Markovian approach for analysis and prediction of monthly precipitation field in the department of Sinfra (Central-west of Côte d'Ivoire)

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Abstract- Regional rainfall trends in Ivory Coast, due to climate change, show a general decrease in rainfall over the entire country. This is likely to disrupt plans streams thereby reducing the availability of surface water resources. The objective therefore assigned to this work is to analyze the precipitation field while incorporating the effect of climate change. For field analysis of precipitation, the approach follows a markovian approach, which is a stochastic approach widely used to analyze and simulate the spatio-temporal evolution of a system from transition probabilities. The study was conducted on a time series of rainfall data (1966-2000) and showed that monthly precipitation echoes are well described by a Hidden Markov Model (HMM). The arkovian approach followed in this work has helped develop a model to analyze and forecast precipitation field in the department that of Sinfra that reflects reality with accuracy about 83 %.

Keywords- remote sensing, geographic information system, hidden Markov model, water resource, precipitation field, monthly rain, forecasting

INTRODUCTION

Several models are used to analyze precipitation data which represent one of the meteorological phenomena the most difficult to analyze because of their high spatio-temporal variability [2]. However the most widely used technique is the one based on the models of Markov ([11], (12), (15), (20)). In this study for modeling the monthly field of precipitation, the model used is a Hidden Markov Model (HMM) because this model has the advantage of well formalize the transitions from one season to another and associate with each monthly contribution a hidden indicator variable which specifies the current season and explicitly describes the seasonal variation of the process generator of observations. The transition from one season to another follows a markovian process. This work will be discussed in two main areas, the first detail the main steps of the design of an unobservable Markov model. . The last axis will indicate the types of exploitation of the Hidden Markov Model through the analysis and forecasting of monthly precipitation field of the department of Sinfra.

State of art

Several stochastic models ([8], [9], (19), (26), (29)) are used to simulate the precipitation field, from observed data from stations or meteorological radars (16). These models include those that are based on the geostatistical methods (24), the disaggregation methods ([14], [25]), the disaggregation methods using Markov models (4)), the probabilistic methods ([10], [12]).

Choice of the model and justification

Prediction models of weather phenomena can be classified into two broad categories: the deterministic models and stochastic models:

- Deterministic models

It is to establish a system of equations (for most from fluid mechanics), for which the settings to the initial moment are determined by the meteorological observations. This type of model is dedicated to climate prediction. It must be reset frequently with actual observations, available, and the calculations must be able to do so in a manner close to the real time (10). The deterministic models represent general laws observed in nature by calculating and transposing into the future the average case of the observed phenomena.

- Statistical models and probabilistic

Unlike deterministic models, stochastic models account for the variability of phenomena using probability. It is here to create a system whose behaviors are of the same type as the real system. For all that, they must not coincide exactly in time, but in convergence. The emphasis is here to make a digital model whose overall characteristics are going to tend on average to those of the real system. This type of model is rather dedicated to the simulation. The one used in this case tools developed from probabilistic mathematics, to assess risks to achieve such temperature or if it rains (10).

The Hidden Markov Models are part of this last category (22), the probabilistic models. As well after having learned the actual

behavior on a set of learning that is the type of modeling that has been chosen for this study. Among the vast field of probabilistic mathematics, tools developed from Hidden Markov Models are spreading of growing way in the modeling involving the temporal phenomena. These are doubly probabilistic models who have the advantage of serve especially to deal with problems with incomplete or uncertain information (12). This type of model of Markov is used in this work to model the field of monthly precipitation, actual process, from time series of rainfall from 1966 to 2000 with a view to make forecasts.
According to the principle of the model of the Hidden Markov Model, rain is regarded as a noisy signal as well before the analysis of the field of precipitation the signal is restored which leads to the denoising data from rain. These models therefore reflect better the echoes of precipitation by integrating the effects of climate change as regards the climate data.

1 LOCATION OF THE AREA OF STUDY

The department of Sinfra, is located in the Central West of Ivory Coast and is part of the administrative region of the Marahoue. The departmental territory includes four (4) sub- prefectures: Sinfra, Bazré, Kouetinfla and Kononfla. The department of Sinfra extends over 1600 km^2 and is bounded to the North by the department of Bouaflé, on the south by the departments of Oumé and Gagnoa, on the east by the department of Yamoussoukro and to the west by the departments of Daloa and Issia . The department of Sinfra is located between longitudes 5.38°W and 6.15°W and latitudes 6.48°N and 6.82°N and is at the intersection of square degrees of Gagnoa and Daloa (figure 1):

ISSN 2091-2730

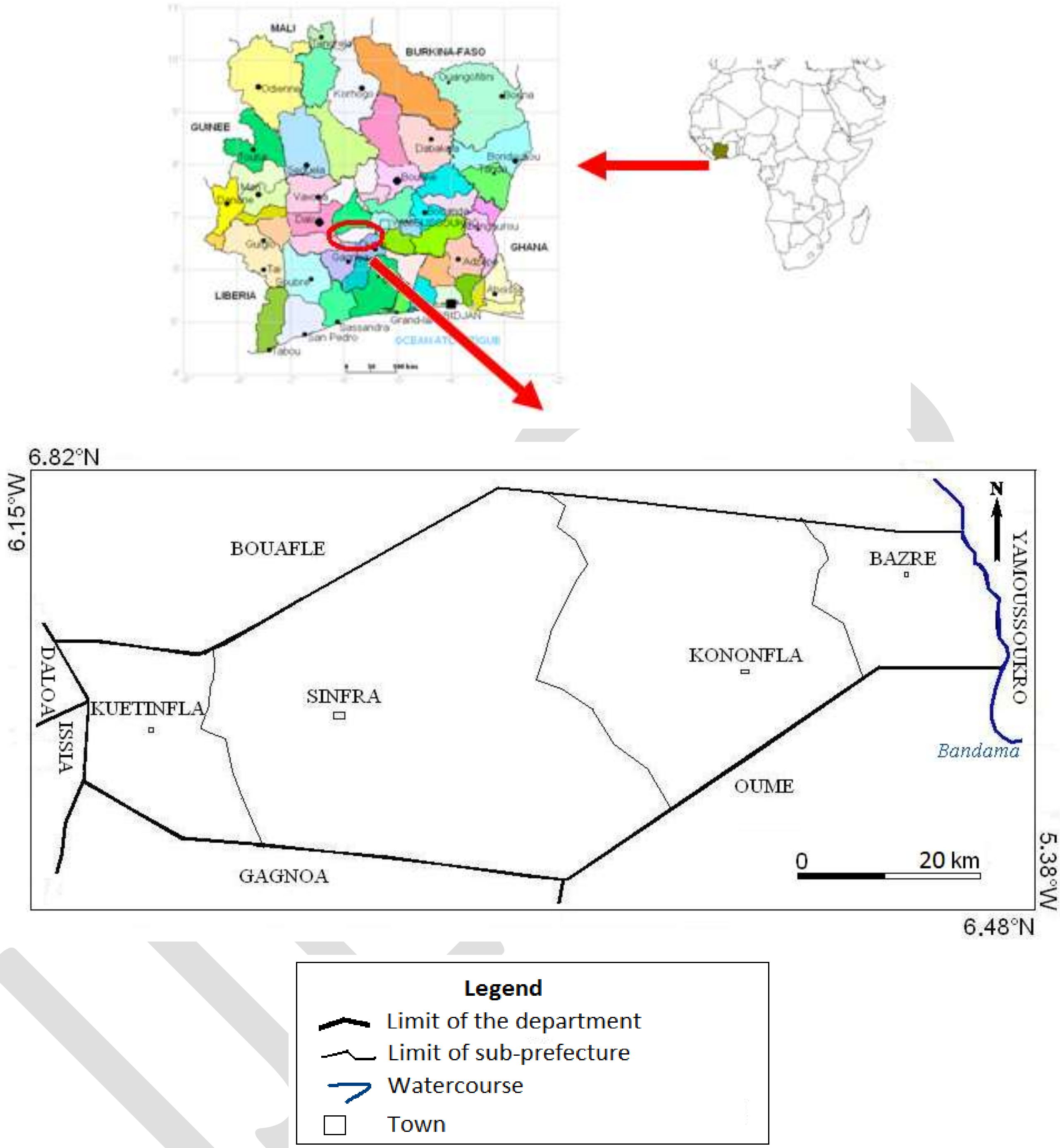

Figure 1. Location of the study area

A satellite image of the study area is given by the figure 2 below:

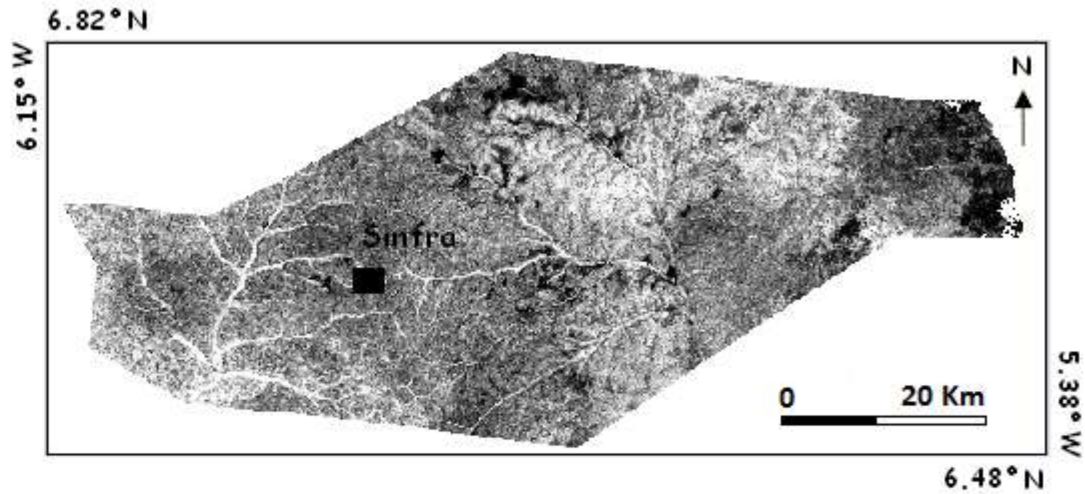

Figure 2. Image of the study area extracted from the band 4 of the satellite images Landsat ETM+ 2003

2. MATERIAL AND METHOD

To carry out this study, several types of data are necessary. The analysis of these data has necessitated the use of several software depending on the type of processing required.

2.1 MATERIAL

Several types of data were needed for the realization of this research work. The processing of Landsat TM satellite images from1986 and ETM+ from 2003 of the scene 197-055, respectively registered on 16 January and on 20 January, has enabled us to extract the study area. The topographic maps of square degrees of Daloa and Gagnoa 1/ 200 000 as scale from the Center of Cartography and Remote Sensing (CTC) have served to the extraction of the hydrographic network .Time series of daily, monthly and yearly amount of rainfall from 1966 to 2000 of the department of Sinfra and 26 rainfall stations surrounding it, from the Operating Company and Airport Development, Aeronautical and Meteorological (SODEXAM) have provided the necessary information to the analysis and prediction of the field of monthly precipitation. Given the character of multisource data, several types of treatment have been required which involves the use of several software.

The extraction of the hydrographic network has been carried out with the software Mapinfo Professional 7.5 as well as the extraction of information contained in the topographic maps. Idrisi Andes (15) was used for the processing of satellite images and the extraction of the study area. For markovian modeling the software Matlab 7 was necessary.

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2.2 METHOD

The modeling of tmonthly precipitation field of the department of Sinfra is performed according to the principle of a Hidden Markov Model which is a doubly markovian probabilistic approach.

2.2.1 MODELING OF MONTHLY PRECIPITATION FIELD USING A HIDDEN MARKOV MODEL

- **DEFINITION**

A Hidden Markov Model is a process doubly stochastic, one component is a non-observable Markov chain. This process can be observed through another set of processes which produces a suite of observations. More simply, it is a model that describes the states of a markovian process using the transition probabilities and the probabilities of observation by states. It is a

Markovian model in which each state corresponds to an event not directly observable and thus applied to certain problems with hidden states. The case where the observation is a probabilistic function of the state is included in the principle of Markov to give a Markov model not observable but can be observed through a set of stochastic process that produces a set of observable symbols (13).

To define a hidden Markov chain, several considerations are made such as:
-All the past of the rainy phenomenon is summarized in its state at the last moment when it is known, in its previous state [20]:
-this is a discrete process, homogeneous in time, with finite state space.
Thus defined the Hidden Markov Model consists of following elements: a transition matrix A, a matrix of emission B and the initial conditions Π.

- **PRINCIPLE OF HIDDEN MARKOV MODEL (HMM)**

According to (3)), the HMM's are characterized by the following parameters:
1) The number N of states of the model.
The set S of individual states of the model: $S = \{S_1, S_2, S_3, \dots, Sn\}$ (1)
and the state at time t qt, qt Є S.
2) The number M of symbols to separate observations when the observation Ot as the physical output of the system is represented discrete outputs. The set of symbols of observations:

$$Ot = vk, vk \in V= \{v1,v2,v3, \dots vm\} \quad (2)$$

can be generated following multiple paths in a HMM
3) The distribution A of transitions probabilities of the states:
$A= \{aij\}$ (3)
Or
$A_{IJ} = P[qt+1= sj/qt= if], 1< i,j\leq N$ (4)
And

$$\sum_{j=1}^{N} aij = 1, 1 \leq i \leq N \quad (5)$$

4) The probability distribution B of observations in each state j:

$$B = \{bj(Ot)\}, j = 1,2,3, \dots, N \quad (7)$$

In the case where the observations are continuous outputs, we have:

$$\int_{-\infty}^{+\infty} b_j(x)dx = 1, 1 \leq j \leq N \quad (8)$$

And in the case where the observations are as discrete outputs we have:

$$BJ (Ot = vk) = P[Ot = vk/qt = sj], 1 < j < N, 1 < k < M \quad (9)$$

With

$$\sum_{k=1}^{M} b_j(O_t = v_k) = 1, 1 \leq j \leq N \quad (10)$$

And in this case B is called the matrix of probabilities of symbols of observations.
5) The probability distribution of initial states. Π :

$$\Pi=\{ \pi_i \} \quad (11)$$

Or

$$\pi_i = P[q_1 = s_i], 1 \leq i \leq N \quad (12)$$

$$\sum_{i=1}^{N} \pi_i = 1 \quad (13)$$

We can conclude that the complete specification of an HMM requires: (12)
• Two parameters (N and M for a discrete HMM);
• Definition of the vectors of observations;

• The distributions of probabilities A, B and Π.

We denote by:

$$Λ = (A,B,Π) \quad (14)$$

A model completely specified.

Given the appropriate values of N, M, A, B and Π, the HMM can be used as a generator of sequence of observations:

$$O = O_1O_2O_3 .... O_T \quad (15)$$

with

$$Ot = vk ,vk \in V, 1 < k < M \quad (16)$$

In the case where the observation is represented as discrete outputs.

T is the number of observations in the sequence.

The design of a HMM requires several steps.

- **DIFFERENT DESIGN STEPS OF A HMM**

The design of a HMM necessarily requires the following stages:

- Evaluation of the model;

-Estimation of the sequence of hidden states;

-Learning and;

-Validation

1) STEP 1: EVALUATION OF THE MODEL

Given a sequence of observations $O = O_1O_2O_3$ .... O_T and a model $\lambda = (A,B,\Pi)$, how can we calculate effectively the probability $P(O/\lambda)$ that the sequence of observation O is produced by λ? In practice, it is to evaluate the model in order to choose among several that which generates the better this sequence of observation O. Several techniques are used to solve this problem: the method of direct assessment, the procedure "Forward Backward" and the algorithm of Viterbi ([3], [12]).

2) STEP 2: ESTIMATION OF THE SEQUENCES OF HIDDEN STATES

This step is essentially the analysis step of the model **.**Given a sequence of observations O = $O_1O_2O_3$ .... O_T and a model $\lambda = (A,B,\Pi)$, how can we choose a sequence of states Q = $Q_1,Q_2,Q_3 \dots Q_T$ according to an adequate criterion? It is often interesting, given a HMM λ and a sequence of observations $O = O_1O_2O_3$ .... O_T to determine the sequence of states Q = $Q_1,Q_2,Q_3 \dots Q_T$ the more likely having been able to generate O. It is to determine all of the sequences of states having been able to generate O, and then to calculate their probabilities in order to determine the most probable. This method is particularly expensive in computation time because, in the general case, there are N^T possible paths. It was therefore recourse to an algorithm of dynamic programming through a lattice associated with the HMM: the algorithm of Viterbi ([3], (12), (13)).

3) STEP 3: LEARNING

How can we adjust the model $\lambda = (A, B, \Pi)$, to maximize $P(O/\lambda)$?

The objective of this step of the design of a model of the HMM is the estimation of model parameters.

The parameters of a HMM are generally not given in advance, they must be estimated from data. A long sequence of observations $O = O_1O_2O_3 .... O_T$, called learning data which is supposed to be representative of the type of data that the HMM can produce is considered at the beginning of the process. In addition the structure of the HMM (the number of states and the possible transitions between states) is fixed. The objective is to determine the parameters which make it the best account of the result of observations O or, in other words, to determine the parameters which, among the set of possible parameters, attribute to O the best probability ([3], (12), (13)).

4) VALIDATION

The validation of the model will consist of a comparison between the observed values and simulated hidden states. This process leads to the calculation of correlation coefficient R which reflects the performance of the model. This coefficient measures the ability of the model to give the sequence of hidden states knowing the sequence of observations.

The different levels of the design of the HMM are grouped in the organization chart below (fig.3):

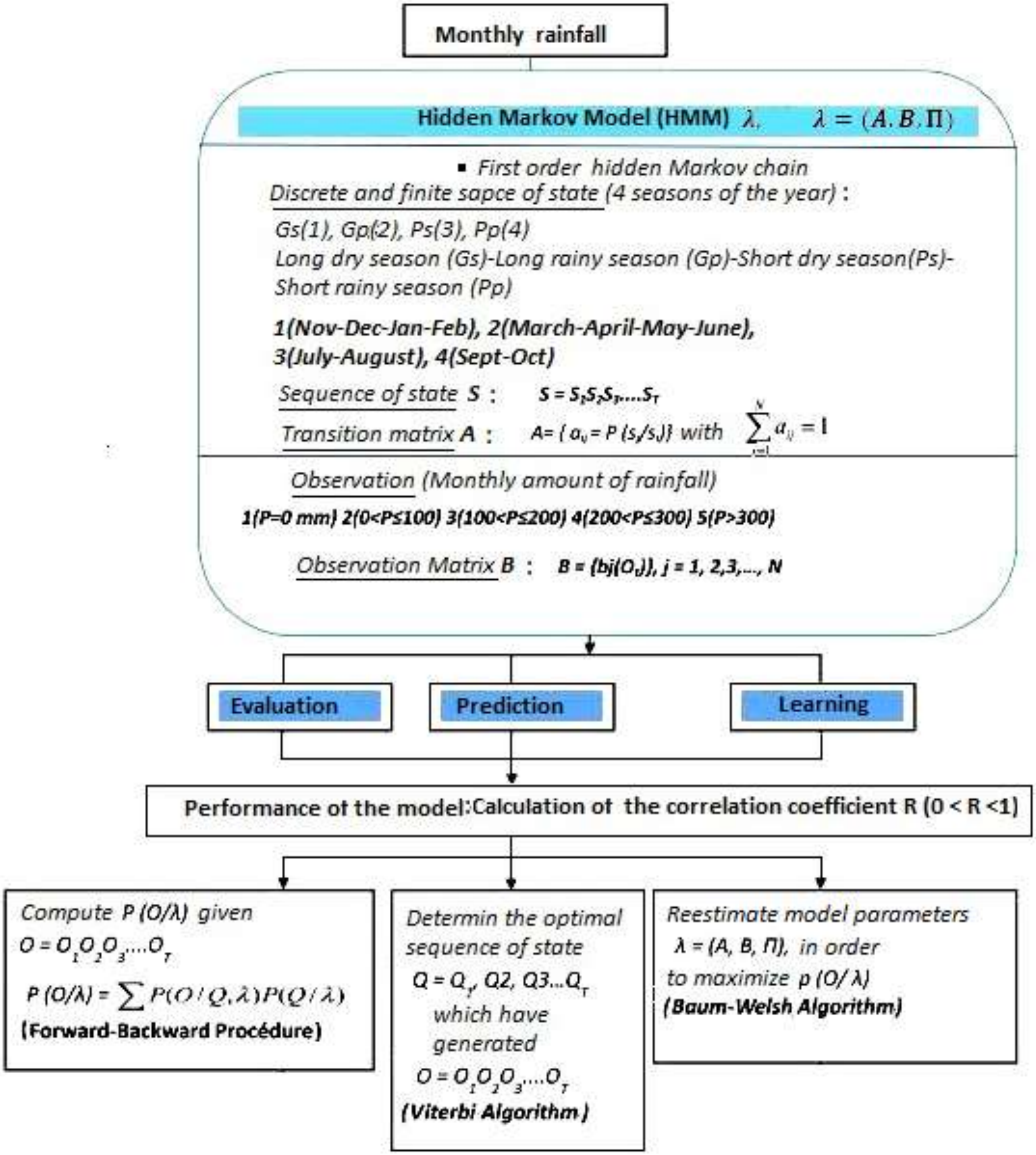

Figure 3. Flowchart of the design of a HMM for monthly precipitations [3]

After the design and validation, the use of the HMM for the analysis and forecasting of monthly field of precipitations will be done through its three modules: Learning, Evaluation and prediction.

- **EXPLOITATION OF THE MODEL**

The exploitation of the HMM is done through its three modules:

-The learning module which has been used to estimate the model parameters through the use of the algorithm of Baum-Welch),

-The analysis module which is used to determine the state in which the system was or will be for a given sequence of observations and also to make a forecast using the algorithm of Viterbi and,

-The evaluation module that allows to achieve the recognition of sequences and the estimated probabilities of occurrence of a given sequence of observations, using the principle of likelihood. This module allows to calculate the probability with which a sequence of given observation would be produced by the model.

Once constituted the model can then be used to analyze the field of precipitation in order to forecast following the flowchart below (fig.4):

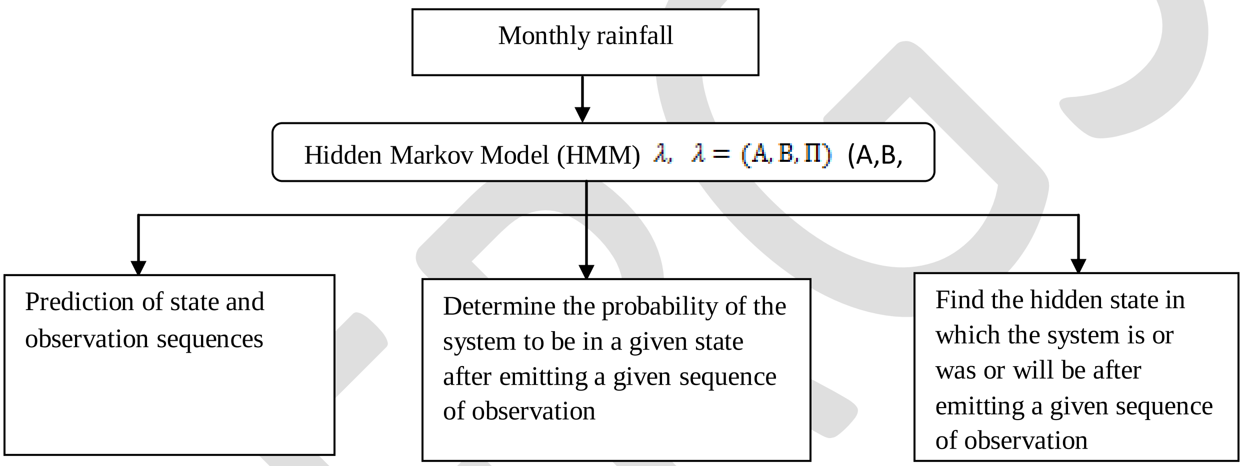

Figure 4. Diagram of operating the HMM [12]

3- RESULTS AND DISCUSSION

In this part of the work the main results are presented and discussed.

3-1 ANALYSIS OF THE PERIOD OF STUDY

The graphs of the gap in the average number of annual rainy days on figure 5 and the rainfall index on figure 6 reveal three major phases of the study period ([6], [7]):

- **First phase: the wet phase,** it is less long and extends over 6 years, from 1966 to 1971. This period is characterized by annual rainfall with a surplus.
- **Second phase: the normal phase,** it is longer and lasted 18 years, from 1971 to 1988. It is characterized by an alternation of years with low deficit and low surplus.
- **Third phase:** it lasted 11 years, from 19888 to 2000. This period is characterized by alternating dry and humid periods causing sudden and intense rain (fig. 5 and 6). Thus, an analysis of the period of study revealed a decrease in the number of rainy days during recent years, marked by a return of rainfall since 1994.

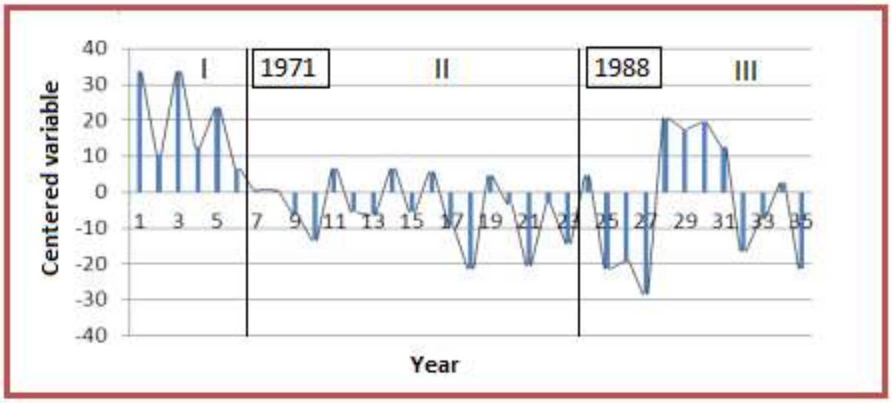

Figure 5. Graph of deviations from yearly average of the number of rainy days

Dividing the study period into three major periods I (1966 to 1971), II (1971 to 1988) and III (1988 to 2000) is confirmed by the graph of Nicholson rainfall index presented by the figure 6:

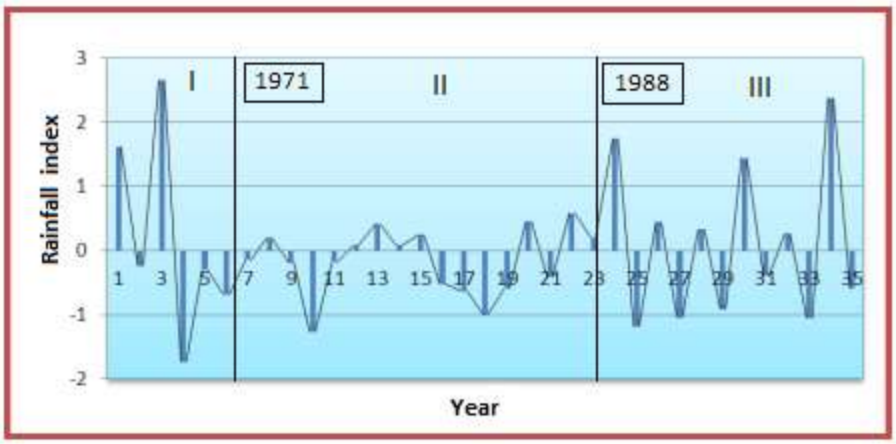

Figure 6. Nicholson Rainfall Index from 1966 to 2000

3.2 RESULT OF THE MODELING OF MONTHLY PRECIPITATION FIELD BY A HIDDEN MARKOV MODEL

The results concern the parameters and the operation of the model.

3.2.1 MODEL PARAMETERS

- **STATES OF THE SYSTEM**

The analysis of the graph of deviations from monthly average of the number of rainy days of figure 7 and the Nicholson rainfall index for monthly precipitation field of figure 8 has allowed us to identify 4 states for the HMM which has been used to model the monthly field of precipitation.

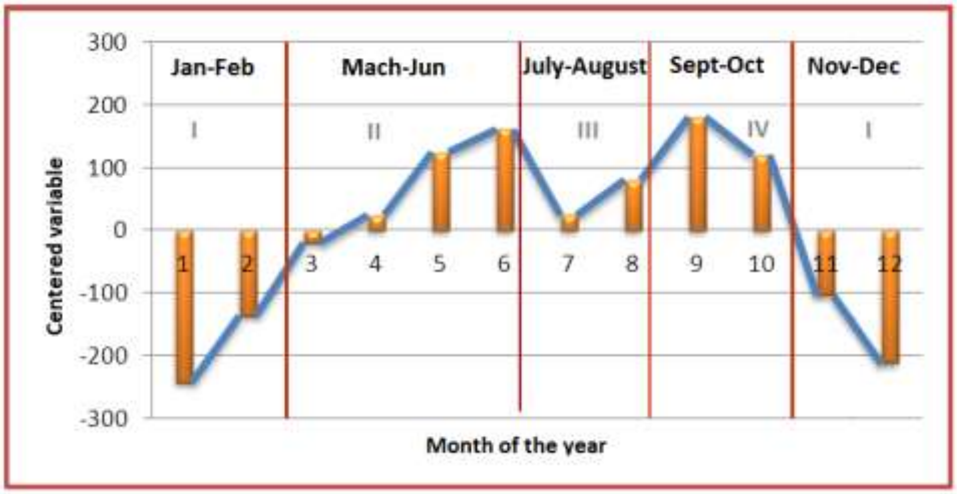

Figure 7. Graph of deviations from monthly average of the number of rainy days. in the department of Sinfra

This splitting of the year into four major periods is confirmed by the Nicholson rainfall index of monthly field of precipitation of figure 8:

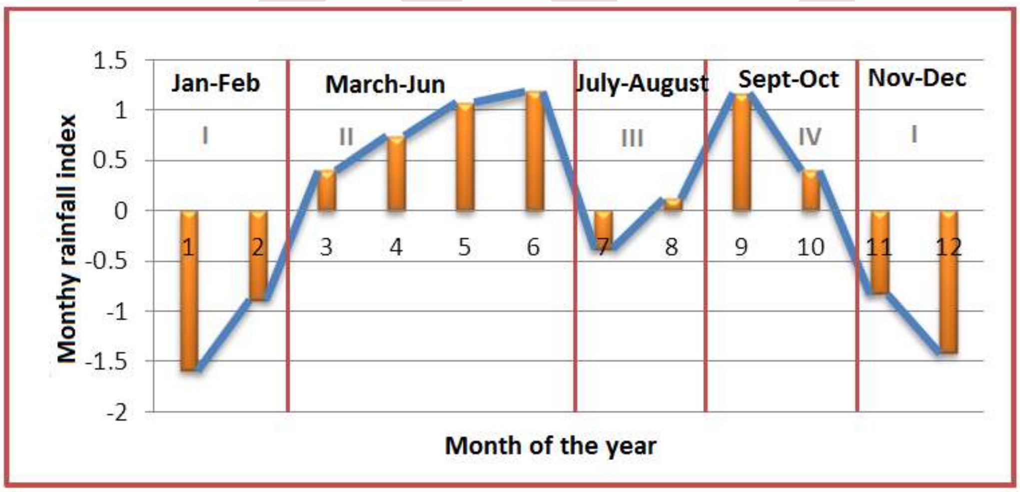

Figure 8. Monthly rainfall index from 1966 to 2000

According to these graphs (Figures 7 and 8) the set of states is constituted by the 4 seasons of the year, as follows:
- the first State corresponds to the long dry season, November and December of the previous year and the first 2 months of the following year, January and February Gs (1),

- The second state is formed by March, April, May and June indicating the long rainy season Gp (2),

-The third state indicates the short dry season, which include July and August Ps (3) and;

-Finally **the fourth state** which corresponds to the months of September and October Pp (4), it is the short rainy season.

- **Initialization Vector**

This vector is formed by the initial probabilities: *Π*= {0.25; 0.167; 0.25; 0.333} which indicate the initial conditions of the system. This vector initializes the model.

- **OBSERVATIONS**

The observations are represented by the total amount of monthly rainfall. The values below have been chosen after analysis of the distribution of amount of rainfall in the months during the entire period of study (1966-2000):

-Observation 1, it includes the null values of rainfall amount,

-Observation 2, it concerns the amount of rainfall less than 100 mm,

- Observation 3, it is formed by the amount of rainfall between 100 mm and 200 mm,

-Observation 4, it contains the amount of rainfall between 200 mm and 300 mm and,

-Observation 5 which indicates the amount of rainfall higher than 300 mm.

3.2.2 ESTIMATION OF PARAMÈTERS (Learning)

Let us consider the following sequence of observations: 1 3 2 1 1 2 2 1 3 3 1 2 and the sequence of states following: 1 2 2 4 1 2 3 4 3 2 3 2. The use of the algorithm of Baum-Welch gives us an estimation of the transition matrix A_f and the matrix of observation B_f after 100 iterations for a tolerance of 10^{-4} (13).

- **TRANSITION MATRIX**

This matrix defines the different transitions of monthly rainy phenomenon from 1966 to 2000. It is the matrix of probability of transition A(ij), it contains the probability of transition of each state to another and also contains the residence time of the process in each state (12). A (ij) is a square matrix NxN, A=P(ij) :

$$Af=\begin{bmatrix} 0,25 & 0,333 & 0,167 & 0,25 \\ 0,25 & 0,25 & 0,5 & 0 \\ 0,222 & 0,555 & 0,222 & 0 \\ 0 & 0,333 & 0,333 & 0,333 \end{bmatrix}$$

- **EMISSION MATRIX**

It includes the probabilities of emission of observations from each state (12). The matrix of emission B is an NxM matrix:

$$Bf=\begin{bmatrix} 0,25 & 0,75 & 0 & 0 & 0 \\ 0 & 0,222 & 0,222 & 0,444 & 0 \\ 0 & 0,2 & 0,2 & 0,6 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

The markovian model designed need a validation before any use.

3.2.2 VALIDATION OF THE MODEL

It is to measure performance and the fidelity of the model. After the learning phase, the performance of the model is evaluated through a rigorous approach which is to use the model to generate the path corresponding to a given observation chosen randomly using the algorithm of Viterbi. Then, the actual path corresponding to this same observation is determined using the rules previously defined (13).

The Sequence of states observed (actual): 1 2 2 4 1 2 3 4 3 2 3 2 and the calculated Sequence: 2 3 2 4 1 2 3 4 3 2 3 2

The two results are compared in order to calculate the error committed by the model.

For the model designed in this work, the error rate calculated is 17 %. Thus the calculation of the correlation coefficient R gives a value of 83 per cent R =0.83. The model reflects the reality at 83% as shown in the figure 9:

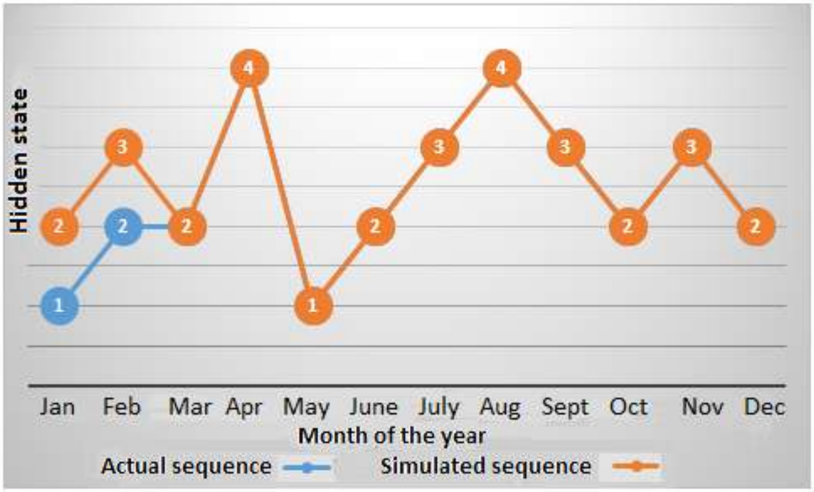

Figure 9. Comparisons of sequences of real hidden and simulated states by the model

3.2.3 EXPLOITATION OF THE MODEL

The model will be exploited through its three modules such as learning, assessment and prediction.

- **ANALYSIS OF THE PERIOD OF STUDY BY THE NON-OBSERVABLE MARKOV MODEL AND PREDICTION OF PRECIPITATION FIELD**

The parameters obtained after the learning phase of the model can be used to analyze the monthly field of precipitation.

1) Learning: The values of the probabilities of transition from one state of the system to another provide several information. In this study a long period has a duration of four months and a short period, a duration of two months.

The null values of probability of transitions A_{41}, A_{24}, A_{34} of the transition matrix A(ij) indicate that in a year and in the study area, it is very unlikely:

- To move from a short period of rain, approximately two months to a long dry period, approximately four months,

- That a short period of rain follows a long period of rain,

- That a short dry period follows a long period of rain.

It is rather likely, according to the probability values for transition a_{23} and a_{32} respectively 0.5 and 0.52:

-Only a short dry period follows a long period of rain, and

-That a long period of rain succeeds a short dry period.

The null values of probability of the matrix of emission B(ij) reveal the following information , in the same year and always in the area studied:

- It is more likely during the long dry season to have total amount of monthly rainfall less than or equal to 100 mm, according to the value of probability b_{12} equal to 0.75 and very unlikely, that the total amount of monthly rainfall may be higher than 100 mm according to the null values of probability b_{13}, b_{14}, b_{15},
- During the long period of rain the total amount of monthly rainfall does not exceed 300 mm, according to the values of probability b_{22}, b_{23} and b_{24},
- From September to October, it is possible to have the total amount of monthly rainfall between 200 mm and 300 mm, according to the probability b_{34} equal to 0.6

- During the short rainy period it is certain that the total amount of monthly rainfall is between 100 mm and 200 mm, information given by the value b_{43} equal to 1.

- **DETERMINATION OF THE LENGTH OR DRY AND WET SEQUENCES**

The length of dry and humid sequences is obtained from the following formula of the mathematical Expectancy of dry and wet durations [28]:

$$E(X_n) = \frac{1}{(1 - a_{ii})}$$

Using the probabilities a_{ii} of the transition matrix A_{IJ}.

$$E(X_{11}) = \frac{1}{(1 - a_{11})} = 1.33$$

It is not certain to have two extended dry consecutive period.

$$E(X_{22}) = \frac{1}{(1 - a_{22})} = 1.33$$

It is not sure to have two long consecutive periods of rain in the department of Sinfra.

$$E(X_{33}) = \frac{1}{(1 - a_{33})} = 1.28$$

A short dry period cannot be followed by another.

$$E(X_{44}) = \frac{1}{(1 - a_{44})} = 1.5$$

By contrast, it is possible that two short periods of rain succeed.

The analysis of the field of monthly precipitation through this first phase of the operation of the model shows a general decline of the amount of rainfall and the rainy events. The disturbance of the regimes of watercourses and rainfall regimes, caused by climate variability including the aggressiveness of the fact of climate change causes the occurrence of rain more and more sudden and intense. It is also clear from this first phase that the length of the dry sequence can reach four months and that of the humid sequence cannot also not exceed four months.

2) EVALUATION: for this step, it will be to say if a given sequence of observations can be generated by the model designed in other term this is to calculate the probability with which the model designed can produce the event considered. The evaluation showed that the model was able to recognize the sequences that it has generated. The model is also capable to give the probability with which an event can occur.

3) FORECASTS: This phase corresponds to the operation of the predictive power of the HMM. It is to plan for the event the more likely at a future date, through the analysis function of the model. For example, for the year 2015 for the following sequence of observations: 1 3 2 1 1 2 2 1 3 3 1 2, through the algorithm of Viterbi, the sequence of states in which the system will be is: 2 3 2 4 1 2 3 4 3 2 3 2 which constitute the event the more likely for this sequence of observation (9) as shown in the figure 10:

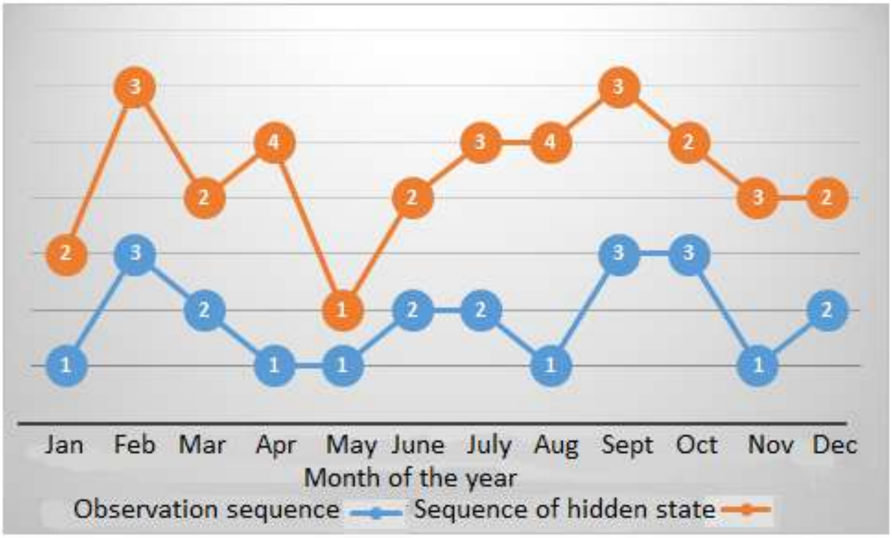

Figure 10. Forecasting of the sequence of hidden states for a sequence of observation in 2015

The sequence of observation can also be predicted that is to say, the total quantities of rainfall for each coming month of the years.

The stochastic model of precipitation thus formed is capable to generate several synthetic series of precipitation having the same statistical and physical properties as the historical data.

3.3 DISCUSSION

The work of [1] and [20] have served to highlight the dynamic nature of the rainfall across two states (rainy, dry). In addition to the dynamic aspect, the work of (20) put the emphasis on the asymptotic behavior of precipitation by increasing the memory effect of the observable Markov models. The work of [12] analyze the time in a day by using the observable Markov models and also show that the seasons of the year are correctly described by a Hidden Markov Model. The relationship between the different seasons of the year and the time in a day was modeled using a HMM with a good precision (12).

In our work, the relationship between the different seasons of the year and the amount of rainfall highlights 4 states (the seasons of the year) and 5 observations (the classes of amount of monthly rainfall in a month). The high number of observation, 5 against 3 as in [12] gives to our analysis an aspect more detailed. Our model has the advantage of providing the total amount of monthly rainfall while specifying the corresponding period of the year. The model can give the amount of rainfall of the months of the coming years. It can therefore be used for the reconstitution of rainfall data base. The use of this type of model in hydrology is advantageous because it proceeded to denoising data before any modeling while integrating the effect of climate variability, thereby improving the results.

ACKNOWLEDGEMENTS

Our thanks go to the University Center for Research and Application in Remote Sensing (CURAT), our institution of affiliation. We also thank the University Agency of the Francophonie. (AUF) for allowing us to do an internship in markovian modeling at the Technical University of Cluj-Napoca in Romania. We also thank Professor Monica BORDA the Scientific Director of this training course as well as his entire team.

CONCLUSION

The echoes of precipitation are well described by the Hidden Markov Model, which are stochastic models doubly stochastic. The structure of the monthly field of precipitation is well described by a HMM with 4 states and 5 observations that models the structures of the dry and wet sequences of the monthly field of precipitation with an accuracy of 83 %. Thus the modeling of actual phenomena by a HMM is effective and reflects the reality .This study shows an alternating of of wet and dry sequence longer which characterize a general trend in the decline in rainfall in the department of Sinfra. This analysis also reveals a tendency to rupture leading to sudden and intense rain.

The Markov models allow, in effect, to better assess the influence of the past on the behavior of the rainy phenomenon and to give a better description of the precipitation. The influence of the past on the behavior of the rainy phenomenon is taken into account by this type of template to give a better description of precipitation The Hidden Markov Models have the advantage of taking into account the effect of memory and are very used to simulate the time evolution of a system from the transition probabilities.

The rainfall is highly variable in time and space, the use of non-homogeneous Markov model in which the transition probabilities vary in time, would improve the results. Rainfall data collected by a meteorological radar can be used in order to have a continuous coverage and follow the fields of precipitation of fine spatio-temporal scales.

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