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Performance of Multi-site Stochastic Weather Generator MulGETS : Application to the Lobo Watershed (Western Center of Côte d'Ivoire)

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Abstract:- The study of the impact of climate variability and change requires long series of quality meteorological data from several sites. Measuring stations are sparse with data gaps and short durations, so time generators are indispensable to generate climate data that are statistically similar to the observed data. This study describes a Matlab-based multi-site stochastic time generator (MulGETS) for generating daily precipitation and temperature data. The daily observation weather stations of Séguéla, Vavoua, Zoukougbeu, Daloa, Issia and Grand-zattry were used and the results show that the model adequately reproduces the meteorological data. The observed and simulated values show a very good correlation with the coefficients of determination very near to 1, indicating the performance of the model.

Keywords:- *Performance, weather generator MulGETS, precipitation, temperature, Lobo watershed.*

I. INTRODUCTION

Many problems in hydrology and agricultural science require extensive rainfall records from several sites [1]. However, it is clear that the measuring stations are not very dense and the observed data are not consistent or available in sufficient quantities. There are gaps and high levels of uncertainty. Climate generators are thus developed to generate climate data that are statistically similar to observed data. They have been widely used to generate climate variables simultaneously at several sites ([2], [3], [4], [5], [6], [7], [8], [9], [10]). Most time generators are based on a single site and are unable to represent the spatial attributes of the observed time series. In other words, although time series can be generated over multiple sites, they are spatially independent even when the stations are correlated. The lack of spatial correlation, particularly for precipitation, makes single-site time generators useless for many applications. However, the simultaneous generation of meteorological variables at several locations is of great importance for hydrological and agricultural applications ([11] [1] [12]). [13] thus presented an algorithm to efficiently find the desired correlation matrices for precipitation occurrence and amounts. They solved the problem of spatial intermittency of precipitation using an index of occurrence approach. Following this algorithm, a Matlab-based multi-site weather generator, called the Multi-Site Weather Generator of the École de Technologie Supérieure (MulGETS), was developed to generate daily precipitation and temperature data. This study was carried out to describe and evaluate the performance of the MulGETS multi-site stochastic time generator in the Lobo watershed at six stations. This paper has been structured in four sections for its understanding. The first section introduced the study area. The second section dealt with the materials and methods used. The results obtained, their interpretation and discussion constituted the third section of this work followed by the conclusion in the fourth section.

II. PRESENTATION OF STUDY AERA

The Lobo watershed is located in central-western Côte d'Ivoire between longitudes 6°05' and 6°55' West and latitudes 6°02' and 7°55' North (Fig. 1).

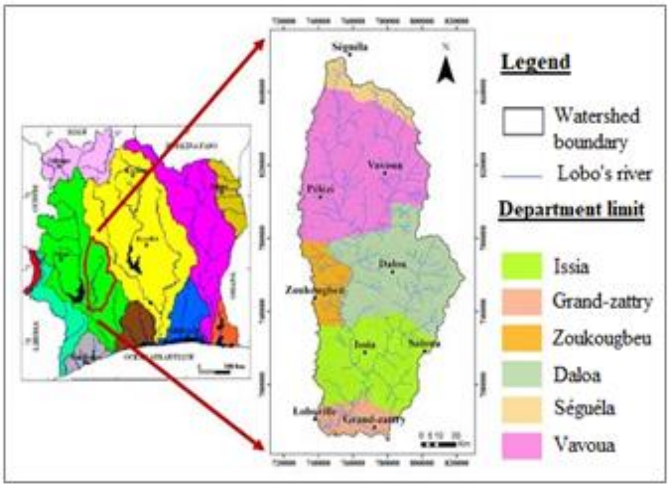

Fig. 1. Localisation of the Lobo watershed

The major part of the watershed belongs to the Haut-Sassandra region, the capital of the region is Daloa. It covers the departments of Daloa, Issia, Vavoua and Zoukougbeu; the extreme north belongs to the department of Séguéla; while in the south it overflows into the department of Soubré. The Lobo watershed is located in a transition zone where there are two types of climate: the equatorial transition climate (Baouléen climate) which is observed in the northern half of the watershed and the equatorial transition climate (Attiéen climate) which is observed in the extreme south. Two main types of relief share the watershed. These are the plains whose altitude varies between 160 and 240 m, located in the south of the watershed, and the plateaus occupying the major part of the watershed correspond to altitudes varying between 240 and 320 m [14]. The soils are essentially of ferrallitic type, strongly or moderately desaturated, modally reworked with an overlay of schists and granites.

III. MATERIAL AND METHOD

A. Data and material

The data used in this study are daily precipitation and temperature data from six weather stations over the period 1980 to 2013 (34 years). These data are obtained from the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR) and are available on the website (http://globalweather.tamu.edu/).

The MulGETS package implemented under the Matlab environment was used to generate the precipitation, maximum and minimum temperature data.

B. Method

Multi-site stochastic weather generator (MulGETS) developed by [15], is based on the Matlab environment and allows to generate daily rainfall, maximum and minimum temperatures (Tmax and Tmin) of unlimited length on several sites based on historical data. It is an extension of the single-site Weather Generator of École de Technologie Supérieure (WeaGETS) and is suitable for small watersheds where a single station can be used to represent the entire watershed [15]. The basic input data includes a file name for the observed meteorological data, a file name for storing the generated data, a precipitation threshold value (a minimum amount of rain in "mm" for a day considered rainy) and the number of years of data to be generated (Fig. 2).

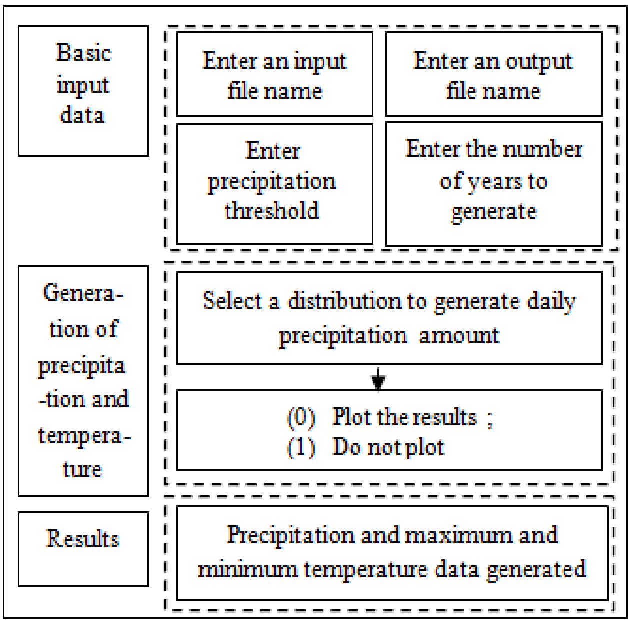

Fig. 2. Organisation chart of the structure of the MulGETS weather generator

➢ *Generation of rainfall occurrence*

The two-state first-order Markov chain is one of the most widely used methods for generating rainfall occurrence ([15]). The probability of precipitation for a given day is based on the wet or dry state of the previous day, which can be defined in terms of two transition probabilities P01 and P11 according to equations 1 and 2 :

P01=Pr{precipitation on day t I no precipitation on day t-1}(1)

P11=Pr{Precipitation on day t I precipitation on day t -1} (2)

The two complementary transition probabilities are :

$$P00 = 1 - P01, \text{ and } P10 = 1 - P11$$

➢ *Generation of precipitation amount*

MulGETS offers the possibility to use multi-gamma distribution and multi-exponential distribution to simulate daily rainfall amounts. Precipitation sequences are produced using two different distributions: a one-parameter exponential and a two-parameter gamma. The probability density function of the exponential distribution is given by equation 3:

$$f(x)= \lambda e^{-\lambda x} \qquad (3)$$

where x is the amount of daily precipitation and its parameter λ is equal to 1/average. The multi-exponential distribution combines several exponential distributions, each of which has its own parameter. The probability density distribution of gamma is given by equation 4 :

$$f(x)= ((x/\beta)^{(\alpha-1)} \exp[-x/\beta])/(\beta\Gamma(\alpha)) \qquad (4)$$

where α and β are the shape and scale parameters respectively, and Γ(α) refers to the gamma function calculated on α. The two parameters (α and β) necessary to use the gamma distribution are directly related to the mean (μ) and standard deviation (σ). They are defined as equations 5 and 6 :

$$\mu= \alpha / \beta \qquad (5)$$

$$\sigma= \sqrt{(\alpha / \beta)} \qquad (6)$$

➢ *Generation of maximum and minimum temperature*

MulGETS uses a 1st order autoregressive model to generate the maximum and minimum temperature data. The observed time series is first reduced to the residuals by subtracting the daily means and dividing by the standard deviations. The means and standard deviations are conditioned by wet or dry conditions. The residual series are then generated by equation 7 :

$$\chi_{(p,i)}(j)=A\,\chi_{(p,i-1)}(j)+B\varepsilon_{(p,i)}(j) \qquad (7)$$

where $\chi_{p,i}(j)$ is a matrix (2×1) for day i of year p whose elements A and B are matrices (2×2) whose elements are defined so that the new sequences have the desired autocorrelation and intercorrelation coefficients. The matrices A and B are determined by equations 8 and 9 :

$$A = M_1 M_0^{-1} \qquad (8)$$

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$$BB^T = M_0 - M_1 M_0^{-1} M_1^T \qquad (9)$$

where the exponents -1 and T denote the inverse and transposition of the matrix, respectively, and M0 and M1 are the covariance matrices of delay 0 and delay 1. The daily values of Tmax and Tmin are obtained by multiplying the residuals by the standard deviation (σ) and adding the mean (μ) (equations 10 and 11) :

$$T_{max} = \mu_{max} + \sigma_{max} \times \chi_{(p,i)} \qquad (10)$$
$$T_{min} = \mu_{min} + \sigma_{min} \times \chi_{(p,i)} \qquad (11)$$

➢ *Performance of the MulGETS weather generator*

Model performance is achieved using monthly precipitation data from 1997 to 2013 (17 years). It consists in making simulations using the model obtained over a period (1997 to 2013) for which precipitation data exist and then comparing the actual data with the data estimated by the Markov model. This process leads to the determination of the correlation coefficient that measures the quality of prediction of meteorological data.

IV. RESULTS

Daily data from the stations of Séguéla, Vavoua, Zoukougbeu, Daloa, Issia and Grand-zattry were used as input data for the MulGETS time generator. The monthly averages of precipitation, maximum and minimum temperatures for the seventeen (17) years (1997-2013) recorded by each of the 30 (thirty) simulations were used to illustrate the performance of the model.

A. *Precipitation amount*

The superposition of the curves of observed monthly mean rainfall heights and those simulated by the model for the validation period from 1997 to 2013 over all stations is given in Fig. 3.

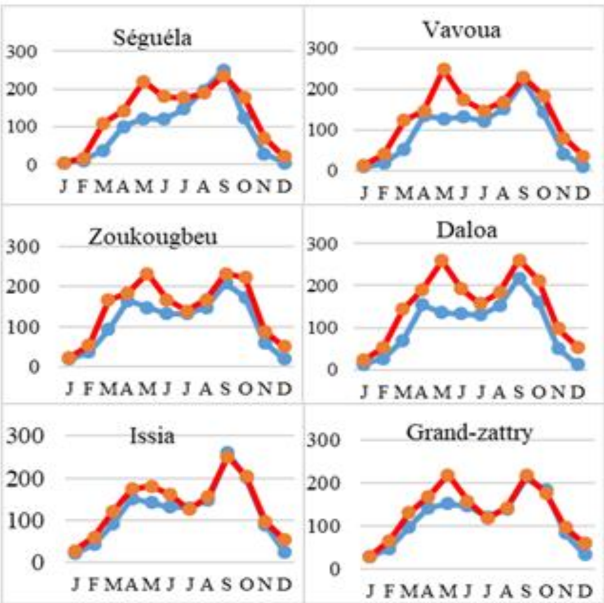

Fig. 3. Comparison of observed (blue) and simulated (red) average monthly rainfall curves for 1997-2013.

These graphs show a good superposition of the curves, which translates into a good estimate of the average monthly rainfall from January to February and from August to September at the stations of Séguéla, Vavoua and Zoukougbeu. This good estimate is also observed in January at the Daloa station, from January to February and from July to November at the Issia and Grand-zattry stations. Rainfall heights are slightly overestimated by the model from March to June at all stations. The performance of the model was also evaluated through the coefficient of determination which varies from 0.8175 to 0.916 (Fig. 4) indicating a good correlation between observed and simulated rainfall amounts.

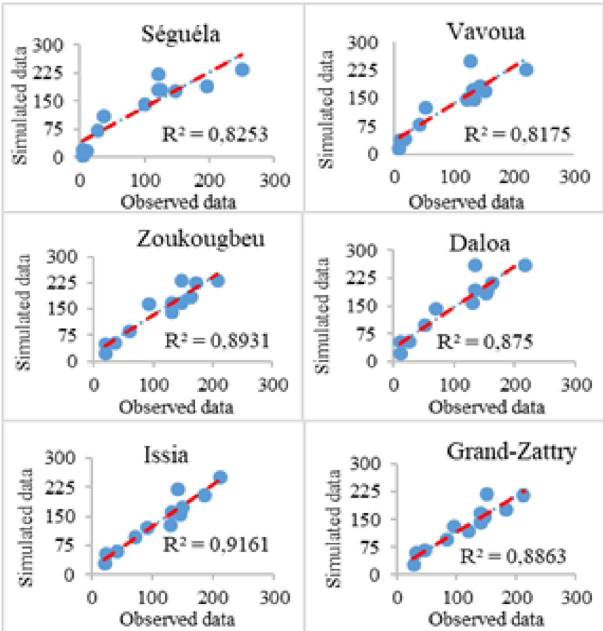

Fig. 4. Correlation between observed average monthly rainfall amounts and simulated average monthly rainfall amounts from 1997 to 2013.

B. *Maximum and minimum temperatures*

Fig. 5 shows the superimposition of the observed and simulated monthly mean maximum temperature curves from 1997 to 2013 for each station.

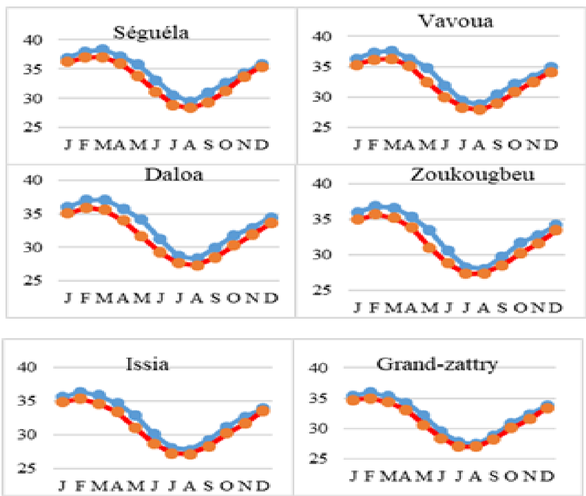

Fig. 5. Comparison of observed (blue) and simulated (red) monthly mean maximum temperature curves for 1997-2013.

The observed and simulated monthly mean maximum temperature curves show a perfect overlap and similar trends in each station. The MulGETS multi-site approach adequately reproduces the maximum temperature data. The observed values are almost identical to the simulated maximum temperature values. The observed and simulated monthly mean maximum temperatures show a very high correlation as indicated by the coefficients of determination which are very close to 1 (Fig. 6) showing a good performance of the model.

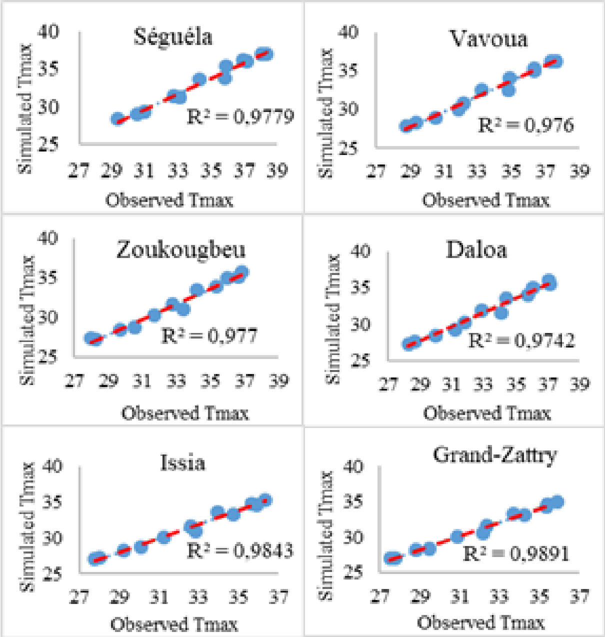

Fig. 6. Correlation between observed monthly average maximum temperatures and simulated monthly average rainfall amounts from 1997 to 2013

As with maximum temperatures, the observed and simulated monthly mean minimum temperature curves are well overlaid and show similar trends (Fig. 7). The MulGETS model adequately reproduces the minimum temperature data.

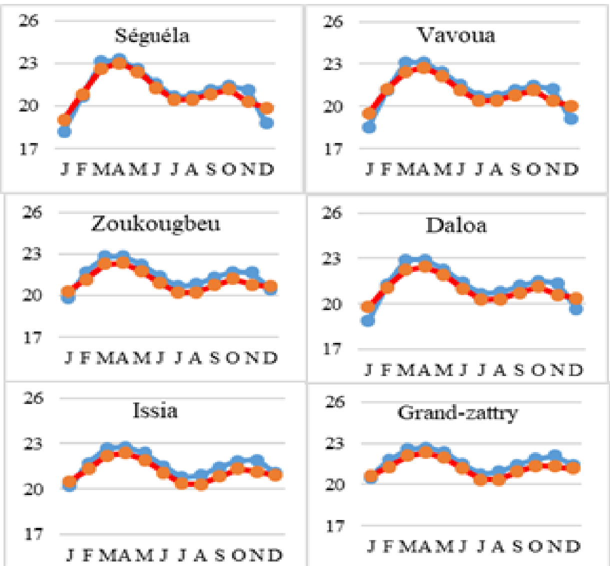

Fig. 7. Comparison of observed (blue) and simulated (red) monthly mean minimum temperature curves from 1997-2013

Figure 8 illustrates the correlations between observed monthly mean minimum temperatures and the monthly mean minimum temperatures simulated by MulGETS. The R^2 coefficients, which range from 0.85 to 0.906 across all stations, are very close to 1, meaning a very good correlation between observed and simulated minimum temperatures.

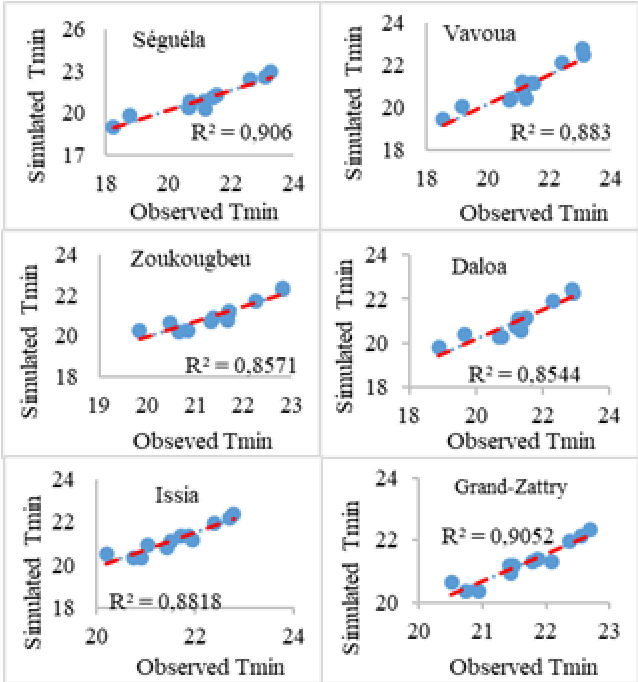

Fig. 8. Correlation between observed monthly mean minimum temperatures and simulated monthly mean rainfall amounts from 1997 to 2013

V. DISCUSSION

This work describes the Multi-site stochastic weather generator of the School of Higher Technology (MulGETS) for generating daily meteorological data (precipitation and temperature) in the watershed of the Lobo river. The daily precipitation and temperature data used in this study come from the Climate Prediction System Reanalysis Centre (CFSR). The use of these data is based on their wide use, availability and daily time step. They have been used and validated by several authors including [16]; [17]; [18]; [19] [20]; [21]; [22]. The Markov chains used in this study have been the subject of several works relating to rainfall analysis ([23]; [24]; [25]; [26]. These authors have shown that Markov chains describe daily rainfall fields well. They have the advantage of taking into account the memory effect to give a better description of rainfall. [27] in his work on Markov rainfall field modelling, came to the same conclusion. The performance of the MulGETS weather generator was evaluated in relation to the generation of precipitation and temperature at six stations. The results show that the model adequately reproduces precipitation and temperature data. The coefficients of determination show a very good correlation between observed and simulated data at all stations. These results are similar to the work of [28] which showed that MulGETS satisfactorily reproduces the observed correlation for both the occurrence and amount of precipitation and maximum and minimum temperatures in a part of the UK north-east of Ireland. Work by [29] also indicated improved model performance in the climate statistics space over the five sub-watersheds of the South Nation watershed, located in eastern Ontario, Canada. [30] in their study on the evaluation of multi-site precipitation generators at different scales, confirm the performance of MulGETS in preserving most of the observed statistics in contrast to the modified Wilks approach, the Stochastic Climate Library (SCL) and the Weather GENerator (WGEN) in simulating precipitation in Taiwan.

VI. CONCLUSION

MulGETS is a stochastic daily weather generator based on Matlab that allows the generation of time series of precipitation and temperature data of unlimited length. Six stations in the Lobo watershed have been selected to illustrate the performance of the model. The results show that the model adequately reproduces daily precipitation and temperature data but overestimates the wet periods (rainy season period). The values of the observed and simulated data are almost similar and show a very good correlation with coefficients of determination ranging from 0.8 to 0.98 over all stations. MulGETS is an efficient and effective model for generating meteorological data.

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