Long-term trends in rainfall erosivity–analysis of high resolution precipitation time series (1937–2007) from Western Germany

Peter Fiener[a,b,*], Peter Neuhaus[a], Johannes Botschek[c]

[a] Geographisches Institut, Universität zu Köln, Albertus Magnus Platz, 50923 Köln, Germany
[b] Indo-German Centre of Sustainability, Indian Institute of Technology Madras, Chennai 600036, India
[c] INRES Bodenwissenschaften, Universität Bonn, Nußallee 13, 53115 Bonn, Germany

Keywords:
Soil erosion
Erosivity
Climate change
Statistics

A B S T R A C T

It is generally assumed that global warming will lead to a more dynamic atmosphere which potentially leads to more frequent high intensity rainfall events in many regions of the world. In consequence, an increase in local flash floods and soil erosion intensity would be expected. This study used one of the very rare long-term (1937–2007) high resolution (≤5-min) data sets of ten stations in Central Europe to analyze long-term trends in summer rainfall erosivity. Furthermore potential changes in frequency and/or magnitude of individual erosive rainfall events, and shifts in seasonality of rainfall erosivity were investigated. The data were intensively tested for consistency and homogeneity and trends were analyzed using linear regressions as well as Mann–Kendall tests. For the period of 1937–2007, a slight, significant increase in summer erosivity (April–November) of 4.4% per decade was observed. This linear trend is much steeper since the early seventies of the last century (1973–2007: an increase of 21.0% per decade). For both periods, the linear trend was confirmed by positive and significant results of the Mann–Kendall test. The increasing trends in summer erosivity resulted from an increasing frequency of erosive events and an increase in magnitude, especially of the largest events. The proof of changes in seasonality is, for methodological reasons, less clear than the overall change in summer erosivity. However, there is a tendency that the period of erosive events was prolonged during the last decades of the observations with comparably higher erosivity between May and July and in October. Depending on adaption strategies of farmers, this changing temporal pattern in erosivity might lead to more pounced erosion events under row crops in spring, and after the harvest of small grains in late summer and autumn. In general, this shift in seasonality seemed to be more important for an increase in erosion potential than an overall slight increase in annual erosivity.

1. Introduction

It is expected that increasing global warming will have multiple effects on the hydrological cycle (Sivakumar, 2011). In most regions an increase and in some a decrease of precipitation is projected (IPCC, 2007). However, apart from regional differences in rainfall depths, it is generally assumed that global warming will lead to a more dynamic atmosphere which potentially leads to more frequent high intensity rainfall events (Groisman et al., 2004; Nearing et al., 2004). Such potential increase in high intensity rainfall events may lead to a number of (unwanted) side effects, e.g. an increase in local flash floods or muddy floods (Boardman et al., 2003; Verstraeten and Poesen, 2000), and an increase in on-site (Lal, 2001) as well as off-site erosion damages (Bilotta et al., 2007; Haygarth et al., 2006).

To evaluate potential effects of changes in rainfall on erosion, traditionally the annual rainfall erosivity (or R factor) of the Universal Soil Loss Equation (USLE; Wischmeier and Smith, 1960), which combines rainfall intensity and depth, is used. The rainfall erosivity can be understood as a variable representing rainfall energy (derived from rainfall intensity) and surface runoff potential (derived from event-based rainfall depth). Since its introduction in the 1970s in the US, the rainfall erosivity was empirically adapted to other regions (e.g. Larionov, 1993; Schwertmann et al., 1990). Moreover, annual rainfall erosivity calculated as the sum of event-based erosivity, is a valuable proxy variable to evaluate the combined change of high rainfall intensities and depths. Hence, its change is also a generally valuable variable for other hydrological purposes.

Climate data derived from a combination of Global Circulation Models and different statistical or dynamical downscaling methods hardly provide the necessary detailed storm information (time

* Corresponding author at: Geographisches Institut, Universität zu Köln, Albertus Magnus Platz, 50923 Cologne, Germany. Tel.: +49 221 470 7802; fax: +49 221 470 5124.
E-mail address: peter.fiener@uni-koeln.de (P. Fiener).

step $\leq$ 10 min) needed to calculate rainfall erosivity. Therefore, existing evaluations of changes in rainfall erosivity are relatively rare and are based on (i) some long-term, high resolution rainfall data (e.g. Meusburger et al., 2012; Verstraeten et al., 2006) and/or (ii) empirical relations between rainfall erosivity and monthly to yearly rainfall depth (e.g. Diodato and Bellochi, 2009). The latter, however, can only lead to reasonable estimates of changes in erosivity if the assumption of a stable relation between rainfall depth and erosivity holds true under changing boundary conditions.

The main objectives of this study are to use one of the very rare long-term (1937–2007) high resolution ($\leq$5-min) data sets of ten stations in the central Ruhr area in Western Germany for a detailed analysis of: (i) long-term trends in summer rainfall erosivity (here: April–November), (ii) potential changes in frequency and/or magnitude of individual erosive rainfall events, and (iii) shifts in seasonality of rainfall erosivity.

2. Materials and methods

2.1. Test area and data

The study area is located in the central Ruhr region in Western Germany ranging from the Lower Rhine Basin in its eastern part to the Westphalian Plain in its western part. In its South, it is bordered by the hills of the Rhenish Massif. The area is relatively flat with altitudes increasing from approximately 30 m a.s.l. in the West to 150 m a.s.l. in the East. In this densely populated and traditionally highly industrialized area, the local water authorities (Emschergenossenschaft and Lippeverband) have a special interest in the effective management of a large number of mid-sized dams along the rivers Ruhr, Emscher and Lippe. As a consequence of this, an extraordinary set of long-term rainfall data exists, covering 71 years (1937–2007) of high resolution ($\leq$5 min) measurements at ten locations (Fig. 1, Table 1). All measuring stations are located within a radius of approximately 60 km (Fig. 1). The mean annual (1937–2007) rainfall over all ten measuring stations was 773 mm with a relatively minor spatial variability (coefficient of variation 4%) and only slight variations of monthly rainfall depths.

The rain gauges are mounted at a height of 1.0 m with a measuring area of 200 cm^2. All measuring locations and all equipment follow the standards of the German weather service, who also uses this data in analysis of recurrence intervals of high intensity rainfall (Bartels et al., 1997). Till the beginning of the 1990s, standard rain gauges registering one week of data on paper were used. These analog data were later digitized and thus resulted in a non-equidistant time series with time steps between 30 s and 5 min in case of heavy rainfall. Successively, these systems were replaced by tipping-bucket rain gauges (mostly between 1991 and 1992, one in 2001), which were again replaced between 2005 and 2007 by weighing precipitation gauges. The tipping-bucket gauges produced triggered data, while the weighing gauges record every minute. The location of four stations was slightly moved since 1937 (Table 1). The precipitation data from all ten stations are included in a larger data-base of the State Office for Nature, Environment and Consumer Protection of the Federal State of North-Rhine Westphalia (LANUV-NRW), containing up to 200 rainfall stations with mostly much shorter time series.

2.2. Data analysis and processing

The LANUV-NRW data-base stores all data as non-equidistant time series of rainfall intensities. Data were tested for consistency before taking them into the data-base. This, amongst others, is documented in the reports of the ExUS project in 2010, focusing on extreme rainfall events (Anonymous, 2010).

Apart from traditional consistency tests focusing on equipment malfunctions, outliers in rainfall data etc., two additional plausibility tests were carried out which are especially important if focusing on rainfall erosivity. Calculated rainfall erosivity is sensitive to event duration and partly interrelated to a correctly determined maximum 30-min rainfall intensity $I_{\max 30}$ (Eqs. (1) and (2)). Hence, we tested whether the data show a constant rainfall intensity smaller than 1 mm h^{-1} over more than 6 h, which can be assumed as a calculation artifact or a result of instrument malfunction. Moreover, it was evaluated if $I_{\max 30} < 10$ mm h^{-1} while event precipitation was >40 mm. In both cases events were individually examined. In the first case, events were subdivided or excluded from further calculations. In the second case, events were only included if the somewhat counterintuitive behavior of large rainfall depths without substantial rainfall intensity, which could result from an incorrect subdivision of events, was clearly supported by the data.

After tests for plausibility, the non-equidistant time series were re-sampled to 5-min intervals. Based on these re-sampled data, event-borders were determined following the standard used in Germany (Deutsches Institut für Normung, 2005; Schwertmann et al., 1990), according to which events are subdivided through rain gaps >6 h. Event rainfall erosivity (consisting of n time-steps) was calculated following Eqs. (1) and (2) (Schwertmann et al., 1990).

$$R_E = \begin{cases} \sum_{i=1}^{n} R_i = \sum_{i=1}^{n} E_i \times I_{\max 30} & P_E \geq 10\text{ mm or } I_{\max 30} \geq 10 \text{ mm h}^{-1} \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

with

$$E_i = \begin{cases} 0 & I_i < 0.05 \\ \{11.89 + (8.73 \times \log I_i)\} \times P_i \times 10^{-3} & 0.05 \leq I_i \leq 76.2 \\ 28.33 \times P_i \times 10^{-3} & I_i > 76.2 \end{cases} \quad (2)$$

where R_E is the erosivity of one event [kJ m^{-2} mm h^{-1}], R_i is the erosivity in time step i [kJ m^{-2} mm h^{-1}], E_i is kinetic energy during time step i [kJ m^{-2}], I_i is rainfall intensity in time step i [mm h^{-1}], P_i is rainfall depth in time step i [mm], P_E is rain depth during event, $I_{\max 30}$ is maximum 30-min rain intensity during event.

Eqs. (1) and (2) are empirical adoptions of the rainfall erosivity equations, as used in the Universal Soil Loss Equation (Wischmeier, 1959), to German conditions (Schwertmann et al., 1990). The German version of rainfall erosivity was chosen in this study, as the results should be utilizable within German authorities and organizations, as well as for further erosion studies, where monthly or annual sums of erosivity are needed. Albeit slightly different from other erosivity calculations, the general trends in changes in rainfall amounts and intensities should be well represented.

The 5-min rainfall erosivity (and precipitation) was aggregated to events as well as daily, monthly and yearly sums. Based on the daily sums, gap-filling was performed on all time series. At first, the time series of all stations were compared to identify the strongest correlation between yearly rainfall erosivity at different stations. After identifying an appropriate partner for each station, we calculated the slope of regression for the yearly rainfall. The gaps where then filled by using these regressions on the rainfall data of the partner station. When mean annual rainfall erosivity is calculated for any location from long-term data, effects of individual large events with recurrence intervals larger than the observation period are typically filtered, as they are not representative (Schwertmann et al., 1990). When analyzing trends in rainfall erosivity based on long-term data, individual extreme events may also dominate the results, even if these extremes are not representative for the time period being studied. In case of our study, we excluded any individual erosive event with a recurrence interval $\geq$100 years. Assuming that the calculated maximum yearly event rainfall erosivity follows a Gumbel distribution (ATV-DVWK, 1985; Coles, 2001), the

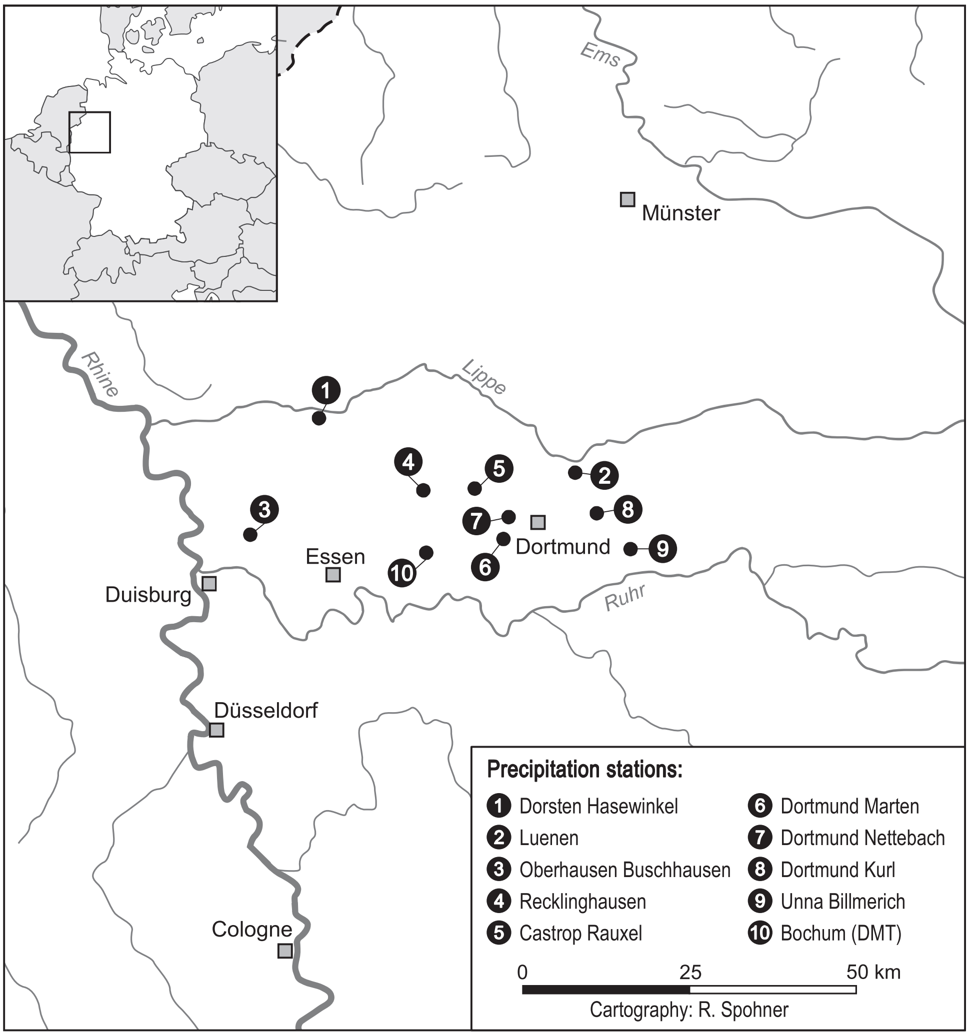

Fig. 1. Location of the precipitation stations in western Germany.

recurrence intervals were determined using a rank approach commonly used to determine recurrence intervals of rainfall events (ATV-DVWK, 1985). Based on this approach, on average, 2.2 events per measuring station were discarded (1–4 events with an erosivity between 70.9 and 293 kJ m^{-2} mm h^{-1}). It is somewhat surprising that, on average, 2.2 events were discarded from the 71 year time series which indicates that the data are not perfectly Gumbel distributed. However, except for one very large event in 1968, which was recorded at five stations in the western part of the test site (Stations: LUE, DMA, DNE, DKU, and UNN), the discarded events only slightly affect the overall yearly erosivity. After gap-filling and exclusion of extreme events, the corrected raw data were again aggregated to events, as well as daily, monthly and yearly sums (Fig. 2).

In a next step, data of cumulative rainfall erosivity and cumulative precipitation (measured between April and November at the ten stations) were tested for homogeneity. The restriction to these 'summer' months follows the major goal of this study to evaluate long-term trends in erosivity which should not be affected by shifts from snow to rainfall due to increasing temperatures during the 71-year observation period (this time span is subsequently referred to a summer precipitation and erosivity, respectively).

Table 1
Location, altitude above sea level, annual mean precipitation of all measuring stations, and indication of changes in the location of the stations during the observation period (1937–2007).

Map ID	Station name	Abbreviation	Altitude a.s.l. (m)	Annual mean precipitation (1937–2007)	Minor change of station location in
1	Dorsten Hasenwinkel	DOR	35	787	1991
2	Luenen	LUE	52	737	2002
3	Oberhausen Buschhausen	OBE	33	748	–
4	Recklinghausen	REC	54	805	–
5	Castrop Rauxel	CAS	56	794	–
6	Dortmund Marten	DMA	81	783	2004
7	Dortmund Nettebach	DNE	70	779	–
8	Dortmund Kurl	DKU	66	747	2006
9	Unna Billmerich	UNN	123	735	–
10	Bochum (DMT)	BOC	77	813	–

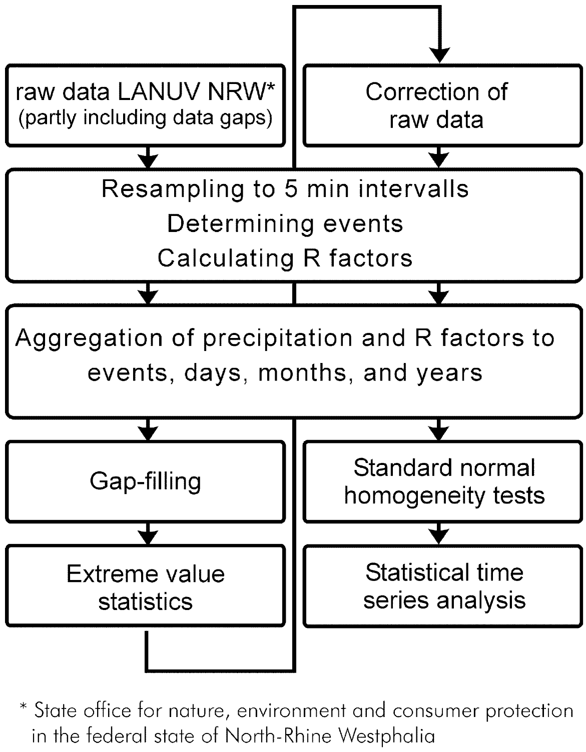

Fig. 2. Data processing scheme from raw data to statistical time series analysis.

Moreover, the winter months are of less importance, as rainfall erosivity in Germany is much more dominant during summer months (e.g. Fiener et al., 2011). To test homogeneity, the standard normal homogeneity test (SNHT) was applied (Alexanderson, 1986). As no isochronous change in measuring equipment or any other isochronous change in the setting of the different stations is known, the SNHT, which is based on a comparison of the different stations, should allow detecting sharp shifts in the data and therefore can be used to identify inhomogeneities. The SNHT was originally developed to analyze precipitation time series (Alexanderson, 1986) and is typically used for annual or sometimes monthly data (Costa and Soares, 2009). As with any other homogeneity tests, shorter time steps are much more difficult to analyze, since a shift in the mean of the series is basically a signal/noise problem, e.g. daily values are in most cases too noisy for a successful test application (Guijarro, 2011). Hence, we restricted our homogeneity analysis to the summer sums. It is worth noting here that this might be not fully satisfactory as cumulative rainfall erosivity might be dominated by individual extremes which might be especially sensitive to changes in measuring equipment etc. Before applying SNHT, both rainfall and rainfall erosivity of the different stations were tested for normality. Summer rainfall erosivities of individual stations were slightly skewed and hence all rainfall erosivity data were root transformed before SNHT application. Data were normalized using a ratio to the mean values. Critical SNHT threshold values of 8.8 were taken from Khaliq and Quarda (2007), representing a critical level of 95% in case of the sample size of 71 years. The software package 'climatol' (Guijarro, 2011) as implemented in the statistical software R (R Development Core Team, 2009) allowed the application of SNHT and the analysis of its results. If any inhomogeneity was detected, the affected data set was discarded from the following trend analysis, as any correction of data would have been only possible for the overall summer erosivity, while partly also monthly and daily values are used in the following analysis.

2.3. *Trend analysis in summer rainfall and rainfall erosivity*

To analyze potential trends in summer rainfall and rainfall erosivity, we calculated the mean summer values from all stations with homogeneous data and applied the following approaches: (i) A local polynomial regression fitting (LOESS; Cleveland et al., 1993); (ii) a simple linear regression analysis; (iii) a non-parametric Mann–Kendall test (Kendall, 1975; Mann, 1945); and (iv) a test for autocorrelation as the basis for further autocorrelation-based approaches (e.g. autoregressive–moving-average [ARMA] or autoregressive-integrated-moving-average [ARIMA], (Brockwell and Davis, 1996)).

As the first two tests require normality, we tested the mean of all stations for normality using Q-Q-plots. The LOESS method is used to smooth the data in order to visually identify their long-term behavior. At each point of the data-set, a 2nd order polynomial function was fitted to a subset of the data near the point to be evaluated, while giving more weight to the nearer points. An α of 0.5 (comparable in effect to an 11 year symmetric moving average) was used for this smoothening procedure. Its advantage compared to using moving averages is that it is less sensitive to yearly values and smoothening can be done from the first to the last year of observation.

As a first trend analysis, a linear regression approach was applied. The explanatory power of these regressions is given as coefficient of determination (R^2). Significance levels ($p \leq 0.05$, $p \leq 0.01$, and $p \leq 0.001$, respectively) were calculated applying two-sided Student's t-tests. Apart from calculating the linear regression over the total observation period of 71 years, a second, more recent, trend period of ca. 30 years was identified. The length of the second period was determined iteratively by moving the start year back in time till a best fit (minimal mean squared error) of the regression was reached.

To further prove the validity of the linear trends, a Bootstrapping approach was also performed. The Bootstrapping approach (e.g. Crawley, 2009) is a non-parametric method which allows one to derive confidence limits independent of the distribution function of the underlying data. From all available yearly summer erosivity measurements, we took 1000 random samples containing 71 yearly values each. As this was done with replacement of samples, we ended up with 1000 new time-series, in which the same values could occur more than once. Based on this new, synthetic data set, slopes of regressions were calculated again, and 95% confidence intervals were derived from the normally distributed slopes. This approach indicates how far the trends are affected by one or a few years of measurements.

As especially the yearly summer rainfall erosivity is not perfectly normally distributed, we also applied the non-parametric Mann–Kendall test (Kendall, 1975; Mann, 1945), which should strengthen the conclusion drawn from the linear regression approach. The Mann–Kendall test is a rank–correlation approach widely used in hydro–meteorological studies (e.g. Brisan et al., 2005) for determining the extent to which the data show a monotonic trend. The strength in monotonic increase or decrease in the data of a time series is given as Mann–Kendall's τ (1: monotone increasing trend; −1: monotone decreasing trend). Moreover, a significance level for each τ can be calculated.

When focusing on trends in time series, it is often intended to not only analyze the data, but also to use existing data as a basis for a forecast. Any forecasting methodology (e.g. ARMA, ARIMA) is, to a certain extent, based on the assumption that the existing data are autocorrelated in time. Hence, an autocorrelation analysis was performed. Due to the large interannual variation in summer rainfall, and especially rainfall erosivity, no significant ($p < 0.05$) autocorrelation could be detected, and hence no further autocorrelation based models were used.

2.4. Analysis of the frequency-magnitude of erosive events

Summer erosivity is a suitable indicator to detect trends in the overall susceptibility of a region against soil erosion. However, as soil erosion is a highly episodic process (e.g. Fiener and Auerswald, 2007), it is also important to understand if this overall change in rainfall erosivity results from changes in event frequency and/or magnitude. To analyze a potential change in frequency/magnitude, all events (1937–2007) of the different stations were sorted with respect to their event-erosivity. Five classes with equal cumulative erosivity (20% of total cumulative erosivity) were established. Based on this classification, the potential change in number of events and cumulative erosivity per class was analyzed.

2.5. Analysis of changes in seasonality

To analyze changes in seasonality of rainfall erosivity, it is necessary to focus on at least monthly data. However, due to the large variability in, e.g. monthly or even daily erosivity, trends in seasonality can be hardly analyzed applying approaches as described above. Therefore, we compare different phases of the period 1937–2007. After a first analysis of changes in yearly summer erosivity, there is some indication that the 71 years of observation might be subdivided into four phases. To determine these phases, the following approach was applied: (i) four phases of at least 10 years each were assumed, (ii) iteratively, all possible permutations of different phases were calculated, (iii) for all possible phases, an analysis of variance was performed, and (iv) the most appropriate phases were determined by choosing the model with the minimum variance over the whole observation period. To elucidate potential changes in seasonality, we compared the last phase before 2007 with the total observation period between 1937 and 2007.

2.6. Statistics

All statistical analysis was performed using the statistical software R (R Development Core Team, 2009). A number of extension packages available via the R community webpage were also used. Most important are the following packages: 'climatol' for SNHT (Guijarro, 2011), 'stats' for LOESS (R Development Core Team, 2009), 'boot' for the bootstrapping approach (Canty and Ripley, 2012), and 'Kendall' for the Mann–Kendall test (McLeod, 2011).

3. Results

Following the data processing (Fig. 2) and the homogeneity tests, nine of the existing ten stations were chosen for trend analysis. SNHT indicates that summer rainfall at station Bochum DMT (Fig. 1, Table 1) is not homogeneous with a shift in the data set detected for the year 1975. This shift does not correspond with information regarding changes in measuring equipment and therefore might result from unknown changes in station set-up. Although no inhomogeneity was determined for summer rainfall erosivity, the station Bochum DMT was excluded from the data set. Hence, nine stations with gap-filled data for the period 1937–2007, with a total number of 9835 erosive events during summer months (April–November) were included in the further analysis.

In general, summer erosivity of the different stations is highly variable in time (Coefficient of variation [CV] 0.45–0.61). This variability can be slightly reduced by calculating the mean of all nine stations (CV 0.37) (Fig. 3). However, even if using the mean of nine stations, it is obvious that a long-term mean erosivity can hardly be used to estimate the erosivity during an individual year.

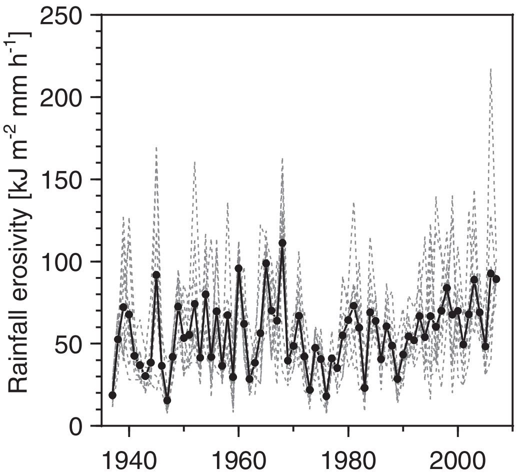

Fig. 3. Long-term summer rainfall erosivity (1937–2007, April–November) at nine measuring stations (see Fig. 1); continuous line with black circles indicate mean of all stations; gray dotted lines represent values of individual stations.

3.1. Trend analysis in summer rainfall and erosivity

Calculating a linear regression over the total observation period (1937–2007) for all nine stations results in a significant ($p < 0.05$) increase in rainfall erosivity. However, this trend is small, with a relative increase of 0.44% (based on the mean) in summer erosivity per year (Fig. 4A). The overall positive trend is also indicated in the 95% confidence interval resulting from the Bootstrapping analysis (Fig. 4A). The positive trend in summer rainfall erosivity is also proven according to the Mann–Kendall test as indicated by a τ of 0.18 ($p = 0.025$).

Determining the most recent period with a clear trend while iteratively increasing backward the observation period was used to calculate the linear regression. This indicates that there was a much more pronounced positive trend in rainfall erosivity between 1973 and 2007 (2.1% increase per year; Fig. 4B). For this time period, the highly significant trend ($p < 0.001$) is also underlined

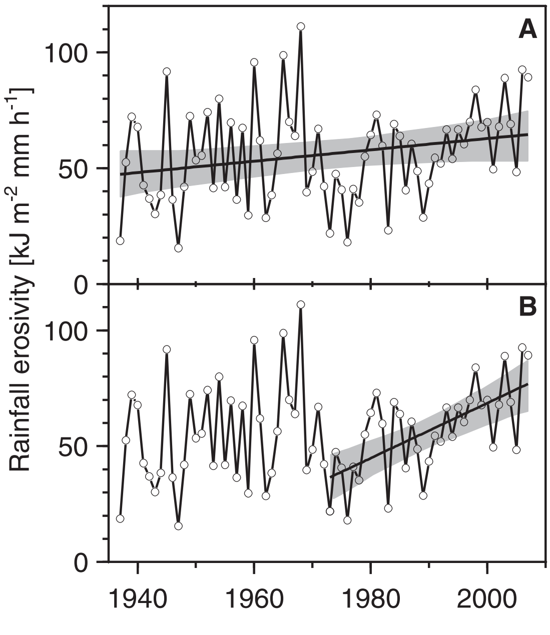

Fig. 4. Trends in summer rainfall erosivity between 1937 and 2007 (A), and 1973 and 2007 (B), gray shaded area indicates the 95% confidence intervals based on the Bootstrapping approach utilized to calculate regressions ($n = 1000$).

Table 2
Slopes of regression, coefficients of determination R^2, and significance levels resulting from regression analyses using all erosive events, all events exclusively the extreme event in 1968, and events restricted to recurrence intervals $\leq$ 100 years.

	All events	All events w/o 1968 extreme event	Events w. recurrence intervals $\leq$ 100 years
1937–2007			
Slope of regression	0.24	0.25	0.25
R^2	0.03	0.05	0.06
Significance level	0.15	0.06	0.04
1973–2007			
Slope of regression		1.19	1.06
R^2		0.28	0.42
Significance level		0.001	0.00001

by the results of the Bootstrapping (Fig. 4B) approach, indicating that even if single or multiple years are taken out or are doubled, all resulting slopes of regressions are significantly positive. Again, these results are proven by the non-parametric Mann–Kendall test (τ = 0.47, p < 0.001).

Slopes of regressions in both periods are not sensitive to the removal of events with recurrence times >100 year or the removal of the catastrophic event in the western part of the test site in 1968 (Table 2). Including the 1968-event and/or all events with a recurrence time >100 years increases data variability. Hence, in case of the whole observation period, this leads to an insignificant slope of regression (Table 2), while no such effect can be recognized for the period 1973–2007. Apart from the catastrophic 1968-event, with recurrence times above 300 years at all stations (half of the stations showed a recurrence time >1000 years), which is not representative for an observation period of 71 years, the other extreme events might slightly shift the distribution from low magnitude/high frequency to high magnitude/low frequency events. However, for consistency reasons and comparability with other studies we still exclude all events with a recurrence time >100 years from the magnitude/frequency analysis, which therefore can be interpreted as a conservative estimate of the potential importance of large magnitude/low frequency events.

In general, it is obvious from the data and the two phases described above (1937–2007 and 1973–2007, respectively) that any kind of trend analysis is sensitive to the chosen observation period. However, calculating regressions for moving 30 year periods shows some interesting behavior of the data (Fig. 5). The most pronounced and significant trends can only be found during the phase of strongest increase in erosivity with starting years of the 30 years regression periods between 1968 and 1977, respectively. This at least indicates that, apart from the overall huge variability in data, the trends over the last decades seemed to be more stable (Fig. 5A–C) while the variability of data declines (Fig. 5D).

3.2. Changes in frequency and magnitude of erosive events

During the observation period (1937–2007), a mean of 165.1 summer rainfall events (Apr.–Nov.) was measured per station, whereas approximately 15.4 (9.3%) of these events were classified as erosive events (Eqs. (1) and (2)). The maximum event erosivity of the stations ranged between 49.5 kJ m^{-2} mm h^{-1} and 72.5 kJ m^{-2} mm h^{-1} (after excluding events with a recurrence interval >100 years). The median of all events measured at all stations was approximately 1.9 kJ m^{-2} mm h^{-1}. No significant trend in the overall number of rainfall events could be determined for both observation periods (1937–2007 and 1973–2007, respectively), while the number of erosive events increased significantly (p = 0.019 and p = 0.023) with 0.33% and 0.90% per year (April–November), respectively. These relative trends in the number of yearly erosive events are by a factor of 1.51 (1937–2007) and 2.44 (1973–2007) smaller than the trends in mean erosivity (Fig. 4).

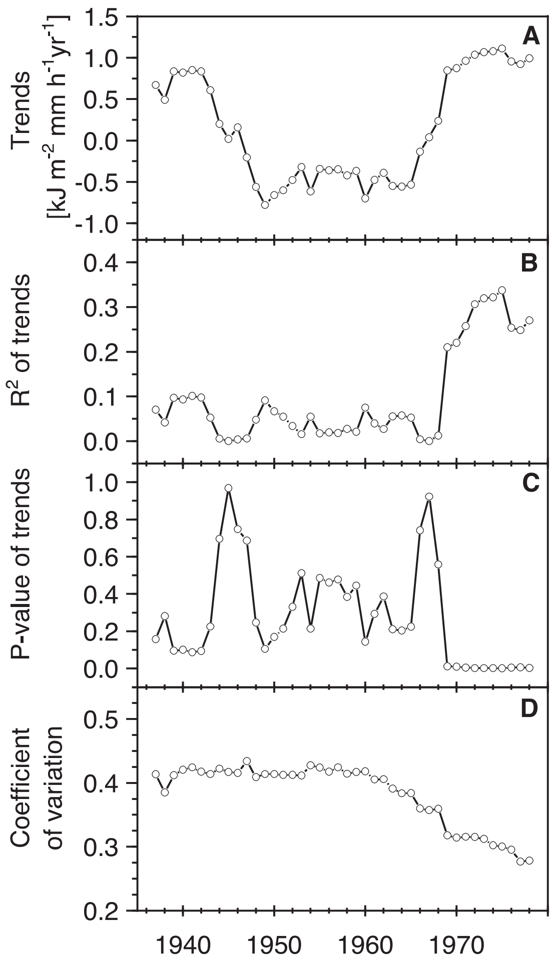

Fig. 5. Regressions calculated from a moving window of 30 years starting in 1937 using the mean summer erosivity of all nine stations; (A) trend as slope of regressions, (B) coefficient of determination (R^2) of the trend, (C) significance level P of the calculated trend, (D) coefficient of variation within each 30 years time window.

Classifying the events into five classes with an equal mean erosivity (Table 3), and analyzing the change in erosivity within these classes indicates that the increase in overall erosivity is mostly a result of an increase in erosivity of large events (Fig. 6). This increase in relative erosivity of the largest events (class V) corresponds to a decrease in relative erosivity of the smallest events (class I). However, these opposing trends are only significant for the period 1973–2007 (Fig. 6). Overall, the results indicate that the increase in erosivity is a result of an increasing frequency and magnitude of erosive events.

Table 3
Classified erosivity-events; the cumulative erosivity of all events per class equals 20% of erosivity measured between 1937 and 2007.

Class	Erosivity interval (kJ mm m^{-2} h^{-1})	No. of events per class	Proportion of cumulative erosivity (1937–2007) (%)
I	0.1–2.3	5811	20
II	>2.3–4.7	2194	20
II	>4.7–9.3	1085	20
IV	>9.3–21.1	526	20
V	>21.1–72.5	219	20

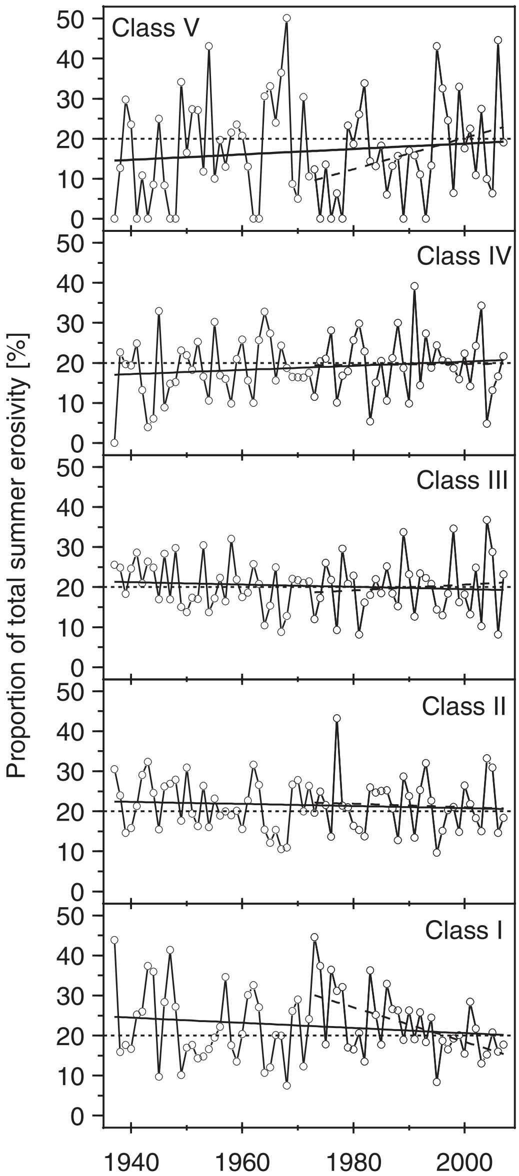

Fig. 6. Relative proportion of different event size classes (class I–V see Table 3) compared to overall summer erosivity; the black lines represent the linear regression over the total observation period (1937–2007), while the slashed line represents the period 1973 to 2007; the dotted line is the mean proportion of 20% of each class; only the decrease in class I and the increase in class V over the period 1973–2007 are significant (R^2 = 0.30 and 0.12; p < 0.001 and p < 0.05, resp.).

3.3. *Changes in seasonality of erosivity*

The iterative determination of different phases of erosivity results in four phases with low, high, low, and high erosivity (Fig. 7). In the following, we compare the seasonality of rainfall and rainfall erosivity of the whole observation period with the last phase (1993–2007). In both phases, as expected, the seasonality in rainfall is much less pronounced when compared to the seasonality in rainfall erosivity. The first is more or less equally distributed over the year while the second has a pronounced peak in July. Comparing monthly rainfall between the two phases indicates a significant (p < 0.001) increase in mean monthly rainfall of 14.5, 18.4, and 22.5% in May, September and October, respectively (Fig. 8A). Overall, the mean rainfall during the summer months (Apr.–Nov.) in the phase 1993–2007 was 6.9% above the mean in the whole observation period. For mean monthly erosivity, the most distinct relative

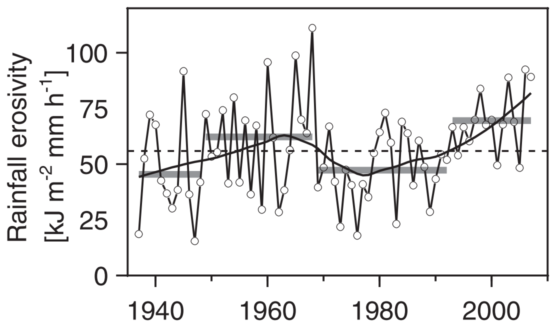

Fig. 7. Optimized four phases of high and low summer erosivity (1937–1948, 1949–1968, 1969–1992, and 1993–2007, respectively) while minimizing variance of all phases (coefficient of variation of all phases R^2 = 0.22, p < 0.001), mean of phases indicated by gray line; LOESS smoothing of data black line; dotted line represents mean summer erosivity between 1937 and 2007.

increase could be found for May, June, July and October with values ranging from 24 to 70% (1.6–5.8 kJ m^{-2} mm h^{-1} month^{-1}; Fig. 8B). However, due to the larger variability of monthly erosivity, this increase was not highly significant for all months (p < 0.5 for May and June, p < 0.001 for July and October). Apart from the general increase in summer erosivity, which is most pronounced in spring and autumn, it is worth noting that the increase in June and especially in July (representing 10% of the overall 24% difference between 1993–2007 and 1937–2007, respectively) does not correspond to an increase in mean monthly rainfall, which is an indication for rarer but heavier rainfall events.

4. Discussion

In general, our results indicate a slight but significant increase in summer rainfall erosivity for the overall observation period (1937–2007) with a most pronounced increase during the last 35 years of observation (Figs. 4 and 5). Due to the comprehensive data pre-processing and the multitude of statistical tests, we can be quite confident in these results. These trends are of most importance for erosion studies but they are also relevant for other hydrological studies dealing with extreme (local) events as rainfall erosivity is a

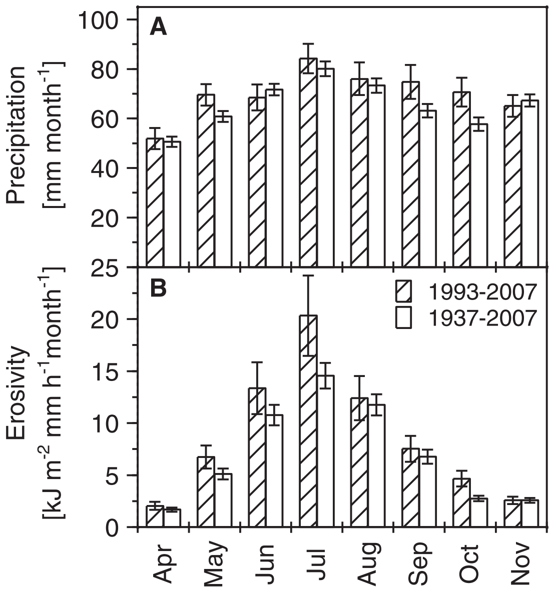

Fig. 8. Seasonality of mean monthly rainfall (A) and mean monthly rainfall erosivity and (B) for the two phases (1993–2007 and 1937–2007, resp.); error bars indicate 95%-confident interval of the monthly means.

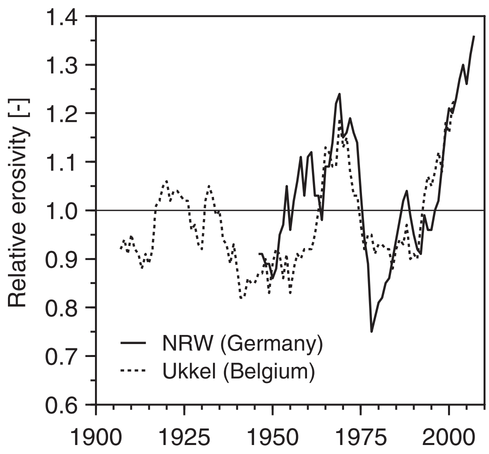

Fig. 9. Relative erosivity standardized to the mean of 1960–1991, data from Ukkel in Belgium taken from Verstraeten et al. (2006); compared to the data from North-Rhine Westphalia the data from Belgium are calculated from annual erosivity, both time series are smoothened by an 10-year moving average.

nice proxy variable cumulating rainfall intensity and rainfall depth of individual events.

To our knowledge, the only study using a comparable data set from Central Europe to derive rainfall erosivities (Station Ukkel near Brussels, 10-min rainfall data from 1989 to 2002) was carried out by Verstraeten et al. (2006). Most other recent studies used shorter time periods (e.g. Meusburger et al., 2012) or were focused on long-term evaluations of Mediterranean areas (e.g. D'Asaro et al., 2007; Diodato and Bellochi, 2009). The data of Verstraeten et al. (2006) strengthen our findings (Fig. 9) even though these authors concluded that there is no significant trend over their entire observation period of 105 years (1889–2002). However, both studies underline the increasing erosivity during the end of the last and the beginning of the present 21st century which was more pronounced in our more recent data set. Hence, based on both erosivity studies and a recent study focusing on high-intensity rainstorm events (Mueller and Pfister, 2011) in the surroundings of our test site, it can be assumed that the determined trends are somewhat representative for the last 70 years in Central Europe.

However, the overall trends in summer erosivity are relatively small (31% increase between 1937 and 2007), and are somewhat sensitive to the observation period. Therefore, it might be argued that these are not very relevant especially if an increase in rainfall erosivity is linearly connected to overall mean erosion as indicated by the Universal Soil Loss Equation (USLE; Wischmeier and Smith, 1960). Before drawing this conclusion, three additional aspects should be taken into account:

(i) The positive trend in summer erosivity was steeper and, to a higher degree, more significant during the last decades, a point also proven by the findings of a change point in the Ukkel data set with higher erosivity from 1991 onwards (Verstraeten et al., 2006). Nevertheless, it must be noted that no extrapolation of this trend was possible based on our data, as the annual summer erosivity values were not autocorrelated.

(ii) The overall increase in summer erosivity is, to a large extent, based on an increasing magnitude of individual large events (Fig. 6) which would be even more pronounced if we would not restrict our data analysis to erosive events with recurrence intervals $\leq$100 years. This finding is in accordance with the general assumption of a more dynamic atmosphere in case of increasing air temperatures following climate change (e.g. Sivakumar, 2011). The increases in individual heavy events in our test region was also underlined through a rain event analysis by Mueller and Pfister (2011). As soil erosion is often dominated by individual large events (e.g. Fiener and Auerswald, 2007), an increase in extreme rainfall events might result in a non-linear increase in total erosion (Nearing et al., 2004). Hence, it is worth noting here that USLE-based models using long-term mean annual erosivity as input will partly fail in addressing changes in erosion due to changes in mean annual erosivity.

(iii) The data indicate an increase in erosivity especially in May–July and October (Fig. 8). Even if this must be treated carefully, as the results are sensitive to the phases used for the comparison, and, moreover, monthly erosivity values could not be properly tested for homogeneity (a general problem in homogeneity analysis in case of less aggregated time series, e.g. (Guijarro, 2011)), such change in seasonality might be generally more important than an overall change in annual erosivity. In Central Europe, an increase in erosivity in late spring will be especially problematic in the case of row crops, while a prolonged phase of high erosivity events in late summer to early autumn will increase erosion under small grain cultivation if no proper soil cover is maintained after harvest.

5. Conclusion

A 71-year data set of high resolution (<5-min) rainfall data from nine stations in the central Ruhr area in Western Germany was used to analyze (i) trends in summer (April–November) erosivity, (ii) changes in the magnitude and frequency of individual erosive events, and (iii) changes in the seasonality of long-term mean daily erosivity.

For the period from 1937 to 2007, we observed a slight but significant increase in summer erosivity of 4.4% (in relation to the mean value) per decade. This trend was much steeper since the early seventies of the last century (1973–2007: increase of 21.0% per decade). Amongst others, these positive linear trends were confirmed by positive and significant results of a Mann–Kendall test. However, due to the high variability of summer erosivity, the data were not autocorrelated and hence no reasonable extrapolations of the results are possible.

The increasing trends in summer erosivity result from an increasing frequency of erosive events (while the overall number of rainfall events did not change significantly), and an increase in magnitude of erosive events, especially of the largest events. Therefore, it can be concluded that the slight increase in summer erosivity might even underestimate the overall increase of erosion potential.

The proof of changes in seasonality is, for methodological reasons, less clear than the overall change in summer erosivity. However, there is a tendency that the period of erosive events during the year was prolonged in the last decades of the observations with comparably higher erosivity between May and July and in October. Depending on adaption strategies of farmers, this changing temporal pattern in erosivity might lead to more pronounced erosion events under row crops in spring, and after the harvest of small grains in late summer and autumn. In general, this shift in seasonality and the potential adaption and/or overall change in arable management seem to be more important than an overall slight increase in annual erosivity.

Acknowledgements

This research was carried out within the framework of the project "Effects of global climate change on the spatio-temporal variability in rainfall erosivity in North-Rhine-Westphalia, Germany" funded by the "Innovationsfonds – Anpassung an den Klimawandel in NRW". Special thanks go to Dr. Andrea

Hädicke for her support of the above mentioned project. The contributions to improve the English of the manuscript by Dr. B. Maxfield and the inputs by three anonymous reviewers should be also acknowledged. Last but not least, we want to acknowledge the Emschergenossenschaft and the Lippeverband for providing the high-resolution rainfall time series.

References

Alexanderson, H., 1986. A homogeneity test applied to precipitation data. J. Climatol. 6, 661–675.
Anonymous, 2010. Extremwertstatistische Untersuchung von Starkniederschlägen in NRW (ExUS)–Veränderung in Dauer, Intensität und Raum auf Basis beobachteter Ereignisse und Auswirkungen auf die Eintretenswahrscheinlichkeit - Abschlussbericht; Aachen. http://www.lanuv.nrw.de/klima/pdf/ExUS_Bericht_1a.pdf (07.06.12).
ATV-DVWK, 1985. Niederschlag - Starkregenauswertung nach Wiederkehrzeit und Dauer, Niederschlagsmessungen, Auswertung. DWA, Hennef.
Bartels, H., Malitz, G., Asmus, S., Albrecht, F.M., Dietzer, B., Günther, T., Ertel, H., 1997. Starkniederschlaghöhen für Deutschland - KOSTRA. Deutscher Wetterdienst, Offenbach a. Main.
Bilotta, G.S., Brazier, R.E., Haygarth, P.M., 2007. Processes affecting transfer of sediment and colloids, with associated phosphorus, from intensively farmed grasslands. Erosion. Hydrol. Proc. 21, 135–139.
Boardman, J., Evans, R., Ford, J., 2003. Muddy floods on the South Downs, southern England: problems and responses. Environ. Sci. Policy 6, 69–83.
Brisan, M.V., Molnar, P., Burlando, P., Pfaundler, M., 2005. Streamflow trends in Switzerland. J. Hydrol. 314, 312–329.
Brockwell, P.J., Davis, R.A., 1996. Introduction to Time Series and Forecasting. Springer, New York.
Canty, A., Ripley, B., 2012. R-package 'boot' (version 1.3-4). http://cran.r-project.org/web/packages/boot/index.html (02.05.12).
Cleveland, W.S., Grosse, E., Shyu, W.M., 1993. Local regression models. In: Chambers, J.M., Hastie, T.J. (Eds.), Statistical models in S. Chapman & Hall, Boca Raton, Florida, pp. 309–379.
Coles, S.G., 2001. An Introduction to Statistical Modelling of Extreme Values. Springer, London.
Coles, S.G., 2011. R-package 'ismev': An introduction to statistical modeling of extreme values (version 1.37). http://cran.r-project.org/web/packages/ismev/ (02.05.12).
Costa, A.C., Soares, A., 2009. Homogenization of climate data: review and new perspectives using geostatistics. Math. Geosci. 41, 291–305.
Crawley, M.J., 2009. The R Book. Wiley, Chichester.
D'Asaro, F., D'Agostino, L., Bagarello, V., 2007. Assessing changes in rainfall erosivity in Sicily during the twentieth century. Hydrol. Proc. 21, 2862–2871.
Deutsches Institut für Normung, 2005. DIN 19708 - Bodenbeschaffenheit - Ermittlung der Erosionsgefährdung von Böden durch Wasser mit Hilfe der ABAG. Beuth Verlag, Berlin.
Diodato, N., Bellochi, G., 2009. Assessing and modelling changes in rainfall erosivity at different climate scales. Earth Surf. Process. Landforms 34, 969–980.
Fiener, P., Auerswald, K., 2007. Rotation effects of potato, maize and winter wheat on soil erosion by water. Soil Sci. Soc. Am. J. 71, 1919–1925.
Fiener, P., Auerswald, K., Van Oost, K., 2011. Spatio-temporal patterns in land use and management affecting surface runoff response of agricultural catchments—a review. Earth-Sci. Rev. 106, 92–104.
Groisman, P.Y., Knight, R.W., Karl, T.R., Easterling, D.R., Sun, B., Lawrimore, J.H., 2004. Contemporary changes of the hydrological cycle over the contiguous United States: trends derived from in situ observations. J. Hydrometeorol. 5, 64–85.
Guijarro, J.A., 2011. User's guide to climatol (version 1.0, January 2011). http://webs.ono.com/climatol/climatol.html (02.05.12).
Haygarth, P.M., Bilotta, G.S., Bol, R., Brazier, R.E., Butler, P.J., Freer, J., Gimbert, L.J., Granger, S.J., Krueger, T., Macleod, C.J.A., Naden, P., Old, G., Quinton, J.N., Smith, B., Worsfold, P., 2006. Processes affecting transfer of sediment and colloids, with associated phosphorus, from intensively farmed grasslands: an overview of key issues. Hydrol. Proc. 20, 4407–4413.
IPCC, 2007. Climate Change 2007: the Physical Science Basis. Cambridge University Press, Cambridge.
Kendall, M.G., 1975. Rank Correlation Methods. Griffin, London.
Khaliq, M.N., Quarda, T.B.M.J., 2007. On the critical values of the standard normal homogeneity test (SNHT). Int. J. Climat. 27, 681–687.
Lal, R., 2001. Soil degradation by erosion. Land Degrad. Dev. 12, 519–539.
Larionov, G.A., 1993. Erosion and Deflation of Soils. Moscow University Press, Moscow.
Mann, H.B., 1945. Nonparametric tests against trends. Econometrica 13, 245–259.
McLeod, A.I., 2011. R-package 'kendall': Kendall rank correlation and Mann-Kendall trend test (version 2.2). http://cran.r-project.org/web/packages/Kendall/index.html (02.05.12).
Meusburger, K., Steel, A., Panagos, P., Montanarella, L., Alewell, C., 2012. Spatial and temporal variability of rainfall erosivity factor for Switzerland. Hydrol. Earth Syst. Sci. 16, 167–177.
Mueller, E.N., Pfister, A., 2011. Increasing occurrence of high-intensity rainstorm events relevant for the generation of soil erosion in a temperate lowland region in central Europe. J. Hydrol. 411, 266–278.
Nearing, M.A., Pruski, F.F., O'Neal, M.R., 2004. Expected climate change impacts on soil erosion rates: a review. J. Soil Water Conserv. 59, 43–50.
R Development Core Team, 2009. R: A Language and Environment for Statistical Computing. http://www.R-project.org
Schwertmann, U., Vogl, W., Kainz, M., 1990. Bodenerosion durch Wasser – Vorhersage des Abtrags und Bewertung von Gegenmaßnahmen. Ulmer Verlag, Stuttgart.
Sivakumar, B., 2011. Global climate change and its impacts on water resources planning and management: assessment and challenges. Stoch. Environ. Res. Risk A 25, 583–600.
Verstraeten, G., Poesen, J., 2000. Estimating trap efficiency of small reservoirs and ponds: methods and implications for the assessment of sediment yield. Progress Phys. Geogr. 24, 219–251.
Verstraeten, G., Poesen, J., Demarée, G., Salles, C., 2006. Long-term (105 years) variability in rain erosivity as derived from 10-min rainfall depth data for Ukkel (Brussels, Belgium): implications for assessing soil erosion rates. J. Geophys. Res. 111, D22109.
Wischmeier, W.H., 1959. A rainfall erosion index for a universal soil-loss equation. Soil Sci. Soc. Am. Proc. 23, 246–249.
Wischmeier, W.H., Smith, D.D., 1960. A universal soil-loss equation to guide conservation farm planning. In: Proceedings of the 7th Intern. Congress of Soil Science, Madison, Wisc, pp. 418–425.