

Determining and predicting single-storm erosion index in Sicily

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ABSTRACT

The single-storm erosion index, Re , expressing the rainfall erosive power, can be either calculated or estimated and it can be used for a variety of analyses, including the probabilistic assessment of soil water erosion phenomena. Calculation of Re according to the original procedure requires rainfall depth, he , and intensity data at short time intervals but their temporal resolution can change with the considered recording rain-gauge station. Estimating Re is sometimes necessary since rainfall intensity data could be unavailable in certain circumstances. An appropriate probability distribution law of the annual maximum values of Re has to be chosen for predicting single-storm erosivity values with a given return period. With reference to 8464 erosive rainfall events collected at 26 Sicilian stations in the 2002–2024 years, this investigation showed that: i) Re calculated by rainfall data measured at $\Delta t = 30$ min time intervals constituted the 88% of the corresponding calculations obtained by rainfall data collected at $\Delta t = 10$ min and time effects were particularly appreciable for relatively small rainfall depths ($he \leq 40$ mm); ii) the power law relationship between Re and he parameterized by minimizing the sum of the squared residuals between the actual and the estimated Re values (optimization approach, OPT) yielded less biased Re predictions than the relationship parameterized by a linear regression analysis of the natural logarithm (ln-) transformed data; iii) power law relationships obtained in two different historical periods (1951–1970 and 2002–2024) yielded different Re predictions, likely as a consequence of climate change; iv) an envelope line of the Re vs. he data was usable to simply distinguish, for a given rainfall depth, expected from unexpected, Re values; and v) the annual maximum values of Re were distributed according to the Extreme Value Type-1 (EV1) distribution. In conclusion, rainfall temporal resolution effects on Re calculation can be expected to decrease as he increases. The OPT approach should be applied for parameterizing the Re predicting relationship. Using Re vs. he relationships developed in the past for estimating current erosivity is not recommended. The highest expected Re value for a given rainfall depth and the quantile, Re_T , corresponding to a given return period, T , can easily be estimated and they should be taken into account for planning appropriate soil conservation measures given that total soil erosion in a long period is mostly due to a few particularly high erosive events.

1. Introduction

Warmer atmospheric temperatures associated with greenhouse warming are expected to lead to a more variable hydrological cycle and also to an increase in the frequency and severity of extreme rainfall events (IPPC, 1995; Dallen et al., 2014a,b). Such increases are expected to influence the rainfall erosive power (Nearing, 2001) and hence exacerbate water-induced soil erosion (Prein et al., 2017).

According to Wischmeier and Smith (1978), a single storm is preceded and followed by 6 h or more of no rain and it is erosive if the

rainfall depth, he , is equal to 13 mm or more. The single-storm erosion index, Re ($\text{MJ mm ha}^{-1}\text{h}^{-1}$), by Wischmeier and Smith (1978) establishes that the rainfall erosive power depends on rainfall depth and intensity according to the following relationships:

$$Re = EI_{30} \quad (1a)$$

$$E = \sum_i^n e_i \quad (1b)$$

$$e_i = e'_i h_i \quad (1c)$$

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$$e_i' = [0.119 + 0.0873 \log(I_i)] \quad I_i \leq 76 \text{ mm/h} \quad (1d)$$

$$e_i' = 0.283 \quad I_i > 76 \text{ mm/h} \quad (1e)$$

in which E (MJ ha^{-1}) is total energy for an erosive rainfall event, I_{30} (mm h^{-1}) is the event maximum 30-minute intensity, n is the number of increments during the event with essentially uniform intensity, e_i (MJ ha^{-1}) is the rainfall energy for an increment with a rainfall depth equal to h_i (mm), e_i' ($\text{MJ ha}^{-1}\text{mm}^{-1}$) is the rainfall energy per unit of rainfall, and I_i (mm h^{-1}) is the rainfall intensity of the i -th increment.

The summation of Re values calculated for all erosive events occurring over a year gives the annual value Ra of the rainfall erosivity factor, and the mean of the annual values over a long time period allows for determining the rainfall erosivity factor, R ($\text{MJ mm ha}^{-1}\text{h}^{-1}\text{yr}^{-1}$), of the Universal Soil Loss Equation (USLE) and its revised versions (Wischmeier and Smith, 1978; Renard et al., 1997; ARS, 2018), having the following expression:

$$A = RKLSCP \quad (2)$$

where A ($\text{t ha}^{-1}\text{year}^{-1}$) is the mean annual soil loss, K ($\text{t ha h ha}^{-1}\text{MJ}^{-1}\text{mm}^{-1}$) is the soil erodibility factor, L is the slope length factor, S is the slope gradient factor, C is the cover and management factor, and P is the support practice factor. By definition, Re should be computed from rainfall measurements at short time intervals during which the intensity is essentially constant.

In practice, the available data for calculating Re can differ widely by their temporal resolution and this circumstance has encouraged an intensive research activity in different areas of the world on the relationship between erosivity calculations and time resolution of rainfall measurements. For example, the topic was investigated in China (Yin et al., 2007; Yue et al., 2020; Zhai et al., 2025), Europe (Panagos et al., 2015) and Italy (Agnese et al., 2006; Porto, 2016; Piccarreta et al., 2024). This investigation is particularly important for determining whether climate change is indeed driving an increase in rainfall erosivity and for properly quantifying the magnitude of this increase, at least within certain environments. In Sicily (Italy), for example, rainfall erosivity calculations available for the past years (1951–1970) refer to a rainfall temporal resolution not shorter than approximately 30 min (D'Asaro and Santoro, 1983) but rainfall data with a higher temporal resolution are now available for relatively long periods (2002–2024). For example, the Servizio Informativo Agrometeorologico Siciliano (SIAS) of the Sicilian region now provides rainfall data collected at $\Delta t = 10$ min time intervals. This circumstance induces to advise against direct comparisons between information relating to the two periods (1951–1970 and 2002–2024) since possible differences could be attributable to the fact that in these two periods erosivity was obtained from rainfall data measured by a low and high time resolution. Therefore, accurately establishing the effect of rainfall data temporal resolution on calculation of Re is required to perform reliable comparisons between erosivity calculations performed in the past and those carried out more recently and to distinguish the effects of time resolution from those of climate change.

According to several investigations, power law relationships can be established between Re and he (Bullock et al., 1990; Posch and Rekolainen, 1993; Bagarello and D'Asaro, 1994; Yu and Rosewell, 1996; D'Asaro et al., 2007; Todisco et al., 2025). These relationships provide a practical approach to extending observed Re values to areas where appropriate rainfall intensity data are lacking (Kinnell, 2010). For the investigations performed in Sicily, the developed power law relationships were parameterized by a linear regression analysis of the $\ln$ -transformed ($\ln =$ natural logarithm) Re and he data (Bagarello and D'Asaro, 1994; D'Asaro et al., 2007). However, another parameterization method could be applied performing a non-linear adaption of the power law relationship to the untransformed (Re , he) data pairs. In general, the choice of the parameterization method can be expected to

influence reliability and accuracy of the fitted relationships (Xiao et al., 2010; Chen et al., 2020) but nothing has been done so far in Sicily with reference to the Re vs. he relationship to establish which of the two approaches provides more statistically robust results.

Regardless of the doubts due to the applied parameterization method of a Re vs. he relationship, it has to be suspected that a relationship obtained in the past could not be still valid in more recent years due to the occurrence of climatic changes determining an increase of rainfall intensities. For example, according to a recent investigation by Dallan et al. (2025), projected changes indicate that intense rainfall will increase across Sicily, especially for short-duration events in lowlands and long-duration events at higher elevation, leading to a corresponding rise in rainfall erosivity. In other terms, the parameters of the Re vs. he relationship could have changed as a result of climate change. Consequently, comparing Re vs. he relationships obtained by rainfall data having the same time resolution and measured in different historical periods can be expected to yield a relevant information on climate change effects on rainfall erosivity.

The (he , Re) data pairs appears also usable for discriminating, for a given rainfall depth, between rainfall erosivity values that have occurred in a certain observation period and those that have never been recorded in the same period. In other terms, the envelope of Re vs. he provides a factual information on the largest Re value associated to a given rainfall depth in a given period of time. This information appears relevant in a historical perspective and also because it could help to evaluate soil erosion events that were not overcome in the past with reference to rainfall erosivity. Development of enveloping curves does not seem frequent in soil erosion studies although some exception can be mentioned (Bagarello et al., 2017). Therefore, establishing if, and with what limits if any, this concept is usable for Re prediction requires specific investigations. Predicting Re values corresponding to an average recurrence interval of T years, Re_T , could be necessary for planning appropriate soil conservation measures (Morgan et al., 2003) since long-term soil loss is frequently due to a few severe rainstorms having high intensity and large rainfall depth (Larson et al., 1997; Bagarello et al., 2010). This prediction requires identifying a theoretical probability distribution that closely fit to the available sample data. According to Aronica and Ferro (1997), Ferro et al. (1999) and Gakunde et al. (2025), the Extreme Value Type-1 (EV1) distribution could be considered an appropriate parent distribution. However, these authors considered annual values of rainfall erosivity in their investigations and not the single-storm erosion index. Therefore, the applicability of the EV1 distribution at this shorter temporal scale still requires testing.

The general objective of this investigation was to improve the ability to calculate, estimate and practically use the single-storm erosion index in Sicily. The specific objectives were to: i) determine the effect of the rainfall measurement interval on the Re calculations; ii) compare two approaches for parameterizing the power law relationship between Re and he ; iii) compare the Re vs. he relationships obtained for the 1951–1970 and 2002–2024 periods; iv) test the possibility to develop envelope curves of Re vs. he at both local and regional scales; and v) test the suitability of the EV1 distribution as parent distribution for the samples of annual maximum values of Re .

2. Materials and methods

2.1. Study area

The study is focused on Sicily, which is the largest island in the Mediterranean Sea and covers an area approximately equal to 25700 km^2 (Fig. 1). The investigated large area and its complex topography, the quality and availability of the recording rain-gauges dataset, and the relevance of the past rainfall erosivity studies conducted in this region (Ferro et al., 1991; Ferro and Porto 1999; Carollo et al., 2018; Carollo et al., 2026; Serio et al., 2019), make Sicily a good benchmark for erosivity assessment.



Fig. 1. View of Sicily (a) and Sicilian recording rain-gauges considered in this investigation (b).

Sicily is located in the southern part of Italy, is characterized by complex landscapes, and its elevation varies from sea level to about 3300 m a.s.l. (Mount Etna). Sicily is characterized by a temperate climate, with average annual temperatures in the range 11–20 °C (Viola et al., 2014). The island average annual precipitation is about 750 mm, with lower amounts, about 360 mm, in the southeast part and the higher amounts, about 1900 mm, in the northeast part where Mount Etna is located (Ferro and Porto, 1999; Caracciolo et al., 2018). The majority of precipitation occurs between October and March, leading to a seasonally skewed rainfall pattern, and summer months are drier.

2.2. Dataset

The rainfall data used in this investigation were provided by the Servizio Informativo Agrometeorologico Siciliano (SIAS) of the Sicilian region, in Italy. The considered data were collected at $\Delta t = 10$ min time intervals at 26 Sicilian stations in the 2002 to 2024 years (23 years) (Fig. 1). At the Agira and Ramacca stations, however, rainfall data were

only available from 2006 and 2007, respectively. Table 1 provides some relevant geographical information for the considered rain-gauge stations. A total of 8464 erosive events ($he \geq 13$ mm) were considered. The number of erosive events varied between 180 at Ramacca and 549 at Messina, with a mean of nearly 326 events per station. During the observation period, the largest rainfall depth for a single event varied from 95.2 mm at Mussomeli to 467.2 mm at Siracusa, with a mean for the 26 stations of 159.4 mm (Table 1). The single-storm erosion index for a time resolution of 10 min, Re_{10} ($\text{MJ mm ha}^{-1}\text{h}^{-1}$), was calculated according to Wischmeier and Smith (1978) for each erosive event ($he \geq 13$ mm).

2.3. Effect of the rainfall measurement interval on single-storm erosion index

For each erosive event, the rainfall data collected at $\Delta t = 10$ min time intervals were aggregated at $\Delta t = 30$ min time intervals and the single-storm erosion index, Re_{30} ($\text{MJ mm ha}^{-1}\text{h}^{-1}$), was also calculated

Table 1

Sicilian rain-gauge stations considered in the investigation, highest event rainfall depth, max(*he*), measured at each station during the sampling years, and number of erosive events for two different values of the rainfall measurement interval, Δt .

Code	Rain-gauge station	Coordinates	Elevation (m a.s.l)	years	max(<i>he</i>) (mm)	Number of erosive events	
						$\Delta t = 10$ min	$\Delta t = 30$ min
1	Acate	36°58'24.0"N 14°23'59.9"E	60	2002–2024	138.0	244	244
2	Agira	37°37'18.2"N 14°30'04.0"E	478	2006–2024	102.6	287	286
3	Agrigento	37°20'29.4"N 13°32'58.6"E	187	2002–2024	123.2	310	310
4	Bronte	37°45'12.7"N 14°47'10.3"E	427	2002–2024	110.4	332	331
5	Calatafimi	37°51'16.5"N 12°52'47.9"E	299	2002–2024	143.8	398	396
6	Caltagirone	37°13'48.0"N 14°34'28.0"E	261	2002–2024	235.2	336	337
7	Caltanissetta	37°25'42.0"N 14°03'04.1"E	365	2002–2024	119.8	280	280
8	Cammarata	37°37'47.0"N 13°45'27.7"E	379	2002–2024	96.4	305	307
9	Caronia	38°01'46.1"N 14°28'47.1"E	38	2002–2024	107.6	384	384
10	Castelvetrano	37°38'45.7"N 12°51'08.4"E	121	2002–2024	259.4	370	371
11	Enna	37°30'17.9"N 14°10'30.5"E	327	2002–2024	125.4	274	274
12	Gela	37°09'18.5"N 14°17'55.4"E	65	2002–2024	115.0	242	243
13	Lascari	38°00'00.6"N 13°55'12.7"E	62	2002–2024	115.6	336	336
14	Marsala	37°47'59.0"N 12°33'40.3"E	108	2002–2024	164.8	319	320
15	Mazarrino	37°17'48.0"N 14°12'46.2"E	504	2002–2024	161.4	324	327
16	Messina	38°02'00.0"N 15°22'27.6"E	420	2002–2024	160.4	549	550
17	Mussomeli	37°30'50.7"N 13°49'35.5"E	413	2002–2024	95.2	307	307
18	Palazzolo Acreide	37°03'37.0"N 14°52'15.4"E	617	2002–2024	318.8	367	369
19	Palermo	38°07'47.3"N 13°19'39.3"E	58	2002–2024	134.0	373	373
20	Petralia Sottana	37°37'55.6"N 14°00'39.2"E	729	2002–2024	104.8	343	346
21	Piazza Armerina	37°18'56.1"N 14°22'44.8"E	577	2002–2024	179.2	299	300
22	Ramacca	37°28'52.1"N 14°38'02.0"E	263	2007–2024	121.0	180	180
23	Sciacca	37°35'30.9"N 13°02'22.9"E	88	2002–2024	210.2	312	312
24	Siracusa	37°03'35.9"N 15°09'27.4"E	92	2002–2024	467.2	306	305
25	Termini Imerese	37°58'16.5"N 13°36'41.9"E	339	2002–2024	110.2	380	381
26	Trapani	37°56'31.1"N 12°33'09.7"E	57	2002–2024	125.6	307	307

according to Wischmeier and Smith (1978) by considering this longer rainfall measurement interval. Therefore, two values of Re , denoted as Re_{10} and Re_{30} , respectively, were obtained for each event.

Separately for each recording rain-gauge and also by considering a single dataset including all stations, a comparison was carried out between Re_{30} and Re_{10} to check differences between the Re values obtained with rainfall data differing by their temporal resolution.

In particular, for a specific dataset, the analysis included determining the linear regression line between Re_{30} and Re_{10} forced to pass through the origin of the axes:

$$Re_{30} = b_1 Re_{10} \quad (3)$$

in which b_1 (dimensionless) represents the fraction of the erosivity described by Re_{10} that is still expressed by Re_{30} . Using the nomenclature by Agnese et al. (2006), this b_1 estimating method was denoted as OCLR (One Coefficient Linear Regression) method.

The OCM (One Coefficient Median) method was also applied to obtain another estimate of b_1 (Agnese et al., 2006). In this case, the Re_{30}/Re_{10} ratio was calculated for each erosive event included in the dataset and the median of these ratios was considered the representative b_1 value for that dataset.

An attempt to identify which method yielded the most representative value of b_1 for a given dataset was made according to Agnese et al. (2006). In particular, Re_{30} was estimated with the two available estimates of b_1 (OCLR and OCM methods) and, for a given dataset, the two means of Re_{30} calculated on the available erosive rainfall events were then compared with the actual mean of Re_{30} .

A similar procedure was applied to verify if a regional value of b_1 was usable instead of site-specific b_1 values. In this case, with reference to the complete dataset (all data together) and the OCM b_1 estimating method, performing a little better than the OCLR method, Re_{30} was calculated with the two available estimates of b_1 (local, regional). The two means of Re_{30} (site-specific and regional) were then compared with the actual mean of Re_{30} .

For this analysis, the erosive events occurring on a given date and having the same rainfall depth for the two Δt values were obviously considered. This clarification was necessary since, in a few cases,

aggregating the data implied the impossibility to establish a correspondence between the two time intervals. Only to provide an example, for the erosive event occurred at Messina on 2 April 2004, the rainfall depth was equal to 35.8 mm with $\Delta t = 10$ min and to 48.2 mm with $\Delta t = 30$ min. This event was obviously excluded from the analysis.

2.4. Parameterization of the power law relationship between single-storm erosion index and rainfall depth

The power law relationship between the single-storm erosion index, Re ($\text{MJ mm ha}^{-1}\text{h}^{-1}$), and the event rainfall depth, he (mm), has notoriously (Richardson et al., 1983) the following form:

$$Re = \alpha he^\beta \quad (4)$$

in which α and β are coefficients. Eq. (4) was parameterized for each recording rain-gauge considering, for the erosive events sampled at $\Delta t = 10$ min (Table 1), the single-storm erosion index calculated according to Wischmeier and Smith (1978), Re_{10} , and the associated rainfall depth, he .

Two parameterization methods were applied. In particular, with the linearization (LIN) method, a logarithmic transformation of Eq. (4) was performed to obtain:

$$\ln(Re) = \ln(\alpha) + \beta \ln(he) \quad (5)$$

Then, the linear regression analysis of $\ln(Re)$ against $\ln(he)$ yielded an estimate of both α and β . In the following, these two estimates were denoted as α_{LIN} and β_{LIN} , respectively, and the associated estimates of Re_{10} were indicated as Re_{LIN} .

With the optimization (OPT) method, α and β were estimated by minimizing the sum of the squared residuals between the actual and the estimated values of Re_{10} . Optimization was performed by using α_{LIN} and β_{LIN} as the initial values of the two parameters. In the following, the parameters obtained with the OPT method were denoted as α_{OPT} and β_{OPT} , respectively, and the associated estimates of Re_{10} were indicated as Re_{OPT} .

For both parameterization methods, the root mean square error,

RMSE, was calculated to express the differences between the estimated (Re_{est} , equal to Re_{LIN} or Re_{OPT} , depending on the considered method) and the actual (Re_{10}) values of the single-storm erosion index:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Re_{est} - Re_{10})_i^2}{N}} \quad (6)$$

where $(Re_{est} - Re_{10})_i$ is the i -th difference between estimated and actual Re_{10} value, and N is the sample size. The percent bias, P_{BIAS} , was also calculated according to Gupta et al. (1999) and Kaur et al. (2025):

$$P_{BIAS} = 100 \times \frac{\sum_{i=1}^N (Re_{10} - Re_{est})_i}{\sum_{i=1}^N Re_{10,i}} \quad (7)$$

where $Re_{10,i}$ is the i -th value of Re_{10} . This statistic measures the average tendency of the estimated Re_{10} values to be larger or smaller than their observed counterparts. The optimal value is zero. Positive values indicate a model bias toward underestimation whereas negative values indicate a bias toward overestimation. A comparison between the LIN and OPT parameterization methods was then performed by considering RMSE and P_{BIAS} .

2.5. Comparing power law relationships for two periods

For 17 Sicilian recording rain-gauges considered in this investigation, Eq. (4) was also parameterized by Bagarello and D'Asaro (1994) with reference to the 1951–1970 period. A comparison was therefore established between this older parameterization of Eq. (4) and the one performed with the more recent rainfall data (2002–2024). The objective of this comparison was to verify if climatic conditions changed enough between the two considered periods as to affect the considered power law relationship.

Preliminarily, it was recognized that, in the investigation by Bagarello and D'Asaro (1994), the rainfall data were plotted on rain-gauge charts that allow for recording all rainfall events occurring in a week. Taking into account the duration of the recorded period on each chart (seven days), temporal resolution of the available rainfall data was likely not shorter than approximately 30 min. Moreover, the LIN method was applied by Bagarello and D'Asaro (1994) to obtain the α and β parameters that, in this investigation, were denoted as α_{old} and β_{old} , respectively. The symbol Re_{old} was used to indicate the estimate of Re obtained according to Bagarello and D'Asaro (1994).

Consequently, in this new investigation, Eq. (4) was parameterized for each recording rain-gauge station considering all erosive events for $\Delta t = 30$ min (Table 1) and using the LIN method. In this case, the α and β parameters were denoted as α_{new} and β_{new} , respectively, and the symbol Re_{new} was used to indicate the corresponding estimate of Re . This choice was made being sufficiently confident that, working with the same temporal resolution, differences between the two expressions of Eq. (4) for a given rain-gauge station were only expressive of climatic differences between the two periods.

For a given rainfall depth, the ratio between Re_{new} and Re_{old} was calculated as:

$$\frac{Re_{new}}{Re_{old}} = \frac{\alpha_{new} he^{\beta_{new}}}{\alpha_{old} he^{\beta_{old}}} = \frac{\alpha_{new}}{\alpha_{old}} he^{(\beta_{new} - \beta_{old})} \quad (8)$$

For each station, the relationship between Re_{new}/Re_{old} and he was then investigated in the $13 \leq he \leq 95$ mm range of values since this range was common to all recording rain-gauges (Table 1).

2.6. Envelope of the single-storm erosion index values

An envelope $Re_{10}(he)$ line was determined separately for each recording rain-gauge and also by considering a single dataset including

all data.

For a particular dataset, the data describing the envelope boundary by points were obtained according to the following steps: i) the data pairs (he, Re_{10}) were sorted by increasing values of he ; ii) the largest value of Re_{10} associated with the smallest he value (13 mm in almost all cases) was identified. This Re_{10} value was the first enveloping data point; iii) the subsequent he value was considered (e.g., 13.2 mm) and the highest Re_{10} value obtained in this case was identified; iv) this new pair of (he, Re_{10}) values was another enveloping point if Re_{10} was larger than the Re_{10} value associated with the previous he value (e.g., Re_{10} for $he = 13.2$ mm greater than Re_{10} for $he = 13$ mm). Otherwise, this point was discarded; v) the procedure was repeated up to achieving the highest value of he .

For each dataset describing the envelope line by points, a regression analysis between Re_{10} and he was then performed by considering the exponential, linear, logarithmic and power relationships and retaining the relationship having the highest coefficient of determination, R^2 .

2.7. Analysis of the maximum annual values of the single-storm erosion index

Developing an estimating procedure of the quantile of given return period T , Re_T , for each recording rain-gauge requires determining i) for each year, j , of a multi-year period, the largest Re value, $\max(Re)_j$; and ii) establishing the theoretical distribution function that agrees with the empirical cumulative distribution function, $F(\max(Re)_j)$, of the available sample of $\max(Re)_j$ values.

In this investigation, according to Aronica and Ferro (1997) and Ferro et al. (1999), the suitability of the Extreme Value Type-1 (EV1) distribution as parent distribution for the $\max(Re)_j$ values was tested by the Gumbel's probabilistic diagram and the skewness test (Matalas et al., 1975).

If the empirical sample of $\max(Re)_j$ is distributed according to the theoretical EV1 distribution, the relationship between the original value $\max(Re)_j$ and the Gumbel's normalized variable y is the following:

$$y = \alpha_G (\max(Re)_j - u_G) \quad (9)$$

in which α_G and u_G are the two parameters of the EV1 distribution that are estimated, using the method of the moments, by the following relationships:

$$\alpha_G = \frac{1.283}{\sigma(\max(Re)_j)} \quad (10)$$

$$u_G = \mu(\max(Re)_j) - \frac{0.5772}{\alpha_G} \quad (11)$$

in which $\sigma(\max(Re)_j)$ and $\mu(\max(Re)_j)$ are the standard deviation and the mean of $\max(Re)_j$, respectively.

The normalized variable can also be calculated by the following relationship (Gumbel, 1958):

$$y = -\ln \left[\ln \left(\frac{1}{F(\max(Re)_j)} \right) \right] \quad (12)$$

for a sample having a size of N years.

The Gumbel's diagram is a plot of the pairs $(\max(Re)_j, y)$, in which y is calculated by Eq.(12). If the empirical sample of $\max(Re)_j$ is distributed according to the theoretical EV1 distribution, the linear relationship corresponding to Eqs. (9)–(11) has to be positively verified (Santner, 1973). In particular, the test is positively verified if the N empirical pairs $(\max(Re)_j, y)$ are close to the straight line corresponding to Eqs. (9)–(11).

The skewness test (Matalas et al., 1975) is based on the comparison between sample skewness of $\max(Re)_j$, G , with the expected theoretical skewness, $E(\gamma)$, corresponding to the sample size N . The statistical

hypothesis is accepted at a probability level of 95% if the absolute difference between G and $E(\gamma)$ is less than twice the expected standard deviation of the skewness coefficient, $\sigma(\gamma)$. In this approach, both $E(\gamma)$ and $\sigma(\gamma)$ were calculated as a function of the sample size N by the following relationships obtained from the data by Matalas et al. (1975) (Aronica and Ferro, 1997):

$$E(\gamma) = 0.2995N^{0.2841} \quad (13)$$

$$\sigma(\gamma) = 0.9474N^{-0.165} \quad (14)$$

Fitting of the EV1 distribution to the empirical sample of $\max(Re)_j$ obtained at a given recording rain-gauge was tested by considering the Re_{10} data.

The analysis was also performed by considering a single dataset including all recording rain-gauges. For each station, the $\max(Re)_j$ values were divided by their mean and all ratios were then pooled together, yielding a dataset with $N = 589$ data points.

3. Results and discussion

3.1. Effect of the rainfall measurement interval on single-storm erosion index

Table 2 lists the number of erosive events considered for comparing Re_{30} with Re_{10} . Sample sizes varied from a minimum of 176 at Ramacca to a maximum of 530 at Messina. On average, 316 erosive events were sampled at each of the 26 considered rain-gauge stations, suggesting a good representativeness of the developed dataset.

The individual values of he recorded at the 26 rain-gauge stations ($N = 8219$) varied between 13 and 467.2 mm whereas those of Re_{30}/Re_{10} varied between 0.43 and 1.01 (Fig. 2). An effect of the event rainfall depth on the Re_{30}/Re_{10} ratio was detected. In particular, for the events with a rainfall depth not exceeding approximately 40 mm, the Re_{30}/Re_{10} ratio varied widely, that is in the entire range of the overall observed

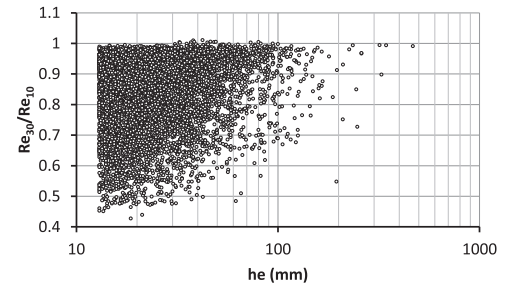


Fig. 2. Ratio between the single-storm erosion index, Re , calculated from rainfall data collected at $\Delta t = 30$ min (Re_{30}) and $\Delta t = 10$ min (Re_{10}) time intervals plotted against event rainfall depth, he (sample size, $N = 8219$).

values. These events represented the 84.6% of the considered events and the fallen rainfall was equal to the 65.3% of total rainfall. The range of variation of Re_{30}/Re_{10} tended to become smaller as he increased above 40 mm due to the disappearance of the lowest values. Therefore, the effect of the rainfall measurement interval on the erosivity determinations was highly variable for relatively low event rainfall depths. The dependence of the erosivity calculations on time resolution of the rainfall data decreased for larger rainfall depths and it tended to become negligible for particularly high he values.

The OCLR method yielded b_1 values varying between 0.78 and 0.94 (range = 0.16), depending on the recording rain-gauge (Table 2), with a mean and a median equal to 0.88 and 0.89, respectively (coefficient of variation, $CV = 4.1\%$). Instead, the b_1 values obtained with the OCM method varied from 0.86 to 0.90 (range = 0.04). In this case, the mean and the median were both equal to 0.88 and the CV value was equal to 1.3%. The ratio between the b_1 values obtained with the two methods varied from 0.90 to 1.06, depending on the recording rain-gauge. The linear regression analysis between the two estimates of b_1 yielded a small, even though statistically significant, correlation coefficient, R ,

Table 2

Results of the comparison between single-storm erosion index, Re , calculations from rainfall data collected at $\Delta t = 30$ (Re_{30}) and $\Delta t = 10$ (Re_{10}) min time intervals.

Code	Rain-gauge station	N	OCLR method		Re_{30}/Re_{10}				
			b_1	R^2	Min	Max	Mean	CV (%)	Median
1	Acate	239	0.8903	0.9738	0.4694	1.0034	0.8450	13.6	0.8709
2	Agira	279	0.9140	0.9812	0.4753	0.9966	0.8549	13.8	0.8957
3	Agrigento	304	0.8604	0.9547	0.4397	1.0048	0.8385	14.8	0.8779
4	Bronte	324	0.8551	0.9606	0.5058	0.9931	0.8529	13.0	0.8849
5	Calatafimi	378	0.8824	0.9715	0.4749	1.0055	0.8331	11.8	0.8628
6	Caltagirone	325	0.9162	0.9842	0.4834	1.0060	0.8611	13.2	0.9016
7	Caltanissetta	278	0.8978	0.9788	0.4514	1.0045	0.8501	11.5	0.8814
8	Cammarata	295	0.8611	0.9693	0.4724	1.0110	0.8505	12.9	0.8809
9	Caronia	373	0.8724	0.9740	0.4614	0.9892	0.8429	13.4	0.8770
10	Castelvetrano	350	0.9192	0.9845	0.4774	0.9898	0.8373	13.9	0.8672
11	Enna	265	0.8994	0.9821	0.4872	0.9915	0.8623	12.3	0.8865
12	Gela	234	0.8685	0.9682	0.4610	1.0037	0.8440	14.6	0.8757
13	Lascari	326	0.7763	0.9594	0.4782	1.0098	0.8275	14.9	0.8622
14	Marsala	311	0.8595	0.9818	0.4841	1.0034	0.8363	14.0	0.8687
15	Mazzerino	321	0.8952	0.9767	0.4764	1.0056	0.8508	13.6	0.8835
16	Messina	530	0.8647	0.9751	0.4273	0.9922	0.8460	13.6	0.8848
17	Mussomeli	303	0.9089	0.9767	0.4901	0.9999	0.8499	13.5	0.8849
18	Palazzolo Acreide	355	0.8518	0.9656	0.4648	0.9948	0.8425	14.4	0.8760
19	Palermo	361	0.8938	0.9804	0.5077	0.9914	0.8380	13.4	0.8616
20	Petralia Sottana	337	0.8158	0.9669	0.4926	0.9927	0.8396	13.4	0.8635
21	Piazza Armerina	288	0.9326	0.9890	0.5276	0.9990	0.8683	11.8	0.8977
22	Ramacca	176	0.8586	0.9782	0.4641	0.9928	0.8480	14.6	0.8895
23	Sciacca	304	0.8951	0.9815	0.4841	0.9977	0.8381	14.1	0.8798
24	Siracusa	296	0.9420	0.9918	0.4771	0.9995	0.8644	13.1	0.8943
25	Termini Imerese	368	0.8904	0.9792	0.4870	0.9952	0.8445	12.6	0.8634
26	Trapani	299	0.9123	0.9806	0.4773	1.0051	0.8327	15.4	0.8711
–	ALL STATIONS	8219	0.8985	0.9797	0.4273	1.0110	0.8457	13.7	0.8789

N = number of considered erosive events. OCLR: one coefficient, linear regression. b_1 = coefficient defined by Eq.(3). R^2 = coefficient of determination. Min = minimum value. Max = Maximum value. CV = coefficient of variation. The median of the Re_{30}/Re_{10} values for a station is the estimate of b_1 with the OCM (one coefficient, median) method.

according to a two tailed t test at $P = 0.05$ (Glantz, 2012) since R^2 was equal to 0.242. The means of b_1 obtained with the two tested methods did not differ significantly according to a paired t test at $P = 0.05$. Therefore, the calculation method of b_1 did not have any appreciable effect on the central tendency measure of this scale parameter but the OCLR method yielded a four times wider range of b_1 values than the OCM method.

The percentage differences, Δ , between the means of the estimated and the actual Re_{30} values varied from -4.5% to $+6.5\%$ with the OCLR method and from -0.2% to $+6.1\%$ with the OCM method (Table 3). The latter method performed better (smaller absolute Δ values, $|\Delta|$) than the former one for 15 rain-gauge stations, that is in the 58% of the cases. Therefore, the performances of both methods were generally acceptable (Agnese et al., 2006) since the highest $|\Delta|$ value was equal to 6.5%. However, the OCM method appeared to yield a little more reliable estimates of b_1 than the OCLR method as the Δ range was smaller and closer to zero.

With reference to a single dataset including all stations and hence 8219 erosive events, the OCLR and OCM methods yielded similar estimates of b_1 , equal in particular to 0.90 in the former case and 0.88 in the latter one (Table 2). The percentage difference between the mean of the estimated Re_{30} values and the actual mean of Re_{30} was equal to $+4.5\%$ with the OCLR method and $+2.3\%$ with the OCM one. Therefore, even in this case, the mean of Re_{30} was better reproduced with the OCM method than the OCLR one.

The comparison between the estimates of Re_{30} obtained for all stations with the single b_1 value obtained with the OCM method (0.88) and those obtained by using the b_1 values obtained with the same method for each station (Table 2) yielded percentage differences between the mean of the estimated Re_{30} values and the actual mean of Re_{30} equal to $+2.2\%$ and $+2.3\%$, respectively. Therefore, a single b_1 value was acceptable for all considered rain-gauge stations.

In summary, this investigation showed that, at the regional scale, the 88% of the erosivity described by Re_{10} was still represented with Re_{30} and also that this percentage locally varied between 86% and 90%.

With reference to 17,139 erosive events collected at 65 stations located in Calabria (Italy), Porto (2016) applied the OCLR method to obtain the constants of proportionality between Re_{15} , that is the single-storm erosion index calculated from rainfall data collected at $\Delta t = 15$ min, and both Re_{30} and Re_{10} . The ratio between the constant for the Re_{15} vs. Re_{10} relationship and that for the Re_{15} vs. Re_{30} relationship yields the b_1 value of Eq. (3). The Calabrian values of b_1 varied from 0.74 to 0.96 with a mean and a median equal to 0.87 and 0.86, respectively. These values are very similar to those obtained in this investigation for Sicily ($0.78 \leq b_1 \leq 0.94$; mean = 0.88; median = 0.89). Taking into account that Sicily and Calabria are two bordering regions both in the centre of the Mediterranean sea, it is plausible to believe that the results of this investigation could generally be representative for the Mediterranean area.

3.2. Parameterization of the power law relationship between single-storm erosion index and rainfall depth

For all stations, plotting Re_{10} against h_e suggested an overall increasing relationship between the two variables but the degree of scattering of the data was high, or also very high, as shown in Fig. 3 for four rain-gauge stations taken as an example. This scattering was an obvious consequence of the fact that Re depends on rainfall depth but also on rainfall intensities.

The α and β values varied with the applied parameterization approach (Table 4). In particular, α_{LIN} varied between 0.143 and 0.930, depending on the rain-gauge station (mean = 0.356, CV = 51.3%) and β_{LIN} varied from 1.333 to 1.904 (mean = 1.645; CV = 9.0%). Instead, α_{OPT} varied between 0.352 and 4.253 (mean = 1.365, CV = 79.9%) and β_{OPT} varied from 1.025 to 1.713 (mean = 1.410; CV = 13.9%). Due to the high data scattering, low or relatively low R^2 values (0.39–0.65) for the LIN approach and high RMSE values ($107.2 \leq RMSE_{LIN} \leq 331.0$ MJ mm ha⁻¹h⁻¹ and $102.8 \leq RMSE_{OPT} \leq 321.1$ MJ mm ha⁻¹h⁻¹) were obtained for the tested rain-gauge stations.

Therefore, as compared with the LIN approach, the OPT approach

Table 3

Comparison between the performances of the OCLR (one coefficient, linear regression) and OCM (one coefficient, median) methods for estimating the constant of proportionality between the single-storm erosion index calculated by rainfall data collected at time intervals $\Delta t = 30$ min (Re_{30}) and the corresponding value obtained with rainfall data collected at $\Delta t = 10$ min (Re_{10}).

Code	Rain-gauge station	Mean of Re_{30} (MJ mm ha ⁻¹ h ⁻¹)			Δ %		Smallest $ \Delta $
		Actual	OCLR	OCM	OCLR	OCM	
1	Acate	122.0	126.9	124.2	+4.1	+1.8	OCM
2	Agira	121.7	127.0	124.5	+4.4	+2.3	OCM
3	Agrigento	90.4	92.2	94.0	+1.9	+4.0	OCLR
4	Bronte	91.2	91.8	95.0	+0.6	+3.5	OCLR
5	Calatafimi	95.6	99.5	97.3	+4.0	+1.7	OCM
6	Caltagirone	116.6	121.3	119.3	+4.0	+2.3	OCM
7	Caltanissetta	100.2	104.2	102.3	+3.9	+2.0	OCM
8	Cammarata	74.9	75.8	77.5	+1.1	+3.4	OCLR
9	Caronia	90.2	92.9	93.4	+3.0	+3.5	OCLR
10	Castelvetrano	123.6	131.6	124.2	+6.5	+0.5	OCM
11	Enna	125.6	128.4	126.6	+2.2	+0.7	OCM
12	Gela	117.5	119.7	120.7	+1.9	+2.8	OCLR
13	Lascari	83.3	79.6	88.4	-4.5	+6.1	OCLR
14	Marsala	104.7	106.6	107.7	+1.7	+2.8	OCLR
15	Mazzerino	109.6	115.0	113.5	+4.9	+3.5	OCM
16	Messina	98.5	100.4	102.7	+1.9	+4.2	OCLR
17	Mussomeli	91.8	97.0	94.4	+5.7	+2.9	OCM
18	Palazzolo Acreide	149.9	149.7	153.9	-0.2	+2.7	OCLR
19	Palermo	90.8	95.9	92.5	+5.6	+1.8	OCM
20	Petralia Sottana	74.0	72.9	77.2	-1.5	+4.3	OCLR
21	Piazza Armerina	109.4	113.6	109.4	+3.8	-0.04	OCM
22	Ramacca	120.4	121.0	125.4	+0.6	+4.2	OCLR
23	Sciacca	127.9	133.2	130.9	+4.1	+2.3	OCM
24	Siracusa	256.0	269.5	255.9	+5.3	-0.05	OCM
25	Termini Imerese	79.5	81.8	79.3	+2.9	-0.2	OCM
26	Trapani	113.1	119.0	113.6	+5.2	+0.4	OCM

Δ = percentage difference between the means of the estimated and the actual Re_{30} values.

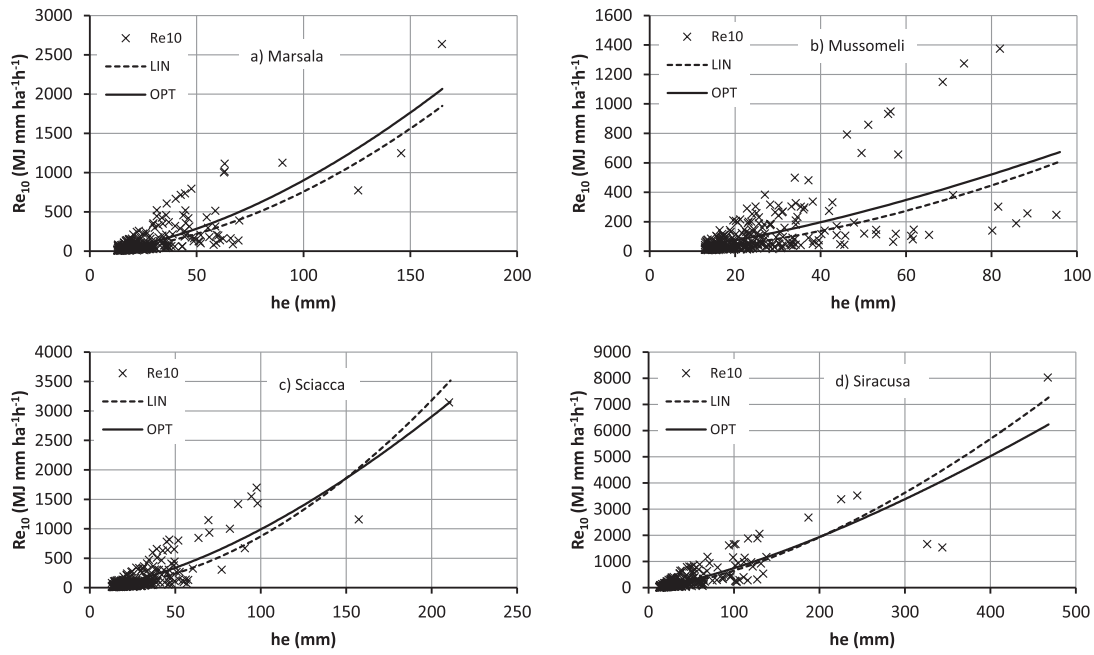


Fig. 3. Examples of the relationships between Re_{10} (single-storm erosion index calculated from rainfall data collected at $\Delta t = 10$ min time intervals) and he (event rainfall depth) parameterized with the linearization (LIN) and optimization (OPT) methods.

Table 4

Parameterization of the power law relationship between single-storm erosion index, Re_{10} ($MJ\ mm\ ha^{-1}\ h^{-1}$), and rainfall depth, he (mm), performed with the linearization and optimization methods.

Code	Rain-gauge station	Linearization					Optimization			
		α_{LIN}	β_{LIN}	R^2	RMSE	P_{BIAS}	α_{OPT}	β_{OPT}	RMSE	P_{BIAS}
1	Acate	0.207	1.820	0.535	176.1	+23.0	2.059	1.281	162.6	-8.3
2	Agira	0.238	1.759	0.474	167.4	+29.2	0.858	1.509	159.5	-2.4
3	Agrigento	0.387	1.585	0.473	121.2	+24.7	1.506	1.296	116.1	-5.3
4	Bronte	0.295	1.681	0.388	115.6	+28.1	1.904	1.249	109.1	-3.4
5	Calatafimi	0.353	1.586	0.478	141.7	+28.8	1.047	1.391	135.6	-3.9
6	Caltagirone	0.930	1.333	0.412	171.0	+28.3	4.253	1.025	163.0	-6.1
7	Caltanissetta	0.209	1.775	0.473	140.3	+28.0	0.609	1.577	134.1	-1.9
8	Cammarata	0.304	1.608	0.407	117.9	+30.0	2.165	1.156	113.1	-4.4
9	Caronia	0.476	1.515	0.495	113.1	+24.2	0.352	1.668	104.5	+2.6
10	Castelvetrano	0.212	1.773	0.535	147.7	+25.4	0.635	1.580	137.2	-6.0
11	Enna	0.159	1.879	0.502	166.3	+29.2	0.806	1.549	156.6	-5.7
12	Gela	0.407	1.616	0.438	147.7	+26.9	1.207	1.408	141.1	-2.2
13	Lascari	0.371	1.590	0.481	121.7	+26.2	0.594	1.546	115.8	-0.8
14	Marsala	0.207	1.782	0.520	141.1	+25.1	0.442	1.655	135.4	+0.4
15	Mazzeo	0.427	1.559	0.493	155.8	+25.9	0.620	1.537	147.6	+1.1
16	Messina	0.269	1.690	0.572	136.1	+18.6	1.707	1.264	127.4	-6.9
17	Mussomeli	0.261	1.699	0.438	148.4	+30.0	1.095	1.407	142.6	-4.9
18	Palazzolo Acreide	0.687	1.417	0.537	227.7	+23.3	3.998	1.073	214.1	-8.1
19	Palermo	0.331	1.577	0.524	140.6	+25.4	0.394	1.599	135.6	+3.4
20	Petralia Sottana	0.265	1.649	0.406	107.2	+29.2	1.434	1.271	102.8	-2.5
21	Piazza Armerina	0.654	1.407	0.431	162.5	+29.2	3.649	1.049	155.1	-6.7
22	Ramacca	0.377	1.622	0.448	150.9	+28.6	0.875	1.488	141.9	-0.7
23	Sciacca	0.160	1.868	0.573	162.8	+24.2	0.776	1.553	149.6	-9.8
24	Siracusa	0.495	1.560	0.651	330.9	+14.8	1.324	1.375	321.1	+1.3
25	Termini Imerese	0.421	1.502	0.483	114.6	+26.6	0.765	1.430	109.5	-2.8
26	Trapani	0.143	1.904	0.561	148.3	+26.8	0.415	1.713	138.8	-5.0

α_{LIN} and β_{LIN} = parameters of the power law relationship obtained by the linearization method. α_{OPT} and β_{OPT} = parameters of the power law relationship obtained by the optimization method. R^2 = coefficient of determination. RMSE = root mean square error. P_{BIAS} = percent bias. The single-storm erosion index values were calculated using rainfall data collected at $\Delta t = 10$ min time intervals.

yielded a larger mean of α , a smaller mean of β and a larger relative variability of both parameters. The two estimates of a given parameter were significantly correlated according to a two-tailed t test at $P = 0.05$ but the R^2 values were rather low for both α ($R^2 = 0.54$) and, especially, β ($R^2 = 0.35$) (Fig. 4).

Using the OPT approach rather than the LIN one implied obtaining in all cases minimally smaller RMSE values (Table 4) since the percentage

difference between $RMSE_{OPT}$ and $RMSE_{LIN}$ varied from -8.1% to -3.0%, depending on the station.

A more appreciable parameterization method effect was instead detected with reference to P_{BIAS} (Table 4). With the LIN approach, P_{BIAS} was positive regardless of the station and it varied between +14.8% and +30.0% (mean = +26.1%). Instead, with the OPT approach, both negative (at 21 stations) and positive (other five stations) values of P_{BIAS}

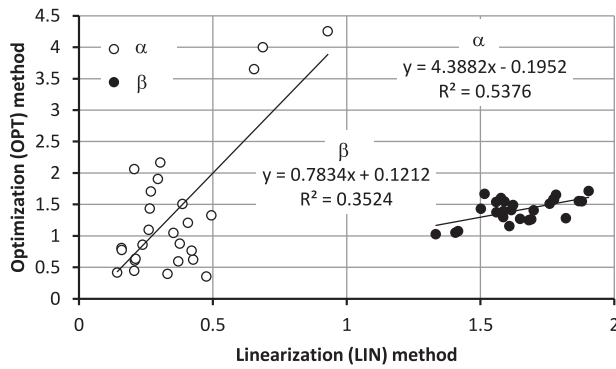


Fig. 4. Relationships between the α and β parameters of the power law relationship between single-storm erosion index and event rainfall depth (Eq.4) parameterized with the linearization (LIN) and optimization (OPT) methods.

($-9.8\% \leq P_{BIAS} \leq +3.4\%$; mean = -3.4%). were obtained. The ratio between the absolute value of P_{BIAS} obtained with the OPT approach and the corresponding value for the LIN approach varied with the station from 0.02 to 0.41. Therefore, the power law relationships parameterized with the LIN approach induced in all cases a bias toward underestimation of Re_{10} . Instead, the OPT approach frequently induced a bias toward overestimation of Re_{10} . In all cases, however, the bias was smaller with the OPT approach than the LIN one since the absolute values of P_{BIAS} were closer to zero with the former approach than the latter one.

In summary, in a context of highly scattered $Re_{10}(he)$ relationships, the OPT approach performed better than the LIN one not so much for the decrease of $RMSE$, which occurred but was minimal, but for the fact that the former approach determined a much smaller bias as compared with the latter approach.

Different approaches have been used in the literature for parameterizing the relationship between event or daily erosion index and the associated rainfall depth. For example, Angulo-Martínez and Beguería (2009) suggested that parameterization should be performed by a weighted ordinary least squares regression of $\ln$ -transformed data in order to counterbalance the excessive leverage of low observations in ordinary least squares arising from the incorrect modelling of the error term. A Generalised Linear Model was used by Beguería et al. (2018) to fit the model with an adequate treatment of its error term. In other investigations, predictive relationships varying with both the location in an area of interest and the period of the year were tested (e.g., Yu and Rosewell, 1996; Davison et al., 2005; D'Asaro et al., 2007; Capolongo et al., 2008; Todisco et al., 2025). In this investigation, simple statistical methods and a unique dataset for a station were considered. Any relationship between erosivity and rainfall depth is unavoidably very scattered (Fig. 3 or Fig. 4 in Beguería et al., 2018) since rainfall depth is one of the variables influencing erosivity but rainfall intensity also plays a central role. Consequently, these relationships can only be used for estimating global erosivity values starting from a simple information to collect (Bagarello and D'Asaro, 1994). Due to its definition (Eq. (7)), the P_{BIAS} statistic is also expressive of the percentage difference between the actual and the estimated rainfall factor, R , of the USLE (Wischmeier and Smith, 1978). For the 26 stations considered in this investigation, this difference did not exceed the 30% with the LIN approach and the 10% with the OPT approach (Table 4). Due to the multiplicative nature of the soil loss prediction model, this error corresponds to the error in soil loss estimate attributable to the use of an estimate of R instead of the actual value (Wischmeier and Smith, 1978). A soil loss prediction error that does not exceed the 10–30% is considered small (Risse et al., 1993; Bagarello et al., 2012; Alewell et al., 2019). Therefore, the LIN and OPT approaches can be expected to yield estimates of the rainfall erosivity factor usable in practical application of the USLE. Between the two approaches, the latter approach should be preferred to parameterize the Re vs. he relationship since, in this case, the maximum error is overall lower

and also nearly negligible.

3.3. Comparing power law relationships for two periods

The comparison between the power law relationships for the more recent (2002–2024) and the older (1951–1970) periods was carried out with reference to 17 rain-gauge stations (Table 5) since, for the other nine stations, Eq.(4) was not parameterized for the 1951–1970 years (Bagarello and D'Asaro, 1994). The α_{new} and β_{new} values obtained for each station by applying the LIN approach to the rainfall data aggregated at $\Delta t = 30$ min were listed in Table 5. This table also lists the values of both $\alpha_{new}/\alpha_{old}$ and $(\beta_{new} - \beta_{old})$ for each considered station. According to Eq.(8), the $\alpha_{new}/\alpha_{old}$ ratio is equal to Re_{new}/Re_{old} if $(\beta_{new} - \beta_{old}) = 0$, that is, if this last ratio does not depend on he . A negative value of $(\beta_{new} - \beta_{old})$ indicates that the Re_{new}/Re_{old} ratio decreases as he increases. A positive value of this difference implies instead that Re_{new}/Re_{old} increases with he .

Table 5 also lists the Re_{new}/Re_{old} values for both $he = 13$ mm and 95 mm, representing the extremes of the range of he values common to the considered stations. Overall, the estimate of Re_{30} obtained with the new $Re(he)$ relationship varied from 0.63 to 2.87 times the corresponding estimate obtained with the older relationship. For the considered range of he values, all Re_{new}/Re_{old} vs. he relationships were reported in Fig. 5.

Three types of results were obtained: i) $Re_{new}/Re_{old} < 1$ regardless of he ; ii) $Re_{new}/Re_{old} < 1$ for part of the he range and > 1 for another part of this range; and iii) $Re_{new}/Re_{old} > 1$ for the entire range of he values.

The first result was obtained at a single station (Termini Imerese), that is in the 6% of the cases.

The second result was instead obtained at seven stations, that is in the 41% of the cases. In particular, $Re_{new}/Re_{old} > 1$ for small he values and < 1 for large he values in three cases (Agrigento, Caltagirone, Gela) whereas the opposite occurred in the other four cases (Calatafimi, Enna, Marsala and Ramacca).

Table 5

Comparison of the power law relationship between single-storm erosion index, Re_{30} ($MJ\ mm\ ha^{-1}h^{-1}$), and rainfall depth, he (mm), obtained with the more recent rainfall dataset (2002–2024) and that obtained with rainfall data collected in the 1951–1970 period.

Code	Rain-gauge station	α_{new}	β_{new}	$\alpha_{new}/\alpha_{old}$	$\beta_{new} - \beta_{old}$	Re_{new}/Re_{old}	
						$he = 13$ mm	$he = 95$ mm
3	Agrigento	0.287	1.619	1.818	-0.145	1.25	0.94
5	Calatafimi	0.269	1.610	0.637	0.170	0.99	1.38
6	Caltagirone	0.635	1.400	1.810	-0.153	1.22	0.90
7	Caltanissetta	0.154	1.817	0.802	0.158	1.20	1.65
11	Enna	0.113	1.900	0.316	0.373	0.82	1.73
12	Gela	0.311	1.643	4.718	-0.439	1.53	0.63
14	Marsala	0.153	1.815	0.399	0.315	0.89	1.68
15	Mazzarino	0.336	1.579	0.858	0.142	1.23	1.64
16	Messina	0.206	1.718	1.145	0.129	1.59	2.06
17	Mussomeli	0.182	1.758	0.780	0.186	1.26	1.82
18	Palazzolo Acreide	0.493	1.460	3.142	-0.244	1.68	1.03
20	Petralia Sottana	0.195	1.686	0.620	0.264	1.22	2.07
21	Piazza Armerina	0.480	1.455	0.979	0.022	1.04	1.08
22	Ramacca	0.264	1.678	0.687	0.128	0.95	1.23
23	Sciaccia	0.114	1.914	0.304	0.492	1.07	2.87
24	Siracusa	0.380	1.592	5.669	-0.348	2.32	1.16
25	Termini Imerese	0.308	1.545	0.606	0.095	0.77	0.94

α_{new} and β_{new} = parameters of the power law relationship obtained with the more recent rainfall data and the linearization method. α_{old} and β_{old} = parameters of the power law relationship reported by Bagarello and D'Asaro (1994). he = rainfall depth. The single-storm erosion index values were calculated using rainfall data collected at $\Delta t = 30$ min time intervals.

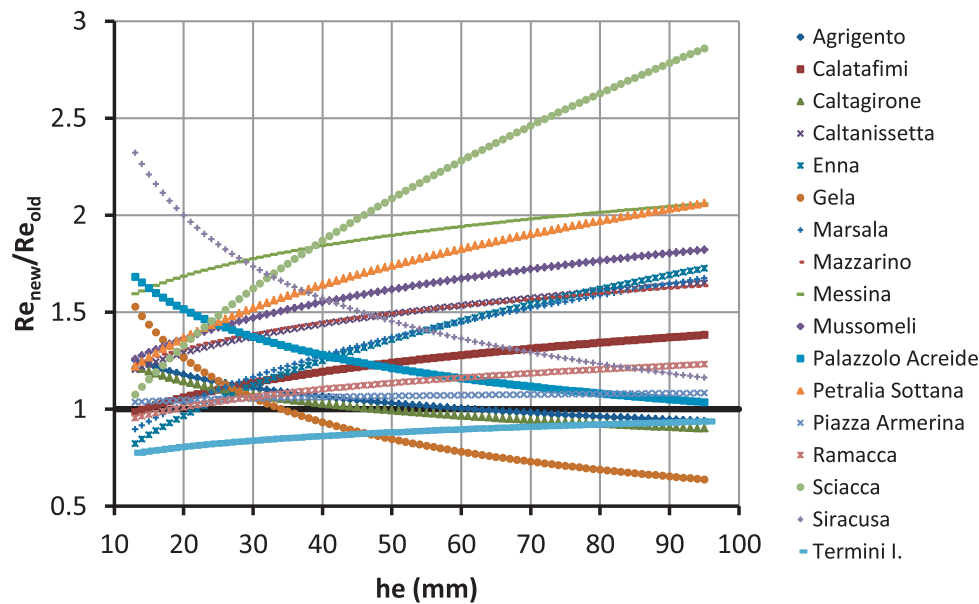


Fig. 5. Ratio between the estimates of the single-storm erosion index obtained by parameterizing Eq.(4) with the more recent (Re_{new} , 2002–2024) and the older (Re_{old} , 1951–1970) rainfall dataset plotted against event rainfall depth, he .

Finally, the third result was obtained at nine stations, that is in the 53% of the cases. The Re_{new}/Re_{old} ratio increased with he at six stations (Caltanissetta, Mazzarino, Messina, Mussomeli, Petralia Sottana, Sciacca), decreased at two stations (Palazzolo Acreide, Siracusa) and was nearly unaffected by the rainfall depth at a single station (Piazza Armerina). Particularly high Re_{new} values as compared with Re_{old} (Re_{new}/Re_{old} ratio larger than 2) were detected at Siracusa for small rainfall depths and at Messina, Petralia Sottana and Sciacca for large rainfall depths.

Therefore, the dataset used for parameterizing Eq. (4) influenced the Re vs. he relationships. For a few stations, using the new dataset implied predicting smaller Re values than those obtained according to Bagarello and D'Asaro (1994) for the entire range of the considered he values or for part of this range. For most stations, however, the new predictions were higher than the older ones. The increase of Re was likely moderate in most cases, as suggested by many Re_{new}/Re_{old} values higher than one by only a little. However, this increase was rather appreciable ($Re_{new}/Re_{old} > 2$) for a few stations and particular rainfall depths.

Overall, this investigation confirmed the need to parameterize Eq. (4) with the more recent rainfall data since, for a fixed value of he , rainfall erosivity has increased from 1951–1970 to 2002–2024 in many cases.

Many investigations have been carried out in recent years to evaluate climate change effects on rainfall erosivity (e.g., Diodato et al., 2011; Almagro et al., 2017; Padulano et al., 2023) but methodological approaches, and hence the specific questions that have been answered, differ widely among different investigations. It is therefore necessary to clarify what question the analysis developed in this investigation addressed. This analysis verified if and how erosivity associated to a given rainfall depth value changed between two different historical periods. Therefore, the suggested approach can be viewed as a tool to locally establish whether climate change effects on Re vary with the event rainfall depth.

A frequently applied method for testing climate change effects on rainfall erosivity is using historical data to empirically calibrate relationships between erosivity values and rainfall depths. These relationships are then applied to projected rainfall depths (Nearing, 2001; Mondal et al., 2016; Grillakis et al., 2020). According to this investigation, a point that should be taken into account in the future is that the relationship between rainfall erosivity and rainfall depth can be

expected to change as a consequence of climatic changes.

Finally, the considered periods in this investigation (1951–1970 and 2002–2024) were rather long and consistent with the recommendation by Wischmeier and Smith (1978) about the necessary number of years to characterize climate at a point. This circumstance explains why the detected differences between the two periods were attributed to climate change. Working in the future with even longer records appears advisable to support this interpretation.

3.4. Envelope of the single-storm erosion index values

An envelope line of Re_{10} vs he was defined for the entire range of he values or at least for a part of this range, depending on the considered dataset. In particular, when the largest Re_{10} value for the highest rainfall depth was larger than the other Re_{10} values describing the envelope, an enveloping line was deduced with reference to the entire range of he values (e.g., Fig. 6a). Instead, obtaining relatively low Re_{10} values for large rainfall depths implied defining the envelope line up to a certain he value (e.g., Fig. 6b).

In general (21 of the 26 considered rain-gauge stations), a straight line best described the relationship between the highest Re_{10} values and he and the same result was obtained by considering a single dataset including all stations (Table 6 and Fig. 6c). With the exception of a single station, yielding a relatively low R^2 value for the fitted relationship (Marsala, $R^2 = 0.87$), all regression lines were rather strong since they were characterized by high R^2 values, that is ≥ 0.95 .

The envelope lines obtained in this investigation have practical interest since they allow distinguishing, for a given rainfall depth falling in a given range of values (Table 6), between expected and unexpected, or less expected, Re_{10} values, with the clarification that expected refers to Re_{10} values that have been documented for a particular, rather long and recent (2002–2024) historical period whereas unexpected or less expected Re_{10} values are larger than the highest values observed in the considered period.

Envelope curves are simple empirical relationships for which it could be possible to develop a probabilistic assessment (Vogel et al., 2007). This topic could perhaps be further explored in the future with reference to the single-storm erosion index since the probabilistic interpretation of these curves offers opportunities in several engineering applications (Castellari et al., 2009) such as, in the case of soil water erosion, the

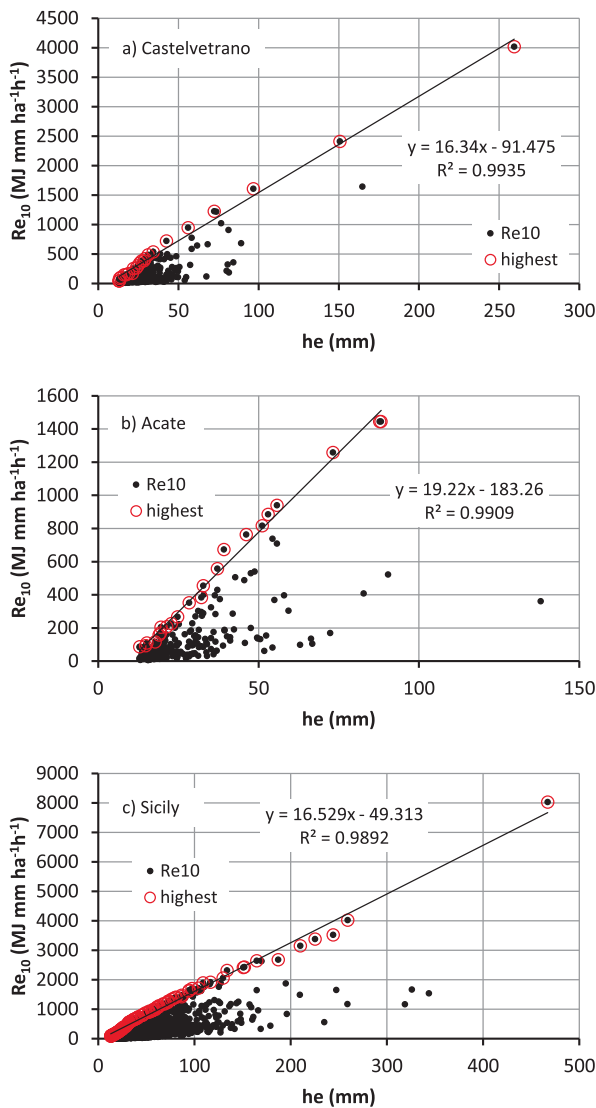


Fig. 6. Enveloping lines of Re_{10} (single-storm erosion index calculated using rainfall data collected at $\Delta t = 10$ min time intervals) vs. he (event rainfall depth) for the a) Castelvetroano and b) Acate rain-gauge stations and c) all Sicilian data.

design of effective control measures in critical conditions with regard to the active agent triggering the phenomenon.

3.5. Analysis of the maximum annual values of the single-storm erosion index

For each investigated rain-gauge station, Table 7 lists the mean, the standard deviation, σ , and the skewness, G , of $\max(Re)_j$. The table also includes the estimated α_G and u_G parameters and the results of the skewness test (ST), expressed as “yes” if the hypothesis that the sample is distributed as an EV1 was accepted and “no” for the opposite case. The negative results of the skewness test were confirmed by the Gumbel’s diagram and they were due to the existence of one or two outliers in the examined samples. For four rain-gauge stations chosen as an example, the comparison between the data and the straight line of Eq. (9) is shown in Fig. 7. For the Enna and Piazza Armerina stations (Fig. 7a,b), Table 7 indicates that the skewness test did not reject the hypothesis that the sample was distributed according to an EV1. This hypothesis was instead rejected for the Palermo and Siracusa stations (Fig. 7c,d).

The hypothesis that the sample was distributed according to an EV1

Table 6

Equations of the lines enveloping the Re_{10} (single-storm erosion index calculated using rainfall data sampled at time intervals, $\Delta t = 10$ min, in $\text{MJ mm ha}^{-1} \text{h}^{-1}$) vs he (rainfall depth, in mm) data points.

Code	Rain-gauge station	N	Equation of the envelope line	R^2	Range of he (mm)
1	Acate	22	$Re_{10} = -183.3 + 19.22 \times he$	0.9909	13.0 – 88.2
2	Agira	25	$Re_{10} = -185.2 + 19.76 \times he$	0.9928	13.0 – 94.6
3	Agrigento	21	$Re_{10} = 0.870 \times he^{1.743}$	0.9554	13.0 – 63.0
4	Bronte	24	$Re_{10} = -1286.9 + 508.5 \times \ln(he)$	0.9578	13.0 – 89.0
5	Calatafimi	21	$Re_{10} = -157.9 + 19.15 \times he$	0.9846	13.0 – 91.2
6	Caltagirone	23	$Re_{10} = -164.2 + 19.38 \times he$	0.9941	13.0 – 109.2
7	Caltanissetta	22	$Re_{10} = -103.5 + 15.87 \times he$	0.9752	13.0 – 107.2
8	Cammarata	16	$Re_{10} = -170.8 + 18.77 \times he$	0.9692	13.0 – 73.6
9	Caronia	16	$Re_{10} = -101.1 + 15.27 \times he$	0.9761	13.0 – 98.6
10	Castelvetroano	24	$Re_{10} = -91.5 + 16.34 \times he$	0.9935	13.0 – 259.4
11	Enna	21	$Re_{10} = -126.2 + 18.18 \times he$	0.9803	13.0 – 116.0
12	Gela	22	$Re_{10} = -128.1 + 17.54 \times he$	0.9841	13.0 – 88.4
13	Lascari	19	$Re_{10} = -1456.3 + 564.8 \times \ln(he)$	0.9662	13.0 – 115.6
14	Marsala	26	$Re_{10} = -27.7 + 13.74 \times he$	0.8742	13.0 – 164.8
15	Mazzerino	21	$Re_{10} = -121.6 + 16.97 \times he$	0.9850	13.0 – 152.0
16	Messina	27	$Re_{10} = -173.8 + 18.45 \times he$	0.9809	13.0 – 104.4
17	Mussomeli	21	$Re_{10} = -185.8 + 19.78 \times he$	0.9963	13.0 – 82.0
18	Palazzolo Acreide	29	$Re_{10} = -126.3 + 17.24 \times he$	0.9881	13.0 – 170.0
19	Palermo	17	$Re_{10} = -187.4 + 18.90 \times he$	0.9912	13.0 – 134.0
20	Petralia Sottana	19	$Re_{10} = -198.0 + 20.20 \times he$	0.9804	13.0 – 65.8
21	Piazza Armerina	23	$Re_{10} = -165.2 + 18.29 \times he$	0.9866	13.0 – 90.8
22	Ramacca	19	$Re_{10} = -1499.3 + 575.5 \times \ln(he)$	0.9548	13.2 – 121.0
23	Sciacca	25	$Re_{10} = -89.9 + 16.34 \times he$	0.9828	13.0 – 210.2
24	Siracusa	32	$Re_{10} = -96.1 + 16.56 \times he$	0.9912	13.0 – 467.2
25	Termini Imerese	17	$Re_{10} = 1.563 \times he^{1.575}$	0.9796	13.0 – 67.6
26	Trapani	21	$Re_{10} = -106.1 + 16.89 \times he$	0.9613	13.0 – 125.6
–	REGIONAL	115	$Re_{10} = -49.3 + 16.53 \times he$	0.9892	13.0 – 467.2

N = number of data points considered for obtaining the envelope line equation.
 R^2 = coefficient of determination.

was accepted for 21 stations. Instead, this hypothesis was rejected in other five cases, mainly because there was a poor agreement between the data and the straight line of Eq. (9) due to the presence of one or two outliers in the sample.

In conclusion, the analysis of Table 7 supported the suggestion that the $\max(Re)_j$ variable can generally be assumed distributed according to the EV1 distribution. This suggestion remained valid, also with reference to the skewness test, by considering a regional dataset of normalized $\max(Re)_j$ values (Fig. 8).

A link between single-storm rainfall erosivity and return period has to be established to evaluate erosion control measures soon after soil disturbance. In the absence of a locally detailed information on the

Table 7Adaption of the EV1 distribution to the maximum annual values of the single-storm erosion index, $\max(Re)_j$.

Code	Rain-gauge station	N	mean	σ	G	α_G	u_G	ST
1	Acate	23	530.2	355.9	1.073	0.00361	370.1	yes
2	Agira	19	684.5	402.3	0.751	0.00319	503.5	yes
3	Agrigento	23	423.6	295.3	1.051	0.00434	290.8	yes
4	Bronte	23	462.4	225.6	0.465	0.00569	360.9	yes
5	Calatafimi	23	607.4	350.5	0.684	0.00366	449.7	yes
6	Caltagirone	23	580.2	406.7	1.615	0.00315	397.2	yes
7	Caltanissetta	23	589.6	388.6	1.534	0.00330	414.8	yes
8	Cammarata	23	385.5	256.6	1.223	0.00500	270.0	yes
9	Caronia	23	513.1	324.5	1.567	0.00395	367.1	yes
10	Castelvetrano	23	901.5	877.8	2.373	0.00146	506.6	no
11	Enna	23	664.4	453.4	0.643	0.00283	460.4	yes
12	Gela	23	531.0	361.2	1.282	0.00355	368.5	yes
13	Lascari	23	457.1	312.7	1.167	0.00410	316.4	yes
14	Marsala	23	662.7	525.0	2.596	0.00244	426.5	no
15	Mazzeo	23	631.1	528.5	2.144	0.00243	393.3	no
16	Messina	23	647.1	398.9	1.326	0.00322	467.6	yes
17	Mussomeli	23	459.6	347.2	1.449	0.00369	303.4	yes
18	Palazzo Acreide	23	1164.5	558.1	0.695	0.00230	913.5	yes
19	Palermo	23	526.8	452.1	3.010	0.00284	323.4	no
20	Petralia Sottana	23	405.3	229.7	1.239	0.00559	301.9	yes
21	Piazza Armerina	23	543.6	384.0	0.957	0.00334	370.8	yes
22	Ramacca	18	544.8	379.8	0.462	0.00338	374.0	yes
23	Sciacca	23	829.8	691.1	1.826	0.00186	518.9	yes
24	Siracusa	23	1610.7	1658.7	2.902	0.00077	864.4	no
25	Termini Imerese	23	473.0	289.2	0.754	0.00444	342.9	yes
26	Trapani	23	678.6	394.7	1.360	0.00325	501.0	yes

N = years of observation. Mean = mean of the annual maximum values of the single-storm erosion index ($\text{MJ mm ha}^{-1}\text{h}^{-1}$). σ = standard deviation of the annual maximum values of the single-storm erosion index ($\text{MJ mm ha}^{-1}\text{h}^{-1}$). G = skewness of the annual maximum values of the single-storm erosion index. α_G and u_G = parameters of the EV1 distribution. ST = result of the skewness test: “yes” denotes that the hypothesis that the sample is distributed as an EV1 was accepted; “no” indicates that the hypothesis was not accepted.

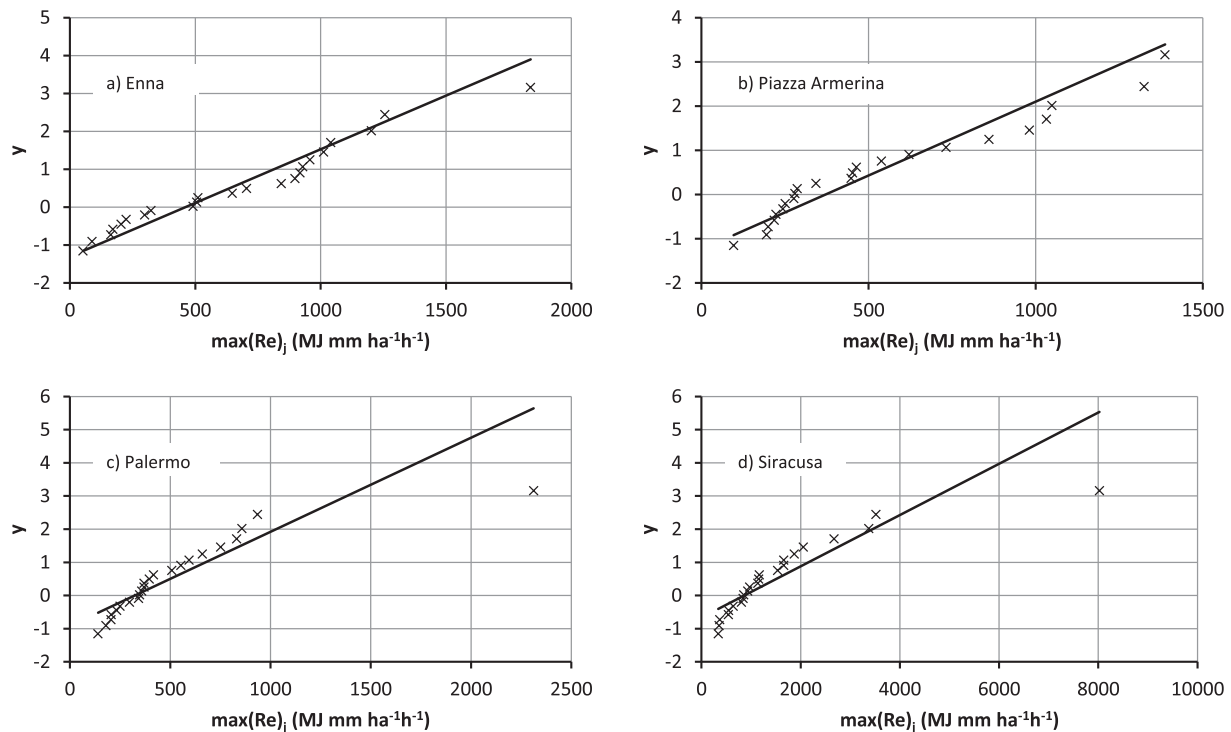


Fig. 7. Examples of acceptable [a) Enna, b) Piazza Armerina] and unacceptable [c) Palermo, d) Siracusa] fitting of the straight line of Eq.(9) to the Gumbel's normalized variable, y , vs. annual maximum values of the single storm erosion index, $\max(Re)_j$.

rainfall regime, Morgan et al. (2003) and Hann and Morgan (2006) suggested that making untested assumptions on rainfall depths and intensities could be unavoidable. According to this investigation, the availability of $\max(Re)_j$ for an appropriate number of years allows simply and accurately determining, for a given return period, the single-

storm erosion index value to be used for solving practical problems.

4. Conclusions

The analysis of the single-storm erosion index, Re , values calculated

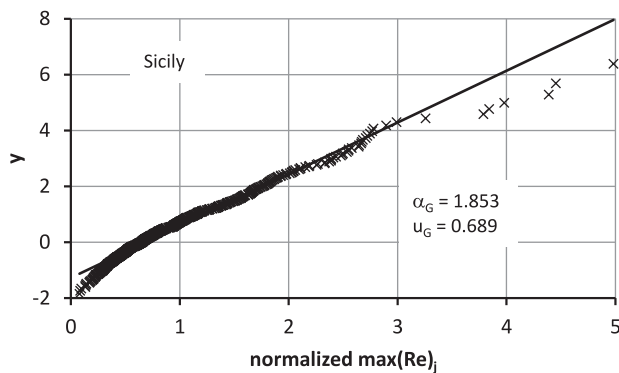


Fig. 8. Plot of the $N = 589$ empirical pairs (normalized $\max(Re)_j$, y) on the Gumbel diagram. For each station, the $\max(Re)_j$ values (annual maximum values of the single-storm erosion index) were divided by their mean to normalize $\max(Re)_j$.

for a total of 8464 erosive events occurred at 26 Sicilian rain-gauge stations in the 2002–2024 years allowed to draw the following conclusions.

The 88% of the erosivity described by Re_{10} can be expected to be represented by Re_{30} . This percentage, specific for Sicily at local and regional scales, appears reliable for other Mediterranean regions as well.

For parameterizing the relationship between Re and he , minimizing the sum of the squared residuals between the actual and the estimated values of Re is better than performing a linear regression analysis of the $\ln$ -transformed data. This conclusion was made since the former approach can be expected to determine a smaller bias of the predictions than the latter approach.

Two power law relationships obtained in different historical periods can be expected to yield different results, likely as a consequence of climate change. In Sicily, parameterization of the power law relationship differed since, for a fixed value of he , rainfall erosivity has increased from 1951–1970 to 2002–2024, even if some exceptions to this general trend were occasionally recognized.

An envelope line of the Re vs. he data can be developed locally and also at a regional scale. This line is expected to have practical interest since it allows to simply distinguish, for a given rainfall depth, expected from unexpected, or less expected, Re values.

Finally, the $\max(Re)_j$ variable can generally be assumed distributed according to the EV1 distribution.

From a practical point of view, the following conclusions can be drawn: (i) neglecting rainfall temporal resolution effects on Re calculation, (ii) considering Re vs. he relationships obtained with different parameterization methods as comparable, and (iii) using Re vs. he relationships developed in the past for predicting current erosivity are not recommended. Finally, tools for estimating the highest expected Re value for a given rainfall depth and the Re_T quantile for a given return period appear attractive for planning appropriate soil conservation measures given that, in a long time period, total soil erosion is due to a few particularly high erosive events.

The results reported in this investigation should improve our ability to calculate, predict and practically use single-storm erosion index values in Sicily. These results should be tested with data collected at other Sicilian recording rain-gauges to validate the obtained conclusions. The investigation should also be extended to other regions and longer periods of records to determine the effects of the geographic differences on these results and making assessment of climate changes effects on rainfall erosivity more robust.

CRediT authorship contribution statement

V. Bagarello: Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **V. Ferro:** Writing –

review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization. **F. Gakunde:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation. **V. Pampalone:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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