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

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Abstract

Accurate rainfall data is 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 2010. 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. Uncalibrated simulation results were compared to observed river discharge and observed sediment loss over a period of 25 years. The conventional weather data resulted in satisfactory discharge outputs for all three watersheds, while the CFSR weather data resulted in unsatisfactory discharge outputs for two of three gauging stations. Sediment loss simulation with conventional weather inputs yielded satisfactory outputs for all three watersheds, while the CFSR weather input resulted in one very good result and two 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 only be used with caution in remote areas with no conventional weather data and might be better adapted to larger watersheds than the ones used in this study.

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, 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 modelled 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 32 years from 1979 through 2010. The CFSR data is based on a spectral model which includes the parameterization 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 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 30 years from 1981 to 2010. The main objective of this paper is to compare the two data sets for annual, interannual, and seasonal cycles in three locations in the Ethiopian highlands. The CFSR and WLRC rainfall data are subsequently used to simulate river discharge and sediment loss in three watersheds using SWAT. Uncalibrated CFSR modelled discharge and sediment loss is then compared to uncalibrated WLRC modelled discharge and sediment loss, and the applicability of the CFSR data for hydrological predictions is statistically evaluated.

2 Methods

The effects of spatial and temporal variability in the CFSR rainfall data for the study areas were examined in two steps. First, the CFSR data were statistically compared to measured WLRC rainfall data for accurate representations of annual, interannual, and seasonal cycles at three watersheds. Second, the impact of spatial and temporal variability of rainfall on hydrology and soil erosion was assessed by modelling discharge and sediment loss with SWAT. This second analysis provided an evaluation of how the change in rainfall input data affects discharge and sediment loss modelling with SWAT. Third, the rainfall (in mm), discharge (in $m^3 s^{-1}$) and sediment loss (t) data were converted to mean monthly millimetres for all years and then compared visually and statistically.

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 (see Fig. 1). 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 one for Anjeni. Land use is dominated by smallholder rain-fed farming-systems with grain-oriented production, ox-plough farming, and uncontrolled grazing practices.

2.1.1 Hydrologic model

SWAT was used to assess the impact of different rainfall patterns on run-off 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; Setegn 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). SWAT 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. Each HRU is used to predict individual hydrology using the water balance equation. 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 SWAT for the present study included the digital elevation model (DEM), land use data, and soil data. 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 (now WLRC) 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 Ph.D. dissertation by Gete Zeleke (2000). The physical and chemical parametrisation of the soil was adapted from the soil database in Zeleke's thesis. The soil characteristics for Maybar were adapted from the SCRP's Soil Conservation Research Report 7 (Weigel, 1986). The Andit Tid DEM was provided by CDE and the physical and chemical soil characteristics were taken 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 and by own surveys in 2008 and 2012. To adapt to annually changing land use patterns, a generic land use pattern was adapted to a mean land use map from the WLRC land use maps of 2008 (Anjeni), and 2010 (Andit Tid, Maybar).

2.3 Hydrometric data

Diurnal temperature and sub-hourly rainfall data have been available at the SCRP/WLRC stations since the early 1980s. At all three stations, rainfall measurements are recorded with Lambrecht mechanical rainfall drum recording gauges. Rainfall data from the Lambrecht gauges are manually pre-processed into digital records and then electronically processed into daily rainfall sums. In addition, air temperature is collected twice a day and discharge data are continuously recorded with an Ott Limnigraph. Sediment data are collected for every rainfall event through collection of one-litre samples at the catchment outlet. The samples are then filtered, dried, and weighed, and total sediment loss is determined through total water outflow. Time series are available at WLRC from 1981 to 2013 with significant gaps in the mid 1990s. The CFSR data set consists of NCEP/NCAR reanalysis data, and comprises daily time series for rainfall, maximum and minimum temperature, wind speed, relative humidity, and solar radiation from 1979 to 2010. The CFSR data set is derived from a global spectral model with a resolution of 2.5° latitude by 2.5° longitude, and is available through the Global Weather Data for SWAT website (http://globalweather.tamu.edu). The CFSR data were obtained for the entire Blue Nile Basin (bounding box: latitude 6.88–13.53° and longitude 32.56–40.64°) and consisted of 650 weather stations. For every WLRC research station, the four to six closest CFSR weather stations were chosen for time series analyses. Rainfall data were compared on a monthly and yearly level, according to the annual seasonal pattern, which is of high importance in the Ethiopian highlands. Maybar and Andit Tid have bimodal rainy seasons from March to May and from June to September, and Anjeni has a unimodal pattern from June to September (SCRP, 2000a, b, c). The seasonal rainfall comparison was divided into three time periods. These divisions comprised a dry season from October to March; a small rainy season from April to May (*belg*); and a long rainy season from June to September (*kremt*). The rainfall data from CFSR and WLRC were compiled into monthly rainfall sums, which were then compared over the maximum overlapping time period. Discharge data were converted from cubic metres per day (SCRP/WLRC) and cubic metres per second (CFSR) to millimetres, for ease of comparison with the rainfall data provided by CFSR and WLRC. The same procedure was applied to sediment loss data, which were converted from tonnes per day to millimetres. All data in millimetres were compared at monthly intervals, from 1986 to 2010.

2.4 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 2000 ha. SWAT compiled 754 HRUs for Anjeni, 925 HRUs for Maybar, and 630 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 3). The SWAT weather generator was used to fill the gaps for rainfall, temperature, solar radiation, and relative humidity. 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 sediment free. The model was run for 28 years from 1984 to 2010 with daily data inputs but monthly outputs. The period from 1984 to 1986 was used as a warm-up period for the SWAT model. To be able to compare results with the study by Dile and Srinivasan (2014) the model was not calibrated for the use of either CFSR or WLRC rainfall data. The raw outputs from the model were compared.

2.5 Model evaluation

Model evaluation is an essential measure to verify the model robustness in general or to verify data usability in the context of this study. Therefore, this study refers to the model evaluation techniques described by Moriasi et al. (2007), who established guidelines for model evaluation and reported ranges of values and corresponding performance ratings for the proposed statistical parameters. The model performance was evaluated applying three commonly used statistical measures: the Nash-Sutcliffe measure of efficiency (NSE); the root-mean-square error observations SD ratio (RSR), which is derived from the root-mean-square error (RMSE); and the percent bias (PBIAS). For further time series evaluation, mean absolute error (MAE) and mean square error (MSE) were computed. 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).

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(Q_{\mathrm{obs}}^{i} - Q_{\mathrm{sim}}^{i})^2}{\sum_{i=1}^{n}(Q_{\mathrm{obs}}^{i} - Q_{\mathrm{obs}}^{\mathrm{mean}})^2} \quad (1)$$

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. Q_{obs}^{i} and Q_{sim}^{i} are the observed and simulated data at the ith time step respectively. $Q_{\mathrm{obs}}^{\mathrm{mean}}$ is the average of the observed data and n is the total number of observations. The NSE is recommended because for one it provides the best objective function for reflecting the overall fit of a hydrograph (Sevat et al., 1991) and second, because it is very commonly used, it provides extensive comparable information on reported values (Moriasi et al., 2007). The model is considered to be "good" if the NSE is between 0.65 and 0.75 and "satisfactory" when the NSE is above 0.5 (Linard et al., 2009).

The RMSE gives the SD of the model prediction error with a smaller value indicating better model performance. The RMSE is a commonly used error index.

$$\mathrm{RMSE} = \frac{1}{N}\sum_{i=1}^{n}(\mathrm{Obs}_i - \mathrm{Sim}_i)^2 \tag{2}$$

The RSR is a standardized RMSE, which is calculated from the ratio of the RMSE and the SD of measured data ($\mathrm{SD}_{\mathrm{obs}}$). 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).

$$\mathrm{RSR} = \frac{\mathrm{RMSE}}{\mathrm{SD}_{\mathrm{obs}}} = \frac{\sqrt{\sum_{i=1}^{n}(Q^i_{\mathrm{obs}} - Q^i_{\mathrm{sim}})^2}}{\sqrt{\sum_{i=1}^{n}(Q^i_{\mathrm{obs}} - Q_{\mathrm{mean}})^2}} \tag{3}$$

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. Discharge PBIAS values between ±10 and ±15 indicate a "good" model simulation, whereas values greater than ±25 indicate an "unsatisfactory" model simulation (Linard et al., 2009). For sediment loss simulations PBIAS values between ±15 and ±30 indicate "good" model simulation, whereas values greater than ±55 indicate "unsatisfactory" model simulation (see Table 4).

$$\mathrm{PBIAS} = \frac{\sum_{i=1}^{n}(Q^i_{\mathrm{obs}} - Q^i_{\mathrm{sim}}) \cdot 100}{\sum_{i=1}^{n}(Q^i_{\mathrm{obs}})} \tag{4}$$

Similarly to the Nash–Sutcliffe Efficiency the PBIAS comes with recommendations by the American Society of Civil Engineers (ASCE, 1993), it is commonly used and it has the ability to indicate poor model performance (Yapo et al., 1996).

For this article the recommendations for reported values were strictly applied. Moriasi et al. suggest that performance ratings be adapted to modelling situations and data availability. As this study focused on the performance rating of an outside source of rainfall data, no adaptations were made to the SWAT simulations, e.g. no calibration was performed and only raw SWAT outputs were compared.

The model performance was also evaluated using the hydrograph visual technique, which allows a visual model evaluation overview. As suggested by Moriasi and Singh 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 and a monthly mean 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. For Andit Tid, situated on the eastern escarpment of the Blue Nile Basin, the seasonality with two rainy seasons was temporally adequately represented; i.e., the timely occurrence of the rainy seasons was correctly represented through the CFSR data. However, total rainfall amounts were not correctly represented: while the small rainy season in the CFSR data showed some overestimation, total rainfall and length of the main rainy season were strongly underestimated. WLRC data distinctly place the main rainy season from July to September, while the CFSR data only showed some mildly increased rainfall in July and August but no distinct rainy season (see Fig. 2).

The CFSR data for Anjeni, situated in the central highlands of the Blue Nile Basin, highly overestimated rainfall in the region. While WLRC data showed a clear trend towards only one long rainy season from May/June to September with average monthly rainfall ranging from 100 mm (May) to 380 mm (July), the CFSR data showed a pronounced main rainy season with monthly averages ranging from 400 mm to over

900 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 (see Fig. 2). WLRC Maybar data showed a clear seasonality, with two rainy seasons, one in March and April, and one from July to August. Both rainy seasons were similar in their mean amount of monthly rainfall of around 150 mm. From the CFSR rainfall data, no clear distinction could be made between the small and the large rainy season. The seasonal trend was not clearly represented, and the total annual rainfall was strongly underestimated (see Fig. 2). 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 distinct seasons (dry season from October to March, small rainy season from April to May, and large rainy season 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 values (AT: 1.68, AJ: 3.55, MA: 1.3) indicating a low model simulation performance and again an unsatisfactory rating (see Table A3 and Fig. A2).

For the small 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 (see Table A2 and Fig. A1).

The main rainy season from June to September is the season with the heaviest rainfall throughout the year. On average some 77 % of the yearly rainfall 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 A1 and Fig. 3) 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 long 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 Monthly discharge simulations with WLRC rainfall data

The monthly discharge simulations in SWAT with WLRC rainfall data yielded different results for the three stations. Using guidelines provided by Moriasi et al. (2007), the model performance was evaluated at monthly intervals (see Table B1). Andit Tid performed best in all three categories with a good NSE and RSR (0.69 and 0.55), and a very good PBIAS (−1.3). Anjeni performed unsatisfactorily for NSE, RSR, and PBIAS (0.34, 0.81, 39.1) and Maybar performed very unsatisfactorily with all three parameters under threshold (NSE: −0.56, RSR: 1.25, PBIAS: 57.5). Hydrograph comparison for Anjeni resulted in satisfactory agreement for the conventional discharge simulation and the measured data. Most discharge peaks were adequately represented with a slight overestimation of discharge maxima. The hydrograph comparison for Andit Tid resulted in an underestimation of discharge for all the years. The hydrograph comparison for Maybar showed an overestimation of measured discharge for the entire monitoring period with a timely shifting of discharge peaks.

3.2.1 Mean monthly results with WLRC data

The comparison of the mean monthly rainfall data and subsequently the mean monthly discharge and mean monthly sediment loss showed far better results than the comparison of daily and monthly data. In general, modelled discharge data with WLRC rainfall showed high agreement for all three stations. The mean monthly discharge data for Anjeni showed very good performance results (see Fig. 6) for RSR (0.42), NSE (0.81) and satisfactory results for the PBIAS (21.4). Discharge data was in high agreement from January to August with a minor overestimation of discharge from September to December. The mean monthly sediment loss comparison showed unsatisfactory results (see Table 6) for NSE (0.38) and RSR (0.75), and a satisfactory result for PBIAS (−49.9). For Andit Tid, the mean monthly discharge modelled with WLRC rainfall showed a very good NSE and RSR agreement, and an satisfactory PBIAS (NSE: 0.84, RSR: 0.39, PBIAS: 20.1). Discharge comparison with the hydrograph was in agreement from January to May with an underestimation of discharge from September to December (see Fig. 4). The sediment loss comparison for Andit Tid showed a similar agreement. NSE, RSR showed a very good agreement (0.80 and 0.43), while the PBIAS for sediment loss was satisfactory (37.5). Hydrograph sediment comparison yielded good agreement for all months but March, May, July, August and September in concordance with the rainfall asymmetry between WLRC and CFSR data in these months. For Maybar, the mean monthly discharge modelled with WLRC rainfall showed a good agreement with the observed data. NSE and RSR showed a satisfactory results (0.61, 0.60), while PBIAS was unsatisfactory (50.2). Observed and modelled discharges were in high agreement from January to August, with a minor but steady discharge overestimation (see Fig. 5). From September to December agreement between observed and modelled discharge was less accurate but still in agreement – modelled discharge did not reach the baseflow water level as fast as the measured discharge. Regarding sediment loss, NSE, RSR, and PBIAS all showed satisfactory results (0.50, 0.68, −33.1). Modelled sediment loss showed solid agreement in the hydrograph for all months except April, May and August.

3.3 Monthly discharge simulations with CFSR rainfall data

The discharge model simulation with CFSR rainfall data without calibration yielded an unsatisfactory result. The results showed a large overestimation of discharge throughout the entire simulation period (see Table A2). For Anjeni, the NSE, RSR, and PBIAS showed unsatisfactory results (−8.76, 3.12, 262.7). The strongly overestimated CFSR rainfall for Anjeni yielded discharge overestimation with almost three times as much discharge at the maximum extension compared to SWAT simulations with measured rainfall data. For Maybar, the discharge model simulations led to unsatisfactory results. The simulation with the CFSR weather at Maybar captured most peaks with some delay. Overestimation and underestimation of observed discharge were in balance, resulting in a PBIAS of 0.0086. NSE and RSR were both unsatisfactory with −1.02 and 1.42. Simulation with CFSR rainfall data yielded inconclusive discharge results. Andit Tid simulations with CFSR rainfall resulted in almost satisfactory results. NSE (0.47), RSR (0.72) were almost satisfactory and PBIAS (−22.2) yielded a good result. In general, discharge was underestimated, which is the result of the observed monthly rainfall underestimation.

3.3.1 Mean monthly results with CFSR modelled data

The mean monthly data comparison with the CFSR data showed better – but still unsatisfactory – results. For Anjeni, the discharge modelling with the CFSR rainfall input showed an unsatisfactory result. NSE, RSR, and PBIAS substantially underestimated the observed data (−9.11, 3.04, 253.5). Hydrograph comparison showed that there was slight agreement for discharge from January to May, and then from June to November CFSR discharge more than tripled the mean monthly observed discharge data (see

Fig. 6). Interestingly, the sediment loss showed a very good performance rating for NSE, and RSR (0.84, 0.39) and a good result for PBIAS (−24.7). For Andit Tid, the mean monthly CFSR discharge modelling performance showed good results for NSE, RSR (0.69, 0.53) and a satisfactory result for PBIAS (−19.1). The hydrograph showed an overestimation of the small rainy season from March to April and an underestimation of the main rainy season from June to September. Although the discharge data performed well, this did not result in representative mean monthly sediment loss. The sediment loss comparison showed unsatisfactory NSE, RSR, and PBIAS (−0.52, 1.18, −91.7) with a consequent underestimation of the sediment loss with CFSR simulations throughout the year.

For Maybar, the CFSR modelled discharge performance showed unsatisfactory NSE and RSR (−0.41, 1.14) results and a very good PBIAS result (−9.61). The hydrograph showed a strong overestimation of discharge for the small rainy season from March to May and a strong underestimation from June to October. This phenomenon is directly linked to the CFSR rainfall data, which is higher than the WLRC rainfall data for the small rainy season and lower for large rainy season. Consequently, the mean monthly sediment showed unsatisfactory performance for NSE and RSR (−1.12 and 1.39) while the PBIAS result showed a very good result (−16.4). This very good PBIAS result despite unsatisfactory NSE and RSR results is made possible because CFSR modelled sediment loss compared to observed sediment loss is tripled during the small rainy season but halved during the main rainy season, resulting in a balanced total sediment loss.

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. Rainfall data was first compared on a monthly basis, then processed into seasonal precipitation and compared. Finally, we modelled discharge and sediment loss for the three stations with the SWAT model and compared uncalibrated results from CFSR rainfall and conventional rainfall.

Modelled monthly discharge with CFSR rainfall data gave unsatisfactory results for all three watersheds with NSE < 0.50, RSR > 0.70. The model performed best in Andit Tid (mean monthly absolute error: 38.47 mm) and worst in Anjeni (mean monthly absolute error: 177 mm). Simulations with WLRC data produced a better result: two of three results (Andit Tid and Anjeni) were satisfactory and one (Maybar) was slightly below the unsatisfactory threshold.

Modelled sediment loss with CFSR and WLRC rainfall data was strongly unsatisfactory in two of three cases and satisfactory in one case. These inconclusive results could suggest that without further calibration rainfall data alone does not allow for satisfactory modelling results and that sediment loss is more complex to model with SWAT. The three stations are in very different climatic and altitudinal zones, resulting in different rainfall intensity and rainfall amount patterns. These patterns might not be adequately represented by the CFSR model rainfall. In general, CFSR modelled rainfall patterns did not adequately represent the seasonality of the measured data. CFSR modelled data overestimated the small rainy season for all three locations and underestimated the large rainy season in two of three locations. The CFSR data heavily overestimated the watershed with only one rainy season. The monthly mean data comparison of CFSR data showed an unsatisfactory result for discharge in Anjeni and Maybar (NSE: −9.11, −0.41), while Andit Tid showed a good result (NSE: 0.69). Simulations with the CFSR data lead to a minor underestimation of discharge for Andit Tid and Maybar (PBIAS: −19.1, −9.61 %) and a very strong overestimation of discharge in Anjeni (PBIAS +253.5 %).

The measured WLRC climatic data provided very good mean monthly discharge results for Anjeni (NSE: 0.81, RSR: 0.42, PBIAS: 21.4 %) and Andit Tid (NSE: 0.84, RSR: 0.39, PBIAS: 20.1 %) and good results for Maybar (NSE: 0.61, RSR: 0.60, PBIAS: 50.2 %). The simulations with the conventional data lead to an overestimation of discharge for all three stations: Anjeni, Andit Tid, and Maybar. However, the hydrographs show clearly that for all three catchments the problem of overestimation comes mainly from the three months after the main rainy season, where the SWAT modelled discharge takes much longer to reach baseflow level than observed data.

The sediment loss comparison from the CFSR and conventional weather simulations also showed distinct results. Mean monthly sediment loss results with CFSR data yielded very good results for Anjeni (NSE: 0.84, RSR: 0.39, PBIAS: −24.7 %), but poor results for Andit Tid (NSE: −0.52, RSR: 1.18, PBIAS: −91.7 %) and Maybar (NSE: −1.12, RSR: 1.39, PBIAS: −14.1 %). Andit Tid simulation with CFSR data resulted in a strong underestimation of sediment loss. In Maybar, sediment loss from CFSR data simulations yielded a very good overall PBIAS result. PBIAS in Maybar only performed well because the model overestimated the sediment loss for the small rainy season and underestimated the sediment loss for the main rainy season, which resulted in a satisfactory PBIAS (see Fig. 4). For Anjeni, the sediment loss simulation with CFSR data showed very good results but discharge levels three times as high as the observed values.

Our results clearly show that no adequate discharge and/or sediment loss modelling was possible with the CFSR data. This suggests that SWAT simulations in small-scale watersheds in the Ethiopian highlands do not perform well with CFSR data, and that 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. 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.

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Table 1. Study sites, location, size and altitudinal range.

	Andit Tid	Anjeni	Maybar
Year of construction	1982	1983	1981
Location	9.815° N 37.711° E	10.678° N 37.530° E	10.996° N 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.

Table 2. SWAT model input data and sources.

Data type	Description	Resolution	Source(s)
Topography map	Digital Elevation Map (DEM)	2 m	SCRP/WLRC/CDE
Land use map	Land use classificatin	2 m	SCRP/WLRC/own
Soil map	Soil types	2 m	SCRP/WLRC/CDE
Climatic data	Daily precipitation	3 stations	SCRP/WLRC
	Daily min and max temp.		
	Daily discharge		
	Daily sediment loss		

Table 3. WLRC and CFSR locations and data availability.

	Andit Tid	Anjeni	Maybar	CFSR
Bounding box	9.523–9.835° N 39.37–40.0° E	10.46–10.77° N 37.5–37.81° E	10.772–11.084° N 39.37–39.68° E	
Precipitation data	1982–2004 2006 2010–2013	1984–2004 2010–2013	1981–2001 2004–2006 2010–2013	1979–2010
Temperature	1982–1993 1997–2002 2010–2013	1984–1993 1998–2004 2010–2013	1981–1993 1995–1998 2010–2013	1979–2010
Discharge	1982–1993 1995–1997 2011–2014	1984–1993 1995–2000 2011–2014	1981–1993 1997–2006 2011–2014	
Sediment	1982–1993 1995–1997 2011–2014	1984–1993 1995–1998 2011–2014	1981–1991 1995–2006 2011–2014	

Table 4. General performance ratings recommended by Moriasi et al. (2007).

Performance Rating	RSR	NSE	PBIAS Streamflow	PBIAS Sediment
Very good	$0.00 \leq RSR \leq 0.50$	$0.75 < NSE \leq 1.00$	$PBIAS < \pm 10$	$PBIAS \leq \pm 15$
Good	$0.50 < RSR \leq 0.60$	$0.65 < NSE \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$	$\pm 15 \leq PBIAS < \pm 30$
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 < NSE \leq 0.65$	$\pm 15 \leq PBIAS < \pm 25$	$\pm 30 \leq PBIAS < \pm 55$
Unsatisfactory	$RSR < 0.70$	$NSE \leq 0.50$	$PBIAS \geq \pm 25$	$PBIAS \geq \pm 55$

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Table 5. Mean monthly discharge CFSR and WLRC compared to observed data.

	Andit Tid		Anjeni		Maybar	
	CFSR	WLRC	CFSR	WLRC	CFSR	WLRC
RSR	0.53	0.39	3.04	0.42	1.14	0.6
RMSE	40.41	29.4	223.8	30.58	47.74	24.96
NSE	0.69	0.84	−9.11	0.81	−0.41	0.61
PBIAS	−19.1	20.1	253.5	21.4	−9.61	50.2

Table 6. Mean monthly sediment loss CFSR and WLRC compared to observed data.

	Andit Tid		Anjeni		Maybar	
	CFSR	WLRC	CFSR	WLRC	CFSR	WLRC
RSR	1.18	0.43	0.39	0.75	1.39	0.68
RMSE	0.62	0.23	0.15	0.29	0.22	0.11
NSE	−0.52	0.8	0.84	0.38	−1.12	0.5
PBIAS	−91.7	37.5	−24.7	−49.9	−16.4	−33.1

Table A1. WLRC and CFSR seasonal comparison of rainfall data (June-July-August-September).

	Andit Tid	Anjeni	Maybar
NSE	−9.79	−50.09	−3.28
RMSE	724.15	1590.30	425.42
RSR	3.23	7.00	2.03
PBIAS	−69.20	128.00	−47.10

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Table A2. WLRC and CFSR seasonal comparison of rainfall data (April–May).

	Andit Tid	Anjeni	Maybar
NSE	−0.79	−5.42	0.24
RMSE	150.54	235.23	94.95
RSR	1.31	2.48	0.85
PBIAS	−39.40	106.10	24.30

Table A3. WLRC and CFSR seasonal comparison of rainfall data (October-November-December-January-February-March).

	Andit Tid	Anjeni	Maybar
NSE	−1.92	−12.19	−0.77
RMSE	196.33	342.87	200.81
RSR	1.68	3.55	1.3
PBIAS	−55.2	134.2	30.7

Table B1. CFSR and WLRC monthly modelled and observed discharge.

	Andit Tid		Anjeni		Maybar	
	CFSR–obs	WLRC–obs	CFSR–obs	WLRC–obs	CFSR–obs	WLRC–obs
NSE	0.47	0.69	−8.76	0.34	−1.02	−0.56
RMSE	69.83	53.7	238.38	61.74	72.79	64.06
RSR	0.72	0.56	3.12	0.81	1.42	1.25
PBIAS	−22.2	−1.3	262.7	39.1	0.0086	57.6

Table B2. CFSR and WLRC monthly modelled and observed sediment loss.

	Andit Tid		Anjeni		Maybar	
	CFSR–obs	WLRC–obs	CFSR–obs	WLRC–obs	CFSR–obs	WLRC–obs
RSR	1.12	6.41	0.72	0.98	2.16	0.98
RMSE	0.88	5.06	2.12	1.76	3.88	1.76
NSE	−0.26	−40.32	0.47	0.04	−3.69	0.04
PBIAS	−45.10	388.90	−17.90	−39.20	67.80	−39.20

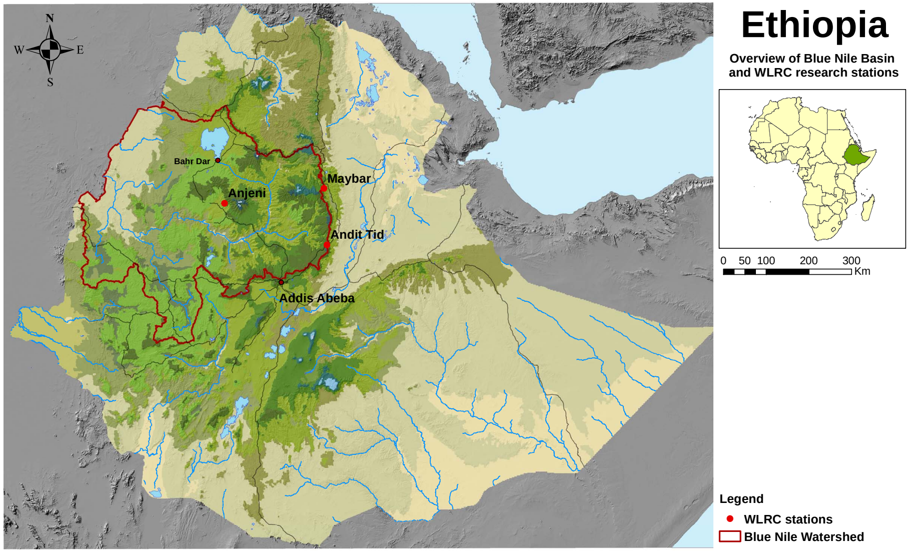

Figure 1. Map overview of Blue Nile (Abbay) Basin with the WLRC research stations.

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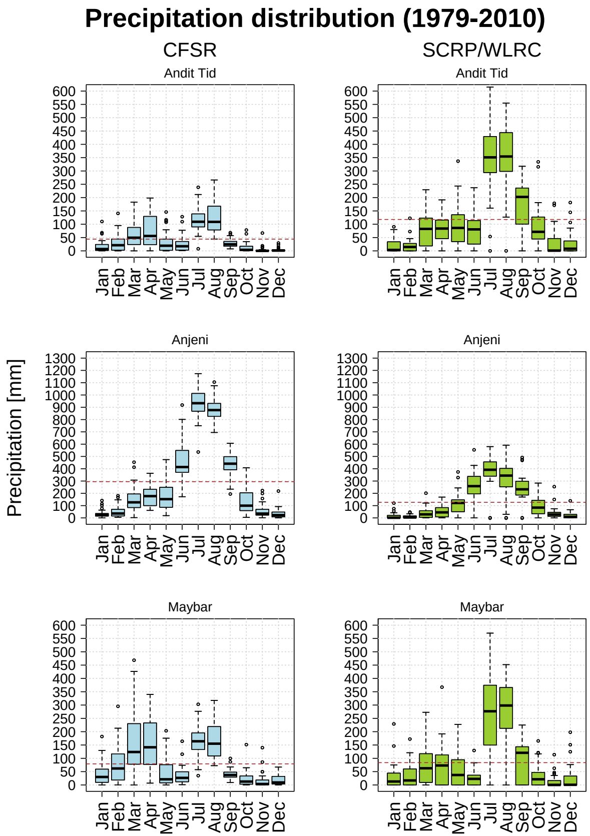

Figure 2. Monthly CFSR and WLRC rainfall distribution of all stations (1979–2010), Andit Tid, Anjeni, Maybar.

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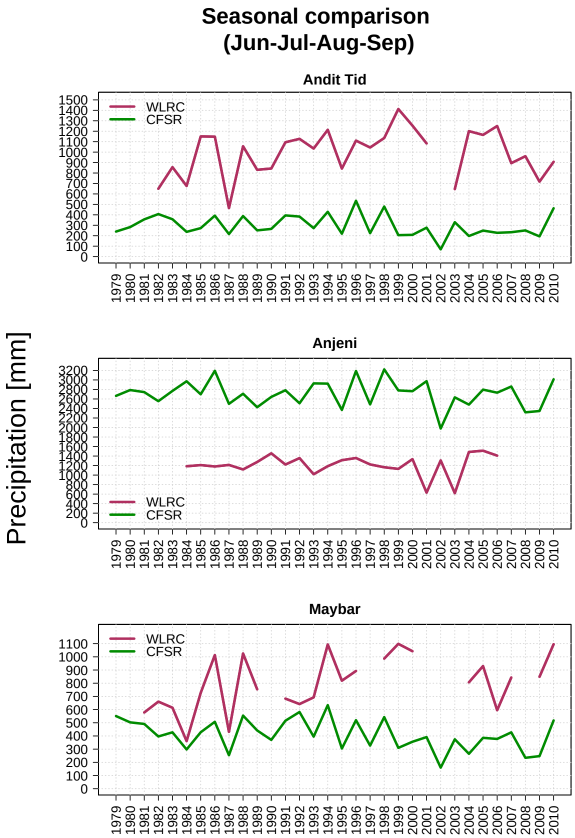

Figure 3. Comparison of main rainy seasons June-July-August-September (1979–2010).

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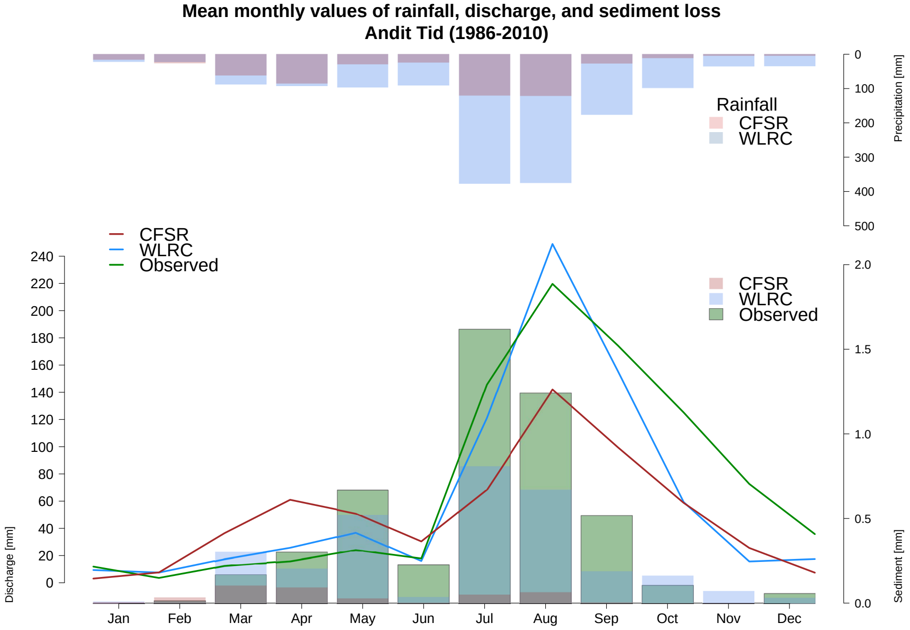

Figure 4. Mean monthly values of rainfall, discharge and sediment loss in mm – Andit Tid.

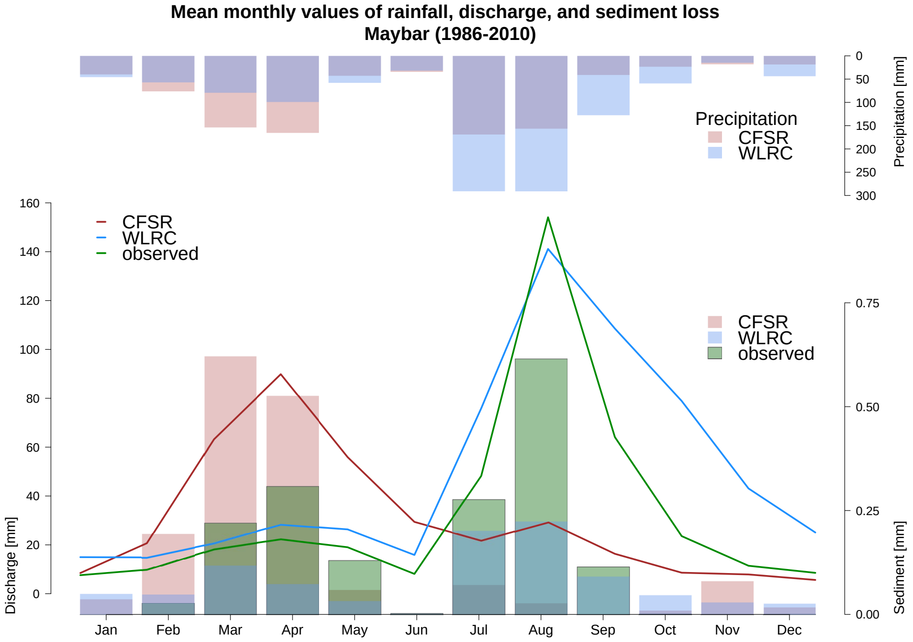

Figure 5. Mean monthly values of rainfall, discharge and sediment loss in mm – Maybar.

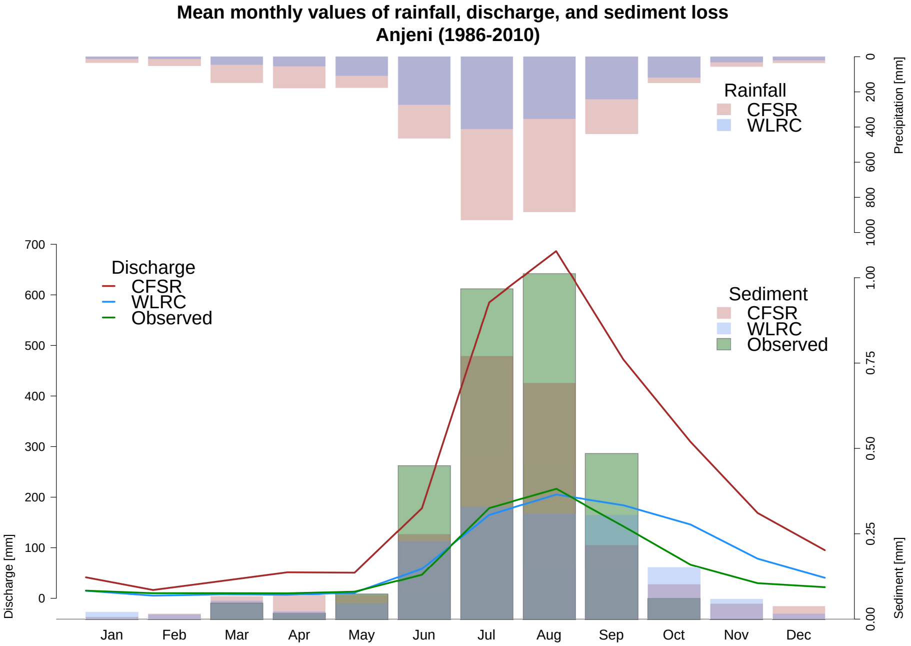

Figure 6. Mean monthly values of rainfall, discharge and sediment loss in mm – Anjeni.

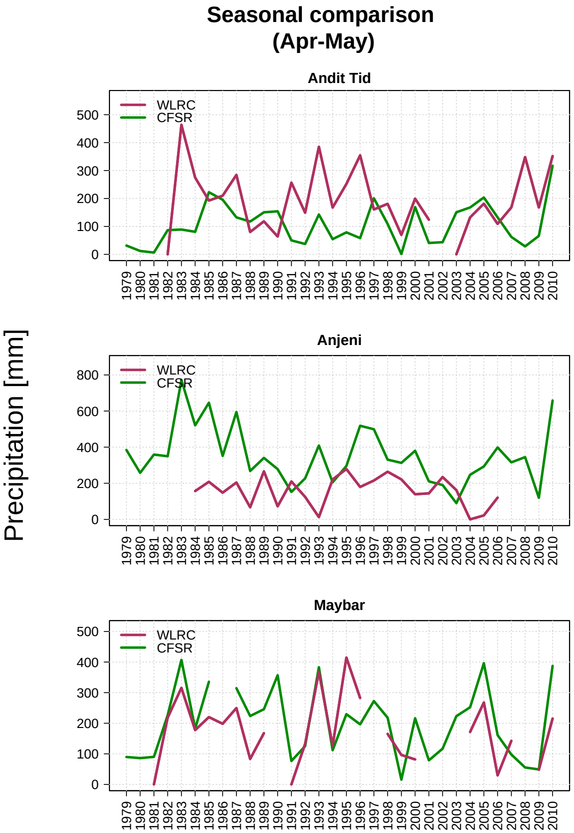

Figure A1. Seasonal comparison of April and May (1979–2010).

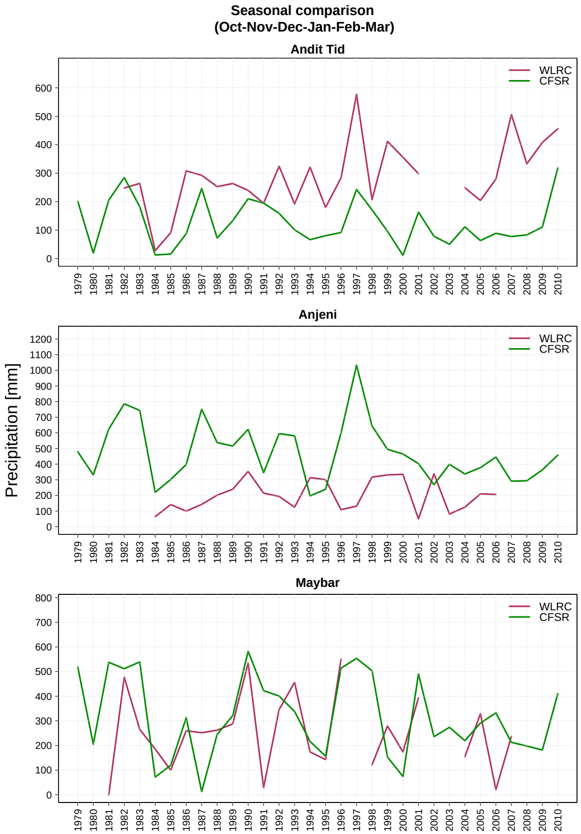

Figure A2. Seasonal comparison of dry season (1979–2010).