Hydrol. Earth Syst. Sci. Discuss., 8, 3571–3597, 2011
www.hydrol-earth-syst-sci-discuss.net/8/3571/2011/
doi:10.5194/hessd-8-3571-2011

Hydrology and Earth System Sciences Discussions

Analysis of projected hydrological behavior of catchments based on signature indices

M. C. Casper[1], G. Grigoryan[1], O. Gronz[1], O. Gutjahr[2], G. Heinemann[2], R. Ley[1], and A. Rock[1]

[1]University of Trier, Physical Geography, Trier, Germany
[2]University of Trier, Environmental Meteorology, Trier, Germany

Received: 31 March 2011 – Accepted: 1 April 2011 – Published: 13 April 2011

Correspondence to: M. C. Casper (casper@uni-trier.de)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

To precisely map the changes in hydrologic response of catchments (e.g., water balance, reactivity or extremes) we need sensitive and interpretable indicators. In this study we defined nine hydrologically meaningful signature indices: five indices were sampled on the flow duration curve, four indices were closely linked to the distribution of event runoff coefficients. We applied these signature indices to the output from three hydrologic catchment models located in the Nahe basin (Western Germany) to detect differences in runoff behavior resulting from different meteorological input data. The models were driven by measured and simulated (COSMO-CLM) meteorological data. It could be shown that application of signature indices is a very sensitive tool to assess differences in simulated runoff behavior resulting from climatic data sets of different sources. The hydrological model acts as a filter for the meteorological input and is therefore very sensitive to biases in mean and spatio-temporal distribution of precipitation and temperature. The selected signature indices allow assessing changes in water balance, vertical water distribution, reactivity, seasonality and runoff generation. Bias correction of temperature fields and adjustment of bias correction of precipitation fields seemed to be indispensable. For this reason, future work will focus on improving bias correction for CCLM data sets. Signature indices may then act as indirect "efficiency measures" or "similarity measures" for the reference period of the simulation.

1 Introduction

The world is presently facing rapid changes to the climate. The understanding and prediction of related hydrologic changes is one main question that hydrologists face today (Blöschl and Montanari, 2010; Schaefli et al., 2011). It is therefore essential that we precisely map the changes in hydrologic response of catchments (e.g., water balance, reactivity or extremes). In this context, hydrological models are applied to detect the impact of a changing climate on the hydrology of catchments (Mahmoud et al., 2009). To achieve this on catchment scale, the output of regional climate models (RCM) is used as forcing data of hydrological models (Teutschbein and Seibert, 2010; Marke et al., 2011).

Precipitation fields from climate model output are defective and introduce errors into hydrological models when used as forcing data (Piani et al., 2010). These errors in the climate model affect the spatial and temporal distribution of rainfall and temperature (Sennikovs et al., 2009). These errors are caused by insufficient representation of precipitation processes, resolution of orography, domain size, length of simulation (Jacob and Podzun, 1997), boundary and initial data (Ebell et al., 2008) and errors from numerics and parameterizations (Gutjahr et al., 2011). Even variation of parameters within reasonable bounds leads to different precipitation performance (Bachner et al., 2008). In this study, a COSMO-CLM (CCLM) run is used as forcing data for a hydrological model. It is well known that CCLM produces too many days with very low precipitation intensities (drizzle) and too few dry days (Bachner et al., 2008). For realistic model output, appropriate bias correction needs to be applied (Piani et al., 2010). Wood et al. (2009) state that “hydrologic simulation is sensitive to biases in the basin mean and spatial distribution and temperature, that nearly all local biases must be removed from climate inputs”.

Assessment of climate induced changes in hydrological response is mostly based on mean annual, monthly or seasonal runoff, and on low flow and high flow quantiles (Arnell, 2011; Xu et al., 2011; Nóbrega et al., 2011; Taye et al., 2011). For long time series, statistical tests are recommended for change detection (Kundzewicz and Robson, 2004).

The flow duration curve (FDC) allows indication and classification of watershed functioning. The FDC summarizes a catchment’s ability to produce discharge values of different magnitudes, and is therefore strongly sensitive to the vertical redistribution of soil moisture within a basin (Yilmaz et al., 2008). Additionally, a steep slope of the FDC indicates flashiness of the stream flow response to precipitation input whereas a flatter curve indicates a relatively damped response and a higher storage (Yadav et al., 2007).

Another diagnostic tool is the analysis of event runoff coefficients. Their distribution represents the runoff generation in catchments, particularly if a larger number of events is to be compared (Merz et al., 2006). Event runoff coefficients are useful to understand how different landscapes “filter” rainfall into event based runoff and to explain the observed differences between catchments. They offer information on watershed response including changes from event to event, or from season to season (Blume et al, 2007).

In order to combine the strengths of both approaches, we define in this study nine hydrologically meaningful signature indices: five indices are sampled on the FDC (similar to Yilmaz et al., 2008), four indices are closely linked to the distribution of event runoff coefficients (Ley et al., 2011).

We apply the signature index concept to the output from three hydrologic catchment models located in the Nahe basin (Western Germany) to detect differences in runoff behavior resulting from different meteorological data sets: the models are driven by measured and simulated (CCLM) meteorological data. We demonstrate the discriminating power of the selected signature indices by pairwise comparison of data sets. This study is not intended to draw substantial conclusions on hydrological impact of climate change of our study area. For this purpose, an ensemble approach would be necessary (Knutti, 2008; Teutschbein and Seibert, 2010). We only intend to develop a sensitive method for change detection in hydrologic systems.

2 Study area

The study area consists of three small gaged catchment areas in the low mountain ranges of the Nahe basin (Fig. 1), Germany: Kronweiler (64 km^2), Kellenbach (362 km^2) and Gensingen (197 km^2). Geology is characterized by Devonian schist, greywacke and quartzite in Kellenbach and most parts of Kronweiler. The south part

HESSD
8, 3571–3597, 2011

of Kronweiler consists of Permian sedimentary and volcanic rocks. Tertiary clay and Pleistocene loess characterizes the geology of Gensingen. Mean annual precipitation reaches 990 mm in Kronweiler, followed by Kellenbach (730 mm) and Gensingen (570 mm). Mean annual potential evapotranspiration reaches 604 mm in Gensingen and about 540 mm in Kronweiler and Kellenbach. Field capacity in Gensingen is much higher than in Kronweiler and Kellenbach. About 75% of the area of Gensingen is used agriculturally, with 20% vineyards and orchards. In Kellenbach and Kronweiler about half the area is forested. All watersheds are rural with little urbanization with less than 6% of the area. The mean slope gradient of Kronweiler is 8.6°, much higher than for Kellenbach and Gensingen (about 4.5°).

The runoff response behavior of the three catchments is quite different: Kronweiler shows high discharges, high reactivity and high runoff coefficients the whole year round. In contrast to this, Gensingen has low reactivity, low discharges and low runoff coefficients with a high variability in winter. Runoff behavior of Kellenbach lies between the two other catchments.

3 Methods

3.1 Hydrological model and input data

The water balance model LARSIM (Large Area Runoff Simulation Model) allows a continuous process- and area-detailed simulation of the medium-scale mainland water cycle (Ludwig and Bremicker, 2006). In simplistic terms, the watershed is subdivided into 1-D elements linked by a flood routing scheme. The temporal resolution of the water balance calculation is one hour. The model needs as meteorological input spatial fields of precipitation, temperature, air pressure, wind speed, global radiation and relative humidity. This study is based on time series of climatic data from different sources. Each data set used has a length of approx. ten years:

HESSD
8, 3571–3597, 2011
Analysis of projected hydrological behavior of catchments
M. C. Casper et al.

1. measured meteorological data from 56 DWD-stations, period 1994–2003;
2. CCLM reference data, period 1988–1997 (scenario C20_1);
3. CCLM projection, period 2015–2024 (scenario A1B_1).

CCLM data originates from a run of version COSMO4.2-CLM3 on 5 km grid resolution within the LandCaRe 2020 project (Berg et al., 2008; Köstner et al., 2008). A bias correction has been applied only for precipitation. Each data set has been bilinearly interpolated on a 1 km grid. Measured runoff at the three gaging stations Kronweiler, Kallenfels and Gensingen covers the period from 1994 to 2003.

3.2 Bias correction – quantile matching

For bias correction of the aggregated CCLM 5 km daily precipitation fields, we chose the quantile matching method (Piani et al., 2010; Michelangeli et al., 2009; Maraun et al., 2010; Sennikovs and Bethers, 2009). The quantile matching is based upon the cumulative distribution function (CDF), defined as:

$$F(x) = P(X \leq x), \tag{1}$$

and the inverse of the CDF, defined as the quantile function:

$$F^{-1}(P) = x(F). \tag{2}$$

The CDF is either a parametric or non-parametric (i.e. empirical) function. Parametric functions for precipitation intensities are usually gamma or exponential functions (Piani et al., 2010). To account for correcting the probabilities for no precipitation (dry day) together with the probabilities of a wet day ($x > 0$), we chose an empirical CDF $F(x) = i/n$, with i the rank and n the sample size.

Let x_c be the daily precipitation intensities of a time series from CCLM and x_s a time series from a precipitation station, then the quantile matching sets:

$$F_s(x_s) = F_c(x_c). \tag{3}$$

By rearranging Eq. (3) using the quantile function it is possible to calculate a new time series for the CCLM from the quantiles of x_s with the probabilities $F_c(x_c)$:

$$x = F_s^{-1}(F_c(x_x)). \tag{4}$$

On the left side of Eq. (4) stands the new time series and on the right a transfer function:

$$T(x_c) = F_s^{-1}(F_c(x_c)). \tag{5}$$

This quantile matching corrects the whole intensity distribution of the modeled precipitation and therefore preserves all moments (Sennikovs and Bethers, 2009). The gained transfer functions can be applied to the future scenario if assumed that the model error is the same for the control and scenario run (van Roosmalen et al., 2011) and the transfer functions do not change with time (stationarity) (Maraun et al., 2010). Provided that the bias correction is optimal in the control period and the model error is removed from the control run as well from the scenario run, the remaining signal is only due to climate change (van Roosmalen et al., 2011).

Because x_c is a discrete time series, $T(x_c)$ has to be interpolated to become a continuous function. This is done with a linear approach (Gutjahr et al., 2011). A spatial interpolation of the three nearest transfer functions is carried out for all grid boxes containing no gaging station by an inverse distance weighting method:

$$\hat{x} = \frac{\sum_{i=1}^{n} \frac{1}{d_i^P} T_i(x_c)}{\sum_{i=1}^{n} \frac{1}{d_i^P}} \tag{6}$$

Finally LARSIM needs hourly input data. Therefore the bias corrected daily precipitation fields from CCLM are disaggregated to hourly fields $H_{i,k}^{\text{cor}}$ by:

$$H_{i,k}^{\text{cor}} = H_{i,k}^{\text{uncor}} \cdot \frac{D_{i,k}^{\text{cor}}}{D_{i,k}^{\text{uncor}}} \tag{7}$$

HESSD

8, 3571–3597, 2011

Analysis of projected hydrological behavior of catchments

M. C. Casper et al.

with $H_{i,k}^{\mathrm{uncor}}$ the original CCLM precipitation fields, $D_{i,k}^{\mathrm{uncor}}$ the original uncorrected aggregated daily CCLM precipitation fields and $D_{i,k}^{\mathrm{cor}}$ the resulting daily fields after the bias correction. Index i denotes the hours and index k denotes the days.

3.3 Flow duration curves

The FDC is the complement of the cumulative distribution function of streamflow. In an FDC, discharge is plotted against exceedance probability and shows the percentage of time that a given flow rate is equaled or exceeded and provides a probabilistic description of stream flow at a given location (Fig. 2).

Opposite to common daily, monthly and annual FDCs (e.g., Vogel and Fennessey, 1994; Yadav et al., 2007), we use FDCs based on hourly discharge.

3.4 Calculation of runoff coefficients

Event runoff coefficients specify the percentage of precipitation that appears as significant runoff above base flow following directly the corresponding rainfall. This study uses the direct approach of event-based runoff coefficient (Eq. 8) as described by Merz et al. (2006) and Norbiato et al. (2009).

$$\mathrm{ERC} = \frac{\sum Q_{\mathrm{d}}}{A_{\mathrm{eo}} \cdot \sum \mathrm{prec} \cdot 1000} \tag{8}$$

with: ERC = Event Runoff Coefficient, Q_{d} = direct event runoff ($\mathrm{m}^3\,\mathrm{h}^{-1}$), A_{eo} = catchment area (km^2) and prec = areal event precipitation ($\mathrm{mm\,h}^{-1}$).

The semi-automatic method to calculate event-based runoff coefficients was developed for Austria by Merz at al. (2006). We adapted this method for catchments in Rhineland-Palatinate by alteration of program parameters and verification of calculated runoff coefficients with manual calculated runoff coefficients. The same set of adapted criteria is used for all catchments in this study.

HESSD

8, 3571–3597, 2011

The calculation of runoff coefficients follows a four-step approach: First, observed runoff is separated into baseflow and direct flow using the digital filter proposed by Chapman and Maxwell (1996). Second, events are identified by an iterative process, based on defined peak flows and thresholds. A characteristic time scale for each event helps to identify start and end of event precipitation. Next, direct event runoff and event rainfall volume are calculated and event runoff coefficients are estimated following Eq. (8). Last, to improve data quality, we eliminate very small events, events caused by snow melt, events with insufficient data and events with poor event separation.

3.5 Signature indices

Signature indices are used to quantify features resulting from the comparison of FDCs or Empirical Cumulative Distribution Functions (ECDF) of runoff coefficients. As a set, these features are a characteristic fingerprint of the differences in hydrological behavior.

We use five indices derived from FDCs, as proposed by Yilmaz et al. (2008). For illustration purposes, Fig. 2 shows two different FDCs: FDC_1 (red) and FDC_2 (blue).

1. BiasRR: percent bias in the mean values:

$$\text{BiasRR} = \frac{\text{mean}(FDC_1) - \text{mean}(FDC_2)}{\text{mean}(FDC_2)} \cdot 100\%. \quad (9)$$

   BiasRR, which is highlighted by circles (Fig. 2), quantifies the differences in balance.

2. BiasFDCmidslope: percent bias in slope of the mid-segment:

$$\text{BiasFDCmidslope} = \frac{(\log(FDC_{1,0.2}) - \log(FDC_{1,0.7})) - (\log(FDC_{2,0.2}) - \log(FDC_{2,0.7}))}{(\log(FDC_{2,0.2}) - \log(FDC_{2,0.7}))} \cdot 100, \quad (10)$$

   where $FDC_{i,p}$ is the runoff with exceedance probability p of FDC number i (red and blue triangles in Fig. 2). It quantifies the flashiness of flows.

HESSD
8, 3571–3597, 2011

3. BiasFHV: percent bias in high-segment volumes:

$$\mathrm{BiasFHV} = \frac{\int_0^{0.02} \mathrm{FDC}_{1,p}dp - \int_0^{0.02} \mathrm{FDC}_{2,p}dp}{\int_0^{0.02} \mathrm{FDC}_{2,p}dp} \cdot 100, \tag{11}$$

which corresponds to the green area in Fig. 2 and compares the peak discharges.

4. BiasFLV: differences in long-term baseflow:

$$\mathrm{BiasFLV} = \frac{\int_{0,7}^{1} \left(\log\left(\mathrm{FDC}_{1,p}\right) - \log(Q_{\mathrm{min}})\right)dp - \int_{0,7}^{1} \left(\log\left(\mathrm{FDC}_{2,p}\right) - \log(Q_{\mathrm{min}})\right)dp}{\int_{0.7}^{1} \left(\log\left(\mathrm{FDC}_{2,p}\right) - \log(Q_{\mathrm{min}})\right)dp} \cdot 100, \tag{12}$$

where Q_{min} is the minimum value of $\mathrm{FDC}_{1,1}$ and $\mathrm{FDC}_{2,1}$, i.e. the lowest runoff at all. The two compared areas are highlighted in red and blue (Fig. 2).

5. BiasFMM: percent bias in mid range flow levels:

$$\mathrm{BiasFMM} = \frac{\mathrm{median}(\mathrm{FDC}_1) - \mathrm{median}(\mathrm{FDC}_2)}{\mathrm{median}(\mathrm{FDC}_2)} \cdot 100. \tag{13}$$

It is highlighted in Fig. 2 by crosses.

We defined BiasRR, BiasFLV and BiasFMM differently compared to Yilmaz et al. (2008).

The other four indices use ECDFs of event runoff coefficients. ECDFs estimate the true underlying distribution function of the points of a sample by empirical measures of the sample.

From the ECDFs of event runoff coefficients we derive four additional indices (Fig. 3):

– rcMean: mean runoff coefficient of all coefficients of a catchment. A change of this value indicates a modification of mean moisture storage of the catchment.

– rcCV: coefficient of variation, describes the variability of runoff coefficients.

– rcMeanSu: mean runoff coefficient in summer (May to October).

– rcMeanWi: mean runoff coefficient in winter (November to April).

In order to compare two data sets, we calculate differences between the corresponding values of indices and name them as signature indices 6. ΔrcMean, 7. ΔrcCV, 8. ΔrcMeanSu and 9. ΔrcMeanWi.

4 Results

To demonstrate the discriminating power of the nine signature indices, we apply the methodology for four different cases: (1) assessment of model error, (2) assessment of CCLM reference run, (3) assessment of bias correction and (4) detection of climate change signal in the CCLM data set.

4.1 Assessment of model error

To assess the error of the hydrological model, deviations between simulated runoff and measured runoff are calculated (Fig. 4). For the catchments Kronweiler and Kellenbach the deviations are reasonable low. In contrast, simulated runoff for Gensingen is much higher than the measured one. The large bias can only be explained by incorrect model calibration based on incorrect runoff data for the gaging station Gensingen.

4.2 Assessment of CCLM reference run (bias corrected)

Deviation between bias corrected CCLM reference run and the measured climatic input is clearly visible (Fig. 5). For Kronweiler a small decrease in overall runoff (BiasRR), reactivity (BiasFDCmidslope) and peak flows (BiasFHV) can be detected. This can be explained by the lower yearly mean precipitation in this catchment (Table 1). In contrast,

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

HESSD

8, 3571–3597, 2011

Analysis of projected hydrological behavior of catchments

M. C. Casper et al.

a much higher mean event runoff coefficient in summer (rcMeanSu) can be observed. The other two gaging stations show a clear increase for all signature indices, though there is no difference in yearly mean precipitation between the two datasets (Table 1). These discrepancies can be explained by the lower mean annual temperatures in the CCLM reference run. A bias of approx. 1.5 °C (Table 2) causes lower evaporation rates resulting in higher mean event runoff coefficients.

4.3 Assessment of bias correction

Bias correction mostly affects the hydrological behavior of the catchment Gensingen, where the simulated runoff decreases by 66% compared to the uncorrected dataset (Fig. 6). For the other two catchments, bias correction of precipitation only causes moderate changes in hydrologic response. Nevertheless, we have to keep in mind that bias correction for the Kronweiler catchment seems to be too low as we can conclude from the reference run (Table 1).

4.4 Detection of climate change signal in CCLM data

A climate change signal can be detected by analyzing the differences between the reference run and the future projection of climate: for the catchments Kellenbach and Gensingen, a small decrease in annual precipitation (Table 1) and a clear increase in temperature (Table 2) cause a decrease in high flows (negative index BiasFHV) and event runoff coefficients. Also the water balance (negative index BiasRR) and the reactivity of the catchment (negative index BiasFDCmidslope) decrease. Partly contrasting, the catchment Kronweiler shows a small increase in annual precipitation which seems to be compensated by the higher evaporation losses, resulting in index values close to zero. Only the high flow periods decrease (negative index BiasFHV). This decrease can only be explained by a different temporal distribution of rainfall, because the indices for the event runoff coefficients remain unchanged compared to the reference run.

HESSD
8, 3571–3597, 2011

5 Discussion/outlook

It could be shown that application of signature indices is a very sensitive tool to assess differences in simulated runoff behavior resulting from climatic data sets of different sources and/or time reference. The hydrological model acts as a filter for the meteorological input and is therefore sensitive to biases in mean and spatial distribution of precipitation and temperature. The selected signature indices allow assessing changes in water balance (BiasRR, BiasMM), vertical water distribution (BiasFHV, BiasFLV), reactivity (BiasFDCmidslope), seasonality (rcMeanSu, rcMeanWi) and runoff generation (rcMean, rcCV).

Probably, the selection of mean (rcMean, rcMeanSu, rcMeanWi) from the empirical distributions of event runoff coefficients does not take sufficiently into account the shape of the distribution itself (Fig. 3). To avoid this, signature indices may be based on slope of a particular segment of the distribution function (Ley et al., 2011).

Figure 4 shows large discrepancies between model behavior and measured discharge. We recommend the use of signature indices for multi-criteria model calibration leading to more behavioral model parameterizations (Herbst et al., 2009a, 2009b). This becomes particularly relevant when we do not expect time stability of model parameters (Merz et al., 2011).

In our case, we showed that the deviations for the reference period (Fig. 5) were much higher than the impact of projected climate change on hydrology of catchments (Fig. 7). Bias correction of temperature fields and adjustment of bias correction of precipitation fields in the mountain region seems to be indispensable. For this reason, future work will focus on improving bias correction for CCLM data sets. Especially the assumptions for the bias correction method used here are stationarity of the transfer functions with time and that all possible extreme values occurred in the reference period, since there is no extrapolation for future extremes implemented. Thus, future extreme values of the CCLM higher than the observed extremes are reset to the highest observed value. This is a restriction but Maraun et al. (2010) and Boé et al. (2007)

HESSD
8, 3571–3597, 2011

argue that a simple linear or constant correction is not valid for the extreme tail of the distribution. Shifting the distribution to an extreme value distribution at the tail with a dynamic mixture model could be a feasible solution (Frigessi et al., 2003; Vrac and Naveau, 2007). This is only possible in case the bias correction was carried out with fitting a parametric distribution (like a gamma distribution). As far as we know there is no method for combining a non-parametric distribution for the core of the precipitation intensities and a parametric extreme value distribution at the tail. The assumption of stationarity is a critical part of bias correction methods affecting the whole distribution. This distribution is a mixture of diverse other distributions depending on the weather conditions (Maraun et al., 2010). If the relative frequencies of weather conditions change in a future climate, the distribution will change too and the transfer functions from the quantile matching are maybe not valid any more (Maraun et al., 2010). This issue occurs mainly when there are no physical processes considered by the bias correction method. Another shortcoming affects the physical consistency if one variable of the climate model is corrected with no respect to any covariance with other variables. This causes internal inconsistency if corrected variables are used together with uncorrected variables (Knutti, 2008). Yang et al. (2010) show an improvement for simulation of river discharge in spring by considering the covariance of precipitation and temperature. Also there can be an improvement if the bias correction is carried out seasonally (Piani et al., 2010). Signature indices could help to evaluate the different approaches for bias correction of precipitation and temperature extending the concept of Johnson and Sharma (2009). This is especially true when calculated for representative sub-catchments in a larger basin area, where only a sparse network of observation points is available for bias correction. In this case, signature indices may act as indirect "efficiency measures" or "similarity measures" for the reference period of the simulation. Therefore, application of signature indices for the reference period will also facilitate the decision on the suitability of the bias corrected data for hydrologic impact studies.

HESSD
8, 3571–3597, 2011

This study is not intended to draw conclusions on hydrological impact of climate change in our study area. For this purpose an ensemble approach would have been necessary (Knutti, 2008; Teutschbein and Seibert, 2010) as well as an improved bias correction method which considers the extreme value problem (Boé et al., 2007). Actually, on the selected scale of 5 km^2, ensemble runs of nested CCLM models are not yet available.

Acknowledgements. This study was partly founded by State Rhineland-Palatinate (Research Initiative Rhineland-Palatinate and federal research project "KlimLandRP"). The authors wish to thank the State Office for Environment, Water Management and Trade Control (LUWG) Rhineland-Palatinate at Mainz for providing data of runoff and precipitation. We also like to thank Burkhardt Rockel and Anne Pätzold from the Helmholtz-Zentrum Geesthacht for providing the COSMO-CLM data.

References

Arnell, N. W.: Uncertainty in the relationship between climate forcing and hydrological response in UK catchments, Hydrol. Earth Syst. Sci., 15, 897–912, doi:10.5194/hess-15-897-2011, 2011.

Bachner, S., Kapala, A., and Simmer, C.: Evaluation of daily precipitation characteristics in the CLM and their sensitivity to parameterizations. Meteorol. Z., 17, 407–419, doi:10.1127/0941-2948/2008/0300, 2008.

Berg, M., Wieland, R., Mirschel, W., and Wenkel, K.-O.: LandCaRe 2020 – ein Entscheidungsunterstützungssystem zur Vorhersage und Beurteilung der Potentiale ländlicher Gebiete unter dem Einfluss regionalen Klimawandels, in: Modellierung und Simulation von Ökosystemen, edited by: Gnauk, A., Shaker Verlag Aachen, 214–229, 2008.

Blöschl, G. and Montanari, A.: Climate change impacts – throwing the dice?, Hydrol. Process., 24, 374–381, doi:10.1002/hyp.7574, 2010.

Blume, T., Zehe, E., and Bronstert, A.: Rainfall-runoff response, event-based runoff coefficients and hydrograph separation. Hydrol. Sci. J., 52(5), 843–862, 2007.

Boè, J., Terray, I., Habets, F., and Martin, E.: Statistical and dynamical downscaling of

the Seine basin climate for hydro-meteorological studies, Int. J. Climatol., 27, 1643–1655, doi:10.1002/joc.1602, 2007.
Chapman, T. G. and Maxwell, A. I.: Baseflow Separation – Comparison of Numerical Methods with Tracer Experiments, I. E. Aust. Natl. conf. Publ. 96/05, 539–545, 1996.
Ebell, K., Bachner, S., Kapala, A., and Simmer, C.: Sensitivity of summer precipitation simulated by the CLM with respect to initial and boundary conditions, Meteorol. Z., 17, 421–431, doi:10.1127/0941-2948/2008/0305, 2008.
Frigessi, A., Haug, O., and Rue, H.: A dynamic mixture model for unsupervised tail estimation without threshold selection, Extremes, 5, 219–235, 2003.
Herbst, M., Casper, M. C., Grundmann, J., and Buchholz, O.: Comparative analysis of model behaviour for flood prediction purposes using Self-Organizing Maps, Nat. Hazards Earth Syst. Sci., 9, 373–392, doi:10.5194/nhess-9-373-2009, 2009a.
Herbst, M., Gupta, H. V., and Casper, M. C.: Mapping model behaviour using Self-Organizing Maps, Hydrol. Earth Syst. Sci., 13, 395–409, doi:10.5194/hess-13-395-2009, 2009b.
Jacob, D. and Podzun, R.: Sensitivity studies with the regional climate model REMO, Meteor. Atmos. Phys, 63, 119–129, 1997.
Johnson, F. and Sharma, A.: Measurement of GCM skill in predicting variables relevant for hydroclimatological assessments, J. Climate, 22, 4373–4382, 2009.
Knutti, R.: Should we believe model predictions of future climate change?, Phil. Trans. Roy. Soc. A, 366, 4647–4664, 2008.
Köstner, B., Berg, M., Bernhofer, C., Franke, J., Gömann, H., Kersebaum, K. C., Kuhnert, M., Lindau, R., Manderscheid, T., Mengelkamp, H.-T., Mirschel, W., Nendel, C., Nozinski, E., Pätzold, A., Simmer, S., Stonner, R., Weigel, H.-J., Wenkel, K. O., and Wieland, R.: Land, Climate and Resources (LandCaRe) 2020 – Foresight and Potentials in Rural Areas under Regional Climate Change, Ital. J. Agron./Riv. Agron., 3(3) Suppl., 743–744, 2008.
Kundzewicz, Z. W. and Robson, A. J.: Change detection in hydrological records – a review of methodology, Hydrol. Sci. J., 49(1), 1–19, doi:10.1623/hysj.49.1.7.53993, 2004.
Kundzewicz, Z. W. and Stakhiv, E. Z.: Are climate models “ready for prime time” in water resources management applications, or is more research needed?, Hydrol. Sci. J., 55(7), 1085–1089, doi:10.1080/02626667.2010.513211, 2010.
Ley, R., Casper, M. C., Hellebrand, H., and Merz, R.: Catchment classification by runoff behaviour with self-organizing maps (SOM), Hydrol. Earth Syst. Sci. Discuss., 8, 3047–3083, doi:10.5194/hessd-8-3047-2011, 2011.

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

HESSD
8, 3571–3597, 2011

Analysis of projected hydrological behavior of catchments

M. C. Casper et al.

Mahmoud, M., Liu, Y., Hartmann, H., Stewart, S., Wagener, T., Semmens, D., Stewart, R., Gupta, H. V., Dominguez, D., Dominguez, F., Hulse, D., Letcher, R., Rashleigh, B., Smith, C., Street, R., Ticehurst, J., Twery, M., van Delden, H., Waldick, R., White, D., and Winter, L.: A formal framework for scenario development in support of environmental decision-making, Environ. Model. Softw., 24, 798–808, doi:10.1016/j.envsoft.2008.11.010, 2009.

Maraun, D., Wetterhall, F., Ireson, A., Chandler, R., Kendon, E., Widmann, M., Brienen, S., Rust, H., Sauter, T., Themeßl, M., Venema, V., Chun, K., Goodess, C., Jones, R.G.and Onof, C., Vrac, M., and Thiele-Eich, I.: Precipitation downscaling under climate change. Recent developments to bridge the gap between dynamical models and the end user, Rev. Geophys., 48, RG3003, doi:10.1029/2009RG000314, 2010.

Marke, T., Mauser, W., Pfeiffer, A., and Zängl, G.: A pragmatic approach for the downscaling and bias correction of regional climate simulations - evaluation in hydrological modeling, Geosci. Model Dev. Discuss., 4, 45–63, doi:10.5194/gmdd-4-45-2011, 2011.

Merz, R., Blöschl, G., and Parajka, J.: Spatio-temporal variability of event runoff coefficients, J. Hydrol., 331, 591–604, 2006.

Merz, R., Parajka, J., and Blöschl, G.: Time stability of catchment model parameters: Implications for climate impact analysis, Water Resour. Res., 47, W02531, doi:10.1029/2010WR009505, 2011.

Michelangeli, P.-A., Vrac, M., and Loukos, H.: Probabilistic downscaling approaches: Application to wind cumulative distribution function, Geophys. Res. Lett., 36, L11708, doi:10.1029/2009GL038401, 2009.

Nóbrega, M. T., Collischonn, W., Tucci, C. E. M., and Paz, A. R.: Uncertainty in climate change impacts on water resources in the Rio Grande Basin, Brazil, Hydrol. Earth Syst. Sci., 15, 585–595, doi:10.5194/hess-15-585-2011, 2011.

Norbiato, D., Borga, M., Merz, R., Blöschl, G., and Carton, A.: Controls on event runoff coefficients in the eastern Italian Alps, J. Hydrol., 375, 312–325, 2009.

Piani, C., Haerter, J., and Coppola, E.: Statistical bias correction for daily precipitation in regional climate models over Europe, Theor. Appl. Climatol., 99, 187–192, 2010.

Rockel, B., Will, A., and Hense, A.: The Regional Climate Model COSMO-CLM (CCLM), Meteorologische Zeitschrift, 17(4), 347–348, 2008.

Schaefli, B., Harman, C. J., Sivapalan, M., and Schymanski, S. J.: HESS Opinions: Hydrologic predictions in a changing environment: behavioral modeling, Hydrol. Earth Syst. Sci., 15, 635–646, doi:10.5194/hess-15-635-2011, 2011.

Sennikovs, J. and Bethers, U.: Statistical downscaling method of regional climate model results for hydrological modeling, 18th World IMACS/MODSIM Congress, 2009.
Steppeler, J., Doms, G., Schättler, U., Bitzer, H. W., Gassmann, A., Damrath, U., and Gregoric, G.: Meso-gamma scale forecasts using the nonhydrostatic model LM, Meteorol. Atmos. Phys., 82, 75–96, 2003.
Taye, M. T., Ntegeka, V., Ogiramoi, N. P., and Willems, P.: Assessment of climate change impact on hydrological extremes in two source regions of the Nile River Basin, Hydrol. Earth Syst. Sci., 15, 209–222, doi:10.5194/hess-15-209-2011, 2011.
Teutschbein, C. and Seibert, J.: Regional Climate Models for Hydrological Impact Studies at the Catchment-Scale: A Review of Recent Modeling Strategies, Geography Compass, 4/7(2010), 834–860, doi:10.1111/j.1749-8198.2010.00357.x, 2010.
van Roosmalen, L., Sonnenborg, T. O., and Christensen, J. H.: Comparison of hydrological simulations of climate change using perturbation of observation and distribution-based scaling, Vadose Zone J., 10(1), 136–150, doi:10.2136/vzj2010.0112, 2011.
Vogel, R. M. and Fennesey, N. M.: Flow Duration Curves I: New Interpretation and Confidence Intervals, J. Water Res. Pl.-ASCE, 120(4), 485–504, 1994.
Vrac, M. and Naveau, P.: Stochastic downscaling of precipitation: from dry events to heavy rainfall, Water Resour. Res., 43, W07402, doi:10.1029/2006WR005308, 2007.
Wilby, R. L.: Evaluating climate model outputs for hydrological applications – Opinion, Hydrol. Sci. J., 55(7), 1090–1093, 2010.
Xu, H., Taylor, R. G., and Xu, Y.: Quantifying uncertainty in the impacts of climate change on river discharge in sub-catchments of the Yangtze and Yellow River Basins, China, Hydrol. Earth Syst. Sci., 15, 333–344, doi:10.5194/hess-15-333-2011, 2011.
Yadav, M., Wagener, T., and Gupta, H.: Regionalization of constraints on expected watershed response behavior for improved predictions in ungauged basins, Adv. Water Resour., 30, 1765–1774, 2007.
Yang, W., Andréasson, J., Graham, L. P., Olsson, J., Rosberg, J., and Wetterhall, F.: Distribution-based-scaling to improve usability of regional climate model projections for hydrological climate change impacts studies, Hydrol. Res., 41(3–4), 211–229, 2010.
Yilmaz, K. K., Gupta, H. V., and Wagener, T.: A process-based diagnostic approach to model evaluation: Application to the NWS distributed hydrologic model, Water Resour. Res., 44, W09417, doi:10.1029/2007WR006716, 2008.

HESSD
8, 3571–3597, 2011

Table 1. Statistics of rainfall fields: mean annual precipitation in mm.

			Kronweiler	Kellenbach	Gensingen	Nahe
1994–2003	measured	mean	937.6	690.9	563.9	754.6
		std	177.9	128.9	116.6	155.6
Reference	CCLM, bias correction	mean	813.0	702.3	557.5	714.4
		std	97.9	96.2	74.2	85.5
2015–2024	CCLM, no bias correction	mean	790.3	728.8	677.7	754.7
		std	76.2	69.0	57.9	53.2
2015–2024	CCLM, bias correction	mean	819.1	673.2	546.1	705.5
		std	82.6	70.2	53.8	52.3

HESSD
8, 3571–3597, 2011

Table 2. Statistics of temperature fields: mean annual temperature in °C.

			Kronweiler	Kellenbach	Gensingen	Nahe
1994–2003	measured	mean	8.63	8.86	10.06	9.35
		std	0.74	0.80	0.67	0.76
Reference	CCLM	mean	7.04	7.32	8.81	7.87
		std	0.65	0.69	0.67	0.67
2015–2024	CCLM	mean	7.74	7.97	9.48	8.63
		std	0.63	0.61	0.61	0.62

HESSD
8, 3571–3597, 2011

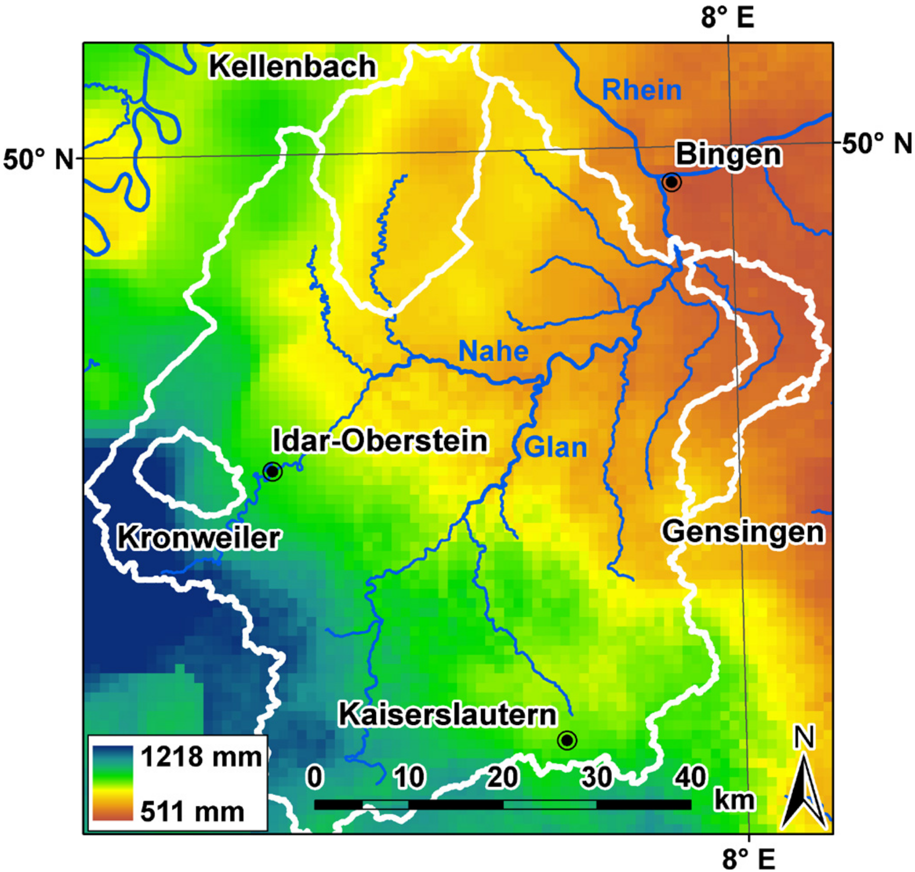

Fig. 1. Areal distribution of annual precipitation and the outlines of the catchments.

HESSD
8, 3571–3597, 2011
Analysis of projected hydrological behavior of catchments
M. C. Casper et al.

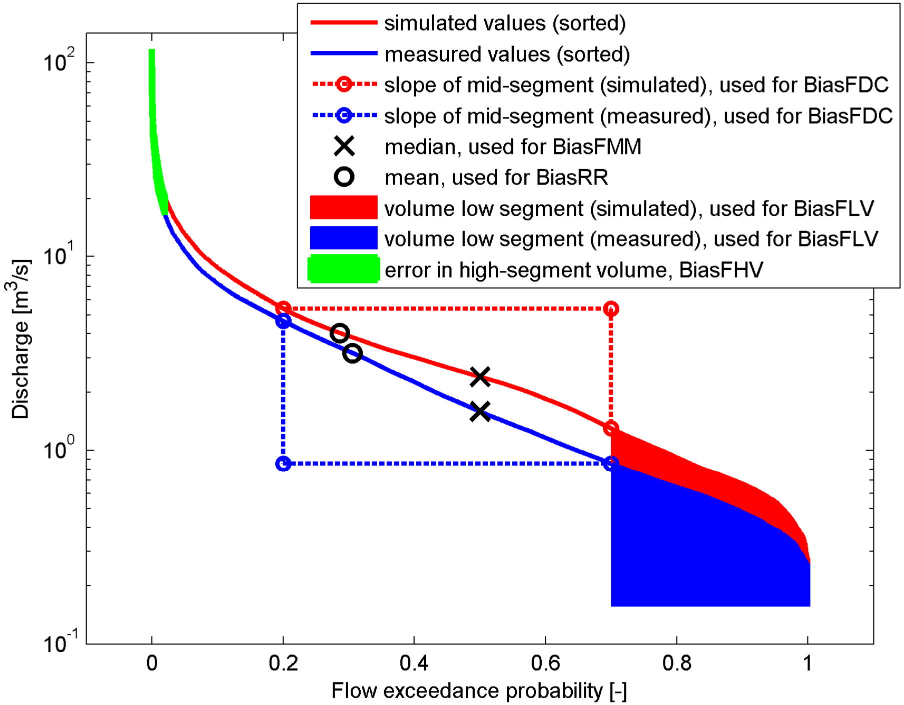

Fig. 2. Two different flow duration curves with highlighted features that are used to determine signature indices.

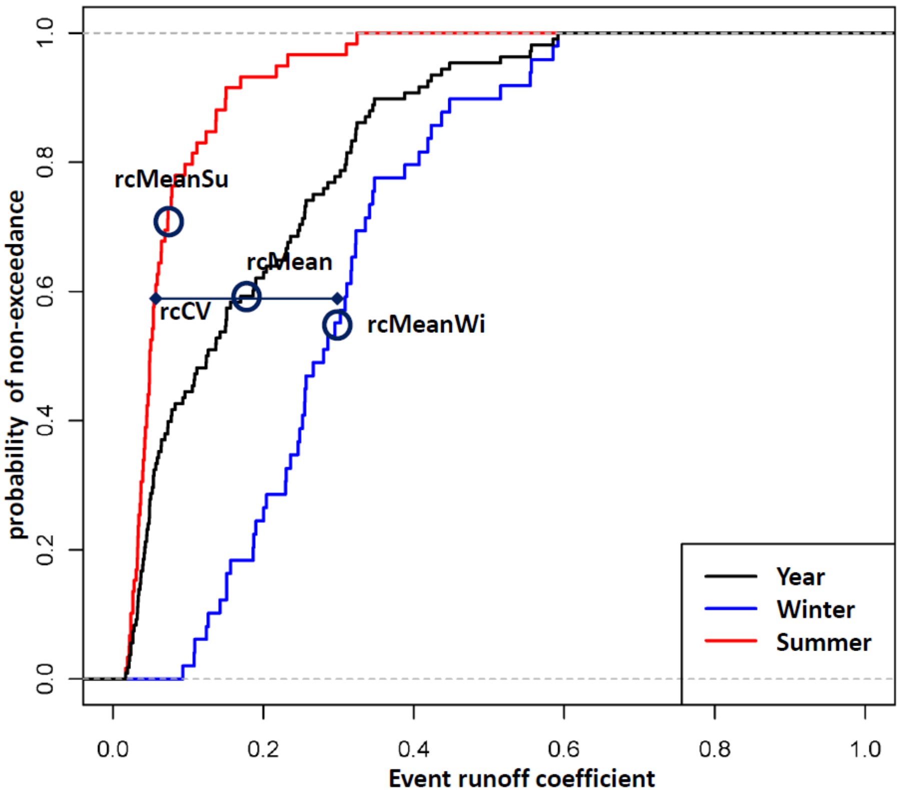

Fig. 3. Empirical Cumulative Distribution Function of runoff coefficients (rc) for catchment Kellenbach and derived signature indices.

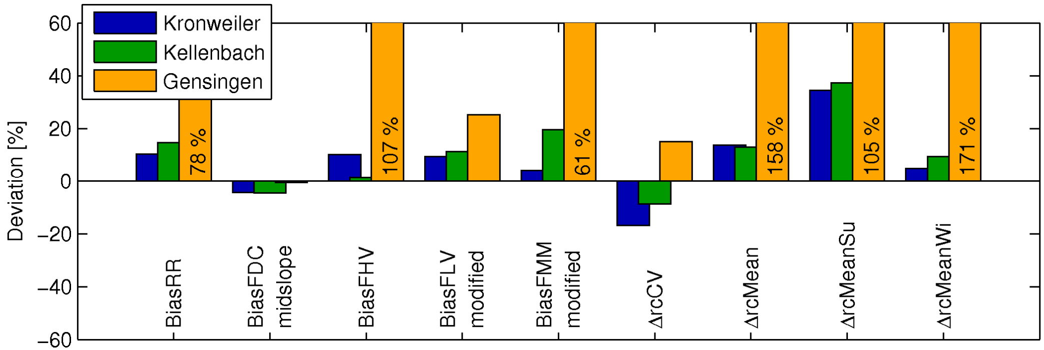

Fig. 4. Signature indices resulting from comparison of (1) the measured discharge time series and (2) the simulated discharge time series using measured meteorological input data, 1994–2003.

HESSD
8, 3571–3597, 2011

Analysis of projected hydrological behavior of catchments

M. C. Casper et al.

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀| |▶
◀ ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

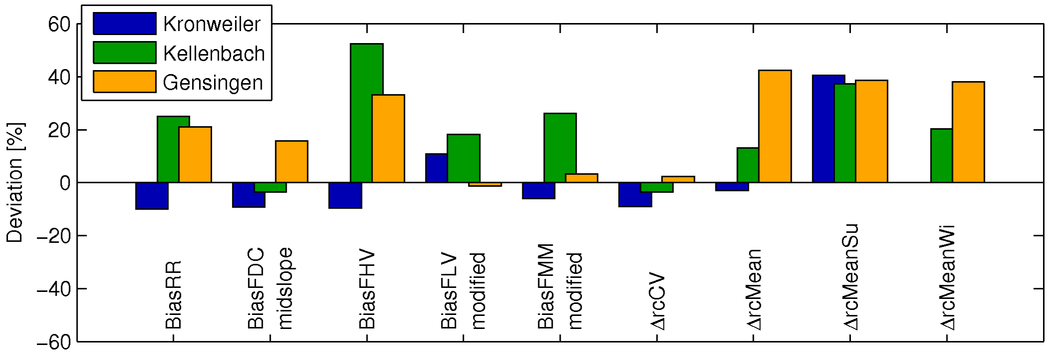

Fig. 5. Signature indices resulting from comparison of simulated discharge time series using (1) measured meteorological input data and (2) bias corrected CCLM-data, reference period.

HESSD
8, 3571–3597, 2011

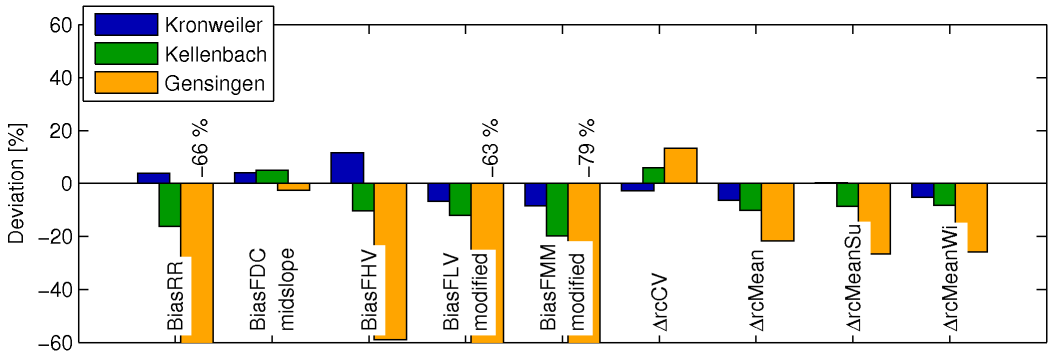

Fig. 6. Signature indices resulting from comparison of simulated discharge time series using (1) original CCLM-data and (2) bias corrected CCLM-data, 2015–2024.

HESSD
8, 3571–3597, 2011

Analysis of projected hydrological behavior of catchments

M. C. Casper et al.

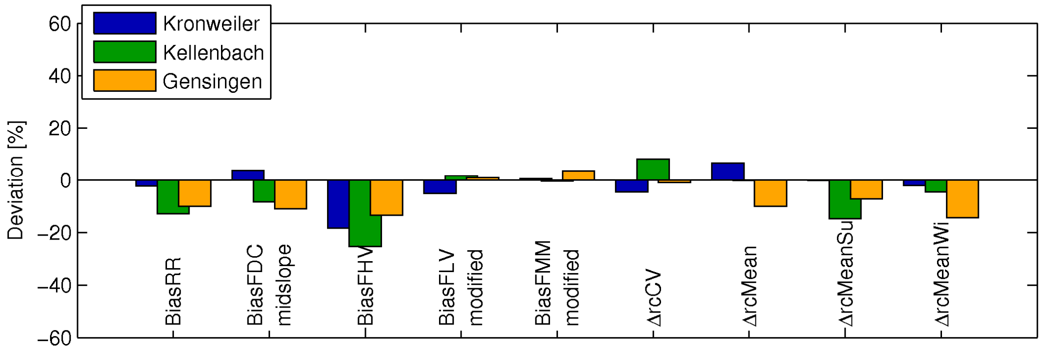

Fig. 7. Signature indices resulting from comparison of simulated discharge time series using bias corrected CCLM-data, 1 km resolution of (1) reference period and (2) 2015–2024.

HESSD
8, 3571–3597, 2011