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ANALYSIS OF MATERNAL MORTALITY USING GEOGRAPHICALLY WEIGHTED POISSON REGRESSION WITH SPLINE TRUNCATED ESTIMATOR

RISKA NURAINUN FADHILAH, ANNA ISLAMIYATI*, NIRWAN
Department of Statistics, Hasanuddin University, Makassar 90245, Indonesia

Abstract: This study analyzes maternal mortality in South Sulawesi in 2020 and identifies the determining factors utilizing the Spline Truncated approach in the Geographically Weighted Poisson Regression method (GWPR-ST). This approach builds on nonparametric regression to manage spatial heterogeneity by calculating local parameters at each observation site. Maternal mortality data often follows a Poisson distribution and exhibits overdispersion, which violates the equidispersion assumption of standard Poisson regression. The GWPR-ST method effectively handles overdispersion while accounting for spatial variability. The model estimation uses 1, 2, and 3 knot points, with the Gaussian Kernel as the weighting function. The selection of optimum bandwidth is carried out with Generalized Cross Validation (GCV). The most suitable model is obtained with an order of $m = 1$ and $h = 3$ knot points, resulting in an R-squared value of 80.04. This shows that the GWPR-ST model accounts for 80.04% of the impact of predictor variables on the maternal mortality rate response variable. The influential predictor variables vary across locations, allowing them to be classified into four groups based on the significant predictor variables. These findings provide valuable insights for targeted public health interventions and demonstrate the effectiveness of GWPR-ST in modeling spatially heterogeneous count data with overdispersion.

Keywords: GWPR; truncated spline; kernel Gaussian; bandwidth; maternal mortality rate.
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*Corresponding author
E-mail address: annaislamiyati701@gmail.com
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1. INTRODUCTION

Regression analysis is a statistical technique that examines the relationship between a dependent variable and one or more predictor variables [1]. In certain situations, research data is often affected by geographic location or the spatial factors where the variables are observed, commonly known as spatial data [2]. One of the developments in regression analysis using spatial data is Geographically Weighted Regression (GWR) [3]. GWR is a statistical technique for examining spatial heterogeneity that arises when identical variables yield varying outcomes at different locations within the study area [4], [5].

In regression analysis, particularly in the GWR model, overdispersion often occurs in spatial data when the observed variance exceeds the expected mean, indicating more significant variability than assumed under the standard Poisson distribution [6]. Therefore, to address the issue of overdispersion, a new statistical approach called Geographically Weighted Poisson Regression (GWPR) was developed, specifically designed to analyze spatial data following a Poisson distribution [7].

The GWPR model effectively addresses spatial regression problems when the underlying data or function is known and follows a linear pattern. However, in practice, not all cases exhibit linearity. Therefore, incorporating a nonparametric approach into the GWPR model is necessary. One widely used nonparametric regression method is truncated spline regression, which allows for greater flexibility in modeling complex relationships within spatial data [8], [9].

Several researchers, including applying the truncated spline nonparametric approach to improve the GWR model [10], [11], [12]. However, some of these methods do not apply to data following a Poisson distribution. Therefore, this study aims to develop a GWPR model using a truncated spline approach.

Maternal mortality is one of the key indicators for assessing public health levels and the quality of healthcare services in a region. Despite efforts to improve maternal healthcare services, many developing countries, including Indonesia, continue to face high maternal mortality rates [13]. Exploratory analysis of maternal mortality data and its affected factors reveals the presence of overdispersion and spatial heterogeneity. This makes it suitable for analysis utilizing the Geographically Weighted Poisson Regression (GWPR) approach. The data distribution does not follow a specific parametric pattern and varies across certain intervals, making the truncated spline approach applicable to enhance model flexibility in capturing local variations. Research on spline methods has been widely conducted in various statistical contexts. [14] developed a biresponse nonparametric regression model with a truncated spline estimator in principal component analysis, demonstrating its effectiveness in capturing complex relationships between response and predictor variables. Furthermore, [15] applied a longitudinal multi-response spline model to detect changes in blood glucose levels among diabetic patients based on lifestyle factors, showcasing the capability of spline methods in analyzing longitudinal data and dynamic response variations. In addition, [16] investigated blood glucose changes two hours after meals in type 2 diabetes patients by considering the duration of treatment, illustrating the effective use of splines in medical studies to describe nonlinear patterns in health data.

These studies demonstrate the effectiveness of spline methods, making them relevant for use in Geographically Weighted Poisson Regression with Truncated Spline Approach on maternal mortality in South Sulawesi. Thus, in this study, the relationship between factors influencing maternal mortality in South Sulawesi Province can be determined by grouping regions according to the factors influencing maternal mortality using the GWPR-ST model. This study will develop the GWPR-ST model by applying geographic weighting using the Gaussian Kernel function. Furthermore, Generalized Cross-Validation (GCV) will be utilized to find the optimum knot points and determine the most suitable bandwidth [12].

2. PRELIMINARIES

This study utilizes secondary data, specifically the Maternal Mortality Rates in South Sulawesi Province in 2020 and the factors influencing them. These data were obtained from the Health Office of South Sulawesi Province. This study classifies the variables into two groups: response and predictor variables. The response variable represents the count of maternal deaths in South Sulawesi Province (y). The predictor variables consist of the proportion of pregnant women involved in the K1 program (x_1), those participating in the K4 program (x_2), and those receiving the Td3 vaccination (x_3).

The response variable is characterized as count data because it indicates the count of maternal fatalities in each region. Therefore, Poisson distribution is suitable for modeling this type of data. It represents a discrete probability distribution that determines the likelihood of a specific number of occurrences happening within a given timeframe or location [17]. The probability mass function for a random variable Y that follows a Poisson distribution with a parameter $\mu > 0$, which indicates the number of events occurring within a specified time period or spatial area, is given by the following equation [18]:

$$P(Y\ ;\ \mu) = \frac{e^{-\mu}\mu^{y}}{y!}\ , y = 0,1,2, \ldots \quad (1)$$

The Poisson regression model assumes equidispersion, meaning that the mean and variance are equal. However, deviations from this assumption can occur, this results in overdispersion (when variance exceeds the mean, dispersion > 1) or underdispersion (when variance is less than the mean, dispersion < 1) [19]. The presence or absence of overdispersion can be determined from the Deviance value, which is given by:

$$\phi = \frac{D^2}{db}\ ;\ D^2 = 2\sum_{i=1}^{n}\left(y_i \ln\left(\frac{y_i}{\widehat{y}_i}\right) - (y_i - \widehat{y}_i)\right) \quad (2)$$

y_i is the observed response variable, $\widehat{y}_i$ is the Poisson regression estimate, $db = n - p$ with p representing the number of parameters, n the number of observations and D^2 is the deviance value. If $\phi > 1$, it indicates that the variance is larger than the mean, suggesting the presence of overdispersion.

Therefore, addressing overdispersion alone is insufficient, as spatial heterogeneity may also influence the variability of the data. Spatial heterogeneity arises when an identical independent variable yields varying responses across different locations in the study area [13]. Spatial heterogeneity is evaluated utilizing the Breusch-Pagan (BP) test statistic with the hypotheses [20]:

H_0 : $\sigma_1^2 = \sigma_2^2 = \cdots = \sigma_n^2 = \sigma^2$ (homoscedasticity)

H_1 : at least there is one $\sigma_i^2 \neq \sigma^2$ (heteroscedasticity)

$$\boldsymbol{BP} = \left(\frac{1}{2}\right)\boldsymbol{f}^T\boldsymbol{Z}(\boldsymbol{Z}^T\boldsymbol{Z})^{-1}\boldsymbol{Z}^T\boldsymbol{f} + \left(\frac{1}{T}\right)\left(\frac{\boldsymbol{e}^T\boldsymbol{W}\boldsymbol{e}}{\sigma^2}\right) \quad \sim X^2_{(k+1)} \quad (3)$$

vector f is,

$$\boldsymbol{f}_i = \left(\frac{\boldsymbol{e}_i^2}{\sigma^2} - 1\right)$$

where $\boldsymbol{e}_i$ is the residual at the i-th data point location, $\boldsymbol{Z}$ is an $n \times (k+1)$ comprising standardized vectors corresponding to each observation with k representing the number of predictor variables, σ^2 is the residual variance (e_i), T is the trace of $[\boldsymbol{W}^T\boldsymbol{W} + \boldsymbol{W}^2]$, and $\boldsymbol{W}$ is the weighting matrix between observation locations. Reject H_0 if $BP > \chi^2_{(k)}$ or $p - value < \alpha$, indicating the presence of spatial heterogeneity.

In addition to addressing spatial heterogeneity, it is also essential to capture complex relationships between the response and predictor variables. This can be achieved using nonparametric regression. Nonparametric regression is a statistical method that investigates the association between a dependent variable and one or more independent variables without assuming any fixed functional form for the regression curve. This method offers greater flexibility in capturing complex data structures. In general, a nonparametric regression model is formulated as follows [8]:

$$y_i = f(x_i) + \varepsilon_i \tag{4}$$

y_i is the response variable, x_i is the predictor variable, $f(x_i)$ is the regression curve that does not follow a specific parametric form and ε_i refers to the error term for the i-th observation. When the regression curve f is represented as an additive model and approximated with a spline function, the regression model is formulated as follows:

$$f(x_i) = \sum_{k=0}^{m} \beta_k x_i^k + \sum_{h=1}^{q} \beta_{h+m} (x_i - K_h)_+^m \tag{5}$$

The truncated function can be expressed as follows:

$$(x_i - K_h)_+^m = \begin{cases} (x_i - K_h)^m, & jika\ x_i \geq K_h \\ 0, & jika\ \ x_i < K_h \end{cases} \tag{6}$$

x_i represents the value recorded for the i-thdata point, K_h denotes the h-th knot point, m is the orde and β is the estimator coefficient.

Next, the determination of optimal knot points is carried out to ensure the model's flexibility and accuracy in capturing data patterns. One of the most popular techniques for identifying optimal knot points is GCV, where the selection is based on the smallest GCV value. The optimal knot points are chosen based on the minimum GCV value [21]. The GCV equation is given as follows:

$$GCV = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\left(1 - \frac{df}{n}\right)^2} \tag{7}$$

y_i is the actual value of the i-th response variable, $\hat{y}_i$ is the estimated value from the i-th observation, n is the total number of observations and df is the degrees of freedom in the spline model.

Next, the Geographic Weights Function and Optimum Bandwidth is determined to enhance the accuracy of spatial weighting. Spatial weights are computed using a weighting function. The weighting function employed in this study is the Gaussian Kernel function [22]. Let w_{ij} be the spatial weight assigned to the observation at location j for the GWPR model at location i, the spatial weight w_{ij} based on the Fixed Gaussian Kernel function is given by:

$$w_{ij} = \exp\left(-\frac{1}{2}\left(\frac{d_{ij}}{b}\right)^2\right), j = 1,2,\dots,n \tag{8}$$

Where $d_{ij} = \sqrt{\left(b_i - b_j\right)^2 + \left(c_i - c_j\right)^2}$ is the Euclidean distance between location (b_i, c_i) to location $\left(b_j, c_j\right)$ and b is a non-negative parameter known as the bandwidth. The optimal bandwidth can be determined using (GCV) [22].

After obtaining spatial weights and optimal bandwidth, these components are utilized in the GWPR model to analyze spatially heterogeneous data. The GWPR model is a localized form of Poisson regression that accounts for geographic location and assumes that the response variable consists of discrete data following a Poisson distribution [7].

$$y_i \sim Poisson\ (\mu_i)$$

with,

$$\mu_i = \exp\left(\beta_0(b_i, c_i)\sum_{j=1}^{p}\beta_j(b_i, c_i)x_{ij} + \varepsilon_i\right) \tag{9}$$

where y_i represents the observed value of the response variable at the i-th observation, x_{ij} denotes the value of the j-th predictor variable for the i-th observation, $\beta_j(b_i, c_i)$ is the regression coefficient for $j = 1,2,\dots,p$, (b_i, c_i) is the coordinate point (latitude, longitude) of the i-th location and ε_i is the regression error for the i-th observation.

Building on the GWPR framework, the model is further enhanced using the Spline Truncated approach to accommodate nonparametric relationships and improve flexibility in capturing complex data patterns. Based on equations (5) and (9), the Geographically Weighted Poisson Regression model with the Spline Truncated approach can be expressed as follows:

$$y_i = \exp\left(\beta_0(b_i, c_i) + \sum_{p=1}^{5}\left(\sum_{j=1}^{m}\beta_{pj}(b_i, c_i)x_{pi}^{j} + \sum_{h=1}^{q}\delta_{p(m+h)}\,(b_i, c_i)\left(x_{pi} - K_{ph}\right)_+^m\right) + \varepsilon_i\right) \tag{10}$$

The equation above represents the GWPR-ST model with degree m and n regions. Its components are defined as follows: y_i is the response variable at location i for $i = 1,2,\dots,n$, x_{pi} is the p-th predictor variable at location i for $p = 1,2,\dots,5$, and K_{ph} is the h-th knot point for the p-th predictor variable with $h = 1,2,\dots,q$. Furthermore, $\beta_0(b_i, c_i)$ is the intercept parameter that depends on the geographic coordinates (b_i, c_i), $\beta_{pj}(b_i, c_i)$ represents the polynomial component parameter of GWPR for the p-th predictor variable at location i, and

$\delta_{p(m+h)}(b_i, c_i)$ is the truncated component parameter, which corresponds to the $(m+h)$-th parameter at the h-th knot point for the p-th predictor variable at location i-th.

After obtaining the GWPR-ST model, Simultaneous parameter significance testing is performed to assess the combined effect of the predictor variables on the response variable. In the GWPR-ST model, this is achieved utilizing the Maximum Likelihood Ratio Test (MLRT). This method assesses if the predictor variables jointly affect the response variable [23].

Hypothesis:

H_0: $\beta_1(b_i, c_i) = \beta_2(b_i, c_i) = \ldots = \beta_j(b_i, c_i) = 0$

H_1: a minimum of one $\beta_p(b_i, c_i) \neq 0, p = 1,2, \ldots, j$

Test Values:

$$D(\hat{\beta}) = -2\ln\left(\frac{L(\hat{\omega})}{L(\hat{\Omega})}\right) = 2\left(\ln L\left(\hat{\Omega}\right) - \ln L\left(\hat{\omega}\right)\right) \tag{11}$$

If the test statistic $D(\hat{\beta}) > x^2_{(a,j)}$, then reject H_0 indicating that at least one predictor variable significantly influences the response variable.

Once the simultaneous parameter significance test is finished, partial significance tests are carried out to analyze the specific influence of each predictor variable. In the GWPR-ST model, the partial parameter test examines the impact of each predictor variable on the response variable at different locations. The hypotheses for the partial parameter test are as follows [24]:

H_0: $\beta_p(b_i, c_i) = 0, p = 1,2, \ldots, j$

H_1: $\beta_p(b_i, c_i) \neq 0$

Test Values:

$$Z = \frac{\hat{\beta}_p(b_i, c_i)}{se\left(\beta_p(b_i, c_i)\right)} \tag{12}$$

If the test statistics $|z| > Z_{(a/2)}$, then reject H_0 this shows that the predictor variable significantly impacts the response variable at every location in the GWPR-ST model.

3. MAIN RESULTS

The analysis begins by examining the Poisson distribution of the response variable to determine its suitability for the GWPR-ST model. This test aims to assess whether the response variable y in this study follows Poisson distribution. The Kolmogorov-Smirnov test is used to assess the Poisson distribution of y. At a significance level of α = 0.05, the output from R-Studio software yields a p_{value} of 0.24. Since $p_{value} > 0.05$, the null hypothesis H_0 is accepted, implying that the maternal mortality data in South Sulawesi Province in 2020 follows a Poisson distribution.

Following the Poisson distribution analysis, the overdispersion test is conducted to assess whether the variance exceeds the mean, which would justify using the GWPR-ST model. Using R-Studio, the overdispersion test results indicate a dispersion parameter ϕ of 1.82 $(\phi > 1)$, suggesting the presence of overdispersion in the maternal mortality data. Consequently, the analysis can be addressed using the GWPR model.

After evaluating overdispersion, the spatial heterogeneity test examines the variability of relationships across different locations. The Breusch-Pagan test statistic obtained is 10.42, with p_{value} 0.04. Since the Breusch-Pagan value exceeds $X^2_{(0,05;3)}$ and the p_{value} is smaller than $\alpha = 0.05$, reject H_0, This indicates the presence of spatial heterogeneity among regions, meaning that the characteristics at each location vary.

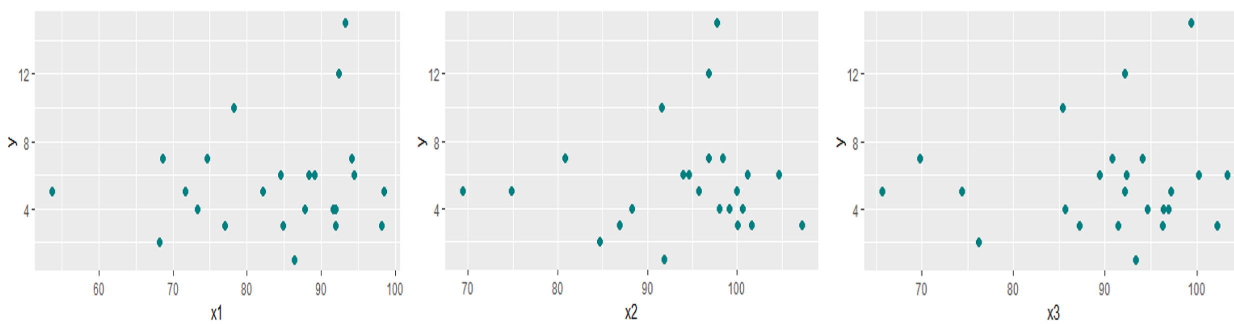

Figure 1. Scatterplot of Maternal Mortality and Predictor Variables

Based on Figure 1, the relationship between the response variable y (Maternal Mortality) and the predictor variables (x_1 to x_3) does not exhibit a distinct functional form. The data points are scattered randomly without following a specific parametric pattern, suggesting that the underlying relationship is better captured using a nonparametric approach.

Next, the best bandwidth is identified through the Gaussian Kernel weighting function by choosing the lowest GCV value, as presented in Table 1.

Table 1. Optimum Bandwidth

Geographic Weighting Function	Bandwidth	GCV
Kernel Gaussian	0,88	9513,79

Table 1 shows that the optimal bandwidth is 0.88, determined through the Gaussian Kernel weighting function by choosing the lowest GCV value.

The optimum knot points are determined to enhance model flexibility following the bandwidth selection, as shown in Table 2.

Table 2. Optimum Knot Point

Knot Point	GCV
1	0.48
2	0.28
3	0.26

Based on Table 2, the optimal knot points are determined using three knot points, yielding the minimum GCV value of 0.26.

Based on the selection of optimal knot points, the following are the parameter estimators for the GWPR-ST model with three knot points.

$$\begin{aligned}\hat{y}_i = \exp\big(&\hat{\beta}_0(b_i,c_i) + \hat{\beta}_{11}(b_i,c_i)x_{1i} + \hat{\beta}_{21}(b_i,c_i)x_{2i} + \hat{\beta}_{31}(b_i,c_i)x_{3i} \\ &+ \hat{\delta}_{11}(b_i,c_i)(x_{1i} - K_{13})_+ + \hat{\delta}_{21}(b_i,c_i)(x_{2i} - K_{23})_+ \\ &+ \hat{\delta}_{31}(b_i,c_i)(x_{3i} - K_{33})_+\big)\end{aligned} \tag{13}$$

The following is one example of the GWPR-ST model, written for the 11th location, which corresponds to Barru Regency.

$$\begin{aligned}\hat{y}_i = \exp\Big(&9.76 - 0.02x_{1;11} - 0.08x_{2;11} - 0.12x_{3;11} - 4.34\big(x_{1;11} - 93.29\big)_+ \\ &+ 18.87\big(x_{2;11} - 98.03\big)_+ - 14.92\big(x_{3;11} - 1.29\big)_+\Big)\end{aligned} \tag{14}$$

After obtaining the GWPR-ST model, simultaneous parameter significance testing is carried out to assess the overall impact of all predictor variables on the response variable. This is followed by partial significance testing to examine the individual impact of each predictor variable at different locations.

Table 3. Results of Simultaneous Parameter Significance Test

Test Statistics $D(\hat{\beta})$	$x^2_{(0,05;3)}$	p_{value}	Hypothesis
10.32	7.82	0.02	Reject H_0

Based on Table 3, the test statistic value is $D(\hat{\beta}) = 10.32 > x^2_{(0,05;3)} = 7.82$, or $p_{value} = 0.02 < \alpha = 0.05$, therefore the null hypothesis is to reject H_0. This suggests that at least one predictor variable significantly influences the GWPR-ST model.

The partial parameter significance test results reveal that the significant predictor variables differ between regions. This leads to the classification of four groups of regencies/cities based on the significant predictor variables. The grouping of regencies/cities based on variables significantly affecting maternal mortality in 2020 in South Sulawesi is presented as follows.

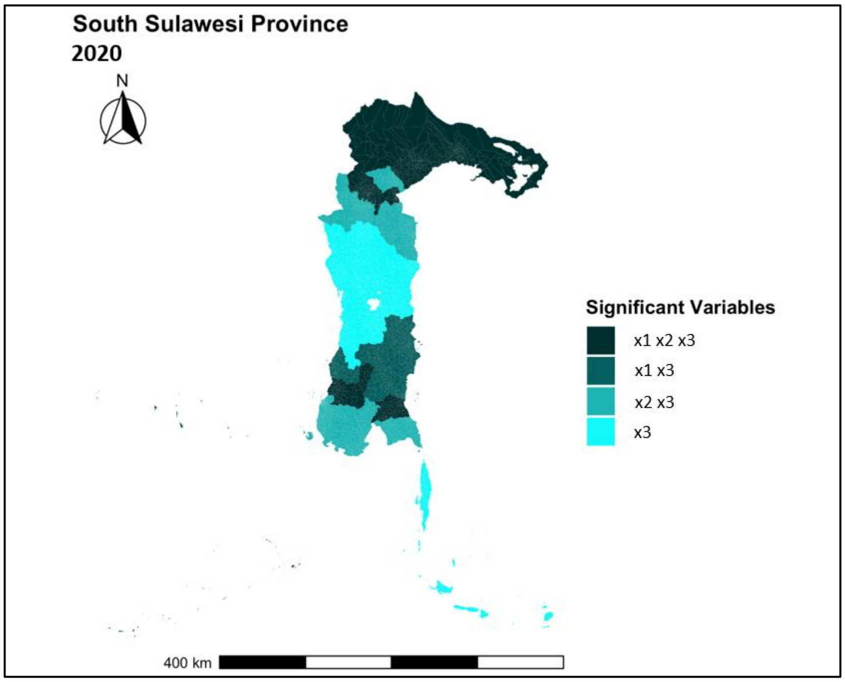

Figure 2. Mapping of Maternal Mortality in South Sulawesi in 2020 Using Relevant Variables

Figure 2 shows Maternal mortality in various regions of South Sulawesi is affected by several factors, which are associated with variables such as x_1, x_2 dan x_3. In areas like Sinjai, Maros, Luwu Utara, Luwu Timur, Toraja Utara, and Palopo, maternal mortality is affected by a combination of factors x_1, x_2 dan x_3. Meanwhile, in Pangkep and Bone, the factors that affected maternal mortality are limited to x_1 dan x_3. On the other hand, regions such as Bulukumba, Bantaeng, Jeneponto, Takalar, Gowa, Luwu, Tana Toraja, and Makassar are more affected by factors x_2 dan x_3. Lastly, in Selayar, Barru, Soppeng, Wajo, Sidrap, Pinrang, Enrekang, and Pare-Pare, the primary factor affecting maternal mortality is x_3.

4. CONCLUSION

The optimal Geographically Weighted Poisson Regression (GWPR) model with the Spline Truncated approach for maternal mortality in South Sulawesi in 2020 is obtained with an order of $m = 1$ and three-knot points $(h = 3)$. The coefficient of determination is $R^2 = 81.04$, indicating that the model explains 81.04% of the variation in the response variable based on the predictor variables. The partial significance test of the estimated parameters classifies the regencies/cities into four groups according to the predictor variables that significantly affect maternal mortality in South Sulawesi in 2020.

CONFLICT OF INTERESTS

The authors confirm that there is no conflict of interests.

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