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Prediction of rainfall using autoregressive integrated moving average model: Case of Kinshasa city (Democratic Republic of the Congo), from the period of 1970 to 2009

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ABSTRACT

Rainfall is natural climatic phenomena for which prediction constitutes a great challenge nowadays. Its forecast is of particular relevance to agriculture and medicinal plants growth and development, which contribute significantly to the economy of Africa. Rainfall is highly non-linear and complicated phenomena, which require mathematical modelling and simulation for its accurate prediction. The present study examined the monthly precipitation using the Box-Jenkins methodology. The monthly precipitations data were collected from Binza Meteorological station of Kinshasa (Democratic Republic of the Congo) during the year 1970 to 2009. The results of the estimated parameters revealed that ARIMA (5, 1, 1) model is appropriate for the series. In the first analysis, we standardized this time series, then we have modeled the resulting series by model ARIMA (5, 1,1). In the second analysis, we carried out a modeling of these quantities using ARIMA model according to three processes: Identification of the model, validation of the model and estimate of the model. In order to compare the results of these two modeling, the average relative quadratic errors (er) and the average quadratic errors (EM) of the forecast adjustment were evaluated. These models appear equivalent in terms of these two errors. In the third analysis, we established a forecast of various corresponding years and we show that the event-based estimation approach yields better forecasts. It can be therefore concluded that the use of ARIMA model as tool for predicting rainfall could help in agricultural research development and in predicting the best period for the harvest of medicinal plant samples for phytotherapy (the quality/quantity of secondary metabolites and bioactivity). This model also makes it possible to predict the implication of rainfall on the lifestyle of the Kinshasa inhabitants.

Keywords: Rainfall, forecast, statistics, ARIMA model

INTRODUCTION

Rainfall is natural climatic phenomena for which prediction constitutes a great challenge nowadays. Its forecast is of particular relevance to agriculture and medicinal plants growth and development, which contribute significantly to the economy of Africa [1].

Plants are a key product for the Congolese population. Almost all Congolese populations, both urban and rural, depend on plants for their health care as source of nutraceuticals or phytomedicines [2-6]. The quantity and quality of the biologically active secondary metabolites in such plant species are affected by climatic factors such as temperature and humidity (rainfall/floods and periods of dryness) [7, 8].

Attempts have been made to predict behavioral pattern of rainfall using autoregressive integrated moving average (ARIMA) technique. ARIMA model is basically a linear statistical technique for modeling the time series and rainfall forecasting which ease to develop [1].

The Democratic Republic of Congo (DRC) has enormous fresh water reserves, however does not have enough data to estimate this reserve. The country has the weather stations which collect rainfall records but these data present gaps following the multiple difficulties encountered by the personnel made at this work. Indeed, DRC is drained in its totality by the Congo River and its effluents thus delivering passage in addition, with great potentialities of the easily flooded grounds whose surface remains not negligible [9].

The series of observations of precipitation from the year 1970 to 2009 are the data used in this study. The database was provided by the Binza Meteorological station of Kinshasa. After the homogeneity of the series checking, we subjected the series to statistical test in order to check the trend of the series before the application of ARIMA. ARIMA models, the acronym standing for Autoregressive Integrated Moving Average, can be used to analyze the prevalent rate of monthly precipitation [10]. Forecasting can also be used for maintaining real-time control (prediction) based on current measurements and anticipated future values of important process variables. To achieve the successful control, reasonably accurate predictions of future values are required. However, few research and published results have reported or even addressed the forecasting accuracy of Box-Jenkins ARIMA models than other types of forecasts. The present work is based on an univariate model in which past relationships are used to forecast future cases because ARIMA models are univariate , that is, they are based on a single time series variable. Box and Jenkins have also developed multivariate modeling analysis method. However, in practice, even their univariate approach, sometimes, is not as well understood as the classic regression method. The goal of this work is to describe the basics of univariate Box Jenkins models in simple and layman terms.

Aims and objectives

This Study aims at using time series analysis to model monthly cases of precipitation in Binza meteorological station with view to achieve the following objectives:

- Testing the stationarity of the series;
- Identification of the model that best fit the data;
- Diagnostic procedure for the model;
- Estimation of the model;
- Forecasting.

Scope and limitation of the study

Kinshasa city is constantly subjected to climatic change with often serious socio-economic and environmental consequences. The climatic forecasts can help to minimize the climatic risk and to contribute to a sustainable development and thus to contribute to the reduction of poverty by improving (medicinal) food production.

The Box Jenkins ARIMA model will help in rainfall forecasting or in tackling the rainfall prevalence rate since research has demonstrated that the Box-Jenkins (BJ) models are more accurate than other types of forecasts. The present study is limited to the analysis of monthly rainfall data from Binza meteorological station of Kinshasa during the period 1970 to 2009.

Study area

The data were collected in Kinshasa, the capital of the Democratic Republic of Congo. Kinshasa is a city located between 4°18 ' and 4°25 'S latitude and between 15°19' and 15°22'E longitude. Its average altitude is 360 m above sea level. Kinshasa is limited in the north by left bank of the Congo River, in the East by Bateke plate, in the South by the Lukaya River and in the West by the Mfuti River. This city covers a surface of 9.965,2 square kilometer and is located in the low altitude climate, characterized by AW4 climate type according to the classification of Koppen. Considering the chorologic subdivisions of the Democratic Republic of Congo, Kinshasa is located in the Guineo-congolian region and belongs to the Congolo-zambezean transition sector [11].

METHODOLOGY

Time series models

Autoregressive processes

Assume that a current value of the series is linearly dependent upon its previous value, with some error. Where ε_t is a *white noise* time series [That is, the ε_t are a sequence of uncorrelated random variables (possibly normally distributed, but not necessarily normal) with mean 0 and variance σ2]. This model is called an *autoregressive* (AR) model, since X is regressed on itself.

An autoregressive model (AR) of order *p*, an AR (*p*) can be expressed as:

$$X_t = C + \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \cdots + \varphi_p X_{t-p} + \varepsilon_t$$
$$\left(1 - \varphi L - \varphi_2 L^2 - \cdots - \varphi_p L^p\right) X_t = \varepsilon_t$$
$$\Phi(L) X_t = \varepsilon_t$$

Moving average processes (MA)

This is a process that the current value of the series is a weighted sum of past white noise terms, a model like this is called a *moving average* (MA) model, since X is expressed as a weighted average of past values of the white noise series.

Considering ε_t (t = 1,2,3,...) as a white noise process, a sequence of independently and identically distributed (I, I, d) random variables is E(ε_t) = 0 and Var(ε_t) = σ2Ɛ . The *q* the order of MA model is given as:

$$X_t = m + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_q \varepsilon_{t-q}$$
$$\left(1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q\right)\varepsilon_t = X_t \quad \text{(Lag form)}$$
$$\theta(L)\varepsilon_t = X_t$$

ARMA process (p, q)

Considering that ε_t is the white noise and X_t the (mixed) Autoregressive Moving Average process of order (p, q) denoted by ARMA (p, q). X_t can be written as:

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \cdots + \phi_p X_{t-p} + \theta_1 X_{t-1} + \theta_2 X_{t-2} + \cdots + \theta_p X_{t-p} + \varepsilon_t$$
$$\left(1 - \varphi L - \varphi_2 L^2 - \cdots - \varphi_p L^p\right) X_t = \left(1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q\right)\varepsilon_t$$
$$\Phi(L) X_t = \theta(L)\varepsilon_t$$

ARMA (p,q) model

Where Φ and θ are the polynomial of degree p and q respectively in L.

Auto Regressive Integrated Moving Average ARIMA (p, d, q) process

The process X_t is expected to be an Autoregressive Integrated Moving Average process ARIMA (p, d, q) if its dth difference ∇dX is an ARMA (p, q) process.

An ARIMA (p, d, q) model can be written as follow:

$$\Delta X_t = c + \phi_1 \Delta X_{t-1} + \phi_2 \Delta X_{t-2} + \cdots + \phi_p \Delta X_{t-p} + \theta_1 \Delta\varepsilon_{t-1} + \theta_2 \Delta\varepsilon_{t-2} + \cdots + \theta_q \Delta\varepsilon_{t-q}$$
$$\Phi(L)\Delta^d X_t = \theta(L)\varepsilon_t$$
$$\Phi(L)(1 - \mathrm{L})^d X_t = \theta(L)\varepsilon_t$$

The covariances, γs, are known as autocovariances. One can find γ1, γ2, γ3, γ4,γt, .and so on.

Here, γ0 = Cov(xt, xt-0) = Var(xt) = σ^2

$$\gamma_t = \frac{\sum_{j+1}^{T}(y_t - \bar{y})(y_{t-j} - \bar{y})}{\sum_{i-1}^{T}(y_t - \bar{y})}$$

Partial autocorrelation functions (PACF)

PACF measures the correlation between an observation *k* periods ago and the current observation, after controlling for observations at intermediate lags (i.e. all lags < *k*). PACF (k) = ACF (k) after controlling the effects of (xt-1, . . , xt-k+1)

xt, (x*t-1*, .. ,*xt-k+1*), *x*t-k

An AR process has

i. a geometrically decaying ACF

ii. number of spikes of PACF = AR order

An MA process has

i. Number of spikes of ACF = MA order

ii. a geometrically decaying PACF

LAG operator

Let X1, X2, . . . Xt be a time series. We define the lag operator L by; LXt = Xt-1

If Φ(L) = 1- ϕL – ϕ2L2 - ... - ϕpLP

Then An AR(p) is defined as

(1- ϕL – ϕ2L2 - ... - ϕpLP) xt = εt

The BOX-JENKINS approach to model building

This section outlines the procedures that Box and Jenkins recommend for constructing a univariate ARIMA model from a given time series.

The Box-Jenkins approach to model building follows steps below. The model may then be used to forecast future values.

i. Identification STAGE

ii. Estimation STAGE

iii. Diagnostic CHECKING STAGE

The identification stage

Identification is the stage at which a tentative model for the series is selected from the large family of candidate ARIMA (p, d, q) models. Clearly there are many possible combinations of the orders p, d, and q. Thus, the identification stage consists of specifying the AR, I, and MA orders (p, d, q).

The estimation process

Considering an ARIMA (p, d, q) process. A parametric model for the white noise is assumed, this parametric model will be that of Gaussian white noise, then the maximum likelihood is used.

We rely on the prediction error decomposition. That is, X1, . . . , Xn have joint density function;

$f(x_1,..x_n) = f(x_1)\prod_{t=2}^{n} f(x_t|f(x_1, ...; x_{t-1})|$

Suppose the conditional distribution of x_t given $x_1, ...; x_{t-1}$ is normal with mean t and variance P_{t-1}, and suppose that $x_1 \sim N(1, P_0)$

Then for the log likelihood:

$$-2logL = \sum_{t=1}^{n} \log(2\pi + logP_{t-1} + \frac{(x_t-\bar{x}_t)^2}{P_{t-1}}$$

Here t and P_{t-1} are functions of the parameters $\theta_1,\dots\ \theta_p, \phi_1,\dots\ \phi_q$ and so maximum likelihood estimators can be found (numerically) by minimising −2 log L with respect to these parameters.

The diagnostic checking stage

Once an appropriate model had been entertained and its parameters estimated, the Box-Jenkins methodology required examining the residuals of the actual values minus those estimated through the model. If such residuals are random, it is assumed that the model is appropriate. If not, another model is entertained, its parameters estimated, and its residuals checked for randomness.

RESULTS AND DISCUSSION

The figure 1 gives the evolution of monthly rainfall from the year 1970 to2001.

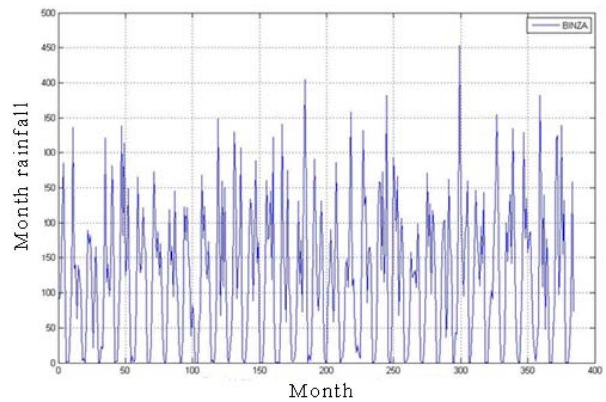

Figure 1: Evolution of monthly rainfall from the year 1970 to2001

The time plot for monthly precipitations of data from Binza meteorological station shows that the data is not stationary and contains trend variation i.e. the mean and variance are not constant and in order to apply certain techniques for identifying the model for the data, the time series data must undergo transformation to attain stationarity. This plot revealed that rainfall is highly non-linear and complicated phenomena, which require mathematical modelling and simulation for its accurate prediction. The statistical method based on autoregressive integrated moving average (ARIMA) is the consistent model.

Indeed, the series is regarded as Nonlinear and Non-Gaussian and can be used to evaluate the effectiveness of the nonlinear model.

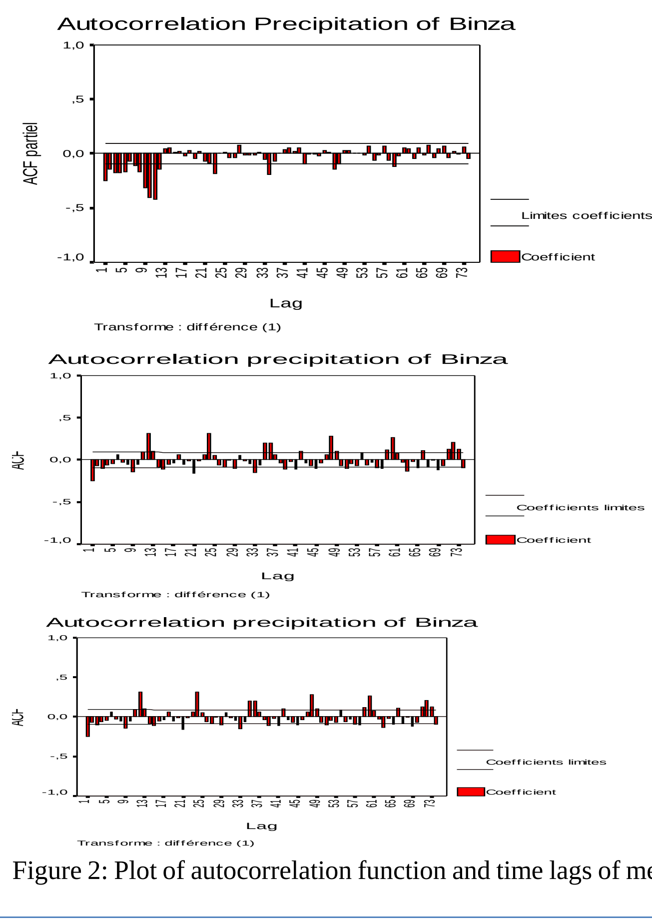

Figure 2: Plot of autocorrelation function and time lags of mean

annual rainfall data

From the graph of autocorrelation function, it is seen that the series is not stationary in mean and variance because it follows a damped cycle and the PACF suddenly cut off after p lags. The PACF also decline steadily, or follow a damped cycle in which tells us about.

Therefore, the series needs to undergo transformation to attain stationarity.

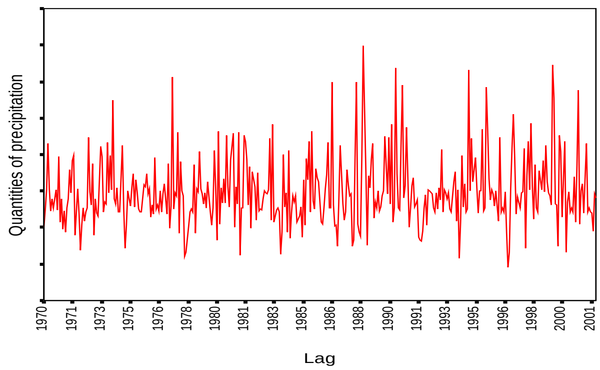

Figure 3: Time plot of transformed data of precipitation and time lags of mean annual rainfall data

The series attains stationarity after taking the first difference i.e the series has a constant mean and finite variance.

Estimation of Model ARIMA (5, 1, 1)

The model $X_t = (1-B)Qstd_{(a,m)}$ is a ARIMA (p, d, q) avec p=5, d= 1, q=1 if and only if one has: $(1 - ar1B^1 - ar2B^2 - ar3B^3 - ar4B^4 - ar5B^5)(1 - B)Qstd_{(a,m)} = (1 - ma1B^1)\varepsilon_t$ It is a question of estimating the various parameters

$ar1, ar2, ar3, ar4, ar5, ma1$.

After analysis, the results obtained of the software R is:

Parameters ARIMA (5, 1,1)

Table 1: Estimation of the ARIMA model coefficients

Coefficients ARIMA (5,1,1)	
ar1	0,0465
ar2	-0,0052
ar3	-0,00052
ar4	-0,0134
ar5	0,0229
ma1	-1,000

The table 1 gives the ARIMA model coefficients after the analysis by the R software, we obtain the following equation:

$$(1 - 0{,}0465B^1 + 0{,}0052B^2 + 0{,}00052B^3 + 0{,}0134B^4 - 0{,}0229B^5)$$

$$(1-B)Qstd_{(a,m)} = (1 + 1{,}000B^1)\varepsilon_t$$

Analyze residues of the model

It is a question of checking the assumptions of the white vibration. After analysis with the R software of the residues obtained from this model, the curve describing the evolution, the car - correlogram and the partial car-correlogram of the residues allow concluding that on the one hand, the chronicles of the residues ε_t are consistent and well stationary. And in addition, by observing the graph obtained by Ljung-Box test of this chronicle of the residues. It can thus conclude that the assumption of the white vibration is preserved for the series of the residues. The histogram of the residues takes the form of a normal distribution of Gauss. So, the process $Qstd_{(a,m)}$ could be evaluated by ARIMA (5,1, 1) model according to the following:

$(1 - 0{,}0465B^1 + 0{,}0052B^2 + 0{,}00052B^3 + 0{,}0134B^4 - 0{,}0229B^5) = (1-B)Qstd_{(a,m)} = (1 - ma1B^1)\varepsilon_t$ where is a white vibration.

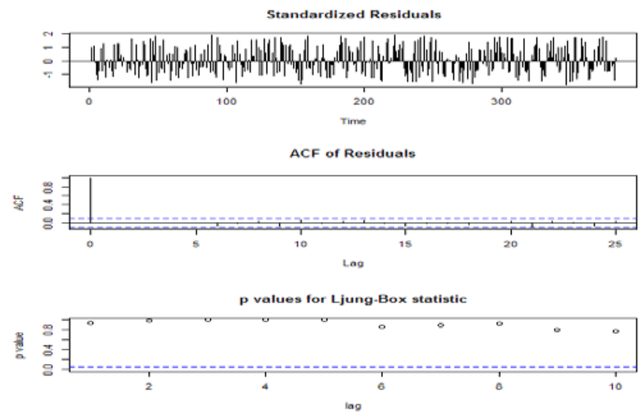

Figure 4: Residues test of ARIMA (5,1,1) model

The figure 4 above show well the normal pace of our adjustment which are white vibrations.

Total reliability of the adjustments

The average and relative quadratic errors related to this adjustment, are presented in the table below, the chronicle of the quantities of water extends up to 384 months:

Table 2: Errors of adjustment of the final model to the real quantities of water

	Number of months	Nash	RMSE (mm)	B (mm)
Adjustment (from 1970 to 2001	384	0,9845	1,42	1,119

The criterion of Nash [13] and the errors quadratic prove with sufficiency that the pace of the model marries well that of the quantities of real precipitations observed in Kinshasa.

Total reliability of the forecasts

The average and relative quadratic errors dependent has this adjustment, are presented in the table below, the chronicle of the quantities of water extends up to 12 months:

Table 3: Errors of forecast

	Number of month	NASH	RMSE (mm)	B (mm)
forecast 2002	12	0,63	0,65	0,19
forecast 2003	12	0,57	0,58	0,12
forecast 2004	12	0,58	1,42	0,26
forecast 2005	12	0,66	0,55	0,07
forecast 2006	12	0,72	0,47	0,05
forecast 2007	12	0,62	0,63	0,007
forecast 2008	12	0,83	0,34	0,065
forecast 2009	12	0,82	0,33	3,29

The criterion of Nash and the quadratic errors show with sufficiency that in a total way the various forecasts conducted by the model are satisfactory.

Forecast cases of precipitation

Forecasts of future for precipitation cases in Binza are of particular interest. We may now use the final form of the best-fit ARIMA model for the time series to estimate future cases. The forecasted case for the next three years is displayed below.

Table 4: Real and predicted rainfall data in Binza meteorological station

2002		2003		2004		2005		2006		2007	2008			2009	
Q mes.	Q pred	Q mes.	Q pred	Q mes.	Q pred	Q mes.	Q pred	Q mes.	Q pred	Q mes.	Q pred	Q mes.	Q pred	Q mes.	Q pred
124,2	157,49	127	154,26	135,6	154,25	107,8	154,26	105,9	154,26	137,6	154,26	139,6	154,26	154,7	154,26
141	160,25	175,2	150,23	111,8	150,22	43,3	150,22	140,7	150,22	143,7	150,22	198,4	150,22	140,7	150,22
122	200,40	115,1	210,89	173,7	210,88	168,7	210,89	180,6	210,88	175,2	210,89	142,2	210,89	175,2	210,89
263,3	216,55	168,2	201,27	119,5	201,27	166,1	201,27	197,4	201,27	121,4	201,27	212	201,27	212	201,27
203,8	130,37	123,5	130,36	4	130,36	109,2	130,36	113,5	130,36	129,9	130,36	137,2	130,36	200,4	130,36
6,2	41,99	4,4	41,98	0,1	41,98	1,3	41,98	6,3	41,98	4,2	41,98	3,6	41,98	6,3	41,98
0,1	-12,15	2,3	-12,16	1,2	-12,16	2,3	-12,16	0,1	-12,16	1,7	-12,16	3	-12,16	3	-12,16
0,1	-2,59	0,1	-2,59	4,8	-2,59	0,1	-2,59	14,2	-2,59	3,7	-2,59	4,8	-2,59	4,8	-2,59
95,8	62,03	48	62,04	16	62,03	42,6	62,04	49,6	62,04	26,1	62,04	43,6	62,04	43,6	62,04
118,4	141,83	92,6	141,84	135	141,83	169,1	141,84	270,5	141,83	250,4	141,84	152,3	141,83	127,4	141,84
322,4	190,13	335,1	190,14	190,2	190,14	269,9	190,14	258,8	190,14	347,8	190,14	258,8	190,14	129	190,14
304,6	180,70	111,3	180,71	240,6	180,71	282	180,71	173,2	180,71	195,2	180,71	173,2	180,71	212,4	180,71

This table gives the rainfall predictions from the year 2002 to 2009 as estimated by ARIMA (5,1,1) model. The results show that the event-based estimation approach yields better forecasts.

CONCLUSION

The aim of the present study was to test a model of simulation on the monthly series of precipitations data from the Binza meteorological station of Kinshasa/Democratic Republic of the Congo. After the stationnarization of the series, we applied an Auto-Regressive Integrated Moving Average (ARIMA) model into the starting series. The criterion of Ljung-Box enabled us to establish the following equation $(1-0{,}0465B^1+0{,}0052B^2+0{,}00052B^3+0{,}0134B^4-0{,}0229B^5)=(1-B)Qstd_{(a,m)}=(1-ma1B^1)\varepsilon_t$. It can be conclude that the use of ARIMA model as tool for predicting rainfall could help in agricultural research development and in predicting the best period for the harvest of medicinal plant samples for phytotherapy (the quality/quantity of secondary metabolites and bioactivity). This model also makes it possible to predict the implication of rainfall on the lifestyle of the Kinshasa inhabitants.

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