

Automating Time Series Analysis to Predict/Forecast Rainfall in AGUELMAM SIDI ALI Watershed in Morocco

Ridouane Chalh, Zohra Bakkoury, Driss Ouazar, Moulay Driss Hasnaoui, Addi Ait-Mlouk

Abstract: Moroccan economy is largely based upon rainfall, use of water resources and crop productivity, for that it's considered as an agricultural country. It's more required and more important for any farmer to forecast rainfall prediction in order to analyze crop productivity. Predicting the atmosphere or forecasting the state of the weather is considered as challenge for scientific research. The prediction of rainfall monthly or/and seasonal time scales is the application of science and technology to invent and to schedule the agriculture strategies. Recently different research articles achieve to forecast and/or predict rainfall monthly or seasonal time scales using different techniques. The methodology followed in this work, be focused on automating time series analysis to forecast / predict precipitation daily, monthly or seasonal in Aguelmam Sidi Ali basin in Morocco for last 32 years ago from 1975 to 2007. We first have to study the rainfall data theoretically using the simplest form statistical analysis, which is the univariate analysis, as long as only one variable is involved in our case study. To get the selected and suitable model of time series to automate, we used different autocorrelation methods based on various criterion such as: Akaike Information Criterion (AIC), estimation of parameters using Yule-Walker (YW) and Maximum Likelihood Estimation (MLE). The results of our experiment show that it is possible using our system to obtain accurate rainfall prediction, with a more details and with a very fast way. It shows also that it's possible to predict for next months or next years. To minimize the risk of floods and natural disasters within a basin in general and within the Aguelmam Sidi Ali basin in particular, accurate and timely rainfall forecasting is required.

Index Terms: Time Series Analysis, Rainfall prediction/Forecast, Precipitation, Autoregressive processes.

I. INTRODUCTION

In terms of geographical location our country Morocco is situated between different regions such as the arid/semi-arid regions of south, and west represented by Moroccan Sahara, Atlantic regions and the moderate Mediterranean.

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Ridouane Chalh, AMIPS laboratory, Department of Computing Science, Ecole Mohammadia d'Ingénieurs, Mohammed V University – Rabat, Morocco.

Zohra Bakkoury, AMIPS laboratory, Department of Computing Science, Ecole Mohammadia d'Ingénieurs, Mohammed V University – Rabat, Morocco.

Driss Ouazar, LASH laboratory, Civil Engineering Department, Ecole Mohammadia d'Ingénieurs, Mohammed V University - Rabat, Morocco.

Moulay Driss Hasnaoui, Water resources department, the Ministry Delegate to the Minister of Energy – Rabat Morocco.

Addi Ait-Mlouk Department of computing Science, Umeå University, Sweden.

Ranging from high of Morocco's map (Tangier) to bottom (Gouira) we observe that we find a variety of climates at the level of wet or semi-humid regions. The prediction/forecast of the Rainfall is some think that's very essential [1]. In this field, the economical and agricultural production depends on mainly rainfall variability and water resources availability [2]. Surely, the forecasting of future scenarios of rainfall in very heterogeneous regions as we said above is still a challenge for the community of research. Many different events were organized in a climatic context, among this events, the 22nd Conference of Parties (COP22), which is being held in 2016 in Marrakech, Morocco [3], it was represented as a first COP at which the stakeholders coming together to build the future through the implementation of technological solutions. An experiment shows that, the rainfall history in Morocco during the period 1991-2015, the data set of this experiment was produced by the University of East Anglia [4].

Rainfall and climate are complicated phenomena and nonlinear, which require sophisticated process computer modeling and simulation models for accurate forecast and / or prediction. Times series forecasting rainfall is considered as critical work to manage and to schedule water resources. Time series predictions model have been applied to this work. Big efforts are already made to automate this model. Predicting behaviors of nonlinear systems, using application of Time series analysis, has become an attractive alternative to traditional statistical methods.

The main idea of this paper is to present a review of automating Time Series (TMS) Analysis using R and SHINY to predict and/or forecast rainfall in Aguelmam Sidi Ali basin in Morocco. This automating tool forecast rainfall situations and allows making predictions on different future scenarios. The basic data needed for this experiment case study are precipitation observed during the period 1975-2007, these datasets are collected by the observation climatological station managed by the Sebou Hydraulic Basin Agency.

This article is organized as follows: we start with the related work the section, which gives a briefly literature review, the second section gives an overview of Aguelmam Sidi Ali basin as study area, in the third second section, we give a theoretical time series background, the fourth section consist to automate time series forecasting model using R and SHINY. The penultimate section, which consist to interpret the results and discussions. The last one presents a conclusion and some of future works.

II. RELATED WORK

Regression is a statistical technique and is mainly used in many different domains such as: climate prediction domain, the social sciences, environmental science [5] and many other fields. The major challenge for the scientific community is how to make rainfall predictions more accurate. Rainfall forecast modeling implies a strong combination of algorithms, computer models, knowledge and observations. Applying this combination of models and methods, the accurate and timely rainfall prediction can be made up.

In this section, we introduce some existing approaches and strategies related to rainfall forecasting and/or predicting using time series analysis. Various research works in this field are proposed, we will review some of these works:

A study is conducted in the same context within a basin located in a semi-arid zone in Morocco, this study is used to study a real neural network coded using genetic algorithm, to predict daily precipitation runoff [6].

Using statistical methods to simulate the impact of climate variability on water resources, the rainfall regime was studied from four observation stations within the Draa basin in Morocco. [7].

Prevent wheat grain yield at the national and provincial level in Morocco using empirical regression models. This forecast is based on NDVI/AVHRR type data for precipitation and monthly air temperatures. [8].

In England and Wales, point precipitation is predicted by the use of geographic variables and atmospheric circulation. The objective here is to predict the average rainfall flow as well as propose dry days for each calendar month [9].

Another study was conducted in the context of risk assessment of soil erosion in Switzerland. The purpose of this study is to assess the spatial and temporal distribution of precipitation erosivity. [10].

A scientific contribution is made in the prediction and modeling of precipitation using the artificial neural network and ARIMA techniques, the objective is to evaluate the effectiveness of the forecasts in the Hyderabad region of India for a period from 1901 to 2003. This contribution defines two approaches, one based on ARIMA and the other based on the emergence of ANN techniques.[11][12].

Also in the aspect of rainfall forecasting, a study was conducted to prevent data from 1955 to 2000 in India and specifically in the Mahanad and Malaprabha regions. [13].

Different contributions research has been conducted on time-series. By definition, Time series data mining is the mechanism of analyzing the sequence of data points that contain successive measurements made over a time interval such as on daily, monthly or seasonally.

According to [14], the authors introduced a study case to forecast rainfall using time series model. The objective here is to prevent precipitation data for a period from 2011 to 2013 using a chronological model Minitab ARIMA. These data are obtained by Indonesia's Meteorological, Geophysical and Climate Centre.

Another study presented as modular technique to predict monthly rainfall using time series model [15]. This work is based on two layers for forecasting in order to understand the link between the input and output parameters of the rainfall regime. The first layer consists of using a Mamdani Fuzzy type system and the second layer called the aggregation layer. The latter used Bayesian learning and non-linear programming to capture uncertainty in the temporal dimension.

In the same thematic, using a Bayesian method based on an ANN filter, a research study consisted of approaching an algorithm to adjust the predictive parameters of the time series of cumulative precipitation. The objective here is to generate a posterior probability distribution of time series values from time series provided that Bayesian inference is taken into account. [16].

An integrated methodology and intelligent technique proposed to create an interpretable fuzzy model in order to predict monthly rainfall using time series [17]. This methodology involves analyzing standard deviations and determining an optimal number of sub-regions using a neural network.

An approach, consist to use auto-regressive and multiple linear regression in order to predict rainfall for all the states of India [18]. In this research contribution two methods were used, the first based on the Box-Jenkins time series approach ARIMA and the second based on multiple linear regressions. We observe in the related works cited above, with respect, that the majority of them are used, applied or integrated time series models or algorithms to forecast/ predict rainfall. Contrariwise to our case, it's also necessary take into consideration the automating aspect of time series analysis, that's our primary objective in this paper to develop and to automate a system for forecasting and predicting a monthly/daily rainfall. This automating stage begins from the stationarity test data, selected model using autocorrelation methods, parameter estimation, and model verification. The present work put forward a strategy that makes using R and Shiny to automate time series analysis to forecast and/or to predict precipitation data set in Aguelmam Sidi Ali watershed in Morocco. The performance of this system is tested by integrating a time series of precipitation for the last 32 years from 1975 to 2007; it is possible to generalize it for other big data.

III. METHODOLOGY

A. Study area overview

The study area of this work is the set of basins that belong to two neighboring regions in the Midlt province of upper Moulouya basin, located in the eastern part of the central Middle Atlas; among these set the Aguelmam Sidi Ali basin and all the basins of the rural municipality of Ait Ben Yacoub. The two zones are delimited by mountains.

Aguelmam Sidi Ali is one of the most important natural lakes in Morocco, In 1975, according to measurements made by Hydraulic Basin Agency of Sebou (HBAS) [19], while the lake was well, the greatest depth reached (43.4 m), the surface of the water body (337 ha) and 35 million m³ of the volume of water stored [19].

Aguelmam Sidi Ali is characterized by the existence of a climatological station which allows us to have the climatological data necessary to realize our study Figure. 1

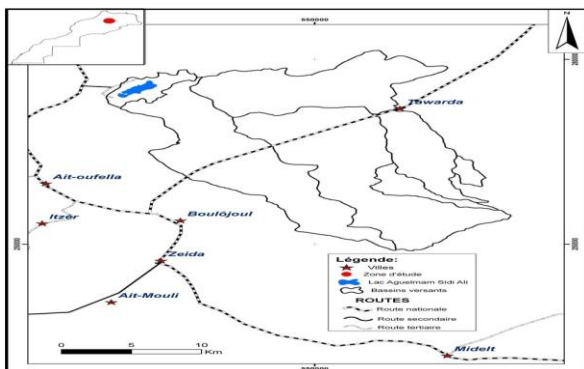


Figure 1: Location of Aguelmam Sidi Ali

Concerning altitude and topography, the median altitude of Aguelmam Sidi Ali watershed is 2158 m. The maximum and minimum altitudes are respectively 2400 m and 1400 m, the highest point is Jebel Bou Khitane with 2270 m of altitude. Figure. 2 show the hypsometrical curve of this basin.

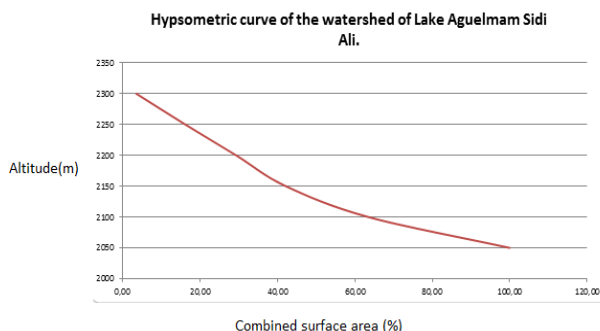


Figure 2: Hypsometrical curve of Aguelmam Sidi Ali

With regard to climatic conditions, Aguelmam Sidi Ali managed by the Sebou Hydraulic Basin Agency. All measurements are made daily by the observation climatological station. It offers a relatively long chronicle of data, the rainfall measurements having started in 1975 [20], but which presents some gaps, particularly troublesome in the case of precipitations.

The type of rainfall in this location is Mediterranean. According to Figure. 3, Figure. 4 and Figure. 5 the wet period lasts from October to May, while the dry period is from September to June. The highest monthly precipitation over the hall period 1975-2007 is in November 1989 (Sum of 189 mm). However, the weakest monthly precipitation is in July 2001 (Sum of 1 mm).

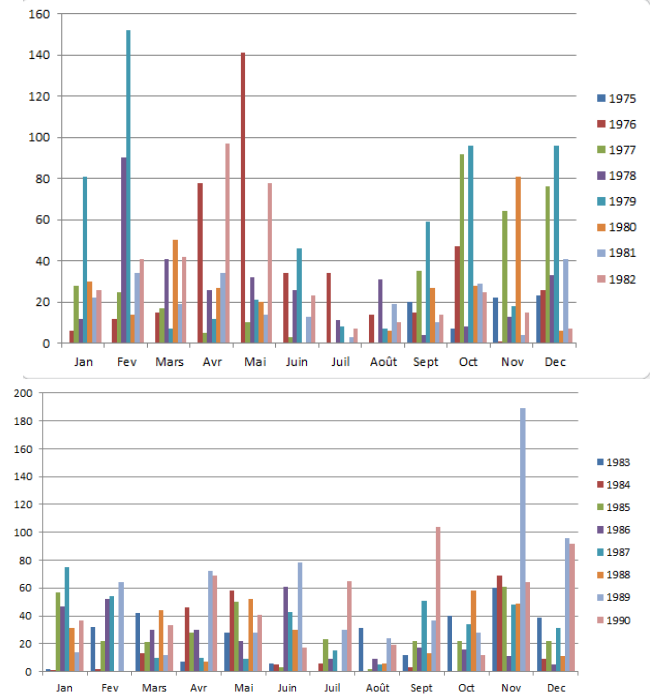


Figure 3: Monthly rainfall in Sidi Ali over the period September 1975 - December 1990.

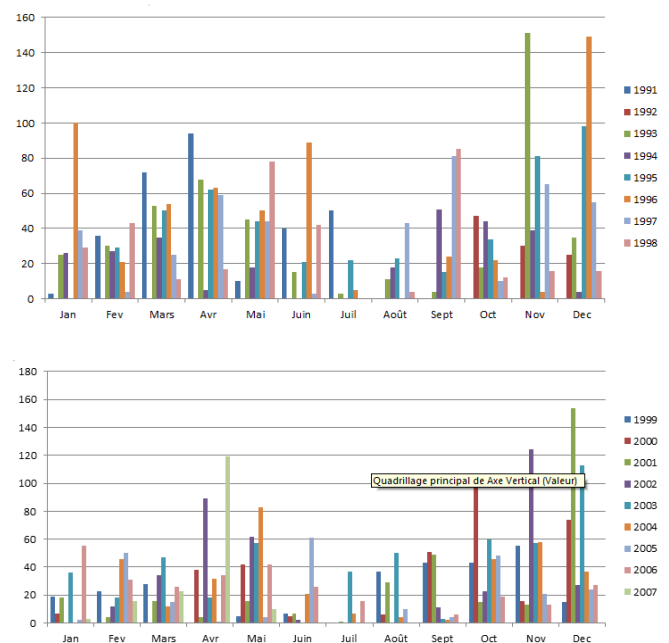


Figure 4: Monthly rainfall in Sidi Ali over the period September 1991 - December 2007.

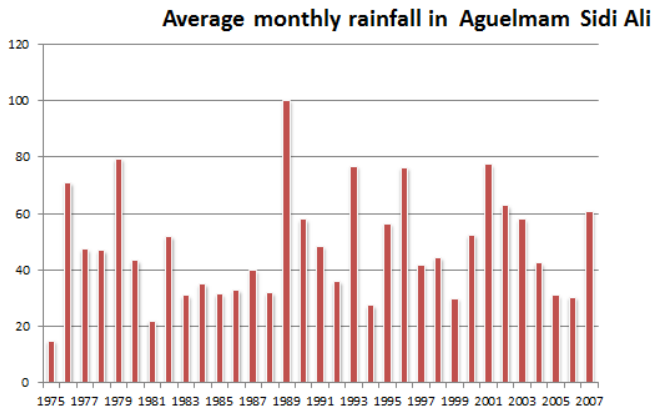


Figure 5: Average monthly rainfall in Aguelmam Sidi Ali over the period September 1975 - December 2007.

IV. TIME SERIES ANALYSIS BASIC CONCEPTS

A. The Univariate Analysis

The univariate analysis considered as the simplest form of statistical analysis; the key fact in this form is that only one variable is involved [21]. Among several works in this field have been addressed like as: A case study applied to process variograms to compare univariate and multivariate approaches [22], Manifold Learning using univariate and multivariate time series [23], another research work, in a fluvial context, accurately river reach delineation, presents an automatic procedures using univariate and multivariate approaches [24].

In this work the univariate approach is applied to daily precipitation in Aguelmam Sidi Ali watershed, over the period from September 1975 to Mai 2007. According to the diagram below (Figure. 6), it should be noted that although the rainfall is showing a year trend in November 1990 and the weakest monthly precipitation is in July 2001.

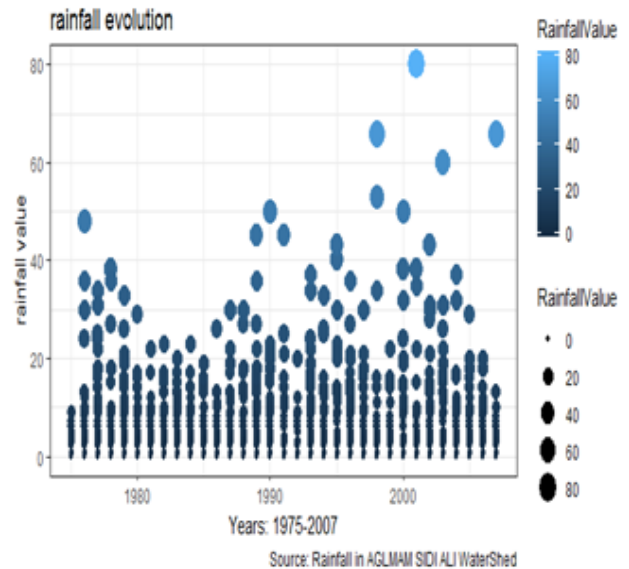
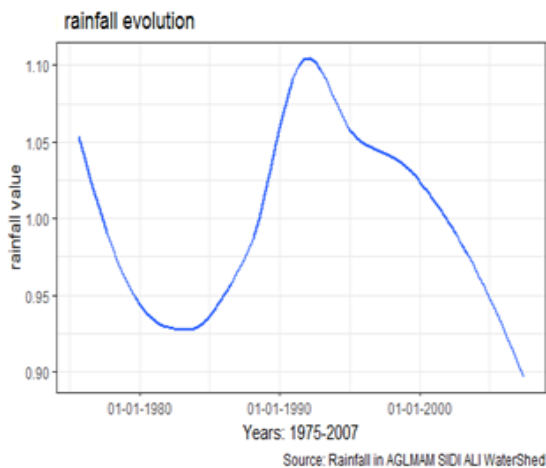


Figure 6: Rainfall evolution in Aglmam Sidi Ali watershed during thirty-two years

In statistic field, by definition a Stochastic Process is a sequence of stochastic variables:

$$Y_1, Y_2, Y_3 \dots Y_n$$

We observe the process begin from $t = 1$ to $t = n$, yielding a sequence of numbers:

$$Y_1, Y_2, Y_3 \dots Y_n$$

The above series is called a time series. The observations of a time series are not independent. At this point we're talking about stationery.

B. Stationarity

We talk about stationarity when data are stationary [25]; the stationarity is a common hypothesis in many time series techniques [26]. In our case study, the application of stationary test for our rainfall dataset is done by using Dickey-Fuller test first [27]. Table 2 summarizes the results. The results show that we do not reject the null hypothesis. In order to meet the requirement of our rainfall time series, it must be stationary. To solve this problem, we take the first differences of rainfall, so we have a new time series called rainfall.diff. Applying the Dickey-Fuller test again, the result in Table 1 shows that we reject the null hypothesis; therefore time series rainfall.diff are stationary.

Table. 1: Output Dickey-Fuller Test Unit Root Test

coefficients	Estimated	Std. Error	T - value	pr value	test-statistic
Intercept	0.754836	0.036296	20.797	< 2e-16	-63.0888
rainfall.lag.1	0.751631	0.011914	-63.089	< 2e-16	
rainfall.diff	0.051823	0.009465	-5.475	4.46e-08	

Table. 2: Rainfall result coefficients summary

Residual standard error: 3.62 on 11591 degrees of freedom				
Multiple R-squared	Adjusted R-squared	F-statistic		DF, p-value
0.3977	0.3976	3827 on 2 and 11591 DF		< 0.00000000000000022
Residuals:				
Min	1Q	Median	3Q	Max
-13.746	-0.747	-0.747	-0.747	79.253
Value of test-statistic	-64.3065			

Series rainfall

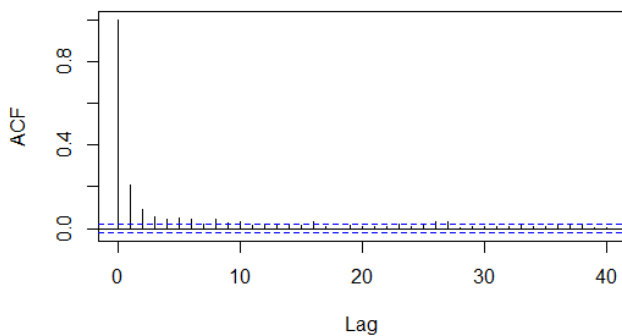


Figure 7: Rainfall reports of Autocorrelation and Correlation Function (acf)

Series rainfall

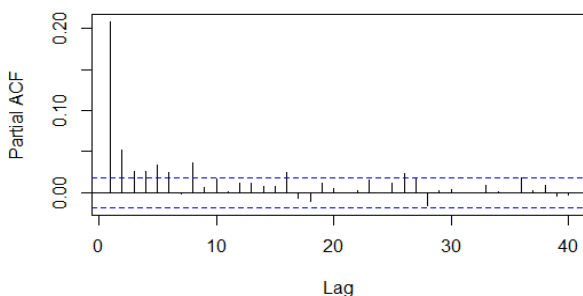


Figure 8: Rainfall reports of Partial Autocorrelation and Correlation Function (pacf)

To study stationarity of rainfall time series, we apply Autocorrelation and Cross Correlation Function (ACF) and Partial Autocorrelation and Cross Correlation Function (PACF) estimation [28]. The Figure. 7 and Figure 8 reports the acf and pacf of rainfall differences series. There are many significant correlations and partial correlations, i.e. the time

series rainfall are stationary; looks like an autoregressive model AR (1).

We obtain the selected order using Akaike Information Criterion (AIC) [29], estimation of parameters using Yule-Walker (YW) [30] and Maximum Likelihood Estimation (MLE) methods [31]. To adjust an autoregressive model, it is enough to minimize the error of the least squares of the forecast.

C. Automating Time Series Analysis Using R & SHINY

There are many functionalities and useful classes in base R, in particular Time Series Analysis package. which are briefly summarized like as: Unit Roots, Dates and Time , Time Series package, Stationarity and Forecasting, Univariate Modeling [32], ... etc.

Shiny is an R [32] package for build interactive web applications. The results provided are reactive, i.e when the user provides a new value of input via a widget, the R codes that depend on this input are re-executed and their output displayed. Shiny actually allows producing web applications using HyperText Markup Language (HTML) and R code, Cascading Style Sheets (CSS) and Javascript remains a plus to produce more personalized applications.

V. RESULTS AND DISCUSSION

The developed system is structured in two principal parts, the first represent the User Interface side which groups all input parameters for the user. The second represent the server side where R codes are executed to produce the outputs (graphics, tables, treatments, etc.) [33]. The users have the possibility to update input values and plot new results.

The first part of the system is the data importation and visualization, it allows users to import and visualize directly the dataset. It proposes a feature to use a new dataset after preprocessing step, by clicking on choose Comma-Separated Values (CSV) file button as shown in Figure. 9.

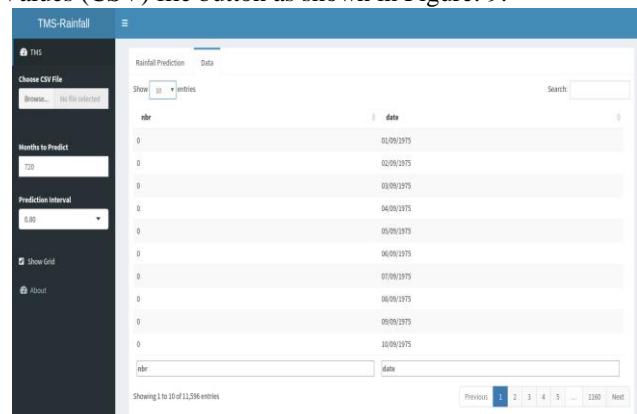


Figure 9: Import and visualization data

Another part of the system is reserved to make a prediction from rainfall data. For this reason, we used time series analysis, which (x_1, \dots, x_n) is a finite sequence of time-indexed data. The time index can be a minute, hour, day, year etc. Time series can be seen as a series of repeated observations of the same phenomenon at different dates (for example the number of daily average temperature at a given hours). We usually represent a time series using a graph in abscissa dates and ordinate the values observed.

The main interface as shown in Figure. 10, allows users to input dataset and thresholds parameters such as month to predict and to define rainfall prediction according to specified inputs and prediction interval. The demo of the system is available on shinyapps cloud [34].



Figure 10: Main application

The system is fully parametric; the user can choose month/year to predict with a specific interval Figure. 11

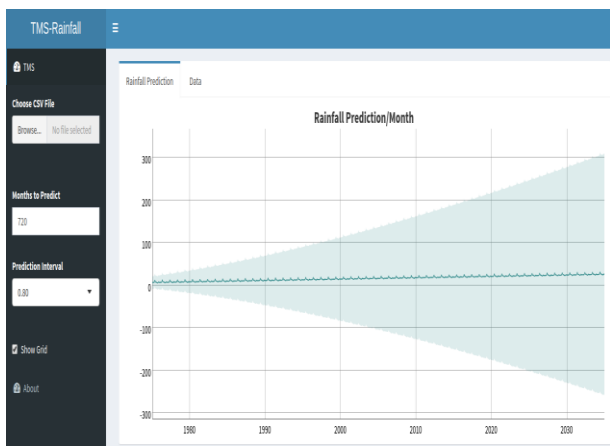


Figure 11: Rainfall prediction / monthly interface

In summary, the integration of TMS technique within rainfall data are contributed overall to a better understanding of the dynamics of rainfall in Morocco and could provide meaningful information that can help the decision makers to improve the performances of plants, human life, Natural Water Storage and Inundation and Flooding problems.

VI. CONCLUSION AND FUTURE WORK

In this article, the forecasting/prediction of rainfall using time-series analysis has been presented through two steps, in the first one, we studied the methodology theoretically using the simplest form statistical analysis, which is the univariate analysis, as long as only one variable is involved. To get the selected and suitable model of time series to automate, we used different autocorrelation methods based on various criterion such as: Akaike Information Criterion (AIC), estimation of parameters using Yule-Walker (YW) and Maximum Likelihood Estimation (MLE). In the second one, we presented an implementation to illustrate the contribution of our different proposed approaches by using time series analysis. Our software allows decision-makers to have an overall view of the problem of rainfall analysis. This system starts with the step of integration and transformation of data, then the use of the time series to forecast and /or predict rainfall for next months or years. By summarizing, the expected results of our system illustrate that predictive performance exists to prevent precipitation. These results have encouraged us to continue to think about other issues in machine learning in a new context. The system can be expanded with new topics on demand.

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