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Influence of rainfall observation network on model calibration and application

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The objective in this study is to investigate the influence of the spatial resolution of the rainfall input on the model calibration and application. The analysis is carried out by varying the distribution of the raingauge network. The semi-distributed HBV model is calibrated with the precipitation interpolated from the available observed rainfall of the different raingauge networks. An automatic calibration method based on the combinatorial optimization algorithm simulated annealing is applied. Aggregated Nash-Sutcliffe coefficients at different temporal scales are adopted as objective function to estimate the model parameters. The performance of the hydrological model is analyzed as a function of the raingauge density. The calibrated model is validated using the same precipitation used for the calibration as well as interpolated precipitation based on networks of reduced and increased raingauge density. The effect of missing rainfall data is investigated by using a multiple linear regression approach for filling the missing values. The model, calibrated with the complete set of observed data, is then run in the validation period using the above described precipitation field. The simulated hydrographs obtained in the three sets of experiments are analyzed through the comparisons of the computed Nash-Sutcliffe coefficient and several goodness-of-fit indexes. The results show that the model using different raingauge networks might need recalibration of the model parameters: model calibrated on sparse information might perform well on dense information while model calibrated on dense information fails on sparse information. Also, the model calibrated with complete set of observed precipitation and run with incomplete observed data associated with the data estimated using multiple linear regressions, at the locations treated as missing measurements, performs well. A meso-scale catchment located in the south-west of Germany has been selected for this study.

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1 Introduction

Precipitation data is one of the most important inputs required in hydrological modeling and forecasting. In a rainfall-runoff model, accurate knowledge of precipitation is a prerequisite for accurately estimating discharge. This is due to that fact that representation of precipitation is crucial in determining surface hydrological processes (Syed et al., 2003; Zehe et al., 2005). No model, however well founded in physical theory or empirically justified by past performance, will be able to produce accurate hydrograph predictions if the inputs to the model do not characterize the precipitation inputs (Beven, 2001). Precipitation is governed by complicated physical processes which are inherently nonlinear and extremely sensitive (Bárdossy and Plate, 1992). Precipitation is often significantly variable in space and time within a catchment (Krajewski et al., 2003). New technologies have been developed such as satellite imaging and weather radar remote sensing (Collier, 1989; Meischner, 2003; Uhlenbrook and Tetzlaff, 2005), in order to obtain spatially and temporally highly resolved precipitation data to meet the requirements of advanced hydrological models. However the reality is that most recording systems for the majority of the catchments are still point-measuring rain-gauges. Raingauges are fundamental tools that provide an estimate of rainfall at a point. Generally, point measurements of raingauge accumulations are distributed in space over the catchment by interpolation techniques (i.e. kriging, Thiessen polygons, and inverse distance method).

A large number of previous studies investigate the effects of raingauge sampling, in terms of number of raingauges and their locations, on the estimation uncertainty of precipitation or hydrological variables. This objective in the research community has been mainly achieved through the following two approaches: (a) applying theoretical models of the rainfall process (Krajewski et al., 1991; Peters-Lidard and Wood, 1994) or (b) using high resolution rainfall data from dense networks or weather radars (Seed and Austin, 1990; Duncan et al., 1993; Finnerty et al., 1997; St-Hilarie et al., 2003). Additionally, many researchers have investigated the influence of the density of the

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raingauge network on the simulated discharge, with both real and synthetic precipitation and discharge data sets. Many studies have reported the effect of raingauge network degradation on the simulated hydrographs (Faures et al., 1995; Brath et al., 2004; Dong et al., 2005). Nevertheless, inadequate representation of spatial variability of precipitation in modeling can be partly responsible for modeling errors. This may also lead to the problem in parameter estimation of a conceptual model (Chaubey et al., 1999).

It may be of interest to investigate the results of the simulations obtained with the rainfall input when the model is parameterized according to a different type of input data. It is, in fact, frequently the case that a raingauge network changes due to an addition or subtraction of raingauges. The raingauge network can be strengthened by the addition of new instruments or using weather radar, so that a more detailed representation of rainfall is allowed, but, for calibration purposes, past observations are available only over the original, less numerous measuring points. On the other hand, in the case of an operational flood forecasting system, the opposite situation may occur. In the flood forecasting system, the rainfall-runoff model is usually calibrated using all the available flood events and precipitation data. However, during the operational forecasting time, the precipitation data from all past observation stations may not be available due to a malfunctioning of a few of the observations in the network or the observation data may not be available online. In such cases, it is crucial to understand if the parameters calibrated using the rainfall coming from one type of network have the ability to represent the phenomena governing the rainfall-runoff process with the input provided by the different configuration of the raingauge network.

The aim of this paper is, thus, to investigate the influence of rainfall observation network on model calibration and application. First, a method based on the combinatorial optimization algorithm simulated annealing (Aarts and Korst, 1989) was used to identify a uniform set of locations for a particular number of raingauges. Second, the semi-distributed conceptual rainfall-runoff model HBV was used to investigate the effect of the number of raingauges and their locations on the predictive uncertainty of

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the hydrological model. The hydrological modeling performances of the networks were analyzed through the comparison of Nash-Sutcliffe coefficient and other goodness-of-fit indices. Latter the influence of the rainfall observation network on model calibration and application is examined. This study seeks to determine whether the parameters calibrated using the rainfall coming from one type of network have the ability to represent the phenomena governing the rainfall-runoff process with the input provided by a different configuration of the raingauge network. The model is calibrated using precipitation interpolated from different raingauge networks. The calibrated model is then run for the validation period using the precipitation obtained from the raingauge network, which was not used for the calibration. Other experiments were carried out to analyze the reliability of supplementing missing precipitation measurements used for the calibration with data estimated using a multiple linear regression and running the model using that precipitation combined with available observed precipitation.

2 The study area and data

The upper Neckar catchment, located in Germany, was selected as test catchment. The study area covers an area of approximately 4000 km². The study catchment area was divided into thirteen subcatchments depending on the available discharge gauges (Fig. 1).

Table 1 shows the sizes of the different subcatchments. The climate of the catchment is characterized by warm-to-hot summers with generally mild winters, and it is wet all seasons. The coldest and hottest months in the study area are January and July respectively. The elevation for the catchment ranges from about 250 m a.s.l. to around 1000 m a.s.l., with a mean elevation of 546 m a.s.l. Slopes in general are mild; approximately 90% of the area has slopes varying from 0° to 15°, although some areas in the Swabian Jura or in the Black Forest may have values as high as 50°. The physiographical factors considered in this study were derived from different sources: (1) Digital Elevation Model with a spatial resolution of 50 m×50 m; (2) a digitized soil

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map of the state of Baden-Württemberg at the scale 1:200 000 and (3) Land use map (LANDSAT satellite image for the year 1993) with a spatial resolution of 30 m×30 m. Daily discharge data from 13 gauging stations was used for model evaluation. All data was provided by the State Institute for Environmental Protection Baden-Württemberg (LUBW). The daily amount of precipitation, daily mean, maximum and minimum temperatures distributed in and around the study catchment was acquired from the German Weather Service (DWD).

2.1 Raingauge selection method and data preparation

The raingauges that have no missing measurements for the period from 1961 to 1990 and are located within or up to 30 km from the study catchment were used as a basis of complete raingauge network. The raingauge networks were selected from the complete network, consisting of 51 raingauges, using the combinatorial optimization algorithm simulated annealing (Aarts and Korst, 1989). The main idea behind the raingauge selection algorithm is to identify a uniform set of locations for a particular number of raingauges.

An appropriate selection algorithm was applied repeatedly to obtain optimal locations of different number of raingauges. Seven networks consisting of different number of raingauges ranging from 5 to 51 were obtained. Figure 2 shows the spatial distribution of the selected networks.

The basic inputs for the HBV model are precipitation, air temperature and potential evapotranspiration. The point measurements obtained from the selected raingauge networks were interpolated on a 1 km² grid using the external drift kriging method (Ahmed and de Marsily, 1987). It should be noted that the rate at which precipitation decrease varies with increasing elevation. The square root of the topographic elevation was assumed as a good approximation to account for this variation and it was used as the drift variable for precipitation (Hundecha and Bárdossy, 2004). Because the temperatures show a fairly constant lapse rate, topographic elevation was used as the drift variable for interpolating the temperature from the available point measurements. The

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potential evapotranspiration was computed using the Hargreaves and Samani method (Hargreaves and Samani, 1985) on the same grid used for the interpolation of meteorological variables.

Figure 3 depicts the standard deviation of the interpolated precipitation over the catchment. It can be observed that the variability of the interpolated precipitation decreases with the increasing number of raingauges, but there is no change in the variability beyond a certain number of raingauges.

3 Model and methods

The HBV model is a semi-distributed conceptual model and was originally developed at the Swedish Hydrological and Meteorological Institute (SMHI) (Bergström and Forsman, 1973). The area to be modelled is divided into a number of subcatchments and each subcatchment is further divided into a number of zones based on elevation, land use or soil type or combinations of them. Snow accumulation and melt, actual soil moisture and runoff generation processes are calculated for each zone using conceptual routines. The snow accumulation and melt routine uses the degree-day approach. Actual soil moisture is calculated by considering precipitation and evapotranspiration. Runoff generation is estimated by a non-linear function of actual soil moisture and precipitation. The dynamics of the different flow components at the subcatchment scale are conceptually represented by two linear reservoirs. The upper reservoir simulates the near surface and interflow in the sub-surface layer, while the lower reservoir represents the base flow. Both reservoirs are connected in series by a constant percolation rate. Finally there is a transformation function, consisting of a triangular weighting function with one free parameter, for smoothing the generated flow. The flow is routed from one node to the other of the river network by means of the Muskingum method. Additional description on the HBV model can be found in Lindström et al. (1997) and Hundecha and Bárdossy (2004).

As elevation affects the distribution of the basic meteorological variables such as

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precipitation and temperature as well as the rate of evaporation and snow melt and accumulation, it represents an important catchment characteristic that was considered in defining zones in this study. Elevation zones were defined using a contour interval of 75 m. Areas between successive contour intervals were considered homogenous with respect to elevation. The elevation of the study area varies from about 250 m to around 1000 m and therefore, a maximum of 10 elevation zones were defined in each subcatchment. In order to model the processes in each zone, the values of the mean daily precipitation amount and the mean daily temperature were assigned to each zone. The meteorological variables for each zone were estimated as the mean of the interpolated values on the regular grids of 1 km² located within a given zone. The potential evapotranspiration was also averaged over each zone from the potential evapotranspiration calculated on 1 km² grids located within a given zone.

3.1 Model calibration and simulations

The HBV model was calibrated using the interpolated precipitation obtained from the different raingauge networks. The other input data, namely daily mean temperature and daily potential evapotranspiration, were kept constant for each calibration. The automatic calibration method based on the combinatorial optimization algorithm simulated annealing (Aarts and Korst, 1989) was used to optimize the model parameters. For this optimization, an objective function composed of Nash-Sutcliffe coefficients of several temporal aggregation scales was maximized, while a reasonable range was fixed to constrain model parameters.

The standard split sampling model calibration procedure was followed. The model calibration period runs from 1961 to 1970. The subsequent period up to 1990 was used to validate the calibrated model. The interpolated precipitation, based on daily recorded observations, from the different raingauge networks was used to simulate the model discharges for the calibration and validation periods. Disaggregation of the daily amount by uniformly distributing it through out the day was implemented and the model was run at a time step of 6 h for the study (Hundecha and Bárdossy, 2004).

3.2 Simulation comparison statistics

The simulation results obtained using different raingauge networks were compared using different statistical criteria, namely, the Nash-Sutcliffe coefficient, the relative accumulated difference, the peak error and the root mean squared error.

5 The Nash-Sutcliffe coefficient (R_m^2) (Nash and Sutcliffe, 1970) is defined as

$$R_m^2 = 1 - \frac{\sum_{i=1}^N (Q_s(t_i) - Q_o(t_i))^2}{\sum_{i=1}^N (Q_o(t_i) - \bar{Q}_o)^2} \quad (1)$$

$Q_o(t_i)$ [m³/s] observed daily discharge

$Q_s(t_i)$ [m³/s] simulated daily discharge

\bar{Q}_o [m³/s] mean observed daily discharge

N [-] number of time steps

The relative accumulated difference and the peak error were computed to judge the performance of the model with regard to its ability to maintain the water balance and its estimation capacity of the peak flow.

10

The relative accumulated difference (*rel. accdif.*) is defined as:

$$rel. \ accdif. = \frac{\sum_{i=1}^N (Q_s(t_i) - Q_o(t_i))}{\sum_{i=1}^N Q_o(t_i)} \quad (2)$$

The *peak error* is defined based on the relative difference of the mean annual maximum simulated and mean annual maximum observed discharges:

$$15 \quad peak \ error = \frac{\bar{Q}_{s(max)} - \bar{Q}_{o(max)}}{\bar{Q}_{o(max)}} \quad (3)$$

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$\bar{Q}_{o(\max)}$ [m³/s] mean annual maximum observed discharge
 $\bar{Q}_{s(\max)}$ [m³/s] mean annual maximum simulated discharge
 The root mean squared error (RMSE) is defined as:

$$\text{RMSE} = \left(\frac{1}{N} \left(\sum_{i=1}^N (Q_s(t_i) - Q_o(t_i))^2 \right) \right)^{0.5} \quad (4)$$

Further, the mean model performance (R_{mm}^2) is calculated using the Nash-Sutcliffe coefficient values obtained at the discharge gauges during the calibration and validation periods.

$$R_{mm}^2 = \frac{1}{L} \sum_{i=1}^L \frac{[R_m^2(\text{calibration})_i + R_m^2(\text{validation})_i]}{2} \quad (5)$$

where:

R_{mm}^2 [-] mean model performance
 $R_m^2(\text{calibration})_i$ [-] Nash-Sutcliffe coefficient during calibration period
 $R_m^2(\text{validation})_i$ [-] Nash-Sutcliffe coefficient during validation period
 L [-] number of subcatchments

Higher values of R_{mm}^2 indicate better mean model performance.

The value of model parameters' transferability (T_m) is also computed to evaluate their transferability during the simulation period when the model parameters were not allowed to change. T_m is calculated using the following equation.

$$T_m = \max \left[\left(R_m^2(\text{calibration})_i - R_m^2(\text{validation})_i \right) \right]_{i=1, \dots, L} \quad (6)$$

As we are more concerned about deterioration of model performance in the validation period, therefore, the maximum positive difference of the model performance was only considered in the above equation.

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Lower values of T_m indicate better model parameters' transferability.

Additionally, the average absolute error (A_E) and root mean squared error (see Eq. 4) were calculated using the model simulated and observed discharges for each annual maximum flood event. A_E is defined as:

$$5 \quad AE = \frac{1}{N_p} \sum_{i=1}^{N_p} | (Q_{sp}(t_i) - Q_{op}(t_i)) | \quad (7)$$

where:

$Q_{op}(t_i)$	[m ³ /s]	observed daily discharge within each annual event
$Q_{sp}(t_i)$	[m ³ /s]	simulated daily discharge within each annual event
N_p	[-]	number of time steps in a particular peak event

3.3 Simulation results

10 A summary of the model performance for the calibration period for selected three gauges is shown in Table 2. The model performance for the validation period using precipitation produced from different raingauge networks are shown in Table 3. The model performances are shown for the gauges at Horb (Neckar) and Suessen (Fils) because there are major variations in the number of raingauges within each network for the drainage area of these two gauges. Considering Table 3 for Horb (Neckar),
15 it can be observed that the network consisting of 5 raingauges yields the minimum model performance, whereby the highest model performance was observed using the 20 raingauge network. Moreover, increasing the raingauge numbers above 20 did not improve the model performance. The best model performance for Suessen (Fils) was observed using the 15 raingauge network. On the other hand, the best model performance for the Plochingen (Neckar) was observed using the 30 raingauge network.
20 This shows the influence of the spatial distribution of raingauges within each subcatchment. The number of raingauges is different for different subcatchments within each selected network (Fig. 2). The difference in number of raingauges within and close to

each subcatchment influences the interpolated precipitation.

Figure 4 shows the average Nash-Sutcliffe coefficients for the calibration and validation periods. The average values were calculated using the Nash-Sutcliffe coefficients obtained for different gauges over the catchment.

5 A considerable deterioration in model performance was observed when using the network consisting of 5 raingauges, both for the calibration and validation periods (as shown in Fig. 4).

Table 4 represents the mean model performance and model parameters' transferability corresponding to the different rainauge networks.

10 It can be observed that the lowest mean model performance was obtained using the 5 rainauge network. The highest value was observed using the 30 rainauge network. However, there was not remarkable change in the mean model performance when the number of raingauges was increased to more than 15. The worst model parameters' transferability was observed using the 5 rainauge network.

15 The inability of the 5 rainauge network to adequately represent the precipitation field seems to negatively influence the estimation of parameters, further increasing the remarkable simulation errors. Moreover, the unsatisfactory results obtained using the 5 rainauge network certainly indicate a definite lack in its ability to represent the precipitation fields. On the other hand, the model performance was not significantly
20 improved when using more than 15 raingauges. This is because there are only 20 raingauges within and close to the catchment. Estimating the precipitation fields using raingauges located considerably at far distance from the boundary of the catchment, perhaps, brings more error in the model simulation.

25 Figure 5 shows the seasonal model performance for the Suesen (Fils) and Plochingen (Neckar) gauges.

Figure 5 indicates that the poorest model performance was observed using the 5 rainauge network. A significant inability to represent the spatial precipitation fields using 5 rainauge network in the smaller subcatchment for the summer season can also be observed. This is due to the fact that there are convective precipitation events

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during the summer season, which are more localized and are not well captured by the 5 raingauge network.

Further, the event statistics were calculated for each annual maximum flood event. Figures 6 and 7 show the average absolute error and root mean squared error for the gauges at Horb (Neckar) and Suessen (Fils), respectively.

On average the absolute error with respect to the annual maximum discharges for the gauge at Horb (Neckar) ranges between 6.9% and 8.4% using the precipitation produced from varying raingauge networks. The same value for the gauge at Suessen (Fils) ranges between 8.2% to 9.2%. The highest errors yielded using the network consisting of 5 raingauges. On the other hand, the errors were not significantly reduced by increasing the number of raingauges to more than 20.

It may be noted that obtaining similar goodness-of-fit indices does not mean that the simulation was insensitive to the spatial variability of the precipitation fields obtained using different number of raingauges. In fact, the two models using different precipitation fields did not give the same hydrograph. In general, it can be noted that using too coarse a raingauge network for estimating the rainfall fields can give rise to remarkable errors. However, the network formed by the threshold number of raingauges (20–30 in the present study) provides an acceptable estimate of the precipitation fields, other model errors dominate in this case.

4 Influence of the rainfall observation network on model calibration and application

In the following section, the aim of the simulation experiment was to investigate the influence of the spatial resolution of the rainfall input on the calibration of a conceptual model. First, the semi-distributed HBV model was calibrated with the precipitation interpolated from the available observed rainfall of varying raingauge networks. The calibrated model was then run using the same precipitation used for the calibration as well as interpolated precipitation based on networks of reduced and increased rain-

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gauge density.

As for example, the model was first calibrated using precipitation interpolated from 10 and 20 raingauges. The calibrated model using 10 raingauges was then run using precipitation obtained from 20 raingauges for the validation period and vice versa. This experiment is indicated in tables and figures, latter on, as follows: **10/10**: calibrated with 10 raingauges and simulated with 10 raingauges; **20/20**: calibrated with 20 raingauges and simulated with 20 raingauges; **10/20**: calibrated with 10 raingauges and simulated with 20 raingauges and **20/10**: calibrated with 20 raingauges and simulated with 10 raingauges.

It can be noticed that the model calibrated using less detailed precipitation (precipitation from 10 raingauges) often slightly improves when it was run using relatively more detailed precipitation (precipitation from 20 raingauges) (Table 5). On the other hand, the model performance obtained using precipitation from 20 raingauges deteriorated when the same model was run using precipitation obtained from 10 raingauges.

In fact, the parameter values in principle may compensate for an incomplete representation of the precipitation field, provided they were updated by performing a new calibration, for which the input precipitation was estimated from the reduced raingauges network. However, there was no such type of compensation for the second case when the calibrated model using 20 raingauges was run using precipitation obtained from the 10 raingauge network. This demonstrates the inability of the 10 raingauges to adequately represent the precipitation field for the catchment.

The following simulation experiment was carried out in order to investigate whether the estimated precipitation at raingauges with missing values (for example offline stations only used for model calibration), together with the precipitation data from the remaining stations that were used during the model calibration, has any benefit over the model operated by precipitation from the reduced raingauges. A new spatial representation of the rainfall input was considered: the precipitation was estimated using a multiple linear regression technique (Montgomery and Peck, 1982) at specific locations (the precipitation data for the 10 raingauges network are treated as missing

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measurements for the model validation period in the present example) of a selected raingauge network (20 raingauges network in the present example). The observed precipitation was considered at the remaining 10 locations of the 20 raingauges network. The model, calibrated with the precipitation data obtained from 20 raingauges, was then run in the validation period using the precipitation field above described.

Thus, in this experiment, the precipitation of the 10 raingauges (the location of these stations are same of the 10 raingauges network) within the 20 raingauges network was considered missing for the validation period. The multiple linear coefficients at the locations of the above 10 raingauges were derived using the precipitation measurements of the neighboring stations and the available precipitation measurements at those 10 raingauges.

Consider that the precipitation for a particular station is missing for some time period. The missing measurements then can be estimated using the measurements of the neighboring stations through the application of the multiple linear regression coefficients. A multiple regression model that can describe this relationship is as follows:

$$R(u_s) = \beta_0 + \beta_1 R(u_1) + \beta_2 R(u_2) + \dots + \beta_k R(u_k) + \varepsilon \quad (8)$$

where $R(u_s)$ denotes the missing precipitation measurements of a particular station at a location u_s ; u_1, u_2, \dots, u_k denotes the precipitation measurement locations of the remaining stations and ε is a statistical error. The parameters $\beta_j, j=0, 1, \dots, k$ are called the regression coefficients (Montgomery and Peck, 1982). Coefficients are calculated using all available observations.

Thus, the missing measurements at the mentioned 10 raingauges were estimated using the derived multiple linear regression coefficient using measurement data excluding the given event. The precipitation was then interpolated using the estimated precipitation at the 10 raingauges and also the remaining 10 raingauges within the 20 raingauge network. As a result, the interpolated precipitation field consisted of 20 raingauges once again, however, with 10 raingauges of precipitation data estimated using the multiple linear regression technique and the remaining 10 from the observed data.

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Figure 8 shows the model performance for selected six gauges during the validation period using the different level of input precipitation information. The data shown in Table 5 is partly used to prepare Fig. 8. In the following tables and figures **20/20Mul-Rgre** indicates model calibrated with 20 raingauges and simulated with 20 raingauges (rainfall estimated at 10 locations considered as missing measurements).

It can be observed that the model performed well when it was calibrated using precipitation from 20 raingauges and was run with an incomplete observed data set combined with data generated using the multiple linear regression technique at the locations of the remaining 10 raingauges.

A summary of the Nash-Sutcliffe coefficients at a 7 day and 30 day time scale in the validation period is shown in Table 6. Regarding modeling of runoff at higher time scales, the model performance in terms of the Nash-Sutcliffe coefficient shows a similar trend as that observed earlier at the daily time scale. It can be observed that the model performance improves at the higher time scales.

Figure 9 shows the seasonal model performance obtained using the different level of input precipitation information for the gauges at Oberndorf (Neckar) and Horb (Neckar).

Figure 10 depicts the average absolute error and root mean squared error for the gauge at Rottweil (Neckar).

On average the absolute error with respect to the annual maximum discharges for the gauge at Rottweil (Neckar) ranges between 6.8% and 8.2%. The highest error was observed when the calibrated model using 20 raingauges was run using 10 raingauges. The error reduced to 6.9% when the calibrated model using 20 raingauges was run using 20 raingauges, however, with 10 raingauges of precipitation data estimated using the multiple linear regression technique and the remaining 10 from the observed data.

This analysis, as represented in Figs. 9 and 10, indicates that model performance reduces when the model calibrated using more detailed input precipitation information is run using precipitation obtained from a reduced raingauge networks. The analysis also highlights that the missing measurements can be supplemented using a simple multiple linear regression technique or another appropriate data filling technique.

5 Conclusions

In this paper attempts have been made to investigate the influence of the spatial representation of the precipitation input, interpolated from different raingauge density, on the calibration and application of the semi-distributed HBV model. The meteorological input was interpolated using the external drift kriging method from the point measurements of the selected raingauge networks. The performance of the HBV model was assessed using different model performance evaluation criteria for the calibration and validation periods.

A number of simulation experiments were carried out in accordance to the study objective. A first set of experiments considered the spatial representation of precipitation from varying raingauge networks. It showed that the number and spatial distribution of raingauges affect the simulation results. It was found that the over all model performances worsen radically with an excessive reduction of raingauges. However, the overall performances were not significantly improved by increasing the number of raingauges more than a certain threshold number. A significant inability to represent the spatial precipitation fields using network consisting of less number of raingauges are observed in the summer season particularly for the smaller subcatchment.

A second set of analysis considered the model calibration using one type of input precipitation and was run using another type of precipitation data. The analysis indicated that models using different raingauge networks might need their parameters recalibrated. Specifically, the HBV calibrated with dense information fails when run with sparse information. However, the HBV calibrated with sparse information can perform well when run with dense information.

A third set of experiments analyzed the reliability of supplementing missing precipitation measurements used for the calibration with data estimated using a multiple linear regression technique, and running the model using that precipitation combined with observed precipitation. The results showed that the model performs well when calibrated with a complete set of observed precipitation and when run with an incomplete

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observed data set combined with estimated data. This result offers an encouraging perspective for the implementation of such a procedure for an operational flood forecasting system. Further research is needed in this direction to prove the practical applicability.

Acknowledgements. The work described in this paper is supported by a scholarship program initiated by the German Federal Ministry of Education and Research (BMBF) and coordinated by its International Bureau (IB) under the program of the International Postgraduate Studies in Water Technologies (IPSWaT). Its contents are solely the responsibility of the authors and do not necessarily represent the official position or policy of the German Federal Ministry of Education and Research.

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Table 1. Summary of the sizes of the different subcatchments. This also contains the drainage area of each discharge gauges.

Gauging station (River)	Subcatchment size [km ²]	Drainage area [km ²]
1 Rottweil (Neckar)	454.65	454.65
2 Oberndorf (Neckar)	240.13	694.78
3 Horb (Neckar)	420.18	1114.96
4 Bad Imnau (Eyach)	322.94	322.94
5 Rangendingen (Starzel)	119.89	119.89
6 Tuebingen Blaesibg (Steinlach)	140.21	140.21
7 Kirchentellinsfurt (Neckar)	613.33	2311.33
8 Wannweil (Echaz)	135.26	135.26
9 Riederich (Erms)	169.84	169.84
10 Oberensingen (Aich)	178.18	178.18
11 Suessen (Fils)	345.74	345.73
12 Plochingen (Fils)	349.09	694.83
13 Plochingen (Neckar)	472.05	3961.49

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Table 2. Model performance using precipitation resulting from different numbers of raingauges during the calibration period.

Number of raingauges	Horb (Neckar)				Suessen (Fils)				Plochingen (Neckar)			
	R_m^2	Rel. accdif.	Peak error	RMSE	R_m^2	Rel. accdif.	Peak error	RMSE	R_m^2	Rel. accdif.	Peak error	RMSE
5	0.82	-0.05	-0.17	7.70	0.72	0.00	-0.14	3.33	0.84	-0.03	-0.06	20.54
10	0.83	0.04	-0.10	7.37	0.77	-0.02	-0.12	3.08	0.86	0.00	-0.10	18.80
15	0.86	0.01	-0.13	6.76	0.75	-0.02	-0.12	3.18	0.87	0.01	-0.10	18.53
20	0.86	0.02	-0.11	6.80	0.77	0.01	-0.10	3.03	0.87	0.00	-0.08	18.42
30	0.85	0.02	-0.08	6.86	0.77	-0.01	-0.11	3.02	0.88	-0.01	-0.12	18.59
40	0.85	0.02	-0.08	7.04	0.77	-0.03	-0.10	3.05	0.86	0.00	-0.07	18.97
51	0.84	0.04	-0.05	7.24	0.76	0.00	-0.12	3.11	0.86	-0.02	-0.08	19.13

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Table 3. Model performance using precipitation resulting from different numbers of raingauges during the validation period.

Number of raingauges	Horb (Neckar)				Suessen (Fils)				Plochingen (Neckar)			
	R_m^2	Rel. accdif.	Peak error	RMSE	R_m^2	Rel. accdif.	Peak error	RMSE	R_m^2	Rel. accdif.	Peak error	RMSE
5	0.81	0.06	-0.12	8.47	0.76	0.08	-0.19	3.03	0.84	0.05	-0.01	20.85
10	0.81	0.05	-0.11	8.61	0.79	0.09	-0.14	2.82	0.87	0.04	-0.09	19.20
15	0.83	0.09	-0.12	8.05	0.80	0.09	-0.19	2.76	0.87	0.07	-0.06	18.96
20	0.85	0.09	-0.12	7.99	0.79	0.13	-0.15	2.86	0.87	0.06	-0.06	18.99
30	0.84	0.09	-0.09	7.80	0.80	0.10	-0.17	2.78	0.89	0.05	-0.10	18.65
40	0.83	0.10	-0.09	7.99	0.79	0.09	-0.15	2.81	0.86	0.06	-0.06	19.35
51	0.82	0.11	-0.07	8.16	0.77	0.12	-0.16	2.93	0.87	0.04	-0.06	19.10

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Table 4. Mean model performance and parameters' transferability obtained using the precipitation produced from different raingauge networks.

Number of raingauges	Mean model performance	Model parameters' transferability
5	0.74	0.12
10	0.78	0.03
15	0.80	0.04
20	0.80	0.04
30	0.82	0.04
40	0.80	0.05
51	0.80	0.05

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Table 5. Model performances using the input precipitation information obtained from different number of raingauges.

		Rottweil (Neckar)	Horb (Neckar)	Riederich (Erms)	Suessen (Fils)	Plochingen (Fils)	Plochingen (Neckar)
10/10	R_m^2	0.74	0.80	0.75	0.79	0.82	0.87
	Rel. acc. diff.	-0.05	0.07	-0.01	0.09	0.12	0.04
	Peak error	-0.23	-0.14	-0.06	-0.14	-0.16	-0.09
	RMSE	3.74	8.61	1.05	2.82	5.03	19.20
20/20	R_m^2	0.78	0.83	0.76	0.79	0.81	0.87
	Rel. acc. diff.	0.00	0.09	0.02	0.13	0.17	0.06
	Peak error	-0.07	-0.12	-0.03	-0.15	-0.16	-0.06
	RMSE	3.49	7.99	1.03	2.86	5.07	18.99
10/20	R_m^2	0.74	0.82	0.77	0.78	0.80	0.88
	Rel. acc. diff.	-0.18	-0.03	0.00	0.13	0.19	0.01
	Peak error	-0.36	-0.25	-0.06	-0.13	-0.12	-0.13
	RMSE	3.75	8.10	1.02	2.91	5.22	18.06
20/10	R_m^2	0.66	0.77	0.75	0.79	0.82	0.84
	Rel. acc. diff.	0.13	0.19	0.00	0.09	0.10	0.08
	Peak error	0.08	0.00	-0.04	-0.16	-0.20	-0.01
	RMSE	4.28	9.32	1.06	2.79	4.95	20.84

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Table 6. Nash-Sutcliffe coefficients at 7 days and 30 days time scale obtained using different level of precipitation input information for selected six gauges for the validation period.

Gauge	Number of raingauges	Nash-Sutcliffe coefficient	
		7 days time scale	30 days time scale
Rottweil (Neckar)	20/10	0.76	0.82
	20/20MulRgre	0.86	0.90
Oberndorf (Neckar)	20/10	0.69	0.77
	20/20MulRgre	0.83	0.88
Horb (Neckar)	20/10	0.80	0.82
	20/20MulRgre	0.89	0.91
Suessen (Fils)	20/10	0.82	0.80
	20/20MulRgre	0.82	0.80
Plochingen (Fils)	20/10	0.85	0.83
	20/20MulRgre	0.85	0.82
Plochingen (Neckar)	20/10	0.88	0.90
	20/20MulRgre	0.90	0.92

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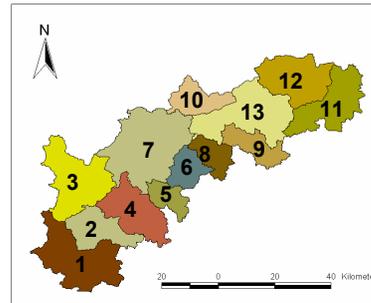
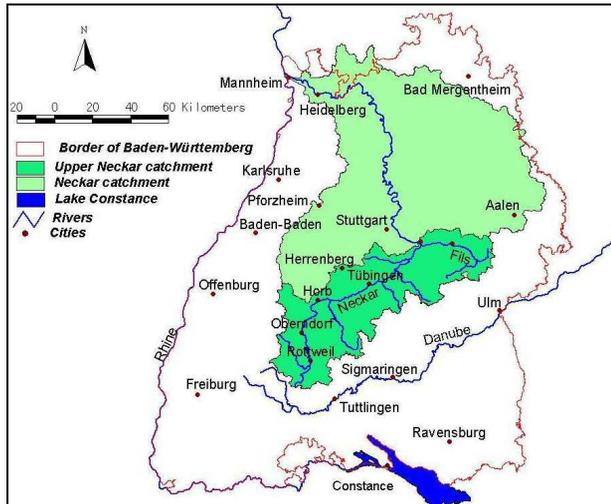


Fig. 1. Study area: Upper Neckar catchment in south-west Germany (upper-right: 13 sub-catchments of the Upper Neckar catchment).

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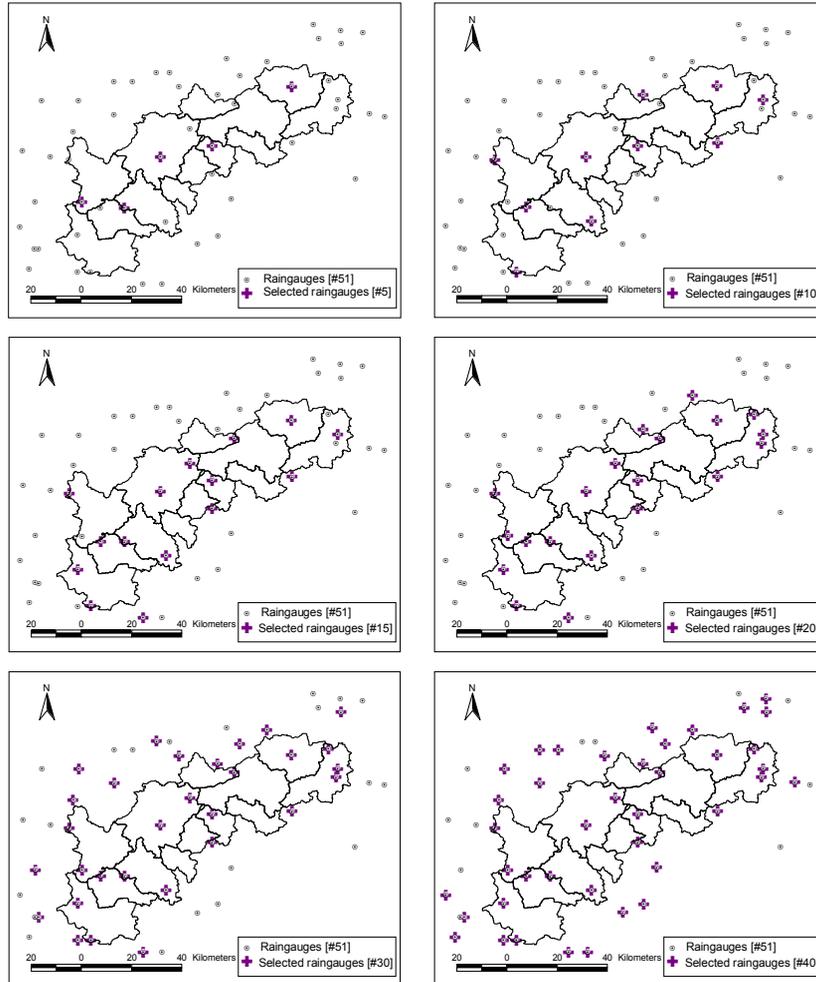


Fig. 2. Geographic locations of selected raingauge networks.

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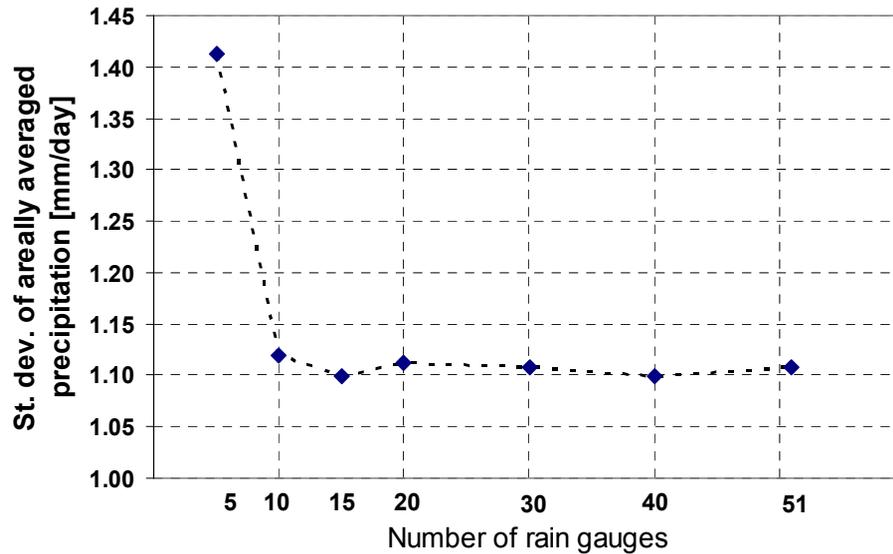


Fig. 3. Standard deviation of areally averaged precipitation vs. number of raingauges.

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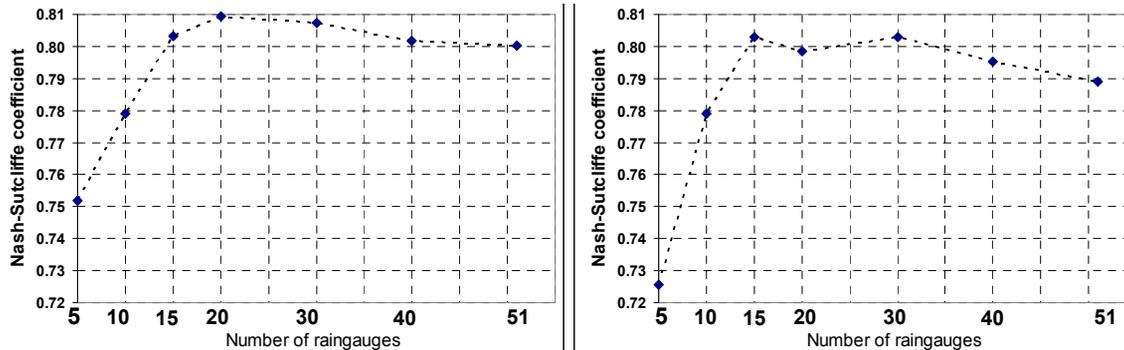


Fig. 4. Overall average Nash-Sutcliffe coefficient using the precipitation resulting from different rain gauge networks for the calibration period (left panel) and validation period (right panel).

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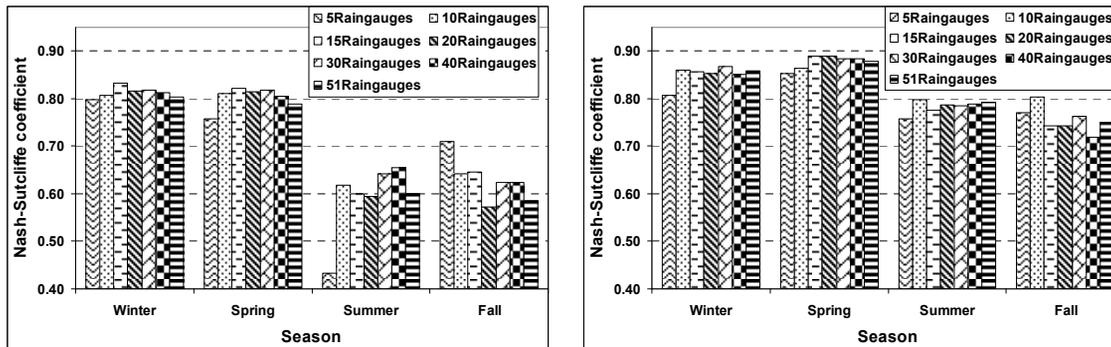


Fig. 5. Seasonal Nash-Sutcliffe coefficients using the precipitation produced from different number of raingauges during the validation period for the gauges at Suessen (Fils) (left panel) and Plochingen (Neckar) (right panel).

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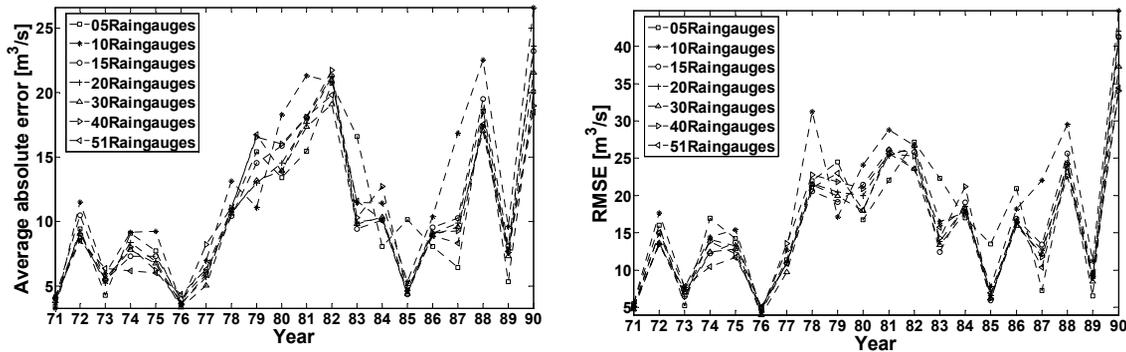


Fig. 6. Event statistics for each annual maximum flood event using different raingauge networks during the validation period for the gauge at Horb (Neckar): average absolute error (left panel) and root mean squared error (right panel).

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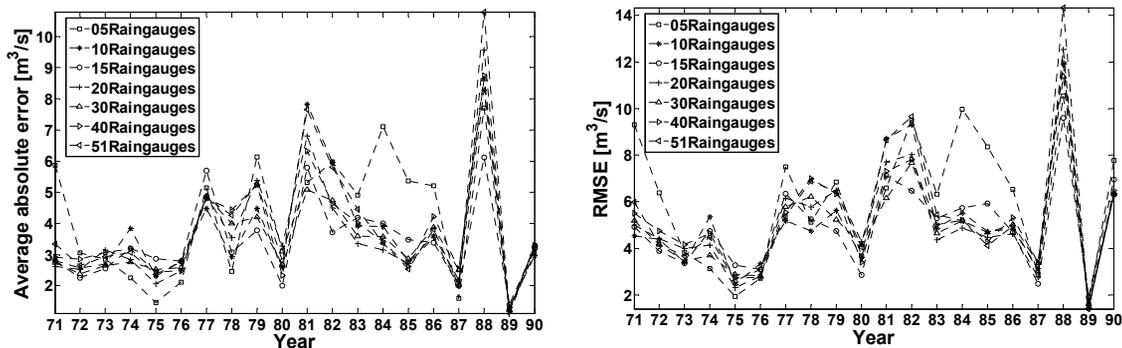


Fig. 7. Event statistics for each annual maximum flood event using different raingauge networks during the validation period for the gauge at Suessen (Fils): average absolute error (left panel) and root mean squared error (right panel).

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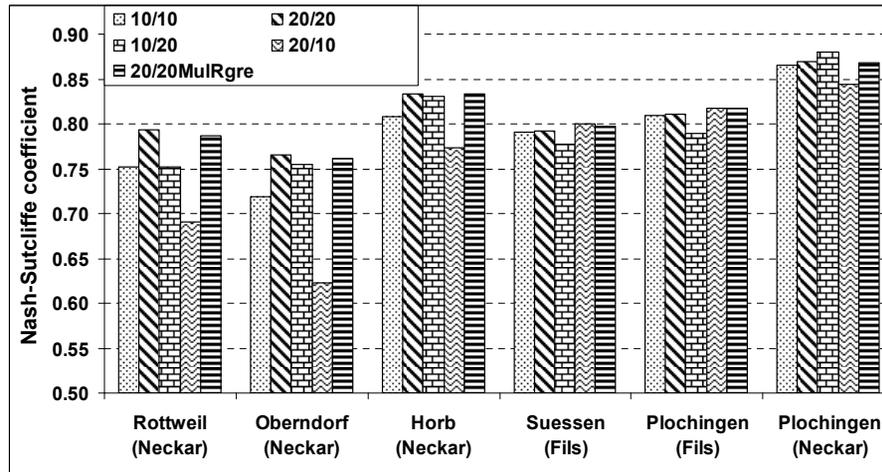


Fig. 8. Nash-Sutcliffe coefficient obtained using different level of precipitation input information for the validation period for selected six gauges.

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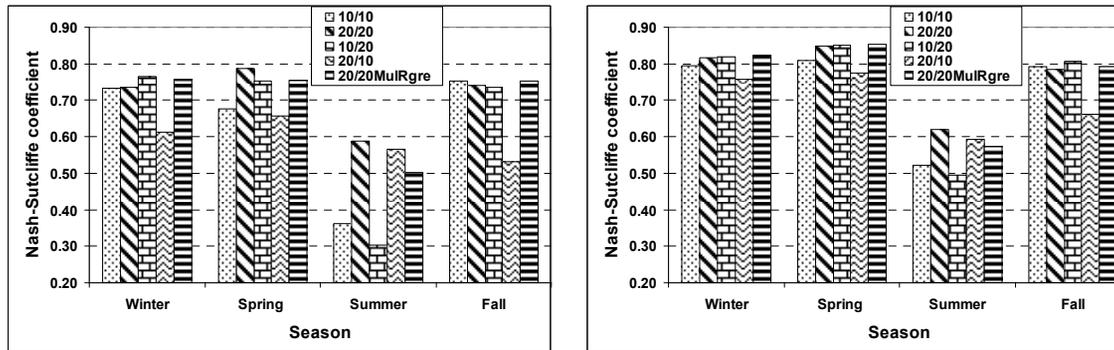


Fig. 9. Seasonal Nash-Sutcliffe coefficient using precipitation obtained from different rain-gauges and estimated precipitation during the validation period for the gauges at Oberndorf (Neckar) (left panel) and Horb (Neckar) (right panel).

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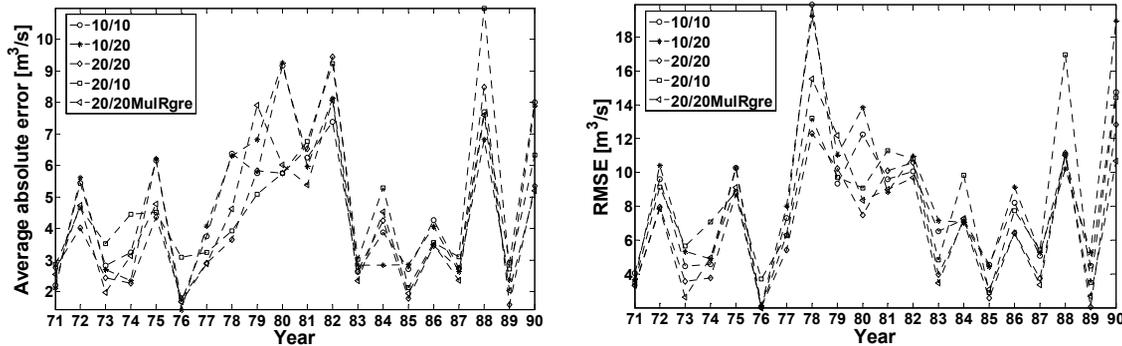


Fig. 10. Event statistics for each annual maximum flood event during the validation period using precipitation obtained from different raingauge networks and estimated precipitation for the gauge at Rottweil (Neckar): average absolute error (left panel) and root mean squared error (right panel).

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