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Characterization of rainfall occurrences using a Markovian approach and artificial neural networks in the Oueme River basin at Savè Outlet in Benin

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The Oueme basin in Benin, like several other basins in the region, is increasingly affected by floods that have numerous environmental, social, and economic impacts. In this context, it is essential to analyze rainfall occurrence to propose mitigation or adaptation measures for water management. This study analyzes rainfall occurrence over the period 1921 to 2020 in the Oueme River basin at the Savè outlet, using Markov chain models and Artificial Neural Networks (ANN). The methodological approach consisted of occurrence of successive rainy years by using Markov chains and RNAs of order one to three. From the rainfall data, the test on sequential trends with the rainfall index confirmed the existence of three major periods during the study period. We observe a wet period from 1921 to 1940 followed by a normal period from 1941 to 1979 and a dry period from 1980 to 2020. We note a decrease in rainfall from the 1970s onwards, which became more pronounced in 1981. A comparison of the probabilities of the Markov matrices of order 1 to 3, as well as those of the ANR over the sub-periods and the total period of 100 years of study in the Oueme River basin at the Savè outlet, shows a general decrease in the distribution of rainfall in all stations. The study also showed that the probability of having four dry decades is certain over the entire basin. The return of a rainy period as long as the 1920s, 1930s, and 1940s is expected as early as 2025.

Key words: Oueme basin at Savè, Markovian approach, artificial neural networks, rainfall occurrence.

INTRODUCTION

Precipitation is a natural phenomenon and is generally the most significant contributor to the water balance in a watershed: drizzle, ice, frost, snow, hail, sleet, and rain. Nevertheless, in West Africa, especially Benin, rain feeds sand and supplies groundwater and rivers (Koffi, 2007). Precipitation is a source of water for the operation of many activities such as agriculture, power generation ecosystem health, etc. A good understanding of seasonal variability will help West African countries, particularly Benin, to better identify areas requiring the use of

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retention ponds for the continuity of off-season agricultural activities, flood management during heavy rains, etc (Diba et al., 2021). However, an excess of rainfall leads to natural disasters such as flooding. Therefore, it is necessary to better control the rainfall occurrence, which requires modeling. These significant major climatic disturbances that have affected many African countries in the south of the Sahara have not spared Benin, especially from the 1970s and 2010. A significant variability in precipitation has been noticed (Amidou et al., 2010). The abnormal extension of the seasons, a strong distribution of rainfall, and a high runoff coefficient has also been recorded, which increase the frequency of floods (Bodian, 2014). Since Savè is an intermediate zone between the seasons of northern and southern Benin, good management of waterworks is essential to maintain the level of acceptable water reservoirs (Kouassi, 2010) for domestic and agricultural use during the dry season (Konkobo et al., 2021). In this context, it is crucial to understand better how the irregularity and rainfall distribution occur and to adopt preventive measures (Souag-Gamane and Dechemi, 2007). Therefore, this study focuses on the occurrence of rainfall and the distribution of wet/dry periods, which can be determined using Markov chain models (Gabriel and Neumann 1962). The purpose of this study is to highlight the occurrence of rainfall in the Oueme River basin at Savè using Markov chain models and artificial neural networks based on annual rainfall recorded from 1921 to 2020 (100 years). Several studies (Riad et al., 2004; Shen, 2017; Lek et al., 1996) (Higgs and Aitken 2003) have already worked on neural network architectures with good results. However, these global models of artificial intelligence have generally been developed under more or less temperate climates.

MATERIALS AND METHODS

Study area

Oueme is a coastal river of Benin in West Africa that covers an area of 46990 km^2 at Bonou's station, the most advanced station before the Delta. It rises at the foot of the Atacora in the Djougou region, flows through Benin towards the coast, and empties into Lake Nokoué, just north of Cotonou (Figure 1).

It is the largest river in Benin, draining more than a third of the territory. This project uses data from these rivers at the Savè outlet (09°12'N; 02°16'E).

Rainfall data used

The data used are from the Météo-Bénin (National Meteorological Agency of Benin). The study area has seven rainfall stations (Savè, Ouesse, Kokoro, Tchaourou, Bassila, Penessoulou, Toui) covering the period from 1921 to 2020. These data contain some gaps (the largest gap is about 1 year in a 100-year series), which we imputed using the principal component analysis (PCA) method (Laborde, 1998). The Kriging method was used to compute the daily average basin precipitation rainfall.

Data preparation

Data homogenization is a statistical analysis of information that helps to make a consistent decision. It consists of the (1) detection of anomalies in the hydrological series and search for their cause and (2) extension of short hydrological series from homogeneous primary series or the estimation of one or more observations of a sample from other observations taken in different places and at different times under the condition of sufficiently close dependencies.

In this study, the Wilcoxon test was chosen to check the homogenization.

Wilcoxon test

Wilcoxon test is a non-parametric test that uses the observations series of ranks, instead of the values series. The test follows this principle: if sample X comes from the same population as Y, sample $X \cup Y$ also comes from it. A series of observations of size N from which we draw two samples X and Y: N_1 and N_2 are respectively the sizes of these samples, with $N = N_1 + N_2$ and $N_1 \leq N_2$. Then the values of our series were classified in ascending order and we are interested in the rank of each element of the samples in this series. If there is a repeated value several times, we associate it with the corresponding average rank (Ghania Boukhari, 2020). We compute the sum W_y of the ranks of y or x. The null hypothesis of homogeneity verifies the relation: $W_{min} < W_y < W_{max}$, with:

$$W_{min} = \frac{(N_1 + N_2 + 1)N_1 - 1}{2} - U_{1-\frac{\alpha}{2}}\sqrt{\frac{N_1 N_2 (N_1 + N_2 + 1)}{12}}$$

$$W_{max} = (N_1 + N_2 - 1)N_1 - W_{min}$$

where $U_{1-\frac{\alpha}{2}}$ represents the value of the reduced centered Gaussian variable corresponding to a probability of $1 - \frac{\alpha}{2}$ (at the 95% confidence level, we have $U_{1-\frac{\alpha}{2}} = 1.96$).

Interannual variability

To assess the evolution of rainfall during the different years, we use the rainfall index method. This method has the advantage of highlighting the periods of surplus and deficit. Thus, for each of the rainfall data selected, we computed the interannual rainfall index which is a reduced centered variable (Paturel et al., 1998) expressed by the equation:

$$\varepsilon_p = \frac{P_i - \bar{P}}{\sigma_P} \quad (1)$$

where P_i is the annual precipitation for the year I, $\bar{P}$ is the average precipitation, and σ_P is the standard deviation of annual precipitation.

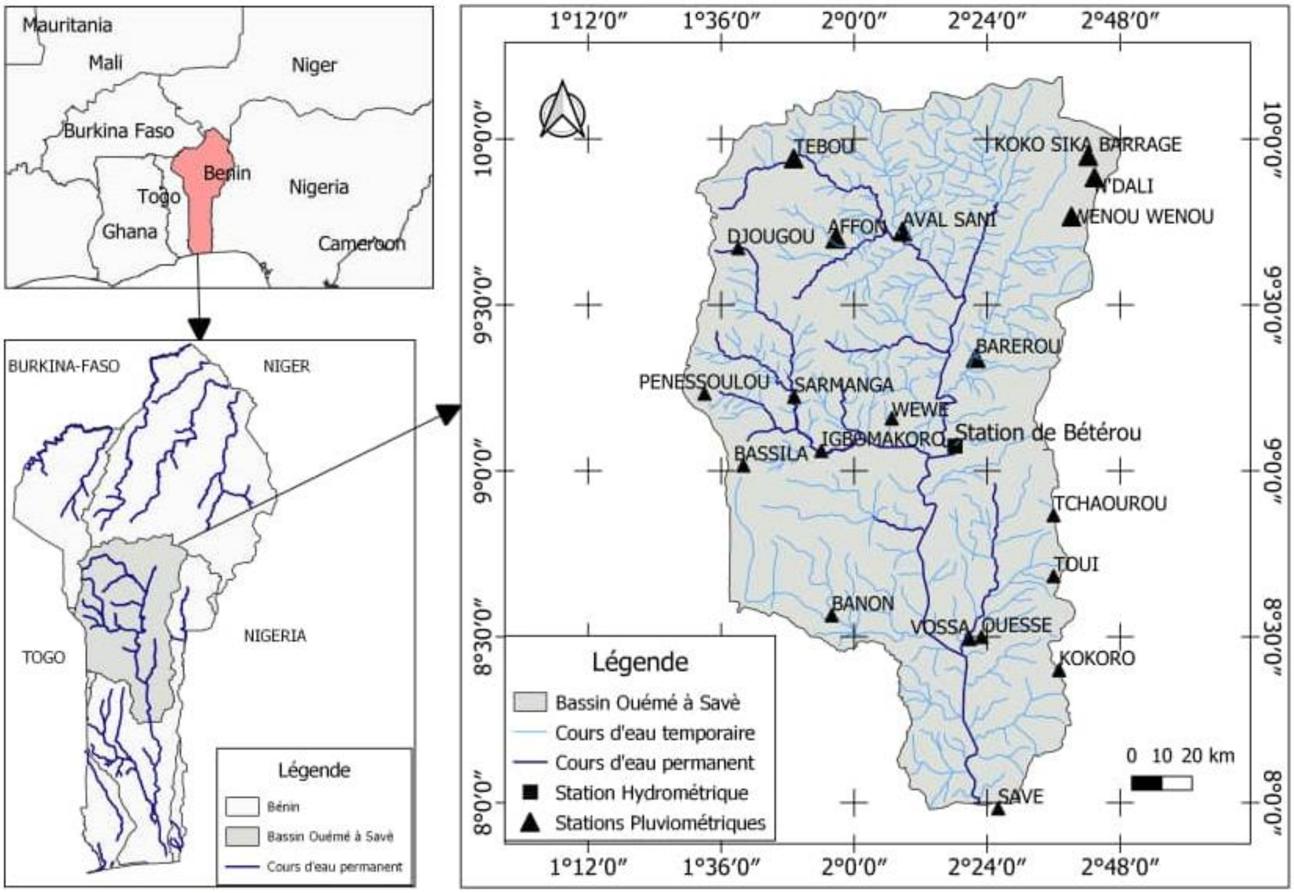

Figure 1. Geographic location of the Oueme basin at Savè outlet.
Source: Authors Study

Daily precipitation using the Markovian approach

Homogeneous Markov chains were used to study the daily precipitation because it consists of neglecting the influence of seasonal variations in the case of daily precipitations. Since the transition probabilities depend on the time t (Darboux-Afouda et al., 1997; Agbossou et al., 2012).

Time settings

The knowledge about the probabilities (of transition and marginal) allows us to calculate the characteristics of the durations (Darboux-Afouda et al., 1997). Let us consider the event of observing a sequence of n days of precipitation. This is realized if we observe the succession of states in the form: 0 1 1 1 ... 1 0 (n times 1). We can therefore introduce the variable describing the duration in the form:

$$S_1 = \min\{n; X_t = 1\}$$

The probability of having exactly n days of precipitation is:

$$P(S_1 = n) = p_{11}^{n-1} p_{10} \quad (2)$$

$$P(S_1 = n) = p_{11}^{n-1}(1 - p_{11}) \quad (3)$$

After some algebraic calculations, we deduce the following results:

(1) The mathematical expectation of the dry durations:

$$m_1(S_1) = \frac{1}{1 - p_{11}} \quad (4)$$

(2) The variance of dry durations:

$$m_2(S_1) = \frac{1 + p_{11}}{(1 - p_{11})^2} \quad (5)$$

(3) The standard deviation of dry durations:

$$\sigma(S_1) = \sqrt{\frac{1}{1 - p_{11}}} \quad (6)$$

(4) The coefficient of variation of dry durations:

$$C_v(S_1) = \sqrt{p_{11}} \quad (7)$$

Table 1. Transition probabilities for the Markov chain of order 1.

Day t-1	Day t	
	0	1
0	α_{00}	α_{01}
1	α_{10}	α_{11}

Source: Authors Study

Table 2. Transition probabilities for the Markov chain of order 2.

Day t-1, Day t-2	Day t	
	0	1
00	α_{000}	α_{001}
01	α_{010}	α_{011}
10	α_{100}	α_{101}
11	α_{110}	α_{111}

Source: Authors Study

The homogeneous Markov chain of the first order (r=1)

Let us consider a daily-scale time interval and a random variable$X_t, t \in T$, with the value 1 representing when the day is rainy and 0 when it is not. We note:

α_{01}: the probability of having today rain (day t) knowing that yesterday (day t-1) there was no rain;

α_{00}: the probability that there is no rain on day t knowing that there was no rain on day t-1;

α_{10}: the probability that there is no rain on day t knowing that there was rain on day t-1;

α_{11}: the probability that there is rain on day t knowing that there was rain on day t-1;

and we have the following transition matrix:

$$T = \begin{pmatrix} \alpha_{00} & \alpha_{01} \\ \alpha_{10} & \alpha_{11} \end{pmatrix}$$

Let N_0 be the number of non-rainy days, N_1 be the number of rainy days, and N_{ij} be the number of pairs (i, j) in the dataset with $(i, j) \in (0,0),; (0,1); (1,0); (1,1)$. We have:

$$\alpha_{ij} = \frac{N_{ij}}{N_i}$$

Then,

$$\alpha_{01} = \frac{N_{01}}{N_0}$$

The transition probabilities of Markov chains of order 1 are presented as follows in Table 1

The marginal probability of a day without precipitation is:

$$\alpha_0 = \frac{N_0}{N}$$

And the one day of precipitation is:

$$\alpha_1 = \frac{N_1}{N}$$

with N the total number of days: $N = N_0 + N_1$

Homogeneous Markov chain of second order

The enumeration of possible states leads to the following transition matrix where α_{ijk} represents the probability of having a doublet of class (j, k) succeeding a doublet of class (i, j) with:

$$\alpha_{ijk} = \frac{N_{ijk}}{N_{ij}}$$

For instance, α_{001} is the probability of having rain today (day t) knowing that there is no rain yesterday (day t-1) and before yesterday (day t-2). This allows us to obtain the transition probabilities of the Markov chains of order 2 presented in Table 2.

Homogeneous third-order Markov chain of order or more (r>3)

It is theoretically possible to extend the aforementioned reasoning to any order. Then, considering two possible states (0 or 1), in order r, we will involve, by the link between r successive days, 2^r possible classes. For example, for r=3, we will have classes of triples that lead, after the assessment of the possible events, to the following transition matrix:

$$T = \begin{pmatrix} \alpha_{0000} & \alpha_{0001} \\ \alpha_{0010} & \alpha_{0011} \\ \alpha_{0100} & \alpha_{0101} \\ \alpha_{0110} & \alpha_{0111} \\ \alpha_{1000} & \alpha_{1001} \\ \alpha_{1010} & \alpha_{1011} \\ \alpha_{1100} & \alpha_{1101} \\ \alpha_{1110} & \alpha_{1111} \end{pmatrix}$$

$\alpha_{ijkl} = \frac{N_{ijkl}}{N_{ijk}}$ represents the conditional probability of having a class triplet (j k l) succeeding a class triplet (i j k), so that we have:

$$\sum_k \alpha_{ijkl} = 1$$

Table 3. Transition probabilities for the Markov chain of order 3.

Day t-1, Day t-2, Day t-3	Day t	
	0	1
000	α_{0000}	α_{0001}
001	α_{0010}	α_{0011}
010	α_{0100}	α_{0101}
011	α_{0110}	α_{0111}
100	α_{1000}	α_{1001}
101	α_{1010}	α_{1011}
110	α_{1100}	α_{1101}
111	α_{1110}	α_{1111}

Source: Authors study

Thus, we obtain Table 3 which presents the transition probabilities of Markov chains of order 3

Characterization of rainfall occurrences using Artificial Neural Networks

Machine learning consists of the combination of only three elements: representation, evaluation, and optimization. In this study, we will use supervised learning which is a type of learning where data is labeled. These systems learn how to combine inputs to make effective predictions on data that has never been observed before; specifically Artificial Neural Networks (ANN).

General principle of ANN

The neuron is characterized by state, connections with other neurons, and activation function. Each neuron's state is influenced by forcing data and then transmitted throughout the neural network, layer after layer, to the output layer through the interconnections, thus giving the ANN its global behavior (Thiria and Lechevallier, 1997). The type of activation function can profoundly influence the performance of a network. Multi-layer perceptrons (MLP) are the most widely used models for simulating non-linear relationships (Zaier et al., 2010). In particular, MLPs are the most widely used and sophisticated. The "learning" step of an ANN consists in calculating and optimizing the informative weight of the nonlinear relationship between input and output. This step is iterative. It is followed by two verification steps 'Test' and 'Validation'. As in any modeling approach, these last steps are essential before asserting an ANN.

MultiLayer perceptrons (MLP)

ANN simulates the principle of functioning of the human brain which manages a flow of information from a learning database (Thiria and Lechevallier, 1997; Kharroubi et al., 2016). It is a powerful model to calculate and establish the non-linearity of the input-output relations of a system (Najjar et al., 1997). MLP are one of the most widely applied types of artificial neural networks in the field of hydrological forecasting. These networks, with a single type of "inter-layer" link, reduce the propagation of errors between neurons and the computation time. Indeed, MLP successively includes an input layer, one or more hidden layers, and an output, layer. These layers are interconnected through the w_{ij} weights of their neurons (calculation elements) (Najjar et al., 1997). The neurons of the same layer are not connected.

The number of layers and the number of neurons per layer determine the architecture of the ANN (Chokmani, 2008). The first layer receives the input variables X_i through the input neurons i, transforms them with the activation function f on the input neuron, and sends them to the neurons j of the first hidden layer (Figure 2). Generally, the activation functions of the input neurons are of the same type, that is, the input signals remain unchanged. The hidden layer consists of the processing neurons that receive the weighted sums $S_j(1)$ from the input layer, then perform their transformations (with the activation function) and at the end transfer them to the next layer (hidden or output depending on the ANN architecture):

$$S_j = \sum_{i=1}^{n} X_i * W_{ij} + W_0$$

where S_j is the weighted sum at the $j^{ième}$ neuron; n is the number of input elements; X_i is the value of the output of the $i^{ième}$ neuron of the previous layer; W_{ij} is the value of the weight between the neuron i and j neuron and W_0 is the bias.

The occurrences are characterized using two approaches operating on a daily time step. We are interested in the one-day forecast without knowledge of the rainfall for that day. We use the Kriging method to obtain the daily basin precipitation.

RESULTS AND DISCUSSION

Rainfall evolution and interannual variation

The variability of precipitation was studied and fit the precipitation to a probability distribution. The knowledge

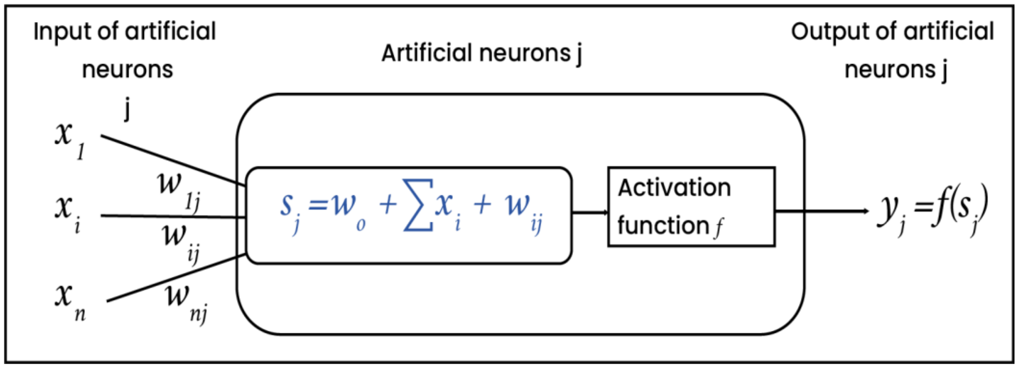

Figure 2. ANN with an input layer, x hidden layers and an output layer.
Source: (Kharroubi et al., 2016)

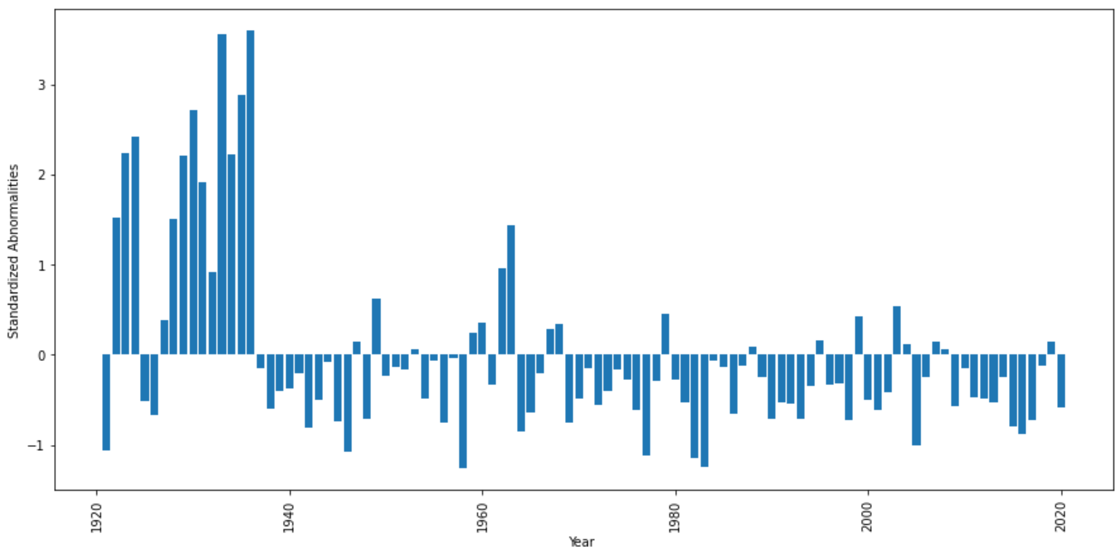

Figure 3. Inter-annual variability of rainfall in Savè.
Source: Authors study

of the data distribution is fundamental as it provides information that can help in the modeling. The analysis of interannual precipitation variability is based on annual precipitation data centered on annual precipitation data reduced by $\bar{P}$ and σ_P. These two parameters are calculated on the whole annual precipitation data. Figure 3 shows the interannual variability of rainfall.

The analysis of rainy days allows us to improve our knowledge of seasonal and annual rainfall deficits or surpluses and other changes that may affect precipitation development. These deficits can be attributed to a decrease in the frequency of precipitation events that reach or exceed a certain threshold.

From the analysis of Figures 4 and 5, it appears that the period from 1921 to 1969 was very wet because of the significant peaks in rainfall observed. Indeed, the years 1933 and 1936 were the wettest during this period. The years 1933 and 1936 were the wettest during this period. The area only recorded dry years of different magnitudes during the following two decades. From 1970 to 1990 (Figure 6), the dry years were more recurrent and corresponded to the great drought observed during the 1970s and 1980s, affecting all of West Africa (Boko, 1998; Afouda, 1990). A recovery of rainfall characterizes the last period from 1991 to 2020 (Figure 7) From 2001-2020 it was observed an extended dry period with the years 2003, 2004, 2007, and 2008 which are nevertheless a little wet contrary to the decade 1990-2000, recorded as the driest after 1970 (Figure 7). It is noted that this period is less dry than in the years 1970 to 1990. In addition, from 2001-2020, there was a long dry period with the years 2003, 2004, 2007, and 2008 which are nevertheless a little wet in contrast to the decade 1990-2000, recorded as the driest after 1970.

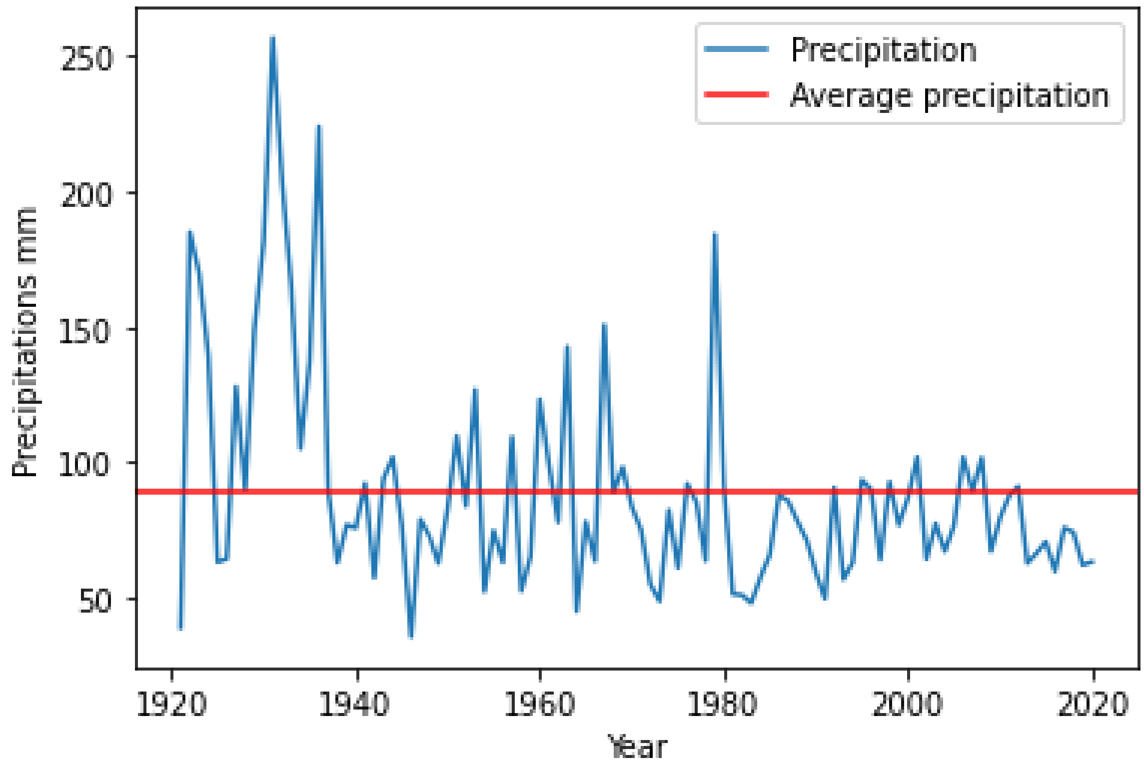

Figure 4. Precipitation trends from 1921 to 2020
Source: Authors study

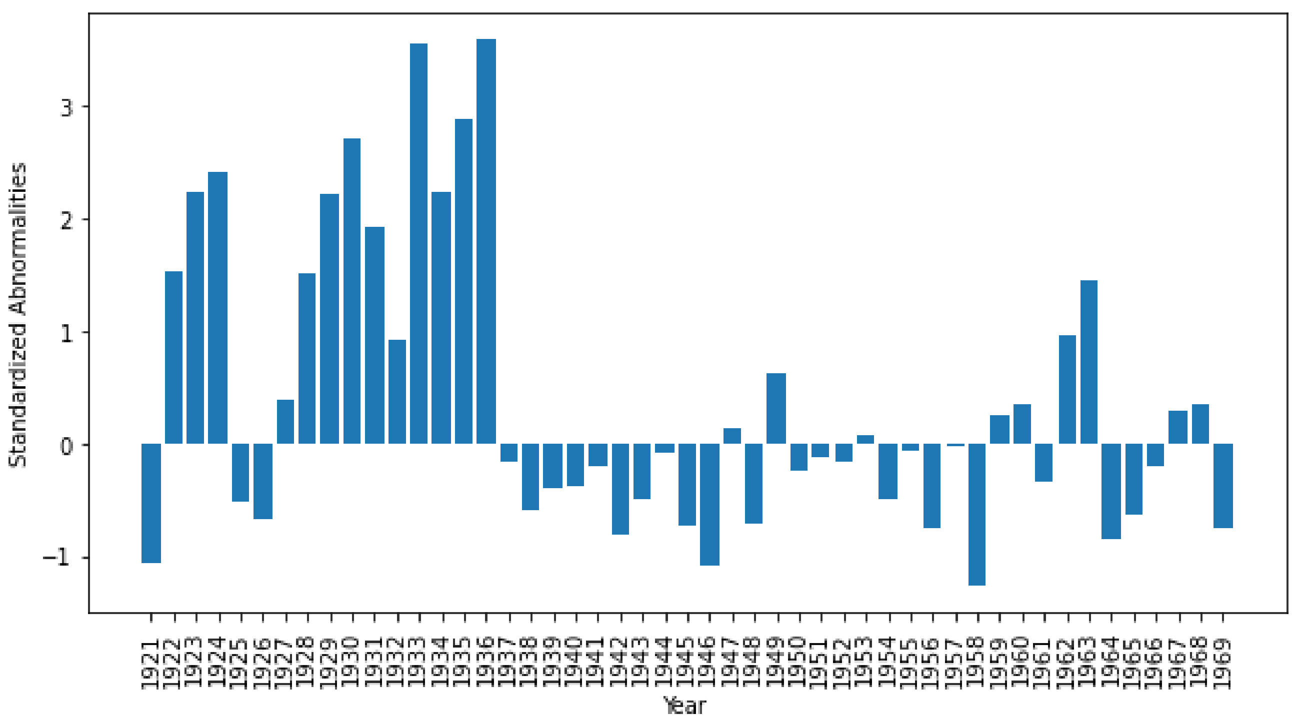

Figure 5. Interannual variability of rainy periods (1921 to 1969).
Source: Authors study

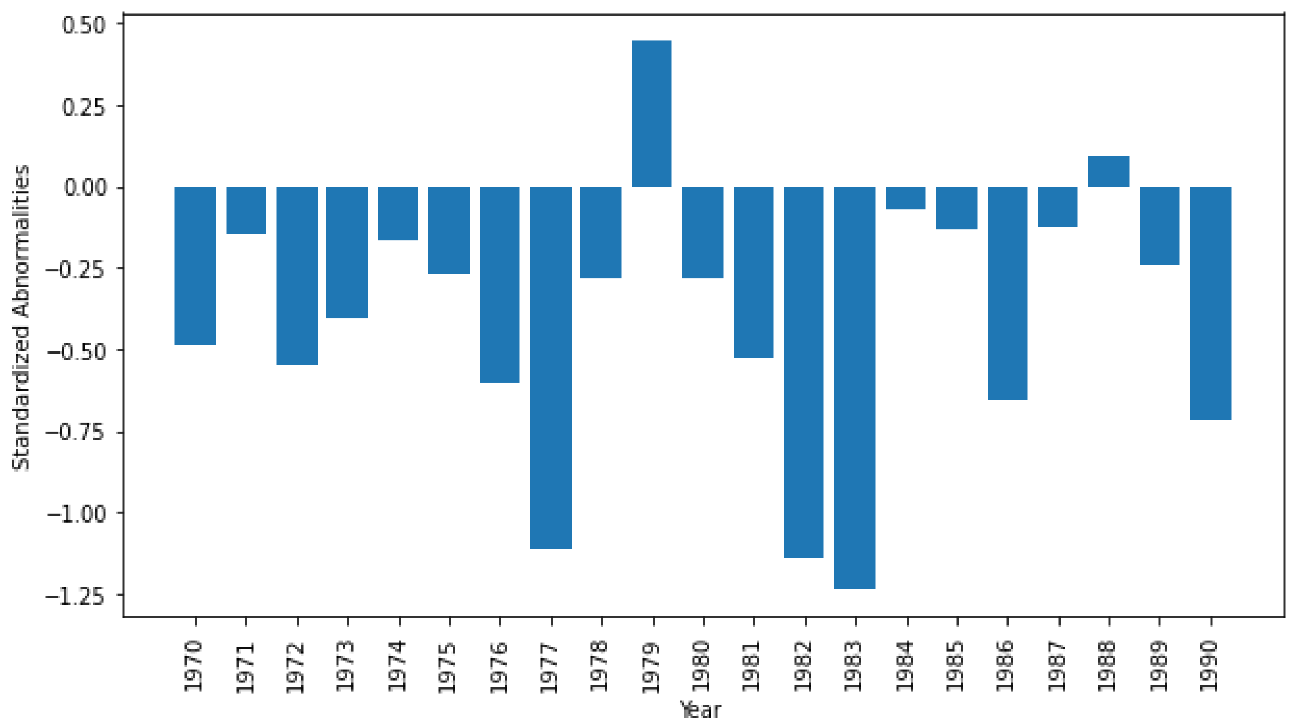

Figure 6. Interannual variability of dry periods (1970 to 1990).
Source**:** Authors study

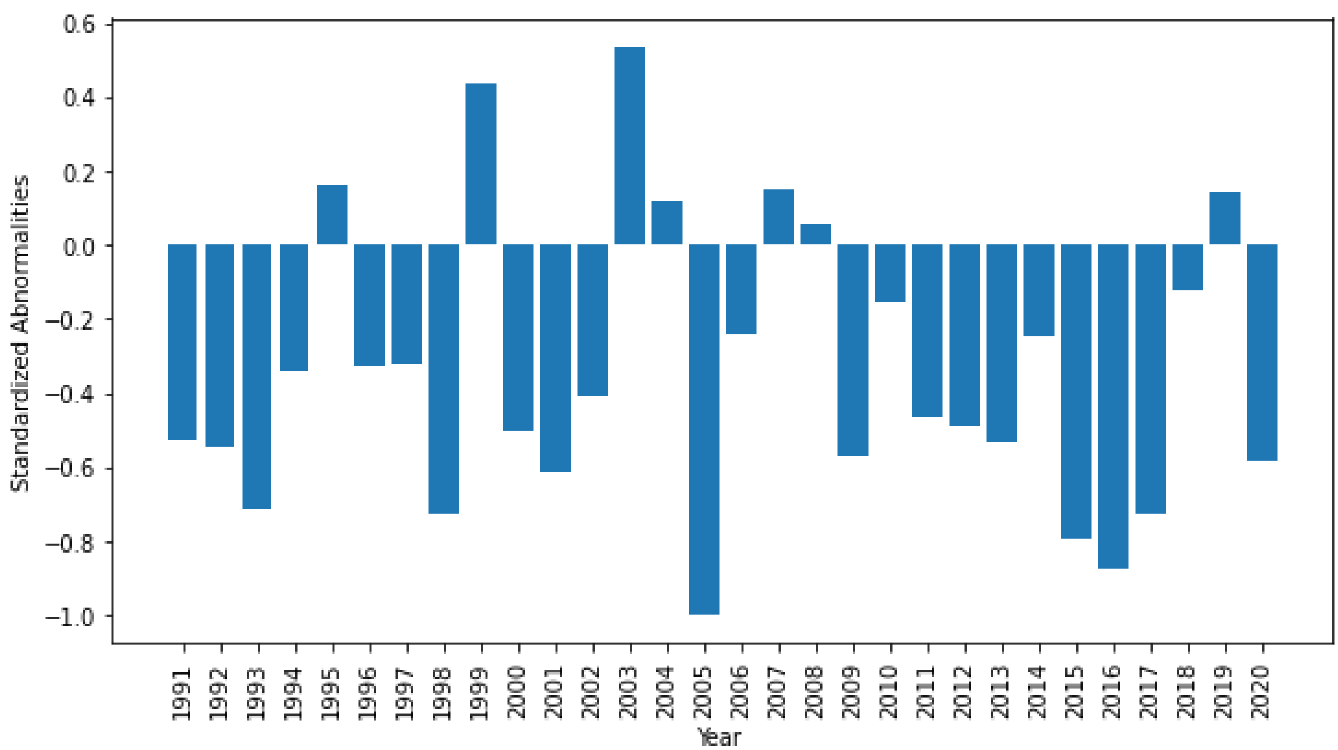

Figure 7. Interannual variability of recovery periods (1991 to 2020)
Source**:** Authors study

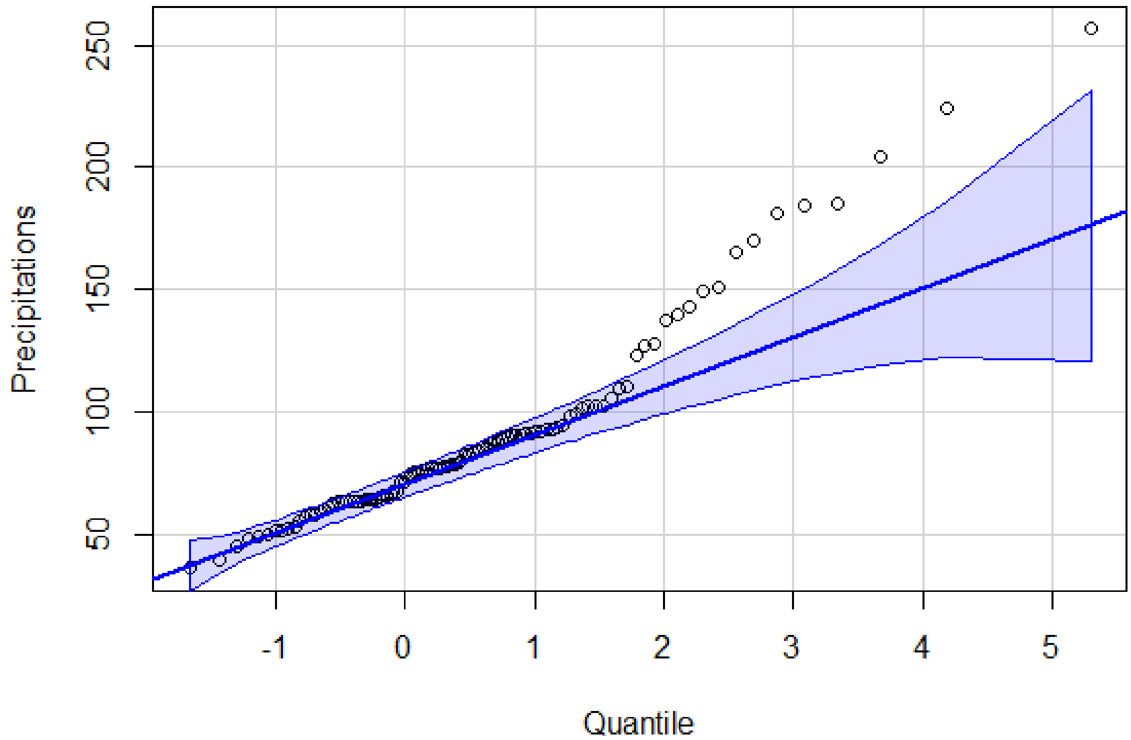

Figure 8.qqPlot of the GEV law
Source**:** Authors study

Table 4. Transition probabilities of the Markov chain of order 1.

Day t-1	Day t	
	0	**1**
0	0.8002	0.1998
1	0.5631	0.4369

Source: Authors study

Fitting of max precipitation to a probability law

Figure 8 illustrates the fit of annual maximum precipitation to the Generalized Extreme Values (GEV).

According to the figure, the annual maximum precipitation fits well with the GEV distribution. The maximum precipitation can be modeled by a GEV distribution. Flood generation in the basin is the gradual rise of water propagated from upstream (Beterou) associated with increasing soil saturation, rather than isolated precipitation episodes.

Occurrence of rainfall using Markov chain

The period from 1921 to 2020 was marked by several types of dry and wet periods. In fact, during this period, there were 27015 days without precipitation and 9585 days of precipitation. The marginal probabilities are: $p_0 = 0.7381$ and $p_1 = 0.2619$.

Given one day of the year, there is a 26.19% chance that it will rain and a 73.81% chance that it will not. In other words, a year has about 96 rainy days and 270 non-rainy days. Table 4 summarizes the transition probabilities obtained for a Markov chain of order 1.

Then we deduce that when there is no precipitation on a given day, there is an 80.02% chance that there will be no precipitation the next day. When there is precipitation on a given day, there is a 56.31% chance that there will be no precipitation the next day. We get the following transition matrix:

$$P = \begin{pmatrix} 0.8002 & 0.1998 \\ 0.5631 & 0.4369 \end{pmatrix}$$

which is a positive and ergodic matrix. The characteristics of the precipitation occurrences over the period from 1921 to 2020 are as follows: Mean: m= 1.7759; Standard deviation: $\sigma = 0.8808$ days; Coefficient of variation: C_v = 0.6610.

It is then retained that if there is a series of rains, it lasts on average two days and with a margin of error of one day. Table summarizes the transition probabilities

Table 5. Transition probabilities for the Markov chain of order 2.

Day t-1, Day t-2	Day t	
	0	1
00	0.8367	0.1633
01	0.5900	0.4100
10	0.6537	0.3463
11	0.5284	0.4716

Source: Authors study

Table 6. Transition probabilities for the Markov chain of order 3.

Day t-1, Day t-2, Day t-3	Day t	
	0	1
000	0.8686	0.1314
001	0.6188	0.3812
010	0.6947	0.3053
011	0.5734	0.4270
100	0.6735	0.3265
101	0.5356	0.4644
110	0.5947	0.4053
111	0.4780	0.5220

Source: Authors study

Table 7. Transition probabilities by ANN of order 1.

Day t-1	Day t	
	0	1
0	0.8036	0.1964
1	0.5571	0.4429

Source: Authors study

obtained for a Markov chain of order two. Thus:

(1) When it does not rain on a day and its eve, there is a chance that it would not rain on the following day;
(2) When it rains one day but not the day before, there is a chance that it will not rain the next day;
(3) When it is not raining on a day but the day before, there is a 65.37% chance that it will not rain the next day;
(4) When it rains on a day and the day before, there is a chance that it will rain the next day.

Table summarizes the transition probabilities obtained for a Markov chain of order 3. The interpretations are the same as for the Markov chain of order 2. For example $p_{010} = 0.6947$ and we will say that there is a 69.47% chance that it will not rain on day t when there was no rain on day t-3, there was rain on day t-2 and there was no rain on day t-1.

The Table 6 summarizes the transition probabilities obtained for a Markov chain of order 3.

Long term forecast

The transition matrix P being positive and ergodic, there exists a stationary long term distribution $\pi = \lim \pi_n = \lim_{x\to\infty} \pi_0 . P^n$ and such that $\pi = \pi . P$

Let $\pi = [i, j]$ stationary distribution, $0 \le i, j \le 1$. Solving the system $\pi = \pi . P$ with $i + j = 1$ leads to the following result: $\pi = [0.7381, 0.2619]$. So in the long run, given a day, there will be a 73.81% chance of no rain and a 26.19% chance of rain. In other words, there will be about 270 days with no rain in a year and 96 days with rain.

Rainfall occurrence using ANN

Here, we use ANNs, more precisely MLPs, to characterize precipitation events. We will consider three orders:

Order 1: knowing the state (rain or not) at t-1, we look for the state at t
Order 2: knowing the states (rain or not) at t-2 and t-1, we look for the one at t
Order 3: knowing the states (rain or not) at t-3, t-2, and t-1, we look for the one at t

The following are the results obtained after learning.

Order 1

From the analysis in Table 7, we can see that when there is no precipitation on a given day, there is an 80.36% chance that there will be no precipitation the next day. When there is precipitation on a given day, there is a 55.71% chance that there will be no precipitation the next day.

Order 2

Thus, when it does not rain on a day and its eve, there is an 83.85% chance that it would not rain the next day; when it rains on a day but not the day before, there is a chance that it will not rain the next day; when it is not raining on a day but the day before, there is a 58.03% chance that it will not rain the next day; when it rains on a day and the day before, there is a chance that it will rain the next day.

Table 8. Transition probabilities by ANN of order 2.

Day t-1, Day t-2	Day t	
	0	1
00	0.8385	0.1615
01	0.6485	0.3515
10	0.5803	0.4197
11	0.5274	0.4726

Source: Authors study

Table 9. Transition probabilities by ANN of order 3.

Day t-1, Day t-2, Day t-3	Day t	
	0	1
000	0.8719	0.1281
001	0.6729	0.3271
010	0.7032	0.2968
011	0.6130	0.3870
100	0.5947	0.4053
101	0.5751	0.4249
110	0.5404	0.4596
111	0.4994	0.5006

Source: Authors study

Table 10. Return period of precipitation.

Return period (year)	5	10	20	50	100
Values (mm)	110.77	135.50	162.90	204.60	241.25

Source: Authors study

Order 3

The interpretations are the same for order 2. For to Table 9 $p_{010} = 0.7032$ and we will say that there is a 70.32% chance that it will not rain on day t when there was no rain on day t-3, there was rain on day t-2 and there was no rain on day t-1. Note that these results obtained with ANNs are very similar to those obtained with the Markov chain method.

Return period of precipitation

According to the analysis of Figure 8, the rainfall sequences of the maximum annual precipitation (P max) estimated for different return periods of 5, 10, 20, 50, and 100 years are presented in Table 10. Applying the GEV to the maximum rainfall values shows an increase in rainfall around 2025 at all stations in our study area.

These results confirm those presented by Meledje et al. (2015), which indicated rainfall return after the persistence of a dry period from 1970 to 2009 in Côte d'Ivoire. The work presents the appearance of a rainfall deficit as early as 1981 and its continuation during the decades 1990, 2000, 2010, and 2020 (Figure 7).

According to Meledje et al. (2015), the standardized rainfall index allows the exact establishment of the duration of the rainfall and its intensity. The application of Markovian approaches in the characterization of rainfall has shown that the probability of having successive years of dry or wet nature is sure. According to Lazri et al., (2007), the second-order long-term probabilities of the Markov chain give more excellent approximations than the first-order ones. The results confirm this expressed at the level of Table and 8 at the level of both Markovian and ANN approaches. The successive probabilities of these two approaches showed an increase in dry conditions during the 1980 to 2020 sub-period, compared to the previous wet sub-period. This inter-annual rainfall variability has heavy consequences on crops and livestock, as agricultural production in Savè is based essentially on rain-fed cropping systems dependent on climatic hazards. In addition, the supply of drinking water to the population is drastically reduced because the level of fresh water at the pumping station has dropped, as the basin no longer has enough water resources to be pumped and treated to serve the population with drinking water.

Conclusion

This study characterized the main manifestations of the temporal dynamics of climate variability in the Oueme River basin in the Savè outlet. The standardized rainfall index made it possible to distinguish three climatic sub-periods, a wet sub-period from 1921 to 1940, followed by a normal sub-period from 1941 to 1979, and a dry sub-period at the end from 1980 to 2020. A significant decrease in rainfall is observed as early as the 1970s; this reduction is accentuated from the 1981s, during which time we record a significant decrease in annual rainfall. The Markovian approaches of order 1 to 3, coupled with the ANN and applied to the data for the characterization of the occurrences of precipitation on the study stations have shown a good indicator of rainfall almost identical to claim a certain return of precipitation in the coming years. Since we note an exponential trend in the probabilities of the "future tomorrows" that increase increasingly.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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