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Use of a parsimonious rainfall–run-off model for predicting hydrological response in ungauged basins

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Abstract:

A new parameter parsimonious rainfall–run-off model, the Distance Distribution Dynamics (DDD) model, is used to simulate hydrological time series at ungauged sites in the Lygne basin in Norway. The model parameters were estimated as functions of catchment characteristics determined by geographical information system. The multiple regression equations relating catchment characteristics and model parameters were trained from 84 calibrated catchments located all over Norway, and all model parameters showed significant correlations with catchment characteristics. The significant correlation coefficients (with p-value$\,< 0.05$) ranged from 0.22 to 0.55. The suitability of DDD for predictions in ungauged basins was tested for 17 catchments not used to estimate the multiple regression equations. For ten of the 17 catchments, deviations in Nash–Sutcliffe efficiency (NSE) criteria between the calibrated and regionalised model were less than 0.1, and for two calibrated catchments within the Lygne basin, the deviations were less than 0.08. The median NSE for the regionalized DDD for the 17 catchments for two time series was 0.66 and 0.72. Deviations in NSE between calibrated and regionalised models are well explained by the deviations between calibrated and regressed parameters describing spatial snow distribution and snowmelt respectively. The quality of the simulated run-off series for the ungauged sites in the Lygne basin was assessed by comparing flow indices describing high, medium and low flow estimated from observed run-off at the 17 catchments and for the simulated run-off series. The indices estimated for the simulated series were generally well within the ranges defined by the 17 observed series.

KEY WORDS predictions in ungauged basins; DDD model; parameter parsimonious; catchment characteristics; ecology

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INTRODUCTION

To make predictions in ungauged basins (PUB, Sivapalan, 2003) is to challenge and overcome the potential problem posed by the 'uniqueness in place' (Beven, 2000) of catchments that may limit the possibilities of extrapolating hydrological behaviour from one catchment to another. The problem is almost insurmountable if accompanied with limited knowledge on how the various hydrological processes, such as run-off generation at land surfaces, evaporation from the soil and water movement through various flow paths on the land surface, the unsaturated zone and in the groundwater, interact to produce the run-off hydrograph. An understanding of these processes and their interactions is hence necessary in order to make realistic PUB. In this respect, it is essential that the hydrological models are parametrically efficient (parsimonious) and identifiable from the available catchment data (Young and Romanowicz, 2004).

Several approaches have been suggested for making progress in predicting in ungauged basins. Seibert (1999) used the Swedish Hydrologiska Byråns Vattenbalans model (HBV; Bergström, 1992; Sælthun, 1996; Lindström *et al*., 1997) and investigated the regionalization of its model parameters. HBV was calibrated for 11 catchments in a relatively homogeneous area in Sweden. He tried to relate the different model parameters to catchment characteristics (CCs) and found that only six out of 13 model parameters exhibited such relations. He further pointed out that parameter uncertainty complicated the regionalization of model parameters and suggested including additional observed data into the calibration process as a way to constrain model parameters. Other studies attempting such a procedure using the HBV model yielded divergent results. When including water quality data in the calibration, Bergström *et al*. (2002) experienced a decrease in the precision of run-off simulation, whereas Parajka and Blöschl (2008) found a

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small increase in the precision of run-off simulation when optical satellite (Moderate-Resolution Imaging Spectroradiometer) scenes of snow cover were included in the calibration. Merz and Blöschl (2004) performed a large-scale experiment where they tried to regionalize the parameters of the HBV model calibrated for 308 catchments over Austria. Very weak correlations were found between CCs and the model parameters, and they concluded that the best procedure was to regionalize the parameters through kriging interpolation. Another conclusion by Merz and Blöschl (2004) is that it is difficult, if at all possible, to find universal relationships between model parameters and catchment attributes. Young (2006) used a very large data set of 260 catchments in the UK to investigate the regionalization of the Probability-Distributed Moisture (PDM) model (Moore, 1985). This model has considerably less parameters to be calibrated than the HBV model (six to HBV's 13). The study tested two methods for regionalizing the model parameters: by relating model parameters to CCs and by using a nearest neighbour approach. The former method gave the best result, which contrasts with the results of Merz and Blöschl (2004). The fact that there are considerably less parameters in the PDM to be calibrated than in HBV may, in our opinion, also have played a role in reaching this conclusion. Yadav *et al*. (2007) acknowledge that structural errors and non-identifiability of model parameters in a conceptual model pose a serious constraint on the ability of these models to give good PUB using regionalized parameters. In order to circumvent this problem, they instead regionalized dynamic characteristics of flow using CCs. The dynamic characteristics of flow provide constraints on model simulations and hence on model parameterizations.

Despite the obvious scientific challenges, PUB became an inspiring initiative launched and driven forward by the International Association of Hydrological Sciences (IAHS) during 2003–2012. Recently, a synthesis (Blöschl *et al*., 2013) and a review (Hrachowitz *et al*., 2013) summing up the decade of the IAHS PUB initiative have been published. Hrachowitz *et al*. (2013) point out that although not all of the goals set out at the beginning of the initiative were reached, several insights on hydrological processes, data quality and use, assessments of uncertainty and principles on hydrological modelling were found. One such principle was the advantages of parameter parsimonious models for the challenge of making PUB. Overparameterization in hydrological models makes parameter identification very difficult (Kirchner, 2006), which is obviously a problem for predicting in ungauged basins because model parameters are often determined from CCs and/or other hydrological and climatic information (Yadav *et al*., 2007). The advantages of few and clearly identified model parameters are also pointed out in other studies, e.g. Seibert (1999) and Young (2006). Despite the somewhat depressing general message that uncertainty in model structure and parameter identifiability will obfuscate or indeed prevent building relationships between model parameters and CCs, this is exactly what we intend to do. We will, however, apply a new parameter parsimonious model, the Distance Distribution Dynamics (DDD) model (Skaugen and Onof, 2014), under the assumption that not all conceptual models suffer from the previously mentioned limitations to the same degree. Sivapalan (2003) pointed out that the catchment system, including topography, the river network, soils, bogs, glaciers and vegetation, is the source of information on which models have to be based (refer also to Beven, 2000; Savenije, 2010). The DDD model is, to a large degree, parameterized from CCs (i.e. distance distributions of landscape elements considered to be important for run-off dynamics such as soils, bogs and the river network) determined from GIS. The parameters in DDD all have a clear physical meaning and are relatively few such that the limited information available (the CCs) may reasonably be expected to determine them. The number of parameters to be calibrated in DDD is considerably reduced compared with the parameter regime of the widely used HBV model that, incidentally, has a reputation as parsimonious (Savenije, 2010). DDD has one calibration parameter in the run-off module compared with seven in the HBV model.

This study was initiated in order to solve a very specific problem, namely that of providing hydrological time series so that biologists could study the interactions between the environment and character species, which is usually investigated by relating averages of large-scale environmental variables to small-scale observations of species ecology. An example of such a study is that of Nilsson *et al*. (2011) on the white-throated dipper (WTD; *Cinclus cinclus*), a visual predator of submerged macro-invertebrates and therefore totally dependent on running clean fresh water. Population fluctuations of the WTD were correlated with the North Atlantic Oscillation Index, average winter temperature, winter precipitation and the timing of ice formation on a nearby lake. Whereas these variables explained the temporal variability in the population dynamics in the region well (84% of the variance is explained), they contain little information on how the key local environment, local stream flow dynamics, influences the ecology and evolution of the birds. The WTD is territorial during breeding and occupies breeding sites located at river stretches along the main river as well as at small tributaries with more variable stream flow regimes. Information on local stream flow dynamics is restricted to gauged sites and usually spatially distant from most of the study population's locations; hence, techniques for modelling stream flow for ungauged sites, or for making PUB, are needed.

The research objectives of this study are as follows:

1. To investigate whether the parsimonious use of calibration parameters in the DDD model has the desired effect in parameter identifiability such that we come closer to the ideal put forward by Parajka *et al.* (2013): 'ideally the relationship between the model parameters and the catchment characteristics should be hydrologically justifiable to give confidence for extrapolation to ungauged basins'
2. To investigate how well DDD can predict in ungauged basins using regionalized parameters.
3. To investigate whether failure in predicting in ungauged basins can reveal weaknesses in model structure or parameterizations.
4. To provide and evaluate time series of hydrological elements for ungauged basins where breeding pairs of the WTD are observed.

DATA AND STUDY AREA

The target area for this study is the Lygne basin situated in southern Norway (Figure 1a). The Norwegian Water Resources and Energy Directorate (NVE) operates two stream gauges, Møska and Tingvatn, in this basin. The size of the entire basin is 1146 km^2, whereas the size of the catchments Møska and Tingvatn is 121.3 and 272.2 km^2 respectively.

The breeding biology of the WTD in the Lygne basin has been monitored at 145 breeding sites since 1978 (Nilsson *et al.*, 2011; Figure 1b). A breeding site contains at least one

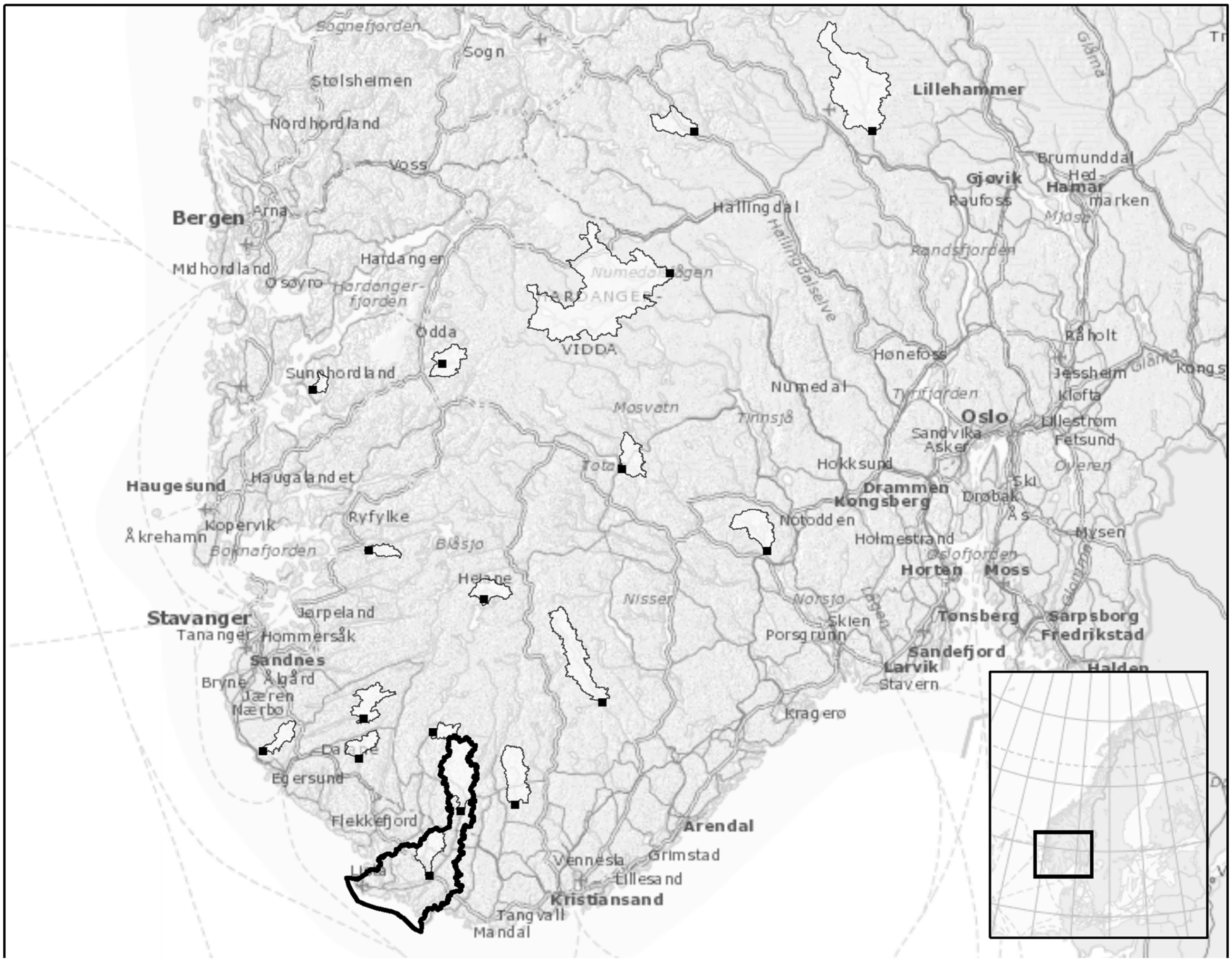

Figure 1. a. Map of study area, southern Norway with the Lygne basin (black solid line) and the 17 control catchments (outlet marked with a black square) that are not part of the set of calibrated catchments used to train the multiple regression equations. b. The Lygne basin with the locations of the breeding sites (black triangle) of the white-throated dipper

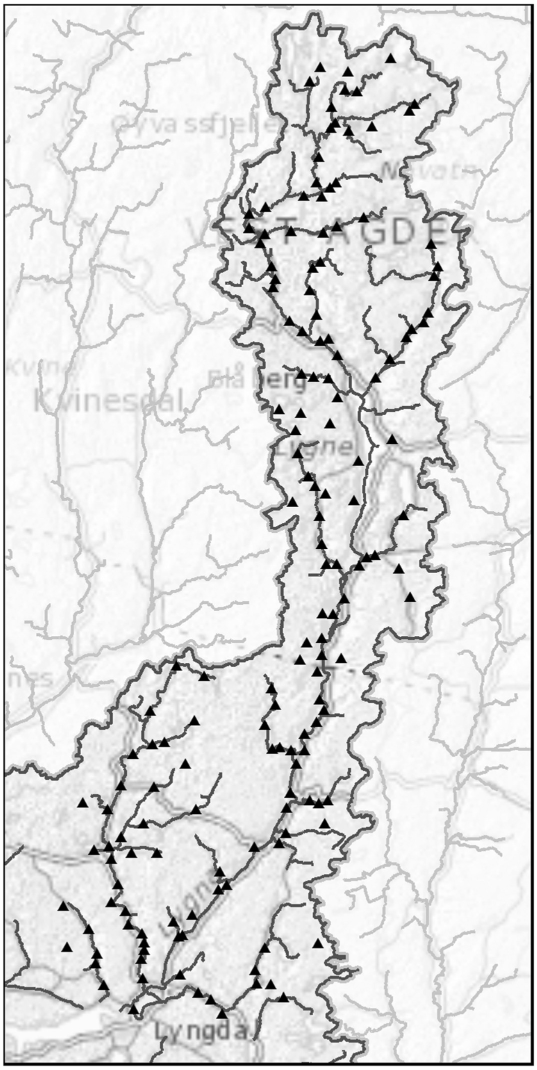

Figure 1. (Continued)

nest site, often more, and the most used nest site is defined here as the main nest site at each breeding site. The WTD build their nests in the immediate vicinity of running water (Nilsson *et al*., 2011) because the nest openings need to be located directly above running water to flush away all traces of the nestlings' activities and thereby avoid nest predation. The breeding site catchments (BSCs) are thus relatively easy to define using GIS.

The 25×25-m national terrain model (www.statkart.no) was used and adjusted to the national river network at NVE (at scale 1 : 50 000) to create a national hydrologically correct terrain model. This was further used to calculate both flow direction and flow accumulation. The main nest site points were first snapped (with a 25-m maximum) to the nearest stream in the river network to allow for differences in accuracy between the breeding site coordinates and the river network. These points were used together with the flow direction raster in a watershed function to calculate the BSCs upstream from the breeding sites. A suite of physiographic CCs has been extracted through GIS for the 145 BSCs.

The DDD model has been calibrated for 101 catchments in Norway, including Møska and Tingvatn, for flood forecasting purposes. Out of this set, 84 catchments are the potential maximum number of catchments from which we can derive relations between CCs and model parameters. Among the catchments located in southern Norway, 17 catchments were kept out of the regression analysis so that the ability of DDD to predict in ungauged basins could be tested on an independent data set. The set of 17 catchments includes Møska and Tingvatn and represents a variety in regard to catchment size (32–1177 km^2) and mean elevation (187–1345 masl). The CCs extracted for the BSCs were also extracted for all the flood forecasting catchments (FFCs).

Input data to the DDD model, daily precipitation and temperature are extracted for all FFCs and BSCs from interpolated meteorological grids ($1 \times 1\ km^2$) that provide daily values of precipitation and temperature for all of Norway from 1957 to present (www.senorge.no).

Figure 2 shows histograms of the relevant CCs extracted for FFCs and BSCs. The CCs presented in Figure 2 are all found, through the regression analysis, to contribute significantly in the multiple regression equations (MREs) used for estimating the model parameters (refer to Equations (2–8) in the Results section). A much larger set of CCs is routinely extracted using GIS at NVE, and this set has been the basis for previous regionalization tasks such as a low-flow map (Engeland *et al*., 2008) and an annual discharge map (Beldring *et al*., 2003). A new characteristic is, however, the mean of the distance distribution used for characterizing unit hydrographs used in the DDD model (refer to the next section for a description of the hydrological model).

It is clearly seen that there is a high frequency of very small catchments ($<20\ km^2$) amongst the BSCs compared with the FFCs (Figure 2d). This is also seen in Figure 2a and f that show the mean of the distance distribution and catchment length respectively. A substantial fraction of the FFCs are located at high altitudes that result in a higher fraction of bare rock compared to the BSCs. CCs such as lake and bog are similarly distributed for FFCs and BSCs.

METHODS

In evaluating objective 1, we will compare correlations between model parameters and CCs with those obtained from similar studies using other hydrological models. Regressing model parameters with CCs is the only method that we will employ for the regionalization of model parameters because parameter identifiability is an objective.

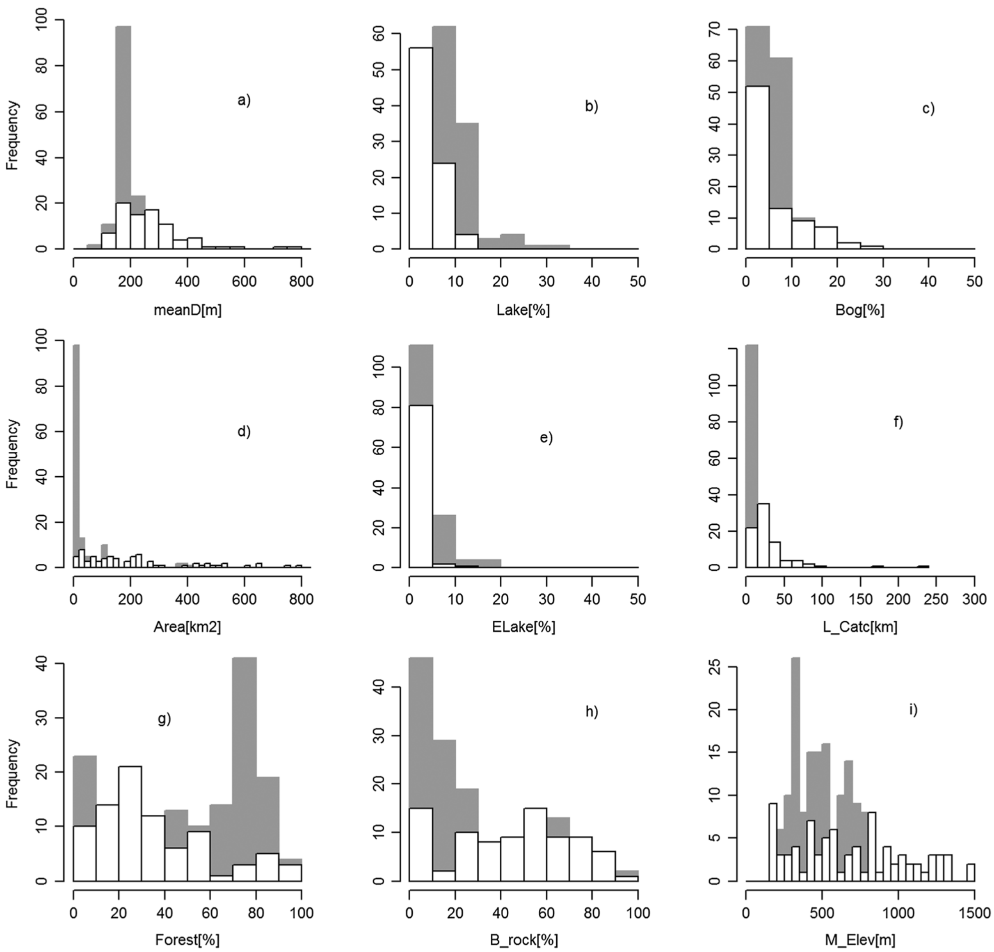

Figure 2. Histograms of the catchment characteristics for the breeding site catchments (BSCs; shaded bars) and for the 84 catchments for which the DDD model has been calibrated (unshaded bars)

For objective 2, we will compare the performance of DDD using regionalized parameters (DDD-PUB) with the performance of DDD with calibrated parameters (DDD-CAL). The definition of successful PUB in this paper is that the DDD-PUB simulates with precision as close as possible to DDD-CAL. This measure of success is also used in previous studies (Seibert, 1999; Young, 2006). It is not expected that DDD-PUB can do a better simulation than the calibrated model, although at some locations, the regressed parameters might be a better representation than those observed because of errors in observations.

For objective 3, we will attempt to link the deviations in performance between DDD-PUB and DDD-CAL for gauged catchments to either model structure or parameterizations. Hence, the quest for successful PUB can also be used to highlight model weaknesses and point in the right direction for model improvements.

The success of objective 4 will not be completely assessed in this study. In order to assess the performance of DDD for the truly ungauged catchments, the breeding sites of the WTD, we will use dynamic characteristics of flow (DCF) suggested by Yadav *et al.* (2007) to determine whether the simulations are behavioural, i.e. are probable predictions of run-off. The DCF used are high flow (i.e. high pulse count, refer to Clausen and Biggs (2000), medium flow (the run-off ratio, e.g. run-off/precipitation) and low flow (the slope of the flow duration curve, e.g. Searcy (1959)). The high-flow characteristic is considered especially important as a constraint on biota in perennial temperate rivers (Clausen and Biggs, 2000) and hence supposedly the breeding success of the WTD, although Lytle and Poff (2004) point out that both floods and droughts are important in regulating water-dependent population sizes. Whether the simulated time series are of sufficient quality to explain temporal variability in population dynamics will be assessed in a future paper.

Hydrological model

The DDD model (Skaugen and Onof, 2014) is a rainfall–run-off model that is coded in the programming language R (www.r-project.org) and currently runs operationally at daily and 3-h time steps at the Norwegian flood forecasting service. Inputs to the model are precipitation and temperature derived from gridded weather maps. The current version of DDD differs from the Nordic HBV model (Sælthun, 1996) in its description of the subsurface and run-off dynamics. In the subsurface module, the volume capacity of the subsurface water reservoir *M* is shared between a saturated zone with volume *S*, called the groundwater zone, and an unsaturated zone with volume *D*, called the soil water zone. The actual water volume present in the unsaturated zone, *D*, is called *Z*.

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*), represents more water than field capacity, *R*, which is set to 30% (*R* = 0.3). If so, excess water, *X*(*t*), is added to *S*(*t*). To summarize,

Excess water:

$$X(t) = Max\left\{\frac{G(t) + Z(t)}{D(t)} - R, 0\right\}D(t) \qquad \text{(1a)}$$

Groundwater:

$$\frac{dS}{dt} = X(t) - Q(t) \qquad \text{(1b)}$$

Soil water content:

$$\frac{dZ}{dt} = G(t) - X(t) - Ea(t) \qquad \text{(1c)}$$

Soil water zone:

$$\frac{dD}{dt} = -\frac{dS}{dt} \qquad \text{(1d)}$$

where *Q*(*t*) is run-off. Actual evapotranspiration, *Ea*(*t*), is estimated as a function of potential evapotranspiration and the degree of saturation. Potential evapotranspiration is estimated as $Ep = \theta_{cea} * T$ (mm/day), where θ_{cea}(mm/°C day) is the degree–day factor that 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*.

M is a calibration parameter, but the equations for the run-off dynamics are completely parameterized from observed catchment features derived using GIS and run-off recession analysis. Water is conveyed through the soil to the river network by waves with celerities determined by the level of saturation in the catchment. The celerities for the different levels of saturation are estimated by assuming exponential recessions with parameter Λ, which varies according to the degree of saturation. The quantiles of the distribution of Λ is then assumed to match the quantiles of saturation, i.e. $F(\Lambda) = \frac{S}{M}$. The celerity v_h (m/s) is associated with the parameter Λ as $v_h = \Lambda\overline{d}/\Delta t$, where $\overline{d}$ is the mean of the distribution of distances between points in the catchment to the nearest river reach. The variable $\overline{d}$ can be viewed as a measure of river network density. This distance distribution and that of the river network, measured from points in the river network to the outlet give, together with the celerities, distributions of travel times and consequently unit hydrographs. These unit hydrographs give the temporal distribution of the run-off response to input of rain and snowmelt. The experience of using the DDD model shows that the subsurface water reservoir *M* controls the variability of the hydrograph to a large degree. Low values of *M* increases the amplitude of the hydrograph because the entire range of the celerities is engaged, and vice versa.

Recent developments of DDD include modelling the distribution of Λ using a two-parameter gamma distribution (instead of a one-parameter exponential distribution), and bogs are now included in the model and treated as an area of overland flow when saturated and a non-contributing area when not saturated. A distance distribution has been calculated for the bog area within the catchment, and water is conveyed to the nearest river reach when the bog is saturated with celerity equal to that of the estimated overland flow (the 99% quantile of the celerity distribution). Figure 3 shows the structure of the DDD model, and further details can be found in Skaugen and Onof (2014).

Table I shows the parameter file of DDD. Seven parameters need to be estimated from relationships between model parameters and CCs. Model parameters are hereafter denoted by θ with subscripts in order to clearly distinguish them from CCs.

Model parameter regionalization

The general method for the regionalization of model parameters in this study is classic and similar to a number of other studies, e.g. Yadav *et al*. (2007), Young (2006), Merz and Blöschl (2004) and Seibert (1999). The DDD model is automatically calibrated against run-off using an R-based Monte Carlo Markov chain routine (Soetart and Petzholdt, 2010) for a number of catchments (in this case, 101 catchments). The calibrated and estimated model parameters are subsequently related to climatic and physiographic CCs through multivariate regression. The model parameters for the ungauged catchments are then estimated using the regression equations. A certain calibration on the parameter correcting the precipitation input, θ_{Pc}, is carried out, tuning it so that the simulated mean annual discharge (MAD) is equal to the observed mean annual run-off at each of the 17 control catchments. When simulating for the BSCs, θ_{Pc} is tuned so that the

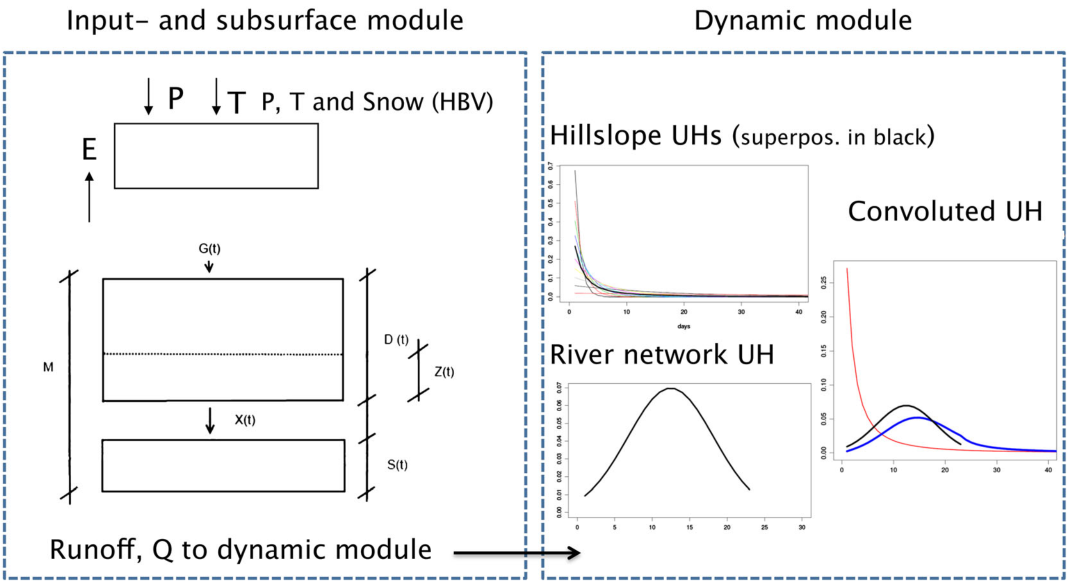

Figure 3. Structure of the DDD model

simulated MAD for the BSCs is equal to the regional estimate determined as the average MAD for Møska and Tingvatn because they are located inside the target area. In using this procedure for the BSCs, we assume that MAD is a variable that exhibits little variation in the target area, an assumption that is supported by the almost identical specific MAD for Møska, 58.1 (l/s km^2), and Tingvatn, 58.5 (l/s km^2), estimated from the record of daily run-off values from 1978 to 2012. The MAD thus represents the only available information on which we may condition the long-term water balance when predicting for the ungauged basins. A direct measure of goodness of fit such as the Nash–Sutcliffe efficiency (NSE) criterion (Nash and Sutcliffe, 1970) for the simulations for the individual BSCs is, of course, not available.

The calibrated performance of DDD for the FFCs varies for several reasons, including model structure uncertainty, the quality of the meteorological input data (precipitation and temperature) and the quality of measured run-off data. Given this variability in performance, the question of whether we should attempt to derive the regression relationships between CCs and model parameters from a subset of the FFCs, for example, a subset of well-performing models, can be posed. In assuming that DDD performs well, for the right reasons (refer to Kirchner, 2006) and hence that the parameter values are well defined, doing the regression analysis on such a subset could provide good results. A possible risk is that the subset does not carry sufficient information for covering the entire range of combinations of CCs, and we may overfit the regression models. Another aspect is that there are still parameters in the DDD model, especially related to snowmelt, that when calibrated, can take on rather non-physical values, suggesting a degree of non-identifiability of parameters and a tendency for calibrated parameters to compensate for model structure and parameter errors. Such parameters are, for example, the degree–day factor for snowmelt, θ_{CX}, the threshold temperature for snowmelt, θ_{TS}, the threshold temperature for solid/liquid precipitation, θ_{TX}, and the capacity of snow to contain liquid water, θ_{Ws}, (Table I). Given such problems, a regional subset of FFCs may be favourable, suggesting that spatial proximity, as well as the CCs, also has an influence on the parameters to be estimated (refer to Merz and Blöschl, 2004; Blöschl *et al.*, 2013 and Parajka *et al.*, 2013). We settled on three different sets of calibrated catchments as the basis for deriving the regression equations predicting model parameters from the CCs.

Set 1 Parameters from all 84 calibrated DDD models were used to relate model parameters to CCs.

Set 2 Parameters from the subset of calibrated DDD models where the *NSE* from the validation data set had to exceed 0.65 together with the constraint that the estimated shape and scale parameters of the subsurface celerity distribution (θ_{Gsh} and θ_{Gsc}, Table I) estimated from the calibration and validation set of run-off data should not deviate more than 25%. These constraints provided us with a subset of 22 calibrated models from which we could relate model parameters and CCs.

Set 3 Parameters from 16 of the calibrated DDD models located in the region of southern Norway close to the target area were used to relate model parameters to CCs.

Table I. Parameters of the DDD model with comments and method of estimation

Parameter	Comment	Method of estimation	Value	Reference
Hypsographic curve	11 values describing the quantiles 0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100	GIS		
$\boldsymbol{\theta_{Ws}}$ (%)	Max liquid water content in snow	Within recommended range for the HBV model	5	Sælthun (1996)
Hfelt	Mean elevation of catchment	GIS		
$\boldsymbol{\theta_{Tlr}}$ (°C/100 m)	Temperature lapse rate(per 100 m)	Within recommended range for the HBV model	−0.65	Sælthun (1996)
$\boldsymbol{\theta_{Plr}}$ (mm/100 m)	Precipitation gradient (mm per 100 m)	Within recommended range for the HBV model	0.01	Sælthun (1996)
$\boldsymbol{\theta_{Pc}}$	Correction factor for precipitation	Calibrated to give mean annual specific discharge of region		
$\boldsymbol{\theta_{Sc}}$	Correction factor for precipitation as snow	Regressed with $\boldsymbol{\theta_{Pc}}$		
$\boldsymbol{\theta_{TX}}$ (°C)	Threshold temperature rain/snow	Standard value	1.0	Sælthun (1996)
$\boldsymbol{\theta_{TS}}$ (°C)	Threshold temperature melting/freezing	Standard value	0.0	Sælthun (1996)
$\boldsymbol{\theta_{CX}}$ (mm/°C/day)	Degree–day factor for melting snow	Regressed		
$\boldsymbol{\theta_{CFR}}$ (mm/°C/day)	Degree–day factor for freezing	Within recommended range for the HBVmodel	0.02	Sælthun (1996)
Area (m^2)	Catchment area	GIS		
maxLbog (m)	Max of distance distribution for bogs	GIS		
midLbog (m)	Mean of distance distribution for bogs	GIS		
Bogfrac	Fraction of bogs in catchment	GIS		
Zsoil	Areal fraction of zero distance to the river network for soils	GIS		
Zbog	Areal fraction of zero distance to the river network for bogs	GIS		
$\boldsymbol{\theta_{NOL}}$	Number of saturation levels	Standard value	5	Skaugen and Onof (2014)
$\boldsymbol{\theta_{cea}}$ (mm/°C/day)	Degree–day factor for evapotranspiration	Regressed		
$\boldsymbol{\theta_{R}}$	Ratio defining field capacity	Standard value	0.3	Skaugen and Onof (2014)
$\boldsymbol{\theta_{Gsh}}$	Shape parameter of gamma distributed celerities	Regressed		
$\boldsymbol{\theta_{Gsc}}$	Scale parameter of gamma distributed celerities	Regressed		
$\boldsymbol{\theta_{CV}}$	Coefficient of variation for spatial distribution of snow	Regressed		
$\boldsymbol{\theta_{rv}}$ (m/s)	Mean celerity in river	Standard value	1.0	Skaugen and Onof (2014)
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		
$\boldsymbol{\theta_{M}}$ (mm)	Max subsurface water reservoir	Regressed		
$\overline{d}$ (m)	Mean of distance distribution for hillslope	GIS		
d_{max} (m)	Max of distance distribution for hillslope	GIS		

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). Other parameter values are assigned standard values as suggested in the literature. The GIS analyses are carried out using the national 25 × 25-m digital elevation model (www.statkart.no).

Correlation analysis

An exploratory correlation analysis between model parameters and CCs was carried out for the three data sets. Spearman rank correlation was used because this is more robust and presupposes no fixed shape of possible functional relationships (Seibert, 1999). Figure 4 shows the correlations. The points in the plots are scaled for significance: Large points signify significant correlations (refer to legend in Figure 4i).

RESULTS

Relations between CCs and model parameters

The correlations between model parameters and CCs are not very high (Figure 4), but several are found to be significant. Two relationships come out quite clearly with high, significant correlations, that of the correlation between the areal percentage of lakes, *% Lake*, (or effective lake, *% ELake*, which takes into account the location of the lake in the catchment) and θ_M (Figure 4b and e) and that of

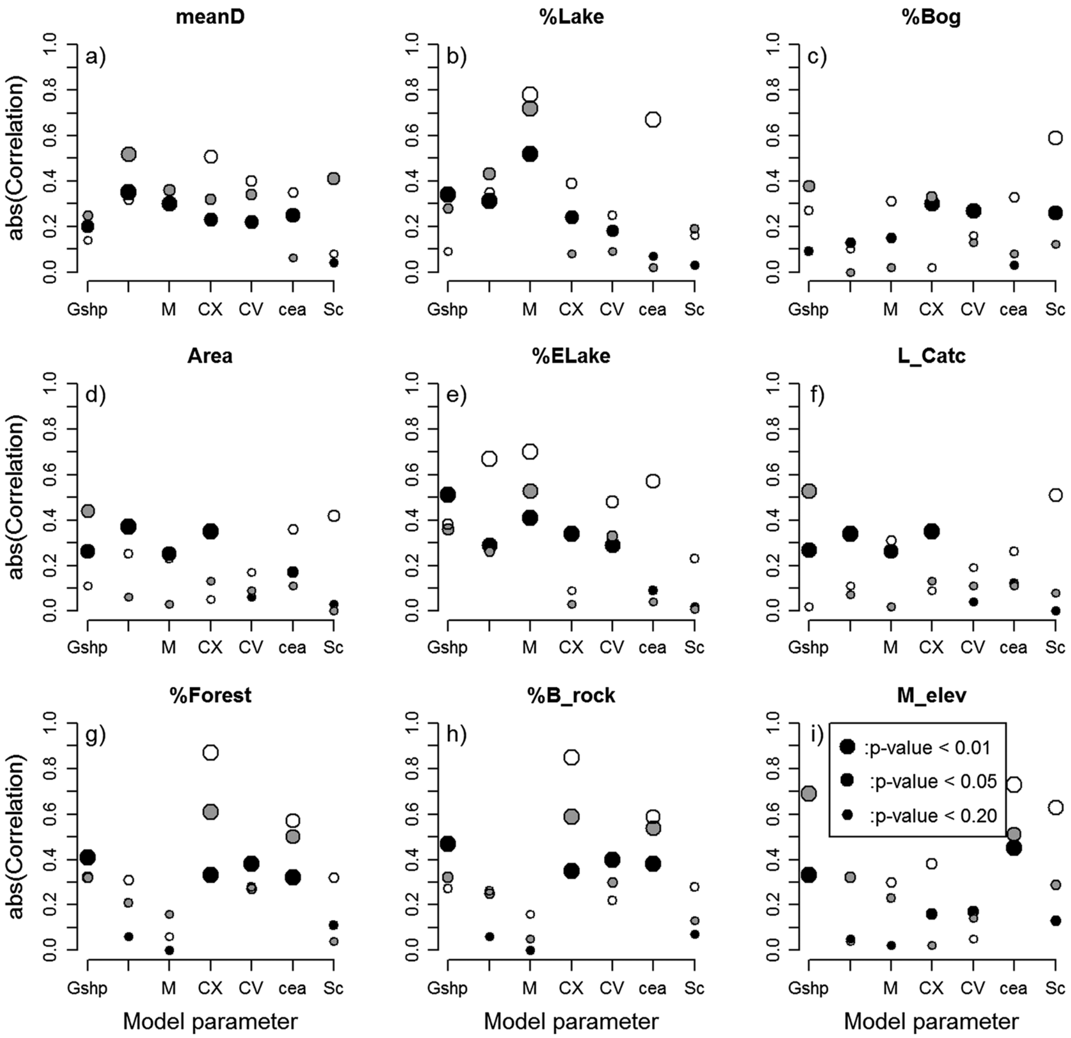

Figure 4. Correlations between model parameters and catchment characteristics for set 1 (black filled circles), set 2 (grey filled circles) and set 3 (white filled circles). The circles are scaled according to significance (p-value, Figure 4 i))

the correlation between the percentage of forest and bare rock with θ_{CX} (Figure 4g and h). We also note that although the correlations for set 1 are often lower than those for sets 2 and 3, we clearly see more significant correlations for set 1, suggesting that more robust regression models may be found using set 1.

MREs estimating model parameters were determined for sets 1–3. Different combinations of the CCs presented in Figure 2 were used. Each CC had to contribute significantly (with a p-value < 0.05) in order to be included in the regression equation. Table II shows the coefficient of determination (multiple R^2) and their significance (p-value) for the different data sets. We see that sets 2 and 3 have a higher coefficient of determination than set 1, but the p-values for set 1 are the lowest for all model parameters.

We also tested the ability of the MREs derived from the different data sets to estimate model parameters for the BSCs. The histograms in Figure 2a–i show that the CCs for the BSCs take on different values than that for the FFCs. It will hence be a measure of robustness of our

Table II. Coefficient of determination (multiple R^2) and their significance (p-value) in brackets for the multiple regression equations relating catchment characteristics to model parameters for the data sets 1–3

Model parameters	Set 1 (84 catchments)	Set 2 (22 catchments)	Set 3 (16 catchments)
θ_{Gsh}	0.45 (0.0000)	0.53 (0.0008)	0.58 (0.0037)
θ_{Gsc}	0.35 (0.0000)	0.62 (0.0005)	0.63 (0.0015)
θ_M	0.40 (0.0000)	0.64 (0.0000)	0.48 (0.0029)
θ_{CX}	0.52 (0.0000)	0.67 (0.0001)	0.78 (0.0002)
θ_{CV}	0.23 (0.0000)	0.35 (0.0158)	0.40 (0.0371)
θ_{cea}	0.32 (0.0000)	0.36 (0.0029)	0.82 (0.0000)
θ_{Sc}	0.20 (0.0002)	0.23 (0.0813)	0.61 (0.0004)

method if the MREs derived from the different data sets produce model parameters that are behavioural (for example, that there are no illegal values such as negative parameters for the gamma distribution). In Figure 5, we show the estimated model parameters for the BSCs using MREs from sets 1–3 compared with those obtained from the 17 calibrated control catchments. We see that the model parameters estimated using the MREs from set 1 are both (i) all behavioural and (ii) closer to those obtained from the calibrated control catchments. Both set 2 and set 3 produce negative values for the scale parameter of the celerity distribution, θ_{Gsc}, and negative values for the θ_{CV} of the snow distribution. Set 2 also gives unrealistic values of θ_M. From these results, it was decided to proceed with the MREs obtained from set 1. Equations (2–8) show the MREs for the model parameters derived from set 1.

$$\theta_{Gsh} = 1.128 + 0.068*\%ELake - 0.003*\%B_{rock} \quad (2)$$

$$\theta_{Gsc} = 0.757 - 0.079*\log(\overline{d}) - 0.025*\log(\%ELake) - 0.042\log(C_len) \quad (3)$$

$$\theta_M = 4.925 - 0.129*\log(\overline{d}) + 7.15*\%Lake \quad (4)$$

$$\theta_{CX} = \exp\big(4.82 - 0.456*\log(\overline{d}) - 0.107*\log(\%Bog) + 0.000115* Area - 0.009*\ C_len - 0.014*\%Forest - 0.007*\%B_{rock} \quad (5)$$

$$\theta_{CV} = 0.228 - 0.0255\log(\%ELake) + 0.0025*\%B_{rock} \quad (6)$$

$$\theta_{cea} = \exp(0.047\mp 0.005*\%Forest - 0.304*\log(M_{elev}) \quad (7)$$

$$\theta_{Sc} = \exp(-0.0965 - 0.072\log(\%Bog) + 0.339*\log(\theta_{Pc})) \quad (8)$$

Most of Equations (2–8) are quite simple involving only two or three CCs. The MRE for the degree–day factor for snowmelt, θ_{CX}, (Equation 5) is the exception. The equation is very complex and quite probably overfitted. Multicolinearity may also be a problem in Equation 5 because obviously correlated CCs (*% Area* and *C_len*) are included in the equation. This is not the case in the other equations. We note that CCs describing lake percentage and drainage density (*% Lake*, *% ELake* and $\overline{d}$) are important for the run-off dynamics, whereas CCs describing landscape types (*% Forest*, *% B_rock*- and *% Bog*) are important for describing snow distribution, snowmelt and evapotranspiration.

Predictions for the 17 control catchments

For the 17 control catchments, we can directly compare the performance of DDD with model parameters estimated using the MRE from set 1 (DDD-PUB) with the performance of DDD calibrated to run-off observa-

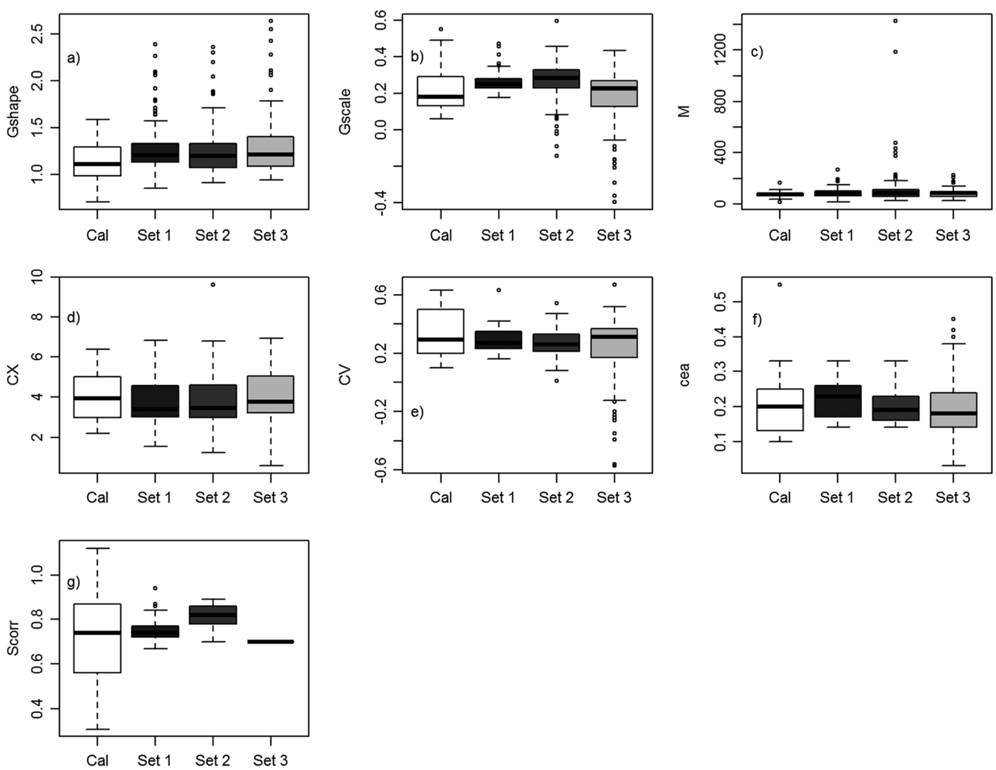

Figure 5. Model parameters estimated for the breeding site catchments (BSCs) for data sets 1–3 compared with those calibrated for the 17 control catchments (denoted as Cal in the figure)

tions (DDD-CAL). DDD-CAL has been calibrated for a data set with records from the period 1995–2011 and validated with a data set with records from the period 1981–1995. DDD-PUB is evaluated for both data sets. Table III shows the performance measured with the NSE. The difference in NSE between DDD-PUB and DDD-CAL is less than 0.1 for ten out of the 17 catchments for both the calibration and validation data set. Four out of the 17 catchments have NSE differences higher than 0.2. The median NSE for DDD-PUB for the two data sets is NSE = 0.72 (calibration data set) and NSE = 0.66 (validation data set). We also note that for the catchments located within the target area, Tingvatn and Møska, the NSE for DDD-PUB is very good, NSE = 0.83–0.86.

Prediction performance versus parameterizations

To investigate why DDD-PUB works well for some catchments and poorly for others, we conducted an analysis where we relate the deviations in NSE results between DDD-CAL and DDD-PUB to deviations between calibrated and fixed/regressed model parameters. Deviations in NSE from both the calibration and validation data sets were assessed. An exploratory correlation analysis showed generally low correlations and high *p*-values (Table IV). In a regression analysis, we searched for the number of significant predictors that explained as much as possible the variability of the deviations in NSE. We adopted a forward approach starting with the predictor most correlated to ΔNSE_{Cal} that according to Table IV is ΔCV. Predictors were added and retained if they contributed significantly (*p*-values 0.05) to the regression equation for both series of ΔNSE. This procedure shows that the deviations between the calibrated and fixed/regressed parameters θ_{CV}, θ_{CX} and θ_{TS} best explained the deviations in NSE between DDD-CAL and DDD-PUB. The coefficients of determination were $R^2 = 0.66$ (p-value = 0.002) and $R^2 = 0.69$ (p-value = 0.001) for the calibration and validation data sets respectively. This split-sample forward procedure for regression analysis proved to be a relatively quick way to determine the significant predictors and is suggested as a procedure for testing the reliability of regression models by Kleinbaum *et al.* (2008, p. 398)

Table III. Performance (NSE) for calibrated DDD (DDD-CAL) and DDD model with regionalized parameters (DDD-PUB) for the 17 control catchments for calibration (cal) and validation (val) data sets

Catchment	DDD-CAL_cal	DDD-CAL_val	DDD-PUB_cal	DDD-PUB_val
Etna	0.88	0.79	0.78 (0.1)	0.67 (0.12)
Orsjoren	0.83	0.88	0.29 (0.54)	0.6 (0.28)
Tansvatn	0.86	0.86	0.63 (0.23)	0.66 (0.2)
Horte	0.7	0.66	0.68 (0.02)	0.62 (0.04)
Austenaa	0.83	0.71	0.81 (0.02)	0.64 (0.07)
Myglevatn	0.83	0.81	0.78 (0.05)	0.73 (0.08)
Møska	0.9	0.85	0.86 (0.04)	0.83 (0.02)
Tingvatn	0.91	0.91	0.83 (0.08)	0.85 (0.06)
Knabaani	0.66	0.66	0.57 (0.09)	0.57 (0.09)
Aardal	0.86	0.81	0.83 (0.03)	0.83 (0.02)
Bjordal	0.78	0.74	0.7 (0.08)	0.63 (0.11)
Hetland	0.8	0.76	0.78 (0.02)	0.74 (0.02)
Djupadalsvatn	0.83	0.78	0.81 (0.02)	0.75 (0.03)
Djupevad	0.57	0.55	0.52 (0.05)	0.49 (0.06)
Reinosvatn	0.76	0.7	0.53 (0.23)	0.37 (0.33)
Gjuvvatn	0.81	0.76	0.3 (0.51)	-0.1 (0.86)
Storeskar	0.86	0.89	0.72 (0.14)	0.77 (0.12)
Median NSE	0.83	0.78	0.72	0.66

The deviation in NSE between DDD-CAL and DDD-PUB is found in brackets in columns 4 and 5.

Table IV. Correlations (Spearman) between deviations of NSE between calibrated DDD model (DDD-CAL) and DDD model with regionalized parameters (DDD-PUB) with deviations between calibrated and fixed/regressed model parameters

Parameter	ΔNSE_{Cal}	ΔNSE_{Val}
ΔW_s	−0.27 (0.30)	−0.17 (0.52)
ΔT_{LR}	−0.38 (0.14)	−0.10 (0.55)
ΔP_{LR}	0.35 (0.17)	0.25 (0.33)
ΔP_C	0.48 (0.05)	0.50 (0.04)
ΔS_C	−0.38 (0.13)	−0.40 (0.11)
ΔTX	−0.30 (0.25)	−0.11 (0.67)
ΔTS	0.17 (0.51)	0.16 (0.53)
ΔCX	−0.24 (0.35)	−0.26 (0.31)
ΔCV	0.56 (0.02)	0.53 (0.03)
Δcea	0.28 (0.27)	0.30 (0.24)
ΔGsh	−0.42 (0.09)	−0.42 (0.09)
ΔGsc	−0,16 (0.55)	−0.16 (0.55)
Δrv	−0.07 (0.78)	−0.06 (0.81)
ΔM	0.22 (0.41)	0.13 (0.63)

p-values for the correlation are in brackets.

Predictions for the BSCs

In order to evaluate the predictions for the truly ungauged catchments, the BSCs, we used hydrological indices that can be assessed for the ungauged catchments without using measured run-off to see whether the hydrological simulations for the BSCs fall within reasonable ranges for these indices. We have chosen the indices suggested by Yadav *et al.* (2007), the slope of the flow duration curve at 30 and 70% to describe the medium flow, the high pulse counts (threshold is set to three times the median flow) for high flows and the run-off ratio (run-off/precipitation) for low flows. Figure 6 shows box plots of the indices for the BSC and the control catchments. We see that the indices computed for the BSCs are well within the range determined by observed run-off at the 17 control catchments for the rainfall ratio (Figure 6a) and for the slope of the flow duration curve

(Figure 6b). For the high pulse count (Figure 6c), there is a slightly larger range for high values.

DISCUSSION

The correlation analysis of relationships between CCs and model parameters shows significant but not very high correlations (Figure 4). It appears that using the set of 84 catchments (set 1) for relating CCs to model parameters provides many significant correlations, and some are quite high. The most convincing correlation is that of the capacity of the subsurface reservoir, θ_M, and the lake characteristics, *% Lake* and *% ELake*. This is as expected, given that a large subsurface reservoir (i.e. large θ_M) dampens the amplitudes of the hydrograph, which is also a well-known effect of lakes. The CCs that are related to the size of the catchment (*% Area* and *C _ len*) and the lake characteristics (*% Lake* and *% ELake*) are all significantly correlated with the parameters of the distribution of subsurface celerity (θ_{Gsh} and θ_{Gsc}). This is also hydrologically justifiable in that increasing catchment size and the presence of lakes will dampen the variability of saturation and hence, according to the assumptions used in deriving the basis for the DDD model, the variability of subsurface celerity. The parameters related to snow accumulation, snowmelt and evapotranspiration, (θ_{CX}, θ_{CV}, θ_{Sc} and θ_{cea}) are significantly correlated to descriptions of landscape types (*% Bog*, *% Forest* and *% B _ rock*). This is also a realistic result because it is well known that the spatial distribution of snow and especially evapotranspiration is related to landscape types (e.g. Dingman, 1994). According to Figure 4, all model parameters are significantly correlated with some CC. This result differs from studies where more parameter-rich hydrological models are used. In Seibert (1999), only six out of the 13 parameters in the HBV model were found to be related to CCs, and in Merz and Blöschl (2004), rather weak correlations were found between CCs and model parameters of the HBV model, but no measure of significance was given. In Peel *et al.* (2000), only one out of seven parameters in the SIMHYD model was found to be significantly correlated to CCs when analysing 331 catchments from various climatic regions in Australia. More parameters, however, were significantly correlated with climatic characteristics.

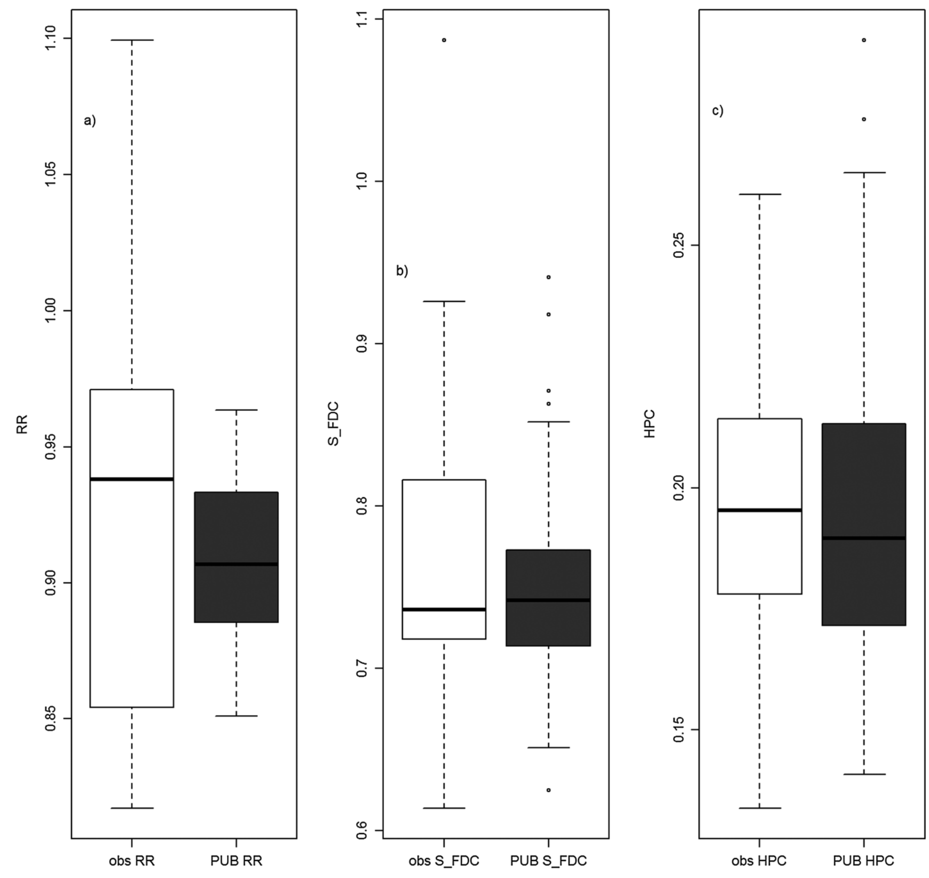

Figure 6. Box plots showing the hydrological indices (a) run-off ratio, (b) slope of flow duration curve and (c) high pulse count. The white box shows results for observed run-off at the 17 control catchments, whereas the grey box shows results for simulated run-off at the breeding site catchments (BSCs)

The median NSE for DDD-PUB for the 17 catchments is 0.72 for the calibration data set and 0.66 for the validation data set. The difference for the calibration and validation data sets is because of DDD-PUB being 'calibrated' to produce a MAD equal to that of the calibration data set. The median NSE results in the present study compare very well with those reported for cold climate in the meta-study of PUB by Parajka *et al*. (2013). In this study, we find the compilation and comparisons of results from nine studies on prediction in ungauged basins for cold climate. Out of the nine studies, eight were carried out using the HBV model. The results from the present study would have ranked amongst the best 30% if they were included in Parajka *et al*. (2013, Figure 2 therein). Of course, the studies are not directly comparable, but, nevertheless, the results presented here are encouraging.

The analysis where deviations in NSE between DDD-CAL and DDD-PUB were related to deviations between calibrated and fixed/regressed model parameters is helpful in designing the strategy to improve the model structure. It is interesting that the analysis concludes that the most possible reason for poor results of DDD-PUB is related to the parameterization of the spatial distribution of snow (θ_{CV}) and snowmelt (θ_{CX} and θ_{TS}). These are exactly the modules identified in the DDD model where further reduction of calibration parameters is due. In Skaugen and Randen (2013), a procedure for estimating the spatial variability of snow was suggested. The procedure is parameterized solely from the observed spatial variability of precipitation (liquid and solid) and calculates the spatial frequency distribution of snow water equivalent (SWE). Implementing this new procedure in the DDD model is in progress and will replace the current procedure that uses the calibrated coefficient of variation of the lognormal distribution (θ_{CV}) to express the spatial frequency distribution of SWE. An energy balance approach may be a suitable alternative model for snowmelt that enables us to replace the parameters θ_{CX} and θ_{TS}. Several such models exist (Liston, 1995; Tarboton and Luce, 1996; Walter *et al*., 2005). Ongoing work at NVE strives to implement an energy balance approach to snowmelt in DDD that uses only precipitation and temperature as input and calculates other important variables, such as wind and radiation, either as fixed regional estimates or as functions of precipitation and temperature. Precipitation and temperature are the only variables for which we have a reliable supply of updated time series from the whole of Norway.

Another interesting aspect of the analysis of deviations is that the parameters in the DDD model that are identified from GIS (the distance distributions) do not appear to be the source of deviations in the NSE between DDD-CAL and DDD-PUB. The same argument can be used regarding the celerities of the subsurface flow that are estimated from run-off recession analysis for DDD-CAL and from MREs for the DDD-PUB model. Also, deviations in these parameters do not explain the deviations in NSE. These results give confidence in the model structure of DDD. If the model structure represented by these parameters was seriously flawed, one would expect deviations in these parameters to explain the observed deviations in the NSE. The parameters significantly explaining the deviations, however, are the parameters left in DDD that clearly have 'effective' properties, i.e. they represent a range of processes and scales and can compensate for structural model errors.

The NSE values for DDD-CAL and DDD-PUB are similar, and, for the two catchments located in the centre of the target area Tingvatn and Møska, the DDD-PUB results are very good (NSE $=0.83$–0.86), lending credibility to the simulations for the BSCs. We note that the NSE for these two catchments is very high for the calibrated model, signifying well-behaved catchments with respect to hydrological response and good-quality data (Table III). This does not necessarily mean that these high-quality simulations can be extrapolated to the BSCs, but the fact that DDD-PUB also gives very good results for these two catchments is an indication that the MREs work well for this region. The only indices calculated for the BSCs that are outside the range of those of the control catchments are for the high pulse counts (Figure 6b). A possible explanation is that the BSC have a much higher frequency of small catchments (Figure 2d) and hence a potential for a higher frequency of flashy catchments that may respond very quickly to intense precipitation or snowmelt. Another way of assessing the quality of the simulated BSC run-off series is, of course, to investigate whether simulated run-off (or perhaps some other simulated hydrological variable such as snow) has implications for the biology of the WTD, i.e. that they explain the variation in population dynamics and individual breeding parameters of the WTD. If such relations are found, then we may have a justified belief that the simulated series are realistic.

There is a lower limit regarding the catchment size and the accuracy of the CCs estimated by GIS. At a catchment size of $1\,\text{km}^2$, there are 1600 cells of $25 \times 25\,\text{m}^2$. This is considered a minimum necessary number of cells in order to have reasonably robust estimates for the CCs. Only five BSCs were smaller than $1\,\text{km}^2$ (17 BSCs are below $2\,\text{km}^2$), and simulated stream flow from these has to be regarded as especially uncertain.

CONCLUSIONS

In this study, we have explored the use of the rainfall–run-off model, DDD, for PUB. The challenge was to simulate run-off at 145 ungauged catchments (BSCs) where breeding pairs of the WTD (*C. cinclus*) have been monitored since 1978. The method for determining the model parameters for the ungauged basins was similar to that of many previous studies, namely that of relating model parameters to CCs through MREs. The contribution of this study, however, has been to apply this classic method to a new parameter parsimonious model, the DDD. Possibly because of the transparent model structure of DDD, many significant and quite high correlations between model parameters and CCs were found, and it was shown that CCs describing lake percentage and size of the catchment were important in parameterizing the dynamics of the rainfall–run-off model. Landscape types were important in parameterizing snow accumulation, snowmelt and evapotranspiration. Relations between CCs and model parameters from 84 calibrated catchments (set 1) gave the most robust set of MREs. The regression equations all gave behavioural estimates of the model parameters, both for 17 control catchments and for the BSCs.

DDD-PUB gave somewhat less precise simulations of run-off compared with DDD-CAL when assessing results for the 17 control catchments. However, the two catchments located within the basin of Lygne, the region of the breeding sites of the WTD, had very good simulations using DDD-PUB, which is encouraging with respect to the simulations for the BSCs. The result varied for the other catchments, and an analysis relating differences in NSE with differences in calibrated and fixed/regressed model parameters identified the parameters describing the spatial distribution of snow (θ_{CV}) and snowmelt (θ_{CX} and θ_{TS}) as significant in explaining the discrepancy in NSE between DDD-CAL and DDD-PUB.

The quality of the run-off simulations for the BSC was assessed through comparing calculated indices describing high, medium and low flows with those of observed run-off at the 17 control catchments. The indices for the BSC were, in general, well within the range defined by observed run-off with a small exception for the indices of high flow, which were slightly higher for the BSCs. The increased frequency of high flows can be ascribed to the higher frequency of small, and possibly flashy, catchments amongst the BSCs.

Future work includes implementing calibration-free algorithms for snow distribution and snowmelt in DDD and repeat the analysis described in this paper. A further reduction of calibration parameters is, at least by these authors, perceived as a promising and necessary way ahead for PUB and to gain insight in hydrological processes.

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