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Adjustment of global precipitation data for enhanced hydrologic modeling of tropical Andean watersheds

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Abstract Global gridded precipitation is an essential driving input for hydrologic models to simulate runoff dynamics in large river basins. However, the data often fail to adequately represent precipitation variability in mountainous regions due to orographic effects and sparse and highly uncertain gauge data. Water balance simulations in tropical montane regions covered by cloud forests are especially challenging because of the additional water input from cloud water interception. The ISI-MIP2 hydrologic model ensemble encountered these problems for Andean sub-basins of the Upper Amazon Basin, where all models significantly underestimated observed runoff. In this paper, we propose simple yet plausible ways to adjust global precipitation data provided by WFDEI, the WATCH Forcing Data methodology applied

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to ERA-Interim reanalysis, for tropical montane watersheds. The modifications were based on plausible reasoning and freely available tropics-wide data: (i) a high-resolution climatology of the Tropical Rainfall Measuring Mission (TRMM) and (ii) the percentage of tropical montane cloud forest cover. Using the modified precipitation data, runoff predictions significantly improved for all hydrologic models considered. The precipitation adjustment methods presented here have the potential to enhance other global precipitation products for hydrologic model applications in the Upper Amazon Basin as well as in other tropical montane watersheds.

1 Introduction

Over the last decade, numerous global weather forcing data have become available for large-scale hydrologic modeling (e.g. Decharme and Douville 2006; Rienecker et al. 2011; Saha et al. 2013; Sheffield et al. 2006; Weedon et al. 2014; Weedon et al. 2011). Based on atmospheric reanalysis or satellite data products, hydrologic models can be set up uniformly and consistently across the globe. Within the second phase of the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP2), Huang et al. (this special issue) evaluated the runoff simulations of a large ensemble of hydrologic models driven by reanalysis forcing data from WATCH (Weedon et al. 2011) for 12 large-scale river basins. They found that most models can adequately reproduce monthly streamflow in most of the basins. However, due to the large number of models and river basins, their analysis was limited to streamflow at river basin outlets where a good fit to observations does not necessarily indicate a correct representation of hydrologic processes at internal gauges (Hall 2004).

This is in particular true for the 1.02 million km^2 Upper Amazon Basin (UAB), for which all ISI-MIP2 models significantly underestimated runoff in mountainous sub-basins along the Eastern Andes. Analyzing the runoff coefficients, i.e. the ratio of observed runoff to precipitation, reveals that the systematic bias in modelled runoff for these basins is probably caused by errors in the precipitation data and/or the observed runoff. While runoff coefficients for humid tropical environments typically range between 0.6 and 0.7 (Buytaert et al. 2006b; Campling et al. 2002), values for mountainous sub-basins in the UAB exceed 0.8. Previous studies found similar difficulties with water balance closure for upper parts of the Amazon Basin (Coe et al. 2002; Guimberteau et al. 2012; Nerini et al. 2015; Zulkafli et al. 2013). Long-term changes in water storage, such as surface and subsurface water and in particular glaciers (due to climate change), might contribute to the unreasonably high runoff coefficients, but to the authors' best knowledge there is no quantitative evidence reported for the UAB. Instead, the difficulties with water balance closure are mainly attributed to errors in precipitation data, although the possibility of high streamflow uncertainty can also not be discounted (Zulkafli et al. 2013).

Tropical mountain regions are among the most challenging environments for reliable precipitation estimates (Scheel et al. 2011; Tian and Peters-Lidard 2010). Complex terrain and orographic effects lead to a high spatio-temporal variability of precipitation (Buytaert et al. 2006a; Houze 2012) which cannot be reflected by point measurements, especially not in data scarce regions like the Andes (Blacutt et al. 2015). For the tropical Andes of south Ecuador, Ward et al. (2011) observed large discrepancies between rain-gauge-based precipitation products and estimates from satellite- (PERSIANN, TRMM 3B42 or also called TMPA) and reanalysis-based products (NCEP R1, ERA-40). Their results indicate that advanced remote sensing products provide new insights into precipitation estimation in data scarce areas, but still have limitations regarding their accuracy. Zulkafli et al. (2014) provided concise explanations for limitations of TMPA in and near tropical mountain regions. However, it has also been shown that the TRMM climatology (Nesbitt and Anders 2009) can resolve clear precipitation gradients in regions with large average daily rain totals including the Andes.

Cloud water interception (CWI) may be a further explanation for the unrealistically high runoff coefficients in Andean watersheds. CWI of tropical montane cloud forests leads to additional water input (Bruijnzeel et al. 2011; Célleri and Feyen 2009; Clark et al. 2014) which is neither represented in conventional precipitation measurements nor in remote-sensing-based products. CWI varies strongly with location, site exposure and the type of montane cloud forests, and can reach values of more than 1000 mm yr.$^{-1}$ (Bruijnzeel et al. 2011; Giambelluca and Gerold 2011). Beyond that, it is assumed that streamflow volumes in cloud forests further increase by reduced evaporative losses under the prevailing low radiation levels and high atmospheric humidity (cf. Bruijnzeel et al. 2011). Tropical montane cloud forests are typically found in foggy, wet and windy environments within the tropical belt (Bruijnzeel et al. 2011). Mulligan (2010) modelled their distribution on the basis of satellite-observed atmospheric cloud presence and/or modeled ground-level condensing conditions. Based on their analysis, 14.2 % of all tropical forests were classified as "significantly cloud-affected forests". Bruijnzeel et al. (2011) modelled CWI inputs across the tropics using the Fog Interception for the Enhancement of Streamflow in Tropical Areas (FIESTA, now called WaterWorld) - a water budget model developed by Mulligan and Burke (2005). According to their results, 12 % of the Latin American land receive fog inputs of more than 100 mm yr.$^{-1}$ with particularly high inputs predicted for the Andes in Ecuador and northern Peru. Recently, Clark et al. (2014) calculated a cloud water contribution of 316 ± 116 mm (or 11 ± 4 %) to annual streamflow for the Kosñipata catchment in the eastern Peruvian Andes using an isotopic mixing model. These studies point out the importance of accounting for CWI when modeling the hydrology of tropical mountainous regions.

In this paper, we propose simple yet plausible methods to adjust global precipitation data for enhanced streamflow simulations in tropical montane watersheds. This is in particular valuable for large-scale modeling studies which are based on globally applicable meteorological forcing data and general hydrologic models. We address both issues - potential errors of global precipitation data over complex terrain and CWI as an unaccounted source of water - by applying suitable correction factors to the globally available WFDEI precipitation data set (Weedon et al. 2014). While topographic correction factors are derived at seasonal time scales based on the high resolution TRMM climatology (Nesbitt and Anders 2009), CWI correction factors were calculated according to the fractional cover of cloud-affected forests as provided by Mulligan (2010). We hypothesize that these modifications will lead to improved precipitation estimates and thus to improved runoff simulations in the UAB. The study is carried out within the ISI-MIP2 project, which provides an excellent framework to test this hypothesis using an ensemble of widely used hydrologic models.

2 Material and methods

2.1 Study area

The UAB (Fig. 1a) is one of 12 large-scale river basins that are modelled within the ISI-MIP2 project to study the impacts of climate change on regional water resources across the globe (Krysanova and Hattermann, this special issue). At the outlet gauge São Paulo de Olivença, the

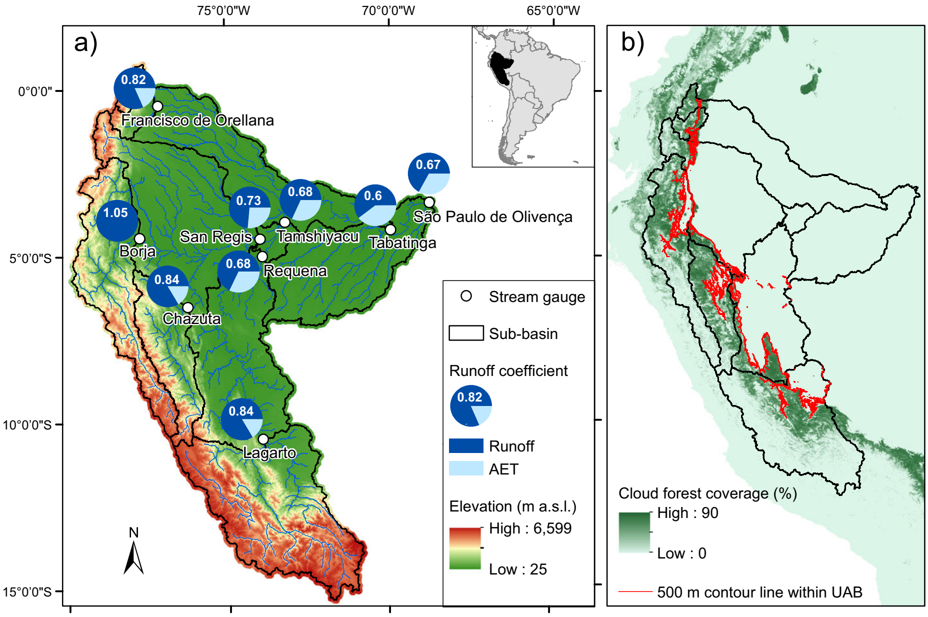

Fig. 1 **a** Elevation map of the UAB including stream gauges and their runoff coefficients based on WFDEI precipitation and observed runoff (AET = actual evapotranspiration after water balance closure); **b** distribution of significantly cloud affected forests (source: Mulligan 2010)

Upper Amazon drains an area of about 1.02 x 10^6 km^2 of which the largest part is located in Peru (76 %). Smaller parts are shared by Ecuador (13 %) in the north-west and Brazil (11 %) in the east. The UAB has an elevation range of almost 6600 m, where 40 % of the area lies above 500 m a.s.l. with average slopes greater than 30 % which defines mountain areas according to Meybeck et al. (2001) and which we hereafter refer to as mountainous Andean region. The lower parts are referred to as Amazonian lowlands. While tropical rainforest dominates the Amazonian lowlands, the Andean region exhibits a large diversity of vegetation types with montane forests in lower altitudes and shrublands as well as montane grasslands dominating in higher altitudes (Eva et al. 2004). Figure 1b shows the distribution of cloud affected forests (Mulligan 2010) whose lower elevation boundary in the UAB matches quite well the 500 m contour line.

Precipitation regimes vary across latitudes and time scales as influenced by large-scale meteorological phenomena, such as the Intertropical Convergent Zone (ITCZ), the South American Monsoon System (SAMS), the El Nino Southern Oscillation (ENSO), and the Pacific Decadal Oscillation (PDO) (Carvalho et al. 2004). The lower northern and northeastern parts of the basin receive relatively high average rainfall of more than 3000 mm $yr.^{-1}$ (Espinoza Villar et al. 2009). Although the distribution of precipitation in the Andean region is highly disparate, Bookhagen and Strecker (2008) found a clear rainfall peak (> 3500 mm $yr.^{-1}$) at a mean elevation of 1300 ± 170 m along the eastern slopes of the Andes. With higher altitudes (> 2000 m a.s.l.), precipitation is generally decreasing to less than 1000 mm $yr.^{-1}$ (Espinoza Villar et al. 2009).

The long-term mean annual precipitation over the entire UAB in period 1981–2010 was 2204 mm of which 1476 mm or 67 % run off as streamflow at outlet gauge São Paulo de Olivença. Streamflow data for this gauge were obtained from the Global Runoff Data Center

(GRDC). Streamflow data for the gauge next to the outlet, Tabatinga, was provided by the Brazilian National Water Agency (ANA), while all other upstream gauges used in this study (Fig. 1a) were obtained from the Observation Service SO HYBAM (www.ore-hybam.org). As shown in Fig. 1a, runoff coefficients increase in Andean sub-basins to unrealistically high values close to or even higher than 1. Similar high runoff coefficients were reported by previous studies using the ground-based HYBAM and several satellite-based precipitation data sets (e.g. Nerini et al. 2015; Zubieta et al. 2015; Zulkafli et al. 2013; Zulkafli et al. 2014). This most likely indicates a systematic underestimation of Andean precipitation caused by observational errors (across products) or unaccounted sources of water (e.g., CWI).

2.2 Modification of WFDEI precipitation data

Our study is based on precipitation data derived from reanalysis, the WATCH Forcing Data methodology applied to ERA-Interim data – WFDEI (Weedon et al. 2014). In the Amazon Basin, ERA-40 reanalysis data (Uppala et al. 2005) were found to underestimate precipitation in the rainy season and to slightly overestimate precipitation in the dry season (Betts et al. 2005). According to the newer interim reanalysis (ERA-Interim), from which the WFDEI data are derived, annual precipitation is largely unbiased although the seasonal amplitude of precipitation remains too small (Betts et al. 2009). Recently, Monteiro et al. (2015) compared different reanalysis-based precipitation products with measurements of more than 2000 rain gauges in Brazil and recommended using WFDEI data for large-scale hydrologic model applications. To consider both potential errors of WFDEI over complex terrain and CWI as an unaccounted source of water, we modified the WFDEI data by applying correction factors.

The topographic modification of WFDEI data utilizes the high resolution precipitation climatology calculated by Nesbitt and Anders (2009) from the TRMM Precipitation Radar (PR) 2 A25 algorithm. An error model developed by subsampling the TMPA as sampled by the PR indicates that the climatology at 0.1° resolution can reasonably capture precipitation gradients in regions of heavy precipitation, notably in the Andes (Nesbitt and Anders 2009). We used an updated version (v2) of the climatology consisting of average seasonal precipitation rates for the period 1998 to 2008 on a 0.05° grid between 36° N/S (https://publish.illinois.edu/snesbitt/data/). From Fig. 2a it is evident that the TRMM climatology reproduces narrow zones with heavy rainfall (> 10 mm day^{-1}) along the eastward slopes of the Andes, largely between 500 and 2000 m in elevation. Aggregating the climatology to a 0.5° resolution (TRMM_aggregated in Fig. 2a) allows for a direct comparison with the WFDEI dataset. While in the TRMM climatology highest precipitation rates occur along the eastern Andes, the WFDEI dataset displays a particularly wet zone also in the north and north-east of the UAB. Moreover, the TRMM climatology reproduces only 80 % of the annual WFDEI precipitation on a basin average, i.e. 1707 compared to 2132 mm. The TRMM climatology most likely underestimates basin wide precipitation since WFDEI compares very well with the estimates of the ground-based HYBAM dataset (2143 mm yr.$^{-1}$) as reported by Zubieta et al. (2015). It nevertheless seems appropriate to impress the spatial pattern of the TRMM climatology with higher precipitation inputs along the eastern flanks of the Andes on the WFDEI dataset while maintaining the basin wide amount of WFDEI precipitation. Therefore, we derived TRMM correction factors (α) for each 0.5° grid cell by dividing the area-normalized average precipitation of TRMM by the area-normalized average precipitation of WFDEI, such that:

$$\frac{T_{i,s}}{\frac{1}{N}\sum_{i=1}^{N} T_{i,s}} = \alpha_{i,s}\frac{\overline{W}_{i,s}}{\frac{1}{N}\sum_{i=1}^{N}\overline{W}_{i,s}} \tag{1}$$

where $\overline{T}$ and $\overline{W}$ represent for TRMM and WFDEI, respectively, the average daily precipitation rate (mm) for each individual 0.5° grid cell i within a season s (DJF, MAM, JJA, or SON) in the period from 1998 to 2008. N is the total number of all grid cells in the UAB (N = 405). The seasonal TRMM factors are shown in Fig. 2b. Values higher than 1 mainly occur in the eastern Andean region, whereas values lower than 1 are concentrated in the highest and lowest parts of the UAB, i.e. in the intra-Andean valleys and in the northern and north-eastern lowlands. A similar spatial pattern is observed across all seasons, although the adjustment factors slightly differ from each other. We applied the seasonal TRMM factors as multipliers to the daily gridded fields of WFDEI rainfall (W) to derive the TRMM-modified WFDEI dataset (W_T), hereafter referred to as WFDEI_TRMM:

$$\mathrm{W}_{T_{\mathrm{i,s,t}}} = \alpha_{\mathrm{i,s}}\mathrm{W}_{\mathrm{i,s,t}} \tag{2}$$

where t is the day within the full period of available WFDEI data, i.e. 1961–2010.

As intercepted cloud water in forested tropical Andean catchments may contribute to streamflow as an unaccounted source of water with more than 10 % across all seasons (Clark et al. 2014), we additionally applied CWI correction factors to the WFDEI precipitation data. CWI factors (β) were derived by rescaling the fractional cover of cloud forests as provided by Mulligan (2010) to the 0.5° resolution of WFDEI (Fig. 2c). We considered two scenarios, one assuming that cloud forests gain 15 % more precipitation (γ = 0.15) which is in agreement with the findings of Clark et al. (2014), and another more extreme scenario with 50 % of additional water input (γ = 0.5):

$$\mathrm{W}'_{\mathrm{i,t}} = (1+\gamma\ \beta_{\mathrm{i}})\mathrm{W}_{\mathrm{i,t}} \tag{3}$$

where $W'_{i,t}$ is referred to as either WFDEI_CWI15 or WFDEI_CWI50 depending on the value used for γ. Likewise, the CWI correction was imposed over the TRMM-modified WFDEI data, leading to two additional datasets: WFDEI_TRMM_CWI15 and WFDEI_TRMM_CWI50.

It is worth mentioning that basin-wide daily precipitation rates of all modified datasets are similar to the rates of the original WFDEI data (Table 1). While the TRMM-based modification had no effect on mean precipitation at the basin scale, the spatial distribution of precipitation changed remarkably (Fig. S1 in the supplements). The CWI correction, in contrast, led to slightly increased mean precipitation rates but generally retained the spatial pattern of WFDEI precipitation. Both methods resulted in increased precipitation rates in the eastern Andean region, mainly at altitudes between 500 and 2000 m. A combination of both modifications (WFDEI_TRMM_CWI) appears reasonable because each method accounts for different potential sources of errors in the precipitation data. Maps of average daily precipitation rates for each of the modified datasets can be found in the supplements (Fig. S1).

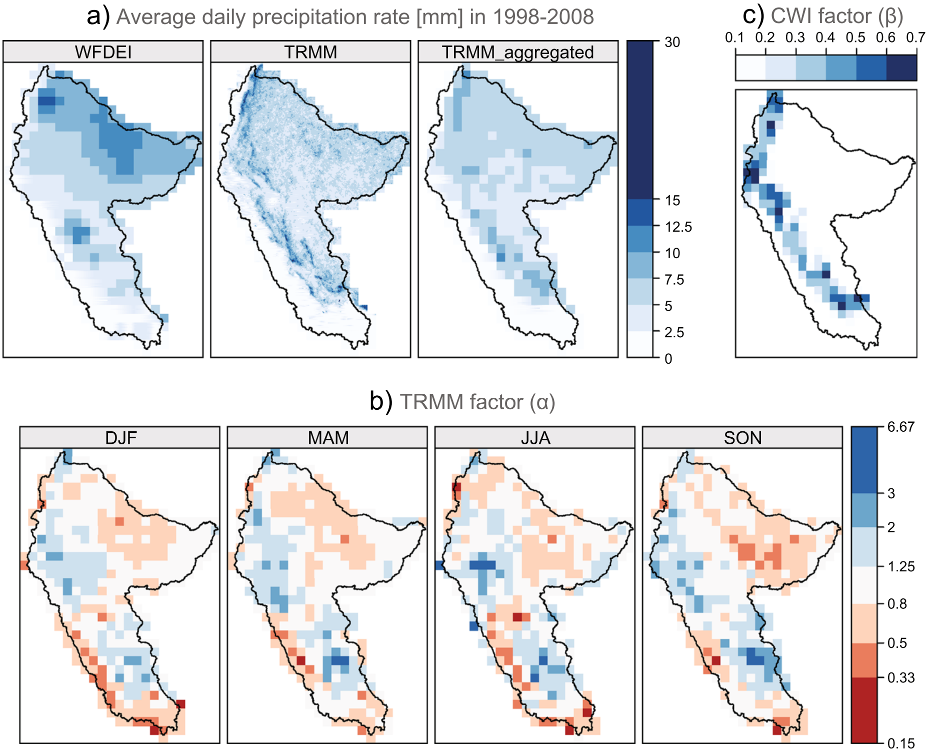

Fig. 2 **a** Average precipitation rates (mm day^{-1}) in period 1998–2008 of the WFDEI dataset, the high resolution 0.05° TRMM climatology, and the aggregated 0.5° TRMM climatology as well as the correction factors used in this study: **b** the topographic correction factors derived for different seasons (Eq. 1) and **c** the CWI correction factors expressed as fractional cover of cloud forests (Mulligan 2010) rescaled to 0.5° resolution

2.3 Hydrologic model simulations

We applied the original WFDEI precipitation and each of the modified datasets in daily resolution to drive five spatially distributed hydrologic models, i.e. (1) the HBV model (Bergström 1995), (2) the Mesoscale Hydrologic Model (MHM) (Kumar et al. 2013; Samaniego et al. 2010), (3) the Soil and Water Assessment Tool (SWAT) (Arnold et al. 1998), updated for improved representation of tropical perennial vegetation (Strauch and

Table 1 Average daily precipitation rates (1998–2008) for the UAB according to WFDEI and all modified datasets

Precipitation dataset	Mean (mm/d)	Minimum (mm/d)	Maximum (mm/d)	Standard dev. (mm/d)
WFDEI	5.8	0.9	13.1	2.8
WFDEI_CWI15	5.9	0.9	14.3	2.8
WFDEI_CWI50	6.1	0.9	17.1	2.9
WFDEI_TRMM	5.8	0.6	12.6	2.7
WFDEI_TRMM_CWI15	5.9	0.6	13.7	2.7
WFDEI_TRMM_CWI50	6.2	0.6	16.3	3.0

Volk 2013), (4) the Soil and Water Integrated Model (SWIM) (Krysanova et al. 1998), and (5) WaterGAP3 (Verzano 2009). A brief description of each model in terms of spatial disaggregation, the representation of soils and vegetation, required meteorological input data, and methods for calculating potential evapotranspiration as well as for runoff routing is provided in the editorial of this special issue (Krysanova and Hattermann), which also lists the shared sets of input data (e.g. topography, land cover, soils) and basic setup and modeling protocols.

For this study, all required meteorological forcing data (i.e. precipitation, temperature, solar radiation, wind speed, and air humidity) were obtained from WFDEI. This is contrary to the ISI-MIP2 model setup guidelines which requested the use of WATCH data, the predecessor of WFDEI, due to the fact that the Global Circulation Model (GCM) climate scenarios were bias-corrected using WATCH data (see Krysanova and Hattermann (this special issue) for more details). This study, however, could not utilize WATCH because the dataset ends in year 2001 and is thus not appropriate for the modification based on the TRMM climatology (1998–2008). None of the hydrologic models was specifically calibrated for this study, neither for a specific gauge nor for a specific precipitation input dataset to avoid the modeling bias introduced by constraining the model to a specific dataset. Each modeler was requested to use a model version with typical, physically meaningful a priori parameter values or the basic setup of the ISI_MIP2 project (Krysanova and Hattermann, this special issue).

The performance of each model to simulate monthly streamflow in the period from 1998 to 2010 at each of the nine stream gauges (Fig. 1) was evaluated based on standard objective metrics, the Nash-Sutcliffe-Efficiency (NSE) and the percentage bias (PBIAS). NSE can range from $-\infty$ to 1. Negative values indicate that the observed mean would be a better predictor for the observed time series than the modelled time series and a value of 1 implies a perfect fit to observations. PBIAS can range from −100 to +∞, where negative values indicate underestimation and positive values indicate overestimation of observed streamflow. Each hydrologic model was run six times, each time using a different precipitation input (Tab. 1) while all other model settings were kept constant.

3 Results & discussion

The modification of WFDEI precipitation based on TRMM and/or CWI correction factors generally improved the performance of each hydrologic model. However, the level of improvement depends on the location (stream gauge), the type of modification, and the hydrologic model. In order to depict the general pattern of model performance in relation to each type of modification we analyzed the ensemble mean (Fig. 3), i.e. the average runoff time series considering all models. The model specific results are also provided in the supplementary material (Figs. S2-S6).

Figure 3 clearly illustrates that - based on the original WFDEI data - the ensemble mean performance was remarkably poor for mountainous sub-basins within the eastern Andean region (i.e. gauges Francisco de Orellana, Chazuta, Borja, and Lagarto), with NSE ranging from −1.43 to 0.10 and PBIAS ranging from −50.9 % to −25.7 %. Figure 4 shows the systematic underestimation of runoff based on WFDEI exemplarily for the gauges Francisco de Orellana and Borja. For these gauges, Zulkafli et al. (2014) reported slightly better performance values using the JULES model based on TMPA version 7 precipitation, with NSE and PBIAS of −0.47 and −16.5 % for Francisco de Orellana and −0.34 and −40.4 % for

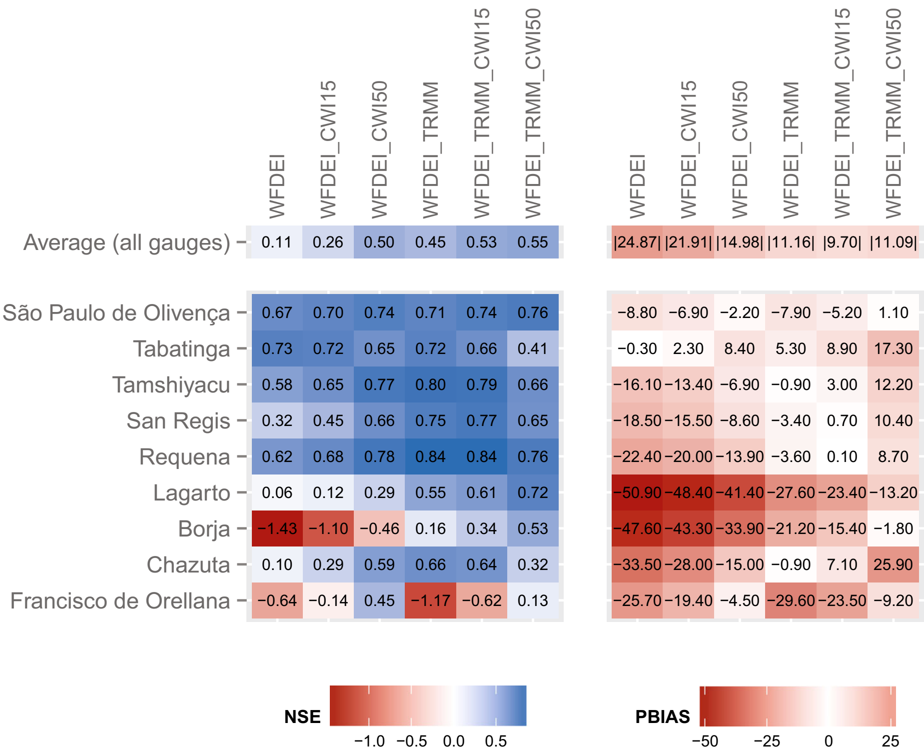

Fig. 3 Heat map of performance metrics as achieved by the model ensemble mean for each precipitation dataset at each stream gauge and on average (i.e. arithmetic mean of NSE and PBIAS across all stream gauges). For the average PBIAS, absolute values are shown because averaging across negative and positive values leads to meaningless results

Borja, respectively. The best, though still poor, modelled runoff results for these gauges were recently published by Zubieta et al. (2015). They report NSE and PBIAS values of −0.15 and −20.1 % for Francisco de Orellana and 0.23 and −3.9 % for Borja, respectively, using the MGB-IPH model driven by ground-based HYBAM precipitation data. For gauge Borja, their results - especially the low PBIAS - are surprising since the runoff ratio according to the HYBAM observations was estimated to be 1.34 (Zubieta et al. 2015); observed runoff in this watershed was thus 30 % higher than observed precipitation. Compared to our WFDEI-based results, model performance was similar or even worse when TMPA version 6 data (Zulkafli et al. 2014) or alternative satellite products, such as CMORPH and PERSIANN were used (Zubieta et al. 2015). These recent results highlight how challenging Andean watersheds are for hydrologic model applications. With increasing catchment area, however, NSE and PBIAS values generally improve to 0.67 and −8.8 % at the outlet gauge São Paulo de Olivença (Fig. 3), confirming that model performance at the catchment outlet is not necessarily representative for the performance at internal gauges (cf. Hall 2004).

The modification of precipitation data considerably improved runoff simulations for all stream gauges, except for gauge Tabatinga. The effect was strongest for the Andean watersheds, especially at gauge Borja where the NSE for the ensemble mean increased by almost two units to 0.53 and PBIAS decreased to only −1.8 % (Fig. 3). This clearly shows the value of accounting for the spatial pattern of the TRMM climatology and CWI in cloud forest affected regions.

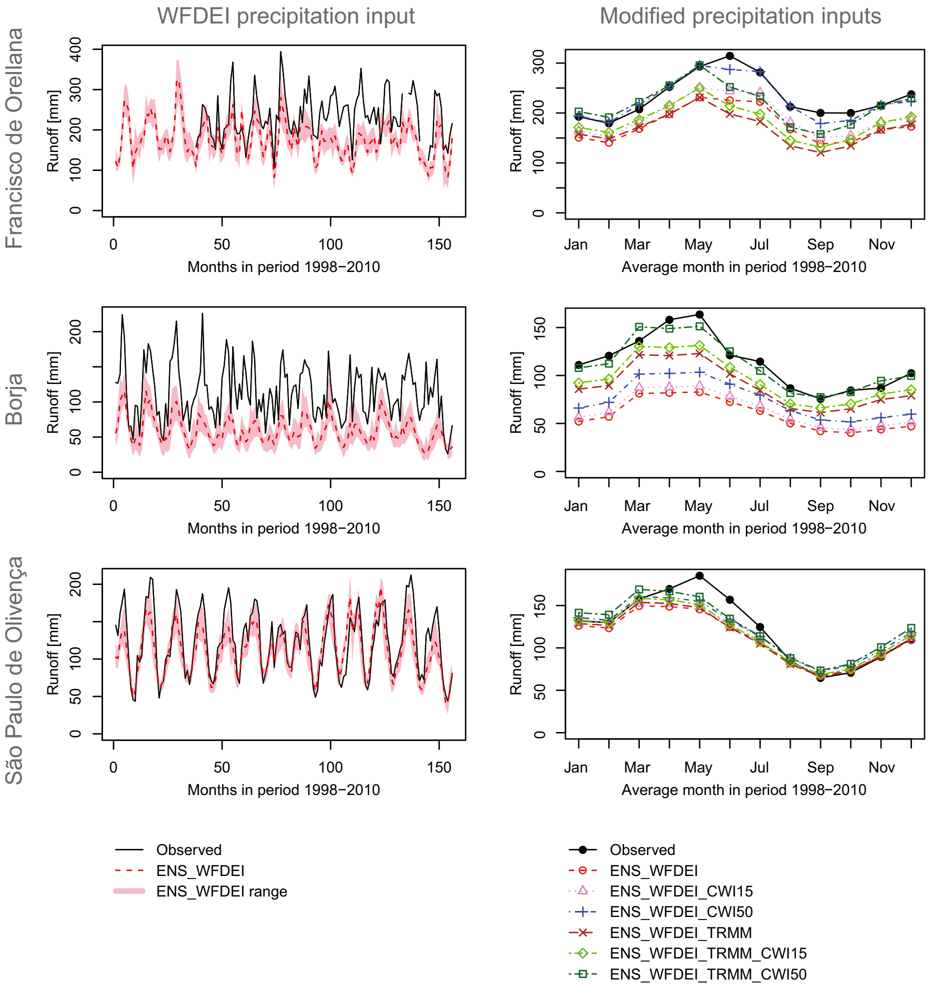

Fig. 4 Modelled monthly runoff (ensemble mean and range) based on WFDEI precipitation input (*left side*) and average monthly runoff (ensemble mean) using each of the different precipitation datasets (*right side*), exemplarily for three stream gauges. Respective plots for each gauge, precipitation input and model can be found in the supplementary material (Figs. S7-S43)

There is, however, no clear indication as to which type of modification is best for the whole UAB. The combined modification including TRMM and the strongest CWI correction, WFDEI_TRMM_CWI50, worked best for gauges Borja (see also Fig. 4), Lagarto and São Paulo de Olivença, while WFDEI_TRMM_CWI15 (combined modification but with lower CWI correction) was best for gauges Requena and San Regis. In contrast, considering only TRMM (WFDEI_TRMM) was most advantageous to simulate runoff at gauge Tamshiyacu and considering only a CWI correction (WFDEI_CWI50) worked best for gauge Francisco de Orellana where the TRMM-based modification in turn has led to worse model performance (see also Fig. 4).

This shows that errors in the original WFDEI data follow a complex spatial pattern that cannot be fully accounted for by any of the modified datasets. For example, the CWI correction factors cannot reflect the strong variability of CWI with location, site exposure and the type of cloud forest as observed in numerous field experiments (Bruijnzeel et al. 2011;

Giambelluca and Gerold 2011). Nevertheless, our results show that simple yet plausible adjustments can already improve hydrologic simulations in the UAB to a large extent. On average – across all models and gauges – NSE and PBIAS could be improved from 0.11 to more than 0.45 and from 25 % to less than 15 %, respectively, using any of the following four modified datasets (sorted by increasing NSE): WFDEI_TRMM, WFDEI_CWI50, WFDEI_TRMM_CWI15, WFDEI_TRMM_CWI50. It is worth mentioning that this sorting and the achieved performance values can vary depending on the hydrologic model selected, but the modifications consistently outperformed the original WFDEI precipitation in every case (cf. Figs. S2-S6 in the supplementary material).

The only gauge where each of the modified precipitation datasets had worsened the model performance was Tabatinga. The gauge appeared already as an exception by having a significantly smaller observed runoff coefficient (0.6) than the four other lowland gauges including the basin outlet (0.67–0.73). Tabatinga was thus the only gauge for which the ensemble simulation did not underestimate observed runoff based on the original WFDEI dataset. The modified precipitation datasets led to increased runoff at all gauges, either directly by assuming additional cloud water input (CWI correction) or indirectly by relocating precipitation to mountainous regions with lower evapotranspiration and higher surface runoff (TRMM correction). This caused an overestimation of runoff for Tabatinga. Though we cannot explain with certainty why the observed runoff ratio and thus the model results are significantly different for this gauge, inconsistencies in streamflow estimates by applying different rating curves may play a major role. Streamflow data for Tabatinga were obtained online from the hydro-meteorological information system of ANA (http://www.snirh.gov.br/hidroweb/), while the data for all other gauges were obtained from HYBAM or GRDC. The uncertainty of streamflow rates measured by HYBAM is usually very low, around 5–10 % for the Amazon foreland (Filizola and Guyot 2004; Filizola et al. 2009).

The results of each hydrologic model are of course dependent on their respective parameterization and model structure. We refused to conduct a comprehensive calibration of each model because this would have increased the risk to compensate potential errors in the precipitation input data and could have introduced biased results. We, however, acknowledge that the model performance could have further increased by allowing the explicit calibration of each individual model to a specific input dataset. Although parameter uncertainty could not be addressed in this study, our approach of using an ensemble of hydrologic models takes into account model structural uncertainty and should therefore allow for a robust assessment of different precipitation datasets. The assessment was based on observed and modelled runoff. However, we also compared the results with an independent dataset on actual evapotranspiration (AET) provided by the MOD16 product (Mu et al. 2013) of MODIS. Both, the observed AET after waterbalance closure (precipitation minus observed runoff) and the simulated AET (precipitation minus simulated runoff) increased and were thus closer to the AET estimated by MOD16, in particular for the 'critical' montane subbasins, when considering the proposed correction of precipitation data (cf. Figs. S44 and S45 in the supplementary material). This further highlights the advantage of the presented approach.

4 Conclusions

This study provides simple methods to adjust globally available precipitation data for hydrologic model applications in the Upper Amazon Basin (UAB), a region prone to precipitation data errors. Our modifications are based on plausible assumptions. First, we assume that the global WFDEI precipitation product can be improved by impressing the spatial pattern of the TRMM climatology, which has been proven to resolve precipitation gradients in regions of heavy precipitation, notably in the Andes (Nesbitt and Anders 2009). Second, we assume that cloud water interception is an important but unaccounted source of water that can be considered by increased precipitation in regions that are significantly affected by cloud forests, as mapped by Mulligan (2010).

By means of hydrologic model ensemble simulations, we found that both types of modification can significantly improve runoff simulations, which supports our aforementioned hypothesis. Combining both modifications further improved the hydrologic simulations, particularly in Andean headwater catchments that are characterized by complex mountainous terrain and high percentages of cloud forest. However, our study assumed static long-term surface and subsurface water storages, although changes of those storages might have had an impact on the runoff observed in the UAB. Therefore, the modeling approach for Andean headwater catchments should be extended if future research can disentangle substantial effects of long-term storage changes (e.g. accelerated glacier melt due to climate change) on large-scale runoff.

Due to their simplicity and plausibility, the presented methods should be easily applicable to other precipitation products and hydrologic model applications, for the UAB or other tropical montane watersheds with similar large precipitation gradients and cloud forest coverages. The data required to apply these methods are open source (TRMM climatology: https://publish.illinois.edu/snesbitt/data/, cloud forest fractional cover: http://www.ambiotek.com/tropicalhydrology/). Users can adjust the amount of additional water input in cloud forests (parameter γ, Eq. 3) according to their region. Although our results are not clear in this regard, a CWI input of 15 % of precipitation is certainly much more realistic than a 50 % scenario (cf. Clark et al. 2014). Additional studies analyzing the catchment-scale water budget in tropical montane cloud forests with particular consideration of CWI, similar to the work of Clark et al. (2014), are needed to improve the empirical basis for the adjustment of precipitation. Since our approach ignores temporal dynamics of CWI, promising avenues for future research could also involve (1) daily adaptation strategies by considering actual temperature and atmospheric moisture as well as (2) climate change induced shifts in the occurrence of fog and the spatial distribution of cloud forests. Smaller-scale studies which do not depend on global datasets should of course prefer local measurements of precipitation and fog deposition (if available). Large-scale or global studies such as ISI-MIP2, however, should benefit from the presented approach to adjust tropical montane precipitation. As an example, global precipitation datasets that are improved for tropical montane regions could be used to bias-correct GCM climate scenario data in order to increase the reliability of climate change impact studies.

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