BE2 – Hydrological modeling

USING GR4J MODEL FOR HYDROLOGICAL MODELLING

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1. INTRODUCTION

1.1. Objective

The objective of this BE were the following:

- Become familiar with the airGRteaching package
- Run a rainfall-runoff model
- Calibrate a rainfall-runoff model
- Perform rainfall-runoff simulations with the R package airGRteaching
- Understand the different steps of hydrological modeling (calibration, validation, simulation and sensitivity analysis)

1.2. Hydrological Model

GR4J is a conceptual water balance model which means it defines the conceptual phenomenon that how rainfall and runoff occurs but it does not define the physical process by using any physical equations. It relates runoff to rainfall and evapotranspiration using daily data. The inputs to the model are precipitation and potential evaporation and gives discharge as the output. It uses a global spatial structure i.e. like a lumped model and the limitation of this consideration is that it cannot take into account heterogeneity. It is based on two reservoir model with 4 following parameters.

- X1: the production store maximal capacity (mm),
- X2: the catchment water exchange coefficient (mm/day).
- X3: the one-day maximal capacity of the routing reservoir (mm).
- X4: the HU1 unit hydro graph time base (days)

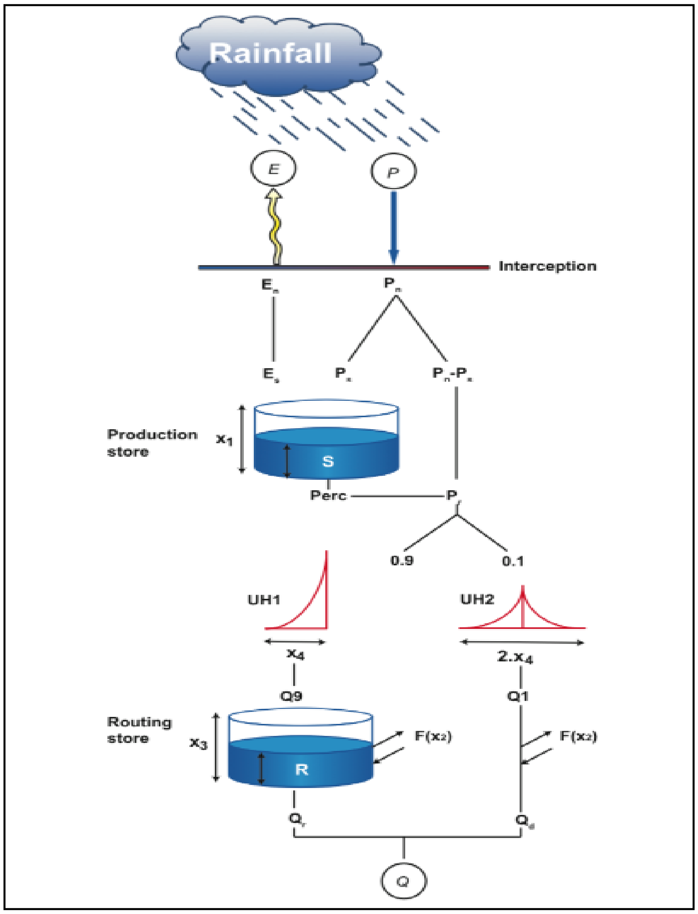

Figure 1: Schematic diagram of the GR4J model (Perrin (2003))

2. RIVER BASIN AND DATA

2.1. Description of the Watershed

Blue River watershed has an area of 360 KM^2. The highest elevation in the watershed is 1278m the median is 577m and the lowest elevation is 286m.

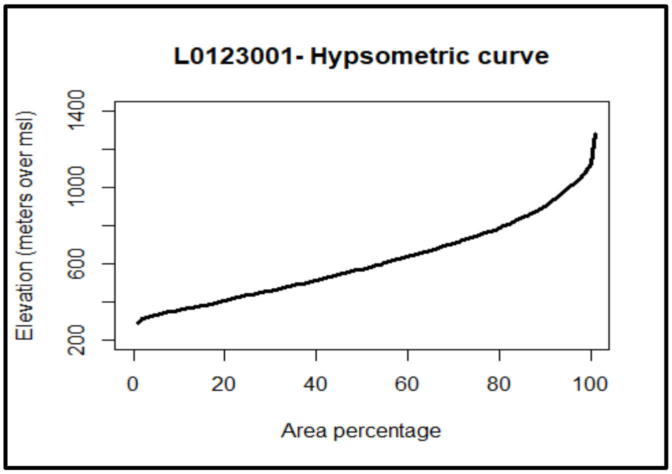

Figure 2: L0123001- Hypsometric curve of the Watershed

From the above graph, it can be concluded that approximately 50% of the area in the watershed is above 600m above MSL (Mean sea level). From this a hypothesis can be derived that as the heights in the watershed are high, so it could be inferred as a mountainous area.

2.2. Time Series:

The time series under study is considered from “1984-01-01 UTC" to "2012-12-31 UTC.

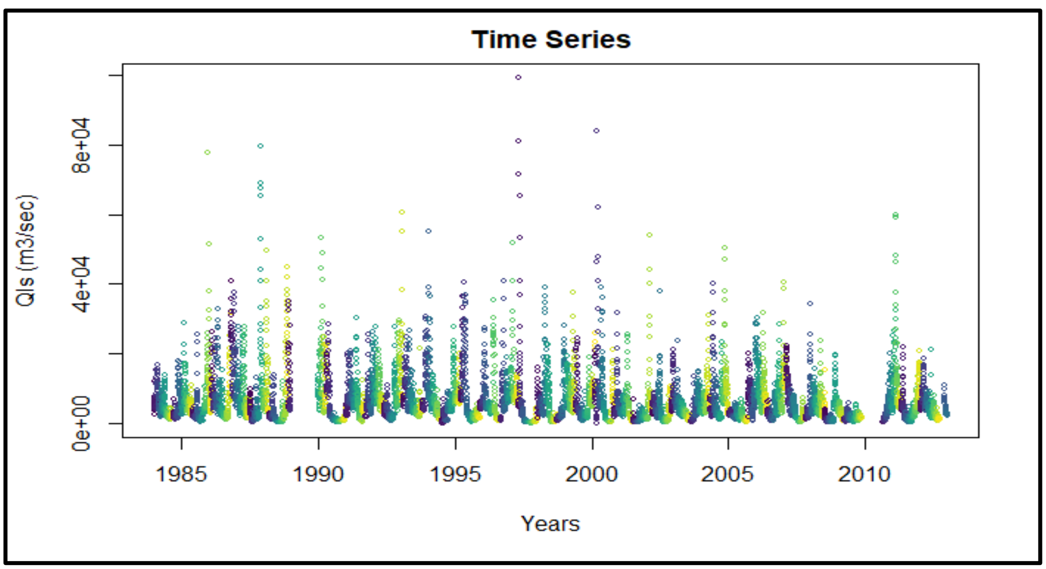

Figure 3: Time series of the Watershed

2.3. Simple Water Balance for the Watershed

The law of water balance states that the inflows to any water system or area are equal to its outflows plus its change in storage during a time interval. The runoff coefficient is a dimensionless coefficient relating the amount of runoff to the amount of precipitation received

$$\text{Water Balance} = Pm - Em - Qm$$

Where

Pm = mean precipitation
Em =potential Evaporation
Qm= Flow (mm)

Pm = 2.914595; **Em** = 1.764099; **Qm** = 1.473169

Water Balance = -0.3226738

The negative sign of the water balance shows that the amount of rainfall system received was less than the losses of the system.

$$\text{Runoff Coefficient} = Qm/Pm$$

Runoff Coefficient = 0.5054458

The runoff coefficient of 0.5 suggests that 50 % of the rainfall that the system receives is converted to flow (Qm). Hence we can say that the response of the system is moderate.

2.4. Hydrological Regime of the Watershed:

From Figure 4 it can be observed that highest discharge is in the winter months (December to February) and lower are in the summer months (June to August), which is common trend in most of the rivers. This lower discharge could be due to dry soil and due to higher evapotranspiration process; the lower evapotranspiration hypothesis is also due to the negative water balance we achieved. One hypothesis of greater agriculture activity during the summer season could be a factor for lower discharge as initial abstraction increases.

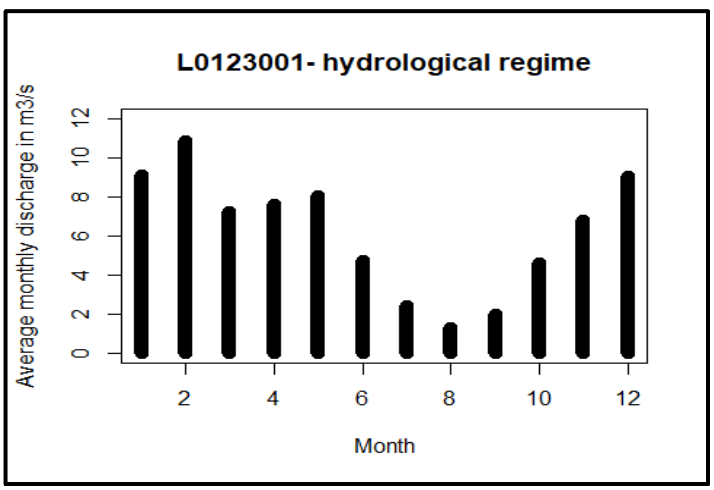

Figure 4: Average Monthly Discharge (m3/sec) VS Months

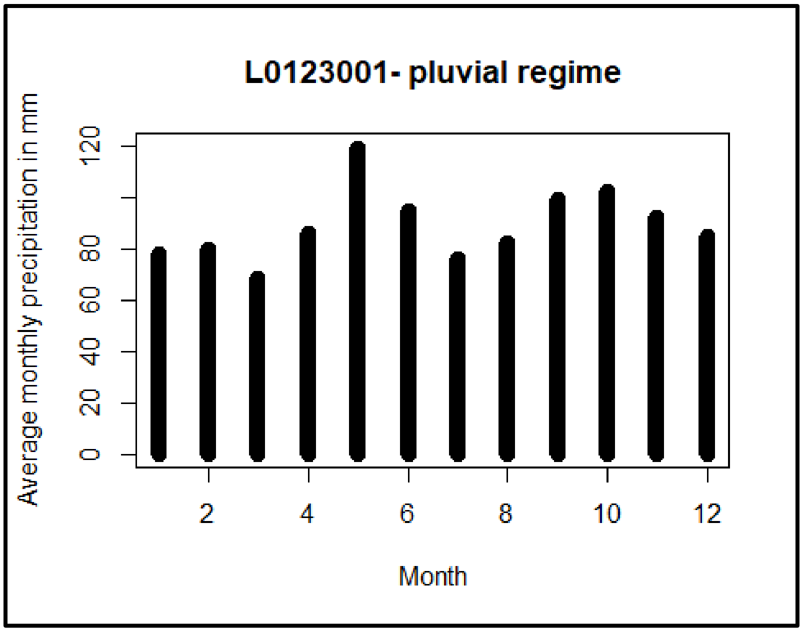

Figure 5: Average Monthly Precipitation (mm) VS Month

From the **Figure 5** we see that the precipitation is subjected to a factor of seasonality with more rainfall in the summer months as compared to winter months. The trend even fortifies the hypothesis that even after having higher rainfall in summer months the discharge is lower because of high evapotranspiration and dry state of the soil or higher agriculture activity

The river has a pluvial regime as it has high water in winter and spring, lower discharge in summer and greater inter-annual variability. The spring months are from March to May, the rainfall in these months increases, so as the discharge. (Wikipedia n.d.)

3. CALIBRATION CRITERIA:

In this section the sensitivity of the parameter calibration to the chosen calibration criterion was analyzed.

Two calibration criterions are used to test the sensitivity of the parameter calibration

1) NSE (the Nash-Sutcliffe Efficiency (NSE))
2) Kling-Gupta Efficiency (KGE2)

$$NSE = 1 - \frac{\sum_{i=1}^{n}(X_i - Y_i)^2}{\sum_{i=1}^{n}(X_i - \mu_X)^2}$$

With i the time step, n the total number of time steps available for calibration, X_i the observed discharge and μ_X its mean, and Y_i the simulated discharge

$$KGE2 = 1 - \sqrt{(1-r)^2 + (\beta - 1)^2 + (\gamma - 1)^2}$$

With β the model bias, r the coefficient of correlation and γ the ratio of the simulated and observed coefficients of variation

$$\beta = \frac{\mu_Y}{\mu_X}$$

$$\gamma = \frac{CV_Y}{CV_X} = \frac{\frac{\sigma_Y}{\mu_Y}}{\frac{\sigma_X}{\mu_X}}$$

$$r = \frac{\sum_{i=1}^{n}(X_i - \mu_X).(Y_i - \mu_Y)}{\sqrt{\sum_{i=1}^{n}(X_i - \mu_X)^2}.\sqrt{\sum_{i=1}^{n}(Y_i - \mu_Y)^2}}$$

3.1.Brief Description of NSE and KGE2:

NSE can be defined as one minus the sum of the absolute squared differences between the predicted and observed values normalized by the variance of the observed values series would have been a better predictor than the model. The largest disadvantage of the Nash-Sutcliffe efficiency is the fact that the differences between the observed and predicted values are calculated as squared values. As a result larger values in a time series are strongly overestimated whereas lower values are neglected. For the quantification of runoff predictions this leads to an overestimation of the model performance during peak flows and an underestimation during low flow conditions. Whereas, KGE2 is an updated version of KGE09 (which is diagonal decomposition of NSE) (Jackson 2019.), this metric separates the different aspects of the flow regime that is correlation (r), the bias(β) , and a measure of relative variability(γ) so if the value of the criteria is small then it can be identified that which parameter needs adjustment.

3.2.Performance of NSE (Q)

From **Figure 6** visually it is difficult to observe the difference in observed and simulated time series. However from the other 3 graphs we can deduce that, the rolling mean for both the series superimpose each other which means that both follow the same trend as per seasonality. Also the cumulative non exceedance probability for both the trends are almost same except the low flow portion where they differ this aspect is very important as we can estimate the probabilities with sheer confidence for high flows but not for low flows. From the scatter plot between the observed and simulated flow we can say that the values are overestimated for the stream flows, as since most of the values are above 1:1 line.

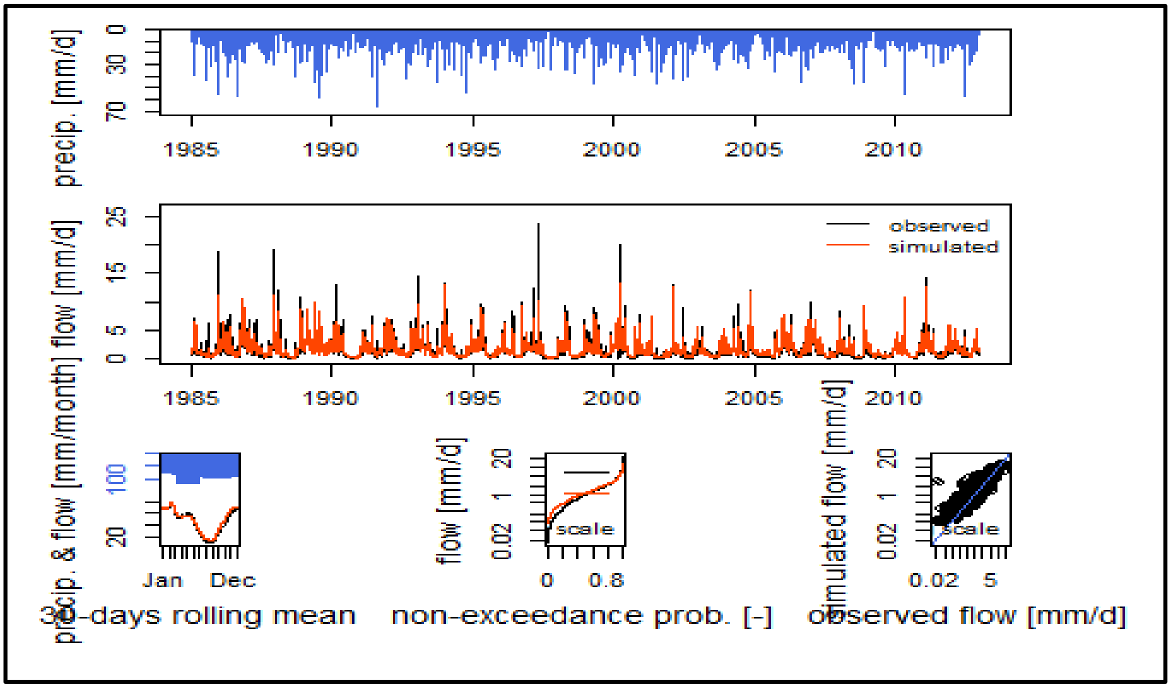

Figure 6: Performance Graph for NSE[Q]

3.3.Performance of KGE2

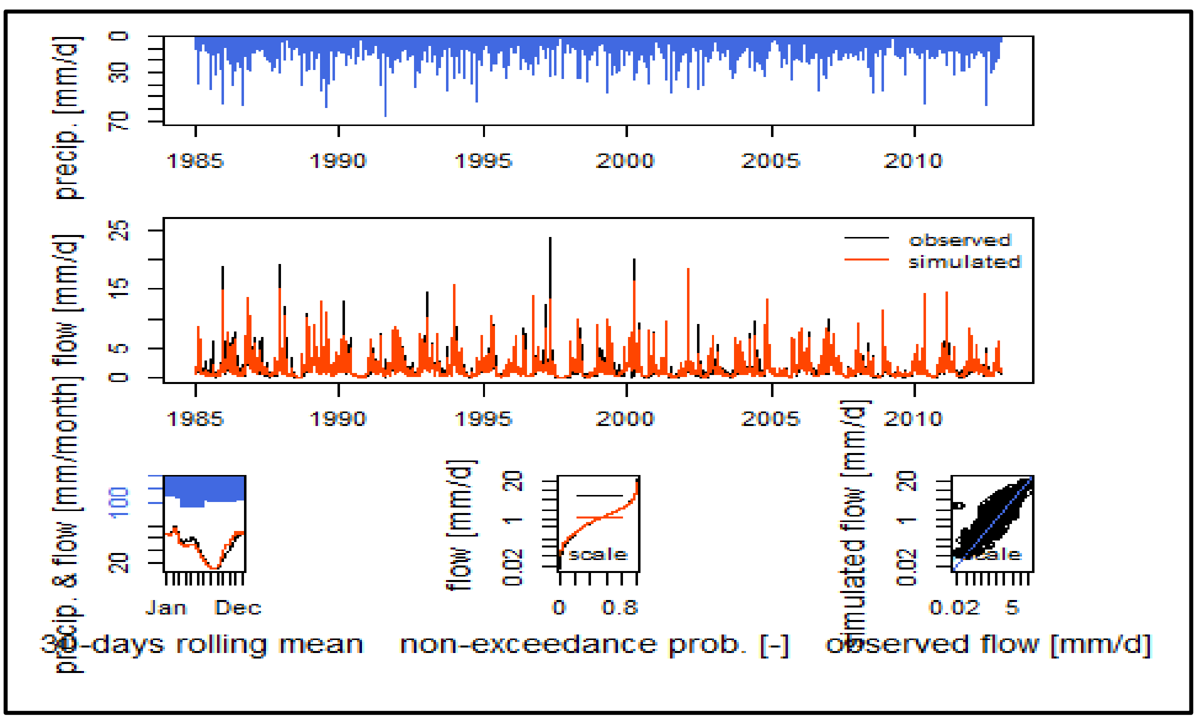

Figure 7: Performance Graph for KGE2

From **Figure 7** visually it is difficult to observe the difference in observed and simulated time series. However from the other 3 graphs we can deduce that, The rolling mean for both the series do not superimpose each other but the trend they follow are same which explains that both the series respect the trend of seasonality. Furthermore, cumulative non exceedance probability for both the trends superimposes each other which is very important as we can estimate the probabilities with sheer confidence for low flows and high flows. From the scatter plot between the observed and simulated flow we can say that the values are still overestimated for the stream flows, since most of the values are above 1:1 line, however if we compare it to the case in NSE it has improved a bit

3.4. Performance of NSE [1/Q]

From **Figure 8** visually it is difficult to observe the difference in observed and simulated time series. However from the other 3 graphs we can deduce that, The rolling mean for both the series do not superimpose each other but the trend they follow are same which explains that both the series respect the trend of seasonality. Furthermore, cumulative non-exceedance probability for both the trends superimposes each other which is very important as we can estimate the probabilities with sheer confidence for low flows and high flows. From the scatter plot between the observed and simulated flow we can say that the values approximately equally divided between 1:1 line and it is much improved than NSE and KGE2 case.

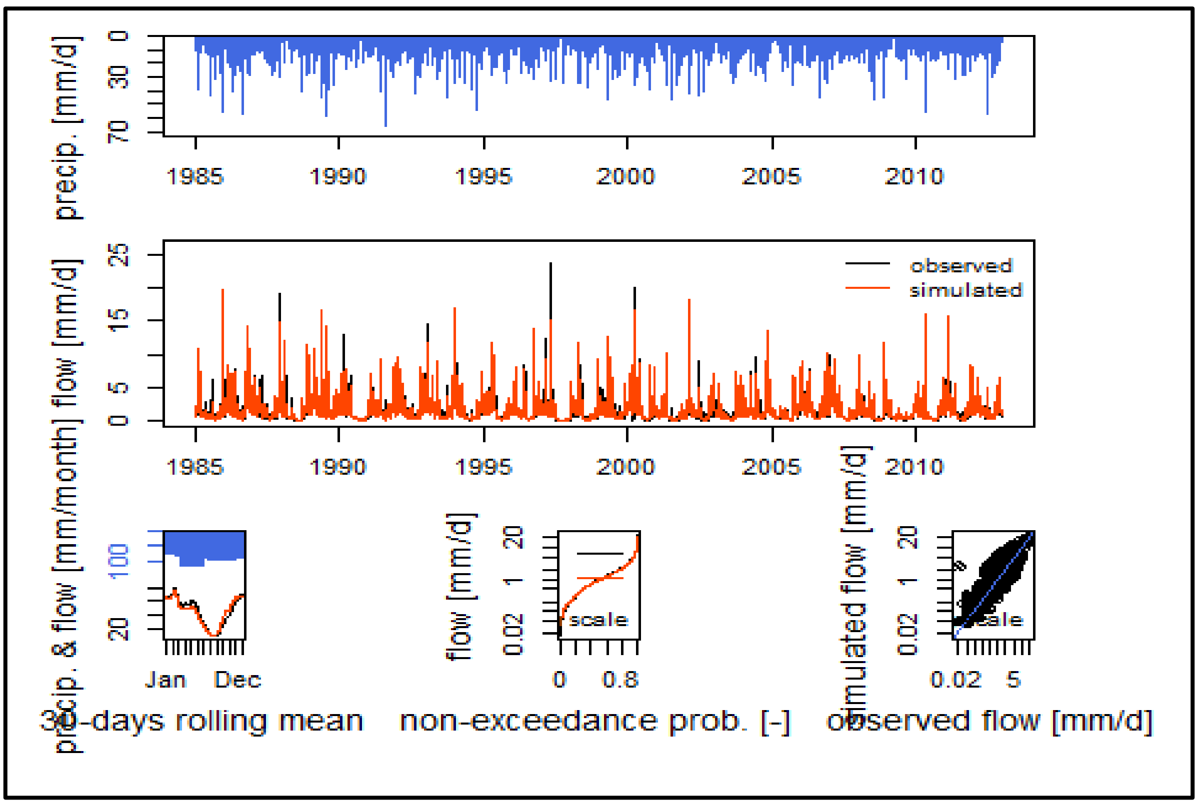

Figure 8: Performance Graph for NSE [1/Q]

CHANGE OF VARIABLE

After observing the performance from both the criterions and 1 modified criteria (i.e. NSE [1/Q]) the change of variable improves the calibration result. As the NSE belongs to the family of mean model square error criteria, so it puts more emphasis on high flows and puts more weight on high flows, therefore transformation of variable to inverse results in more weight on low flows.

FINAL CHOICE:

Although KGE2 gives the highest percentage of closeness between the observed and simulated flows but the NSE (1/Q) is more adequate for low and high flows which could also be observed from the scatter plot graph between observed and simulated flows **(Figure 8)** for NSE (1/Q) as the data is scattered equally between the 1:1 lines. Hence the preference will be to use NSE (1/Q) criteria.

Table 1: Calibration Parameter Values from NSE, KGE2 and NSE [1/Q]

	NSE(Q)	KGE2(Q)	NSE(1/Q)
Criterion	0.7956564	0.8548429	0.7134102
X1	215.9226249	131.630664	172.431490
X2	0.5994375	0.000000	0.000000
X3	99.1834071	68.033484	44.701184
X4	2.1808447	2.295796	2.168919

4. WARMUP PERIOD:

Warm-up period is the duration or period that a model requires to remove the initialization bias by bringing the initial state of the system to equilibrium, if not since it has a major impact on the catchment response, and thus on the model response. By default, the production store of the GR4J model is initialized at a level of 30% and the routing store at a level of 50%. The values simulated during the warm-up period are not included in the calculation of the criterion. By default, this period is fixed as the first year before the beginning of the period of calibration (or simulation).

In this section we ought to find that what should be the optimum warm up period, as if we choose a small warm up period that initial state would not be able to adjust to optimal state and if we choose a period which is longer than it might compromise valuable data that could have been used for the calibration and validation.

Therefore period from "1994-01-01" to "1994-12-31" was selected for the calibration and 4 warm-up periods, respectively of 1 month, 6 months, 1 year and 2 years were taken. Calibration criteria used was KGE2.

WP1 = ("1993-12-01", "1993-12-31")
WP2 = c("1993-06-01", "1993-12-31")
WP3 = c("1993-01-01", "1993-12-31")
WP4 = c("1992-01-01", "1993-12-31")

Where WP1, WP2, WP3 and WP4 are the 4 warm up period

Table 2: Calibration parameters for four Warm-up Periods

	WP1	WP2	WP3	WP4
Criterion	0.9029425	0.9180561	0.9181854	0.9181857
X1	112.892529	179.0798368	182.3404560	182.3404560
X2	0.254166	0.3241509	0.3300811	0.3300811
X3	118.955316	99.1784463	98.1027648	98.1027648
X4	2.187605	2.187605	2.2572024	2.2572024

As the default warm-up period is taken to be 1 year, by doing this analysis it is observed that can say that it is not as that reasonable compromise, as the shortest warm up period (1 month) has an efficiency of 90.30 percent and takes 24 iterations, while the 1 year warm up period gives an efficiency of 91.81 percent only 2 percent more for 4 additional iterations which does not seems a reasonable compromise. The best warm up period for this data seems to be of 1 month as it has a reasonable KGE value (90.30) which is not very less than KGE values for other periods and also it has the lowest number of iterations.

No the warm up period would not have the same influence on a short and long calibration period, as with the warm up period we intend to remove the initialization bias, hence if the period is short and the model takes long to get into equilibrium than it can affect the calibration output as the calibration output might get sensitive to the initialization biasness

5. CALIBRATION-VALIDATION

In this section, a classical split sample test scheme (Klemeš 1986) was used the time series was divided into 2 independent sub–periods of equal length of 10 years, the 1st year of both the sub periods was used as the warm up period. KGE2 was used as the calibration criteria.

P1 = "1985-01-01", "1994-12-31"
P2 = "2003-01-01", "2012-12-31"

Now, at first the model was calibration using P1 (1^{st} sub-period) and was validated on the P2 (2^{nd} sub period). Then after this model was calibration using P2 and was validated on P1.

The advantage of using this methodology is that, it uses the parameter being calibrated by an independent sub period to validate the flows for some other independent sub period which confirms the model parameter robustness to two independent events. But, it is to note that that two independent sub-periods shall be of the same catchment.

Table 3 : Results from Calibration & Validation of Two Sub periods.

	P1	P2
Calibration Criterion	0.8635565	0.8805101
X1	117.919242	164.4637009
X2	0.487496	-0.5339851
X3	76.707539	75.1581575
X4	2.198198	2.2886748
Simulation Criterion	0.7490331	0.777487

From **Table 3**, it can be observed that the difference between KGE values for Calibration and Validation for the case P2 sub-period is smaller hence it means that the parameters obtained in the column of P2 are robust hence these are the best calibration parameters.

6. SIMULATION PHASE:

In this section, discharge corresponding to the observed precipitation and evapotranspiration during the period that has not been considered for the calibration-validation phase was simulated using the parameters calibrated in P2 period.

Simulation Period: "1995-01-01", "2002-12-31"

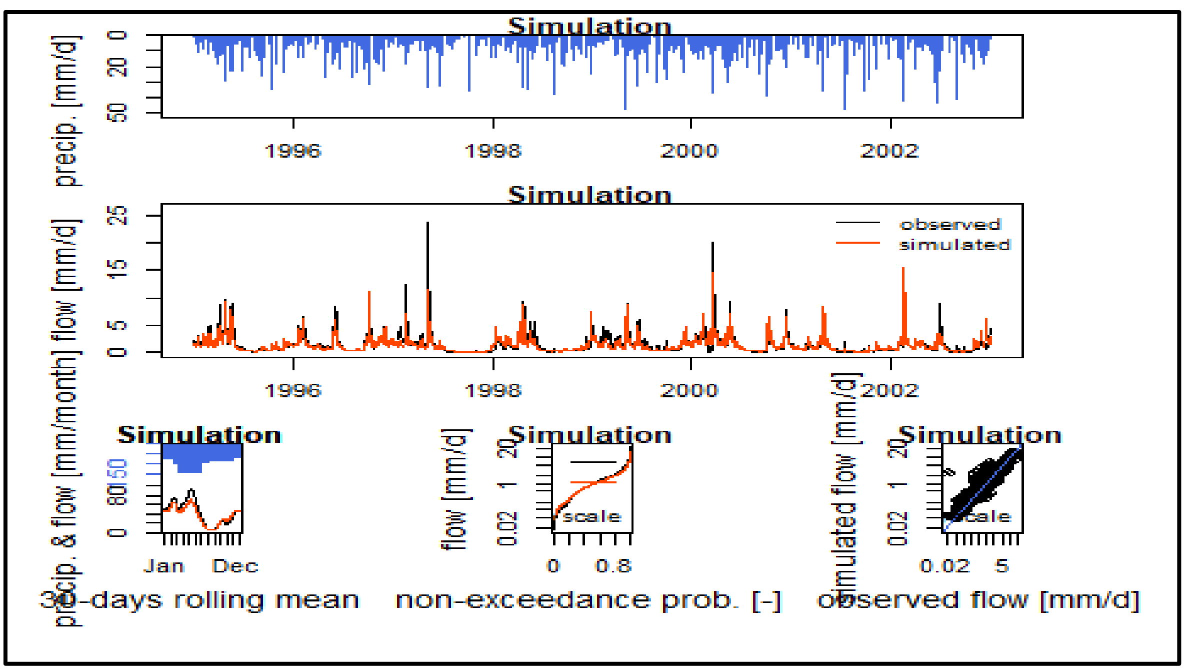

Figure 9: Performance Graph for Simulation Period.

Visually it is difficult to infer much from the observed and simulated time series.. However from the other 3 graphs we can deduce that, in spite that the rolling mean for both the series do not superimpose each other but the trend they follow are same which explains that both the series respect the trend of seasonality. Furthermore, cumulative non exceedance probability for both the trends superimpose each other which is very important as we can estimate the probabilities with sheer confidence for low flows and high flows. From the scatter plot between the observed and simulated flow we can say that the values are approximately equally divided between 1:1 line. Also if we compare the KGE value of this period (79.73%) to the KGE2 value (77.755 %) for simulation of the period ("2003-01-01", "2012-12-31") using the same parameters we can also observe that the parameters simulate the other periods with the same confidence. Hence the model simulations are a robust one.

7. SENSITIVITY ANALYSIS:

The significance of sensitivity analysis is to find out the parameter which is more prone to lend significant changes to the model; conversely which parameter affects more the whole model. For the sensitivity analysis the sub period taken was from "2003-01-01" to "2012-12-31". The interval of parameter values to be tested as -/+50% around the nominal value, then the analysis was performed and following results were obtained.

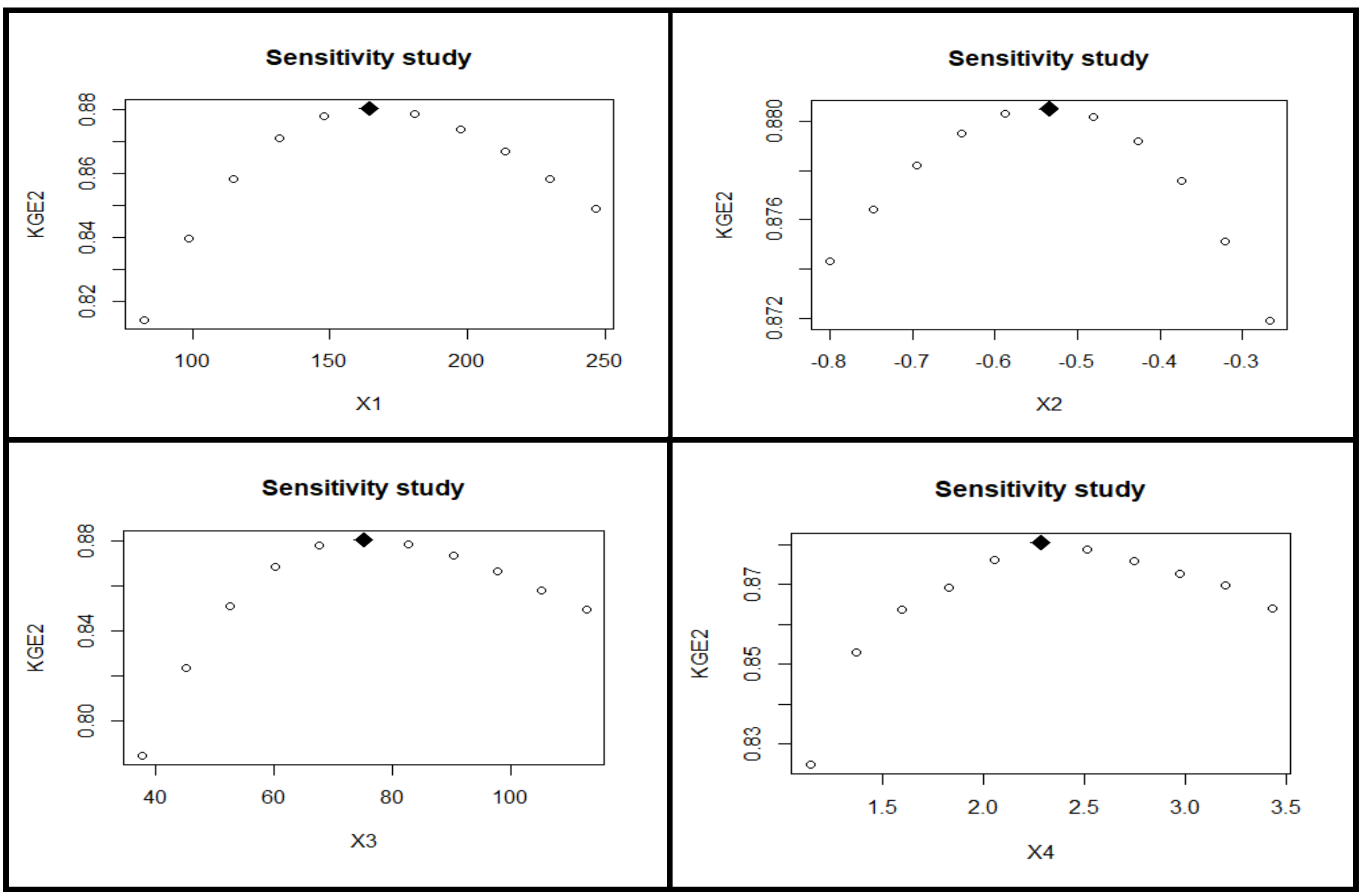

Figure 10 : Results from Sensitivity Analysis

The most sensitive parameter is X3 as it varies KGE2 value the most.

8. USE IN FORCASTING:

No the model cannot be used forecasting discharge, but there is GPR model which is widely used in France for flood forecasting, but the tool is not available in AirGR now.

Bibliography

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