

REDES 2.0: A pan-European rainfall erosivity dataset showing intensifying erosivity trends

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ABSTRACT

Rainfall erosivity (defined as *R-factor* of the Revised Universal Soil Loss equation (RUSLE)), a key driver of soil erosion by water, varies greatly across Europe due to differences in climate regimes, precipitation patterns, storm intensities, and their frequencies. Updated and harmonized rainfall erosivity datasets are therefore important to provide robust input data for soil erosion models and to account for changes in climate that occurred in recent decades. This study presents REDES 2.0, the new pan-European Rainfall Erosivity Database, based on high-frequency sub-hourly and hourly rainfall data from 9138 locations across Europe, which corresponds to an average station density of 1.9 stations per 1000 km². REDES 2.0 represents an order-of-magnitude increase in data availability compared to the 1675 stations included in REDES (henceforth referred to as REDES 1.0). All the collected high-frequency rainfall data was converted to 30-min temporal resolution, either using data aggregation or rainfall disaggregation based on a multiplicative cascade model. Rainfall erosivity was subsequently computed following the RUSLE methodology. As a result, over 2.4 million erosive rainfall events were identified, predominantly covering the 2010–2025 period, with average station data length of 15 years and with an average of around 265 erosive events per station. Spatial patterns of annual *R-factor* values show pronounced differences across Europe, with the highest *R-factor* values concentrated in the Mediterranean and Alpine regions, while northern, eastern and central Europe exhibit comparatively lower values. REDES 1.0 and 2.0 overlap at 1062 locations (approximately 17% of REDES 2.0 and 69% of REDES 1.0) across Europe, where mean annual *R-factor* values increased from 792 MJ-mm-ha⁻¹·h⁻¹·yr⁻¹ in REDES 1.0 to 861 MJ-mm-ha⁻¹·h⁻¹·yr⁻¹ in REDES 2.0. This corresponds to around 9% increase in the rainfall erosivity in the last decades. Moreover, around 65% of stations included in REDES 2.0 exhibit a positive trend in annual *R-factor* for the 2010–2024 period. The standard error of

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the annual *R-factor* for REDES 2.0 was on average around 18% for stations included in REDES 2.0. REDES 2.0 reduces uncertainties and errors in rainfall erosivity in Europe, covers previously unsampled areas, increases temporal coverage, provides trends, and includes many extreme events.

1. Introduction

Soil erosion is a critical and escalating environmental threat with significant negative effects for food security affecting large areas of agricultural land (Hossain et al., 2020). Soil erosion rates are projected to intensify globally due to the accelerating impacts of climate change (Borrelli et al., 2020), which alter precipitation patterns, increase extreme weather events, and exacerbate land degradation (Amundson et al., 2015; Panagos et al., 2022a). Understanding the temporal trends of soil erosion is essential for assessing its long-term consequences and guiding effective mitigation strategies to reduce soil erosion rates. Despite initiatives like the United Nations' Global Soil Erosion Map project (FAO, 2019), there remains a lack of a coordinated, supranational monitoring framework to monitor and measure soil erosion consistently over time. In many regions, erosion monitoring is sporadic or absent, limiting our ability to detect trends and respond proactively. Therefore, global and large-scale modelling tools play a vital role in quantifying soil erosion rates, identifying vulnerable erosion hotspots, and informing various stakeholders and providing basis for soil conservation and adaptation measures (Borrelli et al., 2021). Although soil erosion models are associated with many limitations (Alewell et al., 2019; Batista et al., 2019), these models are still useful tools that are

often used in policy evaluation and implementation of soil conservation management practices. The Universal Soil Loss Equation (USLE, Wischmeier and Smith (1978) and its revised and modified versions (e. g., RUSLE, MUSLE) (Renard et al., 1997; Williams and Berndt, 1977) remain one of the most widely applied models for estimating long-term soil erosion rates by water at various spatial scales (Batista et al., 2019; Borrelli et al., 2021; Majhi et al., 2021). The RUSLE and USLE models calculate average annual (sheet and rill) soil loss caused by rainfall-induced surface runoff and the impact of raindrops on sloped terrain by considering six parameters (Kinnell, 2010; Renard et al., 1997): rainfall erosivity (*R-factor*), soil erodibility (*K-factor*), slope length (*L-factor*), slope gradient (*S-factor*), land cover and management practices (*C-factor*), and erosion control measures (*P-factors*). All six factors are important drivers of soil erosion by water, but *K*, *L*, *S*, and *P* factors are stable and do not change significantly on annual basis while *C* factor can show some inter-annual variations due to phenology and management. However, *R* can vary significantly from year to year, and only a few extreme rainfall events can contribute a significant proportion of the long-term average rainfall erosivity (Bezak et al., 2021). Additionally, rainfall erosivity is characterized by high spatial and temporal variability (Diodato and Bellocchi, 2012; Fenta et al., 2023; Matthews et al., 2022). Therefore, it is essential to regularly update rainfall erosivity

Table 1

Summary of rainfall datasets used for *R-factor* estimation and REDES 2.0 database development.

Country	Number of stations	Original temporal resolution	Data source	Main period covered	Data length (mean, minimum, maximum) (years)
Austria (AT)	152	60-min	JRC	2016–2025	9, 7, 31
Belgium (BE)	163	60-min	JRC	2001–2025	25, 8, 44
Bulgaria (BG)	84	60-min	Bulgarian Meteorological and Hydrological Service (ProData System)	2014–2024	11, 11, 11
Croatia (HR)	68	60-min	Croatian Meteorological and Hydrological Service	2001–2023	22, 10, 24
Cyprus (CY)	39	60-min	ERATOSTHENES Centre of Excellence	2000–2025	21, 7, 33
Czechia (CZ)	40	60-min	JRC	2002–2025	23, 8, 32
Denmark (DK)	124	60-min	JRC	2011–2025	12, 5, 28
Estonia (EE)	21	60-min	JRC	2011–2025	13, 9, 27
Finland (FI)	213	60-min	JRC	2012–2025	14, 5, 31
France (FR)	1986	6-min and 60-min	Meteo France (Meteo France, 2025) and JRC	2008–2023	16, 5, 43
Germany (DE)	1342	10-min and 60-min	DWD (DWD, 2025) and JRC	2008–2025	18, 5, 26
Greece (GR)	106	10-min	National Observatory of Athens	2014–2023	10, 9, 10
Hungary (HU)	30	60-min	Hungarian Meteorological Service	2015–2024	10, 10, 10
Ireland (IE)	31	60-min	JRC	1987–2025	35, 11, 85
Italy (IT)	2294 (including 1 station from San Marino)	From 5-min to 60-min	Regional meteorological authorities and JRC	2012–2025	13, 5, 45
Latvia (LV)	16	60-min	JRC	2017–2025	7, 5, 15
Liechtenstein (LI)	4	60-min	JRC	2008–2015	18, 9, 45
Lithuania (LT)	27	60-min	Lithuanian Hydrometeorological Service	2013–2025	13, 13, 13
Luxembourg (LU)	1	60-min	JRC	1990–2012	23, 23, 23
Malta (MT)	8	60-min	Institute of Earth Systems, University of Malta	2015–2024	10, 9, 10
Netherlands (NL)	34	60-min	JRC	2012–2025	13, 9, 22
Norway (NO)	147	60-min	JRC	2011–2025	12, 5, 28
Poland (PL)	501	10-min	Institute of Meteorology and Water Management (IMGW, 2025)	2009–2024	15, 5, 17
Portugal (PT)	116	60-min	JRC	2008–2025	18, 7, 26
Romania (RO)	157	60-min	JRC	2017–2025	9, 6, 19
Slovakia (SK)	92	60-min	JRC	2009–2025	15, 8, 21
Slovenia (SI)	61	30-min	Slovenian Environment Agency	1991–2024	32, 15, 64
Spain (ES)	395	From 5-min to 60-min	JRC and Regional Water Agencies	2006–2025	19, 5, 35
Sweden (SW)	163	15-min and 60-min	Swedish Meteorological and Hydrological Institute (SMHI, 2025) and JRC	2000–2025	25, 7, 35
Switzerland (CH)	686	10-min and 60-min	Meteo Swiss (MeteoSwiss, 2025) and JRC	2013–2025	13, 5, 45
United Kingdom (UK)	35	60-min	JRC	2020–2025	5, 5, 7

calculations and maps.

Rainfall erosivity also plays an important role in other USLE-type models (e.g., RUSLE, MUSLE, WaTEM-SEDEM, etc.) because it incorporates the effect of precipitation on soil erosion (Wischmeier and Smith, 1978). Long-term high-frequency measurements are needed to provide robust estimates of rainfall erosivity (Nearing et al., 2017; Wischmeier and Smith, 1978) or can be used for assessment of disaster-prone areas (Diodato et al., 2022). But this kind of data is often lacking at large spatial scales (Sun et al., 2018). Therefore, in recent decades various alternative data sources have been evaluated for the assessment of rainfall erosivity at continental or global scales such as satellite-based (Bezak et al., 2022; Emberson, 2023; Fenta et al., 2023), reanalysis-based (Matthews et al., 2022) or radar-based datasets (Matthews et al., 2025a; Matthews et al., 2025b). These studies showed the potential of these alternative data sources, despite some identified limitations, for assessing rainfall erosivity without requiring ground-based data collection. Additionally, ground-based data will also be needed for bias correction and performance evaluation of these data sources. Moreover, the performance evaluation of these data sources was based on REDES 1.0 (Panagos et al., 2015a) or Global Rainfall Erosivity Database (GloREDA) (Panagos et al., 2023). In Europe, REDES 1.0 is still used as the main data source for continental rainfall erosivity assessments. It should be noted that REDES 1.0 is based on high temporal resolution rainfall data collected before 2013. Due to climate change impact on extreme precipitation events (Almagro et al., 2017; IPCC, 2023; Lukić et al., 2019; Panagos et al., 2022a), there is an urgent need to update the REDES 1.0 database with the new rainfall data collection to generate new rainfall erosivity maps of Europe that can be used as input to large-scale soil erosion models.

Therefore, the main objective of this study is to provide an update of the pan-European rainfall erosivity database (REDES 2.0). Compared to REDES 1.0, which was assembled more than 10 years ago, the updated database addresses several limitations of the previous version, including harmonization of rainfall data to a 30-min temporal resolution (with coarser-resolution data disaggregated using a multiplicative cascade model), improved spatial coverage, and the incorporation of recent rainfall records to better reflect climate change impacts, among others. Hence, this study focuses on evaluating rainfall erosivity across Europe using rainfall data with high temporal resolution. The specific aims of this study are to: i) collect high-frequency rainfall data; ii) calculate the rainfall erosivity and compile a new rainfall erosivity database in Europe; iii) analyse spatial patterns and temporal trends of rainfall erosivity across Europe; and iv) provide a harmonized database to be shared with the scientific community and support future rainfall erosivity research in Europe, including the production of annual and monthly erosivity maps, detailed statistical analyses, and assessments of erosive rainfall events.

2. Data and methods

2.1. High temporal resolution rainfall data collection

Similarly to the initial study conducted by Panagos et al. (2015a;2015b) this study focuses on all 27 European Union (EU) Member States, as well as Switzerland, the United Kingdom, Norway and Liechtenstein. Switzerland and Liechtenstein were included in the initial study to avoid spatial gaps (“white spots”) in the rainfall erosivity data coverage. The United Kingdom was included in this study to ensure comparability with the previous study (Panagos et al., 2015a) and Norway was included because the main rainfall data source used in this study (as described below) includes several stations in Norway. The data collection began in January 2025 and was completed in December 2025, involving many contributors under the coordination of the EU Soil Observatory (EUSO). A participatory approach was used to collect the high-frequency rainfall data, and the following steps were taken to ensure adequate density of high-frequency rainfall stations in Europe:

- Hourly rainfall data was obtained from the Disaster Risk Management Unit of the Joint Research Centre (JRC) of the European Commission (EC) (Table 1). Hourly rainfall data is part of European Flood Awareness System (EFAS) of the Copernicus Emergency Management Service.

- High-frequency rainfall data (i.e., less than 30-min temporal resolution) that are publicly available for download were collected for Poland (IMGW, 2025), France (Meteo France, 2025) Switzerland (MeteoSwiss, 2025), Germany (DWD, 2025) and Sweden (SMHI, 2025) (Table 1).

- Researchers from various meteorological services, research centres and the field of environmental data analysis (e.g., rainfall erosivity, soil erosion modelling) were invited to participate in this project to provide data for countries not included in the previous two points. Rainfall data providers from Cyprus, Slovenia, Croatia, Hungary, Greece, Lithuania, Malta, Bulgaria, and Spain (via regional water agencies, hydrometeorological services and research centres) contributed high-frequency precipitation data for their countries.

- The EU Soil Observatory (EUSO) working group on soil erosion (Panagos et al., 2024) contacted the regional meteorological authorities in Italy to provide high-frequency rainfall data for Italian regions that were not included in the JRC dataset.

The preferred data collection period was the last decade (from 2010 onwards), with a minimum continuous data length of 10 years. If such data were not available and station density in a specific region was low, data collected over at least 5 years were included, with a focus on recent periods (Section 3.1). Where available, stations with longer high-frequency data time series were also included. Only stations with a low percentage of missing data were included in the analysis. On average, the stations have about 1% missing rainfall data. It should be noted that a minimum period of 22 years is recommended for the RUSLE calculations (Renard et al., 1997) and that some studies suggested to use even longer time series for rainfall erosivity estimations (Pidoto et al., 2022; Verstraeten et al., 2006). On the other hand, some studies have reported that shorter data periods (e.g., 15 years) may be sufficient to obtain a reasonable estimate of the average *R-factor* (Bonilla and Vidal, 2011; Panagos et al., 2016a). Moreover, for large-scale assessments, it is often challenging to obtain enough stations with adequate data length, and these studies often do not discard stations with less than 10 or 20 years of data. Using all available data helps to improve the spatial representation of rainfall erosivity (Panagos et al., 2017; Panagos et al., 2015a). All stations incorporated in the dataset yield valuable information on the characteristics of erosive events within their respective regions and may serve as a robust basis for subsequent research. Additional discussion about this aspect is provided in Section 3.1. It should be noted that REDES 2.0 is a newly constructed database that does not include any elements (e.g., data about specific erosive events) from the REDES 1.0 database, as the methodology applied differs slightly, as detailed in the following sections. Nevertheless, the two databases share 1062 common locations.

2.2. Rainfall disaggregation model

A temporal resolution of 30-min was used in this study for the calculation of the rainfall erosivity (Section 2.3). If the temporal data resolution was less than 30-min, the rainfall data was aggregated to a 30-min time step. If data with an hourly time step were available (Table 1), a rainfall disaggregation model was applied to disaggregate the hourly data into a 30-min time step. To remove potentially unrealistic (excessively high) rainfall values that could result from measurement errors or data processing issues by data providers, a threshold value of 200 mm for 30-min was applied (Thiemig et al., 2022). For the disaggregation of the 60-min rainfall time series a micro-canonical cascade model (Müller and Haberlandt, 2018) was used, which performed well in previous studies in coastal and flat regions in Europe (Germany: Ebers et al., 2024), but also in mountainous regions (Switzerland: Müller-Thomy

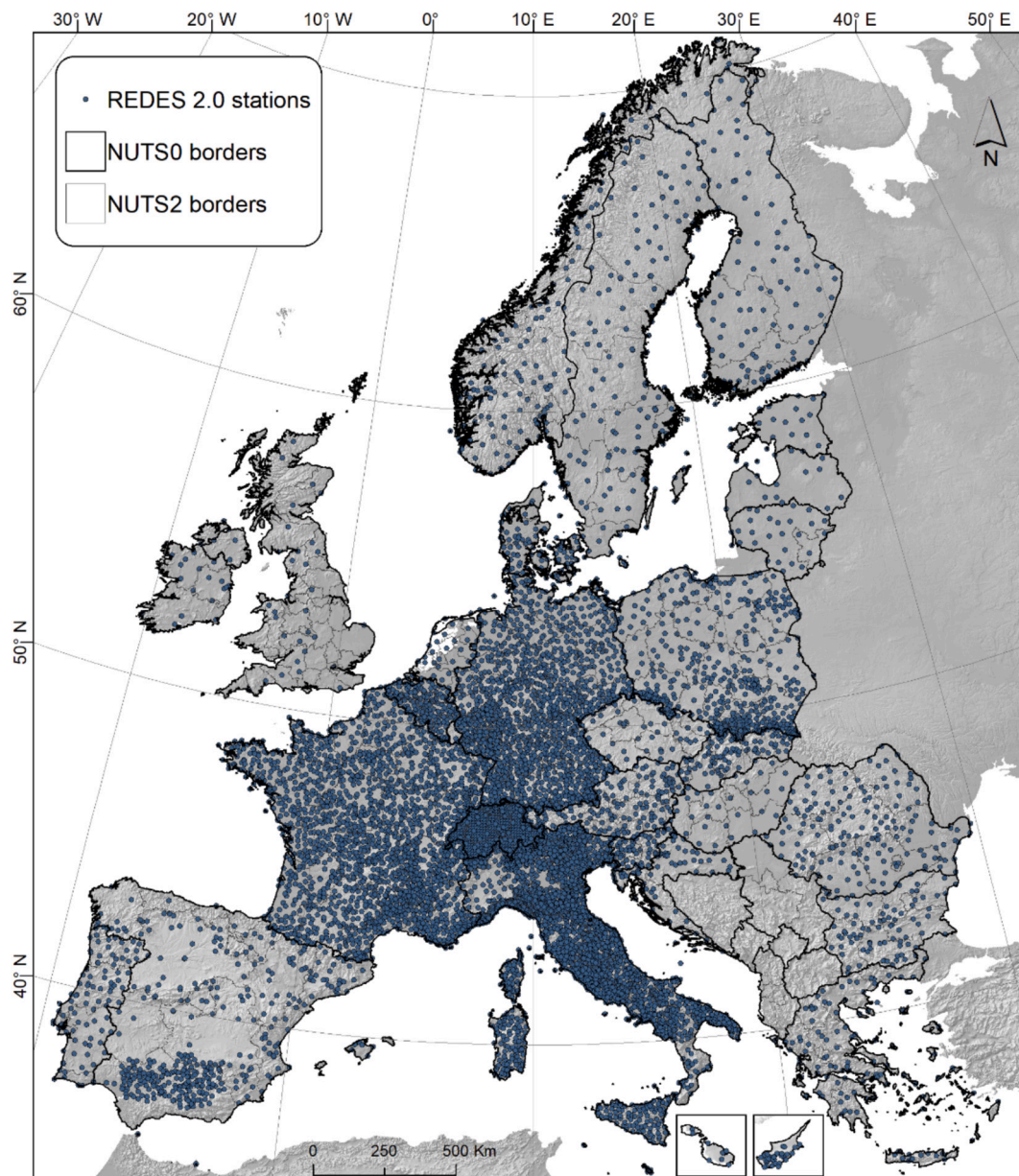


Fig. 1. Location of stations included in REDES 2.0 used for rainfall erosivity calculation (R -factor) with a digital elevation model (DEM) shown as the background (Beck et al., 2020; WorldClim, 2020).

and Sikorska-Senoner, 2019; Austria: Derx et al., 2023; Slovenia: Müller-Thomy et al., 2025; Germany: Müller-Thomy et al., 2018). The resulting 30-min rainfall data was consequently used for the rainfall erosivity calculations. Since cascade models are based on the principle of self-similarity of neighbouring temporal scales, the scale transition from 60-min to 2-h was used for the estimation of the cascade model parameters. The estimated cascade model parameters were used to disaggregate time series from 60-min to 30-min resolution (see Ebers et al., 2024 for further details). The rainfall amount is conserved exactly within each time step. Due to the stochastic nature of the cascade model 100 realisations of disaggregation were simulated for each station. More details about the analysis related to the selection of 100 realisations for the disaggregation model are provided in Section 3.1. It should be noted that, compared to REDES 1.0, we did not use the conversion factors (Panagos et al., 2016b; Panagos et al., 2015a) since these could introduce additional uncertainty.

2.3. Rainfall erosivity calculation

Rainfall erosivity was calculated at the event scale at individual stations using high-frequency (30-min) rainfall time series. The 30-min time step was used to ensure comparability with the previous rainfall erosivity study conducted in Europe (Panagos et al., 2015a) and 30-min time is also commonly used in the USLE-based models for assessing soil loss (Yin et al., 2007). To identify erosive events at each station, criteria outlined in the RUSLE methodology (Renard et al., 1997) were applied: rainfall events were considered independent if separated by at least six hours with less than 1.27 mm of rainfall. Only rainfall events exceeding 12.7 mm in total were included in the further erosivity analysis, while smaller events were excluded to maintain consistency with previous studies (Panagos et al., 2015a; Renard et al., 1997). The specific kinetic energy e_B ($\text{MJ ha}^{-1} \text{h}^{-1}$) was calculated using equation proposed by Brown and Foster (Brown and Foster, 1987) to ensure the compatibility with the previous study (Panagos et al., 2015a):

Table 2Basic statistical characteristics of average annual *R-factor* values calculated from all available data.

Country	Station density (No. stations/ 1000 km ²)	<i>R-factor</i> (MJ mm ha ⁻¹ h ⁻¹ year ⁻¹)			Coefficient of variation
		Mean, median	Standard deviation	1st, 99th percentile	
Austria (AT)	1.8	866, 771	422	300, 2124	0.48
Belgium (BE)	5.3	621, 537	301	346, 1820	0.48
Bulgaria (BG)	0.8	1220, 993	770	464, 4045	0.63
Croatia (HR)	1.2	1592, 1292	1001	342, 4279	0.63
Cyprus (CY)	4.2	947, 783	404	477, 1825	0.42
Czechia (CZ)	0.5	663, 583	419	332, 2223	0.63
Denmark (DK)	2.9	360, 303	215	138, 1299	0.60
Estonia (EE)	0.5	335, 329	144	172, 796	0.43
Finland (FI)	0.6	243, 238	94	93, 431	0.39
France (FR)	3.7	896, 664	703	250, 4018	0.78
Germany (DE)	3.8	629, 547	297	287, 1761	0.47
Greece (GR)	0.8	1796, 1420	1594	281, 7180	0.89
Hungary (HU)	0.3	792, 702	227	531, 1178	0.29
Ireland (IE)	0.4	397, 369	158	240, 879	0.39
Italy (IT)	7.6	2058, 1695	1399	372, 6975	0.67
Latvia (LV)	0.2	473, 463	114	294, 651	0.24
Lithuania (LT)	0.4	481, 484	96	308, 707	0.20
Liechtenstein (LI)	24.9	886, 809	249	685, 1231	0.28
Luxembourg (LU)	0.4	598, 598	/	/	/
Malta (MT)	25.4	1011, 1060	222	571, 1224	0.22
Netherlands (NL)	0.8	453, 436	98	292, 705	0.22
Norway (NO)	0.5	533, 367	484	58, 2256	0.91
Poland (PL)	1.6	716, 665	286	233, 1573	0.40
Portugal (PT)	1.3	851, 726	521	210, 2247	0.61
Romania (RO)	0.7	620, 568	263	230, 1477	0.42
Slovakia (SK)	1.9	905, 787	514	414, 2006	0.57
Slovenia (SI)	3.0	2419, 2028	1307	974, 6374	0.54
Spain (ES)	0.8	791, 603	622	138, 3167	0.79
Sweden (SW)	0.4	254, 229	113	114, 633	0.44
Switzerland (CH)	16.6	1017, 810	787	245, 4546	0.78
United Kingdom (UK)	0.1	351, 299	236	166, 1221	0.67
Total	1.9	1112, 741	1056	157, 5204	0.95

Table 3

Main features of REDES 2.0 include station altitude, data length, and the period covered.

Altitude (m.a.s.l.)	% of stations	Data length (years)	% of stations	Data start year	% of stations
< 500	69.4	< 8	15.3	≤ 2000	12.9
500–1000	20.0	8–15	34.2	2001–2010	38.7
1000–2000	8.6	15–25	30.7	2011–2014	15.5
> 2000	2.0	> 25	10.8	≥ 2015	32.9

$$e_B = 0.29 \bullet [1 - 0.72 \bullet \exp(-0.05 \bullet i)] \quad (1)$$

where *i* is rainfall intensity (mm h⁻¹). In order to derive the average annual *R-factor* (MJ mm ha⁻¹ h⁻¹ yr⁻¹), the following two equations were also used (Renard et al., 1997):

$$E = e_B \bullet i \bullet \Delta t, \quad (2)$$

$$R = \frac{\sum E \bullet I_{30}}{N} \quad (3)$$

where *E* is the kinetic energy (MJ ha⁻¹) of the individual erosive event, Δt is the time interval, and *I*₃₀ is the maximum 30 min rainfall intensity (mm h⁻¹) of erosive event *n* that occurred within a time span of *N* years. The R software (R Core Team, 2025) script for calculating rainfall erosivity prepared by Pidoto et al. (2022) was used.

2.4. Sensitivity analysis of REDES 2.0

To investigate the sensitivity of rainfall erosivity estimates, several supplementary analyses were performed to evaluate how individual calculation steps impact the final result:

-The impact of finer time steps (i.e., less than 30-min) on erosive

Table 4Average annual *R-factor* and standard deviation by biogeographical region, using all available data and data from 2010 onward for REDES 2.0. Additionally, REDES 1.0 values (Panagos et al., 2015a) are shown. Note that the number of stations and station density per region differ between REDES 2.0 and 1.0.

Biogeographical region	% of stations	REDES 2.0				REDES 1.0	
		All data (MJ mm ha ⁻¹ h ⁻¹ year ⁻¹)		From 2010 (MJ mm ha ⁻¹ h ⁻¹ year ⁻¹)		Panagos et al. (2015a) (MJ mm ha ⁻¹ h ⁻¹ year ⁻¹)	
		Average <i>R-factor</i>	Standard Deviation	Average <i>R-factor</i>	Standard Deviation	Average <i>R-factor</i>	Standard Deviation
Alpine	15.7	1389	1320	1414	1361	932	667
Atlantic	13.6	534	289	537	310	678	447
Black Sea	0.1	1446	1689	1446	1689	702	145
Boreal	4.6	303	158	303	159	360	127
Continental	40.9	936	754	949	775	696	394
Mediterranean	24.3	1734	1279	1753	1302	1051	502
Pannonian	0.6	680	225	690	221	660	101
Steppic	0.2	524	234	524	234	730	91

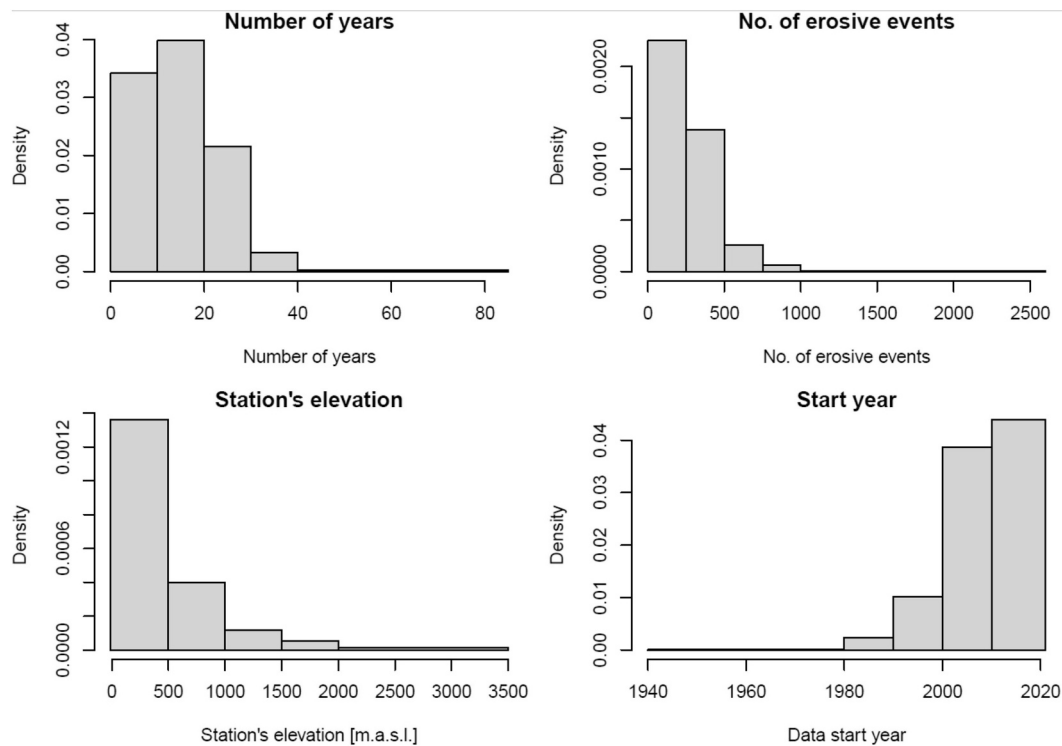


Fig. 2. Histograms of the number of years, number of erosive events, station elevations, and data start years in the REDES 2.0 database. Probability densities are shown on y-axis.

event characteristics was investigated using data from France, Sweden, Switzerland, and Germany (Table 1). These countries are also located in different climate zones (i.e., Mediterranean, Continental, Alpine, Boreal, Atlantic).

The impact of disaggregating rainfall data from hourly to 30-min intervals was evaluated using stations in Poland, France, and Sweden. Analyses were conducted to assess how rainfall disaggregation affects the characteristics of erosive events. These countries are located in different climate zones and have sufficient data to test the performance of the rainfall disaggregation model.

Several stations from Italy (characterized by large variations in rainfall erosivity) were used to quantify the impact of the selected kinetic energy e_B equation on the erosive events characteristics. Besides Eq. 1 (Brown and Foster, 1987), the RUSLE2 equation (Nearing et al., 2017) and van Dijk equation (van Dijk et al., 2002) were used.

We evaluated the impact of excluding stations with less than 10 or 22 years of data from the rainfall erosivity calculation. Additional analyses were conducted regarding the inclusion of all stations versus a limited number of stations in the rainfall erosivity assessment.

2.5. Statistical analysis

Based on the compiled REDES 2.0 database (erosive rainfall events, monthly rainfall erosivity and average annual rainfall erosivity) a basic statistical analysis of the R -factor in Europe was conducted calculating the mean, median, the 1st and 99th percentiles of the annual R -factor. Additionally, the standard deviation and coefficient of variation (the ratio between standard deviation and the mean) were calculated at both the country level (NUTS0) and for the biogeographical regions (EEA, 2016). Calculations were conducted using the complete dataset (all available data) and several sub-sets were tested: (i) using data from 2010 onwards, (ii) using data from 2015 onwards, and (iii) using data from 2010 to 2024. The latter dataset was also used to identify trends in the annual R -factor for the 2010–2024 period using the slope of the linear regression. To quantify the uncertainty in the annual R -factor calculation

(using different data subsets), the standard error (SE) was used:

$$SE = \sigma(R_{year}) / \sqrt{n} \quad (4)$$

where R_{year} is annual R -factor for specific years, σ is standard deviation and n is data sample length (i.e., number of years in the data sample). Additionally, the WorldClim (Fick and Hijmans, 2017; WorldClim, 2020) database was used for the digital elevation model (DEM) and mean annual precipitation (P_{AN}) for the 1971–2000 period. Moreover, the R -factor was normalized using the mean annual precipitation (P_{AN}) in order to calculate the erosivity density (ED) (Diodato et al., 2019; Nearing et al., 2017; Panagos et al., 2016a):

$$ED = R_{factor} / P_{AN} \quad (5)$$

Moreover, the relationship between the R -factor and station characteristics (e.g., location, elevation) was evaluated using the Pearson correlation coefficient and the coefficient of determination (R^2). The interpretation of correlation coefficients provided by Schober and Schwarte (2018) was used to indicate whether the correlation is strong, moderate or weak. All analyses were conducted using R software (R Core Team, 2025).

3. Results and discussion

3.1. Sensitivity analysis of REDES 2.0

Calculating the characteristics of erosive rainfall events using data from France with time steps shorter than 30-min showed that shorter intervals generally yield higher kinetic energy and maximum 30-min rainfall intensity (Fig. S1). As a result, this leads to higher event rainfall erosivity values (Fig. S1). Similarly, higher annual rainfall erosivity values were also observed at stations in France, Germany, Sweden, and Switzerland using time steps shorter than 30-min compared to using 30-min time step (Fig. S2). This pattern was observed in all tested countries. Previous studies often used simple conversion factors (Panagos et al., 2016b; Yin et al., 2007) to convert rainfall erosivity values calculated

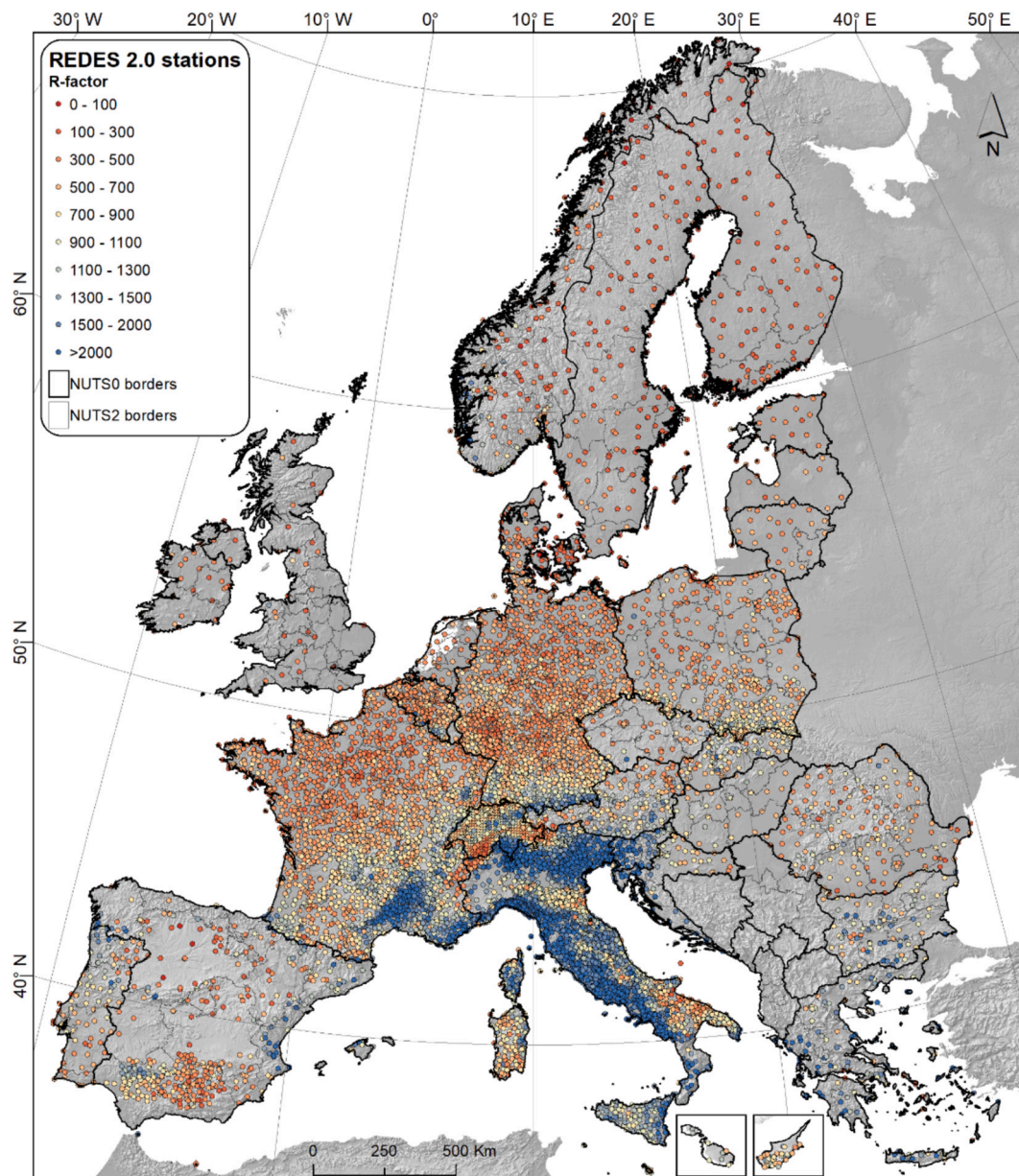


Fig. 3. Annual *R-factor* ($\text{MJ mm ha}^{-1} \text{h}^{-1} \text{year}^{-1}$) values for stations included in REDES 2.0. All available data were used to calculate the mean annual *R-factor*.

using 5-min or 10-min data into 30-min time step. However, preliminary analysis (Fig. S2) showed that such conversion factors would need to be climate-specific, and that constant factors for all of Europe would not yield satisfactory results. Therefore, aggregating data to a 30-min time step is a more robust solution, as applying constant or monthly conversion factors could introduce additional bias to the final *R-factor* values.

For stations in Sweden, Poland, and France (Table 1) with available 30-min (or shorter) time series, we aggregated the rainfall data to a 60-min time step and then disaggregated it back to 30-min using the cascade model. Rainfall erosivity was thus calculated directly from the 30-min data and from the disaggregated data. This enabled comparison of annual rainfall erosivity from observed and disaggregated time series at the same location. From 100 realisations of disaggregation runs for each station, the median provides the closest fit to the erosivity calculated from 30-min observations. The percent bias (for median of 100 realisations) was: -0.8% ($R^2 = 0.99$) for Sweden, -2.5% ($R^2 = 0.98$) for Poland, and 1.9% ($R^2 = 0.99$) for France (Fig. S3). Although selected stations from France, Poland and Sweden show high variation in

elevation and climate zones, which also leads to significant variability in annual rainfall erosivity, no related systematic deviation can be identified in the annual rainfall erosivity of the disaggregated time series (Fig. S3). Therefore, the tested disaggregation approach is valid for a variety of climate zones and elevations in Europe. It should be noted that rainfall disaggregation can affect other characteristics of erosive rainfall events, such as kinetic energy, maximum 30-min intensity, or storm duration, especially when disaggregating from daily to sub-hourly time steps (Pidoto et al., 2022). However, in the case of disaggregation from 60-min to 30-min, this effect can be considered minimal, especially if the focus of the study is to derive annual rainfall erosivity. Additionally, we evaluated whether 100 realisations are sufficient to obtain a robust estimate of annual rainfall erosivity based on the disaggregation process. It was found that using more realisations (e.g., 500 or more) does not decrease the percent bias between 30-min rainfall erosivity and rainfall erosivity derived from the disaggregated data (Fig. S4). Thus, for all stations where rainfall disaggregation was applied (Table 1), the time series that produced the median annual rainfall erosivity was selected from the 100 realisations for all subsequent analyses.

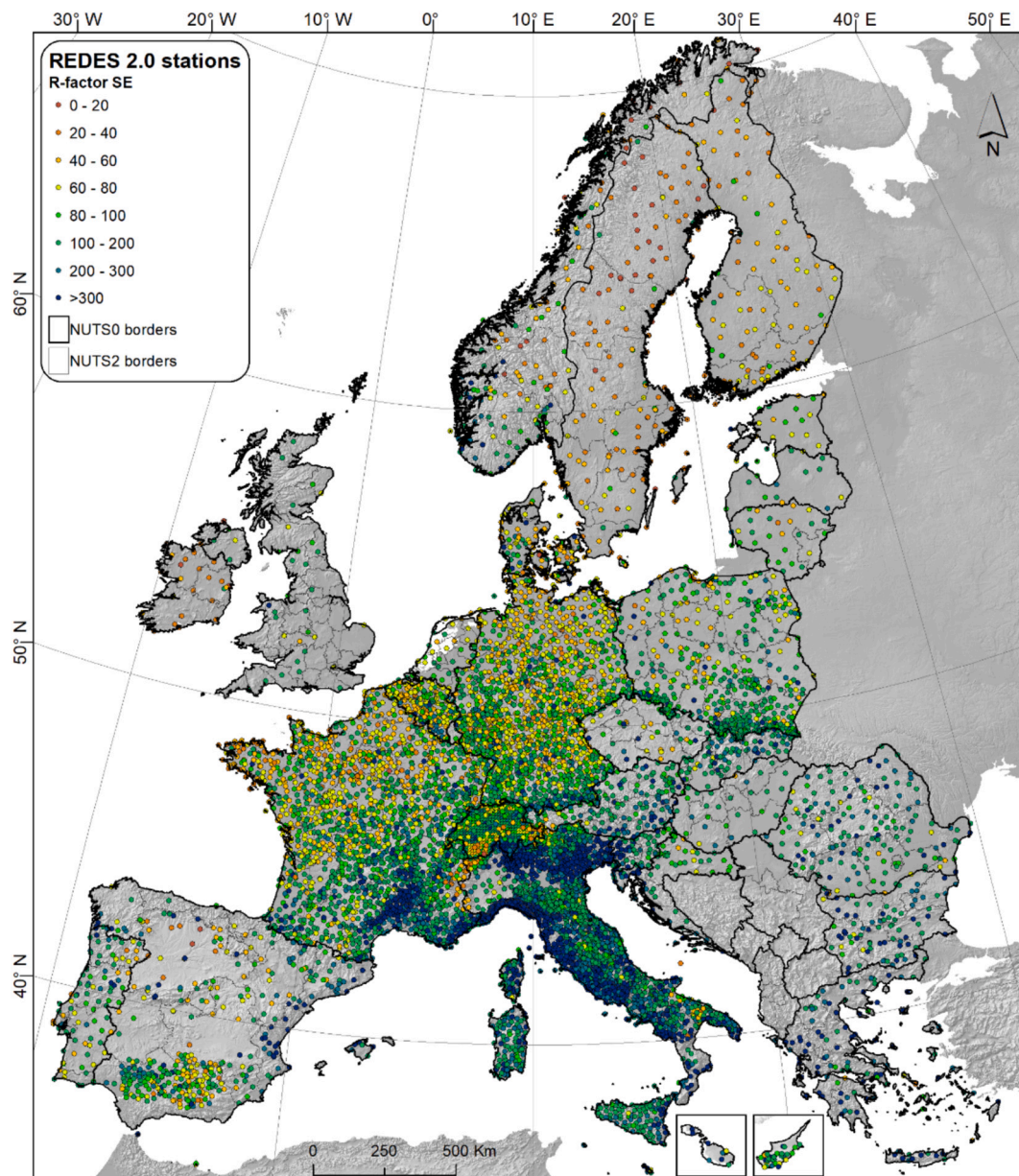


Fig. 4. The standard error related to the *R-factor* ($\text{MJ mm ha}^{-1} \text{h}^{-1} \text{year}^{-1}$) was calculated using all available data as shown in Fig. 3.

Additionally, we analysed the impact of the specific kinetic energy equation (Eq. 1) on the rainfall erosivity of individual erosive events and on annual rainfall erosivity using a sub-set of stations from Abruzzo region in Italy (Fig. S5). RUSLE, RUSLE2 and van Dijk et al. (2002) equations yield similar patterns in erosivity of individual erosive events (Fig. S5). However, it should be noted that both, RUSLE2 and Van Dijk equations, yield higher rainfall erosivity values (Fig. S5). More specifically, considering all erosive events the overestimation was around 13% and 6% for RUSLE2 and Van Dijk equations, respectively, and the mean absolute error was $9 \text{ MJ mm ha}^{-1} \text{h}^{-1}$ and $7 \text{ MJ mm ha}^{-1} \text{h}^{-1}$, respectively. Similar overestimation was also observed for annual rainfall erosivity where mean absolute errors were around $200 \text{ MJ mm ha}^{-1} \text{h}^{-1}$ and $100 \text{ MJ mm ha}^{-1} \text{h}^{-1}$ for RUSLE2 and Van Dijk equations, respectively (Fig. S5). Although results shown in Fig. S5 are valid for a sub-set of stations from Abruzzo region in Italy, similar results were obtained in other studies with equation comparisons (Angulo-Martínez et al., 2016; Brychta et al., 2022; Ciaccioni et al., 2016; Nearing et al., 2017; Verstraeten et al., 2006; Yin et al., 2017). More specifically, Yin et al. (2017) indicated that RUSLE underestimates rainfall erosivity by

about 10% compared to RUSLE2, which is consistent with the results shown in this study (Fig. S5). Additionally, Eq. 1 (Brown and Foster, 1987) is also included in the RIST software, (USDA, 2023) and it is still often used for the rainfall erosivity calculations around the globe (Embersson, 2023; Matthews et al., 2025a; Matthews et al., 2025b; Micić Ponjiger et al., 2023; Panagos et al., 2023; Panagos et al., 2015a). Moreover, to ensure comparability with the study conducted by Panagos et al. (2015a;2015b), we used Eq. 1 for the calculations of the rainfall. However, readers should be aware that the rainfall erosivity values presented in this study may be lower than those associated with the RUSLE2 methodology. This difference is similar to the one that can be attributed to using the 12.7 mm threshold to remove small-magnitude events (Petek et al., 2018). Hence, using all rainfall events for the calculation of annual *R-factor* yields around 10% higher values compared to using only events with more than 12.7 mm of rainfall (Petek et al., 2018).

The impact of data series length was also evaluated using annual rainfall erosivity values for all stations shown in Table 1 (Fig. S6). There is little difference in the distribution of average annual rainfall erosivity

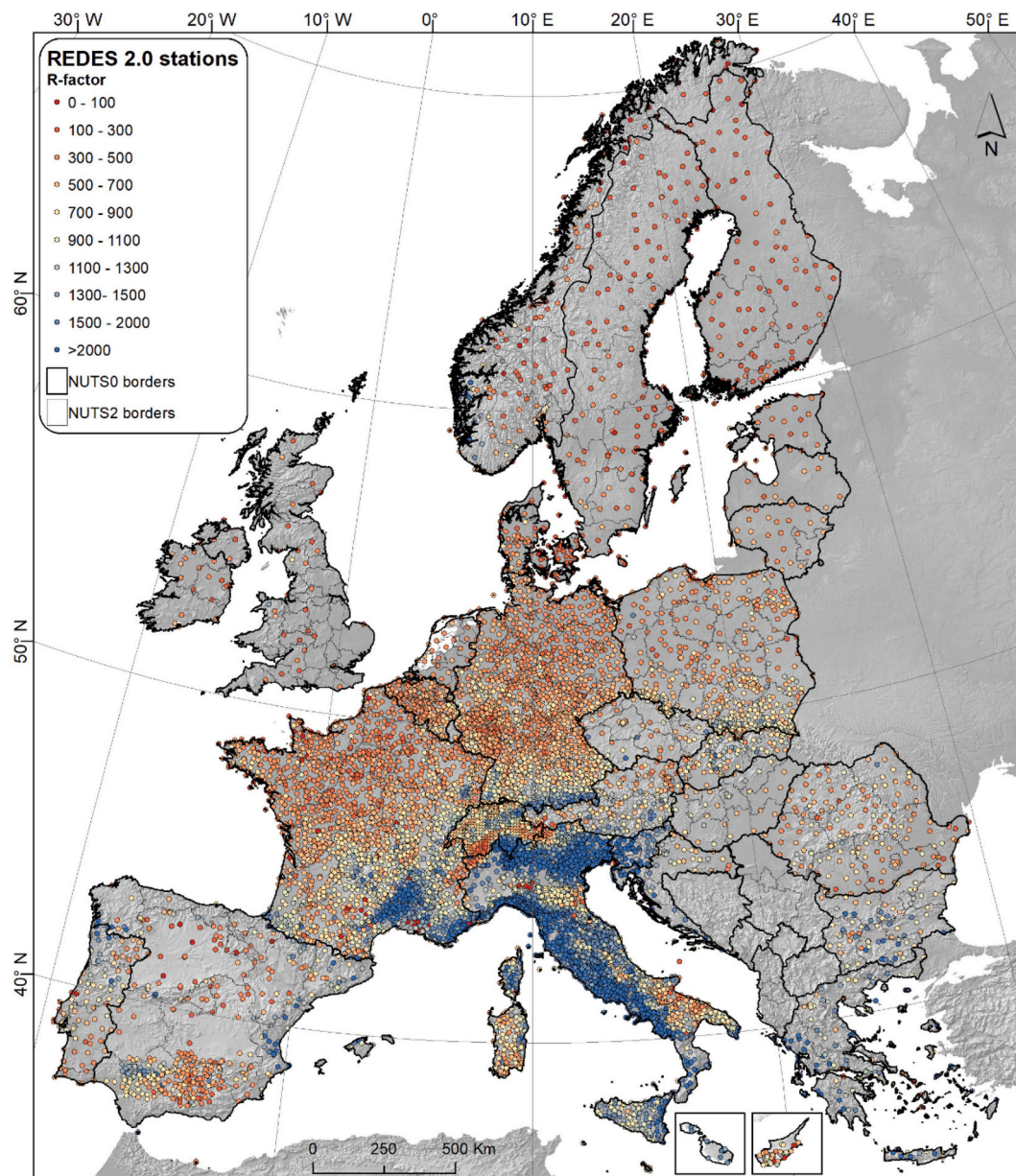


Fig. 5. Annual R -factor ($\text{MJ mm ha}^{-1} \text{h}^{-1} \text{year}^{-1}$) values for stations included in REDES 2.0. Data from 2010 to 2024 were used to calculate the mean annual R -factor.

when stations with less than 5 or 10 years of data are excluded from the analysis. Moreover, the differences in the median values for the first three cases shown in Fig. S6 are below 2%. However, when only stations with more than 22 years of data are used, a notable difference in the distribution of annual rainfall erosivity values is observed, which can be attributed to the significantly smaller number of stations included in the analysis. Specifically, when only stations with 22 years of data are used, only about 1600 stations remain for analysis. In contrast, when stations with more than 10 years of data are included, the total number of stations exceeds 7500. Hence, it is often challenging to obtain long time series of high-frequency data, and in some cases, shorter time periods (e. g., 15 years) may become adequate (Bonilla and Vidal, 2011; Panagos et al., 2016a). This explains why most studies use fewer than 20 years of data for their R -factor calculations (Oliveira et al., 2013). Additionally, when longer time series are used for R -factor calculations, the impact of individual extreme events is smaller than in the case of shorter time series. Therefore, short records are more sensitive to individual extreme events (Petek et al., 2018; Pidoto et al., 2022; Xiao et al., 2023).

3.2. REDES 2.0 main features

After conducting several pre-processing and sensitivity steps (Section 3.1), the final REDES 2.0 database was created. All included stations have at least 5 years of available data, at least 13 erosive events, and are separated by a minimum distance of 500 m. REDES 2.0 contains the following elements:

- A detailed list of all erosive events (Section 2.3) with the identification of start of the event (date and time), E , I_{30} , event rainfall sum (P), event duration (D), average intensity (I) and event rainfall erosivity (R).

- A list of monthly rainfall erosivity values calculated based on the aggregation of the data from the previous step.

- A list of average annual R -factor values together with station characteristics (i.e., ID, station name, altitude, latitude, longitude, start year, end year, sample size, number of erosive events) for all considered stations.

After all pre-processing steps, a total of 9138 stations located in Europe were included in the REDES 2.0 database. In total, 2,427,500 erosive events (Section 2.3) were identified and over 100,000 monthly

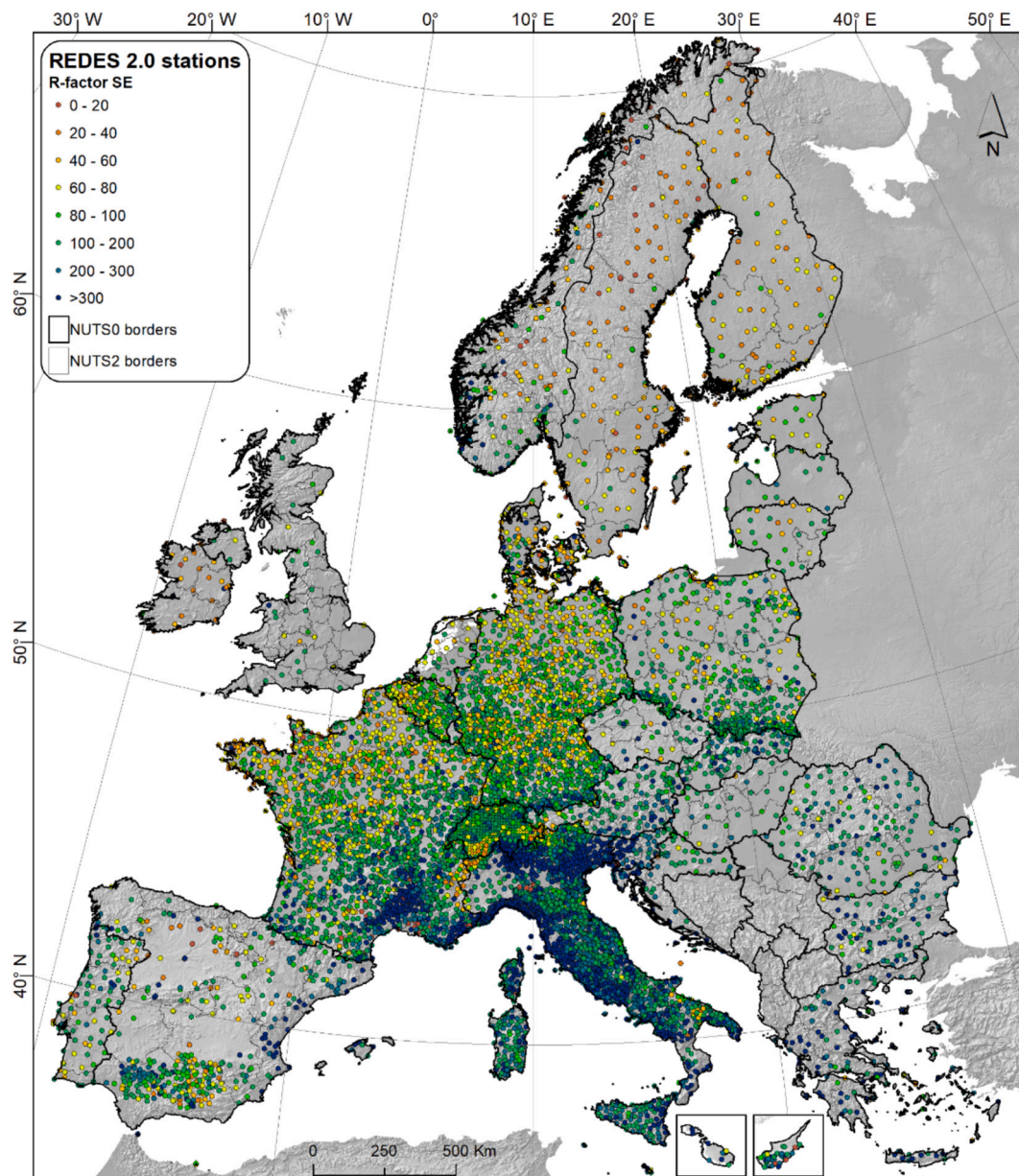


Fig. 6. The standard error related to the R -factor ($\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$) was calculated using data from 2010 to 2024 as shown in Fig. 5.

rainfall erosivity records were included in REDES 2.0. The location of all stations is shown in Fig. 1. Data density is highest in central Europe (e.g., Switzerland, Germany, parts of France) and in some countries partly located in the Mediterranean climate (e.g., Italy, parts of France and Slovenia), while data density is lower in northern countries (e.g., Norway, Sweden) (Table 2), where soil erosion rates are smaller compared to the southern part of Europe (Bezak et al., 2024; Panagos et al., 2021; Panagos et al., 2015b). On average, the station density in REDES 2.0 is about 1.9 stations per 1000 km^2 (Table 2) compared to about 0.4 stations per 1000 km^2 in REDES 1.0 (Panagos et al., 2015a). REDES 1.0 included around 300,000 erosive events, while this study includes about eight times more events. On average, stations have 15 years of data and about 265 erosive events. The average data length is similar to that used in REDES 1.0. It should be noted that REDES 2.0 data coverage is concentrated in the period from 2010 onwards (Table 1) while REDES 1.0 was mostly focused on the period before 2010. In REDES 1.0, 106 stations (6.5%) were located above 1000 m a.s.l. , while in REDES 2.0 there are 995 (10.4%) stations at elevations higher than 1000 m a.s.l. Main features regarding station altitude, number of years, and period

covered are also shown in Table 3.

Based on the identified erosive events, we derived the annual average R -factor using the complete data period (Fig. 3), data from 2010 onwards (Fig. S7), data from 2015 onwards and data from 2010 to 2024 (Fig. 5). Corresponding standard errors were also calculated and are shown in Fig. 4, Fig. S8 and Fig. 6 for all available data, for data from 2010 onwards and for 2010–2024 data, respectively. Spatial R -factor patterns are relatively similar to those derived in previous studies (Panagos et al., 2023; Panagos et al., 2015a) while the inclusion of additional stations allowed us to better capture spatial variations in rainfall erosivity especially in regions with the highest rainfall erosivity rates (e.g., Italy, parts of France, Slovenia, Croatia, Greece). Therefore, this will be very important in future steps where annual and monthly rainfall erosivity maps (Ballabio et al., 2017; Bezak et al., 2020; Panagos et al., 2015a) will be derived. Moreover, the difference between the country-average annual R -factor for countries using REDES 2.0 and REDES 1.0 is shown in Fig. S9. For most countries, the differences in average R -factor using both datasets are relatively small (i.e., within 10%), while for some countries, such as Greece, or Bulgaria, the

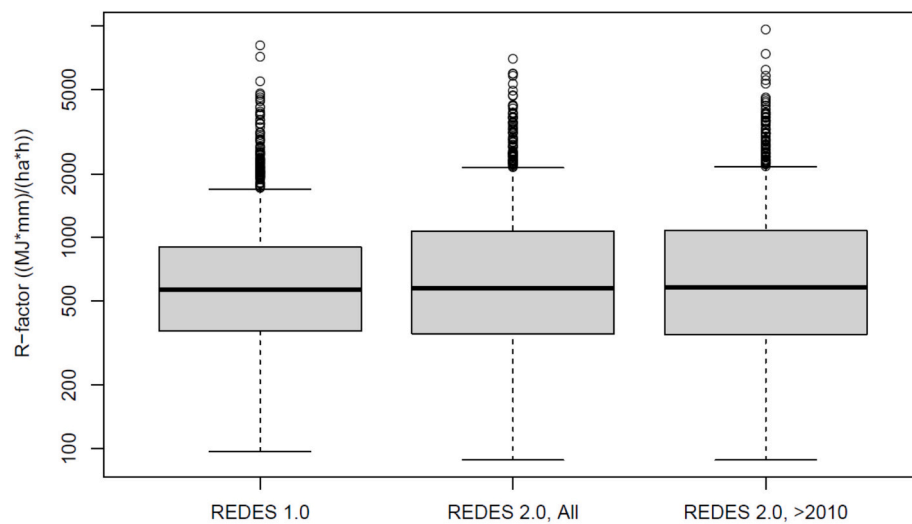


Fig. 7. Boxplots comparing a subset of 1062 locations in Europe that overlap between REDES 1.0 and 2.0. For these stations, average annual R -factor values are shown for REDES 1.0 (Panagos et al., 2015a) and REDES 2.0 (this study) in two cases: using the complete data set and using only data from 2010 onwards.

differences are larger (i.e., above 50%). These differences can be attributed to varying station density, past obsolete data in REDES 1.0 and spatial coverage in these countries (Panagos et al., 2015a). Additionally, some of these regions experienced extreme hydro-meteorological events (Ferrari et al., 2025; He et al., 2024; Mourelatos et al., 2025) in recent years, which contributed to higher rainfall erosivity in REDES 2.0 compared to REDES 1.0 (Panagos et al., 2015a).

Moreover, the median and mean R -factor values based on all available stations in REDES 1.0 (Panagos et al., 2015a) were $668 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$ and $934 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$, respectively. In this study median and mean for all stations are $740 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$ and $1112 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$, respectively. Also, in this case, the increase can be attributed to the higher spatial density of stations in some countries with high rainfall erosivity (e.g., Italy) and to more frequent extreme storms in recent decades, which are also expected to increase further in the future (Little et al., 2023). Moreover, it should be noted that use of different equation for the estimation of e_B could generate up to around 10% higher rainfall erosivity values (Section 3.1). Additionally, we compared the average annual R -factor values for 1062 locations in Europe that overlap between REDES 2.0 and 1.0 (Fig. 7). For these locations, Fig. 7 shows an increase in the average annual R -factor from REDES 1.0 to REDES 2.0. More specifically, the average annual R -factor for the 1062 locations for REDES 1.0 and 2.0 are 792 and $862 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$, respectively (Fig. 7). This represents an approximately 9% increase in the average annual R -factor between REDES 1.0 and 2.0. Additionally, if only data from 2010 onwards are used (REDES 2.0) the average value is $882 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$. However, it should be noted that the data length for these 1062 locations overlapping between REDES 1.0 and 2.0 is not the same and could impact the results. Additionally, there are some methodological differences between the two databases (i.e., REDES 1.0 and 2.0), such as the use of a disaggregation model instead of conversion factors, which could also have a minor impact on this comparison. This increase in rainfall erosivity in recent decades can mainly be attributed to more extreme rainfall events resulting from climate change. For the 2010–2024 subset of REDES 2.0, we also computed the slope of the linear regression fitted to the annual rainfall erosivity values for the 2010–2024 period to quantify the change in annual rainfall erosivity in recent decades. The rainfall erosivity trend in this period is positive for about 65% of stations and negative for the remaining 35% (Fig. 8). This observed increase in rainfall erosivity is also consistent with other studies (Bezak et al., 2020; Panagos et al., 2022a). However, only 15 years of data may be too short for a robust long-term climate trends detection, as individual stations

may be affected by specific extreme erosive events (Xiao et al., 2023). As the REDES 2.0 stations are well-established, further monitoring and more available data in next few years will allow for a more robust assessment of climate change.

Moreover, standard errors (absolute values) related to the annual R -factor calculation are highest in areas with the highest annual R -factor (Fig. 3, Fig. 5, Fig. S7). The average and median ratios between the standard error and annual R -factor are 18% and 16%, respectively (Fig. S10). The 5th and 95th percentiles for the ratio are 8% and 35%, respectively (Fig. S10). Standard error also increases with shorter time periods (Fig. S10). Specifically, the median ratios between the standard error and annual R -factor for two sub-samples (from 2010 and 2015 onwards) are 17% and 19%, respectively (Fig. S10). However, this is not an extreme increase in standard error due to the shorter period used, and some studies have indicated that the impact of sample size can be more significant and can generate relatively large differences in R -factor values (Pidoto et al., 2022; Verstraeten et al., 2006). Additionally, in general, there is no significant difference in the R -factor values when all data is used compared to when data from 2010 onwards is used (or 2010–2024 data; Fig. 9). The same applies to the corresponding standard error (Fig. 9). Using data from 2015 onwards slightly affects the distribution of the average annual R -factor and the corresponding standard error (Fig. 9), which can be attributed to the smaller sample used for the R -factor analysis. A similar conclusion can be drawn for the relationship between the R -factor and standard error (Fig. S10).

Additionally, comparison of R -factor values and standard deviations across biogeographical regions indicates the highest values and greatest variability in rainfall erosivity for the Alpine and Mediterranean zones (Table 4), which is consistent with the REDES 1.0 results. In contrast, lower R -factor values and variability were observed for the Atlantic and Boreal zones (Table 4). It should be noted that some zones include only a limited number of stations; consequently, the average R -factor and standard deviation are less reliable.

Moreover, the erosivity density was also calculated for all stations using the mean annual precipitation from the WorldClim database (Fick and Hijmans, 2017; WorldClim, 2020) (Fig. 10). As in REDES 1.0, the highest erosivity density in REDES 2.0 was observed in Italy, parts of France, Spain, Greece, and Slovenia. In these countries erosivity density was above 2 indicating high erosive power of rainstorms in these regions, which can significantly affect soil erosion rates (Diodato and Bellocchi, 2007; Kouli et al., 2009; Panagos et al., 2016a). On the other hand, the erosivity density is lower than $1 \text{ MJ ha}^{-1} \text{ h}^{-1} \text{ year}^{-1}$ in the western and northern parts of Europe (Fig. 10), indicating that these

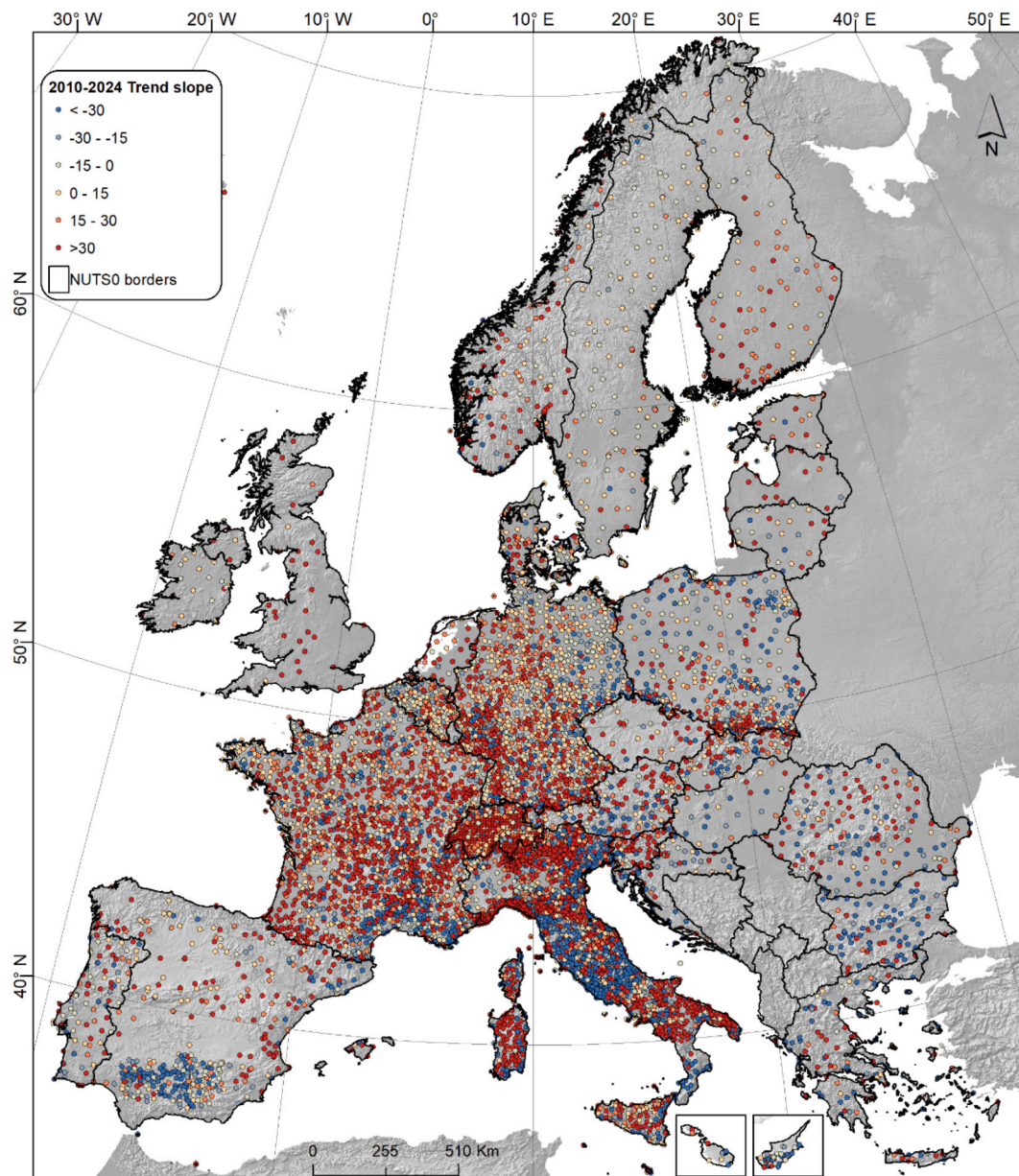


Fig. 8. Slope of the linear regression function for annual rainfall erosivity derived based on the data for the 2010–2024 period. The slope indicates the potential change in annual rainfall erosivity per year during 2010–2024 expressed as $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{year}^{-1}$. Positive values indicate an increase, and negative values indicate a decrease in the annual *R-factor*.

regions have lower rainfall erosivity than the mean annual precipitation and in general the lowest erosivity density in Europe. However, it should be noted that the results depend on the selected input precipitation data source. Moreover, there is only a weak or very weak relationship between the *R-factor* and station characteristics such as location or altitude (Fig. S11). The same applies to the relationship between erosivity density and station characteristics. However, a moderate dependence was observed between the *R-factor* and the number of erosive events (Fig. S11), as expected, since more erosive events usually generate higher total annual rainfall erosivity, although there are differences in the distribution of erosive events across Europe (Bezak et al., 2021). A stronger correlation would probably be obtained if REDES 2.0 stations were classified or divided according to station characteristics such as elevation or distance to the sea.

3.3. Limitations, strengths and further steps

It should be noted that this study has several potential limitations. First, data were obtained from multiple sources, and while some providers include data quality checks, others do not provide data quality labels. Therefore, data preprocessing included several quality checks (e. g., sum of annual rainfall, basic characteristics of erosive events) and the application of threshold values (200 mm for 30-min (Thiemig et al., 2022) to filter and remove potentially problematic data. However, in some cases it was not possible to remove all problematic values, and several manual checks were conducted after the initial creation of the REDES 2.0 database to eliminate potentially unrealistic high values (e. g., annual *R-factor*, event erosivity, event intensity, event rainfall sum, etc.). Firstly, it should be noted that due to the large amount of data (close to 2.5 million erosive events in total), it is possible that not all problematic events were filtered and removed. Secondly, spatial coverage and density differed among the countries considered, and the

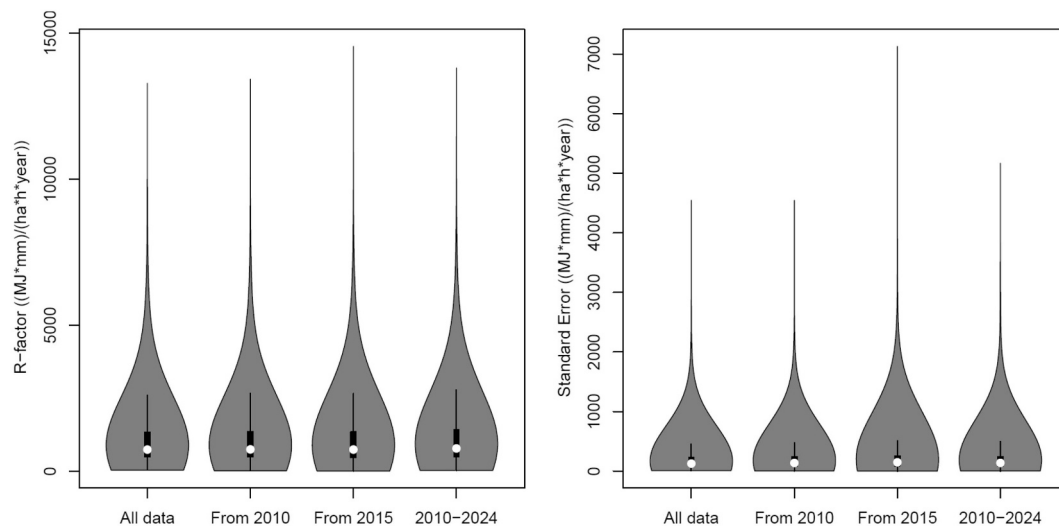


Fig. 9. Violin plot comparing average annual R -factor and corresponding standard error across different data periods.

final country-averaged R -factor values are affected by both the number of stations included and their spatial distribution. Hence, spatial density varies between countries and should be considered in follow-up studies, such as the preparation of rainfall erosivity maps. Thirdly, calculation of the rainfall erosivity involves several steps (e.g., selection of e_B equation or time step used) where some variation in the annual R -factor may have been introduced. Fourthly, although spatial density has increased compared to REDES 1.0, the REDES 2.0 station density remains uneven, and representativeness in complex terrain and coastal zones is still limited in some countries (e.g., Spain, United Kingdom). Additionally, using the data period from 2010 to 2024 for trend evaluation may be too short to identify an actual climate change signal.

Nevertheless, this study managed to convert all high-frequency data to a uniform time step (i.e., 30-min) by either aggregating data or applying the cascade model to disaggregate 60-min data into 30-min intervals. Additionally, the annual R -factor was calculated using different data periods, and the corresponding standard error was calculated to quantify the potential uncertainty in the annual R -factor. Moreover, this study addresses many limitations associated with the REDES 1.0 database (Panagos et al., 2015a), by using harmonized 30-min rainfall data for R -factor calculation, significantly improving spatial coverage (e.g., Poland, Greece, Italy) and using higher number of stations and erosive events, and accounting for the effects of climate change by using recent data. Furthermore, several data subsets and multiple R -factors products were created, including one covering the 2010–2024 period for all included stations. Moreover, extensive sensitivity analyses and validation of the cascade disaggregation procedure were conducted.

The results of this study and the newly constructed REDES 2.0 database could serve as input for several potential future studies: (i) development of annual R -factor maps for Europe with corresponding uncertainty and using different time periods; (ii) creation of monthly rainfall erosivity maps for Europe; (iii) detailed statistical analysis of erosive event characteristics; and (iv) improvements related to the use of satellite-, radar-, and reanalysis-based datasets for predicting the dynamics of rainfall erosivity at shorter time steps (such as daily, weekly, monthly). Moreover, we suggest that future follow-up studies include uncertainty estimation in the rainfall erosivity calculations, as was also done in this study.

4. Conclusions

This study presents a new version of the Rainfall Erosivity Database at European Scale (REDES 2.0), which includes 9138 stations and more

than 2.4 million erosive events, with an average of about 15 years of data, mostly covering the period from 2010 onwards (Table 2, Table 3, Fig. 2). Compared to REDES 1.0, REDES 2.0 includes approximately six times more stations and about eight times more erosive events. REDES 2.0 significantly improves spatial coverage from 0.4 (REDES 1.0) to 1.9 stations per 1000 km². This densification drastically improves the representation of heterogeneous climate regimes, especially in the Mediterranean, Alpine regions, and Eastern European lowlands, which were previously under-sampled. The REDES 2.0 database can be used in future studies to generate annual and monthly rainfall erosivity maps and to provide a solid basis for dynamic assessments of rainfall erosivity at the European scale. These assessments could potentially serve as input for the new generation of soil erosion models that use machine learning and artificial intelligence (Barakat et al., 2023; Barthel et al., 2025; Khosravi et al., 2023). Rainfall erosivity was calculated using the RUSLE methodology and 30-min rainfall data for all stations, where the cascade model was used to disaggregate hourly data into 30-min intervals (Section 2). The highest R -factor values were observed in the Mediterranean and Alpine regions while the lowest R -factor values were detected in the northern part of Europe (Fig. 3, Fig. 5). The corresponding standard errors for most stations were within 20% of the annual R -factor (Fig. 4, Fig. 6 and Fig. S10). Using only a sub-sample of the complete dataset (i.e., from 2010 onwards or using the 2010–2024 period) did not significantly change the annual R -factor or the corresponding standard error compared to using the complete dataset. Additionally, difference between sub-sets: (i) from 2010 onwards and (ii) 2010–2024 was small. A comparison of a subset of 1062 locations overlapping between REDES 1.0 and 2.0 indicates a potential increase in rainfall erosivity in recent decades (Fig. 7), which is further supported by a predominantly positive trend in annual rainfall erosivity for the 2010–2024 period (Fig. 8). However, longer time series would be needed to assess long-term climate impact on rainfall erosivity. The spatial patterns of erosivity density were similar to those of the R -factor. Additionally, only a weak relationship was observed between the R -factor and station characteristics such as altitude or location (Fig. S11), indicating a complex interplay of rainfall erosivity drivers in Europe that may limit the effectiveness of simple regionalization approaches for estimating rainfall erosivity using only mean annual precipitation data or station characteristics as predictor variables. REDES 2.0 can be used as input data for future rainfall erosivity studies, such as soil erosion modelling, mapping, or annual and monthly rainfall erosivity and dynamic erosivity predictions. REDES 2.0 provides new insights into how climate change intensifies rainfall erosivity and serves as a foundational resource for advancing soil erosion modelling, guiding land

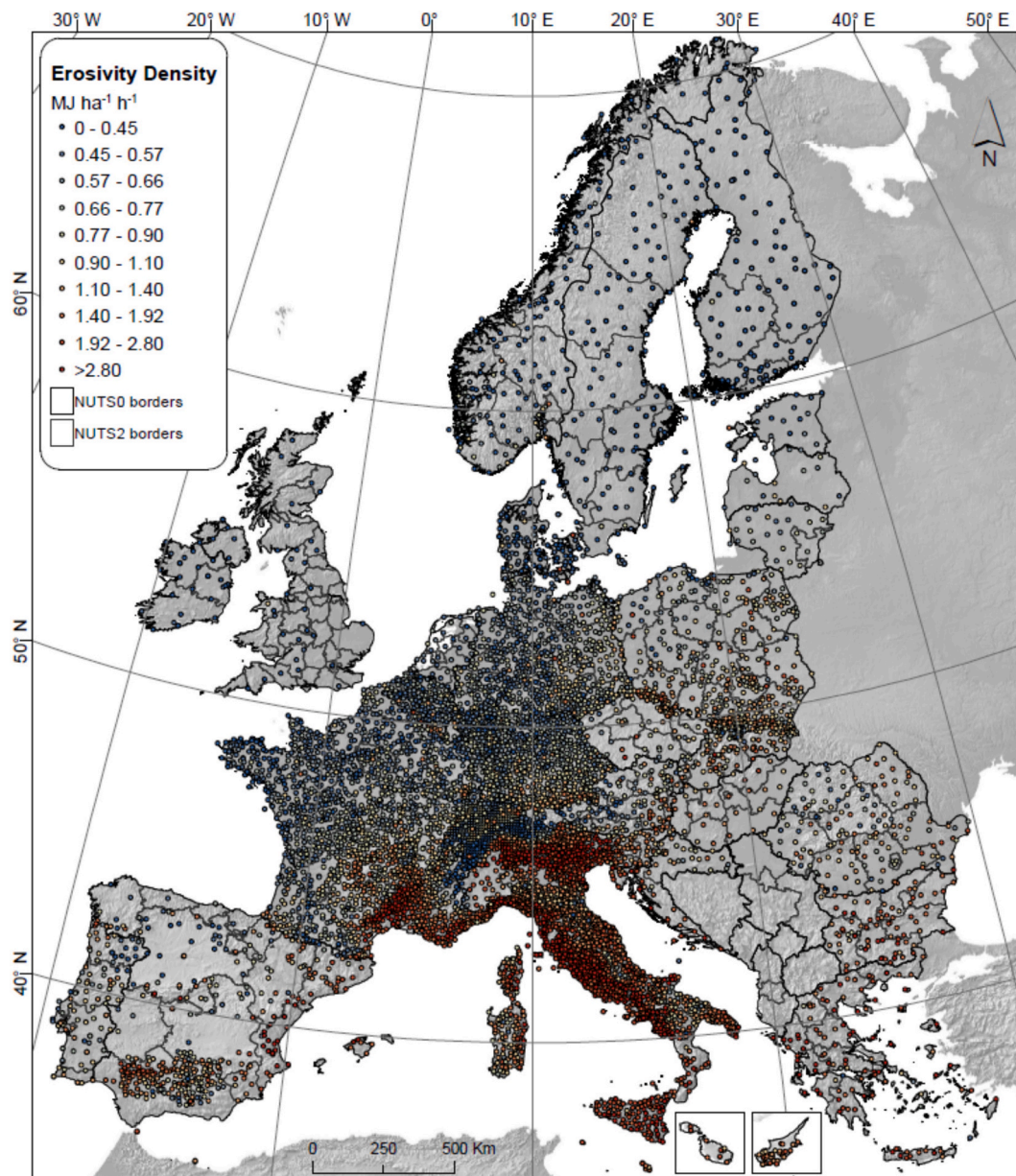


Fig. 10. Erosivity density ($\text{MJ ha}^{-1} \text{h}^{-1} \text{year}^{-1}$) calculated using the R -factor shown in Fig. 3 and the WorldClim dataset (Beck et al., 2020; WorldClim, 2020).

management decisions, and strengthening climate adaptation strategies. Future rainfall erosivity databases and studies should adopt a hybrid approach that combines long-term observations from precipitation stations with high-temporal-resolution and spatially uniform datasets (e.g., ERA5, Copernicus European Regional Reanalysis (CERRA) or European Meteorological Observations (EMO), Matthews et al., 2025a; Matthews et al., 2025b) to take advantage of different available products, aiming to capture both long-term climatic variability and local characteristics of erosive events at adequate spatial density. Additionally, rainfall generators or disaggregation models (Pidoto et al., 2022) could be useful tools to extend the length of data series or to disaggregate coarse temporal resolutions into high-frequency time steps. To sum up, the REDES 2.0 database transforms limited, coarse-scale rainfall erosivity coverage in Europe into a high-definition, continent-wide observational platform, opening new frontiers for climate impact.

CRedit authorship contribution statement

Nejc Bezak: Writing – original draft, Methodology, Formal analysis,

Conceptualization. Pasquale Borrelli: Writing – review & editing, Methodology, Conceptualization. Luigi Cesarini: Writing – review & editing, Data curation. Hannes Müller-Thomy: Writing – review & editing, Software. Francis Matthews: Writing – review & editing, Data curation. Philipp Saggau: Writing – review & editing, Data curation. Konstantinos Kaffas: Writing – review & editing, Data curation. Leonidas Liakos: Writing – review & editing, Data curation. Jana Brettn: Writing – review & editing, Software. Cristiano Ballabio: Writing – review & editing, Data curation. Charles Galdies: Writing – review & editing, Data curation. Sašo Petan: Writing – review & editing, Data curation. Donatas Valiukas: Writing – review & editing, Data curation. Christos-Panagiotis Giannaklis: Writing – review & editing, Data curation. Kostas Lagouvardos: Writing – review & editing, Data curation. Goncalo Gomes: Writing – review & editing, Data curation. Peter Salamon: Writing – review & editing, Data curation. Santiago Beguería: Writing – review & editing, Data curation. Mónica Lakatos: Writing – review & editing, Data curation. Melita Perčec Tadić: Writing – review & editing, Data curation. Ivan Lončar-Petrinjak: Writing – review & editing, Data curation. Hristo Chervenkov: Writing – review

& editing, Data curation. **Silas Michaelides**: Writing – review & editing, Data curation. **Panos Panagos**: Writing – review & editing, Methodology, Conceptualization.

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Declaration of competing interest

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.catena.2026.110393>.

Data availability

REDES 2.0 (Original data) (European Soil Data Centre (ESDAC)) (Panagos et al., 2012; 2022b).

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