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Assessment of USLE-Based Sediment Yield Estimation Using Rainfall Correction Scenarios and Empirical Rainfall Erosivity Equations in Ciputat Sub-watershed, Indonesia

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Abstract: *Sedimentation is one of the major challenges in watershed management, and its estimation is strongly influenced by rainfall data quality and the selection of rainfall erosivity equations in the Universal Soil Loss Equation (USLE) method. This study aimed to compare sediment yield estimates obtained from different rainfall data scenarios and empirical rainfall erosivity equations with field measurements in the Ciputat Sub-watershed, South Tangerang City, Indonesia. Sediment yield was estimated using the USLE combined with the Sediment Delivery Ratio (SDR) and validated using stream discharge and Total Suspended Solids (TSS) data. Model performance was evaluated using the Root Mean Square Error (RMSE) and Nash–Sutcliffe Efficiency (NSE) indices. The results revealed that the original BMKG rainfall data without imputation achieved better agreement with field measurements than all rainfall data correction scenarios, indicating that rainfall data imputation does not necessarily improve the reliability of sediment yield estimation. Furthermore, among the empirical rainfall erosivity equations evaluated, the Abdurachman equation provided the closest agreement with field observations, yielding the lowest RMSE (0.916) and the highest NSE (0.375). In addition, the modeled sediment load was classified as Very Low, consistent with the field measurements, while the Erosion Hazard Level (EHL) was classified as Very Slight. These findings demonstrate that both rainfall data quality and the selection of empirical rainfall erosivity equations compatible with watershed characteristics are critical for improving the reliability of USLE-based sediment yield estimation.*

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INTRODUCTION

Sedimentation is one of the major challenges in watershed management because it reduces river conveyance capacity, decreases the effectiveness of flood control infrastructure, and increases flood risk. One of the primary causes of increased sedimentation is extensive land use change, particularly the conversion of vegetated areas into settlements and other built-up land, which increases surface runoff, accelerates soil erosion, and consequently increases sediment transport into river systems (Asmul Wawan Kirana et al., 2025). The accumulation of sediment within river channels leads to channel aggradation and reduced flow capacity, thereby increasing the likelihood of flooding. Therefore, reliable sediment yield estimation is essential for watershed conservation planning, river maintenance, and flood mitigation, as erosion prediction provides the basis for selecting appropriate soil and water conservation measures (Liastuti et al., 2021).

Among the available empirical approaches, the Universal Soil Loss Equation (USLE) has become one of the most widely applied models for estimating soil erosion because of its relatively simple input requirements, ease of application, and its applicability under various environmental conditions (Maulana et al., 2022). In addition, the USLE model has been widely applied to predict erosion hazard levels, support land-use planning, and evaluate appropriate soil conservation practices in various watershed conditions (Hariyanto et al., 2019). USLE estimates soil loss based on five major factors,

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namely rainfall erosivity (R), soil erodibility (K), slope length and steepness (LS), cover-management (C), and conservation practice (P), which collectively determine the magnitude of soil erosion under different environmental conditions (Atmojo & Suwadji, 2025). Among these factors, rainfall erosivity (R) plays a particularly important role because it directly represents the erosive energy of rainfall events. Furthermore, several empirical rainfall erosivity equations have been developed for USLE applications, and each equation may produce different erosion estimates depending on watershed characteristics, making the selection of an appropriate equation an important consideration (Andriyani et al., 2024).

The reliability of USLE-based sediment yield estimation is strongly influenced by the rainfall erosivity factor (R). The original USLE calculates rainfall erosivity using the EI_{30} index, which requires rainfall intensity records with high temporal resolution. However, such data are rarely available in Indonesia because most rainfall stations only provide daily or monthly rainfall observations. Consequently, several empirical rainfall erosivity equations, including those proposed by Bols, Lenvain, Abdurachman, Utomo, and Soemarwoto, have been widely adopted to estimate rainfall erosivity using available rainfall records. The resulting erosivity estimates, however, depend on the characteristics and completeness of the rainfall data used as inputs.

Besides the selection of rainfall erosivity equations, rainfall data quality also affects sediment yield estimation. Missing rainfall observations frequently occur in long-term rainfall records and are commonly corrected using various rainfall data imputation methods. Although both rainfall data reconstruction and the selection of an empirical erosivity equation can affect the estimated R factor, these two sources of uncertainty are often considered independently. In practice, they are closely connected because rainfall reconstruction alters the temporal and statistical characteristics of the rainfall series, which are subsequently processed by the selected erosivity equation. Different erosivity equations may respond differently to these changes in rainfall characteristics, potentially resulting in substantially different estimates of rainfall erosivity and, consequently, sediment yield. Therefore, evaluating rainfall data reconstruction and empirical erosivity equations simultaneously is important to capture the combined uncertainty in USLE-based sediment yield estimation. Moreover, validation against field measurements remains relatively limited, making it difficult to determine whether the selected rainfall dataset and rainfall erosivity equation adequately represent actual watershed conditions.

This study addresses this gap by systematically evaluating the combined influence of multiple rainfall data scenarios and six empirical rainfall erosivity equations on USLE-based sediment yield estimation. Unlike previous studies that generally focus on a single rainfall dataset or a single erosivity equation, this study examines how variations in rainfall data quality propagate through different erosivity equations and affect the resulting sediment yield estimates. Furthermore, the estimated sediment yield is evaluated against field observations using quantitative performance indicators (RMSE and NSE), as well as qualitative assessments through erosion hazard level, sediment yield classification, and Total Suspended Solids (TSS). This integrated framework provides a more comprehensive assessment of the reliability and uncertainty of sediment yield estimation under tropical watershed conditions.

Therefore, this study evaluates the combined influence of rainfall data scenarios and empirical rainfall erosivity equations on sediment yield estimation in the Ciputat Sub-watershed, South Tangerang, Indonesia. Several rainfall data scenarios, including the original rainfall dataset and rainfall data imputation methods, were compared together with six empirical rainfall erosivity equations. The findings are expected to identify the most reliable combination of rainfall data scenario and rainfall erosivity equation for improving the accuracy of USLE-based sediment yield estimation under the characteristics of the Ciputat Sub-watershed.

RESEARCH METHOD

Soil Loss Estimation (USLE)

Soil loss was estimated using the Universal Soil Loss Equation (USLE) proposed by Wischmeier and Smith (1978) (Santi & Seran, 2022):

$$A = R \,.\, K \,.\, L \,.\, S \,.\, C \,.\, P$$

where A is the annual soil loss (ton ha^{-1} yr^{-1}), R is the rainfall erosivity factor, K is the soil erodibility factor, LS is the slope length and steepness factor, C is the cover-management factor, and P is the support practice factor. Spatial analysis was performed in QGIS by overlaying rainfall, soil, topographic, and land-use maps to produce the soil erosion map.

Rainfall Erosivity (R)

Rainfall erosivity (R) was estimated using six empirical equations commonly applied in Indonesia, namely Utomo A, Utomo B, Abdurachman, Soemarwoto, Lenvain, and Bols. These equations were selected because they utilize rainfall variables commonly available from Indonesian rainfall stations, including monthly rainfall, maximum daily rainfall, and the number of rainy days. The original USLE estimates rainfall erosivity using the EI_{30} index, which is calculated from rainfall kinetic energy and the maximum 30-minute rainfall intensity (Asdak, 2022). However, the application of this approach requires high-temporal-resolution rainfall records obtained from automatic recording rain gauges, whereas most rainfall stations in Indonesia still provide only daily or monthly rainfall observations (Sulistyo, 2011). Consequently, several empirical rainfall erosivity equations have been developed and widely adopted to estimate the R factor using rainfall variables that are readily available under Indonesian climatic conditions (Sulistyo, 2011)(Andriyani et al., 2024).

Table 1. Rainfall Erosivity

	Approach	Equations
1	Utomo (A)	EI = -8,79 + (7,01 x R)
2	Utomo (B)	EI = 10,80 + (4,15 x R)
3	Abdurachman (Adnyana & As-syakur, 2016)	$R_m = \frac{(Rain_m)^{2.263} X\ (MaxP_m)^{0.678}}{40.056\ X\ (Days_m)^{0.349}}$
4	Soemarwoto (1991) (Andriana et al., 2021)	Rm = 0,41 $(Rain_m)^{1.09}$
5	Lenvain	EI = 2,21 X $R^{1,36}$
6	Bols	EI = 6.119 X $R^{1,21} X\ D^{-0,47}\ M^{0,53}$

Where EI is the rainfall erosivity, R is the mean monthly rainfall (cm), Rm is the monthly rainfall erosivity index, $(Days)_m$ is the number of rainy days in a month, $(MaxP)_m$ is the maximum daily rainfall in a month, m is the mean daily rainfall within a month (mm day^{-1}), $Rain_m$ is the total monthly rainfall (mm $month^{-1}$), D is the mean number of rainy days per month (days), and M is the mean maximum 24-hour monthly rainfall over one year (cm).

Rainfall Data Scenarios

Missing rainfall observations were reconstructed using six rainfall data scenarios to evaluate the influence of rainfall data quality on sediment yield estimation. Missing data frequently occur in long-term hydrological records due to equipment malfunction, operational interruptions, or incomplete observations, and therefore require reconstruction using information from neighboring rainfall stations or alternative data sources (Bagiawan et al., 2011). Because no single rainfall imputation method consistently provides the highest accuracy under all climatic and topographic conditions, the performance of each method depends on factors such as inter-station distance, topography, and rainfall variability. Consequently, multiple rainfall reconstruction approaches were evaluated in this study to minimize uncertainty in subsequent USLE-based sediment yield estimation. The evaluated scenarios consisted of the original BMKG rainfall records, four rainfall imputation methods (Mean, ARIMA, Reciprocal, and Normal Ratio), and NASA GPM IMERG rainfall data before and after calibration with BMKG observations (Table 2).

Table 2. Data Correction Method

Scenario	Data Source	Data Correction Method
1	BMKG	Orginal Data
2	BMKG	Aljabar (Average)
3	BMKG	ARIMA
4	BMKG	Reciprocal
5	BMKG	Normal Ratio
6	NASA GPM IMERG	Original Data
7	NASA GPM IMERG	Calibration with BMKG

Satellite-based rainfall products such as GPM-IMERG provide continuous spatial and temporal rainfall coverage, making them valuable in regions with limited ground observations. However, systematic biases caused by retrieval algorithms and local climatic conditions may reduce their accuracy, making calibration against rain-gauge observations necessary before their application in hydrological analyses (Suhartanto et al., 2026).

Soil Erodibility Factor

The soil erodibility factor (K) was calculated using the equation proposed by Wischmeier and Smith (1978). Soil erodibility reflects the inherent susceptibility of soil to erosion and is primarily controlled by soil texture, soil structure, organic matter content, and soil permeability (Naharuddin, 2020). These parameters were obtained from secondary soil datasets covering the study area and subsequently used to estimate the K factor.

$$100k = 2{,}713.10^{-4}(12 - a)M^{1{,}14} + 3{,}25(b - 2) + (c - 3)$$

Where K is the soil erodibility factor, M is the particle-size parameter calculated as (% silt + % very fine sand) × (100 − % clay), a is the organic matter content, where values greater than 6% are assigned the maximum value of 6, b is the soil structure class, and c is the soil permeability class.

Topographic Factor (LS)

The LS factor was derived from the Digital Elevation Model (DEM) using ArcGIS Spatial Analyst. Slope, flow direction, flow accumulation, and raster algebra were used to generate the spatial distribution of the LS factor following the equation proposed by (Andriyani et al., 2024).

$$LS = \left(\frac{y}{22{,}13}\right)^{0{,}4} x \left(\frac{\sin(\theta)}{0{,}00896}\right)^{1{,}3}$$

where y represents the horizontal slope length (m), calculated as flow accumulation multiplied by the raster cell size, and θ is the slope angle derived from the DEM (SRTM) in degrees. The value of sin θ is obtained after converting the slope angle from degrees to radians using a conversion factor of 0.01745.

Cover Management Factor (CP)

The CP factor was assigned according to land-use classification following (Asdak, 2022). Each land-use category was assigned a corresponding CP value as presented in Table 3.

Table 3. Coverage management Factor

No	Land Conservation and Management	CP Value
1	Undisturbed forest	0,01
2	Forest	0,01
3	Mangrove forest	0,01
4	Primary dryland forest	0,03
5	Secondary dryland forest	0,01
6	Shrubland	0,30
7	Paddy field	0,01
8	Dryland agriculture	0,28
9	Dryland agriculture mixed with shrubland	0,19
10	Bare land	0,95
11	Plantation	0,50
12	Settlement	0,95
13	Mining area	1,00
14	Fish pond	0,001
15	Grassland (Imperata grassland)	0,02
16	Cropland	0,28
17	Lake / Pond / Sandbar	0,01
18	Swamp	0,01
19	River	0,001

Erosion Hazard Classification

The estimated annual soil loss was classified into five erosion hazard classes (Very Low, Low, Moderate, High, and Very High) following the Indonesian Ministry of Forestry Regulation No. P.32/Menhut-II/2009. The classification considers both annual soil loss and effective soil depth (Ditjen RLPS, 2009)

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Table 4. Erosion Hazard Classification

Soil Profile (cm)	Erosion Hazard Classification				
	I	II	III	IV	V
	Erosion (ton/ha/years)				
	< 15	15 – 60	60 – 80	180 – 480	> 480
Deep	SR	R	S	B	SB
> 90	0	I	II	III	IV
Medium	R	S	B	SB	SB
60 - 90	I	II	III	IV	IV
Shallow	S	B	SB	SB	SB
30 - 60	II	III	IV	IV	IV
Very Shallow	B	SB	SB	SB	SB
< 30	III	IV	IV	IV	IV

Notation:
0 - SR = Very Light
I - R = Light
II - S = Medium
III - B = Heavy
IV - SB = Very Heavy

Sediment Load Classification

Estimated sediment yield was classified into five sediment load categories ranging from Very Low to Very High according to the classification presented in Table 5 (P. 61/Kemenhut-II, 2014):

Table 5. Sediment Load Classification

Parameter	Value (ton/ha/yr)	Class
Qs = k x Cs x Q MS = A x SDR	$MS \leq 5$	Very Low
	$5 \leq MS \leq 10$	Low
	$10 \leq MS \leq 15$	Medium
	$15 \leq MS \leq 20$	High
	$MS > 20$	Very High

Water Pollution Classification

Measured Total Suspended Solids (TSS) concentrations were classified into four pollution levels (unpolluted, lightly polluted, moderately polluted, and heavily polluted) (Sukmono & Rajagukguk, 2019).

Table 6. Water Pollution Classification

Class	Pollution Level	TSS (mg/l)
1	Not Yet Polluted	0 - 20
2	Lightly Polluted	20 – 50
3	Moderately Polluted	50 – 100
4	Heavily Polluted	> 100

Sediment Yield Estimation

Since not all eroded soil is transported to the watershed outlet, annual soil loss estimated by the USLE model was converted into theoretical sediment yield using the Sediment Delivery Ratio (SDR). The SDR represents the fraction of total eroded material that is delivered to the watershed outlet and is widely used to estimate sediment yield from predicted soil erosion (Tribiyono et al., 2018). The theoretical sediment yield was calculated as follows:

$$MS = A \times SDR$$

where MS is the theoretical sediment yield (ton ha^{-1} yr^{-1}), A is the annual soil loss estimated by USLE (ton ha^{-1} yr^{-1}), and SDR is the Sediment Delivery Ratio. The SDR values were determined according to watershed area following the guideline issued by the Directorate General of Watershed Management (Ditjen RLPS, 2009), as presented in Table:

Table 7. SDR Ratio

No	Watershed Area (ha)	Sediment Delivery Ratio (%)
1	10	53
2	50	39
3	100	35
4	500	27
5	1000	24
6	5000	15
7	10000	13
8	20000	11
9	50000	8,5
10	2600000	4,9

Field Sediment Yield

Observed sediment yield was calculated from stream discharge and Total Suspended Solids (TSS) using the suspended sediment load equation (George Porterfield, 1972). TSS was selected because it represents the concentration of suspended particulate matter in the water column and is widely used as an indicator for evaluating suspended sediment transport and sedimentation processes in aquatic environments (Rachman & Wibowo, 2022).

$$Q_s = Q_w \, x \, C_s \, x \, k$$

where Qs is the suspended sediment load (ton day^{-1}), Qw is stream discharge (m^3 s^{-1}), Cs is the average suspended sediment concentration (mg L^{-1}), and k is the conversion factor (0.0864). The suspended sediment load was then converted into annual sediment yield per unit watershed area using (P. 61/Kemenhut-II, 2014):

$$MS = \frac{Q_s}{A}$$

where MS is the sediment yield (ton ha^{-1} yr^{-1}), Q_s is the suspended sediment discharge (ton yr^{-1}), and A is the watershed area (ha).

Model Performance Evaluation

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The performance of each rainfall data scenario and rainfall erosivity equation was evaluated by comparing the estimated sediment yield with field observations using the Root Mean Square Error (RMSE) and Nash–Sutcliffe Efficiency (NSE). RMSE was used to quantify the average deviation between simulated and observed sediment yield (Ilham et al., 2022):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - y_i)^2}{n}}$$

where x_i is the observed sediment yield, y_i is the simulated sediment yield, and n is the number of observations. Model efficiency was further evaluated using the Nash–Sutcliffe Efficiency (NSE) (Nash & Sutcliffe, 1970):

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{n}(y_i^{obs} - y_i^{sim})^2}{\sum_{i=1}^{n}(y_i^{obs} - y_i^{mean})^2}$$

where y_i^{obs} is the observed sediment yield, y_i^{sim} is the simulated sediment yield, and y_i^{mean} is the mean of the observed sediment yield. Lower RMSE values and higher NSE values indicate better agreement between model predictions and field observations.

Study Area

This study was conducted in the Ciputat Sub-watershed, South Tangerang City, Banten Province, Indonesia.

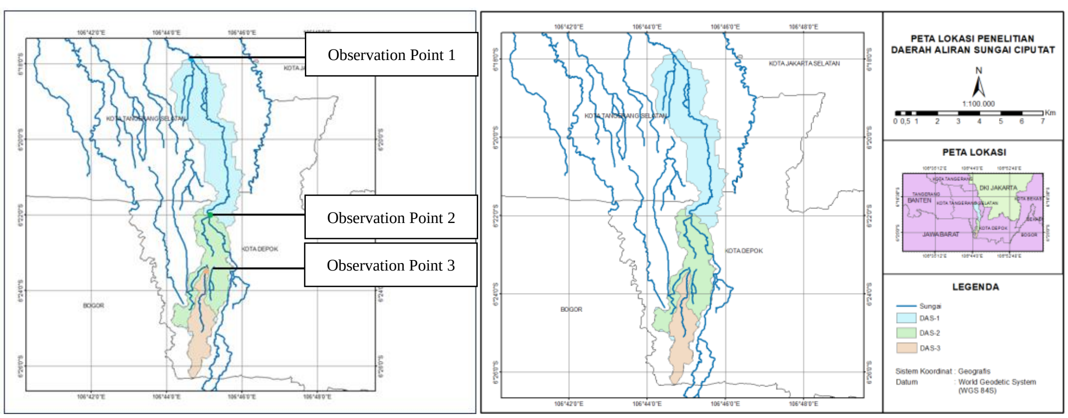

Figure 1. Study Area

The watershed was delineated from a Digital Elevation Model (DEM) and covers an area of approximately 2,531 ha. Geographically, it is located between 106°44′–106°45′ E and 6°18′–6°19′ S, with elevations ranging from 50 to 90 m above mean sea level (amsl). The watershed is generally characterized by flat to gently undulating topography.

Data Analysis

Rainfall Data Processing

Initial examination of the BMKG rainfall records identified several missing observations at the three rainfall stations during the study period. To evaluate the influence of rainfall data quality on sediment yield estimation, missing observations were reconstructed using six imputation methods, while the original BMKG dataset and calibrated NASA GPM IMERG data were included as comparison

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scenarios. Subsequently, rainfall from each station was converted into areal rainfall using the Thiessen Polygon method. The resulting annual rainfall for each rainfall scenario as shown:

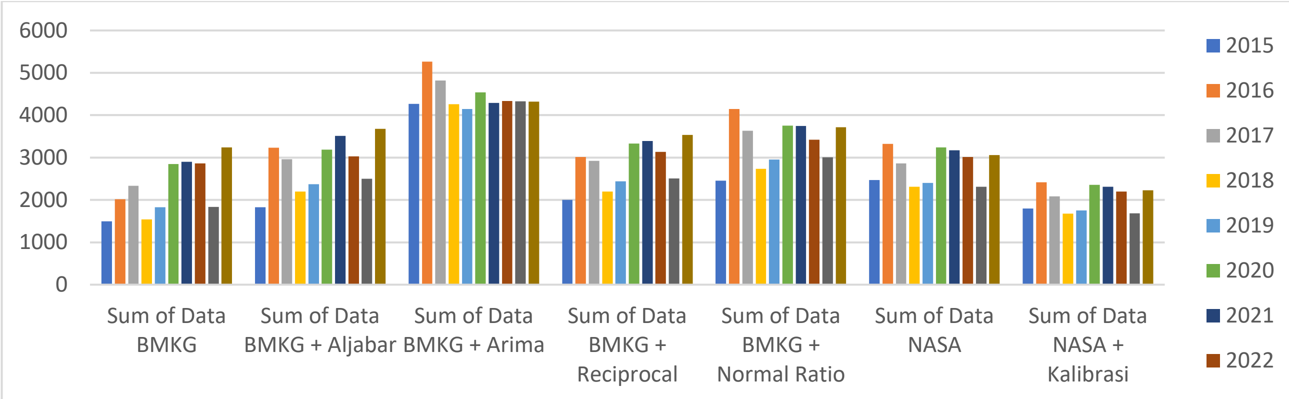

Figure 2. Sub-Watershed 1

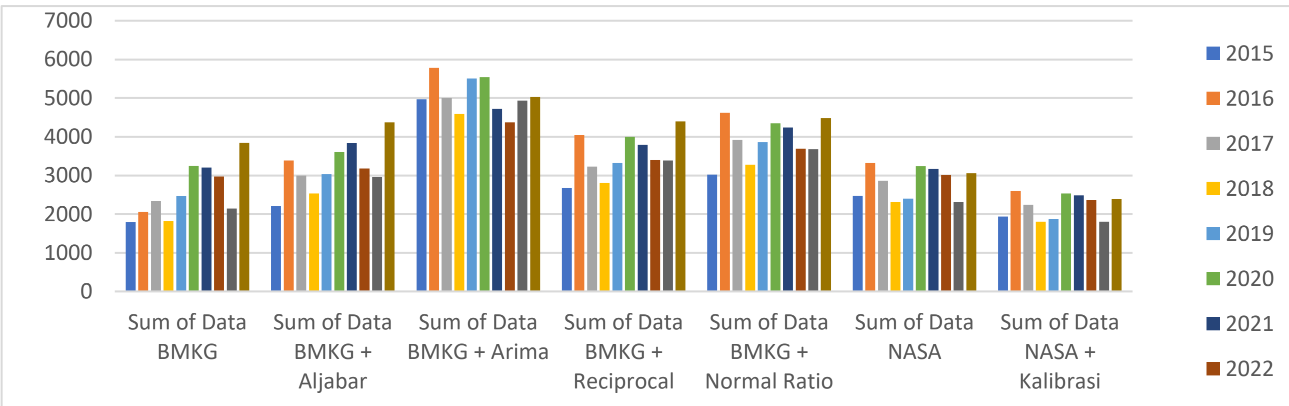

Figure 3. Sub-Watershed 2

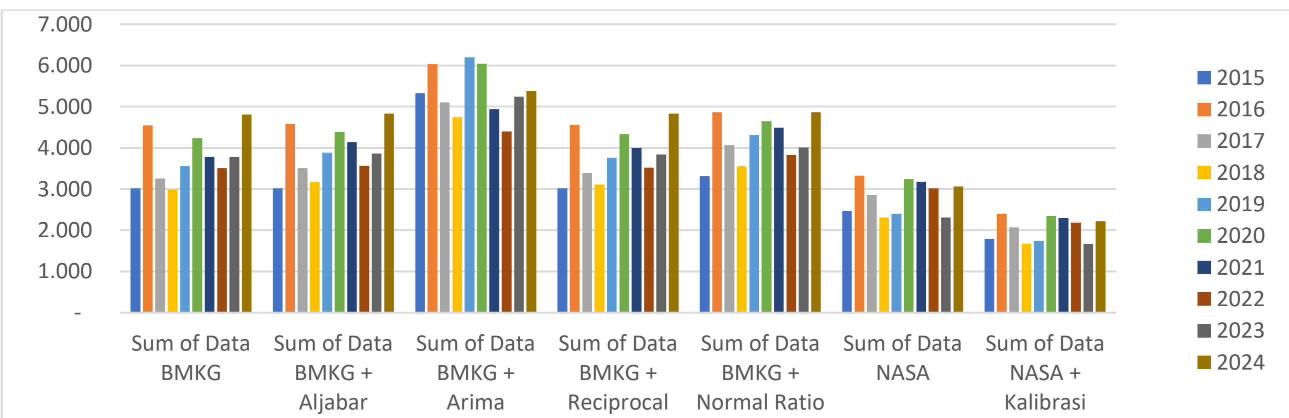

Figure 4.Sub-Watershed 3

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Rainfall Erosivity Factor (R)

Annual areal rainfall obtained from each rainfall data scenario was subsequently used to calculate the rainfall erosivity factor using six empirical equations, namely Utomo A, Utomo B, Abdurachman, Soemarwoto, Lenvain, and Bols. The calculated rainfall erosivity values for each scenario are presented in figure 5-7.

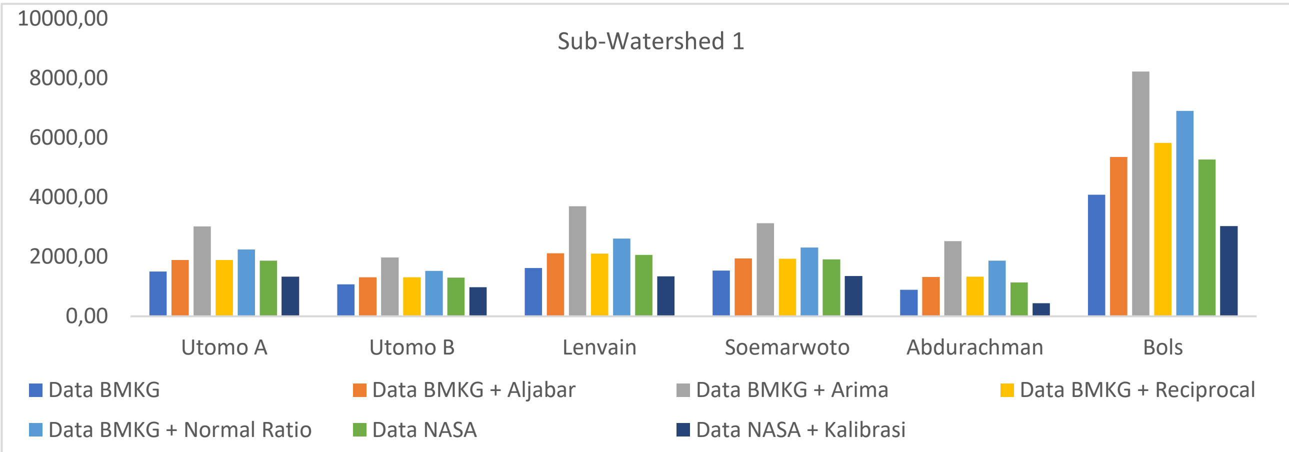

Figure 5. Sub-Watershed 1

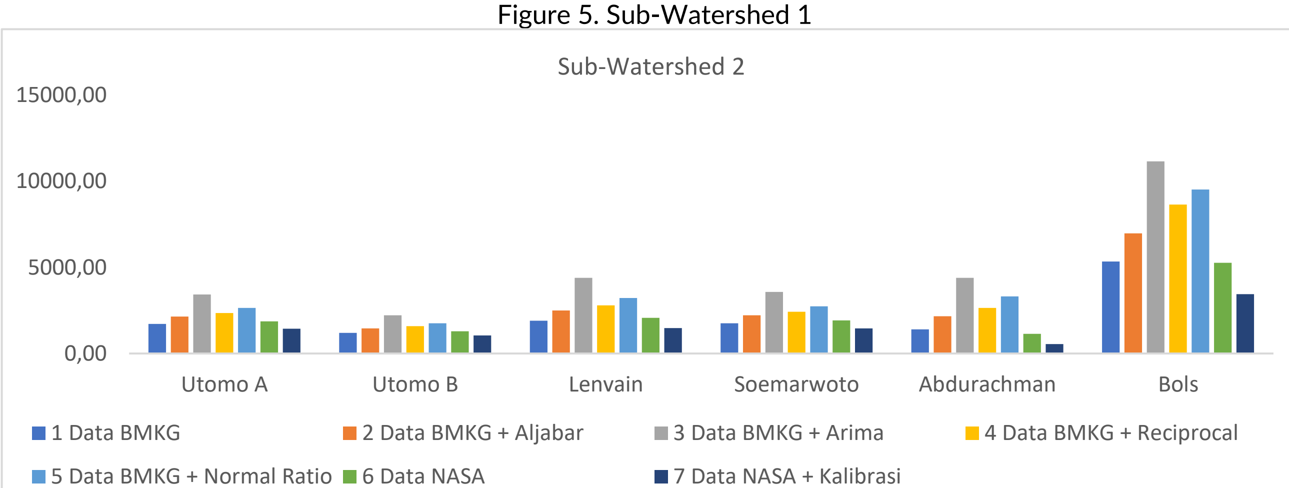

Figure 6. Sub-Watershed-2

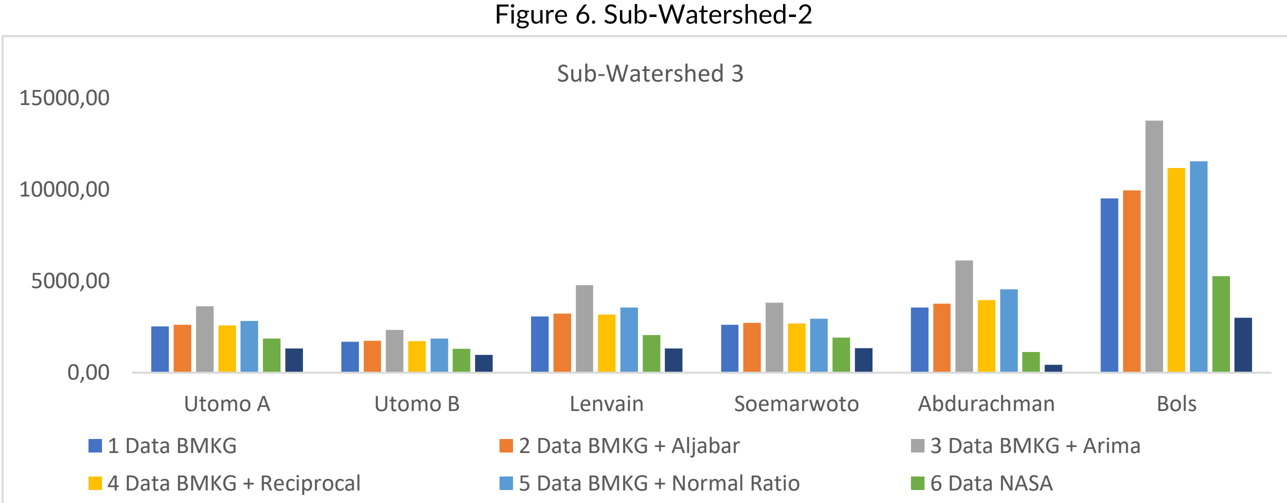

Figure 7. Sub-Watershed 3

The results indicate that the Bols equation consistently produced the highest rainfall erosivity values among all empirical equations. This finding is consistent with Agestia et al. (2023), who reported that the Bols equation generally yields larger erosivity values than the Utomo equation due to differences in the rainfall variables incorporated into each empirical formulation (Agestia et al., 2023). Similar comparisons among empirical rainfall erosivity equations have also been reported in Indonesian watersheds, demonstrating that different equations may produce substantially different erosivity estimates and that the most appropriate equation should be selected according to local watershed characteristics (Nasjono et al., 2022).

Soil Erodibility Factor (K)

The soil erodibility factor (K) was derived from the Harmonized World Soil Database version 2 (HWSD v2). Spatial analysis identified two dominant Soil Mapping Units (SMUs) within the study area, namely SMU 4543 and SMU 7001. Soil physical properties, including soil texture, organic carbon content, soil structure, and permeability, were used to calculate the K factor based on the USLE formulation. The resulting K-factor values for each soil mapping unit are presented in Table:

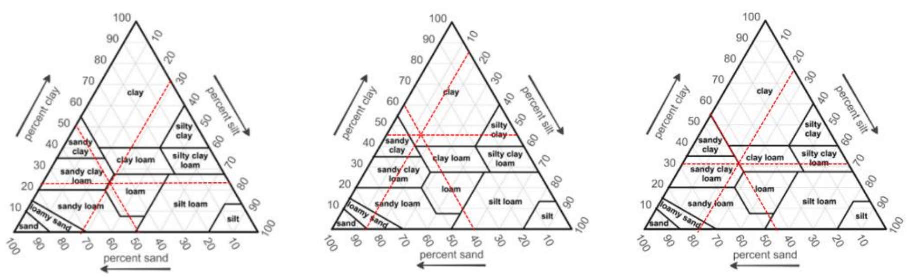

Figure 8. USDA Soil Texture Triangle

Table 8. Soil physical properties

	Code	Share	Depth	Sand	Silt	Clay	Texture Class
1	4543	10%	0-20	49	28	23	Loam
2	4543	10%	0-20	40	15	45	Clay
3	4543	80%	0-20	46	24	30	Clay Loam

Table 9. Soil Erodibility Factor

HWSD2 SMU ID	Share (%)	Depth	Sand	Silt	Clay	ORG Carbon	Van Bemmelen Factor	Organic Properties (a)	Soil Structure (b)	Soil Profile Permeability (c)	Soil Texture Class (M)	Soil Erodibility (K)
4543	10	0-20	49	28	23	1.269	1,724	2,19	3	3	2.156	0,21
4543	10	0-20	40	15	45	3.003	1,724	5,18	2	6	825	0,14
4543	80	0-20	46	24	30	1.537	1,724	2,65	3	4	1680	0,19
										Total 4543		0,190
7001	100	0-20	-9	-9	-9	-9	1,724	-9	-	-	-	0,01
										Total 7001		0,01

Topographic Factor (LS)

The LS factor was derived from the Digital Elevation Model (DEM) using slope and flow accumulation analyses. The resulting raster represents the spatial variation of topographic conditions within the study area, where higher LS values indicate greater erosion potential. The generated LS map was subsequently used as the topographic input in the USLE calculation.

Cover and Management Factor (CP)

The cover-management factor (CP) was determined from the land use/land cover map of the study area. Each land cover class was assigned a corresponding CP value based on the adopted classification, and the spatial distribution of CP was subsequently generated. The dominant land cover classes and their corresponding CP values are summarized in Table (Asdak, 2022).

Table 10. Coverage and management Factor

REMARK	Area	CP Value
Bare/Unvegetated Land	253.31	0.95
Dryland Farm/Field	98.12	0.28
Plantation/Orchard	210.44	0.50
Mixed Crops	256.58	0.19
Other Non-Cultivated Vegetation	1.85	0.30

USLE Soil Loss Estimation

The K, LS, and CP factors obtained from spatial analysis were combined with each rainfall erosivity scenario to estimate annual soil loss using the USLE model. Since the K, LS, and CP factors remain constant for all rainfall scenarios, only the rainfall erosivity factor (R) varied among simulations. A summary of the physical factors used in the USLE calculation is presented in Table 11:

Table 11. K x LS x CP

	Sub-Watershed 1	Sub-Watershed 2	Sub-Watershed 3
K x LS x CP	0.005166	0.006458	0.017584

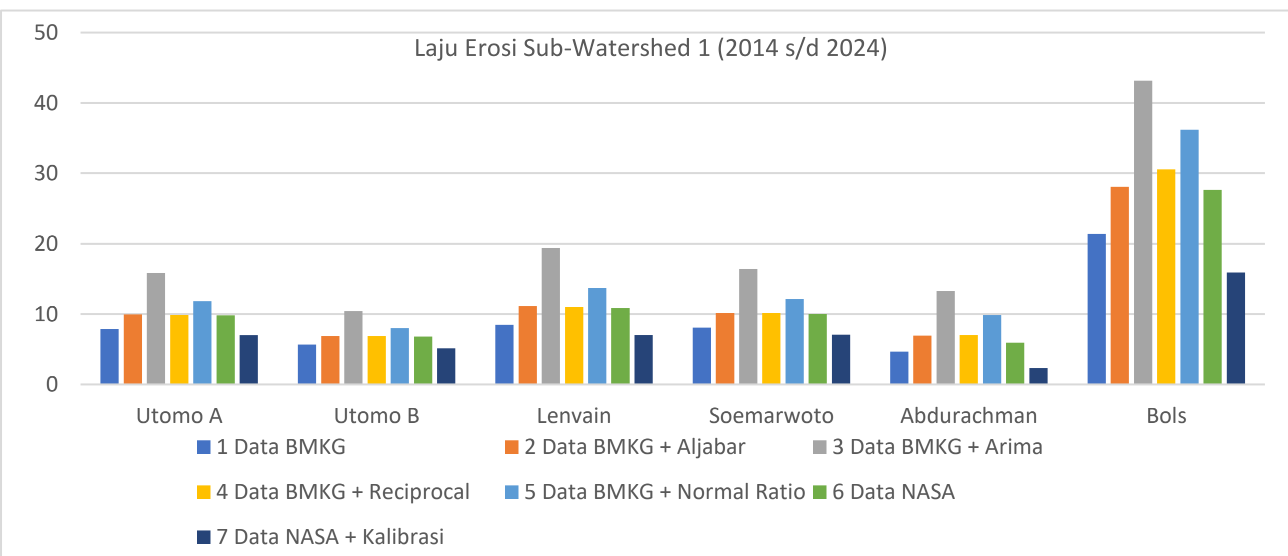

Figure 9. USLE Sub-Watershed 1

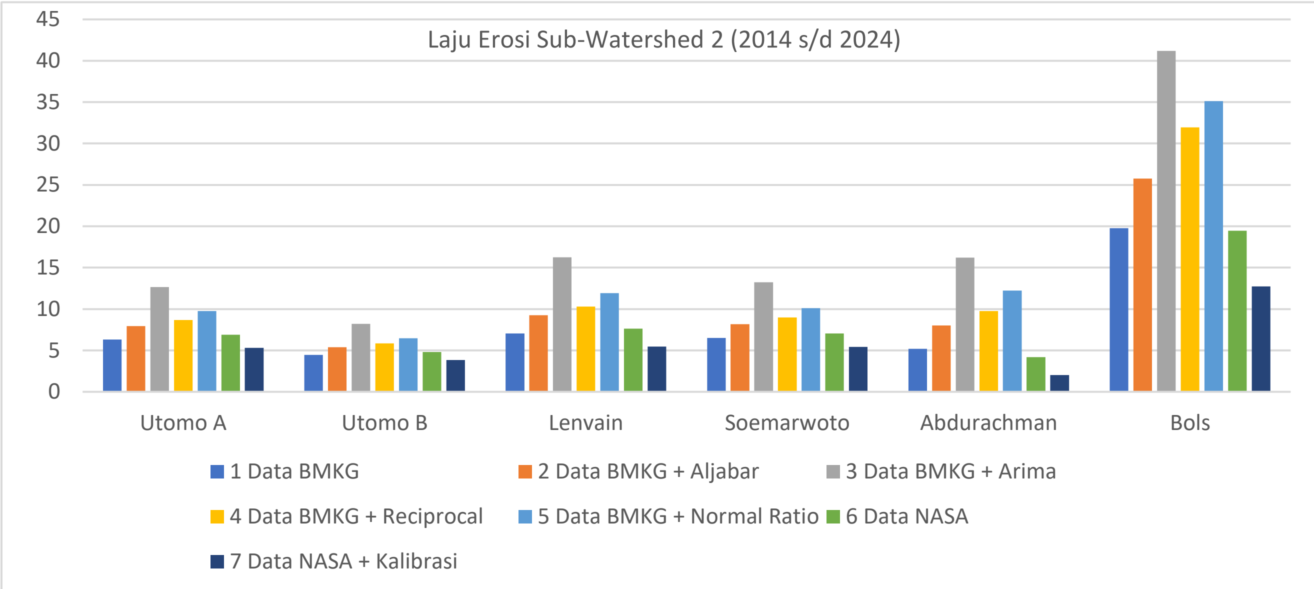

Figure 10. USLE Sub-Watershed 2

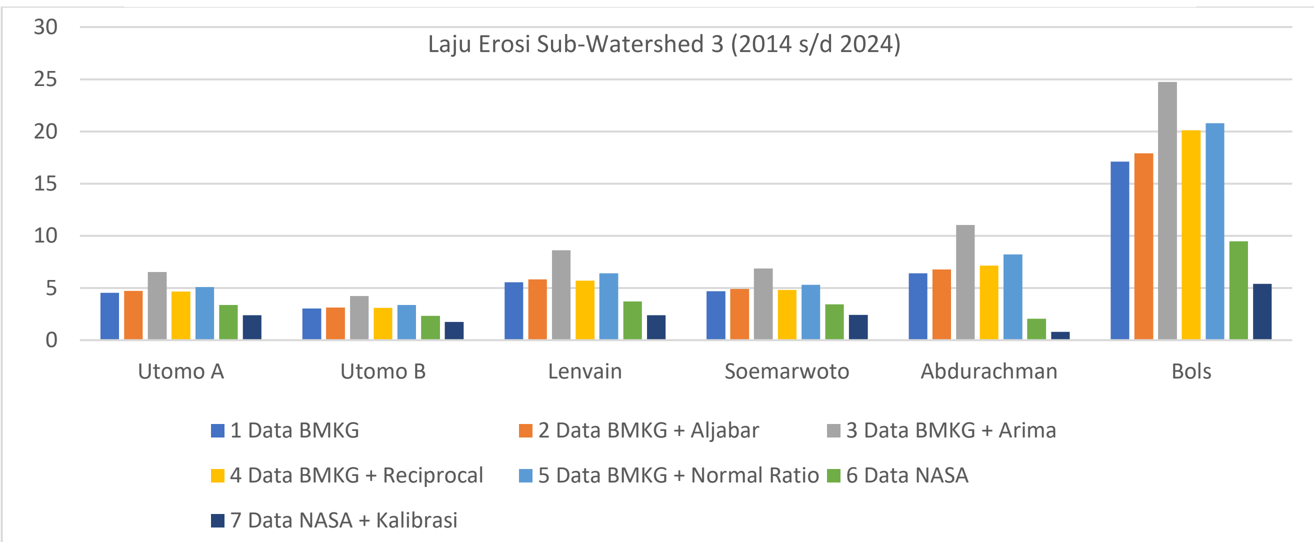

Figure 11. USLE Sub-Watershed 3

Theoretical Sediment Yield

Annual soil loss estimated using USLE was converted into sediment yield through the Sediment Delivery Ratio (SDR). Because the available SDR values were provided for generalized watershed size classes, linear interpolation was applied to estimate SDR values corresponding to the actual watershed areas.

Table 12. Sediment Yield Sub-Watershed 1

No	Rainfall Data	Annual Average 2010 s/d 2024 (Ton/ha/years)					
		Utomo A	Utomo B	Lenva -in	Soemar -woto	Abdur -achman	Bols
1	Data BMKG	0.04	1.15	1.72	1.64	0.95	4.34
2	Data BMKG & Aljabar	0.05	1.39	2.25	2.06	1.41	5.69
3	Data BMKG & Arima	0.08	2.10	3.92	3.32	2.69	8.74

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4	Data BMKG & Reciprocal	0.05	1.39	2.24	2.06	1.42	6.19
5	Data BMKG & Normal Ratio	0.06	1.62	2.77	2.46	1.99	7.33
6	Data NASA	0.05	1.38	2.20	2.03	1.21	5.60
7	Data NASA Calibrated	0.04	1.04	1.43	1.44	0.47	3.22

Table 13. Sediment Yield Sub-Watershed 2

No	Rainfall Data	Annual Average 2010 s/d 2024 (Ton/ha/years)					
		Utomo A	Utomo B	Lenva -in	Soemar -woto	Abdur -achman	Bols
1	Data BMKG	0.07	1.85	2.92	2.70	2.15	8.19
2	Data BMKG & Aljabar	0.09	2.24	3.84	3.39	3.32	10.68
3	Data BMKG & Arima	0.14	3.41	6.74	5.49	6.72	17.09
4	Data BMKG & Reciprocal	0.10	2.43	4.27	3.72	4.05	13.25
5	Data BMKG & Normal Ratio	0.11	2.69	4.94	4.19	5.08	14.57
6	Data NASA	0.08	1.99	3.17	2.93	1.74	8.08
7	Data NASA Calibrated	0.06	1.60	2.27	2.25	0.85	5.27

Table 14. Sediment Yield Sub-Watershed 3

No	Rainfall Data	Annual Average 2010 s/d 2024 (Ton/ha/years)					
		Utomo A	Utomo B	Lenva -in	Soemar -woto	Abdur -achman	Bols
1	Data BMKG	0.78	8.68	15.86	13.48	18.35	49.05
2	Data BMKG & Aljabar	0.81	9.00	16.65	14.05	19.44	51.29
3	Data BMKG & Arima	1.13	12.09	24.69	19.67	31.63	70.94
4	Data BMKG & Reciprocal	0.80	8.87	16.34	13.82	20.46	57.61
5	Data BMKG & Normal Ratio	0.88	9.63	18.35	15.22	23.53	59.55
6	Data NASA	0.58	6.69	10.65	9.86	5.85	27.16
7	Data NASA Calibrated	0.41	5.02	6.86	6.93	2.26	15.46

The resulting sediment yield varied considerably among rainfall scenarios and rainfall erosivity equations. Overall, the Bols equation consistently produced the highest sediment yield estimates, whereas Utomo A generated the lowest values across all rainfall scenarios.

Observed Sediment Yield

Observed sediment yield was calculated from stream discharge and Total Suspended Solids (TSS) measurements at the three sub-watersheds. The calculated sediment yields ranged from 0.43 to 3.27 ton ha^{-1} yr^{-1}, with the highest value observed in Sub-watershed 3, indicating a greater sediment transport potential than the other monitoring locations. The observed sediment yield for each sub-watershed is presented in Table 15:

Table 15. Observed Sediment Yield

	Ton/day ($Q_S = Q_W \times C_S \times K$) a	Ton/year (a/365) b	Area Value c	Ton/Ha/Year (b/c) d
Sub-Watershed 1	3.02	1103.76	2531.06	0.43
Sub-Watershed 2	5.44	1986.77	1125.81	1.76
Sub-Watershed 3	3.45	1261.44	385.27	3.27

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RESULT AND DISCUSSION

The agreement between modeled and observed sediment yield was evaluated using RMSE and NSE.

Table 16. RMSE & NSE

Rainfall Data	RMSE Minium	Method (RMSE Minimum)	NSE Maximum	Method (NSE Maximum)
Data BMKG	0.916	Abdurachman	0.375	Abdurachman
Data BMKG & Aljabar	0.941	Abdurachman	0.340	Abdurachman
Data BMKG & Arima	1.535	Utomo B	-0.754	Utomo B
Data BMKG & Reciprocal	0.951	Abdurachman	0.326	Abdurachman
Data BMKG & Normal Ratio	1.234	Abdurachman	-0.133	Abdurachman
Data NASA	1.607	Utomo A	-0.923	Utomo A
Data NASA Calibrated	1.618	Lenvain	-0.949	Lenvain

Table 16 shows that the original BMKG rainfall dataset combined with the Abdurachman equation produced the lowest RMSE (0.916) and the highest NSE (0.375) among all evaluated combinations. The consistency of these two performance indicators indicates that the BMKG–Abdurachman combination provided the closest agreement with the reference observations within the evaluated scenarios. However, the NSE value of 0.375 also indicates that the predictive performance remained limited, suggesting that rainfall erosivity is not the only source of uncertainty in USLE-based sediment-yield estimation. Nevertheless, the consistent identification of the BMKG–Abdurachman combination by both performance indicators provides a basis for selecting this combination for subsequent comparison with field observations.

The results show that reconstructing the original BMKG rainfall dataset did not necessarily improve sediment-yield estimation. The original BMKG dataset produced the lowest RMSE (0.916), whereas the RMSE increased to 0.941 and 0.951 for the Aliabar and Reciprocal scenarios, respectively, and increased to 1.234 and 1.535 for the Normal Ratio and ARIMA scenarios. A similar deterioration was observed in the NSE values, which decreased from 0.375 for the original BMKG dataset to 0.340, 0.326, −0.133, and −0.754. The deterioration in performance suggests that modifying a substantial proportion of the rainfall record may introduce additional uncertainty into subsequent erosivity estimation. This finding is in line with the caution raised by Bagiawan et al. (2011), who noted that rainfall data imputation should be applied carefully when the proportion of missing data approaches approximately 15% as reconstruction may alter rainfall patterns and reduce data representativeness (Bagiawan et al., 2011). In the present study, the lower performance observed in several reconstructed scenarios indicates that increasing the completeness of the rainfall dataset does not necessarily improve its suitability for erosivity estimation.

Beyond the rainfall data scenario, the results also demonstrate the importance of selecting an appropriate empirical erosivity equation. The same rainfall dataset can produce different sediment-yield estimates when processed using different erosivity formulations because each equation assigns different coefficients and exponents to the rainfall characteristics used to estimate the R factor. For example, both the Abdurachman and Bols equations incorporate rainfall amount, the number of rainy days, and maximum daily rainfall, but their mathematical formulations differ (Erwanto & Lestari, 2021). These differences result in different erosivity responses to the same rainfall input. In this study, the Abdurachman equation produced the lowest RMSE in several BMKG-based scenarios, whereas the Bols equation did not produce the lowest error in any of the evaluated scenarios. The lower RMSE obtained with Abdurachman therefore suggests that its formulation was more consistent with the rainfall characteristics represented in the Ciputat Sub-watershed under the conditions evaluated. However, this finding should be interpreted as a site-specific result rather than evidence that the Abdurachman equation is universally superior to the Bols equation.

A different response was observed for the Utomo equation. Its lowest RMSE was obtained with the BMKG–ARIMA scenario, with an RMSE of 1.535 and an NSE of −0.754, which remained substantially poorer than the original BMKG–Abdurachman combination. This result demonstrates that the performance of a rainfall dataset cannot be evaluated independently from the erosivity equation used to process it. Although the rainfall scenarios provide the input series, the selected empirical formulation determines how the characteristics of that series are translated into the R factor. Consequently, differences in the formulation of the erosivity equations can lead to different levels of sensitivity to the rainfall scenarios. Under the conditions evaluated in this study, the Utomo-based combinations were less consistent with the reference observations than the BMKG–Abdurachman combination.

The NASA rainfall scenarios represent a different issue because they use an alternative rainfall source rather than reconstructing the original BMKG series. The NASA rainfall dataset produced a minimum RMSE of 1.607 with the Utomo A equation, while the calibrated NASA dataset produced an RMSE of 1.618 with the Lenvain equation. Thus, calibration of the NASA rainfall data did not improve the sediment-yield estimation performance in this study. This finding suggests that improving agreement in rainfall magnitude through calibration does not necessarily result in better erosivity estimation, as differences in the temporal and spatial characteristics of rainfall may remain. Therefore, the higher RMSE obtained from the NASA scenarios should not be interpreted as evidence that satellite rainfall products are generally inferior to ground observations, but rather as an indication that the original BMKG dataset was more suitable for the specific erosivity and sediment-yield application evaluated in the Ciputat Sub-watershed.

This finding is particularly relevant in tropical watersheds such as the Ciputat Sub-watershed, where rainfall characteristics may vary considerably between rainfall events and over relatively short temporal scales. Such variability is important for rainfall erosivity estimation because empirical erosivity equations respond to rainfall characteristics rather than rainfall totals alone. Satellite-derived rainfall products can provide valuable spatial information, particularly where ground observations are limited, but differences between satellite estimates and local observations may become important when the data are used to calculate rainfall erosivity. Therefore, the results highlight the importance of locally validating rainfall datasets before their application in USLE-based erosion assessment, particularly in tropical watersheds where local rainfall variability can be substantial.

Comparison with Field Observation

The sediment yield estimated using the best-performing scenario (BMKG–Abdurachman) was compared with field observations.

Table 17. Comparison with Field Observation

	MS = A x SDR		Qs = k x Cs x Q	
	USLE	**Classification**	**Observation**	**Classification**
Sub-Watershed 1	0.96	Very Low	0.44	Very Low
Sub-Watershed 2	1.23	Very Low	1.76	Very Low
Sub-Watershed 2	1.88	Very Low	3.27	Very Low

Both the modeled and observed sediment yields were classified as Very Low, indicating good qualitative agreement despite quantitative differences. This finding suggests that the selected rainfall scenario and rainfall erosivity equation were able to represent the sediment transport condition within the Ciputat Sub-watershed.

Erosion Hazard and Water Quality Assessment

Table 18. Erosion Hazard and Water Quality Assessment

	Modeled		Observation	
BMKG	**Erosion**	**Classification**	**TSS**	**Classification**
Sub-Watershed 1	4.69	Very Light	7	Unpolluted
Sub-Watershed 2	5.19	Very Light	9	Unpolluted
Sub-Watershed 3	6.40	Very Light	8	Unpolluted

The estimated soil loss was classified as Very Slight Erosion Hazard, while the observed TSS concentrations indicated that all monitoring locations remained within the unpolluted category. Although derived from different indicators, both assessments consistently suggest that the watershed is currently characterized by relatively low erosion and sediment transport intensity.

CONCLUSION

This study evaluated the influence of different rainfall data scenarios and empirical rainfall erosivity equations on sediment yield estimation using the Universal Soil Loss Equation (USLE) in the Ciputat Sub-watershed, South Tangerang. Seven rainfall data scenarios and six rainfall erosivity equations were compared and validated against field observations using Total Suspended Solids (TSS) and stream discharge measurements. The evaluation demonstrated that the original BMKG rainfall dataset generally produced better model performance than the rainfall reconstruction and satellite-based rainfall datasets. Among the evaluated rainfall erosivity equations, the Abdurachman equation yielded the best agreement with the reference observations, producing the lowest RMSE (0.916) and the highest NSE (0.375). These results indicate that both rainfall data quality and the selection of an appropriate rainfall erosivity equation substantially influence the reliability of USLE-based sediment-yield estimation.

The best-performing combination, consisting of the original BMKG rainfall dataset and the Abdurachman rainfall erosivity equation, produced sediment-yield estimates that were qualitatively consistent with field observations. Both modeled and observed sediment yields were classified as Very Low, while the estimated erosion hazard was categorized as Very Slight and the observed TSS concentrations indicated an unpolluted condition. Although the numerical sediment-yield estimates differed from the field observations, their consistent classification indicates that the selected rainfall–erosivity combination was able to represent the general sediment-yield condition of the study area. The novelty of this study lies in the systematic evaluation of multiple rainfall data scenarios together with various empirical rainfall erosivity equations and direct field validation, allowing the identification of the most suitable rainfall–erosivity combination for the Ciputat Sub-watershed.

This study has several limitations. First, field sampling for sediment concentration and stream discharge was conducted only once due to time constraints. Therefore, the field observations may not adequately represent temporal and seasonal variations in sediment transport, particularly under different rainfall conditions. Second, the rainfall datasets used in this study contained missing observations. Although several rainfall reconstruction methods were evaluated, the use of incomplete rainfall records may still introduce uncertainty into rainfall erosivity and sediment-yield estimation. In addition, the analysis was conducted in only one tropical urbanizing watershed, which limits the direct generalization of the findings to watersheds with different climatic, rainfall, topographic, soil, and land-use characteristics.

Therefore, future research should prioritize the use of rainfall stations with more complete and continuous records to minimize missing observations and improve the reliability of rainfall erosivity estimation. Further research is also recommended to investigate combinations of rainfall data reconstruction methods according to the characteristics and duration of missing periods, such as applying specific methods for isolated one-day gaps and different approaches for consecutive two- or three-day gaps, in order to reduce cumulative reconstruction errors. Field sediment concentration and stream discharge should also be monitored periodically, preferably at least once a month over one full year, to capture seasonal variations in sediment transport under wet, transitional, and dry conditions and provide a more representative validation dataset. In addition, future studies may incorporate higher-resolution satellite imagery combined with machine-learning algorithms, such as Random Forest or Support Vector Machine, within the Google Earth Engine (GEE) platform to improve land-cover classification and the detection of seasonal conservation patterns. These improvements would enhance the reliability, temporal representativeness, and generalizability of USLE-based sediment-yield estimation in tropical watersheds.

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