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Modeling of Runoff as a Function of Temperature and Precipitation: Application to the Litani River in Lebanon

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Abstract

Runoff is critically important for humans in their ecological and economic activities; hence, the ability to estimate the possible runoff change in response to changes in precipitation and temperature is highly desirable. In this article, two advanced methods are used to evaluate and quantify the relation and the impact of the runoff, precipitation and temperature in the Litani river in Lebanon. Firstly, the classical regression linear model method showed the relationships and the correlation between the factors; also, the regression lag linear model was used to evaluate the dependency of these factors at different times. Secondly, the advanced optimization shuffled complex method is a general method which can be used during the absence of the nonlinearity data in order to evaluate the impact of the temperature and precipitation data on the runoff data of the Litani river at different period.

Keywords: Litani river; Precipitation; Runoff; Regression model; Shuffled complex method; Temperature

Introduction

Water resources are a main component of natural systems that might be affected by climate change; several series hypothetical scenarios are imposed with regard to the precipitation and temperature data in order to make a hydrological model relating to the climate change. The Middle East and the adjacent Mediterranean region have been identified as a hot spot for climate change, projected with strong decrease in precipitation and increase in temperature for the near future [1]. Lebanon is in the Eastern Mediterranean area; the climate is characterized by hot dry summers and short wet winters. The rainy season of the Lebanese country is between December and February and the dry season occurs between June and August. This article focuses on the study of the relation between three climatology factors on the Litani river in Lebanon. The Litani river is the largest and longest river in Lebanon, generating about 30% of the total surface of water runoff in all the rivers that runoff in the Lebanese territories [2]. The total drainage area of the basin is about 2,175 km^2 with a channel length of about 170 km and an annual runoff of 750 million m^3. The Litani basin is divided into two parts, the Upper Litani basin (ULB) and the Lower Litani basin (LLB) and has nine tributaries. The ULB is located between altitudes 615 and 800 m and drains to the Qaraoun reservoir. It occupies about 70% of the total Litani basin with a length of 5.4 km and a width of 2.1 km in which the total water capacity is 220 Million m^3. The Qaraoun reservoir divides the basin into two distinct entities with contrasting climatic conditions: the ULB is considered mountainous, and the LLB is almost in the coastal zone; this provides an opportunity to study and compare the hydrological responses of climate change in a watershed divided into two heterogeneous orographic features, illustrating the importance of controlling local characteristics. Therefore, since the upper basin is dominated by a relatively large elevation zone, it is expected to be subject to higher precipitation and snow rates thus affecting the runoff sustainability and seasonality while the lower coastal basin should be more exposed to higher temperatures and lower precipitation.

Runoff, the most important component of the hydrological cycle, is subject to variation that should be influenced by climate change and human activities [3,4]. The runoff of Litani river in a given period, which is affected by the current meteorological factors and the meteorological and fluvial factors of the preceding periods have major influences on the precipitation and the temperature.

The average global temperature on Earth has increased by about 1.1°C since 1880. In addition, the Intergovernmental Panel on Climate Change (IPCC) predicts an increase of 2° to 4 °C over the next 100 years. According to the World Bank studies in Lebanon, the cost of damage caused by climate change to its economy would exceed 80 billion dollars in 2040. As such, the economic cost in the agricultural sector will therefore be 300 million dollars in 2020. In recent decades, the temperature in Lebanon is increasing from year to year, the precipitations have become radically different and the level of the snowfall is decreasing gradually.

The average annual precipitation value is estimated to be between 700 and 1100 mm in the coastal zone, 200 to 800 mm in the Beqaa Valley and around 2000 mm in the mountains. The annual precipitation is capable of generating an average annual runoff of 8600 million cubic meters, which feeds the 40 main rivers and streams (including 17 perennial rivers) and more than 2000 springs.

Most runoff modeling studies on the rivers have focused on the application of deterministic and stochastic models which require

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significant level of expertise. There are other simpler and similar effective approaches that have been rarely considered in this article, namely the multiple linear regression model (MLRM) and shuffled complex method (SCM) which are adopted in this study on the Litani river.

The main goal of this article is to study the evolution of the relationship between the three climatological factors (Runoff, Temperature, and Precipitation) in the Litani river in Lebanon while noting that the annual data for the three variables are available as recorded from 1962 to 2017. Such data are collected from the World Bank, the Litani National Authority and the Lebanese State Agricultural Research Authority [5]. Also, this article presents the runoff modeling at Litani in order to show the impacts of temperature and precipitation on runoff in the Litani river in Lebanon using the multiple linear regression model (MLRM) and the shuffled complex method (SCM) to optimize the proposal model by using the minimum meteorological factors and to compare the performance of these two methods. For this study, the data is used to perform the modeling of the runoff, temperature and precipitation since these variables have the greatest impact on the river runoff in the Litani and are most often available. The selection of these data is based on two criteria, namely the availability of data and the increased correlation between these parameters as demonstrated by several previous studies [6-9]. The data used in this study are annual averages covering the period from 1962 to 2017. To test the validity of both models, the data series were divided into series of training (calibration) (1962-2000) and evaluation series (validation) (2001-2017).

Method

The Two categories of models are used for processing the time series [10]. The first category considers that the data is a function of time and can be adjusted by the least squares method, or other iterative methods [11]. The second category determines each value of the series according to the previous values in which we used the multiple lag-linear regression model (MLLRM) [12]. The MLRM attempts in this article are to show the relationship between several independent variables (Temperature, Precipitation) and a dependent variable (Runoff) by adopting a linear equation to the observed data. Regression methods are based on the assumption of linearity hence we use the least square method for estimating the parameters to indicate if the independent variable has significant relationship with dependent variable [13,14].

After using the classical model (MLRM), the objective of the optimization method (SCM) is to determine the coefficients of the model by finding the minimum of the cost function. However, the approach would not be necessarily reliable if the problem is poorly posed or difficult and if the number of parameter is large. The calculation time can be long if we often have to call the physical model [15]. Moreover, a convergence towards a local minimum is possible in giving a degraded solution. There are several approaches in solving this difficulty [16].

During the 1980s, several efficient optimization algorithms were developed, such as simulated annealing [17], genetic algorithms [18], SCE-UA and Simulated Annealed Simplex [15-19]. These algorithms have been applied to runoff model problems [15,20-22,24]. Although the SCEUA algorithm is distinct from other optimization algorithms for the calibration problem of runoff models with respect to efficiency and the efficiency criteria as evidenced by several studies [22,25], it did not stop researchers from proceeding with the work in the direction of improving the performance of this algorithm by testing new techniques and modifying the exploration and exploitation mechanisms of this algorithm [23-26]. Some researchers have tried to introduce modifications to the SCE-UA's Simplex evaluative procedure by implementing further additional steps to their search mechanism to reduce the volume of search space, or by modifying the method with this algorithm generating its initial population [26-28]. The best modification to SCE-UA is that issued by Mutill and Liong who proposed the addition of a step to the SCE-UA engine algorithm the Evaluative Simplex [27]. In this article, we also propose to apply this change to model calibration SCE-UA. We note that the MLRM consist of studying the linear relation between several hydro meteorological factors, whereas the SCM method consists to study these factors in a non-linearity case.

The SCE method is based on a global optimization strategy, which combines several concepts of evolutionary theories, the Nelder-Mead method (downhill simplex procedure), a random draw on populations, the 'complex shuffling' and an evolution of populations 'Competitive Complex Evolution'.

The function $f\ (x)$ is the cost function we want to minimize. In our case, it is defined by the average annual runoffs calculated and measured:

$$f(x) = \sum_{i=1}^{Max} \ (Runoff^{\,calculated}(x,t_i) - Runoff^{\,measured}(x,t_i))^2$$

In this article, the statistical software R3.5.1, XLSTAT and C++ are respectively used to develop the MLRM models and the Shuffled Complex Method [29,30].

In order to compare the results between the different numerical methods (SCM and MLRM), three performance indices were calculated for each series: the coefficient of determination (R^2); standard error (E) and bias. The coefficient of determination (R^2); is the percentage of the total error on the dependent variable (*R (t)*: Runoff) explained by the model. This coefficient is expressed by:

$$R^2 = \frac{\sum\ (\overline{R(t)} - \overline{R(t)})^2}{\sum\ (R(t) - \overline{R(t)})^2} \times 100$$

Where *R (t)* is the observed value, $\overline{R(t)}$ is the average of the observed values and $\hat{R}\ (t)$ is the estimated value by the model. The standard error (E) is given by the following equation:

$$E = \sqrt{\frac{\sum\ \left(\overline{R(t)}? - R(t)\right)^2}{n}}$$

While the bias is given by the following equation:

$$Bias = \sum \overline{(R(\mathrm{t})} - R(\mathrm{t}))$$

Results and Discussion

Descriptive statistics

In order to discover the variation of the three factors we illustrate each of them based on the some descriptive statistics.

Table 1 shows the descriptive statistics for each factor: for example, we note that the annual mean for each 3 factors (Temperature, Precipitation, and Runoff) during the 1962-2017 are respectively equal to 16.12, 653.43, and 10.30. In addition, we notice that the variation of annual mean temperature is high ranging at Max 17.98 and Min 14.65. It is clear that 25% (1st Quartile) of the mean annual runoff over 55 years is less than 5.49 and 25% of the mean annual precipitation less than 558.82 and 50% (Median) of the annual mean temperature greater than 16.15.

Multiple Linear Regression Model (MLRM)

The objective of this subsection is to evaluate the relation between the hydro meteorological factors in the Litani basin in Lebanon. As such, it is important to study the correlation between runoff *R (t)* and meteorological variables (temperature *(T (t)*), precipitation *(P (t)*)) at annual mean scales. The changes in the correlations between runoff and other variables were determined for different years. In order to study the relationship between different factors, we use the MLRM which is a statistical tool used to process multidimensional data. The variable "runoff" is considered as the dependent variable to be explained the two independent variables "temperature" and "precipitation". The model is as follows:

$$R(t) = a_0 + a_1 * P(t) + a_2 * T(t) + \epsilon(t)$$

With "a_0, a_1, a_2" are the parameters of the model, and ϵ is the error of the model.

Coefficient of correlation

The coefficient of correlation gives the form of the relation between the three factors (runoff, temperature, precipitation) during 1962-2017 **(Table 2)**.

We remark a strong positive relation between the precipitation and runoff factors and a weak negative relation between temperature and runoff in addition to a very weak relation between precipitation and temperature, for the annual period 1962-2017

Estimation of the parameters

The quality of the (MLRM) is reflected from calculating the coefficient of determination (R^2=65.4%>50%), which confirms that the MLRM can be improved by studying the MLLRM in the next section. Also, the global model is significant, with a significance equal to 0 (sig=0<0.05). To test the significance of the variables (t), $T(t)$ we use the statistical test (t-test) and we find the significance:

$Sig\ (Temperature)$=0.024<0.05, the temperature is significant in the model, and a current impact of the temperature on the runoff factor in the Litani river.

$Sig\ (Precipitation)$=0<0.05, the precipitation variable is significant, and a current impact of the precipitation on the runoff factor in the Litani river.

In general, we notice that the influence of precipitation on the runoff is more important than the temperature since the degree of the significance for the variable precipitation is smaller than that of the temperature. So the adjusted model is given by the following equation:

$$\text{R } (t) = 20.003 - 1.802 * T\ (t) + 0.03 * P\ (t)$$

$$for\ 1962 \leq t \leq 2017$$

Multiple Lag- Linear Regression Model (MLLRM)

In this section we construct the general regression model for different period to study the relationship between the three factors (Runoff R (t), Temperature T(t), Precipitation P(t)). The follow equation shows:

$$\text{R } (t) = f\ (P\ (t), P\ (t-1), T\ (t), T\ (t-1), R\ (t-1))$$

Where, (t) represent the Runoff at time t; $(t - 1)$ is the Runoff at time t-1. The time lag of precipitation is given by (t): at time t and $(t - 1)$: at time t-1. Similarly, for the time lag of the variable temperature.

Based on **Table 3**, we can find the significance correlation between the factors at different time, which depends on the matrix distribution. Therefore, we remark from the model ($p\ \ value$=0.241>0.05 (significance level) that the impact of temperature at time t can be negligible, so the absence of correlation between the temperature and runoff at time t. In other side, there exists a significant relation between the runoffs at time t with (t), $(t - 1)$ and $(t - 1)$.

This relation between $R\ (t)$, $R\ (t - 1)$, $P\ (t)$, $T\ (t - 1)$ taking in consideration the runoff at t-1 and the temperature at t-1 the coefficient of determination (R^2) is bigger than R^2 in case of using only the factors at time t.

Regression of variable runoff (t)

The regression equations developed for the Litani river using stepwise regression approach (1962-2017) are given by the following models **(Table 4)**:

I. $Model$ 1: (t)=a+$b * P\ (t)$

II. $Model$ 2: (t)=a+$b *$ P (t)+$c * T\ (t - 1)$

III. $Model$ 3: $(t) = a$+$b *$ P (t)+$b * R\ (t - 1) + c * T\ (t - 1)$

The best model which corresponds to the higher, R^2=71%. The estimated parameters of the model 3 are given by the following **Table 5**.

So we can write the final best model of MLLRM:

$R(t)$ = 24.38 + 0.03 * $P(t)$ + 0.17 * $R(t -1)$ – 2.11 * $T(t\text{-}1)$

It was observed that the Multiple Linear Regression model got simulated very well with a small value of Mean Square Error, and a high value of R^2, revealing that the model is quite efficient in predicting the runoff of Litani river. To verify this model we plot in the same axis the two series the observed and the adjusted value and we remark that the series of the model is compatible with the series of the observed value, noting that we detect three extremes values of the runoff in the years 1966, 1967 and 1968 (**Figure 1**).

Shuffled Complex Evolution (SCE)

In this article, predicative analysis has to be applied for correctly modelling runoff (R), temperature (T) and precipitation (P) relationships. The follow equation shows this relationship between the factors:

$$F = f\ (P\ (t), P\ (t-1), \dots, P\ (t-m), \dots T\ (t-1), T\ (t-2), \dots T\ (t-n), R\ (t-1), \dots, R\ (t-p))$$

Descriptive Statistics	Temperature	Precipitation	Runoff
Number of observation	56	56	56
Minimum	14.65	309	1.93
Maximum	17.98	1121.5	32.12
Range	3.33	812.5	30.18
1st Quartile	15.73	558.82	5.49
Median	16.15	636.9	9.08
3rd Quartile	16.55	732.02	13.19
Mean	16.12	653.43	10.30
Standard deviation	0.65	166.24	6.21

Table 1: Descriptive statistics for the three factors.

Variables	*R* (t)	*P* (t)	*T* (t)
R (t)	1	0.78	-0.16
P (t)	0.78	1	0.04
T (t)	-0.16	0.04	1

Table 2: Correlation matrix (Pearson).

Variables	*R* (t)	*P* (t)	*T* (t)	*R* (t-1)	*P* (t-1)	*T* (t-1)
R (t)	0	<0.0001	0.241	0.008	0.056	0.036
P (t)	<0.0001	0	0.773	0.149	0.280	0.709
T (t)	0.241	0.773	0	0.357	0.071	0.008
R (t-1)	0.008	0.149	0.357	0	<0.0001	0.241
P (t-1)	0.056	0.280	0.071	<0.0001	0	0.830
T (t-1)	0.036	0.709	0.008	0.241	0.830	0

Table 3: Significance test of the correlation between the factors at different time.

Model	Variables	MSE	R^2
1	*P* (t)	15.60	0.61
2	*P* (t); *T* (t-1)	13.38	0.67
3	*P* (t); *R* (t-1); *T* (t-1)	12.47	0.71

Table 4: Summary of the variables selection Runoff (t).

Variables	Value	Pr>|t|
P (t)	0.03	<0.0001
R (t-1)	0.17	0.035
T (t-1)	-2.11	0.007

Table 5: Estimate parameters of the Model 3.

Where, *R* (t-p): runoff at time t-p; p: maximum steps of time lag of runoff and *P* (t-m): precipitation at time t-m with m: maximum steps of time lag of precipitation. *T* (t-n): temperature at time t-n; n: maximum steps of time lag of temperature.

Different steps taken into consideration to construct the general model which we can apply for any value at the time t **(Figure 2)**.

Validation of the SCM

In this paper, our model is a 4-dimensional function (constant value, precipitation of the current year, temperature and rain of the previous year). In such cases, the parameters ranges are:

$-1000 < parameters_i < 1000$

The following figure shows, the efficiency of the model in which convergence of the objective function was carried out before 1500 iterations for all different runs **(Figure 3)**.

Figures 3b-3d shows the varied value of parameter of the variables (*R* (t-1), *P* (t), *T* (t-1)) according to the number of objective function calls during the calibration process with 20 runs (20 different initial random number seeds). In each run, the stopping criteria, which is used, is "the trial reached 2,000 function evaluations".

The calculation of the runoff is sensitive to the parameters of the modelling. Based on **Figure 3e**, the results show clearly that this model is very sensitive to the precipitation parameter (the convergence is obtained before 300 iterations) whereas it is less sensitive to the parameters of the previous runoff and the previous temperature (convergence is realized between 600 and 1000 iterations).

Validation of the model

In the current study MLLRM technique was utilized on the normalized data using the software XLSTAT. The analysis of variance was done and the R^2 and the root mean squared error (RMSE) were computed. The MLLRM model was validated by plotting the predicted runoff *vs.* actual runoff curve for years 1962-2000 in order to validate the prediction of years 2001-2017.

Table 6 gives the coefficients of the (MLLRM) and the standard error of each coefficient. According to this table, we find that there is a close relationship between the runoff and the dependent variables (*R* (t-1), *P* (t), and *T* (t-1)) due to the fact that all coefficients of the Student's t-test gave very low probability values (less than 5%). This means that each variable has a significant contribution on the runoff.

We obtain the following regression equation:

$$\mathrm{R}\ (t) = 36.32+0.028*(t)+0.079*R\ (t-1)-2.81*T\ (t-1)$$

The coefficient of determination obtained for the training data (1962-2000) is equal to 65.1% (>50%) for the MLLRM, and 63.8% for the SCM, which gives a standard error of 2.85 for the MLLRM and 3.95 for SCM. For validation data (2001-2017), the coefficients of determination are equal to 91.4% for MLLRM and 88.7% for SCM, with a standard deviation of errors 1.42 for MLLRM and 2.89 for SCM. During the study period (2001-2017), the calculated bias was equal to zero for the MLLRM and 0.407 for SCM. As such, we can conclude that it is possible to predict Litani water runoff using the optimal model function with respect to temperature at time t-1 *T* (t-1), runoff at time t-1 *R* (t-1) and precipitation at time t *P* (t); however, both of these modeling approaches demonstrate good performance in predicting water runoff in Litani river for the future. The results of these models are very similar to those observed, that is to say a good performance during the years 1962-2000 (**Figure 4a**) and 2001-2017 (**Figure 4b**). The MLLRM slightly improves the quality estimation of the runoff in Litani river compared to the SCM model.

Based on the **Table 7** we can deduce the following graphs of the observed and adjusted value by the MLLRM in the training series (1962-2000) and validation series (2001-2017) **(Figures 4a and 4b)**.

Conclusion

The objective of this study is to evaluate the runoff from the available climatological factors using models that are very rarely used in the literature, namely the SCM model and the MLLRM. The use of such models can subsequently predict or estimate the runoff in Litani river in various meteorological conditions or during periods of missing data. Each of the two models used has advantages and disadvantages; the SCM optimization method is very efficient but offers an unclear description of the relationship between input and output data whereas by use of MLLRM, an equation is determined that clarifies the relationship between input variables and runoff in Litani river. As demonstrated by our results, these two models give quite acceptable results with an overall standard error to 3.95 for the (SCM) and 2.85

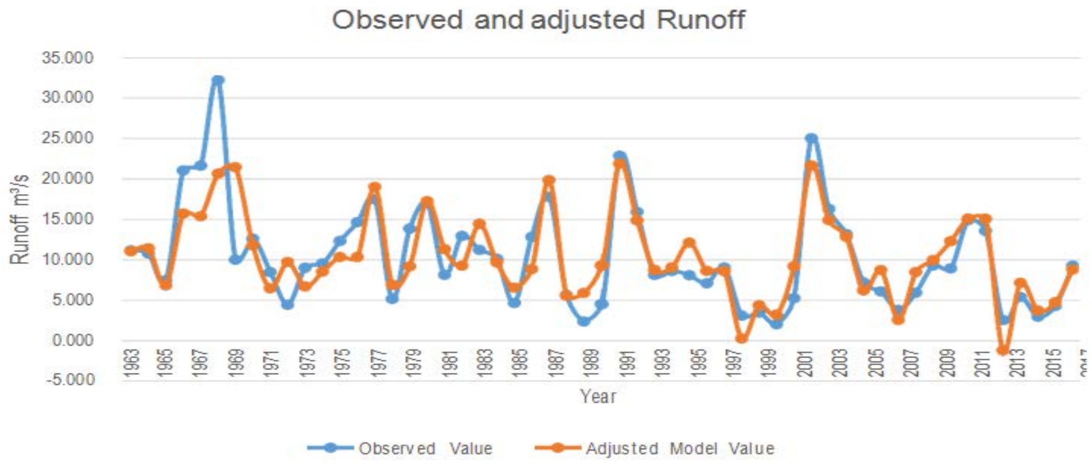

Figure 1: Time series of the runoff (observed *vs.* predicted) value.

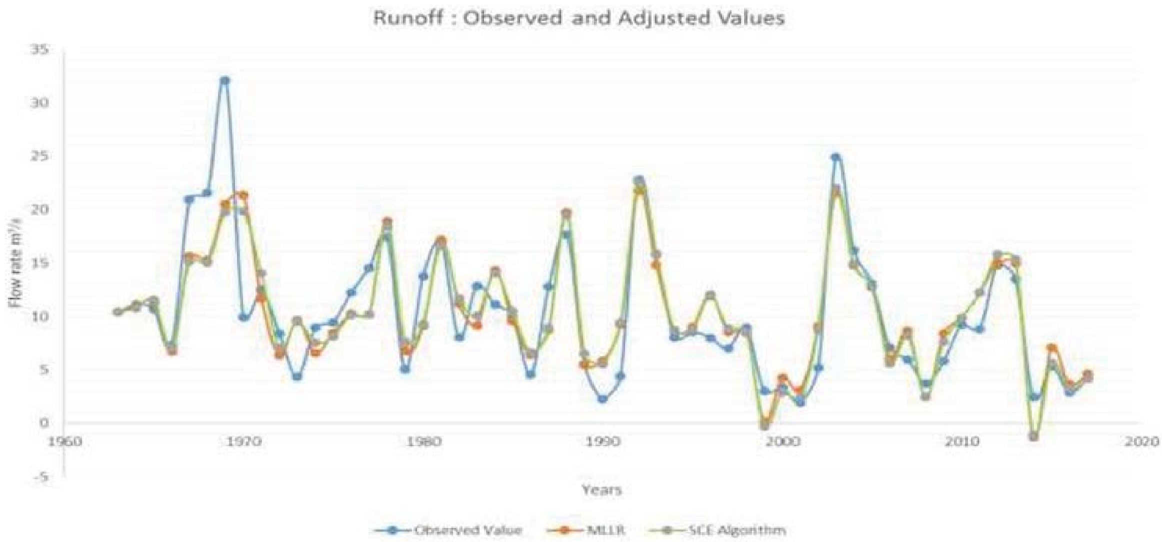

Figure 2: Runoff by the SCE method.

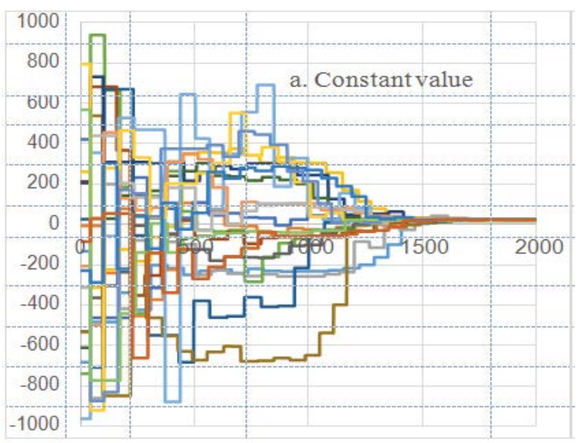

Figure 3a: Variations of each parameter by SCM (1962-2000) (Constant Value).

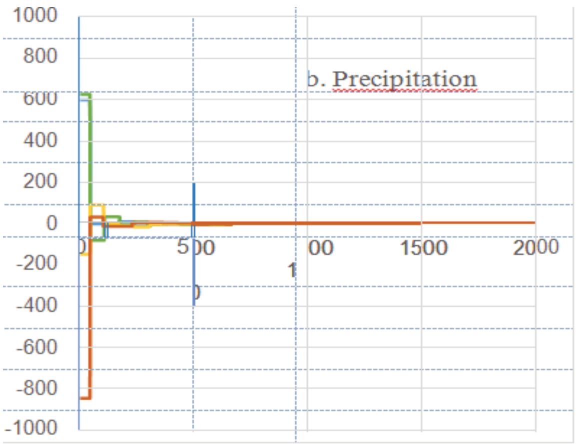

Figure 3b: Variations of each parameter by SCM (1962-2000) (Precipitation).

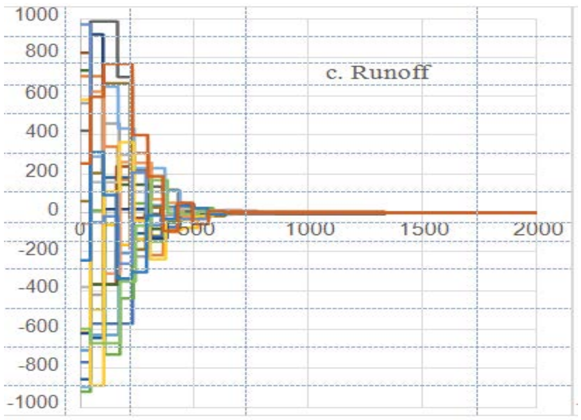

Figure 3c: Variations of each parameter by SCM (1962-2000) (Runoff).

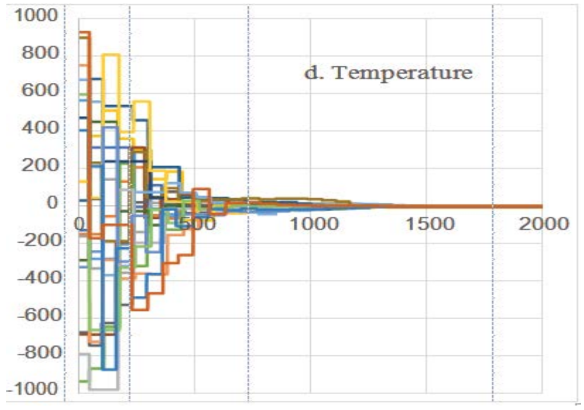

Figure 3d: Variations of each parameter by SCM (1962-2000) (Temperature).

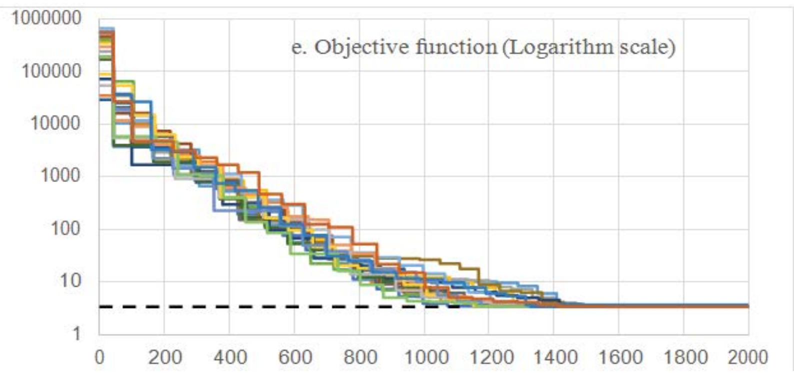

Figure 3e: Variations of each parameter by SCM (1962-2000) (Objective function (Logarithm Scale)).

Variables	Coefficient	Standard error
Constant	36.32	7.244
P (t)	0.028	0.004
R (t-1)	0.079	0.112
T (t-1)	-2.81	0.062

Table 6: Coefficients and standard error of coefficients for the regression model.

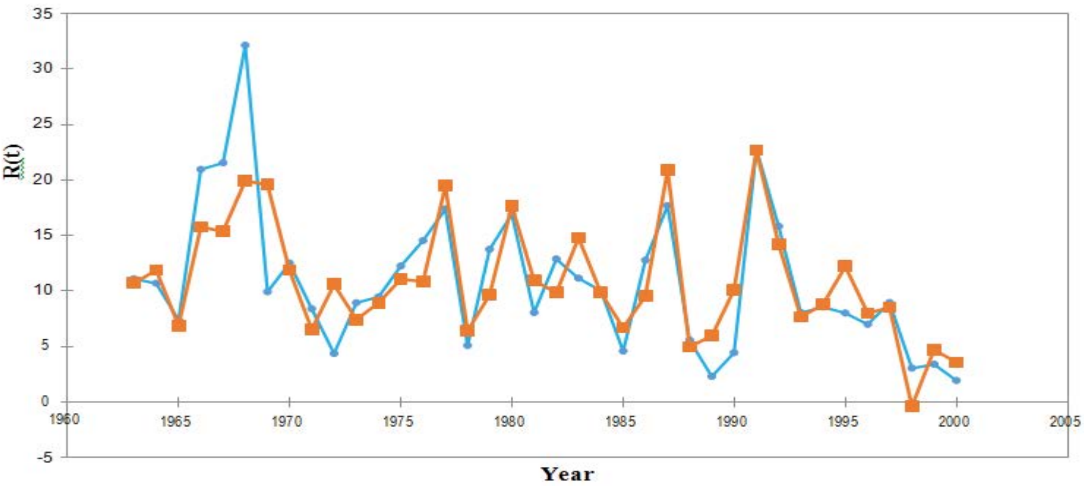

Figure 4a: Observed and predicted runoff calculated with the MLLRM (1962-2000).

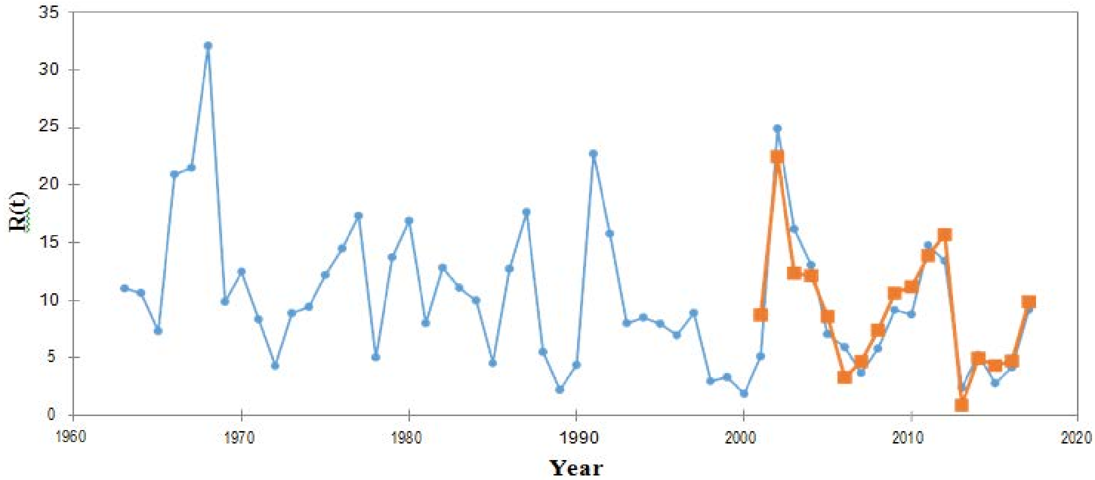

Figure 4b: Observed and predicted runoff calculated with the MLLRM (2001-2017).

Year	*R* (t) observed	*R* (t) adjust (MLRM)	*R* (t) adjust (Shuffled)
2001-2002	5.18	7.10	6.14
2002-2003	24.94	21.26	23.46
2003-2004	16.22	15.58	12.33
2004-2005	13.09	12.92	10.09
2005-2006	7.11	9.12	4.64
2006-2007	5.98	6.58	6.24
2007-2008	3.73	1.95	2.41
2008-2009	5.85	6.94	9.07
2009-2010	9.21	9.45	10.23
2010-2011	8.83	11.65	11.02
2011-2012	14.82	13.61	15.58
2012-2013	13.48	15.60	14.45
2013-2014	2.45	-0.22	2.62
2014-2015	5.30	5.48	6.82
2015-2016	2.87	2.78	3.80
2016-2017	4.21	3.49	5.14
2017-2018	9.20	9.136	8.84
Biais (2001-2017)		0	0.41

Table 7: Comparison between MRLLM and SCM.

for the MLLRM. The advantage of the models presented in this study are mainly of their relative simplicity (development, application and updating of the model), compared to stochastic and deterministic models.

All obtained results allow us to conclude that the two proposed methods can be exploited for the estimation of Litani runoff. Indeed, the MLLRM has demonstrated a significant ability to learn and predict runoff. Besides, for the approach of the SCM, it also allows to have similar and effective results. The coefficients of determination for the training data which equal to 65.1% for the MLRM and 63.8% for the SCM with a standard errors equal to 1.42 for the MLRM and 2.89 for the SCM.

For validation data, the coefficients of determination are equal to 91.4% for the MLRM and 88.7% for the SCM with standard errors equal to 1.42 for MLRM and 2.89 for MLRM. During the study for period (2001-2017), the calculated bias was equal to 0 for the MLRM and 0.43 for SCM. As such, we can conclude that it is possible to predict the runoff water by using the optimal model function with respect to temperature at time t-1; *T* (t-1); Runoff *R* (t-1) at time t-1 and precipitation at time t *P* (t); however, both of these modeling approaches demonstrate good performance in predicting the future runoff in Litani river.

It is worth noting that while both models have similar deviations of similar errors over the entire study period, the bias criterion distinguishes these two sets of results. The variability of the variables during years of studying suggests good functioning of the two models in such conditions in a global manner. However, this study also shows low performance for the years subject to extreme runoff (low in 2000 and high in 1968). On the other hand, variability appeared to be lower for average runoff, especially during the validation period of the regression model. We note a largest standard errors attributed mainly to the poor performance of the model in 1968 showing the presence of the extreme values. This suggests that the studies on models may be slightly more performance in average runoff conditions than extreme runoff thus making the interest of studying these extremes in future works.

Finally, we note the effect of human activities on runoff response is only implicitly captured since human actions and decisions are increasingly having a larger proportional impact on the basin-scale changes. As such, future research is needed to explicitly account wherein we recommend the simpler regression models that are more suitable for scenario analysis and planning whereas the autoregressive time series are primarily applicable to improve our understanding in the operational purposes that will be useful to study in future work.

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