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Rainfall erosivity estimation: Comparison and statistical assessment among methods using data from Southeastern Brazil

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ABSTRACT: Rainfall erosivity (R factor) is one of the six factors of the Universal Soil Loss Equation, being calculated based on the product of rainfall kinetic energy multiplied by its 30-minute maximum intensity. However, the lack of detailed and reliable rainfall data in many parts of the world has driven the use of other methods to estimate rainfall erosivity based on daily, monthly or annual data. These methods still need to be assessed to determine if their estimates are consistent with the standard method for calculating rainfall erosivity. This study aimed to select a consistent method for such replacement in Brazilian conditions without access to the rainfall intensity data. The tested methods included: modified Fournier, MF; modified Fournier by Zhang, MF-Z; modified Fournier by Men, MF-M; Rainfall Disaggregation, RD; TRMM Satellite with modified Fournier coefficient, TRMM-F; and TRMM Satellite with monthly rainfall, TRMM-M. The rainfall data were obtained from the USP Meteorological Station, referring to the period from 2009 to 2015. The analyses were performed according to the Additive Main effects and Multiplicative Interaction (AMMI) model and Scott-Knott statistical tests. Considering the 1:1 line, all methods had a good adjustment, presenting similar behavior in relation to the standard method. The methods behaved differently for monthly and annual periods. The MF method proved to be capable of consistently replacing the standard method in all aforementioned situations. Considering the driest period, any method can be used. For annual rainfall erosivity estimation, the RD, MF, TRMM-F and TRMM-M methods can be applied; highlighting that the TRMM-based methods are optimal for locations without on-site rain gauges. Additionally, it was computed that the modified Fournier by Men and the modified Fournier by Zhang underestimated and overestimated the rainfall erosivity, respectively.

Keywords: modified Fournier, rainfall disaggregation, TRMM.

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INTRODUCTION

Erosive potential of rainfall, defined as the rainfall erosivity index, can be calculated using datasets from automated weather stations or even pluviographs. The rainfall erosivity index –also represented as the R factor of EI_{30} – is computed as the product of rainfall kinetic energy multiplied by its 30-minute maximum intensity (Wischmeier and Smith, 1978). The R factor is one of the six factors in the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978) and its revised versions.

In some areas of the globe there is insufficient rainfall data with high-resolution and also with a long data series for a reliable calculation (Trindade et al., 2016), since it is recommended to use historical precipitation series with more than 20 years (Renard and Freimund, 1994; Vantas et al., 2019), and some rainfall stations do not present homogeneity in their distribution (Moraes et al., 2015). Although long rain data series are ideal for recording extreme rainfall events, smaller historical series have been frequently applied throughout the world (Panagos et al., 2017). The lack of good resolution rainfall data –mainly rainfall intensity– is another challenge that has driven researchers to develop alternative methods to estimate the rainfall erosivity such as the Fournier index (Fournier, 1960), Modified Fournier index (Arnoldus, 1980) or variations of these methods, e.g., adjustment of potential equations, use of erosivity per day in half a month, maximum daily rainfall, among others (Zhang et al., 2002; Men et al., 2008; Diodato and Bellocchi, 2010; Diodato et al., 2013).

Other methodologies, such as rainfall disaggregation (Silveira, 2000) –considering annual or monthly totals for hourly or shorter periods–, or techniques based on orbital remote sensing to estimate rainfall depth (Duarte and Silva Filho, 2019; Li et al., 2020; Moreira et al., 2020), can be used at locations with low density of rain gauge data points. Rainfall erosivity mapping for Africa utilizing Tropical Rainfall Measurement Mission (TRMM), based on TMPA 3B43 satellite data (precipitation data) coupled with the modified Fournier index, proved to be a reliable methodology (Vrieling et al., 2010). Although regions use available databases and automated data collection systems –automatic rain gauges, and real-time data transfer– provide reliable hourly or daily rainfall records, even some with 5-, 10-, or 15-minute resolution (Angulo-Martínez and Beguería, 2009; Porto, 2016; Diodato et al., 2017; Todisco et al., 2019; Yue et al., 2020), this is not the case for less technologically advanced countries (Waltrick et al., 2015; Di Raimo et al., 2018).

In Brazil, a country of continental proportions and one of the world's leading crop producers (USDA, 2020), the most reliable rainfall datasets are available on the websites of the National Water and Sanitation Agency (ANA, 2020), the National Institute of Meteorology (Inmet, 2020), and the Centre for Monitoring and Early Warnings of Natural Disasters (Cemaden, 2020). Despite these large databases, rain information is not available with high-resolution to calculate rainfall erosivity by Wischmeier and Smith (1978). Moreover, there is still a gap in utilizing the correct method for estimating rainfall erosivity based on the specific characteristics of the studied area (Trindade et al., 2016).

Studies conducted by Angulo-Martínez and Beguería (2009) compared different methods to estimate rainfall erosivity (R factor) and assessed each of them via RUSLE. They reported some methods that could be applied in other regions, provided the availability of high-resolution rainfall data (pluviographic data). Nearing et al. (2017) reported that calculations of rainfall erosivity resulted in underestimation of soil erosion using RUSLE compared to USLE and RUSLE2. In the southern region of China, six models to estimate rainfall erosivity were compared, including a model adjusted for Brazilian conditions (Zhu et al., 2021). The authors observed that a model adjusted for Brazilian conditions overestimated the rainfall erosivity in comparison to the other models. Thus, the importance of testing models already adjusted for particular climatic conditions is to assess their applicability in different regions. Vantas et al. (2019) presented the correlation between the R factor and annual precipitation for several countries using

parametric equations and geostatistical models. Regression models based on annual precipitation (coarser resolution) to estimate the R factor were compared with rainfall erosivity obtained by high-resolution data in Korea (Lee and Heo, 2011). Thus, these methodologies have proved to be useful for the estimation of rainfall erosivity in regions with insufficient rainfall data, as high-resolution rainfall data may not be accessible for locations at a certain time range.

Studies comparing methodologies for estimating rainfall erosivity are sparse. Among these studies, we can highlight the one conducted by Ma et al. (2014), which compared three models for estimating the R factor, including those proposed by Zhang et al. (2002) and Men et al. (2008). The different methods presented discrepancies over the months of the year. Thus, alternative methods should be evaluated for accuracy compared to the standard method.

Although there are great advancements in having readily useful rainfall erosivity data in Brazil (Oliveira et al., 2013), some regions still lack reliable instrumentation and data acquisition. For these regions, the focus is on identifying the best alternatives for estimating rainfall erosivity from monthly, daily, or hourly precipitation data. Currently, China is the country providing most researches on rainfall erosivity; therefore we opted to test the Modified Fournier equations of Zhang et al. (2002) and Men et al. (2008) to verify if they could be helpful in Southeastern Brazil conditions.

This study aimed to statistically assess alternative methods for the estimation of the R factor, as proposed by Wischmeier and Smith (1978) (WS), via a comparison of estimations using: modified Fournier (MF); modified Fournier by Zhang (MF-Z); modified Fournier by Men (MF-M); rainfall disaggregation (RD); TRMM Satellite with modified Fournier coefficient (TRMM-F); and TRMM Satellite with monthly rainfall (TRMM-M). These computational tools for R factor estimation can benefit different stakeholders: engineers, extensionists, policy makers, and research groups across Brazil, South America and other developing tropical regions worldwide.

MATERIALS AND METHODS

Characterization of the study area

The selected study area was the municipality of Pirassununga, located in the state of São Paulo, between the coordinates of 21° 50' and 22° 8' south latitude and between 47° 10' and 47° 40' WGr longitude. The climate of the municipality according to Köppen classification system is Cwb, *i.e.*, humid subtropical climate with dry winters and rainy summers (Alvares et al., 2013).

Due to the difficulty in obtaining a long historical series, the rainfall data were obtained from the Meteorological Station of the University of São Paulo (USP) located at the Fernando Costa *campus* (Figure 1). This study was performed with a time series of seven years, referring to the period from 2009 to 2015. The automatic rain gauge was configured to record the frequency of rain every 10 min, with an accuracy of 0.1 mm, using the Davis climatic station, vantage pro2 model. The average rainfall in the study period was 1,564.4 mm.

Methods for determining rainfall erosivity

Wischmeier and Smith, WS

The methodology proposed by Wischmeier and Smith (1958), Wischmeier (1959) and Wischmeier and Smith (1978) is adopted as the standard method in this study according to studies conducted by Nearing et al. (2017). The method considers individualized events of rain, where the previous rain is separated from the subsequent one for at

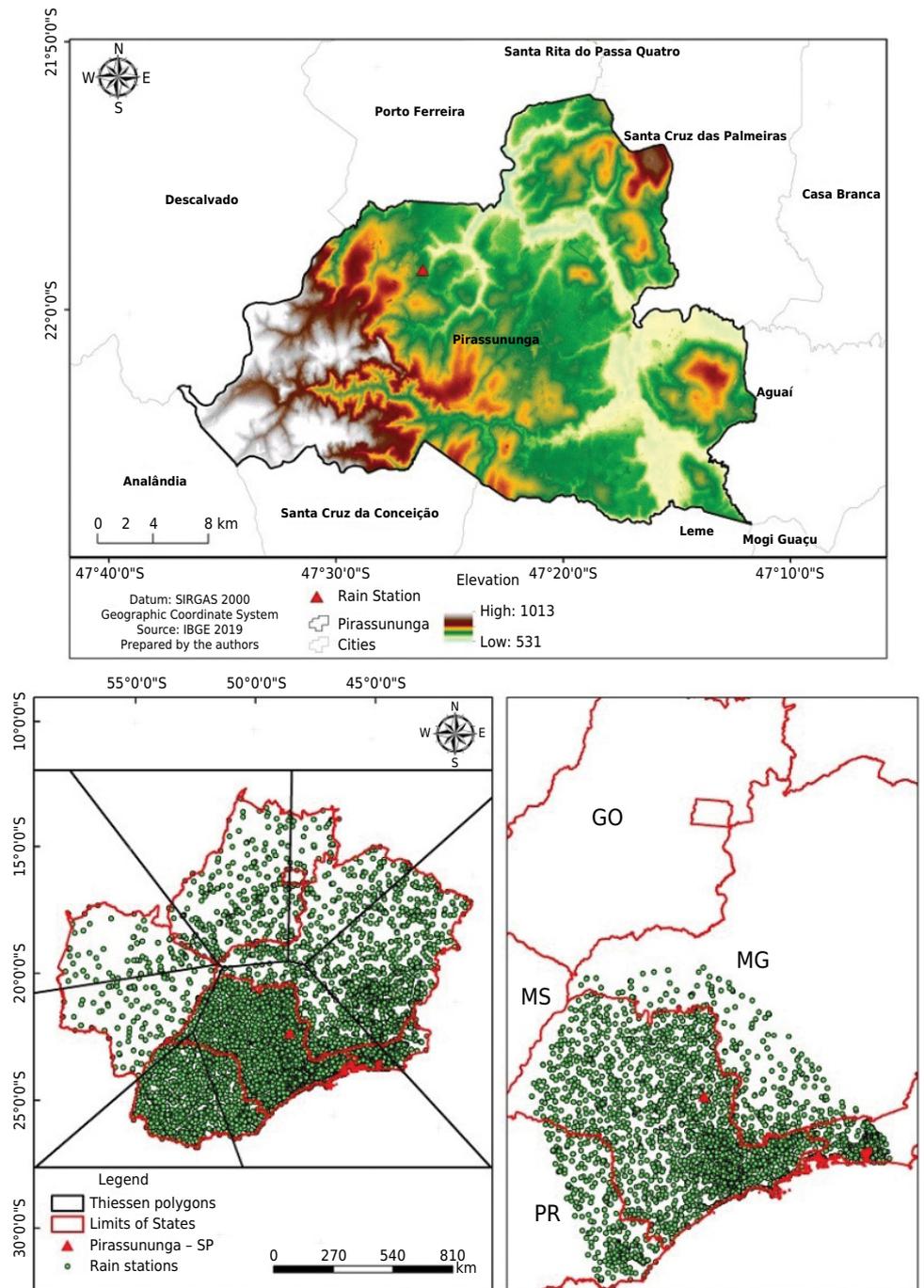


Figure 1. Location of the Meteorological Station at the University of São Paulo, Fernando Costa campus, Pirassununga, Brazil.

least six hours for rains up to 1 mm. Rainfall events are considered erosive for rain with more than 10 mm, or rain duration more than 15 min and rainfall greater than 6 mm (Wischmeier and Smith, 1958). The kinetic energy of rainfall was calculated by equation 1:

$$E_c = 0.119 + 0.0873 \times \log I \quad \text{Eq. 1}$$

in which: E_c is the kinetic energy ($\text{MJ ha}^{-1} \text{mm}^{-1}$); and I is the rainfall intensity (mm h^{-1}).

The rainfall erosivity index (EI_{30}) is the product of the kinetic energy of the rainfall event by the maximum intensity in 30 min (Brown and Foster, 1987):

$$EI_{30} = E_c \times I_{30} \quad \text{Eq. 2}$$

in which: El_{30} is the erosivity index ($MJ\ mm\ ha^{-1}\ h^{-1}$); Ec is the kinetic energy ($MJ\ ha^{-1}$); and I_{30} is the maximum intensity in 30 min ($mm\ h^{-1}$). For this determination, the RainfallErosivityFactor package (Cardoso et al., 2020) was run in the R environment (R Development Core Team, 2020) to compute the R factor.

Methods estimating rainfall erosivity

Modified Fournier Index, MF

To estimate the rainfall erosivity, we first computed the rainfall coefficient of the modified Fournier index (Arnoldus, 1980), using equation 3:

$$MF = \sum_{i=1}^{12} \frac{p^2}{P} \quad \text{Eq. 3}$$

in which: MF is the rainfall coefficient (mm); p is the monthly average rainfall (mm); and P is the annual average rainfall (mm).

Subsequently, this rainfall coefficient was used to estimate the rainfall erosivity. The adjusted equation between rainfall erosivity index and rainfall coefficient for Pirassununga was calculated by equation 4 (Cardoso et al., 2017):

$$El_{30} = 128.39 \times MF^{0.7214} \quad \text{Eq. 4}$$

in which: El_{30} is the rainfall erosivity index ($MJ\ mm\ ha^{-1}\ h^{-1}$); and MF is the rainfall coefficient (mm).

Modified Fournier by Zhang, MF-Z

Rainfall erosivity index was obtained according to the methodology proposed by Zhang et al. (2002), with local calibrations of the parameters. The model uses daily rainfall amounts to estimate half-month rainfall erosivity. Thus, rainfall erosivity was estimated by equation 5:

$$M_i = \alpha \sum_{j=1}^k (D_j)^\beta \quad \text{Eq. 5}$$

in which: M_i is the half-month rainfall erosivity ($MJ\ mm\ ha^{-1}\ h^{-1}$); D_j is the erosive rainfall for day j in half-month (D_j is equal to the actual rainfall, if the actual rainfall is greater than 12.7 mm, otherwise D_j is equal to zero) K is the number of days in half-month; b and a are empirical parameters adjusted locally, determined by the following equations:

$$\beta = 0.8363 + \frac{18.144}{P_{d12}} + \frac{24.455}{P_{y12}} \quad \text{Eq. 6}$$

$$\alpha = 21.586\beta^{-7.1891} \quad \text{Eq. 7}$$

in which: P_{d12} is the average daily rainfall greater than 12.7 mm; and P_{y12} is the annual average rainfall for days with rainfall greater than 12.7 mm.

Modified Fournier by Men, MF-M

In this method, Men et al. (2008) proposed an exponential equation to estimate the rainfall erosivity index by calculating the modified Fournier index (equation 8):

$$R_a = \alpha MF^\beta \quad \text{Eq. 8}$$

in which: R_a is the annual rainfall erosivity index ($MJ\ mm\ ha^{-1}\ h^{-1}$); MF is the modified Fournier index calculated by equation 3; α and β are empirical parameters. The β parameter was calculated by equation 6, and α was determined by equation 9:

$$\alpha = 10^{2.124 - 1.495\beta + 0.00214P_{dmax}} \quad \text{Eq. 9}$$

in which: P_{dmax} is the maximum daily rainfall in an average year.

Rainfall disaggregation, RD

For locations where only total annual precipitation amount is available, Cedeño and Villavicencio (2017) and Cedeño and Sinichenko (2017) proposed rain disaggregation to estimate rainfall erosivity. The procedure divides the annual total amount by the number of months and then to daily amounts. Originally, the aforementioned authors proposed 15 rainfall events per month (Cedeño and Sinichenko, 2017; Cedeño and Villavicencio, 2017). In this paper, rainfall disaggregation was applied only from monthly to daily amounts. However, instead of 15 events, monthly rainfall was divided by six, since, for months during the dry season (Figure 2), the average number of rainfall events ranged from one to two events per month. Considering the rainiest months are the ones with the greatest erosion, the number of rainfall events between November and March were evaluated. Thus, six rainfall events were adopted as the average number of erosive rainfalls per month. Then, daily rainfall was computed by dividing monthly rainfall by 6.

To apply the methodology developed by Wischmeier and Smith (1978), the daily precipitation was disaggregated using coefficients obtained by Silveira (2000) for Brazilian rainfall characteristics. Silveira (2000) proposed disaggregation coefficients considering the daily duration of rainfall totals for shorter durations (sub-event). Disaggregation coefficients of 0.17 for the 10-minute duration, and 0.31 for 30-minute duration were used to estimate the rainfall amount as input for equations 1 and 2, respectively (Silveira, 2000). After estimating the rainfall erosivity for such rainfall event, the value was multiplied by six rain events to obtain the monthly rainfall erosivity value.

TRMM Satellite with modified Fournier coefficient, TRMM-F

For this methodology, monthly average rainfall data (Figure 4) for Pirassununga, from 2009 to 2015, were obtained from the Tropical Rainfall Measuring Mission (TRMM) satellite. This information is available on the Giovanni platform of the National Aeronautics and

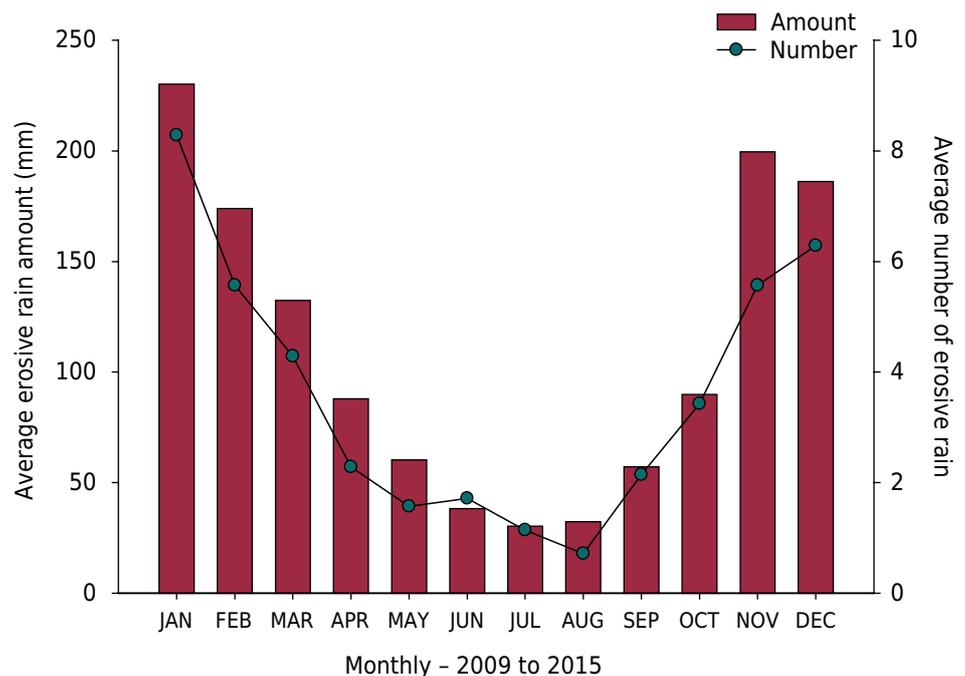


Figure 2. Average monthly rainfall amount of erosive events, and average number of erosive rains, from 2009 to 2015, at Pirassununga, state of São Paulo, Brazil.

Space Administration (NASA, 2019). These monthly data were transformed into 90-m spatial resolution.

Using the raster calculator tool of the ArcGIS 10.3 software (ESRI, 2014), the average monthly and annual rainfall were extracted from TRMM satellite data. Then, equations 3 and 4 were applied to estimate the rainfall erosivity.

TRMM Satellite with monthly rainfall, TRMM-M

Average monthly rainfall amount was also obtained from the Tropical Rainfall Measuring Mission (TRMM) satellite (Figure 4). However, rainfall erosivity was estimated by equation 10 (Cardoso et al., 2017), which was calibrated for Pirassununga and was based on rainfall erosivity and average monthly rainfall. The raster calculator was used to estimate the rainfall erosivity by the TRMM-M method, replacing p of equation 10 with the TRMM satellite's precipitation data, which consisted of monthly precipitation from January to December.

$$EI_{30} = 7.7255 \times p - 213.75 \quad \text{Eq. 10}$$

in which: p is the average monthly rainfall.

Statistical assessment of the methods

The reference methodology for rainfall erosivity calculation was that one proposed by Wischmeier and Smith (1978). After estimation of rainfall erosivity index by the other utilized methods, a statistical assessment of these methods was performed using the Additive Main effects and Multiplicative Interaction (AMMI) model. The AMMI is a hybrid analysis that incorporates both, the additive and multiplicative, components of the two-way data structure. The AMMI model uses analysis of variance (ANOVA) followed by the principal component analysis (PCA) applied to the sums of squares allocated by the ANOVA to analyze the two-factor interaction effects (Sabaghpour et al., 2012). In this study, the different methods tested correspond to one factor and the month corresponds to the second factor. When the interaction was significant, the Scott-Knott test was performed at 5 % significance level to compare methods in each month.

The modified equation of Perkins and Jinks (1968) was applied to analyze the behavior of the different methods in the estimation of the monthly rainfall erosivity over a 5-year period:

$$Y_{ij} = \mu + Me_i + Mo_j + (MeMo)_{ij} \quad \text{Eq. 11}$$

in which: Y_{ij} is the observation of the i -th method and j -th month; μ is the general average; Me_i is the effect of the i -th method; Mo_j is the effect of the j -th month; and $(MeMo)_{ij}$ is the effect of the interaction of the i -th method and j -th month.

Principal Component Analysis (PCA) was applied to describe the structure of the interaction of methods and months, based on the method of least squares, allowing the experimental error to be estimated from the effect of the interaction and the application of the statistical tests. According to Hirai (2019) equation, it is possible to separate the deterministic part, given by $k = 1, 2, \dots, K$ eigenvalues containing the highest variability of the interaction effect (methods \times months), from the residual part (noise) $k = K+1, K+2, \dots, n$ eigenvalues with the lowest variability of the interaction effect:

$$(\widehat{ge})_{ij} = \sum_{k=1}^K \lambda_k \gamma_{ik} \delta_{jk} + \sum_{k=K+1}^n \lambda_k \gamma_{ik} \delta_{jk} = \sum_{k=1}^K \lambda_k \gamma_{ik} \delta_{jk} + \rho_{ij} \quad \text{Eq. 12}$$

in which: λ_k is the square root of the k -th eigenvalues of interaction (k -th singular value); γ_{ik} is the i -th element of the column vector $\bar{\gamma}_k$ associated with λ_k ; and δ_{jk} is the j -th element of the line vector $\bar{\delta}_k$ associated with λ_k .

Thus, the final AMMI model is expressed as:

$$Y_{ij} = \mu + Me_i + Mo_j + \sum_{k=1}^K \lambda_k \gamma_{Meik} \delta_{Mok} + \rho_{ij} \quad \text{Eq. 13}$$

in which: Y_{ij} is the response of the i -th method and j -th month; μ : general average; Me_i is the effect of the i -th method; Mo_j is the effect of the j -th month; λ_k is the square root of the k -th eigenvalues of the matrix methods x months; γ_{ik} is the i -th element of the column vector $\vec{\gamma}_k$ associated with λ_k ; δ_{jk} is the j -th element of the line vector $\vec{\delta}_k$ associated with λ_k ; and ρ_{ij} is the noise from the multiplicative part used as an error, being $\rho_{ij} \sim N(0, \sigma^2)$ considered the experimental error.

The analysis was carried out according to the AMMI model (Crossa, 1990), through the Stability Program. We used the Mapgen computer program developed by Ferreira and Zambalde (1997) to perform the Scott-Knott test.

RESULTS

Rainfall erosivity estimations

According to the coefficient of determination (Figure 3), all models had a good adjustment. The critical point (x -critical) of the standard model (WS) occurred at 6.69 months. This point corresponds to the derivative of the adjusted equation. In practical terms, it corresponds to the lowest value of the rainfall erosivity (EI_{30}), consequently, it refers to the change in rainfall erosivity behavior. For all tested models, the inversion point occurred between the end of June and the beginning of July.

Considering the critical point for the WS (6.69 months; EI_{30} equal to $119.06 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ month}^{-1}$), the rainfall erosivity in such point, obtained by interpolation, for the other methods, corresponded to 86.91, 91.49, 0.0, 0.0, 56.41, and 94.98 $\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ month}^{-1}$ for MF, MF-Z, MF-M, RD, TRMM-F and TRMM-M, respectively (Figure 3). Therefore, the evaluation of the critical points and the respective minimum rainfall erosivity values revealed that the methods presented minimum rainfall erosivity values lower than the WS, pointing out an underestimation of such values for the peak of the dry season.

The fit plots (Figure 4) presented high values of coefficient of determination, varying from 0.8908 (TRMM-F method) to 0.9747 (MF method). Besides a better determination coefficient, the MF best fitted to the WS, presenting little dispersion around the 1:1 line.

The method MF-Z overestimated the rainfall erosivity values (Figure 4) when compared to the WS, particularly for greater rainfall erosivity values, which are of paramount importance to predict water erosion. Conversely, the MF-M underestimated the rainfall erosivity: it is noteworthy to mention that the method shifted the adjustment above to the 1:1 line, underestimating the rainfall erosivity values, but maintaining the same proportion, both for greater and lower EI_{30} values.

The methods based on obtaining rainfall data by satellite or disaggregation also showed good adjustments (Figure 4). However, the rainfall erosivity estimation showed greater dispersion around the 1:1 line compared to the MF method. In these cases, methods RD, TRMM-F and TRMM-M may be inaccurate for the most extreme rainfall erosivity values.

Statistical comparison of methods

The selected methods were further classified by grouping, through the principal component analysis (Table 1) for rainfall erosivity and the Scott-Knott test -AMMI technique. The interaction of the methods with the months was significant at the 5 % level (Table 2). Therefore, the methods responded differently for the analyzed months. The principal

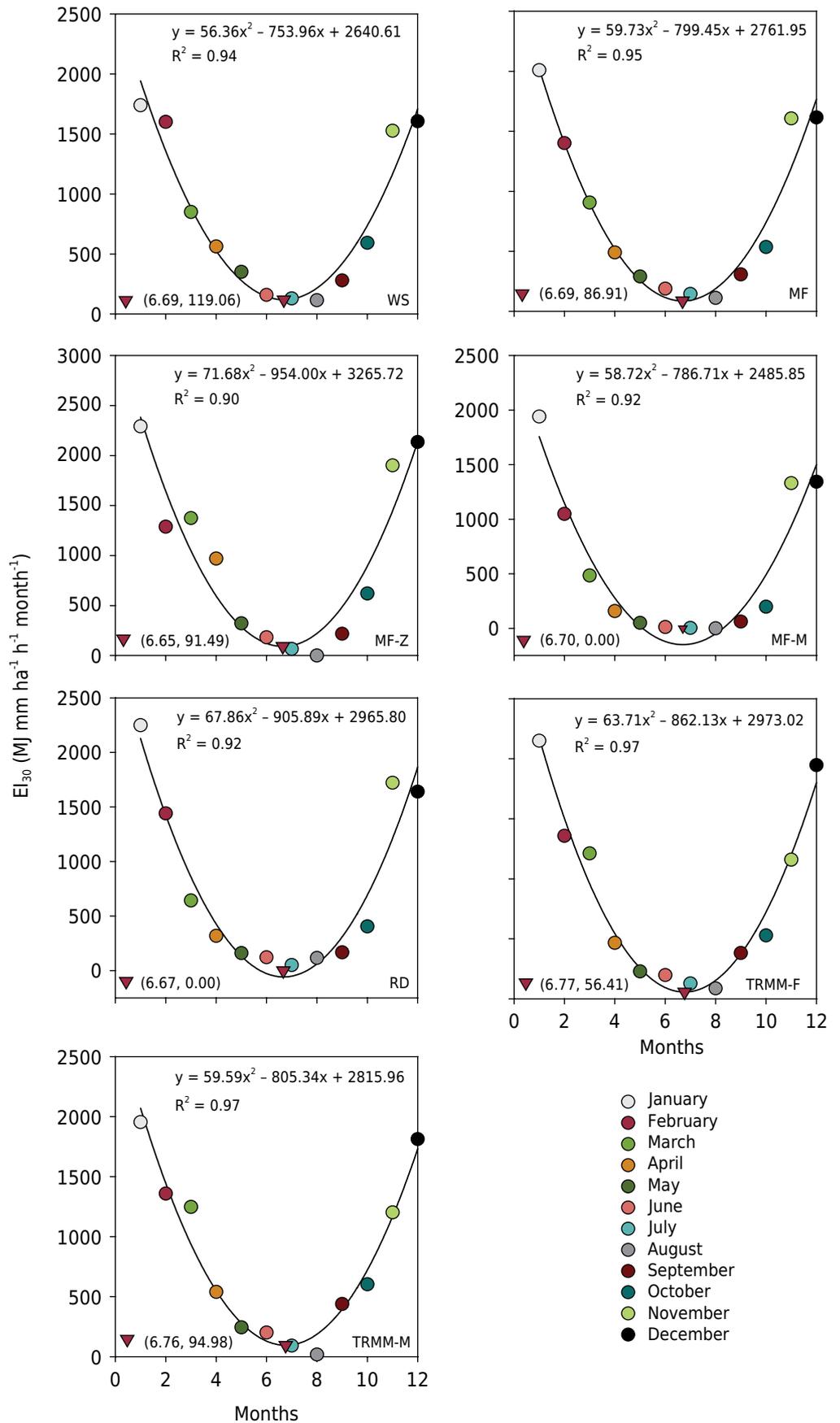


Figure 3. Adjusted equations, coefficients of determination, critical points, and rainfall erosivity indexes (EI_{30} , $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{month}^{-1}$) corresponding to critical point for the evaluated methods (WS, MF, MF-Z, MF-M, RD, TRMM-F and TRMM-M).

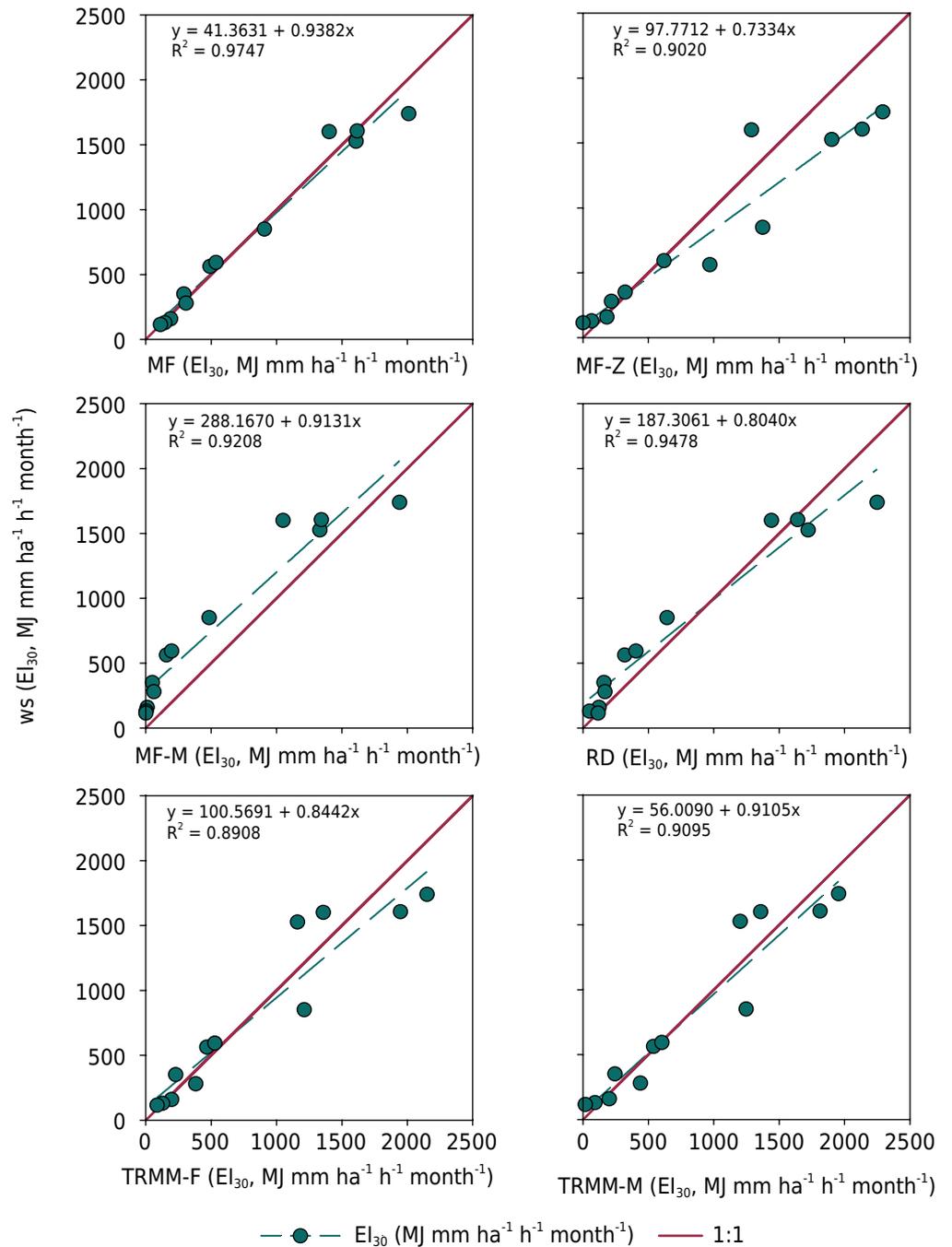


Figure 4. Comparison between standard (WS) and other estimated rainfall erosivity (El₃₀) methods. WS: Wischmeier and Smith; MF: modified Fournier; MF-Z: modified Fournier by Zhang; MF-M: modified Fournier by Men; RD: Rainfall Disaggregation; TRMM-F: TRMM-M Satellite.

components, PC1 and PC2, explained together 79.87 % of the variation in rainfall erosivity, being 47.44 and 32.43 % explained by PC1 and PC2, respectively (Table 1).

The AMMI technique provides a joint analysis of ANOVA and principal component analysis. In this way, the significance level of the parameters was separated from the interaction between them, in this case, utilized methods and months. The formed groups indicated that the methods belong to the same group and are statistically equal, *i.e.*, they do not differ from each other. In this study, for all the methods compared, the WS method was considered the baseline -blue color- (Figures 5, 6 and 7); in this way the compared methods were grouped as 1) statistically equal, 2) methods that underestimate or 3) methods that overestimate the rainfall erosivity index values.

Table 1. Percentages of the sum of total squares (methods × months) associated with each main axis, being the individual and accumulated values according to AMMI analysis for the standard method (WS) and the other methods (MF, MF-Z, MF-M, RD, TRMM-F and TRMM-M) use to estimate the rainfall erosivity of Pirassununga-SP

Principal component	% Explanation	% Accumulated explanation
PC1	47.44	47.44
PC2	32.43	79.87
PC3	15.73	95.60
PC4	3.48	99.08
PC5	0.86	99.94
PC6	0.06	100.00

Table 2. Summary of the analysis of variance and mean squares associated with the effect of the interaction between methods and months, referring to the rainfall erosivity of Pirassununga-SP

Source	GL	QM	Fc	Pr>Fc
Methods	6	167056.6107	55.23	0.00*
Monthly	11	3491670.0616	1154.36	0.00*
Methods × Monthly	42	37554.72892	12.42	1.00e ⁻⁸ *
Residual	24	3024.7772		

* Significance level of 5 %.

Considering the month of January (Figure 5), the methods were divided into three groups. The method considered a standard (WS) was the only one in group 1. Thus, all methods assessed overestimated the rainfall erosivity, being statistically grouped into Group 2: MF-M, TRMM-M and MF methods; and Group 3: TRMM-F, RD, and MF-Z –greater overestimation than Group 2- methods.

Considering the month of February (Figure 5), methods were statistically grouped into Group 1: MF-M –greatest underestimation–; Group 2: MF-Z, TRMM-F, TRMM-M, MF and RD; and Group 3: WS-standard method. Conversely to January, for this month all methods underestimated the rainfall erosivity indexes.

Considering March (Figure 5), the methods were separated into three groups. The first group underestimated the EI_{30} (MF-M and RD), the second group was statistically equal (WS and MF) and the third one overestimated the rainfall erosivity indexes (TRMM-F, TRMM-M and MF-Z).

As well as March, for April (Figure 5), the methods were also classified into three groups. Group 1 (MF-M and RD), Group 2 (TRMM-F, MF, TRMM-M and WS) and Group 3 (MF-Z). For this month, the MF-M and RD methods underestimated, and the MF-Z method overestimated the rainfall erosivity index values.

Concerning May, the methods were stratified by only two groups (Figure 5), with underestimating rainfall erosivity values in Group 1 (MF-M and RD), and considered equal values for Group 2 (TRMM-F, TRMM-M, MF, MF-Z and WS). For the driest period of the year –June (Figure 5), July and August (Figure 6)–, there was no statistical difference between the methods evaluated and the standard one (WS).

For the month of September (Figure 6), the MF-M, RD and MF-Z methods (Group 1) underestimated the EI_{30} , while the other methods (MF, TRMM-F and TRMM-M) showed to be equal to the WS. Considering October (Figure 6), there were three groups. The methods TRMM-F, MF, TRMM-M and MF-Z (Group 3) were equal to the WS. The methods MF-M (Group 1) and RD (Group 2) underestimated the rainfall erosivity index values.

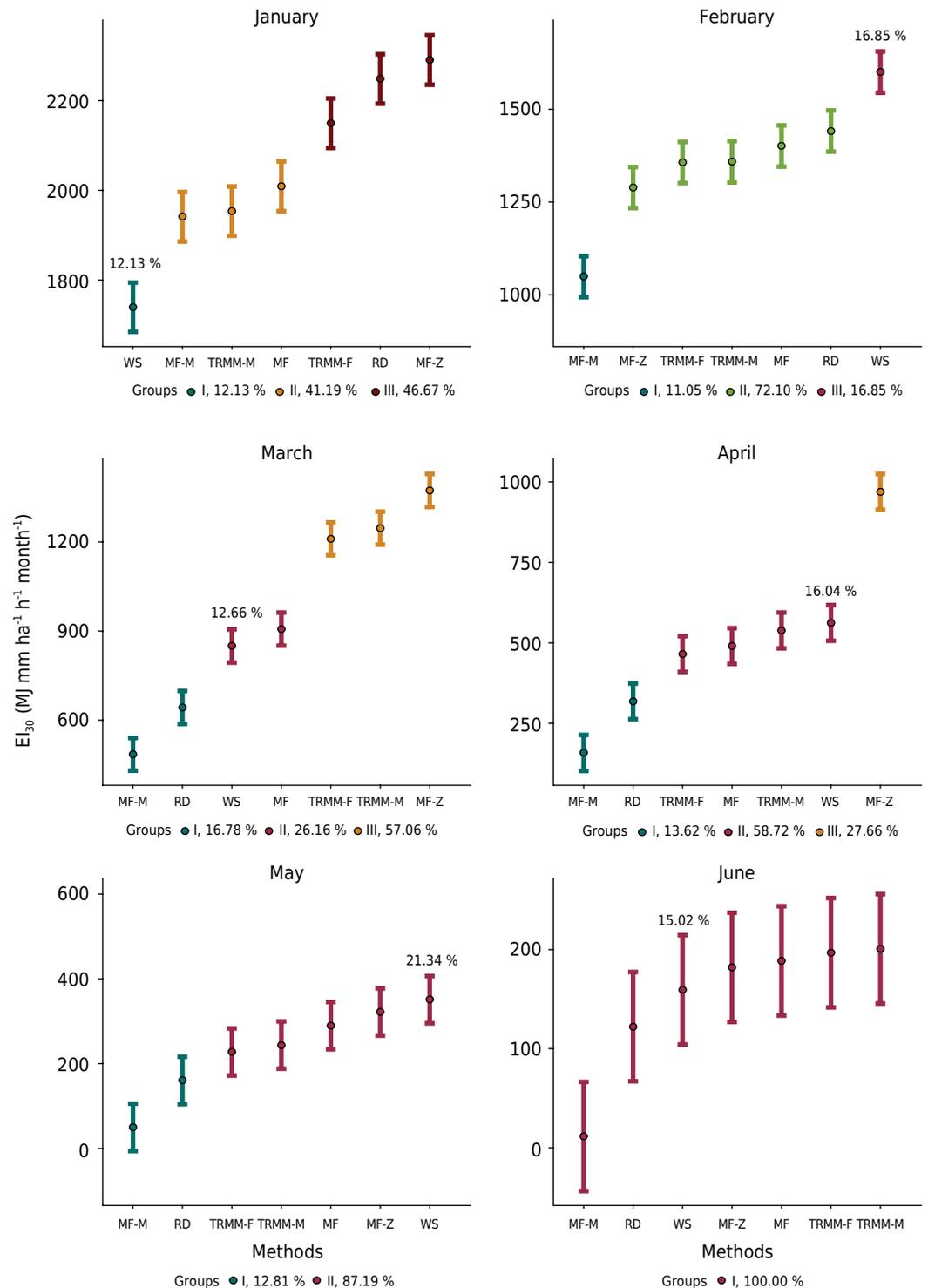


Figure 5. The univariate grouping of methods of estimation of the monthly rainfall erosivity indexes (January to June), by Scott and Knott (1974), with a Chi-squared significance level of 5%. The blue color refers to the standard method (WS), the shades of green or red were attributed to the methods that underestimate or overestimate the rainfall erosivity, respectively.

For November (Figure 6), the groups were classified as 1 (TRMM-F, TRMM-M, and MF-M), 2 (WS, MF, and RD) and 3 (MF-Z). The WS belongs to group 2, therefore group 1 underestimated and group 3 overestimated the rainfall erosivity values. Finally, for December (Figure 6), the methods were classified into Group 1 (MF-M), Group 2 (WS, MF, and RD), Group 3 (TRMM-F and TRMM-M) and Group 4 (MF-Z), being the values of the rainfall erosivity index underestimated by Group 1 and overestimated by Groups 3 and 4 in comparison to the WS method.

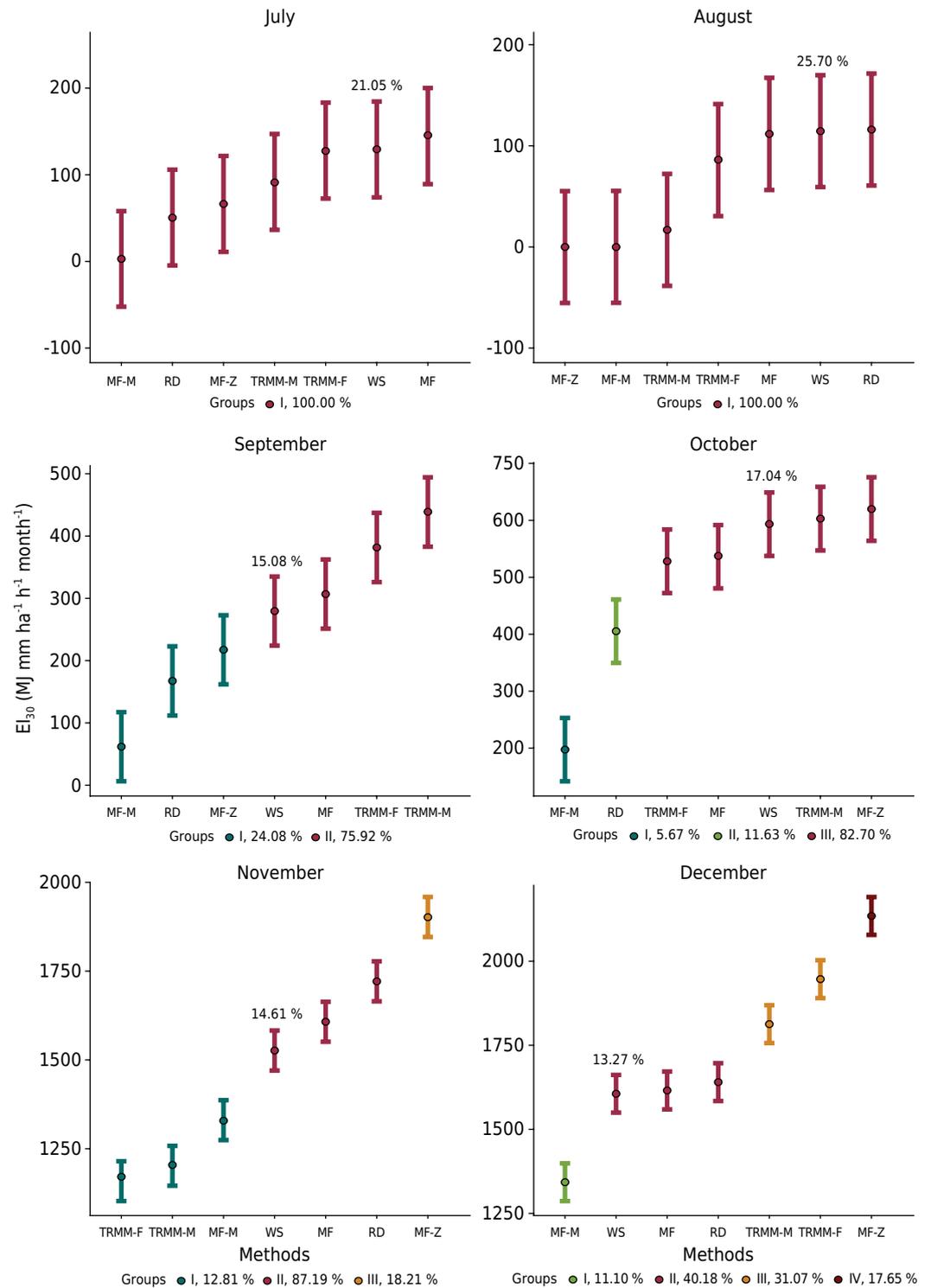


Figure 6. The univariate grouping of methods for estimation of the monthly rainfall erosivity indexes (July to December), by Scott and Knott (1974), with a Chi-squared significance level of 5 %. The blue color refers to the standard method (WS), the shades of green or red, were attributed to the methods that underestimate or overestimate the rainfall erosivity, respectively.

For the rainy season (November to March), the MF method was statistically equal or grouped very close to the WS (Figures 5 and 6), reflecting the adequate fit between them (Figure 4). Therefore, in this period, with a lack of more detailed rainfall data -short intervals-, the MF method can replace the WS with accuracy. For the dry season (from June to August), the methods did not differ from WS.

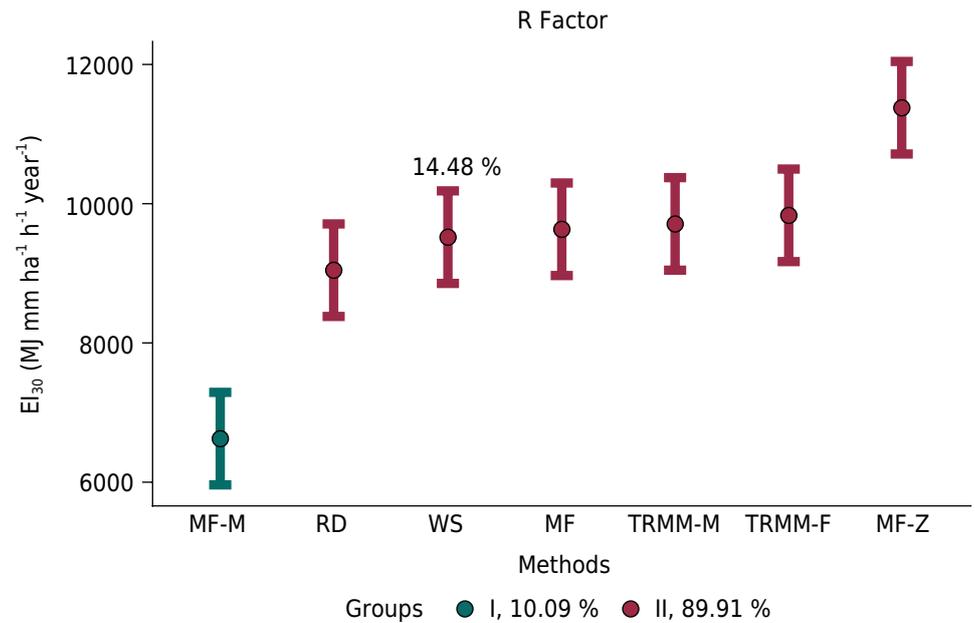


Figure 7. The univariate grouping of methods for estimation of the rainfall erosivity (R Factor), by Scott and Knott (1974), with a Chi-squared significance level of 5 %. The blue color refers to the standard method (WS), the shades of green or red were attributed to the methods that underestimate and overestimate the rainfall erosivity, respectively.

The annual rainfall erosivity or R Factor was classified into 2 groups (Figure 7), with Group 1 represented by the MF-M method, and Group 2 represented by the RD, WS, MF, TRMM-M, TRMM-F and MF-Z methods. Group 1 underestimated the rainfall erosivity values in relation to the WS. By analyzing the 1:1 fitting line (Figure 4), the predictions were parallel to the line. However, for the other methods (Figure 4), the estimates always crossed the 1:1 line, which means under or overestimation according to greater or lower rainfall erosivity values.

In general, regardless of the estimated rainfall erosivity values (monthly or annual) (Figures 5, 6 and 7), the MF-M, and MF-Z methods underestimated and overestimated EI₃₀ values in relation to the WS method, respectively. The MF method showed to be always closer to the standard method (Figures 5, 6 and 7).

All models were tested for the study area located in Pirassununga (Figure 1). Thus, in areas around this region, all models could be used as presented by this study. Conversely, it would be recommended to calibrate the model equations when estimating rainfall erosivity in locations outside this region. Nevertheless, the applicability of the assessed models for rainfall erosivity estimation in Brazil, as presented in this study, would be expected.

Based on equations proposed by WS, Cardoso et al. (2020) calculated the R factor for Pirassununga-SP, obtaining the value of 9,512.9 MJ mm ha⁻¹ h⁻¹ yr⁻¹. Therefore, this value was similar to that reported by Oliveira et al. (2013), and also by Silva (2004) for the municipality of Pirassununga, even when estimated by equations adjusted for a proximal location to Pirassununga.

DISCUSSION

According to our results, rainfall erosivity estimates are a reliable alternative to the product of kinetic energy and intensity of the rain. Regardless of the model employed, R-factor and its estimates were low between June and August, these months corresponding to the dry season. Additionally, coarse temporal resolution of the data, such as monthly data in relation to the sub-event intervals, can result in low estimated values for rainfall

erosivity. The monthly evaluation of rainfall erosivity index is important for the planning of farmers' activities on a small-time scale, while the total annual soil and water losses estimation is crucial to assess the impacts of the cultivations for the correct management and adoption of conservation practices.

Irregular distribution of weather stations, lack of maintenance and failure of older stations, together with little automated data acquisition systems are some problems that can be easily overcome by using precipitation data from TRMM 3B42-v7 (Galvão et al., 2020). These authors compared rainfall stations data –only the ones with continuous rainfall data– to the data extracted from the TRMM; they found these data could be reliable and useful in regions with no pluviometric stations installed. Similarly, we found the usage of TRMM 3B42-v7 data to estimate rainfall erosivity using two adjusted equations for Pirassununga resulted in useful estimates for annual rainfall erosivity values. Li et al. (2020), mapping rainfall erosivity with TRMM in China, found underestimations when precipitation data pointed to great rainfall erosivity, while overestimating when rain data pointed to the opposite (low rainfall erosivity). However, for tropical conditions, our results pointed to an opposite trend.

An innovation for the assessment of different methodologies was the usage of the Additive Main effects and Multiplicative Interaction (AMMI) model. This AMMI model is a hybrid analysis that incorporates both, the additive and multiplicative, components of the two-way data structure. Other studies used other statistical methodologies to determine the accuracy of the estimates between methods: mean square root error, mean absolute percentage, correlation coefficient or determination coefficient (Lee and Heo, 2011; Ma et al., 2014; Vantas et al., 2019; Li et al., 2020). The AMMI model allowed to apply the ANOVA and PCA to the sums of squares allocated by the ANOVA to analyze the two-factor interaction effects. This way, we verified the methods' efficiency while statistically grouping them and identifying them as more or less reliable estimates of rainfall erosivity (R factor).

According to our results, the modified Fournier (MF) index was the closest estimate to rainfall erosivity. This is in accordance with the results of Oğuz (2019), while it opposes what Angulo-Martínez and Beguería (2009) reported. Using the unit kinetic energy calculation of the RUSLE model, the MF index underestimated rainfall erosivity for the Ebro basin in Spain (Angulo-Martínez and Beguería, 2009). Nearing et al. (2017) compared three different methodologies (USLE, RUSLE and RUSLE2) to calculate the kinetic energy, and the results showed the kinetic energy values determined by the RUSLE method were underestimated as compared to USLE and RUSLE2. Thus, it is possible that discordance with Angulo-Martínez and Beguería (2009) may be due to an embedded underestimation of the kinetic energy due to RUSLE methodology. Although there was still no test of the effectiveness of the modified Fournier index –until this study–, the MF method has been used for Brazilian conditions as a rainfall erosivity estimator in several parts of the country, as the states of Santa Catarina (Back et al., 2018), Espírito Santo (Moreira et al., 2020), Tocantins (Avanzi et al., 2019), Mato Grosso (Di Raimo et al., 2018), São Paulo (Lombardi Neto, 1977), and Amazonas (Silva et al., 2020), along with large areas for regional studies (Mello et al., 2013, 2015; Oliveira et al., 2013).

Annual rainfall erosivity was overestimated by the MF-Z (Zhang et al., 2002) and underestimated by MF-M method (Men et al., 2008). These methods were developed for other climatic conditions, helping to explain such results. The other methods (MF, RD, TRMM-F and TRMM-M) used local rain characteristics, improving the estimations. Our results agreed well with those of Ma et al. (2014), as they presented negative values of MSDE; nevertheless, the MF-M had lower absolute MSDE and RMSE values than the MF-Z method.

Finally, the usage of precipitation data obtained by TRMM proved to be a viable alternative to estimate annual rainfall erosivity. Our results were in accordance with those reported

in other parts of the world (Vrieling et al., 2010; Fan et al., 2013). For African climatic conditions, the best performance was obtained using the MF index derived from monthly data from TRMM Multisatellite Precipitation Analysis (TMPA) 3B43 (Vrieling et al., 2010). In our study, the usage of this product in an adjusted equation based on the MF was less accurate as an estimator (R-squared values around to 0.9), although it would be useful for locations with scarce or irregular pluviographic or pluviometric data. Thus, regions with small number of meteorological stations can very well use precipitation data obtained by TRMM as a viable alternative for the R factor estimation.

CONCLUSIONS

The best method for rainfall erosivity estimation is the Modified Fournier Index, which shows great potential to replace the standard method in the absence of more detailed rainfall data. For monthly and annual estimations, the methods modified Fournier by Men and modified Fournier by Zhang underestimate and overestimate the values of rainfall erosivity indexes in relation to the Wischmeier and Smith method (standard), respectively. The rainfall data obtained through satellite (TRMM) may be a viable alternative for locations without on-site rainfall instrumentation, since its annual rainfall erosivity estimation is situated in the same statistical group as the standard method. Nevertheless, inaccuracy is noted for monthly estimates. For the months of low rainfall erosivity (June to August), the methods of estimating rainfall erosivity are not different from the standard one, so any method can be potentially adopted. Heterogeneous performance in estimating monthly rainfall erosivity is observed by the analyzed methods depending on the data associated with rainy or dry seasons.

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SUPPLEMENTARY DATA

The rainfall data (2009-2015) used in the preparation of this article can be found online at https://www.rbcsjournal.org/wp-content/uploads/articles_xml/1806-9657-rbcs-46-e0210122/1806-9657-rbcs-46-e0210122-suppl01.pdf. The results found for the town of Pirassununga-SP can be extrapolated to other towns selected by neighboring regions according to the supplementary materials Rain Stations.

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Writing - review & editing:  Daniel Furtado Ferreira (equal),  Dione Pereira Cardoso (equal),  Fábio Ribeiro Pires (equal),  Junior Cesar Avanzi (equal),  Marx Leandro Naves Silva (equal),  Nilton Curi (equal) and  Salvador Francisco Acuña-Guzman (equal).

REFERENCES

- Agência Nacional de Águas e Saneamento Básico - ANA. Portal HidroWeb v3.1.1 - Séries históricas de estações. Brasília, DF: ANA; 2020 [cited 2021 Nov 10]. Available from: <http://www.snirh.gov.br/hidroweb/serieshistoricas>.
- Alvares CA, Stape JL, Sentelhas PC, Gonçalves JLM, Sparovek G. Köppen's climate classification map for Brazil. *Meteorol Z*. 2013;22:711-28. <https://doi.org/10.1127/0941-2948/2013/0507>
- Angulo-Martínez M, Beguería S. Estimating rainfall erosivity from daily precipitation records: A comparison among methods using data from the Ebro Basin (NE Spain). *J Hydrol*. 2009;379:111-21. <https://doi.org/10.1016/j.jhydrol.2009.09.051>
- Arnoldus HMJ. An approximation of the rainfall factor in the Universal Soil Loss Equation. New York: John Wiley; 1980.
- Avanzi JC, Viola MR, Mello CR, Giongo MV, Pontes LM. Modeling of the rainfall and R-Factor for Tocantins state, Brazil. *Rev Bras Cienc Solo*. 2019;43:e0190047. <https://doi.org/10.1590/18069657rbcs20190047>
- Back AJ, Alberton JV, Poleto C. Erosivity index and characteristics of erosive rainfall from the far western region of Santa Catarina, Brazil. *J Environ Eng*. 2018;144:04018049. [https://doi.org/10.1061/\(ASCE\)EE.1943-7870.0001388](https://doi.org/10.1061/(ASCE)EE.1943-7870.0001388)
- Brown LC, Foster GR. Storm erosivity using idealized intensity distributions. *Trans ASAE*. 1987;30:379-86. <https://doi.org/10.13031/2013.31957>
- Cardoso DP, Silva EM, Avanzi JC, Muniz JA, Ferreira DF, Silva MLN, Acuña-Guzman SF, Curi N. RainfallErosivityFactor: An R package for rainfall erosivity (R-factor) determination. *Catena*. 2020;189:104509. <https://doi.org/10.1016/j.catena.2020.104509>
- Cardoso DP, Silva BPM, Duarte SFP, Silva MLN, Viola MR, Avanzi JC. Modelo matemático para estimativa da erosividade da chuva para região de Pirassununga-SP. In: XXXVI Congresso Brasileiro de Ciência do Solo - Amazônia e seus Solos: Peculiaridades e Potencialidades; Jul 30 - Aug 04, 2017; Belém, Pará. Belém: Sociedade Brasileira de Ciência do Solo; 2017.
- Cedeño AC, Sinichenko EK. Características de sistemas fluviales pequeños y recursos hídricos de la demarcación hidrográfica de Manabí, perspectivas de desarrollo. eLibrary; 2017.
- Cedeño AC, Villavicencio CIP. Evaluation of potential water erosion of manabí basin. *Int J Dev Res*. 2017;7:14213-7.
- Centro Nacional de Monitoramento e Alertas de Desastres Naturais - Cemaden. Dados da rede de monitoramento de desastres naturais do Cemaden/MCTIC. Brasília, DF: Cemaden; 2020 [cited 2021 Nov 10]. Available from: <http://www.cemaden.gov.br/mapainterativo/>.
- Crossa J. Statistical analyses of multilocation trials. *Adv Agron*. 1990; 44:55-85. [https://doi.org/10.1016/S0065-2113\(08\)60818-4](https://doi.org/10.1016/S0065-2113(08)60818-4)
- Di Raimo LADL, Amorim RSS, Couto EG, Nóbrega RLB, Torres GN, Bocuti ED, Almeida COS, Rodrigues RV. Spatio-temporal variability of erosivity in Mato Grosso, Brazil. *Rev Ambient Água*. 2018;13:e2276. <https://doi.org/10.4136/ambi-agua.2276>

- Diodato N, Bellocchi G. MedREM, a rainfall erosivity model for the Mediterranean region. *J Hydrol.* 2010;387:119-27. <https://doi.org/10.1016/j.jhydrol.2010.04.003>
- Diodato N, Borrelli P, Fiener P, Bellocchi G, Romano N. Discovering historical rainfall erosivity with a parsimonious approach: A case study in Western Germany. *J Hydrol.* 2017;544:1-9. <https://doi.org/10.1016/j.jhydrol.2016.11.023>
- Diodato N, Knight J, Bellocchi G. Reduced complexity model for assessing patterns of rainfall erosivity in Africa. *Glob Planet Change.* 2013;100:183-93. <https://doi.org/10.1016/j.gloplacha.2012.10.016>
- Duarte ML, Silva Filho EP. Estimativa da erosividade da chuva na bacia hidrográfica do rio Juma com base em dados do satélite TRMM. *Cad Geogr.* 2019;29:45-60. <https://doi.org/10.5752/p.2318-2962.2019v29n56p45>
- Environmental Systems Research Institute - ESRI. ArcGIS Professional GIS for the desktop [computer program]. Version 10.3. Redlands, CA: Environmental Systems Research Institute; 2014.
- Fan J, Chen Y, Yan D, Guo F. Characteristics of rainfall erosivity based on Tropical Rainfall Measuring Mission data in Tibet, China. *J Mt Sci.* 2013;10:1008-17. <https://doi.org/10.1007/s11629-013-2378-1>
- Ferreira DF, Zambalde AL. Simplificação das análises de algumas técnicas especiais da experimentação agropecuária no Mapgen e softwares correlatos. In: Congresso da Sociedade Brasileira de Informática - Aplicada à Agropecuária e Agroindústria; 1997; Belo Horizonte, Minas Gerais. Belo Horizonte: Sociedade Brasileira de Informática; 1997. p. 285-91.
- Fournier F. Climat et érosion: la relation entre l'érosion du sol par l'eau et les précipitations atmosphériques. Paris: Press Universitaires de France; 1960.
- Galvão JMF, Duarte ML, Castro AL, Silva TA, Valente KS. Statistical evaluation between the estimates of precipitation of the TRMM satellite and surface stations: An analysis to the Mesoregion sul Amazonense. *J Hyperspectral Remote Sens.* 2020;10:108-16.
- Hirai WY. Caracterização da estrutura de interação genótipo e ambiente utilizando modelo AMMI e W-AMMI por meio de biplot [dissertation]. Piracicaba: Universidade de São Paulo; 2019.
- Instituto Nacional de Meteorologia - Inmet. Banco de dados meteorológicos para ensino e pesquisa-BDMEP. Brasília, DF: Inmet; 2020 [cited 2021 Nov 10]. Available from: <https://bdmep.inmet.gov.br/>.
- Lee JH, Heo JH. Evaluation of estimation methods for rainfall erosivity based on annual precipitation in Korea. *J Hydrol.* 2011;409:30-48. <https://doi.org/10.1016/j.jhydrol.2011.07.031>
- Li X, Li Z, Lin Y. Suitability of TRMM products with different temporal resolution (3-hourly, daily, and monthly) for rainfall erosivity estimation. *Remote Sens.* 2020;12:3924. <https://doi.org/10.3390/rs12233924>
- Lombardi Neto F. Rainfall erosivity-its distribution and relationship with soil loss at Campinas, Brazil [dissertation]. West Lafayette: Purdue University; 1977.
- Ma X, He Y, Xu J, Noordwijk MV, Lu X. Spatial and temporal variation in rainfall erosivity in a Himalayan watershed. *Catena.* 2014;121:248-59. <https://doi.org/10.1016/j.catena.2014.05.017>
- Mello CR, Viola MR, Beskow S, Norton LD. Multivariate models for annual rainfall erosivity in Brazil. *Geoderma.* 2013;202-203:88-102. <https://doi.org/10.1016/j.geoderma.2013.03.009>
- Mello CR, Viola MR, Owens PR, Mello JM, Beskow S. Interpolation methods for improving the RUSLE R-factor mapping in Brazil. *J Soil Water Conserv.* 2015;70:182-97. <https://doi.org/10.2489/jswc.70.3.182>
- Men M, Yu Z, Xu H. Study on the spatial pattern of rainfall erosivity based on geostatistics in Hebei Province, China. *Front Agric China.* 2008;2:281-9. <https://doi.org/10.1007/s11703-008-0042-2>
- Moraes BC, Sodr  GRC, Souza EB, Ribeiro J, Meira Filho LG, Ferreira D. Climatologia da precipita o na Amaz nia. *Rev Bras Geogr F sica.* 2015;8:1359-73.

- Moreira LL, Novais RR, Schwaback D, Carvalho Júnior SM. Spatial-temporal dynamics of rainfall erosivity in the state of Espírito Santo (Brazil) from remote sensing data. *World J Sci Technol Sustain Dev.* 2020;17:297-309. <https://doi.org/10.1108/wjstsd-08-2019-0059>
- National Aeronautics and Space Administration - NASA. Data tropical rainfall measuring mission. Washington, DC: NASA; 2019 [cited 2019 Feb 10]. Available from: <https://giovanni.gsfc.nasa.gov/giovanni/>.
- Nearing MA, Yin S, Borrelli P, Polyakov VO. Rainfall erosivity: An historical review. *Catena.* 2017;157:357-62. <https://doi.org/10.1016/j.catena.2017.06.004>
- Oğuz I. Rainfall erosivity in north-central Anatolia in Turkey. *Appl Ecol Environ Res.* 2019;17:2719-31. https://doi.org/10.15666/aeer/1702_27192731
- Oliveira PTS, Wendland E, Nearing MA. Rainfall erosivity in Brazil: A review. *Catena.* 2013;100:139-47. <https://doi.org/10.1016/j.catena.2012.08.006>
- Panagos P, Borrelli P, Meusburger K, Yu B, Klik A, Lim KJ, Yang JE, Ni J, Miao C, Chattopadhyay N, Sadeghi SH, Hazbavi Z, Zabihi M, Larionov GA, Krasnov SF, Gorobets AV, Levi Y, Erpul G, Birkel C, Hoyos N, Naipal V, Oliveira PTS, Bonilla CA, Meddi M, Nel W, Al-Dashti H, Boni M, Diodato N, Van Oost K, Nearing M, Ballabio C. Global rainfall erosivity assessment based on high-temporal resolution rainfall records. *Sci Rep.* 2017;7:4175. <https://doi.org/10.1038/s41598-017-04282-8>
- Perkins JM, Jinks JL. Environmental and genotype-environmental components of variability: III. Multiple lines and crosses. *Heredity (Edinb).* 1968;23:339-56.
- Porto P. Exploring the effect of different time resolutions to calculate the rainfall erosivity factor R in Calabria, southern Italy. *Hydrol Process.* 2016;30:1551-62. <https://doi.org/10.1002/hyp.10737>
- R Development Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing. Vienna, Austria; 2020. Available from: <http://www.R-project.org/>.
- Renard KG, Freimund JR. Using monthly precipitation data to estimate the R-factor in the revised USLE. *J Hydrol.* 1994;157:287-306. [https://doi.org/10.1016/0022-1694\(94\)90110-4](https://doi.org/10.1016/0022-1694(94)90110-4)
- Sabaghpour SH, Razavi F, Danyali SF, Tobe D, Ebadi A. Additive main effect and multiplicative interaction analysis for grain yield of Chickpea (*Cicer arietinum* L.) in Iran. *Int Sch Res Netw.* 2012;2012:639381. <https://doi.org/10.5402/2012/639381>
- Scott AJ, Knott M. A Cluster analysis method for grouping means in the analysis of variance. *Biometrics.* 1974;30:507-12. <https://doi.org/10.2307/2529204>
- Silva AM. Rainfall erosivity map for Brazil. *Catena.* 2004;57:251-9. <https://doi.org/10.1016/j.catena.2003.11.006>
- Silva DSS, Blanco CJC, Santos Junior CS, Martins WLD. Modeling of the spatial and temporal dynamics of erosivity in the Amazon. *Model Earth Syst Environ.* 2020;6:513-23. <https://doi.org/10.1007/s40808-019-00697-6>
- Silveira ALL. Equação para os coeficientes de desagregação de chuva. *Rev Bras Recur Hídricos.* 2000;5:143-7.
- Todisco F, Vergni L, Vinci A, Pampalone V. Practical thresholds to distinguish erosive and rill rainfall events. *J Hydrol.* 2019;579:124173. <https://doi.org/10.1016/j.jhydrol.2019.124173>
- Trindade ALF, Oliveira PTS, Anache JAA, Wendland E. Variabilidade espacial da erosividade das chuvas no Brasil. *Pesq Agropec Bras.* 2016;51:1918-28. <https://doi.org/10.1590/s0100-204x2016001200002>
- United States Department of Agriculture - USDA. World agricultural production. Washington, DC: USDA; 2020 [cited 2020 Dec 12]. Available from: <https://downloads.usda.library.cornell.edu/usda-esmis/files/5q47m72z/cr56ns297/00000r529/production.pdf>
- Vantas K, Sidiropoulos E, Evangelides C. Rainfall erosivity and its estimation: Conventional and machine learning methods. In: Hrissanthou V, Kaffas K, editors. *Soil erosion-rainfall erosivity and risk assessment.* Rijeka: IntechOpen; 2019. p. 1-19.

- Vrieling A, Sterk G, Jong SM. Satellite-based estimation of rainfall erosivity for Africa. *J Hydrol.* 2010;395:235-41. <https://doi.org/10.1016/j.jhydrol.2010.10.035>
- Waltrick PC, Machado MAM, Dieckow J, Oliveira D. Estimativa da erosividade de chuvas no estado do Paraná pelo método da pluviometria: Atualização com dados de 1986 a 2008. *Rev Bras Cienc Solo.* 2015;39:256-67. <https://doi.org/10.1590/01000683rbcsc20150147>
- Wischmeier WH. A rainfall erosion index for a Universal Soil-Loss Equation. *Soil Sci Soc Am J.* 1959;23:246-9. <https://doi.org/10.2136/sssaj1959.03615995002300030027x>
- Wischmeier WH, Smith DD. Predicting rainfall erosion losses: a guide to conservation planning. Washington, DC: USDA; 1978. (Agricultural Handbook, 537).
- Wischmeier WH, Smith DD. Rainfall energy and its relationship to soil loss. *Trans Am Geophys Union.* 1958;39:285-91. <https://doi.org/10.1029/TR039i002p00285>
- Yue T, Xie Y, Yin S, Yu B, Miao C, Wang W. Effect of time resolution of rainfall measurements on the erosivity factor in the USLE in China. *Int Soil Water Conserv Res.* 2020;8:373-82. <https://doi.org/10.1016/j.iswcr.2020.06.001>
- Zhang WB, Xie Y, Liu BY. Rainfall erosivity estimation using daily rainfall amounts. *Sci Geogr Sin.* 2002;22:705-11.
- Zhu D, Xiong K, Xiao H. Multi-time scale variability of rainfall erosivity and erosivity density in the karst region of southern China, 1960–2017. *Catena.* 2021;197:104977. <https://doi.org/10.1016/j.catena.2020.104977>