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Regional parameter estimation from catchment properties prediction in ungauged basins

YESHEWATESFA HUNDECHA, ERWIN ZEHE & ANDRÁS BÁRDOSSY
Institute of Hydraulic Engineering, University of Stuttgart, 70550 Stuttgart, Germany
zehe@iws.uni-stuttgart.de

Abstract This study presents an advanced approach for linking available catchment properties to model parameters through a Lippschitz continuous transfer function. This assures that "similar" catchments are mapped on "similar" parameter sets. Using runoff data from gauged catchments in a region of interest, the parameters of the transfer function are optimized for a sample of calibration catchments. Once obtained, this characteristic transfer function allows the *a priori* derivation of model parameters sets for ungauged catchments based on available catchment properties. This approach has been used to build a hydrological model for the entire German part of the Rhine basin (100 000 km^2) and yielded promising results.
Key words Lippschitz continuous transfer function; model parameters; regional parameter estimation; Rhine basin

INTRODUCTION

Prediction in Ungauged Basins (PUB) is one of the most challenging tasks in hydrology of the 21st century. However, from our point of view, PUB may have different meanings depending on the region of interest and the envisaged goals, such as:

– the statistical characterization of the runoff behaviour (average, variance, return period) on the basis of available landscape characteristics and average regional climate;
– the stochastical generation of a runoff times series by transposing parameters from "similar" basins;
– predicting the rainfall–runoff process, water budget, or even the impact of changes in land-use and climate.

All these different levels of PUB require to some extent: (a) understanding of how the dominating hydrological processes are determined by typical basin properties in different regions; (b) the assessment of input data and typical basin properties with appropriate measurement techniques; (c) the *a priori* estimation of model parameters based on the available basin properties; but also (d) the development of new modelling approaches such as the REW concept (Reggiani *et al*., 1999).

Addressing point (c), the present study introduces an advanced approach to estimate parameter sets of conceptual hydrological models from simple basin properties. It is well known that estimating model parameters is even a crucial topic for gauged catchments, as optimal parameter sets are mostly not unique (Beven, 2000; Beven & Freer, 2002). Thus, predictions by conceptual models are considerably uncertain, even

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for gauged catchments. Hence, one could argue that a conceptual hydrological model is not the right tool to predict runoff from an ungauged catchment. In principle, physically-based models such as MIKE SHE (Refsgaard & Storm, 1995) would do better, but they require a large number of parameters such as the very important soil hydraulic functions. Although soil hydraulic functions may, in principle, be estimated by means of pedo-transfer functions, this requires detailed information about soil texture and soil layering at a high spatial resolution, due to the high spatial variability of natural soils. This information might not be available in most of the ungauged basins. Furthermore, estimated soil hydraulic functions cause a considerable uncertainty in the model results, as recently shown by Christiaens & Feyen (2001). Thus, physically based models could in principle do better, but they will not actually do better.

The approach to estimate model parameter from catchment properties presented here, was developed by Bárdossy *et al*. (2001) to quantify the impact of land-use changes on floods and water budget in the Rhine catchment. As the estimation of model parameters is a mapping from the space of "catchment properties" into the space of model parameters, we defined a transfer function for that purpose and optimized the parameters of the transfer function within a calibration process. By recommending that "similar" catchments have to be mapped on "similar" parameter sets, the above mentioned equifinality of model parameter sets is considerably reduced. The optimization, carried out with runoff data from gauged catchments in the region of interest, yields a characteristic transfer function that allows *a priori* estimation of model parameters sets for ungauged catchments. Furthermore, changes in land-use may be mapped on different parameter sets and the impact of land-use changes on flood events may be simulated. In the following, we explain the approach for regional parameter estimation in detail and present promising results that were obtained for the Rhine catchment.

METHODOLOGY

Basin scale hydrological model

Our objective was to develop a parameter estimation that allows the quantification of the impact of land-use changes on floods in the Rhine basin using the conceptual HBV-IWS model (Bergström, 1995). The HBV-IWS is a semi-distributed model that allows further subdivision of a subcatchment into zones according to the elevation, land-use and soil type. The soil model consists of a simple nonlinear soil reservoir, an upper nonlinear reservoir to describe fast runoff components and a deep linear reservoir for groundwater storage and baseflow. Snow melt is simulated using a precipitation dependent modification of the degree day method. Actual evaporation is a function of soil saturation and potential evaporation. Runoff concentration and flood routing are modelled by means of a triangular unit hydrograph and the Muskingum approach.

The 100 000 km^2 large Rhine basin was subdivided into 101 subcatchments (Fig. 1), each of the subcatchments was further subdivided into individual zones as a function of elevation, soil type and land-use. Input data at daily resolution came from more than 900 raingauges and up to 200 synoptic stations, which were interpolated to the individual zones using external drift kriging. For the development and testing of the parameter estimation approach, runoff data from more than 60 gauges was available.

Parameter estimation using a characteristic transfer function

To establish a quantitative relation between a vector of catchment properties e and a vector of model parameters p a transfer function G_p was defined. The components of the catchment property vector e were the parts of the catchment that were covered by different land-use classes l_k, different soils s_j, as well as parameters that describe catchment size and shape f_i. To assure that similar catchments are mapped on similar parameter sets, the recommended transfer function is the Lippschitz-continuous. Defining a distance function D one has to assure:

$$e = (l_k, s_j, f_i)$$

$$p = G_p(e) \tag{1}$$

$$D(p_i, p_j) \leq K_{Lipp} D(e_i, e_j)$$

For reasons of simplicity we choose a linear transfer function:

$$G_p = \sum \alpha_k l_k + \sum \beta_j s_j + \sum \gamma_k f_k \tag{2}$$

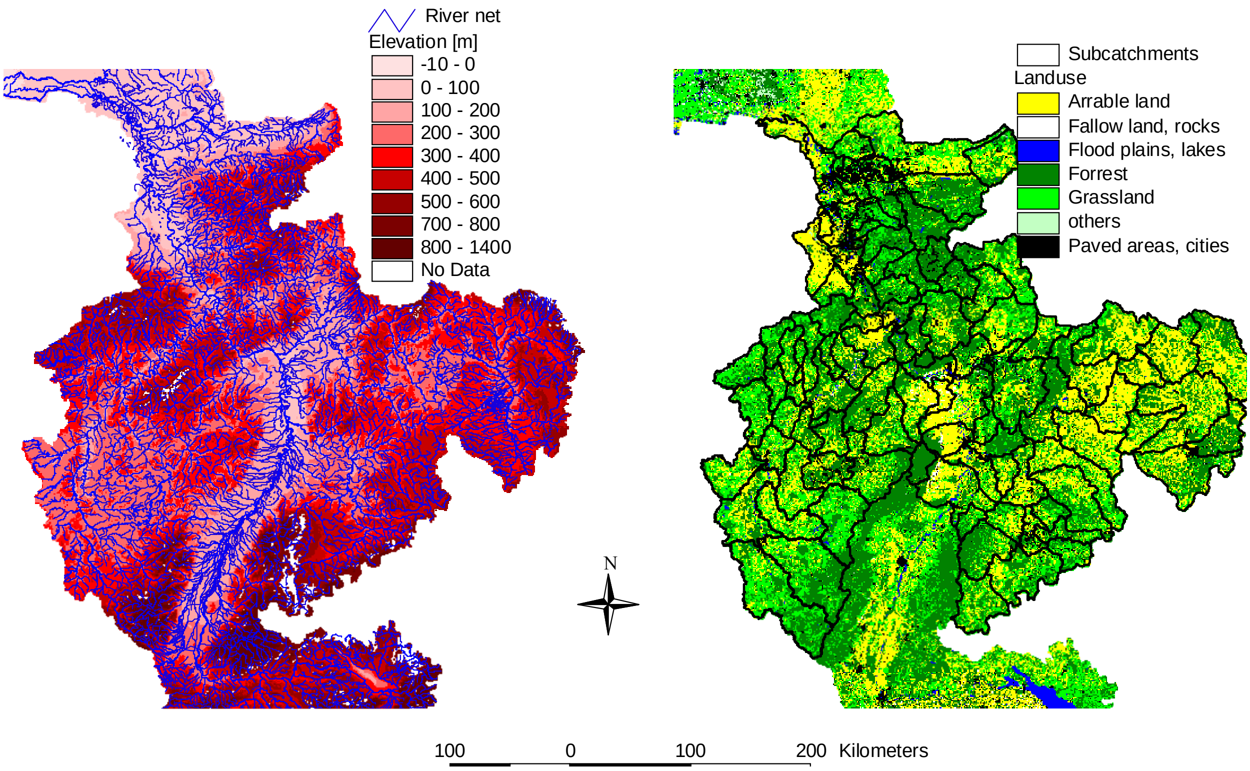

Fig. 1 Elevation, river net, land-use pattern and subcatchments in the Rhine basin.

Thus, in this approach we did not optimize the parameter sets of the hydrological model directly, but we optimized the parameter vectors α, β and γ of the transfer function in the whole model area. The Lippschitz condition constrained the coefficients α, β and γ, which assured that closely related catchments were indeed mapped to nearby model parameter sets in the parameter space. Furthermore, this constraint also assured spatial consistency of the model parameters. Based on the optimized transfer function, the parameters of the hydrological models may be computed as a function of the subcatchment properties. Consequently, this transfer function may be used to estimate model parameters for ungauged catchments in the same region.

In order to assess an optimal parameter set of the transfer function, 30 subcatchments that reflected the full variability of land-use, soil types and morphological properties were selected, and an arbitrary initial parameter set of the transfer function was chosen. Using these starting values, the parameter of the HBW-IWS were estimated and the water cycle of the selected catchments was simulated. By means of the simulated and observed discharge $Q_c^m(t)$ and $Q_o^m(t)$ an objective function O_m was defined, that had to be minimized for each subcatchment in the calibration sample:

$$O_m = \sum_t w(t)\left(Q_c{}^m(t) - Q_o{}^m(t)\right)^2 \tag{3}$$

The weighting function $w(t)$ gives emphasis to the peak flows, m is the catchment number in the calibration sample. To aggregate the objective functions of the subcatchments into a single one, the individual objective functions were normalized to avoid the influence of the different scales of the discharges originating from the subcatchments. A weighted Nash-Sutcliffe efficiency coefficient was introduced for that purpose, where $\overline{Q}_o{}^m$ is the average observed discharge in the simulation period:

$$R^2{}_m = 1 - \frac{\sum_t w(t)\left(Q_c{}^m(t) - Q_o{}^m(t)\right)^2}{\sum_t w(t)\left(Q_c{}^m(t) - \overline{Q}_o{}^m\right)^2} \tag{4}$$

The aggregated objective function O for model calibration was then formulated as:

$$O = \sum_m R^2{}_m \to \max \tag{5}$$

Unfortunately the aggregated objective function only measures the average performance of the model, which might lead to an unbalanced model performance in individual catchments. Although a poor performance of the model in some subcatchments might be offset by a good performance in others, the aggregated objective function was modified by giving much emphasis to the subcatchment in which the model performance was the worst:

$$O = \sum_m R^2{}_m + M \min R^2{}_m \to \max \tag{6}$$

In order to reduce the dimensionality of the optimization, only sensitive parameters of the HBV-IWS were used to form the target vector within the optimization scheme. The sensitivities of the model parameters, the related hydrological process and catchment properties are shown in Table 1.

Table 1 Sensitivities of the model parameters, related process and catchment property.

Parameter and related process	Sensitivity	Catchment property
CC (snow melt)	+	land-use
TT (snow melt)	+	land-use
FC (soil water/evapotranspiration)	+++	soil type
LP (soil water/evapotranspiration)	–	soil type
β (soil water/evapotranspiration)	+	soil type
C_{ET} (interception)	–	land-use
α (runoff generation)	+++	land-use
k_1, k_2, perc (runoff generation)	+++	soil type
MAXBAS (runoff generation)	–	topography, size

Validation of the model parameter sets that were computed by means of the optimized transfer function for the calibration catchments was done by simulating the water cycle for a period that was not included in the optimization. To evaluate the feasibility of the transfer function approach to derive model parameters for ungauged catchments, we computed the model parameters *a priori* for validation catchments that were not in the calibration sample. Based on these estimated parameters, runoff was predicted for these catchments and the predicted discharge was compared with the observed values. The catchments that were not included in the calibration sample will be referred to as validation catchments. The model results were generally evaluated by computing the Nash-Sutcliffe efficiency, the average relative peak error as well as the relative accumulated difference cd_r between the average observed $\overline{Q}_o$ and average simulated discharge $\overline{Q}_c$:

$$cd_r = \frac{\overline{Q_c} - \overline{Q}_o}{\overline{Q}_o} \tag{7}$$

RESULTS

The model parameters that were computed for the catchments in the calibration sample yielded, in general, a good model performance, especially for the peak discharges during flood events. Exemplary Fig. 2 presents the simulated and observed runoff at the outlet of the Kocher catchment for the years 1988 and 1995 in the calibration and validation period, respectively. The peak flows are somewhat overestimated in spring 1995, nevertheless the simulation yields a reasonable fit.

Table 2 summarizes the model performance in the four major sub basins Neckar, Main, Lahn and Lippe that contained the calibration catchments to optimize the parameter of the transfer function. The Nash-Sutcliffe effiency is greater than 0.9 for each of these sub basins. The simulation for Kleinheubach (Main) shows a negative bias of 10% in terms of the long-term average discharge. The average relative peak errors are smaller than 5%. Thus, the model obviously matched the peak flows quite well.

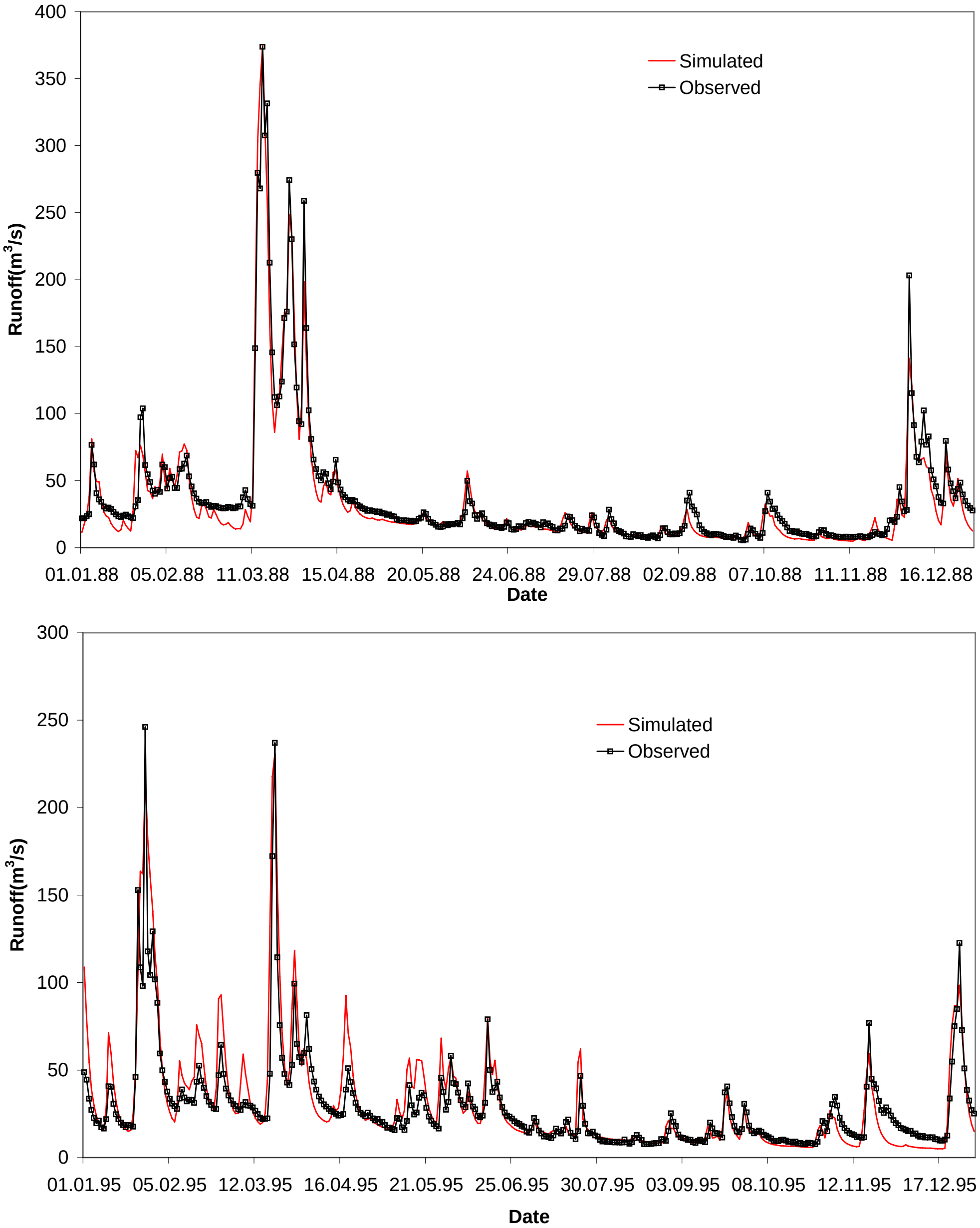

Fig. 2 Simulated and measured runoff at the outlet of the Kocher catchment shown for 1 year in the calibration period (upper graph) and validation period (lower graph).

Table 2 Summary of the model performance in different parts of the study area.

Gauge	Drainage area (km^2)	Nash-Sutcliffe coeff.	rel.acc. diff.	peak error
Rockenau (Neckar)	12655	0.925	0.030	0.031
Kleinheub. (Main)	21505	0.912	–0.106	–0.010
Kalkofen (Lahn)	5304	0.926	0.068	0.050
Schermbeck (Lippe)	4783	0.943	–0.081	–0.043
Hattingen (Ruhr)**	4118	0.888	–0.004	–0.107
Cochem (Mosel)**	27088	0.955	0.003	0.080
Grolsheim (Nahe)**	4013	0.865	0.189	–0.168
Menden (Sieg)**	2825	0.931	0.033	–0.185

** Validation catchments that were not in included in the calibration sample.

Figure 3 shows the predicted and observed discharge for the validation catchment Grolsheim in the Nahe basin, that was not included in the calibration sample. Although discharge is overestimated in summer time, the performance is reasonable, especially in the case of extreme floods in winter. Note that the underlying model parameters were derived from the catchment properties using the transfer function, so the model was not calibrated to the observed hydrograph. Table 2 summarizes the quality of the model predictions for four large validation catchments.

The Nash-Sutcliffe efficiency is in a reasonable range, between 0.87 and 0.95. As indicated in Fig. 3, the prediction for Grolsheim yields a remarkable overestimation of the average discharge of nearly 19%. The relative peak errors are clearly higher than in the calibration catchments, but they are still in a tolerable magnitude. Thus, we may conclude that the model parameters that were derived *a priori* from the properties of the validation catchments yield reasonable predictions of the rainfall–runoff process.

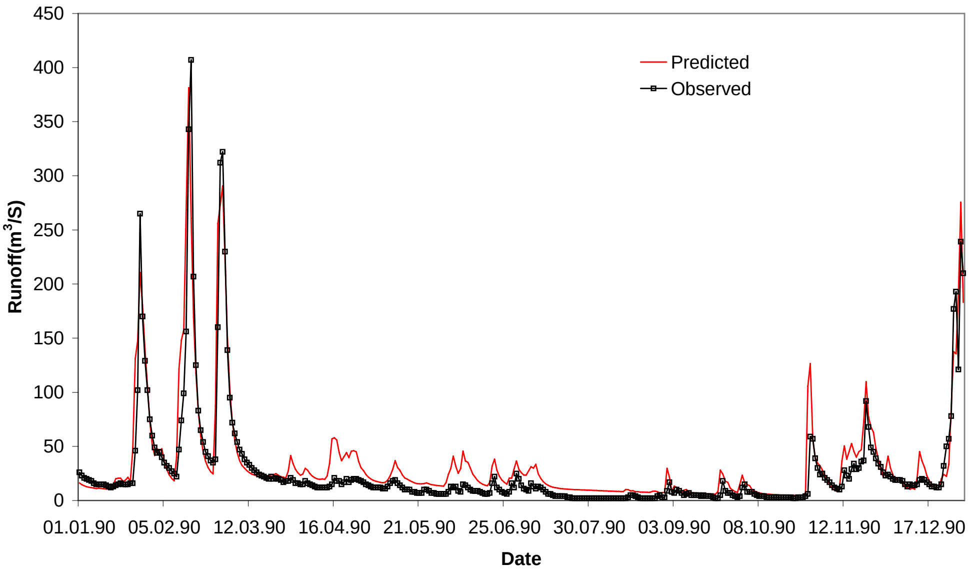

Fig. 3 Predicted and observed discharge for the catchment Grolsheim in the Nahe basin.

DISCUSSION AND OUTLOOK

Predicting the rainfall–runoff process in ungauged basins requires suitable measurement techniques of model input data and catchment characteristics, but also the estimation of model parameters from catchment characteristics. The last point leads to one of the cardinal problems in hydrological modelling. Parameters of physically-based models may be directly measured or estimated *a priori* from pedological or morphological catchment properties. However, these data are certainly not available in the required resolution and quality for most of the ungauged basins. Furthermore the performance of physically-based models in heterogeneous soils is still limited, e.g. in the case of preferential flow. Conceptual hydrological models require a smaller number of parameters, but the relation between these parameters and catchment properties are not obvious. Thus, the application of conceptual models requires calibration and therefore runoff data. However, if model calibration is understood as the search for an optimal functional relation between catchment properties and model parameters as suggested here, at least part of the hurdle may be overcome. In the presented approach we end up with a typical transfer function for the Rhine basin, which allowed the derivation of parameter sets that yielded reasonable predictions of the rainfall–runoff process.

Similar concepts of parameter estimation and regionalization based on different input data and hydrological models were successfully developed by Wooldridge *et al.* (2001) for the Williams River catchment in Australia, Abdulla & Lettenmaier (1997a,b) for the Arkansah River basin, and by Dunn & Lilly (2001). The general approach to relating catchment properties and model parameters is flexible as it is not restricted to a special model, nor to special input data. For PUB it would be interesting to test the introduced regional parameter estimation with: (a) different hydrological models and (b) remote sensing data as input to the transfer function. For example, similarities between images of spectral brightness or greenness could be defined by means of pattern recognition. If successful, this would be a reasonable progress towards the prediction of ungauged catchments. Remote sensing data could be used to "measure" catchment similarity and to optimize a transfer function from gauged catchments in a region of interest. Model parameters for ungauged catchments could be derived from the remote sensing information and used for model predictions.

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