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Article

Assessment of Climate and Catchment Control on Drought Propagation in the Tekeze River Basin, Ethiopia

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Abstract: It is crucial to understand the development of hydrological drought which is unique to a sub-basin to derive management strategies that can address the cause. In this study, relationships between climate and catchment control against hydrological drought development in the Tekeze River Basin (TRB), Ethiopia, were assessed. The Water Evaluation and Planning (WEAP) modeling tool was selected to mimic the behavior and historical characteristics of the basin which was modeled for the period 1981 to 2018. The most severe drought events and historical drought years were selected and analyzed on a monthly basis, where the classical rainfall deficit drought was identified to be the most common typology within the basin. Once modeled, both meteorological and hydrological drought analyses were performed using the Threshold Level Method (TLM) where 168 months of meteorological drought with magnitudes as high as 110 mm/month and 60 months of streamflow anomalies with magnitudes of up to 17 mm/month were observed. While the temporal resolution impacts results pertaining to hydrological drought development, the analysis showed that the basin is fast responding, where storage characteristics did not play a significant role in delaying a hydrological drought onset. Compared to naturalized streamflow, the construction of the Tekeze Dam on the main river was indicative of an over 900% increase in dry season flows but a reduction of 23% of wet season flows, showing the potential to redistribute runoff in space and time.

Keywords: hydrological drought; classical rainfall deficit drought; climate control; catchment control; threshold level method (TLM)

Citation: Zeleke, E.B.; Melesse, A.M.; Kidanewold, B.B. Assessment of Climate and Catchment Control on Drought Propagation in the Tekeze River Basin, Ethiopia. *Water* **2022**, *14*, 1564. https://doi.org/10.3390/w14101564

Academic Editor: Maria Mimikou

Received: 13 April 2022
Accepted: 10 May 2022
Published: 13 May 2022

1. Introduction

The dubious and creeping nature of drought makes it the least managed natural hazard. Owing to being blindsided, conventional drought management approaches fail to offer timely and proactive solutions to societies that suffer the drastic, long-lasting consequences. In the period 1900 to 2021, over 2.7 billion people have been affected worldwide, of which 11.7 million people died along with a worldwide economic impact that exceeded 184 billion USD [1]. Ethiopia, located in East Africa, is a country that continuously experiences extreme weather conditions. The historical 1984 drought, among others, is a depiction of a multi-year drought that societies failed to cope with. It was characterized by long-term crop failure and lack of drinking water which led to a two-year famine where 300,000 people [1] have died. In 2015, an El Niño triggered drought resulted in the failure of two rainy seasons that fed 80–85% of the population which affected the livelihoods of many and increased malnutrition across the country.

Awareness of drought and its long-term impacts are recently growing through historical drought reconstruction, which helps to understand its recurrence. Among others, [2] and [3] have developed meteorological drought predictions based on climate models that use historical precipitation and temperature, which is a step closer to enhancing drought early warning systems. However, the apparent mismatch of scale between global climate estimates and local-level management often leaves decision-makers overwhelmed. This supports the reality that the societal impact of drought emanates not only from a global scale driven precipitation deficit but when that deficit transforms into water level reduction in existing water resources and soil moisture depletion in agricultural land. This opens an opportunity to use local systems, datasets, expertise, and indigenous knowledge that represent local impacts–i.e., bringing predictions to the scales relevant for decision-making. Local dataset, particularly terrestrial features, and human intervention that either alter or complicate the way a drought signal propagates [4] through scales essentially shapes how drought is felt and anticipated. Streamflow hydrological drought occurs as a result of a drought signal propagating from the atmosphere, through the terrestrial hydrological cycle [5]. As such, drought components (severity, magnitude, and timing) may be impacted by both climate and catchment drivers, with the dependence varying based on climate characteristics, local storage, and degree of human influence.

The dynamic, two-way feedback of anthropogenic influence in drought modeling is relatively difficult to quantify because it could range from water withdrawal from a reservoir or groundwater well to alterations in water management strategies in response to climate variability. The difficulty largely stems from the fact that modelers are not equipped with such detailed information [6] or due to a lack of documentation of water withdrawal. In some cases, the data could be documented but not accessible [7,8] or may lack accuracy due to illegal withdrawal [9]. As a result, medium and long-term modelers end up using simplistic approaches to extrapolate land use changes, agricultural practices [8], and failing to include the adaptive responses of humans. It is particularly more difficult in large-scale (ex. national scale) drought modeling that is driven by global parameters. This is due to the heterogeneity of local climate and catchment feedback, where adding man-made alterations to this equation largely increases the degree of uncertainty and hinders the potential for reproducibility.

In [10], the importance of using modeling-based studies over statistical analysis in terms of representing the underlying physical processes responsible for carrying a drought signal was highlighted. Although modeling basin hydrology comes with uncertainty, it can be a useful tool for separating the causes that contribute to the occurrence of drought as they allow simulation of near-normal conditions. This is particularly important when considering catchments that are altered by human activities. The use of hydrological models and even preserving benchmark catchments that can be used as a control for modeling highly human-modified catchments is presented in several studies [7,11–13]. These studies mostly combine hydrological models with statistical approaches to derive relationships and attribute drought severity and magnitude to its dominant cause. In this study, an effort is made to assess the effect of human intervention in potentially avoiding a drought onset.

Different statistical measures, ranging from evaluating spatio-temporal variability through indices [14,15] to quantifying deficit volume through threshold level methods [16–18] have been conducted to study drought propagation. We believe that the underlying physical characteristics responsible for drought propagation are better understood when using models coupled with statistical measures. As such, in this study, we aim to analyze meteorological and hydrological drought in the Tekeze River Basin and investigate drought propagation by considering climate and catchment controls. In doing so we: (a) account for 'the missing water' in both rainfall in the area and the main river as well as the timing, (b) identify the prominent drought typology and the underlying factors contributing to the propagation of a drought signal and (c) evaluate the effect of human intervention on hydrological drought development after the construction of the Tekeze Dam on the main river. To address the effect of human intervention, we use the observation-based approach [13] which we consider to be more appropriate for basins where reservoirs make a significant alteration to natural catchment conditions.

2. Materials and Methods

2.1. Description of the Basin

The Tekeze River Basin is located in northern Ethiopia, East Africa, between longitudes 36°30′–39°30′ E and latitudes 11°24′ and 14°30′ N (Figure 1). The area of the basin is approximately 83,293.73 km^2 where the climate varies depending on altitude but is overall characterized by a semi-arid climate in the east and north and partly semi-humid in the south [19]. The annual rainfall in the area, on average, ranges from 600–800 mm in the lowlands to 1300 mm in the highlands and temperatures vary from 3 to 21 °C in the highlands of the Semien Mountains and 19 to 43 °C in the lowland areas. During months from July to August, over 80% of rainfall falls in the area. Runoff from approximately 70% of the basin flows into the Tekeze River which is a perineal river with streamflow varying depending on rainfall seasonality. In 2009, the Tekeze Dam, a 70-km long and 188 m high double-curvature hydroelectric dam, was constructed on the Tekeze River. About 44% of the total area contributes to the dam where the storage volume of the reservoir is 9293 million cubic meters [20]. Regions in the Tekeze River Basin are highly susceptible to frequent droughts with recurrent periods ranging from two to ten years [1] commonly followed by harvest failure, illness, and death.

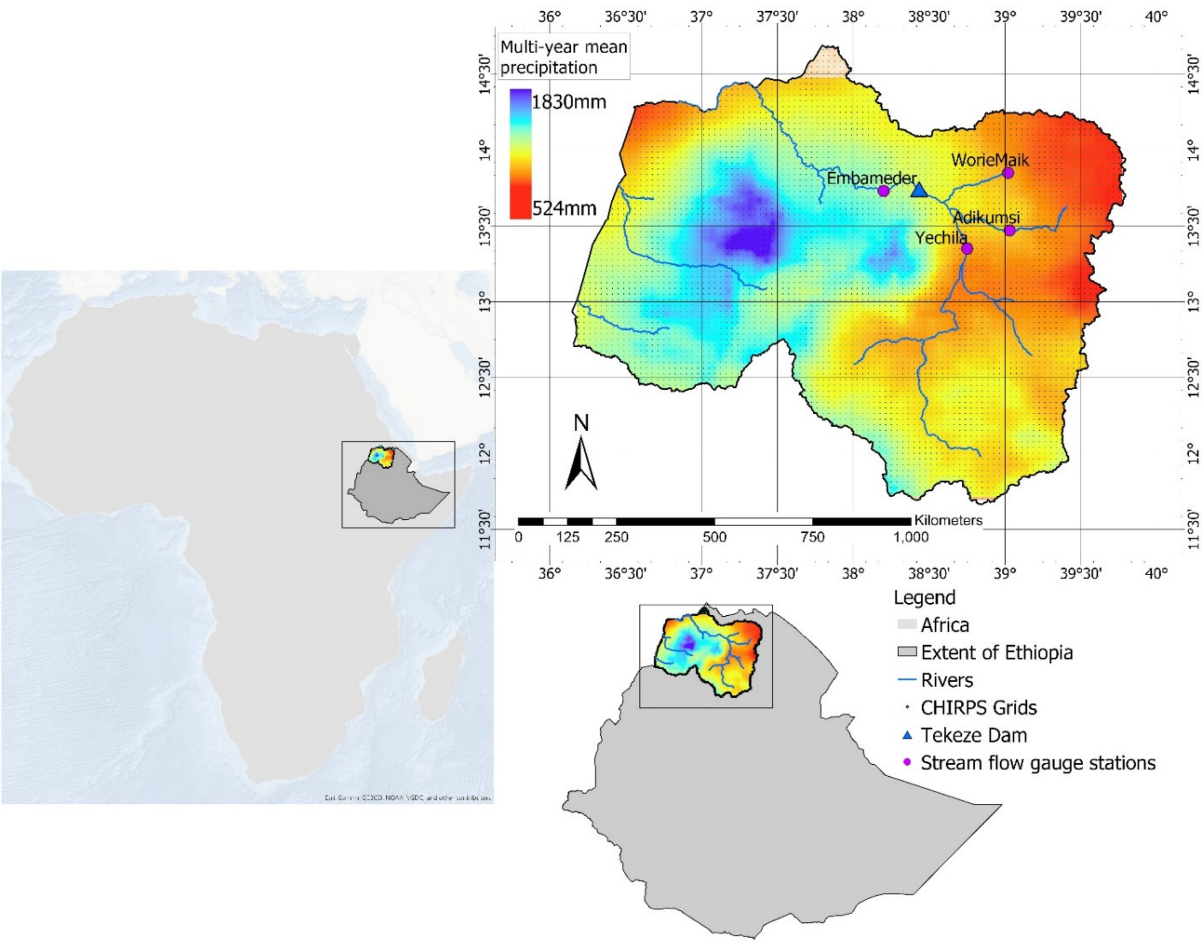


Figure 1. Location map of Tekeze River Basin relative to Ethiopia showing multi-year mean CHIRPS precipitation.

2.2. Data

Daily gridded Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset with 5 km spatial resolution starting from January 1981 to July 2019 was accessed through the WaPOR (https://wapor.apps.fao.org/) portal accessed on 25 February 2021.

The accuracy of CHIRPS can be attributed to the combination of station observation and physiographic predictors which makes it relatively reliable given the complexity of the terrain and limited gauges available in the basin. In addition to precipitation, data acquired to be used as input into the hydrological model includes observed average monthly temperature, Climate Forecast System Reanalysis (CFSR) humidity, and wind speed.

Catchment parameters for model input were land use and water withdrawal. Land use–landcover data of Tekeze River Basin was extracted from the WaPOR portal https://wapor.apps.fao.org/catalog/WAPOR_2/1/L1_LCC_A) accessed on 22 March 2021. These data are available on a continental scale with a spatial resolution of 100 m and take into account the seasonal phenology information from the crop calendar. They use the Land Cover Classification System (LCCS) developed by the Food and Agriculture Organization (FAO) and provide 23 landcover classes. This was also used to distinguish between rain-fed and irrigated cropland so that monthly variation of water abstraction for irrigation could be applied to the model based on the FAO crop coefficient corresponding to each landcover class.

Observed streamflow data at four gauging stations were collected from the Ethiopian Ministry of Water, Irrigation and Energy (MoWIE) for variable periods between 1981–2018 to calibrate the model for representing near-normal conditions. The stations and corresponding periods for which data were obtained are: Worie Maikental (2009–2018) and Adikumsi (1999–2005) which are tributaries to the main Tekeze River; Yechilla (1998–2002) and Embameder (1995–2007) which are stations located on the main river, just upstream and downstream of the Tekeze Hydropower Dam, respectively. Reservoir release data (2012–2018) and stage-volume data were obtained from the Ethiopian Electric Power (EEP), which was used to define zones of the minimum operating, maximum retention, and live storage reservoir levels in WEAP.

2.3. Hydrological Modeling of Tekeze River Basin (TRB)

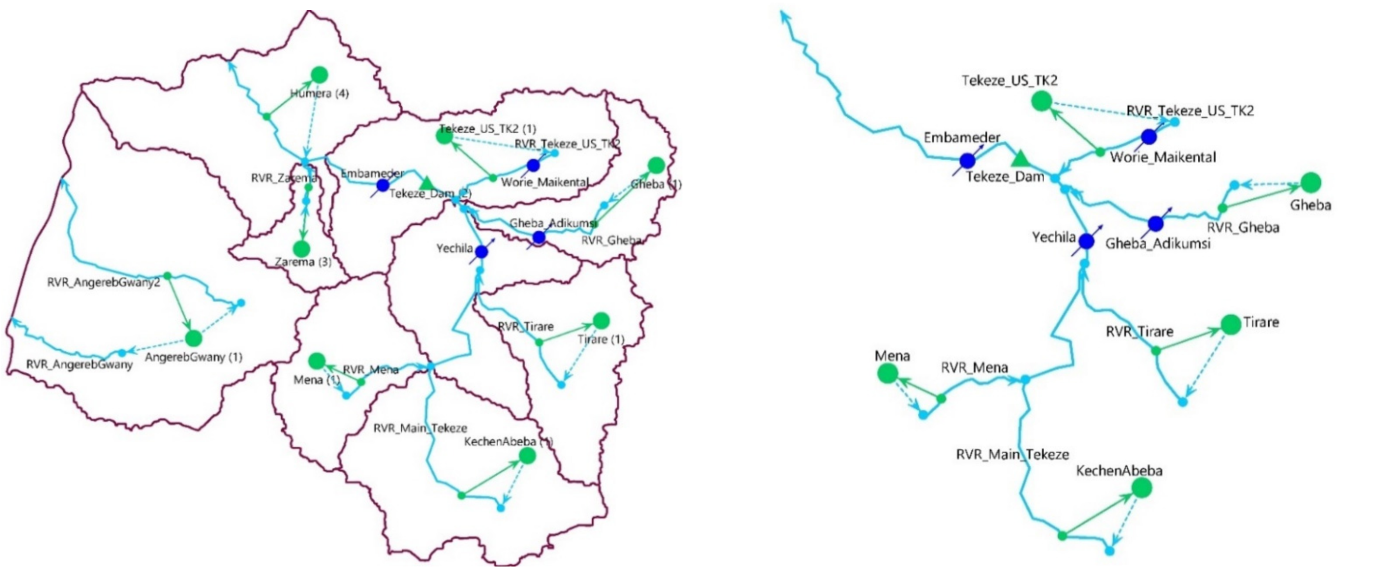
Hydrological models are often used to replicate flow sequences or patterns with a focus on peak flows. References [7,21] discuss that low flows are not satisfactorily captured by models which makes hydrological drought modeling difficult. In this study, the soil-moisture, two bucket rainfall-runoff method in WEAP is selected to model the hydrology of the basin, and the ability of the model to capture low flows is also assessed. Within the model, integration of the modified Penman-Monteith equation and empirical relationships that represent characteristics of each land use category was used to estimate actual evapotranspiration where each delineated sub-catchment is divided into independent landcover classes.

While setting up the model, we divided the basin into nine sub-basins each containing node-based climate data that are used as drivers for the routines that estimate the hydrological response. These data include monthly time series of remotely sensed and site corrected CHIRPS precipitation product (mm), average observed temperature (deg C), relative humidity (%), and wind speed (m/s). An area-weighted average method was used to convert the gridded climate data into a unique set of climate-forcing data usable by WEAP for each of the nine sub-basin nodes.

Percentage of landcover classification (Table 1) for each of the nine sub-basins were added into the model, particularly for assigning crop coefficients and for identifying irrigation water demand. This was important, as the model was configured to have irrigation within the sub-basin node and not an external demand node (as shown in Figure 2). This means water withdrawal for landcover classes under irrigated agriculture will take place when soil moisture falls below the default lower threshold and cease when it exceeds the upper threshold. Water that is not used for irrigation consumption is returned into the river, as a return flow. This was applied to all sub-basins with irrigation. Demand priority for all sub-basin nodes was assigned, with higher values for upstream nodes and lower at downstream nodes to represent the priority of water use from the river. It is, however, important to note that only six of the nine sub-basin nodes contribute to the section of the main river upstream of Embameder gauge station. The Tekeze Dam was incorporated into the post-impact period where the representation of stored water requires the use of generic reservoir objects in WEAP that divide the storage volume into zones. The size of each zone may vary throughout the year according to regulatory guidelines such as volume-elevation rule curves, hence, it was applied as a reservoir input.

Table 1. Percentage land use–landcover of the catchments in the study area (figure taken from WaPOR portal https://wapor.apps.fao.org/catalog/WAPOR_2/1/L1_LCC_A accessed on 22 March 2021 and restructured).

Name of Sub-Basin	Area (km^2)	Forest	Woodland	Shrub/ Bush	Cropland	Grassland	Barrenland	Water Body	Afroalpine	Built-Up
Tekeze Humera	11,422.77	1.40%	15.61%	38.00%	18.20%	23.94%	2.74%	0.01%	0.00%	0.09%
Gheba	5,008.57	2.65%	5.05%	28.78%	43.85%	5.38%	12.90%	0.11%	0.00%	1.28%
Zarema	2,277.20	4.23%	19.36%	29.51%	18.14%	19.85%	8.85%	0.00%	0.00%	0.06%
Tekeze US TK2	10,940.97	4.01%	13.57%	32.41%	33.94%	5.14%	10.30%	0.02%	0.32%	0.29%
Tekeze TK1	7,199.85	3.49%	11.49%	15.46%	22.40%	4.98%	38.18%	1.40%	2.58%	0.03%
Angereb Gwany	21,625.93	1.35%	23.02%	33.57%	23.70%	13.94%	4.33%	0.00%	0.00%	0.10%
Mena	6,174.08	2.39%	4.76%	15.05%	49.07%	7.46%	19.76%	0.00%	1.13%	0.38%
Tirare	7,419.70	3.97%	9.32%	15.67%	38.10%	4.66%	27.52%	0.39%	0.25%	0.13%
Kechen Abeba	11,224.66	3.43%	14.03%	23.16%	32.22%	5.83%	20.01%	0.00%	1.22%	0.10%



(**a**) (**b**)

Figure 2. WEAP schematics showing objects used to simulate the basin hydrologic process for the Tekeze River Basin. (**a**) shows the overall model boundary is hown where green circles represent the sub-basins; rivers that receive catchment runoff (represented by blue broken arrows) are connected by transmission lines (green arrows) to represent water diversion back to the catchment for irrigation. (**b**) shows the main Tekeze River and tributaries with gauging stations (deep blue circles) are used for flow calibration. Green Triangle shows the Tekeze Hydropower Dam.

Following model configuration, historical streamflow records at four gauging stations were used to calibrate streamflow using manual iterative calibration methods. To replicate the observed flow patterns, the Rainfall Resistance Factor (RRF) was the most sensitive land use and soil parameter that was modified throughout the year with a particular focus on the rainy season. For each sub-basin node, the RRF was varied between 2, representing higher runoff, and 10, representing higher infiltration. While varying this parameter, we took into consideration the relative slope and the percentage of landcover class, where the parameter was varied differently for each landcover (with built-up land represented by a low RRF and forest with high). Seasonality of precipitation was also considered for the cropland landcover class to account for the variation in soil moisture during wet and dry periods. As such, monthly variation of RRF was applied, with wet seasons having lower RRF than dry seasons.

To calibrate flows during the dry period which occurs in almost 8–9 months of the year, parameters that have a direct influence on baseflow were adjusted. This is because streamflow gains, when there is little to no rainfall, originate from the release of stored groundwater [21]. These parameters include Soil Water Capacity (SWC) and Deep conductivity (DC). Varying the SWC, which controls the depth of the upper 'bucket' in WEAP, altered sub-surface flow characteristics and essentially controlled the amount of water that could either percolate into the lower 'bucket' or be released as interflow. Deep Conductivity, which varies between 0 and 100% had higher control over baseflow (i.e., the bottom bucket) and was entered as a single value for the sub-basin, meaning that it does not vary based on landcover class. A combination of monthly variation in RRF, SWC, and DC was therefore used to calibrate flow beginning from the most upstream sub-basin. Headwaters from Kechen Abebea, Mena, Tirare, and Tekeze TK1 sub-basins were collectively calibrated at Yechila station. Adjoining sub-basins (Gheba and Tekeze US TK2) were calibrated at Adikumsi and Worie Maikental, respectively. These were then calibrated at the downstream station of Embameder.

To evaluate how well the modeled streamflow matched the observed data, we used Nash–Sutcliffe Efficiency (NSE) [22] for both average monthly stream-flows and monthly time series flows. It is amongst the frequently used statistical measures in hydrology and considers squared differences between observed and simulated flows.

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

where: n is the number of months used, P_{obs} is the observed streamflow, P_{sim} is the simulated streamflow, P_{obs}^{mean} is the average of the observed streamflow.

An NSE value of 1.0 indicates a perfect fit between observed and modeled values. if equal to 0, it is an indication that the modeled flow is better predicted by the observed mean and an NSE < 0 indicates poor model performance. Generally, NSE > 0.6 is desired in hydrologic modeling. NSE, along with the correlation coefficient was used to evaluate the accuracy with which the model was able to capture wet and dry month flows. To do this, the wet months (June–September) were separated from the dry months and the statistical measures were re-calculated.

2.4. Selection of a Threshold

To make comparisons between different drought categories, i.e., when studying drought propagation, as well as to avoid discrepancies that occur as a consequence of the fitted probability distribution in standardized indices, threshold level methods [18] were utilized for time series propagation between meteorological and hydrological drought in this study. The Threshold Level Method (TLM) entails drought characteristics derived from hydrometeorological variables using a predefined threshold level which is used to analyze deficit characteristics. It essentially compares each depth of precipitation or streamflow to its threshold counterpart to determine the magnitude and level of severity of a drought episode. This deficit volume plays a major advantage in water resource management that drought indices do not. In [23], they discuss the range of threshold levels for perennial rivers as between 70% and 95% flows to be reasonable.

A threshold that changes magnitude with time is recommended for catchments with high seasonality. A variable threshold that can cater to seasonal variations can therefore be used to define streamflow deficiencies as departures from the normal seasonal flow. As the main Tekeze River, originating from the most upstream sub-catchments Kechenabeba and Tirare, is a perennial river, a monthly threshold was derived from the 80th percentile of monthly duration curves.

To account for the introduction of the Tekeze Hydropower Dam in 2009 on the main Tekeze River, the period of analysis was divided into: pre-impact period (1981–2008), representing the naturalized or undisturbed period and post-impact (2009–2015). The latter accounts for changes to the natural storage characteristics of the catchment due to human influence which may affect the onset, magnitude, and duration of hydrological drought. To derive thresholds for estimating the streamflow deficit, the pre-impact period (1981–2009) was used as it is expected to represent near-normal conditions of the river. The same threshold was then applied to the post-impact period to disentangle the effect of human influence on drought characteristics. Analysis and comparisons were conducted on the main river, and the main gauging station used is at Embameder station (i.e., just downstream of the dam site). The computational procedure of the TLM as adopted by [7] and [23] is shown below:

The duration of a drought event is calculated as

$$\delta(t) = \begin{matrix} 1 \text{ if } x(t) < \tau(t) \\ 0 \text{ if } x(t) \geq \tau(t) \end{matrix} \quad (2)$$

where $\delta(t)$ is a binary variable indicating a drought situation on time t, x(t) is the hydrometeorological variable at time t, τ (t) is the threshold level of that hydrometeorological variable at time t, and t is measured in discrete time steps.

$$\Delta t = \sum_{t=1}^{T} \delta(t) \cdot \Delta t \quad (3)$$

where Δt is the duration of a drought event from its onset (t = 1) to the drought end (t = T), and the time step adopted in this study is 1 month.

Deficit volume (D) was calculated for both meteorological and hydrological drought, by summing the difference between the simulated flow and its corresponding 80% dependable threshold value; and by summing the difference between the rainfall of each month and its corresponding threshold value over the drought period given in Equations (2) and (3)

$$d(t) = \begin{matrix} \tau(t) - x(t) & \text{if } x(t) < \tau(t) \\ 0 & \text{if } x(t) \geq \tau(t) \end{matrix} \quad (4)$$

$$Dt = \sum_{t=1}^{T} d(t) \cdot \Delta t \quad (5)$$

where d(t) is the deviation from the threshold (τ) at time t (mm/month) and Dt is the deficit volume of a drought event (in mm)

2.5. Deriving Monthly Drought Thresholds

Using the calibrated time series streamflow at Embameder station, flow duration curves (FDC) for streamflow in the period 1981–2008 were developed for each month. A threshold value for the precipitation time series for locations upstream of the Embameder gauging station was also computed. However, the precipitation time series was transformed by applying a 30-day moving average as there are many zero values in most months that would make the 80% dependable precipitation zero. This is expected to alleviate complications that may arise when deriving relationships with droughts identified in other variables [16]. With an established threshold, it is possible to identify underlying processes for drought development and recovery. Establishing the mechanism through which drought develops, requires identifying the main climate drivers as contributors (precipitation and temperature) and consecutively defining the prominent drought type from drought typologies introduced in [24]. We base our definition of drought typology in the TRB on climatology and the ability to explicitly show propagation features (i.e., pooling, attenuation, lag, and lengthening) identified in [24]. A thorough examination of the magnitude and timing of rainfall and streamflow deficits was performed to explain the common drought typology in the basin.

A conceptual flow diagram for the main components of the methodology applied in this study is shown in Figure 3. The main input variables are shown in green, while the approach to generate required outputs is shown in blue.

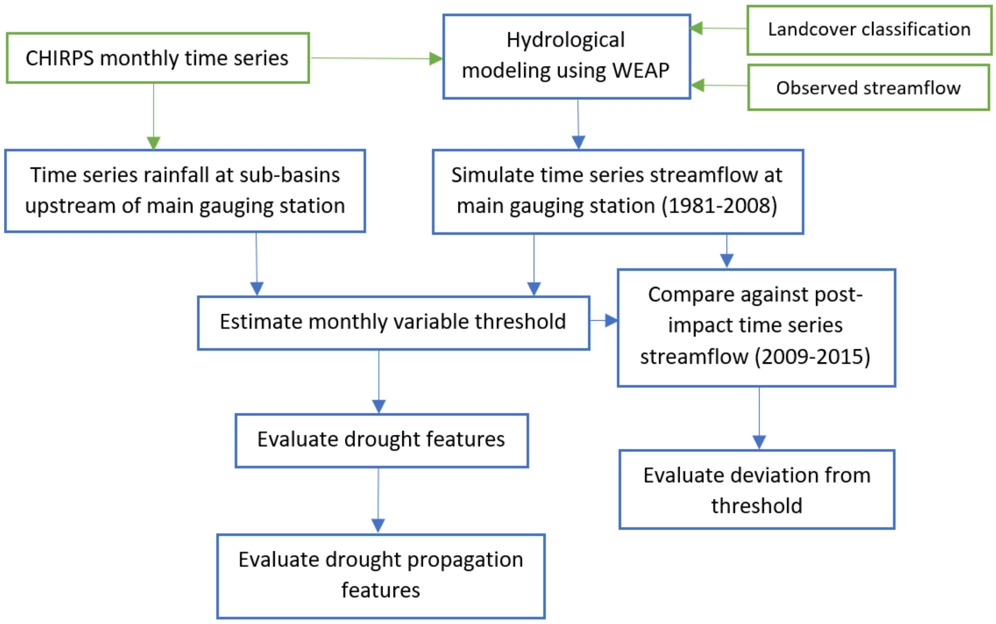


Figure 3. Approach followed for analyzing drought propagation in TRB.

3. Results and Discussion

3.1. Calibration and Validation of Streamflow in TRB

NSE was used as a measure of the model's ability to match historical streamflow at four gauging stations indicated in Section 2.3. Figure 4 shows the time series of streamflow under observed and simulated conditions for varying periods. Hydrological drought analysis in the river basin was performed on the main Tekeze River at Embameder station where the model's ability to capture low flows was evaluated.

NSE for the calibration period (2001–2007) for streamflow at Embameder station yielded a value of 0.89 and the validation period (1995–2000) resulted in 0.64, which indicates a good correlation between observed and simulated flows. Separately calculating the statistical measures of NSE and correlation coefficient for the observed and simulated flow during the dry and wet months was an indication that the model had relative strength in capturing high flows compared to low flows. This can be attributed to the fact that data quality at low flows is usually poor. In addition to instrument defects and man-made inaccuracies, particular problems during a low flow may be attributed to sediment erosion and deposition as well weed growth that is facilitated in the rainy season and highly impacts gauge measurement during the dry season [25]. Generally, the good performance of the model in the undisturbed period (1981–2008) provided confidence in its ability to simulate the hydrology of the basin in the disturbed period. The monthly FDC indicated in Figure 5 was plotted using the simulated streamflow of the undisturbed period. Seasonality of streamflow is also apparent as streamflow is largely concentrated in July–September and relatively less during May–June and October.

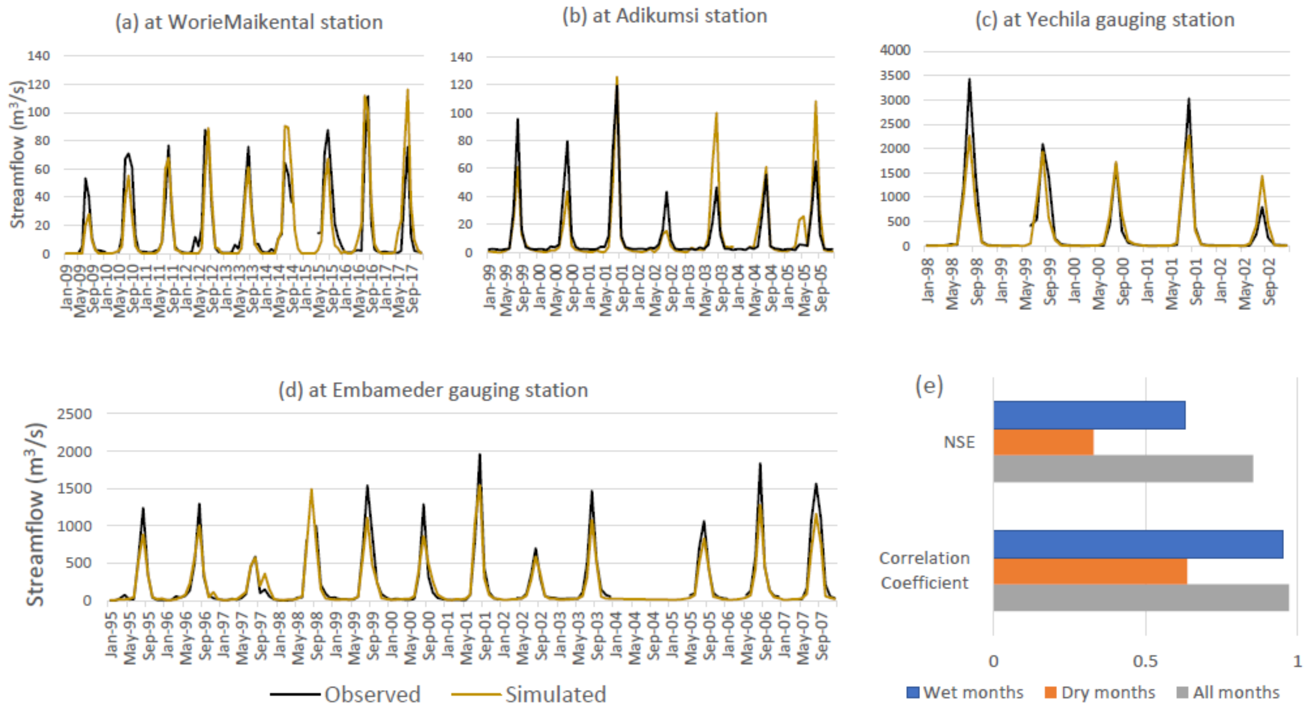


Figure 4. (**a**–**c**) Observed vs. simulated streamflow at gauging stations upstream of Tekeze Dam, (**d**) observed vs. simulated streamflow at Embameder gauging station, (**e**) statistical measures of streamflow at Embameder gauging station for wet and dry months.

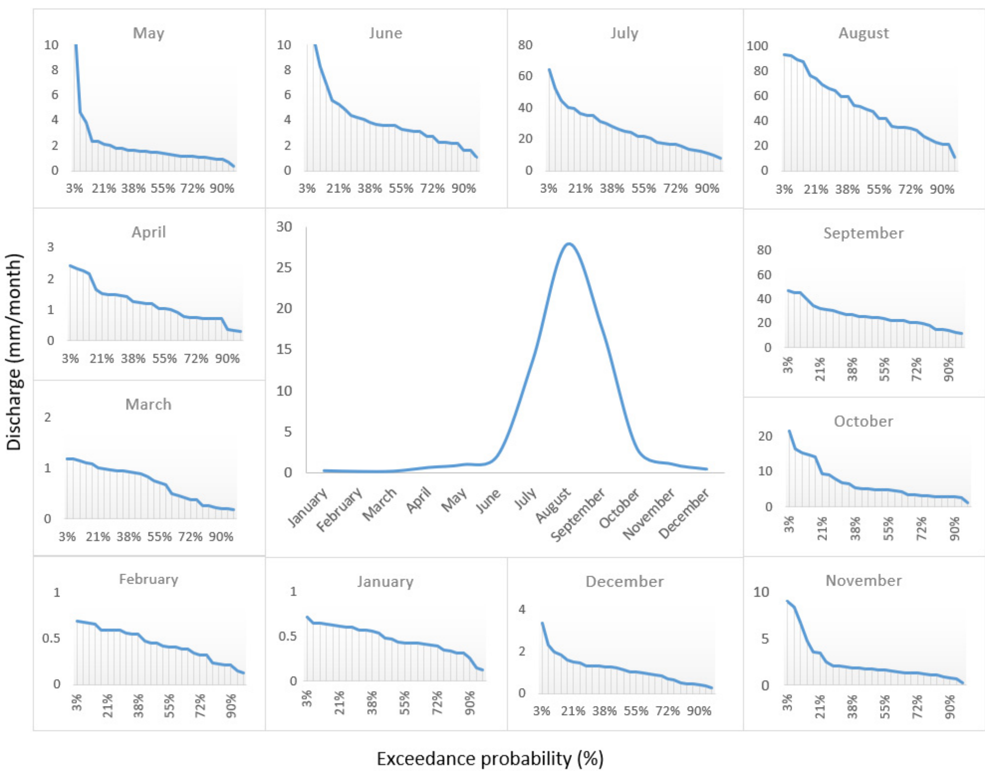


Figure 5. Derivation of monthly threshold level from monthly streamflow duration curves for Embameder station for the pre-impact period (1981–2008) (graphical representation adopted from [16]).

Following a similar approach, the 80% thresholds adopted for precipitation to evaluate the timing and magnitude of drought characteristics in the main river are included in Figure 6. This evaluation was conducted with regard to precipitation variabilities in the contributing headwater catchments.

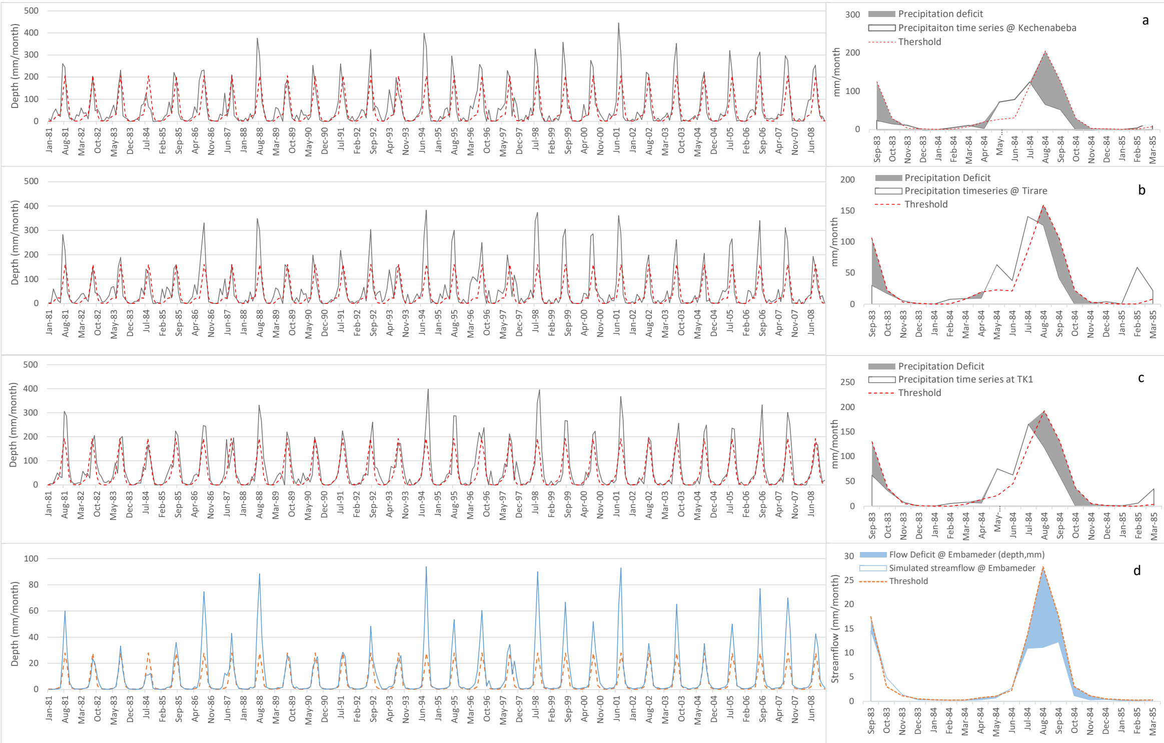


Figure 6. Left: Monthly precipitation (**a**) at Kechenabeba sub-basin, (**b**) at Tirare sub-basin, and (**c**) at Tekeze TK1 sub-basin and simulated streamflow ((**d**) at Embameder station) with corresponding 80% thresholds. Right: Illustrating monthly drought propagation in the year 1984. The shaded region (in grey for precipitation and blue for streamflow) shows the deficit.

3.2. Duration and Magnitude of Drought

Overall, 168 drought months (14 years) of precipitation deficit and 60 drought months (5 years) of streamflow deficit were observed. For this, consecutive drought periods for meteorological drought were separately analyzed and precipitation deficits below 10 mm/month were ignored to avoid minor drought events. As such, within the pre-impact period, the maximum number of consecutive drought events were 3 months mostly occurring in the mid-to-end of the rainy season (August, September, and October) having a maximum deficit depth of 180 mm. Other years seldom had drought deficit periods in May and rarely in April with a total maximum deficit depth of up to 32.5 mm.

The occurrence of streamflow deficit, in almost all cases, corresponds to the precipitation deficit. The majority of large deficit depths are again observed in the rainy season (July–September) with some exceptions during the semi-wet season (April–June). Although the occurrence periods match, it was not possible to identify a single rainfall deficit value (or a trigger) that can serve as an indicator of a potential streamflow deficit for all years under analysis. The magnitude of rainfall deficit causing streamflow deficit varied between 15 mm/month and 82 mm/month in different years. For instance, a rainfall deficit of 7.6 mm in August 1982, resulted in a streamflow deficit of 4.45 mm; an 82.14 mm rainfall deficit in August 1984, resulted in a streamflow deficit of 16.72 mm. However, a rainfall deficit of 19.35 mm in August 1997 did not result in a streamflow deficit in that same month. This may be due to the coarse temporal resolution used which is on a monthly basis but can also be due to the pooling effect obvious in some periods compared to others. The onset and end of both meteorological and hydrological droughts were simultaneous in the majority of the drought periods, meaning that they did not show a distinct lag. However, in a few months such as in August 1997, drought onset did not match and pooling is observed, where the combined rainfall deficit of two consecutive months resulted in a streamflow deficit. The drought end period, however, was simultaneous in all months analyzed, implying that an end to a meteorological drought would mean the same for streamflow drought in the same month. This shows that the lengthening feature of drought propagation is not present as both drought types cease simultaneously when subject to high rainfall.

These features, lengthening, pooling, and lag are governed by both climate and catchment control. However, the latter is governed completely by catchment [23] and shows that the lack of lag may be due to the minimal effect that catchment control has on drought propagation in the TRB.

The following section tries to explain the magnitude differences in precipitation deficit that resulted in streamflow deficit to address the last feature, attenuation. To do this, the most significant drought periods for studying drought propagation were identified as those having relatively large streamflow deficits. These years are 1982/3/4, 1987/89/90, 1993/7, and 2004. Magnitudes concerning all years of the pre-impact period are shown in Figure 7. As there is a relative monthly variation of magnitude in the selected years, we have also extracted the most significant years associated with months in the rainy season in Tables 2 and 3.

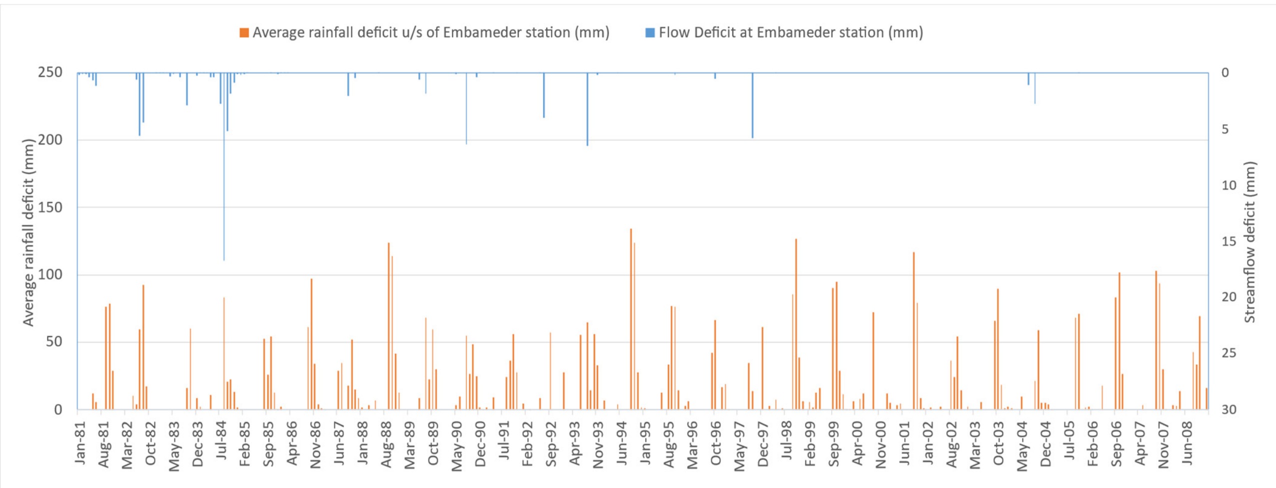


Figure 7. Time series average precipitation deficit at sub-basins upstream of Embameder station and streamflow deficit at Embameder station (1981–2008).

Table 2. Years with precipitation and streamflow deficit for September.

	Precipitation Deficit at Gauges Upstream of Embameder Station (Depth, mm)			Flow Deficit Embameder (Depth, mm)
Year	Kechenabeba	Tirare	Tekeze-TK1	
1983	101.21	76.01	67.70	2.89
1984	73.23	64.46	69.85	5.20
1987	99.99	74.22	84.50	2.04
1997	102.47	78.17	110.89	5.79
2004	85.74	98.14	97.93	2.78

Table 3. Years with precipitation and streamflow deficit for August.

	Precipitation Deficit at Gauges Upstream of Embameder Station (Depth, mm)			Flow Deficit Embameder (Depth, mm)
Year	Kechenabeba	Tirare	Tekeze-TK1	
1982	1.53	13.65	0	4.45
1984	139.74	32.83	73.84	16.72
1989	21.10	12.59	8.31	1.87
1990	43.37	35.79	35.14	6.35
1993	79.61	5.79	20.30	6.49

Streamflow deficit depth of months in the summer and spring rainy seasons had a combined maximum deficit of 26.56 mm with maximum peaks in August of approximately 17 mm. This shows that the deficit of water in streamflow is lower than in rainfall and therefore the magnitude is attenuated. Monthly deficit depths in most years also show a similar feature, where streamflow deficit magnitudes are reduced by 3–6 times the rainfall deficit magnitude. Although this is an anomaly, with negative deviations from the defined threshold, the streamflow deficit is fairly small to make quantifiable consequences in water resource use, indicating low stress on streamflow in the basin, even during the most significant drought period of 1984. The lack of catchment memory primarily comprised of shallow soil (with less than 0.5 m depth) and low water holding capacity [26], is an indication that the basin is fast responding. This, combined with the lack of lag and lengthening and in some cases reduced pooling show that catchment control has little effect on drought propagation.

Conventionally, a slow responding catchment is characterized as having natural storage and highly permeable geology, significantly increasing the time required for rainfall to convert into streamflow that reaches an outfall. Whereas it may also be a consequence of human alterations such as the construction of artificial reservoirs, varying release, and changing land use—where the effects are felt at different temporal scales. This modifies the natural temporal migration of streamflow as well as its magnitude. Fast responding catchments, on the other hand, have precipitation that converts into streamflow in relatively less time—termed near-natural flow. However, once again, human impacts such as urbanization and land use change may modify these characteristics.

In the TRB, land degradation and deforestation are significant anthropogenic driven factors that have reduced the water holding capacity of the soil [26] resulting in increased climate control for hydrological drought development. While climate characteristics dictate drought in the basin, reducing catchment memory is a critical challenge as 95% of arable land, in northern Ethiopia, is rain-fed [27]. The large difference between rainfall deficit and streamflow deficit is an indication that sectors that heavily rely on rainfall timing and duration face drastic consequences, particularly in these semi-arid regions where rainfall distribution determines crop production. The negligible streamflow anomaly is thus an indication that future plans for sustainable water withdrawal are attainable, especially when it comes to supplemental irrigation without posing a significant reduction in streamflow levels. To evaluate the role of water resources development in altering the behavior of hydrological drought and its potential for future use as a source of supplemental irrigation, the effect of the post-impact period due to the construction of the Tekeze Dam on the main river upstream of Embameder station was assessed and is presented in Section 3.4.

3.3. Drought Typology

Illustrated by streamflow reduction during the rainy season of drought years 1982, 1984, and 1990, the classical rainfall deficit drought typology was identified to be the most common in this basin. The classical rainfall deficit drought occurs solely due to prolonged meteorological drought, can occur in any season, in any catchment (fast responding or slow responding), and in any climate region as long as precipitation falls as rain [24]. As this drought type is a very common one, it can have all possible durations, deficit volumes, and deviations. These below-threshold stream-flows were pronounced in September and August but when considering a rainfall trigger for hydrological drought development, the magnitude was different. It was therefore apparent that at a small precipitation deviation from the threshold, in September, no significant streamflow deficits occur. Streamflow deficits often occurred when precipitation deficit surpassed 70 mm (without being preceded by a below normal threshold meteorological drought). However, for August, which is considered the peak rainfall period, small deficits of precipitation as low as 13 mm (without being preceded by precipitation that was below normal) were able to result in a streamflow drought.

The relatively smaller deficits of August (rainy month) which are an indication that there was rain, although below the threshold, were also checked against actual evapotranspiration (AET) obtained at a point upstream of Embameder gauge station from WaPOR portal to justify why such small deficits cause hydrological drought in the wet period.

From Figure 8, it can be seen that for the rainy season, AET starts to rise starting from June and peaks in August which is an indication that available precipitation was partly used by evapotranspiration during that same month. This characteristic could be a possible explanation for why small deficits in precipitation result in a large streamflow reduction in the wettest month. However, there is no clear wet-to-dry season drought observed as no long streamflow values below the threshold were seen. Water used up by AET may also explain why some prominent meteorological droughts with deficits over 100 mm (shown in Figure 7) did not develop into a hydrological anomaly.

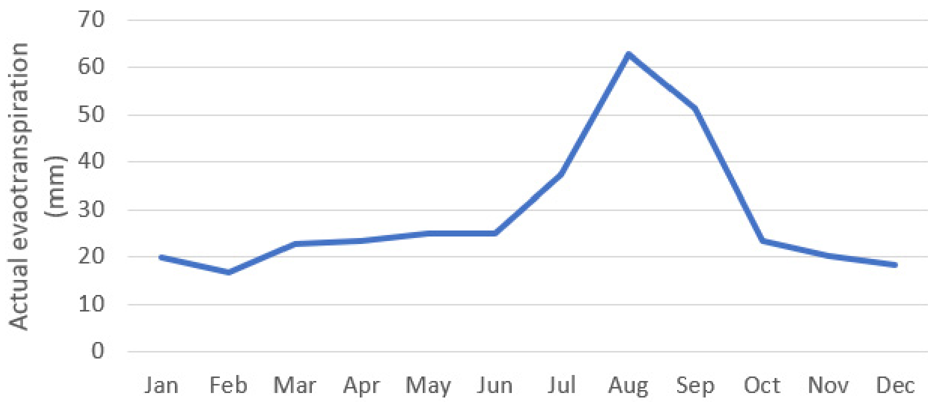


Figure 8. Actual mean evapotranspiration at a point upstream of Embameder station.

3.4. Hydrological Drought in the Post-Impact Period

Most hydrological drought modeling challenges lie in attribution to cause: is the drought human-induced or climate influenced or both? If so, in what proportion? This is important for drought managers in deciding whether they ought to devise adaptation strategies for climate-induced or mitigations actions for human-induced drought. However, in locations such as TRB where water abstraction is not a significant man-made alteration, the cause is relatively easier to separate. We used the observation-based approach [13] where the impact of a reservoir as a significant contributor to variation in drought onset was characterized. This approach demonstrated the quantification of human impact due to the presence of a surface water reservoir on streamflow, where a drought threshold was derived from the catchment upstream of the reservoir and was applied downstream. Using thresholds derived from the undisturbed catchment would reduce the possibility of underestimating human influence on impacted areas, which is commonly seen in streamflow indices [13].

Thresholds estimated for the undisturbed period were used to assess the impact of human influence on drought development in the Tekeze River Basin categorized under the post-impact period (2009–present). Available data for the post-impact period were collected from the Ministry of Water, Irrigation, and Electricity from the period of 2009 to 2015 and the graph in Figure 9 indicates the deviation of naturalized and human-influenced flows from the 80% threshold within that period.

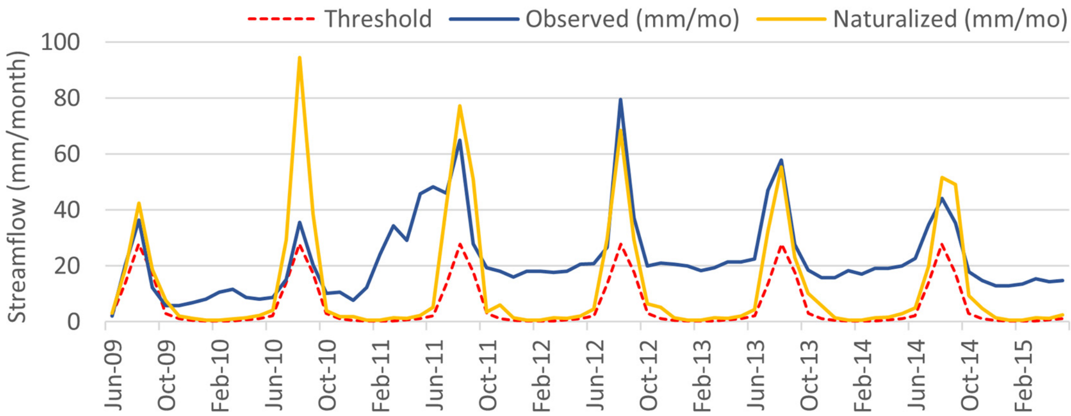


Figure 9. Naturalized vs. disturbed period streamflow (mm/month) for the period 2009–2015.

The observed discharge, especially during the low flow season (October–June) has a significantly larger deviation from the 80% threshold compared to the naturalized/calibrated flow which does not consider any human impact. Considering historical drought years specific to northern Ethiopia, a significant portion of the basin was subject to meteorological drought in 2009, 2011, and 2013 [1] which has not propagated into a hydrological anomaly. The deviation of flow from the 80% threshold for both cases (wet and dry season) is summarized in Table 4. Although there were no hydrological droughts observed during the 2009–March 2015 (disturbed period), in terms of increasing water level in the dry period, the control released from the Tekeze reservoir has a positive impact. Low flows are significantly increased and the potential for a drought onset could be avoided under such conditions.

Table 4. Positive flow deviation from threshold (mm) for the dry and wet periods.

Dry Period		
Month (2009–2015)	**Deviation (mm, Human-Influenced)**	**Deviation (mm, Naturalized)**
January	87.76	1.86
February	100.16	2.54
March	115.95	6.47
April	106.31	3.64
May	124.31	7.72
June	111.71	12.83
October	73.54	23.10
November	79.31	18.84
December	76.90	5.80
Total	875.96	82.8
Wet Period		
Month (2009–2015)	**Deviation (mm, Human-Influenced)**	**Deviation (mm, Naturalized)**
July	107.53	89.72
August	151.28	222.26
September	60.95	104.72
Total	319.75	416.71

Although there is an estimated increase of about 900% in streamflows during the dry period, high flows are also attenuated to maintain a controlled release which lowers the peak flows by about 23%. This is evident in the reduction of the water in the case where human influence is considered compared to that of the naturalized condition. If a meteorological drought that has developed due to a large reduction in precipitation during the wet season were to occur, the fact that high flows are attenuated may impact hydrological flows leading to a wet-to-dry season hydrological drought. Reservoir operation should thus take into consideration the drought threshold so that wet season flows are not reduced to a level that is below normal.

In semi-arid areas such as these, the distribution of rainfall is favored compared to the total amount of rainfall giving the stored water an edge in overcoming nuances created by variabilities in rainfall magnitude, timing, and duration. The potential to use this water as a form of supplemental irrigation during, or even at the end of the rainy period, as well as a means of maintaining soil moisture during sowing stages, can address problems of food insecurity and can serve as a means to rehabilitate damaged soil.

4. Conclusions and Recommendations

Understanding the space and time development and propagation of drought from a meteorological to a hydrological anomaly on a basin-scale can provide insight into sectors that can be developed sustainably. It also paints a finer picture in regard to which areas require immediate action and ultimately aligns it to the underlying cause. In this study, the threshold level method was applied to study drought development and to quantify the missing water in rainfall and streamflow that causes meteorological and hydrological drought, respectively. In doing so, the main drought propagation features, pooling, lag, and lengthening were rare, if none, and attenuation was highly pronounced. Overlap of months where a drought develops, and ends was an indication that catchment characteristics through storage had a minimal contribution to drought propagation. Attenuation of drought magnitude on the other hand, as the signal propagated from meteorological to streamflow drought, showed that streamflow deficit was negligible during significant rainfall deficits. The highest streamflow deficit was 17 mm during the most historical drought year of 1984. This indicated that stress on the river was minimal and sectors that suffered most were those that relied on rainfall timing and duration such as rain-fed agriculture.

Knowledge of the underlying cause of drought propagation also provides the potential to anticipate and address drought impacts before the effects occur. This will assist decision-makers to propose infrastructure development based on seasonal water availability ranging from local-level water harvesting structures to large-scale reservoirs. It will also allow them to devise water allocation strategies among various water-use sectors during water stress periods. As identified in this study, the classical rainfall deficit drought was the most common drought typology in many drought months which indicates that hydrological drought, even though highly minimal, occurs mainly as a direct consequence of rainfall deficit. Rain-fed agriculture, as part of the sectors directly influenced, can benefit from supplemental irrigation for increasing both the yield and soil resilience. Analysis of the post-impact period supports potential alleviation of water stress in sectors that are reliant on rainfall, through water storage and managed release. By capturing the sizeable summer rainfall in this basin, an effort should be made on distributing runoff over space and time. However, due to the reduction of streamflow by 23% during the rainy season, which is when most of the hydrological drought occurs, caution is necessary when developing water resources as a slight reduction in wet season flows may cause human-induced drought. Future studies in this basin should thus focus on how human intervention can be used to proactively manage drought, while considering key findings on factors that influence drought propagation in this basin. Some noteworthy considerations are discussed below, which may be beneficial when embarking upon such studies.

Depending on topography, shape, and geology, classifying the hydrological response of a basin into slow and fast as well as acknowledging potential man-made alteration is necessary as these modifications can make a hydrological drought occur in a different season than that of the meteorological drought. The spatial differences amongst basins must be considered as anthropogenic influence is dominant in some basins than others and therefore requires a different means of quantification. Fast responding catchments, as mentioned in most studies can relatively be modeled using existing drought indices but whether it is naturally slow responding and was modified by urbanization or land use alterations needs to first be evaluated as it largely affects the perception of drought timing. At the same time, the slow hydrological response of a basin is mostly human-modified (intensified/alleviated) and requires further reckoning. To avoid crude representation of regions, indigenous knowledge of the basins under scrutiny is necessary, especially with regard to identifying the type and degree of human influence. Thus, local-level data collection efforts need to be prioritized to model what matters to stakeholders and avoid simplified forecasts. For stakeholders to devise either adaptation strategies to climate-modified drought or mitigation actions for human-influenced, proper attribution to cause is needed. Where long-term data are a significant limitation, two solutions are suggested. The first is to capitalize on the skill of current models to reconstruct past near-natural conditions and the second is to adopt an ensemble approach for quantifying human impact. When making decisions on how human modification can positively contribute to tackling food insecurity, the influence and feedback should be closely evaluated because of the intricate contribution of anthropogenic influence as a driver and modifier of drought.

Author Contributions: Conceptualization, E.B.Z. and B.B.K.; methodology, E.B.Z.; software, E.B.Z.; validation, E.B.Z.; formal analysis, E.B.Z.; investigation, E.B.Z.; resources, E.B.Z. and A.M.M.; data curation, E.B.Z.; writing—original draft preparation, E.B.Z.; writing—review and editing, E.B.Z., A.M.M., B.B.K.; visualization, E.B.Z.; supervision, A.M.M. and B.B.K.; project administration, A.M.M. and B.B.K.; funding acquisition, E.B.Z. and A.M.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the FIU Graduate School Presidential Fellowship and SIDA Female research grant (Ref. No. SPCO/411/11/19).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Precipitation and Landuse data used in this study are publicly available. The data can be found here [https://wapor.apps.fao.org accessed on 25 Febryary 2021]. Restriction apply to the availability of observed streamflow and reservoir operation data. Data was obtained from MoWIE and EEP and are available from the authors with permission from MoWIE and EEP.

Acknowledgments: The authors are grateful for the funding support from Florida International University Graduate School, Presidential Fellowship. We would also like to thank Zelalem Berhanu from the Ethiopian Electric Power for providing us with necessary data under challenging cirumstances.

Conflicts of Interest: The authors declare no conflict of interest.

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