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Comparison of four regionalisation methods for a distributed hydrological model

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Summary This study presents a grid-based modification of the HBV model concept and four regionalisation approaches using widely available catchment characteristics in the meso-scale Neckar catchment. The HBV model was adapted to allow for the simulation of catchment runoff and daily groundwater recharge in a high spatial discretisation. The resulting large number of model parameters requires the use of a regionalisation method which also ensures consistent parameter estimation. Therefore, in the first approach, functional relationships between catchment characteristics and model parameters have been defined a priori. These established relationships were used to calibrate the model by modifying the parameters of the transfer functions instead of the model parameters themselves. The results are compared to relationships derived from simultaneously calibrated model parameters constrained to form a function of catchment characteristics by a modification of the Lipschitz condition, a monotony condition and a combination of both constraints. Through this reduction of the available parameter space for optimisation, the problem of equifinality is avoided which often results in weak regression relationships between model parameters and catchment characteristics. The methodology is demonstrated using six subcatchments of the Neckar basin to set up the relationships and 51 other subcatchments to evaluate its performance. All four methods were able to produce reasonable parameter sets for most of the regionalisation catchments. As expected, all four methods failed to reproduce the observed discharge in karstic areas and in heavily modified or regulated river basins, which indicates their sensitivity to catchment characteristics. The modified Lipschitz condition produced the most efficient simulations of observed discharges in the regionalisation at the cost of some inconsistencies in the physical interpretation of the resulting relationships. The monotony condition preserved the assumed trends in the functions between cell properties and model parameters but produced sharp jumps which are not considered plausible. The combination of both methods seems to be the most promising because it produced equally good regionalisation results with much more consistent regression relationships.

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The approach can reproduce derived trends and the resulting relationships match our understanding of how the underlying processes are represented in the model.

Introduction

Relationships between catchment characteristics and model parameters are important prerequisites for the parameterisation of distributed hydrological models, assessment of land use changes and predictions in ungauged basins Sivapalan et al., 2003. As distributed information is used more and more in water resources management and planning, there is a continuing need for improved parameterisation strategies of distributed models. As the effect of land use changes can not always be assessed with experimental data, distributed models are currently the most promising way to solve this problem (Hundecha and Bárdossy, 2004).

Vogel (2005) provides a comprehensive overview of regionalisation studies and approaches. Besides bi- and multivariate regression, clustering, kriging, neural networks and hydrologically homogeneous regions have been used but so far with only limited success. The biggest problem in most of these studies has been the existence of multiple optimal parameter sets which results in weak regression relationships when the regionalisation is carried out after individual calibration.

Parajka et al. (2005) found that a kriging approach and a similarity approach performed best when they tested 17 methods of the types arithmetic mean, spatial proximity, regression and similarity on the HBV model parameters of 320 Austrian catchments. Lee et al. (2005) attempted to find relationships between suitable conceptual rainfall-runoff model structures and catchment types to improve the reliability of model regionalisation to ungauged catchments. They investigated 28 UK catchments and 12 potential model structures but did not find strong correlations to area, baseflow index or annual average rainfall. Maréchal and Holman (2005) developed a catchment-scale rainfall-runoff model parameterised by the UK Hydrology of Soil Types classification. They calibrated the model to three distinct catchments and found promising results for the regionalisation of the parameters throughout the UK.

However, scale-differences between the variables the relationships were developed for and those they are applied on require additional attention. Xu (2003) found that the parameters of a monthly water balance model could be transferred by regression from 22 meso-scale subcatchments in the NOPEX area to the 30 times larger Lake Mäaren basin in Sweden.

Nevertheless, for distributed water balance models, regionalisation of the parameters is often the only possibility to reduce the uncertainty from overparameterisation, effective grid scale parameters and the model structure or sometimes to find appropriate parameter values at all (Beven, 2001). Engeland et al. (2001) therefore used a Bayesian approach to parameterise the 2 km^2 gridded ECOMAG model for nine catchments of the NOPEX region in Sweden, based on six soil and five land use classes. A limit in the identifiability was reached for three snow related parameters after data from seven catchments was included. On the other hand two retention related parameters (depression storage and vertical conductivity) could not be defined appropriately with information from all nine catchments.

Beldring et al. (2003) calibrated six parameters for five land use classes in their 1 km^2 distributed HBV model of Norway. They ran the model with a daily time step but used monthly mean runoff for calibration in 141 catchments. Although they used 31 parameters to describe the altitude gradients, they found that the major problem was the spatial interpolation of the meteorological input data.

In this study, five parameters of a 1 km^2 gridded version of the HBV model are estimated based on soil properties, topography and six land use classes. Four regionalisation methods are compared: The first approach estimates the relationships between catchment characteristics and model parameters directly. Following the ideas of Hundecha and Bárdossy (2004), transfer functions are defined and the parameters of the transfer functions are calibrated instead of the model parameters themselves. The other three more general approaches use prior knowledge about the form of these functions. By imposing conditions on the relationships between model parameters and catchment characteristics the available parameter space for calibration is significantly reduced. This is demonstrated with a modified Lipschitz condition as a measure of similarity, a monotony condition and a combination of both constraints. The model is calibrated to the central European Neckar basin.

Data

The Neckar basin, located in south-western Germany, covers an area of about 14,000 km^2 (Fig. 1). The elevation in the catchment varies from 91 m a.s.l at the catchment outlet to about 1030 m a.s.l in the Swabian Alb in the south of the catchment. The climate can be characterised as humid with a long-term average annual precipitation of 950 mm, ranging from 750 mm in the lower part to over 1200 mm in the Black Forest.

Land use (Landsat 1993, resolution 30 m), soil (Bodenübersichtskarte 200, scale 1:200,000) and topographic data (resolution 50 m) were aggregated to a common resolution (1 km). Precipitation and temperature data for model input was interpolated from observation station data using external drift kriging (Ahmed and de Marsily, 1987). Daily discharge data from 57 gauging stations was used for model evaluation. All data was provided by the State Institute for Environmental Protection Baden-Württemberg.

The distributed HBV model

The HBV model concept was developed by the Swedish Meteorological and Hydrological Institute in the early 1970s. It has conceptual routines for calculating snow accumulation and melt, soil moisture and runoff generation,

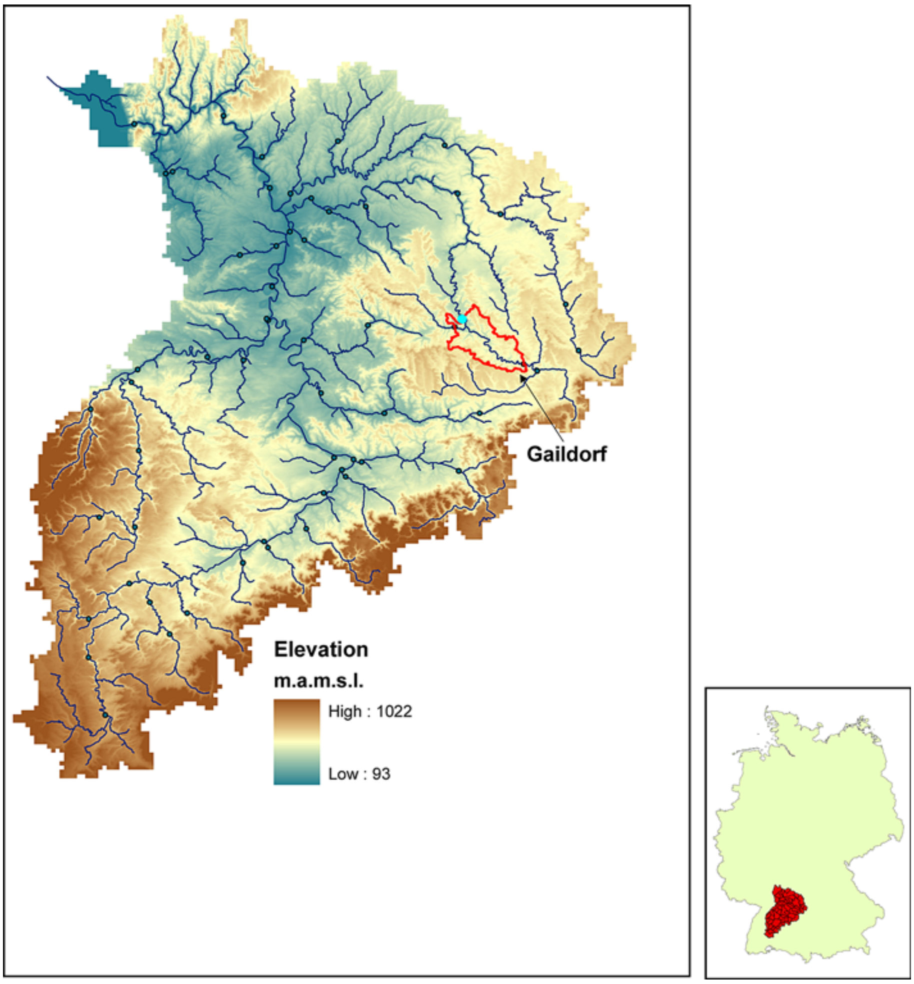

Figure 1 Topography of the Neckar catchment and location of the subcatchment Gaildorf (Kocher); Inset: Location of the Neckar catchment in Germany.

runoff concentration within the subcatchment and flood routing of the discharge in the river network. The snow routine uses the degree-day approach. Soil moisture is calculated by balancing precipitation and evapotranspiration using field capacity and permanent wilting point as parameters. Mean monthly potential evapotranspiration is calculated outside the model in this case based on Hargreaves and Samani (1985). The actual daily evapotranspiration is adjusted based on the actual temperature and a calibrated coefficient and reduced linearly below the permanent wilting point. Runoff generation is simulated by a non-linear function of actual soil moisture and precipitation. The runoff concentration is modeled by two parallel reservoirs representing the direct discharge and the groundwater response. Flood routing between the river network nodes uses the Muskingum method. Additional information about the HBV model can be found in Bergström (1995), Hundecha and Bárdossy (2004) and Hundecha (2005).

The main difference to the original HBV model is the use of square grid cells as primary hydrological units. This modification is necessary for two reasons:

- All input data (precipitation and temperature) and catchment properties (e.g., soil and land use data) are calculated for the common model grid.
- To simulate the effects of changes in spatial land use patterns including the effects of a changed distribution within a subcatchment.

For these reasons, snowmelt, soil moisture, evapotranspiration and runoff concentration are calculated for each grid cell individually. The only exception is the runoff response which is represented conceptually by reservoirs for direct discharge and baseflow, respectively. The groundwater reservoir for the subcatchments is aggregated because the processes in the groundwater systems are taking place on larger scales. A further improvement is a more physically based soil moisture module.

In the original HBV model, discharge is generated by the soil module based on saturation. The direct runoff reservoir has two outlets of which the bottom outlet is considered groundwater recharge and feeds into the groundwater reservoir. The soil moisture is only reduced by evapotranspiration.

The new soil module also considers drainage from the soil to the groundwater system as a sink term in the soil moisture balance. The maximum soil moisture storage is defined by the field capacity. Based on actual soil moisture, a variable part of precipitation and snow melt is turned into direct runoff and transferred to the direct runoff reservoir like in the original version. The main difference is that the percolation is now connecting the soil moisture storage to the groundwater reservoir controlled by a maximum percolation rate and the saturation of the grid cell (Fig. 2).

The performance of the old and new soil module was not compared specifically. Considering only the efficiency in simulating observed discharges, the fully distributed version with the new soil module was slightly inferior. It was still used in this study because it provides more information and is supposed to represent the natural system in a more realistic way. Thus facilitating the regionalisation of parameters because the process description is closer to the processes observed in the field.

Despite the large number of parameters, this modified version is expected to produce spatially more reasonable results than the original HBV model because the spatial distribution of the processes is taken into account rather than averaging over larger areas or elevation bands. Similar results were obtained by Uhlenbrook et al. (2004). Nonetheless, improved results are contingent on the accuracy of the input data.

Runoff production in the soil (P_{eff}) is calculated using a non-linear relationship between actual soil moisture (SM), field capacity (FC) and rainfall plus snowmelt (P) (Eq. (1)). Direct runoff, percolation from the grid cells and baseflow from each sub catchment is calculated using the following formulas (Eqs. (2)–(4)):

$$P_{\mathrm{eff}} = (\mathrm{SM}/\mathrm{FC})^{\beta} \cdot P \tag{1}$$

$$Q_{\mathrm{perc}} = k_{\mathrm{perc}} \cdot \mathrm{SM} \cdot (\mathrm{SM}/\mathrm{FC})^{5-\beta} \tag{2}$$

$$Q_1 = k_1 \cdot S_1^{1+\alpha} \tag{3}$$

$$Q_2 = k_2 \cdot S_2 \tag{4}$$

Q_i is the discharge from the respective outlet of the reservoirs; k_i is the respective recession coefficient, α is the exponent and S_i is the water level of the reservoirs (Eqs. (3) and (4)). The non-linearity parameter β describes the variability of the runoff coefficient of the soil at different saturations (Eq. (1)). The percolation is limited by a maximum rate when the soil is saturated (k_{perc}). Below field capacity, the percolation is also reduced in a non-linear way using the same parameter β but with opposite direction and depending on the range of the parameter. In this case, it varies between one and four leading to higher infiltration rates for soils with high β (Eq. (2)). Using β in Eqs. (1) and (2) assumes that soils with higher runoff coefficients (small β) will also show smaller infiltration capacities. Hence, there is scope for further research in the formulation of the soil moisture module.

The regionalisation methods

The calibration parameters of the routines described above were regionalised based on catchment characteristics for two reasons:

- Calibrating a model with a significant number of free parameters for every grid cell is not reasonable for meso-scale catchments.
- If the model is to reflect changes in catchment properties, then the parameters must be linked to natural features of the basin since calibration for future scenarios is not possible.

Four different regionalisation approaches were used. The idea behind all four is to reduce the parameter space available for optimisation by some form of constraint and therefore be able to find reasonable regression relationships, avoiding the problem of equifinality which often leads to weak correlations between model parameters and catchment properties.

Transfer functions

In this method the model parameters, p, are expressed by transfer functions of catchment characteristics:

$$p = f(\text{flow time},\ \text{land use},\ \text{soil properties},\ \text{area},\ \text{geology}) \tag{5}$$

Regionalisation was completed by a priori assumption of linear or logistic relationships between model and transfer

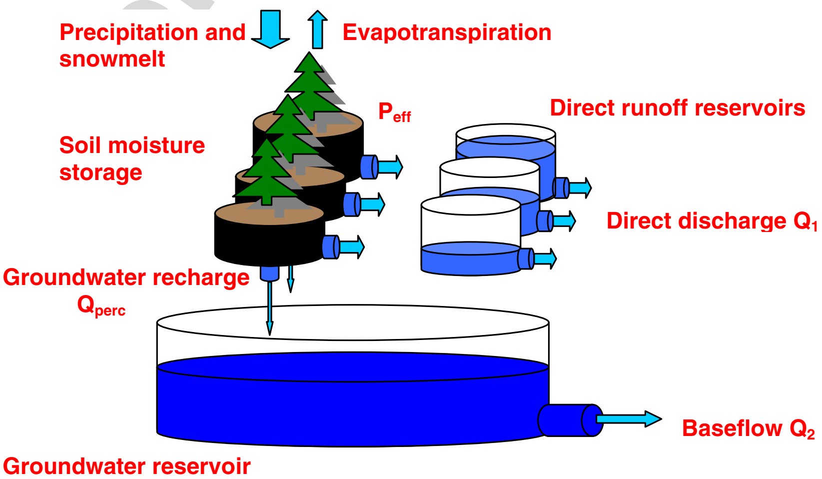

Figure 2 Representation of the main processes in the modified HBV model.

function parameters. The model was then calibrated by adjusting the parameters of the transfer functions instead of the model parameters themselves following the method proposed by Hundecha and Bárdossy (2004). Table 1 shows the combinations of catchment characteristics and model parameters used for calibration. The cell properties which are most closely related to the respective model parameters were selected. As several possible alternatives were suitable, the most successful combinations were chosen for further application.

Other parameters such as the degree-day factor, threshold temperature, and additional evapotranspiration are calibrated directly and held constant throughout the study area. The areal weighted mean soil properties (field capacity, permanent wilting point, hydraulic conductivity of two soil layers) for the grid cells are calculated from the attributes of the soil classes identified in the catchment. Automatic calibration was accomplished using simulated annealing (Aarts and Korst, 1989), maximising an objective function composed of Nash–Sutcliffe efficiencies of several temporal aggregation steps. Daily discharges are used to calibrate the runoff concentration parameters (α, k_1, k_{perc} and k_2) to adjust the retention of the discharge. Weekly and mean annual discharges are used to calibrate the runoff generation parameter β, which controls the water balance.

Thus, a more detailed and realistic representation of the underlying physical processes is achieved with less free calibration parameters than a lumped model approach. This approach was successfully tested in the upper Neckar basin (Götzinger and Bárdossy, 2005). But in general the definition of the functional form of the relationship a priori is difficult. The method is relatively static and suitable coefficients are hard to find for a larger range of catchment characteristics. As the results for the whole Neckar basin were not as good as expected, another methodology was developed.

Modified Lipschitz condition

To improve the efficiency of the regionalisation procedure another strategy was tested and compared. The same parameters were calibrated directly for the whole catchment and the combinations of parameters and catchment characteristics described in Table 1 were also used. However, in this strategy the parameters of a selected set of subcatchments were calibrated simultaneously under the condition that similar cell properties must lead to similar model parameters. This assumption can be enforced using the continuity of the regionalisation relationship. In analysis, a function is said to be Lipschitz continuous if Eq. (6) holds:

$$|f(x_1) - f(x_2)| \leqslant K \cdot |x_1 - x_2| \tag{6}$$

This concept of continuity is widely accepted in natural sciences. It is generally assumed that any entities with similar properties will also behave similarly. This assumption is utilised in the parameter estimation problem by a modified Lipschitz condition:

$$|p_i - p_j| \leqslant \sum_{k=1}^{L} |c_{ki} - c_{kj}| \cdot K_k \tag{7}$$

where p are the model parameters, c are the utilised cell properties indexed by k, whereas i and j are indices for all the cells of the respective set. K_k is the so called Lipschitz constant for each cell property and L is the number of characteristics used to estimate one parameter. In this study, L is two for all parameters (Table 1). During the optimisation process only those parameter sets which fulfil this condition and yield satisfactory discharge simulations are accepted. The functional relationship is enforced by lowering K_k in subsequent calibration runs until an acceptable regression is found. By excluding all parameters which do not fulfil the Lipschitz condition, only the discharge simulations of those parameters which fall into the corridor defined by K_k are evaluated. Here and also in the following two approaches, the regression relationships themselves were not evaluated statistically. Nevertheless, their successful application in the regionalisation catchments shows that they are reasonable. Since some of the results of this method were difficult to interpret another constraint was tested.

Monotony condition

The trend of the results of a change of catchment properties is usually known, e.g. a higher storage capacity of the soil will generally lead to lower runoff values. This knowledge can be translated into model parameters by prescribing that the relation to catchment properties should be monotonously increasing or decreasing as shown.

$$\text{if } c_{ki} \leqslant (\geqslant) c_{kj} \text{ for all } k \text{ then } p_i \leqslant (\geqslant) p_j \tag{8}$$

Again, p are the model parameters, c are the utilised cell properties indexed by k, and i and j are indices for all the cells of the calibration set. All combinations of trends are possible and have been used in this study, e.g. the recession coefficient of the groundwater reservoir (k_2): A larger bedrock permeability or a smaller catchment area will both lead to a quicker groundwater reaction, i.e. a smaller k_2. The inequalities are adapted to represent the assumed trends in each case. The same parameters were calibrated directly, the same combinations of parameters and catchment characteristics were used and the parameters of the same set of subcatchments were calibrated simultaneously. Again, only those parameter sets which fulfil this condition

Table 1 Regionalised parameters and basis for regionalisation

Parameter	Regionalised by	Regression type
β	Upper soil layer permeability, permanent wilting point	Logistic
k_{perc}	Bedrock permeability, lower soil layer permeability	Logistic
k_1	Flow time, land use	Linear
α	Land use, field capacity	Logistic
k_2	Bedrock permeability, catchment area	Linear

and can reproduce the observed discharge are accepted and the model is calibrated until a suitable regression relationship is found. By excluding all parameters which do not fulfil the monotony condition, only the discharge simulations of those parameters which follow the assumed trends are evaluated. Although this approach ensures the overall trend of the dependencies it leads to jumps in the relationships which are hard to explain from physics. Therefore a combination of the last two approaches was tested.

Combination of Lipschitz and monotony

Using both conditions simultaneously combines their advantages. It ensures that the relationships are sufficiently smooth and follow the trends assumed a priori. Therefore in this last trial only parameter sets which fulfil the Lipschitz and the monotony condition are accepted during calibration. The combination of both conditions ensures that only parameter sets which follow the assumed trends in a smooth way are used in the calibration. By optimising the simulation efficiencies mentioned above the model is calibrated until a useful regression relationship can be derived.

Examples

As can be seen from Table 1 each model parameter is combined with two cell properties which results in two-dimensional functions in the case of cardinal features. For classified attributes, a one-dimensional function for each class is defined. As an example the resulting relationships between field capacity and the exponent α of the non-linear direct runoff reservoir (Eq. (3)) for the six dominant land use classes are shown in Figs. 3–6.

Fig. 3 shows the smooth transition of the logistic transfer function from high values of α to lower ones with increasing field capacity. The course of Fig. 4 is quite different. The modified Lipschitz condition defines only the maximum absolute slope of the resulting trend line fitted through the points of the graph. The consequent local maxima, minima and changes in absolute slope make a physical interpretation difficult. Therefore the monotony condition was introduced which follows the same transition as the transfer functions but with much more flexibility. The many sharp jumps which can be observed in Fig. 5 can not be explained physically by threshold behavior but are more likely artifacts of the optimisation routine. Finally, the combination of both constraints (Fig. 6) follows the trend derived from our understanding of the processes but without sharp jumps, which occur if only the monotony condition is used. As mentioned earlier, trend lines can now be fitted through the resulting points of Figs. 4–6 . Those relationships or the transfer functions can then be applied in ungauged catchments to determine the model parameters from the prevailing catchment properties.

Results and discussion

In this case study, six subcatchments with areas from 45 km^2 to 340 km^2 were used to calibrate the model on rainfall, temperature and runoff data from 1980 to 1989. The subcatchments were selected in order to cover the whole range of available catchment characteristics. The regionalisation relationships determined in the calibration were then validated in the remaining 51 subcatchments of the Neckar basin. As an example of the application of the presented methodologies, the simulated and observed hydrographs from the 140 km^2 subcatchment Gaildorf (Kocher) are shown in Figs. 7–10.

The model could not be calibrated successfully to the smallest subcatchment (Schwaigern, Lein) with any of the methods. Only the combination of Lipschitz and monotony condition produced discharge simulations which

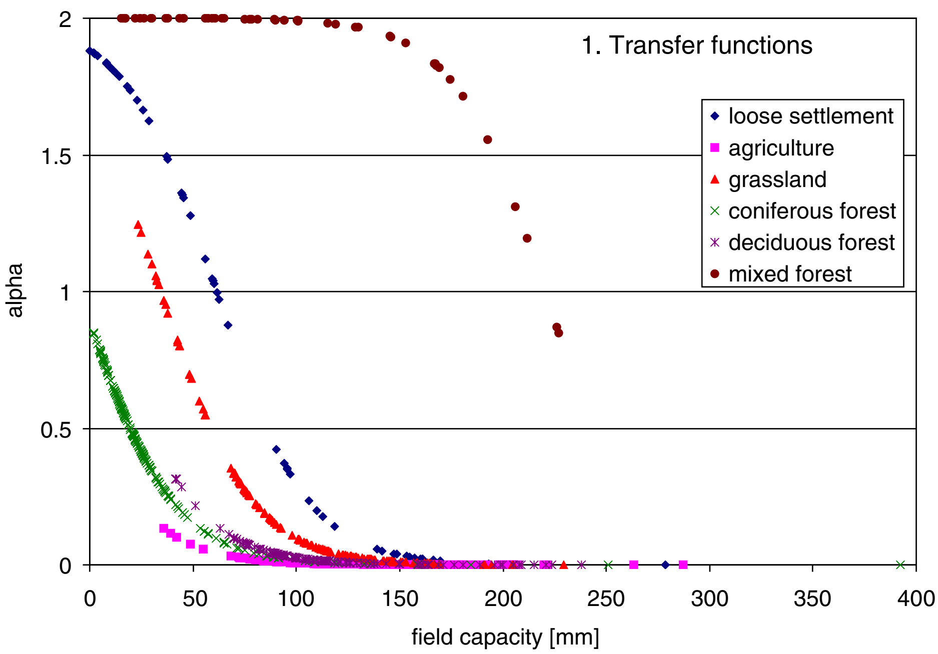

Figure 3 Relationships between field capacity and α resulting from transfer functions.

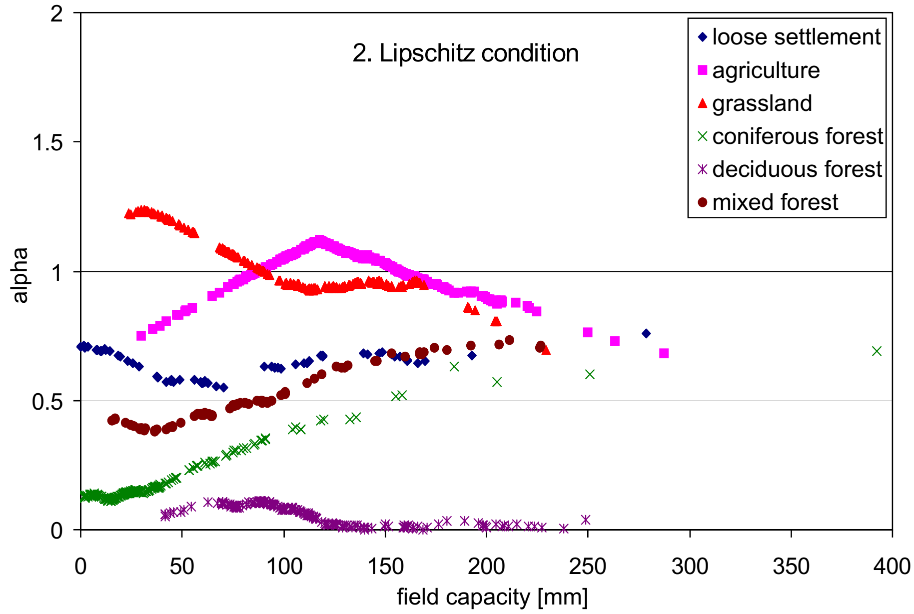

Figure 4 Relationships between field capacity and α resulting from the Lipschitz condition.

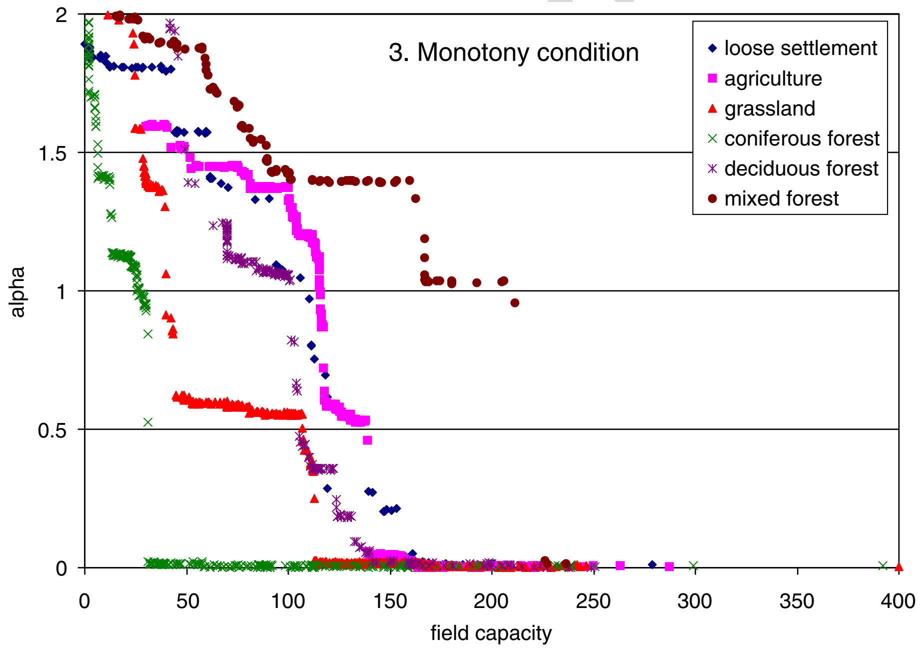

Figure 5 Relationships between field capacity and α resulting from the monotony condition.

were better than the mean measured values (Nash-Sutcliffe model efficiency > 0). The subcatchment was still included in the calibration set to account for the smaller subcatchments in the regionalisation set. Table 2 shows the mean and the median of the daily Nash-Sutcliffe model efficiencies of the four methods for the calibration and the regionalisation subcatchments. The average regionalisation model efficiency of the Lipschitz method is slightly better than the other approaches. All four methods were able to produce reasonable parameter sets for most of the 51 regionalisation catchments. The calibration efficiency of the monotony condition is lower than the others because the method could not fit the discharge hydrograph of one other calibration subcatchment. But the developed regression relationships could still be used to generate reasonable parameter sets for the regionalisation subcatchments.

As expected, all four methods failed to reproduce the observed discharge (Nash-Sutcliffe model efficiency < 0) in karstic areas and in heavily modified or regulated river basins, which indicates their sensitivity to catchment characteristics. The transfer functions failed in eight subcatchments

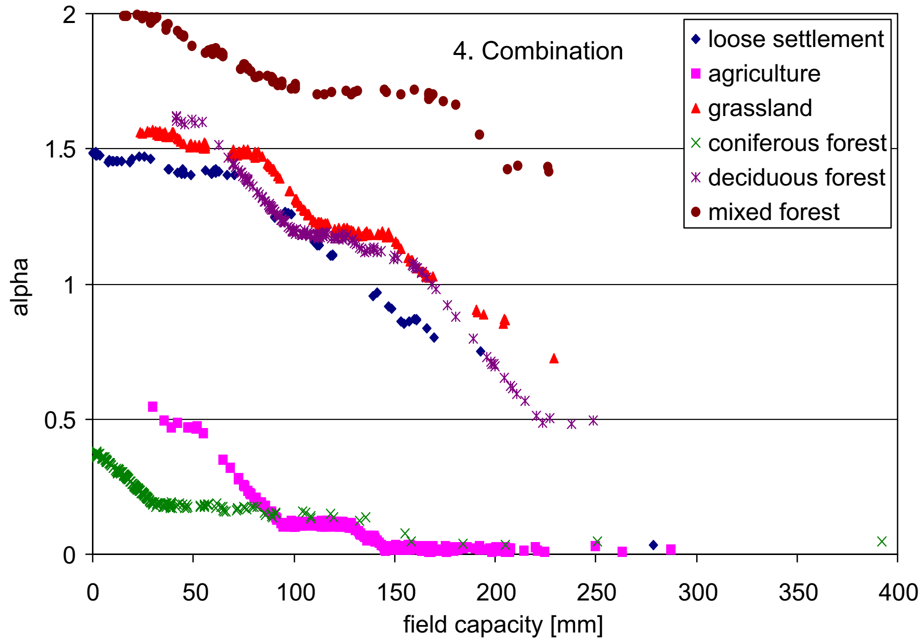

Figure 6 Relationships between field capacity and α resulting from the combination of Lipschitz and monotony condition.

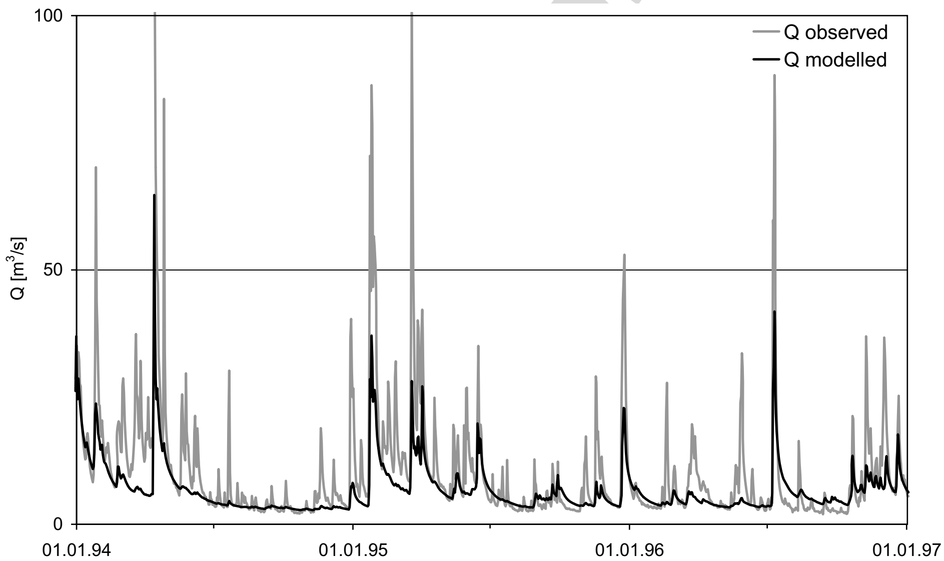

Figure 7 Observed and simulated discharge at Gaildorf (Kocher) resulting from transfer functions (Nash-Sutcliffe model efficiency NS = 0.69).

(16%) and the Lipschitz and monotony condition in 15 and 16 subcatchments (29% and 31%), respectively. This shows that the transfer functions are more robust in producing the general flow behavior of catchments. The Lipschitz and monotony condition are more flexible and are adjusted specifically to the calibration catchments. They are therefore also more sensitive to the characteristics of the landscape they are applied in.

The combination of Lipschitz and monotony condition also failed in eight subcatchments. This shows that the combination of both constraints is more robust than both methods individually. It can also describe a wider range of flow behavior because the developed relationships are not so strictly conditioned to the specific calibration catchments. Six of those eight catchments could also not be simulated with the transfer functions. This supports the hypothesis that the methods can not work in karstic and regulated river stretches. Furthermore, the developed relationships are not universally applicable physical laws. They are valid only for the physiographic setting they were calibrated in. They must be estimated again based on available observations if applied in differing basins.

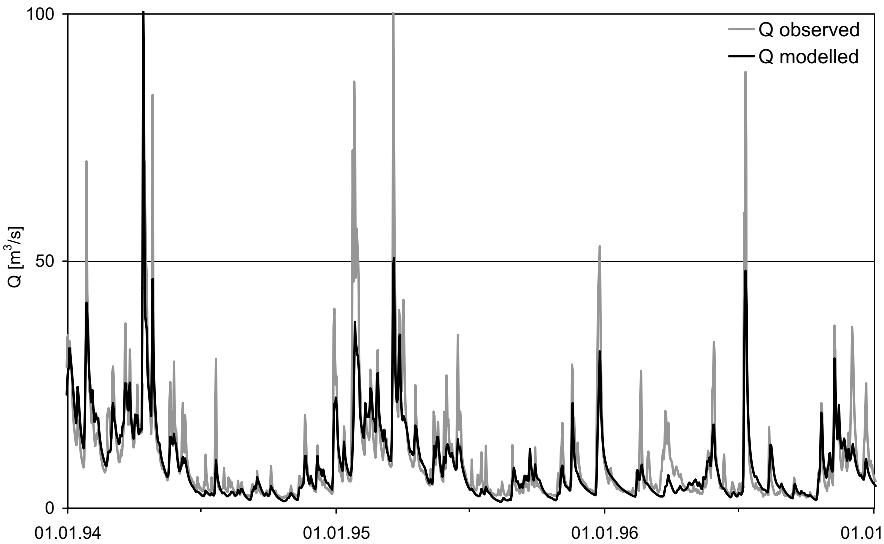

Figure 8 Observed and simulated discharge at Gaildorf (Kocher) resulting from the Lipschitz condition (NS = 0.71).

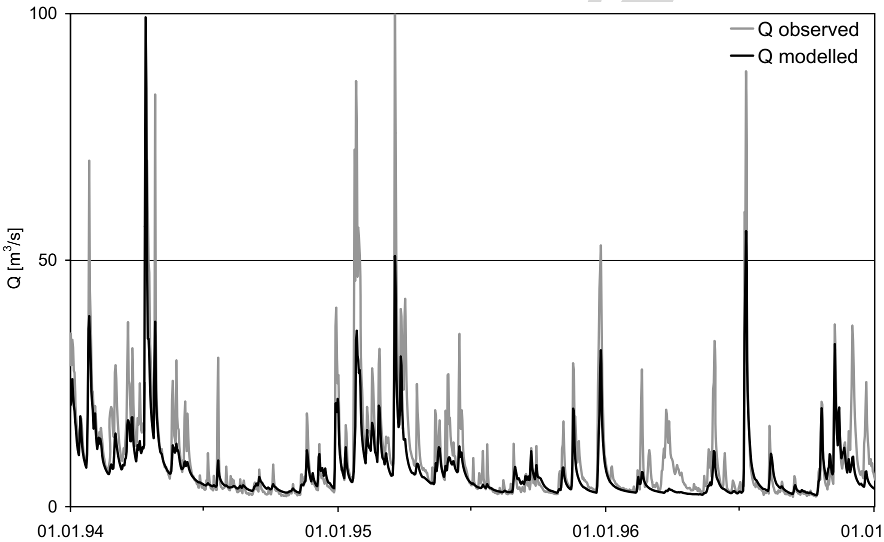

Figure 9 Observed and simulated discharge at Gaildorf (Kocher) resulting from the monotony condition (NS = 0.68).

Summary and conclusions

The HBV model concept was modified to run on 1 km^2 raster cells and generate distributed predictions of water balance components. This modification, but also the need for prediction at ungauged sites and the possibility to simulate the impact of land use change, required the development of a regionalisation method for parameter estimation from readily available catchment characteristics. In general, all four presented methods were capable of estimating reasonable parameter sets for the regionalisation catchments.

The first method using transfer functions turned out to be the most challenging in terms of prior process knowledge and optimisation. The other two methods that use conditions imposed on the parameters during simultaneous calibration are much more flexible especially in the following adaptation of suitable regression relationships. The modified Lipschitz condition produced the most efficient simulations of observed discharges in the regionalisation at the cost of some inconsistencies in the physical interpretation of the resulting relationships. The monotony condition preserved the assumed trends in the functions between cell properties and model parameters but produced sharp jumps which are not considered plausible. These jumps also resulted in slightly weaker regression relationships in the regionalisation. The combination of both methods seems to be the most promising because it produced equally good regionalisation results with much more consistent regression relationships. The approach can reproduce the derived trends with much more realistic variations in slope and the resulting relationships match our understanding of how the underlying processes are represented in the model.

The results support the findings of Vogel (2005), Parajka et al. (2005), Lee et al. (2005) and Beldring et al. (2003).

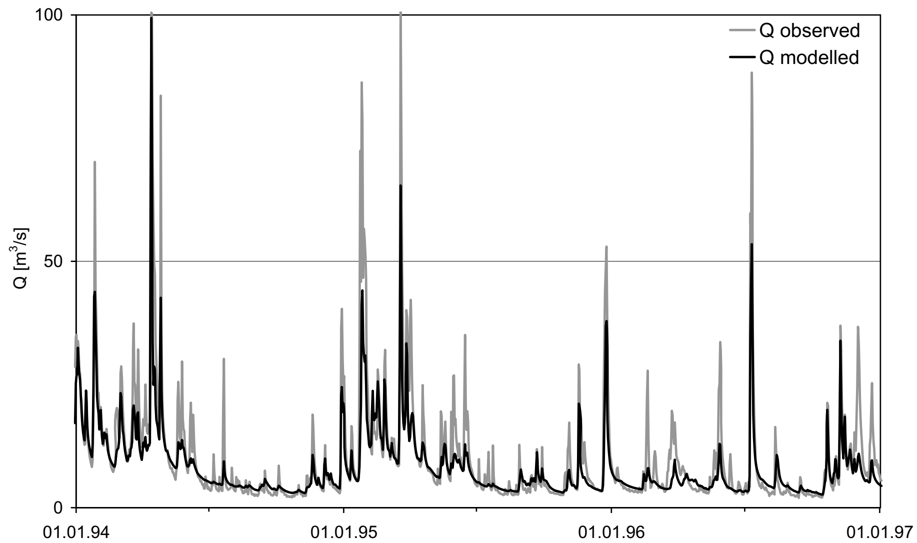

Figure 10 Observed and simulated discharge at Gaildorf (Kocher) resulting from the combination of Lipschitz and monotony condition (NS = 0.70).

Table 2 Mean and median of the Nash-Sutcliffe model efficiencies of the regionalisation methods in the validation period

	Transfer functions	Lipschitz condition	Monotony condition	Combination
Calibration mean	0.35	0.21	0.06	0.47
Calibration median	0.49	0.41	0.30	0.53
Regionalisation mean	0.47	0.50	0.47	0.47
Regionalisation median	0.51	0.53	0.50	0.50

The uncertainty from input data, model structure and parameter interaction results in many equally good parameter sets which significantly disturbs a posteriori regression analysis. The reduction of the available parameter space of distributed models through the link to catchment characteristics can crucially decrease these uncertainties and yield better regionalisation results if applied to ungauged catchments. A possible subdivision of the area according to geology and river regulations might improve the methodology. Further research in this direction is needed to prove this hypothesis.

Acknowledgements

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