

1 **Response to Referee #2 on the review of “Estimating catchment scale groundwater**
2 **dynamics from recession analysis- enhanced constraining of hydrological models”, by T.**
3 **Skaugen and Z. Mengistu.**

Formatert: Skriftfarge: Tekst 2

4
5 **General comments:**

6 The paper is much improved (compared to the previous version which I reviewed) in terms of
7 readability, and justification of the parameter estimation method. My remaining concern is the
8 justification for the chain of manipulations made in section 2.3. The assumptions made are plausible and
9 pragmatic, e.g.,

10 “the temporal distribution of catchment scale storage can be considered as a scaled version to that of
11 the recession characteristic”

12 “the mean value of the sampled Λ 's, Λ , represents the slope of recession in a state of mean storage in
13 the catchment,”

14 “The water left in the soils, S_{ss} , at steady state (after J time intervals) and hence assumed to represent
15 the mean storage”

16 However, a different assumption could have been made in every case, the alternatives are not
17 considered, and only the first of the three listed here is later discussed. As a result it is difficult to know
18 whether all of the choices made were critical to the success of the new model. At the very least, I think
19 the authors should list in the discussion any assumptions which have not been tested.

20
21 Response: We agree to that and have included a paragraph, which lists and discusses the
22 remaining two assumptions (see p20, l 3-19 in marked MS).

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24 **Specific points:**

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26 P2 “A single linear reservoir is, however, too simple for describing the variability and non-linearity of
27 hydrological response.” Please cite some references for this.

28 Response: done, see p4, l 23 in marked MS.

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29
30 P6 18 “In the current version of DDD, MM is a calibrated parameter and is divided into storage levels,
31 i_i .” Are these equal-sized intervals?

32 Response: Yes, see p8, l 18 in marked MS.

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33
34 P6 19 “which are all assigned different wave velocities, or celerities”. Are these the linear reservoirs
35 arranged in parallel referred to above? If yes, it would help to use the same terms to describe the same
36 thing.

37 Response: see p8, l 19 in marked MS.

38
39 P7 15 “The distance distributions (Figure 2)” Which catchments are these?

40 Response: we have included the information in the figure caption (see p34, l 7-8 in marked MS).

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41
42
43 P11 8 “If we assume that the mean value of the sampled Λ 's, Λ , represents the slope of recession in a
44 state of mean storage in the catchment” Why is it reasonable to assume the mean recession rate occurs
45 at the mean storage?

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46 Response: We assume a very strong association between the recession characteristic Λ , and storage (see
47 discussion at p20, l 3-19 in marked MS).

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49 Eq 17: S_i appears on both sides of this equation – is that correct? Is it really an integral equation which
50 must be solved?

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1 Response: Yes it is correct. The integral is just a standard probability calculation from the gamma
2 distribution. No corrections.

3

4

5 P17 L23 “the distribution of Λ remains quite incentive to” change incentive to insensitive
6 Response: corrected (see p19,123 in marked MS).

7

8 In addition; we have corrected the reference to Skaugen and Weltzien, 2016, since the paper is
9 published and included our gratitude to the referees and editor in the acknowledgements.

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11

Formatert: Skriftfarge: Tekst 2

1 **Estimating catchment scale groundwater dynamics from**
2 **recession analysis – enhanced constraining of hydrological**
3 **models.**

4
5 **T. Skaugen and Z. Mengistu**

6 {Dept. of Hydrology, Norwegian Water Resources and Energy Directorate}

7 Correspondence to: T. Skaugen (ths@nve.no)

8
9 **Abstract**

10 In this study we propose a new formulation of subsurface water storage dynamics for use in
11 rainfall-runoff models. Under the assumption of a strong relationship between storage and
12 runoff, the temporal distribution of catchment scale storage is considered to have the same shape
13 as the distribution of observed recessions (measured as the difference between the log of runoff
14 values). The mean subsurface storage is estimated as the storage at steady-state, where moisture
15 input equals the mean annual runoff. An important contribution of the new formulation is that its
16 parameters are derived directly from observed recession data and the mean annual runoff. The
17 parameters are hence estimated prior to model calibration against runoff. The new storage
18 routine is implemented in the parameter parsimonious Distance Distribution Dynamics (DDD)
19 model and has been tested for 73 catchments in Norway of varying size, mean elevation and
20 landscape type. Runoff simulations for the 73 catchments from two model structures; DDD with
21 calibrated subsurface storage and DDD with the new estimated subsurface storage, were
22 compared. Little loss in precision of runoff simulations was found using the new estimated
23 storage routine. For the 73 catchments, an average of the Nash-Sutcliffe Efficiency criterion of
24 0.73 was obtained using the new estimated storage routine compared with 0.75 using calibrated
25 storage routine. The average Kling-Gupta Efficiency criterion was 0.80 and 0.81 for the new and
26 old storage routine, respectively. Runoff recessions are more realistically modelled using the

1 new approach since the root mean square error between the mean of observed and simulated
2 recession characteristics was reduced by almost 50 % using the new storage routine. The
3 parameters of the proposed storage routine are found to be significantly correlated to catchments
4 characteristics, which is potentially useful for predictions in ungauged basins.

5

6 **1 Introduction**

7 The movement of groundwater to streams is an important component of catchment hydrology
8 and simulating its movement is key to accurately reproducing the hydrograph. Unfortunately, at
9 the spatial scale of interest for studying the dynamics of hydrological systems, the catchment
10 scale, we are not able to actually see and learn how water is transported in the subsurface.
11 Hence, for many decades the (subsurface) storage-runoff relationship has been the basis for
12 countless hydrological model concepts. The subsurface water storage, hereafter denoted
13 subsurface storage or storage, is to be understood as the dynamics storage, i.e. the variation in
14 storage between wet and dry period (Kirchner, 2009). In this paper we will develop and test a
15 new formulation for storage dynamics. The proposed subsurface storage model is based on linear
16 reservoir theory and its parameters are derived directly from recession analysis, digitized maps
17 and the mean annual runoff.

18 The linear reservoir, often visualised as a straight-sided bucket with a hole in the bottom (Beven,
19 2001; Dingman, 2002), has an exponentially declining outflow and is the basis for the
20 exponential unit hydrograph (UH). It has served as the most commonly used storage-runoff
21 relationship and plays a fundamental role in conceptual rainfall runoff models. A single linear
22 reservoir is, however, too simple for describing the variability and non-linearity of hydrological
23 response ([Brutsaert and Nieber, 1977](#); [Lindström et al., 1997](#)). Some groundwater models
24 conceptualise the stream- aquifer interactions as the drainage of an infinite number of
25 independent linear reservoirs (Sloan, 2000; Pulido-Velasquez et al., 2005; Bidwell et al. 2008;

1 Rupp et al., 2009). This comes as a result of solving the linearized Dupuit- Boussinesq equation
2 for saturated flow as an eigenvalue and eigenfunction problem. In order to capture the variability
3 in hydrological response, most conceptual rainfall-runoff models also use a system of several,
4 often modified, linear reservoirs to describe the soil moisture accounting and runoff dynamics.
5 The system may vary in complexity (and hence in the inclusion of free calibration parameters),
6 but the linear reservoir remains the basic building block. Examples of such models are the UH
7 models of Nash (1957) and Dooge (1959) and the explicit soil-moisture accounting (ESMA)
8 models, of which the work-horse of operational Nordic hydrology, the Hydrologiska Byråns
9 Vattenbalans (HBV) model (Bergström, 1992) serves as an example (see Beven (2001) for a
10 discussion on the evolution of rainfall-runoff models). In Lindström et al. (1997) the upper zone
11 (the reservoir responsible for quick response) of the HBV model was formulated as a non-linear
12 reservoir, $Q = \vartheta S^{1+\delta}$ where Q is runoff, S is storage and ϑ and δ are calibrated constants. For
13 $\delta = 0$, this is, of course an ordinary linear reservoir.

14 Recession behaviour should be characteristic for a specific catchment (Tallaksen, 1995;
15 Kirchner, 2009; Stoelzle et al., 2013; Berghuijs et al., 2016) since it provides hydrological
16 information integrated over the catchment. Such a scaled-up hydrological signal contrasts that of
17 information derived from the extrapolation of point measurements. Recession data have often
18 been used to derive the storage-runoff relationship and Brutsaert and Nieber (1977) discuss
19 several theoretical models from the soil sciences as a basis for describing the non-linearity of
20 storage- runoff relationships and investigate this relationship using recession events. Lamb and
21 Beven (1997) developed a tool that used recession data to parameterize non-linear storage-runoff
22 relationships but were not always able to fit single analytical functions. In Kirchner (2009),
23 runoff is assumed to depend solely on the amount of water stored in the catchment and very
24 carefully selected recession events are used to parameterize the storage- runoff relationship. The

1 recession events were selected such that the possible contaminating effect of precipitation and
2 evapotranspiration on the recession data was minimized. For two rivers in the UK, highly non-
3 linear relationships between storage and runoff were found using this approach.

4 Recession characteristics are, in this paper, used to estimate parameters characterising the
5 storage dynamics. The parameters associated with storage are hence estimated directly from
6 observed data and apriori model calibration to runoff. Such an approach has many attractive
7 features. First, when we use the precipitation-runoff relationship in model calibration, the
8 estimated parameters will be conditioned on both inputs (precipitation and temperature) and the
9 output (runoff). The calibrated parameters will therefore be sensitive to biases and errors in the
10 inputs. Consequently, the more uncertain and biased the precipitation input, the more uncertain
11 and biased parameter estimates (e.g. Dawdy and Bergman, 1969; Kuczera and Williams, 1992;
12 Andréassian et al., 2001; Engeland et al., 2016). Second, when a single parameter is estimated
13 directly from data you remove the possibility that its value is conditioned on the value of the
14 other parameters, i.e. that the calibrated parameter values compensate for structural or data errors
15 (Beven, 1989; Kirchner, 2006; Kirchner, 2009). Third, when a single parameter is estimated
16 directly from observed data and not through the optimizing of a model, one does not have to take
17 into account the possible (and probable) errors associated with the model structure (Beven, 2001.
18 p. 21; Kirchner, 2009). In such a way, the errors associated with the modelling of processes such
19 as snow accumulation and -melt, groundwater- and soilmoisture dynamics do not influence the
20 parameter estimate. In this paper we distinguish between calibrated and estimated parameters.
21 The term “calibrated parameters” refers to parameters being part of a set that is simultaneously
22 optimized when minimizing the difference between observed and simulated runoff. The term
23 “estimated parameters” refers to parameters estimated independently and directly from observed
24 data. These values are not tuned to minimize the difference between simulated and observed
25 runoff as would be the case if they were calibrated.

1 The new formulation of storage dynamics proposed in this paper is implemented in the in the
2 Distance Distribution Dynamics (DDD) model (Skaugen and Onof, 2014; Skaugen et al. 2015),
3 which is briefly reviewed in the next section. In this model, the dynamics of runoff are modelled
4 using linear reservoirs (unit hydrographs (UHs)) arranged in parallel, a principle which
5 resembles the stream- aquifer interaction model described by for example Bidwell et al. (2008).
6 The UHs are turned on and off according to the level of saturation in the catchment. The UHs are
7 parameterized from recession data and digitized maps, so the DDD model incorporates many of
8 the modelling approaches presented above.

9 The main objective of this study is to assess how the new formulation of storage with its
10 parameters estimated directly from recession characteristics and the mean annual runoff
11 compares with the current formulation of the storage, where its parameter is calibrated against
12 runoff. The comparison will be carried out for a large number of catchments and for runoff and
13 recession behaviour. In the discussion, some implications with respect to predictions in
14 ungauged basins and spatially variable groundwater modelling are discussed.

15

16 **2 Methods**

17

18 **2.1 Hydrological model**

19 The DDD model (Skaugen and Onof, 2014; Skaugen et al.2015) is a rainfall- runoff model
20 written in the programming language **R** (www.r-project.org) and currently runs operationally at
21 daily and 3-hourly time steps at the operational flood forecasting service of the Norwegian Water
22 Resources and Energy Directorate (NVE). The DDD model introduces new concepts in its
23 description of the subsurface and of runoff dynamics. Input to the model is precipitation and
24 temperature. In the subsurface module (see Figure 1), the capacity of the subsurface water

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1 reservoir M [mm] is shared between a saturated zone, S [mm], called the groundwater zone and
 2 an unsaturated zone with capacity D [mm], called the soil water zone. The actual water present in
 3 the unsaturated zone, Z , is called Z [mm].

4 The subsurface state variables are updated after evaluating whether the current soil moisture,
 5 $Z(t)$, together with the input of rain and snowmelt, $G(t)$, represent an excess of water over the
 6 field capacity, R , which is fixed at 30% ($R = 0.3$) of $D(t)$ (Grip and Rohde, 1985, p.26;
 7 Colleuille et al. 2007). If so, excess water $X(t)$ is added to $S(t)$. To summarize:

8 Excess water:
$$X(t) = \text{Max} \left\{ \frac{G(t)+Z(t)}{D(t)} - R, 0 \right\} D(t). \quad (1a)$$

9 Groundwater:
$$\frac{dS}{dt} = X(t) - Q(t). \quad (1b)$$

10 Soil water content:
$$\frac{dZ}{dt} = G(t) - X(t) - Ea(t). \quad (1c)$$

11 Soil water zone:
$$\frac{dD}{dt} = -\frac{dS}{dt}, \quad (1d)$$

12

13 where $Q(t)$ is runoff. Actual evapotranspiration, $Ea(t)$, is estimated as a function of potential
 14 evapotranspiration and the level of storage. Potential evapotranspiration is estimated as $Ep =$
 15 $\theta_{cea} * T$ [mm/day], where θ_{cea} [mm/°C day] is the degree-day factor which is positive for
 16 positive temperatures and zero for negative temperatures. Actual evapotranspiration thus
 17 becomes $Ea = Ep \times (S + Z)/M$, and is drawn from Z .

18 In the current version of DDD, M is a calibrated parameter and is divided into equal-sized
 19 storage levels, i , for which their associated UHs are all assigned different wave velocities, or
 20 celerities, v_i [m/s]. The celerities increase for increasing i (see next section). Experience using
 21 the DDD model shows that the subsurface water capacity parameter M largely controls the
 22 variability of the hydrograph. Low values of M increase the amplitude of the hydrograph, since
 23 the entire range of celerities is engaged, and vice versa.

Slettet: which are

1 Calibrated model parameters are hereafter denoted by θ with subscripts (e.g. θ_M), in order to
2 clearly distinguish between estimated and calibrated parameters.

3

4 **2.2 Runoff dynamics**

5 The runoff dynamics are completely parameterized from observed catchment features derived
6 using a Geographical Information System (GIS) and runoff recession analysis. Central for the
7 formulation of runoff dynamics for a catchment is the distance distribution derived using GIS.

8 The distances, d [m], from points in the catchments to the nearest river reach are calculated for
9 each catchment and for more than 120 studied catchments in Norway the exponential distribution
10 describe the distribution of distances well. Figure 2 shows the empirical and exponential
11 distributions for two Norwegian catchments and although the mean distance \bar{d} is different, the
12 exponential distribution is a good fit for both catchments. The parameter γ , of the exponential
13 distribution

$$14 \quad f(d) = \gamma e^{-\gamma d}, \quad (2)$$

15 equals $\gamma = 1/\bar{d}$. The distance distributions (Figure 2) express the areal fraction of the catchment
16 as a function of distance from the river network. In appendix A, analytical relations between
17 exponential distance distributions and linear reservoirs are described.

18 In the DDD model, water is conveyed through the soils to the river network by waves with
19 celerities determined by the actual storage, $S(t)$ in the catchment. The celerities associated with
20 the different storages are estimated by assuming exponential recessions with parameter Λ , in
21 $Q(t) = Q_0 \Lambda e^{-\Lambda(t-t_0)}$, where Q_0 is the peak discharge immediately before the recession starts
22 (Nash, 1957). We can determine the parameter $\Lambda(t)$ from the difference:

$$23 \quad \Lambda(t) = \log(Q(t)) - \log(Q(t + \Delta t)), \quad Q(t) > Q(t + \Delta t), \quad (3)$$

1 at any time t , during the recession due to the lack of-memory property of the exponential
 2 distribution (Feller, 1971, p. 8). The parameter Λ is thus the slope per Δt of the recession (of
 3 $\log Q(t)$). From eqs. A2 and A7 in Appendix A, we find the celerity v [m/s] as a function of Λ :

$$4 \quad v = \frac{\Lambda \bar{d}}{\Delta t} \quad (4)$$

5 If we sample Λ 's from all recession events (the only condition is that $Q(t) > Q(t + \Delta t)$)
 6 according to Eq. (3), we find that they can be fitted to a gamma distribution. This is a
 7 development from the exponential model used in Skaugen and Onof (2014) and is based on more
 8 detailed analysis of a much larger number of runoff records. For the 73 catchments us in this
 9 study, the gamma distribution was a good fit for all catchments. In Figure 3 we have plotted the
 10 empirical and the gamma distribution of Λ for six catchments with estimated shape, α , and scale,
 11 β , parameters of the gamma distribution, and it is clearly seen that the flexibility of the gamma
 12 distribution is needed in order to model the observed quantiles (see for example Figure 3 d) and
 13 f)).

14 The capacity of the subsurface reservoir θ_M , is divided into storage levels of equal capacity. The
 15 storage levels i corresponds to the quantile of the distribution of Λ under the assumption that the
 16 higher the storage, the higher the values of Λ . Each level is further assigned a celerity $v_i = \frac{\lambda_i \bar{d}}{\Delta t}$
 17 (see Eq. 4), where λ_i is the parameter of the individual unit hydrograph for storage level i , and
 18 estimated such that the runoff from several storage levels will give a UH equal to the exponential
 19 UH with parameter Λ_i , i.e.:

$$20 \quad \Lambda_i e^{-\Lambda_i(t-t_0)} = \varpi_1 \lambda_1 e^{-\lambda_1(t-t_0)} + \varpi_2 \lambda_2 e^{-\lambda_2(t-t_0)} + \dots + \varpi_i \lambda_i e^{-\lambda_i(t-t_0)}, \quad (5)$$

1 where ϖ are the weights associated with the discharge from each level estimated by $\varpi_i =$
2 $\frac{\Lambda_i}{\sum_{k=1}^i \Lambda_k}$. From Eq. 5, λ_i are solved successively for increasing i under the assumption that
3 $\lambda_1 = \Lambda_1$ (see Skaugen and Onof, 2014).

4 The quantiles of Λ are mapped to a uniform distribution of S , $F(\Lambda) = \frac{S}{\theta_M}$, which implies that all
5 storage levels are equally probable and that the equally-spaced storage levels have equal capacity
6 of water, i.e. if $\theta_M = 50mm$ and we use 5 storage levels ($i = 1 \dots 5$), each level has a capacity of
7 10 mm. In Skaugen and Onof (2014), no increase in the precision of daily runoff simulations
8 was found using more than 5 storage levels.

9

10 **2.3 Reformulation of the subsurface of DDD**

11 An obvious problem of the approach described above is that we attempt to estimate an extreme
12 value, the maximum catchment scale storage θ_M , a task which is obviously associated with more
13 uncertainty than estimating the mean catchment scale storage, m_s . Another problem is the
14 assumption of a uniform distribution of storage levels. A quick investigation of observed
15 groundwater level fluctuations suggests that this is not the case. Figure 4 shows histograms of
16 observed groundwater levels from three observation boreholes located in a small catchment (the
17 Groset catchment, 6.33 km²) in southern Norway. The figure clearly illustrates that fluctuations
18 in storage and groundwater levels are spatially variable and should ideally be treated as such in
19 rainfall-runoff models (Rupp et al. 2009; Sloan, 2000). This is a consequence of the differences
20 in water level fluctuations depending on the location of the borehole relative to the river, i.e. top
21 of a hillslope vs. adjacent to a river and also of the catchment variability of topography and soil
22 porosity (Refsgaard et al., 2015). It is therefore very difficult to parameterize the distribution of
23 the catchment-scale groundwater fluctuations from such single observation points (Kirchner,

1 2009). In addition, the distribution is unlikely to be uniform as none of the individual histograms
2 exhibits such a behaviour.

3 To overcome the problems identified above, we attempt to develop a storage model that differs
4 from the previous model in that the groundwater reservoir is parameterised by its mean storage,
5 m_s , as opposed to the maximum storage, θ_M . In addition, regarding the practical problems
6 associated with the observation of catchment scale fluctuations of storage, we make the
7 assumption that recession and its distribution carries information on the distribution of
8 catchment-scale storage. More precisely, we assume that the temporal distribution of catchment
9 scale storage can be considered as a scaled version to that of the recession characteristic, Λ .
10 Consequently, the subsurface reservoir no longer increases linearly with the quantiles (which is
11 the case with storage levels of equal capacity), but rather, increases non-linearly according to the
12 shape of the distribution of Λ .

13 Since the distribution of Λ is modelled as a two parameter gamma distribution, we can write:

$$14 \quad f(\Lambda) = \frac{1}{\beta^\alpha \Gamma(\alpha)} \Lambda^{\alpha-1} \exp(-\Lambda/\beta), \quad \alpha > 0, \beta > 0 \quad (6)$$

15 where α and β are the shape and scale parameters respectively and estimated from observed Λ 's
16 (using Eq. 3).

17 The distribution of S is hence also modelled as a two-parameter gamma distribution:

$$18 \quad f(S) = \frac{1}{\eta^\alpha \Gamma(\alpha)} S^{\alpha-1} \exp(-S/\eta), \quad \alpha > 0, \eta > 0 \quad (7)$$

19 where the scale parameter, η , is

$$20 \quad \eta = \beta/c, \quad (8)$$

21 and c is a constant and equal to

1
$$c = \bar{\Lambda}/m_s, \quad (9)$$

2 where $\bar{\Lambda}$ is the mean value of Λ , estimated from the parameters of the fitted gamma distribution
 3 and representing the mean recession characteristic. Note that since the distribution of S is a
 4 scaled version of Λ , the shape parameter α is equal for the two distributions.

5 In order to model the storage as a two-parameter gamma distribution we need to estimate the
 6 mean storage, m_s . We can then determine the constant c from Eq. 9, and finally, the scale
 7 parameter η using Eq. 8.

8 If we assume that the mean value of the sampled Λ 's, $\bar{\Lambda}$, represents the slope of recession in a
 9 state of mean storage in the catchment, then the associated unit hydrograph (UH) is,

10
$$u_{\bar{\Lambda}}(t) = \bar{\Lambda} e^{-\bar{\Lambda}(t-t_0)} \quad . \quad (10)$$

11 The temporal scale of the UH in Eq. 10 is $t_{h,max} = d_{max}/\bar{v}_h$, where d_{max} is the observed
 12 maximum distance of the hillslope distance distribution and \bar{v}_h is the celerity associated with $\bar{\Lambda}$
 13 through $\bar{v}_h = \frac{\bar{\Lambda} \bar{d}}{\Delta t}$ (see Eq. 4). Let $t_{h,max}$ be divided into suitable time intervals, Δt , then the
 14 number of time intervals it takes to drain the hillslope is $J = t_{h,max}/\Delta t$. When Eq. 10 is
 15 integrated over successive time intervals we obtain weights, μ_j , which, if multiplied by the
 16 excess moisture input, $X(\Delta t)$, give the response (the water entering the river network) for the
 17 different time intervals. The weights are calculated as:

18
$$\mu(\bar{\Lambda})_j = \int_{(j-1)\Delta t}^{(j)\Delta t} u_{\bar{\Lambda}}(t) dt \quad j = 1..J, \quad \sum \mu(\bar{\Lambda})_j = 1, \quad (11)$$

19 and scaled so that the sum of weights equals 1. The runoff at time interval j is calculated as

20
$$Q(j\Delta t) = X(\Delta t)\mu(\bar{\Lambda})_j. \quad (12)$$

1 For estimating the mean storage m_s we first calculate the mean annual runoff, MAR , which
 2 corresponds to a daily excess moisture input X of

$$3 \quad X[mm/day] = (1000 * MAR[m^3/s] * 86400[s]) / A[m^2], \quad (13)$$

4 where A is the catchment area.

5 After J successive days of input X , routed with the UH of Eq. 10, we reach a steady state where
 6 the volume of the input equals the output (MAR). The total sum of moisture input after J days is

$$7 \quad J \cdot X = S_{SS} + Q_{SS} \quad (14)$$

8 where total runoff, Q_{SS} , after J days is

$$9 \quad Q_{SS} = \sum_{k=1}^J \sum_{j=1}^k X \cdot \mu(\bar{\Lambda})_j, \quad (15)$$

10 and k is the number of days and the subscript denotes “steady state”. The water left in the soils,
 11 S_{SS} , at steady state (after J time intervals) and hence assumed to represent the mean storage m_s ,
 12 is $S_{SS} = J \cdot X - Q_{SS}$, which can also be calculated as:

$$13 \quad S_{SS} = \sum_{k=1}^{J-1} \sum_{j=k+1}^J X \cdot \mu(\bar{\Lambda})_j = m_s. \quad (16)$$

14 With an estimate of the mean storage, m_s , we can use eqs. 8 and 9 to estimate the scale
 15 parameter, η , of the distribution of S . The shape parameter, α , is already determined and equal to
 16 that of the distribution of Λ . The gamma distributed storage levels S_i are calculated as quantiles
 17 of the gamma distributed storage:

$$18 \quad \frac{S_i}{M} = \int_0^{S_i} \frac{1}{\eta^\alpha \Gamma(\alpha)} S^{\alpha-1} \exp(-S/\eta) dS, \quad (17)$$

19 where M is now estimated as the 99% quantile of the distribution of S .

20

21 **2.4 Test of new storage routine**

1 We will test the performance of the new formulation of storage by replacing the formulation of
2 the storage where θ_M is a calibrated parameter and storage is uniformly distributed with a
3 formulation where storage is gamma distributed with parameters, η and α , derived from
4 recession data and *MAR*. The model with the current storage routine is denoted DDD_{θ_M} and the
5 model with the new storage routine is denoted DDD_{m_S} .

6 DDD_{m_S} and DDD_{θ_M} are tested for 73 catchments distributed across Norway (see Figure 5).
7 The catchments vary in latitude, size, elevation and landscape type (see histograms of selected
8 catchment characteristics in Figure 6) and constitute thus a varied, representative sample of
9 Norwegian catchments.

10 The time series for precipitation and temperature are mean areal catchment values extracted from
11 an operational meteorological grid (1 x 1 km²) produced by MET Norway, which provides daily
12 values of precipitation and temperature for Norway from 1957 to the present day (see
13 www.senorge.no). The runoff data is provided by the NVE. The time series of precipitation ,
14 temperature and runoff were split into a calibration data set (1.9.1995- 31.12.2011) and a
15 validation data set (1.1.1980- 31.8.1995).

16 DDD_{θ_M} is calibrated using an R-based Monte-Carlo Marko Chain method (Soetart and
17 Petzhold, 2010). All together 11 parameters (including θ_M) are calibrated (see parameters
18 denoted by θ with subscripts in Table 1). The calibrated parameters, except for θ_M , are also used
19 when running DDD_{m_S} .

20 **3 Results**

21 Figure 7 (a-e) shows different skill scores obtained for the simulations for the 73 catchments
22 with DDD_{θ_M} (skill is shown with red crosses) and for DDD_{m_S} (skill is shown with blue
23 circles) for the validation data set. The figure is organised such that the catchments are sorted
24 geographically starting from the South-East (S-E), then follows the South-West (S-W) and Mid-

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1 Norway (M-N) and finally Northern-Norway (N-N). Figure 7 a) shows the Nash-Sutcliffe
2 efficiency criterion (NSE, Nash and Sutcliffe, 1970), 7 b) the Kling-Gupta Efficiency criterion
3 (KGE, Gupta, et al. 2009, Kling et al. 2012) and 7 c-e) the three components of the KGE,
4 correlation, bias and variability error, respectively. The variability error is given by the ratio of
5 the coefficients of variation of simulated and observed runoff as suggested in Kling et al. (2012).
6 The mean values of the skill scores for DDD_ θ_M and DDD_ m_S are shown as straight lines in the
7 plots. We have also added a moving average of the results for enhanced readability. We see from
8 Figure 7 that little precision is lost in the results for DDD_ m_S . The mean values of NSE and
9 KGE are slightly better for DDD_ θ_M . The result for bias is better for DDD_ m_S (Fig. 7d) whereas
10 the results for the correlation and variability errors favor DDD_ θ_M . Overall, the differences in
11 skill between DDD_ m_S and DDD_ θ_M are very small. Mean values of the skill scores for
12 DDD_ m_S and DDD_ θ_M are shown in Table 2.

13 The observed distribution of the recession characteristic Λ , is crucial for both the estimation of
14 the subsurface celerities and the estimation of m_S . If the distribution of simulated Λ , denoted $\hat{\Lambda}$,
15 is similar to that of the observed, this suggests that recessions are well simulated and hence, that
16 the dynamics of the model are realistic. Figure 8 shows scatter plots of the mean and standard
17 deviation of observed Λ and simulated $\hat{\Lambda}$ for DDD_ m_S (blue circles) and DDD_ θ_M (red
18 crosses). The root mean square error (RMSE) of the mean $\hat{\Lambda}$ is clearly less for DDD_ m_S ,
19 whereas the RMSEs of standard deviation of $\hat{\Lambda}$ for DDD_ m_S and DDD_ θ_M are similar (see
20 Table 3).

21 Figure 9 shows histograms of simulated storage from DDD_ θ_M (a) and DDD_ m_S (b) with
22 empirical CDFs (c) of the observed Λ (black line) and simulated $\hat{\Lambda}$ (DDD_ θ_M , red line and
23 DDD_ m_S , blue line) for a specific catchment. The CDF of $\hat{\Lambda}$ simulated with DDD_ m_S is clearly
24 in better agreement with that of the observed. The shape of the histograms of storage fluctuations

1 are very different, and as we have no data to estimate the true empirical distribution of storage at
2 the catchment scale we cannot claim that the fluctuations simulated with DDD_{m_S} are closer to
3 the truth than those simulated by DDD_{θ_M} . However, since the parameters of the subsurface-
4 and dynamic module of DDD_{m_S} are estimated prior to model calibration and that the recessions
5 are demonstrably better simulated, it is reasonable to suggest that the catchment scale storage
6 fluctuations simulated with DDD_{m_S} are closer to the truth.

7 **4 Discussion**

8 The new formulation for the subsurface storage gives good results, and it is promising that the
9 replacement of a routine with calibrated parameters with a routine with estimated parameters
10 produces runoff simulations which are equally precise and robust. In addition, the simulated
11 recessions $\hat{\Lambda}$, are much closer to those observed, suggesting a more realistically modelled
12 storage-runoff relationship (i.e. the non-linearly increasing storage capacity). Comparing
13 simulated runoff in such a manner constitutes a rather strict test for DDD_{m_S} . DDD_{θ_M} has an
14 advantage since the parameter θ_M is optimized together with the other calibration parameters.
15 These optimized parameter are not necessarily optimal for DDD_{m_S} .

16 The reduction of calibrated parameters in the storage and dynamic module of the DDD model
17 has attractive implications for the problem of predictions in ungauged basins (PUB) (see eg.
18 Sivapalan, 2003; Parajka et al, 2013; Hrachowitz, 2013; Blöschl et al, 2013; Skaugen et al.
19 2015). In Skaugen et al.(2015), 7 model parameters of the DDD model (including θ_M and the
20 parameters for the distribution of λ) were estimated from catchment characteristics (CC's) using
21 multiple regression analysis. All model parameters were found to correlate significantly with the
22 CC's. The median NSE for 17 catchments was found to be 0.66 and 0.72 for two timeseries
23 when DDD was run with model parameters estimated from CC's. The change in the model
24 structure of DDD presented in this paper with respect to predictions in ungauged basins implies

1 that we need to estimate the parameters for the distribution of Λ from CC's. The estimation of θ_M
2 through multiple regression with CC's, however, is no longer needed. Although it is not within
3 the scope of this study to conduct a full PUB analysis, we investigated how the parameters of the
4 distribution of Λ can be regionalized. Since λ is a function of Λ (see Eq. 5) the parameters of the
5 distribution of λ and Λ are obviously highly correlated (from a sample of 84 Norwegian
6 catchments we found correlations between the shape, α , and the scale, β , parameters of Λ and λ
7 of $\rho(\alpha)_{\Lambda,\lambda} = 0.97$ $\rho(\beta)_{\Lambda,\lambda} = 0.98$). In Skaugen et al. (2015) the parameters for the distribution
8 of λ could be expressed as functions of the mean of the distance distribution, \bar{d} , percentage of
9 lake, percentage of bare rock and catchment length with significant coefficients of determination
10 of $R_{\lambda}^2(\alpha) = 0.45$ and $R_{\lambda}^2(\beta) = 0.35$ respectively. A similar analysis using the new model
11 structure (DDD_ m_S), with an added new subroutine for the spatial distribution of SWE (Skaugen
12 and Weltzien, 2016), showed that the parameters of the distribution of Λ were significantly
13 correlated (p-value < 0.01) to the mean of the distance distribution, \bar{d} , areal percentage of lake
14 and the catchment gradient (see Table 4). From Table 4, we note that the shape parameter is
15 positively correlated to the areal percentage of lake (L%). In Figure 3 f), this catchment has L%
16 of 9.5 % whereas in Figure 3 c) L% is only 4.4 %. The significant correlations yield significant
17 multiple regression equations with coefficients of determination of $R_{\Lambda}^2(\alpha) = 0.59$ and $R_{\Lambda}^2(\beta) =$
18 0.54. Hence, the potential for improved predictions in ungauged basins is promising.

19 The assumption of equal shape for the distributions of Λ and S is, of course, difficult to verify as
20 no direct observations of S are at hand. Myrabø (1997) conducted groundwater measurements on
21 a very dense spatial grid over a tiny catchment (0.0075 km²) in Southern Norway for a short
22 period of time in order to investigate subsurface dynamics over an entire catchment. These data
23 are unfortunately not available and no other similar experiment from Norway is known.

24 However, if we use the equation for the linear reservoir in Appendix A (Eq. A4) and express the

1 rate constant as a function of Λ (Eq. 4 and Eq. A6), we can, for observed recession values of Q
2 and Λ , calculate the corresponding values of S and compare the distributions of Λ and (the
3 scaled) S .

$$4 \quad S(t) = \frac{Q(t)\Delta t}{1 - e^{-\Lambda(t)}} \quad (18)$$

5 Figure 10 shows such a comparison for two catchments, and, except for the highest quantiles, the
6 distributions of Λ and (scaled) S are almost identical and hence supporting our assumption. The
7 high frequency of high S values present in Figure 10, also seen for several other catchments (not
8 shown), is the result of the combination of high Q values and low values of Λ , i.e. very modest
9 recession for situations with high runoff values. Such events are probably not representative for
10 describing recession characteristics of the catchment. By sampling $\Lambda(t)$ and estimating $S(t)$
11 under the condition that precipitation at the time $(t + \Delta t)$ could not exceed a low threshold of 0,
12 2 and 5 mm, we found that the frequency of very high values of S estimated by Eq. 18 were
13 reduced. Hence, the very high values of S did not represent storage for true recession events.
14 Moreover, the distribution of Λ was insensitive to such conditioning, implying that Eq. 3 is a
15 robust estimate of recession characteristics, whereas the distribution of S is highly sensitive. This
16 way of conducting recession analysis differs, mainly in the manner of sampling the recession
17 events, from those described in recession analysis reviews such as Tallaksen (1995) and Stoelzle
18 et al. (2013). Common for many of the recession selecting algorithms reported in the literature is
19 the censoring of the recession events with exclusion of events with rainfall or periods of high
20 evapotranspiration (e.g. Kirchner, 2009) and exclusion of the early stages of the recession to
21 avoid the influence of preceding storm and surface flow (Stoelzle, 2013). In this study, all
22 recession events that satisfy $Q(t) > Q(t + \Delta t)$ are used to estimate the parameters of the
23 distribution of Λ . We have found that the distribution of Λ remains quite insensitive to

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1 precipitation (see above) and equally important, that the parameters of the distribution of Λ are
2 correlated to, and can be estimated from catchment characteristics.

3 There are other assumptions presented in this paper that remain difficult to test
4 because S is not observed at the catchment scale. We assume that i) $\bar{\Lambda}$ represents
5 the slope of recession in a state of m_S and ii) that water left in the soils at steady
6 state for MAR represents m_S . These assumptions are needed so that we can
7 estimate m_S , and hence have an analytical expression for the distribution of S
8 through equations 8 and 9. Since we are interested in a mean behaviour, linking
9 the two known means, MAR and $\bar{\Lambda}$, with the unknown mean, m_S , seems
10 reasonable and the most straight forward. The actual, spatially distributed
11 subsurface state for mean storage (see below for more detailed discussion on
12 subsurface states) can, of course, vary and be associated with different recessions
13 (different Λ 's), but this does not rule out that $\bar{\Lambda}$ and m_S are good representatives
14 for describing a mean behaviour. A catchment under steady-state for MAR,
15 where water is routed through the hillslopes with a unit hydrograph parameterised
16 using $\bar{\Lambda}$, is a very simplistic way of describing runoff dynamics. However, it
17 serves the purpose of establishing a scenario of mean behaviour where input
18 (precipitation) balances the storage and output (runoff), and hence gives a
19 plausible estimate of m_S .

20 In Kirchner (2009) the storage-runoff relationship is assumed to be a single-valued function, i.e
21 S is a single valued function of Q . This leads to a very simple model with regards to the number
22 of states in the subsurface, namely one. The number of states in DDD, however, can be very
23 high. If we consider Eq. 16, the number of summations (time-steps) constituting S_{SS} can be
24 viewed as a number of subsurface states since each summation represents a volume water that

1 will sooner or later propagate into the river network. Eq. 16 describes the subsurface using only
2 one (mean) UH. In the DDD model, the number of storage levels is fixed to 5, and the UH's
3 constituting the storage levels all have the same shape (exponential) but have different temporal
4 scales. The temporal scale (level of discretisations) of the UH's vary according to their
5 associated celerity, and the slowest (lowest) storage level may be discretised such that hundreds
6 of time steps are necessary for the complete attenuation of the UH. Such a system actually
7 provides a 2-D representation of the subsurface (Rupp et al. 2009; Sloan, 2000) and gives
8 numerous subsurface states (Harman, 2015). It is hence entirely possible to have different
9 configurations of states associated with the same runoff. Figure 11 shows a snapshot of how
10 DDD models the storage S . The catchment is represented as one hillslope where the x-axis
11 shows the distance (in metres) from the river reach (at the right hand-side) to the top of the
12 hillslope (at the left hand side). The y-axis shows the different storage levels. We see the outline
13 of boxes (especially for the higher storage levels) which represents the temporal discretisation of
14 the UHs. Each box represents an area according to the distance distribution and the associated
15 celerity that will drain pr. time interval. The higher the celerity, the more of the catchment area is
16 represented by each box. The darker the blue colour, the more water is present in the box. Figure
17 11 can be seen together with Figure 1 A in appendix A, which illustrates how the distance
18 distribution (and the travel time distribution) determines the fractional areas that drain pr. time
19 interval for a given celerity (see also Harman (2015) for distribution of storage and water age). In
20 Figure 11 we can also note that it is more or less dry at the top of the hillslope and saturated near
21 the river. This is consistent with the wetting up of a catchment from the riparian zone outwards
22 and up the hillslope (Dunne and Black, 1970; Kirkby, p.275,1978; Myrabø, 1997).

23 Figure 12 shows simulated storage, S , plotted against simulated runoff, Q , for two catchments of
24 different size (49 km³ 1833 km³). It is quite clear that the relationship between Q and S is not
25 single valued. The variability of Q for the same S (and vice versa) is to be expected given the

1 multitude of possible configurations of the subsurface states (i.e. the discretisations of the UHs).
2 The shape of the clouds of points resembles those found for observations of groundwater vs
3 runoff (Rupp et al. 2009; Laudon et al. 2004 and Myrabø, 1997). The points in Figure 12,
4 however, do not level off to the same degree as does for groundwater observations. This can
5 probably be explained by the fact that storage in DDD is simulated for an entire catchment, and
6 it is more unlikely that an entire catchment will reach full saturation than individual groundwater
7 boreholes, located relatively close to the river (Myrabø, 1997; Laudon et al. 2004).

8 The parameters of the subsurface and the dynamical modules of the DDD model are all
9 estimated prior to calibration against streamflow and we see this as a necessary development if
10 we are to effectively test new algorithms for snow distribution, snowmelt, evapotranspiration etc.
11 at the scale that matters for most practical applications, the catchment scale (Clarke, 2011).

12 Multi-variable parameter estimation (Bergström et al., 2002) has been put forward as a means to
13 increase confidence in hydrological modelling and models. Although we agree that such
14 procedures indeed narrows the parameter-space (although not its number of dimensions), the
15 interaction and compensating nature of the calibration parameters makes it almost impossible to
16 reject flawed model structures so that we can concentrate on building models that work well for
17 the right reasons. In this paper, and in previous ones (Skaugen and Onof, 2014; Skaugen et al.
18 2015), information ready at hand such as GIS-derived distance distributions functions and runoff
19 records have proved useful for parameterising algorithms describing basic hydrological
20 processes.

21

22 **5 Conclusions**

23 In this paper a new formulation of the subsurface in the DDD model is presented. In the new
24 formulation, the storage capacity increases non-linearly with saturation, following a two-

1 parameter gamma distribution. The parameters of the gamma distribution are estimated directly
2 from observed runoff recession data and the mean annual runoff and not through model
3 calibration against runoff. The new storage formulation has been tested for 73 catchments in
4 Norway of varying size, mean elevation and landscape type, with little loss in precision. In
5 addition, more realistic runoff recessions are found using the new subsurface routine suggesting
6 a more realistic storage-runoff relationship.

7 A preliminary analysis shows that the parameters of the new storage routine can be estimated
8 from catchment characteristics, which is promising for continued advances in prediction in
9 ungauged basins.

10 The DDD model exhibits a spatially variable representation of the subsurface and allows for
11 different subsurface states associated with the same value of runoff. This constitutes a more
12 realistic representation of the subsurface and is more in line with more dedicated groundwater
13 models.

14 Future work includes implementing a more physically based energy balance approach for
15 snowmelt in DDD and testing the new model structure for predictions in ungauged basins in a
16 similar analysis to that of Skaugen et al. (2015).

17

18 **Data availability**

19 The precipitation, temperature and runoff data used in this study are available by contacting the
20 corresponding author.

21

22 **Appendix A**

23 **Distance distributions and linear reservoirs**

1 In Figure A1 the information of the distance distribution is visualised differently from Figure 2.
 2 In Figure A1, for the same two catchments as in Figure 2, the consecutive fractional areas for
 3 each distance interval Δd are plotted against the distance to the river network, and the ratio, κ
 4 between consecutive fractional areas is a constant and it has been showed (Skaugen, 2002) that
 5 the parameter γ of the exponential distribution relates to κ as

$$6 \quad \gamma = -\log(\kappa) / \Delta d. \quad (A1)$$

7 If we assume that a uniform moisture input (i.e. excess rainfall or snowmelt) is transported
 8 through the hillslope to the river network with a constant velocity, v , (or celerity, see Skaugen
 9 and Onof, 2014, Beven, 2006), then Δd is the distance travelled by water during a suitable time
 10 step, Δt , i.e., $\Delta d = v\Delta t$. When d Eq. 2 is replaced with d/v , the distance distribution hence
 11 becomes a travel-time distribution with mean equal to $\frac{\bar{d}}{v}$ and parameter

$$12 \quad \xi = -\log(\kappa) / \Delta t, \quad (A2)$$

13 which constitutes a unit hydrograph (Maidment, 1993, Bras, 1990, p.448). The variable κ , is
 14 now the ratio between volumes of water drained pr. time step, i.e. the volume of water drained
 15 into the river network is reduced by κ for each time step.

16 A linear reservoir has this same property of consecutive runoff values having a constant ratio.
 17 This can be seen if we compute successive volumes and runoff values according to a linear
 18 reservoir in recession with rate constant ϑ , i.e. $Q(t) = \vartheta S(t)$. The ratio between consecutive
 19 values of runoff,

$$20 \quad \kappa = Q(t + \Delta t) / Q(t) \quad (A2)$$

1 remains constant and equal to $1 - \vartheta\Delta t$. Hence, a catchment with an exponential distance
2 distribution and a constant celerity is equivalent to a linear reservoir with a rate constant equal to
3 $(1 - \kappa)/\Delta t$, i.e.

$$4 \quad Q(t) = \frac{(1-\kappa)}{\Delta t} S(t). \quad (\text{A3})$$

5 Furthermore, from eqs. A2 and A3 we see that the rate constant of a linear reservoir relates to the
6 parameter of the travel time distribution as:

$$7 \quad \vartheta = \frac{1 - e^{-\xi\Delta t}}{\Delta t}. \quad (\text{A4})$$

8 Since the mean of the travel-time distribution is $\frac{1}{\xi} = \frac{\bar{d}}{v}$, the rate constant relates to the mean of the
9 distance distribution as:

$$10 \quad \vartheta = \frac{1 - e^{-(v/\bar{d})\Delta t}}{\Delta t}, \quad (\text{A5})$$

11 and the celerity can hence be formulated as:

$$12 \quad v = \frac{-\log(1 - \vartheta\Delta t)\bar{d}}{\Delta t} = \frac{-\log(\kappa)\bar{d}}{\Delta t}. \quad (\text{A6})$$

13 This brief discussion on the distance distribution and linear reservoirs shows that if a catchment
14 exhibits an exponential distance distribution, linear reservoirs comes as a natural choice for
15 modelling the interaction between hillslopes and the river network. Furthermore, the distance
16 distribution suggests a geometrical configuration of the hillslope (or aquifer) (Figure A1) and the
17 linear reservoir model is partly parameterised from the parameter of the distance distribution
18 (Eq. A5). These latter statements assumes, of course, that the topographical catchment area and
19 that of the aquifer are equal, an assumption that does not always hold (Bidwell et al. 2008).

20

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Slettet: .

Formatert: Skrift: Kursiv

Slettet: Discuss.

Formatert: Skrift: Fet

Slettet: 2016-

Slettet: 43

Slettet: in review,

Feltkode endret

1 **Table1.** Parameters of the DDD model with description and method of estimation. Some
 2 parameters have fixed values obtained through experience in calibrating DDD for gauged
 3 catchments in Norway. These values are within the recommended range for the HBV model
 4 (Sælthun,1996). The GIS analyses are carried out using the national 25 X 25 m DEM (www.
 5 statkart.no).

Parameter	Description	Method of estimation
Hypsographic curve	11 values describing the quantiles 0,10,20,30,40,50,60,70,80,90,100	GIS
θ_{Ws} [%]	Max liquid water content in snow	Calibrated
Hfelt	Mean elevation of catchment	GIS
θ_{Tlr} [°C/100 m]	Temperature lapse rate for (pr 100 m)	Calibrated
θ_{Plr} [mm/100 m]	Precipitation gradient (mm per 100 m)	Calibrated
θ_{pc}	Correction factor for precipitation	Calibrated
θ_{sc}	Correction factor for precipitation as snow	Calibrated
θ_{Tx} [°C]	Threshold temperature rain /snow	Calibrated
θ_{Ts} [°C]	Threshold temperature melting / freezing	Calibrated
θ_{cx} [mm/°C/day]	Degree-day factor for melting snow	Calibrated
C_{Glac} [mm/°C/day]	Degree-day factor for melting glacier Ice	$1.5 \times \theta_{cx}$
CFR [mm/°C/day]	Degree-day factor for freezing	Fixed value: 0.02, Sælthun (1996)
Area[m ²]	Catchment area	GIS
maxLbog[m]	Max of distance distribution for bogs	GIS
midLbog[m]	Mean of distance distribution for bogs	GIS
Bogfrac	Fraction of bogs in catchment	GIS
Zsoil	Areal fraction of zero distance to the river network for soils	GIS
Zbog	Areal fraction of zero distance to the river network for bogs	GIS
<i>NOL</i>	Number of storage levels	Fixed value: 5, Skaugen and Onof (2014)
θ_{cea} [mm/°C/day]	Degree day factor for evapotranspiration	Calibrated

R	Ratio defining field capacity	Fixed value: 0.3, Skaugen and Onof (2014)
α	Shape parameter of gamma distributed celerities	Estimated from recession
β	Scale parameter of gamma distributed celerities	Estimated from recession
θ_{cv}	Coefficient of variation for spatial distribution of snow	Calibrated
θ_{vr} [m/s]	Mean celerity in river.	Calibrated
m_{Rd} [m]	Mean of distance distribution of the river network	GIS
s_{Rd} [m]	Standard deviation of distance distribution of the river network	GIS
Rd_{max} [m]	Max of distance distribution in river network	GIS
θ_M / m_S [mm]	Max subsurface water reservoir/ Mean of subsurface water reservoir	Calibrated/ Estimated from recession
\bar{d} [m]	Mean of distance distribution for hillslope	GIS
d_{max} [m]	Max of distance distribution for hillslope	GIS
Glacfrac	Fraction of bogs in catchment	GIS
m_{GI} [m]	Mean of distance distribution for glaciers	GIS
s_{GI} [m]	Standard deviation of distance distribution for glaciers	GIS
Areal fraction of glaciers in elevation zones	10 values	GIS

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1 **Table 2** .Mean values of skill scores obtained with simulating with DDD_ m_S and DDD_ θ_M for
2 73 catchments. KGE_r measures correlation, KGE_b, the bias error and KGE_g the variability
3 error. All skill scores have an ideal value of 1.

	NSE	KGE	KGE_r	KGE_b	KGE_g
DDD_ m_S	0.73	0.80	0.87	0.92	0.94
DDD_ θ_M	0.75	0.81	0.88	0.91	0.97

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1 **Table 3.** Root mean square error (RMSE) values for the mean and standard deviation of
 2 simulated $\hat{\Lambda}$ for the 73 catchments

	RMSE mean Λ	RMSE std Λ
DDD_ m_S	0.04	0.045
DDD_ θ_M	0.07	0.049

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 5 **Table 4.** Significant spearman correlation (p-value < 0.01) between catchment characteristics
 6 and the shape, α , and scale, β , parameters of the distribution of Λ . The correlations are based on
 7 estimated model parameters for 83 Norwegian catchments.

Correlation	Mean of distance distribution, \bar{d}	Lake percentage, L%	Catchment gradient
α	-	0.33	-
β	-0.36	-0.44	0.31

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2 **Figure 1.** Schematic of the subsurface water reservoir M of DDD. $G(t)$ represents moisture
3 input, rain and snowmelt. The dotted horizontal line is the actual level Z , of soil moisture in D .
4 The ratio $(G(t) + Z(t))/D(t)$ controls the release of excess water to S and hence to runoff.
5 Note that D , S and Z are functions of time, whereas M is fixed.

6 **Figure 2.** Empirical and fitted (exponential, red line) CDFs of distances from a point in the
7 catchment to the nearest river reach for two Norwegian catchments, Møska (top) and Narsjø
8 (bottom). The catchments are located south and north-east, respectively, in Southern Norway.
9 The mean distance (denoted d_{mean} in the figure) and catchment size differ, but the shape of
10 the distribution is similar.

11 **Figure 3.** Empirical and fitted (gamma, blue line) CDFs of Λ for 6 Norwegian catchments. Λ is
12 sampled using Eq. 3 for all observed recession events.

13 **Figure 4.** Histograms (in black, green, and red) of groundwater levels at three different locations
14 in the Groset catchment (6.33 km²) located in southern Norway.

15 **Figure 5.** Location of the 73 catchments used to evaluate the new storage routine

16 **Figure 6.** Histograms of catchment characteristics for the 73 catchments. a) mean of the hillslope
17 distance distribution, \bar{d} , b) areal percentage of lakes, c) areal percentage of bogs, d) catchment
18 area, e) mean elevation, f) areal percentage of glaciers, g) areal percentage of forests and h) areal
19 percentage of bare rock.

20 **Figure 7.** Skill scores for DDD_{m_S} (blue circles) and DDD_{θ_M} (red crosses) for 73 Norwegian
21 catchments. Mean skill score values are shown in horizontal lines (same color code). a) NSE, b)
22 KGE, c) KGE_r (correlation), d) KGE_b (bias) and e) KGE_g (variability error).

1 **Figure 8.** Scatterplot of mean a) and standard deviation b) of observed Λ and simulated with
2 DDD_ m_S (blue circles) and DDD_ θ_M (red crosses) $\hat{\Lambda}$ for 73 catchments.

3 **Figure 9.** Histograms of storage simulations with DDD_ θ_M a) and DDD_ m_S b). Empirical CDFs
4 of observed Λ (black line) and simulated $\hat{\Lambda}$ with DDD_ θ_M (red line) and DDD_ m_S (blue line)
5 are shown in c).

6 **Figure 10.** Empirical CDFs of Λ (circles) and scaled $S(t)$ (blue line) for two Norwegian
7 catchments .

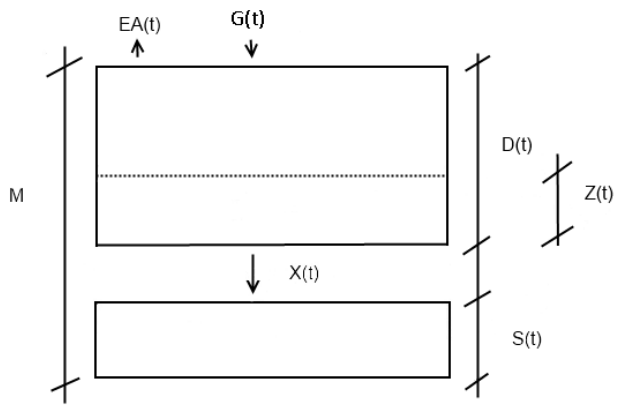
8 **Figure 11.** Snapshot of the saturated zone S of the DDD model. The catchment is represented as
9 one hillslope. The x-axis shows the distance from the river (right hand-side) to the top of the
10 hillslope (left hand-side). The y-axis show the storage levels. The darker the blue colour, the
11 more water is present in the storage level.

12 **Figure 12.** Simulated storage S plotted against simulated runoff Q for a catchment of 49 km² (a)
13 and a catchment of 1833 km² (b).

14 **Figure A1.** Fractional catchment area as a function of distance from the river network for the
15 same two catchments as in Figure 2. The ratio κ , between consecutive areas is shown as "Ratio".

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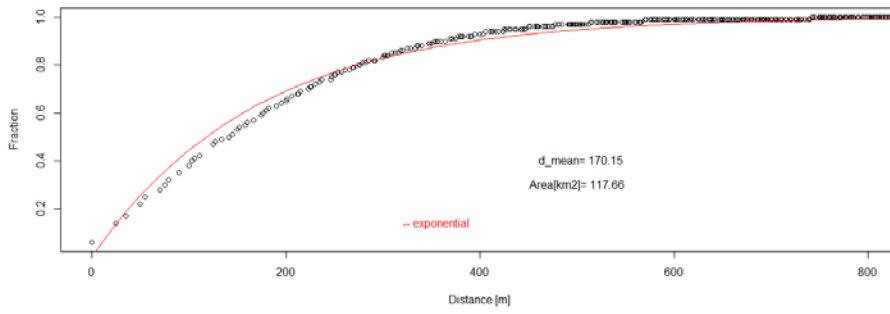
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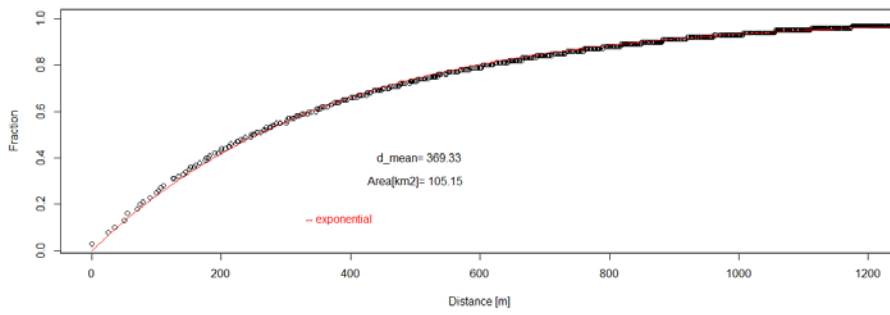
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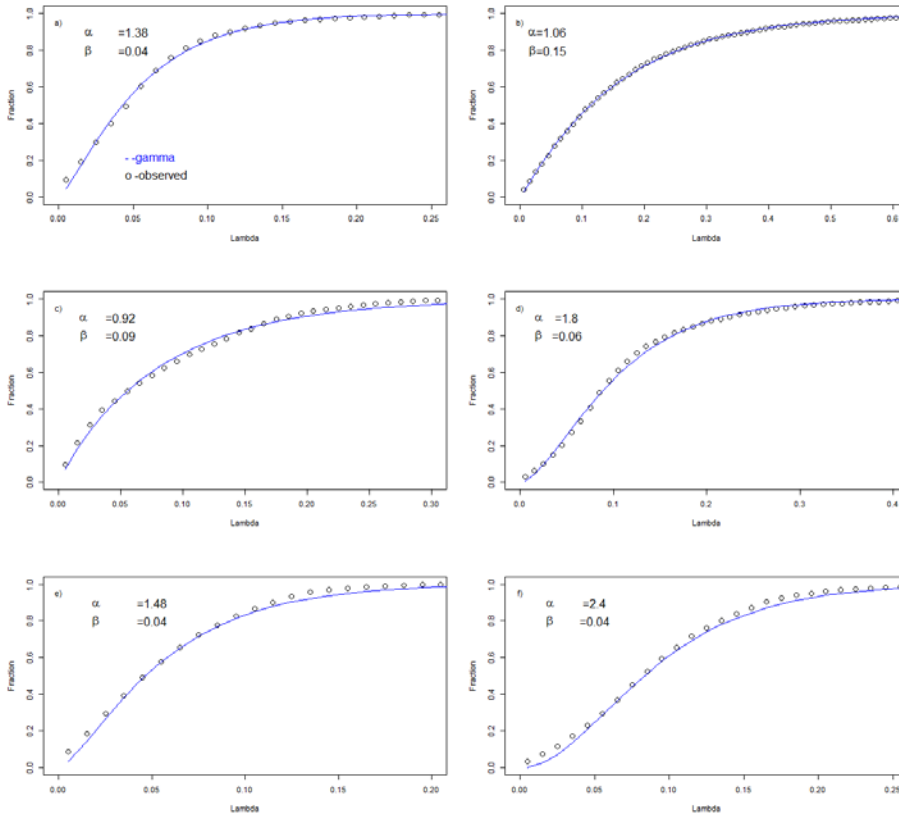


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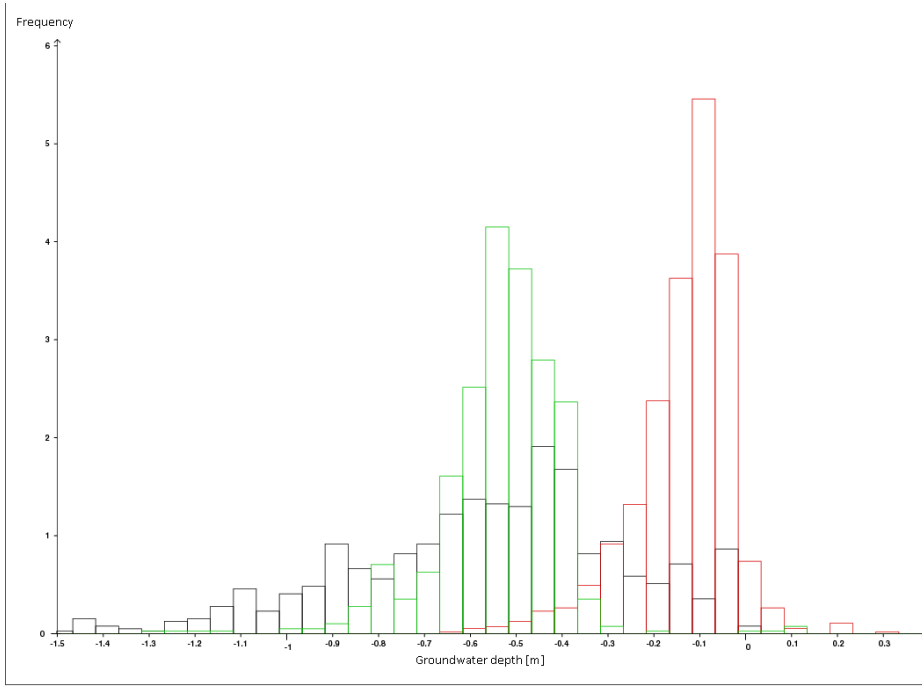
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1 Fig4



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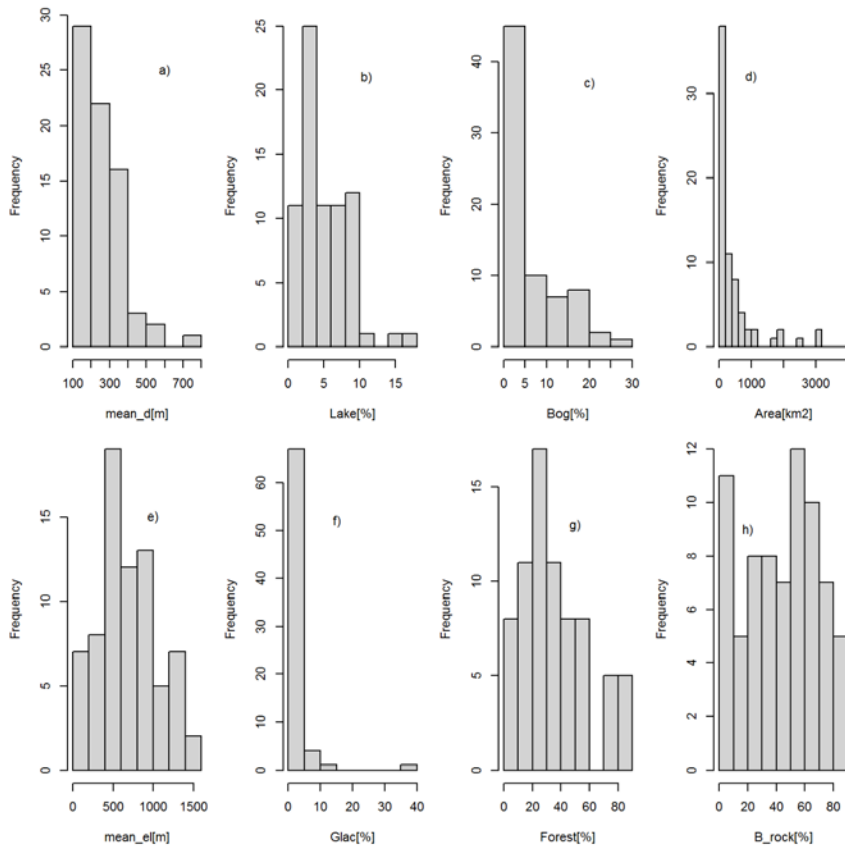
1 Fig 5



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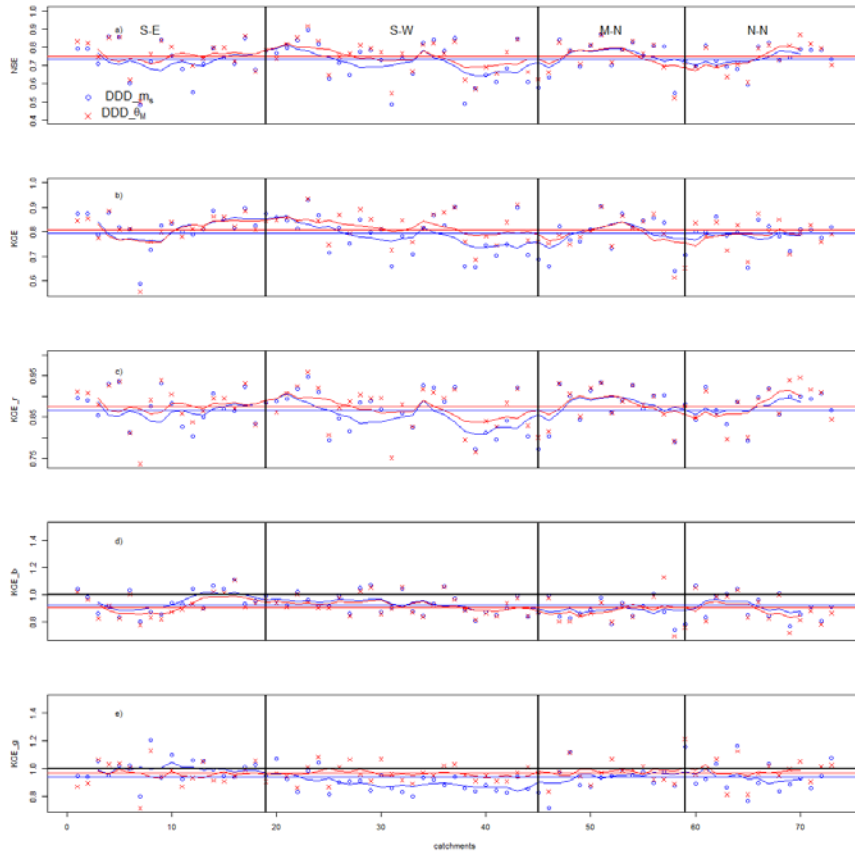
1 Fig 6



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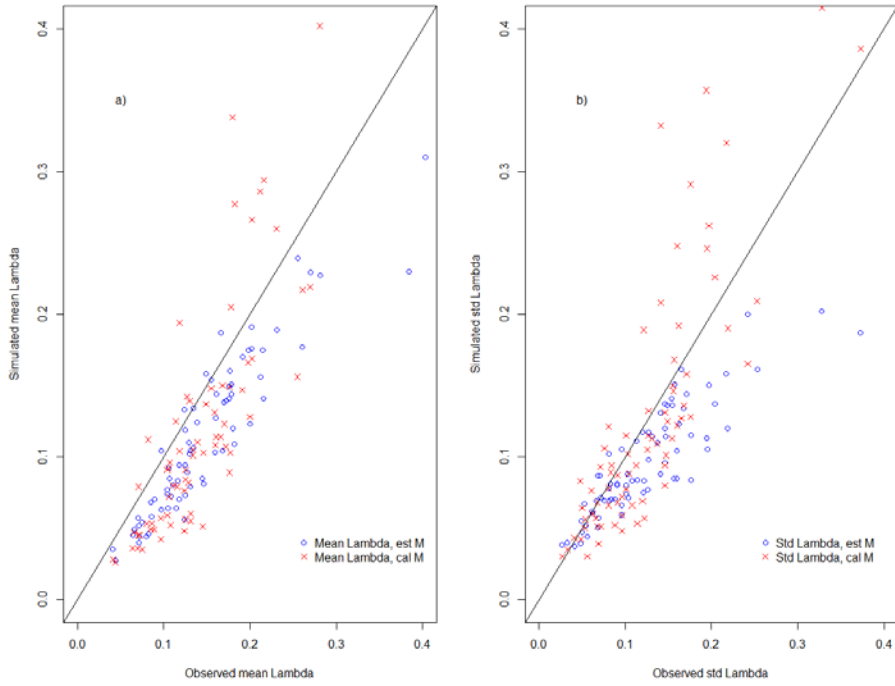
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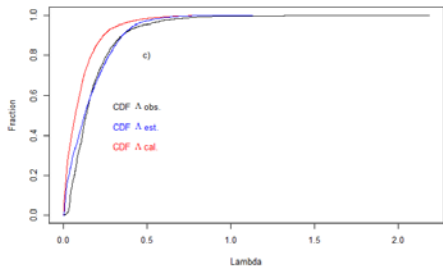
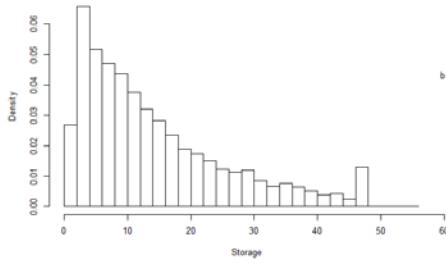
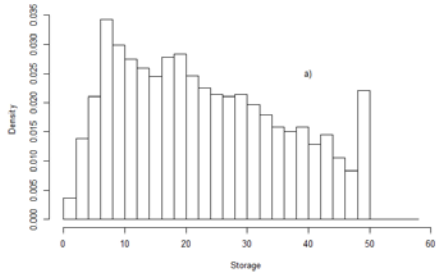
1 Fig 8



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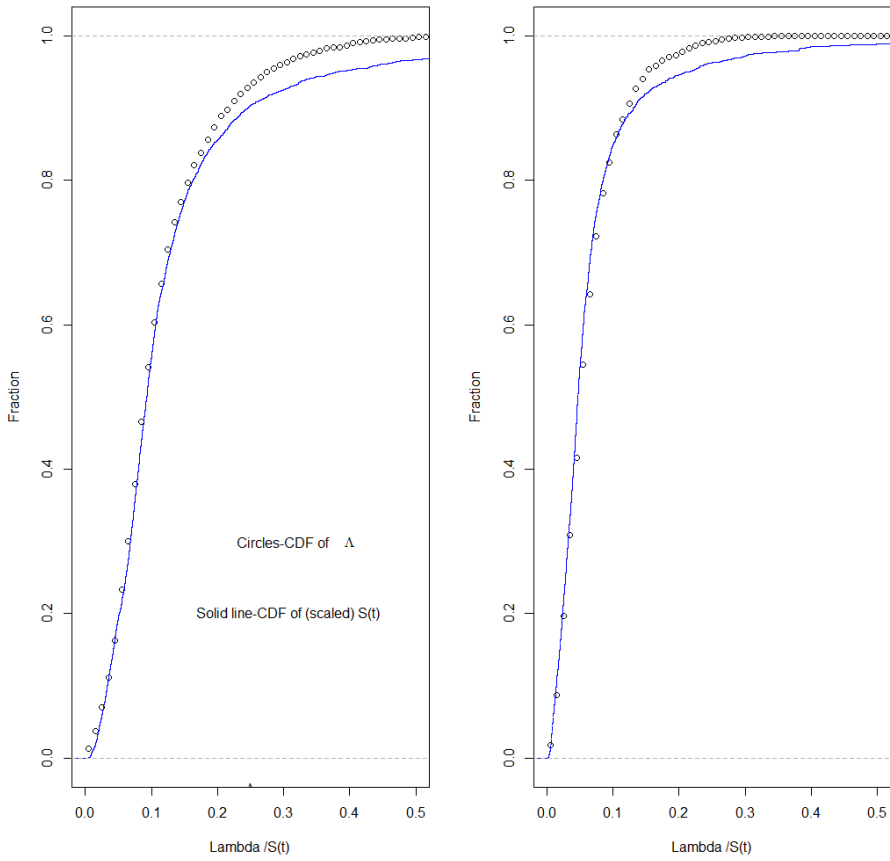
1 Fig 9



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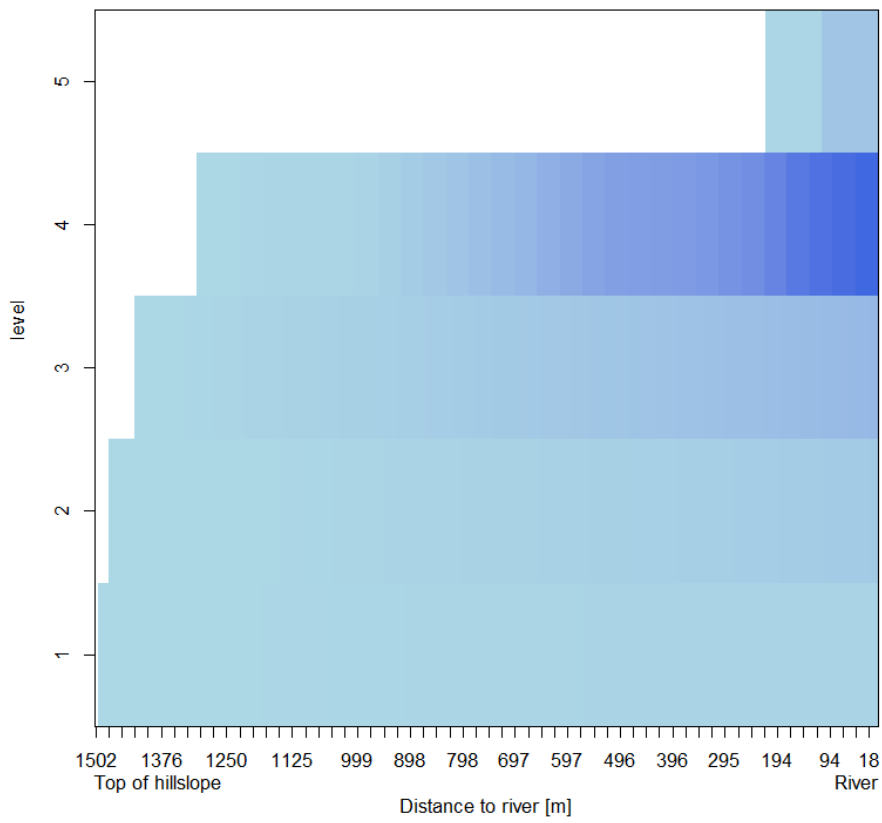
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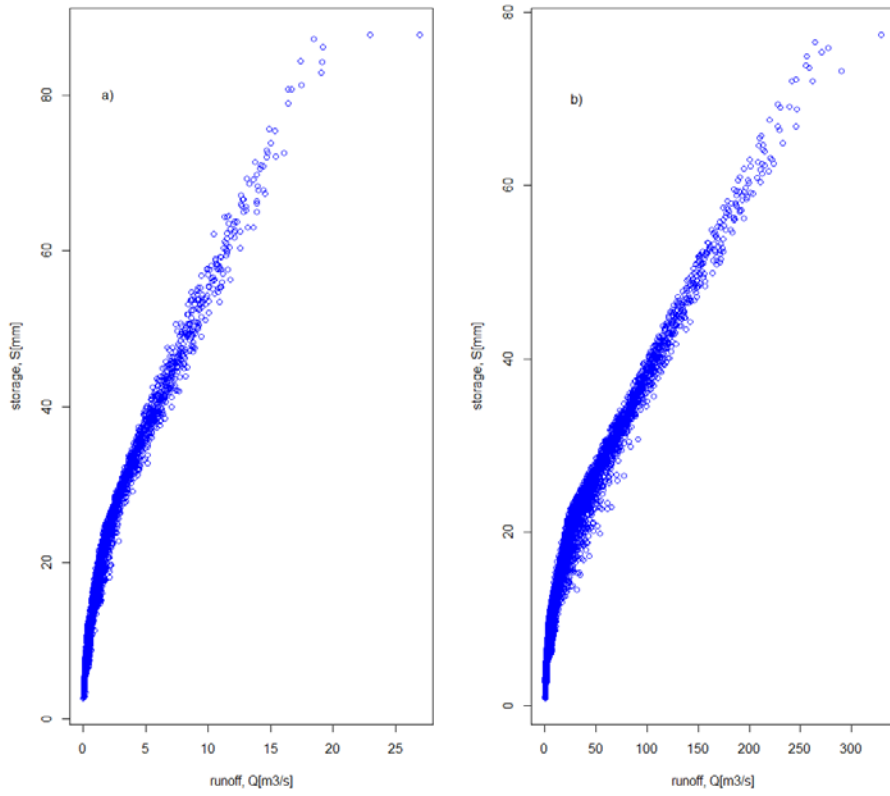
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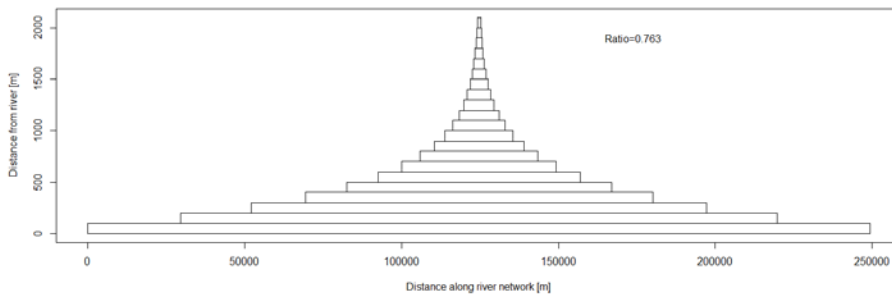
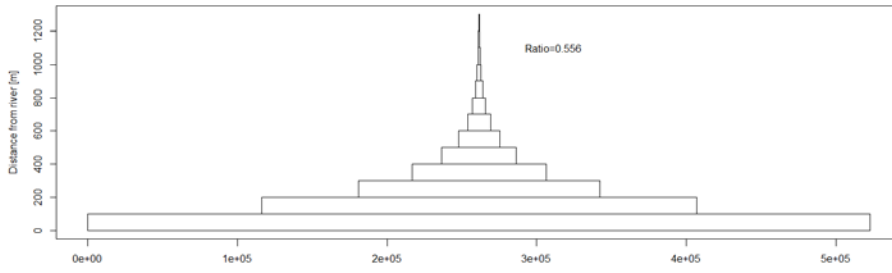
1 Fig 12



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1 Fig A1



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