Rainfall Erosivity in Europe

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Abstract

Rainfall is one the main drivers of soil erosion. The erosive force of rainfall is expressed as rainfall erosivity. Rainfall erosivity considers the rainfall amount and intensity, and is most commonly expressed as the R-factor in the USLE model and its revised version, RUSLE. At national and continental levels, the scarce availability of data obliges soil erosion modellers to estimate this factor based on rainfall data with only low temporal resolution (daily, monthly, annual averages). The purpose of this study is to assess rainfall erosivity in Europe in the form of the RUSLE R-factor, based on the best available datasets. Data have been collected from 1,541 precipitation stations in all European Union(EU) Member States and Switzerland, with temporal resolutions of 5 to 60 minutes. The R-factor values calculated from precipitation data of different temporal resolutions were normalised to R-factor values with temporal resolutions of 30 minutes using linear regression functions. Precipitation time series ranged from a minimum of 5 years to maximum of 40 years. The average time series per precipitation station is around 17.1 years, the most datasets including the first decade of the 21st century. Gaussian Process Regression(GPR) has been used to interpolate the R-factor station values to a European rainfall erosivity map at 1 km resolution. The covariates used for the R-factor interpolation were climatic data (total precipitation, seasonal precipitation, precipitation of driest/wettest months, average temperature), elevation and latitude/longitude. The mean R-factor for the EU plus Switzerland is 722 MJ mm ha^{-1} h^{-1} yr^{-1}, with the highest values (>1,000 MJ mm ha^{-1} h^{-1} yr^{-1}) in the Mediterranean and alpine regions and the lowest (<500 MJ mm ha^{-1} h^{-1} yr^{-1}) in the Nordic countries. The erosivity density (erosivity normalised to annual precipitation amounts) was also highest in Mediterranean regions which implies high risk for erosive events and floods.

Keywords: RUSLE, R-factor, rainstorm, rainfall intensity, modelling, erosivity density, precipitation, soil erosion

1 Introduction

Soil erosion by water affects soil quality and productivity by reducing infiltration rates, water-holding capacity, nutrients, organic matter, soil biota and soil depth (Pimentel et al., 1995). Soil erosion also has an impact on ecosystem services such as water quality and quantity, biodiversity, agricultural productivity and recreational activities (Dominati et al., 2011; Dale and Polasky, 2007).

Since soil erosion is difficult to measure at large scales, soil erosion models are crucial estimation tools at regional, national and European levels. The high heterogeneity of soil erosion causal factors, combined with often poor data availability, are obstacles to the application of complex soil erosion models. The empirical Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997), which predicts the average annual soil loss resulting from raindrop splash and runoff from field slopes, is still most frequently used at large spatial scales (Kinnell, 2010; Panagos et al., 2014a). In RUSLE, soil loss may be estimated by multiplying the rainfall erosivity factor (R-factor) by five other factors: Soil erodibility (K-factor), slope length (L-factor), slope steepness (S-factor), crop type and management (C-factor), and supporting conservation practices (P-factor).

Among the factors used within RUSLE and its earlier version, the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), rainfall erosivity is of high importance as precipitation is the driving force of erosion and has a direct impact on the detachment of soil particles, the breakdown of aggregates and the transport of eroded particles via runoff. Rainfall erosivity is the kinetic energy of raindrop's impact and the rate of associated runoff (Wischmeier and Smith, 1978). The R-factor is a multi-annual average index that measures rainfall's kinetic energy and intensity to describe the effect of rainfall on sheet and rill erosion. However, the erosive forces of runoff due to snowmelt, snow movement, rain on frozen soil, or irrigation are not included in this factor. Besides (R)USLE, the rainfall erosivity can be used as input in other models such as USPED, SEMMED and SEDEM. Further, this dataset could also be interesting for natural hazard prediction such as landslide and flood risk assessment that are mainly triggered by high intensity events.

A precise assessment of rainfall erosivity requires recordings of precipitation at short time intervals (1 – 60 minutes) for a period of at least several years. The rainfall erosivity is calculated by multiplying the kinetic energy by the maximum rainfall intensity during a period of 30-minutes for each rainstorm. The R-factor accumulates the rainfall erosivity of individual rainstorm events and averages this value over multiple years.

Field experiments using plot-sized rainfall simulators provide precise results of rainfall erosivity (Marques et al., 2007). However, since field experiments are expensive and often not easily transferable to large scales, researchers develop models for estimating rainfall erosivity. Two approaches are used to model rainfall erosivity: a) calculate the R-factor based on high-temporal-resolution precipitation data, and b) develop functions that correlate the R-factor with more readily available (daily, monthly, annual) rainfall data (Bonilla & Vidal, 2011). Only a few studies in Europe have determined the R-factor directly from high-temporal-resolution data (the first approach), including those carried out in Slovenia (Mikos et al., 2006), the Ebro catchment in Spain (Angulo-Martinez et al., 2009), Switzerland (Meusburger et al., 2012), and one of the federal states of Germany, North Rhine Westphalia (Fiener et al., 2013). At the continental scale, a recent study has accounted for the rainfall erosivity in Africa based on time series of 3-hours precipitation data (Vrieling et al., 2014)

In most soil erosion studies, the calculation of rainfall erosivity is limited due to the lack of long-term time series rainfall data with high temporal resolution (<60 min). Following the second approach (called the empirical approach), equations have been developed to predict R-factor based on rainfall data with lower temporal resolution (Loureiro and Coutinho, 2001; Marker et al. 2007; Diodato and Bellocchi, 2007; Panagos et al., 2012). In those cases, expert knowledge of local conditions and seasonal characteristics plays an important role in estimating rainfall erosivity. Authors have suggested that rainfall erosivity equations should be used with caution in different applications, as the empirical relationships are location dependent and, in most cases, cannot be applied to larger areas (Oliveira et al., 2013). Moreover, those empirical equations cannot capture the high rainfall intensities which have significant influence on the average rainfall erosivity. R-factor equations developed for a specific region cannot be applied to the whole of Europe.

The main objective of this study is to estimate rainfall erosivity based on high-temporal-resolution precipitation data in Europe. It aims to:

a) present the spatial and temporal extent of high-resolution precipitation data available in Europe,
b) compute rainfall erosivity for 1,541 precipitation stations in Europe, and propose a pan-European database of stations with R-factor data,
c) produce a European R-factor map based on a regression approach,
d) identify spatial patterns and map the relationship of the R-factor to precipitation (erosivity density), and
e) identify the possible use of the final R-factor dataset in situations beyond soil erosion monitoring.

2 Data Collection

The geographical extent of this study includes the 28 Member States of the European Union (EU) plus Switzerland. High-resolution precipitation data were also available for the Swiss territory, which permitted us to avoid the “white lake” effect in the European rainfall erosivity map.

Given the growing concerns about climate change, climatic data is particularly important for the scientific community and society in general, as decisions of individuals, business and governments are dependent on available meteorological data (Freebairn and Zillman, 2002). More than 15 years ago, Petterson et al. (1998) recognised that data Infrastructures hosting climatic data are becoming more important and that their contributions are becoming more valuable to policy making.

The present data collection exercise is based on an initiative to develop a network of high-temporal-resolution precipitation stations, which could also be useful for other research purposes such as climate change studies. Generally, climatic data of high temporal resolution are not easily accessible in Europe, or are only available for a fee.

The data collection exercise began in March 2013 and was concluded in May 2014. Previous attempts to collect soil erosion data from Member States used a top-down approach, and the response from countries was rather limited. In a recent top-down data collection exercise, only 8 Member States from a network of 38 countries provided estimates on soil loss (Panagos et al., 2014a). For the present rainfall erosivity data collection exercise, a participatory approach has been followed in order to collect data from all Member States.

The participatory data collection approach followed the steps listed below. Each step was followed in a sequential manner in case the preceding step was not successful:

a) High-temporal-resolution precipitation data are publicly available for download. This was the case for data from the Royal Netherlands Meteorological Institute (Netherlands) only.
b) The European Soil Data Centre (ESDAC) contacted the national meteorological services calling for precipitation data at high temporal resolution. Meteorological services such as Meteo-France, the Deutscher Wetterdienst – DWD (Germany), the Flemish Environmental Agency and the Service Public de Wallonie (Belgium), the Estonian Environment Agency, the Latvian Meteorology Centre and the Agrarmeteorologisches Messnetz (Luxembourg) responded to this request as some of them have bilateral agreements with the Joint Research Centre, which hosts ESDAC.
c) If the data were not available to ESDAC, recognised scientists of the various meteorological services were invited to participate in this project. Meteorologists from Cyprus, Finland, Croatia, Hungary and

Romania participated in estimating the rainfall erosivity of their respective countries, based on their datasets.

d) By means of a literature review, scientists who have developed similar research activities in their countries and have access to or have developed their own R-factor datasets (based on high-temporal-resolution precipitation data) were identified and contacted.

e) High-resolution precipitation datasets were identified in research project databases such as Hydroskopio (Greece) and Sistema National de Recursos Hidricos (Portugal).

f) A review of the 'grey' literature and searches with national language terms led to the discovery of data sources in Lithuania, Slovakia and Poland.

In Italy and Spain, high-resolution precipitation data were collected at the regional level from regional meteorological authorities (Italy) and water agencies (Spain).

The conditions set for the data collection exercise were:

- Continuous records for at least 10 years. If such data were not available, data collected over a period of at least five years were included. Vrieling et al. (2014) also stated that the R-factor may be cumulated for shorter timespans in calculating rainfall erosivity trends.
- Preference was given to datasets that cover the last decade. Where this was not possible, older time series were also included, e.g. for Bulgaria, Greece, the Czech Republic, Poland and Slovakia. As the priority of this study was to capture the spatial trends of rainfall erosivity by averaging erosive events over several years, we consider this time discrepancy to be of minor importance (Table 1).
- Data of up to 60 minutes resolution were included.
- In Italy, which has a larger pool of available stations (> 500), 251 stations were selected in order not to bias the pan-European results. A stratified random sample of the Italian stations were selected, covering all climatic conditions (Mediterranean, Continental and Alpine) and all elevation levels.

Priority was given to datasets with high temporal resolution, independent of the period covered, because the objective of this data collection exercise was to capture the spatial trends of rainfall erosivity. In the majority (> 75%) of countries, the time-series include the first decade of the 21st century, except for Bulgaria, Greece, the Czech Republic, Poland and Slovakia. However, the time-series for those five countries are long enough (> 25 years) to capture the average rainfall erosivity

Data have been collected from all EU Member States except Malta (the smallest EU Member State). In Malta, precipitation data were available only at a daily time step and, as they do not satisfy the criteria requirement of high temporal resolution, could not be used for R-factor estimation. However, Malta is only 80 km distant from the southern Italian island of Sicily, where a very dense network of stations is able to capture the spatial variability of rainfall erosivity. High-temporal-resolution data was available for Poland, but only against payment. In this case, data from literature sources were used.

Table 1: Overview of the precipitation data collected to estimate the R-factor.

Country		No. of Stations	(Main) Period Covered	Years per station (average)	(Main) Temporal resolution: 5 Min, 10 Min, 15Min, 30Min, 60 Min	Source of data
AT	Austria	31	1995 - 2010	21	12 stations: 10Min 19 stations: 15Min	Hydrographic offices of Upper Austria, Lower Austria, Burgenland, Styria, Salzburg
BE	Belgium	20	2004 - 2013	10	Flanders (20 stations): 30 Min	Flemish Environmental Agency (VMM),
		29	2004 - 2013	10	Wallonia (29 stations): 60 Min	Service Public de Wallonie
BG	Bulgaria	84	1951 - 1976	26	30 Min	Rousseva et al. (2010)
CY	Cyprus	35	1974 - 2013	39	30 Min	Cyprus Department of Meteorology
CZ	Czech Republic	32	1961-1999	35	30 Min	Research Institute for Soil and Water Conservation (Czech Republic)
CH	Switzerland	71	1988 - 2010	22	10 Min	Meusburger et al. (2012)
DE	Germany	148	1996- 2013	18	60 Min	Deutscher Wetterdienst (DWD)
DK	Denmark	30	1988 - 2012 2004 - 2012	15	60 Min	Danish Meteorological Institute (DMI), Aarhus University
EE	Estonia	20	2007 - 2013	7	60 Min	Estonian Environment Agency
ES	Spain	113	2002 - 2013	12	14 stations: 10 Min,	Regional water agencies

					81 stations: 15 Min 18 stations: 30 Min	
FI	Finland	64	2007 - 2013	7	60 Min	Finnish Climate Service Centre (FMI)
FR	France	60	2004 - 2013	10	60 Min	Météo-France DP/SERV/FDP
GR	Greece	80	1974 - 1997	30	30 Min	Hydroskopio
HR	Croatia	42	1961 - 2012	40	10 Min	Croatian Meteo & Hydrological Service
HU	Hungary	30	1998 - 2013	16	10 Min	Hungarian Meteorological Service
IE	Ireland	13	1950 - 2010	56	60 Min	Met Éireann – The Irish National Meteorological Service
IT	Italy	251	2002 - 2011	10	30 Min	Regional meteorological services, Regional agencies for environmental protection (ARPA)
LT	Lithuania	3	1992 - 2007	16	30 Min	Mazvila et al. (2010)
LU	Luxembourg	16	2000 - 2013	11	60 Min	Agrarmeteorologisches Messnetz
LV	Latvia	4	2007 - 2013	7	60 Min	Latvian Environment, Geology and Meteorology Centre
NL	Netherlands	32	1981 - 2010	24	60 Min	Royal Netherlands Meteorological Institute
PL	Poland	9	1961- 1988	27	30 Min	Banasik et al. (2001)
PT	Portugal	41	2001- 2012	11	60 Min	Agência Portuguesa do Ambiente
RO	Romania	60	2006 - 2013	8	10 Min	Meteorological Administration

SE	Sweden	73	1996 - 2013	18	60 Min	Swedish Meteorological and Hydrological Institute (SMHI)
SI	Slovenia	31	1999 - 2008	10	5 Min	Slovenian Environment Agency, Petan et al. (2010)
SK	Slovakia	81	1971 - 1990	20	60 Min	Malasik et al. (1992)
UK	United Kingdom	11 27	1993 – 2012 2001 - 2013	20 11	60 Min 60 Min	NERC & UK Environ. Change Network(ECN) British Atmospheric Data Centre (BADC)

3 Methods

Besides the high-temporal-resolution precipitation data collection, the estimation of the R-factor in Europe includes three further steps: a) The calculation of the R-factor for each precipitation station, b) the normalisation of R-factor values calculated using rainfall data with different time steps (5 min to 60 min), and c) the spatial interpolation of R-factor point values.

3.1 R-factor calculation

The erosive power of precipitation is accounted for by the rainfall erosivity factor (R-factor), which gives the combined effect of the duration, magnitude and intensity of each rainfall event. In this study, the original RUSLE R-factor equation was used to create an R-factor database of 1,541 precipitation stations in Europe.

The R-factor is the product of kinetic energy of a rainfall event (E) and its maximum 30-min intensity (I_{30}) (Brown and Foster, 1987):

$$R = \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{mj}(EI_{30})_k \qquad (1)$$

where R = average annual rainfall erosivity (MJ mm ha ^{1} h ^{1} yr^{-1}), n is the number of years covered by the data records, m_j is the number of erosive events of a given year j, and EI_{30} is the rainfall erosivity index of a single event k. The event erosivity EI_{30} (MJ mm ha ^{1} h ^{1}) is defined as:

$$EI_{30} = \left(\sum_{r=1}^{0} e_r v_r\right) I_{30} \qquad (2)$$

where e_r is the unit rainfall energy (MJ ha ^{1} mm ^{1}) and v_r the rainfall volume (mm) during a time period r. I_{30} is the maximum rainfall intensity during a 30-min period of the rainfall event (mm h ^{1}). The unit rainfall energy (e_r) is calculated for each time interval as follows (Brown and Foster, 1987):

$$e_r = 0.29[1 \quad 0.72\exp(\quad 0.05 i_r)] \qquad (3)$$

where i_r is the rainfall intensity during the time interval (mm h ^{1}).

The R-factor calculation requires the identification of erosive rainfall events (m_j) for each station. Three criteria for the identification of an erosive event are given by Renard et al. (1997): (i) the cumulative rainfall of an event is greater than 12.7 mm, or (ii) the event has at least one peak that is greater than 6.35 mm during a period of 15 min (or 12.7 mm during a period of 30 min). A rainfall accumulation of less than 1.27 mm during a period of six hours splits a longer storm period into two storms. The 12.7-mm threshold defines precipitation events that have erosive power. Interestingly, a reduction of the threshold from 12.7 mm to 0 mm leads to an increase in the R-factor of no more than 3.5% (Lu and Yu, 2002).

The Rainfall Intensity Summarisation Tool (RIST) software (USDA, 2014) was used to calculate the R-factor. The RIST can be used for R-factor calculations using precipitation data that have the same temporal resolution (Klik and Konecny, 2013).

3.2 Normalisation procedure for R-factors with different precipitation recording intervals

The precipitation data collected from the 28 countries across Europe have different temporal resolutions: 60-min, 30-min, 15-min, 10-min and 5-min. This variation in temporal resolutions is due to high numbers of data providers (minimum one per country; data from Spain, Italy, Austria, Belgium and the United Kingdom came from more than one data source, see Table 1).

According to the literature, the R-factor is underestimated as time steps increase from 5, 10, 15, 30 to 60 min (Yin et al, 2007; Williams and Sheridan, 1991). In order to homogenise the R-factor results calculated using different time-step data, conversion factors were established in the present study. The conversion of 60-min-resolution data to very fine resolution introduces quite a high level of uncertainty. As a compromise, the 30-min temporal resolution data was used, even though the most abundant time-step is 60 min. In addition, Yin et al. (2007) recommended that it is not needed to move towards time intervals of less than 30-min to obtain reliable erosivity estimations.

The data at very fine resolution were aggregated to coarse resolutions, and the R-factor was estimated for different temporal resolutions. For example, data of 30-min resolution were aggregated to 60-min resolution, and the R-factor was calculated both at 30-min and 60-min resolution. Data of 10-min resolution were aggregated to 30-min resolution, and the R-factor was calculated using both 10-min and 30-min resolutions. Regression functions between R-factors based on high and low resolution data were established to normalise the R-factor values to 30-min resolution.

3.3 Spatial prediction of the R-factor

Given the relatively low observation density for the European continent and the huge climatic variability of the study area, interpolation by kriging was not expected to produce realistic results. Instead, given the likely correlation between the R-factor and climatic data, a regression approach was used to infer the distribution of rainfall erosivity from a series of related, but independent, climatic covariates (Goovaerts, 1998). Basically, this approach aims to find a statistical relationship between the property to be predicted and a set of spatially exhaustive covariates. Once this relationship is established, the dependent property, here the R-factor, can be estimated for the area of interest. Various covariates were considered for the regression model, but three main types were identified as being significant:

1. Climatic data: average monthly precipitation, average minimum & maximum monthly precipitation, average monthly temperature, precipitation of the wettest month, precipitation of the driest month and precipitation seasonality (variation of precipitation over seasons). The climatic data are derived from the WorldClim database (Hijmans, 2005), which reports monthly averages of precipitation and temperature for the period 1950-2000 at 1-km resolution.
2. Elevation derived from the Digital Elevation Model of the Shuttle Radar Topography Mission (SRTM).

3. Latitude and longitude spatial coordinates, derived from the measuring stations location, were added explicitly to the regression model in order to model spatial correlation.

In the late 1990's, Goovaerts (1999) introduced the geostatistical interpolation method for calculating rainfall erosivity based on regionalised variables such as elevation. This linear model for spatial R-factor prediction has been widely used because it allows for non-biased estimation at non-sampled points with minimum variance. The high dimensionality (number of degrees of freedom) of the data used and the likely non-linear relation between the target variable and the covariates, discouraged the use of linear regression. Instead, this study adopted Gaussian Process Regression (GPR) (Rasmussen and Williams 2006; Stein 1999), a non-linear regression approach.

Compared to linear regression, GPR can model non-linear processes by projecting the inputs into some high dimensional space using basis functions and applying linear model in said space. In this study the Radial Basis Function (RBF) Gaussian kernel has been used; this is a kernel commonly applied in machine learning (Hoffmann et al., 2008). The kernel function is equivalent to a covariance function in kriging and its value is considered as a measure of similarity between the two feature vectors. In this respect, GPR is mathematically equivalent to kriging (Stein 1999); however, while kriging is usually performed on two- or three-dimension geographical space, GPR can be performed over an arbitrary number of covariates, including terrain features and geographical coordinates. The main advantages of GPR are that it can model complex non-linear relations between covariates and the target variable, and directly model both average and variance estimation, thus providing information about prediction uncertainty.

Gaussian Process Regression was selected as the best performing model in terms of cross validation among a series of candidate models (including OLS, GLM, GAM, and Regression Kriging). The criteria chosen for the selection were the minimization of the root-mean squared error and the maximization of the R^2. The GPR model performance was tested for both a fitting and a cross-validation dataset. The cross-validation is carried out by random sampling with 10% replacement of the original dataset used for validation.

4 Results and Discussion

4.1 Rainfall Erosivity Database on the European Scale (REDES)

In preparing the Rainfall Erosivity Database on the European Scale (REDES), high temporal resolution precipitation data were collected from 1,541 precipitation stations within the European Union (EU) and Switzerland, covering a territory of 4,422,661 km^2. The average density of the precipitation stations is one every 53.5 km x 53.5 km (or 2,869 km^2). The variability is quite high, with a dense network of stations in Cyprus and Luxembourg, and a sparse network in Poland and some regions of Spain (Fig. 1).

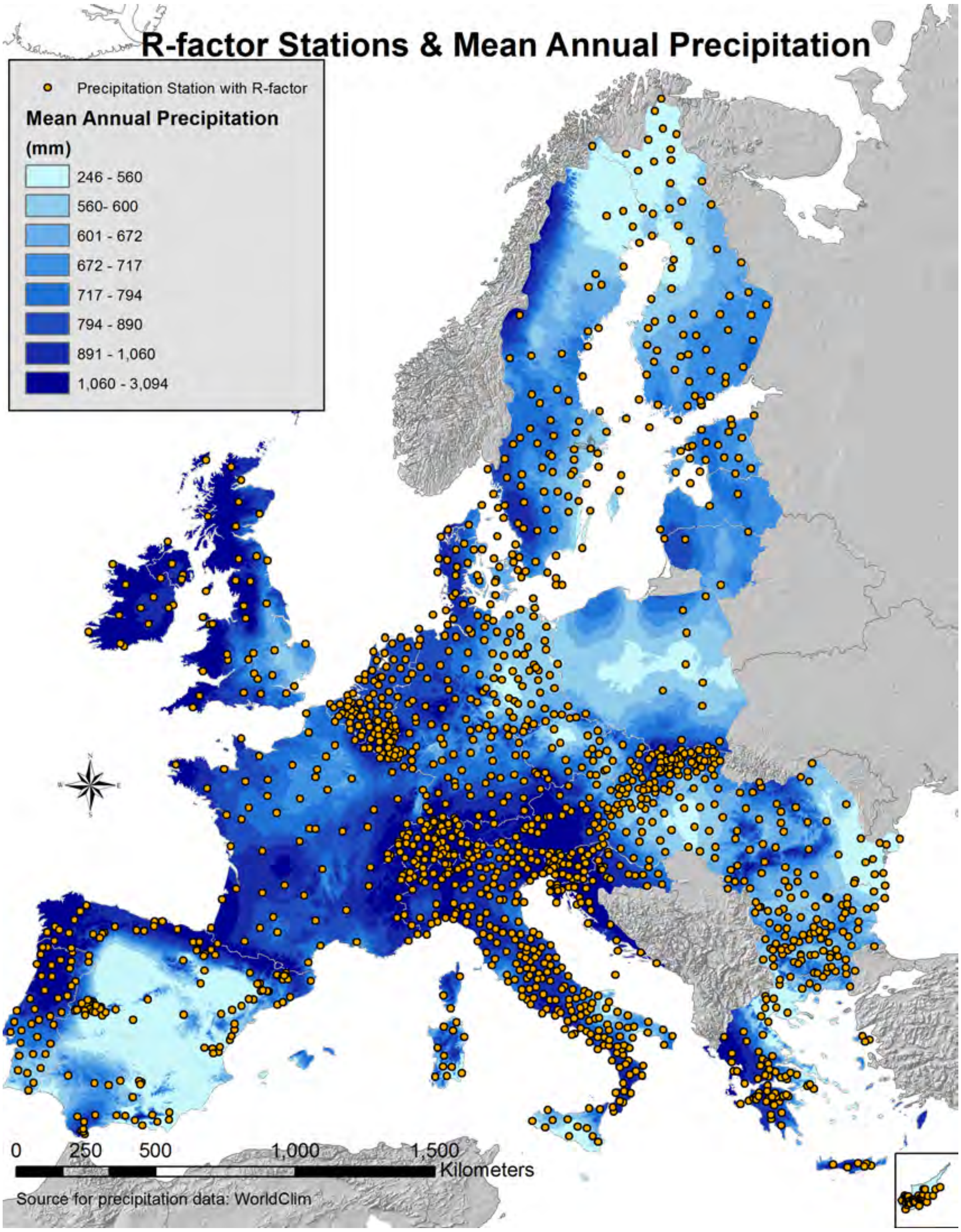

Fig. 1: Spatial distribution of precipitation stations used for the R-factor calculation

Since erosivity varies significantly from year to year, at least 15 years of data are required to obtain representative estimates of annual erosivity (Foster et al., 2003). Oliveira et al. (2013) carried out an extensive literature review (ISI Web of Science, Scopus, SciELO, and Google Scholar databases) of rainfall erosivity studies using different time series. They identified 35 studies, but only

15% of these used data covering more than 20 years. The Rainfall Erosivity Database on European Scale (REDES) of precipitation stations is the result of calculating the R-factor for a total of 26,394 years with a mean value of 17.1 years per station (Table 1). In almost all countries, the average time-series per station is more than 10 years, except in Estonia, Finland, Latvia and Romania, where the average recorded period was 7 years.

REDES, with its 1,541 precipitation stations, covers all elevation levels. 106 of the stations are at an altitude of more than 1,000 m above sea level (asl), in order to reflect the fact that around 6.5% of the total study area has an elevation greater than 1,000 m asl. The majority of the stations at high elevations are located in the Alps (Switzerland, Italy, France, Slovenia and Croatia), the Apennines (Italy), Troodos (Cyprus) and Spain.

In terms of the time resolution of precipitation data, 42.3% of the stations (in 13 countries) make hourly recordings, 34.4% make recordings every 30 minutes (in 8 countries), 6.5% record their data at 15-minutes intervals (major part of Spain and Austria), 14.9% make recordings every 10 minutes (4 countries) and only 2% (in Slovenia) of the data records are at a 5-minute time step.

The availability of data is not scarce in the domain of rainfall intensity. During the past decade (2004-2013), the development of automatic weather stations in many European countries (Belgium, Germany, France, Denmark, Estonia, Finland, Hungary, Italy, Luxembourg, Latvia, Portugal and Romania) led to the generation of more high resolution precipitation data. Besides the data availability, the data quality is considered sufficient for this study as the main source of the high resolution precipitation datasets were the official meteorological services or environmental agencies of the Member States (Table 1). The main limitation was the non-availability of high resolution precipitation data from some Meteorological services (Poland, Slovakia and UK). This limitation will be bypassed by the INSPIRE directive which foresees the data sharing between public authorities. Following the experience of REDES, this data collection can potentially extended to Norway, Turkey and Balkan states in a later phase.

4.2 Conversion factors for different temporal resolutions

Using a very representative pool of stations (in terms of geographical coverage, R-factor values), regression functions have been developed to convert the R-factor from different temporal resolutions to 30-min resolutions (Table 2). According to the conversion factors (Table 2), there is a strong underestimation of the R-factor (circa 56%) whenever 60-min data are used. The results are in accordance with previous literature findings (Yin et al., 2007; Williams and Sheridan, 1991). However, the R^2 values for the regression between R-factors calculated using precipitation data with different temporal resolutions show that 60-min data in combination with a conversion factor can be successfully used to estimate the R-factor where fine-resolution data are not available (Table 2). The conversion factors for recording time-steps of < 30 min are less than 1, which implies that the homogenised 30-min-based R-factor dataset slightly underestimates the " real" rainfall erosivity.

Table 2: Conversion factors for the calibration of temporal resolutions

Source data resolution	No. of Stations	Countries covered	Regression function	R^2 Coefficient of determination
60-min	82	BE, CZ, CH, CY, DE, EE, FR, IT, LU, RO	$R_{30min} = 1.5597 * R_{60min}$	0.994
15-min	31	BE, ES	$R_{30min} = 0.8716 * R_{15min}$	0.998
10-min	31	CZ, CY, CH, DE, EE, HR, HU, LU, RO	$R_{30min} = 0.8205 * R_{10min}$	0.998
5-min	12	CZ, CY, FR, HR, LU	$R_{30min} = 0.7984 * R_{5min}$	0.998

Unfortunately, in Ireland, UK and Scandinavian countries, no data were available at both resolutions (30-min and 60-min) necessary to contribute to the calibration of temporal resolutions.

4.3 *Rainfall erosivity in Europe*

The mean R-factor of the 1,541 precipitation stations included in REDES is 911.3 MJ mm ha^{-1} h^{-1} yr^{-1} with a high standard deviation of 844.9 MJ mm ha^{-1} h^{-1} yr^{-1} as expected due to the high climate variability in Europe. The smallest R-factors were calculated for two stations of the Ebro catchment (Spain), two stations in Slovakia (Gabcikovo, Komarno), and the stations in Tain Range (UK) and Inari Kaamanen (Finland) with values less than 100 MJ mm ha^{-1} h^{-1} yr^{-1}. The maximum values were calculated for five stations in Slovenia (Kneške Ravne, Vogel, Kal Nad Kanalom, Log Pod Mangartom and Lokvein) and one station in north-eastern Italy (Tramonti di Sotto, close to Slovenia) with values greater than 5,000 MJ mm ha^{-1} h^{-1} yr^{-1}.

The map of rainfall erosivity in Europe (Fig. 2) gives a spatial overview of the erosive energy of rain. The Gaussian Process Regression (GPR) model used to interpolate the R-factor point values to a map showed a good performance for both the cross-validation dataset (R^2 = 0.63) and the fitting dataset (R^2 = 0.72). From the large pool of parameters used in calculating the R-factor, the precipitation seasonality (coefficient of the variation of seasonal precipitation), latitude and elevation were found to have the strongest influence.

The R-factor map (Fig. 2) of the 28 European Union Member States and Switzerland has an average value of 722 MJ mm ha^{-1} h^{-1} yr^{-1} and a standard deviation of 478.6 MJ mm ha^{-1} h^{-1} yr^{-1}. The range of R-factor in Europe is 51.4 – 6,228.7 MJ mm ha^{-1} h^{-1} yr^{-1}. The distribution of R-factor values is skewed to the right, with 610 MJ mm ha^{-1} h^{-1} yr^{-1} in the 50th percentile, which implies that a few extremely high values increase the overall mean. The 25% of the study area with the lowest R-factor values (< 410 MJ mm ha^{-1} h^{-1} yr^{-1}) is located in Scandinavia, western UK and eastern Germany (Fig. 2). As the definition of high rainfall erosivity depends on the study location, we adopt a statistical approach to define the values in the 4th quartile as high R-factors. The 25% of the study area shows high R-factor values exceeding 900 MJ mm ha^{-1} h^{-1} yr^{-1}. In a quantitative comparison, the rainfall erosivity spatial pattern (Fig. 2) is similar to the results produced by Diodato and Bosco (2014). Both studies predicted rainfall erosivity higher than 1,000 MJ mm ha^{-1} h^{-1} yr^{-1} in Italy, southern France, Switzerland, Slovenia, western Croatia, Pyrenees, Andalusia, Galicia (Spain) and North Portugal.

The regions found to have the highest rainfall erosivity levels are in line with the three major regions identified by van Delden (2001) as having the highest frequency of thunderstorms. The first region includes the Southern Alps, the Apennines, Istria and Slovenia. The second region includes the gulf of Liguria and Corsica. In both regions the rainfall erosivity exceeded the 1,500 MJ mm ha^{-1} h^{-1} yr^{-1} in agreement also with the findings of Diodato and Bosco (2014). The third region expands (in an arch form) from the higher parts of Bavaria in southern Germany, to cross the Swiss plateau and the area close to Dijon, and ends in the Lyon valley. All of those regions have the three characteristics likely to produce thunderstorms: potential instability of atmospheric pressure (indicated by a decrease of the equivalent potential temperature with increasing height), high levels of moisture in the atmospheric boundary layer, and forced lifting (McNulty, 1995). Little thunderstorm activity was found in the Scandinavian countries studied (Finland and Sweden) by van Delden (2001).

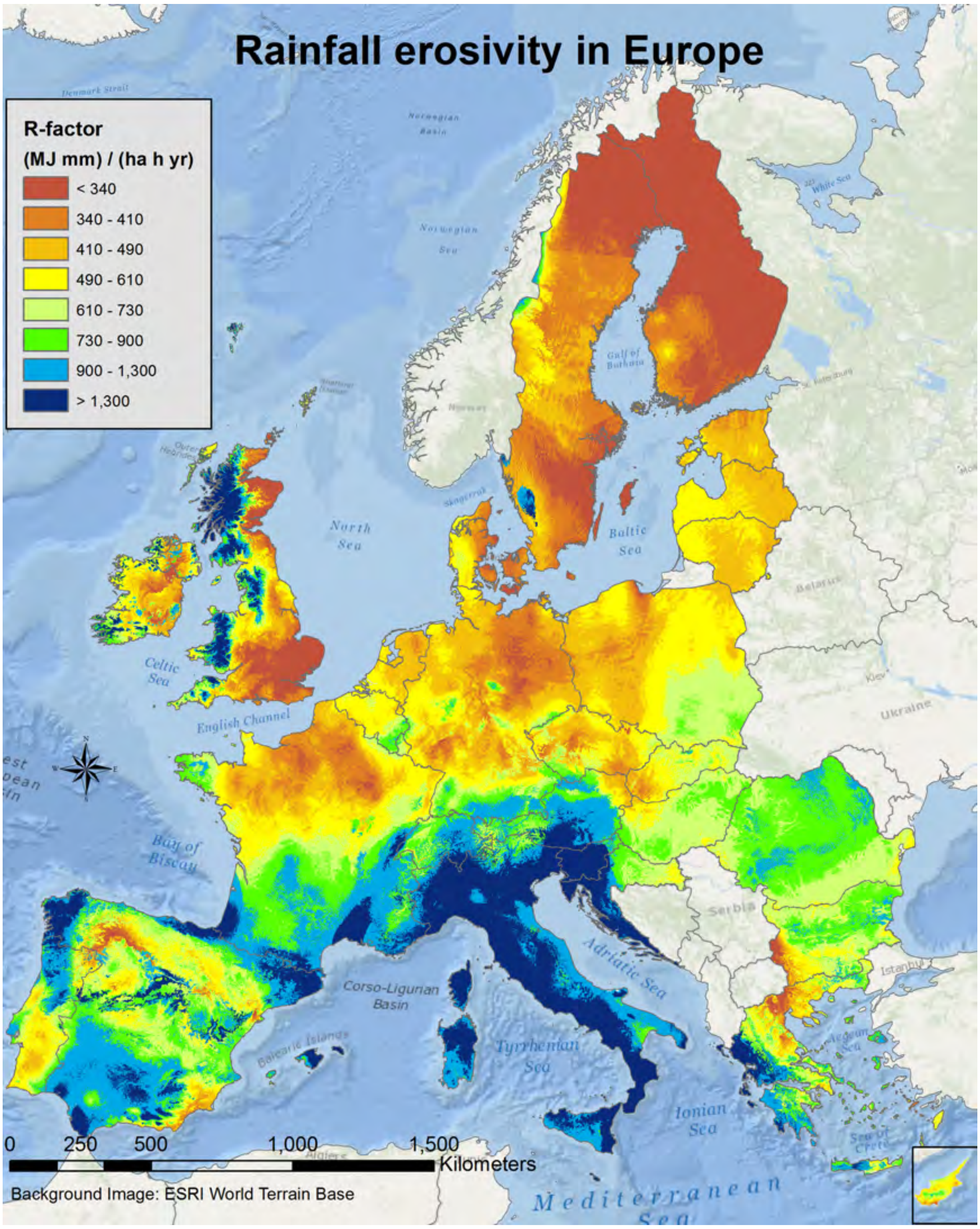

Fig. 2: High-resolution (1-km grid cell) map of Rainfall Erosivity in Europe.

At country level, the highest levels of rainfall erosivity(R-factor) are found in Italy and Slovenia, while Croatia and Austria also have mean values that are greater than 1,000 MJ mm ha^{-1} h^{-1} yr^{-1} (Table 3). The lowest values were identified in Sweden and Finland followed by Denmark, the Netherlands and the three Baltic states (EE, LT, LV). The mean R-factor values of all of those North European countries are less than 500 MJ mm ha^{-1} h^{-1} yr^{-1} (Table 3).

The coefficient of variation (CV) is used as an indicator to identify the degree of variability of the R-factor inside a country. The Netherlands and Baltic States show a very smooth distribution of the R-factor, with a CV of less than 10% (Table 3). By contrast, the United Kingdom has a very pronounced erosivity gradient with a CV of more than 81%, with extremely high R-factors in Western Wales and Scotland and very low R-factors in the eastern parts of England and Scotland. Medium to high variability is found in Croatia (Adriatic coast–inland), France (north–south gradient) and Greece (west–east gradient). The distribution of the R-factor values in the countries is skewed to the right with the exception of Baltic States, Hungary, Netherlands and Romania (normal).

Table 3: R-factor descriptive statistics per country

Country		Mean	Standard Deviation	Minimum	Maximum	Coefficient of Variation
		MJ mm ha^{-1} h^{-1} yr^{-1}				
AT	Austria	1,075.5	517.1	346.9	4,345.7	0.48
BE	Belgium	601.5	106.6	412.7	1,253.8	0.18
BG	Bulgaria	695.0	151.8	79.8	1,447.1	0.22
CH	Switzerland	1,039.6	449.3	367.2	4,249.6	0.43
CY	Cyprus	578.1	115.1	223.6	1,353.5	0.20
CZ	Czech Republic	524.0	118.5	218.0	1,093.5	0.23
DE	Germany	511.6	160.9	262.3	1,489.3	0.31
DK	Denmark	433.5	93.6	143.8	800.5	0.22
EE	Estonia	444.3	33.2	330.1	568.3	0.07
ES	Spain	928.5	373.0	164.8	3,071.2	0.40
FI	Finland	273.0	67.0	65.5	555.6	0.25
FR	France	751.7	353.5	235.2	2,661.1	0.47
GR	Greece	827.7	387.6	152.0	2,728.5	0.47
HR	Croatia	1,276.2	633.5	523.4	3,522.7	0.50
HU	Hungary	683.3	73.1	361.4	1,000.8	0.11
IE	Ireland	648.6	389.6	205.1	3,403.3	0.60
IT	Italy	1,642.0	598.0	477.6	6,228.8	0.36

LT	Lithuania	484.2	32.6	371.5	605.3	0.07
LU	Luxembourg	674.5	97.6	436.8	1,002.8	0.14
LV	Latvia	480.4	42.1	373.9	602.4	0.09
MT	Malta	1,672.4	65.6	1,491.4	1,869.2	0.04
NL	Netherlands	473.3	46.1	348.3	646.0	0.10
PL	Poland	537.1	100.0	247.7	1,055.3	0.19
PT	Portugal	775.1	317.5	226.4	2,758.1	0.41
RO	Romania	785.0	95.6	462.2	1,150.1	0.12
SE	Sweden	378.1	152.6	51.4	2,033.8	0.40
SI	Slovenia	2,302.0	954.6	757.0	5,655.8	0.41
SK	Slovakia	579.7	93.6	330.8	1,111.2	0.16
UK	United Kingdom	746.6	604.9	78.1	4,107.4	0.81

The rainfall erosivity was further evaluated in the context of climatic zones. The official Biogeographical regions dataset (EEA, 2011) delineates the main climatic zones in Europe, and is independent of political boundaries. The Mediterranean climatic zone, which has hot summers and mild winters, has the highest mean rainfall erosivity, followed by the Alpine zone, which covers the Alps and the Pyrenees (Table 4). The Atlantic zone, which has a humid climate, has a high variability with high erosivity values in northern Spain, western France and western UK, and relatively low R-factor values in the Netherlands, eastern UK and northern France. The highest spatial variability is noticed in Alpine and Continental zones mainly due to orographic effect. The Continental zone, which is characterised by warm summers and cold winters, is the largest climatic zone and also has a high variability of rainfall erosivity. The Boreal zone (which is dominated by forests) includes the greater part of Scandinavia and the Baltic states, and has the lowest R-factor. The Boreal zone has a relatively low variability of rainfall erosivity considering its spatial extent. The mean R-factor of the Pannonian zone, also known as the central Danubian basin, is similar to that of Hungary. Finally, the Black Sea and Steppic zones have a relatively minor spatial extent in the study area, covering the eastern parts of Bulgaria and Romania. The third highest R-factors were mapped for this climatic zone.

Table 4: R-factor descriptive statistics per Biogeographical region

Climatic Zone	Proportion of the study area	Mean	Standard Deviation	Coefficient of Variation
	%	MJ mm ha^{-1} h^{-1} yr^{-1}		
Alpine	9.2	932.3	666.9	0.72
Atlantic	17.7	678.2	446.7	0.66
Black Sea	0.2	702.1	144.8	0.21
Boreal	19.1	359.5	126.6	0.35
Continental	29.7	695.7	394.3	0.57
Mediterranean	20.4	1050.6	502.0	0.48
Pannonian	2.9	660.1	100.5	0.15
Steppic	0.8	729.8	91.0	0.12

The R-factor map (Fig. 2) and the related statistics (Tables 3, 4) can be used for soil erosion modelling at European and national scale. At regional or local scale, it is recommended to modellers to use REDES plus local high resolution data for making their interpolations. Combining the relatively high R-factor values with the relatively high K-factor values (> 0.038 t ha h ha^{-1} MJ^{-1} mm^{-1}) of the soil erodibility dataset (Panagos et al., 2014b), the modellers may identify the areas at high risk of soil erosion. The development of the remaining factors (topography, support practices, land use and management practices) will contribute to the perfecting of soil erosion modelling at the European scale. Furthermore, the calculation of monthly R-factor values in REDES will contribute to the seasonal estimation of rainfall erosivity in Europe.

4.4 *Erosivity density*

In the present study, the erosivity density is used for a post-assessment of rainfall erosivity patterns and type of precipitation involved in erosive events in Europe. Annual erosivity density is the ratio of the mean annual erosivity to the mean annual precipitation (Kinnell, 2010). In practice, erosivity density (ED) measures the erosivity per rainfall unit (mm), and is expressed as MJ ha ^{1} h ^{1}.

$$ED = R / P \quad (4)$$

where R is the average annual rainfall erosivity (MJ mm ha^{-1} h^{-1} yr^{-1}) and P is the average annual rainfall (mm yr^{-1}) according to the WorldClim database (Hijmans 2005).

According to WorldClim statistics, the mean annual precipitation in the study area is 788.4 mm with a range from 246 to 3,094 mm and a standard deviation of 253 mm (Fig. 1). High erosivity density areas indicate that the precipitation is characterised by high intensity events of short duration (rainstorms). Particularly high erosivity density is observed in Italy, Slovenia and Spain (Fig. 3), where the R-factor is 2-3 times higher than the amount of precipitation. By contrast, the rain distribution is much smoother in northern parts of Europe (northern Germany, France, and the Netherlands), where relatively high amounts of precipitation have a smaller erosive effect (Fig. 3).

The erosivity density has a mean value of 0.92 MJ ha^{-1} h^{-1}, with high variability ranging from 0.1 to 4.47 MJ ha^{-1} h^{-1}. This high variability highlights the fact that rainfall erosivity is not solely dependent on the amount of precipitation. Consequently, it is impossible to predict the R-factor in Europe exclusively based on precipitation levels. Regional patterns can be identified, and although regression functions may be developed, they cannot be extrapolated to other regions with different climatic characteristics.

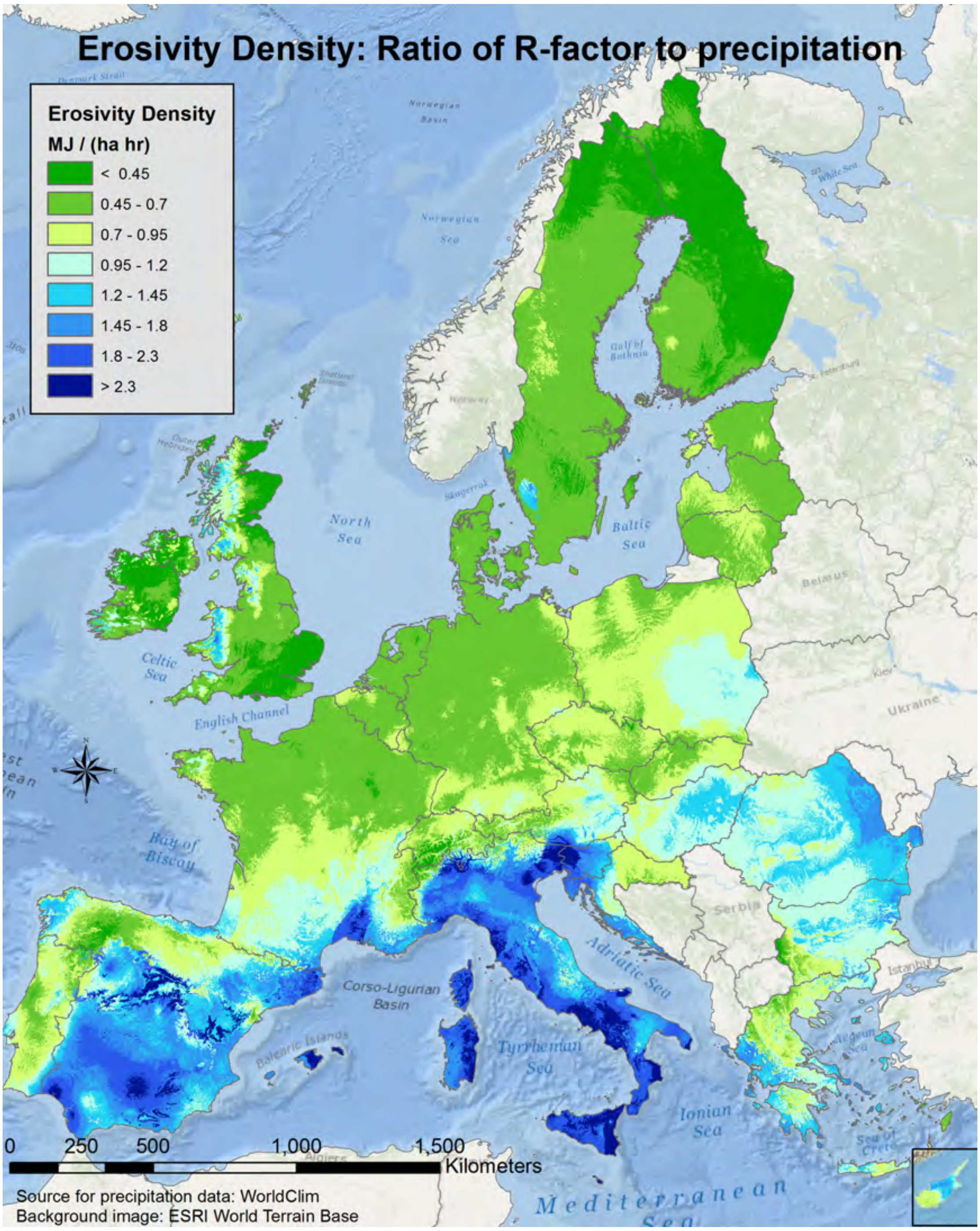

Fig. 3: Erosivity density (rainfall erosivity per mm of precipitation).

The erosivity density may contribute to the identification of risk areas, taking into account the precipitation volume. The precipitation (Fig. 1) and erosivity density (Fig. 3) data sets have been classified in nine combined categories that represent the four quartiles of each parameter. The highest risk is identified in areas where low annual mean precipitation is accompanied by high erosivity. Thus, highly erosive rainfall hits long-period dry soils which usually causes great damage and is connected to a very high flood risk (Diodato et al., 2011). We define this category as the highest overall risk (1st quartile of precipitation volume which is less than 600 mm annually) with values of erosivity density higher than 1.2 MJ ha $^{-1}$ h $^{-1}$(4th quartile). The lowest risk is identified in those areas where, even though annual precipitation levels are high, the precipitation is relatively homogenously distributed and therefore has low erosivity (green in Fig. 4). Dry soils, which account for 9.6% of the study area, are identified in central and southern Spain, Sicily, Sardinia and Puglia (IT), the Greek islands, Cyprus, western Romania and central Hungary (Fig. 4). Most of Ireland, the northern United Kingdom and small parts of Germany were found to have the lowest risk (4th quartile of precipitation which is higher than 890 mm annually), with erosivity density values that are lower than 0.55 (1st quartile). The combination of high levels of rainfall and high erosivity densities (blue areas in Fig. 4) may also be associated with some risk: high rainfall amounts falling on moist or even saturated soils could trigger landslides or wetland erosion.

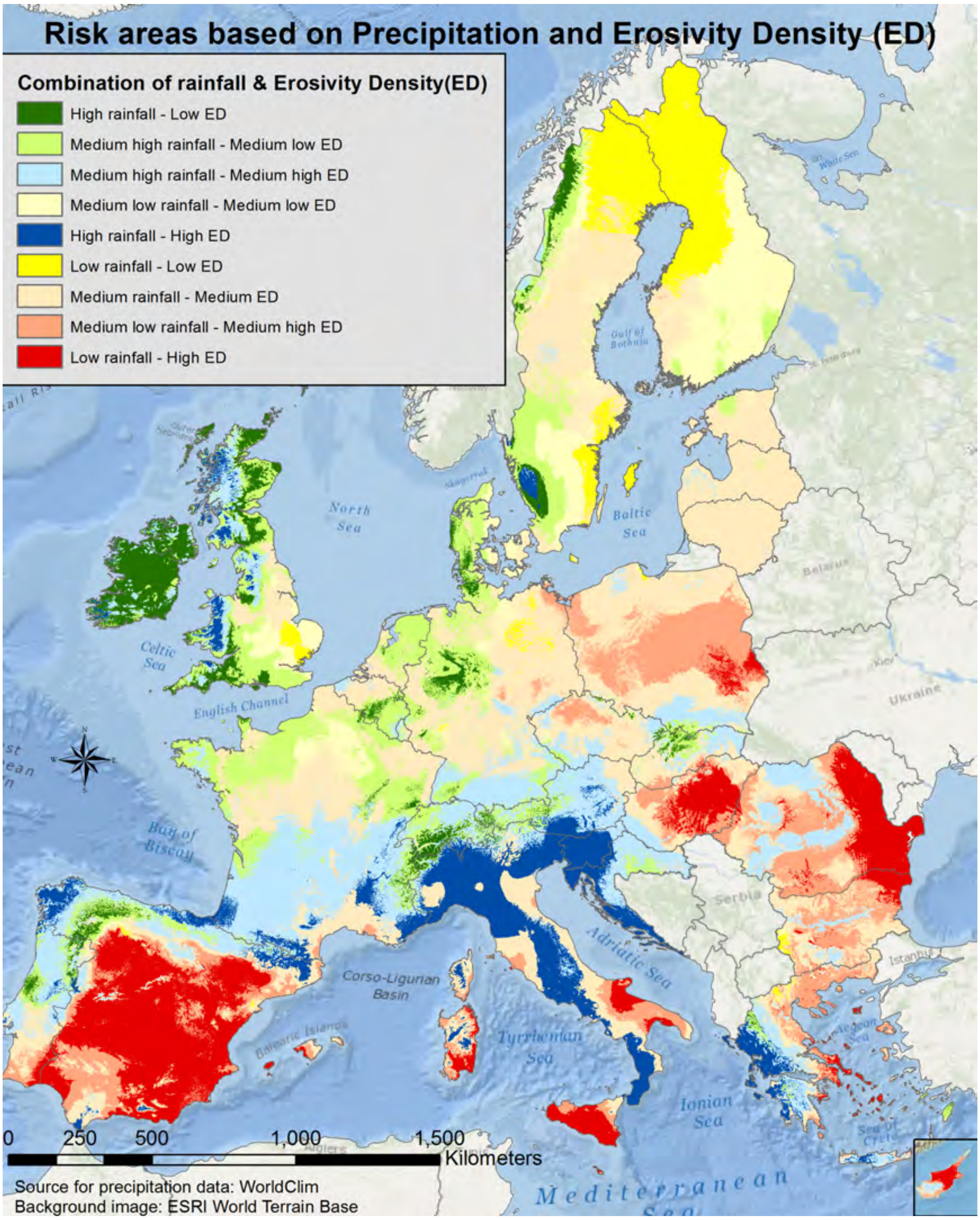

Fig. 4: Risk areas based on precipitation and erosivity density

4.5 *Mapping of rainfall erosivity and related uncertainties*

Catari et al. (2011) identified the following main sources of uncertainty in estimating rainfall erosivity:

(1) measurement errors of precipitation stations,

(2) the efficiency of the equation used (methodology) to derive the kinetic energy of rainfall from its intensity,

(3) the efficiency of regressions obtained between daily precipitation (or even annual precipitation) levels and the R-factor,

(4) the temporal variability of annual rainfall erosive values, and

(5) the spatial variability.

The third point is not addressed here, as the R-factor values were calculated based on high temporal resolution precipitation data. While the calibration of different temporal resolutions could be considered to be a source of uncertainty, this source of uncertainty is minimised by the amount of experimental data and the excellent performance of the regression functions used (Table 4).

With respect to instrumental errors, the participatory approach of involving the major meteorological services in Europe has a high likelihood of yielding high data quality. In addition, the RIST software calculates all the individual erosive events. Possible outliers (single events of >1,000 MJ mm ha^{-1} h^{-1}) were verified with the source data. The RUSLE R-factor equation used to derive rainfall kinetic energy from intensity (see equation 3) is empirical and was derived from long-term experiments (Brown and Foster, 1987). It is applied in the majority of studies worldwide.

In the present study, the uncertainty due to temporal variability is lessened by averaging long-term time-series (average 17.1 years per station). Regarding the spatial uncertainty, the extensive data collection exercise was carried out on a dense network with good geographical coverage. Furthermore, the dataset is representative of all possible elevation and climatic levels covered in the regression analysis.

The application of the Gaussian Process Regression (GPR) spatial interpolation model allowed us to derive not only the R-factor but also the standard error of the estimate. In this study, the map of standard error (Fig. 5) was directly used to estimate the uncertainty of the prediction model. Using the standard error to estimate the dispersion of prediction errors, the highest uncertainty was found to be in north-western Scotland, north-western Sweden and northern Finland due to the relatively small number of precipitation stations and high diversity of environmental features (Fig. 5). The model prediction was also found to have increased uncertainty levels in the southern Alps and the Pyrenees. Medium uncertainty is noticed in Spain, northern Poland, the west of Ireland, North Cyprus and the Aegean islands due to a lack of stations. In general, the model had a good prediction rate with low standard errors in the majority of the study area.

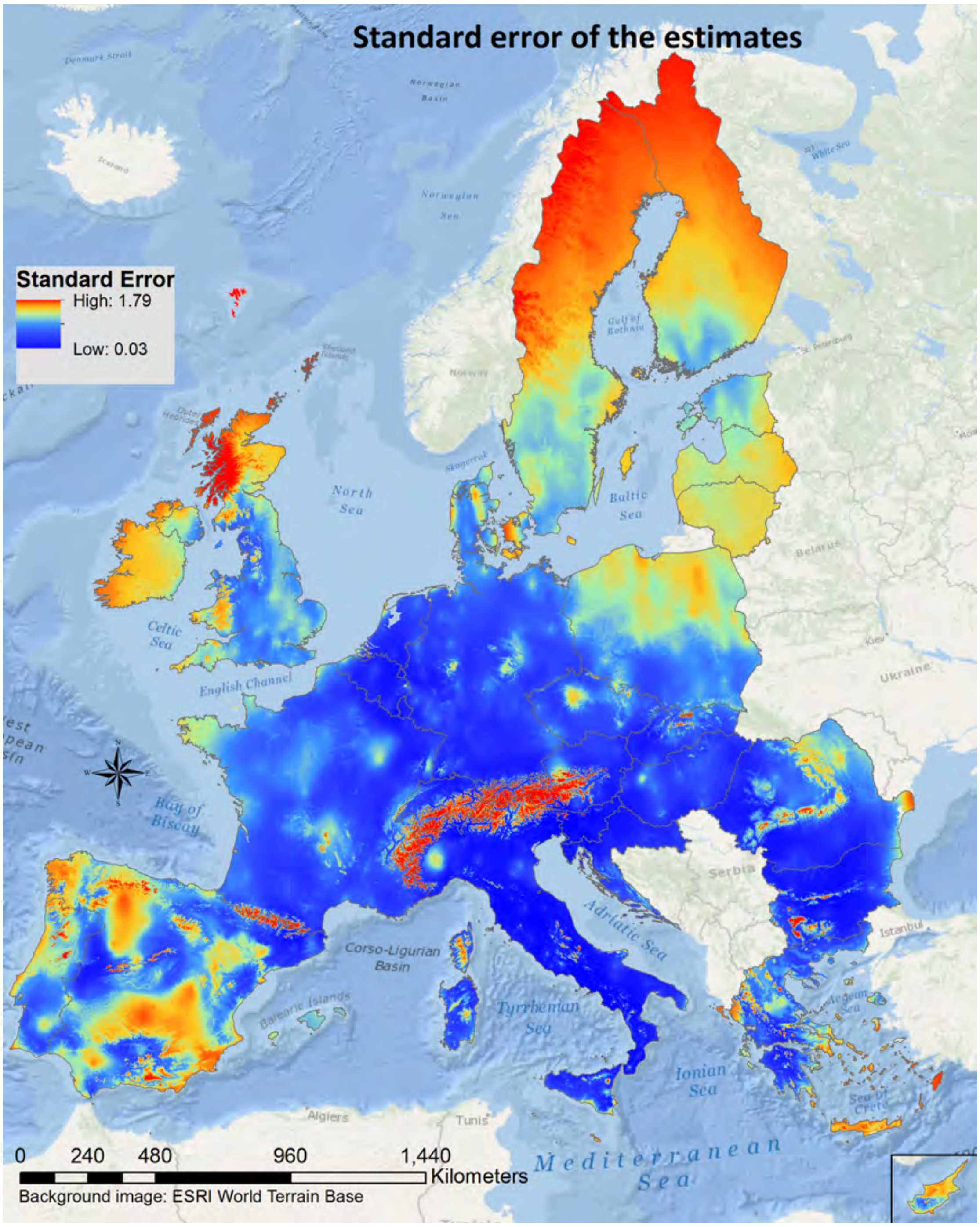

Fig. 5: Uncertainty of the R-factor prediction calculated with the GPR spatial interpolation model

4.6 *Potential applications of R-factor dataset*

Rainfall erosivity (R-factor) in Europe is a key parameter for estimating soil erosion loss and soil erosion risk, but the use of this dataset can be widely extended to other applications. The R-factor dataset can be used by landslide experts as a predictor to improve landslide susceptibility assessment in Europe (Günther et al., 2014). The landslide susceptibility map is the spatial probability of generic landslide occurrence based on topographic and climatic conditions.

Flood risk is of crucial importance for civil protection, due to the large numbers of people affected and the related economic costs. According to Barredo (2007), 40% of the flood-related casualties in Europe during the period 1950–2006 were due to flash floods. Flash floods are associated with short and high-intensity rainfall events, and their likelihood of occurrence increases exponentially when such rainfall events occur on dry and hydrophic soils (see Fig. 4). Flash flood occurrence is generally more intense in Mediterranean countries than in continental areas (Marchi et al., 2010), in line with the rainfall erosivity pattern. Differences in the spatial and temporal scales of the rainfall events (and rainfall erosivity) should be taken into account in the design of flash flood forecasting and warning systems.

Most forest fires in Europe occur in the south - 75% of the total area burnt every year in the European Union is located in Portugal, Spain, the south of France, Italy, Greece and Cyprus (European Commission, 2009). The post-fire effect in areas that susceptible to highly erosive events may accelerate the risk of flash floods and soil loss due to lack of vegetative protection. The rapid damage assessment carried out by the European Forest Fire Information System (EFFIS) (San-Miguel-Ayanz et al., 2012) generates burnt area maps at 250-m spatial resolution. In combination with the R-factor dataset, such maps can help identify areas that are at high risk of soil erosion, in order to decide where critical prevention measures should be swiftly applied so as to avoid further disasters.

In the context of the European Common Agricultural Policy (CAP), sustainable agricultural practices should take into account the soil and water resources and specific local or regional conditions such as climate. As an example, Renschler et al. (1999) showed the high impact of rainfall erosivity in evaluating the vulnerability of different crop rotation scenarios in Andalusia. It has been found that extreme rainfall events and high erosivity can reduce or completely destroy yields of permanent crops (olives, vineyards, fruit trees), which are of particular importance in the Mediterranean (Maracchi et al., 2005). The R-factor dataset should therefore be taken into account in the application of crop-rotation scenarios, agricultural management, and conservation policies.

REDES can also be used to identify the trends and threats of climate change. It was found that the increase of extreme rainfall events between 1960 and 2001 in the Carpathian region (Romania, Slovakia, Czech Republic, Hungary, southern Poland) was coupled with a lower frequency, leading to constant precipitation totals (Bartholy and Pongrácz, 2007). On the other hand, Fiener et al. (2013) and Verstraeten et al. (2006) have reported higher erosivity values in their areas of study (North Rhine Westphalia, Ukkel) after the 1990s. Also, Diodato et al. (2011) have found increased erosive events in low Mediterranean latitudes in the last 50 years. Future research will focus on subset of REDES precipitation stations with high temporal scale (<30 minutes) and long continuous records (>20 years) well distributed in Europe. The objective will be to identify trends of rainfall erosivity in Europe and incorporate them in future climatic scenarios for predicting soil loss.

The R-factor data availability is a key issue for modellers who have no access to high temporal resolution data. With the publication of this study, modellers and in general scientists will be able to download the R-factor dataset from the European Soil Data Centre (ESDAC, 2012). Besides the application for soil erosion modelling, the European rainfall erosivity dataset can be used in different areas such as landslide risk assessment, flood risk forecasting, post-fire conservation measures, agricultural management and design of crop rotation scenarios.

5 Conclusions

The R-factor was successfully mapped at 1-km grid cell resolution for the European Union and Switzerland, applying the Gaussian Process Regression model. The spatial interpolation model showed a very good performance (R^2 = 0.62 for the cross validation, R^2=0.73 for the fitting dataset). The low number of stations and the high diversity of environmental features resulted in high prediction uncertainty in North Scandinavia, West Ireland, Scotland, high Alps and parts of Spain. The high variability of climatic and terrain conditions in an area of more than 4.4 Million km^2 resulted in a broad spectrum of rainfall erosivity, ranging from 51.4 to 6,228.7 MJ mm ha^{-1} h^{-1} yr^{-1}, with a mean value of 722 MJ mm ha^{-1} h^{-1} yr^{-1}. The Mediterranean and Alpine regions were found to have the highest R-factor values, while Scandinavia countries were found to have the lowest.

There is a large amount of data available regarding rainfall intensity. The inclusive participatory data collection approach applied in this study showed that high temporal precipitation data is available free of charge for the European Union. Even though the selected approach was time-consuming and requested laborious pre-processing, it has resulted in Rainfall Erosivity Database at European Scale (REDES), with R-factor estimations for 1,541 stations across Europe.

Due to different temporal resolutions of input data, the proposed conversion to 30-min based R-factor was an important step towards a homogeneous database. Comparisons between different temporal resolutions showed that the use of 60-min precipitation data for the calculation of the R-factor results in a strong underestimation (56%) compared to the use of 30-min data.

Using the large number of R-factor stations available on a large scale (Europe), it was found that R-factor does not solely depend on precipitation.

The erosivity density indicator showed that the R-factor per unit of precipitation is highly variable. Therefore, the choice of regression equations should be made with caution and should be based on local climate studies and high temporal resolution data. The Mediterranean countries and the Alpine areas have a relatively high erosivity density and high rainstorm frequency compared to northern Europe, where the erosivity density is much lower. Furthermore, an assessment of the erosivity density and the risk areas which combine low amounts of precipitation with high erosivity density demonstrates that the Mediterranean regions have the highest risk not only of erosive events, but also of floods and/or water scarcity.

Conflict of interest

The authors confirm and sign that there is no conflict of interests with networks, organisations, and data centres referred in the paper.

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