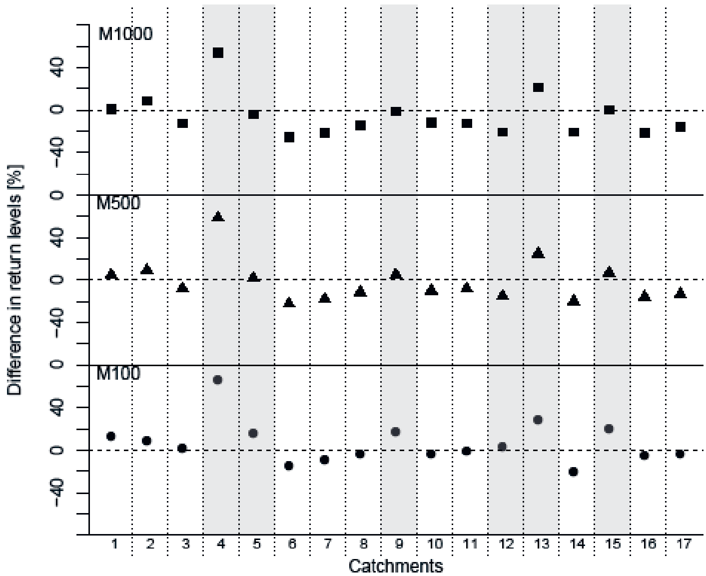

Fig. 9 Percentage difference in M100 (circle), M500 (triangle), and M1000 (square) between SB-gf and GBGEV estimates. Grey background indicates catchments with large difference in PN used in the two methods.

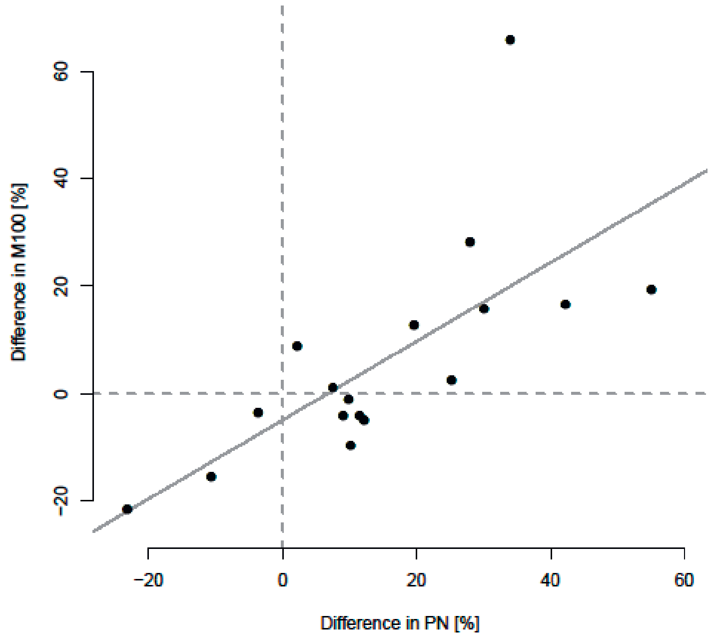

Fig. 10 Percentage difference in M100 between SB-gf and GB-GEV estimates, against difference in PN used in the two methods. The grey solid line indicates the result of the linear regression, and the two grey dashed lines indicate no difference between the methods.

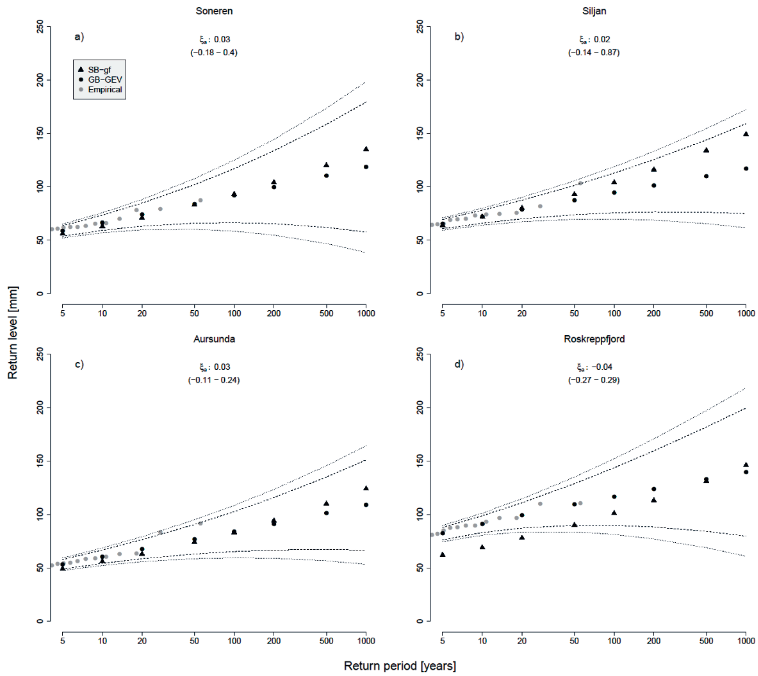

Fig. 11 Estimated return levels for areal precipitation at (a) Soneren, (b) Siljan, (c) Aursunda and (d) Roskreppfjord catchments, using SB-gf and GB-GEV. Empirical values are from the gridded dataset. Dashed (dotted) line indicates the 95% (99%) confidence intervals.