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An Automatic Parameter Calibration Method for the TUW Model in Streamflow Modeling

Muhammet YILMAZ

Highlights:

- TUW model was created for the study area
- The parameters of the TUW model were determined automatically with the DEoptim algorithm
- Simulation of streamflow data was carried out

Keywords:

- TUW model
- DEoptim algorithm
- Streamflow
- Objective function
- Türkiye

ABSTRACT:

The accurate modelling of streamflow is highly significant for hydrological monitoring, water resource management, and climate change studies. Streamflow simulation with lumped hydrological models has been widely performed by researchers. However, the parameter calibration process is a major obstacle in these models. In the present study, a conceptual rainfall-runoff model (TUW model) was used to simulate streamflow in the sub-basin of the Upper Euphrates Basin during the time period 1991-2009. The Differential Evolution Optimization (DEoptim) algorithm were tested for the automatic parameter calibration of the lumped version of TUW model, in the study area. The model is calibrated using two objective function named and Nash–Sutcliffe efficiency (NSE) and Kling-Gupta Efficiency (KGE). Additionally, percent bias (PBias) was used to evaluate the performance of the model. For the objective function NSE, calibration and validation results indicated good agreement between observed and simulated streamflow data with NSE, 0.76 and 0.76 and KGE, 0.73 and 0.75 and PBias (%), -0.8 and -7.5, respectively. Similarly for KGE objective function, the calibration results produced a NSE of 0.71, KGE of 0.85, and PBias (%) of -0.9, while validation results revealed a NSE of 0.72, KGE of 0.84, and PBias (%) of -7.2. It can be concluded that the applicability of the DEoptim algorithm for the estimation of the parameters of the TUW model is confirmed by the case study. The findings of the study can serve as a guide for researchers and be useful in achieving watershed management goals.

Muhammet YILMAZ (**Orcid ID:** 0000-0002-9844-6654), Erzurum Techinical University, Faculty of Engineering and Architecture, Department of Civil Engineering, Erzurum, Türkiye

Corresponding Author: Muhammet YILMAZ, e-mail: muhammet.yilmaz@erzurum.edu.tr

INTRODUCTION

Water resources are constantly under threat due to climate change, one of the urgent problems of the modern world (Nhemachena et. al., 2020). Simulation of runoff is one of the most prominent research areas in the field of climate change in terms of adaptation to global warming (Adnan et al., 2017). Reliable prediction of water balance-related components is important for solving many water-related problems, such as flood forecasting, hydroelectric potential estimates, flood risk assessments, drought management, and agricultural activities (Farkas et al., 2016). Hydrological models are an effective tool for flow simulation and prediction. With the developing technology in recent years, models have become indispensable for the effective management of water resources (Brziak et al., 2020).

Numerous studies have investigated the simulation of runoff using various hydrological models in different basins. For example, Ye et al. (2014) used the Xin'anjiang model (XAJ), a conceptual rainfall runoff model, to simulate the runoff in Yanduhe basin in China. The results showed that compared to single-objective optimization results, the multi-objective optimization method extracts the parameter set more successfully. Piniewski et al. (2017) used the Soil and Water Assessment Tool model, a physically based semi-distributive model, to simulate the hydrological process for 80 different basins. In their results, they emphasized that the median KGE value during the calibration period was 0.76. Sleziak et al. (2021) analyzed the climate change impact on the runoff regime by using TUW (Technische Universität Wien) model in Slovakia. Their results showed the runoff increase during winter months, and decrease in the summer season compared to the historical period. To evaluate the skill of the TUW model, Zhong et al. (2021) divided the base period into two parts: the calibration period (1970–1984) and the validation period (1985–1989). The results showed that the observed runoff corresponds well with the simulated runoff, achieving the NSE values of 89% during the calibration period and 86% during the validation period. In this study, the conceptual TUW hydrological model, which has been successfully tested in various studies (Neri et al., 2020; Hafizi & Sorman, 2022; Durgut & Ayvaz, 2023), is employed.

The hydrological model contains quite a lot of parameters and it is not possible to measure them directly. Therefore, model calibration is an indispensable step for hydrological models to improve model performance (Behrouz et al., 2020). The traditional procedure of model calibration is usually done manually by trial and error or using graphical analysis to determine parameter values (Legates & McCabe, 1999; Shamsi & Koran, 2017), which is quite time-consuming. Thus, automatic calibration methods are becoming popular techniques to determine the optimal parameters of a model by reducing model calibration effort (Mancipe-Munoz et al., 2017; Sirisena et al., 2020; Alizadeh & Yazdi, 2023; Tiwari et al., 2024). There are a few studies around the world using the Differential Evolution Optimization (DEoptim) algorithm for automatic calibration of hydrological models (Sleziak et al., 2020; Garna et al., 2023; Rozos, 2023), but these are quite limited. Within the scope of the study, the TUW model was automatically calibrated with the DEoptim algorithm.

Hydrological models play a crucial role in a wide array of domains, including climate modeling, water resource management, the planning and design of hydraulic structures, as well as the early prediction of droughts and floods. For the reasons mentioned above, a hydrological model with calibrated parameters is very important for researchers. A possible explanation for the low frequency of application of lumped models such as the TUW model may be that tools linking hydrological model with multi-objective search algorithms are not readily available. This study presents the applicability of the DEoptim algorithm for the calibration of the TUW model.

The Euphrates basin, where many water resources structures have been constructed, is a very important basin in terms of water potential. For this reason, simulation of flow data in sub-basins can be a preliminary analysis for water resources management and climate change studies. Therefore, the aim of this study is to investigate the applicability of the TUW model for the simulation of flows in the sub-basin of the Euphrates basin and to automatically calibrate the model with the DEoptim algorithm. Additionally, to the best of the author's knowledge, there is no published study in the literature on the application of the DEoptim algorithm for hydrological model calibration in Turkey.

MATERIALS AND METHODS

Study Area

The Euphrates River Basin, which is located in the southeastern Anatolia region of Turkey, covers approximately 127,304 km^2 and is the largest of 25 river basins in Turkey (Hopur, 2017). The Euphrates River is formed by the combination of two main rivers: one of them is the Karasu river which springs from the Dumlu Mountain in Erzurum City and the other is the Murat river which originates from the Tendurek Mountain in Ağrı City (Yenigun et al., 2010).

A sub-basin of the Upper Euphrates River, is selected as study area for application of hydrological models as shown in Figure 1. The study area is located within the borders of Tunceli province in Turkey. Continental climate prevails in the study area. The summer months are very short and hot and dry, while the winters are very cold and rainy and last a long time. The basin is the drainage area of 2133 flow gauging station controlled by General Directorate of State Hydraulic Works in Turkey. The main reasons for concentrating on this basin in the study are; 1) snow melt contributes significantly to the total annual flow 2) the catchment has not been significantly affected by human intervention such as urbanization and reservoir regularization, 3) the gauging stations do not have missing data and are homogeneously distributed over the catchment. The study area has an area of 3284.8 km^2, which is approximately 2.57% of Euphrates Basin.

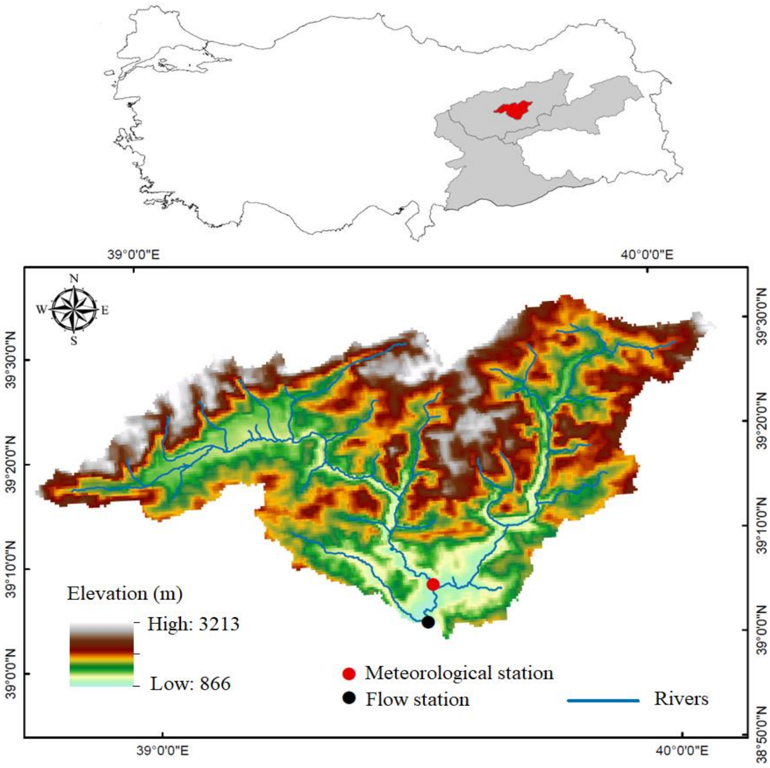

Figure 1. Study area with the location of the selected stations

Data

Daily observed precipitation and temperature data from Tunceli station (17165) were used to validate TUW model in the study area. Daily streamflow data of 2133 station were used to evaluate the performance of the model. The mean, median, and standard deviation for the daily flow series during the observation period are 88.67 m^3/s, 53.5 m^3/s, 83.09 m^3/s, respectively. The coefficient of skewness quantifies the asymmetry of a distribution relative to its mean and is expressed without units. Its value is 2.35 for the observation period. A positive skewness indicates that the data is skewed towards the right. Nondimensionalization is typically carried out to facilitate comparisons of parameter magnitudes across different series. In practical terms, the coefficient of variation, calculated as the ratio of the standard deviation to the arithmetic mean, is the widely employed metric for this purpose. The value of the coefficient of variation for the data of station 2133 is 0.93.

All data mentioned were evaluated in hydrological modeling for the water years between October 1990 and September 2009. The locations of the streamflow station and meteorological station used in the study are given in Figure 1. Table 1 shows detailed information about streamflow and meteorological stations.

Table 1. Streamflow and meteorological stations used for model calibration and validation

Station type	Station Name	Station ID	Latitude	Longitude	Data Length
Steramflow	Melekbahçe	2133	39.0458	39.52611	1968-2009
Meteorological	Tunceli	17165	39.1058	39.5408	1960-present

TUW hydrologic model

Within the scope of the study, the lumped version of the TUW model (Viglione & Parajka, 2014) was used. The TUW model follows the structure of the Swedish Hydrologiska Byråns Vattenbalansavdelning (HBV) model (Parajka et al., 2007). The model has been widely used in many studies in the field of hydrology (Ceola et al., 2015; Sleziak et al., 2016). The model operates on a daily time step and requires the following data: daily precipitation totals (mm), average daily air temperature (^oC), and daily potential evapotranspiration (mm). The potential evaporation data were calculated using the Blaney-Criddle approach (Parajka et al., 2005). The TUW model has 15 parameters to calibrate snow, soil moisture, and runoff routines (Table 2).

Table 2. TUW model parameters

Symbol	Description of the model parameters	Units	Range
1. SCF	Snow correction factor	-	0.9–1.5
2. DDF	Degree day factor	mm/^{o}C/day	0.0–5.0
3. Tr	Threshold temperature above which precipitation is rain	^{o}C	1.0–3.0
4. Ts	Threshold temperature below which precipitation is snow	^{o}C	-3.0–1.0
5. Tm	Temperature threshold above which melt starts	^{o}C	-2.0–2.0
6. Lprat	Parameter related to the limit for potential evaporation	-	0.0–1.0
7. FC	Field capacity	mm	0.0–600
8. BETA	Non-linear parameter for runoff production	-	0.0–20
9. K0	Storage coefficient for a very fast response	day	0.0–2.0
10. K1	Storage coefficient for a fast response	day	2.0–30
11. K2	Storage coefficient for slow response	day	30–250
12. lsuz	Threshold storage state	mm	1.0–100
13. cperc	Constant percolation rate	mm/day	0.0–8.0
14. bmax	Maximum base at low flows	day	0.0–30
15. croute	Free scaling parameter	day^2/mm	0.0–50

Calibration of the TUW model

The DEoptim algorithm was first developed by Storn and Price (1997) to avoid complex mathematical operations and also to give reliable solutions to engineering and finance models.

DEoptim is a population-based stochastic algorithm that searches for the global optimum for a specified objective function (Mullen et al., 2011). DEoptim algorithm has been widely used for optimization problems by different researchers in the literature (Cao et al., 2009; Yilmaz et al., 2021; Atanaw et al., 2023). In present study, the DEoptim algorithm of the package DEoptim developed by Ardia et al. (2016) in R software is utilized to calibrate the TUW model. The DEoptim algorithm was iterated one thousand times to optimize the fit between the simulated streamflow values and the observed values within a dependable range. The model was run daily for the calibration from 1991 to 2002, the validation period from 2003 to 2009.

Two objective functions: 1) Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe 1970) and 2) Kling-Gupta Efficiency (KGE) (Gupta et al., 1998; Kling et al., 2012) were utilized for parameter estimations. Thus, different aspects of streamflow estimations were examined in detail according to the results of two different objective functions widely used in hydrology. Additionally, Percent Bias (PBias) was used to evaluate model performance. Formulation of NSE KGE, and PBias are given in Equation 1, 2, and 3 respectively.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - Q_m)^2} \tag{1}$$

$$PBias = \frac{\sum_{i=1}^{n}(S_i - O_i)}{\sum_{i=1}^{n} O_i} \times 100 \tag{2}$$

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_s}{\sigma_o} - 1\right)^2 + \left(\frac{\mu_s}{\mu_o} - 1\right)^2} \tag{3}$$

where Q_i indicates the observed streamflow, Q_m represents the mean observed streamflow, and S_i is the simulated streamflow, r indicates Pearson's correlation, σ_o and σ_s are the standard deviations in observation and simulated streamflow data, respectively; μ_o is the observation mean, and μ_s is the simulated data mean.

Table 3 was used to classify model performance.

Table 3. Performance ratings for evaluation metrics (Moriasi et a., 2007; Thiemig et al., 2013)

Performance Criteria	Very Good	Good	Satisfactory	Unsatisfactory
NSE	0.75 <NSE ≤ 1	0.65 <NSE ≤ 0.75	0.5 <NSE ≤0.65	NSE ≤0.5
PBIAS	PBIAS < ±10	±10 ≤PBIAS < ±15	±15 ≤PBIAS < ±25	BIAS≥+-25
KGE	0.9 ≤ KGE ≤ 1	0.75 ≤ KGE < 0.9	0.5 ≤ KGE < 0.75	KGE <0.5

RESULTS AND DISCUSSION

19-year measured runoff data were collected from 2133 station in the upper Euprates Basin. In this study, 1991–2002 (12 years) was selected as the calibration periods, and 2003–2009 (7 years) was the verification periods of the TUW model. The parameters of the study area were automatically calibrated with the DEoptim algorithm. The calibration step was carried out in two steps. Firstly, NSE was used as the objective function and secondly, the KGE metric was used. Thus, a detailed evaluation was carried out in terms of NSE and KGE indices in reproducing the streamflow data.

With the NSE objective function, the graph of simulated and observed streamflow during calibration and validation were given in Figure 2. Figure 2 showed that the calibrated model generally underestimated peak flows, and this result was especially evident for the validation period. In the 2007 water year, the model underestimated extreme events. This is probably due to missing rainfall data in the study area because of flood events in that year. Statistical metrics results for the NSE objective function are presented in Table 4. The NSE, KGE and PBias (%) values calculated in the calibration step were 0.76, 0.73, and -0.8, respectively. According to Moriasi et al., (2007), the model demonstrates ‘very good’ performance in terms of NSE and PBias, whereas it performed ‘good’ based on the KGE result.

In the validation stage, values of 0.76, 0.75, and -7.5 were obtained for The NSE, KGE and PBias (%) coefficient, respectively. Findings showed good agreement between the recorded and simulated daily streamflow data. When the objective function is considered as NSE, the optimal parameters obtained are presented in Table 5.

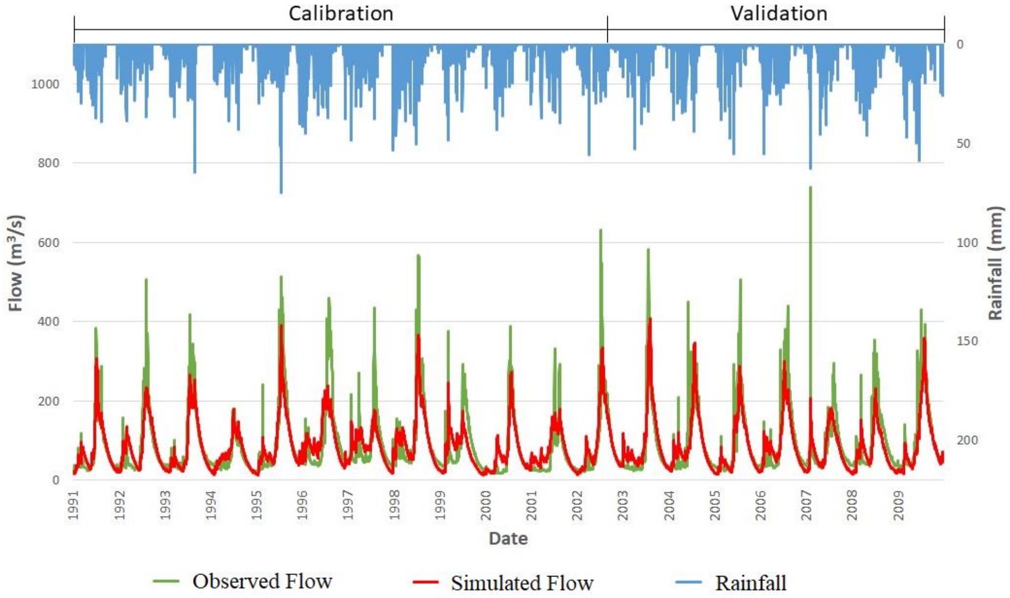

Figure 2. Comparison of daily observed and simulated streamflow at the station for NSE objective function

Table 4. Evaluation of the accuracy of calibration and validation periods of daily runoff for the NSE objective function

	Evaluation Statistics					
	KGE		NSE		PBias (%)	
No	Calibration	Validation	Calibration	Validation	Calibration	Validation
2133	0.73	0.75	0.76	0.76	-0.8	-7.5

Table 5. The optimum tuw model parameters for NSE and KGE objective functions in the study area

	Objective function	
Parameter Name	NSE	KGE
1. SCF(-)	1.49	1.49
2. DDF(mm/°C/day)	1.10	0.84
3. Tr(°C)	2.99	2.99
4. Ts(°C)	0.99	0.99
5. Tm(°C)	1.99	1.99
6. Lprat(-)	0.99	0.99
7. FC(mm)	232.36	221.97
8. BETA(-)	0.06	0.06
9. K0(day)	0.18	0.25
10. K1(day)	28.62	29.86
11. K2(day)	57.40	38.43
12. lsuz(mm)	67.24	25.02
13. cperc(mm/day)	7.99	7.99
14. bmax(day)	7.44	2.78
15. croute(day^2/mm)	24.03	19.23

The calibrated results of KGE for the selection of the objective function were similar to those of NSE. Figure 3 showed that there are years where peak flows are underestimated, and this result is evident in the water years 2002 and 2007. Table 6 shows the performance metrics values for the measured and simulated flow in the monitoring stations during calibration and validation periods, when KGE is considered as the objective function. The values of the statistical function were found to be 0.71 (NSE), 0.85 (KGE) and -0.9% (PBias) during calibration period. The model classified as "good" calibration period except for PBias, which displayed a "very good" performance. The NSE, KGE and PBias values calculated in the validation step were 0.72, 0.84, and -7.2 %, respectively. According to Moriasi et al., (2007), validation results are in the same class as calibration results. Table 5 presented the optimal parameters for the KGE objective function.

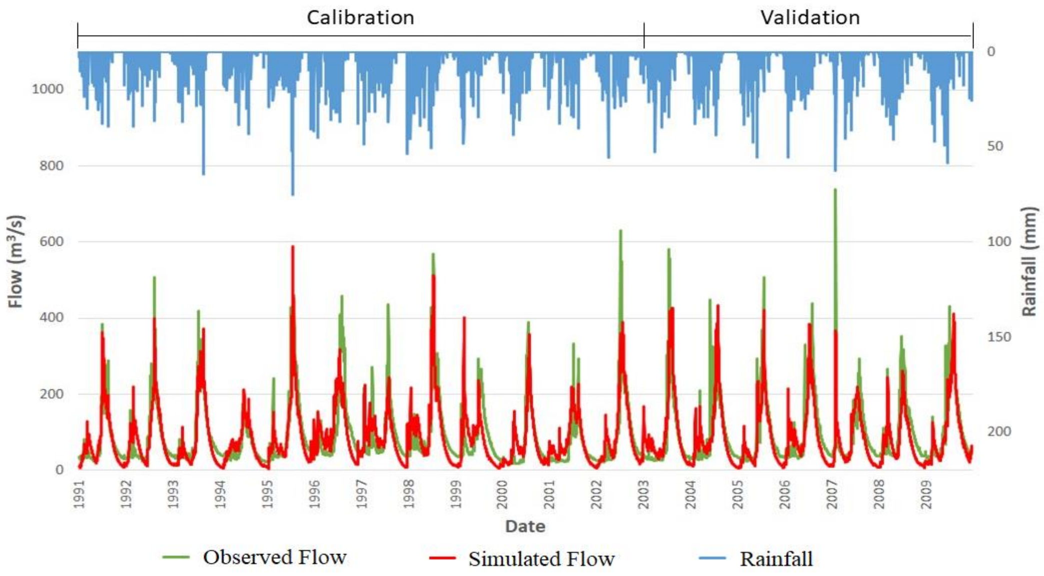

Figure 3. Comparison of Daily Observed and Simulated Streamflow at the Station for KGE Objective Function

Table 6. Evaluation of the accuracy of calibration and validation periods of daily runoff for the KGE objective function

	Evaluation Statistics					
	KGE		NSE		PBias (%)	
No	**Calibration**	**Validation**	**Calibration**	**Validation**	**Calibration**	**Validation**
2133	0.85	0.84	0.71	0.72	-0.9	-7.2

Evaluation between NSE and KGE objective functions showed that while the model is classified as "very good" for two metrics (NSE and PBias) in terms of NSE objective function, it is evaluated as "very good" for one index (PBias) in terms of KGE objective function.

The study site stands out as an area characterized by substantial snowmelt and determining water availability is critical in the region due to its contribution to the overall yearly streamflow. In the study area, as the weather warms up in late spring under the changing climate conditions, melting snow leads to high flows, and predicting these high flows becomes important for early flood warning systems. In fact, a general evaluation showed that maximum flows were successfully predicted except for the years when extreme events occurred (see Figures 2 and 3). Hence, the model's ability to accurately simulate peak flows is satisfactory in terms of achieving another aim of the study.

Consequently, the TUW model is able to reproduce the observed daily streamflow at the outlet of the study basin with a high level of accuracy.

CONCLUSION

Accurate estimation of flow data is very important for the effective management of a basin's water resources. Moreover, a successfully calibrated hydrological model for any basin is a preliminary analysis for climate change studies. TUW model was used to investigate the hydrological component of the sub-basin of the upper Euphrates basin, which is controlled by 2133 flow observation stations in Turkey. The model was calibrated in daily steps and the calibration process was carried out with the DEoptim algorithm. The performance of the TUW model in the calibration and validation phase was calculated using NSE, PBIAS and KGE evaluation criteria, which are widely used in the literature. When NSE was selected as the objective function, NSE, KGE, and PBIAS (%) values reached 0.76, 0.73 and -0.8, respectively, during the calibration period. In the validation phase, NSE, KGE, and PBIAS (%) values were 0.76, 0.75, and -7.5, respectively. For KGE objective function, the statistical values of NSE, KGE, and PBIAS (%) were established to be 0.71, 0.85, and -0.9 respectively for the time of calibration. Similarly, the statistical values of NSE, KGE, and PBIAS were established to be 0.72, 0.84, and -7.2 respectively for the time of validation. According to the classification of Moriasi et al. (2007), the NSE objective function gave a more successful prediction result than the KGE in reproducing the streamflow data. The results showed that the automatically calibrated model is capable of reproducing the observed daily streamflow data in this basin with a high level of accuracy. According to the results of the study, the DEoptim algorithm showed successful results. In this context, it is planned to conduct climate change studies using a model calibrated with the DEoptim algorithm in future studies.

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