



Validation and comparison of event-based sediment yield estimations using MUSLE and RUSLE/SDR models: the case of çarşamba suyu sub-basin, southwest central Anatolia, Türkiye

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Abstract

Accurate sediment yield estimation is essential for watershed management, yet modeling uncertainties persist, particularly in the absence of continuous event-based observations. This study evaluates event-scale sediment yield predictions for 62 storm events over four years using RUSLE/SDR and MUSLE within a GIS-based framework for the Çarşamba Suyu Sub-Basin, Türkiye. Model parameters were derived from rainfall erosivity, soil data, topographic features, and satellite imagery. Calibration incorporated energy-based erosivity metrics rainfall kinetic energy (R -factor) and runoff energy ($Q \cdot qp$) to enhance predictive performance. Although official records have shifted from event-based to monthly discharge monitoring in recent years, available observations allowed model calibration and partial validation. Both MUSLE and RUSLE showed strong internal consistency ($R^2 = 0.95$), and significant correlations with observed data (MUSLE: $R^2 = 0.70$, RUSLE/SDR: $R^2 = 0.56$). Overestimation was noted in 2017 (MUSLE: $1.189 \text{ t ha}^{-1} \text{ yr}^{-1}$, RUSLE/SDR: $1.419 \text{ t ha}^{-1} \text{ yr}^{-1}$, observed: $0.328 \text{ t ha}^{-1} \text{ yr}^{-1}$), while MUSLE closely aligned with observations in 2018 (0.952 vs. $0.991 \text{ t ha}^{-1} \text{ yr}^{-1}$). By 2019, both models converged on observed values (MUSLE: 0.259 , RUSLE/SDR: 0.288 , observed: $0.238 \text{ t ha}^{-1} \text{ yr}^{-1}$). Integration of the Composite Weighted Connectivity Index (CWCi) and seasonal adjustment of the soil erodibility factor (K) further improved accuracy. The findings highlight RUSLE's suitability for long-term trend analysis, while MUSLE provides event-specific resolution. A hybrid framework combining both models alongside connectivity-based calibration and regression between R and $Q \cdot qp$ is recommended to improve sediment yield prediction, especially in data-limited basins.

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1 Introduction

Soil erosion is a significant environmental challenge worldwide (Reda et al. 2024). It leads to nutrient losses from the soil surface, degrades land, contaminates water, and transports sediment into water bodies (Ghosh et al. 2022). Among the various forms of land degradation, water-induced soil erosion is particularly severe (Aiello et al. 2015). Water erosion mainly occurs through the detachment of soil particles caused by the impact force of raindrops or runoff, followed by the movement of these displaced sediments through rainfall or runoff (Deviren Saygin and Erpul 2019). Several hydro-environmental factors and human activities contribute to soil erosion, including climate conditions, topography, soil characteristics, land cover, deforestation, and overgrazing (Dragovic and Vulevic 2020). Soil erosion and sedimentation are resulting from both hill slope and channel erosion due to rainfall and runoff present serious environmental concerns, leading to water pollution in lakes and rivers and reduced water storage capacity in dams (Shinde et al. 2011).

Türkiye is highly susceptible to water erosion due to the interplay of its semi-arid climate, steep topography, and shallow soils with low organic matter content. This vulnerability is particularly evident in regions such as Central Anatolia, Eastern Anatolia, and the Mediterranean, where traditional tillage, limited vegetation cover, and unsustainable land use practices such as deforestation and overgrazing accelerate soil degradation. Intense and irregular rainfall events, especially in transition zones between Continental and Mediterranean climates like Central Anatolia and the Aegean, further increase surface runoff and erosion risk. These impacts are amplified under drought conditions, which reduce soil infiltration capacity and resilience through the depletion of organic matter (UNCCD 2016, Berberoglu et al. 2020). These factors collectively increase the land's susceptibility to water erosion processes. Thus, 12.67% of the country's land area is exposed to "severe" or "very severe" erosion damage, with approximately 642 million tons of soil transported by water erosion annually. In terms of erosion severity, 79.4% of the total area experiences very low-to-low erosion, while 20.6% is affected by moderate to very severe erosion (Iskender and Erpul 2024). The distribution of these losses has been calculated as 248.6 million tons in agricultural areas, 344.6 million tons in rangelands, and 26.8 million tons in forest areas. Across Türkiye, soil loss averages $8.42 \text{ t ha}^{-1} \text{ y}^{-1}$ in agricultural areas, $18.36 \text{ t ha}^{-1} \text{ y}^{-1}$ in rangeland, and $1 \text{ t ha}^{-1} \text{ y}^{-1}$ in forested areas (Erpul et al. 2018).

Given the increasing frequency and intensity of extreme rainfall events due to climate change, event-based sediment yield estimation is crucial for understanding erosion dynamics and managing high sediment flows. The soil erosion and sediment yield prediction provides valuable insights for adaptive watershed management, particularly in managing high sediment flows resulting from such events. Various models have been developed for the evaluation of soil erosion according to their complexity and applicability which are categorized into three main types, such as, empirical, physical and conceptual (Deviren Saygin et al. 2018; Andualem et al. 2023).

Empirical soil erosion models such as the Universal Soil Loss Equation (USLE) (Wischmeier and Smith 1978), the Revised Universal Soil Loss Equation (RUSLE) (Renard et al. 1997), and the Modified Universal Soil Loss Equation (MUSLE) (Williams 1975) are widely used for predicting catchment soil erosion and sediment yield due to their simplicity

and reliance on readily available data (Angima et al. 2003, Hajigholizadeh et al. 2018, Andualem et al. 2023). These models, validated across agricultural and watershed scales (Merritt et al. 2003), differ in their applications. The RUSLE estimates rainfall-driven erosion using the R factor, while the MUSLE incorporates runoff volume and peak discharge to estimate event-based sediment yield (Sadeghi et al. 2014, Wenhai 2022). Both models rely on factors such as soil properties, landform, and vegetation (Prasannakumar et al. 2011). The RUSLE model is suitable for predicting long-term average soil erosion rates but does not account for gully erosion or sediment yield without incorporating a sediment delivery ratio (Deviren Saygin et al. 2014). In contrast, the MUSLE model, developed for event-based sediment yield estimation, is more effective in small catchments due to its use of flow variables like runoff volume and peak discharge (Koç 2014, Reda et al. 2024).

Remote sensing and GIS techniques have provided great benefits in terms of accuracy and speed in analyzing complex natural data in erosion modeling studies (Bouhadeb et al. 2018, Deviren Saygin et al. 2018). Furthermore, significant progress has been made with the integration of Google Earth Engine into these techniques, which is now integrated into GIS, offering enhanced capabilities for large-scale analysis (Alebachew et al. 2025). Berteni et al. (2021) applied the MUSLE model to assess the impact of climate change on sediment yield in a small alpine catchment in Northern Italy. Their study found that sediment yield could increase by 24–44% under future climate scenarios, emphasizing the need to incorporate climate projections into sediment transport assessments. Similarly, Arekhi et al. (2012) applied the MUSLE model to the Kengir watershed in Iran, where they simulated sediment yields for six storm events. The results showed a high degree of accuracy, with sediment yield estimates within 2.30% to 25.24% of observed values, validating the model's effectiveness for sediment yield prediction in the region. In a different study, Zhang et al. (2009) used the ArcMUSLE tool in Black Hawk County, Iowa, predicting a sediment yield of 6669 tons and a runoff volume of 765,370 m³. Their results demonstrated a strong correlation between runoff and sediment yield, with areas of high LS factor and hydrologic soil group D contributing the most to sediment delivery, highlighting the tool's effectiveness in prioritizing critical erosion areas. In contrast, Cambazoglu and Oguz (2004) compared sediment yield predictions in the Western Black Sea region using USLE with weighted average factors and GIS-based USLE. They found a strong correlation between both methods ($R^2 = 0.967$), and after optimizing the USLE equation with nonlinear regression, the correlation improved to $R^2 = 0.978$, indicating more accurate predictions. Moving forward, Ricker et al. (2008) used RUSLE and SDR models to estimate sediment yield in two sub-watersheds of the Rappahannock River. Their study revealed consistent sediment yield predictions in Little Falls Run but over-predictions in Horsepen Run, likely due to anthropogenic disturbances such as ATV trails. This finding suggests that such factors should be incorporated into sediment yield modeling for improved accuracy. Furthermore, the MUSLE model has been widely employed by researchers, including Odongo et al. (2013), Sadeghi et al. (2014), Ezzaouini et al. (2020), Hao et al. (2022), and Hara et al. (2024). The Çarşamba Suyu Sub-Basin in Southwest Central Anatolia, Türkiye, with its varied topography and susceptibility to rainfall- and runoff-induced erosion, offers an ideal environment to test these models. This region enables a robust comparison of the event-based predictive capabilities of RUSLE and MUSLE.

Connectivity evaluation has become a crucial component in hydrology, particularly for analyzing runoff and sediment transport within watersheds. This approach is valuable for assessing sediment sources, soil loss distribution, and sediment transport, contributing significantly to watershed and river channel management (Fryirs et al. 2007). From a sediment delivery perspective, not all eroded materials reach to the watershed outlet, as buffers and

barriers disrupt connectivity within drainage networks. Their impact on sediment transport depends on their shape, location, and interaction with the surrounding landscape (Hooke et al. 2021). Therefore, selecting appropriate sediment connectivity indices is critical for accurately evaluating hydrological responses in terms of both water and sediment fluxes. Previous studies have shown a strong positive relationship between sediment yield and sediment connectivity, as observed in 11 sub-watersheds (Arabkhedri et al. 2021).

However, assessing sediment connectivity remains a challenging task, as it cannot be directly measured, and multiple factors influence its dynamics (Bombino et al. 2020). Various frameworks have been proposed for its evaluation across different climatic and environmental settings (Upadhayay et al. 2020). The Index of Connectivity (IC), initially proposed by Borselli et al. (2008) and later refined by Cavalli et al. (2013), integrates upslope and downslope factors to assess sediment connectivity in small watersheds.

This study proposes that the MUSLE model, which incorporates runoff-related variables, provides more accurate event-based sediment yield estimations than RUSLE/SDR, which relies on rainfall erosivity. The significance of this research lies in its comparative assessment of these models using observed data, offering a comprehensive evaluation of their applicability across various erosion-driving factors.

This study aims to evaluate the applicability of the MUSLE and RUSLE/SDR models in predicting event-based sediment yield by comparing their predictions with observed data. A total of 62 rainfall events will be analyzed, and the accuracy of the model predictions will be evaluated. Key factors, such as the R factor in RUSLE and the (Q-qp) factor in MUSLE will be calibrated to improve prediction accuracy. Regression analysis will be conducted to establish the relationship between the (Q-qp) and (R) factors, ensuring consistency in the representation of erosivity. To refine predictions, a Composite Connectivity Index (CCI) will be employed, incorporating spatial factors like slope, flow length, flow accumulation, and land use, which enhance the accuracy of sediment yield predictions.

2 Material and methods

2.1 Site description

The Sub-Basin area of Çarşamba Suyu - Sorkun is located in the near the Seydişehir sub-basin in the southwest part of Konya Basin in Türkiye, covering approximately 80.35 km² (Fig. 1). The climate of Konya province is classified as cold semi-arid steppe climate (BSk) (GDM 2016). The study area is characterized by a semi-humid to Mediterranean climate, influenced by continental conditions with cold, rainy winters and hot, dry summers. The average annual precipitation is approximately 750.3 mm (Sarı & İnan 2011; Buldur and Sarı, 2012). The average annual temperature typically ranges between −0.4 °C and 23°C. July and August are the hottest months while January and February are the coldest. The highest total rainfall occurs in December (150.4 mm) and January (124 mm), while the lowest rainfall observed in July (8.8 mm) and August (10.5 mm) (Gürler 2017).

The study area is characterized by a highly mountainous and rugged landscape, with elevations in southern and western regions reaching up to 2500 meters (Buldur & Sari 2012). Frequent high-intensity rainfall events contribute to significant erosion and sedimentation challenges, particularly in the steep and mountainous areas of the watershed. According to the General Directorate of Rural Services (1992), the soils in the study area are categorized

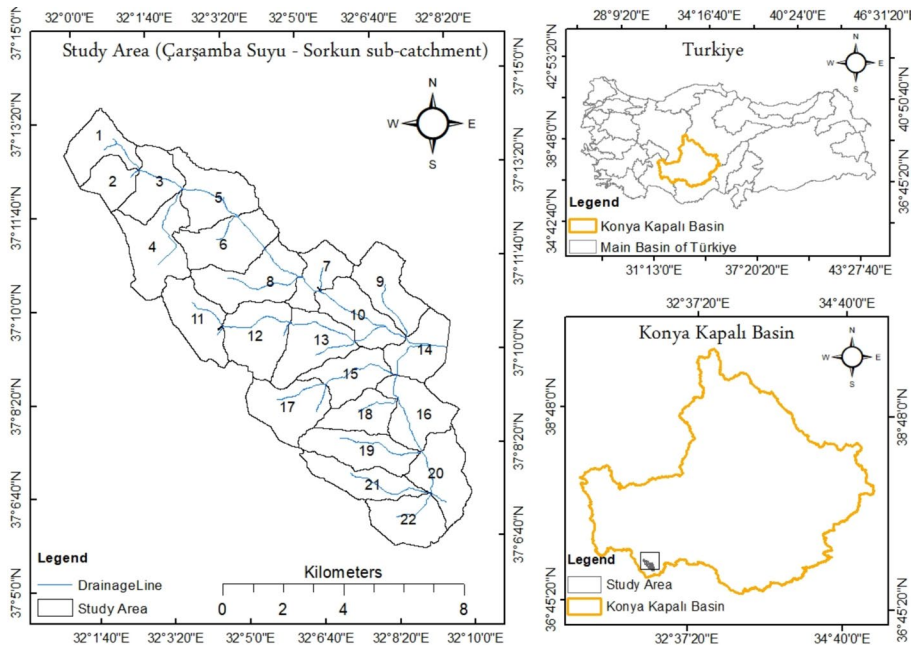


Fig. 1 Sub-catchments and drainage network of the Çarşamba Suyu-Sorkun Sub-basin, located within the Konya Basin, Türkiye

primarily as Chromic Luvisols in the southern and western regions, whereas Haplic Kastanozems dominate the northern areas, which are mainly used for forest and pasture.

In this study, the RUSLE and MUSLE models were applied with a GIS-based technique to estimate event-based sediment yield in the study area. Meteorological data (precipitation and runoff) were obtained from local stations, while soil properties were derived from detailed soil survey maps. Topographic information, flow direction, flow accumulation and stream channels were extracted from Digital Elevation Models (DEM) with 10-meter resolution. These data provided by the Ministry of Urbanization, Environment and Climate Change of Türkiye. Satellite imagery (Landsat 8 OLI) for 2016 and 2018 was obtained from the United States Geological Survey (USGS), which provides reliable land cover data and remote sensing resources for environmental analysis.

ArcGIS Hydro Tools were used for watershed delineation, slope length and steepness calculations, and the determination of hydrological variables, while the Google Earth Engine (GEE) platform was employed to derive vegetation indices (NDVI) and land use classifications. These spatial datasets were integrated to compute RUSLE factors (R, K, LS, C, and P) and determine runoff volume and peak discharge components for the MUSLE model, enabling sediment yield prediction across the study area.

Both models share common factors, such as the K factor (soil erodibility), LS factor (length and steepness), C factor (cover management), and P factor (support practices). For event-based sediment yield prediction, RUSLE cannot directly estimate sediment yield. Therefore, it was adapted by incorporating the sediment delivery ratio (SDR), which represents the proportion of eroded soil transported from a given area to the watershed outlet. The SDR was determined based on the slope of the main stream channel within the sub-catchment (Erpul et al. 2013a, b, c, Das and Sarma 2017).

Both RUSLE and MUSLE were applied to estimate sediment yield on an event basis. Although the K factor is common to both models, they differ in their use of climatic drivers: RUSLE uses rainfall erosivity (R), while MUSLE replaces this with a runoff factor. As a result, their output formats vary with RUSLE traditionally producing soil loss in $\text{t ha}^{-1} \text{yr}^{-1}$, and MUSLE providing sediment yield in tons. However, in this context, both models were adapted to estimate event-based sediment yield across 22 sub-catchments and 62 rainfall events. Figure 2 presents the study workflow.

2.2 Revised Universal Soil Loss Equation (RUSLE)

The Revised Universal Soil Loss Equation (RUSLE) was applied to estimate event-based sediment yield in this study and the general form of RUSLE Equation as shown in (Eq. 1).

$$A_e = R_e \cdot K \cdot L \cdot S \cdot C \cdot P \tag{1}$$

- A_e : Event-based soil loss ($\text{t ha}^{-1} \text{event}^{-1}$)
- R_e : Event-based rainfall-runoff erosion factor ($\text{MJ mm ha}^{-1} \text{h}^{-1} \text{event}^{-1}$)
- K : Soil erodibility factor ($\text{t ha}^{-1} \text{MJ}^{-1} \text{mm}^{-1}$)
- L : slope length factor (dimensionless)
- S : slope steepness factor (dimensionless)
- C : Cover management factor (dimensionless)
- P : Conservation practices factor (dimensionless)

To estimate sediment yield at the watershed outlet, the Sediment Delivery Ratio (SDR) was incorporated into the model as follows (Williams and Berndt 1977):

$$Y_e = A_e \cdot \text{SDR} \tag{2}$$

$$\text{SDR} = (0.627 \cdot \text{SLP})^{0.403} \tag{3}$$

- Y_e : Event-based sediment yield ($\text{t ha}^{-1} \text{event}^{-1}$)
- SDR : Sediment delivery ratio (dimensionless)

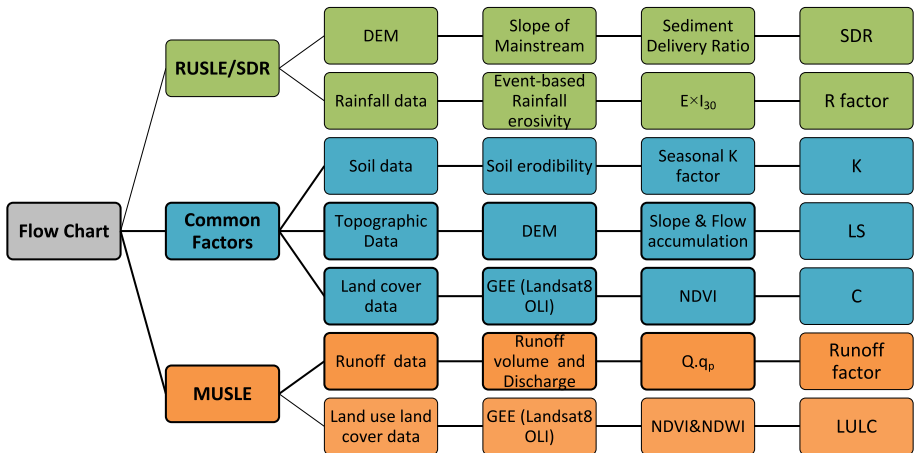


Fig. 2 Study action plan flow chart

SLP: Slope of the main stream channel (%)

Equation (2) calculates the sediment yield by applying SDR to the estimated soil loss (A_e), while Eq. (3) defines SDR as an empirical function of the main stream slope (*SLP*), representing the fraction of eroded soil that reaches the watershed outlet. The *SDR* varies depending on factors such as topography, drainage size, and vegetation cover, which affect sediment transport efficiency within catchments (Kumar and Pandey 2019)

2.2.1 Event-based rainfall Erosivity (R_e)

The event-based rainfall and runoff erosivity factor (R_e) varies based on geographic location and storm characteristics. The erosion potential is directly influenced by the intensity and duration of a storm; as the storm's intensity and duration increase, the erosion potential also increases (McKague 2023). The R factor, as defined by Wischmeier and Smith (1978), is calculated as the product of the total kinetic energy of a storm and its maximum 30-minute rainfall intensity, representing the storm's erosive potential (Eq. 4).

$$Re = (E_T) \cdot (I_{30}) \quad (4)$$

where, R_e is the event-based rainfall erosivity factor, E_T is equal to the product of the total kinetic energy of a given precipitation (E_T , MJ ha^{-1}) and the I_{30} is the highest intensity of that precipitation in 30 min (I_{30} mm h^{-1})

To calculate the event-based erosivity factor (Re) over multiple storms, the following equation is used (Eq. 5).

$$Re = \frac{1}{N} \sum_{j=1}^n (E_T \cdot I_{30})_j \quad (5)$$

where,

Re : is the rainfall erosivity factor ($\text{MJ mm ha}^{-1} \text{h}^{-1}$).

n : is the total number of storms in the dataset (62 storms).

E_T : is the total kinetic energy of a given storm ($\text{MJ ha}^{-1} \text{mm}$).

I_{30} : is the maximum 30-minute rainfall intensity (mm h^{-1}) for each storm.

A direct computation of R factor (R_e) requires continuous rainfall intensity data at 30-minute time intervals. In this study, 62 storm events were analyzed over a four-year period to estimate sediment yield in the selected watershed using an event-based approach (Renard et al. 1997).

2.2.2 Soil erodibility (K-factor)

The K factor represents soil erodibility, indicating the soil's susceptibility to erosion. It is determined based on several soil parameters, including the proportion of sand, silt and clay particles, as well as organic matter content (Djoukbala et al. 2018). The annual K factor dataset was obtained from the Dynamic Erosion Modeling and Monitoring System (DEMIS) (Erpul et al. 2018). This dataset was compiled by the General Directorate of Combating Desertification and Erosion in Türkiye and includes all relevant soil properties necessary for calculating the K factor. The K factor was annually computed using the equation developed by Torri et al. (1997 2002), which has been validated and tested in multiple

studies in Türkiye and was used in the preparation of the Türkiye Soil Erosion Map (Akgoz et al. 2022, Deviren Saygin et al. 2011, 2014).

$$K = 0.0293 \cdot a \cdot B \quad (6)$$

$$a = (0.65 - DG + 0.24DG^2) \quad (7)$$

$$B = \exp \left[-0.0021 \frac{OM}{C} - 0.00037 \cdot \left(\frac{OM}{C} \right)^2 - 4.02C + 1.72C^2 \right] \quad (8)$$

where, K represents the soil erodibility factor to erosion, DG is the geometric mean of soil particle size, C is the percentage of clay content, and OM refers to the organic matter content.

In this study, the event-based K factor values were calculated by using seasonal equations (Eqs. 9–15). Initially, the K factor was determined on semi-monthly (15-day). Several key variables were considered for this calculation (Eq. 19 and 20), including monthly temperature variations, periods of soil freezing, and precipitation distribution. These factors directly influence soil erodibility by affecting the duration and intensity of erosion-prone conditions. The timing of maximum (t_{max}) and minimum (t_{min}) soil erodibility within the calendar year plays a crucial role in the formulation of the equations used (Kiciman et al. 2024).

$$\text{If } t_{max} < t_i < t_{min} \text{ then} \quad (9)$$

$$K_i = K_{max} \left(\frac{K_{min}}{K_{max}} \right)^{\frac{t_i - t_{max}}{\Delta t}} \quad (10)$$

where, K_i represents the soil erodibility factor at any time t_i (in calendar days), K_{max} and K_{min} are the soil erodibility factors at times t_{max} and t_{min} , respectively. Δt represents the growing season or frost-free period (≤ 183 d); and T_{av} is the average daily temperature.

$$\text{If } t_i < t_{max} \text{ or } t_i > t_{min} \text{ then} \quad (11)$$

$$K_i = K_{min} \exp [0.009(t_i - t_{min} + 365)\delta] \quad (12)$$

$$\text{If } (t_i - t_{min}) \leq 0, \delta \text{ and if } t_i - t_{min} > 0, \delta = 0 \quad (13)$$

$$\text{If } T_{av} \leq -2.7^\circ C, K_i = t_{min} \quad (14)$$

$$\text{where } K_i < K_{min} \text{ then } K_i = K_{min} \quad (15)$$

The values of K_{max} , K_{min} , t_{max} and t_{min} to be used in the above relationships are determined with Eqs. (16) and (18), using event-based rainfall energies ($RUSLE-R$, EI) (Deviren Saygin 2021).

$$\frac{K_{max}}{K_{min}} = 8.6 - 0.19 R \quad (16)$$

$$\frac{K_{\max}}{K_{\text{nom}}} = 3.0 - 0.005 R \quad (17)$$

$$T_{\max} = 154 - 0.44 R \quad (18)$$

Semi-monthly R factor distributions (15-day EI %) were computed using the following Eqs. (19) and (20). This approach divided the monthly R factor into two 15-day periods based on percentage erosivity index (EI) values (Bozdir 2022).

$$EI_1 = EI \frac{0.75(EI - 1) + 0.25(EI + 1)}{(EI - 1) + (EI + 1)} \quad (19)$$

$$EI_2 = EI \frac{0.25(EI - 1) + 0.75(EI + 1)}{(EI - 1) + (EI + 1)} \quad (20)$$

where,

EI: the value for the desired month.

EI-1: the value for before of the desired month.

EI+1: The value for the after of the desired month.

EI₁: the value calculated for the first 15 days of the desired month.

EI₂: The value calculated for the second 15 days of the desired month.

2.2.3 Slope length and steepness (LS-factor)

The LS Factor represents the combined impact of slope length and slope steepness on soil erosion (Chang et al. 2016). It is calculated as ratio of soil loss from a given slope length and steepness to the soil loss from a standard unit plot (fallow plot, up-down slope clean tilled, 22.1 m long plot at 9% slope) (Wischmeier and Smith 1978; Renard et al. 1997). The total surface runoff and its velocity which causes soil loss, increase with slope length and steepness (Ghosal and Bhattacharya 2022; Handique et al. 2023). The LS factors can be obtained by multiplying the length and steepness of the slope values together (Eq. 21). In this study, a Digital Elevation Model (DEM) with resolution 10-meters was used to estimate LS values. These values were calculated based on flow accumulation (χ) and slope degree (θ) using Raster Calculator in ArcGIS. The flow accumulation term (χ) indicates the amount of water flow contributing to erosion over the slope length, while the slope steepness (θ) reflects the steepness of the area (Lee 2004). The LS factors were calculated using the equations developed by Moore and Bruch (1986a, b), and cell based average LS values for each sub-catchment was derived by applying Cell Statistics tools in ArcMap.

$$LS = \left(\frac{\chi \eta}{22.13} \right)^{0.4} \cdot \left(\frac{\sin \theta}{0.0896} \right)^{1.3} \quad (21)$$

where, χ ; flow accumulation derived from DEM using a GIS accumulation algorithm, η ; cell size, and θ ; slope steepness in degrees.

2.2.4 Land use land cover (C-factor)

The C factors were derived from images captured by the Landsat 8 Operational Land Imagery (OLI) satellite. Two Landsat 8 images from 2016 and 2018 were downloaded and selected based on their relevance to the study period. Normalized Difference Vegetation Index (NDVI) processing was applied. The C factor was calculated using Eq. (22) developed by van der Knijff et al. (2000), with coefficients $\alpha = 2$ and $\beta = 1$. These coefficients were chosen based on their empirical validation for Mediterranean climatic conditions, effectively capturing the impact of land cover on soil erosion. $\alpha = 2$ reflects the significant effects of vegetation changes in such climates, while $\beta = 1$ adjusts for the specific relationship between vegetation management and erosion observed in the Mediterranean conditions. The cell-based average C values were derived using GIS cell statistic tools and applied to each sub-catchment within the study area.

$$C = \text{Exp} \left[-\alpha \cdot \frac{\text{NDVI}}{\beta - \text{NDVI}} \right] \quad (22)$$

2.3 Modified universal soil loss equation model (MUSLE)

The MUSLE model (Williams 1975) is a modified form of the USLE model (Wischmeier and Smith 1978). It is a sediment yield prediction model that can be applied to individual storms. Unlike RUSLE, where the rainfall erosivity factor (R factor) is used, MUSLE replaces this with a runoff factor that includes runoff volume (Q) and the peak discharge rate (q_p). This model has been widely validated and tested in numerous countries (Jaramillo 2007). In this study, runoff volume (Q) and peak discharge rate (q_p) were computed utilizing the unit hydrograph triangular and rational methods. These methods were selected for their suitability and applicability for small to medium sized catchments, particularly in contexts where detailed runoff and rainfall data are available. As both methods are relying on the time of concentration concept and they are appropriately aligned with the specific hydrological characteristics of the study area's sub catchments. This alignment ensuring that the methods are suitable to capture the time sensitive runoff and discharge pattern relevant to each sub-catchment's unique response storm events. The unit hydrograph and rational methods are widely used to predict runoff in response to storm events, making them well suited for study area to ensure the consistency in runoff volume and peak discharge prediction. Williams (1975) proposed the general form of MUSLE model (Eq. 23).

$$Y = \frac{11.8(Q \times qp)^{0.56} K \times LS \times S \times C \times P}{100A} \quad (23)$$

where,

Y: Sediment yield caused by the storm event (t ha^{-1})

Q: Runoff volume (m^3)

q_p : Peak discharge ($\text{m}^3 \text{s}^{-1}$)

A: Drainage area (km^2)

The factors K , LS , C and P are defined as in the RUSLE equation for the specific storm event. In the equation (Eq. 25), A is the drainage area in km^2 , multiplied by 100 to convert to hectares. Resulting sediment yield will be in tons per hectare (t ha^{-1}) (Shi et al. 2022).

2.3.1 Runoff volume (Q)

The runoff volume (Q) is calculated using the Triangular Unit Hydrograph method, developed by the Soil Conservation Service (SCS 1969). This method assumes that the sub-catchments have a triangular shape, with the base equal to the sum of the time to peak and the time of recession, and the height equal to half of the peak discharge (Eq. 24).

$$Q = \left(\frac{qp}{2} \right) \cdot (Tp + Tr) \cdot 60 \quad (24)$$

where, Q represents the runoff volume (m^3), q_p refers to the peak runoff discharge ($\text{m}^3 \text{s}^{-1}$), T_p is the time to peak (min), T_r indicates the time of recession (minutes).

2.3.2 Runoff discharge rate (q_p)

The runoff discharge rate ($\text{m}^3 \text{s}^{-1}$) for each micro-catchment is calculated using the rational method as proposed by Tomas (1851). In this method the surface flow coefficient is initially determined using land use land cover classification; along with the time of concentration using Kirpich method (Eq. 25) (Kirpich 1940) is employed in the following manner to calculate the flow discharge rate.

$$q_p = \frac{CrIA}{360} \quad (25)$$

where, q_p represents the surface flow rate ($\text{m}^3 \text{s}^{-1}$), I refers to the rainfall intensity for a specific duration (mm hour^{-1}), A indicates catchment area (ha) and C_r represents a surface flow coefficient that is dimensionless.

2.3.3 Land use land cover (LULC)

Land Use Land Cover (LULC) maps play a crucial role in natural resource management and environmental monitoring. High-accuracy LULC data is essential for various scientific studies, including climate change monitoring, water resource management, and agricultural land assessment (Akgoz et al. 2022). With the growing demand for reliable LULC data, machine learning techniques have become increasingly important, especially with cloud-based platforms like Google Earth Engine (GEE), which offer large storage and high processing power (Xie et al. 2019).

This study utilized Landsat-8 surface reflectance data from July 2016 to July 2018 to classify land use types. The Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) calculated for the given period (Eq. 26–27). The Random Forest (RF) classifier was selected for classification due to its robustness against outliers, strong performance with high-dimensional datasets and efficient processing speed. Five classes of land cover were identified: forest, agricultural land, grassland, barren and urban.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (26)$$

RED: The reflectance value of the red band.

NIR: The reflectance value of the near-infrared band

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \quad (27)$$

SWIR: The reflectance value of the short-wave infrared band.

NIR: The reflectance value of the near-infrared band.

The runoff coefficient (C_r): The C_r for each land use type was determined using Landsat8 OLI images from 2016 and 2018. The images were classified using a supervised classification method to create a detailed *LULC* map, categorizing areas into forest, agriculture, pasture, settlement, and bare land. The classified map was then converted to raster format and integrated with a slope spatial map to extract slope percentage for each land use type using ArcGIS spatial analysis tool. Runoff coefficient values were assigned based on the surface flow coefficient standard proposed by Schwab (1981), considering both slope percentage and soil texture within each sub-catchment. The weighted average runoff coefficient for each sub-catchment was calculated based on the proportional area of each land use type using (Eq. 28).

$$Cr = \frac{1}{A} \sum_{i=1}^n (C_{ri} \times A_i) \quad (28)$$

where, C_r refers to the weighted runoff coefficient for a sub-catchment; A is the total area of a sub-catchment. C_{ri} is the runoff coefficient for each land use type i , and A_i is the area that occupied by a land use type i

Time of concentration (T_c): it measured in minutes, is a key parameter in the calculation of the peak flow rate. In order to calculate the peak flow using the rational method, it is first necessary to determine the time of concentration (T_c). A number of formulas have been proposed for calculating the time of concentration. In this study, the Kirpich (1940) is employed for the calculation of the time of concentration (Eq. 29).

$$T_c = \frac{0.01947L^{0.77}}{S^{0.385}} \quad (29)$$

where, T_c represents the time of concentration in minutes. L represents the maximum length of runoff in a given watershed, and is expressed in meters. S is the slope of the watershed expressed as $\Delta H/L$, where ΔH is the difference in elevation between the initial flow length point and the endpoint in the watershed.

2.4 Conceptual and empirical bridging between RUSLE and MUSLE

2.4.1 Conceptual equivalence of erosivity terms in RUSLE and MUSLE

Despite their differing formulations, both the RUSLE and MUSLE models aim to quantify the erosive forces exerted during storm events. At their core, each model reflects a shared physical principle—erosion as an energy-driven process. In RUSLE, the rainfall erosivity

factor (R) quantifies the product of rainfall kinetic energy and maximum 30 min intensity, effectively representing the detachment force imposed by precipitation. In contrast, MUSLE replaces R with the product of runoff volume (Q) and peak runoff rate (q_p), representing the hydraulic energy mobilized during overland flow events.

Conceptually, both R and $Q \cdot q_p$ express the energy available to detach and transport soil, shaped by storm intensity, duration, and catchment response. At the event scale, a functional relationship between these energy metrics is not only plausible but also physically grounded, given their mutual dependence on storm dynamics and hydrologic behavior.

Mechanistic studies of overland flow (Zhang et al. 1998a, b; Kinnell 1993, 1999, 2005; Erpul et al. 2003, 2004, 2013a, b) support this view, suggesting that soil loss (A) is best represented as a function of both rainfall energy and surface flow hydraulics. In this context, erosion is commonly expressed as (Eq. 30):

$$A \propto KE \times I(\text{RUSLE}) \text{ or } A \propto Q \times q_p(\text{MUSLE}) \quad (30)$$

Within this proportionality framework, the soil erodibility factor (K) can be interpreted as the slope of an empirical relationship between observed soil loss and the applied energy term. That is:

$$K \approx \frac{\Delta A}{\Delta(KE \times I)} \text{ or } K \approx \frac{\Delta A}{\Delta(Q \times q_p)} \quad (31)$$

depending on whether the analysis is rainfall-driven (RUSLE) or runoff-driven (MUSLE). In this interpretation, K is not merely a static soil property but reflects the landscape's sensitivity to erosive energy input, making it a critical linkage between process understanding and empirical calibration. This conceptual symmetry between rainfall and runoff erosivity drivers enables cross-framework consistency, facilitating comparative erosion assessments even when data availability varies.

2.4.2 Empirical justification and cross-model calibration

To operationalize this physical connection, a regression-based calibration was performed between R and $Q \cdot q_p$ using event-scale hydrological and meteorological data. This approach does not redefine either factor, but rather derives a transfer function that enables substitution or estimation of one parameter when the other is unavailable.

This calibration is particularly advantageous in data-sparse contexts, where high-resolution runoff records are often lacking, but meteorological estimates of R are more accessible. By statistically relating R and $Q \cdot q_p$, it becomes possible to apply MUSLE for event-based sediment yield predictions using only rainfall-based erosivity data.

Importantly, this approach:

- Preserves the internal structural assumptions of both RUSLE and MUSLE;
- Provides a unified erosivity signal applicable across both models;
- Enables model cross-validation and integration in multi-framework erosion studies.

Such statistical bridging underscores the broader utility of energy-based conceptualization in erosion modeling and highlights the feasibility of framework interoperability without compromising model integrity.

To achieve this, both a power regression model (aX^b) and a polynomial regression model ($aX^2 + bX + c$) were applied and tested. The power regression model was chosen for its ability to capture scale effects between $Q \cdot q_p$ and R , while the polynomial model was used to represent complex non-linear relationships. These models were tested across different rainfall intensity ranges to evaluate which provides the most accurate and consistent results between MUSLE and RUSLE. Additionally, the adjustment of the climatic index in MUSLE was intended to extend the RUSLE approach for sediment yield estimation without modifying the assessment of other factors, including the K factor.

1. Power regression model:

$$Q \cdot q_p = aR^b \quad (32)$$

The empirical coefficient values in Eq. (32), (a) and (b) obtained from the power regression conducted between R and $Q \cdot q_p$, and incorporated them into the MUSLE equation.

2. Polynomial regression model:

$$Q \cdot q_p = aR^2 + bR + c \quad (33)$$

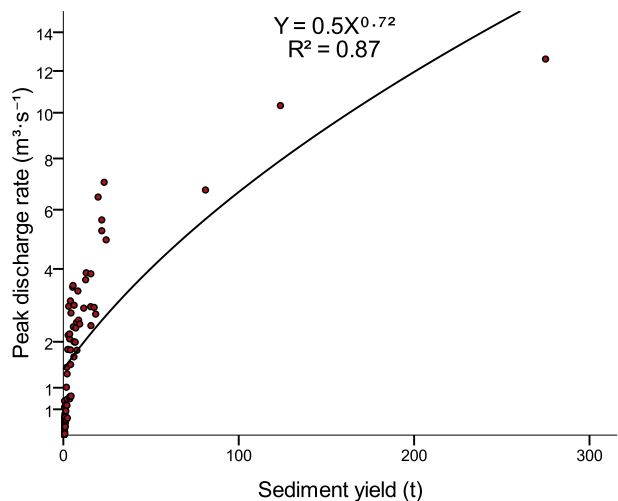
The coefficient values in Eq. (33), (a), (b), and (c) obtained from the polynomial regression applied between R and $Q \cdot q_p$, and incorporated these values into the MUSLE equation.

These adjustments help to harmonize the models and enhance the accuracy of prediction. Figure 3 indicates an example of calibration process conducting a power regression between R and $Q \cdot q_p$.

2.5 Weighted average sediment yield for the entire watershed

The area weighted average method was applied in both models to accurately represent the amount of sediment yield in the entire watershed. This approach ensures that the contributions of individual sub-catchment are proportionally reflected in the overall

Fig. 3 Power regression curve between runoff discharge rate and sediment yield, developed by the General Directorate for State Hydraulic Works (DSI) of Türkiye



sediment yield based on their respective areas. The study area consists of 22 sub-catchments (Fig. 1), and the weighted average sediment yield for each storm event using (Eq. 34). As a result, this process yielded 62 values for Y_e -*RUSLE* and 62 values for Y_e -*MUSLE*, corresponding to the 62 individual erosive rainfall events evaluated.

$$\text{Weighted}_{\text{Ave}} = \frac{\sum_{i=1}^n (Y_{ei} \times A_i)}{\sum_{i=1}^n A_i} \quad (34)$$

where,

Y_{ei} : Event-based Sediment yield from sub-catchment i .

A_i : Area of sub-catchment i .

n : Total number of sub-catchments within the study area.

2.6 Observed Sediment Yield Data

Runoff discharge and sediment yield data from 2009 to 2019 were obtained from the General Directorate of State Hydraulic Works of Türkiye. These data were collected on a monthly basis throughout each year. To estimate sediment yield based on flow discharge, a power regression model was developed using observed runoff discharge and sediment yield data (Fig. 3). The regression model was constructed using data from the period 2012 to 2018, yielding a strong correlation between these variables ($R^2 = 0.87$). The resulting regression equation was subsequently used to estimate observed sediment yield values.

This study primarily employs the *RUSLE*/*SDR* and *MUSLE* models for event-based sediment yield estimation. However, due to limited availability of observed event-based sediment yield data, a direct event based comparison was not feasible. To address this limitation, runoff discharge values calculated from event-based rainfall for the *MUSLE* model were incorporated into the regression equation developed by the General Directorate of State Hydraulic Works of Türkiye to estimate observed event-based sediment yield for the study area. The estimated observed sediment yield values were then compared on an event-based scale with the sediment yield predicted by the *RUSLE*/*SDR* and *MUSLE* models. To ensure consistency in evaluation, all sediment yield values were expressed in tons per hectare per year (Eq. (35)).

$$A_{\text{annual}} = \sum_{i=1}^n A_i \quad (35)$$

where

A_{annual} : Annual soil loss ($\text{t ha}^{-1} \text{ yr}^{-1}$)

A_i : Soil loss for an individual event (t ha^{-1})

n : Total number of events in a given year.

2.7 Sediment Connectivity Analysis (SCA)

The calculation of the Sediment Connectivity Index (SCI) for each sub-catchment was based on the combination of multiple spatial and statistical datasets ensuring a comprehensive and accurate assessment of sediment dynamics within the study area. A Digital

Elevation Model (DEM) was used to derive slope, flow direction, flow accumulation and flow path downstream in a GIS environment. These parameters are essential for computing Connectivity Indices (CI) within the watershed. Multiple connectivity factors calculated to develop a Composite Weighting Connectivity Index (CWCI) representing the study area's watershed characteristics.

2.7.1 Index of connectivity (IC)

The Index of Connectivity (IC), developed by Borselli et al. (2008), is utilized to assess structural connectivity and describe the transport of sediment from its source to its deposition area. The IC calculation is divided into upslope and downslope component (Eq. 36).

$$IC = \log_{10} \left(\frac{D_{up}}{D_{dn}} \right) \quad (36)$$

where,

D_{up} : representing the upstream factor, which integrates flow distance (Flow length-downstream) to the outlet or stream with the slope mean and land use/land cover mean (C factor).

D_{dn} : represents the contributing downstream area, which is related to flow accumulation and combined with the slope percentage and land use/land cover mean (C factor).

The D_{up} was calculated using (Eq. 37):

$$D_{up} = W \times S \times \sqrt{A} \quad (37)$$

W : Average weighting factor of the upslope contributing area, it was determined using the C factor in RUSLE, (dimensionless).

S : Average slope gradient of the upslope contributing area (m/m).

A : Upslope contributing area (m²).

The D_{dn} was calculated using (Eq. 38):

$$D_{dn} = \sum_i \frac{di}{Wi \times Si} \quad (38)$$

di : flow length to the downstream main channel along the i^{th} cell

Wi : Weighting factor related to the vegetation cover of the i^{th} cell (dimensionless).

Si : Slope gradient of the i^{th} cell (m/m).

The Connectivity Index (IC) is defined within the range $(-\infty, +\infty)$ and was calculated using (Eq. 39):

$$IC = \log_{10} \left(\frac{D_{up}}{D_{dn}} \right) = \log_{10} \left(\frac{W \times S \times \sqrt{A}}{\sum_i^n \frac{di}{Wi \times Si}} \right) \quad (39)$$

2.7.2 Topographic wetness index (TWI)

Topographic Wetness Index (TWI) was calculated to estimate the wetness of the landscape, providing insight into areas prone to water accumulation and potential sediment transport. TWI was computed using equation (Eq. (40)) (Atalla et al. 2024).

$$TWI = \ln \left(\frac{A}{\tan(\beta)} \right) \quad (40)$$

where,

A : Flow accumulation, representing the water volume contributing to specific location in the watershed ($\text{m}^2 \text{m}^{-1}$).

$\tan(\beta)$: Tangent of the slope angle at a given point.

2.7.3 Stream Power Index (SPI)

The Stream Power Index (SPI) is a topographical model designed to quantify the erosive potential of runoff within a watershed. Flow accumulation and slope percentage were integrated and calculated by Eq. (41), (Heckmann et al. 2018).

$$SPI = A^{0.5} \cdot S \quad (41)$$

where,

A : Contributing area (km^2)

S : Local slope (decimal form calculated by dividing slope % by 100).

The sediment delivery ratio (SDR) represents the proportion of eroded soil reaching to the watershed outlet. It was calculated using two empirical approaches: one based on slope percentage of the main flow length as previously calculated for the RUSLE model to convert soil loss to the sediment yield (Eq. 3) and the other calculated based on drainage area (Eq. 42) (USDA SCS 1979). The Sub-catchment area (km^2) was also incorporated into the composite index, affecting sediment and flow contribution within the watershed.

$$SDR = 0.51 A^{-0.11} \quad (42)$$

where,

A : Drainage Area (km^2)

2.7.4 Normalization of Connectivity Indices

To ensure comparability among the various connectivity indices, all indices were normalized to a common scale. Min-max normalization approach was applied to rescale the values between 0 and 1, using (Eq. 43).

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (43)$$

where,

X' : Normalized value.

X : Original value

$X_{\min}$: Minimum value in the dataset.

$X_{\max}$: Maximum value in the dataset.

2.7.5 Composite weighting factor

The composite weighting factor was determined using Principal Component Analysis (PCA) and calculated using Equation (Eq. 44).

$$SCI_i = W_1 * CI + W_2 * TWI + W_3 * SPI + W_4 * SDR_s + W_5 * SDR_a + W_6 * DA \quad (44)$$

where,

CI: Borrel connectivity index.

TWI: Topographic wetness index.

SPI: Stream power index.

SDR_s: Sediment delivery ratio based on slope.

SDR_a: Sediment delivery ratio based on area.

DA: Drainage area.

W₁ to *W₆* are the weights assigned to each factor, determined through Principal Component Analysis (PCA).

Since the RUSLE and MUSLE models overestimated sediment yield, the composite weighted connectivity index was applied to adjust model results and improve alignment with observed sediment yield values. The adjusted sediment yield was calculated using equations (Eq. 45).

$$Y_{\text{adjusted}} = \sum_{i=1}^n (WSCl_i \cdot Y_i) \quad (45)$$

A_{adjusted}: Adjusted predicted sediment yield, refined to align with observed values.

Y_i: Predicted sediment yield for sub-catchment *i* from the RUSLE and MUSLE models.

n: Total number of sub-catchments in the watershed.

WSCl_i: Weighted sediment yield contribution index for sub-catchment *i*, integrating multiple factors influencing sediment transport.

2.8 Validation assessment

To validate the performance of the models, validation metrics were employed to compare the predictions from RUSLE and MUSLE, as well as to assess the agreement between predicted and observed sediment yield. The validation metrics included Pearson correlation coefficients and the Root Mean Square Error (RMSE), to evaluate the accuracy of the models. The Pearson correlation coefficient was used to evaluate the strength of the linear relationship between RUSLE and MUSLE predictions, and the observed data. The RMSE was conducted to assess the mean magnitude of prediction error between the RUSLE, MUSLE and observed sediment yield (Eq. 46 and 47).

$$r = \frac{\sum_{i=1}^n (O_i - O_{\text{mean}})(P_i - P_{\text{mean}})}{\sqrt{\sum_{i=0}^n (O_i - O_{\text{mean}})^2 \sum_{i=0}^n (P_i - P_{\text{mean}})^2}} \quad (46)$$

O_i: Refers to the observed value for the *ith* observation.

P_i: Refers to the predicted value for the *ith* observation.

O_{mean}: Refers to the mean of the observed values.

P_{mean}: Refers to the mean of the predicted values.

n : Refers to the number of observations.

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (47)$$

O_i : Refers to the observed value for the i^{th} observation.

P_i : Refers to the predicted value for the i^{th} observation.

n : Number of observations.

3 Results

The event-based rainfall erosivity varied across the study area, reflecting differences in rainfall intensity and frequency. Figure 4 shows the variations in rainfall erosivity patterns over the 4 years. This factor was determined using data from a single rain gauge located in the study area. Due to the lack of multiple rainfall stations, it was assumed that rainfall was uniformly distributed across the watershed. The event based rainfall erosivity factor was calculated by using the EI_{30} method (Eq.4), which considers the total kinetic energy of rainfall and the maximum 30-minute intensity for each of 62 events.

Figure 5 represents the mean LS factor values over the 22 sub-catchments (Fig. 1), ranging from 3.51 to 7.45 with an average of 5.23. The highest LS values were observed in sub-catchments 9, 1, 19 and 2, respectively. These values highlight varying erosion risks across the sub-catchments. Figure 6 also presents the LS and C factor map for the study area, generated using ArcGIS.

The C factor values were derived from satellite imagery captured during specific years of the study period. These values were calculated as cell-based averages for each sub-catchment within a GIS framework and integrated into event-based sediment yield predictions using the RUSLE and MUSLE models. Across the study area, the C factor

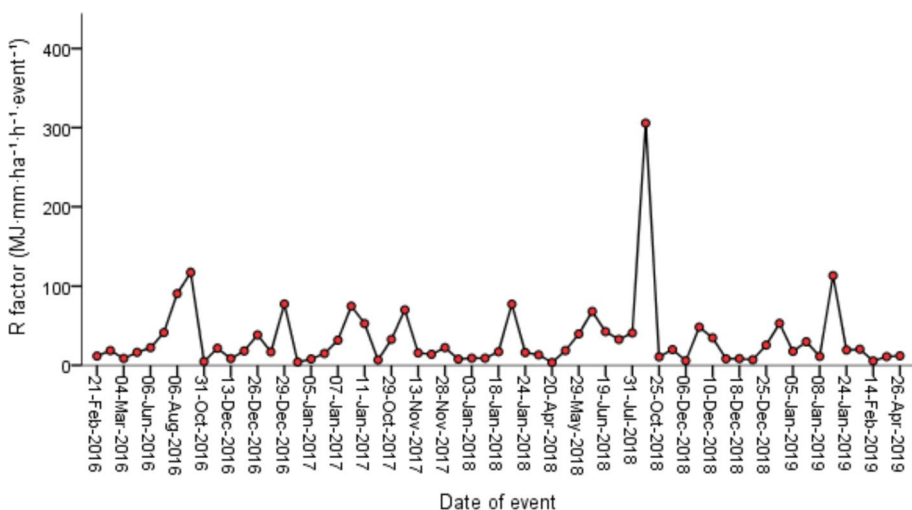


Fig. 4 Variations in the rainfall erosivity factor (R_{30}) across 62 rainfall events during the study period

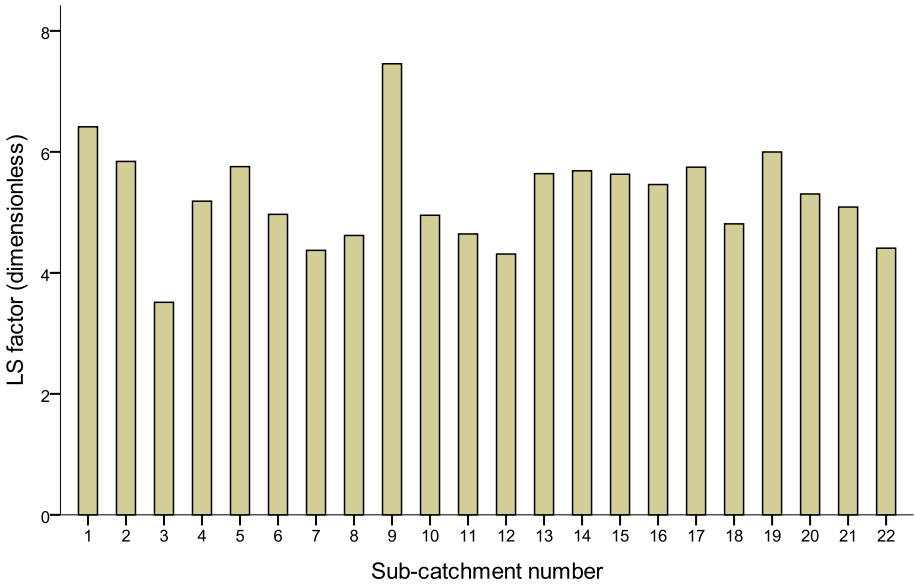


Fig. 5 The LS factor distribution over the study area

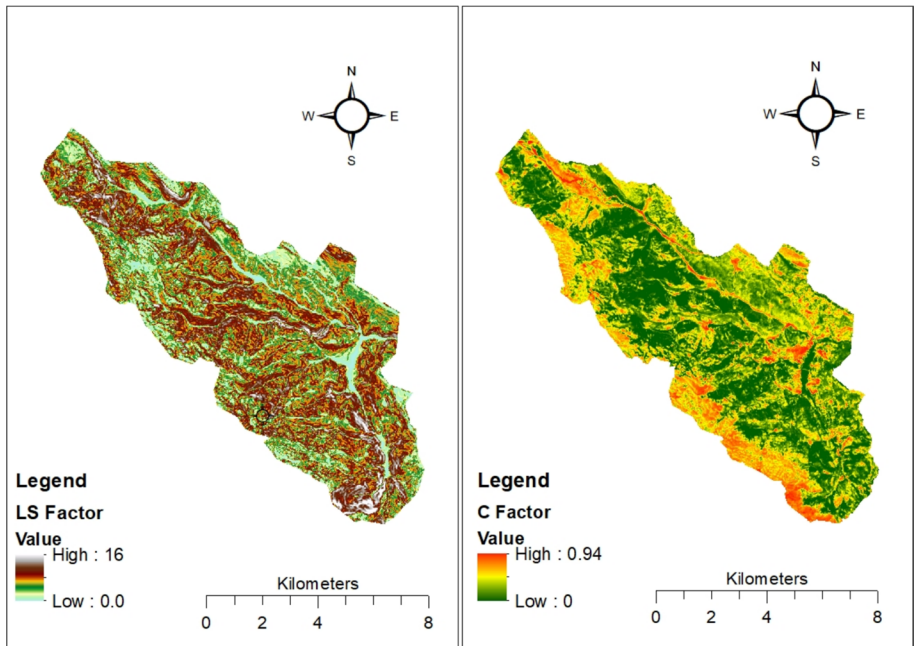


Fig. 6 Spatial distribution maps of the LS (slope length and steepness) factor and the C (cover-management) factor across the study area

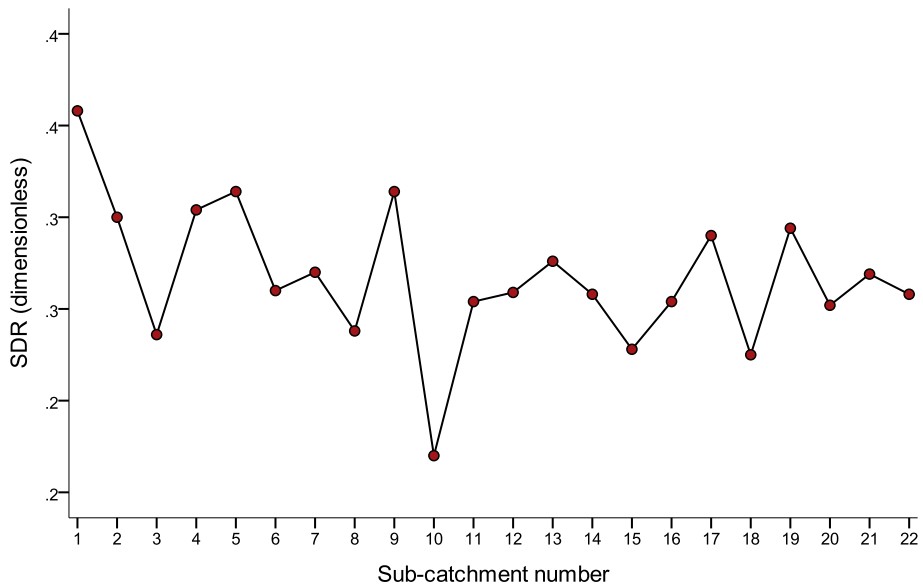


Fig. 7 Sediment Delivery Ratio (*SDR*) Across the Study Area for 22 Sub-Catchments

values varied at the cell level, ranging from 0.0 to 0.942 (Fig. 6). When averaged at the sub-catchment level, the values ranged between 0.102 and 0.427. These variations reflect differences in land cover and vegetation conditions across different years, which significantly influence soil erodibility and potential soil losses. Higher *C* factor values indicate areas with low protective land cover, increasing the risk of severe soil erosion. In contrast, lower *C* factor values correspond to areas with effective vegetation cover, which helps reduce soil loss potential by enhancing soil protection.

Figure 7 indicates the sediment delivery ratios (*SDR*) calculated based on slope percentage of the sub-catchment area. The findings show that the *SDR* value varied over the entire catchment, indicating different levels of sediment transport potential from the sub-catchments to the outlet points. This variation reflects the effects of slope and topographic features on the sediment transportation process within the study area.

Fig. 8 Land use/land cover classification of the study area (2016) used for calculating *C_r* values

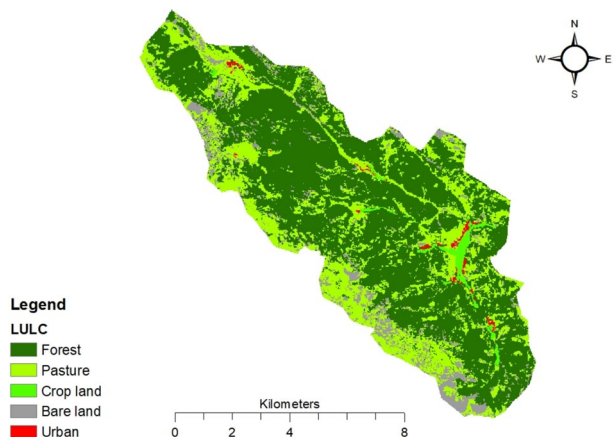


Table 1 Runoff coefficient (C_r) derived from the 2018 land use/land cover classification map for Sub-catchment No. 7 within the Çarşamba Suyu–Sorkun Sub-basin. The soil texture across the entire sub-catchment is classified as clay

Code	Land use type	Area (ha)	Area %	Slope (%)	Runoff coefficient (C_r)	Weighted runoff coefficient (C_r)
1	Bare land	7.53	2.93	56.21	0.500	0.015
2	Crop land	5.05	1.96	43.85	0.450	0.009
3	Forest Areas	171.11	66.66	61.93	0.300	0.200
4	Pasture Area	60.59	23.60	55.90	0.400	0.094
5	Urban Area	4.58	1.78	45.28	0.550	0.010
Total weighted Average Runoff Coefficient for a sub-catchment: 0.328						

Soil texture information was obtained from the Dynamic Erosion Modeling and Monitoring System (DEMIS), compiled by the General Directorate of Combating Desertification and Erosion in Türkiye (Erpul et al. 2018).

Figure 8 shows the land use land cover classification map. In the 2016 LULC classification, Overall Accuracy was found as 0.9515% and Kappa Coefficient was 0.9284%. In the 2018 LULC classification, Overall Accuracy was 0.9563% and Kappa Coefficient was 0.9401%. The high accuracy suggests that the classification method effectively distinguished different land cover types in both years. The Kappa values of 0.9284 (2016) and 0.9401 (2018) suggest a good classification accuracy and minimal misclassification errors. The slight improvement from 2016 to 2018 reflects enhancements in data quality, classification techniques, or land cover stability over time.

Table 1 presents an example of the runoff coefficient (C_r) values which were derived from the land use land cover classification map generated from the Landsat8 imagery using ArcGIS. These values were calculated (Eq. 30) as area weighted averages based on cells occupied by each land use type and applied for the runoff calculation used in the MUSLE model. The results show varying level of average (C_r) values across the study area within each sub-catchment ranging from 0.298 to 0.414 with an average of 0.364 highlighting variation in runoff potential over the land use types.

Fig. 9 A Power regression analysis between Q_{qp} vs. R_c factor for Sub-catchment No. 7 within the study area

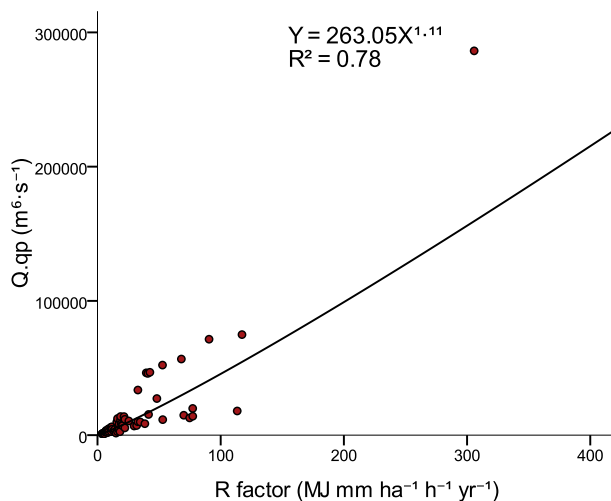


Figure 9 illustrates the relationship between the R factor and $Q \cdot q_p$, as captured through a power regression model. The fitted equation, $y=263.05x^{1.119}$, along with an R^2 value of 0.78, suggests a strong correlation between these variables, indicating that higher rainfall erosivity generally leads to increased runoff and peak discharge.

This figure provides empirical evidence of the link between rainfall erosivity and runoff-driven sediment transport, supporting the rationale for adjusting RUSLE's climatic inputs when adapting the model for runoff-based applications such as MUSLE.

3.1 Comparison of predicted sediment yield

Event-based calibration of RUSLE and MUSLE better account for the interactions between soil detachment and transport, particularly when using $Q \cdot q_p$ as a proxy for runoff-driven sediment transport. While this approach improves representation compared to long-term averaging, it still has some limitations in fully capturing all dynamic interactions.

In traditional RUSLE applications, long-term averaging masks event-specific soil detachment and transport dynamics, leading to underestimation of erosion from extreme storms. By calibrating at the event scale, the impact of short-duration, high-intensity rainfall events on both detachment (via R) and transport (via $Q \cdot q_p$) can be more accurately assessed.

Rainfall erosivity is a primary driver of soil detachment, but not all detached sediment is transported; transport depends on runoff volume and velocity. Using $Q \cdot q_p$ as a calibration factor introduces an essential transport component, making the relationship between detachment and transport more explicit.

- **Detachment-limited conditions:** Where rainfall energy is the dominant control on erosion, high erosivity (R) leads to detachment, but transport capacity may not be sufficient to move all the sediment.
- **Transport-limited conditions:** Where sufficient sediment is available, but transport depends more on runoff and flow velocity ($Q \cdot q_p$), meaning events with high runoff may mobilize more material than predicted by R alone.

Event-based calibration bridges this gap by linking erosivity with runoff-driven transport potential, improving model applicability across different hydrologic conditions.

Long-term RUSLE calculations assume an average relationship between erosivity and yield, but erosion occurs in pulses, with sediment detachment and transport varying event-by-event. By using event-based R values and calibrating them against $Q \cdot q_p$, the temporal variability of erosion processes is better reflected. This helps differentiate between short, intense events and longer, lower-intensity events, leading to improved sediment yield predictions.

Despite these improvements, event-based calibration alone does not fully resolve all detachment-transport interactions. The following limitations remain:

- MUSLE is still an empirical model and does not explicitly simulate sediment transport thresholds, flow competence, or detachment mechanisms.
- Sediment availability and connectivity are not explicitly accounted for; detachment may occur, but whether sediment reaches the outlet depends on landscape features and hydrological pathways.

- Soil type, vegetation cover, and land management factors influence detachment but are often not explicitly modeled in RUSLE/MUSLE.

In conclusion, event-based calibration significantly enhances the representation of detachment-transport interactions by integrating rainfall-driven erosivity (R) with runoff-driven transport potential ($Q \cdot q_p$). While it does not fully resolve all process complexities, it bridges a critical gap between empirical RUSLE-based estimates and runoff-driven sediment transport in MUSLE. Future refinements could incorporate physically-based hydrological and sediment transport models to further improve accuracy.

Table 2 Predicted Sediment Yield ($\text{t ha}^{-1}\text{event}^{-1}$) using RUSLE and Calibrated MUSLE ($Q \cdot q_p$ vs. R_{30}) with Polynomial and Power Regression Models

Event no.	RUSLE/SDR	MUSLE polyno- mial	MUSLE Power	Event no.	RUSLE/SDR	MUSLE polyno- mial	MUSLE power
1	0.058	0.098	0.075	32	0.059	0.077	0.070
2	0.102	0.126	0.119	33	0.276	0.187	0.211
3	0.034	0.096	0.057	34	0.059	0.080	0.072
4	0.062	0.109	0.086	35	0.086	0.133	0.111
5	0.099	0.134	0.121	36	0.029	0.129	0.058
6	0.320	0.354	0.352	37	0.183	0.226	0.213
7	0.590	0.482	0.537	38	0.583	0.485	0.539
8	0.651	0.426	0.477	39	0.980	0.683	0.775
9	0.534	0.336	0.366	40	0.493	0.399	0.446
10	0.013	0.045	0.024	41	0.355	0.321	0.347
11	0.051	0.058	0.057	42	0.294	0.241	0.269
12	0.023	0.049	0.034	43	0.914	0.546	0.508
13	0.053	0.066	0.062	44	0.029	0.052	0.040
14	0.116	0.098	0.108	45	0.044	0.052	0.050
15	0.052	0.068	0.062	46	0.013	0.040	0.023
16	0.241	0.163	0.184	47	0.117	0.090	0.102
17	0.013	0.052	0.025	48	0.085	0.075	0.082
18	0.026	0.059	0.040	49	0.021	0.045	0.031
19	0.050	0.071	0.062	50	0.022	0.048	0.033
20	0.106	0.097	0.105	51	0.019	0.047	0.030
21	0.257	0.175	0.198	52	0.071	0.073	0.075
22	0.183	0.137	0.155	53	0.160	0.120	0.135
23	0.019	0.051	0.032	54	0.054	0.069	0.064
24	0.090	0.082	0.088	55	0.092	0.087	0.093
25	0.180	0.125	0.142	56	0.035	0.062	0.049
26	0.036	0.050	0.045	57	0.381	0.241	0.263
27	0.030	0.046	0.039	58	0.070	0.085	0.081
28	0.052	0.058	0.058	59	0.078	0.092	0.089
29	0.023	0.053	0.036	60	0.032	0.097	0.055
30	0.027	0.056	0.040	61	0.070	0.124	0.097
31	0.029	0.060	0.043	62	0.129	0.216	0.174

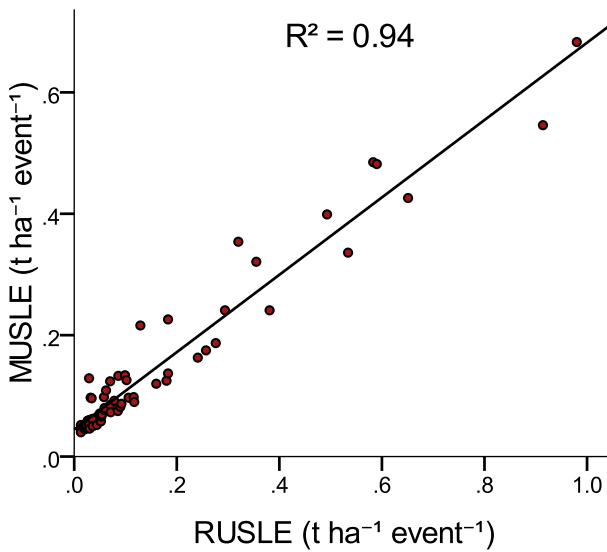


Fig. 10 Regression analysis between predicted sediment yield from RUSLE and MUSLE, calibrated with polynomial regression of R_{30} (rainfall erosivity) and Q_{qp} (runoff discharge rate)

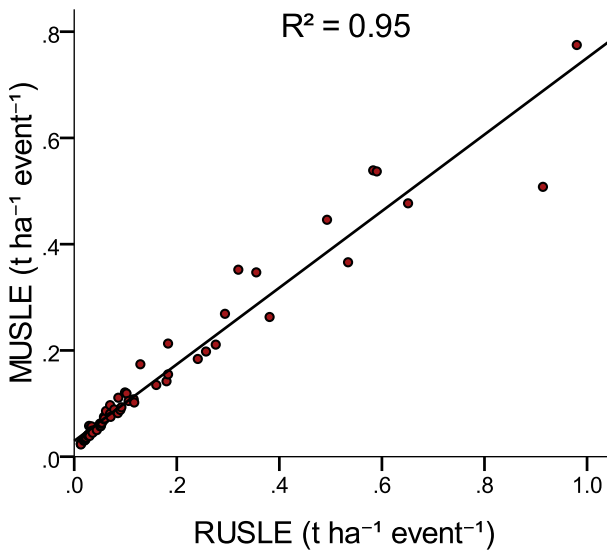
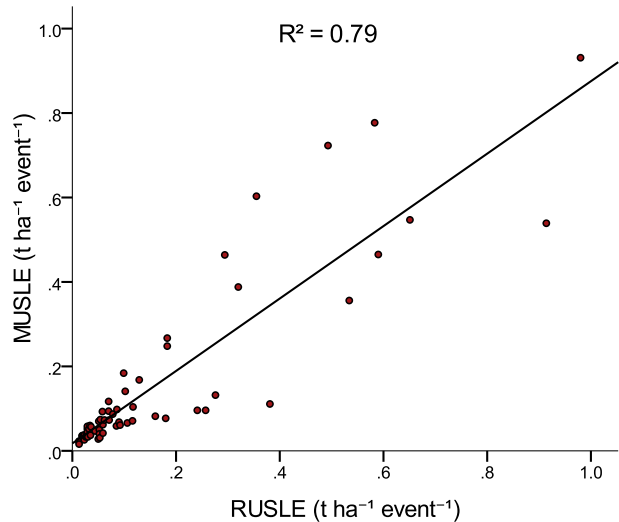


Fig. 11 Regression analysis between predicted sediment yield from RUSLE and MUSLE, calibrated with power regression of R_{30} (rainfall erosivity) and Q_{qp} (runoff discharge rate)

The predicted sediment yield using the RUSLE/SDR and MUSLE models are presented and discussed in the following sections (Table 2).

Figures 10 and 11 compare the predicted sediment yield using the RUSLE and MUSLE models, calibrated with both polynomial and power regression models based

Fig. 12 Regression analysis between predicted sediment yield from MUSLE and MUSLE without calibration



on the relationship between runoff volume and runoff discharge rate ($Q.q_p$) from the MUSLE model and rainfall erosivity factor (R_{30}) from the RUSLE model. While both regression models fit the data well and show significantly high R^2 values (0.95 and 0.94) in the linear regression analysis. This shows that the calibration performance in both models were highly effective.

Figure 12 indicates the relationship between the MUSLE and RUSLE models in predicting sediment yield through linear regression analysis without calibration. The data points are not aligned closely on the regression line with R^2 value of (0.79), which is lower value compared to the findings obtained through calibration.

Figures 13 and 14 indicate the comparison of the predicted sediment yield using the RUSLE and MUSLE models, calibrated with both polynomial and power regression

Fig. 13 Regression analysis between predicted sediment yield from RUSLE and MUSLE, calibrated with polynomial regression of R_{20} (rainfall erosivity) and $Q.q_p$ (runoff discharge rate)

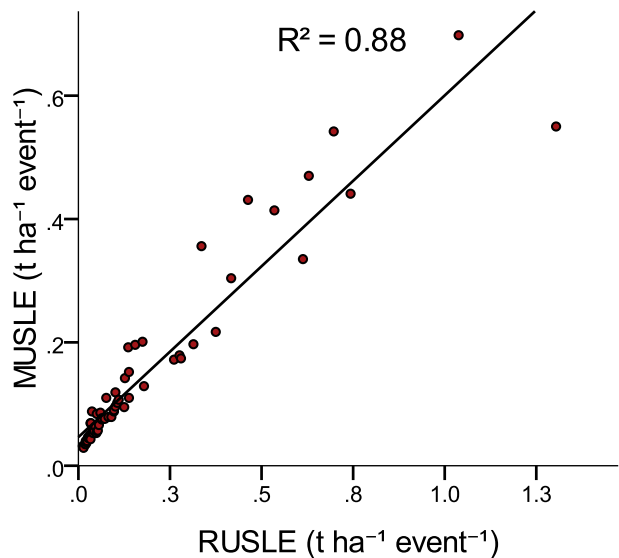


Fig. 14 Regression analysis between predicted sediment yield from RUSLE and MUSLE, calibrated with polynomial regression of R_{20} (rainfall erosivity) and $Q.qp$ (runoff discharge rate)

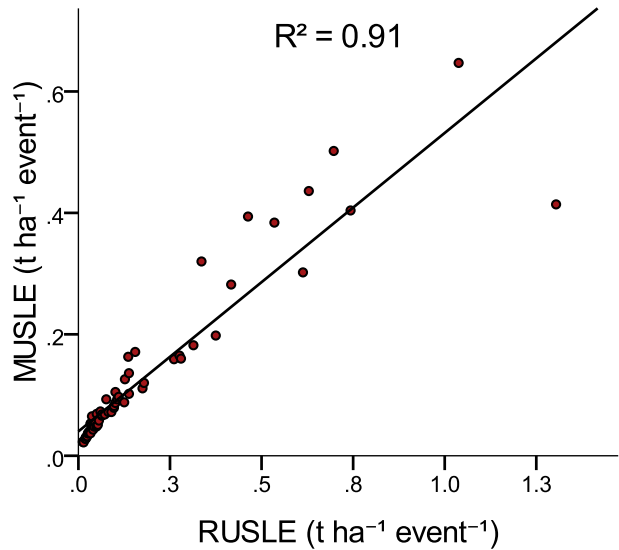
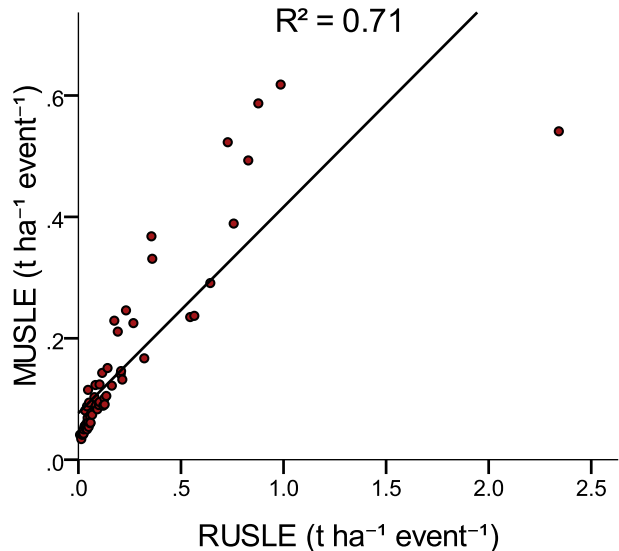


Fig. 15 Regression analysis between predicted sediment yield from RUSLE and MUSLE, calibrated with polynomial regression of R_{10} (rainfall erosivity) and $Q.qp$ (runoff discharge rate)



models based on the relationship between runoff volume and runoff discharge rate ($Q.q_p$) and rainfall erosivity factor (R_{20}). Both regression models fit the data well and show high R^2 values (0.91 and 0.88), in the linear regression analysis. This indicates that the calibration performance in both models were effective.

Figures 15 and 16 present the comparison of the predicted sediment yield using the RUSLE and MUSLE models, calibrated with both polynomial and power regression models based on the relationship between runoff volume and runoff discharge rate ($Q.q_p$) and rainfall erosivity factor (R_{10}). Both regression models fit the data well, but the data points are not aligned closely with the regression line, its R^2 values of (0.71 and 0.66), which are lower

Fig. 16 Regression analysis between predicted sediment yield from RUSLE and MUSLE, calibrated with polynomial regression of R_{10} (rainfall erosivity) and Q_{qp} (runoff discharge rate)

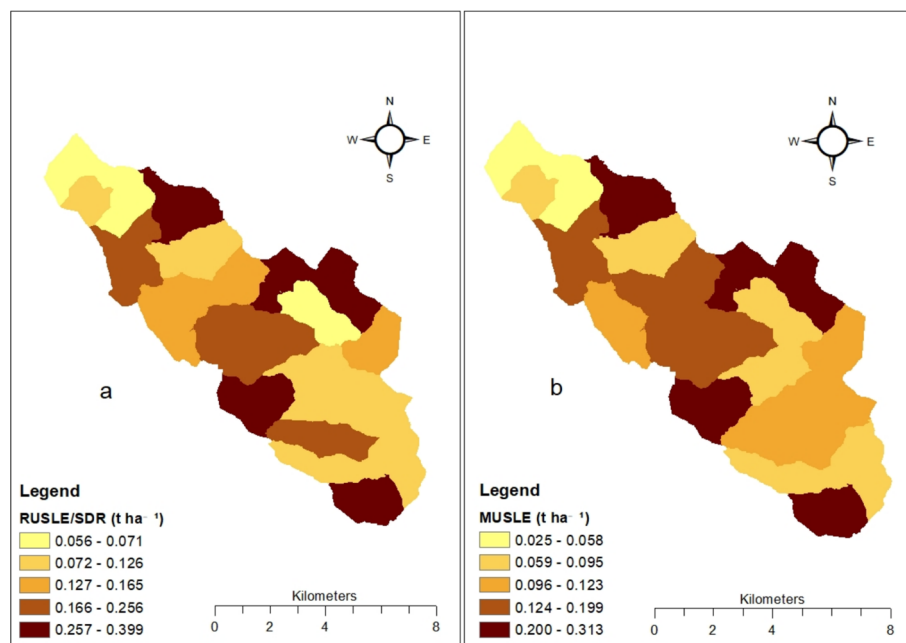
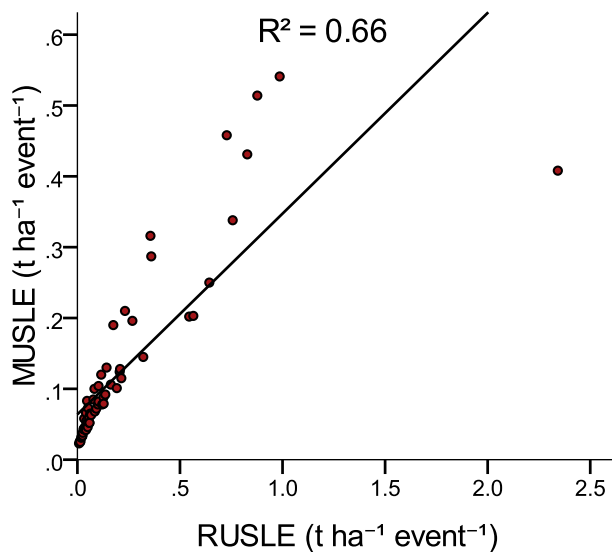


Fig. 17 Predicted sediment yield distribution at the sub-catchment scale derived from **a** RUSLE/SDR and **b** MUSLE, highlighting spatial variations and identifying sub-catchments with high sediment yield potential

than those obtained with R_{30} and R_{20} , that showing higher R^2 values of (0.95 and 0.91), in the linear regression analysis. This indicates that the calibration performance using R_{10} was less effective compared to R_{30} and R_{20} in the MUSLE model.

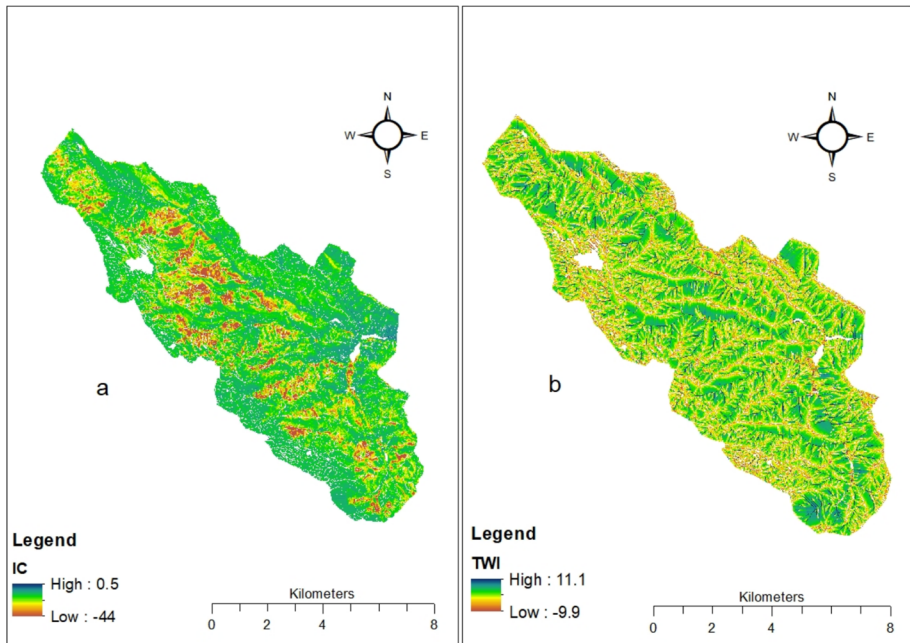


Fig. 18 Spatial distribution of **a** Connectivity Index (CI) derived from the method of Borselli et al. (2008) and **b** Topographic Wetness Index (TWI) across the study area

Figure 17 demonstrates the sediment yield results for RUSLE/SDR, using event-based rainfall erosivity factor (R_{30}), and MUSLE runoff factor ($Q \cdot q_p$) across the 22 sub-catchments. RUSLE values range from 0.056 t. ha⁻¹ to 0.399 t. ha⁻¹, while MUSLE values range from 0.025 to 0.313 t. ha⁻¹. These variations are attributed to key factors such as rainfall intensity, runoff, slope, vegetation, and soil erodibility, all of which were incorporated into the model calculations and are well-established influences on sediment yield in similar studies.

Figure 18 highlights two different connectivity indices: the Connectivity Index (CI) developed by Borselli et al. (2008) and the Topographic Wetness Index (TWI). These indices illustrate differences in sediment connectivity estimation based on topographic and hydrological controls. The CI values range from negative to positive ($-\infty$, $+\infty$), where negative values indicate low connectivity or disconnected sediment transport potential, while positive values represent higher connectivity and increased sediment transfer efficiency.

3.2 Comparison of predicted sediment yield with observed data

Figures 19 and 20 present the regression analysis between the predicted sediment yields from the (RUSLE and MUSLE models) with the observed data. The results indicate statistically significant positive correlation, with R^2 values of 0.70 and 0.56, respectively, based on the power regression curve.

Fig. 19 Power regression analysis between predicted sediment yield from RUSLE and observed data

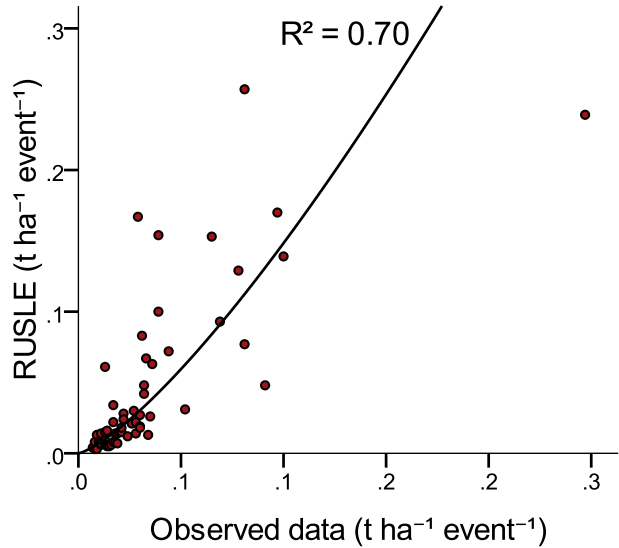
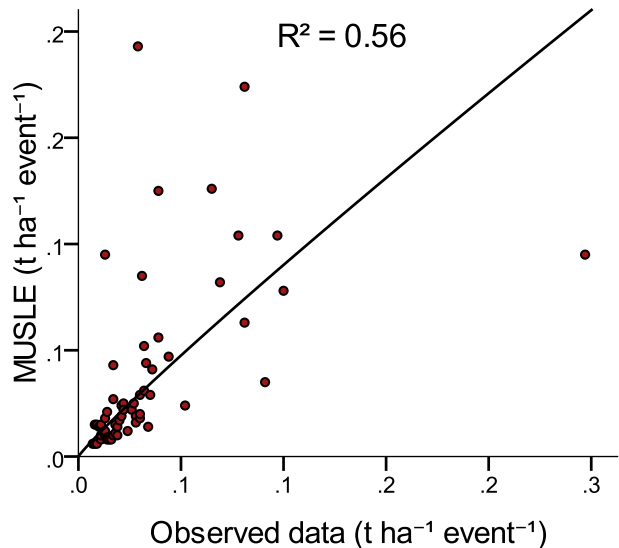


Fig. 20 Power regression analysis between predicted sediment yield from MUSLE and observed data



3.3 Validation results

The validation results presented in Table 3 demonstrate the performance of the RUSLE and MUSLE models. A strong correlation was observed between the RUSLE/SDR and MUSLE outputs, with Pearson correlation coefficients of $r = 0.970$ for the polynomial model and $r = 0.973$ for the power model ($p < 0.01$), both models indicating a high degree of agreement. The MUSLE model calibrated with the polynomial approach had a lower RMSE (0.071) compared to the power model (0.085), suggesting better predictive

Table 3 Summary of Validation Results for RUSLE/SDR vs. MUSLE Models (calibrated with Power and Polynomial Models) and Observed Data

Validation assessment between RUSLE and MUSLE		
Metric / Statistic	MUSLE (Polynomial Model)	MUSLE (Power Model)
Pearson Correlation	0.970**	0.973**
Sig (2-tailed)	0.000	0.000
RMSE	0.071	0.085
MSE	0.007	0.005
Validation assessment between RUSLE/MUSLE and Observed data		
Metric/Statistic	RUSLE/SDR	MUSLE
Pearson Correlation	0.413**	0.316*
Sig (2-tailed)	0.001	0.012
RMSE	0.099	0.073

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4 Comparison of total predicted sediment yield with observed Sediment Yield

Year	MUSLE	RUSLE/SDR	Observed Sediment Yield
2016	0.628 t ha ⁻¹ yr ⁻¹	0.782 t ha ⁻¹ yr ⁻¹	0.525 t ha ⁻¹ yr ⁻¹
2017	1.189 t ha ⁻¹ yr ⁻¹	1.419 t ha ⁻¹ yr ⁻¹	0.328 t ha ⁻¹ yr ⁻¹
2018	0.952 t ha ⁻¹ yr ⁻¹	1.253 t ha ⁻¹ yr ⁻¹	0.991 t ha ⁻¹ yr ⁻¹
2019	0.259 t ha ⁻¹ yr ⁻¹	0.288 t ha ⁻¹ yr ⁻¹	0.238 t ha ⁻¹ yr ⁻¹

accuracy. In comparison to observed data, the RUSLE model showed a moderate correlation of $r = 0.413$ ($p < 0.01$), while the MUSLE model had a lower correlation of $r = 0.316$ ($p < 0.01$). However, MUSLE outperformed RUSLE with a lower RMSE (0.073 vs. 0.099), indicating improved accuracy in sediment yield prediction. These results confirm the reliability of both models.

3.4 Comparison of total predicted sediment yield with observed data

The total predicted sediment yield, aggregated annually, was compared with the observed sediment yield. The results presented in Table 4.

The total predicted sediment yield from the MUSLE and RUSLE/SDR models varied in comparison to the observed data across the study period (Table 5). In 2016 and 2017, both models overestimated sediment yield, with the largest discrepancy occurring in 2017, where MUSLE and RUSLE/SDR predicted 1.189 t ha⁻¹yr⁻¹ and 1.419 t ha⁻¹yr⁻¹, respectively, compared to the observed 0.328 t ha⁻¹yr⁻¹. In 2018, the MUSLE model closely aligned with the observed value (0.952 t ha⁻¹yr⁻¹ vs. 0.991 t ha⁻¹yr⁻¹), while RUSLE/SDR slightly overestimated sediment yield. In 2019, both models provided estimates close to the observed data, with MUSLE predicting 0.259 t ha⁻¹yr⁻¹ and RUSLE/SDR predicting 0.288 t ha⁻¹yr⁻¹, compared to the observed 0.238 t ha⁻¹yr⁻¹.

4 Discussions

The RUSLE/SDR and MUSLE models exhibited a moderate correlation ($R^2 = 0.79$) in predicting sediment yield. However, both models tended to overestimate sediment yield compared to observed data, suggesting that their application in the Çarşamba Suyu Sub-Basin's Mediterranean climate requires further refinement. In this region, where rainfall energy is the primary erosive force, RUSLE relies on the erosive rainfall criteria (R factor) (Renard et al. 1997), while MUSLE incorporates peak discharge rate ($Q \cdot q_p$) as a proxy for runoff-driven sediment transport (Williams 1975).

This methodological distinction introduces a tendency toward overestimation in both models, as each integrates a peak-based approach RUSLE through rainfall intensity and erosive energy, and MUSLE through flow-driven transport capacity. As a result, RUSLE may overpredict sediment detachment in high-intensity but short-duration rainfall events consistent with findings from Benavidez et al. (2018), whereas MUSLE may amplify sediment yield estimates during peak runoff conditions, especially when concentrated flow events dominate the hydrological response. Given that both models introduce peak elements rain intensity in RUSLE and peak discharge in MUSLE into the estimation process, this approach inherently risks overestimation by emphasizing maximum erosive and transport forces rather than the overall sediment dynamics throughout an event.

This variability aligns with findings in previous studies, where MUSLE's sensitivity to concentrated runoff events led to overestimation under moderate runoff conditions. Similarly, a study by Shi et al. (2022) showed that the original MUSLE tended to underestimate sediment yield during large events while overestimating it for smaller sediment yield events. Likewise, RUSLE's reliance on rainfall intensity as a sole driver of erosion may overestimate sediment detachment in cases where transport capacity is not fully realized. Supporting this, Gianinetto et al. (2019) found that RUSLE model overestimated erosion rate in Val Camonica (Italy) during autumn and winter, largely due to its inability to account for seasonal factors such as snow cover and vegetation dynamics. These differences highlight the need for careful calibration and potential integration of event-based criteria that consider both rainfall erosivity and hydrological transport capacity for improved sediment yield predictions.

A primary distinction between the RUSLE/SDR and MUSLE models lies in their differing emphasis on erosion drivers rainfall-driven (RUSLE/SDR) versus runoff-driven (MUSLE) processes. The RUSLE/SDR approach utilizes rainfall erosivity (R factor) to estimate sediment displacement caused by raindrop impact and rainfall energy, making it particularly sensitive to sheet and interrill erosion, splash detachment, and shallow flow transport key mechanisms in raindrop-impacted erosion dynamics.

The RUSLE model exhibited a moderately significant positive correlation ($R^2 = 0.70$), with observed sediment yield in power regression analysis. However, event-based predictions from RUSLE/SDR tended to overestimate sediment yield, suggesting potential limitations in its capacity to fully capture runoff-driven transport mechanisms, which influence sediment delivery at the watershed scale.

Given the inherent interdependence of detachment and transport processes, an overemphasis on either rainfall erosivity (detachment) or runoff (transport) in isolation may lead to biased or incomplete sediment yield estimates. Since detachment and transport are highly interconnected and intertwined, an effective erosion model must account for both processes simultaneously rather than treating them as separate or dominant factors. Models integrating both detachment and transport dynamics rather than focusing disproportionately on one

are likely to provide more reliable sediment yield predictions by capturing the full range of erosion processes operating within a watershed.

4.1 Detachment-limited vs. transport-limited conditions in MUSLE predictions

In contrast to RUSLE, MUSLE emphasizes runoff ($Q \cdot q_p$) as a key driver of sediment mobilization, making it particularly suitable for predicting sediment transport in rill erosion and channelized flow conditions. However, the model's reliance on runoff volume and peak discharge introduces significant variability, particularly during moderate rainfall events with limited runoff, where it tended to over-predict sediment yield similar findings were reported by Noor and Rostami (2018), who observed that MUSLE significantly overestimated sediment yield in the Sanganeh research micro-watershed. Consequently, MUSLE predictions exhibited a weaker correlation with observed sediment yield ($R^2 = 0.56$), in power regression analysis. This discrepancy can be better understood through the lens of detachment-limited and transport-limited conditions:

- Detachment-limited conditions occur when rainfall energy (R factor) controls soil detachment, but the available runoff is insufficient to transport all detached sediment. Under such conditions, MUSLE may overestimate sediment yield because, despite high $Q \cdot q_p$ values, sediment transport is constrained by limited detachment.
- Transport-limited conditions, on the other hand, arise when sediment availability (detachment) is high, but the transport capacity is limited by low runoff and peak discharge. In such cases, RUSLE's reliance on R factor alone may overestimate erosion, as it does not explicitly account for the hydraulic efficiency of runoff to transport detached sediment.

These observations highlight the critical need for models to untangle the complex interactions between rainfall erosivity and runoff-driven transport. While RUSLE captures detachment mechanisms well, it does not account for runoff-driven sediment transport, and MUSLE, despite incorporating runoff, does not explicitly model detachment processes.

To address this, our study sought to bridge the gap between these models by relating $Q \cdot q_p$ with R , using a common parameter soil erodibility (K factor) which represents the unit soil loss or detachment per unit rainfall energy. This approach provides a physically justified link between the two models, offering a better conceptual framework for understanding the role of erosivity and transport capacity in sediment yield predictions.

In addition to calibration, which focuses on a process-based approach between the two models for event-based predictions, connectivity is another critical issue. The spatial scale of the catchment, divided into sub-catchments to capture spatial variations in model parameters, poses a challenge. Sediment is observed at only one outlet, representing the entire catchment. Therefore, any parameter that can represent connectivity among the sub-catchments relative to the whole catchment can help identify variations and potentially represent sediment detachment and transport processes. For example, composite or interactive indices that account for topography, slope, soil erodibility, land cover, and other factors influencing runoff, detachability, and transportability of soil and sediment can significantly enhance the predictive capacity of both models. Evaluating the spatial patterns of connectivity is crucial for understanding the variability in landform characteristics and the potential for sediment delivery (Yuwen et al. 2022), further highlighting the importance of incorporating connectivity indices to capture spatial differences in sediment transport.

These results highlight the inherent limitations of both the RUSLE/SDR and MUSLE models in accurately capturing sediment transport dynamics across varying hydrological conditions. While RUSLE tends to overemphasize the impact of rainfall, potentially leading to overestimation in moderate events, MUSLE's reliance on the runoff factor ($Q \cdot q_p$) introduces uncertainty in cases where rainfall does not generate substantial discharge. Several models, including USLE-derived models (Renard et al. 1997, Wischmeier and Smith 1978), fail to incorporate deposition processes, resulting in unrestrained sediment transport and unrealistic predictions at the watershed scale (Kinnell 2004). This discrepancy underscores the need for further model refinement, not only through event-based calibration but also by incorporating spatial connectivity factors that account for hydrological variability and sediment transfer across different sub-catchments.

Given the spatial scale of the study area, where the catchment is divided into sub-catchments to capture localized variations in model parameters, it is essential to recognize that sediment yield is measured at a single outlet, which represents the integrated response of the entire catchment. Consequently, any parameter that quantifies connectivity among sub-catchments relative to the entire catchment can help unravel spatial variations in sediment detachment and transport processes. The Connectivity Index (CI) serves as an indicator of the potential linkage between sediment sources on hillslopes and the stream network, considering land use patterns, topographic features, and surface conditions that influence sediment and water movement (Borselli et al. 2008). To address these challenges, connectivity index was incorporated to refine and adjust predicted sediment yields against observed data.

Beyond simple calibration, the incorporation of the connectivity index includes key landscape attributes such as topography, slope, soil erodibility, land cover, and hydrological pathways which collectively influence runoff generation, sediment detachability, and transportability. Integrating this factor led to improved model predictions that aligned more closely with observed sediment yields across different years. As, in 2016 and 2017, both models overestimated sediment yield, with the largest discrepancy observed in 2017 (MUSLE: $1.189 \text{ t ha}^{-1} \text{ yr}^{-1}$, RUSLE/SDR: $1.419 \text{ t ha}^{-1} \text{ yr}^{-1}$, compared to the observed $0.328 \text{ t ha}^{-1} \text{ yr}^{-1}$). In 2018, MUSLE more closely aligned with the observed value ($0.952 \text{ t ha}^{-1} \text{ yr}^{-1}$ vs. $0.991 \text{ t ha}^{-1} \text{ yr}^{-1}$), while RUSLE/SDR slightly overestimated it. In 2019, both models provided estimates close to the observed data (MUSLE: $0.259 \text{ t ha}^{-1} \text{ yr}^{-1}$, RUSLE/SDR: $0.288 \text{ t ha}^{-1} \text{ yr}^{-1}$, compared to the observed $0.238 \text{ t ha}^{-1} \text{ yr}^{-1}$). These results demonstrate that integrating spatial connectivity factors significantly enhances the predictive capacity of both models, underscoring the importance of model refinement and calibration to improve sediment yield predictions under varying hydrological conditions. Several researchers, including Ferro and Porto (2000) and Lu et al. (2006), as cited by Borselli et al. (2008), have used the SDR to adjust model outputs, improving sediment transport estimations.

This refined approach highlights the importance of incorporating both process-based calibration and spatial connectivity analysis to improve the reliability of event-based sediment yield predictions. By integrating composite or interactive indices that capture key erosion drivers including runoff dynamics, detachment potential, and transport efficiency both models can better represent sediment movement across complex landscapes, particularly in Mediterranean climates with highly variable rainfall-runoff interactions.

4.2 Enhancing model calibration by integrating R and $Q \cdot q_p$ interactions

The calibration process was essential for reconciling the structural differences between MUSLE's rainfall-based approach and MUSLE's runoff-based design (Ezzaouini et al. 2020). By employing regression-based calibration using polynomial and power models, the study established a strong correlation between MUSLE's runoff factor ($Q \cdot q_p$) and MUSLE's rainfall erosivity factor (R), improving model fit with R^2 values of 0.95 and 0.94, respectively.

A key outcome of this calibration was the identification of R_{30} and R_{20} as the most effective rainfall metrics, demonstrating their ability to capture both storm energy and duration. The higher predictive accuracy observed with R_{30} underscores the importance of using high-resolution erosivity factors that integrate rainfall intensity, duration, and storm variability for event-based sediment modeling. In contrast, lower-resolution R_{10} factors exhibited weaker alignment with sediment yield predictions, confirming R_{30} 's superiority in event-scale assessments.

Beyond model calibration, these results suggest that explicitly incorporating the interactions between R and $Q \cdot q_p$ enhances the predictive strength of sediment yield models. Since erosion is neither purely detachment-driven (MUSLE) nor purely transport-driven (MUSLE), but rather a coupled process, integrating these interactions bridges the conceptual gap between the two models. By linking runoff-driven transport capacity ($Q \cdot q_p$) with rainfall-driven erosivity (R) through regression-based calibration, MUSLE's predictive performance was improved for rainfall-driven erosion contexts. This approach reinforces the need for hybrid modeling frameworks that incorporate both detachment and transport interactions rather than isolating them as separate mechanisms.

4.3 Spatial variability of LS and C factors and the role of connectivity in model calibration

The spatial distribution of LS and C factors across sub-catchments revealed significant variations in erosion potential, driven by differences in topography and land cover. Higher LS values in mountainous sub-catchments corresponded with elevated sediment yields, reinforcing the strong relationship between slope steepness and sediment transport capacity (Ansari and Tayfur 2023). Similarly, C factor variability, particularly high C values in low-vegetation areas, correlated with increased erosion potential, emphasizing the influence of land cover on soil detachment and transport (Negese 2024).

To better capture these spatial variations, event-based sediment yield analysis was conducted using GIS-based integration of LS and C factors, allowing for a spatially explicit representation of erosion dynamics. However, given the complex interactions between topography, land cover, and soil erodibility, the use of a composite connectivity index that integrates these factors could further enhance model calibration and predictive accuracy. Such an index would not only better represent sub-catchment connectivity but also improve the model's ability to capture interactions between rainfall erosivity and runoff-driven transport capacity.

The Sediment Connectivity Index (SCI) was calculated for each sub-catchment using a combination of spatial and statistical datasets, including DEM-derived slope, flow direction, and flow accumulation. This approach enabled a comprehensive assessment of sediment transport dynamics across the study area. Key indices, such as the

Connectivity Index (*CI*) developed by Borselli et al. (2008), Topographic Wetness Index (*TWI*), Stream Power Index (*SPI*), and Sediment Delivery Ratio (*SDR*), were integrated to assess sediment transport and identify areas of high sediment connectivity. These indices, normalized to a common scale, were integrated into a Composite Weighting Connectivity Index (*CWCI*) using Principal Component Analysis (*PCA*). The *CWCI* effectively combined multiple factors affecting sediment transport, such as topography, drainage area, flow accumulation, and land use, providing a more accurate measure of sediment connectivity.

By incorporating a connectivity-based approach, model adjustments could account for both detachment and transport processes, offering a more physically consistent calibration framework. This would refine event-based sediment predictions, ensuring that models more accurately reflect the spatial heterogeneity of sediment movement across different hydrological and topographic conditions. The integration of connectivity metrics into GIS-based modeling could thus provide a more holistic approach to sediment yield estimation, bridging gaps in existing models that either overemphasize rainfall impact or rely too heavily on runoff-driven transport, aligning with studies by Cavalli et al. (2013), who demonstrated that sediment connectivity indices improve event-based erosion modeling.

4.4 Seasonal adaptation of the *k* factor for improved calibration and validation

Instead of using long-term average values of the *K* factor in both models, this study applied a seasonal *K* factor that reflects the interactive response of soil to climate variations, rainfall, and temperature, together with its inner properties such as texture, structure, hydraulic connectivity, and organic matter. This approach was more physically justifiable in the context of event-based modeling and calibration.

The study's seasonal *K* factor calculations utilized R_{30} , as it more accurately represents the kinetic energy and intensity of Mediterranean rainfall events compared to lower-resolution R_{20} and R_{10} . The application of seasonally varying *K* values, rather than relying on long-term average *K* factors, allowed for a more physically consistent approach in event-based sediment yield predictions (Deviren Saygin 2021). This method acknowledges the interactive response of soil properties to seasonal climate variations, particularly fluctuations in rainfall intensity, temperature, and soil moisture dynamics.

By incorporating seasonally adaptive *K* factors, the study accounted for key soil characteristics including texture, structure, hydraulic connectivity, and organic matter content that influence soil detachability and transport capacity under different climatic conditions. This approach not only enhanced model calibration and validation but also ensured that the *K* factor reflected real-time soil vulnerability to erosion, rather than a static mean value applied across all events.

The use of R_{30} in seasonal *K* factor calculations resulted in better alignment of predicted sediment yields with observed data, as it effectively captured the energy dynamics critical to soil detachment during high-intensity storms. However, further calibration with R_{20} and R_{10} could provide additional insights into model responsiveness under varying event intensities and rainfall distributions, particularly in regions experiencing a mixture of high-energy and moderate rainfall events. Such refinements would further optimize sediment yield predictions across different seasonal conditions, strengthening the model's applicability to climate-driven erosion dynamics.

The validation metrics applied between the RUSLE and MUSLE models reveal that the polynomial model of MUSLE (RMSE = 0.071, MSE = 0.007) demonstrates better predictive

accuracy than the power model ($RMSE = 0.085$, $MSE = 0.005$), as indicated by the lower $RMSE$ and MSE values. Pearson correlation results show a very strong and highly significant correlation ($r = 0.97$) between both MUSLE models and RUSLE/SDR, highlighting a high degree of alignment between the models in predicting sediment yield.

The validation metrics comparing the models to observed data indicate that the RUSLE model exhibits a stronger relationship with the observed data ($r = 0.41$, $p < 0.01$) compared to the MUSLE model ($r = 0.31$, $p < 0.05$). This suggests that RUSLE more effectively captures the general trend of sediment yield. However, the $RMSE$ values reveal that MUSLE provides more accurate predictions with a lower error magnitude ($RMSE = 0.07$) compared to RUSLE ($RMSE = 0.09$). While RUSLE demonstrates a better overall correlation with observed data, MUSLE offers more precise, event-specific predictions. The trade-off between correlation strength and error magnitude emphasizes the potential to complement both models, depending on the analytical focus.

5 Conclusions

This study compared sediment yield predictions from the RUSLE/SDR and MUSLE models in the Çarşamba Suyu Sub-Basin, providing important insights into model suitability, calibration, and environmental responsiveness. Both models generally overestimated sediment yield compared to gauged data, showing moderate correlation in power regression analysis. However, MUSLE demonstrated closer alignment with observed data in certain years, suggesting it may require less calibration than RUSLE/SDR for accurate predictions in runoff-driven environments like the Çarşamba Suyu Sub-Basin.

The high correlation between RUSLE/SDR and MUSLE models indicates both are responsive to environmental factors such as climatic variability and land management practices. Despite this, RUSLE/SDR consistently overestimated sediment yield, particularly in 2017, where large discrepancies were observed. In contrast, MUSLE's predictions were more closely aligned with observed data in 2018 and 2019. This emphasizes the importance of aligning model calibration factors, such as the rainfall erosivity (R factor) in RUSLE and the runoff component ($Q \cdot q_p$) in MUSLE, with the specific hydrological conditions of the study area.

To correct the overestimation in both models, a composite connectivity index was integrated with the predicted sediment yield. This index, derived from the integration of LS and C factors, topography, flow accumulation, and land cover, effectively captured sediment transport dynamics across the watershed. The spatial variability of LS and C factors across sub-catchments, particularly in areas with steep slopes and low vegetation cover, was shown to strongly influence erosion potential. By incorporating the connectivity index, which accounts for both soil detachment and transport processes, the predictions more closely aligned with the observed sediment yields. This adjustment allowed for a more accurate representation of sediment transport and improved model calibration. The study further highlights the critical influence of environmental factors, including climatic conditions, topography, and land cover, on sediment yield estimations. The spatial variability of LS and C factors across the watershed underscores the importance of incorporating topographic and land cover heterogeneity into model frameworks.

In this study, internal calibration of both RUSLE and MUSLE models was successfully conducted. However, the most critical limitation lies in the lack of event-based

measurements. Accurate model calibration and validation ultimately depend on such high-resolution, event-scale observations. Unfortunately, in many cases including our study area official hydrological datasets have transitioned over time from event-based sediment and discharge records to monthly average flow data after a certain year. This shift poses a significant constraint on fully evaluating model performance under real storm-driven conditions. Therefore, future efforts should prioritize the collection or reconstruction of event-based data to enhance the physical relevance and reliability of model applications.

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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