Hydrol. Earth Syst. Sci. Discuss., 12, 11053–11082, 2015
www.hydrol-earth-syst-sci-discuss.net/12/11053/2015/
doi:10.5194/hessd-12-11053-2015

Hydrology and Earth System Sciences
Open Access
Discussions

This discussion paper is/has been under review for the journal Hydrology and Earth System Sciences (HESS). Please refer to the corresponding final paper in HESS if available.

Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT in small catchments in the Ethiopian Highlands

V. Roth[1,2,3] and T. Lemann[1,2,3]

[1]Centre for Development and Environment (CDE), University of Bern, Switzerland
[2]Sustainable Land Management Research Group, University of Bern, Switzerland
[3]Water and Land Resource Centre (WLRC), Addis Abeba, Ethiopia

Received: 7 August 2015 – Accepted: 10 October 2015 – Published: 27 October 2015

Correspondence to: V. Roth (vincent.roth@cde.unibe.ch)

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

Abstract

Accurate rainfall data are the key input parameter for modelling river discharge and sediment loss. Remote areas of Ethiopia often lack adequate precipitation data and where it is available, there might be substantial temporal or spatial gaps. To counter this challenge, the Climate Forecast System Reanalysis (CFSR) of the National Centers for Environmental Prediction (NCEP) readily provides weather data for any geographic location on earth between 1979 and 2014. This study assesses the applicability of CFSR weather data to three watersheds in the Blue Nile Basin in Ethiopia. To this end, the Soil and Water Assessment Tool (SWAT) was set up to simulate discharge and sediment loss, using CFSR and conventional weather data, in three small-scale watersheds ranging from 102 to 477 ha. Calibrated simulation results were compared to observed river discharge and observed sediment loss over a period of 32 years. The conventional weather data resulted in very good discharge outputs for all three watersheds, while the CFSR weather data resulted in unsatisfactory discharge outputs for all of the three gauging stations. Sediment loss simulation with conventional weather inputs yielded satisfactory outputs for two of three watersheds, while the CFSR weather input resulted in three unsatisfactory results. Overall, the simulations with the conventional data resulted in far better results for discharge and sediment loss than simulations with CFSR data. The simulations with CFSR data were unable to adequately represent the specific regional climate for the three watersheds, performing even worse in climatic areas with two rainy seasons. Hence, CFSR data should not be used lightly in remote areas with no conventional weather data where no prior analysis is possible.

1 Introduction

Accurately represented, spatially distributed rainfall is one of the most important input parameters for hydrological modelling with the Soil and Water Assessment Tool (SWAT). Although a great deal of effort is being invested into rainfall data collection,

HESSD
12, 11053–11082, 2015

many areas of Ethiopia have no adequate precipitation data, and where such data are available, the monitoring network contains substantial temporal and spatial gaps. This makes it necessary to use other sources of modeled rainfall data for SWAT modelling. The Global Weather Data for SWAT website readily provides, for any coordinates on the globe, a Climate Forecast System Reanalysis (CFSR) data set for download. This data set is the result of the close cooperation between two United States organizations, the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR), which have completed a global climate data reanalysis over 35 years from 1979 through 2014. The CFSR data is based on a spectral model which includes the parametrisation of all major physical processes as described in detail in Kalnay et al. (1996); Kistler et al. (2001); and Saha et al. (2010).

However, a first comparison of CFSR-modelled rainfall data with that measured by the Water and Land Resource Centre (WLRC, formerly the Soil Conservation Research Programme, SCRP) in Ethiopia has shown substantial differences in daily, monthly, and annual rainfall. So far, few studies have been conducted in the Ethiopian context on the impact of rainfall data on streamflow simulations. The impact of spatial variability of precipitation on model run-off showed that standard uniform rainfall assumptions can lead to large uncertainties in run-off estimation (Faurès et al., 2000). Several studies evaluating the CFSR data set have suggested that climatic models tended to overestimate interannual variability but underestimate spatial and seasonal variability (Diro et al., 2009). A recent study (Dile and Srinivasan, 2014) evaluated the use of CFSR data for hydrological prediction using SWAT in the Lake Tana basin, Ethiopia. The study achieved satisfactory results in its simulations for both CFSR and conventional data. While the outcome was better with conventional weather data, the study concludes that CFSR could be a valuable option in data-scarce regions. In another study, Cavazos and Hewitson (2005) performed statistical downscaling of daily CFSR data with Artificial Neural Networks, and their predictions showed low performance in near-equatorial and tropical locations, which led them to conclude that the CFSR data is most deficient in locations where convective processes dominate. Another study found the CFSR

HESSD
12, 11053–11082, 2015

data set performed well on a continental scale but that it failed to adequately reproduce some regional features (Poccard et al., 2000). A study in China performed streamflow simulations by SWAT using different precipitation sources in a large arid basin using rain gauge data combined with Tropical Rainfall Measuring Mission (TRMM) data (Yu et al., 2011). The study established that streamflow modelling performed better using a combination of TRMM and rain gauge, as opposed to rain gauges only. Different interpolation schemes with the use of univariate and covariate methods showed that Kriging and Inverse Distance Weighting performed similarly well when used with the SWAT model (Wagner et al., 2012).

In this paper, WLRC and SCRP rainfall data (hereafter called WLRC data) are compared to CFSR data over a period of 35 years from 1981 to 2014. The main objective of this paper is to compare the two data sets for annual, interannual, and seasonal cycles and subsequently to compare the effects on discharge and sediment loss modeling when using these data sets in three locations in the Ethiopian highlands (see Fig. 1). Calibrated CFSR modeled discharge and sediment loss is then compared to calibrated WLRC modelled discharge and sediment loss, and the applicability of the CFSR data in small-scale catchments for hydrological predictions is statistically evaluated and compared.

2 Methods

The effects of spatial and temporal variability in the CFSR rainfall data set for the study area were examined in several steps. First the CFSR data were statistically compared to measured WLRC rainfall data for accurate representation of annual, interannual, and seasonal cycles. Second, the impact of spatial and temporal variability of rainfall on hydrology and soil loss was assessed by modeling discharge and sediment loss with the SWAT model. The SWAT model was calibrated for discharge once using WLRC rainfall data and once using the CFSR rainfall data set. Afterwards sediment loss was calibrated for each catchment. In a last step discharge and sediment loss on a monthly basis were statistically and visually compared using performance ratings established by Moriasi et al. (2007).

2.1 Study area

The study areas of the three micro-scale catchments are located in the eastern and central part of the Blue Nile Basin. The Anjeni (AJ) and the Andit Tid (AT) are sub-basins of the Blue Nile Basin, which drains towards the west into the main Nile at Khartoum. The Maybar (MA) catchment drains into the Awash river to the East of the Ethiopian highlands. The catchment sizes range from 104 to 447 ha and their altitudinal ranges extend from 2400 to 3548 m a.s.l. (see Table 1 for details). The catchments have a sub-humid to humid climate with an annual temperature ranging from 12 to 16 °C and a mean annual rainfall ranging from 1211 to 1690 mm. The rainy seasons are divided into two seasons for Andit Tid and Maybar and into one for Anjeni. Land use is dominated by smallholder rain-fed farming-systems with grain-oriented production, ox-plough farming, and uncontrolled grazing practises.

2.1.1 Hydrologic model

ArcSWAT (Version 2012.10_1.14) was used to assess the impact of different rainfall patterns on run-off and sediment loss dynamics (Arnold et al., 2012). Here, we present the SWAT model only briefly, as it has been widely used in the past, with extensive review of its performance and parameterization in Ethiopia and other regions (Gessesse et al., 2014; Mbonimpa, 2012; Betrie et al., 2011; Tibebe and Bewket, 2011; Lin et al., 2010; Stehr et al., 2008; Schuol and Abbaspour, 2007). SWAT is a physically-based river basin or watershed modelling tool. The SWAT model requires specific information about weather, soil properties, topography, vegetation, and land management practices occurring in the watershed (Arnold et al., 2012). ArcSWAT divides the catchment into hydrological response units (HRUs) based on unique combinations of soil type, land use, and slope classes that allow for a high level of spatial detail simulation. Runoff is predicted separately for each HRU and routed at subbasin level to obtain the total runoff for the watershed (Neitsch et al., 2011). The surface run-off is estimated in the model using one of two options (1) the Green and Ampt method (Green and Ampt, 1911) or (2) the Natural Resources Conservation Service Curve Number (SCS-CN) method (USDA-SCS, 1972). The flow routing is estimated using the variable storage coefficient method (Williams, 1969), or the Muskingum method (Chow, 1959). Sediment loss for each HRU is calculated through the Modified Universal Soil Loss Equation (MUSLE). Sediment routing in channels is estimated using stream power (Williams, 1980) and deposition in channels is calculated through fall velocity (Arnold et al., 2012; Gassman et al., 2007).

2.2 Spatial data

The spatial data used in ArcSWAT for the present study included the digital elevation model (DEM), land use data, and soil data (see Table 1 for details). The DEM for the three WLRC watersheds was developed by the Centre for Development and Environment (CDE) of the University of Bern, Switzerland, for the former SCRP (SCRP and CDE, 2000a, b, c) and has a resolution of 2 m. The spatial distribution of soils for Anjeni was adapted from a soil survey carried out by the SCRP (Kejela, 1995) and a PhD dissertation by Gete Zeleke (2000). The physical and chemical parametrisation of the soil was adapted from the soil database in Zeleke's thesis and from Kejela's report. The soil characteristics for Maybar were adapted from the SCRP's Soil Conservation Research Report 7 (Weigel, 1986) and for Andit Tid from the SCRP's Research Report 3 (Bono and Seiler, 1984). Land use data were adapted from yearly surveys carried out by SCRP and WLRC through land use mapping and interviews and by own surveys in 2008 and 2012. To adapt to annually changing land use patterns, a generic map was adapted from the WLRC land use maps of 2008, 2012, 2014 (Anjeni), and 2010, 2012, 2014 (Andit Tid, Maybar). The planting and harvesting times were averaged over the entire period and planted at similar dates for the entire simulation. To simulate crop growth we used the heat unit function in ArcSWAT. Teff, for example, was

HESSD
12, 11053–11082, 2015

planted beginning of July and harvested beginning of December with several tillage operations preceding planting. Tillage operations were adapted to the usage of the traditional Ethiopian plough called "Maresha" according to Temesgen et al. (2008).

2.3 SWAT model setup

The watersheds were delineated using the Arc–SWAT delineation tool and its stream network compatibility was checked against the stream network from satellite images. The sub-basin sizes were fixed at 2 ha. SWAT compiled 1038 HRUs for Anjeni, 1139 HRUs for Maybar, and 728 HRUs for Andit Tid respectively. All HRUs were defined using a zero percentage threshold area, which means that all land use, soil, and slope classes were used in the process. Daily precipitation and minimum and maximum temperature data at three WLRC stations were used to run the model with conventional weather inputs. All three WLRC stations had substantial gaps in the time series, mostly in the early 1990s and after 2000 (see Table 1 for details). The SWAT weather generator was used to fill the gaps for rainfall, temperature, solar radiation, and relative humidity. Potential evapotranspiration (PET) was estimated using the Hargreaves method (Hargreaves et al., 1985). Daily river flow and sediment concentration data were measured at the outlet of the three WLRC watersheds. The flow observations are available throughout the entire year while sediment concentrations are only available during rainstorm events, when sediment concentrations are visible in the river. During the dry season and outside rainfall events the monitored rivers are assumed sediment free. The model was run for 32 years from 1983 to 2014 with daily data inputs but monthly outputs. Calibration and validation periods were chosen equally balanced regarding high-flow and low-flow years in all three catchments. The model was first calibrated and validated for discharge and then calibrated and validated for sediment loss (see Table 1 for details).

HESSD
12, 11053–11082, 2015

2.4 Calibration, parameterization and uncertainty analysis

The SUFI-2 algorithm (Abbaspour et al., 2004, 2007) in SWAT-Cup was used for the calibration and validation procedure and for sensitivity, and uncertainty analysis. SWAT-Cup calculates the 95 % prediction uncertainty band (95PPU) in a iterative process. For the goodness of fit two indices called "*p-factor*" and "*r-factor*" are used. The *p-factor* is the fraction of measured data inside the 95PPU band, and varies from 0 to 1 where 1 indicates perfect model simulation. The *r-factor* is the ratio of the average width of the 95PPU band and the standard deviation of the measured variable. There are different approaches regarding balance of *p-factor* and *r-factor*. The *p-factor* should preferably be above 0.7 for discharge and the *r-factor* value should be below 1.5 (Abbaspour et al., 2015), but when measured data are of lower quality other values apply. Once acceptable *p-factor* and *r-factor* are reached statistical parameters for time series analysis are compared.

For this study we used the Nash–Sutcliff Efficiency (NSE), standardized Root Mean Square Error (RSR), and the Percent Bias (PBIAS). All are very commonly used statistical parameters. This study refers to the model evaluation techniques described by Moriasi et al. (2007), who established guidelines for the proposed statistical parameters (see Table 3 below for details). The NSE is a normalised statistic that indicates how well a plot of observed vs. simulated data fits the 1 : 1 line and determines the relative magnitude of the residual variance compared to the measured data variance (Nash and Sutcliffe, 1970). NSE ranges from $-\infty$ (negative infinity) to 1, with a perfect concordance of modelled to observed data at 1, a balanced accuracy at 0 and a better accuracy of observations below zero. The RSR is a standardized RMSE, which is calculated from the ratio of the RMSE and the standard deviation of measured data. RSR incorporates the benefits of error index statistics and includes a scaling factor. RSR varies from the optimal value of 0, which indicates zero RMSE or residual variation, which indicates perfect model simulation to a large positive value (Moriasi et al., 2007).

HESSD
12, 11053–11082, 2015

The PBIAS measures the average tendency of the simulated values to be larger or smaller than their observed counterparts. The optimal value of PBIAS is zero. PBIAS is the deviation of data being evaluated, expressed as a percentage. A positive PBIAS value indicates the model is under-predicting measured values, whereas negative values indicate over-predicting.

For this article the recommendations for reported values were strictly applied for discharge and lowered for sediment loss.

The model performance was also evaluated using the hydrograph visual technique, which allows a visual model evaluation overview. As suggested by Legates and McCabe (Legates and McCabe, 1999) this should typically be one of the first steps in model evaluation. Adequate visual agreement between observed and simulated data was compared on discharge and sediment loss plots on a monthly basis.

3 Results and discussion

3.1 General comparison of CFSR and WLRC rainfall data

The raw CFSR and WLRC rainfall input data showed significantly different patterns and rainfall amounts. For Andit Tid, situated on the eastern escarpment of the Blue Nile Basin, the belg and kremt rainfall seasons were temporally adequately represented; i.e., the timely occurrences of the rainy seasons were correctly represented through the CFSR data. However, total rainfall amounts were far from adequately represented: while the belg rainfall season in the CFSR data showed some overestimation, the total rainfall and length of the kremt rainy season were strongly underestimated. WLRC data distinctly show a main rainy season from July to September and a light rainy season from March to May, while the CFSR data only show mildly increased rainfall in March, April, July, and August but no distinct rainy season (see Fig. 2 for comparison).

The CFSR data for Anjeni highly overestimated rainfall in the region. While WLRC data showed a clear trend towards only one main rainy season from May/June to

HESSD
12, 11053–11082, 2015

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

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper

September with average monthly rainfall ranging from 100 (May) to 380 mm (July), the CFSR data showed a pronounced main rainy season with monthly averages ranging from 400 to 1000 mm from June to September and a distinct small rainy season from March to May with monthly averages three times as high as the WLRC rainfall data. The total annual CFSR rainfall was three times the WLRC annual rainfall.

WLRC Maybar data showed a clear seasonality, with two rainy seasons, one in March and April, and one from July to August. The belg rainy season showed only mild increase of average rainfall to around 75 mm $month^{-1}$ and the kremt rainy season showed a distinct increase of rainfall to an average of 270 mm $month^{-1}$. From the CFSR rainfall data, no clear distinction could be made between the belg and the kremt rainy season – both showed a rainfall increase to around 150 mm $month^{-1}$ and the total annual rainfall was strongly underestimated.

In general, all CFSR rainfall patterns showed a similar composition: data variability was more uniformly distributed and the distinct seasonality of the WLRC data was not well represented. CFSR data underestimated the bimodal rainfall climates and strongly overestimated the unimodal rainfall climate. The WLRC data has a highly variable rainfall range in the bimodal rainfall locations, which is not reflected by the CFSR data. In general, the CFSR rainfall data does not represent the high variability of rainfall measured by WLRC data.

3.1.1 Seasonal comparison of rainfall data

The seasonal components of the CFSR rainfall were assessed for the three stations by breaking the monthly data into seasons (dry season from October to March, small rainy season (belg) from April to May, and large rainy season (kremt) from June to September) and by comparing only these. The comparison of measured rainfall to modelled rainfall for the dry season from October to March was *unsatisfactory* (NSE < 0.50) with negative NSEs for three stations (AT: –1.92, AJ: –12.19, MA: –0.77). The PBIAS indicated model underestimation for Anjeni and Maybar (AJ: 134.2, MA: 30.7) and an overestimation of the rainfall for Andit Tid (AT: –55.2). The RSR showed large positive

HESSD
12, 11053–11082, 2015

values (AT: 1.68, AJ: 3.55, MA: 1.3) indicating a low model simulation performance and again an *unsatisfactory* rating (see Table 4).

For the belg rainy season from April to May the model performed badly. Surprisingly, the model performed worst in Anjeni, where no small rainy season occurs. The CFSR model performance for Anjeni was *unsatisfactory*, with an NSE of –5.42, a PBIAS of 106.1, and an RSR of 2.48. The CFSR model overestimated the monthly rainfall in all but 5 out of 22 years. Andit Tid and Maybar were slightly more adequate but still *unsatisfactory*. NSE was –0.79 and –0.24 respectively, indicating *unsatisfactory* performance. PBIAS was –39.4 and 24.3, respectively. RSR was 1.31 and 0.85, which again indicates an *unsatisfactory* result.

The kremt rainy season from June to September is the season with the heaviest rainfall throughout the year. On average some 77 % of the yearly rain falls within this time period. This is also the time period where the heaviest soil erosion occurs induced by rainfall. For Anjeni, Andit Tid, and Maybar the CFSR model performed unsatisfactorily (see Table 4 and Fig. 2) with NSEs below 0.50 (AT: –9.79, AJ: –50.09, MA: –3.28), RSRs above 0.70 (AT: 3.23, AJ: 7.0, MA: 2.03), and PBIAS values ranging from –69.2 (AT) and –47.1 (MA) to +128 (AJ).

The kremt rainy season was underestimated by the CFSR model for the bimodal rainfall pattern in Andit Tid and Maybar, while the unimodal rainfall pattern was heavily overestimated by the CFSR model.

3.2 Discharge modeling with WLRC and CFSR data

The performance ratings for each of the three catchments including SWAT–Cup *p-factor* and *r-factor* are summarised in Table 5. The table is divided into discharge comparison and sediment loss comparison. Each model was calibrated with one to five iterations using 500 simulations each. The data was split into calibration and validation periods, which contained similar amplitudes (see Fig. 3 for further details) over their respective periods. Parameters initially contained original ranges, which were gradually adapted according to modeling results. The final ranges are presented in Table 2.

HESSD
12, 11053–11082, 2015

3.2.1 Andit Tid

Calibration of Andit Tid with WLRC rainfall data yielded *very good* results. With an *p-factor* of 0.71 and a *p-factor* of 0.53 (see Sect. 2.4 for performance rating) the statistical parameters RSR, NSE and PBIAS yielded *"very good"* results (0.46, 0.79, 3.1 respectively). Validation for Andit Tid yielded *satisfactory* results with The CFSR rainfall data, which underestimated the WLRC rainfall pattern, yielded *unsatisfactory* results with RSR, NSE, and PBIAS of 0.80, 0.36, and 31.4. Parameter ranges settings were maximised, but still inside SWAT absolute values (Abbaspour et al., 2007). The hydrograph in Fig. 3 shows that the underestimation of rainfall amounts for Andit Tid did result in a constant underestimation of peak flows and of base flows throughout the whole time period.

3.2.2 Anjeni

Anjeni showed *very good* result for calibration with WLRC rainfall data. RSR, NSE and PBIAS were well inside the optimal performance ratings (0.39, 0.85, and 3.7 respectively), see Table 3 and Fig. 3 for comparison.

Calibration with CFSR data, where the CFSR rainfall data did strongly overestimate the measured rainfall data proved impossible. With parameter ranges set to maxima, neither baseflow, nor peaks could be adequately represented. With a *p-factor* of 0.49 and an *r-factor* of 1.91 the statistical parameters were *unsatisfactory* (RSR: 2.70, NSE: −6.27, and PBIAS: −226.0). The hydrograph (Fig. 3) shows that the strong overestimation of CFSR rainfall data during belg lead to a modelled discharge with extreme peaks during kremt, which do not correspond to the discharge regime of measured WLRC data.

3.2.3 Maybar

Calibration of Maybar with WLRC rainfall data proved to be less straight forward than Anjeni and Andit Tid. The rugged topography of Maybar combined with a inadequate cross-section proved challenging to model. Nonetheless, *satisfactory* result were achieved for discharge with RSR, NSE, and PBIAS of 0.63, 0.60, and –23.4 respectively.

The CFSR rainfall data yielded an *unsatisfactory* discharge simulation result with RSR:, NSE:, and PBIAS:. As the CFSR modelled rainfall shows two similar rainy seasons where WLRC rainfall data has distinct belg and kremt rainy season, SWAT modelled discharge showed similar trends. The hydrograph with CFSR data in Fig. 3 shows discharge peaks from February to April for every year, when there are none measured while showing only small CFSR peaks for the main rainy season from June to September, when measured discharge is significantly increasing. Again, the SWAT modelled discharge reflected the input rainfall pattern adequately, which lead to discharge peaks during belg, when there are none in the measured data. At the same time it lead to reduced discharge peaks during kremt, when the measured WLRC data are clearly pronounced.

3.3 Sediment loss modelling with WLRC and CFSR data

Sediment loss modelling was calibrated using the same set of 9 parameters for each catchment (see Table 2 for description). Calibration of soil loss was conducted using the parameter ranges for discharge calibration, and adapting the sediment parameters while leaving discharge parameters untouched. Performance ratings for each of the three catchments including SWAT–Cup *p-factor* and *r-factor* are summarised in Table 5 and visually represented on Fig. 4. Performance rating levels were considerably lowered for sediment loss modeling. Threshold for the *p-factor* was set at 0.40 with an *r-factor* below 1.80 and standard performance ratings for RSR, NSE and PBIAS.

3.3.1 Andit Tid

The *good* results from WLRC discharge modeling facilitated sediment loss calibration and resulted in *satisfactory* performance ratings for RSR, NSE (0.69, 0.65), and an *unsatisfactory* PBIAS, which was slightly below threshold with –56.3. Graphic representation showed good visual results (see Fig. 4) in general, but also showed constant overestimation of the modelled data except for three years 1988, 1989, and 1994.

Sediment loss modelling with CFSR data reflected the results from discharge modeling.

3.3.2 Anjeni

Sediment loss modeling with WLRC rainfall data and calibrated discharge yielded *satisfactory* results. With a *p-factor* of 0.40 and an *r-factor* of 0.65, and statistical parameters RSR: 0.67, NSE: 0.55, and PBIAS: −19.9 the model was just *satisfactory*. The graphic showed adequate results with a constant overestimation of the model except for two years in the early nineties. Modelling with CFSR data, resulted in strongly unsatisfactory results (RSR: 1.01, NSE: –0.02, and PBIAS: −33.9), which can easily be explained with the strong model overestimation of rainfall and subsequently discharge. Parameters could not be adapted further to achieve better results as they were already set to the edge of the possible ranges.

3.3.3 Maybar

Sediment loss calibration with WLRC rainfall data and calibrated discharge resulted in *unsatisfactory* statistical results (RSR: 1.24, NSE: –0.54, PBIAS: –34.1). *p-factor* and *r-factor* were 0.42 and 0.60, respectively.

Calibration with CFSR rainfall data yielded *unsatisfactory* results (RSR: 1.02, NSE: –0.03, PBIAS: 54.4). As described in the discharge calibration section (Sect. 3.2.3), CFSR rainfall data in Maybar tended towards overestimation of belg and underestimation of kremt, which resulted in overestimation of monthly discharge during belg and underestimation during kremt. This trend was redrawn with sediment calibration resulting in small but distinct peaks during belg and smaller peaks than measured during kremt. There was no *satisfactory* calibration possible with CFSR rainfall data.

4 Conclusions

In this paper we studied the applicability of CFSR weather data to three small-scale watersheds in the Ethiopian highlands with the goal of assessing the usability for future modelling in data-scarce regions. First, we compared CFSR and WLRC rainfall data at three stations in the Ethiopian Highlands and therefore rainfall data was compared on a monthly basis. Second, we modelled discharge with the SWAT model; once with WLRC data and once with CFSR rainfall data. Third, we modelled sediment loss for the three stations with the SWAT model and compared calibrated results from CFSR rainfall and conventional rainfall to measured data.

The rainfall data comparison for CFSR and WLRC data showed strong discrepancies in seasonal and monthly rainfall amounts for all three catchments. For Andit Tid, both, belg and kremt rainy season were levelled downwards resulting in *unsatisfactory* results for each season with strongest deviations for kremt (see Table 4 for details). Anjeni rainfall data from the CFSR model overestimated the measured WLRC rainfall very strongly. This resulted in strong deviations with performance ratings well below *satisfactory* thresholds. Maybar rainfall data from CFSR showed the highest deviation for the representation of seasonality. Neither belg, nor kremt or the dry season were adequately modelled. Deviation ranged from slight (dry season) to overestimation of belg season and a strong underestimation of kremt season. All in all the CFSR model could not adequately render rainfall patterns for Maybar.

Discharge simulation comparisons with WLRC data produced *very good* results: the three catchments could be modelled with *very good* performance ratings for RSR and

HESSD
12, 11053–11082, 2015

NSE except for the PBIAS, which was only *satisfactory* in the case of Maybar and *very good* for Andit Tid and Anjeni.

Discharge simulations with CFSR rainfall data resulted in *unsatisfactory* performance ratings for the three catchments. Discharge modelling results yielded results in line with rainfall data comparison: Anjeni discharge was highly overestimated, Andit Tid discharge was underestimated and Maybar discharge had overestimation of belg discharge and underestimation of kremt discharge.

Sediment loss modeling with WLRC rainfall data and calibrated discharge resulted in two *satisfactory* (Andit Tid and Anjeni) and one *unsatisfactory* (Maybar) calibrations. For Andit Tid the model could render sediment loss adequately except for some peaks in the mid and late nineties. For Anjeni the model performed even better with a slight overestimation over the whole period. For Maybar calibration failed.

Sediment loss performance ratings from simulations with CFSR rainfall data and calibrated discharge yielded in *unsatisfactory* results for the three catchments. The same deviation patterns observed in discharge calibration ensued in sediment loss calibration. Catchments with high discharge model overestimation resulted in high sediment loss overestimation and catchments with displaced seasonal discharge patterns resulted in displaced sediment loss patterns.

Andit Tid sediment loss modelling with CFSR data resulted in *unsatisfactory* results. The underestimation of the discharge modelling did not allow for *satisfactory* sediment loss calibration. The hydrograph (see Fig. 4) shows that the general underestimation of rainfall data lead to underestimation of discharge, which lead to reduced sediment loss modelling. Sediment loss modeling with CFSR data in Anjeni resulted in a constant overestimation of sediment loss and performance ratings were *unsatisfactory*. For Maybar the misplaced seasonal rainfall lead to higher discharge for belg and lower discharge for kremt, which resulted in a shift of sediment loss peaks from kremt to belg. Performance ratings were *unsatisfactory*.

Our results clearly show that adequate discharge and sediment loss modelling was not possible with the CFSR data in present case. This suggests that SWAT simulations

HESSD
12, 11053–11082, 2015

in small-scale watersheds in the Ethiopian highlands do not perform well with CFSR data in every case, and that sometimes there is no substitute for high-quality conventional weather data. Such weather data – with high spatial and temporal climatic data resolution – were available for the three small-scale catchments used in the study but are not in many other cases. In these other cases one should carefully check CFSR data against similar climatic stations with conventionally measured data. In addition, discharge and sediment loss modelling showed that usage of CFSR weather data not only resulted in substantial deviation in both total discharge and total sediment loss, but also in the seasonal rainfall pattern. The seasonal weather pattern is one of the major drivers of sediment loss and is especially pronounced in the Blue Nile Basin, with one long rainy season occurring as fields are ploughed and sowed. Thus, contrary to Dile and Srinivasan (2014), this study suggests that CFSR data may not be applicable for small-scale modelling in data-scarce regions: the authors even suggest that outcomes of SWAT modelling with CFSR data alone may yield erroneous results which cannot be verified and may lead to wrong conclusions. Nonetheless, the advantage of CFSR data is its completeness over time, which would allow for comprehensive watershed modelling in regions with no conventional weather data or with longer gaps in conventionally recorded rainfall records.

The Supplement related to this article is available online at doi:10.5194/hessd-12-11053-2015-supplement.

References

Abbaspour, K. C., Johnson, C. A., and van Genuchten, M. T.: Estimating uncertain flow and transport parameters using a sequential uncertainty fitting procedure, Vadose Zone J., 3, 1340–1352, doi:10.2113/3.4.1340, 2004. 11060

Abbaspour, K. C., Yang, J., Maximov, I., Siber, R., Bogner, K., Mieleitner, J., Zobrist, J., and Srinivasan, R.: Modelling hydrology and water quality in the pre-alpine/alpine Thur water-

HESSD

12, 11053–11082, 2015

Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT

V. Roth and T. Lemann

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

shed using SWAT, J. Hydrol., 333, 413–430, doi:10.1016/j.jhydrol.2006.09.014, 2007. 11060, 11064

Abbaspour, K. C., Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., and Klø ve, B.: A continental-scale hydrology and water quality model for Europe: calibration and uncertainty of a high-resolution large-scale SWAT model, J. Hydrol., 524, 733–752, doi:10.1016/j.jhydrol.2015.03.027, 2015. 11060

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R. D., Van Griensven, A., Van Liew, M. W., Kannan, N., and Jha, M. K.: SWAT: model use, calibration and validation, T. ASABE, 55, 1491–1508, 2012. 11057, 11058

Betrie, G. D., Mohamed, Y. A., van Griensven, A., and Srinivasan, R.: Sediment management modelling in the Blue Nile Basin using SWAT model, Hydrol. Earth Syst. Sci., 15, 807–818, doi:10.5194/hess-15-807-2011, 2011. 11057

Bono, R. and Seiler, W.: The Soils of the Andit-Tid Research Unit (Ethiopia) Classification, Morphology and Ecology, with soil map 1:10'000, University of Bern, Switzerland, Bern, 1984. 11058

Cavazos, T. and Hewitson, B. C.: Performance of NCEP – NCAR reanalysis variables in statistical downscaling of daily precipitation, Climate Res., 28, 95–107, 2005. 11055

Chow, V. T.: Open-Channel Hydraulics, McGraw-Hill, Boston, MA [etc.], ISBN 07-010776-9, 1959. 11058

Dile, Y. T. and Srinivasan, R.: Evaluation of CFSR climate data for hydrologic prediction in data-scarce watersheds: an application in the Blue Nile River Basin, J. Am. Water Resour. As., 50, 1226–1241, doi:10.1111/jawr.12182, 2014. 11055, 11069

Diro, G. T., Grimes, D. I. F., Black, E., O'Neill, A., and Pardo-Iguzquiza, E.: Evaluation of reanalysis rainfall estimates over Ethiopia, Int. J. Climatol., 29, 67–78, doi:10.1002/joc.1699, 2009. 11055

Faurès, J.-M., Goodrich, D. C., Woolhiser, D. A., and Sorooshian, S.: Impact of small-scale spatial rainfall variability on runoff modeling, J. Hydrol., 173, 309–326, 2000. 11055

Gassman, P. W., Reyes, M. R., Green, C. H., and Arnold, J. G.: The Soil and Water Assessment Tool: Historical development, applications, and future research directions, Am. Soc. Agric. Biol. Engin., 50, 1211–1250, 2007. 11058

Gessesse, B., Bewket, W., and Bräuning, A.: Model-based characterization and monitoring of runoff and soil erosion in response to land use/land cover changes in the Modjo watershed, Ethiopia, Land Degrad. Dev., 26, 711–724, doi:10.1002/ldr.2276, 2014. 11057

HESSD
12, 11053–11082, 2015
Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT
V. Roth and T. Lemann

Green, W. A. and Ampt, G. A.: Studies on soil phyics, J. Agric. Sci., 4, 1–24, doi:10.1017/S0021859600001441, 1911. 11058

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., Iredell, M., Saha, S., White, G., Woollen, J., Zhu, Y., Chelliah, M., Ebisuzaki, W., Higgins, W., Janowiak, J. E., Mo, K. C., Ropelewski, C., Wang, J., Leetmaa, A., Reynalds, R., Jenne, R., and Joseph, D.: The NCEP/NCAR 40-year reanalysis project, B. Am. Meteorol. Soc., 77, 437–471, 1996. 11055

Kejela, K.: The soils of the Anjeni Area – Gojam Research Unit, Ethiopia, University of Bern, Switzerland, Bern, Switzerland, research r edn., 1995. 11058

Kistler, R., Kalnay, E., Collins, W., Saha, S., White, G., Woollen, J., Chelliah, M., Ebisuzaki, W., Kanamitsu, M., Kousky, V., Dool, H. V. D., Jenne, R., and Fiorino, M.: The NCEP – NCAR 50-year reanalysis: monthly means CD-ROM and documentation, B. Am. Meteorol. Soc., 82, 247–268, 2001. 11055

Legates, D. R. and McCabe, G. J.: Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation, Water Resour. Res., 35, 233–241, doi:10.1029/1998WR900018, 1999. 11061

Lin, S., Jing, C., Chaplot, V., Yu, X., Zhang, Z., Moore, N., and Wu, J.: Effect of DEM resolution on SWAT outputs of runoff, sediment and nutrients, Hydrol. Earth Syst. Sci. Discuss., 7, 4411–4435, doi:10.5194/hessd-7-4411-2010, 2010. 11057

Mbonimpa, E. G.: SWAT model application to assess the impact of intensive corn-farming on runoff, sediments and phosphorous loss from an agricultural watershed in Wisconsin, J. Water Resour. Protect., 04, 423–431, doi:10.4236/jwarp.2012.47049, 2012. 11057

Moriasi, D. N., Arnold, J. G., Liew, M. W. V., Bingner, R. L., Harmel, R. D., and Veith, T. L.: Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, Am. Soc. Agric. Biol. Engin., 50, 885–900, 2007. 11057, 11060, 11076

Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models: Part 1. – A discussion of principles, J. Hydrol., 10, 282–290, 1970. 11060

Poccard, I., Janicot, S., and Camberlin, P.: Comparison of rainfall structures between NCEP/NCAR reanalyses and observed data over tropical Africa, Clim. Dynam., 16, 897–915, doi:10.1007/s003820000087, 2000. 11056

Saha, S., Moorthi, S., Pan, H.-L., Wu, X., Wang, J., Nadiga, S., Tripp, P., Kistler, R., Woollen, J., Behringer, D., Liu, H., Stokes, D., Grumbine, R., Gayno, G., Wang, J., Hou, Y.-T., Chuang, H.-Y., Juang, H.-M. H., Sela, J., Iredell, M., Treadon, R., Kleist, D., Van Delst, P., Keyser, D., Derber, J., Ek, M., Meng, J., Wei, H., Yang, R., Lord, S., Van Den Dool, H., Kumar, A., Wang,

HESSD

12, 11053–11082, 2015

Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT

V. Roth and T. Lemann

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

W., Long, C., Chelliah, M., Xue, Y., Huang, B., Schemm, J.-K., Ebisuzaki, W., Lin, R., Xie, P., Chen, M., Zhou, S., Higgins, W., Zou, C.-Z., Liu, Q., Chen, Y., Han, Y., Cucurull, L., Reynolds, R. W., Rutledge, G., and Goldberg, M.: The NCEP climate forecast system reanalysis, B. Am. Meteorol. Soc., 91, 1015–1057, doi:10.1175/2010BAMS3001.1, 2010. 11055

Schuol, J. and Abbaspour, K. C.: Using monthly weather statistics to generate daily data in a SWAT model application to West Africa, Ecol. Model., 201, 301–311, doi:10.1016/j.ecolmodel.2006.09.028, 2007. 11057

SCRP and CDE: Digital Elevation Model (DEM) of Anjeni, Gojam, Centre for Development and Environement (CDE), University of Bern, Switzerland, 2000a. 11058

SCRP and CDE: Digital Elevation Model (DEM) of Andit Tid, Shewa, Centre for Development and Environement (CDE), University of Bern, Switzerland, 2000b. 11058

SCRP and CDE: Digital Elevation Model (DEM) of Maybar watershed, Wello, Centre for Development and Environement (CDE), University of Bern, Switzerland, 2000c. 11058

Stehr, A., Debels, P., and Romero, F.: Hydrological modelling with SWAT under conditions of limited data availability: evaluation of results from a Chilean case study, Hydrol. Sci. J., 53, 588–601, 2008. 11057

Temesgen, M., Rockström, J., Savenije, H. H. G., Hoogmoed, W. B., and Alemu, D.: Determinants of tillage frequency among smallholder farmers in two semi-arid areas in Ethiopia, Phys. Chem. Earth, 33, 183–191, doi:10.1016/j.pce.2007.04.012, 2008. 11059

Tibebe, D. and Bewket, W.: Surface runoff and soil erosion estimation using the SWAT model in the Keleta Watershed, Ethiopia, Land Degrad. Dev., 22, 551–564, doi:10.1002/ldr.1034, 2011. 11057

USDA-SCS: Design Hydrographs, in: National Engineering Handbook, chap. 1-22, p. 824, USDA Soil Conservation Service, Washington D.C., Washington D.C., available at: http://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/water/?cid=stelprdb1043063 (last access: January 2015), 1972. 11058

Wagner, P. D., Fiener, P., Wilken, F., Kumar, S., and Schneider, K.: Comparison and evaluation of spatial interpolation schemes for daily rainfall in data scarce regions, J. Hydrol., 464–465, 388–400, doi:10.1016/j.jhydrol.2012.07.026, 2012. 11056

Weigel, G.: The Soils of the Maybar Area, Wello Research Unit, Ethiopia, University of Bern, Switzerland, Bern, research r edn., 1986. 11058

Williams, J. R.: Flood routing with variable travel time or variable storage coefficients, T. ASABE, 12, 100–103, 1969. 11058

HESSD

12, 11053–11082, 2015

Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT

V. Roth and T. Lemann

Williams, J. R.: SPNM, a model for predicting sediment, phosphorus, and nitrogen yields from agricultural basins, Water Resour. Bull., 16, 843–848, 1980. 11058

Yu, M., Chen, X., Li, L., Bao, A., and Paix, M. J. D. L.: Streamflow Simulation by SWAT using different precipitation sources in large arid basins with scarce raingauges, Water Resour. Manage., 25, 2669–2681, doi:10.1007/s11269-011-9832-z, 2011. 11056

Zeleke, G.: Landscape Dynamics and Soil Erosion Process Modeling in the North-Western Ethiopian Highlands., Phd thesis, University of Bern, Switzerland, 2000. 11058

Table 1. Study sites, model input data, and available data.

	Andit Tid	Anjeni	Maybar
Year of construction	1982	1983	1981
Location	9.815° N	10.678° N	10.996° N
	37.711° E	37.530° E	39.657° E
Size	477.3 ha	113.4 ha	112.8 ha
Altitudinal range	3040–3538 m a.s.l.	2406–2506 m a.s.l.	2530–2857 m a.s.l.
		Data sources and resolution	
DEM		2m	
Land use map		field scale	
Soil map		field scale	
Climatic data		Daily precipitation	
		Daily min. and max. temperature	
Hydrology data		Daily discharge	
Soil loss data		Daily sediment loss	
Sources		SCRP/WLRC/CDE/own	
		Data availability	
	Andit Tid	Anjeni	Maybar
Precipitation data	1982–2004	1984–2004	1981–2001
	2006	2010–2014	2004–2006
	2010–2014		2010–2014
Temperature	1982–1993	1984–1993	1981–1993
	1997–2002	1998–2004	1995–1998
	2010–2013	2010–2013	2010–2013
Discharge	1982–1993	1984–1993	1981–1993
	1995–1997	1995–2000	1997–2006
		2011–2014	2010–2014
Sediment	1982–1993	1984–1993	1981–1991
	1995–1997	1995–1998	1995–2006
	2011–2014	2011–2014	2011–2014
		Subdivision of data	
Calibration	1984–1993	1986–1998	1983–2006
Validation	1994–1997	2010–2014	2008–2014

HESSD
12, 11053–11082, 2015

Table 2. SWAT parameters and fitted value ranges.

Variable	Parameter name	Fitted parameter values		
		Andit Tid	Anjeni	Maybar
Discharge	a_CN2.mgt	16.7 to 18.7	–7 to –4	15 to 25
	v__GWQMN.gw	4761 to 4990	0 to 1611	2500 to 5000
	a__ESCO. hu	–0.0038 to 0.046	0.0023 to 0.067	0 to 0.35
	v__GW_REVAP.gw	0.18 to 0.19	0.17 to 0.21	0.15 to 0.2
	a__CH_K2.rte	6 to13	–11 to 58	–0.01 to 15
	a__CH_N2.rte	0.0012 to 0.067	–0.15 to 0.062	0.025 to 0.065
	a__SURLAG.bsn	–0.084 to 3.98	0 to 6.63	0.05 to 12
	a__RCHRG_DP.gw	0.36 to 0.66	–0.51 to 0.23	0 to 1
	v__EPCO. hu	0.78 to 1.55	0.22 to 0.745	0 to 1
	v__SOL_AWC(1).sol	0.13 to 0.22	0.19 to 0.47	0 to 1
Sediment	a__SLSUBBSN. hu	8.85 to 42.34	–6.24 to –4.60	–5 to 5
	a__HRU.SLP. hu	–0.16 to –0.04	–0.12 to –0.09	–0.5 to 0.72
	a__USLE_K(1).sol	0.079 to 0.14	0.44 to 0.49	0.04 to 0.31
	a__USLE_C.plant.dat	0.0009 to 0.004	0.48 to 0.5	0.34 to 0.626
	a__USLE_P.mgt	–0.41 to 0.19	0.16 to 0.26	0.09 to 0.92
	v__SPCON.bsn	0.005 to 0.007	0.0067 to 0.010	–0.01 to 0.01
	v__SPEXP.bsn	1.27 to 1.53	1.32 to 1.37	–0.5 to 0.5
	v__CH_COV1.rte	0.2 to 0.39	0.057 to 0.099	–0.02 to 0.02
	v__PRF_BSN.bsn	0.9 to 1.1	1.2 to 1.6	0.89 to 1.2

HESSD
12, 11053–11082, 2015

Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT

V. Roth and T. Lemann

Table 3. General performance ratings recommended by Moriasi et al. (2007).

Performance Rating	RSR	NSE	PBIAS Streamflow	PBIAS Sediment
Very good	0.00 ≤ RSR ≤ 0.50	0.75 < NSE ≤ 1.00	PBIAS < ±10	PBIAS ≤ ±15
Good	0.50 < RSR ≤ 0.60	0.65 < NSE ≤ 0.75	±10 ≤ PBIAS < ±15	±15 ≤ PBIAS < ±30
Satisfactory	0.60 < RSR ≤ 0.70	0.50 < NSE ≤ 0.65	±15 ≤ PBIAS < ±25	±30 ≤ PBIAS < ±55
Unsatisfactory	RSR > 0.70	NSE ≤ 0.50	PBIAS ≥ ±25	PBIAS ≥ ±55

HESSD
12, 11053–11082, 2015

Table 4. Seasonal comparison of rainfall data.

	Dry season		
	Andit Tid	Anjeni	Maybar
RSR	1.68	3.55	1.3
NSE	–1.92	–12.9	–0.77
PBIAS	55.2	134.2	30.7
	Belg		
	Andit Tid	Anjeni	Maybar
RSR	1.31	2.48	0.85
NSE	–0.79	–5.42	–0.24
PBIAS	–39.4	106.1	24.3
	Kremt		
	Andit Tid	Anjeni	Maybar
RSR	3.23	7.0	2.03
NSE	–9.79	–50.09	–3.28
PBIAS	–69.2	128	–47.1

HESSD
12, 11053–11082, 2015

Table 5. Calibration and validation results, monthly CFSR and WLRC modelled discharge and sediment loss.

	Andit Tid		Anjeni		Maybar	
	CFSR	WLRC	CFSR	WLRC	CFSR	WLRC
			Discharge			
p-factor	0.37	0.71	0.49	0.85	0.44	0.57
r-factor	0.14	0.53	1.91	0.86	0.80	0.85
RSR	0.80	0.46	2.70	0.39	1.10	0.51
NSE	0.36	0.79	−6.27	0.85	−0.21	0.74
PBIAS	31.4	3.1	−226.0	3.7	−14.6	−16.7
			Sediment loss			
p-factor	0.54	0.45	0.32	0.40	0.33	0.42
r-factor	7.39	0.59	1.30	0.65	0.19	0.60
RSR	0.81	0.69	1.01	0.67	1.02	1.24
NSE	−11.63	0.65	−0.02	0.55	−0.03	−0.54
PBIAS	−214.4	−54.3	−33.9	−19.9	54.4	−34.1

HESSD
12, 11053–11082, 2015

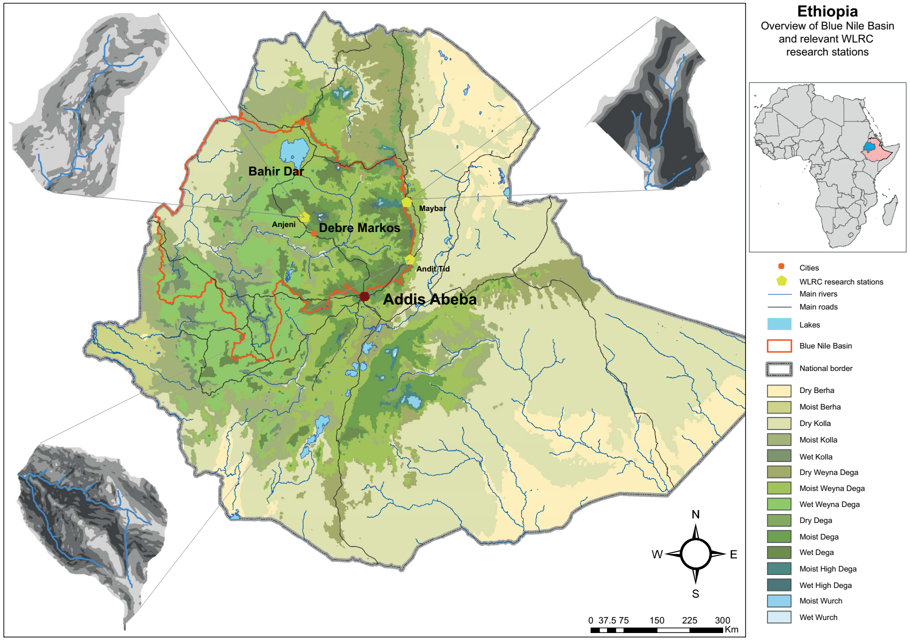

Figure 1. Map overview of Blue Nile (Abbay) Basin with the WLRC research stations.

HESSD
12, 11053–11082, 2015

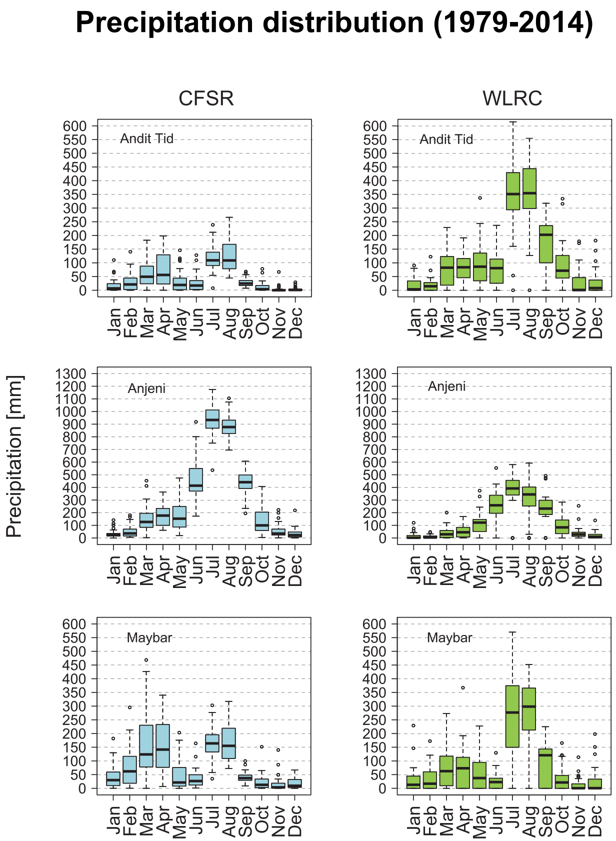

Figure 2. Monthly CFSR and WLRC rainfall distribution of all stations (1979–2010), Andit Tid, Anjeni, Maybar.

HESSD
12, 11053–11082, 2015

Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT

V. Roth and T. Lemann

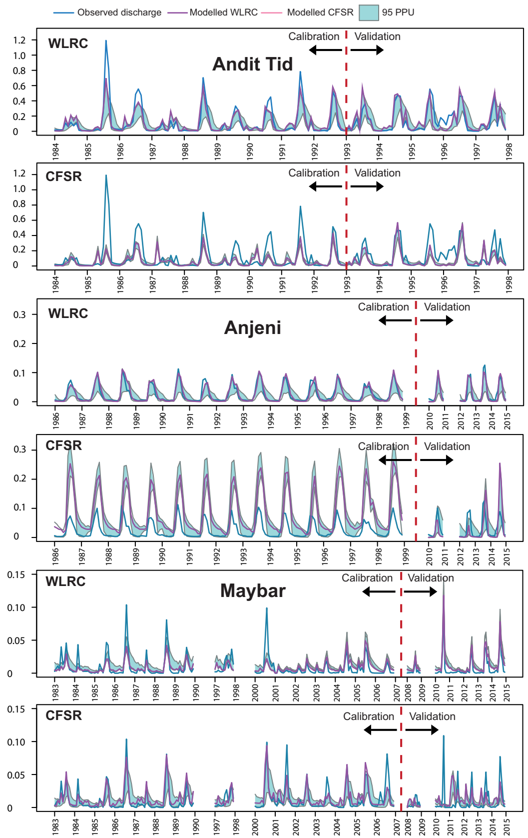

Figure 3. Calibration and validation of discharge with WLRC and CFSR data. Data in $m^3 s^{-1}$.

HESSD

12, 11053–11082, 2015

Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT

V. Roth and T. Lemann

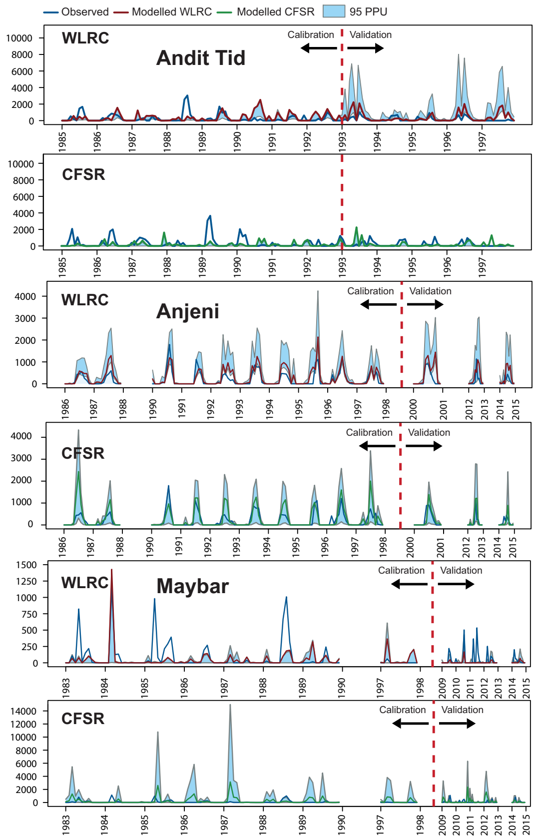

Figure 4. Calibration and validation of sediment loss with WLRC and CFSR data. Data in t.

HESSD
12, 11053–11082, 2015

Comparing CFSR and conventional weather data for discharge and sediment loss modelling with SWAT

V. Roth and T. Lemann

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