



Flood estimation in natural and urban catchments using hydrological simulation and Bayes theorem

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Abstract. There are many methods developed for the estimation of design flood values. If sufficient runoff data are available, statistical methods for flood frequency analysis (FFA) can be applied. In cases where runoff data are scarce, methods involving hydrological simulation are often used. These methods range in complexity from the very simple, formula-based Rational Method to the simulation of runoff using very detailed, complex hydrological models. Often, when using these models, the return period of runoff inherits the return period from the input, i.e. the precipitation, and significant assumptions are necessarily made regarding initial soil moisture states (S). This study investigates the relationship between extreme precipitation, the precipitation sequence, the initial S and extreme flows and provides a method for estimating floods by combining a continuous rainfall-runoff model (DDD) and a stochastic event model (DDDEvent). The models share the same model parameters, and the continuous model provides the required distributions of the initial S for the event model. When running the event model for a specific precipitation intensity, the initial S and precipitation sequence are stochastically sampled, generating a range of runoff responses to a given rainfall intensity. When we simulate runoff for a single precipitation intensity and vary the initial S and precipitation sequences, we obtain a conditional distribution of runoff, given the precipitation intensity. Similarly, when we simulate runoff for all possible (realistic) precipitation intensities, we obtain a conditional distribution of precipitation given a runoff value. From such (empirical) conditional distributions we can use Bayes theorem to assess the exceedance probability for a specific value of runoff given the exceedance probability of the precipitation event. Results for estimating peak flows are promising for catchments with areas ranging from 0.06 to 1092 km² where high flows are generated primarily by rainfall. The estimates are comparable to those obtained using the well-established SCHADEX method for design floods. In contrast to purely statistical FFA based on observed discharge, we can, with the proposed method, perform an analysis of flood quantiles as a function of initial S , precipitation intensities and sequences. We can also investigate the composition of the total runoff with respect to water originating from the precipitation event and water originating from the initial S for extreme flood quantiles in a given catchment. The proposed method can also be applied for estimating floods in ungauged catchments using a regionalised version of the DDD model.

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1 Introduction

Design flood estimates remain a subject of great importance due to their economic and environmental implications (Smithers, 2012). The number of sites needing design flood values for building safe and economically and ecologically sustainable infrastructure in our water ways is infinite. For example, a railway line placed in a valley in a mountainous region is an important transport artery for goods and people. Such an infrastructure has a high risk of being severed in multiple places during an extreme rainfall event due to the numerous culverts and bridges associated with the railway line. In Norway, the national railway authority is faced with the considerable task of maintaining and keeping 4200 km of railway flood-proof (Bane Nor, 2024).

Design flood estimates are, in principle, needed at all sites where culverts, bridges and other important infrastructure are installed. Some of these sites often have quite small upstream catchment areas and are typically ungauged. Providing flood estimates of sufficient precision for sites with little or no data is a remaining challenge in operational hydrology and is an important motivation for the flood estimation method presented in this paper.

The vast literature on design flood estimation methods can largely be organised into three groups (Filipova et al. 2019, Smithers et al. 2012; Camici et al, 2011): 1) statistical flood frequency analysis (FFA); 2) single design event simulation; and 3) derived flood frequency simulation. For gauged sites with long records of observation, group 1), FFA, is the standard choice. For high return periods beyond the record length, however, the extrapolation of the fitted statistical distribution involves a high degree of uncertainty. To account for non-stationarity in floods (e.g. Katz et al. 2002) or predictions in ungauged catchments (e.g. Thorarinsdottir et al, 2018), the parameters of the extreme value distributions can be linked to climatic and/or physiographic catchment descriptors. In this context there are unresolved issues regarding the physical basis for the functional relationship between parameters of extreme value distributions and their covariates, as well as the physical interpretation of such statistical models that are fitted to hydrologic extremes (Katz et al. 2002; Dyrddal et al. 2015). An alternative approach is to classify flood events to different flood generating processes that are directly accounted for in the statistical models based on mixture distributions (e.g. Fischer et al, 2025). In the second group, a hydrological model with a single realisation of initial conditions and input provides a design flood value which usually has the same return period as the input (Tuyls et al 2018). Examples of such models are the Rational Method (Grimaldi and Petroselli, 2014) and the Norwegian event model PQRUT (Andersen et al. 1983). In the Rational method, the design flood is a fraction of the design precipitation volume, and the runoff is assumed to take on the same return period as the precipitation. The “fraction” is essential here and is called the “runoff coefficient” and accounts for the water lost due to infiltration and the temporal delays and attenuation in the upstream catchment. The “runoff coefficient” is loosely related to the land surface in the catchment, i.e. grass, concrete, etc. The PQRUT (Andersen et al. 1983) is a simplified version of the well-known Hydrologiska Byråns Vattenbalans modell (HBV model) (Bergström, 1992). PQRUT only has three calibration parameters but is a dynamically more complex model than the Rational Method. Common for both methods is that they are dependent on correct initial soil moisture states (S) to give realistic results, which can be difficult to validate. The sensitivity of peak discharge to initial moisture conditions is also highlighted by Packman and Kidd (1980), and Camici et al. (2011) recognised the importance of the initial S and proposed a procedure for estimating and regionalising the “design storm soil moisture” to be used in design storm models.



In the third group of derived flood frequency simulation, Filipova et al (2019) and Svensson et al. (2011) are examples where the stochastic simulation of important input variables and hydrological states (i.e. precipitation, snow, snowmelt, S) are used through event models to derive distributions of runoff and their extremes. In addition, the continuous simulation approach serves as an example of the third group, where hydrological models provide long time series from which empirical flood distributions can be derived (Calver and Lamb, 1995; Boughton and Droop, 2003). An extension of the continuous simulation approach is the semi-continuous simulation SCHADEX method for flood estimation, developed by Électricité de France (EDF) for the design of hydropower dams (Paquet, et al., 2006; 2013). In this method stochastically sampled extreme precipitation sequences are used to replace observed precipitation events within an historical time series of precipitation and a hydrological model is run for the sampled event. The process is repeated nearly 2 million times, and this produces a database of catchment responses to extreme precipitation under an extensive range of possible hydrological initial conditions. Flood estimates can then be obtained from derived (i.e. simulated), empirical flood distributions. The actual SCHADEX methodology is rather complex and special training is required for use of the SCHADEX method in practise (Paquet, 2021).

The objective of this study is to develop a new methodology based on hydrological models for estimating design floods. We want the method to compare well to approaches used in practise, work well in data scarce catchments, and be simple to implement in operational tools. Most importantly, the methodology should improve the understanding of the complex interaction of different flood- generating processes in a catchment. The novelty of this study is that we develop a model system that includes both continuous- and stochastic event-based modelling. Continuous modelling is necessary to provide a description and distributions of relevant hydrological states in addition to quantifying model parameters. The stochastic event model is necessary to ensure that all relevant hydrological states are sampled a sufficient number of times for the chosen precipitation input. With this approach we avoid one of the major limitations with continuous simulations, i.e. the need for long observed or simulated time series of inputs to reduce their sensitivity to the impact of singular extremes that can affect the results of traditional FFA (Abbasin et al. 2025), and we address the limitation of event-based models, i.e. the need of a realistic sample of initial S . Moreover, we will investigate how precipitation depth and sequence affect the peak discharge and thereby addressing some of the points of concern made by Watt and Marsalek (2013).

The continuous and the event-based models are based upon the same parameter parsimonious Distance Distribution Dynamics model (DDD, Skaugen and Onof, 2014). The models hence share much of the same model structure and parameters, maintaining the parameter parsimony of the system. The parameter parsimony of the DDD model allows for a regionalised version of DDD (see Skaugen et al. 2026, Skaugen et al, 2015). In this study we will also briefly address how well the proposed method estimates floods in ungauged catchments using this regionalised version of DDD.

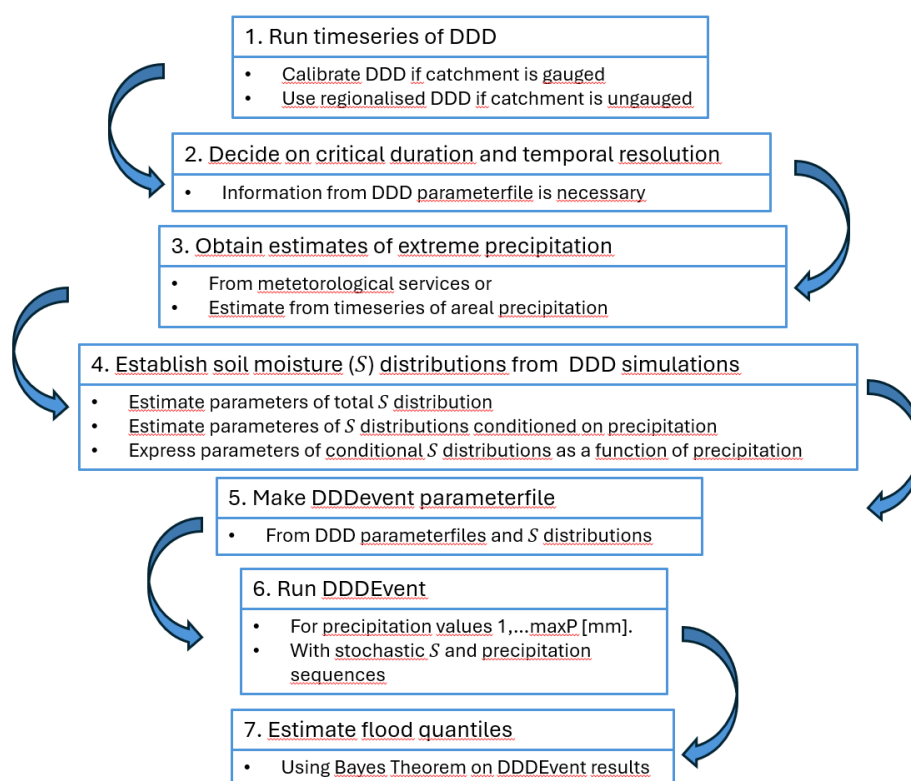
In the following sections we first present the hydrological models and the method for estimating flood, and then the study areas and the available data. In the results section we show and compare flood estimates from the proposed method with the SCHADEX method and statistical FFA estimates. In the last two sections we discuss the results and conclude on the proposed method's ability to estimate floods and to what extent insights into the nature of floods are obtained.

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2 Method

The proposed method for estimating floods at a catchment outlet, consists of several steps. Figure 1. illustrates the workflow and the different steps are presented below.



120 **Figure 1: Workflow for estimating floods using DDD and DDDEvent**

Firstly, the model parameters for the continuous rainfall runoff model (DDD) need to be estimated either by calibrating against observed time series of runoff or using regionalised estimates based on catchment characteristics and climate information. Some of these parameters will also be used in the DDDEvent model later in the workflow. The next subsections describe the DDD and DDDEvent models.

2.1 DDD

The DDD rainfall runoff model (see Figure 2) was introduced by Skaugen and Onof (2014). The main motivation behind its development was to minimize the number of calibrated parameters while trying not to



130 compromise the precision and required detail of the hydrological simulations. The model currently runs
 operationally at the Norwegian flood forecasting service and has been applied at spatial scales from 50 m² to
 12760 km² and at temporal scale from 1 minute to 24 hours (Viker-Walsøe and Valle, 2020 and Nazeer et al.
 2021). Since its advent, the model has continuously been developed in order to reduce the number of calibration
 parameters and to make it useful for other applications. Skaugen and Mengistu (2015) derived a method for
 135 estimating the subsurface capacity of the model using the mean annual runoff, and Skaugen and Weltzien (2016)
 parameterised the spatial frequency distribution of snow water equivalent (SWE) from precipitation data.
 Skaugen et al. (2018) and Nazeer et al. (2021) introduced energy balance equations for estimating snowmelt,
 glacial melt and evapotranspiration and, hence, removed the need to calibrate the empirical degree-day factors
 (Omura, 2001). In Skaugen et al. (2020) a version of the DDD model for modelling runoff in urbanised areas is
 140 presented. This latter model version takes into account infiltration capacities and runoff from both permeable and
 impermeable areas, which makes it suitable for modelling runoff from urban areas, as well as from glaciers and
 wetlands. This version has now become the standard model at Norwegian Water Resources and Energy
 directorate (NVE) and is used in this study. Further details of the DDD model can be found in the literature
 referenced above.

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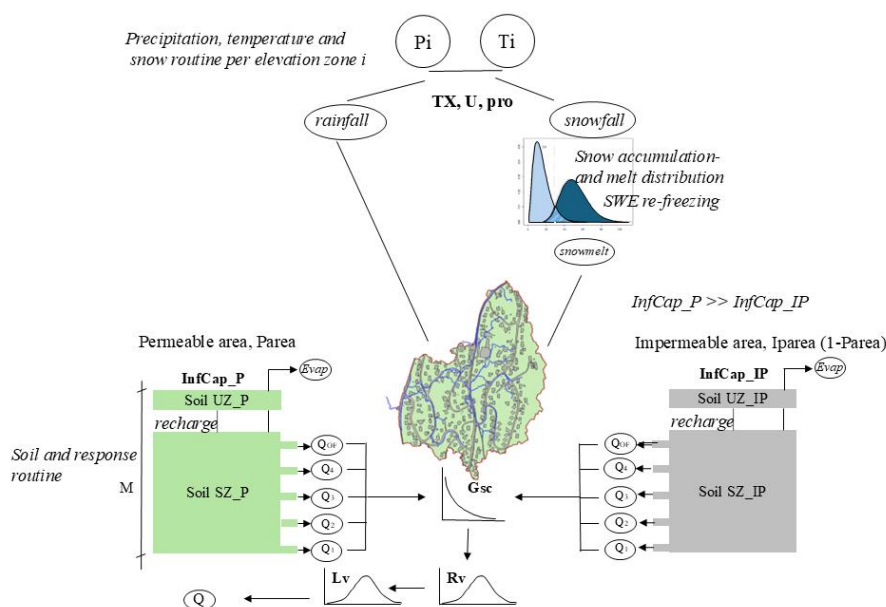
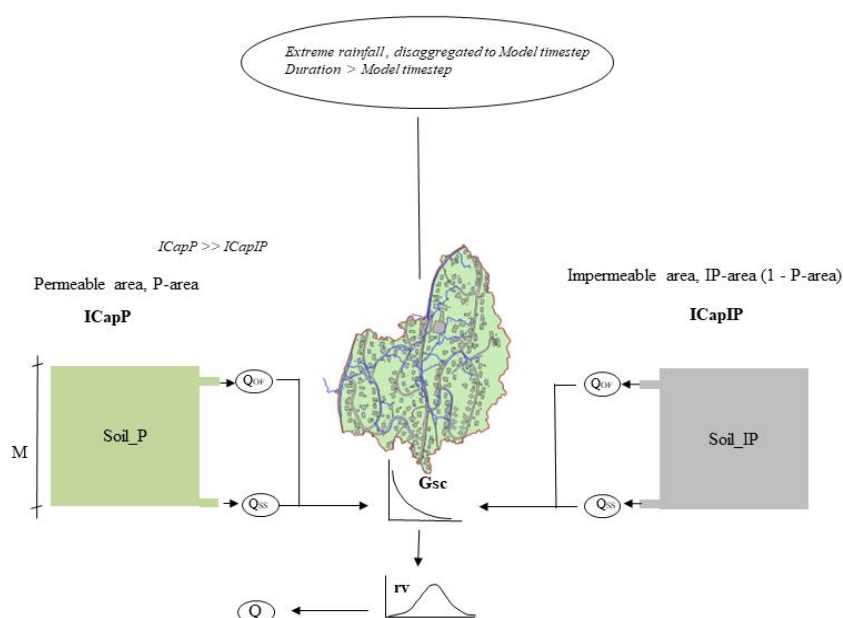


Figure 2: Model structure of DDD. The model consists of two DDD models, one for permeable areas (green) and one for impermeable areas (grey).



150 2.2 DDDEvent

The event model, DDDEvent (Figure 3) is largely parameterised from the DDD model presented above. The DDDEvent model is a stochastic model in that it draws the initial S from a distribution of S conditioned on a precipitation value, P . The parameters of the S distribution are obtained empirically from sampling the S prior to a precipitation event from timeseries of S provided by running the DDD model for a historic timeseries. In addition, DDDEvent draws a random precipitation sequence (a hyetograph) with timesteps equivalent to the temporal resolution of the models. The shape of the precipitation sequence (i.e. the hyetograph) is modelled using a two- parameter beta distribution. A random sampling of the two shape parameters is used to generate a sample of precipitation sequences where all have the same total volume over the critical duration of the event, which is typically longer than the temporal resolution of the model.



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Figure 3: The structure of the DDDEvent model, which is a simplified version of DDD, but retains DDD's flexibility for stratifying subsurface celerities with soil moisture content S .

2.3 Moisture dependent celerity in DDDEvent

165 In the subsurface component of DDDEvent, the initial soil moisture state S and the precipitation input P are distributed as runoff in time using a unit hydrograph (UH). The UH has a shape and a scale derived from the estimated subsurface celerity [m/s] and the distance distribution [m], which together give the response time distribution [s] (see Skaugen and Onof, 2014). The subsurface celerity is a function of the sampled initial moisture content S and the precipitation event P . This implies that for each randomly drawn moisture content



170 and assigned precipitation event, there is a different celerity and hence a different UH. The celerity relates to the sum of S and P , through the parameters describing the celerity as a function of subsurface moisture in DDD. The $S + P$ value represent a quantile of the empirical, total distribution of the moisture states S (not to be confused with the initial soil moisture distribution conditioned on precipitation which is further described below) from DDD. This quantile is used to extract the celerity from the celerity distribution with parameters specified by DDD. The celerity distribution decreases exponentially or, according to a gamma distribution, with the value of $S + P$. This is, in principle, the same as the procedure used in DDD, although the soil moisture in DDD is organised by saturation levels, each with an assigned celerity.

2.4 Time parameters

Following the flow chart in Figure 1, the next step is to determine the temporal characteristics of the catchment. 180 The relevant characteristics are typically the critical duration/time of concentration (see Beven 2020; Skaugen 2022) and the necessary temporal resolution of measurement and model required for approximating the instantaneous flood, which is often the target flood level for mitigation measures. The temporal resolution used for both DDD and DDDEvent model is higher than the time of concentration for the catchment in question in order to resolve runoff values close to the instantaneous peak flow. In this study, the time of concentration and 185 the critical duration are equal (see also Gericke and Plessis (2011)) and referred to as the critical duration, T_d hereafter. T_d is estimated according to Skaugen (2022) as the time it takes for water to travel through the river network. This definition is in line with those of Beven (2020) and Dingman (2002, p. 400).

2.5 The total and conditional distributions of subsurface storage

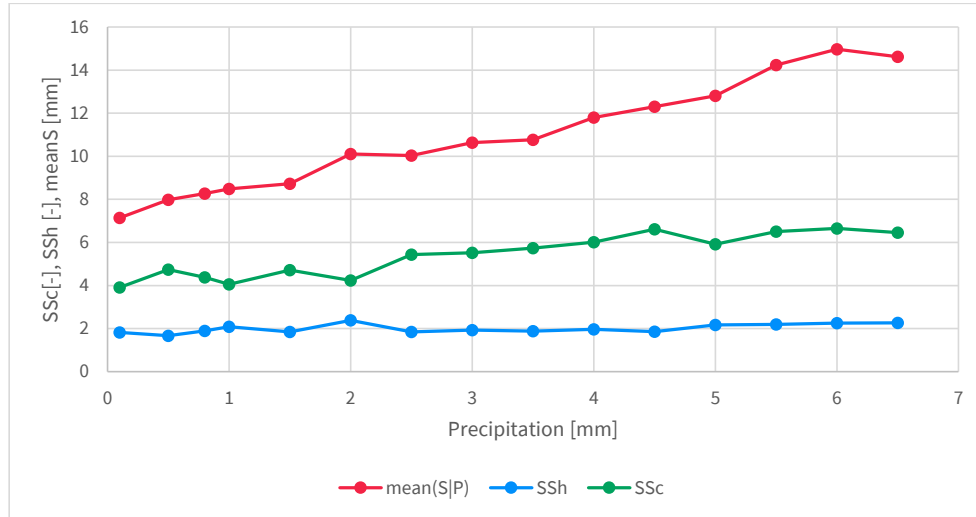
The stochastic event model DDDEvent, requires parameters for the total distribution of the subsurface states S , 190 and the parameters of the distributions of the subsurface states, when conditioned on precipitation, $S|P$. When examining the timeseries of S produced by the DDD model, it is clear that, for some catchments, precipitation P , and S are correlated, implying that for a given precipitation value P of T_d , there is an associated distribution of values for the initial soil moisture S giving us a conditional distribution $S|P$. The gamma distribution has been chosen as an analytical approximation to the distribution of $S|P$. 195 We can sample the $S|P$ vs. P relationship from the simulated timeseries of S from the output of the DDD model. For a given liquid precipitation value of T_d of P ($+\Delta P$) we sample the corresponding simulated value of $S(t)$ prior to $P(t + T_d)$. ΔP is set to a relatively small value as a function of the temporal resolution of the model, for example 1 mm for a 3h temporal resolution and 0.1 mm for temporal resolutions less than 1 h. Precipitation which falls as snow are of course excluded since no correlation between the subsurface saturation and snowfall is 200 expected. The mean, $\bar{S}|P$ and variance, $VarS|P$ of the sample are used to estimate the scale $SSc|P$, and shape $SSh|P$, parameters of the gamma distribution as

$$SSc|P = \frac{VarS|P}{\bar{S}|P} \quad (1)$$

$$SSh|P = \frac{\bar{S}|P}{SSc|P} \quad (2)$$



205 This procedure is followed for increasing values of P until the number of sampled values is too low (about 200 events) to provide reasonable estimates. Figure 3 shows the sample for Lye2, a small (1.9 km²), urbanised catchment in southwest Norway.



210 **Figure 4: $\bar{S}|P$ and $SSc|P$ and $SSH|P$ for Lye2. This catchment is considered to be of type 2 as described below with $C_0 = 7.5$, $C = 7.15$ and $a = 6$.**

When we plot $\bar{S}|P$, $SSc|P$ and $SSH|P$ (see Fig.4) for the catchments investigated in this study, we can identify three types of S vs P behaviour. Fortunately, all of them display a quite simple relationship between P and $\bar{S}|P$, $SSc|P$ and $SSH|P$ as a linear, a constant or a combined relationship. We have chosen to use a functional relationship similar to a linear variogram model (see for example Journel and Huijbregts, C. J., 1978) to describe the relationship between the $\bar{S}|P$ and P . We hence have to estimate 1) a value for the Nugget, C_0 , which is the intercept, the $S|P$ at zero precipitation, 2) the Range a , which is the precipitation value where the mean $S|P$ becomes constant, and finally 3) the Sill, C which together with the nugget is the level of a constant mean $S|P$.
 220 With these parameters estimated, we can further estimate the shape and scale parameters of the gamma distributed $S|P$ so that S can be drawn for a given P . The shape and scale parameters are estimated as a function of P as follows:

As the data for many catchments suggest, the shape parameter, SSH , is chosen to be a constant (the mean of the estimates). The scale parameter, SSc , can be estimated as:

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$$SSc|P = \begin{cases} \frac{1}{SSH} (C_0 + \left(\frac{C}{a}\right) * P), & P < a \\ \frac{1}{SSH} (C_0 + C), & P \geq a \end{cases} \quad (3)$$



230 The three types of S vs P behaviour are: Type 1: a linearly increasing $\bar{S}|P$, without a clear sill. When fitting a linear regression line to $\bar{S}|P$, C_0 is set to the intercept of regression equation, and C is set equal to a times the slope of the regression. The a can be chosen as the most extreme precipitation event that will be modelled, implying that there is no finite sill. Type 2: a linearly increasing $\bar{S}|P$ with a sill. When fitting a linear regression line to $\bar{S}|P$, C_0 is set to the intercept of regression equation, C is set equal to a times the slope of the regression, but a is the precipitation value where we find a constant mean $\bar{S}|P$. Type 3: a constant $\bar{S}|P$, and hence not influenced by precipitation intensity. When fitting a linear regression line to $\bar{S}|P$, C_0 is set to the intercept of the regression equation, C can be set to zero and the value of a is irrelevant.

2.6 Simulating runoff using DDDEvent

240 The DDDEvent model simulates a short time series of length twice the Td . In this way the rising limb of the hydrograph, the peak flow of the event, and the first timesteps of the recession are simulated. Figure 5 shows peak runoff simulations for the catchment Røykenes using DDDEvent for each precipitation value ranging from 1 to 300 mm, with a 0.5 mm interval. The catchment area is 50 km², the Td is estimated to be 15 hrs and the temporal resolution of the model is 3 hrs. For each precipitation value of Td , we sample the subsurface moisture state and precipitation sequence 2500 times, so that 1500000 peak values are simulated. Using such a procedure, runoff due to an exhaustive range of realistic precipitation values (1, 1.5, ..., 300 mm) for the chosen duration have been tested for all possible initial moisture states and precipitation sequences.

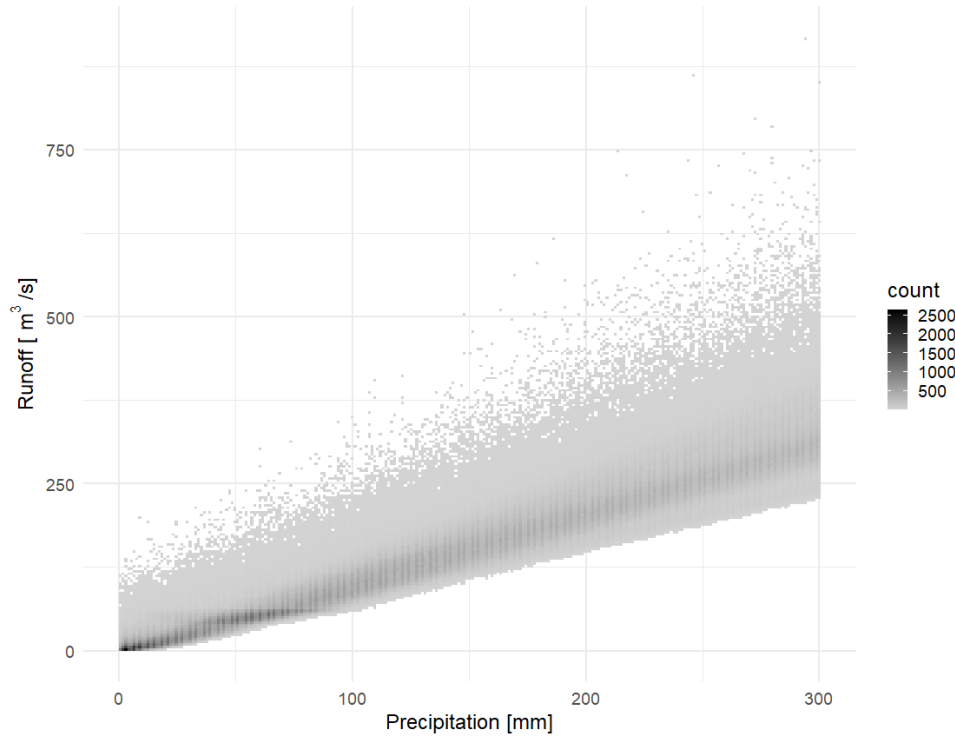


Figure 5: Runoff simulations for precipitation intensities ranging from 1 to 300 mm for the Røykenes catchment plotted as a heat map. For each precipitation intensity the model simulates 2500 short timeseries of runoff from which the peak flow is extracted. The variability of runoff for a given precipitation intensity is due to variability in the initial S and to variability in the precipitation sequence.

2.7 Estimating flood values using Bayes Theorem

Figure 5 shows the range of runoff values produced for a given precipitation intensity. That implies that each vertical slice of runoff values for a given precipitation value represents an empirical conditional distribution of runoff Q given a precipitation intensity $P = P_T$:

$$f(Q|P = P_T) \quad (4)$$

Furthermore, the empirical distribution of precipitation values producing a given value of runoff is found by extracting the horizontal slice for a given runoff value, $Q = Q_T$:

$$f(P|Q = Q_T), \quad (5)$$



Examples of the resulting conditional distributions for P_T and Q_T for the Røykenes catchment thus obtained are shown in Figure 6.

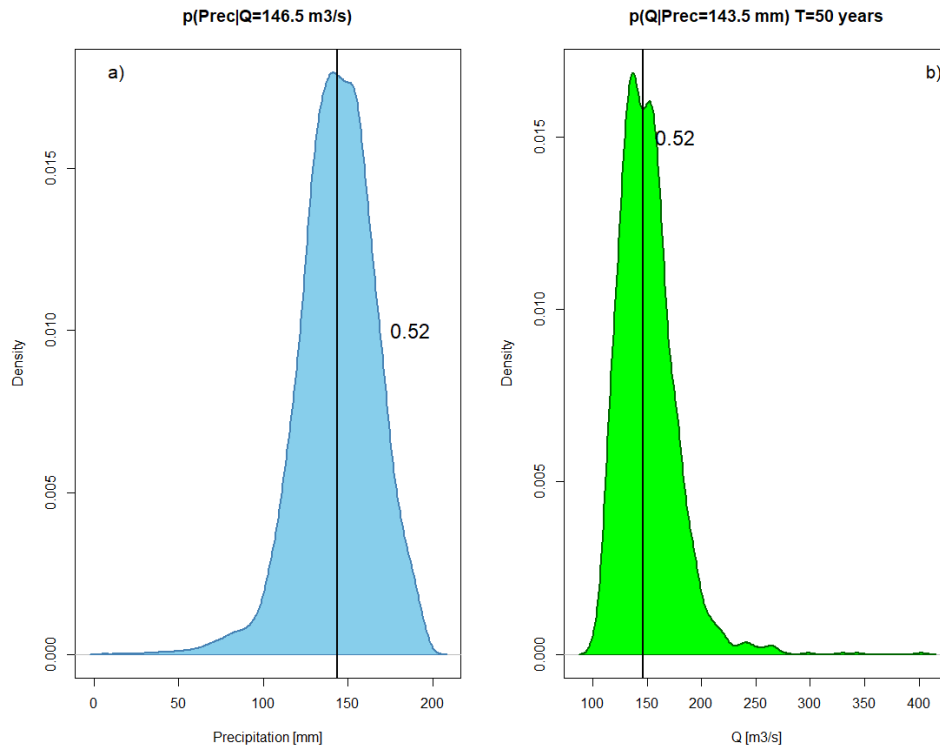


Figure 6: Empirical conditional distributions for a) precipitation conditioned on $Q = 146.6 \text{ m}^3/\text{s}$, and b) runoff conditioned on precipitation = 143.5 mm, which is the estimated 50-year return level for precipitation with a duration of 15 hrs for the Røykenes catchment. The empirical distributions are smoothed by a kernel density function using the programming language R (<https://www.r-project.org/>).

Bayes' theorem (see for example Haan 1977, p. 14) can now be applied to estimate the exceedance probability of runoff given a precipitation value of a known exceedance probability $pr(P \geq P_T)$, hereafter denoted $pr(P_T)$:

$$pr(Q) = \frac{pr(Q|P_T)pr(P_T)}{pr(P|Q)} \quad (6)$$

Of particular interest in design flood estimation is the value of Q for which the exceedance probabilities of both conditional distributions are equal, which by Eq. 6 is the Q that renders the exceedance probability of Q equal to that of P . Figure 6 also illustrates how the exceedance probabilities of the empirical conditional distributions are obtained by integrating the mass under the probability curve to the right of the vertical line.



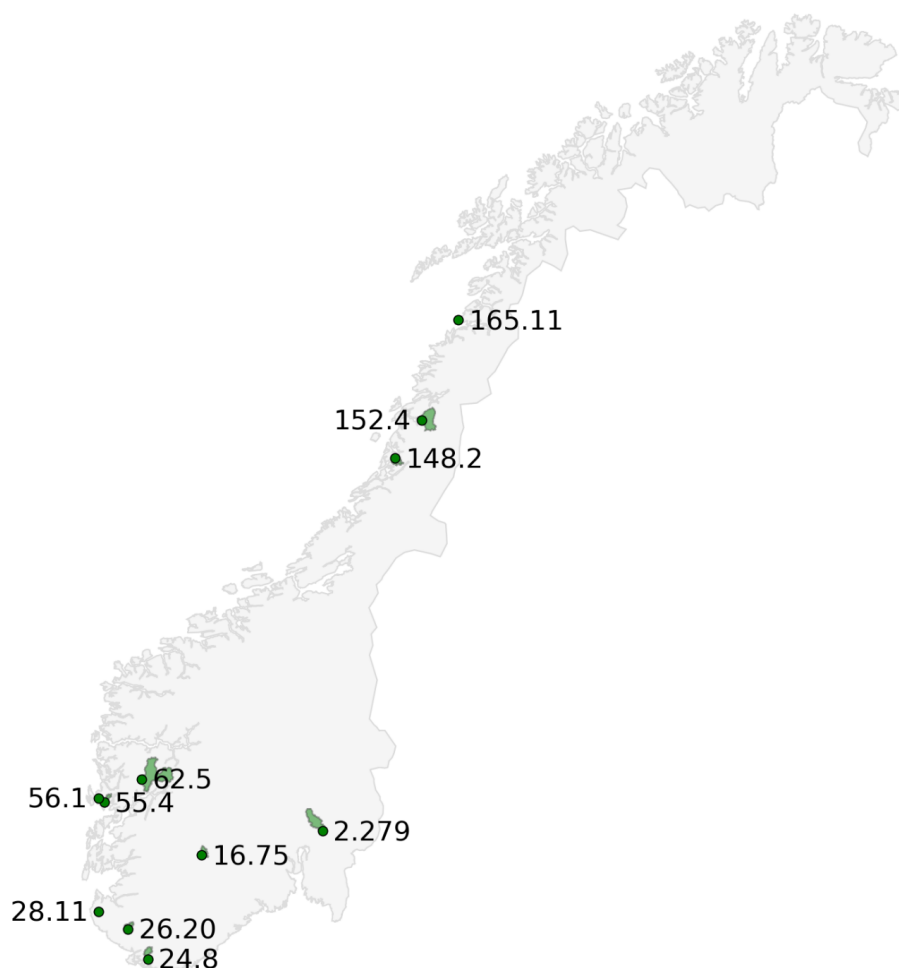
The joint distribution in Figure 5 does not have a marginal precipitation distribution from which we can derive exceedance probabilities of extreme precipitation. However, the conditional distribution in Eq. 4, representing runoff conditioned on precipitation, can be considered a true conditional distribution since its shape is not dependent on the frequency of the precipitation value. In our case we assume that the number of samples (2500) is sufficient to provide a stable empirical distribution. It is less clear how a marginal uniform distribution of precipitation influences the distribution for precipitation conditioned on runoff in Eq. 5. For a more realistic marginal distribution of precipitation one would expect, for the extreme values, that their relative frequencies would decrease as the intensities increased, whereas this is not the case using a uniform distribution. When using a uniform distribution one would expect the conditional distribution of precipitation given runoff (Eq.5) to be more skewed to the right since the uniform distribution gives a too high frequency of occurrence to a given precipitation intensity compared to a precipitation intensity which is slightly less. However, since the relevant precipitation intensities typically are on the tail of distribution where the relative frequencies do not have a very sharp negative gradient for increasing precipitation values, we assume that a uniform distribution will be an acceptable approximation for this part of the marginal distribution of precipitation. Note that this assumption is only used to estimate the empirical conditional distribution of $f(P | Q = Q_T)$ and not used to derive exceedance probabilities of extreme precipitation, which is discussed in the subsection 3.1 Extreme precipitation below. Since we obtain a distribution for runoff conditioned on precipitation, $f(Q | P = P_T)$, quantiles of this distribution are readily available and we can illustrate the variability of runoff given an explicit precipitation value caused by the variability of the initial soil moisture S , and precipitation sequence. This will be further discussed in the results section.

2.8 Estimating floods for ungauged catchments.

The DDD model has been regionalised so that for a catchment with an outlet at a location in the river network selected using a GIS-based tool, DDD model parameters are estimated from digital databases of catchment characteristics and climate information (Skaugen et al., 2026; Skaugen et al., 2015). Timeseries for model input data (precipitation and temperature) at the chosen temporal resolution (1h, 3hrs or 24hrs) are obtained from the national meteorological grids, so the parameters and results from the regionalised DDD model can hence be used by the DDDEvent model for stochastic simulations for the ungauged catchment.

3 Data

We have tested the proposed method for 11 Norwegian catchments of various sizes, differing climates and hence, hydrological regimes (see map in Figure 7).



315 **Figure 7: Norwegian streamflow gauging stations used in this study. Most of the catchments have predominantly**
rainfall-driven flood regimes, as the contribution of snowmelt is not fully resolved in the current version of the
DDDEvent model.

Catchment characteristics, calibration results, and an evaluation of whether rain vs. snowmelt is the dominant
 flood generating process (Vormoor, et al. 2016) are shown in Table 1. All catchments have reasonably good
 320 model calibrations calibrated with a minimum Kling-Gupta Efficiency criterion (KGE) of 0.85 (KGE; Gupta et
 al., 2009; Kling et al., 2012). The selection of catchments is a mix of larger, natural catchments and smaller
 urban catchments. The urban catchments 28.11 Lye2, 56.1 Sandsli and 165.11 Skivika are typically quite small
 (0.06 – 1.9 km²) and have fractions of impermeable surfaces of 17%, 19% and 10%, respectively, leading to a
 rapid runoff response. Those catchments require hydrological model runs with high temporal resolution (on the



325 scale of minutes), and the corresponding observed discharge times series for model calibration tend to be short.
 We used local temperature and precipitation observations as input data for these catchments. For the eight
 larger catchments, the DDD model was calibrated against 3 hourly discharge data provided by the HYDRAII
 database of the NVE using 3 hourly gridded temperature and precipitation data from MET Norway (Lussana et
 al. 2018). Meteorological grids (1 x 1 km²) of precipitation and temperature are available for Norway at temporal
 330 resolutions of 1 hr, 3hrs and 24 hrs (Lussana et al. 2018). The starting date of the time series varies (i.e. 1.9.1958
 for 24hrs, 1.9.1972 for 3hrs and 1.9.2013 for 1h), but in all cases the time series extend to today's date. Annual
 maximum flood series (AMS) used as basis for the statistical FFA estimates used later for comparison are also
 extracted from the HYDRAII database of the NVE. Table 1 provides information about the temporal resolution,
 the calibration period, and the AMS period for each catchment.

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3.1 Extreme precipitation

For the smaller, urban catchments with short Tds , the exceedance probabilities of precipitation for various
 durations have been obtained from the Norwegian Climate Service Centre (<https://klimaservicesenter.no>) from
 the stations Time-Lye (SN44190) for Lye2, Bergen-Sandsli (SN50480) for Sandsli and Bodo-Skivika (SN82310)
 340 for Skivika. For the larger catchments with longer Tds , exceedance probabilities of precipitation are estimated
 from a 32-year long time series (1990-2023) of areal precipitation derived from the SeNorge2018 meteorological
 grids using a GEV extreme value distribution fitted using the method of L-moments. Extreme values for areal
 precipitation for ungauged basins (PUB) are obtained using the same method, but are based on a 52 -year long
 timeseries from the same source as above. The reason for choosing a different period for the PUB experiment
 345 was two-fold: 1) to see how sensitive the flood estimates are to differences in length of the timeseries, and 2) in
 practice, one would often choose the longest times series available for estimating precipitation values of high
 return periods in a PUB application. The temporal resolution of the extreme values of floods follows that of the
 time steps used in of DDD and DDDEvent models.



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Table 1: Catchment characteristics for the study areas. Td = critical duration, ΔT temporal resolution of timeseries, AMS= annual maxima series, TS = timeseries.

Station	Area [km ²]	Td [hrs]	ΔT [hrs]	Flood Rain [%]	Flood Snowmelt [%]	Flood Mixed [%]	AMS series for floods and precipitation	TS for estimating soilmoisture dist.	TS for calibration of DDD	Calibration result KGE
Rain dominated flood regime										
24.8 Møska	121.3	30	3	96.6	0	3.4	1990-2023	1990-2023	2001-2014	0.94
26.20 Årdal	77.3	15	3	98.3	0	1.7	1990-2022	1990-2023	2009-2024	0.89
55.4 Røykenes	50.1	15	3	98.5	0	1.5	1990-2023	1990-2023	2009-2024	0.91
148.2 Mevatnet	108.5	24	3	82.9	2.4	14.6	1990-2023	1990-2023	2004-2014	0.94
Mixed rain-snow flood regime										
2.279 Kråkfoss	423.4	18	3	68.6	19.6	11.8	1990-2023	1990-2023	2009-2024	0.87
62.5 Bulken	1092	30	3	64.6	27.7	7.7	1990-2023	1990-2023	2009-2024	0.92
152.4 Fustvatn	525.9	18	3	61.1	24.1	14.8	1992-2022	1990-2023	2009-2024	0.9
Snowmelt dominated flood regime										
16.75 Tannsvatn	118.3	30	3	20.7	72.4	6.9	1990-2023	1990-2023	2009-2024	0.92
Urban catchments										
56.1 Sandsli	0.06	0.23	0.03				1985-2023	2020.04- 2022.12	2020.04- 2022.12	0.86
28.11 Lye2	1.9	1.5	0.17				1989-2023	2019.09- 2021.12	2019.09- 2021.12	0.87
165.11 Skivika	0.19	0.17	0.03				1997-2023	2018.9- 2021.7	2018.9- 2021.7	0.85

4 Results

Results of the applications of the DDDEvent method for the larger catchments are organised according to the role of precipitation vs. snowmelt as the dominating generator of extreme flows. Flood estimates developed with the proposed method are compared with estimates based on a statistical FFA using a general extreme value (GEV) distribution. For the 8 non-urban catchments (Table 1), results are also compared with those estimated by the semi-continuous stochastic simulation method SCHADEX (Paquet et al. 2006;2013). For these catchments,



360 SCHADEX simulations have been set up and run for the same period used for DDDEvent model (1990-2023)
 and with a timestep of 3- or 24-hours, depending on the catchment size and response time. This entailed
 calibration of the MORDOR hydrological model, fitting of the MEWP (Multi-exponential Weather-Pattern
 based) distribution for extreme precipitation (Garavaglia, et al., 2010; 2011), and running of the final stochastic
 simulations for each catchment. Earlier work has evaluated the suitability of the MEWP distribution for
 365 modelling extreme precipitation in Norway (Blanchet, et al., 2015) and of the SCHADEX method for simulating
 the principal types of flood regimes found in Norway (Lawrence, et al., 2014). For the 4 larger catchments in
 which floods are mostly generated by precipitation events (Møska, Årdal, Røykenes and Mevatnet), PUB
 estimates using the DDDEvent model are also included for comparison with the calibrated methods.

Flood discharges are estimated for 2, 5, 10 20 50 ,100 and 200 year-return periods for each catchment. For the
 370 larger catchments, for which we have estimates of extreme precipitation with a 1000-year return period, the 1000
 year flood has also been estimated. The length of the AMS for each catchment can be found in Table 1.
 DDDEvent flood estimates (Eq.6), the observed AMS plotted using the Gringorten plotting formula (Gringorten,
 1963) and the flood estimates of the SCHADEX simulations are shown in Figures 8-10 for the larger catchments.
 Results for the urban catchments are in Figure 11. Confidence bounds (5%-95%) are also plotted for the FFA
 375 estimates. We have not addressed the uncertainty caused by the model structures of DDDEvent and SCHADEX
 in this study, but in the discussion section an example of uncertainty in the flood estimates due to uncertainty in
 the estimates of extreme precipitation is shown.

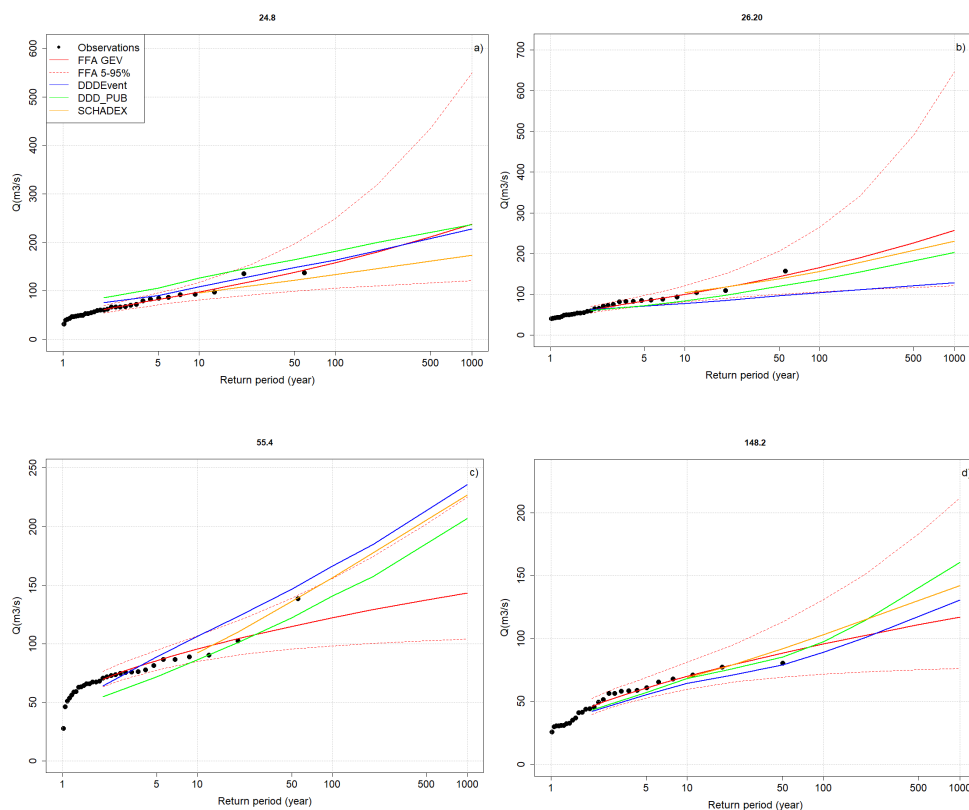


Figure 8: Flood estimates for catchments with a rain-dominated flood regime, a) 24.8 Møska, b) 26.20 Årdal, c) 55.4 Røykenes and d) 148.2 Mevatn. The blue line represents the results from the DDDEvent method, the red line represents the FFA-GEV, the orange line represents the SCHADEX estimates and the green line represents the DDDEvent-PUB estimates.

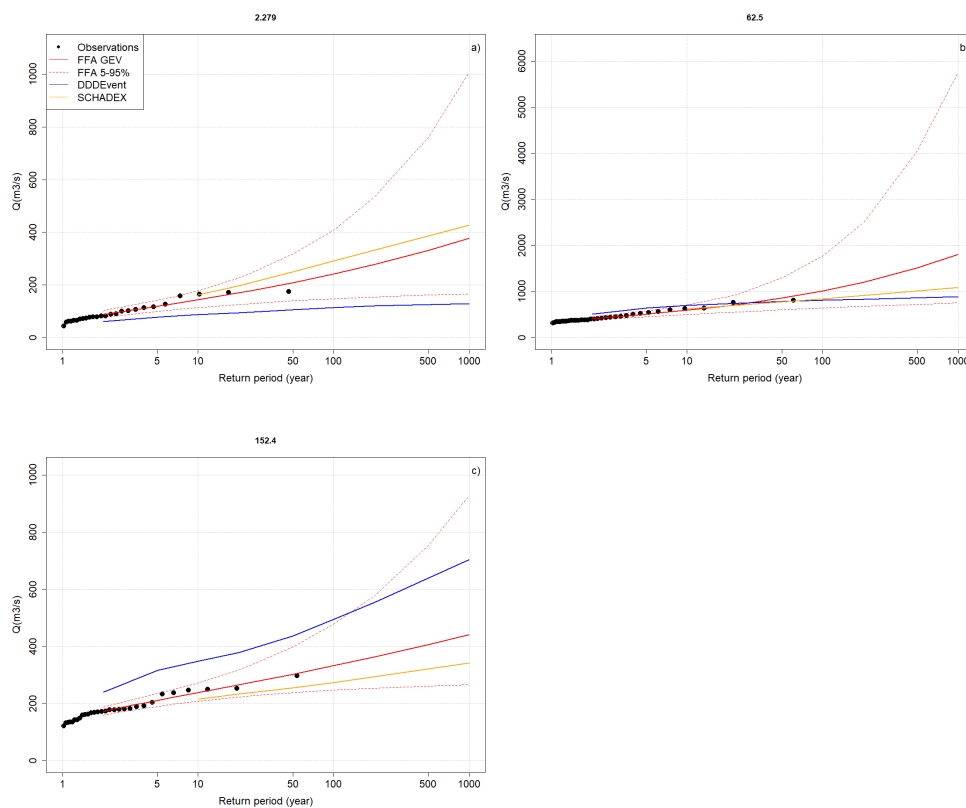


Figure 9: Flood estimates for catchments with a mixed rain- and snowmelt-dominated flood regime a) 2.279 Kråkfoss, b) 62.5 Bulken and c) 152.4 Fustvatn. The blue line represents the results from the DDDEvent method, the red line represents the FFA-GEV, the orange line represents the SCHADEX estimates.

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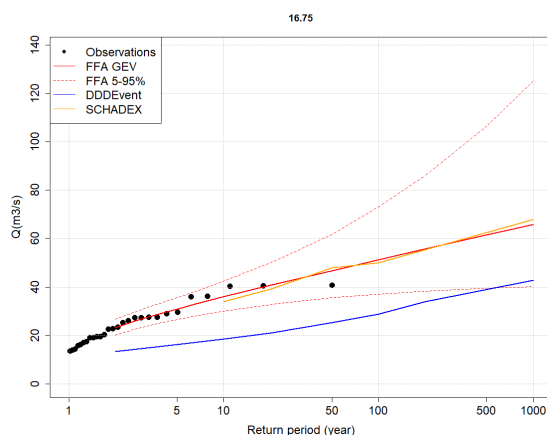


Figure 10: Flood estimates for 16.75 Tannsvatn with a snowmelt-dominated flood regime. The blue line represents the results from the DDDEvent method, the red line represents the FFA-GEV, the orange line represents the SCHADEX estimates.

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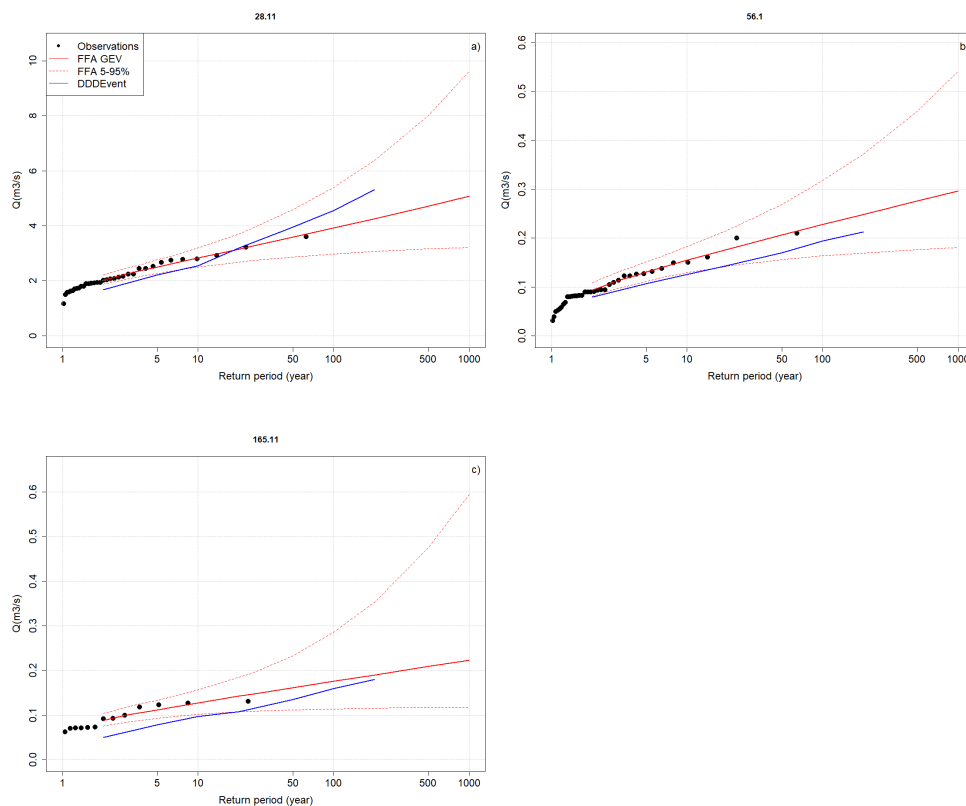


Figure 11: Flood estimates for the small urban catchments a) 28.11 Lye2, b) 56.10 Sandsli and c) 165.11 Skivika. The blue line represents the results from the DDDEvent method and red line represents the FFA-GEV.



Deviations in exceedance probability (EP) between observed and modelled values, expressed in the deviations of the Gumbel reduced variate, $U = -\text{Log}(-\text{Log}(EP))$ are quantified in Table 2. The differences in U between
 395 observed and simulated floods are summed up using the “SimScore” statistic (Paquet, 2025):

$$\text{SimScore} = 1 - \sum_{i=1}^{n-1} [\text{abs}(U_{\text{mod}_i} - U_{\text{obs}_i})(U_{\text{obs}_i} - U_{\text{obs}_{i+1}})] \quad (7)$$

In Eq. 7, n is the length of the annual maxima series, U_{mod} is the Gumbel reduced variate for the simulated series and U_{obs} for the observed series. U values are sorted from the highest to the lowest and we only evaluate those estimated to have a return period higher than two years. In Table 2 we also show deviations in the mean absolute
 400 percentage error ($\text{MAPE}_X = \left| \frac{x-y}{y} \right| * 100$). The SimScore implicitly weights the highest values, so results are not always consistent with MAPE. In Table 2 we have also included the MAPE of the median of the conditional distribution of runoff Q given a precipitation value P (Eq.4), since the distribution shown in, for example, Figure 6 indicate that the median could potentially also serve as a reasonable flood estimate.



405 **Table 2: Simscore for the different flood estimation methods and MAPE differences between the GEV estimates and**
1) DDDEvent- Bayes estimate, 2) DDDEvent- median of the distribution in (Eq.4) and 3) the SCHADEX estimate.

Station	SimScore DDDEvent	SimScore GEV	SimScore SCHADEX	SimScore DDDEvent (Bayes)_PUB	MAPE DDDEvent (Bayes)- GEV [%]	MAPE DDDEvent (median)- GEV[%]	MAPE SCHADEX- GEV[%]
Rain dominated flood regime							
24.8 Møska	-1.17	0.18	-0.97	-3.97	9	10	12
s26.20 Årdal	-8.31	0.09	-0.47	-2.1	28	28	5
55.4 Røyknes	-0.7	-2.1	-0.11	-0.17	27	27	21
148.2 Mevatnet	-0.83	0.0	-0.33	-0.79	12	10	11
Mixed rain-snow flood regime							
2.279 Kråkfoss	-25.37	-0.33	-0.83		47	46	15
62.5 Bulken	-1.59	0.02	-0.15		23	23	14
152.4 Fustvatn	-6.37	0.17	-2.59		28	27	29
Snowmelt dominated flood regime							
16.75 Tannsvatn	-10.8	-0.57	-0.96s		43	43	4
Urban catchments							
28.11 Lye2	-2.45	0.32			13	12	
56.1 Sandli	-3.5	0.16			17	4	
165.11 Skivika	-5.07	-0.62			22	11	

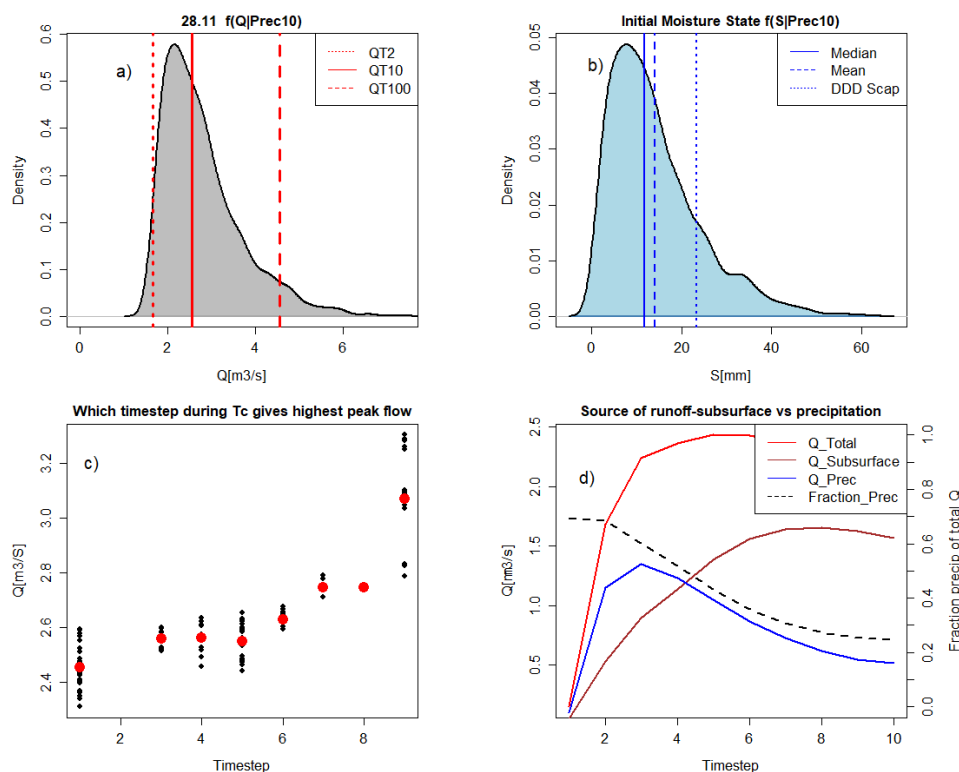
For the larger catchments where rainfall is the dominant cause of flooding, the flood frequency plots (Fig.87), the SimScore and the MAPE (Table 2) show that the DDDEvent model compares well with the SCHADEX method. An exception is found for the Aardal catchment (26.20). This deviation is discussed below and is seen in relation to uncertainties in the extreme value estimates for precipitation. Deviations from FFA-GEV (MAPE) are on the order of 5-28%. The deviations in MAPE for DDDEvent- Bayes for 55.4 Røykenes are high, but the SimScore for Røykenes, is, on the other hand, quite good and better than the FFA-GEV. For the rain-dominated catchments (Fig 8) we can also see that the flood estimates from the PUB procedure are in good agreement, and according to the SimScore, three catchments obtain better flood estimates using the PUB version than the calibrated version.



The SimScore deteriorates and MAPE increases with the increasing contribution of snowmelt to flood generation (Fig. 9-10). Floods in these catchments are largely underestimated, and this can be expected given that the spring snowmelt flood is the main flood event of the year and we only consider the extreme moisture input during an event to be precipitation rather than snowmelt combined with precipitation.

The DDDEvent procedure also works reasonably well for the urban catchments (Fig. 11), with a SimScore slightly poorer than for the larger rain-dominated catchments and with a MAPE deviation ranging between 4- 22 %.

Modelling the extreme values using hydrological simulations instead of FFA offer possibilities to study the flood generating processes and their dynamics in more detail. In figures 12-15 we have plotted an analysis of the simulated 10- and 100-year floods for the small urban catchment Lye 2 and the larger, natural catchment Møska. The plots illustrate a) the variability of the conditional distribution of runoff given a 10- and 100-year precipitation event due to variability in the initial S and the precipitation sequence, and b) the variability of the initial S distribution for a given precipitation event. *DDD Scap* is the estimated subsurface capacity of the DDD model. Note that the initial S sometimes exceeds the *DDD Scap*. In such cases the excess water is routed as overland flow in DDDEvent. In panel c) we have sampled all peak flows resulting from a T-year precipitation of Td and with an initial S corresponding to the average initial S of all T-year floods. This sample is assumed homogenous enough so that we can test for the sensitivity of the flood values to the precipitation sequence, i.e. are the flood peaks sensitive to when, during the Td , the most intense precipitation occurs? Finally, in d) we plot the isolated contribution to the total runoff of the initial S , and from precipitation. This is carried out by estimating the runoff when precipitation is zero so that the draining of the initial S is the only contribution to the flow. On the other hand, the runoff solely due to precipitation is the difference between the total runoff and that of the initial S .



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Figure 12: For 28.11 Lye2. a) the conditional distribution of runoff given a 10-year precipitation event, b) the distribution of initial soil moisture states, given a 10-year precipitation event, c) the variability of peak flow due to the sequence of precipitation, and d) the contribution of initial S and precipitation to the flood for a single example event.

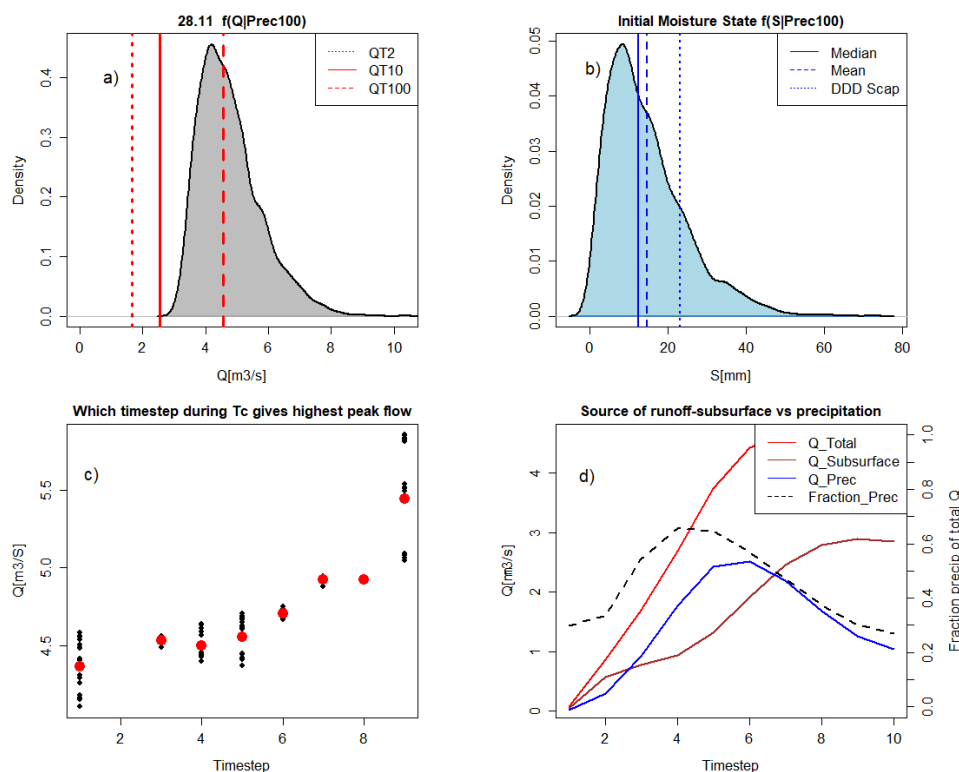


Figure 13: For 28.11 Lye2. a) the conditional distribution of runoff given a 100-year precipitation event, b) the distribution of initial soil moisture states given a 100-year precipitation event, c) the variability of peak flow due to the sequence of precipitation, and d) the contribution of initial S and precipitation to the flood for a single example event.

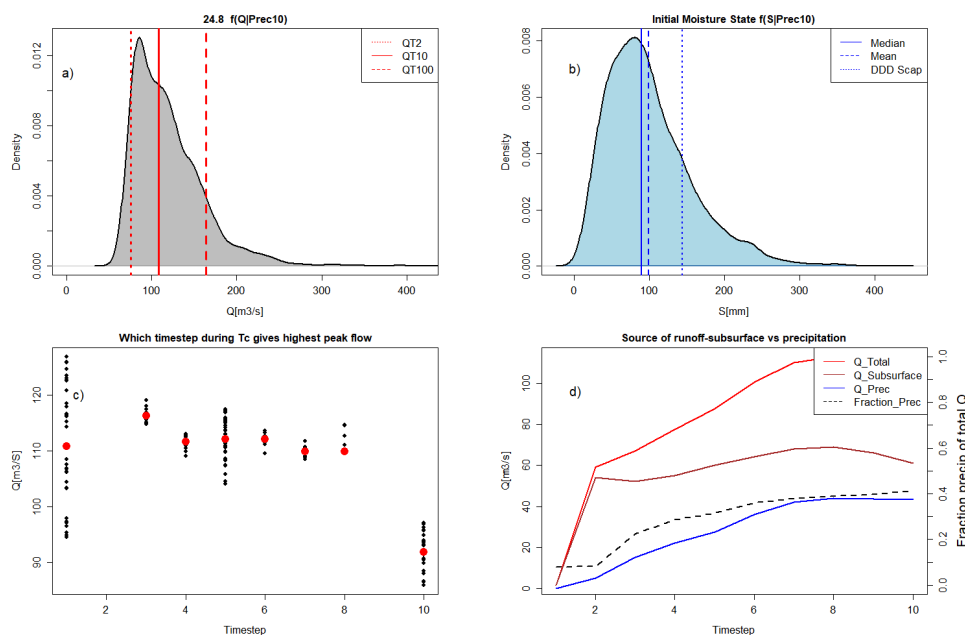


Figure 14: For 24.8 Møska. a) the conditional distribution of runoff given a 10-year precipitation event, b) the distribution of initial soil moisture states given a 10-year precipitation event, c) the variability of peak flow due to the sequence of precipitation, and d) the contribution of initial S and precipitation to the flood for a single example event.

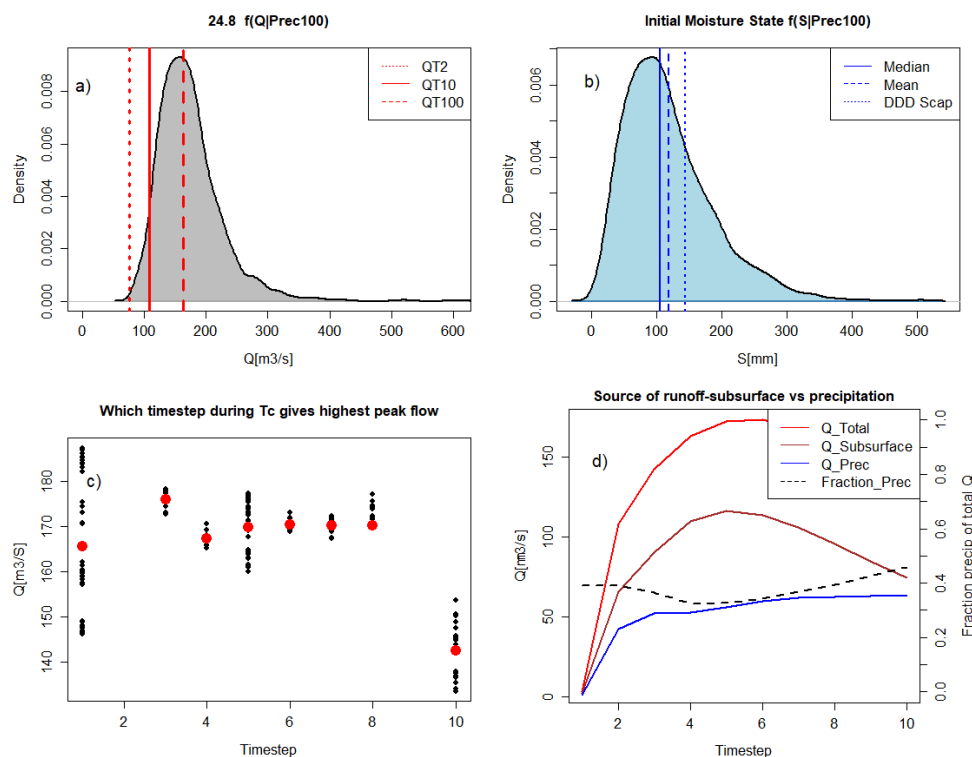


Figure 15: 24.8 Møska. a) the conditional distribution of runoff given a 100-year precipitation event, b) the distribution of initial soil moisture states given a 100-year precipitation event, c) the variability of peak flow due to the sequence of precipitation, and d) the contribution of initial S and precipitation to the flood for a single example event.

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From panel a) in figs. 12-15 we note that for both 28.11 Lye2 and 24.8 Møska there is a small but clear probability for runoff with a return period of less than 2 years, given a 10-year precipitation event. There is also a small but clear probability for a 100-year flood event given a 10-year precipitation event. This illustrates the dependence of simulated runoff on the initial S , which variability for the given precipitation event is seen in the panel b). In panel c) we can see the dependence of the timing and of the magnitude of peak runoff on the sequence of precipitation. Depending on whether the intensity is highest at the start, at the middle or at the end of the event, the resulting flood peak may differ by approximately 20 % for both catchments and return periods. One reason for the different behaviour for the two catchments may be the difference in T_d which is estimated to be 90 minutes for the Lye2 catchment and 30 hours for Møska. Although the mean response time (the estimated time it takes to drain half of the catchment under average conditions, see, for example Skaugen et al. (2023)), is five times as rapid for Lye2 than for Møska (2 days v.s. 10 days) the T_d is twenty times longer for Møska than for Lye2. For Lye2, water does not have time to drain during the T_d and the subsurface obtains a maximum that coincides with a maximum precipitation intensity towards the end of the T_d . This is illustrated in panel d) where we can see how the water content in the subsurface increases throughout the event model timeseries (of length twice the T_d). A different behaviour is seen for Møska where the water level in the subsurface has started to decrease at the end of the duration so that high rainfall intensity at the end of the event model timeseries is not sufficient to maintain a high runoff. Another important feature shown in the panel d)

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is the fraction of the runoff due to the precipitation event. For Lye2, an urban catchment, this fraction is at its maximum 60%. The rest of the total runoff is due to the initial S . For Møska this fraction is at the order of 40-50 % for the events considered.

5 Discussion and outlook

480 The figures 8-11 show that the performance of the proposed DDDEvent method varies when compared to the other methods FFA (using GEV) and SCHADEX. The SimScore compares all models with the observed data. The observed data have, however been assigned an exceedance probability by the Gringorten plotting position formula, which also is a model, but the SimScore represent to some degree a direct comparison between observations and the model estimates. The GEV distribution is a 3-parameter model that is actually fitted to the
 485 observed values, whereas this is not the case for either DDDEvent or SCHADEX, as observed discharge values are only used for the calibration of the hydrological model. Therefore, we could expect the GEV models to have the SimScore closest to one, which represents a perfect fit between the frequencies of the observed and the estimated flood values. DDDEvent and SCHADEX are comparable for most of the rain-dominated catchments, although SCHADEX is clearly better when snowmelt is an important part of the flood generating processes.
 490 This is not surprising as snowmelt is explicitly included in the semi-continuous simulation strategy behind the SCHADEX estimates.

The mean absolute percentage error (MAPE) is calculated across the flood quantiles for the larger catchments and compares the degree of correspondence between the simulation-based methods (DDDEvent and SCHADEX) and the statistical FFA-GEV. However, one needs to be aware that quality of flood data potentially has a high
 495 impact on both flood frequency estimates and evaluation metrics, in particular when the highest flood data are based on a large degree of extrapolation of the rating curve (Steinbakk et al, 2016). Velásquez and Krajewski (2024) reported errors as high as 50 % or 100 % depending on the return period and di Baldassarre et al. (2012) reported errors of 30 % due to measurement errors. The MAPE between the GEV estimates and DDDEvent using a Bayes estimate are in the range 9-28 % for the rain-dominated catchments and in the range of 13-22% for
 500 the urban catchments. There is no indication that the proposed method is systematically over- or underestimating the floods, so at present we can only conclude that the proposed method deviates from FFA in a range comparable to the uncertainty in FFA caused by measurements errors.

The DDDEvent method is, of course, totally dependent on the quality of the extreme value estimates of precipitation. For the SCHADEX method, estimation of extreme precipitation was the most significant player in
 505 explaining flood estimation variability (Brigode et al. 2014) in most catchments. For the larger catchments we have used the time series of areal precipitation derived from the 3h meteorological grids for Norway described above (Lussana et al. 2018) and estimated the extreme values using a GEV distribution. In Figure 16 we have plotted the uncertainty bounds of the flood estimate due to uncertainty in the precipitation estimates. We have used the 5 and 95 % percentiles of the precipitation estimates and estimated the floods according to the procedure
 510 described above. This is more of an uncertainty assessment in line with that of the FFA, and characterises the uncertainty in the flood estimates due to uncertainty in the precipitation estimates.

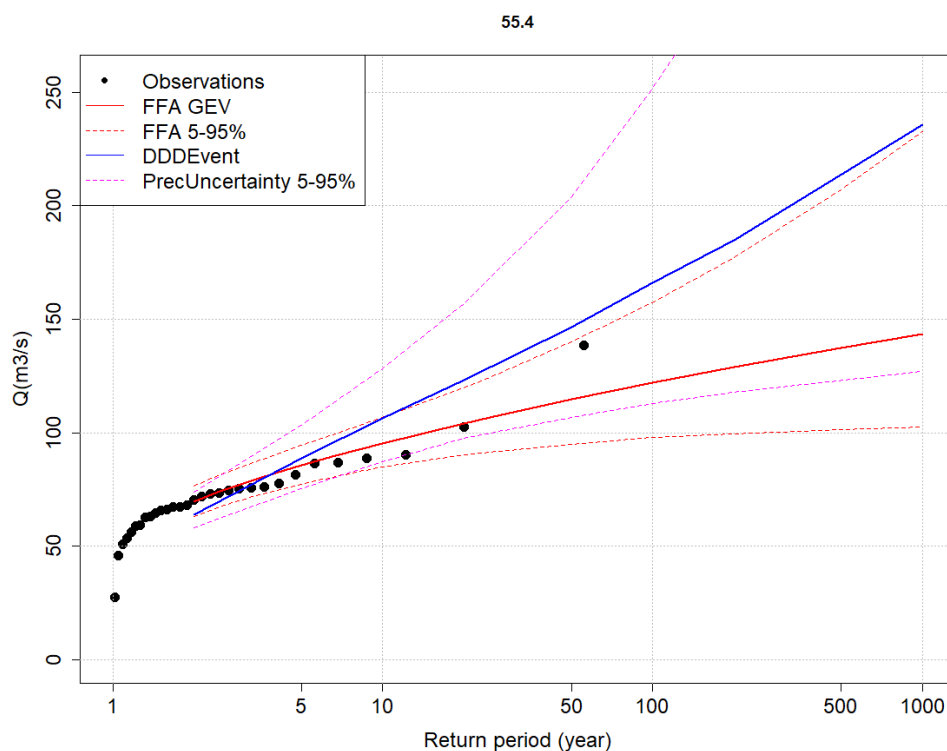


Figure 16: Flood estimates for Røykenes (55.4). In this plot the confidence bounds due to the uncertainty in the extreme value precipitation estimates are included (dashed lines in magenta).

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However, for some catchments, the estimation of extreme precipitation is very sensitive to the chosen time period of the precipitation series, due to the number of precipitation stations available for the interpolation procedure and to climate variability. For example, in Table 3 we show extreme precipitation values estimated with GEV for the catchment 26.20 Årdal for different time periods. The values in Table 3 are highly variable and explain why the DDDEvent method underestimates flood values as compared with SCHADEX and FFA-GEV. In Figure 17 we have used the extreme values of precipitation derived from the longer timeseries to estimate the floods for Årdal and we can see that the agreement between the three methods is much better. We can also note that the period of calibration is not similar for DDD (2009-2024) and SCHADEX (1990-2023) for Årdal which may also explain the different results for the two methods.

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Table 3: Dependence on time period for estimating extreme precipitation using GEV for Årdal (26.20) catchment.
 Gumbel extreme value estimates are in parentheses and illustrate the effect the shape parameter has on the tail of the GEV distribution.

Return period [years]	P1: 1972-2025 [mm]	P2:1990-2023[mm]	Difference (P1- P2)/P1 [%]
2	66.1(67.3)	67.9 (67.5)	-3
5	82.6(84.0)	80.8 (80.4)	2
10	94.8(95.0)	89 (89)	6
20	107.5(105.6)	96.5 (97.2)	10
50	125.5(119.4)	105.9(107.9)	16
100	140.3(129.7)	112.6(115.9)	20
200	156.3(139.9)	119.1(123.8)	24
1000	198.5(163.7)	133.22 (142.2)	33

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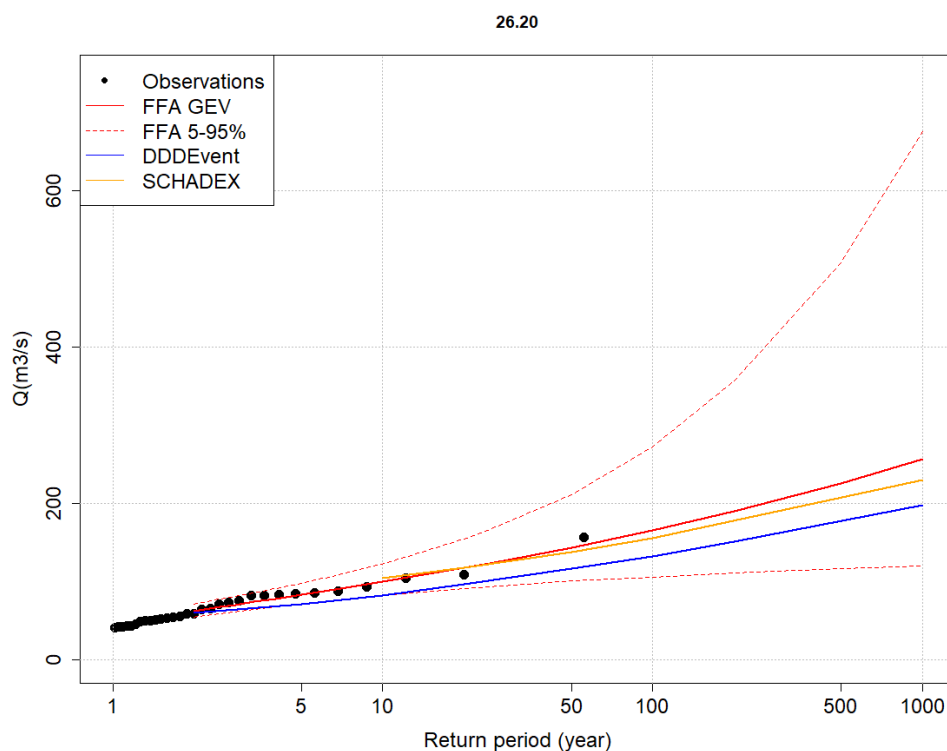


Figure 17: Flood estimates for Årdal (26.20) using extreme values of areal precipitation estimated from a 1972-2025 times series.

In the proposed method snowmelt events are, at present, only a part of the initial S and not a part of the input to the model. To make the method useful for most regions in Norway we will have to include snowmelt *and* precipitation (i.e. rain-on-snow events, Feng et al. 2026) as possible extreme value inputs. For catchments such as Tannsvatn (16.75), the snowmelt spring flood is the main hydrological event of the year, and extreme precipitation alone cannot be expected to generate floods. To perform extreme value analysis on the combination of extreme rain intensities and snowmelt we will have to rely on simulated values of snowmelt, for example from a hydrological rainfall runoff model.

From Table 2 it is evident that the median value of the distribution of runoff conditioned on the T- year precipitation gives an equally good, or sometimes slightly better, estimate of the T-year flood than the Bayes approach. An explanation for this is that provided that the conditional distributions of eqs. 4 and 5 are symmetrical, the median, with its exceedance probability of 0.5 is the only value that gives an equal exceedance probability to precipitation P and Q (see eq. 6). The differences between the flood estimates using the Bayes method and that using the median of the conditional distribution are very small, indicating that the conditional distributions can be assumed to be close to symmetrical when assessing such robust, first order central statistical characteristics as the median. The implication of this find is, however, a vastly simplified procedure for estimating design floods. All that would then be required is that the DDDEvent model is run with the T-year



550 precipitation value. The median of the resulting conditional distribution will hence be an estimate of the T-year flood.

The Bayes approach (Eq. 6), however, is still useful as it offers the possibility to provide an estimate of the T-year flood using a precipitation estimate with a different return period. The return period of the precipitation should, however, not be too different from that of the flood estimate. Table 4 shows the flood estimates for
 555 Røykenes when extreme precipitation values of different return periods are available. This might be a useful feature if a flood estimate for a certain return period is needed which does not correspond to the return period of the extreme precipitation event at hand. From Table 4 we see that the higher the difference in return periods between precipitation and runoff, i.e. the farther away from the diagonal and the more uncertain the flood estimates are. This is most likely due to the fact that we are estimating exceedance probabilities from the tails of
 560 the empirical conditional distributions (see Figure 18 and eqs. 4 and 5) which involves a high degree of uncertainty. In Figure 18 we show an example of the conditional distributions involved for estimating a 20-year flood using a 5- year precipitation event. The estimate is $106.7 \text{ m}^3/\text{s}$, whereas the estimate where the exceedance probabilities are equal is $123.2 \text{ m}^3/\text{s}$, a deviation of 13 %.

565 **Table 4: Estimated floods for 55.4 Røykenes using precipitation intensities of, $T_d = 15$ hrs for f different return periods. We note that floods for all return periods cannot be estimated if we are beyond the range of the empirical conditional distributions (see Figure 18 and eqs. 4 and 5).**

	Prec[mm]	Q2	Q5	Q10	Q20	Q50	Q100	Q200	Q1000
P2	71.2	63.2	75.3	85.1	93				
P5	92.2	78.5	88.9	98.2	106.7	120.2			
P10	107.2	88.2	97.1	106.2	115.1	128.2	137.9		
P20	122.5		106.3	113.9	123.2	137.2	148.1	158.8	
P50	143.7			125.7	133.6	146.5	158.6	170.8	
P100	160.8				143.2	155.2	166	178.4	210.4
P200	178.8					163.8	174.4	184.7	218.4
P1000	224.8						196	207.1	235.7

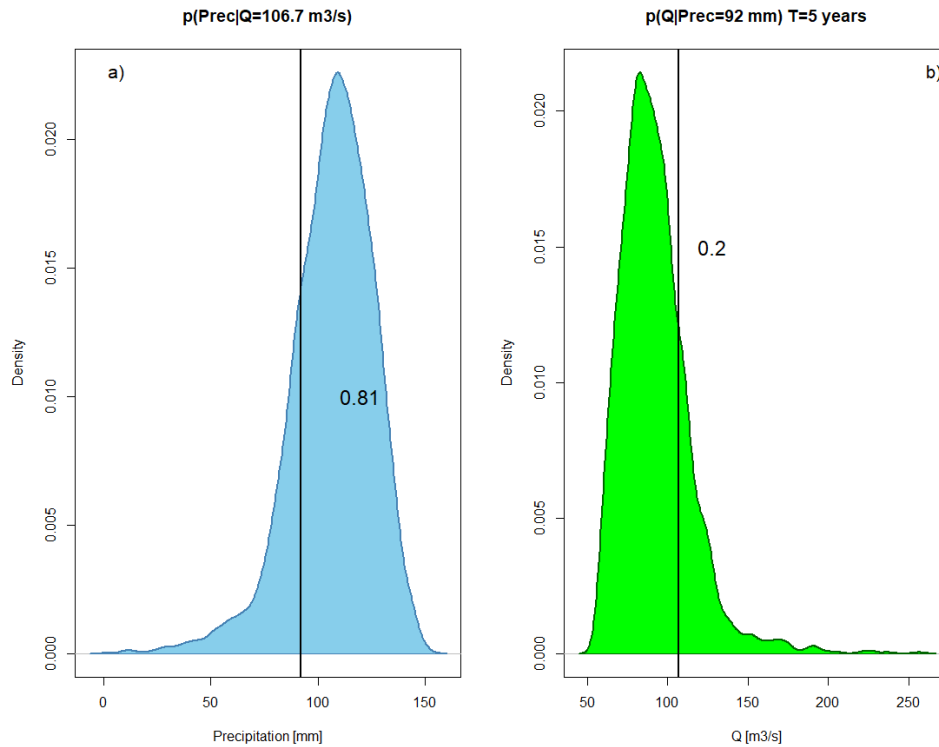


Figure 18: Conditional distributions a) $f(P|Q)$ and b) $f(Q|P)$ used for estimating a 20-year flood using a 5-year precipitation. The exceedance probabilities are the integral of the PDF to the right of the vertical lines. The Bayes formula (Eq. 6) will hence give: $pr(Q) = \frac{pr(Q|P_T)pr(P_T)}{pr(P|Q)} = \frac{0.2 \cdot 0.2}{0.81} = 0.05$, the exceedance probability for a 20-year flood.

The flood analysis in figs. 12-15 reveals that the contribution of the antecedent moisture to the total runoff volume is significant and, for the two example catchments, is more than 50% of the peak flow. This is an important finding and insight for the practise of flood estimation in urban catchments, where the contribution of groundwater generally is overlooked and it is commonly assumed that the return period of the flood derived from the routing of precipitation is equal to that of the input precipitation (Packman and Kidd, 1980; Tuyls et al. 2018). Such an assumption only holds for a totally impermeable catchment and, even then, different precipitation sequences will also lead to variability in peak flow magnitudes. Since the contribution of the subsurface plays such an important role in the runoff volume, it is clear that S is a very important compounding element of flooding. This has also been confirmed by Seidenfaden et al. (2025) in a coastal Danish catchment where a high pre-event groundwater state (termed wet preconditioning of the catchment) coincides with more extreme flooding and higher river water levels.



585 We tested the regionalised version of DDD and hence also the DDDEvent model for estimating floods in
 ungauged catchment with good results (see Skaugen et al. 2015; Skaugen et al. 2026 , for the development of the
 regionalised version of the DDD). For 3 of four catchments, the PUB estimates appear to be better than those
 obtained using a calibrated version of the DDD model (see Fig 7 and Table 2). The regionalised version is
 currently only available in Norway for temporal resolutions of 24, 3 and 1 h, so it is not yet applicable to very
 590 small catchments requiring temporal resolutions on the order of minutes. In addition, the GIS-based tool
 currently in use does not resolve a sufficiently dense river network suitable for the delineation of smaller
 catchments, and neither is the land surface presently classified as permeable and impermeable, as required for
 modelling urban catchments (Skaugen et al. 2020).

The proposed approach appears to be less demanding with respect to the length of required timeseries of runoff,
 595 as compared to classical FFA. However, a sufficiently long times series is needed for a robust calibration of
 DDD and well defined full- and conditional distributions of S . Examples from this study indicate that the DDD
 model can be reasonably well calibrated with just a few years of data. For the Sandsli case, reasonable results
 were obtained using a times series of only 2 years (on a 2-minute temporal resolution) for estimating the S
 distributions and model parameters.

600 **6 Conclusions**

In this study we have developed a model system combining a historical simulation using a rainfall-runoff model
 and a stochastic event model for generating a quasi-joint distribution of runoff and precipitation. The exceedance
 probability of runoff can be estimated if the exceedance probability of precipitation is known using Bayes
 theorem. The results for catchments where rainfall is the dominating generator of floods are good and
 605 comparable to the established flood estimation method SCHADEX (Paquet, et al., 2013).

A procedure for estimating floods that is model- and processed-based, provides insights into the contribution of
 various factors in flood generation. The results show that the subsurface contribution to the total runoff is
 significant and an important compounding element that must be incorporated when developing design flood
 estimates. The variability in runoff response to precipitation due to S and precipitation sequence is very high, and
 610 the hydrological response to a T-year precipitation event may have a much higher or lower return period
 dependent on the S . The method presented here presents an easily implemented approach for incorporating the S
 in design flood estimates using simulation methods.

The catchments respond differently to differing precipitation sequences, and this appears to be dependent on the
 catchment's response time and Td . In the examples shown in this study, the flood peak may vary by about 20 %
 615 depending on whether the most intense precipitation is at the beginning or end of the Td .

The regionalised version of the model system gives promising results for ungauged catchments for the four test
 catchments considered. Further testing of this approach is warranted. Inclusion of the contribution of snow
 meltwater combined with rainfall to flood generation is required before the method can be deemed suitable for
 wide application in Nordic catchments and other areas where snowmelt plays a role in extreme flooding.



620 **Code and data availability**

The hydrological data used is available from the database HydraII at the Norwegian Water resources and Energy directorate (NVE). The precipitation data is freely available from the Norwegian Meteorological Institute, and the Norsk Klimaservicesenter. The code for the co-authors hydrological models is available at NVEs GitHub pages <https://github.com/NVE/DDDmodels>

625 **Author contribution**

Thomas Skaugen and Deborah Lawrence designed the experiment. Thomas Skaugen, Matthew Lee Newell and Tiia Pedusar developed the code, and Thomas Skaugen prepared the manuscript with contribution from all co-authors.

Competing interests

630 The author team are not aware of any competing interests regarding this article

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 635 Jørgensen (NVE) helped prepare figures for the manuscript and Kolbjørn Engeland (NVE) commented on and improved an earlier draft of the manuscript.

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