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Research article

Can hydrological drought be efficiently predicted by conceptual rainfall-runoff models with global data products?

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Abstract

The seasonally-dry tropics of northern Costa Rica are characterized by recurrent drought events with negative socio-economic impacts on a vulnerable population. Scarce hydroclimatic observational data constraints reasonable water management and often results in water scarcity issues. This study analyses hydrological drought situations using freely available Global Precipitation Products (GPP) and a Regional Climate Model (RCM) that drive a relatively simple, semi-distributed rainfall-runoff model (HBV-Light). Firstly, the GPP and observed rainfall were used to calibrate the model simulating streamflow dynamics. Secondly, drought detection and estimates of drought duration, intensity and severity were determined with a daily variable threshold approach. Thirdly, we developed future hydrological drought scenarios based on a RCM. Generally, the GPP CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) resulted in the best streamflow simulations (KGE > 0.6) compared with the model driven by observed rainfall (KGE > 0.7). CHIRPS also correctly identified the observed streamflow drought periods of 1994, 1997-1998 and 2001-2002. Average observed streamflow drought severity was 27.9 mm compared to the CHIRPS-derived severity of 20.6 mm (error estimate of ±7.3 mm). The model in combination with global data can be successfully used to identify drought periods and their duration, but model uncertainty currently prevents from forecasting streamflow deficit with volume errors below 50%. The future hydrological drought scenario showed more severe drought periods between 2039-2041 and 2042-2043. This study responds to the need for drought assessments in the seasonally-dry tropics with scarce observations as a tool for adaptation to climate change and water resource management.

1 Introduction

Drought is a recurrent extreme climate event characterized by below-normal precipitation (van Loon, 2015), that can occur globally, in contrast to the permanent aridity that prevails in arid zones (Dai, 2011). Droughts are mainly classified into meteorological, agricultural, hydrological, and socio-economic events (Van Loon, 2015). Meteorological drought is related to precipitation deficit during a prolonged period, while the agricultural drought is the reduction of water availability in the soil for vegetation use, resulting in crop losses (Van Loon, 2015). Hydrological drought is defined as the deficit of streamflow and/or volume of surface-or groundwater levels (Marcos, 2001). Finally, the socio-economic drought characterizes the impacts by each previous types of drought (Van Loon, 2015).

Drought analysis suffers from inaccessible and unreliable hydrometeorological in-situ observations particularly in tropical regions where hydrological droughts are recurrent events and are expected to become more frequent in the future (Nauditt et al., 2017). Drought research has so far been less focused in tropical regions than in other geographical areas (Nauditt & Ribbe, 2017), limiting the prospects of a robust monitoring (Ndehedehe et al., 2016), and constraining the understanding of spatio-temporal dynamics of drought occurrence at different spatial and temporal scales. To partly overcome this data scarcity, freely available Global Precipitation Products (GPP) provide spatially and temporally precipitation estimates in relation to the sparse in situ measurements. GPP together with Regional Climate Models (RCM) that forecast weather conditions are useful input information for rainfall-runoff models. This assembly can help to characterize and forecast drought events (Van Loon, 2015), with the aim to improve water resources management and to reduce their related socio-economic impacts. Many studies have evaluated the performance of GPP (Behrangi et al., 2011; Thiemig et al., 2012; Adler et al., 2001; Shen et al., 2010) and their ability to generate accurate precipitation estimates for hydrological modelling (Artan et al., 2007; Liechti et al., 2012; Maggioni & Massari, 2018). Zambrano-Bigiarini et al., (2017) highlighted the opportunities of using GPP for hydrological applications such as modelling and evaluation of droughts and floods. Moreover, conceptual hydrological models are considered the main tools for drought assessment (Van Loon, 2015). In a context of data scarcity, such as in Central America, the use of such technologies to monitor drought-related variables, forecast and quantify drought impacts (AghaKouchak et al., 2015) should be perceived as an opportunity to improve the understanding of droughts at different spatial and temporal scales.

Central America is climatologically influenced by the Caribbean Sea and the Eastern tropical Pacific Ocean weather patterns resulting in a pronounced seasonality of precipitation and flow regimes. This seasonality presents periods of water deficit during the dry season, that in a context of climatic variability is often considered as drought. The region has historically been affected by droughts with negative consequences for the agricultural sector, impacting the food security of the population (Calvo-Solano et al., 2018; Quesada-Montano et al., 2018). One of the most affected locations is found across the Central American Dry Corridor (CADC), where the dry season lasts on average 5 months. This area is inhabited by 50% of the total population and 67% of the rural population living in poverty (Gotlieb et al., 2019) and socio-economic vulnerability (Calvo-Solano et al., 2018). One of the main concerns is that the unregulated water use for industry and irrigation, affects this population particularly during the dry season (Guzmán, 2013). In northern Costa Rica – a part of the CADC - recent droughts resulted in drinking water supply issues and economic losses (Birkel, 2006). Our study site, the Tempisque catchment located in the CADC is one of the most vulnerable regions to climate change in the country (Hidalgo & Alfaro, 2012) and often affected by hydrological droughts. However, the aim of this research is to evaluate past and near-future hydrological drought in this catchment, using GPP, RCM and the relatively parsimonious hydrological model HBV-Light.

The specific objectives are to:

I Analyze the performance of GPP used as input to the HBV-Light model in a gauged Tempisque River sub-catchment.

II Perform a hydrological drought analysis calculating severity, duration, and intensity for a historic period that covered observed and documented extreme droughts.

III Analyze the predictive capability of the calibrated model to estimate future hydrological drought scenarios using climate projections of precipitation from a Regional Climate Model for the Central American and Caribbean domain.

2 Methods

2.1 Study site: The Tempisque catchment

The Tempisque-Bebedero catchment (5 400 km2) is located in the Guanacaste province, north-west Costa Rica (Figure 1), extending from the Central Volcanic cordillera to the Gulf of Nicoya (Pacific Ocean) (Monge & Gómez, 2007). This catchment with mean elevation of 260 m.a.s.l. and a mean slope of 6° exhibits rivers with a low transport capacity particularly in the lowlands and floodplains. Their tributaries originate in the foothills of the Guanacaste Volcanic Range, which has maximum altitudes of around 1900 m.a.s.l. (Barrantes, 2010). Although forests and wetlands were the original land cover of the catchment, forests have been partly replaced by crops, pastures and urban areas. The extension of protected areas has increased over the past twenty years and today, the only intensification of agricultural activities is related to cash crops such as sugar cane, rice and melon (Mateo-Vega, 2001). The study catchment is geologically composed of Tertiary and Quaternary materials, with a predominance of young Quaternary volcanic rocks (Guzmán, 2013).

The Tempisque sub-catchment used for modelling purposes is defined by the discharge gauging station La Guardia (Figure 1, right

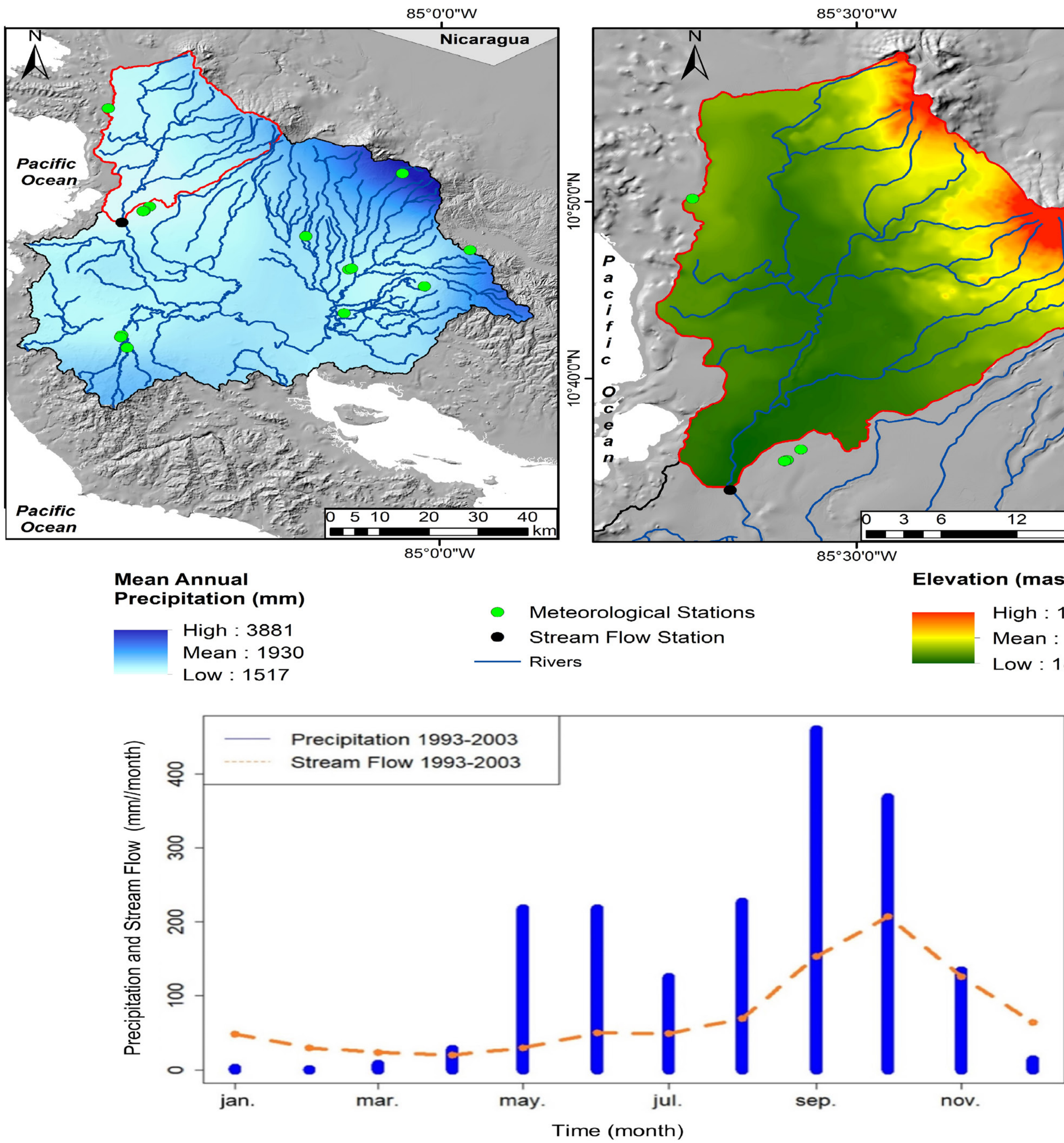


Figure 1: The right panel shows the topographic representation and drainage network of the gauged Tempisque subcatchment, Guanacaste, Costa Rica. The left panel shows a CHIRPS V2.0 interpolated mean annual precipitation (1981-2017) map for the Tempisque-Bebedero catchment. The green points indicate meteorological stations and black point shows the streamflow gauging station La Guardia. The bottom panel represents the monthly precipitation (blue bars) and streamflow (dotted red line) regime of the Tempisque sub-catchment for 1993 to 2003.

panel) and drains an area of 990 km2 (Table 1) (Guzmán, 2013). Here, twelve soil subgroups have been identified, most of them part of two taxonomic orders: entisols and inceptisols (56% and 34% of the catchment area, respectively) (Guzmán, 2013; ITCR, 2004).

A seasonal tropical climate with a clear cycle of dry and wet periods dominates the Tempisque catchment (Birkel et al., 2017). The Caribbean climate influences the upper part of the catchment close to the continental divide with consistent rain and high relative humidity throughout the year (Figure 1). The Pacific Ocean influence is associated with rainfall events mainly between May and November and a marked dry season from December to April (Duran-Quesada et al., 2010). The dry season presents low to zero precipitation (Figure 1, bottom panel) with maximum values in September and October. The monthly temperature varies between 30.2°C and 24.6°C throughout the year (Mateo-Vega, 2001). The streamflow regime closely follows the climatic variability as shown in Figure 1, bottom panel.

Table 1: Precipitation and physical characteristics of the Tempisque subcatchment.

Descriptor		Units	Tempisque
Precipitation	Min	mm/ year	1517
	Max	mm/ year	3881
	Mean	mm/ year	1930
Area	Total	km2	990
Geology	-	-	Tertiary and Quaternary materials (Quaternary volcanic rocks)
Land cover	-	-	Forest, wetland, crops, pastures and urban areas
Soils	-	-	Taxonomic orders: Entisols and inceptisols
Elevation	Min	m.a.s.l.	18
	Max	m.a.s.l.	1916
	Mean	m.a.s.l	332

Table 2: Summary of the tested daily Global Precipitation Products.

Product	Spatial Resolution	Temporal Resolution	Time period
CHIRPS v2.0	0.05°	Daily	1981- Current
MSWEPv2.1	0.10°	Daily	1979-2018
PGFv3	0.25°	Daily	1979-2010
TRMM-3B42v7	0.25°	Daily	1998-2019

2.2 Data

2.2.1 Ground-based and Global Precipitation data sources

The Center for Geophysical Research (CIGEFI) of the University of Costa Rica provided daily in situ precipitation data from 14 meteorological stations. Daily streamflow time series (1993-2003) from the La Guardia station were provided by the National Electricity Institute (ICE). The potential evapotranspiration (PET) was derived from the Moderate Resolution Imaging Spectroradiometer (MODIS;Kanniah et al., 2009), and spatially averaged to represent the mean catchment PET. The spatio-temporal resolution and available data of the GPP products CHIRPS v2.0, MSWEPv2.1, PGFv3 and TRMM-3B42v7 are summarized in Table 2 and are briefly described below. All data sets were spatially averaged for the Tempisque catchment and for the period from 1993 to 2003 for model analysis. The study period was selected according to the most reliable streamflow data record. The benchmark model used a single best precipitation station close to the streamflow gauging station (Figure 1) after initial tests with different spatial interpolations of all available 14 stations that performed worse in hydrological modelling.

CHIRPS v2.0

The Climate Hazards Group InfraRed Precipitation with Station Data (https://data.chc.ucsb.edu/products/CHIRPS-2.0/) version 2.0 has a relatively high spatial resolution of 0.05° and covers from 50°S to 50°N. The product uses an "intelligent interpolation" approach, which works with anomalies in high-resolution climatology. It also contains a daily, pentadal and monthly precipitation estimate from 1981 to present and was designed primarily for monitoring agricultural drought and global change (Funk et al., 2015).

MSWEPv2.1

The Multi-Source Weighted-Ensemble Precipitation (http://www.gloh2o.org) version 2.1 provides daily precipitation data from 1979 to 2018, with a spatial resolution of 0.10°. It was designed to analyze and understand differences in precipitation, as well as hydroclimatic processes to improve the performance of hydrological models (Beck et al., 2019).

PGFv3

The PGFv3 (http://hydrology.princeton.edu/data/pgf/v3/0.25deg/daily/) as an improved global precipitation product from Princeton University, that presents information combined through a re-analysis of data from various products, such as from the National Center for Environmental Prediction for Atmospheric Research (NCEP-NCAR) and the TRMM mission. The spatial resolution is 0.25° within a time window from 1979 to 2010 (Zambrano- Bigiarini et al., 2017).

TRMM-3B42v7

The Tropical Rainfall Measuring Mission (TRMM) global precipitation product (https://giovanni.gsfc.nasa.gov/giovanni/#service=MpAn&starttime=&endtime=&data=TRMM_3B42_Daily_7_precipitation) provides an estimate of the quasi-global precipitation of a wide variety of modern global products that relate to satellite-borne rainfall. It presents a spatial resolution of 0.25° with an extension of 50°N-S from 1998 to present (Huffman et al., 2010).

The Regional Climate Model (RCM) projections

The Regional Climate Model (RCM) has a spatial domain covering northern Central America and the Caribbean, and uses the coupled system ROM, which consists of a regional atmosphere model coupled to a global ocean and is based on the CORDEX (Coordinate Regional Downscaling Experiment) spatial domain (Cabos et al., 2018). REMO, is the Regional atmosphere Model with prognosis of the surface pressure, horizontal wind components, rainfall, temperature, water vapor, and cloud ice (Sein et al., 2015). In ROM, REMO is coupled with the global ocean model, MPIOM that includes sea-ice, marine biogeochemistry modules and a global hydrological discharge model and was dynamically downscaled matching the climatic features of Central America (Cabos et al., 2018). Therefore, we directly used the ROM near-future climate projections as a possible future scenario for hydrological modelling until 2045.

After different tests with regional climate models detected that none was suitable for calibrating the hydrological model. However, the in situ precipitation from a meteorological station in Tempisque sub-catchment was used to compute the benchmark calibration model used for further evaluations.

2.2.2 Hydrological modelling and drought assessment

The conceptual rainfall-runoff model HBV-Light

The HBV-Light model (https://www.geo.uzh.ch/en/units/h2k/Services/HBV-Model/HBV-Download.html) is a conceptual, semi-distributed model, widely used in hydrological forecast and water balance studies (Paredes et al., 2014). The model structure (Figure 2) incorporates the most important runoff generation processes with relatively few parameters (see Seibert & Vis, 2012 and Table 3 for more details). The model uses a soil water redistribution reservoir (3 calibrated parameters: FC, LP and BETA) that determines the volume of water recharging (PERC) the two runoff generation reservoirs from which streamflow is generated. Runoff is generated from an upper, quicker (ALPHA and K1) and a lower, slower (K2) reservoir. A simple triangular algorithm with one parameter (MAXBAS) is used for streamflow routing. The previously described GPP were used as model input and tested against an in-situ observational benchmark, in order to determine the most suitable product for drought analyses. A one-year warm-up period from 01 January 1993 to 01 January 1994 was used, allowing the model reservoirs to evolve from initial conditions (Montalván, 2017).

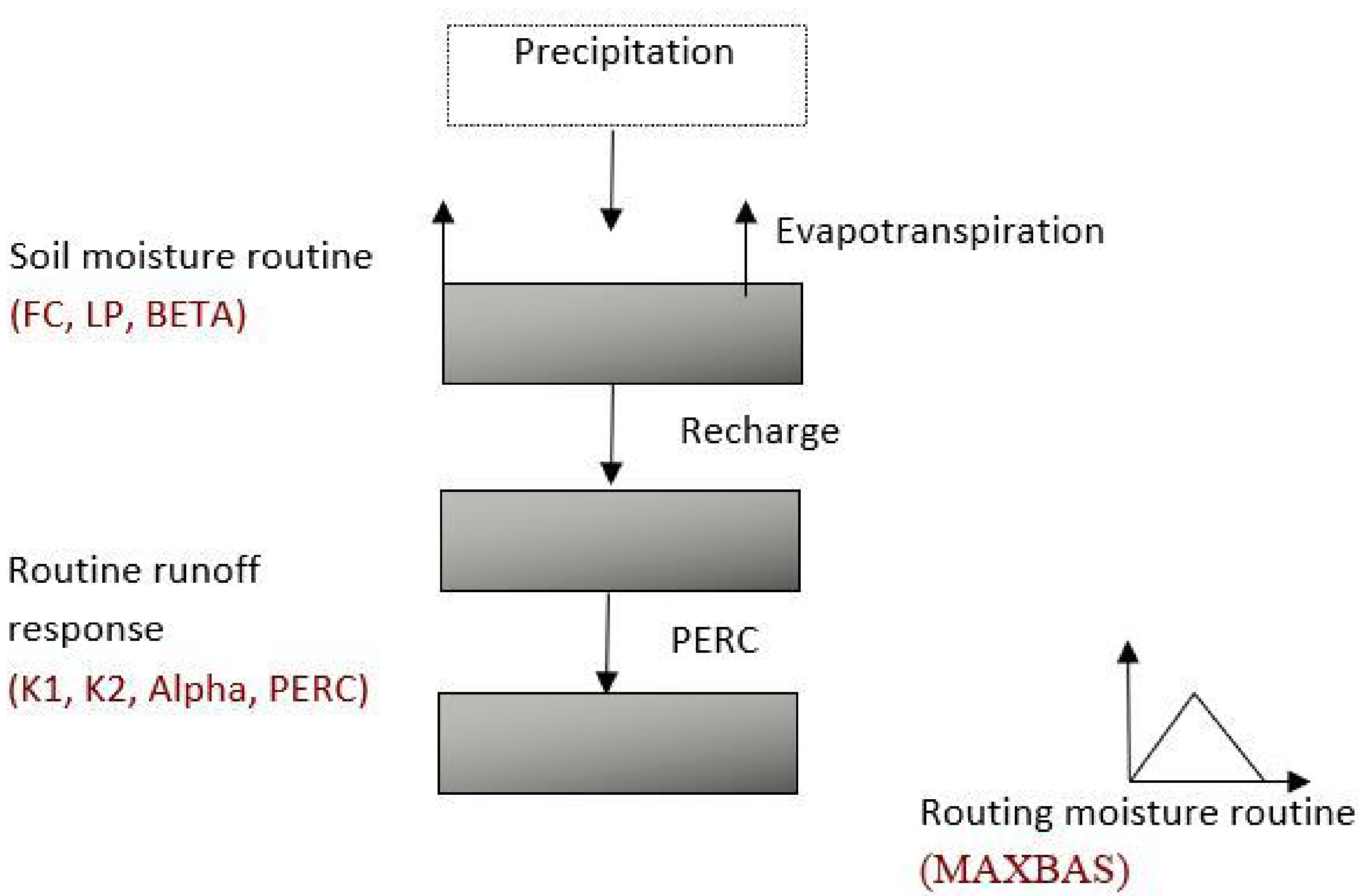


Figure 2: Structure of the conceptual hydrological model HBV-Light with calibrated parameters in red according to Seibert & Vis (2012).

Model calibration

After a one-year warm-up period (1993-1994), the model was calibrated for in situ and all GPP data from 1994-2003. Due to the relatively short streamflow record, we did not apply a split-sample test for validation.

The calibration process was carried in three steps:

I Calibration using in situ precipitation data as a benchmark for model evaluation.

II The benchmark calibration was refined using the posterior parameter ranges (5th and 95th percentiles) as parameter intervals in a second calibration.

III Each GPP was used as input for calibration using the parameter intervals established in the second step. The 100 best parameters were subsequently used for streamflow simulation for each independently calibrated product, to calculate performance statistics and to indicate the parameter uncertainty in form of the 5th/95th percentiles of simulated streamflow from the 100 best parameter sets (Nauditt et al., 2016).

From the calibration of each global precipitation product and the benchmark, we analyzed the relationships between the calibrated parameters attempting to detect changes and co-linearity between parameters as an indicator of limited sensitivity. Finally, the global product with the highest logarithmic Nash-Sutcliffe (LogReff) performance criterion was selected for the hydrological drought analysis.

This calibration process was carried out using a Monte Carlo parameter sampling strategy over 1 million iterations each (Westerberg & Birkel, 2015). The initial parameter values (Table 3) established by Birkel et al., (2012) in similar climate conditions were used. We additionally evaluated model performance using the Nash-Sutcliffe criterion (Reff), the modified Kling-Gupta efficiency (KGE) of Kling et al. (2012) and the Volumetric Error (VE).

Table 3: Initial parameter ranges and constrained parameter range after the first calibration step of HBV-Light in the Tempisque sub-catchment according to Birkel et al. (2012).

	Parameter	Initial lower Limit	Initial upper Limit	5th Percentile	95th Percentile
Soil Moisture Routine	FC	0.1	1500	32.7	1390.3
	LP	0.6	0.6	0.6	0.6
	BETA	1	10	1.0	3.7
Response Routine	PERC	0	10	2.9	9.8
	Alpha	0	1	0.1	0.2
	K1	0.05	0.9	0.1	0.2
	K2	0.0001	0.1	0.002	0.01
	PCALT	0	50	8.1	48.7
Routine Routing	MAXBAS	1	4	1.1	2.0

2.2.3 Hydrological drought detection and simulation

A hydrological drought event occurs when precipitation, soil moisture, water storage or discharge are below a defined threshold (Van Loon & Van Lanen, 2012). A hydrological drought can be characterized by its duration (length of a dry spell in days), severity (deficit volume in mm) and intensity (deficit volume in mm per time unit) (Van Loon et al., 2014).

- Duration (d) = days of drought below threshold.
- Severity (s) = ∑ (d(t) * Δt); where ***d(t)*** is the deviation from the threshold and ***Δt*** represents the time difference.
- Intensity (i) = s / d; where s is the severity in mm and ***d*** is the drought duration in days.

In this study, a dynamic threshold level was used, based on the hydroclimatic seasonality (dry and rainy season) of the catchment, with a high probability of shifts during the seasons and the persistence of droughts caused by a deficit of precipitation in the dry and/or rainy season.

The threshold level (Figure 3) was assumed as a dynamic 30-day moving window of the recorded 80th percentile from streamflow measurements, which is based on previous studies and the dynamic nature of the study streamflow regime (e.g. Van Loon & Van Lanen, 2012). A variable threshold can be chosen when seasonal patterns need to be taken into account (Van Loon, 2015). According to Hisdal et al., (2001) and Van Loon & Van Lanen, (2012) the recommended method for capturing such hydroclimatic characteristics is the minimum monthly moving threshold. The analysis was carried out for the observed streamflow and the simulation results from 1994 to 2003 (1993 was the model warming up) using the statistical language R according to Van Loon, (2015).

2.2.4 Future hydrological drought scenario

Future hydrological drought periods were derived following the same methodology of the dynamic threshold level as described before. However, streamflows were simulated driving the calibrated benchmark HBV-Light model with the projected climate variables from ROM as input data. The precipitation data from ROM and the simulated streamflow data were divided in two equal periods (24 years each) for comparison, the historic period from 1994 to 2019 and the projection from 2020 to 2045. Finally, the possible future hydrological droughts scenarios were characterized based on their intensity, severity and duration.

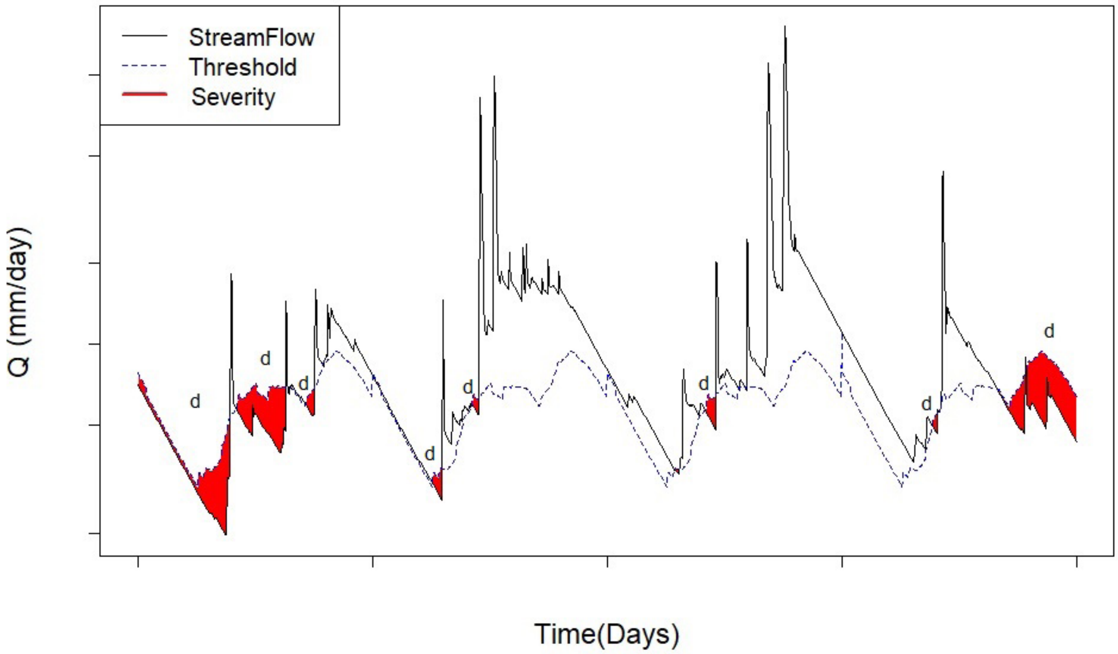


Figure 3: Representation of the daily threshold level method with an arbitrary hydrograph.

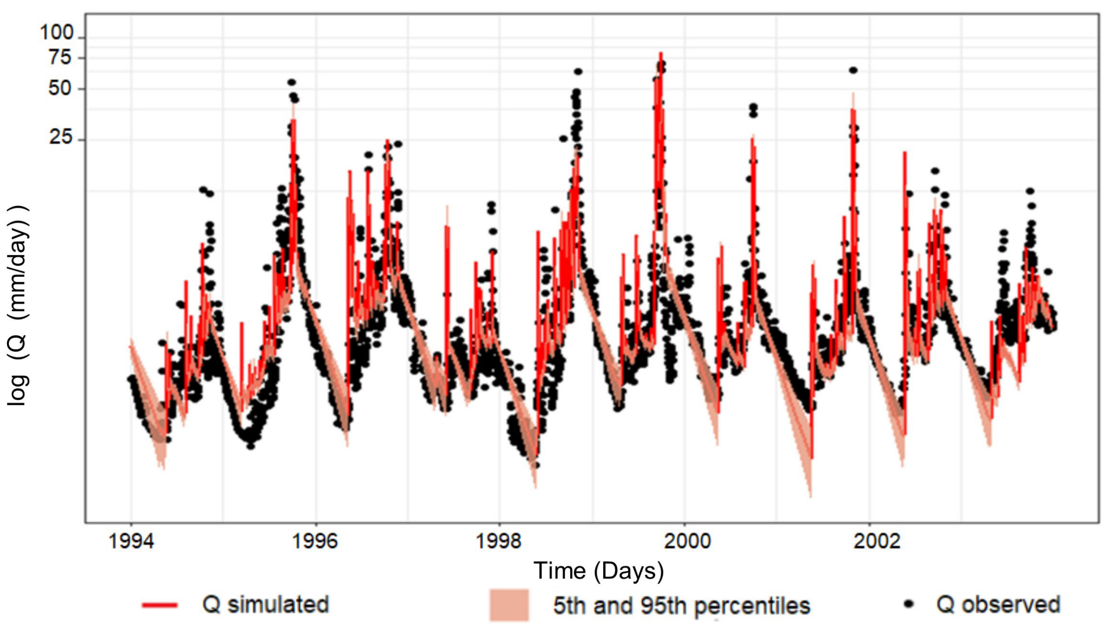


Figure 4: Observed streamflow time series (black dots) against the simulated best-fit streamflow generated with the benchmark in situ data (red line). The 5th and 95th percentiles from the best 100 results indicate parameter uncertainty (salmon color).

3 Results

3.1. Streamflow modelling in the seasonally-dry tropics with HBV-light

The model was capable of simulating the streamflow time series maintaining the climatic seasonality (Figure 4). The model was trained to match low flows using LogReff as calibration criterion and reproduced the major drought period recorded in 1998. Despite a more systematic underestimation of peak flows, the model was able to match the largest recorded peak flow in 2000. The best-fit Reff resulted in 0.59 for the benchmark model and a LogReff of 0.68. The model also did not exhibit problems in reproducing the re-wetting period after the dry season. In general, the model seemed a well-balanced representation of the streamflow dynamics of the Tempisque River over the study period from 1994 to 2003.

In comparison to the benchmark model, the calibration of each global precipitation product is presented in Table 4. The global products CHIRPS, TRMM and MSWEP resulted in best-fit KGE values of around 0.5. The PGF product showed a lower performance. All products resulted in acceptable volumetric errors with a maximum of 0.9. CHIRPS was identified as the most suitable global precipitation product for drought simulation due the highest LogReff value (0.65 – 0.5, table 4) compared with the results of the other products (TRMM, 0.65- 0.5; MSEWP, 0.3-0.003 and PGF, 0.3 -0.01). Furthermore, CHIRPS has the longer record with respect to the similar TRMM performance and was subsequently used for hydrological drought simulation.

Table 4: Evaluation of the 100 best HBV-Light calibrated model parameter sets using the in-situ station data benchmark and the Global Precipitation Products used for calibration. The CHIRPS product with the best LogReff rating (0.65-0.5) is highlighted in bold.

Parameters	Calibrated Products	Maximum Value	Minimum Value
Reff	Benchmark	0.6	0.5
LogReff		0.7	0.6
KGE		0.8	0.6
Volumetric Error		0.9	0.9
Reff	**CHIRPS**	0.5	0.4
LogReff		**0.65**	**0.5**
KGE		0.5	0.4
Volumetric Error		0.9	0.9
Reff	TRMM	0.5	0.4
LogReff		0.6	0.5
KGE		0.5	0.4
Volumetric Error		0.9	0.8
Reff	MSWEP	0.3	0.1
LogReff		0.3	0.003
KGE		0.5	0.3
Volumetric Error		0.9	0.7
Reff	PGF	0.1	-0.2
LogReff		0.3	-0.01
KGE		0.01	-0.2
Volumetric Error		0.9	0.5

The streamflow simulation based on CHIRPS as input data were compared visually to the benchmark simulation in Figure 5. Both precipitation inputs showed relatively similar low flow simulations. However, CHIRPS did underestimate the high flows.

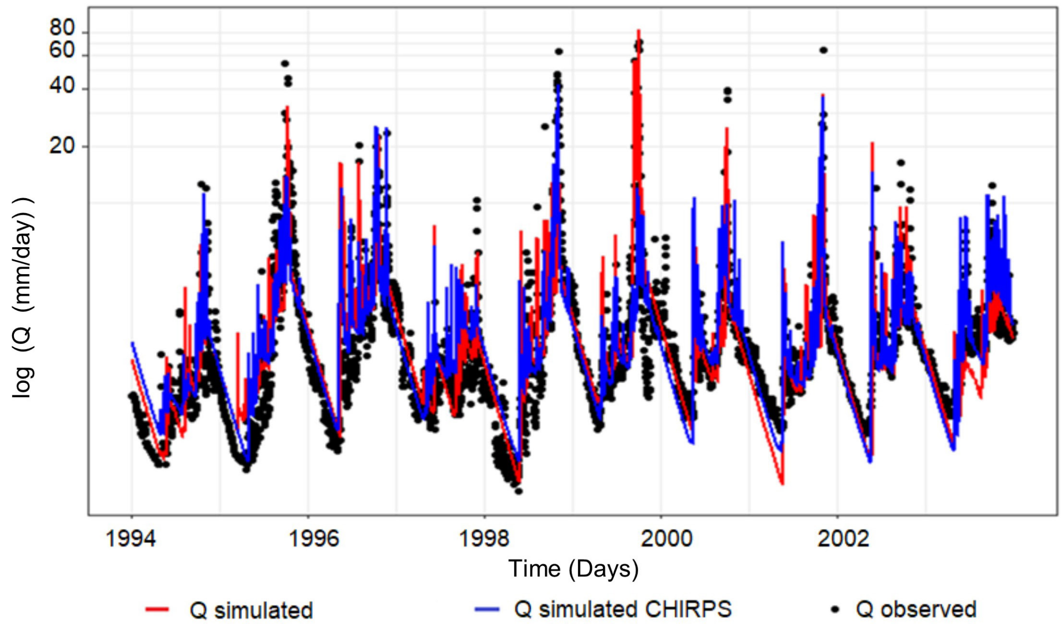


Figure 5: Visual comparison of the simulated best-fit streamflow time series from in situ benchmark precipitation input (red line) and from calibration with CHIRPS data (blue line). The black dots represent the observed streamflow.

Table 5: Hydrological drought parameters for the upper Tempisque river: duration, severity and maximum intensity using the observed streamflow, and simulations with in situ station data and with CHIRPS (1994 to 2003). The latter overall average drought parameters are compared to the major drought events with an absolute error estimate.

Hydrological drought parameters for the upper Tempisque river						
	Average Duration (days)	Max Duration (days)	Max Intensity Avg. (mm/day)	Max Intensity (mm/day)	Average Severity (mm)	Max Severity (mm)
Observed Flow	91.4	307	0.9	2.2	27.9	108.1
Simulated Flow CHIRPS	78.5	358	0.7	1.6	20.6	147.2
Simulated Flow in situ Station	99.8	329	0.6	1.3	25.4	99.8

Major hydrological drought periods with absolute error estimates							
Period		Average Duration (days)	Average Severity (mm)	Max Intensity Average (mm/day)	Absolute Error Average Duration (days)	Absolute Error Average Severity (mm)	Absolute Error Max Intensity Average (mm/day)
Observed Flow	1994	27.3	9.8	0.7			
Simulated in situ		26.8	9.1	0.5	-0.5	-0.7	-0.2
Simulated CHIRPS		48	21	0.9	20.7	11.3	0.3
Observed Flow	1997	9.9	7.1	0.6	---	---	---
Simulated in situ		18.9	9.3	0.7	8.9	2.3	0.2
Simulated CHIRPS		7.4	3.4	0.3	-2.5	-3.6	-0.2
Observed Flow	1998	10.5	2.3	0.3	---	---	---
Simulated in situ		23.4	4.1	0.3	12.9	1.8	0.04
Simulated CHIRPS		9	1.9	0.3	-1.5	-0.4	-0.01
Observed Flow	2001 - 2002	4.8	1.2	0.3	---	---	---
Simulated in situ		23.1	4.7	0.3	18.2	3.4	-0.05
Simulated CHIRPS		19.8	4.2	0.5	15	2.9	0.2

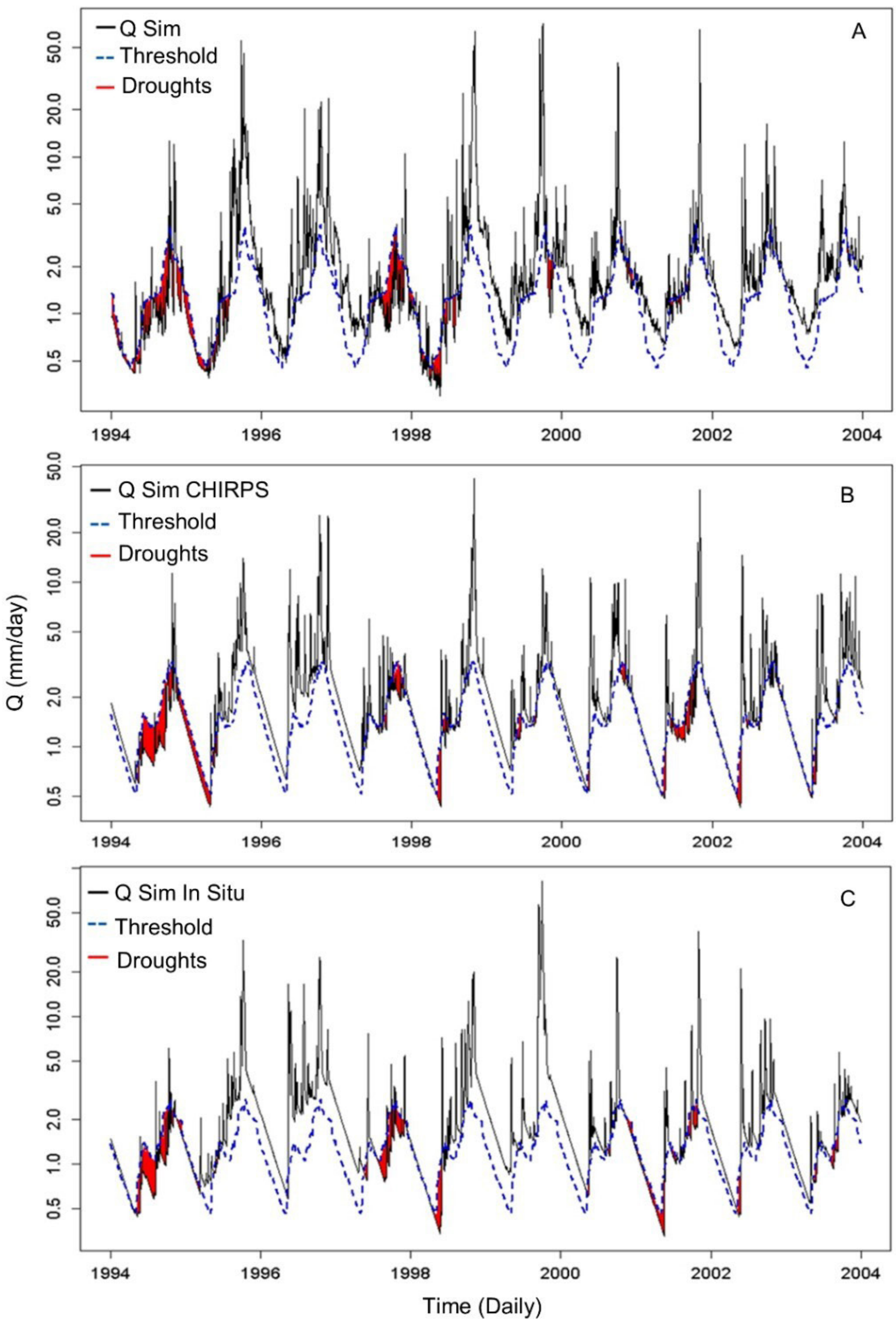
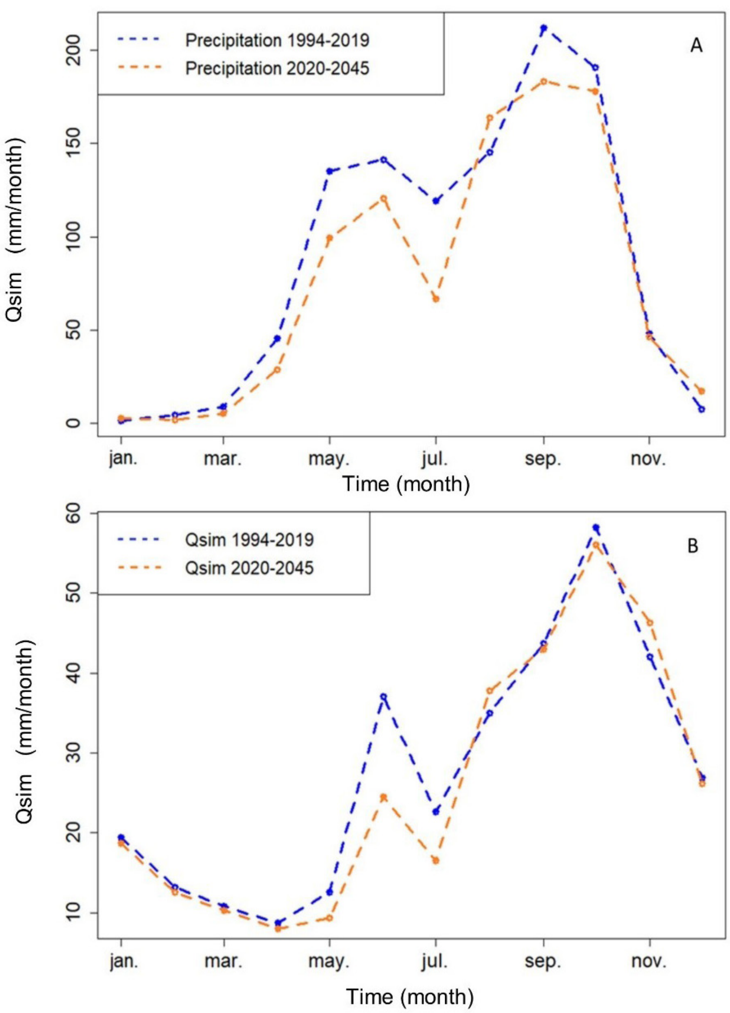


Figure 6: Logarithmic scale representation of the variable threshold level for drought detection (red shaded area below the threshold in blue) for (A) the observed streamflow time series (black line), (B) the CHIRPSv2.0 simulated flow (black line) and (C) the simulated flow (black line) by in situ data.

3.2 Hydrological drought analysis

The hydrological drought duration, severity and intensity are presented in Table 5. These parameters were derived from observed flow as a benchmark and from the HBV-Light best-fit streamflow simulations using CHIRPS and in situ precipitation observations. In Table 5, the observed flow showed an average drought duration of 91.4 days for the 1994-2003 study period with a maximum duration of 307 days and a maximum intensity of 0.9 mm/day.

We detected an overestimation of simulated drought severity compared to the streamflow derived severity. The maximum severity with CHIRPS resulted in 147 mm compared to only 108 mm from observed streamflow. The simulated drought intensity resulted closer to the observed benchmark of 1.6 mm/day. Generally, the simulated results showed acceptable estimates of hydrological drought parameters in comparison to observed values. In Table 5, we show the absolute error of simulated hydrological drought parameters with respect to the observed benchmark for the major drought events of 1994, 1997, 1998 and 2001 to 2002.



The model simulations using in situ and CHIRPS data correctly identified the major observed drought periods during 1994, 1997-1998 and 2001-2002. The panel A of Figure 6 shows the hydrological drought detection from observed streamflow. In comparison, the hydrological drought analysis with CHIRPS resulted in slightly longer drought duration and larger maximum severity than observed flow (Figure 6A). The in-situ precipitation input simulated drought (Figure 6C) particularly well and captured the minimum flow of the major drought 1997-1998.

3.3 Future hydrological drought

The projected precipitation data from the Regional Climate Model ROM resulted in an overall trend of decreasing precipitation for the period from 2020 to 2045 compared to 1994 to 2019 (Figure 7A). Mostly decreasing precipitation was projected for July corresponding to the mid-summer drought phenomenon. The climate projections were used to simulate a future streamflow scenario with the calibrated HBV-light model (Figure 7B). The scenario resulted in mainly lower streamflows at the beginning of the rainy season from April to June and for July, while the peak rainy season from August until October exhibited similar mean monthly streamflows.

The projected daily streamflow simulations from 2020 to 2045 for hydrological drought analysis are presented in Figure 8B in relation to the baseline from 1994 to 2019 (Figure 8A).

The hydrological drought analysis using the variable threshold level showed the main periods of streamflow deficit (Figure 8). Droughts described by the duration, severity and intensity for each period are summarized in Table 6.

Generally, the hydrological droughts detected between 2020 to 2045 increased in terms of the number of events, duration and severity compared to the baseline period 1994-2019. The latter increase was mainly caused by the projected lower precipitations. The major future drought periods detected were 2020-2021, 2021-2022, 2025-2027, 2033-2034. The largest drought event was identified for 2039-2041 and 2042-2043 resulting in a severity exceeding 125 mm of deficit volume in both cases (Table 6) as well as the duration indicating higher persistence and multi-year droughts (duration > 700 days).

Figure 7: A) Projected monthly precipitation data by ROM for 2020 to 2045 compared to the baseline period of 1994-2019. B) Simulated monthly streamflow regime using ROM as input to the calibrated HBV-Light model for 2020 to 2045 with respect to the observed baseline period.

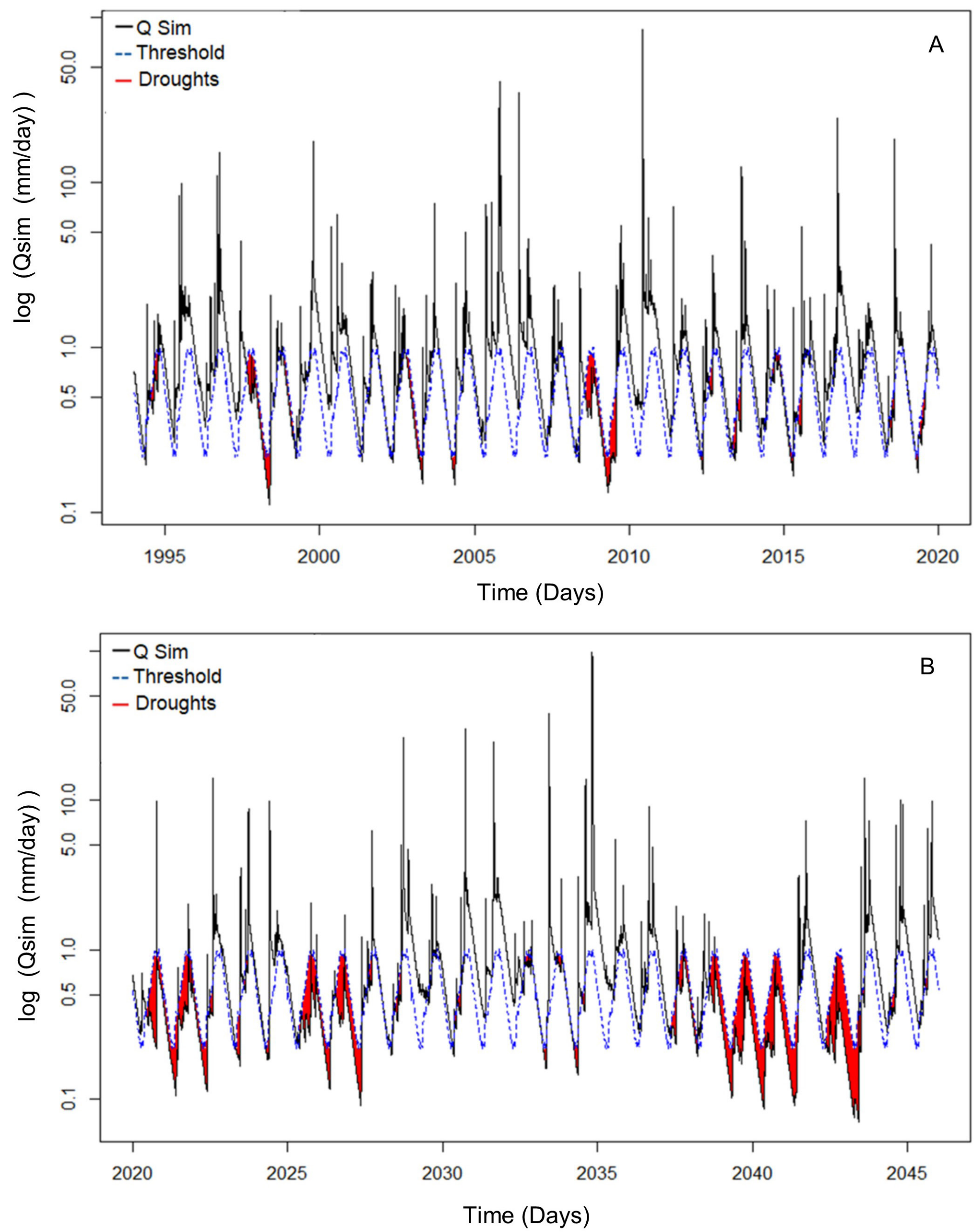


Figure 8: A) The drought analysis using the simulated best-fit baseline is compared to B) the projected future streamflow with identical threshold levels for 2020 to 2045 on a logarithmic scale.

Table 6: Projection of hydrological drought (2020-2045) with respect to the best-fit simulated baseline from 1994-2019.

Simulated hydrological drought events (1994 - 2019)				
Start Date	End Date	Duration (Days)	Severity (mm)	Max Intensity (mm/day)
22/8/1994	2/10/1994	42	11.0	0.4
20/8/1997	24/5/1998	278	48.5	0.5
25/10/1998	28/3/1999	155	13.9	0.2
9/10/2002	28/4/2003	202	21.2	0.2
21/3/2004	20/5/2004	61	3.4	0.2
28/7/2008	5/8/2009	374	77.2	0.5
3/8/2012	14/9/2012	43	10.1	0.4
11/5/2013	19/6/2013	40	4.8	0.2
28/6/2013	16/8/2013	50	9.2	0.4
10/9/2014	24/4/2015	227	16.9	0.2
16/6/2015	28/7/2015	43	7.0	0.3
27/5/2018	26/7/2018	61	5.8	0.2
15/5/2019	28/7/2019	75	8.0	0.2
Projected hydrological drought events (2020 - 2045)				
6/7/2020	5/10/2020	92	40.2	0.7
15/10/2020	20/6/2021	249	32.9	0.3
24/6/2021	21/10/2021	120	44.3	0.6
30/11/2021	28/5/2022	180	17.6	0.3
25/4/2023	24/6/2023	61	8.1	0.3
16/6/2025	2/10/2025	109	39.7	0.7
5/12/2025	25/5/2026	172	16.3	0.2
20/7/2026	30/10/2026	103	45.3	0.6
2/11/2026	25/5/2027	205	38.2	0.4
16/1/2033	8/5/2033	113	2.3	0.1
1/11/2033	17/5/2034	198	6.8	0.2
12/10/2037	28/3/2038	168	17.8	0.2
16/10/2038	6/5/2039	203	38.7	0.4
9/5/2039	25/6/2041	779	215.0	0.8
6/5/2042	8/6/2043	399	127.9	0.7

4. Discussion

4.1. The performance of Global Precipitation Products applied to simulate streamflow with HBV-Light

The HBV-Light model simulations driven by GPP in the Tempisque subcatchment (Table 4) showed potential in the data scarcity context of the seasonally-dry tropics in Costa Rica. A similar concept has been applied in other tropical regions with limited data, where GPP were evaluated with and without bias corrections and used for streamflow simulations via HBV-Light (Koutsouris et al., 2017). Zambrano-Bigiarini et al. (2017) highlighted the great opportunity that the use of GPP offers in conceptual hydrological modelling. However, other authors reported that streamflow simulations strongly depend on the product type (Bitew & Gebremichael, 2011) and that the global product must be carefully evaluated (Zambrano-Bigiarini et al., 2017). Despite notorious data scarcity in Latin America (Birkel et al., 2019), we were in a position to use constrained historic daily rainfall and streamflow records (1993 to 2003) to benchmark the global product driven model against station data. The CHIRPSv2.0 product (Funk et al., 2015) showed together with the TRMM product the best skill in reproducing observed streamflow dynamics similar to Zambrano-Bigiarini et al. (2017) who evaluated these products against the Chilean rainfall station network. We selected the CHIRPSv2.0 product for hydrological drought analysis over TRMM despite similar model performance due to the longer data record availability. Despite the challenge to achieve a good model performance in the tropics (Strauch et al., 2017; Zubieta et al., 2015) even with corrected GPP input data (Strauch et al., 2017), our modelling showed a reasonably good performance (KGE = 0.6). The model succeeded in simulating low flows particularly over the dry season (e.g. Figure 5), when hydrological models usually perform better for wetter periods (Pilgrim et al., 1988; Lidén & Harlin 2000; Nauditt et al., 2016). However, an initial quality check of the CHIRPSv2.0 data against the in-situ observations did apart from volumetric differences not show any temporal bias. Hence, the relatively acceptable simulations using the global precipitation product allowing for a more in-depth hydrological drought analysis.

4.2. Simulating hydrological drought with Global Precipitation Products

Clearly, the hydrological drought analysis will crucially depend on the model performance (van Loon & van Lanen, 2012) and we cannot expect the GPP to outperform the overall better simulations with in situ data. Nonetheless, the model simulations correctly identified the observed drought periods of 1994, 1997-1998 and 2001-2002 with the highest simulated severities, intensities and durations. These periods were related to strong El Niño events (2002-2003) and very strong El Niño (1997-1998) events emphasizing the potential drought behavior during such warm sea surface temperature (SST) episodes (Wolter & Timlin, 2011; NOAA, 2017; Muñoz-Jiménez et al., 2018). The hydrological droughts simulated by CHIRPSv2.0 (Table 5) were benchmarked against an average duration of 91 days during the study period 1994-2003, with a maximum duration of 307 days and with maximum intensities of 0.96 mm/day using observed streamflow as a benchmark. The model's absolute errors showed despite a variability from event to event a tendency of a slightly overestimated drought duration and under-estimated drought severity. In direct comparison, the CHIRPSv2.0-driven model showed less errors predicting drought duration compared to the deficit volume (severity) with errors up to 50 %. Similar to Van Loon and Van Lanen (2012), our analysis identified the rain deficit as one of the main causes of hydrological drought in regions with pronounced wet and dry seasons. Our results, additionally pointed in the same direction compared to findings from Hoyos et al., (2019). They found that rain and subsequently groundwater recharge strongly controls the occurrence of droughts by simulating synthetic scenarios in the seasonal tropics of Colombia.

4.3. Predictive capability of the model to estimate future hydrological drought

The RCM model ROM simulated precipitation regime revealed a slight decrease in precipitation from 2020-2045 (Figure 7A), compared to precipitation for the period 1994-2019. Similar to climate simulations from Neelin et al. (2006), where precipitation trends showed a drying trend for the Caribbean and Central American region. Moreover, the ROM model previously showed to match the intra-annual climatic behavior of rainfall in the Central American Dry Corridor (Cabos et al., 2019) with a characteristic bimodal distribution with two rainfall maxima in June and September/October (Taylor & Alfaro, 2005; Hidalgo et al., 2019). The precipitation decreases used as input to the calibrated HBV-Light model subsequently resulted in less future streamflow as a possible future scenario. Water deficit for particular months are often evidenced in future scenarios (Avilés et al., 2020), despite undeniable uncertainty in such projections. Here, such a deficit was identified around the first rainfall peak in May/June (Figure 7B). Comparable results were presented for a case study in Cuba, where future projections suggested a regional decrease of about 38 % of the mean annual precipitation and up to 61 % in streamflow (Montecelos-Zamora et al., 2018). According to Hidalgo and Alfaro (2012), changes in the magnitude and the seasonal cycle of precipitations most likely affect Central American ecosystem dynamics and water availability with most importantly, an increase in water scarcity in the region. Central America will experience a drought intensification (Imbach et al., 2018; Rauscher et al., 2008), as supported by our simulated future droughts. As shown in Table 6, increases in duration and severity were evident, which was also found for a larger scale study by Hidalgo et al., (2013). Reduced precipitation and strengthened mid-summer drought may have consequences for farming and energy production (Imbach et al., 2018), and according to Quesada-Montano et al., (2018), projecting hydrological droughts is necessary for an improved water management in the socio-economically vulnerable region of Central America. Finally, this study might pave the way towards an early drought warning system, which is fundamental to proactive decision making and disaster preparedness (AghaKouchak et al., 2015).

5. Conclusions

We used and evaluated GPP as input to the conceptual hydrological model HBV-Light for hydrological drought analysis in the seasonally-dry and data scarce tropics of Costa Rica. The use of GPP was encouraged due to limited information for modelling. We found that the CHIRPSv2.0 product showed the best skill to represent the Tempisque streamflow compared to in situ benchmark precipitation data. The hydrological model driven by CHIRPSv2.0 successfully simulated observed streamflow variability and subsequently allowed detection of hydrological droughts. A relatively successful simulation of historic streamflow also gave confidence in projecting potential future hydrological drought behavior. We specifically conclude that:

- Global Precipitation Products can provide an alternative source of input data for hydrological modelling if carefully evaluated against in situ data.
- The CHIRPSv2.0 product showed the best skill in simulating low flows in the Tempisque catchment at a relatively high spatial resolution with daily data.
- The conceptual model HBV-Light was able to reproduce observed streamflow with the minimum parameterization (8 calibrated parameters) and resulted in a maximum KGE of 0.8.
- The model driven by CHIRPSv2.0 data correctly detected the major drought events.
- The model driven by CHIRPSv2.0 data also correctly simulated the drought duration, but care has to be taken in using the simulated drought severity.
- The simulated drought severity suffered from errors of 50% overestimating the volume deficits.
- According to the results obtained future hydrological droughts will increase in duration and severity.

Our novel drought research in the tropics provides some alternatives in the implementation of hydrological models based on GPPs as a tool for drought management in areas where the amount and timing of precipitation is closely related to hazards and economic sustainability.

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