REGIONAL STATISTICAL AND PRECIPITATION-RUNOFF MODELLING FOR ECOLOGICAL APPLICATIONS: PREDICTION OF HOURLY STREAMFLOW IN REGULATED RIVERS AND UNGAUGED BASINS

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Short Title: Modelling for prediction of hourly streamflow in ungauged basins

Abstract

Prediction of natural streamflow in regulated rivers for derivation of ecologically relevant streamflow metrics (ERSFMs) and prediction in ungauged basins (PUB) are important in management of water resources. However, specific studies on comparison of methods for predicting hourly flow regime relevant to ecological study in regulated (hydropeaking) rivers are rare in literature. Therefore, using catchments in mid Norway, we performed comparative evaluation of prediction of hourly streamflow series and flow duration curves (FDCs) in ungauged basins. We developed a regional regression model based on relationships among streamflow percentiles and drainage areas and performed a regional calibration of a streamflow recession based Precipitation-Runoff (P-R) model.

A leave one out cross-validation procedure was used to evaluate the regional models. The results indicate that the regional regression model with transferring of streamflow information based on the nearest neighbor performed better than both transferring optimal parameters from local calibration and regional parameter sets corresponding to maximum regional weighted average Nash-Sutcliffe efficiency of the P-R model (NSE_{MRWA}). We also evaluated the models based on prediction of some environmental indices: the daily range, daily standard deviation, flashiness, maximum ramping rate, number of rise and falls and daily flow changes. However, both modelling strategies predicted hourly streamflow indices well and appeared stable over most indices while the largest differences occurred in the rise and fall counts.

The models were further applied for prediction of the natural streamflow time series at Sokna hydropeaking plant. The observed hydrograph exhibits continuous sudden fluctuations while the predicted natural flow hydrograph exhibits smooth pattern. The within a year FDCs for observed flow exhibits sharp transitions from high to low flows. There is clear differences between the environmental indices obtained for the observed and the modelled data series, with the general observation that the NSE_{MRWA} computing a smaller variability than the regression model.

Key words:

Regression model; Precipitation-runoff model; Hourly streamflow; Environmental flow; Prediction in ungauged basins; Ecologically relevant streamflow metrics; Hydropeaking at Lundesokna; Flow duration curves.

INTRODUCTION

River regulation for hydropower may create considerable alterations of natural streamflow regime that have profound ecological, geomorphologic and hydraulic repercussions. Pre-regulation or 'baseline' natural flow regime can be obtained from pre-regulation observed streamflow if available, which frequently is not the case. Moreover, humans have altered streamflow for a long time and hence the assumption that streamflow records prior to regulation represent a 'natural' condition can be flawed mainly due to the impacts of land use and climate change. In addition, streamflow simulation by calibration of Precipitation-Runoff (P-R) models is not possible for a regulated reach of river. Prediction of streamflow may also be required at ungauged sites where ecological data is available in order to study the impacts of hydrological alterations on the riverine ecology. Furthermore, there are interests to predict contributions from ungauged streams to the environmental flow (e-flow) and reservoir inflow.

To obtain information on temporal flow pattern alterations compared to the natural (i.e. pretending no regulation) to study the impacts of regulations, a methodology for predicting a time series of natural streamflow hydrographs and duration curves that excludes the effects of regulation are required. The concept of inflow controlled environmental flow regime (e.g. Alfredsen et al., 2012) can also be better evaluated if a continuous time series of natural flow can be predicted rather than assessed based on a pre-regulation natural flow regime. Furthermore, the predicted natural time series is the basis in the derivation of ecologically relevant streamflow metrics (ERSFMs). Alteration in the hydrographs and flow duration curves (FDCs) would indicate potential alteration in other streamflow characteristics that are relevant for assessment of ecological integrity. Comparison of the indices derived from the predicted (natural) versus the actual flow under regulation would help to characterize flow related changes and devise improved mitigation and management in regulated rivers.

Continuous streamflow Prediction in Ungauged Basins or PUB (Sivapalan *et al*., 2003) through regional Precipitation-Runoff (P-R) modelling is a highly researched area (e.g. He *et al*., 2011; Hrachowitz *et al*., 2013; Parajka *et al*., 2013; Razavi and Coulibaly, 2013). Besides the PUB, the regional modelling enables thorough and comparative study using a large number of catchments in the region. Current scientific understanding of hydrologic controls on riverine ecosystems and experience gained from individual river studies support development of environmental flow standards at the regional scale [Poff *et al*., 2010]. Several regionalization attempts for prediction of flow characteristics (e.g. regime, hydrograph, seasonality, frequency, extremes such as flood and drought) at ungauged basins are available in literature in both hydrological and ecological sciences. However, the task remain challenging.

A number of approaches for prediction of ERSFMs at ungauged sites are reported. In a more recent time, the two main modelling approaches for prediction of ERSFM are statistical regression (e.g. Sanborn and Bledsoe, 2006; Sickle *et al*., 2006; Carlisle *et al*., 2011; Knight *et al*., 2011, Murphy *et al*., 2012) and the P-R models (e.g. Kennen *et al*., 2008; Poff *et al*., 2010; Murphy *et al*., 2012; Shrestha *et al*., 2014). Some applications of various statistical models for direct prediction of ERSFMs using characteristics of watershed include Nathan and McMahon (1990), Moliere *et al*. (2006), Engeland and Hisdal (2009), Castiglioni *et al*. (2011), Knight *et al*. (2011) and Murphy *et al*. (2012). However, there is no many studies that compare methods for predicting streamflow for assessment of ecological flow regime. Engeland and Hisdal

(2009) compared regional regression based on 24 potential catchment characteristics as independent variables and the HBV P-R model for prediction of low flow index for daily streamflow from 51 catchments in Southern Norway and found that the regression method generally gives better estimates. Castiglioni *et al*. (2011) compared physiographical space based interpolation and top-kriging and noted that both techniques provide plausible and accurate predictions of a low-flow index (Q_{355}) in ungauged basins. Murphy et al. (2012) compared a regional regression model and a P-R model and noted limitations of the P-R model to effectively predict ecological flow regimes in ungauged basins. Farmer et al. (2014) examined 19 different statistical and P-R based streamflow prediction methods using a wide set of performance metrics for Southeast region of the United States and found that a nonlinear spatial interpolation technique using flow duration curves with the nearest-neighbor donor gauges produced the most reliable predictions of continuous records of daily streamflow. Shrestha *et al*. (2014) evaluated the ability of the Variable Infiltration Capacity (VIC) P-R model to replicate hydro-ecologically relevant indicators and noted a need to exercise caution in the use of model-simulated indicators. Vis et al. (2015) studied calibration criteria for the HBV-light P-R model for estimating 12 ecological flow characteristics and found that the most suitable calibration strategy varied according to the streamflow characteristic or the objectives. However, these comparisons mainly focused on daily or coarser temporal resolution.

Previous studies related to environmental flow and ecological flow regime (e.g. Schofield and Burt, 2003; Tharme, 2003; Arthington *et al*., 2006; Carlisle *et al*., 2009; Poff *et al*., 2010; Kennard *et al*., 2010; Alfredsen *et al*., 2012; Costa *et al*., 2012; Vezza *et al*., 2012), alterations of natural flow regime due to regulation or hydropeaking (e.g. Poff *et al*., 1997; Jones, 2014) and impacts of climate change (e.g. Gibson *et al*., 2009; Wenger *et al*., 2010) mainly focused on coarse temporal resolutions such as annual, monthly and daily streamflow. However, contemporary operation practices in regulated rivers such as for hydropeaking require high-resolution prediction, which allows close examination of relevant ecological indicators from high-resolution hydrographs. The lists of suggested ERSFMs and softwares used to calculate the ERSFMs reported in literature (e.g. Richter *et al*., 1996; Poff *et al*., 1997; Olden and Poff, 2003; Mathews and Richter, 2007; Knight *et al*., 2011; Thompson et al., 2014) are also based on daily or coarser time series that may not be representative for the hydropeaking flow that is variable at high resolution (e.g. hourly). To our knowledge, study on prediction of 'unimpaired' or natural hourly streamflow series in regulated rivers for ecological purposes is not widely reported in literature. Sauterleute and Charmasson (2014) developed a computational tool, which enables the quantification of short-term (rapid) fluctuations of flow and stage occurring in rivers resulting from hydropeaking, by means of processing the time series. However, the authors noted that the tool was not developed to enable comparisons between rivers with and without hydropeaking, or those with natural flow regimes. Bevelhimer et al. (2014) presented a variety of metrics for characterizing sub-daily (hourly) flow variation to evaluate general trends among streams affected by hydropeaking, run-of-river plants and streams that are largely unaffected by regulation. The present study is a comparative evaluation of methods for prediction of hourly streamflow series and environmental indices in ungauged or regulated basins in a region of mid Norway. In the study region, regulation of rivers is common and hydropeaking operation is increasing while environmental legislations are stringent and important aquatic ecosystems (e.g. salmonid fish) are abundant.

The main objectives and scope of this study are: (i) To develop a regional regression model for prediction of FDCs from relationship between streamflow percentiles and watershed characteristics and to propose FDCs based transfer of streamflow time series information from gauged to ungauged catchments; (ii) Comparative evaluation of the regional regression model and a Precipitation-Runoff model for prediction of natural streamflow time series at ungauged basins and; (iii) Application and comparative evaluation of the models to a regulated hydropeaking river to predict hourly natural streamflow time series and to compute specific sub-daily ERSFMs mainly based on the work by Bevelhimer et al. (2015).

STUDY REGION AND DATA

The study region is located in mid Norway that has a large number of highly regulated catchments. We used hourly streamflow data from 26 unregulated catchments (40 to 3090 km^2) that was obtained from the Norwegian Water Resources and Energy Directorate (NVE). Four of the catchments (catchments no. 3, 6, 8 and 14) are located inside the Gaula watershed (Figure 1). The catchments, drainage areas, mean runoff and ratio of mean to median flow are listed in Table 1. Ratio of mean to median flow is greater than one for all catchments showing that the streamflow distributions are right skewed. We used the data from 2006 to 2011 to develop relationships between drainage areas and streamflow percentiles using the regional regression model and from 2008 to 2010 for calibration of the P-R model, transfer of streamflow information and associated cross-validation procedures. Hourly climate data include precipitation from 44 stations, temperature from 54 stations, wind speed from 40 stations, relative humidity and global radiation from 12 stations, which are spatially interpolated on 1x1 km^2 grids for calibration of the P-R model. We obtained climate data from public services and private companies. For instance, we obtained temperature data from 9 stations owned by the Norwegian Meteorological Institute, 12 stations owned by the Norwegian Institute for Agricultural and Environmental Research (Bioforsk) and the remaining from stations owned by various hydropower companies. The high flow regime for the study catchments occurs from snowmelt events in most cases, but for some of the catchments high flow is associated with rainfall on snowmelt or summer rainfall events. The dominant land use/land cover types in the study area are bare rock, low vegetation above timberline and forests. Predominant soil formation is glacial tills. We found land use and hypsography data from the NVE, and soil data from the Norwegian Geological Survey (NGU). Terrain slope was processed in ArcGIS from a Digital Elevation Model (DEM).

We applied the proposed methods in the present study to predict the 'unimpaired' or natural streamflow series for the regulated Lundesokna catchment at the outlet of the Sokna hydropower plant (total catchment area 243.4 km^2). Lundesokna river flows from the Samsjøen reservoir to Gaula, which is one of the best salmon rivers in Norway. Sokna hydropower plant is a hydropeaking plant and has the following salient features: installed capacity of 30 MW, a gross head of 185 meters, intake regulation height of 9 meters and total catchment area at intake of 217 km^2. We constructed the regulated streamflow time series of the Lundesokna catchment by adding a modelled time series using the P-R model for the local catchment between Sokna intake and outlet (area = 26.4 km^2) to the observed time series of discharge data from the Sokna power plant.

METHODS AND MODELS

There are several inherent uncertainties associated to both regional regression and P-R modelling for prediction in ungauged basins. The accuracy of predictions of streamflow characteristic is important because of the potential consequences a poor prediction can have on estimates of ecological health (Murphy *et al*., 2012). Some of the main problems associated with P-R models are predictive uncertainty due to uncertainty in inputs, parameter calibration, model structure and regionalization methods. Vis et al. (2015) illustrated uncertainties in various simulated ecological flow characteristics using a P-R model calibrated using different objective functions. The regression approach is also associated with several assumptions such as randomness, normality and homoscedascity of residuals, and non-collinearity among the independent variables. In addition, dependence between regression model parameters and subjectivity in selection and pre-processing of the independent variables are prevailing challenges if large numbers of independent variables and hence parameters are used.

Statistical (regression) model

Nathan and McMahon (1990) and Moliere *et al*. (2006) illustrated regression among different catchment attributes and discharge for prediction of low flow hydrograph in ungauged basins in Australia. The regression approach in previous studies focused on deriving separate relationships among various dependent variables (i.e. each ERSFMs) and selected catchment attributes. For instance, Knight *et al*. (2011) conducted regional regression analyses based on 16 potential independent variables (watershed characteristics) to predict 19 presupposed ecologically relevant streamflow characteristics for Tennessee and Cumberland river basins (USA). Selection of a small number of independent variables reduces the number of regression parameters and hence the uncertainties related to dependence among parameters and collinearity among independent variables. Therefore, the regression model in the present study focus on parametrical parsimony, simplicity and consistency for a particular dependent variable.

Identification of independent variables and choice of dependent variables are important for the regression model. In the study on global environmental assessment methodologies, Tharme (2003) stated that flow duration curves and other single flow indices comprise the second largest subgroup of the hydrological approaches for environmental flow assessment in rivers. Kennen (2008) used the ratio of 25 % to 75 % exceedance flows to evaluate the effect of changes in the flow regime on aquatic-invertebrate assemblage structure. Wenger *et al*. (2010) used frequency of high flows (Q_{95} and Q_{99}) during winter and summer, mean annual and mean summer flows, and frequency of summer low flows (Q_{10} and Q_{20}). Yin *et al*. (2012) used 10 % and 20 %, and 30% respectively of average daily flow for baseflow in dry and wet seasons and the 25th percentile flow as a minimum high pulse discharge. Alfredsen *et al*. (2012) defined flow regimes based on flow percentiles (low < 25%, high > 75% and normal 25% to 75%) to represent dry, wet and normal years to develop an inflow controlled environmental flow regime. The natural flow regime paradigm of Poff *et al*. (1997) and Richter *et al*. (1997) focuses on a full range of intra-and inter annual variability of streamflow characteristics pertinent to magnitude, frequency, duration, timing and rate of change to study comparative relationships between natural and altered hydrological conditions and riverine ecology. Therefore, due to the various utilization of streamflow characteristics in environmental assessment, the main focus of the present study is to evaluate methods to derive the two main runoff ‘signatures’ namely flow duration curves and time series of streamflow for ungauged or regulated rivers from which further ERSFMs can be extracted.

To construct flow duration curves, we fitted separate linear regressions between each streamflow percentile (0 % to 100 % at 1% intervals) values as the dependent variable with the independent variable (drainage areas of catchments). Flow duration or the percentage of time flow equaled or exceeded is computed as 100-percentile. The fine interval of 1% interval was preferred to obtain better accuracy in prediction of percentiles. Coarse intervals augmented by interpolation might reduce the accuracy by introducing an additional source of uncertainty on the prediction. The drawback of estimation of large number of regression parameters at 1% intervals can be tackled by carrying out parameter estimation for all percentiles at once. The flow percentiles rather than the various ERSFMs exhibit similar relationships to watershed characteristics and make the regression approach more consistent. Mohamoud (2008) performed prediction of flow duration curves (FDCs) and streamflow for ungauged catchments by fitting multiple non-linear regression model among 15 drainage-area normalized streamflow percentiles and landscape–climate descriptors and found that the FDC-based method shows great promise for predicting streamflow in ungauged basins compared to the drainage area ratio method (e.g. Stedinger et al., 1993). Yu et al. (2002) compared polynomial regression that uses annual rainfall, altitude and drainage area as catchment descriptors with a simple regression model that uses only drainage area as catchment descriptor and found that both regional analysis methods could generate reasonable FDCs. However, the authors reported that the polynomial regression has less uncertainty, but it resulted in unrealistic values for extrapolation beyond $Q_{90\%}$ and $Q_{10\%}$.

To identify influential catchment descriptors, we performed linear correlation analysis among streamflow percentiles and several catchment characteristics. The results of the linear correlation analysis are presented in Table 2 for drainage area, lake percentage, forest percentage, minimum elevation, maximum elevation, median terrain slope and maximum terrain slope. We did not expect reliable mean annual runoff (MAR) for the catchments from the sparse precipitation gauging stations in the region and hence we did not use the MAR as a descriptor variable. In Nordic catchments, lake percentage is often used as an independent variable for both low-and high flows (e.g. Engeland and Hisdal, 2009, Sælthun, 1997). However, among the descriptor variables assessed in the present study, only drainage area exhibited marked correlations with streamflow percentiles from low- to high flow ranges. Therefore, using only drainage area as an independent variable we fitted the following simple linear regression model with the assumptions of normal and homoscedastic residuals:

$$\underline{Y} = \underline{X}\underline{\beta}^* + \underline{\varepsilon} \text{ or } Y_i = \beta_0^* + \beta_1^* x_{1i} + \varepsilon \tag{1}$$

$$\underline{\varepsilon} \approx N\left(\underline{0}, \underline{I}\sigma^2\right) \text{ and } \underline{Y} \approx N\left(\underline{X}\underline{\beta}^*, \underline{I}\sigma^2\right) \tag{2}$$

We estimated the set of parameters (β) using the ordinary least-square technique and their lower and upper confidence levels (UCL and LCL) from the t-statistics:

$$\underline{\hat{\beta}} = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{pmatrix} = \left(\underline{X}'\underline{X}\right)^{-1}\underline{X}'\underline{Y}\ ; \quad \text{UCL, LCL} = \hat{\beta}_i \pm t_{\alpha/2,n-p}\sqrt{S^2\left(\underline{X}'\underline{X}\right)^{-1}_{ii}}\ , \tag{3}$$

where $\underline{Y}$ is a nx1 column vector of the dependent variable, $\underline{X}$ is a nxp matrix of the independent variable, $\underline{\varepsilon}$ is a nx1 column vector of the error term that indicates the deviation of the estimate from the true value, $\underline{I}$ is the nxn identity matrix, S^2 is estimate of error variance, * represents the 'true' values, the underline represents the vector or matrix notation, n is the number of observations (data points), p is the number of model parameters, N stands for the assumed Normal distribution, $(X'X)_{ii}^{-1}$ is the main diagonal element corresponding to i^{th} row and i^{th} column of a $(X'X)_{ii}^{-1}$ matrix of size pxp, the $'$ notation represents a transpose and α is the significance level.

We performed diagnostic analyses of the residuals to verify the adequacy of the regression model. We performed a significance test of the model parameters through an F-test and computed the percentage of variability in the data explained by the regression model (R^2). Outlier catchments were identified by plots of drainage areas versus flow percentiles (Figure 2). Randomness of the residuals were tested by plots of regression residuals versus the predicted dependent variable. We verified the normality of the residuals by probability plots and presented the model prediction error in terms of 95 % confidence intervals (CI). An outlier catchment in the present study is defined as a catchment which has streamflow percentiles and drainage area relationships that deviates from the rest and hence an outlier catchment is excluded from the regional regression model.

Streamflow percentiles or flow duration curves alone cannot provide sufficient information for ecological studies and hence prediction of complete time series of streamflow at ungauged basins is required. Various regionalization methods that are useful for either regional transfer of calibrated parameters of the P-R models or for transfer of streamflow information (e.g. Parajka et al., 2013; Hailegeorgis et al., 2015; Farmer et al., 2014) are reported in hydrological sciences literature. For the regression model in the present study, we proposed a simple method to derive streamflow time series (hydrographs) for ungauged catchments from relationships between flow percentiles and drainage area and observed streamflow data at the gauged catchments. We transferred streamflow information among the catchments based on an assumption that a streamflow at a time *T* exhibit the same percentile for the donor (gauged) catchment and the recipient (ungauged) catchment using a simple lookup function in Microsoft excel:

$$Q_T^{ungauged} = lookup\left(Per_T^{Qgauged}, Per^{0:1:100}, Q_{Per}^{regression:ungauged}\right), \tag{4}$$

where Q_T is time series of streamflow, Per_T are percentiles for observed time series of streamflow at gauged basin, $Per^{0:1:100}$ are percentiles from 0 % to 100 % at 1% intervals and Q_{Per} is streamflow corresponding to the percentile *Per* for the ungauged basin, which is calculated from the results of the regional regression model. Evaluation of various regionalization methods, strategy for selection of donors, and assessment of associated uncertainties with specific application to prediction of ERSFMs in ungauged basins require a thorough investigation, which is outside the scope of the present study. Rather we evaluated the regional transfer of streamflow information from the regression model and the look-up function for prediction in ungauged basins based on the nearest neighborhood (spatial proximity) between donors and recipients using the leave one out cross-validation procedure. The Nash-Sutcliffe efficiency (Nash and Sutcliffe, 1970) or *NSE* performance measure was used as an evaluation metric.

Precipitation-Runoff (P-R) model

The P-R model allows prediction of continuous time series of streamflow from which one can derive ecological indices of interest. Following the results of assessment of performance of different P-R models for the region of study (Hailegeorgis *et al.*, 2015), we selected a parsimonious recession based 'top-down' model, which was proposed by Kirchner (2009) for the present study. The model was based on inferring model structure and equations from observed streamflow during recession. The main basis of the model is a water balance equation:

$$\frac{dS}{dt} = I - AET - Q = I - AET - Q \tag{5}$$

$$\frac{dQ}{dt} = \frac{dQ}{dS}\frac{dS}{dt} = \frac{dQ}{dS}\left(I - AET - Q\right) = g\left(Q\right)\left(I - AET - Q\right) \approx g\left(Q\right)\left(-Q\right)\Big|_{I<<Q,AET<<Q}, \tag{6}$$

where the actual evapotranspiration (AET), infiltration (I) = rainfall + snow melt (SM) and discharge (Q) are given in mm/hr, bulk catchment storage (S) is in mm, t is a time variable and g(Q) is discharge sensitivity function (Kirchner, 2009) that is the sensitivity of discharge to change in storage. However, the response routine used in the present study was based on a 1x1 km^2 grid cells rather than lumped for the whole catchment. The following relationship was used based on a streamflow recession analysis:

$$\ln\left(g\left(Q\right)\right) \approx \ln\left(\frac{dQ}{dS}\right) \approx \ln\left(\frac{-dQ/dt}{Q}\Big|_{P<<Q,AET<<Q}\right) \approx \alpha_0 + \alpha_1 \ln\left(Q\right), \tag{7}$$

where α_0 and α_1 are model parameters. Runoff computation follows integrating the following storage-discharge relationship in time:

$$S\left(Q\right) = \int dS = \int \frac{1}{g\left(Q\right)} dQ \tag{8}$$

We computed the potential evapotranspiration (PET) based on the Priestly Taylor method

(Priestley and Taylor, 1972), and actual evapotranspiration from the PET, discharge and evapotranspiration ratio parameter (EvR). We simulated a snow accumulation and snowmelt outflow (SNOWOUT) based on a gamma distributed snow depletion curve (Kolberg and Gottschalk, 2006) and implemented a simple travel time zone isochrones routing to translate the hillslope runoff response of each 1x1 km^2 grid cell to the catchment outlet based on travel time lags. There are six calibrated parameters in the P-R model: threshold temperature (TX), wind speed sensitivity of snow (WS), the EvR, velocity of flow for runoff routing (V), α_1 and α_0.

A regional calibration of the P-R model was performed using streamflow data from the 26 gauged catchments. The Differential Evolution Adaptive Metropolis algorithm or DREAM (Vrugt *et al*., 2009) with residual based log-likelihood (*L-L*) objective function implemented in an open source ENKI hydrological modelling platform (Kolberg and Bruland, 2012), which was developed at the company for industrial and scientific research or SINTEF, was used:

$$L-L\left(\delta/\sigma_i^2, \sum_{i=1}^{N_C}\sum_{t=1}^{n_i}\left(Qsim_{t,i}^{(\theta)}-Qobs_{t,i}^{(\theta)}\right)^2\right)=\left\{\sum_{i=1}^{N_C}\left(\frac{-n_i}{2}\log\left(2\pi\right)-\frac{n_i}{2}\log\left(\sigma_i^2\right)-\frac{\sum_{t=1}^{n_i}\left(Qsim_{t,i}^{(\theta)}-Qobs_{t,i}^{(\theta)}\right)^2}{2\sigma_i^2}\right)\right\}\times f, \tag{9}$$

where $Qobs^{(\theta)}$ and $Qsim^{(\theta)}$ respectively are Box-Cox (Box and Cox, 1964) transformed non-missing observed time series and corresponding simulated streamflow time series of length n_i, N_C is the total number of catchments (N_C = 26 in this case), δ is a model parameter, θ is the Box-Cox transformation parameter, f is the fraction of effectively independent observations and σ^2 is the variance of error.

The objective function for the regional calibration utilizes streamflow data from all catchments in the region, but would also provide optimal parameter set for each catchment, which is termed as the local calibration. Hence, the algorithm is useful to calibrate large number of catchments at once. Hailegeorgis et al. (2015) obtained acceptable performance of the regional calibration based on transferring regional parameter set that provides maximum regional weighted average (MRWA) *NSE* compared to other advanced regionalization methods. In the present study, we also evaluated the performance of regional transfer of parameter sets that provide the best MRWA *NSE* compared to the regional regression model:

$$NSE_{MRWA}=\frac{1}{N_C}\sum_{i=1}^{N_{Ca}}\left(\frac{n_{ia}}{N_{TS}}\right)NSE_i, \tag{10}$$

where N_{Ca} is the total number of catchments included to compute the NSE_{MRWA} ($N_{Ca} = N_C$ -1) since a donor catchment is excluded for the leave one out cross-validation), n_{ia} is the length of timestamp with non-missing observed streamflow series for each catchment i, N_{TS} is the total length of timestamp for the calibration period. The weights are the term in the parenthesis assigned for each catchment based on the length of their non-missing streamflow records during the calibration period. The term regional calibration and the NSE_{MRWA} are interchangeably used in the present study. We used a cross-validation procedure to evaluate the performance of transfer of optimal parameter sets of the local calibration. We used a leave one out cross-validation procedure by excluding the donor catchments for the regression model and the NSE_{MRWA} since the procedure is more appropriate to evaluate the models for prediction in ungauged basins. Detailed descriptions of the evapotranspiration routine, the snow routine and the calibration algorithm can be found from Hailegeorgis *et al*. (2015).

Environmental Flow Indices

To evaluate and illustrate the application of the regression method and the precipitation-runoff model in flow assessment we computed environmental flow indices for two cases studies. Since sub-daily prediction is a focus for this work, we used the recently proposed method by Bevelhimer et al. (2015) to compute ecologically relevant streamflow metrics (ERSFMs) with an hourly resolution. We computed the daily range and daily standard deviation as a measure of habitat variability, the flashiness as a measure of flow oscillations and the maximum ramping rate as measures of drying out habitat and potential fish stranding. Finally, we computed the number of rise and falls and the daily flow changes (10 % reversals) as a measure of flow stability and regularity in habitat access. First, we compared predicted and observed indices that was derived from the predicted and observed streamflow, which was obtained from the cross-validation procedure, for Øyungen or catchment 26. Further, we compute the same indices for the Lundesokna catchment where the pre-regulation flow is now known, but where we have a rapidly changing production regime today. For Lundesokna we also computed the indicators outlined by Carolli et al. (2015) to assess if a flow regime is peaked or not.

RESULTS AND DISCUSSION

The study focused on evaluation of parsimonious and simple approaches for prediction of hourly streamflow for ungauged basins to derive streamflow characteristics of ecological relevance. In the first approach, we proposed a simple linear regression model with catchment area as independent variable to predict streamflow percentiles and hence flow duration curves, and transfer of streamflow time series information based on the flow duration curves. In the second approach, we tested prediction of streamflow from calibration of a P-R model.

The Trangen or catchment 22 was identified to be an outlier based on preliminary plots of streamflow percentiles versus drainage area (Figure 2), and later confirmed by the diagnostics of residuals of the regional regression model. Exclusion of the outlier catchment increased the explained variability or R^2 from 0.73 to 0.80, from 0.79 to 0.88 and from 0.85 to 0.94 respectively for the 10th, 25th and 50th percentiles (Figure 2 and Figure 3). Therefore, we excluded the catchment from the regional regression analysis. Outlier catchment may occur due to poor quality data, or because the drainage area is not related to the flow percentiles or drainage area versus percentiles relationships is peculiar for the catchment. Figure 3 presents results of estimated parameters along their confidence intervals for the regional regression model at 1 % percentile intervals. The β_1, which is an influential parameter being the coefficient of the independent variable, monotonically increases with percentiles and the intercept parameter β_0 also increases with the percentiles except for a little deviation at some higher percentiles. The lower and upper confidence intervals of parameters also exhibited the same trend. Therefore, for any drainage area the estimated higher percentile flows (e.g. 75th percentile) are found to be always greater than those estimated for lower percentile flows (e.g. 74th percentile). Mohamoud (2008) reported the need for reconstruction of FDCs to ensure that percentile flows estimated for higher magnitudes are always larger than those estimated for lower magnitude percentile flows. The causes of the problem are probably due to uncertainty or identifiability issues in the estimation of regression parameters from fitting the non-linear regression to more than one and different combinations of landscape–climate descriptors for different streamflow percentiles. Such problem is not expected for the linear regression model with one and the same independent variable for all percentiles used in the present study. However, the problem needs to be checked for a non-linear regression or a linear regression that use several and different combinations of independent variables for different percentiles.

In Table 3, we presented the results from the comparative evaluation of the methods using the cross-validation procedures for the 11 catchments that have no or small amount of missing streamflow records. Table 3 presents the *NSE* values obtained from spatial transfer of information when donor catchments are excluded from the regional regression model while deriving streamflow percentiles and drainage area relationships and while computing the NSE_{MRWA} from the P-R model. Similarly, Table 3 also shows *NSE* values from transferring optimal local parameters from donor to recipient catchments. The *NSE* values along the diagonals (bold fonts in Table 3) indicate the performance of regression model and local calibration of the P-R model for a particular catchment. These *NSE* values indicated that for most of the catchments the regional regression model outperformed the local calibration of the P-R model. The *NSE* values along the diagonals for the regression model that was obtained from the leave one out cross-validation by excluding donors also indicated that the performance of percentiles-drainage area relationships for construction of flow duration curves at ungauged basins is not sensitive to the choice of donor catchment. Therefore, the proposed regression model is very useful for prediction of FDCs at ungauged basins for any water resources planning purpose. However, regional transfer of information of streamflow time series among the catchments (Eq. 4) is more sensitive to the choice of donor catchment than the P-R model does. However, the regression method with transfer of information of streamflow time series based on the nearest neighbor or spatial proximity between donor and recipient (Figure 1) resulted in regional performance better than the local calibration and regional calibration (NSE_{MRWA}) of the P-R model. For instance, regression based prediction by transferring streamflow information from Gaulfoss (no 6) to one of its internal subcatchment of Eggafoss (no. 3) (Table 3) indicated NSE value of 0.89 versus the local calibration of the P-R model (NSE = 0.81) and the NSE_{MRWA} (NSE = 0.68). Similarly, transfer of streamflow information from Krinsvatn (no. 12) for prediction at its nearest neighbor Øyungen (no. 26) (Table 3 and Figure 4) indicated NSE value of 0.78 versus the local calibration of the P-R model (NSE = 0.71) and the NSE_{MRWA} (NSE = 0.64). The *NSE* values in Table 3 further showed in most of the cases better transferability of streamflow information using the regional regression model and spatial proximity among catchments, for instance, among pairs of catchments 6 and 14 (36 km), 3 and 6 (54 km), 10 and 17 (15 km), 12 and 26 (64 km), 14 and 3 (33 km), 21 and 1 (28 km), and 21 and 26 (40 km) than parameter transfer from local calibration and regional calibration (NSE_{MRWA}) of the P-R model. The spatial proximity in the present study was defined as the shortest Euclidian distance in x and y co-ordinates spaces between catchment outlets. The parameter sets and hence the performance measure NSE_{MRWA} are the same except slight differences when a donor catchment no. 16 is excluded that shows less sensitivity of the NSE_{MRWA} to the choice of donors (Table 3). This is probably because all catchments were included in the regional calibration objective function (Eqn. 9) to utilize the advantages of local calibration of each catchments at once.

The better performance of the regression model in the present study comply with the results from Engeland and Hisdal (2009) and Murphy *et al*. (2012) who found that regression model outperformed the P-R models respectively for Southern Norway and Kentucky (USA). The results also comply with Farmer et al. (2014) who obtained that methods based on flow duration curves with the nearest-neighbor donor gages performed better. Murphy *et al*. (2012) and Vis *et al*. (2015) noted the importance of better predictions on estimates of ecological health. There are various uncertainties that need to be addressed in regionalization and prediction in ungauged basins through transfer of calibrated parameters of P-R models such as uncertainty in the model calibration (input data, model structure, and parameter uncertainty and identifiability issues) (e.g. Wagener and Wheater, 2006) and uncertainty in identification of suitable regionalization methods (e.g. Hailegeorgis et al., 2015). The regression based prediction in the present study transfers characteristics of the observed streamflow from gauged to ungauged catchments while the regional calibration of the P-R model derives regional model parameters by utilizing the available streamflow data in the region. The relationships obtained between the readily available physiographic characteristics of catchments (i.e. the drainage area) and streamflow percentiles is also promising for the regression model for prediction in ungauged basins. However, there are marked uncertainty bounds of prediction by the regression model as demonstrated by confidence intervals of the estimated parameters (Figure 3). In addition, some catchments such as catchments 10 and 16 exhibit large prediction errors and hence poor *NSE* that shows poor spatial transferability of streamflow information for the catchments based on the regression model. If a large number of catchments are available, certain additional criteria can be set to exclude less performing catchments from the region or the region can be divided into several sub-regions. Evaluation of various regionalization methods, for instance, similarity of catchments in physiographic characteristics compared to the spatial proximity for prediction related to ecological flow assessment at ungauged basins is also important.

Figure 5a-f shows a comparison between computed environmental flow indices for Øyungen or catchment 26 computed for observed data, and the predicted inflow series from the regression model and the P-R model (NSE_{MRWA}) that are presented in Figure 4. Both modelling strategies predicted the streamflow indices well and appeared stable over most indices. The largest differences occurred in the computation of the rise and fall counts (Figure 5f).

Figure 6 presents observed hydrographs and FDC under hydropeaking versus the predicted natural streamflow and FDCs for Lundesokna river downstream of the outlet of the Sokna hydropower plant. We transferred information of streamflow time series from the Gaulfoss to the Lundesokna river based on the regression model and nearest neighbor (spatial proximity) and regional calibration (NSE_{MRWA}) of the P-R model. Both the Gaulfoss and Lundesokna are parts of the Gaula catchment and the streamflow gauging station for Gaulfoss and the outlet of the Sokna hydropower are only about 5.7 km apart (Figure 1). Even if there are similarities between the general patterns of hydrographs predicted from the regional regression model (Q_{est}) and simulation by the P-R model (Q_{sim}), and their corresponding FDCs, the results show that there are significant differences in predicted streamflow magnitudes for specific times and durations. The predicted hydrographs from both methods show that the catchment runoff generation responds well to the catchment-averaged precipitation events. However, based on the leave one out cross-validation results, the regional regression method was found to be more reliable than the regional calibration (NSE_{MRWA}) for prediction of hourly streamflow series. Figure 6 shows significant hydrological alterations due to regulation and hydropeaking for Lundesokna river. The observed streamflow (Qobs. regulated in Figure 6) for Lundesokna river downstream of the outlet is highly influenced by the hydropeaking operation. The results indicate typical differences between the regulated or hydropeaking flow and the predicted natural flow. The within a year FDC for observed regulated (hydropeaking) flow exhibits sharp bend transitions from high to medium flows and from medium to low flows. High flow (e.g. Q > 22 m^3/s) occurs only about 1 % of the time (< 100 hours duration), low flow (e.g. Q < 5.0 m^3/s) occurs for more than 68 % of the time (6000 hours) while the middle portion of the FDC that is 1% to 60 % of the time (100-5250 hours) is characterized by a nearly constant streamflow. The observed regulated hydrograph also shows continuous sudden fluctuations of streamflow magnitudes while the predicted streamflow hydrographs and FDCs exhibit smoothly varying patterns, which are typical characteristics of natural flow.

Computing the magnitude index (HP1) of Carolli et al. (2015) for Lundesokna we obtained an average of 0.16 for the regression model and 0.12 for the P-R model while the observed data gave a value of 1.08. The threshold value for peaking has an average of 0.75. The temporal index (HP2) produced a value of 0.71 for the regression model, 0.25 for the P-R model and 1.9 for the observed. Here the threshold is 1.26. Figure 7a-f shows the environmental flow indices for Lundesokna. There is clear differences between the observed (regulated) data and the two modelled data series, even if a difference also can be observed between the regression and the P-R models, with the general observation that the P-R model computing a smaller variability in indices than the regression model. Compared to the patterns seen by Bevelhimer et al. (2015)

for a number of regulated and unregulated cases, the results obtained from Lundesokna are similar.

Alteration in the FDCs and hydrographs also indicate alterations in several streamflow characteristics, which probably affect the ecological integrity in regulated rivers. However, Knight et al. (2014) noted that at sites with reference hydrology other environmental factors and their interactions with hydrology may influence fish species richness. Bevelhimer et al. (2014) illustrated that sub-daily (hourly) flow metrics reveal variation among and within streams that is not captured by daily flow statistics. The authors also noted that multiple sub-daily statistics were not correlated with daily statistics despite being similar in purpose and scope, which showed the importance of assessing rapid flow variations for studies on flow-ecology relationships.

CONCLUSIONS

The study indicate that a simple regression model to develop relationships between flow duration curves and drainage areas, and transfer of streamflow time series information based on spatial proximity between donor and recipient catchment outperformed the transfer of optimal parameter sets from local calibration and regional parameter sets corresponding to maximum regional weighted average performance (NSE_{MRWA}) of the precipitation-runoff model. Therefore, the simple regression based derivation of natural streamflow hydrographs and duration curves at ungauged rivers would be useful for an operational environment in terms of better prediction of ecological relevant streamflow metrics to study ecological impacts of hydrological alterations. It would also relieve people working with management issues from relying on scarce or short data series. Furthermore, it contributes to the endeavors for the prediction in ungauged basins, which is one of the important but challenging tasks in hydrology. The models were applied in a boreal region but the methodologies should also be applicable in other climate regimes. Improved results for the hourly resolution are expected from regional modelling based on larger set of catchments.

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Table 1. Descriptions for the study catchments

Catchment No.	Name of catchments	NVE's Station No.	Catchment area, km^2	Observed mean runoff [a]		Observed median flow or P50[a]	Observed Mean/Median flow[a]
				m^3/s	$l/s/km^2$	m^3/s	
1	Dillfoss	127.13	480	17.59	36.64	9.86	1.78
2	Driva v/Risefoss	109.9	745	18.33	24.61	9.30	1.97
3	Eggafoss	122.11	668	18.50	27.70	7.86	2.35
4	Embrethølen	139.26	495	23.29	47.06	11.48	2.03
5	Feren	124.13	220	10.45	47.41	7.38	1.42
6	Gaulfoss	122.9	3090	80.31	25.99	40.70	1.97
7	Gisnås	121.29	95	2.76	29.24	1.25	2.21
8	Hugdal bru	122.17	546	15.62	28.60	9.42	1.66
9	Høggås bru	124.2	495	21.16	42.75	12.86	1.65
10	Isa v/Morstøl bru	103.2	44	3.28	73.89	1.75	1.87
11	Kjeldstad i Garb.	123.31	145	7.74	53.36	4.06	1.91
12	Krinsvatn	133.7	207	12.00	57.98	5.69	2.11
13	Lenglingen	308.1	450	12.78	28.41	6.68	1.91
14	Lillebudal bru	122.14	168	6.35	37.82	3.39	1.87
15	Murusjø	307.5	346	7.41	21.42	5.07	1.46
16	Osenelv v/Øren	105.1	138	6.01	43.56	4.05	1.48
17	Rauma v/Horgheim	103.4	1100	35.99	32.72	17.73	2.03
18	Rinna	112.8	91	4.19	45.98	2.30	1.82
19	Skjellbreivatn	139.25	546	11.97	21.93	7.04	1.70
20	Søya v/Melhus	111.9	138	8.75	63.52	4.26	2.05
21	Støafoss	128.5	477	19.97	41.86	11.72	1.70
22	Trangen	139.35	852	32.76	38.45	27.03	1.21
23	Valen	117.4	39	1.30	33.16	0.68	1.92
24	Valldøla v/Alstad	100.1	226	13.61	60.23	7.84	1.74
25	Vistdal	104.23	67	4.12	61.89	2.51	1.64
26	Øyungen	138.1	239	10.68	44.71	4.91	2.18

[a] Calculated from 2006 to 2011 hourly streamflow data.

Table 2. Linear correlation coefficients between streamflow percentiles and some catchment characteristics

Sreamflow (m^3/s) at FDC (%)	0	10	20	30	40	50	60	70	80	90	100
Catchment area (km^2)	0.85	0.98	0.96	0.95	0.94	0.92	0.91	0.90	0.88	0.85	0.92
Lake percentage	-0.32	-0.12	-0.11	-0.07	-0.04	-0.01	0.02	0.04	0.06	0.09	-0.03
Forest percentage	-0.03	-0.02	-0.03	-0.01	0.03	0.07	0.10	0.11	0.09	0.09	0.11
Minimum elevation, masl	-0.22	-0.24	-0.26	-0.27	-0.26	-0.26	-0.26	-0.27	-0.28	-0.28	-0.18
Maximum elevation, masl	-0.03	0.15	0.18	0.19	0.16	0.14	0.13	0.14	0.17	0.17	0.14
Median terrain slope (degree)	-0.25	-0.22	-0.21	-0.22	-0.23	-0.24	-0.25	-0.26	-0.25	-0.24	-0.16
Maximum terrain slope (degree)	0.09	0.19	0.22	0.24	0.22	0.21	0.21	0.22	0.23	0.23	0.13

Table 3. Cross-validation for evaluation of the regional regression and P-R models

Donor catchments	Recipient catchments										
	1	3	6	10	12	14	16	17	20	21	26
	Regional regression model[a]										
1	**0.94**	0.31	0.39	-1.00	0.50	-0.05	-1.13	-0.42	0.42	0.69	0.48
3	0.35	**0.96**	0.88	-0.35	-0.13	0.57	-2.22	0.47	0.33	0.02	-0.22
6	0.42	0.89	**0.94**	0.07	-0.07	0.58	-1.75	0.38	0.37	0.12	-0.15
10	0.04	0.39	0.42	**0.38**	-0.21	0.22	-2.54	0.61	0.44	-0.21	-0.36
12	0.53	-0.32	-0.25	-1.53	**0.76**	-0.65	-0.43	-0.54	0.16	0.65	0.78
14	0.23	0.80	0.77	-0.07	-0.17	**0.75**	-1.90	0.53	0.34	-0.07	-0.25
16	-0.01	-0.62	-0.46	-2.32	0.28	-0.92	**0.53**	-1.12	-0.08	0.16	0.26
17	-0.08	0.52	0.49	0.16	-0.31	0.32	-2.20	**0.98**	0.14	-0.30	-0.41
20	0.49	0.34	0.41	-0.31	0.22	0.13	-1.36	-0.14	**0.82**	0.23	0.10
21	0.71	-0.03	0.06	-1.42	0.59	-0.41	-0.77	-0.75	-0.34	**0.88**	0.65
26	0.47	-0.33	-0.27	-1.78	0.71	-0.72	-0.51	-1.02	0.07	0.65	**0.86**
	P-R model: local calibration[b]										
1	**0.74**	0.79	0.82	0.48	0.63	0.53	0.03	0.44	0.56	0.71	0.66
3	0.73	**0.81**	0.83	0.51	0.71	0.53	0.14	0.23	0.53	0.72	0.71
6	0.70	0.79	**0.83**	0.54	0.49	0.56	-0.59	0.15	0.65	0.67	0.54
10	-0.14	0.10	0.18	**0.58**	0.19	0.23	-0.23	0.16	0.31	0.24	0.06
12	0.68	0.78	0.70	0.50	**0.75**	0.52	0.12	0.41	0.51	0.70	0.71
14	0.62	0.66	0.74	0.47	0.27	**0.58**	-0.34	0.18	0.62	0.57	0.47
16	0.44	0.48	0.50	0.40	0.50	0.38	**0.67**	0.66	0.28	0.46	0.42
17	0.29	0.31	0.44	0.35	0.29	0.28	0.56	**0.77**	0.20	0.30	0.21
20	0.58	0.69	0.75	0.56	0.23	0.56	-1.16	-0.11	**0.67**	0.55	0.32
21	0.69	0.73	0.74	0.56	0.69	0.54	0.17	0.35	0.53	**0.71**	0.63
26	0.64	0.71	0.61	0.45	0.71	0.48	0.30	0.56	0.44	0.65	**0.72**
	P-R model: NSE_{MRWA}[c]										
1	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
3	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
6	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
10	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
12	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
14	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
16	0.66	0.70	0.73	0.42	0.69	0.47	0.52	0.67	0.44	0.63	0.66
17	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
20	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
21	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64
26	0.65	0.68	0.72	0.42	0.69	0.47	0.55	0.68	0.43	0.63	0.64

[a] Streamflow prediction for the recipient catchments from percentiles and catchment area relationships of 24 catchments by leaving out a donor catchment from the regional regression model (leave one out cross-validation) and transfer of streamflow time series information from the donor using the look-up function.

[b] Streamflow simulation for the recipient catchments by transferring optimal parameters of the local calibration of the P-R model from the donor catchments.

[c] Streamflow simulation for the recipient catchments by transferring parameter sets providing NSE_{MRWA} of the P-R model using 25 catchments by leaving out a donor catchment while calculating the NSE_{MRWA} (leave one out cross-validation).

Figure captions

Figure 1. Locations of modelled catchments, streamflow stations, climate stations and the Sokna catchment-hydropower systems.

Figure 2. Relationships between drainage areas and some streamflow percentiles to identify outlier catchments for the regional regression model.

Figure 3. Estimated regional regression parameters along their 95 % confidence intervals and R^2 for the percentiles.

Figure 4. Observed and predicted hourly streamflow hydrographs from transfer of regional information from Krinsvatn or catchment 12 to its nearby Øyungen or catchment 26 (regression) and simulation from transfer of local calibration and NSE_{MRWA} parameters (P-R model).

Figure 5. Indices from Bevelhimer et al. (2015) computed for Øyungen or catchment 26. The dashed line is for the observed streamflow, the dotted line is for the regression model and the solid line is for the P-R model (NSE_{MRWA}).

Figure 6. Regulated (observed) and predicted natural hourly streamflow hydrographs from transfer of streamflow information from Gaulfoss catchment to a nearby regulated Lundesokna river (regression) and transfer of parameter corresponding to the NSE_{MRWA} (P-R model).

Figure 7. Indices from Bevelhimer et al. (2015) computed for Lundesokna. The dashed line is for the regulated flow regime; the dotted line and solid line represent the unregulated (natural) flow regime for the regression and P-R model (NSE_{MRWA}) respectively.