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Research Article

A Review of Techniques of Low Stream Flow Analysis for the Yobe River Basin, North-Eastern Nigeria

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ABSTRACT

The Yobe River Basin, situated in the semi-arid region of Africa, has experienced low river flows attributed to climate variability, high infiltration rates and obstruction of river channel capacity by weeds such as Typha Australis. These low stream flows have reduced the volumes of water from rivers, directly affecting water availability, distribution, ecosystem and crop failures, leading to significant food security concerns and financial losses. Particularly in the Yobe River Basin, mitigatory interventions have been hampered by insecurity challenges prevalent in the region for almost two decades, leading to inconsistencies in available data for policy making and management. Several techniques are available depending upon purpose, data requirement and hydrological characteristics. The climatic variability, data insufficiency and the need for water supply planning and management of the Yobe River Basin stress the need for the combination of two or more methods of analysis. The PRMS and PREMHYCE application packages have shown promise in their applications for watersheds of varying locations, coupled with the threshold level method. Data inconsistencies are recommended to be treated using climatic/hydrological indices such as the TSI, which integrates both Precipitation and Streamflow, making it more predictive.

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INTRODUCTION

Drought occurs when water availability falls substantially below normal levels and supply cannot meet demand over a defined period (Zhou *et al.*, 2021). It is commonly classified into four categories: meteorological, hydrological, agricultural, and socio-economic drought (Esit & Yuce, 2022; Smakhtin, 2001). Drought represents a water shortage affecting humans, livestock, and agriculture, often associated with but not limited to deficits in rainfall (MAFGWI, 2017).

Low stream flow is defined as the deficit of streamflow and/or surface water volume (Corderro *et al.*, 2021). Streamflow is highly sensitive to variations in precipitation, while large hydrologic structures can reduce flow and consequently limit access to surface water (Dan'azumi & Ibrahim, 2022). Low flows typically occur seasonally and represent the driest portions of a hydrograph. Hydrological drought, which is closely associated with low stream flows, is characterised by persistent reductions in stream discharge over one or more consecutive years (Smakhtin, 2001).

Goal 6 of the United Nations Sustainable Development Goals emphasises ensuring global availability and sustainability of water and sanitation through Integrated Water Resources Management (He & James, 2021). Analogies exist between flood and low flow frequency analyses in water resources design, planning, and operations. However, little effort has been directed at integrating flood and low stream flow assessment knowledge (Islam *et al.,* 2021). Consequently, researchers and water policy experts have emphasised formulating policies and frameworks to secure water and soil as essential environmental resources (Doro *et al.,* 2020).

Reduced streamflow is among the most direct and observable indicators of low flows, significantly impacting freshwater supply and agricultural systems (Ahsan *et al.,* 2023). In the Near East and North Africa, drought has long been associated with famines, large-scale migrations, and the collapse of civilisations. Over the past four decades, the region has witnessed an increase in the frequency, duration, and extent of drought events, often with severe socio-economic and environmental impacts, primarily attributed to climate change (Bazza, 2018). Climate change reduces available water volumes from rivers, lakes, and groundwater, affecting water distribution and energy supplies. It also increases tree mortality and wildfire incidence, and reduces vegetation carbon uptake, which collectively influences terrestrial carbon storage. Furthermore, crop failures linked to climate variability raise food security concerns and financial losses (Jiao *et al.,* 2021).

Despite their global importance, tropical regions have received less attention in drought research, limiting the reliability of monitoring and restricting understanding of spatiotemporal drought dynamics across scales (Corderro *et al.,* 2021). However, satellite-based platforms have gained prominence in drought studies in recent years, offering spatial and temporal advantages. Advances in algorithms, cloud computing, and storage capacity have expanded the application of remote sensing in drought monitoring and assessment (Jiao *et al.,* 2021).

In the Yobe River system, surface water generally appears from August to October, with groundwater as the only source in the remaining dry months (Adamu *et al.,* 2020). Parts of the river are heavily infested with reeds and weeds such as Typha, which obstruct flow and cause water diversion along undefined pathways. This invasion has been linked to the progressive recession of the Yobe River (IUCN, 2013). Lake Chad has been particularly affected, with its open water surface shrinking from over 26,000 km² in 1963 to approximately 1,500 km² in 2021, mainly due to losses from the Yobe River and other tributaries. This decline has severely affected regional economic activity and food security (Kombe, 2009). The problem is compounded by limited institutional and technological capacity to adopt conservation and engineering solutions (Salman & Momha, 2009).

This study, therefore, reviews methods of low stream flow analysis applicable to the Yobe River Basin, to contribute to a broader framework for catchments with similar climatic and geographic conditions.

General Criteria for Low Stream Flow Analysis

Low stream flow analysis methods are usually categorised based on several factors, including the purpose of analysis, the availability of data, temporal and spatial scales, and hydrological features. These standards aid in identifying the best techniques for examining and evaluating low-flow conditions in rivers and streams (Semananda & Hewa, 2022).

The purpose of the analysis relates to the objective, which may be forecasting, frequency analysis, or drought severity estimation. The probability of low flow episodes, such as 7-day or 10-year low flow, is the primary focus of hydrologic frequency analysis. The length, severity, and volume deficit of periods of low flows are highlighted in the description of low flow. Regression, machine learning, and time

series modelling are some of the methods used in forecasting and modelling to anticipate low flow circumstances (Delsanto *et al.* 2023).
The available data for any given case of study refers to Temperature, Precipitation, and simulated or observed streamflow data. Techniques for Observed Streamflow make use of measured flow records. Techniques involve the use of climatic and hydrological indices in order to establish relationships for forecasting. Simulating low flows using hydrological models (Macedo *et al.,* 2025)
The time-scale of interest, such as the daily, multi-day, seasonal or annual low flow conditions, is also a factor in determining the method of selecting a technique. Examples of methods are time series modelling and frequency-duration curves (Vogel & Fennesey, 1994).
Low-flow analysis techniques based on hydrological features are classified based on several features. The Flow regime characteristics require techniques that can handle zero flow and discontinuities for Perennial or Intermittent rivers. Recession analysis or event-based modelling is also ideal for stable and flashy flow regimes (Smakhtin, 2001; Tallaksen & Van Lanen, 2004). The Baseflow Index is used to determine the Baseflow contribution to a river. Watershed characteristics such as catchment size and geology type need high-resolution models, seasonal low-flow analysis and models that simulate rapid recharge and delayed baseflow. Low flow duration or persistence is another criterion that affects the technique to be adopted with respect to hydrologic features of a catchment; the 7-day minimum flow statistics for short duration and monthly or seasonal indices, drought duration-severity curves for longer durations are considered (Mishra & Singh, 2010).

Any one or a combination of methods would depend upon the particular case of study concerning the above-mentioned criteria.

Table 1: General Criteria for selecting Technique of Low Flow Analysis

Criterion	Description	Method
Purpose of Analysis	Frequency, low flow severity, forecasting etc.	Time Series Modeling, Streamflow Duration Curves
Data Availabilty	Temperature, Precipitation, Relative Humidity, Evapotranspiration, Solar Radiation, Wind Speed, Streamflow	Hydrological/Climatic Indices and Models, Regression and machine learning, Streamflow Duration Curves
Time-Scale	Daily, multi-day, seasonal or Annual	Time-series modeling/Frequency analysis
Hydrological Features	Flow Regime, Catchment size, Perennial/Intermittent streams etc.	Hydrological models, GIS and Remote sensing methods.

The Yobe River Basin

The area under study is the Yobe River which drains into the Lake Chad in North-East Nigeria. The catchment lies within the geographical locations of $12^0$44'49.42''N and $11^0$02'56.17''E in Gashua to $13^0$41'43.49''N and $13^0$22'14.49''E in Malum-Fatori. The basin has a catchment area of 32,000Km^2 measured with ArcGIS 10.7.1. Annual rainfall amount is strongly contrasted throughout the basin ranging from 1,500mm to less than 100mm annually. Due to high temperatures throughout the year, the potential evapo-transpiration exceeds 2,000mm per year (Adamu *et. al.,* 2020). The Yobe river basin has exhibited a significant level of sensitivity to weather variability and demographic characteristics amongst others. The trend in this reduction had been recorded in which water level had been estimated in Bol (a village situated in Chad in the southern pool of the lake) and N'Guigmi (a village in Niger at the northern pool of the lake). Estimated levels from the Topex/Poseidon satellite had also been estimated where the Yobe River intersects the Lake Chad (Martinson, 2010).

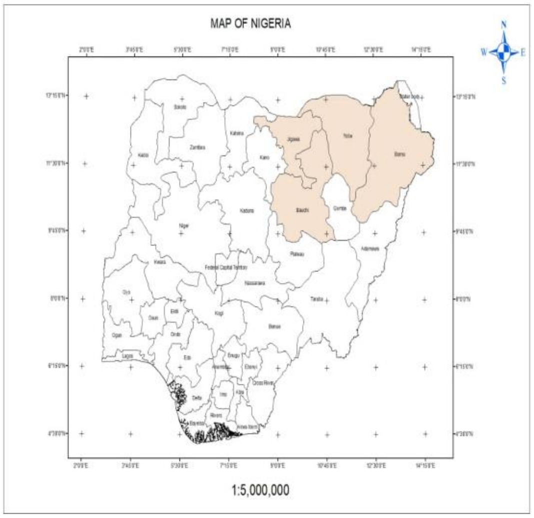

Figure 1: Map of Nigeria showing states covering the study area

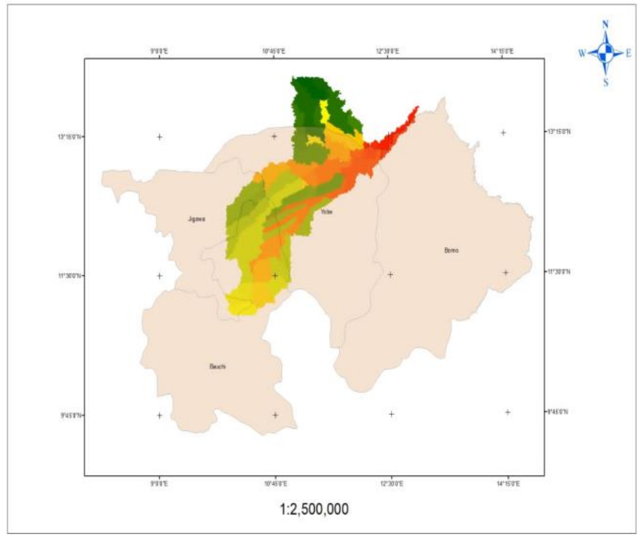

Figure 2: Map of the study area

The Chad formation overlays the Yobe River Basin and is separated into three aquiferous zones: Upper, Middle and Lower aquifers. The Upper aquifer is unconfined and semi-confined, while the Middle and Lower aquifer zones are confined. The Middle aquifer consists mainly of fine to medium-grained sand sandwiched between the silty and clayey part of the Chad formation at a depth of about 250 m with an average thickness of about 50 m. The Lower aquifer is encountered in Maiduguri, Gudumbali, Kukawa and Monguno areas of Borno State and ranges in depth from 250 m to 500 m depending on the local geology (Adamu *et al.*, 2020). The majority of the population in the basin, who are mainly traditional smallholders producing staple foods for household consumption and have marginal connections to the market, are overwhelmed by the depletion of water in the basin. Interest has been developing in recent years due to the failure of large-scale irrigation schemes, which have led to seeking ways to improve the productivity and livelihood of the small-scale farmer (Salman & Momha, 2009). There is a high tendency for the situation in the basin to worsen in the future as the population and wildlife continuously migrate in search of areas with water for survival. The situation has made climatic refugees from the vulnerable populations as they migrate across the borders (Kombe, 2009).

Techniques of Low Stream Flow Analysis in the Yobe River Basin

A few techniques are considered suitable for the analysis of Low Stream Flow in the Yobe River Basin, considering the need for water resources planning and management due to climatic variability in terms of purpose and long-term stream flow inconsistencies in data availability.

Climatic data are available with inconsistent stream flow data due to the insurgency in the region. Subsequently, the methods are classified according to the criteria set in Table 1. The methods are hereby classified in terms of Low flow severity and duration, data availability and hydrologic features.

Low Flow Severity and Duration Method.

Low flow severity quantifies the volume of flow deficit below a predetermined threshold over a low-flow period. It is the cumulative shortfall compared to normal conditions or a set threshold. Low flow duration refers to the time, typically in days, weeks, or months, Streamflow remains below a defined threshold (Salehabadi *et al.*, 2024). The threshold level method of low flow analysis involves defining a level below which Streamflow is considered "low flow" or part of a drought event. The method helps to identify low-flow events and their characteristics, such as duration, frequency, and deficit volume (Tallaksen *et al.*, 2004). Yevjevich (1967) introduced the threshold level method based on the theory of runs. It defines droughts as periods when the water supply exceeds the current demand. Yevjevich (1983) later simplified this method by applying a constant demand represented by a threshold level; thus, low flows are defined as periods during which the Streamflow is below the threshold level. Based on the runs theory, a run is a period between two consecutive crossings of the truncation level, and it delineates a low-flow event. The run length then explains the duration of the drought event, and the run sum describes the cumulative deficit volume. The low flow characteristics include deficit volume and duration.

Yahiaoui *et al*. (2009) conducted a frequency analysis of the flows in the Oued Mina catchment of Western Algeria. Yearly streamflow data were plotted to obtain the water deficit volume corresponding to its duration. Both volume and duration were plotted independently against the probability of occurrence. Using Weibull, Generalised Pareto and Log-Normal distributions, Log-Normal gives the best distribution. Deficit characteristics derived by the threshold level method gave comparable results for different kinds of streams, provided that comparable threshold levels are chosen according to the stream flow regimes.

Sung and Chung (2014) developed a streamflow drought Severity-Duration-Frequency (SDF) curve in Gwangju, Republic of Korea, using the Threshold Level Method, which resembles the rainfall intensity duration frequency curve. Severity was the total water deficit volume to the target threshold for a drought duration. The method employed the threshold level for discharge. SDF curves for drought were developed for a specific volume according to a specific duration and frequency. They were designed to identify the relationship between streamflow drought severity, duration, and frequency. The severities increased with increasing durations and frequencies. The SDFs were recommended to be extended to conduct regional frequency analyses, which can estimate streamflow drought severity at ungagged sites.

Yahiaoui (2019) conducted a frequency analysis of the extreme Streamflow using the threshold level method in the Wadi Mekerra catchment in the North-West of Algeria. The frequency analysis of the streamflow drought regime of the catchment was analysed with the Weibull distribution for both deficit volume and drought duration, combined with the probability of occurrence, to forecast the streamflow drought in the catchment. According to the goodness-of-fit tests, the Weibull distribution is adequate for both deficit volume and drought duration and can be used with the probability of occurrences for prediction. Therefore, it can be an effective tool to identify any streamflow droughts, as the probability plot correlation gave values of 0.990 for both parameters.

Sarigil *et al.* (2024) constructed flow duration curves, and the upper 10 and lower 10 percentiles were considered high and low, respectively. Specifically, Q1, Q5, and Q10 were categorised for the high flows, while Q90, Q95 and Q99 were classified for the low flows. An overall assessment of results shows that the best-fit probability distribution function does not change considerably from one Streamflow augmentation (SGS) to another for low flows. At the same time, each SGS has its own probability distribution function for high flows.

The threshold level method may be easy to understand and implement, especially for data-scarce regions, and helps identify and analyse discrete low flow events, including duration, frequency and severity. It can also help define water management policies' minimum flow requirements or drought conditions. The threshold can be set based on statistical measures or specific environmental or operational criteria and is customizable to different ecological thresholds, water supply needs, and drought analysis. Despite these advantages, results are susceptible to the chosen threshold, which can be subjective and inconsistent across studies. The analysis also requires long-term, high-quality streamflow records for reliable threshold setting and analysis. The method may also ignore seasonal variations or changes due to climate and land use, and classify flows strictly as above or below the threshold, potentially oversimplifying the complex low-flow behaviour. The method also does not inherently account for ecological, socio-economic or spatial factors unless supplemented by other analyses (Yahiaoui, 2019).

Methods based on Data availability

Streamflow records for direct low-flow analysis may sometimes be inconsistent or scarce. Available data may be used to obtain specific indices, or regression analyses are conducted to relate two or more parameters required for water management decision-making. Researchers and water managers use climatic and hydrological indices to estimate or predict low flows. Climatic indices are standardised metrics that summarise weather or climate conditions over time, used to detect and assess the potential causes of low flow events (Gebrechorkos *et al.,* 2023). Hydrological indices are statistical or descriptive metrics derived from streamflow records to quantify and characterise low-flow behaviour in a river or watershed (Zhao *et al.*, 2025).

Nikravesh et al. (2020) investigated low flow episodes in two basins with different meteorological regimes, utilising multivariate frequency analyses of drought length, severity, and severity peak, based on constructing a Two-variate Standardised Index (TSI). The Index was constructed based on a copula, using rainfall-runoff data and comparing them with two common drought indices, the Standardised Precipitation Index (SPI) and Standardised Stream Flow Index (SSFI), in terms of derived drought features. According to the findings, TSI identified more severe drought conditions with shorter return durations during a particular drought episode than SPI and SSFI. This suggests that TSI may not have the drawbacks of SPI and SSFI.

Esit and Yuce (2022) used the Standard Precipitation Index (SPI 1-, 3-, and 6-time series) for 24-gauge stations in the Ceyhan Basin, Turkey, to characterise drought situations when the value drops below zero. Mann-Kendall was used to test the relationship between length and severity. The duration and severity data were fitted to a distinct marginal distribution function. It was determined that the Weibull and Lognormal distributions were more suited for drought duration, while the Gamma and Weibull distributions were better suited for drought severity. Numerous indices have been created in drought analysis to evaluate and track droughts.

Ahsan *et al.* (2023) assessed the response of hydrological extremes, i.e, flood and drought, to observed climate variability. The hydrological drought or low flows was estimated using the Streamflow Drought Index (SDI) in the Jhelum basin, NW Himalaya. Trend analysis was conducted using the Mann-Whitney test, and the breakpoint in the data set was detected with the Pettit test. Pearson's Correlation coefficient was used to determine the relationship between climatic variables and the streamflow data before using the SDI. For prediction, the Gumbel Probability Distribution was used for flood frequency analysis. The method revealed that the effects of the significant changes in river flow regimes brought about by climate change are particularly noticeable across the Jhelum River.

Daide *et al.* (2024) used the Standardised Precipitation Index (SPI) and Baseflow Index (BFI) to assess low flow trends in four hydrometric stations in Chile. The SPI is frequently applied in hydrological studies, and the values were derived by using the rainfall data selected from the stations and correlated with March flows, which mark the end of the dry season in the southern hemisphere and the 7-day minimum ultimatum. Time series plots showed flow indices over the study period. Spatial distribution maps were created to visualise trends across different stations and helped identify areas with significant flow declines or increases over time.

The SPI allows precipitation deficits to be detected early, before they appear in streamflow records. It can be calculated over short-term to long-term time scales, which is helpful for seasonal streamflow prediction. This factor is beneficial in regions where streamflow is closely tied to rainfall variability. The Index only requires precipitation data, which makes it effective for low-flow prediction, especially in data-scarce or ungauged basins. The SPI can be used to develop SPI-low flow regression models to estimate streamflow anomalies based on climatic conditions. Despite the above advantages of the SPI, it is solely based on precipitation, which means that the river may still be experiencing low flows due to high temperatures or dry soils. Also, in catchments with delayed runoff, SPI may not correlate well with actual flows, as the timing of precipitation and its transformation into runoff is complex and not directly captured by SPI. SPI is a meteorological index since rivers with strong groundwater support may still have healthy flows. The Index must be calculated over a specific time window (i.e 1, 3, 6,12) months because choosing the wrong time scale could lead to misleading results. The SPI typically assumes that the precipitation follows a normal distribution, which may not hold in arid, semi-arid or highly variable climates where rainfall is erratic or skewed. The Index also does not account for spatial variability in catchment response and needs to be combined with hydrological models or observed flow statistics (Esit & Yuce, 2022).

The Streamflow Drought Index (SDI) and Baseflow Drought Index (BDI) are typical hydrological indices. The Streamflow Drought Index, on the other hand, reflects the total water availability, including quick flow and baseflow and is suitable for hydrological drought detection on a catchment-wide scale, captures combined impacts of rainfall variability and catchment response, and is easy to apply using observed streamflow records. In short, it is suitable for general stream drought monitoring, including rivers where baseflow and surface runoff matter. However, the SDI is sensitive to short-term high flows, which may mask ongoing baseflow deficits (Huang *et al.,* 2024). The Index is less effective in baseflow-dominated catchments where flow is more stable. The BDI focuses on sustained low flow conditions driven by groundwater contributions, which is key in dry season or drought analysis. It is better at capturing long-term hydrological stress than SDI, which can fluctuate more with short-term rainfall. The BDI is more resilient to high flow bias from short-term rainfall events and is especially useful in baseflow or groundwater-dominated catchments. The BDI, however, requires baseflow separation from total streamflow and hence ignores the surface runoff component, which can still be relevant in low flow after rainfall events and is less valuable in runoff-dominated catchments (Laaha, 2023).

Braden *et al.* (2024) determined the low flow statistics for continuous and partial record gauges in Ohio, USA. A Streamflow-Variability Index (SVI) was chosen as the explanatory variable for regression equations to predict the harmonic mean and annual and seasonal low-flow yields. A model with explanatory variables consisting of drainage area, decimal longitude, and, in most cases, SVI, was used to predict. The SVI values used in the regression analysis were obtained from a geospatial grid of SVI values developed for the study. The SVI helps differentiate between baseflow-dominated and runoff-dominated catchments, which is key for understanding flow regimes. It also improves regression model performance and can be calculated from historical daily streamflow data. However, short or incomplete streamflow records can skew the SVI, especially in basins with occasional extreme events or recording errors.

Lonita and Nagavciuc (2018) forecasted low flow events over the Rhine and Elbe Rivers basin in Germany months in advance through teleconnection patterns with particular emphasis on the summer of 2018. Teleconnections are significant relationships or links between weather phenomena at widely separated locations on Earth. The results showed that the 2018 summer low flow situation, over the Rhine and Elbe Rivers basin, could have been predicted up to two seasons ahead using previous months' sea surface temperature, sea level pressure, precipitation, mean air temperature, and soil moisture. The forecast scheme can provide early warnings for the upcoming low-flow situations, thus offering the possibility for better management of the water resources.

Stravs and Brilly (2010) developed a low-flow forecasting model using the M5 (Neural Network) machine learning method in the Sava River in Europe. The M5 machine learning is based on an algorithm developed by Quintan (1992), which uses regression and model trees generated from data, and performs hydrograph recession analysis of the available data. The regression and model trees generated with the M5 machine learning method gave a structural insight into the hydrological process that is being modelled. The M5 Machine Learning can provide powerful insights, especially in modelling linear relationships and integrating diverse hydrological inputs. It can also handle multivariate inputs like precipitation, temperature, soil moisture, etc., and is suitable for large datasets or real-time applications. However, it also requires good quality and quantity of data. It is susceptible to input variables and may struggle with sharp transitions or policy-defined thresholds unless explicitly trained to account for them.

The Standardised Streamflow Index directly works well with daily and monthly records and strongly correlates with actual river conditions. It, however, requires long-term streamflow data (often 20 years plus) and has a lagged response to precipitation. It is considered robust and reliable for site-specific low flow analysis, especially when precipitation cannot explain stream conditions.

The Two Variate Standardised Index, on the other hand, combines climate and hydrology in a single index, captures compound drought, helps explain low flow causes and can identify lagged relationships. However, it requires precipitation and streamflow data, is computationally more complex and is less commonly used in some operational settings like the SSI (Cuartas *et al.*, 2024).

The Two Variate Standardised Index is more effective for comprehensive low-flow analysis because it integrates precipitation and streamflow, making it more diagnostic and predictive, especially for compound low-flow events. The SSI is more efficient for observed flow analysis and monitors streamflow anomalies over time, especially at daily and monthly scales. The SDI is more suited for long-term or seasonal water planning and is best for capturing cumulative drought intensity over seasons or water years.

Methods based on hydrological characteristics

Due to the peculiarity of each catchment, hydrological models are used for prediction by considering spatial characteristics. In hydrology, algorithms and models are essential tools used to analyse, simulate, and predict various hydrological cycle components. A hydrological model is a simplified, conceptual or mathematical representation of part of the hydrological cycle used to simulate or predict hydrological processes (Wannasin *et al.*, 2021).

Damirel *et al.* (2015) investigated the skill of a 90-day low-flow forecast using hydrological models, i.e. Hydrologiska Byråns Vattenbalansavdelning (HBV) and Génie Rural à 4 paramètres Journalier (GR4J), for the Moselle River in Western Europe. The models used forecasted meteorological inputs (precipitation and potential Evapotranspiration). The results of the comparison of forecast skills with varying lead times showed that GR4J was less skilful than HBV. The low-flow forecasts issued by HBV were more reliable compared to GR4J. HBV oversimplifies processes like groundwater recharge, deep percolation or capillary rise, which may limit accuracy. The HBV's parameters are not directly measurable; hence, their values depend heavily on calibration, which may not generalise well in changing conditions. The package in its standard form is classified as either lumped or semi-distributed, which can be a drawback in heterogeneous catchments where low flow behaviour varies spatially. Despite its robustness in various works, HBV has underperformed in very low flows unless carefully calibrated (Furqani *et al.,* 2024).

Cordero *et al.* (2021) assessed hydrological drought using publicly available Global Precipitation Products (GPP) and a Regional Climate Model (RCM), which provides input data to a very straightforward, semi-distributed rainfall-runoff model (HBV-Light). The study examined hydrological drought scenarios. First, the model simulating streamflow dynamics was calibrated using the GPP and observed rainfall. Second, a daily variable threshold approach was used to identify drought and assess its length, intensity, and severity. Third, an RCM was used to create future hydrological drought situations. Compared to the model driven by observed rainfall, the GPP CHIRPS (Climate Hazards Group InfraRed Precipitation with Station Data) model produced the best streamflow simulations overall. Additionally, the observed streamflow drought periods were accurately detected by CHIRPS. When combined with worldwide data, the model can effectively identify dry periods and their durations; however, at this time, model uncertainty prevents it from anticipating streamflow deficits with volume errors less than 50%.

Jiao *et al.* (2021) reported using satellite-based products for multi-sensor drought characterisation based on precipitation, land Surface temperature, soil moisture, groundwater, surface water storage, evaporation, snow data and vegetation vigour. Research on surface water has demonstrated that NASA's Gravity Recovery and Climate Experiment (GRACE) satellite's terrestrial water storage observations might offer crucial information about drought behaviour. However, GRACE data does have certain limits. Significant limitations are presented by GRACE's coarse spatial resolution (i.e., pixel sizes of about 300–400 km) and post-processing requirements. Furthermore, because of the significant seasonal variations in water storage and the propagation uncertainty of the signal from all hydrological processes, it was discovered that GRACE-based terrestrial water storage estimates had a greater bias in humid locations.

Ahmadalipour *et al.* (2017) projected both the meteorological and hydrological droughts of the Willamette River basin in the Pacific Northwest area of the USA. The hydrologic modelling was conducted using the Precipitation Runoff Modelling System (PRMS), a Physically Based semi-distributed hydrologic model for the Willamette River Basin. The calibration results revealed that streamflow simulations from the PRMS are in good agreement with observed flows for almost all calibration points.

Nicolle *et al.* (2020) reviewed an operational tool for low stream flow forecasting called PREMHYCE. PREMHYCE includes five hydrological models: one uncalibrated physically-based model and four storage-type models of various complexities calibrated on gauged catchments. PREMHYCE was tested on 118 selected catchments in France with catchment sizes ranging from 9 to 111,000 km2. Results on the 2017 low-flow periods showed interest in using such a tool to help end-user decisions. The application, which comes close to the PRMS in terms of robustness, is the PREMHYCE. The PRMS can be more advantageous in detailed, process-based low flow simulation and for complex basins with deep groundwater interactions. PREMHYCE, on the other hand, is more advantageous in operational forecasting and quick deployment across regions, as well as for data-scarce regions needing simpler methods. In a nutshell, PRMS is more efficient for physically detailed, spatially distributed simulation of low flows. At the same time, PREMHYCE is effective due to its ensemble capabilities and operational efficiency (Nicolle *et al.,* 2020).

Vogel and Kroll (2021) highlighted low stream flow applications such as STREAMSTATS, GLSNET, SWToolBox, SWSTAT, DFLOW, and HEC-SSP. The need to compute various low streamflow statistics, such as the 7-day, 10-year low streamflow or the daily streamflow with an annual exceedance probability of 95% was outlined. Such low-flow statistics are required in various water resource design, planning, operations, and management settings. The HEC-

SSP is more robust because it supports detailed frequency analysis, confidence intervals, customizable low flow events, and is accepted for formal reporting. It is best suited for in-depth, site-specific low-flow studies. The SWToolBox is considered to be next with excellent flow duration curves, baseflow separation, trend analysis, and historical comparison. STREAMSTATS is considered unbeatable if quick low-flow estimates at ungauged sites are required. DFLOW is more relevant for water quality-based design flow analysis. Using indices with some of the applications mentioned can boost their efficiency.

Although the HBV remains effective in operational settings, data-limited basins and situations where simplicity and speed are priorities, the PRMS is more robust in low flow analysis in hydro-geologically complex basins, data-rich environments and watersheds where spatial variability matters. The PRMS is also more effective than Teleconnection patterns, a method that offers large-scale predictive insights through early warning of drought or low flow periods and is valuable in seasonal water resources planning, drought preparedness and reservoir operations (Roland, 2023). The method can be used with limited data requirements without detailed physical catchment data. The method, however, does not simulate streamflow but only correlates with it. Teleconnection patterns are region-specific and effective but lack spatial resolution and hydrological process representation (Xie *et al.*, 2023).

Between HEC-SSP, PRMS and PREMHYCE, the PRMS would be considered the best overall scientifically robust for low flow simulation because it models all processes contributing to low flow (infiltration, groundwater flow, Evapotranspiration, etc.) and is perfect for understanding and predicting low flows under real or future scenarios. The HEC-SSP is best for regulatory, site-specific low flow statistics, while the PREMHYCE is best for operational, regional or Ensemble Forecasting. Combining the three will give complete low-flow assessment data. Table 2 provides a summary of methods with their respective advantages and limitations.

Table 2: Summary of Methods of Low Flow Analysis Measurement in the Yobe River Basin

S/N	Criteria	Method	Advantage	Limitation
1	Severity and Duration	Threshold Level Method, Streamflow Duration Curves	Easy to understand and implement, helps in identifying and analyzing discrete low flow events, useful in defining minimum flow requirements, set based on statistical measures or specific environmental or operational criteria, customizable to different ecological needs	Results are highly sensitive to the chosen threshold, analysis requires long-term, high quality streamflow records for reliable threshold analysis, method ignores seasonal variations or changes due to climate and land use, oversimplifying the complex low flow, does not inherently account for spatial factors unless supplemented by other analyses
2	Data Availabilty	Climatic/Hydrologic Indices, Teleconnection Patterns	Helps understand causes of low flows, enables comparison across space and time, improves modeling and forecasting, connects local flow to global climate, early detection of low flow events, and evaluates	Reduces complex systems to single values, missing key nuances, Indices may not match the spatial or temporal scale of the analysis, may not account for changing land use, requires long-term, reliable data, climatic indices may not directly control low flows and do not reflect

			climate change effects.	anthropogenic changes to flow
3	Hydrologic Characteristics	HBV, HBV-light, GR4J, PRMS, PREMHYCE, SREAMSTATs, GLSNET, SWToolBox, SWSTAT, DFLOW, and HEC-SSP	Models physical flow processes, not just statistical correlations, accounts for heterogeneity in soils, land use, climate, and topography, works with GIS and remote sensing, better suited for detailed watershed representation	High data needs, Sensitive baseflow behavior hard to capture, tuning models for low flow is difficult, weak groundwater modeling, fine resolution needed, but expensive, not built for dry season hydrology

CONCLUSION

The nature of the Yobe River Basin in Northeastern Nigeria and its large catchment area of 32,000 km2 would require a physically distributed model to account for its spatial variability. Hence, the PRMS and PREMHYCE have shown more promise than other packages. However, due to the difficulty of the physically based models in representing low flows, an additional method may be required to achieve this. As such, the threshold level method may be ideal by constructing a flow duration curve and obtaining a threshold level capable of yielding low flow severity and duration. The above combination of methods may yield sufficient information for management and policy making, provided adequate data is available. Due to inconsistent data for the catchment area, however, using the Climatic/Hydrological Indices for data projection and forecasting may be used before applying the physically based model. The Two Variate Standardised Index may be used because it integrates precipitation and streamflow, making it more diagnostic and predictive.

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