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Article

Spatio-Temporal Variability of Extreme Precipitation and Flow Indices in the Lower and Middle Ouémé Valley in Benin

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Abstract: The urgent need to study rainfall variability and its link to river flows is well established, given its direct impact on the socio-economic development of nations. This study analyzed the variability of extreme precipitation and flow indices at several stations in the lower and middle Ouémé valley in Benin. Five extreme precipitation indices (RX1DAY, RX3DAY, RX10DAY, SPI, PRCPTOT), as well as two extreme river flow indices (Q50 and Q95) were used. To conduct this analysis, we employed the non-parametric Mann-Kendall test to examine trends and the Pettitt test to identify stationarity breaks in the data series. The results indicate strong spatio-temporal variability in the indices studied. The break years are generally similar among indices but vary from one station to another. Three main breaks were identified over the study period (1960-2022): the first in 1970, the second in 1990, and the third after the 2000s. Regarding trends and the distribution of water surplus and deficit years, a cyclical pattern emerges. There is an overall downward trend in precipitation indices, with three distinct periods: a first and third water surplus period, separated by a deficit period, which is the longest. Concerning flow indices, two main breaks have been identified: one in 1970 and another in 1990. Trend analysis reveals a significant decrease in the Q95, while the Q50 shows an upward trend. Finally, an examination of the relationships between precipitation and flow indices shows that only the Q95 is significantly influenced by precipitation indices, especially the SPI and PRCPTOT. However, the relationship between Q95 and PRCPTOT is inversely proportional.

Keywords: climate change; extreme; precipitation indices; flow indices; trend analysis; stationarity break point

1. Introduction

The variability of precipitation and extreme flows, both temporally and spatially, is a major concern for communities worldwide. This challenge is further compounded by the urgent threat of climate change, which directly impacts water resources, affecting ecosystems, agriculture and socio-economic activities (Nouradine et al., 2022; Goula Bi Tié et al., 2007; Kholiquzzaman Ahmad, 2006). Countries face significant environmental challenges that exacerbate the risk of floods and droughts. Several authors (Kodindo et al., 2025; Easterling et al., 2000) have revealed that these phenomena are largely driven by climatic factors, including rising temperatures and shifting precipitation patterns. Additionally, previous studies have highlighted notable variations in rainfall in lower Benin (Hounvou et al., 2023; Kingbo et al., 2022; Obada et al., 2021). Research shows that the climatic variability observed in West Africa has significantly increased the frequency and intensity of extreme events since the 1970s (Obada et al., 2021; USAID, 2018). Addressing these challenges is urgent due to the devastating impacts of extreme climate events on local communities, agriculture, and the economy. Moreover, population growth and rapid urbanization are transforming natural landscapes, further disrupting hydrological regimes and affecting water resource management (Yang et al., 2024).

The Lower and Middle Ouémé Valley (BMVO) in Benin, an economically and ecologically significant area (rich in agricultural resources), is particularly vulnerable to flooding due to its geography and hydrological characteristics. Floods in the BMVO typically occur during the rainy season, exacerbating their impact on local communities (Cocker et al., 2019). Since agriculture is the primary livelihood for most of the residents and depends heavily on rainfall patterns, the local economy is particularly affected. Research conducted by Azian et al., 2023 and Vissin et al., 2016 confirms this link between the economy and climate change, showing that rainfall fluctuations can lead to excess water in soil moisture, making crops more vulnerable. Additionally, Ouémé River floods cause severe damage to infrastructure, homes, and farmland. The region's growing population and rapid urbanization in recent years have further increased its exposure to climate-related hazards, heightening the need for effective flood management and adaptation strategies. Given these challenges, understanding the spatial and temporal variability of precipitation and extreme flow indices in the BMVO is essential for anticipating and mitigating associated risks. However, despite its significance, knowledge gaps persist regarding the spatio-temporal patterns of these hydroclimatic variables.

Existing studies (Ebodé, 2022; Bougara et al., 2020; Gbohoui et al., 2018; Amoussou et al., 2016) often focus on either spatial or temporal variability, rarely integrating both perspectives across historical and future periods. Additionally, research is constrained by data availability and duration, limiting comprehensive assessments. Statistical analyses of hydroclimatic variability have primarily examined historical trends in precipitation and streamflow. For example, studies indicate a 15-20% decline in precipitation from 1970 to 1990 compared to 1960-1969, followed by a modest 2% recovery in the late 1990s (Vissin et al., 2016). Other studies have identified disruptions in stationarity of precipitation series around the 1970s, indicating shifts in climatic regimes (Ogouwalé et al., 2022). In summary, recent studies have utilized statistical analyses of precipitation and streamflow time series, climate indices developed by the Expert Team on Climate Change Detection and Indices (ETCCDI) (Dosio, 2016), and hydrological models to simulate river flows in watersheds. These approaches have provided valuable insights into the evolution of hydroclimatic phenomena across different regions and the underlying relationships influencing these changes. Furthermore, advanced statistical methods (Pettitt Test, Hubert Segmentation, Lee and Heghinian Test, etc.) are often used to detect breaks in stationarity in precipitation and streamflow time series (Ebodé, 2022; Obada et al., 2021; Bougara et al., 2020). However, persistent challenges such as the availability and quality of historical data and a lack of integration between indices remain. Moreover, most studies in the BMVO have not sufficiently explored the variability of indices in both spatial and temporal dimensions, nor the potential interactions and correlations between different hydroclimatic indices. There is, therefore, a n urgent need for a multi-index approach to effectively assess the impacts of climate change on hydrological variability in this region, providing a more comprehensive and detailed view of the subject.

Given these findings and the urgency of the issue, this study aims to conduct a comprehensive analysis of the variability and trends of extreme precipitation and flow indices over the historical period from 1960 to 2020. Additionally, the study seeks to establish correlations between extreme precipitation and flow indices to identify those most directly influencing streamflow. As indicated above, recent research also emphasizes the need for integrated approaches that analyze both spatial and temporal dynamics of hydroclimatic indices, rather than treating them in isolation. Unlike many previous works that consider spatial or temporal variability separately, this study combines both dimensions across an extended historical period (1960–2022). It also investigates how hydrological indices relate to precipitation indices, providing insights into potential drivers of streamflow behavior. By providing a detailed understanding of the spatio-temporal variability of extreme precipitation and flow indices in the BMVO, this study will contribute to the development of climate risk adaptation and management strategies, thereby strengthening the resilience of local communities to the challenges posed by climate change.

2. Study Area, Data and Methods

2.1. Study Area

The Lower and Middle Ouémé Valley (BMVO), the focus of this study, is located in southern Benin and spans 19 communes (Figure 1). Endowed with a highly diversified ecosystem that facilitates several activities, it is an alluvial plain zone characterized by a very gentle slope of the watercourse (5 m gradient over 85 km^2) and a dense hydrographic network. This network feeds Lake Nokoué to the west and the Porto-Novo lagoon to the east, forming the Ouémé delta before flowing into the Atlantic Ocean. It lies between latitudes 6°19 and 7°40 North and longitudes 1°48 and 2°50 East. In terms of climate, BMVO is characterized by two types of climates: a sub-equatorial climate in the lower valley and a Sudano-Guinean climate in the middle valley, with a bimodal rainfall pattern. The region is strongly influenced by climate change, leading to changes in its hydrological cycle.

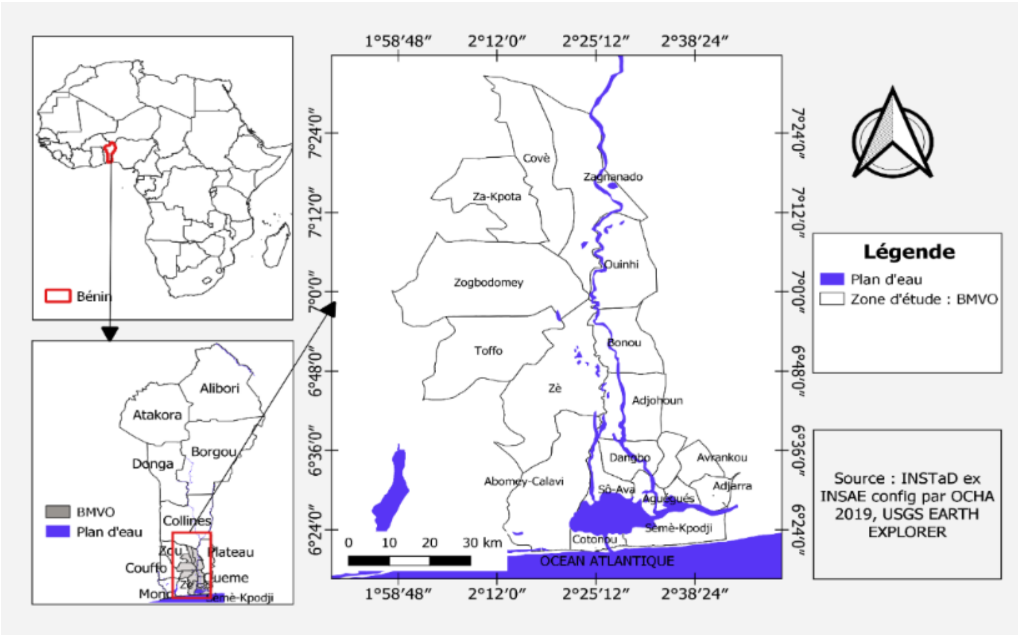

Figure 1. Administrative map of the Lower and Middle Ouémé Valley.

2.2. Data and Methods

2.2.1. Data

Daily rainfall data (1960-2022) and flow data (1960-2022) were used in this study. The rainfall data came from the National Meteorological Agency (Météo-Bénin), while the flow data were collected from the General Directorate of Water (DGEau). Rainfall was recorded at 22 stations (Abomey, Adjohoun, Allada, Bétérou, Bohicon, Bonou, Cotonou, Dassa, Djougou, Gouka, Kétou, Kokoro, Kouandé, Parakou, Pobè, Porto-Novo, Sakété, Savè, Tchaourou, Tchétti, Toffo and Zagnanado), while flow data came solely from the Bonou hydrometric station. As the reliability of the results is closely linked to the quality and quantity of the data used, rigorous processing was applied. Outliers, such as negative precipitation, were replaced by missing values (NA). These missing data were then filled by spatial interpolation, using the inverse distance weighting (IDW) method: a widely used spatial interpolation technique known for its simplicity and reasonable performance in hydrometeorological studies (Wuthiwongyothin et al., 2021). Stations with high proportions of missing data were dropped to avoid bias in trend estimation. Similarly, a year was excluded from analysis if more than 40% of its data were missing. Table 1 summarizes the conditional imputation strategy applied to streamflow series, based on gap duration and data availability. While this approach improves continuity, we acknowledge the potential uncertainty it introduces in trend detection and breakpoint analyses. This limitation is considered in the interpretation of results.

Table 1. Flow series imputation methods.

Gap Duration	**Imputation Method**	**References**	**Conditions / Remarks**
≤2 days	Linear interpolation, Ffill, Bfill		Suitable for very short gaps without strong trend
3 to 14 days	- Ridge regression- or spline interpolation (PCHIP)	Kumar et al. 2023	Depending on availability of correlated donor stations
15 to 60 days	Iterative imputation using **Random Forest**, with seasonal features (Julian day encoded as sine/cosine)	Kumar et al. 2023	Requires at least one strongly correlated donor

> 60 days	Regression using **Random Forest** with ≥2 donor stations	Kumar et al. 2023	If no reliable donors are available, gaps are left as missing
No reliable predictors	Gaps left unfilled		Prevents introducing artificial continuity
Post-processing	Smoothing (e.g., moving average or spline)	Baddoo et al. 2021	Reduces artifacts or noise introduced by heterogeneous gap-filling methods (conditional)

The selected indices provide an accurate assessment of the overall trend in average variations in extreme rainfall values over the study period. Table 2 shows these extreme rainfall and flow indices.

Table 2. Precipitation indices and extreme flow.

Indices	Description	Unit
RX1day	Maximum daily precipitation	mm
RX3day	Maximum 3-day precipitation	mm
Rx10day	Maximum 10-day precipitation	mm
SPI	Standardized Precipitation Index	
PRCPTOT	Annual total precipitation	mm
Q50	Median flow	m^3/s
Q95	Flow below which 95% of the observations fall	m^3/s

2.2.2. Methods

- Mann Kendall test

The Mann-Kendall trend test was used to analyse trends in the precipitation and discharge index series. The Mann-Kendall test (Kendall, 1957; Khoi & Trang, 2016; Sanogo et al., 2023), is a non-parametric statistical test for detecting the presence of a monotonic trend within a time series in the absence of any seasonality or other cycles. The Mann-Kendall statistic is expressed as follows:

$$S_n = \sum_{i=2}^{n} \sum_{j=1}^{i=1} sgn(x_i - x_j) \quad (1)$$

where n is the length of the series; x_i and x_j are generic values of sequential data; and the function $sgn(x_i - x_j)$ is defined by:

$$sgn(x_i - x_j) = \begin{cases} 1 \; si \; (x_i - x_j) > 0 \\ 0 \; si \; (x_i - x_j) = 0 \\ -1 \; si \; (x_i - x_j) < 0 \end{cases} \quad (2)$$

Under this assumption, S is approximately a normal distribution with mean E(S) and variance var(S) defined respectively by the following equations:

$$E(S) = 0 \quad (3)$$

$$Var(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p - 1)(2t_p + 5)\right] \quad (4)$$

where n is the number of non-missing data values in group p; and q is the number of ties. The second term of the equation $E(S) = 0$ represents an adjustment of linked or censored data. The values of S and var(S) are used to calculate the standardised statistical test Z, which can be written using the following formula:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} \ si\ S > 0 \\ 0\ si\ S = 0 \\ \frac{S-1}{\sqrt{Var(S)}} \ si\ S < 0 \end{cases} \quad (5)$$

The presence of a statistically significant trend is assessed by studying the value of Z.

- Sen-Theil test

The Sein-Theil test (Sanogo et al., 2023; Sen, 1968; Theil, 1950), is oa non-parametric test used to estimate the trend slope of a time series. In the Sen test, a set of slopes Q_{jk} is estimated for each of the $n(n-1)/2$ pairs of data as follows:

$$\forall\ k\ \in [1, n-1], \forall\ j\ \in [k+1, n], Q_{jk} = \frac{x_j - x_k}{j-k} (j > k) \quad (6)$$

The Sen-Theil slope is then the median of all the estimated Q_{jk} slopes. It is expressed in units of concentration per year or as a percentage per year. The lower and upper limits of the confidence interval correspond to the M_1th and (M_2+1)th values in the sorted list of n slope estimates, respectively (Haruna et al., 2023). This test has been used, and its robustness has been demonstrated in several studies (Drouiche et al., 2019; Lubes-Niel et al., 2005; Yue & Wang, 2004).

- Pettit test

The Pettitt test (Ebodé, 2022; Pettitt, 1979) is a rank order test: it is therefore non-parametric and free for detecting breakpoint in time series. This test is considered robust and its performance in terms of power is superior to that of Wilcoxon. The statistic is defined by:

$$K = max|U_k| \quad (7)$$

where U_k is a cumulative sum of the ranks.

The test identifies the point k where this statistic is maximum as the potential breaking point.

In line with several recent studies (Drouiche et al., 2019), these statistical tests were performed at the 95% confidence level ($\alpha = 0.05$) to determine the significance of trends and breakpoints. The null hypothesis (H_0), which assumes no monotonic trend, was rejected when the p-value was less than 0.05. In cases where a significant trend was detected, its magnitude was estimated using the Sen's slope method (Sen, 1968), which computes the median of all pairwise slopes between data points (Drouiche et al., 2019).

- Principal Component Analysis (PCA)

PCA (Maćkiewicz & Ratajczak, 1993) is a method used to construct a variable that is as similar as possible to all the variables in the table under study. This variable is called the summary variable or principal component. The principal component then has the property of being as correlated as possible with all the variables in the table. PCA provides the dispersion of individuals around factorial axes. The distance between individuals, reflecting their similarity, is measured quantitatively by generalising the square of the Euclidean distance defined between two points on the plane (Kiki & Moumouni, 2020). Each point M in the plane is identified by two coordinates x_M and y_M, and the squared distance between two points M and M' is:

$$d^2(M, M') = (x_M - x_{M'})^2 + (y_M - y_{M'})^2 \quad (8)$$

- Partial least squares (PLS) regression

PLS is a statistical method that has some relation to principal component regression and is a reduced rank regression. PLS regression consists of performing a principal component analysis of the set of variables X under the constraint that the (pseudo-) principal components of the X_j are as 'explanatory' as possible of the set of variables Y. Instead of finding hyperplanes of maximum variance between the response and the independent variables, it finds a linear regression model by projecting the predicted variables and the observable variables into a new space of maximum covariance. Since the X and Y data are projected into new spaces, the PLS family of methods is known as bilinear factor models (Abdi, 2003; Sicard, 2004; Tenenhaus et al., 1995).

3. Results

3.1. Interannual Variability, Trends and Breaks in the Indices

Figures 2–6 illustrate changes in extreme precipitation indices over the study period from 1960 to

2022. Significant changes in rainfall patterns were observed across all studied stations based on the RX1day (Maximum daily precipitation) index. Trend analysis reveals mostly downward trends, with upward tendencies at Bonou, Bohicon, and Adjohoun.

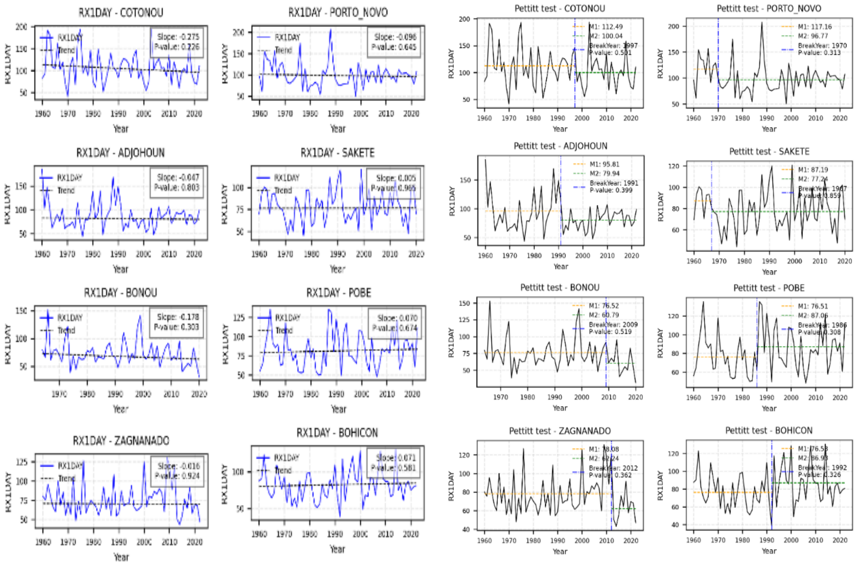

Figure 2. Evolution, trend and break in the RX1DAY index at the study stations (1960–2022).

However, none are statistically significant at the 95% level (Figure 2). The Pettitt test (Figure 3) identified non-significant change points, mainly around the 1970s, 1990s, and post-2000 depending on the station. These shifts reflect modifications in the behavior of extreme rainfall, generally indicating a decline. Only Pobè and Bohicon showed slight increases in RX1day averages after the break. For RX3day (Maximum 3-day precipitation), change points occurred around similar periods, though Adjohoun exhibited a break after 2000. Most stations experienced a decrease in post-break averages, while Adjohoun, Bohicon, and Zagnanado showed slight increases. The trend test corroborates these patterns, with non-significant downward trends dominating, except for the three aforementioned stations (Figure 3).

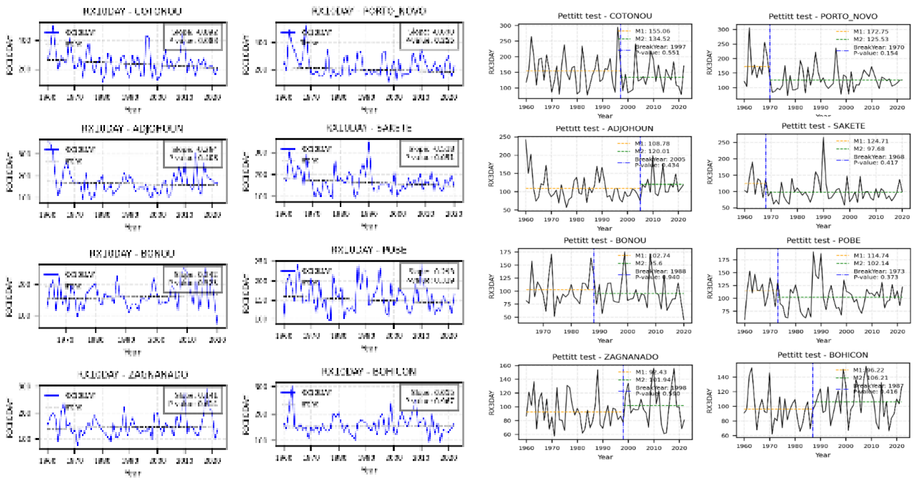

Figure 3. Same as Figure 2 but for RX3DAY

For the RX10DAY (Maximum 10-day precipitation) index, breakpoints generally occur around 1970, 1990, and after 2000, though their distribution is less consistent than in previous indices. For example, breaks are detected around 1970 at Cotonou and Adjohoun, while they appear later (after 1990) at Sakété and Pobè. Although the trends are mostly downward but not statistically significant, the RX10DAY index seems to reflect changes in rainfall events earlier than RX1DAY and RX3DAY.

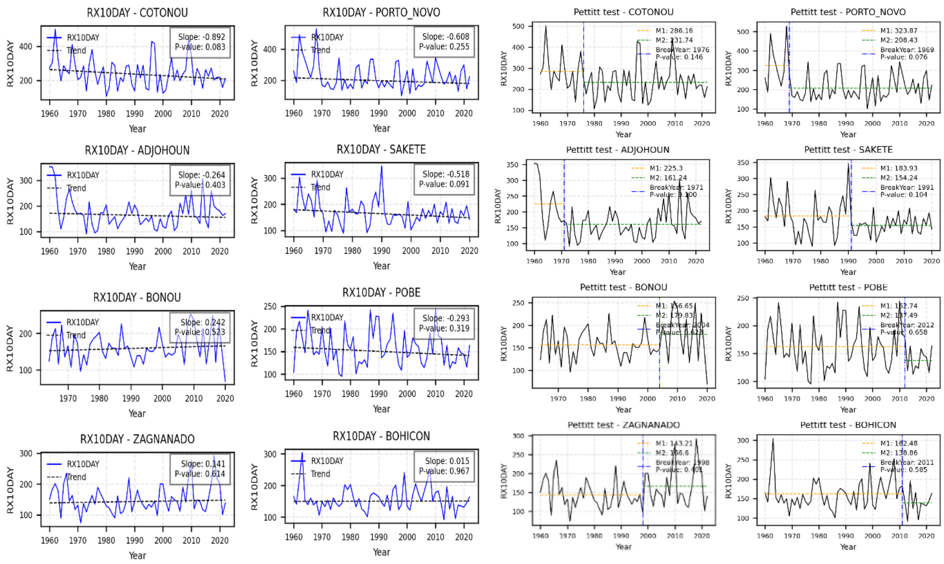

Figure 4. Same as Figure 2 but for RX10DAY.

The SPI (Standardized Precipitation Index) shows marked temporal (1960–2022) and spatial variability across stations. Figures 5 and 6 reveal alternating wet and dry periods, with some synchronization across sites. Notably, Cotonou and Adjohoun experienced wet phases from 1960 to 1969 and from 2006 to 2022, separated by a prolonged dry spell (1970–2005). The Pettitt test detects a break in 1969 at Cotonou followed by a decrease in SPI averages, and another in 2005 at Adjohoun followed by an increase.

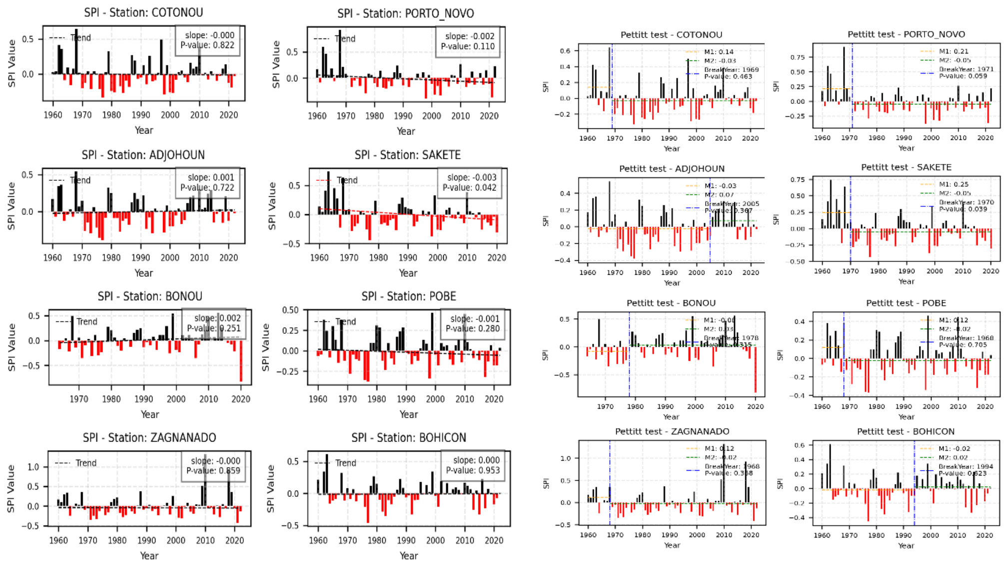

Figure 5. Same as Figure 2 but for SPI.

The PRCPTOT (Annual total precipitation) index analysis reveals a general decline at most stations. Cotonou shows a decrease of 4.8 mm per decade, while Adjohoun exhibits a slight increase of 10 mm per decade. At Porto-Novo and Sakété, a wet period from 1960 to 1970 was followed by a deficit phase (1971–2022), with Sakété showing a significant decrease of 43 mm per decade. Pobè and Zagnanado display a shift from surplus (1960–1968) to deficit conditions, although the decline is milder at Zagnanado (–3.2 mm/decade). Pobè presents alternating wet and dry periods every 2 to 4 years, with an average loss of 15 mm per decade.At Bohicon and Bonou, the early decades (1960–1978 and 1960–1994, respectively) were drier, followed by wetter conditions with intermittent dry years. Trends are upward at both stations, with increases of 28 mm per decade at Bonou and 2 mm per decade at Bohicon. Overall, the results highlight a shift in climatic regimes at different times across stations, with statistically significant trends detected only at Sakété ($p < 0.05$).

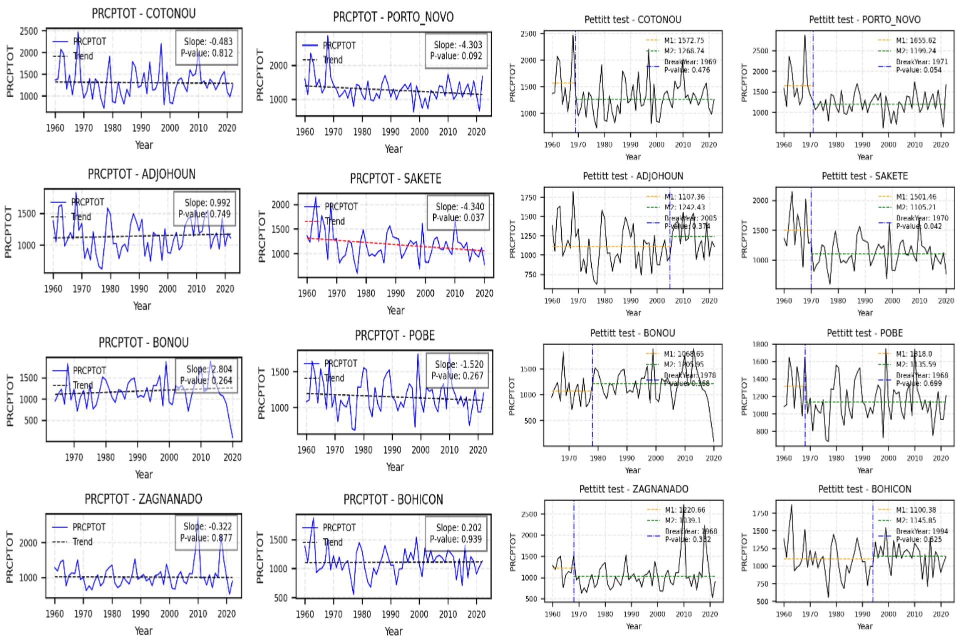

Figure 6. Same as Figure 2 but for PRCPTOT.

The findings highlight a progressive shift in the regional rainfall regime. They are summarized in Tables 3 and 4 and are particularly relevant in the context of climate change.

Table 3. Break years summary.

Station	RX1DAY Break	RX3DAY Break	RX10DAY Break	SPI Break	PRCPTOT Break
Cotonou	1997	1997	1976	1969	1969
Adjohoun	1991	2005	1971	2005	2005
Bohicon	1992	1987	2011	1994	1994
Bonou	2009	1988	2004	1978	1978
Sakété	1967	1968	1991	1970	1970
Zagnanado	2012	1998	1998	1968	1968
Porto-Novo	1970	1970	1969	1971	1971
Pobè	1986	1973	2012	1968	1968

Table 4. Trend and slope summary with 95% confidence intervals (**P_v:** P_value**; CI:** Confidence Interval).

Station		**ADJOHOUN**	**BOHICON**	**BONOU**	**COTONOU**	**POBE**	**PORTO_NOVO**	**SAKETE**	**ZAGNANADO**
RX1DAY	**Slope**	-0.047	0.071	-0.178	-0.275	0.07	-0.096	0.005	-0.016
	CI	[-0.393, 0.291]	[-0.200, 0.375]	[-0.456, 0.156]	[-0.824, 0.203]	[-0.271, 0.423]	[-0.538, 0.276]	[-0.298, 0.300]	[-0.256, 0.275]
	P_v	0.803	0.581	0.303	0.226	0.674	0.645	0.965	0.924
RX3DAY	**Slope**	0.074	0.18	-0.105	-0.463	-0.096	-0.293	-0.187	0.067
	CI	[-0.371, 0.467]	[-0.173, 0.508]	[-0.605, 0.304]	[-1.200, 0.200]	[-0.457, 0.296]	[-0.896, 0.336]	[-0.624, 0.176]	[-0.275, 0.424]
	P_v	0.687	0.427	0.653	0.2	0.553	0.322	0.31	0.627

RX10 DAY	**Slo pe**	-0.264	0.015	0.242	-0.892	-0.293	-0.608	-0.518	0.141
	CI	[-1.056, 0.435]	[-0.483, 0.496]	[-0.625, 1.075]	[-1.888, 0.129]	[-0.850, 0.293]	[-1.770, 0.500]	[-1.139, 0.146]	[-0.452, 0.734]
	P_ v	0.403	0.967	0.523	0.083	0.319	0.255	0.091	0.614
SPI	**Slo pe**	0.001	0	0.002	0	-0.001	-0.002	-0.003	0
	CI	[-0.002, 0.004]	[-0.003, 0.003]	[-0.002, 0.006]	[-0.003, 0.002]	[-0.004, 0.001]	[-0.005, 0.000]	[-0.007, -0.000]	[-0.003, 0.003]
	P_ v	0.722	0.953	0.251	0.822	0.28	0.11	0.042	0.859
PRCP TOT	**Slo pe**	0.992	0.202	2.804	-0.483	-1.52	-4.303	-4.34	-0.322
	CI	[-2.895, 4.728]	[-3.707, 3.193]	[-1.928, 8.145]	[-5.354, 4.222]	[-5.097, 1.631]	[-8.839, 0.608]	[-8.742, -0.338]	[-4.048, 3.717]
	P_ v	0.749	0.939	0.264	0.812	0.267	0.092	0.037	0.877

Figure 7 presents the results of the Mann-Kendall and Pettitt tests applied to the streamflow indices Q50 (Median flow) and Q95 (Flow below which 95% of the observations fall) at the Bonou station. The Q50 ranges from 0 to 75 m³/s, with two notable peaks recorded in 2012 (260 m³/s) and 2020 (125 m³/s), while Q95 shows greater variability, fluctuating between 110 and 1120 m³/s. Trend analysis reveals a significant increase in Q50, with an estimated slope of +5.4 m³/s per decade. Q95 also exhibits an increasing trend, though not statistically significant, with a slope of +7.9 m³/s per decade. The Pettitt test detects a change point in 1990 for Q50 and in 1970 for Q95. The 1990 shift indicates a transition to higher median flows, suggesting increased runoff and changes in local hydrological dynamics, possibly linked to more intense rainfall or land use changes. Similarly, the 1970 break for Q95 reflects a rise in extreme flows, which may point to a faster hydrological response of the watershed to rainfall events. Overall, these results suggest a general intensification of the hydrological regime at Bonou over the study period.

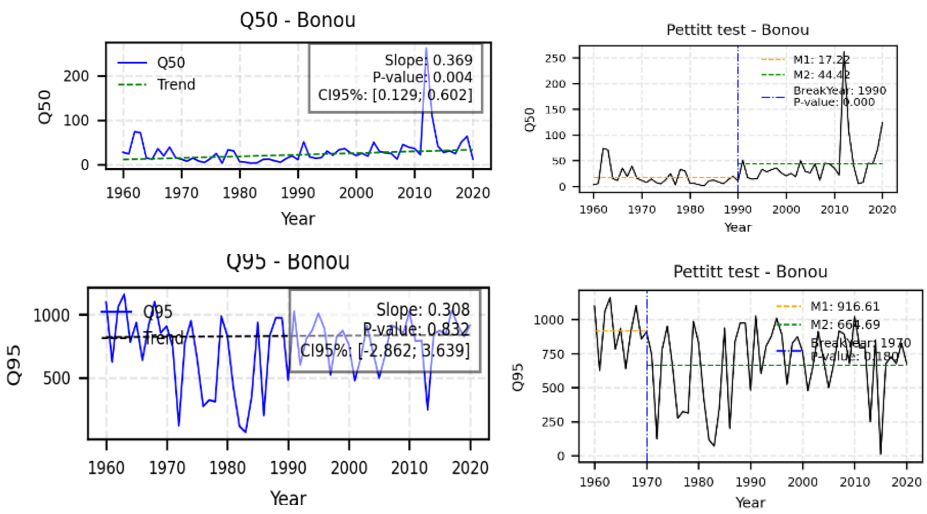

***Figure** 7*. Evolution, trend and break in the Q50 and Q95 indices at Bonou (1960 to 2022).

3.2. Spatial Variability of Trend Patterns

Figure 8 illustrates the spatial distribution of the RX1DAY, RX3DAY, and RX10DAY indices across the Lower and Middle Ouémé Valley (BMVO) from 1960 to 2022. The results reveal a heterogeneous distribution of extreme rainfall trends over one-, three-, and ten-days periods. While RX1DAY shows no statistically significant trends, a moderate increase (0 to 6 mm/decade) is observed in the central and northwestern parts of the BMVO, whereas the southern and northern areas exhibit stable or slightly decreasing trends (around –2 mm/decade). Similar spatial patterns are observed for RX3DAY and RX10DAY, with trend variations ranging from –4 mm to +8 mm/decade for RX3DAY and –5 mm to +15 mm/decade for RX10DAY. Statistically significant trends are detected for these latter indices in specific areas, indicated by asterisks on the map.

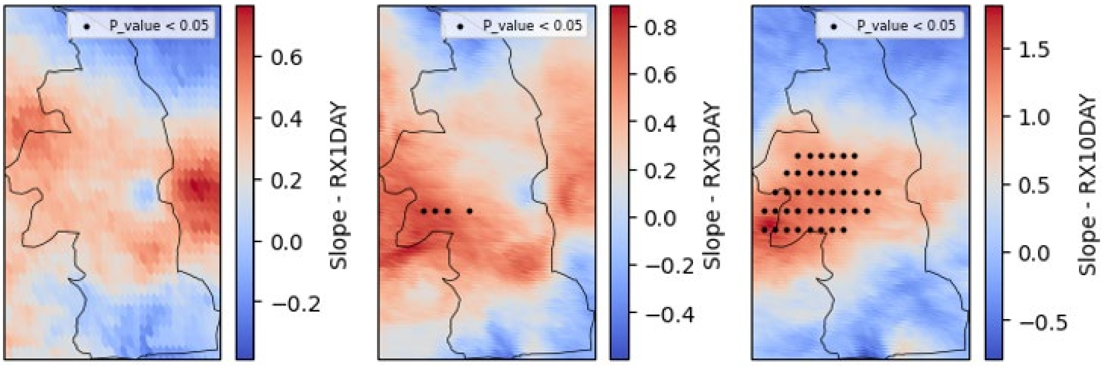

Figure 8. Spatial variability of trends in the RX1DAY, RX3DAY and RX10DAY indices on the BMVO.

Figure 9 shows comparable spatial patterns for the SPI and PRCPTOT indices. The southern and northern zones are characterized by stable or declining annual rainfall, with reductions of up to 20 mm/decade, reflecting persistent rainfall deficits from 1960 to 2022. In contrast, the central and northeastern regions exhibit significant increases in annual rainfall, ranging from +30 mm to over +120 mm/decade, indicating a surplus that is statistically significant at the 95% level.

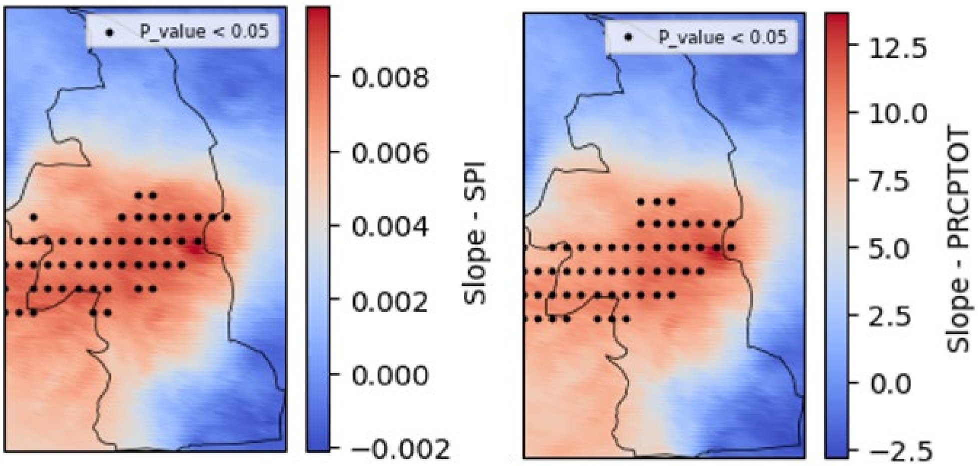

Figure 9. Spatial variability of SPI and PRCPTOT index trends in BMVO.

3.3. Relationship between Precipitation and Streamflow Indices

Several statistical methods were employed to explore the relationship between precipitation and streamflow indices, including Pearson correlation analysis, Principal Component Analysis (PCA), Partial Least Squares Regression (PLS), and Hierarchical Classification. The Pearson correlation matrix (Figure 10) reveals that Q50 shows no significant correlation (r = 0.07 to 0.19) with the precipitation indices used in this study. In contrast, Q95 exhibits strong correlations, particularly with RX3DAY (r = 0.65), SPI (r = 0.73), and PRCPTOT (r = 0.73). These correlations indicate a strong relationship, warranting further investigation.

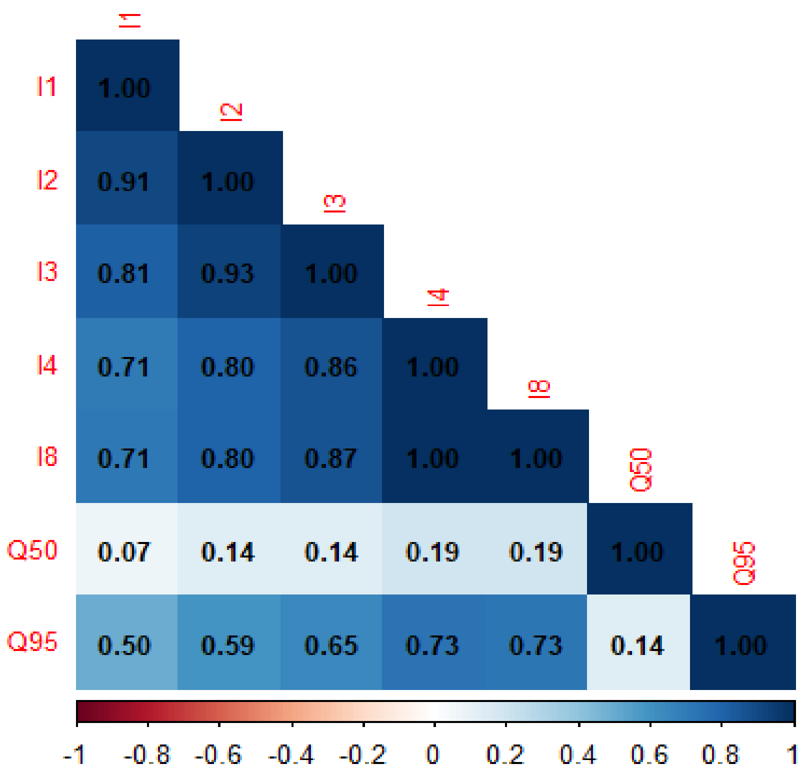

Figure 10. Pearson correlation matrix between rainfall and discharge indices.

The PLS regression analysis indicates that Q50 is not significantly explained by precipitation indices (R^2 = 6.2% with 5 components). However, Q95 exhibits a significant rainfall-runoff relationship, explaining 54.4% of the variance. Notably, only two components are needed to capture this relationship (Table 5).

Table 5. PLS regression.

Components	Rainfall Indices	Q50	Q95
1	87.10%	2.70%	48.40%
2	96.40%	4.30%	53.60%
3	97.40%	5.50%	53.60%
4	99.90%	5.50%	53.60%
5	100.00%	6.20%	54.40%

The Q95 flows are therefore more dependent on these precipitation indices than the Q50 flows. This suggests that other factors, apart from rainfall, have a greater influence on Q50. Therefore, Q95 appears to be a better indicator of the basin's hydrological response to extreme rainfall events and thus deserves special attention. However, a complementary analysis integrating other indices and local factors could be necessary to better understand the behavior of Q50 flows. This observation is based on the indices used in this study and the selected stations. The results may vary with different indices or in other regions.

By analyzing the dendrogram built with a threshold of two clusters following the PCA, we identified two major groups of precipitation and streamflow indices: The first group (RX1DAY, RX3DAY, RX10DAY, SPI, and Q50) and the second group (PRCPTOT and Q95). The indices within the same group exhibit similar behavior and could have a similar impact on the hydrological variability of the BMVO (Figure 11).

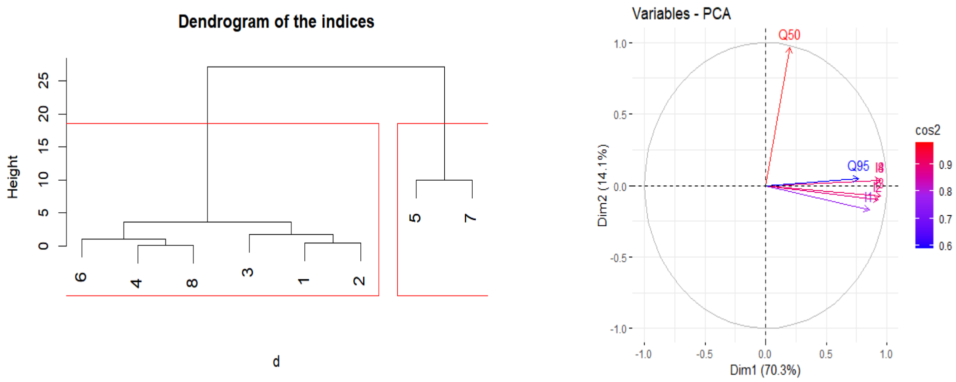

Figure 11. PCA Results.

Figure 12 shows the influence of each precipitation index on the streamflow indices, calculated using multiple linear regression. The results are more significant for Q95, with a p-value less than 5%. The analysis of the figure and the regression coefficients reveals that the SPI index has a strongly positive effect on Q95, while PRCPTOT has a strongly negative effect, but with the same magnitude as SPI. These results confirm the similarities observed between these two indices in the previous analyses.

The overall analysis shows that there are groups of precipitation indices with similar behavior and that some indices have a stronger influence on Q95 flows. The SPI and PRCPTOT indices appear to be key determinants of extreme flow (Q95), while they have opposite effects on Q50. The PCA further supports these findings by distinguishing groups of variables that may have different impacts on hydrological regimes. These results are crucial for selecting appropriate indices for extreme flow modeling.

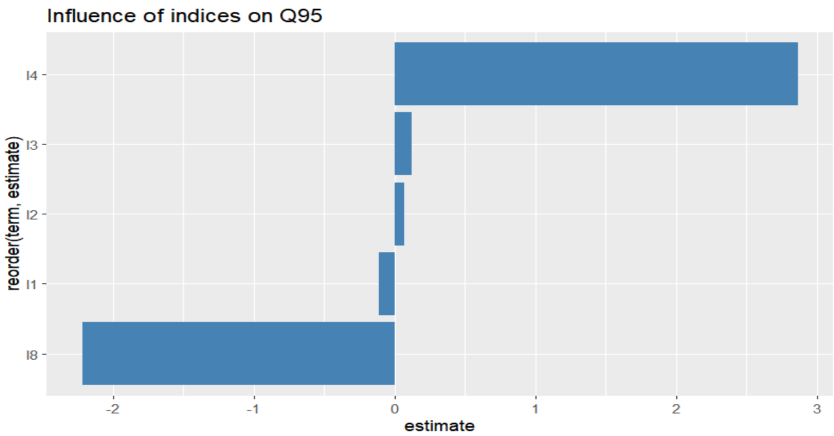

Figure 12. Influence of indices.

4. Discussion

In this study, we analyzed the variability of extreme rainfall and streamflow in the BMVO in Benin from 1960 to 2022. Like previous studies, we selected and calculated key indices to conduct our analysis. However, this study's originality lies in its integrated approach, combining temporal and spatial analyses and directly exploring the links between multiple precipitation and streamflow indices. The results are not always consistent across studies, which can be attributed to the choice of indices, the approaches adopted, and the study period covered. By applying the Mann-Kendall and Pettitt tests, we detected both significant and non-significant trends and breakpoints in our data. The overall finding is a decreasing trend in RX1DAY, RX3DAY, and RX10DAY, with non-significant breakpoints around 1970, 1990, and after 2000. These results are consistent with those of (Vissin et al., 2016), who reported a 15-20% decrease in rainfall in the lower Ouémé Valley around the 1970s, followed by a slight recovery after 1990. Several other studies (Gbohoui et al., 2018; Obada et al., 2021) support these findings, including (Amoussou et al., 2016), who analyzed climate variability in Benin from 1950 to 2010 and its impact on surface water resources. Their results revealed a general decline in annual rainfall across multiple stations, leading to a significant reduction in streamflow. However, unlike our results, (Kodja, 2018) identified significant breakpoints in 1968 and 1987, with a 15% increase in rainfall between 1988 and 2015. These differences could be explained by the different study periods or methodologies used. Nevertheless, the significant increase in Q50 (5.4 m^3/s per decade) and the significant decrease in Q95 (24 m^3/s per decade) at Bonou, with breakpoints in 1990 for Q50 and 1970 for Q95, are consistent with Kodja's (2018) findings, which reported a 65% increase in mean annual flows between 1988 and 2015. This suggests a modification in hydrological dynamics, potentially influenced by rainfall variability and other factors, such as land-use changes. Furthermore, we identified significant correlations between Q95 and RX3DAY, SPI, and PRCPTOT, while Q50 showed no significant relationship with these precipitation indices. This distinction suggests that extreme flows (Q95) are more directly influenced by extreme rainfall events, while median flows (Q50) may be influenced by anthropogenic pressures, such as changes in land use or irrigation withdrawals. In fact, several studies highlight the impact of urban expansion, deforestation and hydraulic infrastructure on baseflow dynamics and flood response (Aich et al., 2014; Kholil et al., 2015). These results therefore confirm that Q95 is a robust indicator of hydrological sensitivity to extreme precipitation events, particularly in tropical basins (Lemaitre-Basset et al., 2021). A detailed analysis of the results suggests an intensification of the hydrological cycle, likely driven by rainfall variability and land use changes. Such dynamics may increase the frequency of flash floods, particularly in lowland areas that are highly vulnerable. In a context where agriculture in Benin remains predominantly rain-fed and exposed, these trends constitute a warning signal for crop planning, water resource management, and spatial planning, as also highlighted in other regional contexts such as in several Asian countries by Muhammad et al. (2025). The observed increase in both Q95 and Q50 may compromise agricultural water availability and expose infrastructures to higher risks of congestion or saturation. These findings underscore the need for better integration of climate indices into early warning systems, and for strengthening local capacities in seasonal forecasting, water storage, and climate-resilient agricultural practices. Beyond its scientific contributions, this study also provides practical insights for water-related risk management in the Lower and Middle Ouémé Valley. By identifying hydroclimatic indices that exhibit significant trends, whether upward or downward, our results can inform a variety of applications, including flood forecasting, land use planning, and agricultural risk reduction. For instance:

- **Early warning systems**: Identifying indices with clear trends and strong precipitation–streamflow correlations enable the development of more responsive and localized flood forecasting tools.
- **Agriculture**: In flood-prone zones, knowledge of increasing Q95 values and shifts in seasonal patterns can help guide crop calendar adjustments, optimize irrigation scheduling, and support the selection of flood-resilient crop varieties.
- **Infrastructure and planning**: The observed increase in Q50 suggests that hydraulic infrastructure design must consider not only extreme events, but also evolving baseline flows that may overwhelm drainage or storage systems.

5. Conclusion

This study analyzed the variability and trends of extreme precipitation and streamflow indices in the lower and middle Ouémé Valley (BMVO) in Benin. The results reveal a general decreasing trend in precipitation indices in the region, although this decline is not statistically significant at the 5% threshold. Three main breakpoints were identified around 1970, 1990, and after 2000, corresponding to periods of alternating hydrological surpluses and deficits. The analysis of the relationship between precipitation and streamflow indices showed a significant correlation between precipitation indices and Q95, while no significant relationship was found with Q50. This suggests that Q50 might be influenced by other hydrological or anthropogenic factors that regulate streamflow dynamics in the BMVO. The observed variations in rainfall, potentially linked to climate disturbances, could have important implications for extreme hydrological events, such as floods. These findings highlight the need for enhanced monitoring of hydroclimatic trends, the implementation of targeted climate adaptation policies, and better integration of climatic and anthropogenic factors in water resource management in the region. In future studies, it would be interesting to explore the sensitivity of different hydrological indices in different regions and with different data sets to assess the consistency of the Q95 as an indicator of the response to extreme precipitation events. It would also be important to identify the precipitation indices that influence other extreme flow indices, to improve water resource management.

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