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Rainfall erosivity assessment over a flooding basin, Kelani River basin, Sri Lanka

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ABSTRACT

This study evaluates the rainfall erosivity (RE) and erosivity density (ED) over the Kelani River basin, Sri Lanka for a period of 31 years (1990–2020). The river basin is well known for its annual floods during the southwestern monsoon season and severe erosion including landslides can be observed. The catchment was analyzed for its RE using the Wischmeier and Smith algorithm and for its ED using Kinnel's algorithm. The monthly rainfall data spreading over the river basin were used to analyze the monthly, seasonal, and annual RE and ED. Interestingly, the annual RE showed a linear increasing trend line over 31 years, and a maximum value of 2,831.41 MJ mm ha^{-1} h^{-1} yr^{-1} was able to be observed in the year 2016. The RE peaks in May which is in the southwestern monsoon season. This reveals that the risk of soil erosion in the basin is high in the southwestern monsoon season. In addition, land use and land cover changes over the years have adversely impacted the erosion rates. Therefore, it is highly recommended to investigate soil erosion in-depth and then implement relevant regulations to conserve the soil layers upstream of the river basin.

Key words: erosivity density, Kinnell's algorithm, rainfall erosivity, Wischmeier and Smith algorithm

HIGHLIGHTS

- Evaluates the rainfall erosivity and erosivity density over the Kelani River basin, Sri Lanka
- The annual rainfall erosivity showed a linear increasing trend line over 31 years
- Peaks can be observed during the southwest monsoon time.
- Highlights the importance of regulating policy decisions to conserve the soil layers.

1. INTRODUCTION

Soil erosion is a process of nature causing the displacement and conveyance of the uppermost layer of soil to low-lying regions (Karunaratne *et al.* 2022; Chen *et al.* 2023). This is a complicated phenomenon that is influenced by many kinds of interrelated factors. Rainfall and land use changes are two key factors of them because they represent a critical pathway for sediment mixing with rainwater and subsequent deposition processes (Xiao *et al.* 2015; John *et al.* 2021). The rainfall erosivity (RE) is one of the most crucial elements that describes the erosive processes and suggests conservation strategies when utilizing soil erosion simulations (Panagos *et al.* 2017a). The factor, referred to as RE, is incorporated into indicating the capability of rainfall to induce soil erosion (Zhu *et al.* 2021; de Sousa Teixeira *et al.* 2022). That is one significant reason to select RE in this study.

Studying RE is essential for understanding and predicting the impact of rainfall on soil erosion. By studying RE, it is able to develop models and equations that help estimate soil loss, identify erosion risks, and formulate effective soil conservation measures (Mamedov *et al.* 2011). Addressing erosion processes occurring at the bed surfaces and banks of natural rivers, as well as engineered waterways, is crucial for effective water resources management (Pandey *et al.* 2021). This knowledge is crucial in various fields such as agriculture, land management, and environmental planning (Lee & Heo 2011). For farmers and land managers, understanding RE allows them to make informed decisions about how to manage their land in order to mitigate erosion risks (Panagos *et al.* 2017a; Nabi *et al.* 2020). Furthermore, studying RE is important for addressing the larger issue of sediment delivery in river catchments. As land clearance, intensification of land use, and population growth increase, sediment delivery in river catchments becomes a significant problem (Li & Ye 2018). Understanding the erosive force of rainfall is necessary to develop effective strategies for sediment control and watershed management (Nazuhan *et al.* 2018). Furthermore, this analysis can offer insights into the implications of climate change and variability. By examining patterns and trends in RE, experts can gain a deeper understanding of how alterations in precipitation intensity and distribution might influence soil erosion rates across diverse regions. This understanding is essential for devising adaptation strategies and implementing effective soil conservation measures to mitigate the adverse effects of erosion amid a changing climate. Future climate projections project potential threats of soil erosion and its consequences, including land degradation, diminished agricultural yields, and the depletion of soil carbon. Moreover, soil erosion compromises the soil's capacity to mitigate global warming by sequestering carbon (Borrelli *et al.* 2020; Panagos *et al.* 2022). The deposits of sediment load in reservoirs downstream have identified significant challenges with the management of water resources and hydraulic structures. That is the importance of studying RE of a particular region. Therefore, this particular research broadly studies one of Sri Lanka's major river basins to showcase this problem.

Various assessment methods are employed to measure RE and its potential impact on soil erosion. One common approach involves using indices such as the R factor in the Universal Soil Loss Equation (USLE) or the RUSLE model. These indices consider factors like rainfall amount, intensity, and distribution to estimate erosive power. Rainfall simulators represent another assessment type, utilizing artificial rainfall systems to study erosive effects under controlled conditions. Additionally, remote sensing techniques analyze rainfall patterns and characteristics over an area to assess RE. These assessment methods are vital for understanding and managing the influence of rainfall on soil erosion.

Other assessment types of RE include the following: (1) The use of RE maps derived from long-term rainfall data to identify areas with high erosivity potential (Xiao *et al.* 2015; Zhao *et al.* 2023). (2) Development of regression models or equations that predict RE based on easily obtainable rainfall data, such as average annual precipitation or monthly rainfall patterns (Panagos *et al.* 2017b; Fenta *et al.* 2024). (3) Analysis of historical rainfall data and its correlation with erosion measurements to determine the erosive power of different rainfall events (Brychta & Janeček 2017; Di Lena *et al.* 2021). (4) Several hydrological models, such as the Soil and Water Assessment Tool (SWAT) or the Soil Conservation Service Curve Number (SCS-CN) method, integrate RE assessments into their soil erosion predictions (Gupta *et al.* 2023; Jadhao *et al.* 2023).

In the context of Italy, one of the most effective ways to determine a rainstorm's potential for erosive impact is to use the comprehensive rainfall–runoff erosivity factor R, which is included in the USLE and Revised Universal Soil Loss Equation (RUSLE) soil erosion prediction models. USLE-based models are commonly used to estimate soil loss rates at various scales across Europe. Accurate calculation of the R-factor requires continuous, high-temporal-resolution rainfall data, but due to limitations in available data, it is often computed at 15- to 30-min intervals with the use of conversion factors to compensate for underestimations. However, the lack of pluviographic records and the time-consuming nature of R-factor calculation have limited its application in some studies, especially at regional and large-scale levels. Some studies have employed geostatistical methods that incorporate secondary information (elevation and environmental variables) to predict RE spatially, achieving good results in regions like the Algarve in Portugal, the Ebro catchment in Spain, Switzerland, and Greece (Borrelli *et al.* 2016). A study has focused on assessing RE in São Paulo State, Brazil which employs hierarchical clustering analysis to define homogeneous regions based on RE. This categorization highlights distinct patterns of erosivity across the state. Regionalized regression models are created to estimate RE within each of the defined homogeneous regions, providing accurate tools for predicting RE (Teixeira *et al.* 2022). There are two main approaches to estimate RE, this method takes into account the kinetic energy of rainfall. It recognizes that higher rainfall kinetic energy corresponds to a greater potential for causing erosion. It considers the energy associated with the falling raindrops. The second approach is simpler and directly uses daily, monthly, or annual rainfall data to estimate RE. It does not factor in the kinetic energy of rainfall but focuses on quantifying erosivity based on the volume or amount of rainfall received over a specific period. This approach is more straightforward and does not involve the specific energy component of the rainfall (Wang *et al.* 2024). The USLE prediction equation involves RE, or the R-factor, as one of its input parameters. These mean monthly R-factor values are used to predict global monthly erosivity datasets at a 1-km resolution using ensemble machine learning. The resulting monthly raster data in GeoTIFF format has applications in soil erosion prediction modeling, sediment distribution analysis, climate change assessments, and flood and disaster evaluations, and can serve as valuable inputs for Land and Earth Systems modeling (Panagos *et al.* 2023). Globally, soil erosion is predicted to occur at mean rates of 12–15 Mg ha^{-1} yr^{-1} (Marondedze & Schütt 2020). According to the baseline scenario, at a continental level, South America shows the highest prediction of average soil erosion rate (3.53 Mg ha^{-1} yr^{-1}) in 2001, followed by Africa (3.51 Mg ha^{-1} yr^{-1}) and Asia (3.47 Mg ha^{-1} yr^{-1}) (Borrelli *et al.* 2017). In order to identify the regional variability of soil erosion in farming systems, the study used a time-series analysis of several factors, including rainfall, land use land cover (LULC), and crop diversification. Regression analysis, in conjunction with rain-use efficiency (RUE) and residual trend analysis (RESTREND), was used to separate soil erosion resulting from both human and climate-induced land degradation (Senanayake *et al.* 2022).

Determining and mapping the Samanalawewa watershed's rate of soil erosion is, thus, the main goal of this project. Using remote sensing and the geographic information system, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) Sediment Delivery Ratio model was used. The study's findings showed that the watershed's current rate of human-induced soil erosion ranges from 0 to 320 t/ha/year, with an average of 12.51 t/ha/year. Due to irresponsible forest removal, the bulk of the area has experienced land degradation at a rate that exceeds the natural rate of soil erosion (Kumarasiri *et al.* 2023). The close connection between the Sustainable Development Goals (SDGs) and soil-related activities, emphasizing the crucial role of healthy soil ecosystems in sustaining life on Earth has been studied in another study which has focused on the Central Highlands of Sri Lanka. This is s region vulnerable to climate threats and susceptible to soil erosion. The research employs a RUSLE (Piyathilake *et al.* 2021; Somasiri *et al.* 2022) to track and predict soil erosion in response to rainfall variations. It aims to reduce soil erosion in agricultural systems and contribute to the achievement of the SDGs. The study analyzed rainfall trends and erosivity to understand soil erosion dynamics. Using various machine learning techniques like artificial neural networks (ANNs), support vector machines (SVMs), and adaptive network-based fuzzy inference system (ANFIS), (Avand *et al.* 2022) the research predicts that soil erosion rates will increase (Sahour *et al.* 2021). Specifically, it highlights a positive trend in RE and extreme rainfall indices. The highest monthly erosion rates are expected in October, and the erosion rates could range from 4 to 22% by 2040 based on 2020 rates. Under different climate scenarios (RCP 2.6 and 8.5), the study predicts an increase in soil erosion rates. The findings underscore the growing vulnerability of the Central Highlands and the threat this poses to achieving the SDGs. In response, the research offers strategies for monitoring and anticipating soil erosion to safeguard the soil ecosystem and support the SDGs. The methodology developed in this study can potentially be applied to reduce soil erosion in agricultural systems in other regions as well.

The country's forests and vegetation have reduced, whereas the amount of land utilized for agriculture in Sri Lanka has expanded over the past three decades (Palliyaguru *et al.* 2022). It has been shown verification that the Kelani River basin experiences greater rates of soil erosion. Approximately 70% of the river basin area exhibited low to moderate erosion severity (less than 12 tons per hectare per year), highlighting the urgent need for erosion control measures (Fayas *et al.* 2019). Therefore, it is now essential that soil be conserved in this basin (Kottagoda & Abeysingha 2017). Thus, to obtain an in-depth comprehension of the soil parameters and the circumstances of the riverbed, this study completes the knowledge of the soil erosion pattern of the Kalani River Basin over a period of 31 years.

Therefore, this research aimed to provide evidence of how important sediment deposition in downstream reservoirs is for the long-term management of water resources and hydraulic systems in the Kelani River basin, Sri Lanka. In order to achieve this aim, the specific objective is to estimate the quantitative variations in RE and erosivity density (ED) on a monthly, annual, and seasonal basis. Soil erosivity is unlikely to be significant on a daily basis, which is why the assessment was conducted across these three scenarios.

To fulfill this goal, authors employed two main equations, one internationally recognized, and one locally adapted. After a careful comparison, it was evident that the international Wischmeier and Smith equation provided the most accurate results. Overall, this combination provides a comprehensive framework to find RE and DE, versatility, grounded in an empirical basis, accessible to wide range, and especially longstanding use are made both of these equations special in this study. Not only that the Premalal's equation plays a crucial role in soil erosivity studies in Sri Lanka by providing a locally calibrated model for estimating soil erosion rates (Piyathilake *et al.* 2021). Its importance lies in its ability to offer more accurate predictions, inform policy and planning decisions, support research and monitoring efforts, and contribute to capacity building in soil erosion management. Therefore, by utilizing this equation, the study successfully achieved the particular aim.

2. MATERIALS AND METHODS

2.1. Study area

The Kelani River basin (Figure 1) is the second largest basin in Sri Lanka with an area of 2,336.12 km^2. The Kelani River runs for 145 km from Adams Peak and ends at Colombo. The river is one of the main sources of drinking water for the people of Colombo, also it is being used for transportation purposes and agricultural works in the basin (Kottagoda & Abeysingha 2017; Diodato *et al.* 2021a). The basin extends between the latitudes 6.75–7.23 and the longitude 79.85–80.78. The Elevation of the Kelani River basin varies from 0 to 2,335 m above mean sea level. The basin includes the following districts: Colombo, Gampaha, Kalutara, Kandy, Kegalle, Nuwara Eliya, and Rathnapura. The basin extends over the Western, Sabaragamuwa, and Central provinces. 46.83% of the area of the basin is in the Sabaragamuwa Province, 34.77% of the area of the basin is in the Western Province and 18.40% of the area of the basin is in the Central Province. The basin receives an average rainfall of 3,522 mm during the 31 years (1990–2020). The basin lies within the Southwest Monsoon season. The seasonal rainfall during the period 1990–2020, in the Southwest monsoon season (Liyanage *et al.* 2021; Diodato *et al.* 2021b) from May to September is 1,689.3 mm (48%), Second Inter Monsoon Season (October–November) is 848.76 mm (24%), First Inter Monsoon Season (March–April) is 481.13 mm (14%) and Northeast Monsoon Season (December–February) is 502.22 mm (14%) (Nandalal 2017; Talbot *et al.* 2018; Alahacoon & Edirisinghe 2021).

2.2. Rainfall data

The data used are monthly rainfall data. The data were collected from 10 stations for a period of 31 years (1990–2020) (Renard *et al.* 1991). The rainfall stations are Angoda, Awissawella, Chesterford, Colombo, Labugama, Maliboda, Norton, Champion, Castlereigh, and Deraniyagala. The locations and elevation of the rainfall stations are given in Table 1. The monthly rainfall data collected were summarized as monthly, annual, and seasonal rainfall data for the assessment of the RE (Cecílio *et al.* 2013; Parisouj *et al.* 2020). For the weighted average rainfall, RE, and ED of basin, the Thiessen polygon method was used (Zekai 1998; Милентијевић *et al.* 2021).

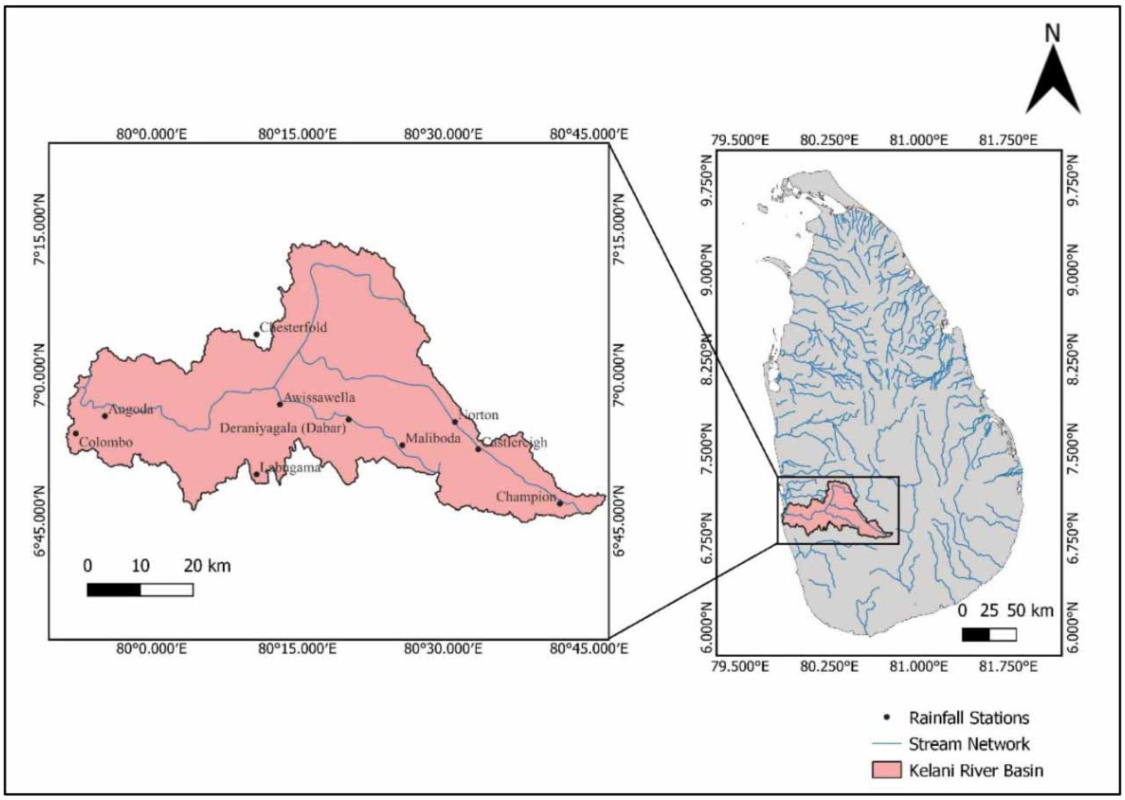


Figure 1 | The Kelani River basin with the rainfall stations.

Table 1 | Rainfall station characteristics

Name of the rainfall station	Longitude	Latitude	Elevation, m (above mean sea level)
Angoda	6.93	79.92	8
Awissawella	6.95	80.22	18
Chesterford	7.07	80.18	198
Colombo	6.90	79.87	6
Labugama	6.83	80.18	131
Maliboda	6.88	80.43	542
Norton bridge PO	6.92	80.52	1,029
Campion estate	6.78	80.70	1,471
Castlereigh	6.87	80.56	1,181
Deraniyagala (Dabar)	6.92	80.34	94

2.3. Methods and equations

2.3.1. RE factor (R-factor)

By using these formulas, one can determine the amount of soil erosion by multiplying the RE (R-factor) by five input factors: soil erodibility (K-factor), slope length (L-factor), slope steepness (S-factor), cover management (C-factor), and support practices (P-factor) (Lee *et al.* 2022). The impact of raindrops and the separation of soil particles by surface runoff are the main causes of soil erosion, hence the R-factor is generally the most significant indicator when assessing the quantity of soil erosion (Wischmeier & Smith 1978). In calculating the R-factor there are two equations used as mentioned in the following. Equation (1) was developed for Sri Lanka by Premalal in 1986 (Co-investigator 2013).

$$\mathrm{RE} = \frac{(972.75 + 9.95 \times F)}{100} \tag{1}$$

where RE is the R-factor (MJ mm $\mathrm{ha^{-1}\ h^{-1}\ yr^{-1}}$) and F is the Average annual rainfall (mm). Equation (2) was predicted by Wischmeier and Smith and later altered by Arnoldus (Belasri & Lakhouili 2016) from which we can calculate the annual RE.

$$\mathrm{RE} = \sum_{\mathrm{i}=1}^{12} 1.735 \times 10^{\left(1.5\log\left(\frac{P_i^2}{P}\right) - 0.8188\right)} \tag{2}$$

The RE is the annual rainfall erosivity (MJ mm $\mathrm{ha^{-1}\ h^{-1}\ yr^{-1}}$), P_i is the monthly rainfall (January to December) (mm) and P is the annual rainfall (mm). For the monthly RE simplification of Equation (2), we can use the following equation (refer to Equation (3)).

$$\mathrm{RE}_i = 1.735 \times 10^{\left(1.5\log\left(\frac{P_i^2}{P}\right) - 0.8188\right)} \tag{3}$$

where RE_i is the monthly rainfall erosivity (MJ mm $\mathrm{ha^{-1}\ h^{-1}\ yr^{-1}}$), P_i is the monthly rainfall (January to December) (mm) and P is the annual rainfall (mm) (Cardoso *et al.* 2022).

2.3.2. Erosivity density

The ED, which represents the erosivity content per unit of rainfall as determined by Equation (4), is given as the ratio of monthly RE to monthly rainfall. The ratio of the mean annual RE to the mean annual rainfall was used to estimate the mean annual ED. To evaluate the ED the following equation has used, Kinnell's algorithm (Kinnell 2010).

$$\mathrm{ED}_i = \frac{\mathrm{RE}_i}{\mathrm{P}_i} \tag{4}$$

where ED_i is the erosivity density (MJ ha^{-1} h^{-1}), RE_i is the monthly erosivity, and P_i, is the monthly rainfall. For the annual ED calculation, Equation (4) can be used as Equation (5) as mentioned in the following.

$$ED = \sum_{i=1}^{12} \frac{RE_i}{P_i} \tag{5}$$

where ED is the annual erosivity density (MJ ha^{-1} h^{-1}), RE_i is the monthly erosivity, and P_i is the monthly rainfall.

3. RESULTS AND DISCUSSION

3.1. RE results

RE results were estimated using two equations as above mentioned(1) Premalal Equation (2). Wisehmeier and Smith equation. The results obtained using both equations separately were compared to obtain the most accurate results (Tesfahunegn *et al.* 2014; Karunaratne *et al.* 2022).

3.1.1. Premalal's equation

Premalal's equation needs average annual rainfall data. The annual RE varies between 289.83 and 446.59 MJ mm ha^{-1} h^{-1} yr^{-1}. The highest RE was found in 2008 and the lowest RE was predicted in 2001. The annual RE results obtained for the basin are shown in Figure 2(a).

3.1.2. Wisehmeier and Smith equation

The equation developed by Arnoldus (Singh & Singh 2020) requires monthly rainfall data and annual rainfall data in order to calculate the RE. Furthermore, the monthly RE and annual RE can be obtained using this equation. The annual RE varies between 592.84 and 2,831.41 MJ mm ha^{-1} h^{-1} yr^{-1}. The highest RE was in 2016 and the lowest RE was in 2001. The annual RE results obtained for the basin are shown in Figure 2(b).

3.1.3. Comparison of two equations

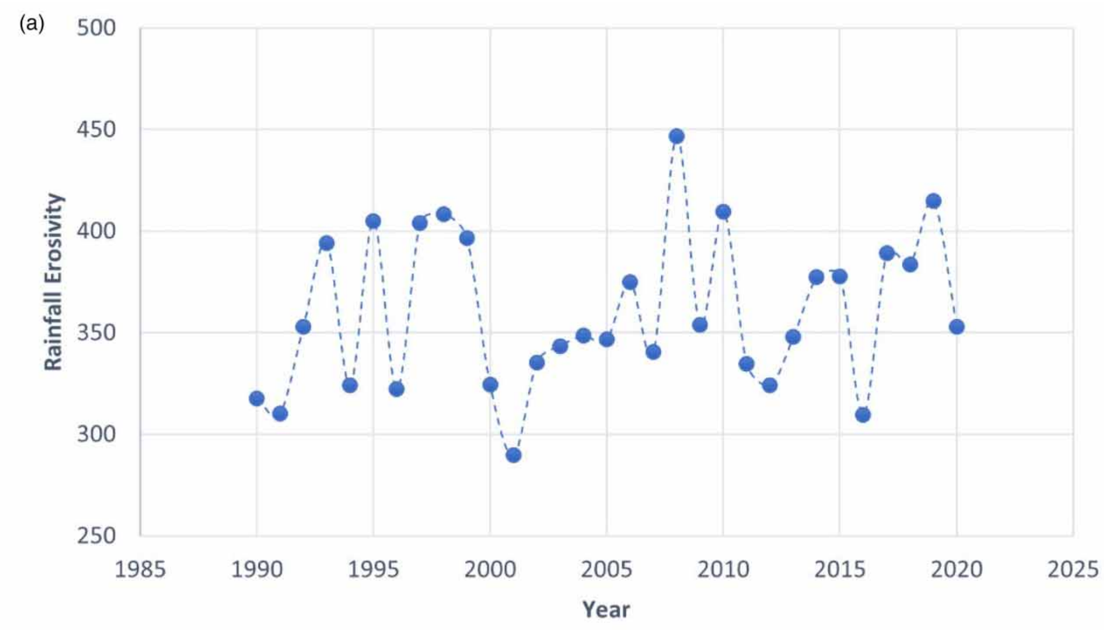
Because the input data are different, there is a significant difference between the two equations. Premalal's equation uses annual average rainfall data, while the Wischmeier and Smith equation uses monthly and annual rainfall data. The Wischmeier and Smith equation yields more accurate answers since it initially determines the monthly RE before calculating the annual RE, whereas Premalal's equation directly calculates the annual RE simultaneously (Cherif *et al.* 2020; Chen *et al.* 2023). Table 2 illustrates the corresponding results. When referring to the RE listed in Table 2, the value has dropped in 2016 in Premalal's equation but in Wischmeier and Smith equation, the value has increased by a large amount. Meanwhile considering the reason for this, the annual rainfall of 2016 was 3,012.54 mm and the rainfall in the month of May 2016 was 1,145 mm. As Premalal's equation calculation is based on annual rainfall data, monthly rainfall does not affect the calculation but in Wischmeier and Smith's algorithm the annual RE is calculated by summation of monthly RE, as we can see it depends on monthly rainfall, the annual RE differs concerning monthly rainfall.

As mentioned above in 2016, the RE spiked according to the Wischmeier and Smith algorithm. If we consider the rainfall data of May 2016 it has increased in large value due to Tropical Storm Roanua occurring on 15 May 2016 and causing severe damage to the lives of people as well as properties. Due to the severe landslides and floods, 104 deaths, and 99 missing were recorded and more than 300,000 people were affected. Therefore, we can come to the conclusion the results obtained using Wischmeier and Smith's algorithm are more accurate than Premalal's equation.

3.2. Variation in RE

3.2.1. Monthly variation

Equation (3) is used to calculate the RE which was developed by (Singh & Singh 2020). A summary of the average monthly RE of the Kelani River basin for the period of 1990–2020 is listed in Table 3. Figure 3 gives a clear illustration of the variation of the monthly RE simultaneously. The average monthly RE of the basin for the selected period of 31 years, varies between 13.60 to 211.77 MJ mm ha^{-1} h^{-1} yr^{-1}. The lowest monthly RE was observable in the month of February and the highest was recorded in the month of May. The monthly RE of each rainfall station varies from 0 to 4,762.51 MJ mm ha^{-1} h^{-1} yr^{-1}. The highest value for monthly erosivity was recorded in the month of May 2016 in the Deraniyagala (Dabar) rainfall station.



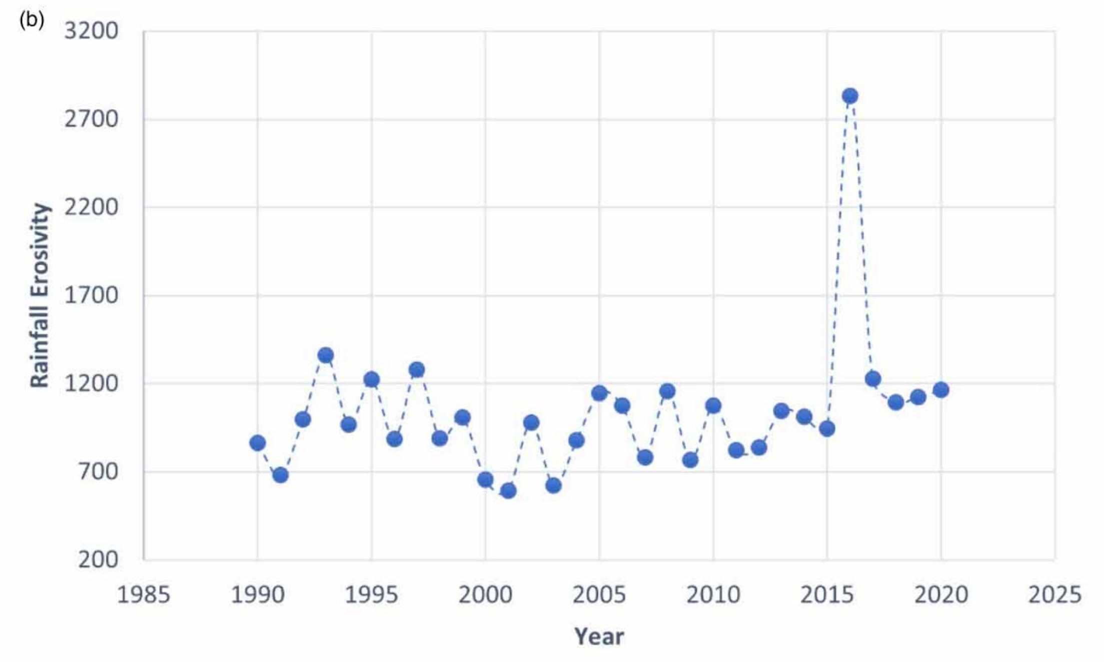


Figure 2 | (a) Rainfall erosivity (Premalal's Equation) and (b) rainfall erosivity (Wischmeier and Smith Equation).

Table 2 | Annual rainfall erosivity (2015–2017) calculated using Premalal's equation and Wischmeier and Smith algorithm

	Rainfall erosivity (MJ mm ha^{-1} h^{-1} yr^{-1})	
Year	**Premalal's equation**	**Wischmeier and Smith algorithm**
2015	377.70	944.86
2016	309.48	2,831.40
2017	389.13	1,227.70

Table 3 | Average monthly rainfall erosivity (1990–2020)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rainfall erosivity	28.74	13.6	14.45	82.53	211.77	103.31	64.65	64.36	114.26	190.21	112.71	31.24

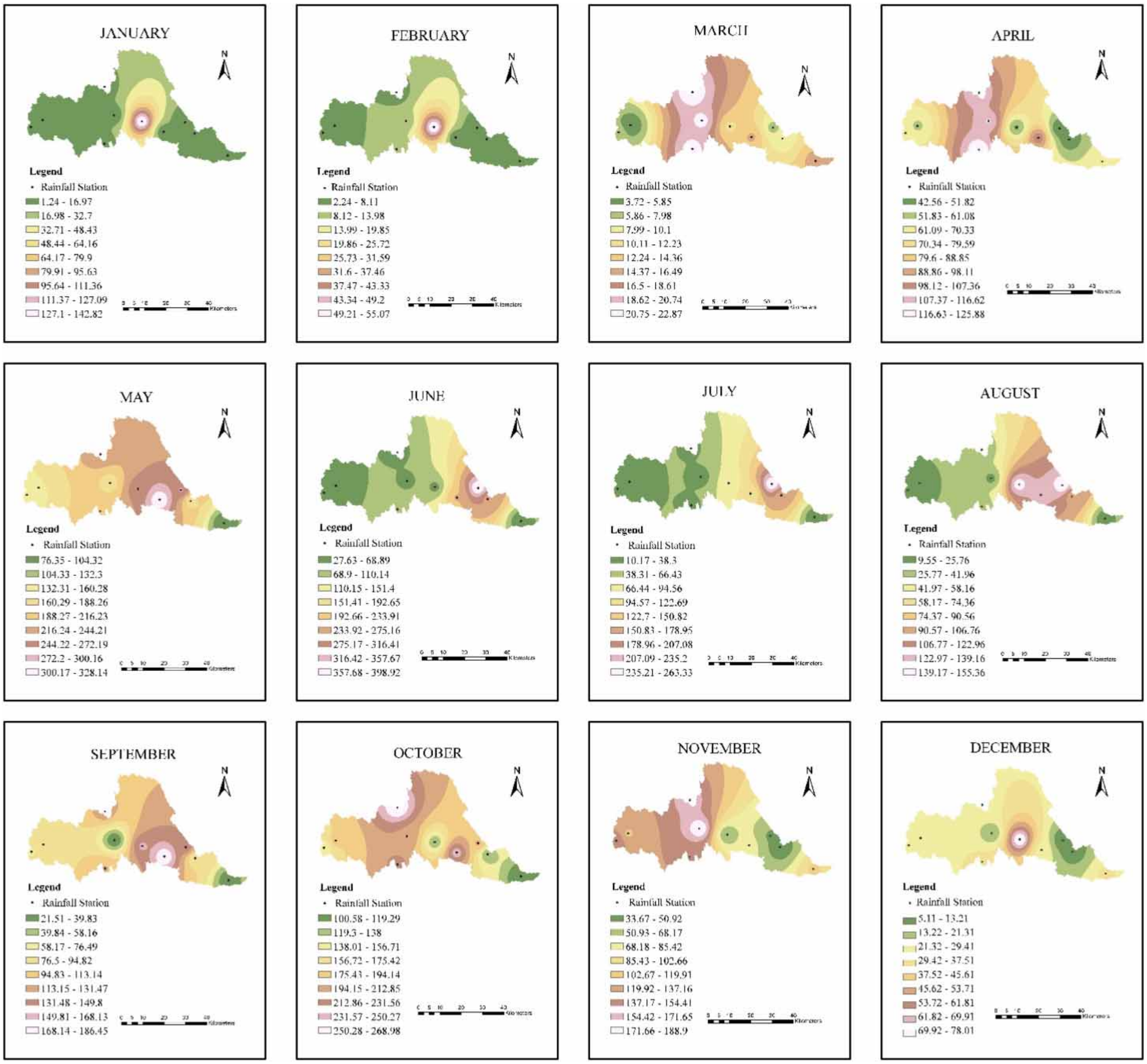


Figure 3 | Variation of monthly rainfall erosivity during 1990–2020.

Additionally, the highest monthly RE of each rainfall station occurred in the month of May 2016. This is due to tropical Storm Roanua occurred on 15 May 2016. This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

3.2.2. Annual variation

For the estimation of annual rainfall, Equation (2) was used, and the results obtained for the particular period of the study are shown in Figure 4(a). Table 4 presents the average value of RE of each rainfall station, for the 31 years. The RE of the basin

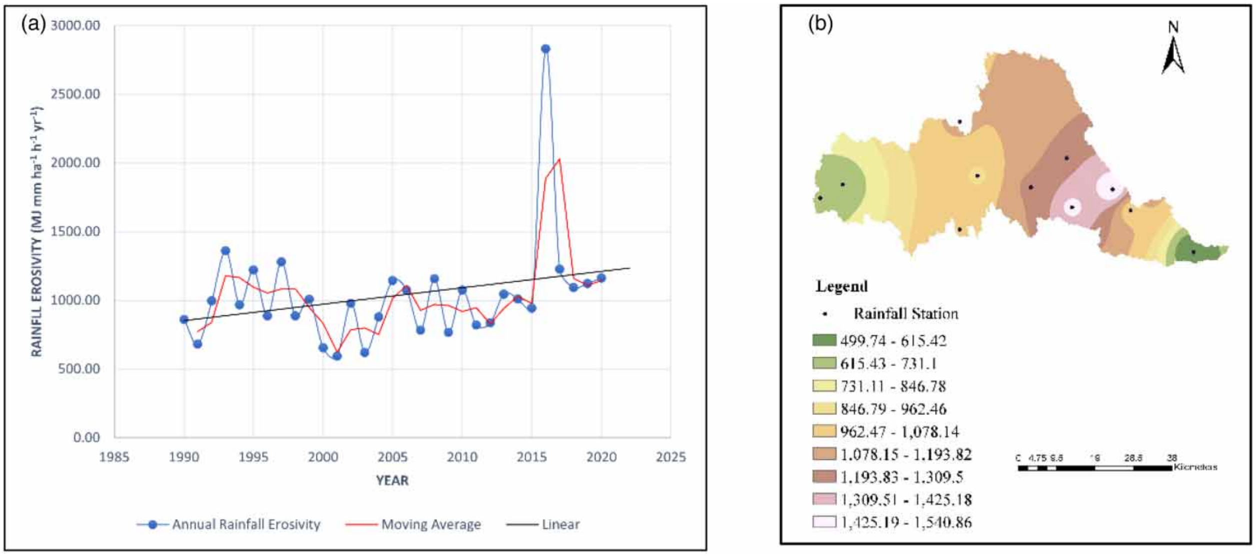


Figure 4 | (a) Annual rainfall erosivity and (b) 1990–2020 average annual variation.

Table 4 | Average annual rainfall erosivity of rainfall stations

Rainfall station	Rainfall erosivity
Angoda	679.16
Awissawella	947.43
Chesterford	1,094.74
Colombo	671.81
Labugama	1,020.52
Maliboda	1,452.25
Norton	1,540.96
Champion	499.73
Castlereigh	1,011.19
Deraniyagala (Dabar)	1,208.25
Basin	1,031.81

varies from 592.84 to 2,831.41 MJ mm ha^{-1} h^{-1} yr^{-1}. This lowest value was recorded in the year of 2001 and the highest value was recorded in the year of 2016. The annual RE of rainfall stations varies from 226.34 to 5,132.01 MJ mm ha^{-1} h^{-1} yr^{-1}. The lowest annual RE is in the Champion rainfall station in the year of 1998 and the highest annual RE is in the Deraniyagala (Dabar) rainfall station in the year of 2016. The RE map (Figure 4(b)) was obtained using IDW interpolation in ARC-GIS software.

3.2.3. Seasonal variation

The seasonal RE was filtered from the monthly RE results obtained according to the seasonal division of months. The results obtained for the seasonal RE for each rainfall station are shown in Figure 5(a) and the seasonal RE variation with the year is shown in Figure 5(b). The seasonal average RE of the 31 years varies from 73.57 to 558.34 MJ mm ha^{-1} h^{-1} yr^{-1}. Figure 5(c) provides a better illustration. The highest RE was recorded in the Southwest – monsoon season and the lowest RE was recorded in the Northeast – monsoon season. If we consider the basin, it extends over the Western, Sabaragamuwa, and Central provinces. 46.83% – Sabaragamuwa Province, 34.77% – Western Province, and 18.40% – Central Province. As we can observe the basin lies in the Western part of the country. As the rainfall is high in the Southwestern part of the country in

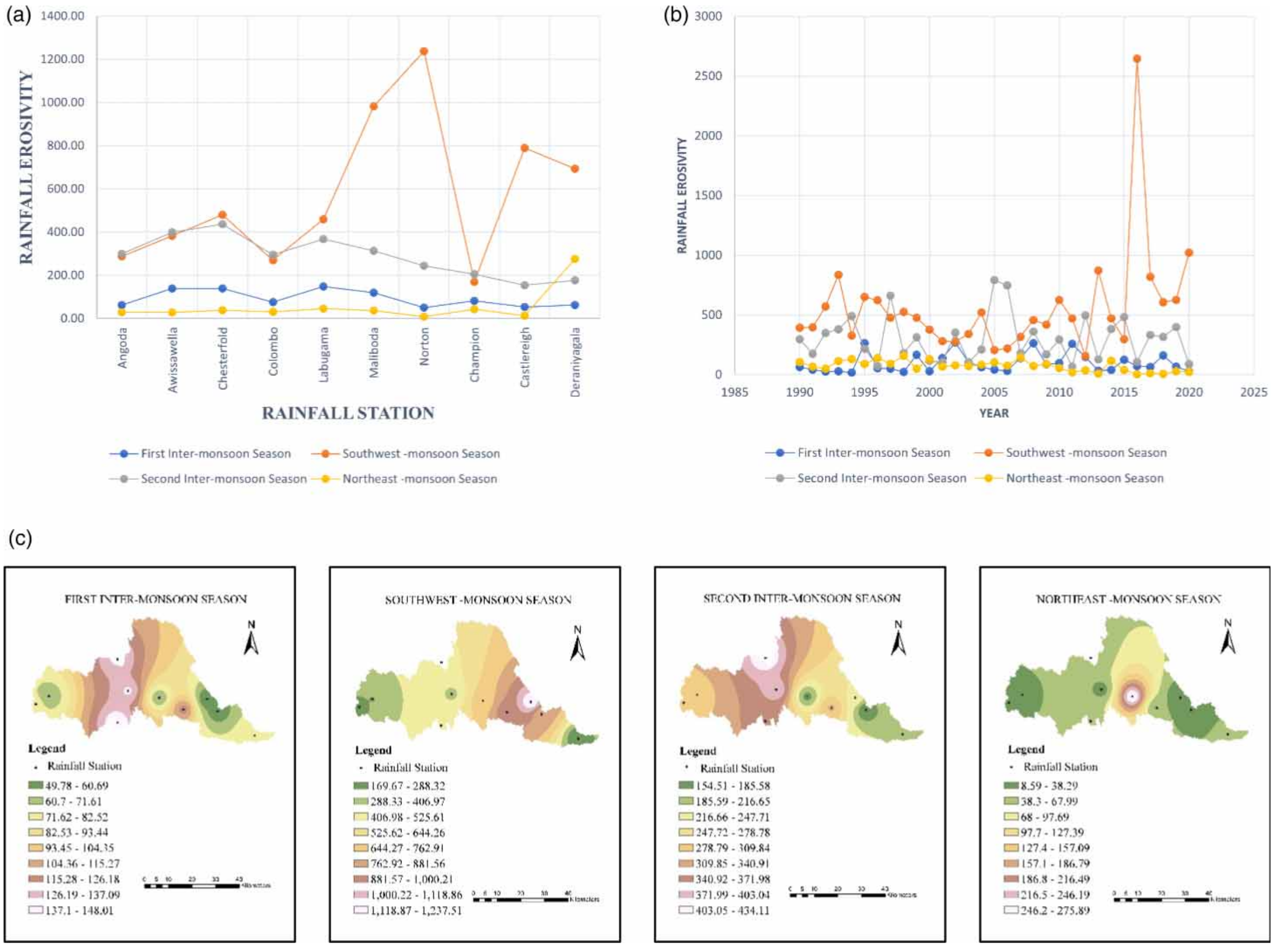


Figure 5 | (a) Seasonal variation of rainfall erosivity; (b) seasonal variation of rainfall erosivity with the years; and (c) seasonal variation of rainfall erosivity.

the Southwest – monsoon season the RE in the season is comparatively higher than the other seasons. The RE in the Southwest monsoon peaked at a value of 2,646.26 MJ mm ha^{-1} h^{-1} yr^{-1} in the year 2016. The reason for the peak if we consider is the tropical storm which occurred in the month of May 2016.

3.3. Variation in erosivity density

3.3.1. Monthly variation

Monthly ED was calculated using the Kinnell's algorithm (Equation (4)). The average monthly ED of the basin for the selected period of 31 years (1990–2020) (Table 5) varies between 0.04 and 0.32 MJ ha^{-1} h^{-1}. Figure 6 illustrates the variation clearly. The lowest monthly ED was recorded in the month of February and the highest was recorded in the month of October. The monthly ED of each rainfall station varies from 0 to 2.96 MJ ha^{-1} h^{-1}. The highest monthly ED was recorded in the month of May 2016 in the Chesterfold rainfall station.

3.3.2. Annual variation

From the collected monthly rainfall data and calculated monthly RE, the monthly ED was calculated, summation of the monthly ED was obtained as annual ED (Equation (5)). The calculated values of ED from 1990 to 2020. The average

Table 5 | Average monthly rainfall erosivity (31 years)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Rainfall Erosivity	28.74	13.6	14.45	82.53	211.77	103.31	64.65	64.36	114.26	190.21	112.71	31.24

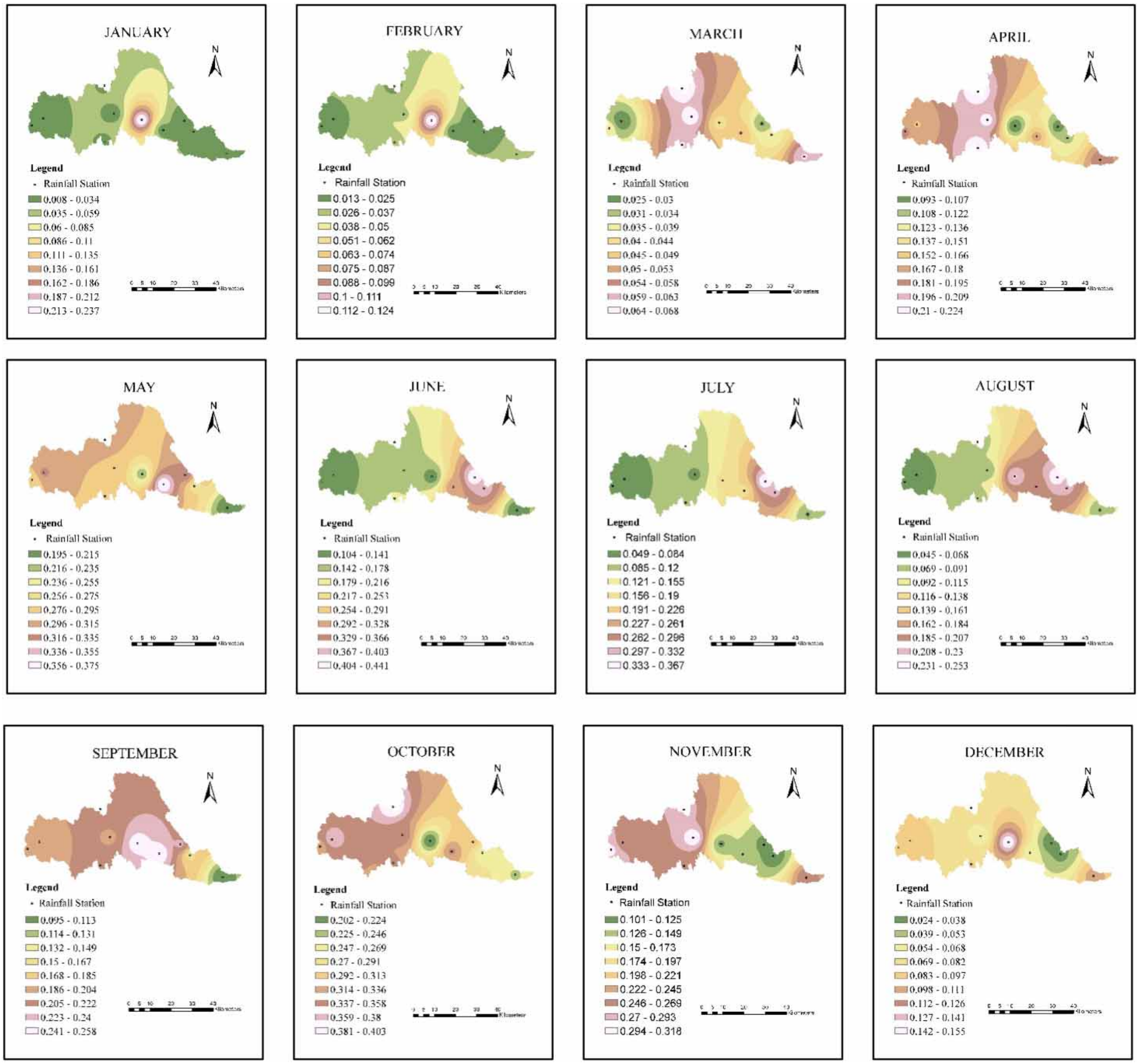


Figure 6 | Variation of monthly erosivity density during 1990–2020.

value of ED for the period of 31 years of each rainfall station is given in Table 6. Also, Figure 7(a) shows the annual ED graph version and Figure 7(b) presents the average annual variation of the same data. To calculate the annual ED of the basin, Thiessen polygon method was used. The average ED of the basin varies from 1.55 to 2.89 MJ ha^{-1} h^{-1}. The lowest value was recorded in the year of 2003 and the highest value was recorded in the year of 2016. The annual ED of rainfall stations varies from 1.13 to 3.64 MJ ha^{-1} h^{-1}. The lowest annual RE was in the Champion rainfall station in the year 2000 and the highest annual RE is in the Deraniyagala (Dabar) rainfall station in the year 2016.

3.3.3. Seasonal variation

For the four seasons, ED results were obtained for the selected 31-years period. The seasonal average ED of the 31 years varies between 0.18 and 0.94 MJ ha^{-1} h^{-1}. The highest ED was recorded in the Southwest – monsoon season and the lowest ED was recorded in the Northeast – monsoon season. Figure 8(a) illustrates the seasonal variation of RE the Figure 8(b) illustrates the seasonal variation of RE with years. Also, Figure 8(c) shows the seasonal variation of ED as

Table 6 | Average annual erosivity density of rainfall stations

Rainfall station	Average annual erosivity density
Angoda	1.66
Awissawella	1.84
Chesterfold	1.94
Colombo	1.66
Labugama	1.88
Maliboda	2.12
Norton	2.21
Champion	1.48
Castlereigh	1.89
Deraniyagala (Dabar)	1.96
Basin	1.88

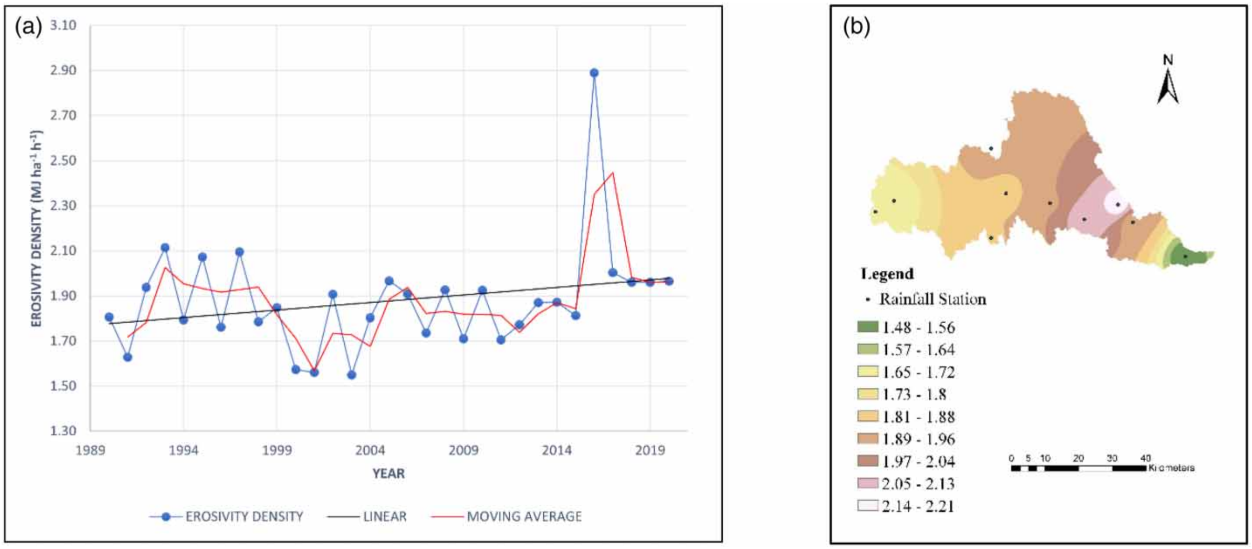


Figure 7 | (a) Annual erosivity density and (b) 1990–2020 average annual variation.

below mentioned. As discussed above, as the basin lies in the Western part of the country, the rainfall is high in the Southwestern part of the country in the Southwest monsoon season the ED in the season is comparatively higher than the other seasons (Senanayake *et al.* 2020; Singh & Singh 2020). The ED in the Southwest monsoon peaked at a value of 2.34 MJ ha^{-1} h^{-1} in the year 2016. The reason for the peak if we consider is the tropical storm that occurred in the month of May 2016 (Sri Lanka 2017).

As it is discussed, the Kelani River basin in Sri Lanka is one of the most important river basins to the economy of the country. This includes various water resources management processes and direct and indirect relationships to the water resources. Therefore, understanding soil erosion in this tricky catchment is highly essential which was pointed out in the introduction. The sustainability of food production is one of the most important and challenging aspects and is given a higher priority even in the SDGs. Zero hunger is considered the second sustainable development goal and soil erosion can adversely influence agricultural production. Therefore, continuous research has been carried out to understand soil erosion and its correlations to the water sector, agriculture and food sector, energy sector, etc. throughout the world. Being one of the most important catchments in Sri Lanka, the presented research in this paper has a greater potential to look at the required responsible strategies to mitigate any adverse impacts.

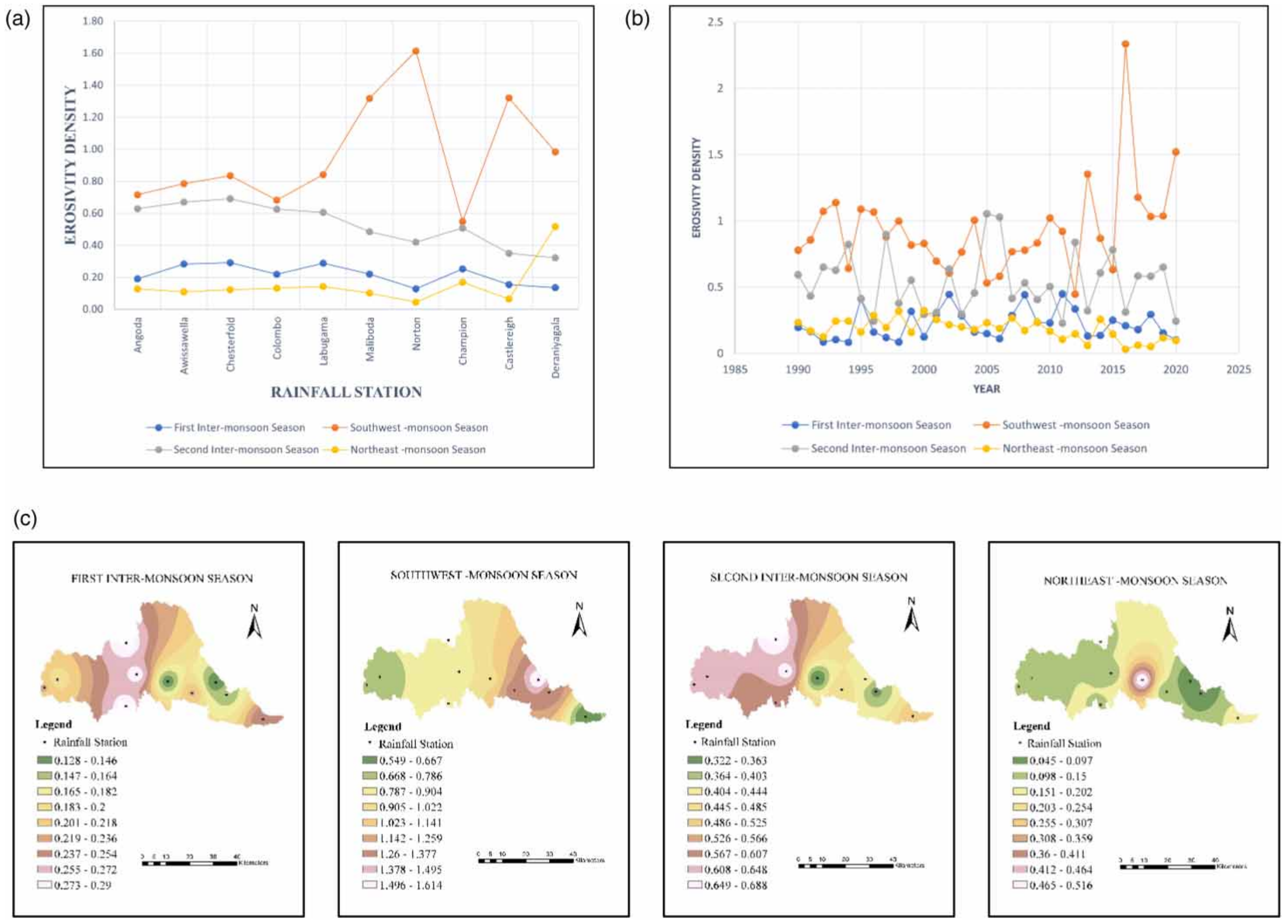


Figure 8 | (a) Seasonal variation of rainfall erosivity; (b) seasonal variation of rainfall erosivity with the years; and (c) seasonal variation of erosivity density.

As it was stated, continuous research is being undertaken to assess the RE of river basins throughout the world. (de Sousa Teixeira *et al.* 2023) have modeled the RE over Brazil from 5,166 rain gauge data. This was a comprehensive study carried out to bring up national-scale policies identifying the importance of soil erosion due to precipitation. Understanding the importance of climate change for future scenarios, (Wang *et al.* 2023) have showcased the projected RE in mainland China. They have used gridded precipitation data with an acceptable bias correction. They have found that the RE is projected to increase due to intensified precipitation scenarios. However, (Feng *et al.* 2023) looked at the RE trends in Three Gorges Reservoir, China. This is important in order to understand the temporal behavior of RE and then to plan the other activities. Related studies in mountainous catchments are highly important. (Baniya *et al.* 2023) analyzed the RE for the Himalaya catchment during the Melamchi flood in Nepal. Analyzing sediment dynamics is essential in river basins due to various issues including understanding impacts on hydropower development and turbine blade damage in countries such as Nepal.

Nevertheless, analyzing RE on highly important catchments in Sri Lanka is limited. Data limitation is one of the major reasons for the lack of studies. In a recent study, (de Silva *et al.* 2022) investigated the spatial variability of soil erosion in the Nalanda Oya catchment in Sri Lanka. The authors concluded the possible use of their findings in the management of soil erosion due to changing climates. The central highlands of Sri Lanka were chosen by (Senanayake *et al.* 2024) to investigate the RE and then to understand the possible remedy measures for achieving SDGs. However, a comprehensive study of the Kelani River basin is missing in the literature. Therefore, the presented research herein fulfills the research gap in understanding RE in one of the most rainfall-rich catchments in Sri Lanka. Various policy decisions including sustainable urban drainage systems (Srishantha & Rathnayake 2017) have to be implemented in conserving the Kelani River basin from increased RE. These conserving strategies are highly important under climate change.

4. CONCLUSIONS

In this study, we carried out an assessment of RE in the Kelani River basin spanning a 31-year period, from 1990 to 2020. We utilized two distinct equations for this assessment: The Wischmeier and Smith algorithm and Premalal's equation. Using both equations, we calculated the annual RE and subsequently compared the outcomes. Upon a comprehensive evaluation, it became evident that the Wischmeier and Smith algorithm yielded the most accurate results for determining RE in the Kelani River basin. Furthermore, we employed the Wischmeier and Smith algorithm to determine annual, monthly, and seasonal RE, while we applied Kinnell's algorithm to assess ED. In both the estimations of monthly RE and ED, we noted that the month of May 2016 stood out as a peak period by proving the extreme rainfall event that we had on May 2016. The highest monthly RE recorded was 4,762.51 MJ mm ha^{-1} h^{-1} yr^{-1}, while the maximum monthly ED reached 2.96 MJ ha^{-1} h^{-1}. Likewise, the highest annual RE was observed in 2016, totaling 5,132 MJ mm ha^{-1} h^{-1} yr^{-1}, coinciding with the period of May. During the same year, the highest ED was 3.64 MJ ha^{-1} h^{-1}. When examining the seasonal variations, we found that the highest RE occurred in 2016, reaching 558.34 MJ mm ha^{-1} h^{-1} yr^{-1}. This peak was observed during the southwest monsoon period. The ED was also at its highest during the same period, at 0.94 MJ ha^{-1} h^{-1} in 2016's southwest monsoon period. Both the annual RE and ED reached their highest levels in the year 2016. Monthly values also peaked in May 2016. These findings indicate a significant soil erosion event occurred in that year. Being evidence of these results, on May 15, 2016, a tropical storm collided with Sri Lanka, leading to severe landslides and floods. This catastrophic event resulted in 104 fatalities, and 99 missing individuals, and affected over 300,000 people. This study proves that assessing the RE of a basin is crucial in calculating soil loss using the USLE method. Based on the observed trends in RE, we can conclude that soil erosion in the basin due to rainfall is likely to remain high in the future. Therefore, it is imperative to take necessary measures to mitigate the damage. In summary, the study's results affirm that the methodology employed was consistently and successfully applied to obtain reliable findings by the end of the study. The Kelani River basin, renowned for its provision of various benefits such as potable water, hydropower, agricultural support, and urban utilities, underscores the need for investments in erosion control. This study serves as a valuable tool for crafting ecosystem-centered benefit distribution and financing strategies. By leveraging potential ecosystem benefits identified through such analyses, these investments can be recouped. Moreover, this approach fosters collaboration among diverse stakeholders and socio-economic sectors. The authors are recommending the following in order to enhance understanding in future studies because there exists a notable research gap concerning these scenarios within this specific study area. It is recommended to model soil erosion in this river basin using GIS as well as in sub catchment basis, also to prepare a soil hazard map for whole catchment and to assess soil retention in the Kelani River basin.

USE OF AI TOOLS DECLARATION

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

REFERENCES

Alahacoon, N. & Edirisinghe, M. 2021 Spatial variability of rainfall trends in Sri Lanka from 1989 to 2019 as an indication of climate change. *ISPRS Int. J. Geo-Inf.* **10** (2). doi:10.3390/ijgi10020084.

Avand, M., Kuriqi, A., Khazaei, M. & Ghorbanzadeh, O. 2022 DEM resolution effects on machine learning performance for flood probability mapping. *J. Hydro-Environ. Res.* **40** (October 2021), 1–16. doi:10.1016/j.jher.2021.10.002.

Baniya, B., Tang, Q., Neupane, B., Xu, X., He, L., Adhikari, T. R., Shamsi, S. R. & Dhital, Y. P. 2023 Rainfall erosivity and sediment dynamics in the Himalaya catchment during the Melamchi Flood in Nepal. *J. Mountain Sci.* **20** (10), 2993–3009. https://doi.org/10.1007/s11629-023-8231-2.

Belasri, A. & Lakhouili, A. 2016 Estimation of soil erosion risk using the Universal Soil Loss Equation (USLE) and geo-information technology in Oued El Makhazine Watershed, Morocco. *J. Geogr. Inf. Syst.* **08** (01), 98–107. doi:10.4236/jgis.2016.81010.

Borrelli, P., Diodato, N. & Panagos, P. 2016 Rainfall erosivity in Italy: A national scale spatio-temporal assessment. *Int. J. Digital Earth* **9** (9), 835–850. doi:10.1080/17538947.2016.1148203.

Borrelli, P., Robinson, D. A., Fleischer, L. R., Lugato, E., Ballabio, C., Alewell, C., Meusburger, K., Modugno, S., Schütt, B., Ferro, V. & Bagarello, V. 2017 An assessment of the global impact of 21st century land use change on soil erosion. *Nat. Commun.* **8** (1), 1–13.

Borrelli, P., Robinson, D. A., Panagos, P., Lugato, E., Yang, J. E., Alewell, C., Wuepper, D., Montanarella, L. & Ballabio, C. 2020 Land use and climate change impacts on global soil erosion by water (2015–2070). *Proc. Natl. Acad. Sci.* **117** (36), 21994–22001.

Brychta, J. & Janeček, M. 2017 Evaluation of discrepancies in spatial distribution of rainfall erosivity in the Czech Republic caused by different approaches using GIS and geostatistical tools. *Soil Water Res.* **12** (2), 117–127. doi:10.17221/176/2015-SWR.

Cardoso, D. P., Avanzi, J. C., Ferreira, D. F., Acuña-Guzman, S. F., Silva, M. L., Pires, F. R. & Curi, N. 2022 Rainfall erosivity estimation: Comparison and statistical assessment among methods using data from southeastern Brazil. *Revista Brasileira de Ciência Do Solo* **46**. https://doi.org/10.36783/18069657rbcs20210122.

Cecílio, R. A., Moreira, M. C., Pezzopane, J. E. M., Pruski, F. F. & Fukunaga, D. C. 2013 Assessing rainfall erosivity indices through synthetic precipitation series and artificial neural networks. *An. Acad. Bras. Cienc.* **85** (4), 1523–1535. doi:10.1590/0001-3765201398012.

Chen, W., Huang, Y. C., Lebar, K. & Bezak, N. 2023 A systematic review of the incorrect use of an empirical equation for the estimation of the rainfall erosivity around the globe. *Earth-Science Rev.* **238** (February), 104339. doi:10.1016/j.earscirev.2023.104339.

Cherif, I., Hermass, T. & Mechergui, M. 2020 Comparing between ten regression equations to estimate rainfall erosivity using a long-term precipitation dataset in Tunisia. *Int. J. Water Sci. Environ. Technol.* **1**, 137–144. Available from: http://jistee.org/volume-v-2020/

de Silva, S. S., Abeysingha, N. S., Nirmanee, K. G., Sandamali Pathirage, P. D. & Mallawatantri, A. 2022 Effect of land use–land cover and projected rainfall on soil erosion intensities of a tropical catchment in Sri Lanka. *Int. J. Environ. Sci. Technol.* **20** (8), 9173–9188. https://doi.org/10.1007/s13762-022-04606-w.

de Sousa Teixeira, D. B., Cecílio, R. A., Moreira, M. C., Pires, G. F. & Fernandes Filho, E. I. 2022 Recent advancements in rainfall erosivity assessment in Brazil: A review. *CATENA* **219**, 106572. doi:10.1016/j.catena.2022.106572.

de Sousa Teixeira, D. B., Cecílio, R. A., Moreira, M. C., Pires, G. F. & Fernandes Filho, E. I. 2023 Assessment, regionalization, and modeling rainfall erosivity over Brazil: Findings from a large National Database. *Sci. Total Environ.* **891**, 164557. https://doi.org/10.1016/j.scitotenv.2023.164557.

Di Lena, B., Curci, G. & Vergni, L. 2021 Analysis of rainfall erosivity trends 1980–2018 in a complex terrain region (Abruzzo, central Italy) from rain gauges and gridded datasets. *Atmosphere (Basel)* **12** (6). doi:10.3390/atmos12060657.

Diodato, N., Ljungqvist, F. C. & Bellocchi, G. 2021a OPEN a millennium-long climate history of erosive storms across the Tiber River Basin, Italy, from 725 to 2019. *Sci. Rep.* 1–18. doi:10.1038/s41598-021-99720-z.

Diodato, N., Ljungqvist, F. C. & Bellocchi, G. 2021b Climate patterns in the World's longest history of storm-erosivity: The Arno River Basin, Italy. *Front. Earth Sci.* **9** (April), 1–19. doi:10.3389/feart.2021.637973.

Fayas, C. M., Abeysingha, N. S., Nirmanee, K. G. S., Samaratunga, D. & Mallawatantri, A. 2019 Soil loss estimation using rusle model to prioritize erosion control in KELANI river basin in Sri Lanka. *Int. Soil Water Conserv. Res.* **7** (2), 130–137. doi:10.1016/j.iswcr.2019.01.003.

Feng, Q., Dong, L., Liu, J. & Liu, H. 2023 Detection framework of abrupt changes and trends in rainfall erosivity in Three Gorges Reservoir, China. *Sustainability* **15** (3), 2062. https://doi.org/10.3390/su15032062.

Fenta, A. A., Tsunekawa, A., Haregeweyn, N., Yasuda, H., Tsubo, M., Borrelli, P., Kawai, T., Belay, A. S., Ebabu, K., Berihun, M. L. & Sultan, D. 2024 An integrated modeling approach for estimating monthly global rainfall erosivity. *Sci. Rep.* **14** (1), 8167.

Gupta, L. K., Pandey, M. & Raj, P. A. 2023 Numerical modeling of scour and erosion processes around spur dike. *Clean – Soil, Air, Water*. doi:10.1002/clen.202300135.

Jadhao, V. G., Pandey, A. & Mishra, S. K. 2023 Modeling of rain erosivity employing simulated rainfall and laser precipitation monitor. *Model. Earth Syst. Environ.* **9** (4), 4477–4492. doi:10.1007/s40808-023-01727-0.

John, C. K., Pu, J. H., Pandey, M. & Hanmaiahgari, P. R. 2021 Sediment deposition within rainwater: case study comparison of four different sites in Ikorodu, Nigeria. *Fluids* **6** (3), 124. doi:10.3390/fluids6030124.

Karunaratne, A. S., Wimalasiri, E. M., Piyathilake, U., Gunatilake, S. K., Muttil, N. & Rathnayake, U. 2022 Modelling potential soil erosion and sediment delivery risk in plantations of Sri Lanka. *Soil Syst.* **6** (4), 97.

Kinnell, P. I. A. 2010 Event soil loss, runoff and the universal soil loss equation family of models: A review. *J. Hydrol.* **385** (1–4), 384–397. doi:10.1016/j.jhydrol.2010.01.024.

Kottagoda, S. D. & Abeysingha, N. S. 2017 Morphometric analysis of watersheds in Kelani river basin for soil and water conservation. *J. Natl. Sci. Found. Sri Lanka* **45** (3), 273–285. doi:10.4038/jnsfsr.v45i3.8192.

Kumarasiri, A. D. T. N., Udayakumara, E. P. N. & Jayawardana, J. M. C. K. 2023 Modeling soil erosion: Samanalawewa watershed, Sri Lanka. In: *Multi-Hazard Vulnerability and Resilience Building*. Elsevier, pp. 205–220. doi:10.1016/B978-0-323-95682-6.00009-7.

Lee, J.-H. & Heo, J.-H. 2011 Evaluation of estimation methods for rainfall erosivity based on annual precipitation in Korea. *J. Hydrol.* **409** (1–2), 30–48. doi:10.1016/j.jhydrol.2011.07.031.

Lee, S., Bae, J. H., Hong, J., Yang, D., Panagos, P., Borrelli, P., Yang, J. E., Kim, J. & Lim, K. J. 2022 Estimation of rainfall erosivity factor in Italy and Switzerland using Bayesian optimization based Machine Learning Models. *CATENA* **211**, 105957. https://doi.org/10.1016/j.catena.2021.105957.

Li, X. & Ye, X. 2018 Variability of rainfall erosivity and erosivity density in the Ganjiang river catchment, China: characteristics and influences of climate change. *Atmosphere (Basel)* **9** (2), 48. doi:10.3390/atmos9020048.

Liyanage, G. Y., Illango, A. & Manage, P. M. 2021 Prevalence and quantitative analysis of antibiotic resistance genes (ARGs) in surface and groundwater in meandering part of the Kelani River Basin in Sri Lanka. *Water Air Soil Pollut.* **232** (9), 1–11. doi:10.1007/s11270-021-05300-2.

Mamedov, A. I., Levy, G. J. & Huang, C.-H. 2011 Erosion as affected by soil inherent properties and extrinsic conditions. In *International Symposium on Erosion and Landscape Evolution (ISELE)*, 18–21 September 2011, Anchorage, Alaska, St. Joseph, MI, American Society of Agricultural and Biological Engineers. doi: 10.13031/2013.39208.

Marondedze, A. K. & Schütt, B. 2020 Assessment of soil erosion using the RUSLE model for the Epworth District of the Harare Metropolitan Province, Zimbabwe. *Sustainability* **12** (20), 8531. doi:10.3390/su12208531.

Milentijević, N., Ostojić, M., Fekete, R., Kalkan, K., Ristić, D., Bačević, N. R. & Pantelić, M. 2021 Assessment of Soil Erosion Rates Using Revised Universal Soil Loss Equation (RUSLE) and GIS in Bačka (Serbia). *Polish Journal of Environmental Studies* **30**(6), 5175–5184. https://doi.org/10.15244/pjoes/135617.

Nabi, G., Hussain, F., Wu, R.-S., Nangia, V. & Bibi, R. 2020 Micro-watershed management for erosion control using soil and water conservation structures and SWAT modeling. *Water* **12** (5), 1439. doi:10.3390/w12051439.

Nandalal, K. D. W. 2017 Changes in rainfall in Sri Lanka during 1966–2015 changes in rainfall in Sri Lanka during 1966–2015. doi:10.4038/engineer.v50i2.7251.

Nazuhan, M., Rahaman, Z. A. & Othman, Z. 2018 A review on rainfall erosivity (R factor) in universal soil loss equation. *Int. J. Acad. Res. Bus. Soc. Sci.* **8** (2). doi:10.6007/IJARBSS/v8-i2/3988.

N. Co-investigator 2013 Extraction of parameters and modelling soil erosion using gis in a grid environment. *J. Chem. Inf. Model.* **53** (November), 1689–1699.

Palliyaguru, C., Basnayake, V., Makumbura, R. K., Gunathilake, M. B., Muttil, N., Wimalasiri, E. M. & Rathnayake, U. 2022 Evaluation of the impact of land use changes on soil erosion in the tropical Maha Oya River Basin, Sri Lanka. *Land* **12** (1), 107.

Panagos, P., Borrelli, P., Meusburger, K., Yu, B., Klik, A., Jae Lim, K., Yang, J. E., Ni, J., Miao, C., Chattopadhyay, N. & Sadeghi, S. H. 2017a Global rainfall erosivity assessment based on high-temporal resolution rainfall records. *Sci. Rep.* **7** (1), 1–12.

Panagos, P., Ballabio, C., Meusburger, K., Spinoni, J., Alewell, C. & Borrelli, P. 2017b Towards estimates of future rainfall erosivity in Europe based on REDES and WorldClim datasets. *J. Hydrol.* **548**, 251–262. https://doi.org/10.1016/j.jhydrol.2017.03.006.

Panagos, P., Borrelli, P., Matthews, F., Liakos, L., Bezak, N., Diodato, N. & Ballabio, C. 2022 Global rainfall erosivity projections for 2050 and 2070. *J. Hydrol.* **610**, 127865.

Panagos, P., Hengl, T., Wheeler, I., Marcinkowski, P., Rukeza, M. B., Yu, B., Yang, J. E., Miao, C., Chattopadhyay, N., Sadeghi, S. H. & Levi, Y. 2023 Global rainfall erosivity database (GloREDa) and monthly R-factor data at 1 km spatial resolution. *Data Brief* **50**, 109482.

Pandey, M., Valyrakis, M., Qi, M., Sharma, A. & Lodhi, A. S. 2021 Experimental assessment and prediction of temporal scour depth around a spur dike. *Int. J. Sediment Res.* **36** (1), 17–28. doi:10.1016/j.ijsrc.2020.03.015.

Parisouj, P., Mohebzadeh, H. & Lee, T. 2020 Employing machine learning algorithms for streamflow prediction: A case study of four river basins with different climatic zones in the United States. *Water Resour. Manage.* **34** (13), 4113–4131. doi:10.1007/s11269-020-02659-5.

Piyathilake, I. D. U. H., Udayakumara, E. P. N. & Gunatilake, S. K. 2021 GIS and RS based soil erosion modelling in Sri Lanka: A review. *J. Agric. Sci. – Sri Lanka* **16** (1), 143–162. doi:10.4038/jas.v16i1.9192.

Renard, K. G., Foster, G. R., Weesies, G. A. & Porter, J. P. 1991 RUSLE: Revised universal soil loss equation. *J. Soil Water Conserv.* **46** (1), 30–33.

Sahour, H., Gholami, V., Vazifedan, M. & Saeedi, S. 2021 Machine learning applications for water-induced soil erosion modeling and mapping. *Soil Tillage Res.* **211**, 105032. doi:10.1016/j.still.2021.105032.

Senanayake, S., Pradhan, B., Huete, A. & Brennan, J. 2020 Assessing soil erosion hazards using land-use change and landslide frequency ratio method: A case study of Sabaragamuwa province, Sri Lanka. *Remote Sens.* **12** (9). doi:10.3390/RS12091483.

Senanayake, S., Pradhan, B., Huete, A. & Brennan, J. 2022 Spatial modeling of soil erosion hazards and crop diversity change with rainfall variation in the Central Highlands of Sri Lanka. *Sci. Total Environ.* **806**, 150405. doi:10.1016/j.scitotenv.2021.150405.

Senanayake, S., Pradhan, B., Wedathanthirige, H., Alamri, A. & Park, H.-J. 2024 Monitoring soil erosion in support of achieving sdgs: A special focus on rainfall variation and farming systems vulnerability. *CATENA* **234**, 107537. https://doi.org/10.1016/j.catena.2023.107537.

Singh, J. & Singh, O. 2020 Assessing rainfall erosivity and erosivity density over a western Himalayan catchment, India. *J. Earth Syst. Sci.* **129** (1). doi:10.1007/s12040-020-1362-8.

Somasiri, I. S., Hewawasam, T. & Rambukkange, M. P. 2022 Adaptation of the revised universal soil loss equation to map spatial distribution of soil erosion in tropical watersheds: A GIS/RS-based study of the Upper Mahaweli River Catchment of Sri Lanka. *Model. Earth Syst. Environ.* **8** (2), 2627–2645. doi:10.1007/s40808-021-01245-x.

Sri Lanka 2017 Ministry of Disaster Management, Sri Lanka. Ministry of Planning & Economic Affairs, United Nations, World Bank, and European Union, *Sri Lanka rapid post disaster needs assessment: floods and landslides: May 2017*.

Srishantha, U. & Rathnayake, U. 2017 Sustainable urban drainage systems (SUDS) – what it is and where do we stand today? *Eng. Appl. Sci. Res.* **44** (4), 235–241. https://doi.org/doi:10.14456/easr.2017.36.

Talbot, C. J., Bennett, E. M., Cassell, K., Hanes, D. M., Minor, E. C., Paerl, H., Raymond, P. A., Vargas, R., Vidon, P. G., Wollheim, W. & Xenopoulos, M. A. 2018 The impact of flooding on aquatic ecosystem services. *Biogeochemistry* **141**, 439–461.

Teixeira, D. B. D. S., Cecilio, R. A., de Oliveira, J. P. B., de Almeida, L. T. & Pires, G. F. 2022 Original Research Article Rainfall erosivity and erosivity density through rainfall synthetic series for Sao Paulo State, Brazil: Assessment, regionalization and modeling. *Int. Soil Water Conserv. Res.* **10** (3), 355–370.

Tesfahunegn, G. B., Tamene, L. & Vlek, P. L. G. 2014 Soil erosion prediction using Morgan-Morgan-Finney model in a GIS environment in northern Ethiopia catchment. *Appl. Environ. Soil Sci.* **2014**. doi:10.1155/2014/468751.

Wang, W., Yin, S., He, Z., Chen, D., Wang, H. & Klik, A. 2023 Projections of rainfall erosivity in climate change scenarios for Mainland China. *CATENA* **232**, 107391. https://doi.org/10.1016/j.catena.2023.107391.

Wang, L., Li, Y., Gan, Y., Zhao, L., Qin, W. & Ding, L. 2024 Catena rainfall erosivity index for monitoring global soil erosion. *Catena* **234** (October 2023), 107593. doi:10.1016/j.catena.2023.107593.

Wischmeier, W. H. & Smith, D. D. 1978 *Predicting Rainfall Erosion Losses: A Guide to Conservation Planning*.

Xiao, L., Yang, X., Chen, S. & Cai, H. 2015 An assessment of erosivity distribution and its influence on the effectiveness of land use conversion for reducing soil erosion in Jiangxi, China. *CATENA* **125**, 50–60. doi:10.1016/j.catena.2014.10.016.

Zekai, B. 1998 Average real precipitation by percentage weighted. *J. Hydrol. Eng.* **3** (January), 69–72.

Zhao, X., Huang, G., Li, Y. & Lu, C. 2023 Responses of hydroelectricity generation to streamflow drought under climate change. *Renewable Sustainable Energy Rev.* **174**, 113141. doi:10.1016/j.rser.2022.113141.

Zhu, D., Xiong, K. & Xiao, H. 2021 Multi-time scale variability of rainfall erosivity and erosivity density in the karst region of southern China, 1960–2017. *CATENA* **197**, 104977. doi:10.1016/j.catena.2020.104977.

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