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

First of all, we would like to thank the referees and the editor for taking their time to read closely and comment thoughtfully on our paper. Time for such tasks is hard to find so it is very appreciated. In the marked manuscript "Slettet" means deleted and "Flyttet" means moved. Unfortunately the MS Word is in Norwegian, sorry for that.

Response to Editor

1)Properly evaluate and discuss the issues of using streamflow signatures (in this case MRC) as a form of calibration that they can be considered (there are ways this could be assessed as to the strength of this information in comparison to the overall calibration scheme). I suggest further in depth analyses is needed here that needs to be compelling

Response: In the revised and, we believe, more focused introduction we have devoted a paragraph to recession analysis and how the literature have treated it as a catchment signature (see p. 3, l.14-p.4, l.3 in marked MS). This point is revisited in the discussion where we discuss the literature's different ways of sampling recession events and how they compare to our method of sampling (see p. 17, l.15-p.18, l.2 in marked MS). In the discussion we also point out that the recession characteristics are indeed catchment specific in that we find significant correlations between the parameters of the distribution of Λ and catchment characteristics (the new Table 4).

2) Tone down any comments of this being 'calibration free' unless they can bring in the work of their colleagues where these parameters have been attributed to catchment characteristics and show therefore this as the main comparison made. I would strongly suggest the paper is more unique and novel if this could be related to some form of true 'un-gauged' analyses.

Response: To address this issue we have made it clear in the introduction what we mean by calibration and estimation (see p.4, l.4-25 in marked MS) and the phrase "calibration–free" is removed. Here we also point out, supported by the literature, the advantages of estimating model parameters apriori model calibration against streamflow. In addition, we have elaborated upon the potential for prediction in ungauged basins using the new models structure (see p.p.15,l.16- p.16, l.18 in marked MS). The new Table 4 shows significant correlations between the parameters of the distribution of Λ and catchment characteristics and we can show significant coefficients of determination for the multiple regression equations from which we can estimate these parameters.

3) I would add that there is a need to better articulate in the paper what parts of the recessions they have extracted to fit the parameters 'pre-calibration' as it wasn't clear to me how these series had been quantified. I would also be interested in knowing as part of this how consistent these recessions are from the overall set used and how much variability there is in this characteristic for a few example catchments.

Response: We have made it more clear how these series are extracted in the subsection 2.2 (see p. 8, l. 1-6 in marked MS) and we have included the estimated parameters values in the Figure 3 (used to be Figure 4). This point is also revisited in the discussion section where the correlations between the parameters of the distribution of Λ is shown and discussed (see p.15. l.16-p. 18, l.2 in marked MS).

Response to Referee #1

General comments

R#1: Replacing some of the calibration by recession analysis effectively breaks the parameter estimation into two steps, but it does not reduce reliance on extracting information from the hydrograph.

Response: There is indeed a reliance on extracting information from the hydrograph. However, in the introduction we point out, with support from the literature, the benefit of estimating model parameters directly from observations and not through model calibration against runoff (see p.4, l.4-25 in marked MS). In addition, we show that the model parameters estimated from observations are significantly correlated to catchment characteristics and are hence possible to estimate for ungauged catchments (see p.15, l.16- p.16, l.18 in marked MS).

R#1:The authors have a particular way of deriving their model structure, including the way subsurface flows are drawn from different levels in the soil (e.g. Fig 12), with a particular distribution in the vertical. However this remains a hypothesis which is not directly tested. If there is evidence to support the authors' hypothesis, that would be of more interest, e.g. spatially-distributed monitoring of lateral water flow through different soil horizons, water tracer data implying the that contributions to river flow come from particular levels in the soil column.

Response: It is correct that the hypothesis is not tested directly. On the other hand we have indirectly justified the distribution of S in the vertical, see Figure 10 in revised MS and the accompanying discussion (p. 16, l.19- p.18, l.2). In Figure 10 we have estimated S for recession events (Eq. 18 in revised MS) and plotted its distribution. The similarity in shape to the distribution of Λ is clear.

The basis for the model structure is, apart from the distance distributions, the *observed* distribution of Λ, the recession characteristic, from which we derive the celerities of flow. Λ is typically small for low flows (flat recession) and high for high flows (steep recession), so it is natural (and we do not think very controversial) to relate it to low and high storage, S. We have chosen to discretize the distribution of Λ (and hence the celerities) which gives the levels of the subsurface, S. These levels could be discretized much finer at the expense of computing time and little gain in precision (see Skaugen and Onof, 2014).

Catchments in which the subsurface fluctuations are investigated to such a detail as suggested by R#1 are very hard to find, especially for normally sized catchments (10-1000 km2). There is an example from Norway where a tiny catchment of 0.0075 km^2 was instrumented with over 100 manually read (intermittently) groundwater tubes for a short period of time, 1986-1989. We have mentioned this experiment in the revised MS (p.16. l. 20-23 in the marked MS). The data (Myrabø, 1997) is, at present, not available but we hope to retrieve it later and use it for the purpose suggested by R#1.

Specific comments

1. P11134 L1 "and an unsaturated zone with volume D (mm), called the soil water zone. The actual water volume present in the unsaturated zone, D, is called Z (mm)." It is hard to understand the difference between D and Z from this text. I think it would be clearer to start this phrase "and an unsaturated zone with capacity D (mm) …"

   Response: A good reformulation. It is changed see p.6, l.2 in marked MS.

2. P11134 L20 “Experience using the DDD model shows that the subsurface water reservoir M largely controls the variability of the hydrograph.” I think it clearer to say “the subsurface water capacity parameter M”

   Response: Again a good reformulation. It is changed, se p.6, l.21 in marked MS.

3. P11134 L21 “Low values of M increase the amplitude of the hydrograph, since the entire range of celerities is engaged, and vice versa.” This sentence is impossible to interpret without a description of the role that celerities play in the model.

   Response: We agree that this comment is perhaps difficult to understand at this point in the paper. We have reformulated the paragraph so that the mentioning of celerities does no longer come as a surprise, see p.6, l.19-20 in marked MS.

4. P11136 L6 “according to a linear reservoir in recession with runoff coefficient ϑ” It seems confusing to call this a runoff coefficient. That term is generally reserved for a ratio of runoff to precipitation. This parameter seems more like a rate constant, since it presumably has units of 1/time.

   Response: Agreed, it is changed to “rate constant”, see Appendix A, p.22 l.3 in marked MS.

5. P11136 L7 “The ratio between consecutive values of runoff, Q(t + 1)/Q(t)” Do the authors mean Q(t + Δt) rather than Q(t + 1)?

   Response: Yes, it is changed. See Eq A2 (p.22, l.5) in marked MS.

6. P11136 L14 Equation 6 indicates that ϑ is dimensionless, but since Q is presumably a flux (mm/day) and S is a storage (mm), the linear reservoir equation Q(t) = ϑ S(t) indicates that ϑ has units of 1/day. This inconsistency needs to be resolved, as ϑ is closely linked to Λ and κ, which are pure ratios.

   Response: Thank you for this. Somehow, a “Δt” was lost during the derivation. The correct relation between κ and ϑ is $\vartheta = \frac{1-\kappa}{\Delta t}$. This is corrected in eqs. A3-6 (p.22), and Eq.18 (p.17) in the marked MS but is of no consequences for the other equations.

7. P11136 L20 “This brief discussion on the distance distribution and linear reservoirs is relevant because it suggest that if a catchment exhibits an exponential distance distribution the linear reservoir comes as a natural choice for modelling the interaction between hillslopes and the river network.” This is true only if hillslope celerity is effectively constant. A rather strong assumption given the nonlinearity of some soil water processes! If I understand correctly, the DDD model has a celerity which varies with water storage, i.e. the effective celerity is not constant. Thus I am unclear why the discussion on linear reservoirs is seen as especially relevant.

   Response: This part of the paper is moved to Appendix A (p.21-23 in marked MS) in order to enhance readability
   The celerity is indeed not constant, but varies with storage. The runoff dynamics in DDD is taken care of by basically 4 different celerities, 5 when you include overland flow. Each of these celerites (which are determined from observed recession) are associated with a unit hydrograph. The shape of the unit hydrographs are identical, due to the common distance distribution, but the scale of the UH varies due to the associated celerity. The actual storage determines which UH are active (for example, if it is relatively dry, then no water is routed using the UH for overland flow). The actual runoff is the superposition of active UH’s. The UH’s are “triggered” for each moisture input event, so after the model has been running for a while, quite a few UH’s are at

work to convey water to the river network. So, being able to relate analytically the observed distance distribution to UH's and hence to linear reservoirs is a very important result of this study, and we believe this is a first time such a link is demonstrated.

8. P11137 L15 "The parameter Λ is thus the slope per Δt of the recession in the log-log space". This is not correct. If one plots $\log(Q(t+\Delta t))$ against $\log(Q(t))$ (the only log-log space I can see in the paper), the slope of the line is unity, and the offset is Λ. Isn't Λ the recession slope when log flow is plotted against (linear) time?

   Response: Yes, you are correct. The sentence is reformulated, see p.8, l.3-4 in marked MS.

9. P11143 L8 "We will test the performance of the new calibration-free formulation for the subsurface." It seems overstated to call the new approach calibration-free, because calibration-free is often interpreted to mean that no flow record is required to estimate the parameter. Parameter estimation by recession analysis still requires measured streamflow. The new approach differs in that parameter estimation does not use traditional hydrograph-matching using a time-stepping model, but instead uses recession analysis.

   Response: We have removed the words calibration-free and made it clear in the introduction what we mean by "calibration" and "estimation" (see p.4, l.4-25 in marked MS).

10. P11146 L16 "as we have no way of actually knowing the true empirical distribution of storage at the catchment scale" It would be entirely possible to install a spatially distributed monitoring network which measured the changes in unsaturated and saturated storage at multiple locations. If a stratified sampling approach was taken when selecting sites, then this could be used to estimate catchment-scale storage. This may not be practical for the authors' specific situation, but it is possible, and has been done in other situations.

    Response: This comment is similar to the second general comment. You are, of course, correct, and as soon as such data is at hand (see response to the second general comment) we will investigate how the data compares with the concepts in DDD. For normally sized catchments, (10-1000 km2), however, such a sampling approach is extremely challenging and would still involve some non-trivial upscaling (interpolation) of point values.

11. P11147L7 "The estimation of θM is, however, no longer needed." But surely the calibration has merely been replaced by recession analysis to determine the parameter?

    Response: This discussion is related to estimating model parameters from catchment characteristics. We have replaced the sentence with "The estimation of θM through multiple regression with catchment characteristics, however, is no longer needed." (see p.16, l.1-2 in marked MS)

12. P11148 L21 "Figure 13 shows simulated storage S, plottet against observed runoff Q, for two catchments of different size (50 and 1833 km2). It is quite clear that the relationship between Q and S is not single valued." Some of the reason for the scatter could just be that the model is not well correlated with the observations? Why not plot simulated storage against simulated runoff?

    Response: A good point, and we have done so. The new plot, new Figure 12, also demonstrates this point.

13. P11150 L9 "An important contribution of the new formulation is that its parameters are estimated solely from observed recession data and the mean annual runoff (i.e. not through

calibration).” To me, it is still calibration (albeit multi-stage calibration), if it is necessary to use measured flow to estimate parameter values. If instead the parameters could be reliably estimated from catchment and climate characteristics, that would be of great interest.

Response: This comment is similar to the first general comment and to comment 9, see response to those. We have elaborated further on the PUB potential of the new structure of the DDD model (see p.15, l.16- p.16, l.18 in the marked MS). The new model structure of DDD has effectively one parameter less (θM) to estimate from catchment characteristics for application to PUB. We have also shown that the parameters of the distribution of Λ are significantly correlated to catchment characteristics and can be estimated from those.

Response to Referee #2

General comments

1.They show that the performances of both models are comparable but that the new version of the model produces more realistic recessions. With these results the authors conclude that their new approach is another step towards simulation of ungauged basins.

Response: The point of this study was to see if we could estimate the parameters of the subsurface routine from observations apriori to model calibration against runoff (and precipitation and temperature) and still obtain reasonable hydrological simulations (see response to first general comment of R#1 and revised introduction). The fact that a reduction in free calibrations parameters will enhance the model’s ability to predict in ungauged basins (see Seibert, 1999; Skaugen et al. 2015) is a pleasant consequence. We have elaborated further on the PUB potential of the model (see p.15, l.16- p.16, l.18 in the marked MS).

2. First of all, I found the manuscript very hard to read. The theory is too long and the structure of the manuscript is structure confusing. This is particularly true for the explanation of the theory: I definetly recommend reordering the sections (2.1 Hydrological model, 2.2 Runoff dynamics, 2.3 Reformulation, 2.3.1 Estimating the mean storage, 2.4 Example..) The old calibrated model should be explained in much less detail supported by more detail in the appendix. The Reformulation should be structured in a better way and if there is no 2.3.2 there is no purpose in having a subsection 2.3.1, etc. Generally, discard all information that is not completely necessary.

Response: We agree that the theory part (section 2) is long. We have restructured the paper as follows:
-The introduction is more focused where we put our approach in the framework of linear reservoirs, recession analysis and the difference between estimating parameters directly from observed data and through model calibration against runoff.
The entire section 2 is restructured:
-We have moved the part where we relate the distance distribution to the linear reservoirs to Appendix A..
-In the original subsection 2.3, the part where we justify the similarity in shape of the distributions of Λ and S, is moved to the discussion.
-In the original subsection 2.4, the discussion around large sample hydrology is deleted in order to keep the paper focused.
- We only use one meteorological grid in order to make the paper more easy to read.
- We have revised Table 1 by deleting two columns, but keeping the relevant information.

3. Also, more focus should be put on the example where application, parameter estimation, evaluation and data should be explained in a structured way (more subsections). A lot of theory is also presented at the beginning of 2.4 (1st and 2nd paragraph), which should rather be moved to the discussion as the studies methods and the methods of other studies are quite mixed up now.

Response: Yes, see response above (for comment #2)

4. As new calibration is performed for DDD_M a strict evaluation of the observation derived parameters of the subsurface routine is difficult. I recommend rather remaining with all calibrated parameters of the old surface routine with the old meteorological grid V1, which would allow estimating the skills of the new parameter estimation scheme without any calibration. Also this would make the approach simpler and the paper easier to read.

Response: We have revised as suggested, see above.

5. Finally, as the new parameter estimation scheme still requires discharge data I also do not see the real advantage in terms of simulating ungauged catchments. I agree with referee #1 that there is the need to apply the new approach for simulating catchments without discharge data as mentioned in the discussion. Most desirably at least first try should be part of the study indicating the advantages of this new approach.

Response: This comment is similar to the first general comment and to comment 13 of R#1, please see response to those and in the discussion in the revised MS (p.15, l.16- p.16, l.18 in the marked MS). The correlation analysis between parameters and catchment characteristics and the multiple regression serves as a “first try”.

Specific comment

1.p11131, L25.. mention importance of reliable estimation of storage –discharge relations as pointed out by Berghuijs et al.2016)

Response: We are not certain this is a correct place to have this reference, since we discuss linear reservoirs. It fits very well, however, at P3, l.15 in marked MS.

2.p11138-L10: mention height of each storage level

Response: Yes. We have mentioned storage levels of equal capacity at p.8, l.15 in marked MS

3. p11130-L9. mention variability of aquifer porosity

Response: Yes, a good point, see p.9-l.22 in marked MS

4.11144-L16 it is enough just to mention which data was used

Response: This part is rewritten (see response to general comment #2, and new section 2.4 in MS)

5. 11144-L24 Can these parameters be assumed to be constant?, see studies Merz et al. 2011 and Berghuijs et al, 2014.

Response: Only partly, temperature threshold for snow melt should be 0 °C, but the others account for data and model structure errors. This part is anyway be deleted in the revised paper.

6. 11147-L15 This should be part of the study (PUB excersise)

Response: See response to general comment #1 and #5 and p.15, l.16- p.16, l.18 in the marked MS.

7.11148-L3: this makes sense even more in regions with heterogeneous subsurface, see studies (Refsgaard et al (2012) and Hartmann et al. 2015)

Response: Thank you for the references. Refsgaard et al. (2012) is referenced at p.9-l.22 in marked MS

8. 11148-L15 refer to TTD papers that make a similar point (Harman C.J 2014 and Kirchner, 2016.)

Response: Thank you for the references. Harman (2015) is referenced at p.18, l.15 and at p.19,l.2. in marked MS.

9. Figure 4 Increase font size

Response: Yes. It has become the new Figure 3 with increased font size, inserted parameter values and letters marking the different panels.

10. Have lambda symbol in Figure 6.

Response: It has become the new Figure 10 with inserted lambda symbol.

Estimating catchment scale groundwater dynamics from recession analysis – enhanced constraining of hydrological models.

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Abstract

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

Slettet: and

Slettet: . Key principles guiding the evaluation of the

Slettet: subsurface

Slettet: have been a) to minimize the number of parameters to be estimated through the, often arbitrary fitting to optimize runoff predictions (calibration) and b) maximize the range of testing conditions (i.e. large-sample hydrology). The new storage routine has been

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

Slettet: recessions

1 Introduction

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

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The linear reservoir, often visualised as a straight-sided bucket with a hole in the bottom (Beven, 2001; Dingman, 2002), has an exponentially declining outflow and is the basis for the exponential unit hydrograph (UH). It has served as the most commonly used storage-runoff relationship and plays a fundamental role in conceptual rainfall runoff models. A single linear reservoir is, however, too simple for describing the variability and non-linearity of hydrological response. Some groundwater models conceptualise the stream- aquifer interactions as the drainage of an infinite number of independent linear reservoirs (Sloan, 2000; Pulido-Velasquez et al., 2005; Bidwell et al. 2008; Rupp et al., 2009). This comes as a result of solving the

Slettet: ; Beven, 2001

Slettet: served as the most commonly used basic storage-runoff relationship. Such a reservoir has

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Slettet: Therefore, most conceptual models use a system of several, possibly modified, linear reservoirs to describe the soil moisture accounting and runoff dynamics. The system may vary in complexity (and hence in the inclusion of calibration parameters), but the linear reservoir remains the basic building block of conceptual models. Examples of such models are the UH models of Nash (1957) and Dooge (1959) and the explicit soil-moisture accounting (ESMA) models, of which the work-horse of operational Nordic hydrology, the HBV model (Bergström, 1992) serves as an example (see Beven (2001) for a discussion on the evolution of rainfall-runoff models). In addition to the fundamental role the linear reservoir has played in simple conceptual rainfall- runoff models, some

Slettet: Rupp et al., 2009; Bidwell et al. 2008;

Slettet: Sloan, 2000

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

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

Slettet: Despite the popularity of linear reservoirs, the non-linear relationship between storage, S and runoff Q has long been recognised and simple solutions for manipulating a single reservoir for taking into account non-linearity have been put forward. In Lindström et al.,

Flyttet ned [1]: arranged in parallel, a principle which resembles the stream- aquifer interaction model described by for example Bidwell et al. (2008).

Slettet: . The recently published rainfall-runoff model DDD (Distance Distribution Dynamics, Skaugen and Onof, 2014; Skaugen et al. 2015) is also based upon a high dependence between runoff and storage and uses linear reservoirs as its primary building block. In this model, the dynamics of runoff are modelled using linear storages

Slettet: The non-linearity of the response in DDD comes from exponential UHs of different temporal scale

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Slettet: data from runoff

Slettet: Recession data have often been used to derive the storage-runoff relationship and recession events were selected such that the possible contaminating effect of precipitation and evapotranspiration on the recession data was minimized. For two rivers in the UK, highly non-linear relationships between storage and runoff were found using this approach.

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

Slettet: As in Brutsaert and Nieber (1977) and Kirchner (2009), recession data are fundamental in DDD for describing the runoff dynamics. The temporal scales of the UHs are estimated assuming that the recessions provide the parameters of exponential UHs, which together with the distribution describing the distances from points in the catchment to their nearest river reach, are used to derive celerities and, hence, the temporal scale of the UHs. The linearity of the parallel reservoirs is not assumed but is dictated by the empirical distance distributions, which for Norwegian hillslopes can usually be modelled as exponential (Skaugen and Onof, 2014; Skaugen et al. 2015). The UHs are turned on and off according to the level of saturation (or storage) in the catchment.

Formatert: Engelsk (USA)

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

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

Flyttet (innsetting) [1]

Slettet: The DDD model was developed with the aim of investigating how far one could parameterize a rainfall-runoff model using information obtained from maps and runoff records prior to model calibration. The result was a model that had no loss in precision or detail when compared with the HBV model, although the number of calibration parameters in the subsurface- and dynamic modules was reduced from 7 (HBV) to 1 (DDD). This study is a continuation of that approach, and the aim is to investigate how storage dynamics can be related to runoff dynamics within the DDD framework. The recession data continue to play a crucial role in the model formulation and using these data together with the distance distributions and the mean annual runoff (MAR), we attempt to estimate all parameters of the subsurface and runoff dynamics prior to model calibration.

2 Methods

2.1 Hydrological model

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

Feltkode endret

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

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

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

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

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

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

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

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

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Slettet: volume

Slettet: volume

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

2.2 Runoff dynamics

The runoff dynamics are completely parameterized from observed catchment features derived using a Geographical Information System (GIS) and runoff recession analysis. Central for the formulation of runoff dynamics for a catchment is the distance distribution derived using GIS. The distances, d $[m]$, from points in the catchments to the nearest river reach are calculated for each catchment and for more than 120 studied catchments in Norway the exponential distribution describe the distribution of distances well. Figure 2 shows the empirical and exponential distributions for two Norwegian catchments and although the mean distance $\bar{d}$ is different, the exponential distribution is a good fit for both catchments. The parameter γ, of the exponential distribution

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

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

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

Flyttet (innsetting) [2]

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Flyttet ned [3]: , for the same two catchments as in Figure 2, the consecutive fractional areas for each distance interval Δd are plotted against the distance to the river network, and the ratio, κ between consecutive fractional areas is a constant and it has been showed (Skaugen, 2002) that the parameter γ of the exponential distribution relates to κ as ¶
$\gamma = -\log(\kappa)/\Delta d$.

Flyttet ned [4]:)¶
If we assume that a uniform moisture input (i.e.

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Flyttet ned [5]: (or celerity, see Skaugen and Onof, 2014, Beven, 2006), then Δd is the distance travelled by water during a suitable time step, Δt, i.e., $\Delta d = v\Delta t$. When d Eq. 2 is replaced with d/v, the distance distribution hence becomes a travel-time distribution with mean equal to $\frac{\bar{d}}{v}$ and parameter
$\xi = -\log(\kappa)/\Delta t$, (

Flyttet ned [6]: which constitutes a unit hydrograph (Maidment, 1993, Bras, 1990, p.448). The variable κ, is now the ratio between volumes of water drained pr. time step, i.e. the volume of water drained into the river network is reduced by κ for each time step. ¶
A linear reservoir has this same property of consecutive runoff values having a constant ratio. This can be seen if we compute successive volumes and runoff values according to a linear reservoir in recession with

Flyttet ned [7]: $Q(t) = \vartheta S(t)$.

Flyttet ned [8]: The ratio between consecutive values of runoff,

Flyttet ned [10]: and the celerity can hence be formulated as:¶

Slettet: $v = \frac{-\log(1-\vartheta)\bar{d}}{\Delta t} = \frac{-\log(\kappa)\bar{d}}{\Delta t}$
(8)¶
This brief discussion on the distance distribution and linear reservoirs is relevant because it suggest that if a catchment exhibits an exponential distance distribution the linear reservoir comes as a natural choice for modelling the ...

Flyttet ned [11]:). These latter statements assumes, of course, that the topographical catchment area and that of the

Slettet: In Figure 3 the information of the distance distribution is visualised differently. Here

Slettet: excess rainfall or snowmelt) is transported through the hillslope to the river network with a constant velocity v,

Slettet: 4 and 5 we see that the runoff coefficient of a linear reservoir relates to the parameter of the travel time ...

Slettet: 4)¶

Slettet: runoff coefficient ϑ, i.e.

Slettet: $Q(t+1)/Q(t)$ remains constant and equal to $1-\vartheta$. Hence, a catchment with an exponential distance distributio ...

Flyttet ned [9]: Furthermore, from eqs.

Slettet: , $log(Q(t)) - log(Q(t+\Delta t))$,

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

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

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

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

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

$$\Lambda_i e^{-\Lambda_I(t-t_0)} = \varpi_1 \lambda_1 e^{-\lambda_1(t-t_0)} + \varpi_2 \lambda_2 e^{-\lambda_2(t-t_0)} + \ldots + \varpi_i \lambda_i e^{-\lambda_i(t-t_0)}, \qquad (5)$$

Slettet: 8),

Slettet: $\Lambda(t) = \log(Q(t)) - \log(Q(t+\Delta t))$. (9)¶
The parameter Λ is thus the slope per Δt of the recession in the log-log space and we see the relation between the variable $\kappa = Q(t+\Delta t)/Q(t)$ and Λ as:¶
$\Lambda = -\log(\kappa)$ (10)¶
¶
From Eq. 8 we have that the celerity v as a function of Λ is:¶
$v = \frac{\Lambda \bar{d}}{\Delta t}$ (11)¶

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

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

2.3 Reformulation of the subsurface of DDD

An obvious problem of the approach described above is that we attempt to estimate an extreme value, the maximum catchment scale storage θ_M, a task which is obviously associated with more uncertainty than estimating the mean catchment scale storage, m_s. Another problem is the assumption of a uniform distribution of storage levels. A quick investigation of observed groundwater level fluctuations suggests that this is not the case. Figure 4 shows histograms of observed groundwater levels from three observation boreholes located in a small catchment (the Groset catchment, 6.33 km^2) in southern Norway. The figure clearly illustrates that fluctuations in storage and groundwater levels are spatially variable and should ideally be treated as such in rainfall-runoff models (Rupp et al. 2009; Sloan, 2000). This is a consequence of the differences in water level fluctuations depending on the location of the borehole relative to the river, i.e. top of a hillslope vs. adjacent to a river and also of the catchment variability of topography and soil porosity (Refsgaard et al., 2015). It is therefore very difficult to parameterize the distribution of the catchment-scale groundwater fluctuations from such single observation points (Kirchner,

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Slettet: $M = 100\ mm$

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Flyttet opp [2]: Calibrated model parameters are hereafter denoted by θ with subscripts (e.g. θ_M), in order to clearly distinguish between estimated and calibrated parameters. ¶

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

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

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

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

where α and β are the shape and scale parameters respectively and estimated from observed $\Lambda's$ (using Eq. 3).

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

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

where the scale parameter, η, is

$$\eta = \beta/c, \qquad (8)$$

and c is a constant and equal to

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Slettet: Λ.

Slettet: The assumption of equal shape for the distributions of Λ and S is, of course, difficult to verify as no direct observations of S are at hand. However, if we use the equation for the linear reservoir (Eq. 5) and express the runoff coefficient as a function of $\Lambda(t)$ (Eq. 10), we can, for observed values of $Q(t)$ and $\Lambda(t)$, calculate the corresponding values of $S(t)$ and compare the distributions of $\Lambda(t)$ and (the scaled) $S(t)$.

Slettet: $S(t) = \frac{Q(t)}{1-e^{-\Lambda(t)}}$
(13)¶
Figure 6 show such a comparison for two catchments, and, except for the highest quantiles, the distributions of $\Lambda(t)$ and (scaled) $S(t)$ are almost identical and hence supporting our assumption. The high frequency of high $S(t)$ values present in Figure 6, also seen for several other catchments (not shown), is the result of the combination of high $Q(t)$ values and low values of $\Lambda(t)$, i.e.

Flyttet ned [12]: very modest recession for situations with high runoff values.

Slettet: Such events are probably not representative for describing recessions, and by sampling $\Lambda(t)$ and estimating $S(t)$ under the condition that precipitation at the day of $(t+\Delta t)$ could not exceed a low threshold (for example 0, 2 and 5 mm) we found that the frequency of very high values of $S(t)$ were reduced. Hence, the very high values of $S(t)$ did not represent recession events.

Flyttet ned [13]: Moreover, the distribution of Λ was insensitive to such conditioning, implying that Eq.

Slettet: 9 is a robust estimate of recession characteristics, whereas the distribution of $S(t)$ was highly sensitive. ¶

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Slettet: 14

Slettet: Λs

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Slettet: $\eta = \beta/c$
(16)¶

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

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

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

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

Slettet: Λs

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

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

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

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

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

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

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

where A is the catchment area.

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

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

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

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

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

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

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

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

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

2.4 Test of new storage routine

Slettet: 2.3.1 Estimating
Slettet: m_S ¶ From runoff observations,
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Slettet: $\frac{S_i}{\theta_M} = \int_0^{S_i} \frac{1}{\eta^\alpha \Gamma(\alpha)} S^{\alpha-1} \exp(-S/\eta) dS$ (25)¶
Slettet: θ_M
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Slettet: subsurface

We will test the performance of the new formulation of storage by replacing the formulation of the storage where θ_M is a calibrated parameter and storage is uniformly distributed with a formulation where storage is gamma distributed with parameters, η and α, derived from recession data and MAR. The model with the current storage routine is denoted DDD_θ_M and the model with the new storage routine is denoted DDD_m_S.

DDD_m_S and DDD_θ_M are tested for 73 catchments distributed across Norway (see Figure 5). The catchments vary in latitude, size, elevation and landscape type (see histograms of selected catchment characteristics in Figure 6) and constitute thus a varied, representative sample of Norwegian catchments.

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

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

3 Results

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

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Slettet: subsurface

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Slettet: It is seldom straightforward to evaluate new algorithms for, at times, heavily parameterized rainfall-runoff models. Due to the tendency for calibration parameters to compensate for the models' structural errors (Kirchner, 2006; Beven

Slettet: Binley, 1992), it may be difficult to identify the effect of changing an algorithm or parameterization from the calibrated results of the model (Clarke, 2011). Kirchner (2006) points out the need to develop models that

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Slettet: minimally parameterized, and which therefore stand a chance of failing the tests they are subjected to, which is exactly the problem faced when assessing the introduction of new algorithms with fewer parameters. Gupta et al. (2014) propose the use of large sample hydrology as a means for the testing of hypothesis and model structures, in order to a) arrive at conclusions more general than can be achieved using a single catchment, b) establish a range of applicability, and c) ensure sufficient information to enable the identification of statistically significant relationships. These are certainly valid points, but, in addition, a minimal use of calibration parameters should increase the efficiency in isolating and ...

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Feltkode endret

Slettet: This meteorological grid is denoted V1.

Flyttet (innsetting) [14]

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Flyttet ned [15]: θ_{CV}

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Slettet:), whereas the parameter of interest for this study ...

Flyttet opp [14]: DDD_θ_M

Slettet:) and the DDD model with estimated storage ...

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Slettet: calibrated storage with parameter θ_M,

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

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

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

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Slettet: mean value of KGE for DDD_m_S is slightly worse due to a lower correlation between simulated and observed (Fig. 9 c). The
Slettet: bias
Slettet: m_S
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Slettet: Λ has been identified, in this and in previous studies, as being
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are very different, and as we have no data to estimate the true empirical distribution of storage at the catchment scale we cannot claim that the fluctuations simulated with DDD_m_S are closer to the truth than those simulated by DDD_θ_M. However, since the parameters of the subsurface- and dynamic module of DDD_m_S are estimated prior to model calibration and that the recessions are demonstrably better simulated, it is reasonable to suggest that the catchment scale storage fluctuations simulated with DDD_m_S are closer to the truth.

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4 Discussion

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

Slettet: The reduction of calibration parameters from the subsurface

Flyttet (innsetting) [16]

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

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

The assumption of equal shape for the distributions of Λ and S is, of course, difficult to verify as no direct observations of S are at hand. Myrabø (1997) conducted groundwater measurements on a very dense spatial grid over a tiny catchment (0.0075 km^2) in Southern Norway for a short period of time in order to investigate subsurface dynamics over an entire catchment. These data are unfortunately not available and no other similar experiment from Norway is known. However, if we use the equation for the linear reservoir in Appendix A (Eq. A4) and express the

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Slettet: In Skaugen et al. (2015) and in Skaugen and Væringstad (2005), MAR, was found to be a parameter varying smoothly in space for southern Norway, depending largely on regional scale climatic conditions and hence quite straightforward

Slettet: estimate for an ungauged catchment. The

Slettet: were estimated in Skaugen et al. (2015)

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

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

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

Flyttet (innsetting) [12]

Flyttet (innsetting) [13]

Slettet: . Since λ is a function of Λ (see Eq. 12), a similar dependency between Λ and catchment characteristics is expected, but is to be investigated. Provided that MAR and the parameters of the distribution of Λ are as easy to estimate for an ungauged catchment as expected we may hope for improved predictions for ungauged basins. In a future paper we will redo the analysis of Skaugen et al. (2015), using the new model structure presented in this paper and compare results.

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

Formatert: Engelsk (Storbritannia)

In Kirchner (2009) the storage-runoff relationship is assumed to be a single-valued function, i.e S is a single valued function of Q. This leads to a very simple model with regards to the number of states in the subsurface, namely one. The number of states in DDD, however, can be very high. If we consider Eq. 16, the number of summations (time-steps) constituting S_{SS} can be viewed as a number of subsurface states since each summation represents a volume water that will sooner or later propagate into the river network. Eq. 16 describes the subsurface using only one (mean) UH. In the DDD model, the number of storage levels is fixed to 5, and the UH's constituting the storage levels all have the same shape (exponential) but have different temporal scales. The temporal scale (level of discretisations) of the UH's vary according to their associated celerity, and the slowest (lowest) storage level may be discretised such that hundreds of time steps are necessary for the complete attenuation of the UH. Such a system actually provides a 2-D representation of the subsurface (Rupp et al. 2009; Sloan, 2000) and gives numerous subsurface states (Harman, 2015). It is hence entirely possible to have different configurations of states associated with the same runoff. Figure 11 shows a snapshot of how DDD models the storage S. The catchment is represented as one hillslope where the x-axis shows the distance (in metres) from the river reach (at the right hand-side) to the top of the hillslope (at the left hand side). The y-axis shows the different storage levels. We see the outline of boxes (especially for the higher storage levels) which represents the temporal discretisation of the UHs. Each box represents an area according to the distance distribution and the associated celerity that will drain pr. time interval. The higher the celerity, the more of the catchment area is represented by each box. The darker the blue colour, the more water is present in the box. Figure 11 can be seen together with Figure 1 A in appendix A, which illustrates how the distance

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distribution (and the travel time distribution) determines the fractional areas that drain pr. time interval for a given celerity (see also Harman (2015) for distribution of storage and water age). In Figure 11 we can also note that it is more or less dry at the top of the hillslope and saturated near the river. This is consistent with the wetting up of a catchment from the riparian zone outwards and up the hillslope (Dunne and Black, 1970; Kirkby, p.275,1978; Myrabø, 1997).

Figure 12 shows simulated storage, S, plottet against simulated runoff, Q, for two catchments of different size (49 km^3 1833 km^3). It is quite clear that the relationship between Q and S is not single valued. The variability of Q for the same S (and vice versa) is to be expected given the multitude of possible configurations of the subsurface states (i.e. the discretisations of the UHs). The shape of the clouds of points resembles those found for observations of groundwater vs runoff (Rupp et al. 2009; Laudon et al. 2004 and Myrabø, 1997). The points in Figure 12, however, do not level off to the same degree as does for groundwater observations. This can probably be explained by the fact that storage in DDD is simulated for an entire catchment, and it is more unlikely that an entire catchment will reach full saturation than individual groundwater boreholes, located relatively close to the river (Myrabø, 1997; Laudon et al. 2004).

The parameters of the subsurface and the dynamical modules of the DDD model are all estimated prior to calibration against streamflow and we see this as a necessary development if we are to effectively test new algorithms for snow distribution, snowmelt, evapotranspiration etc. at the scale that matters for most practical applications, the catchment scale (Clarke, 2011). Multi-variable parameter estimation (Bergström et al., 2002) has been put forward as a means to increase confidence in hydrological modelling and models. Although we agree that such procedures indeed narrows the parameter-space (although not its number of dimensions), the interaction and compensating nature of the calibration parameters makes it almost impossible to reject flawed model structures so that we can concentrate on building models that work well for

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Slettet: new formulation for the subsurface gives good results, and it is promising that the replacement of a calibrated routine with an algorithm with

Slettet: estimated prior to calibration produces runoff simulations which are as precise and robust as those produced by the calibrated routines.

Flyttet opp [16]: In addition, the simulated recessions Ȧ, are much closer to those observed, suggesting a more realistically modelled storage-runoff relationship (i.e. the non-linearly increasing storage capacity).

Slettet: The parameter

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the right reasons. In this paper, and in previous ones (Skaugen and Onof, 2014; Skaugen et al. 2015), information ready at hand such as GIS-derived distance distributions functions and runoff records have proved useful for parameterising algorithms describing basic hydrological processes.

5 Conclusions

In this paper a new formulation of the subsurface in the DDD model is presented. In the new formulation, the storage capacity increases non-linearly with saturation, following a two-parameter gamma distribution. The parameters of the gamma distribution are estimated directly from observed runoff recession data and the mean annual runoff and not through model calibration against runoff. The new storage formulation has been tested for 73 catchments in Norway of varying size, mean elevation and landscape type, with little loss in precision. In addition, more realistic runoff recessions are found using the new subsurface routine suggesting a more realistic storage-runoff relationship.

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

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

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

Slettet: easily derived

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Slettet: sufficient

Slettet: This approach will be continued, and algorithms with a minimum of calibration parameters for describing the spatial distribution of snow and for snowmelt will be implemented in the DDD model structure and tested with the approach of large-sample hydrology as proposed by Gupta et al. (2014).

Slettet: subsurface

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Slettet: subsurface

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Slettet: . An important contribution of the new formulation is that its parameters are estimated solely from observed recession data and the mean annual runoff (i.e. not through calibration).

Slettet: With increased parameter parsimony in the already parameter parsimonious DDD model, important tasks such as predictions in ungauged basins (PUB) and testing new algorithms for different hydrological processes are more feasible. Large-sample hydrology has proven useful for revealing and quantifying the effects of the introduction of a new formulation of the hydrological subsurface.

Formatert: Engelsk (Storbritannia)

Data availability

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

Appendix A

Distance distributions and linear reservoirs

In Figure A1 the information of the distance distribution is visualised differently from Figure 2.

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

Flyttet (innsetting) [3]

$$\gamma = -\log(\kappa)/\,\Delta\, d. \qquad \text{(A1)}$$

Flyttet (innsetting) [4]

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

Flyttet (innsetting) [5]

$$\xi = -\log(\kappa)/\,\Delta\, t, \qquad \text{(A2)}$$

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

Flyttet (innsetting) [6]

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

$$\kappa = Q(t + \Delta t)/Q(t) \quad \text{(A2)}$$

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

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

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

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

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 distance distribution as:

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

and the celerity can hence be formulated as:

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

This brief discussion on the distance distribution and linear reservoirs shows that if a catchment exhibits an exponential distance distribution, linear reservoirs comes as a natural choice for modelling the interaction between hillslopes and the river network. Furthermore, the distance

Flyttet (innsetting) [7]

Flyttet (innsetting) [8]

Flyttet (innsetting) [9]

Flyttet (innsetting) [10]

distribution suggests a geometrical configuration of the hillslope (or aquifer) (Figure A1) and the linear reservoir model is partly parameterised from the parameter of the distance distribution (Eq. A5). These latter statements assumes, of course, that the topographical catchment area and that of the aquifer are equal, an assumption that does not always hold (Bidwell et al. 2008).

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Slettet: M.
Slettet: J.L.
Slettet: M.
Slettet: G.
Slettet: , 2013.
Slettet: ., 2005.
Slettet: RA,
Slettet: VJ. 2009.
Slettet: Saloranta, T. M.: Simulating snow maps for Norway: description and statistical evaluation of the seNorge snow model, *The Cryosphere*, **6**, 1323-1337, 2012.¶
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Slettet: Skaugen, T and T. Væringstad, 2005. A methodology for regional flood frequency estimation based on scaling properties.
Flyttet opp [18]: Hydrol.
Slettet: *Process*. **19**, 1481-1495.¶ Skaugen T. and C. Onof, 2014.
Formatert: Skrift: Ikke Kursiv, Engelsk (USA)
Slettet: I. O.
Slettet: A.
Slettet: 2015.
Slettet: ., 2000.
Slettet: , 2010.
Feltkode endret
Flyttet (innsetting) [20]
Formatert: Engelsk (Storbritannia)

Sælthun, N. R.: *The ``Nordic'' HBV model. Description and documentation of the model version developed for the project Climate Change and Energy Production*, NVE Publication no. 7-1996, Oslo, 26 pp., 1996.

Tallaksen, L.M.: A review of baseflow recession analysis, J. Hydrol., 165, 349-370, 1995.

Slettet: ., 1996.

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

Parameter	**Description**	**Method of estimation**		
Hypsograpic 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	1.5xθ_{CX}		
CFR [mm/°C/day]	Degree-day factor for freezing	Fixed value: 0.02, Sælthun (1996)		
Area[m²]	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		
NOL	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		

Slettet: comments…escription and method of estimation.
Slettet: Comment
Slettet: Value
Slettede celler
Slettet: Ref
Slettede celler
Slettet: est.
Slettet: θ_{WS}
Slettet: (V1)
Slettet: 5
Slettet: cathment
Slettet: Standard value
Slettet: 0.0
Slettet: Standard value
Slettet: 0.0
Slettet: Standard value
Slettet: 1.0
Slettet: Standard value
Slettet: 1.0
Slettet: Standard value
Slettet: 0.5
Slettet: Standard value
Slettet: 0.0
Slettet: θ_{CX}
Slettet: (V1)
Formatert tabell
Slettet: *
Slettede celler
Slettet: θ_{CX}
Slettet: Sælthun (1996)
Slettet: *
Slettet: 0.02
Slettede celler
Slettede celler
Slettede celler
Formatert tabell
Slettet: Standard value¶
Slettede celler
Slettet: 5
Slettede celler
Slettet: θ_{cea}
Slettet: (V1)
Slettede celler
Slettede celler
Formatert tabell
Slettet: Standard value¶
Slettede celler
Slettet: 0.3
Slettede celler
Formatert
Slettede celler
Slettede celler
Formatert

θ_{CV}	Coefficient of variation for spatial distribution of snow	Calibrated		
θ_{v_r} [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_{Gl}[m]	Mean of distance distribution for glaciers	GIS		
s_{Gl}[m]	Standard deviation of distance distribution for glaciers	GIS		
Areal fraction of glaciers in elevation zones	10 values	GIS		

Flyttet (innsetting) [15]
Slettet: θ_{CV}
Formatert: Skrift: 10 pkt, Norsk (bokmål)
Formatert: Skrift: 10 pkt, Norsk (bokmål)
Formatert: Skrift: Ikke Fet
Slettet: Coeff.
Slettet: (V1)
Slettet: v_r
Slettet: Standard value
Slettet: 1.0
Slettet: Beven (1979)
Slettet: θ_M
Slettet: (V2)/

Table 2 .Mean values of skill scores obtaind with simulating with DDD_m_S and DDD_θ_M for 73 catchments. KGE_r measures correlation, KGE_b, the bias error and KGE_g the variability 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

Slettet: 68

Slettet: 69

Slettet: 83

Slettet: 85

Slettet: 1.

Slettet: 66

Slettet: 70

Slettet: 85

Slettet: 83

Slettet: 1.04

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

	RMSE mean Λ	RMSE std Λ
DDD_m_S	0.04	0.045
DDD_θ_M	0.07	0.049

Slettet: 275

Slettet: 389

Slettet: 511

Slettet: 392

Table 4. Significant spearman correlation (p-value < 0.01) between catchment characteristics and the shape, α, and scale, β, parameters of the distribution of Λ. The correlations are based on 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

Slettet: Sideskift
¶

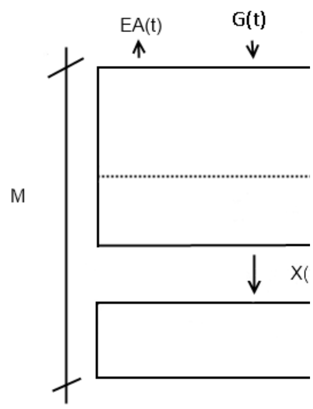

Figure 1. Schematic of the subsurface water reservoir M of DDD. $G(t)$ represents moisture input, rain and snowmelt. The dotted horizontal line is the actual level Z, of soil moisture in D. The ratio $(G(t)+Z(t))/D(t)$ controls the release of excess water to S and hence to runoff. Note that D, S and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

Figure 2. Empirical and fitted (exponential, red line) CDFs of distances from a point in the catchment to the nearest river reach for two Norwegian catchments. The mean distance (denoted d_mean in the figure) and catchment size differ, but the shape of the distribution is similar.

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

Figure 4. Histograms (in black, green, and red) of groundwater levels at three different locations in the Groset catchment (6.33 km^2) located in southern Norway.

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

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

Figure 7. Skill scores for DDD_m_S (blue circles) and DDD_θ_M (red crosses) for 73 Norwegian catchments. Mean skill score values are shown in horizontal lines (same color code).a) NSE, b) KGE, c) KGE_r (correlation), d) KGE_b (bias) and e) KGE_g (variability error).

Figure 8. Scatterplot of mean a) and standard deviation b) of observed Λ and simulated with DDD_m_S (blue circles) and DDD_θ_M (red crosses) $\dot{\Lambda}$ for 73 catchments.

Slettet: Sideskift ¶

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Flyttet ned [21]: Fractional catchment area as a function of

Slettet: ¶

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Slettet: are

Slettet: 9

Slettet: Sideskift

Flyttet ned [22]: **Figure 5**.

Formatert: Engelsk (USA)

Slettet:

Slettet: Sideskift

Flyttet (innsetting) [22]

Formatert: Engelsk (USA)

Flyttet ned [23]: **Figure 6**.

Slettet: Empirical CDFs of Λ (circles) and scaled $S(t)$(blu

Slettet: subsurface

Formatert: Engelsk (Storbritannia)

Slettet: ¶

Flyttet (innsetting) [23]

Formatert: Engelsk (USA)

Slettet: ¶

Slettet: 9

Slettet: ¶

Slettet: 10

Figure 9. Histograms of storage simulations with DDD_θ_M a) and DDD_m_S b). Empirical CDFs of observed Λ (black line) and simulated $\dot{\Lambda}$ with DDD_θ_M (red line) and DDD_m_S (blue line) are shown in c).

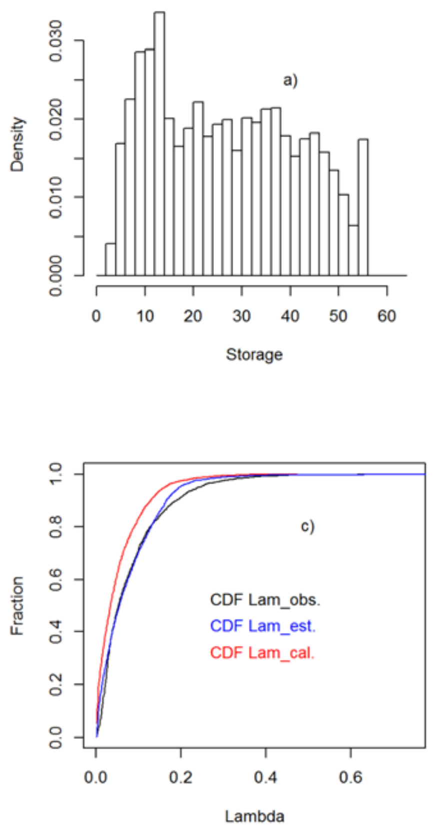
Figure 10. Empirical CDFs of Λ (circles) and scaled $S(t)$ (blue line) for two Norwegian catchments .

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

Figure 12. Simulated storage S plotted against simulated runoff Q for a catchment of 49 km^2 (a) and a catchment of 1833 km^2 (b).

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

Slettet: Sideskift
¶



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Slettet: Sideskift
¶

Slettet: Sideskift
¶

Slettet: 13

Slettet: observed

Slettet: 50

Flyttet (innsetting) [21]

Fig1

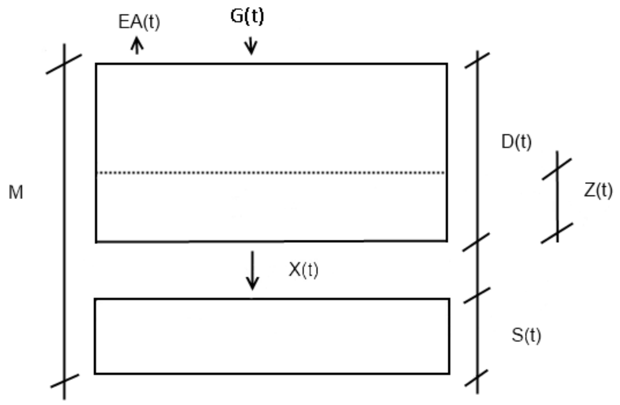


Fig2

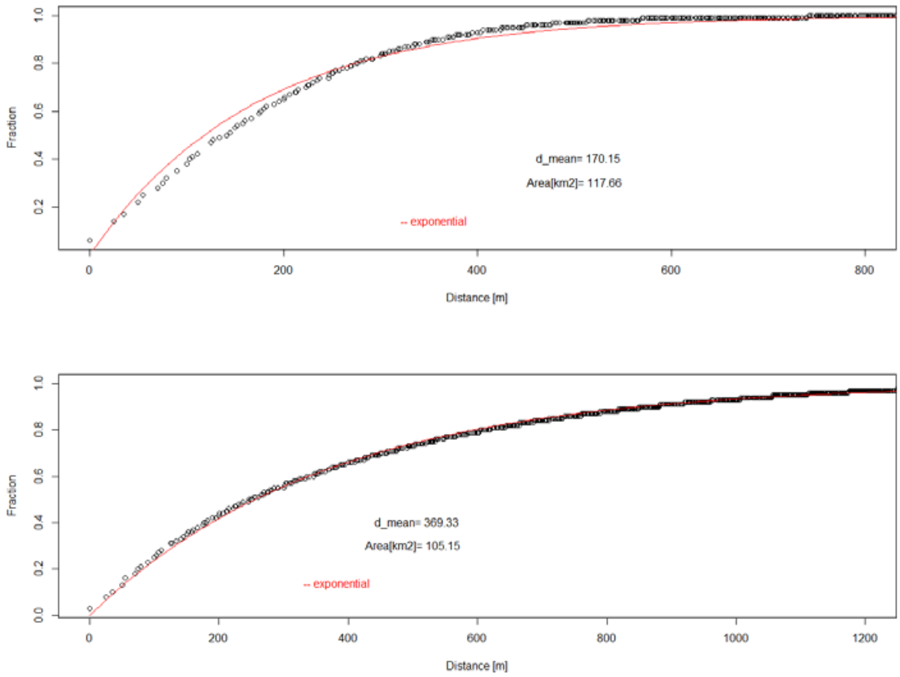

Fraction
d_mean= 170.15
Area[km2]= 117.66
-- exponential
Distance [m]
Fraction
d_mean= 369.33
Area[km2]= 105.15
-- exponential
Distance [m]

Fig 3

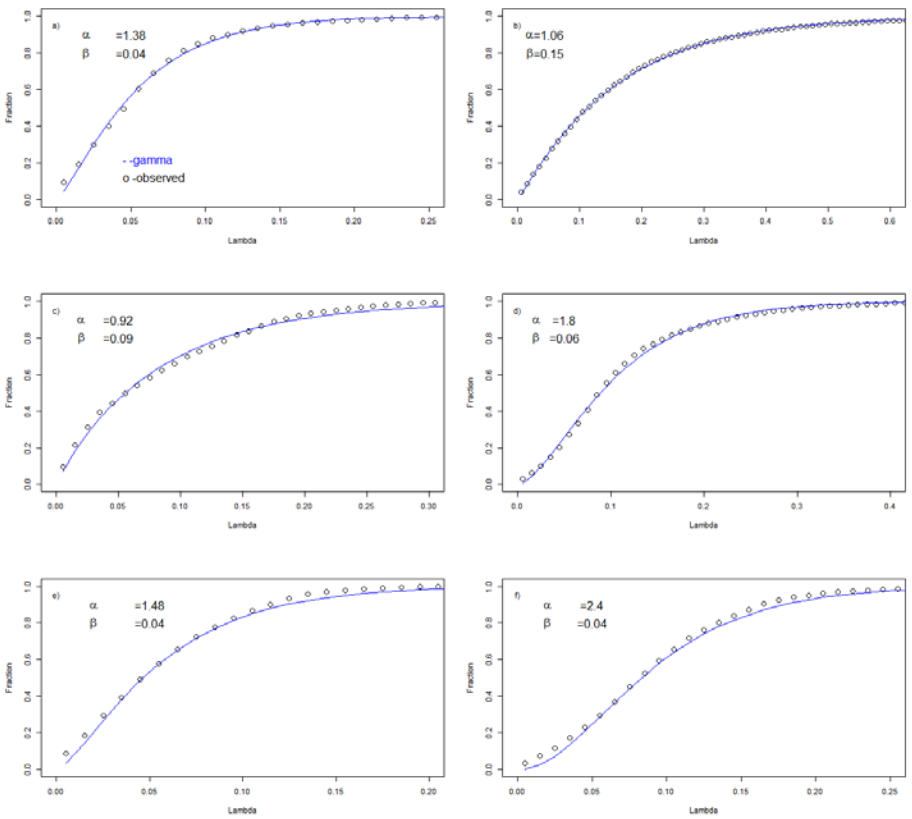

a)
α =1.38
β =0.04
- -gamma
o -observed
b)
α=1.06
β=0.15
c)
α =0.92
β =0.09
d)
α =1.8
β =0.06
e)
α =1.48
β =0.04
f)
α =2.4
β =0.04
Fraction
Lambda

Fig4

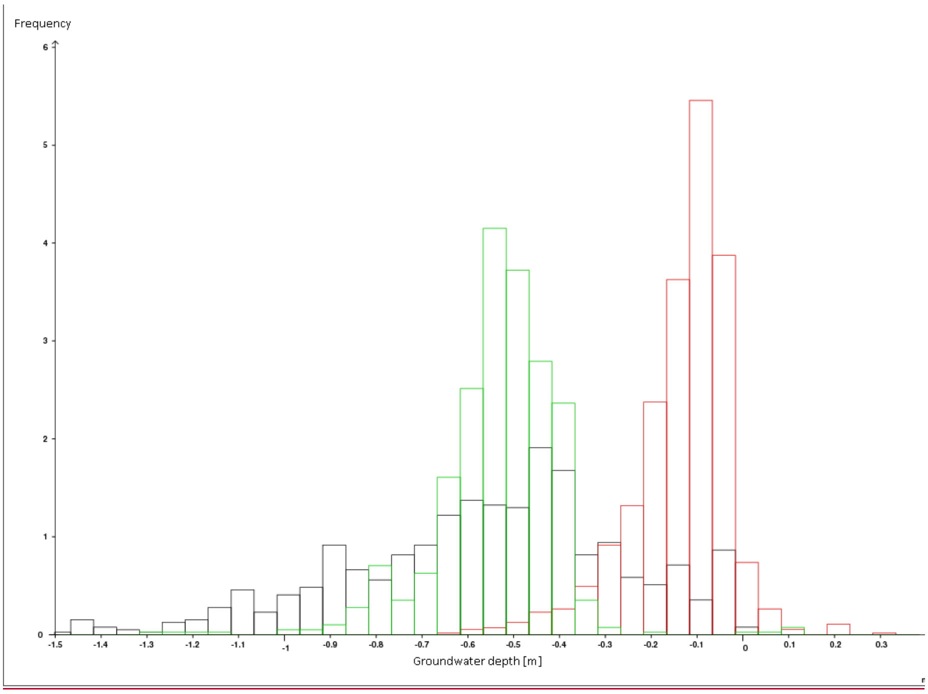
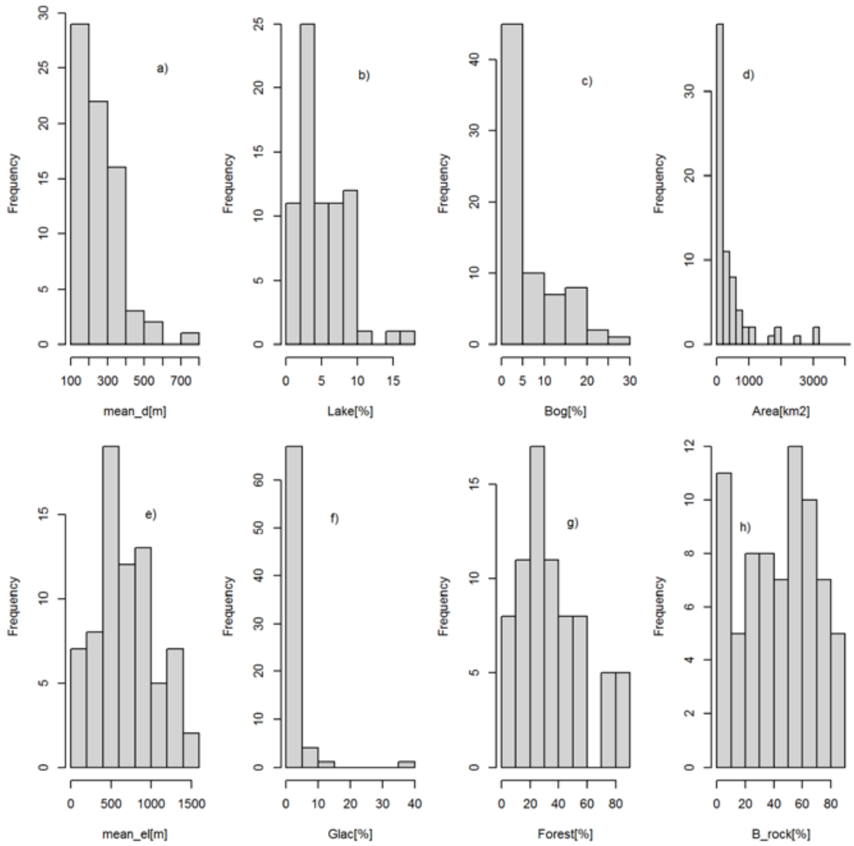

Frequency
6
5
4
3
2
1
0
-1.5
-1.4
-1.3
-1.2
-1.1
-1
-0.9
-0.8
-0.7
-0.6
-0.5
-0.4
-0.3
-0.2
-0.1
0
0.1
0.2
0.3
Groundwater depth [m]

Fig 5


Tromsø
Kirkenes
Norwegian Sea
Bodø
Bottenviken
SVERIGE
FINLAND
Trondheim
NORG
Bergen
Oslo
Stavanger
Stockholm
Tallinn
ESTLA
Gulf of
Helsing

Fig 6



a)
b)
c)
d)
e)
f)
g)
h)
Frequency
mean_d[m]
Lake[%]
Bog[%]
Area[km2]
mean_el[m]
Glac[%]
Forest[%]
B_rock[%]

Fig 7

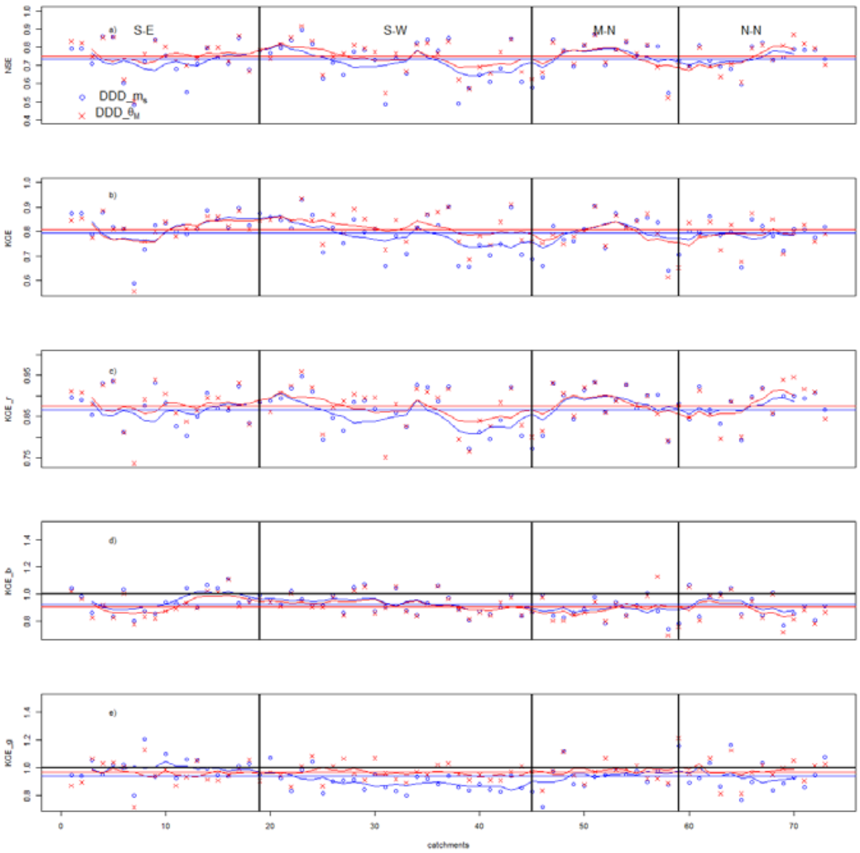


Fig 8

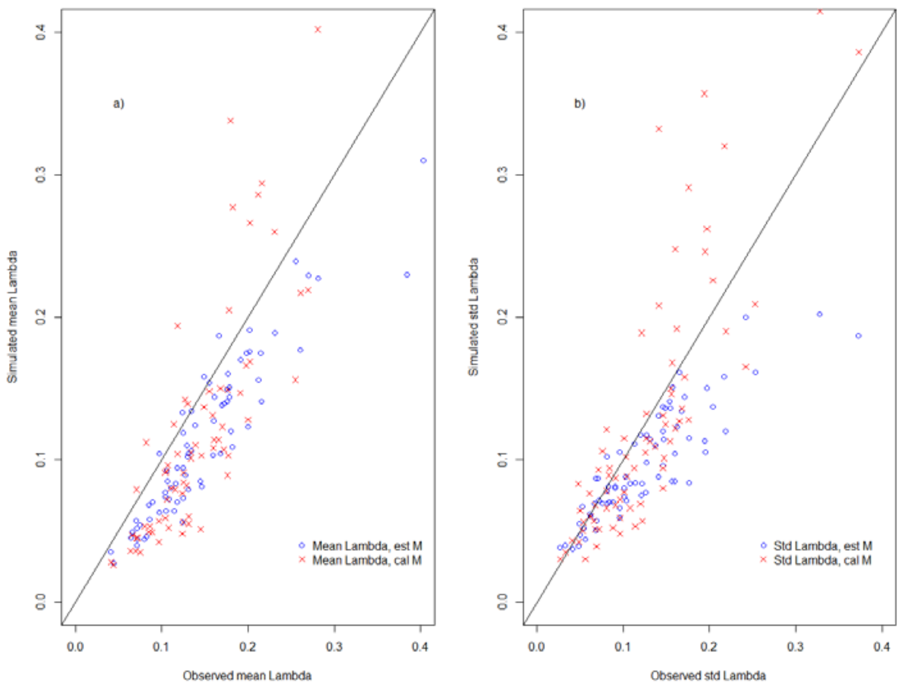
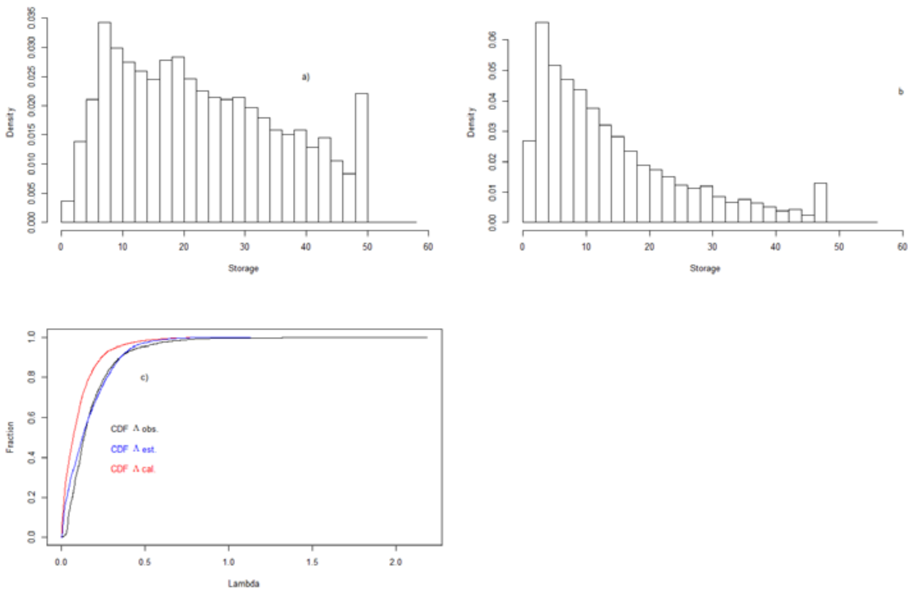

a)
Simulated mean Lambda
Observed mean Lambda
Mean Lambda, est M
Mean Lambda, cal M
b)
Simulated std Lambda
Observed std Lambda
Std Lambda, est M
Std Lambda, cal M
0.0
0.1
0.2
0.3
0.4

Fig 9



a)
Density
Storage
b
Density
Storage
c)
CDF Λ obs.
CDF Λ est.
CDF Λ cal.
Fraction
Lambda

Fig 10

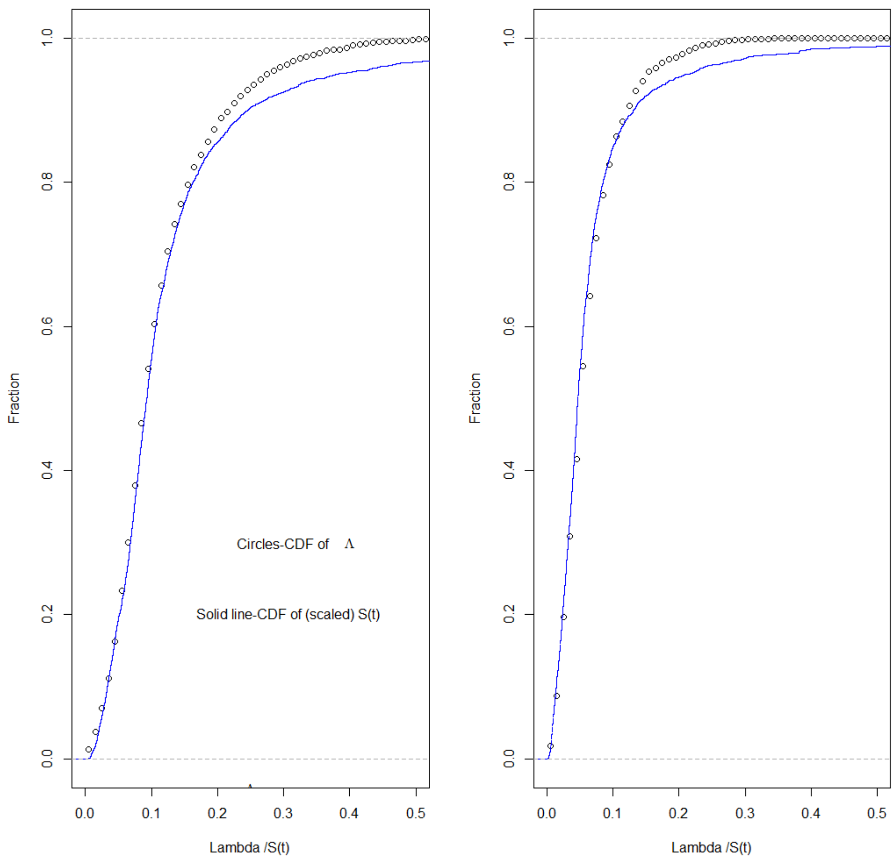

Fraction
Lambda /S(t)
Circles-CDF of Λ
Solid line-CDF of (scaled) S(t)
0.0
0.2
0.4
0.6
0.8
1.0
0.1
0.3
0.5

Fig 11

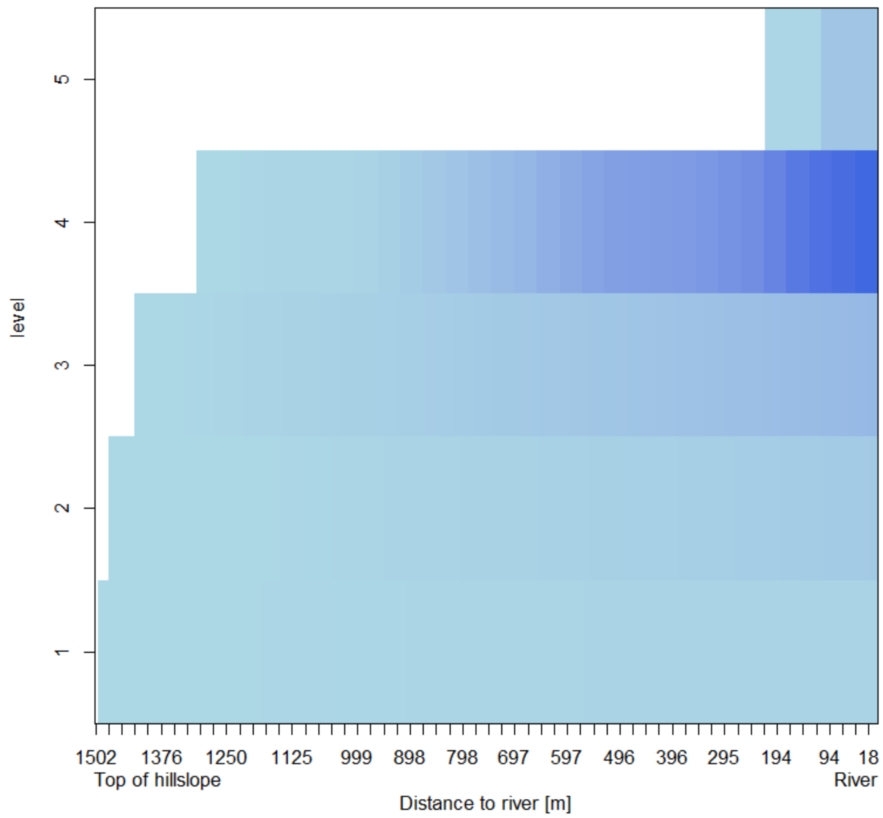

level
1
2
3
4
5
1502
1376
1250
1125
999
898
798
697
597
496
396
295
194
94
18
Top of hillslope
River
Distance to river [m]

Fig 12

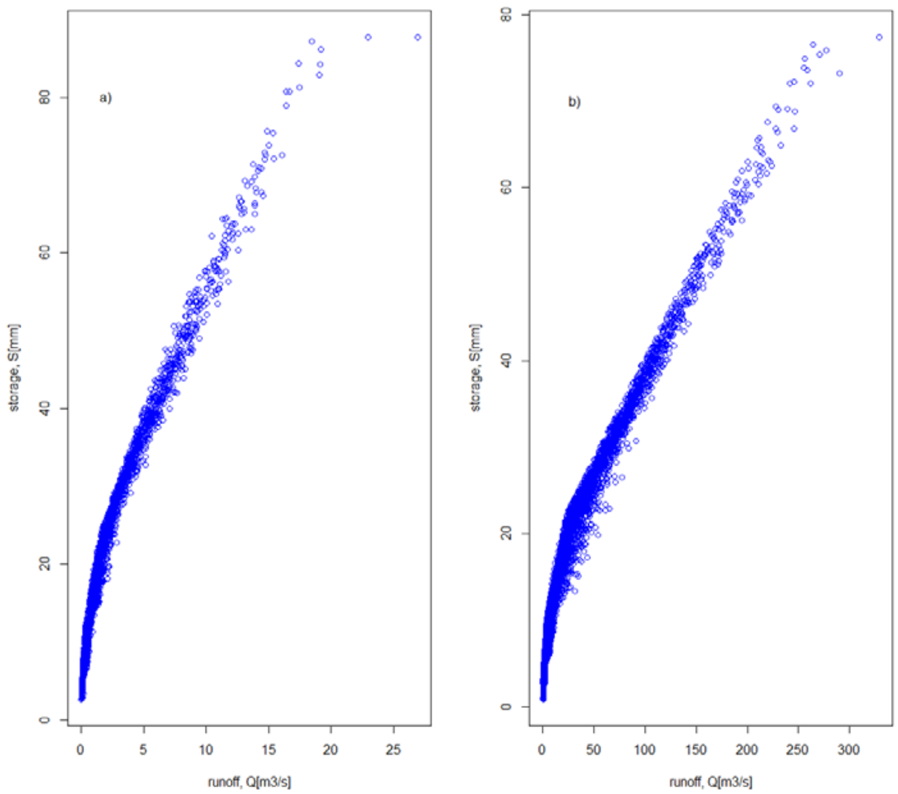
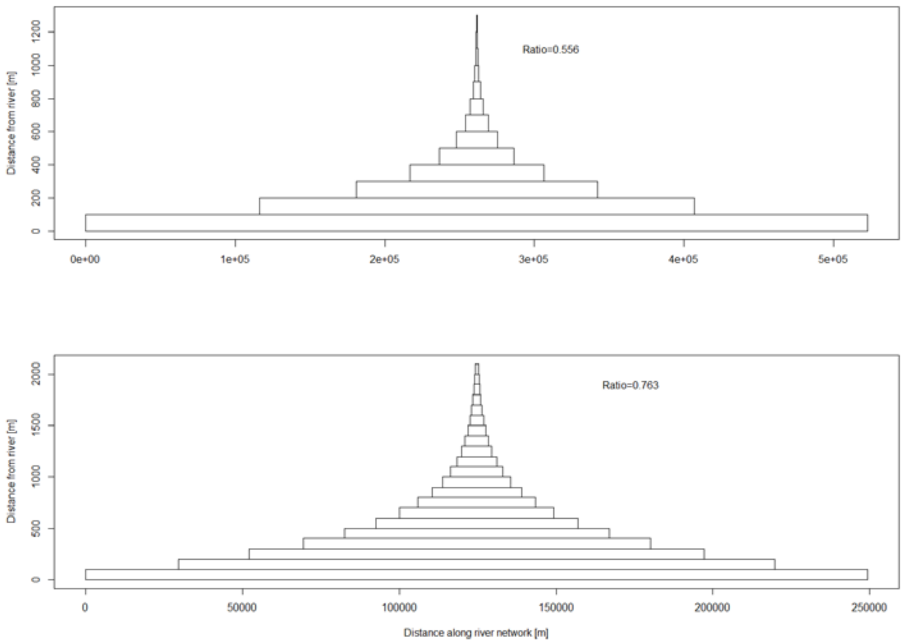

a)
storage, S[mm]
runoff, Q[m3/s]
0
20
40
60
80
0
5
10
15
20
25
b)
storage, S[mm]
runoff, Q[m3/s]
0
20
40
60
80
0
50
100
150
200
250
300

Fig A1



Formatert: Linjeavstand: Dobbel

Formatert: Skrift: 12 pkt, Engelsk (USA)

Formatert: Engelsk (USA)