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Computation of rainfall erosivity from daily precipitation amounts

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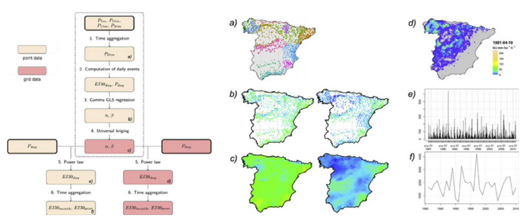
HIGHLIGHTS

- Rainfall erosivity can be computed from daily rainfall records using a power law.
- Upscaling parameters α and β obtained by Gamma GLS are distributed by universal kriging.
- Unbiased estimates of EI30 and USLE R index were obtained for mainland Spain.
- Cross-validation R^2 went from 0.63 (daily) to 0.80 (annual) and 0.85 (mean annual).

GRAPHICAL ABSTRACT



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ABSTRACT

Rainfall erosivity is an important parameter in many erosion models, and the *EI*30 defined by the Universal Soil Loss Equation is one of the best known erosivity indices. One issue with this and other erosivity indices is that they require continuous breakpoint, or high frequency time interval, precipitation data. These data are rare, in comparison to more common medium-frequency data, such as daily precipitation data commonly recorded by many national and regional weather services. Devising methods for computing estimates of rainfall erosivity from daily precipitation data that are comparable to those obtained by using high-frequency data is, therefore, highly desired. Here we present a method for producing such estimates, based on optimal regression tools such as the Gamma Generalised Linear Model and universal kriging. Unlike other methods, this approach produces unbiased and very close to observed *EI*30, especially when these are aggregated at the annual level. We illustrate the method with a case study comprising more than 1500 high-frequency precipitation records across Spain. Although the original records have a short span (the mean length is around 10 years), computation of spatially-distributed upscaling parameters offers the possibility to compute high-resolution climatologies of the *EI*30 index based on currently available, long-span, daily precipitation databases.

1. Introduction

Soil erosion by water is recognised as one of the major problems affecting agricultural productivity and food security, as well as impacting ecosystem services such as water quality and regulation, net primary production, biodiversity, and others. Most models for estimating soil erosion rates by water often include one term accounting for the ability of rainfall to cause erosion, i.e. a rainfall erosivity factor. The best known rainfall erosivity index is the R-factor used in the Universal Soil Loss Equation, USLE (Wischmeier, 1959; Wischmeier and Smith, 1978), and its two revised versions, RUSLE (Renard et al., 1997) and RUSLE2 (USDA-ARS, 2013). At many sites worldwide the R-factor has been shown to be highly correlated with soil loss (Van der Knijff et al., 2000; Diodato, 2004; Shi et al., 2004; Hoyos et al., 2005; Cruse et al., 2006; Onori et al., 2006; Romero et al., 2007), and

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it is without doubt the most commonly used rainfall erosivity index. A recent review on the R-factor can be found on Nearing et al. (2017).

The development of regional or even larger scale maps or rainfall erosivity (sometimes referred to as iso-erodent maps) is crucial for quantifying soil loss by water erosion and for understanding its spatial patterns. Recent efforts include the rainfall erosivity map of Europe at the annual and monthly time scales (Panagos et al., 2015a; Ballabio et al., 2017), or the global erosivity map (Panagos et al., 2017b), all based on the R-factor. A larger number of studies have been published that produced erosivity maps at the country or more local scales, as summarized in the review by Yin et al. (2017). The development of long time series is also desirable for understanding the temporal patterns of rainfall erosivity, allowing to characterise its inter-annual variation and return period curves, assess the existence of temporal trends, the role of atmospheric teleconnections, or even the effects of climate change (Angulo-Martínez and Beguería, 2012; Fiener et al., 2013; Hanel et al., 2016; Hoomehr et al., 2016; Qin et al., 2016; Lai et al., 2016; Panagos et al., 2017a; Wang et al., 2017; Chen and Zha, 2018).

Reliable estimation of rainfall erosivity requires continuous recording rain gauge (hyetograph) data or, alternatively, high-frequency (sub-hourly) time interval precipitation records. There are fewer rain gauges recording at these high-frequency intervals, and the length of their record is usually shorter, than more accessible daily precipitation records. This poses a problem of spatial but also temporal representativity, since long time series are required in order to compute reliable average seasonal or annual values. As revealed by a selection of recent regional studies, usually the number of rain gauges used is low with respect to the study area covered, and the temporal length of the records is, in most cases, short (Table 1). It has been noted, however, that R-factor values vary largely from one year to the next, even much more than precipitation, so long data series are required for calculating mean erosivity values within an acceptable level of certainty. It is widely accepted that 30-year periods are the norm in most climatological studies, and Wischmeier and Smith (1978) proposed using 22 years of data for obtaining a representative estimate of the USLE R-factor. Foster et al. (2003) recommended at least 15 years of data for the same purpose.

Coarser precipitation records, such as daily or monthly data, are on the other hand much more frequent and cover longer time spans. A method for computing rainfall erosivity from coarse precipitation records is, therefore, highly desirable. The general idea is to fit an empirical relation between erosivity values computed from high-frequency and coarser resolution precipitation data, using typically a limited dataset of a few high-frequency rain gauges. Once such relationship is established, it can be used for estimating rainfall erosivity based on a much larger set of (coarse resolution) rain gauges. Developing this basic idea, there are approximations based on annual or monthly rainfall, despite the inaccuracies involved in using low-frequency precipitation data (Banasik and Górski, 1994; Renard and Freimund, 1994; Ferro et al., 1999; Apaydin et al., 2006; Hernando and Romana, 2015); while other studies proposed estimating rainfall erosivity from daily precipitation data (Richardson et al., 1983; Bagarello and D'Asaro, 1994; Yu and Rosewell, 1996; Yu et al., 2001; Petkovšek and Mikoš, 2004; Angulo-Martínez et al., 2009; Yang and Yu, 2015). However, as we shall discuss later, these approaches are often sub-optimal since they tended to produce biased results that often result in underestimation of rainfall erosivity.

The main objective of this study is to develop a method for estimating daily rainfall erosivity, $EI30_{day}$, from records of daily precipitation, P_{day}, with the purpose of computing long-term mean annual and monthly erosivity values. Alternative modeling approaches are discussed, and optimal regression tools for the problem under study, such as the Gamma Generalised Linear Model and universal co-kriging, are presented. A large database of high-frequency precipitation records covering continental Spain is used to illustrate the method. The use of a better statistical approach is the main difference with respect to our previous work (Angulo-Martínez and Beguería, 2009), but also the analysis of a much larger dataset encompassing a greater climatic variability offers a much more robust validation of the methodology.

The article is structured as follows: Section 2 describes the dataset; Section 3 explains the computation of event erosivity values, $EI30$, and discusses technical issues related to using datasets with different time resolutions; Section 4 describes the computation of daily erosivity, $EI30_{day}$, and shows that event-based and daily-based erosivity yield comparable results; Section 5 develops the statistical model of the relationship between $EI30_{day}$ and daily precipitation, P_{day}, and discusses different model configurations; Section 6 discusses the seasonal variation of the relationship between $EI30_{day}$ and P_{day}, while Section 7 does the same but for the spatial variation; Section 8 presents a summary of the process and explains how to use the results of the previous analyses for computing monthly and annual $EI30$ aggregates based on daily precipitation data; Section 9 discusses the practical consequences of some assumptions required in the previous steps; and Section 10 concludes.

2. Description of the dataset

We collected a dataset comprising 1587 high-frequency precipitation records from 12 different data providers, including regional weather services and water basin authorities. The data varied in terms of their temporal length, sampling frequency δT and precision δP (Table 2).

The mean temporal span of the dataset was around 10 years, although some sets where shorter (CAN, DUE, GUA, MIN) while others had more than 15 years of data (EBR, GAL, HID, JUC, NAV, SEG, TAJ). The sampling frequency of the data δT varied between 5 and 30 min, with most records having a frequency of 15 min. The sets also varied in their precision δP, ranging between 0.1 and 0.2 mm.

The dataset had an uneven spatial distribution, with some areas more densely represented than others (Fig. 1). Most notably, no data could be collected for the Guadiana River basin.

3. Computation of event erosivity, *EI*30

The USLE R-factor is the long-term mean annual sum of individual storm erosivities. The erosivity of a given rainfall event, $EI30$ ($MJ\,mm\,ha^{-1}\,h^{-1}$) is calculated as the product of the storm total

Table 1
Some regional studies on rainfall erosivity and characteristics of theirs datasets: location, number of rain gauges (N), temporal length of the series (Years; range and mean value, if available), and sampling frequency (δT).

Reference	Location	N	Years	δT
Panagos et al. (2017b)	World	3625	5–30	3–60 min
Panagos et al. (2015a)	Europe	1541	7–40 (17)	5–60 min
Hanel et al. (2016)	Czech Republic	17	51	30 min
Xie et al. (2016)	East China	16	30–40	1 min
Yin et al. (2015)	East China	18	30–40	1 min
Lee and Lin (2015)	South Taiwan	55	10	10 min
Fiener et al. (2013)	West Germany	10	70	1–5 min
Klik et al. (2015)	New Zealand	35	4–16 (11)	10 min
Borrelli et al. (2016)	Italy	386	5–10 (8.8)	30 min
Lobo and Bonilla (2015)	Central Chile	30	3–28	60 min
Bonilla and Vidal (2011)	Chile	16	17–22	30 min
Ma et al. (2014)	Yunan, China	7	5	10 min
Sanchez-Moreno et al. (2014)	Cape Verde	2	2, 7	3 min, 15 min
Panagos et al. (2016a)	Greece	80	(29.7)	30 min
Risal et al. (2016)	South Korea	76	15–19 (18)	10 min