doi: 10.17221/176/2015-SWR

Evaluation of Discrepancies in Spatial Distribution of Rainfall Erosivity in the Czech Republic Caused by Different Approaches Using GIS and Geostatistical Tools

Jiří BRYCHTA and Miloslav JANEČEK*

Faculty of Environmental Sciences, Czech University of Life Sciences Prague, Prague, Czech Republic

**Corresponding author: brychtajiri@fzp.czu.cz*

Abstract

Brychta J., Janeček M. (2017): Evaluation of discrepancies in spatial distribution of rainfall erosivity in the Czech Republic caused by different approaches using GIS and geostatistical tools. Soil & Water Res., 12: 117–127.

The study presents all approaches of rainfall erosivity factor (R) computation and estimation used in the Czech Republic (CR). A lot of distortions stem from the difference in erosive rainfall criteria, time period, tipping rain gauges errors, low temporal resolution of rainfall data, the type of interpolation method, and inappropriate covariates. Differences in resulting R values and their spatial distribution caused by the described approaches were analyzed using the geostatistical method of Empirical Bayesian Kriging and the tools of the geographic information system (GIS). Similarity with the highest temporal resolution approach using 1-min rainfall data was analyzed. Different types of covariates were tested for incorporation to the cokriging method. Only longitude exhibits high correlation with R and can be recommended for the CR conditions. By incorporating covariates such as elevation, with no or weak correlation with R, the results can be distorted even by 81%. Because of significant yearly variation of R factor values and not clearly confirmed methodology of R values calculation and their estimation at unmeasured places we recommend the R factor for agricultural land in the Czech Republic R = 40 MJ/ha·cm/h +/– 10% depends on geographic location.

Keywords: covariate; geostatistics; R factor; rainfall intensity; rainfall total; USLE/RUSLE-GIS method

The Universal Soil Loss Equation (USLE) (Wischmeier & Smith 1978) or its updated version, the Revised Universal Soil Loss Equation (RUSLE) (Renard *et al.* 1997), are worldwide used methods for calculating average annual soil loss. Nowadays these methods are used mainly with the help of the geographic information system (GIS) tools (the USLE/RUSLE-GIS method). The integration with GIS in inappropriate way caused a lot of simplifications resulting in distortions and discrepancies. The rainfall erosivity effect is expressed by R factor (R) in USLE/RUSLE. Many authors have developed different methods due to the lack of optimal data for calculation according to the original methodology. Currently there exist two basic approaches for R calculation – based on low temporal resolution data (average annual, growing period, monthly or daily totals) and high temporal resolution data (1–30-min totals). The differences and used parameters of computations for the CR are summarized in Table 1. Most authors used the methodology by Schwertmann *et al.* (1987) and Pretl in Toman *et al.* (1993) due to the lack of optimal data. In the case of high temporal resolution method there is a specific problem of erosive rainfall criteria. The authors coincidently calculate with the minimum rainfall total of more or less 12.5 mm. The main difference is in the minimum intensity and precondition OR/AND which determines if rainfall total and intensity criteria have to be fulfilled simultaneously or not. The objective of the present study is to summarize and compare all approaches used for the CR to figure out the dif-

doi: 10.17221/176/2015-SWR

ferences in R values and their spatial distribution. Analyses were focused on erosive rainfall criteria, temporal resolution of rainfall data, interpolation methods, and distortions caused by covariates. This research should help select an appropriate R map or the methodology of R map creation in the field of water erosion risk assessment.

R factor estimation. First R maps were created using a various number of rain gauges stations (RS), time periods, and erosive rainfall criteria (Table 1) with similar average R close to 20 MJ/ha·cm/h (further in the text without units) (Janeček *et al.* 1992; Sokolová 1992; Toman *et al.* 1993; Švehla & Skořepa 1995). Van der Knijff *et al.* (2000) estimated R according to Schwertmann *et al.* (1987) in the R-factor map of Europe within a range 60–70 for the CR. Krása (2004) tested a method according to Rogler and Schwertmann (1981) for the CR with resulting average R = 61 (Figure 1b).

R factor calculation using high temporal resolution data. Janeček *et al.* (2006) using 1-min rainfall data from 13 ombrographs (OS) for a 40-year period detailedly analyzed the R calculation by the original methodology of Wischmeier and Smith (1978). Rainfalls with totals > ≥12.5 mm (condition A) and intensity > 6 mm/15 min (condition B) were considered. If conditions A or B (precondition OR) were fulfilled, there were 8.3 erosive rainfalls per station on average resulting in average R = 65.8. If conditions A and B (precondition AND) were fulfilled, there were 2.3 erosive rainfalls per station on average with average R = 44.9. Based on a 9-year experimental runoff plots monitoring the precondition AND was confirmed and resulting average R = 45 was recommended (Janeček *et al.* 2006). The R map by Dostál *et al.* (2006) was created according to Wischmeier and Smith (1978) based on data of 37 RS for the period 2000–2005 with different erosive rainfall criteria – total > 12.5 mm OR intensity >

Table 1. Outline of criteria used for all created rainfall erosivity factor (R) maps for the Czech Republic

Author	Period	RS	Method	Erosive rainfall criteria		R	Ø R
				total (mm)	intensity		
Pretl in Toman *et al.* (1993)	long-term	9	W	> 12.5	> 6.25 mm/15 min	30–72	–
	long-term	–	S (1)		P	30–110*	50*
Toman *et al.* (1993)	20 years	25	W (2)	> 10	> 20 mm/h	18–26	22
Sokolová (1992)	15–50 years	21	W (3)	> 10	> 20 mm/h	–	19
Janeček *et al.* (1992)	15–50 years	102	W	> 10	> 20 mm/h	3–37	20
Janeček *et al.* (1992)	1952–1992	3	W (5)	> 12.5	–	–	20
Švehla and Skořepa (1995)	long-term	95	S		P_S	35–90*	50*
Van der Knijff *et al.* (2000)	1989–1998	–	S		P_S	60–70	–
Krása (2004)	1962–2001	87	S		P_S	35–80	61
Dostál *et al.* (2006)	2000–2005	37	W (5)	> 12.5	> 24 mm/h	44–85	73
Janeček *et al.* (2006)	1961–2000	13	W (6)	≥ 12.5	> 6 mm/15 min	–	45
Janeček *et al.* (2012b, 2013)	1971–2000	31	W (6)	> 12.5	> 6.25 mm/15 min	18–113	41
Rožnovský in Krása *et al.* (2014)	2003–2012	106	W (6)	≥ 12.5	≥ 0.4 mm/min	37–110	69
Hanel in Krása *et al.* (2014)	1989–2003	96	W (5)	> 12.5	> 6 mm/10 min	35–150	64
Panagos *et al.* (2015)	1961–1999	35	W (5)	> 12.7	> 12.7 mm/30 min	22–109	52
Hanel *et al.* (2016)	1989–2003	96	W (5)	> 12.7	> 8.5 mm/20 min	32–152	64
Rožnovský (2017)**	1971–2014	> 245**	W**	> 12.5	> 6.25 mm/15 min	**	**

RS – No. of rain gauges stations; W – Wischmeier and Smith (1978); S – Schwertmann *et al.* (1987); P – average annual rainfall total; P_S – average rainfall total for the period May 1 to October 31; (1) – north and north-east Bohemian region; (2) – south Moravian region; (3) – south Bohemian region; (4) – central Bohemian region; (5) – precondition OR; (6) – precondition AND; *approximate estimation from analogue isolines map; **not published ongoing research of the Czech Hydrometeorological Institute; long-term – more than 20 years

doi: 10.17221/176/2015-SWR

24 mm/h (Figure1c), and average R = 72.6. The map was created by linear interpolation and filtering methods in GIS for reducing extreme values. Janeček *et al.* (2012a) performed detailed analyses of erosive rainfall criteria based on experimental runoff plots monitoring with bare soil and various crops with different agrotechnics in the period 2001–2009. He found out that significant soil loss events were caused by rainfall total > 10 mm AND intensity > 6 mm/15 min. The difference between the 15-min and 30-min intensity effect was minimal. The dependence between R and soil loss was mainly G = 0.35 R and with consideration of all USLE factors G = 0.5 R. These results were influenced by soil moisture content which also caused soil losses by rainfalls which did not fulfil the erosive rainfall criteria. That is why the mentioned criteria set by Wischmeier and Smith (1978) do not correspond to R = 0 but approximately R = 4. Janeček *et al.* (2012b, 2013) created the R map using 31 OS for the period 1971–2000 and precondition AND (Figure 1d). According to this map average R = 40 was recommended for agricultural areas (without mountainous border areas).

R factor calculation using tipping rain gauges. Hanel (2013) in Krása *et al.* (2014) used 96 rain gauges stations (RS) for the period 1989–2003 with resulting average R = 64 (Figure 1e) (Krása *et al.* 2014). Rožnovský *et al.* (2013) in Krása *et al.* (2014) used 106 RS for the period 2003–2012 with resulting average R = 69 (Figure 1f) (Krása *et al.* 2014) (Table 1). Hanel *et al.* (2016) used 106 RS for the period 1989–2003 with resulting average R = 64. These time series contain measurements of different types of RS – floating rain gauges or ombrographs OS (used until 2000) and tipping (used since 1997). There were found errors in measurements using tipping rain gauges during intensive rainfalls based on the research of the Czech Hydrometeorological Institute (CHMI). This error affected resulting R computed after the year 2000 and it is probably a major cause of excessively increased R values. Panagos *et al.* (2015) created a revised R map for Europe using temporal resolutions 5–60 min (normalized to 30-min using linear regression functions) and time series 5–40 years (17.1 years on average). For the CR, data from 35 OS for the period 1961–1999 were used and resulting average R = 52.4. The R map currently created by the CHMI is based on more than 200 RS for the period 1971–2014 and a correction coefficient for tipping RS data.

Geostatistical approach for R values interpolation. Among erosive rainfall criteria, preconditions (OR/AND) and R calculation approach is the

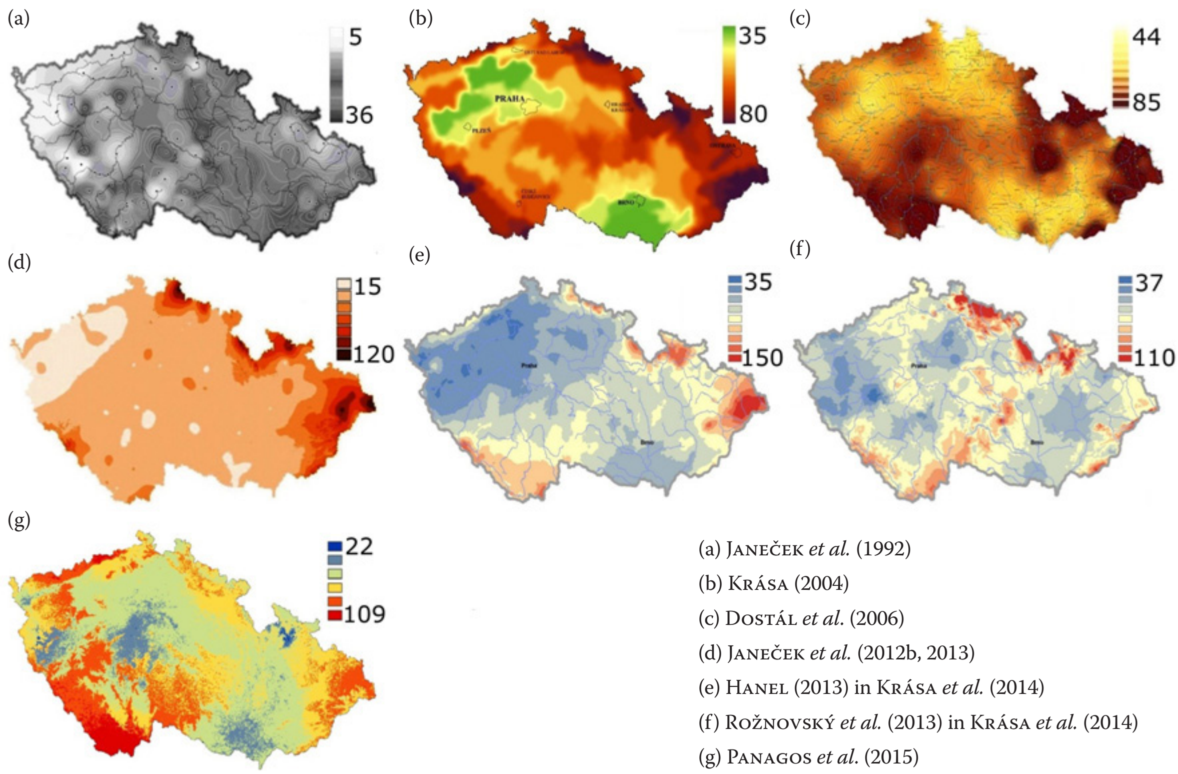

Figure 1. Overview of all rainfall erosivity factor (R) maps created for the Czech Republic

doi: 10.17221/176/2015-SWR

most important spatial prediction of R at unmeasured places based on interpolation techniques. Many studies confirmed the advantages of kriging or cokriging methods (Philips *et al.* 1992; Goovarets 1999, 2000; Moral 2010; Hanel *et al.* 2016). Kriging compared with deterministic models uses to calculate weights to determine the projected points, not only the distance between measured and predicted points, but also the spatial arrangement of measured points around the predicted point. Spatial autocorrelation of measured points has to be determined to create a semivariogram. Different covariates were used, mainly elevation data, longitude, latitude, and annual or growing period totals. However there must exist a spatial autocorrelation in the used dataset and correlation with the used covariates, otherwise the cokriging method cannot be satisfactorily applied. Therefore further objective of this study is to verify covariates most frequently used for the CR conditions. Goovarets (1999, 2000) presented three multivariate geostatistical algorithms for incorporating a digital elevation model into the spatial prediction of rainfall totals and rainfall erosivity. In most situations a cross validation process indicated smaller prediction errors than the linear regression. The best results were obtained using cokriging with elevation data. Krása (2004) and Dostál *et al.* (2006) used linear interpolation (Figure 1b, c). Janeček *et al.* (2013) used the cokriging method with incorporating elevation and daily rainfall totals ≥ 12.5 mm from 257 RS with truncated arithmetic mean (without 2 maximal and minimal values) (Figure 1d). Panagos *et al.* (2015) used Gaussian Process Regression and climatic data as covariates (rainfall totals, seasonal total, totals of driest/wettest months, average temperature), elevation, latitude, and longitude (Figure 1e). Detailed methodology by Rožnovský *et al.* (2013) in Krása *et al.* (2014) was not published. Hanel *et al.* (2016) used generalized least-square model which reduced the uncertainty due to short record lenght.

MATERIAL AND METHODS

Rainfall data of 71 stations for the period 1961–1990 were collected for R factor calculation using low temporal resolution data method according to Pretl in Toman *et al.* (1993):

$$R = 0.058P + 10.5 \quad (1)$$

and Schwertmann *et al.* (1987):

$$R = 0.141\ P_S - 1.48 \quad (2)$$

$$R = 0.083\ P - 1.77 \quad (3)$$

where:

P_S – average rainfall total for the period May 1 to October 31 (growing period total)

P – average annual rainfall total (mm)

Next the R based on high temporal resolution data method according to Dostál *et al.* (2006), Janeček *et al.* (2013), and Panagos *et al.* (2015) were collected for each used station. To avoid the distortions of different used interpolation methods and covariates, the Empirical Bayesian Kriging (EBK) was used (Figure 4). Compared with other kriging methods, the EBK uses a large number of semivariogram models. After estimating the semivariogram model from input data, new values are simulated at input data locations and other semivariogram models are estimated. For these semivariograms are calculated weights using Bayes' rule, which shows how likely the observed data can be generated from the semivariogram (Pilz & Spöck 2007). The EBK predicts more accurate standard errors than other kriging methods and allows accurate predictions of moderately nonstationary data (Krivoruchko & Gribov 2014). If the autocorrelation was not found, the Inverse Distance Weighting (IDW) method was used. Semivariogram models and interpolation parameters were chosen for best fitting to the empirical semivariogram with the help of results of the cross validation process. The resulting maps with cross validation process – regression function of predicted and measured values and QQ plot, are shown in Figure 4. Best fitting gave the K-Bessel function. These results were compared with the R map according to Janeček *et al.* (2012b, 2013) based on the highest temporal resolution (1-min) rainfall data for the same time period interpolated using the EBK method (Figure 5). The R according to Janeček *et al.* (2012b, 2013) was calculated using equations (4), (5), (6):

$$R = E \times i_{30}/100 \quad (4)$$

where:

R – rainfall erosivity factor (M/ha·cm/h)

E – total kinetic energy of rainfall (J/m^2)

i_{30} – maximum 30-min intensity (cm/h)

The total kinetic energy of rainfall is:

$$E = \sum_{i=1}^{n} E_i \quad (5)$$

where:

E_i – kinetic energy of rainfall in the section i

n – number of section

doi: 10.17221/176/2015-SWR

$$E_i = (206 + 87 \log i_{si}) \times H_{si} \quad (6)$$

where:

i_{si} – intensity of rainfall in the section i (cm/h)

H_{is} – rainfall total in the section i (cm)

For calculation we considered rainfalls with total > 12.5 mm AND intensity > 6.25 mm/15 min separated from the next rainfall by at least 6 h or less if the section was considered as one erosive rainfall. The most often used covariates incorporated in the cokriging method (annual and growing period rainfall totals, elevation, longitude and latitude) were tested for the CR. The correlations were verified by regression analyses using linear, polynomial, exponential, logarithmic, and power functions. Best functions were chosen according to the coefficient of determination (r^2). Absolute values of resulting correlation coefficients (r) were compared with critical values (r_c) determined for the significance level of 5% to figure out significance of the correlation. All created R maps were compared using map algebra in GIS environment to figure out differences in R spatial distributions caused by the mentioned different approaches. The tolerance limit was set at 5 MJ per ha·cm/h and for covariates verification at 1 MJ per ha·cm/h (in Figures 3, 5, and 6, the places where the limit was not exceeded are hatched). A new R map was created using regression analyses with growing period rainfall total and the EBK method (Figure 3). The R maps on Figure 6 were compiled by the cokriging method using longitude, latitude, and elevation as covariates to figure out how they can affect R spatial distribution.

RESULTS AND DISCUSSION

The objectives of the analyses were to find out the differences in R values and their spatial distribution:

(1) calculated by low and high temporal resolution data approaches,

(2) calculated by high temporal resolution data using different erosive rainfall criteria – especially the minimal intensity and preconditions OR/AND,

(3) interpolated by different methods – especially using different covariates as elevation data, longitude, latitude, P, and P_S.

The mentioned covariates were tested for the CR conditions (Figure 2). There is no statistically sig-

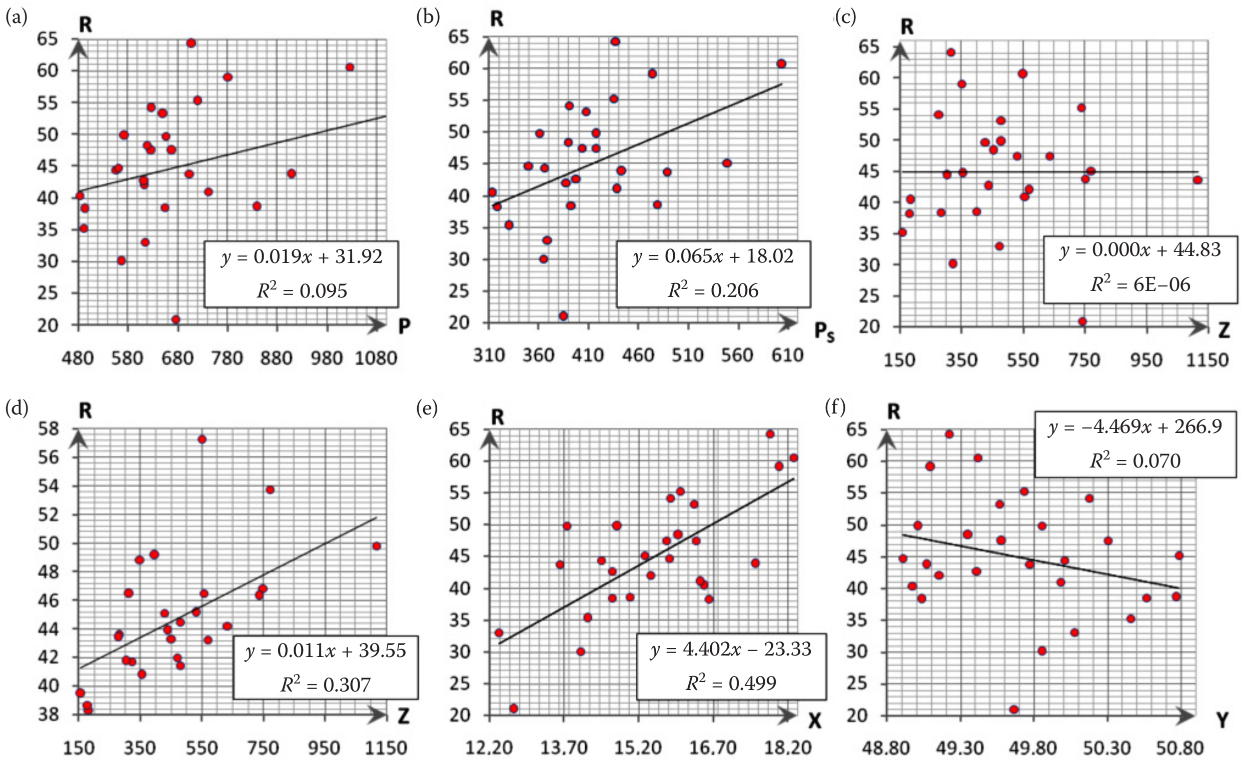

Figure 2. Verification of the correlation between covariates and rainfall erosivity factor (R) for the Czech Republic: (a) average annual rainfall total (P), (b) average rainfall total for the period May 1 to October 31 (P_S), (c) elevation (Z), (d) correlation between Z and R calculated using P_S, (e) longitude, (f) latitude

doi: 10.17221/176/2015-SWR

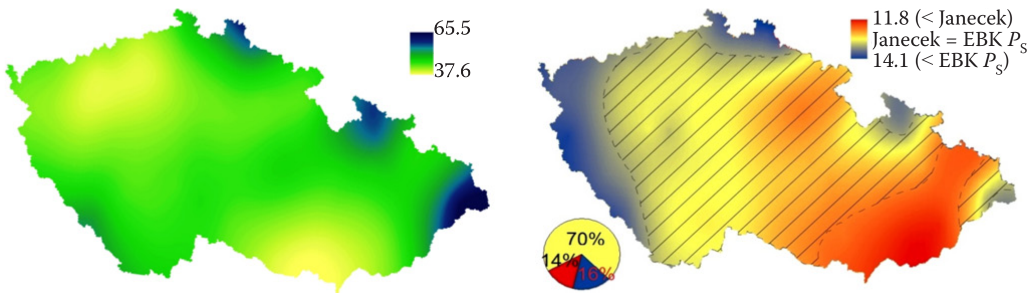

Figure 3. A new rainfall erosivity factor (R) map based on linear regression with growing period totals and the Empirical Bayesian Kriging (EBK) method
Janecek – methodology according to Janeček *et al.* (2012b), EBK Ps – R map based on linear regression function (7) and Empirical Bayesian Kriging (EBK) method

nificant correlation between R and P (r = 0.31 < $r_{critical}$) but the correlation exists with P_S (r = 0.45 > $r_{critical}$). Even though the correlation with low temporal resolution rainfall data is weak for the CR, it was confirmed by many authors for several other countries – Mikhailova *et al.* (1997) for Honduras, Torri *et al.* (2006) for Italy, Renard and Freimund (1994) for the USA, Hermando and Romana (2015) for Spain, Bonilla and Vidal (2011) for Chile, Lee and Heo (2011) for Korea, Schwertmann *et al.* (1987) for Bavaria. These authors used linear, power or polynomial regression function. Renard and Freimund (1994) stated that power function gave the highest coefficient of determination (r^2). Bonila and Vidal (2011) recommended power function for locations with average annual precipitation < 850 mm and polynomial for > 850 mm. However the mentioned statement was not confirmed for the CR. The linear function best fits to rainfall totals < 850 mm (Figure 2a, b).

The following linear function based on low temporal resolution data was newly derived for the R map creation:

$$R = 0.065P_S + 18.025 \quad (7)$$

This map exhibits 70% similarity with the methodology of Janeček *et al.* (2012b, 2013) for a tolerance limit of 5 MJ/ha·cm/h (Figure 3) and 21% for 1 MJ/ha·cm/h. Goovarts (2000) found high correlation with elevation data for the Portugal conditions with r^2 = 0.75. This correlation was not confirmed for the CR but it highly increases if low temporal resolution data are used (Figure 2c, d). Panagos *et al.* (2015) used elevation, longitude, and latitude as covariates for the European R map based on 30-min temporal resolution rainfall data and precondition OR. Results of verifying this correlation for the CR using 1-min data and precondition AND (Figure 2e, f) confirm a high correlation with longitude (r = 0.71) but with

Table 2. Results of comparison of different approaches to rainfall erosivity factor (R) calculation and estimation in GIS

Method	Data	RS	Period	Range	Ø	SD	RMSE	RF PM	SM (%)
Swertmann *et al.* (1987)	P	71	1961–1990	37.1–97.3	52.6	9.5	11.7	0.42x + 31.63	14[1]
Swetmnann *et al.* (1987)	P_S	71	1961–1990	41.2–98.3	55.5	8.5	9.8	0.5x + 29.1	34[1]
Pretl in Toman *et al.* (1993)	P	71	1961–1990	37.7–79.5	48.5	6.6	8.2	0.43x + 28.8	59[1]
Janeček *et al.* (2012b, 2013)	1-min	30	1961–1990	30.7–58.9	44.4	6	6.9	0.54x + 21.58	100[1]
Janeček *et al.* (2012b, 2013)	1-min	30	1961–2000	29.4–64.9	46	8.5	8.4	0.51x + 22.36	100[2]
Dostál *et al.* (2006)*	1-min	37	2000-2005	38–136	74.2	11.7	25.7	0.03x + 77.14	3[2]
Panagos *et al.* (2015)	30-min	29	1961–1999	32.7–71.3	51.1	8.2	7.2	0.42x + 28.68	54[2]
EBK P_S**	P_S	71	1961–2000	37.6–65.5	44.3	4	4.4	0.55x + 20.24	70[1]

RS – No. of rain gauges stations; P – average annual rainfall total; P_S – average rainfall total for the period May 1 to October 31; SD – standard deviation; RMSE – root mean square error; RF PM – regression function of predicted and measured values; SM – similarity with Janeček *et al.* (2012b, 2013);*Inverse Distance Weighting (IDW) method; **R map based on linear regression function (Eq. (7)) and Empirical Bayesian Kriging (EBK) method; [1]comparison with R data 1961–1990; [2]1961–2000

doi: 10.17221/176/2015-SWR

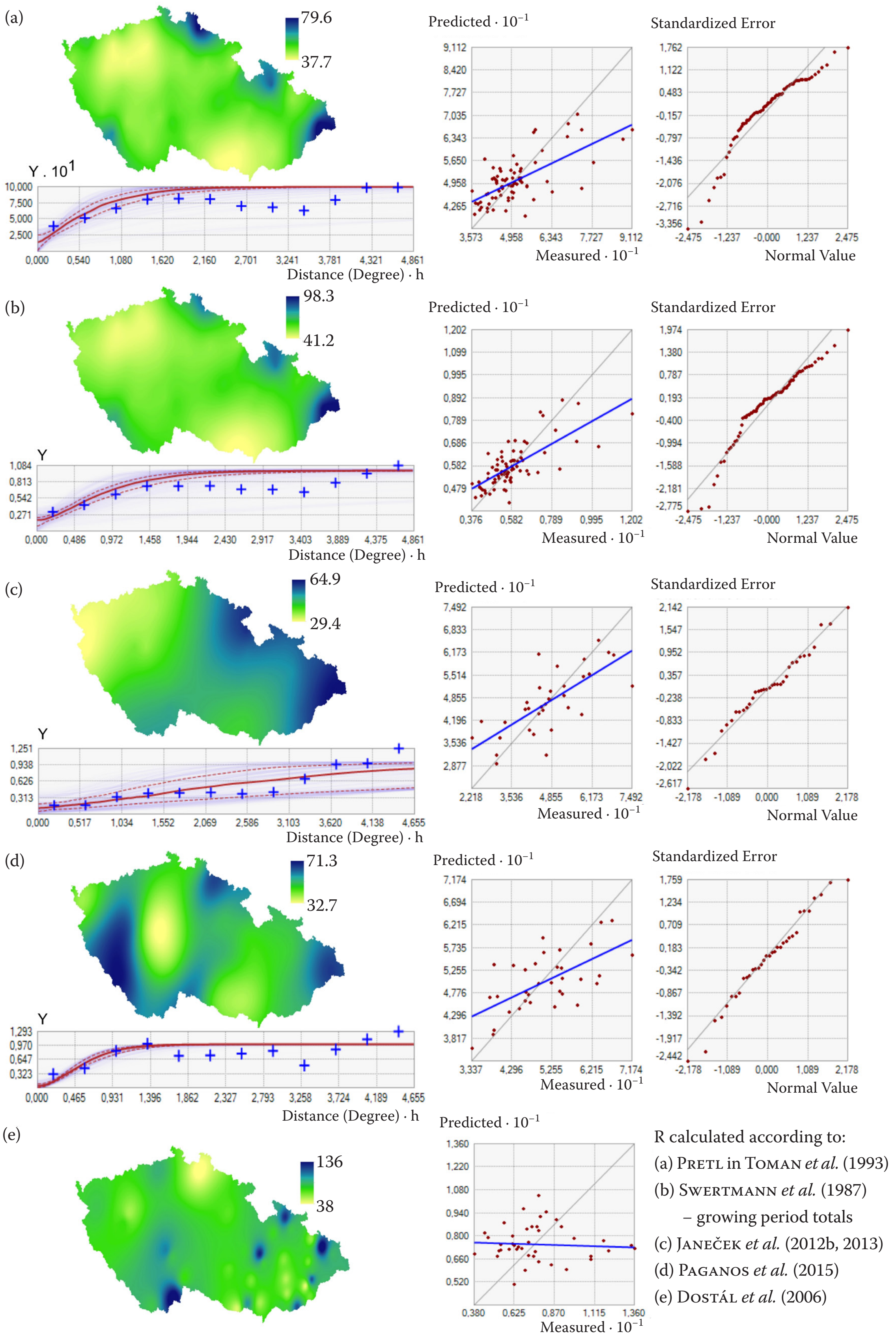

Figure 4. Rainfall erosivity factor (R) values interpolation using the Empirical Bayesian Kriging (EBK) method

doi: 10.17221/176/2015-SWR

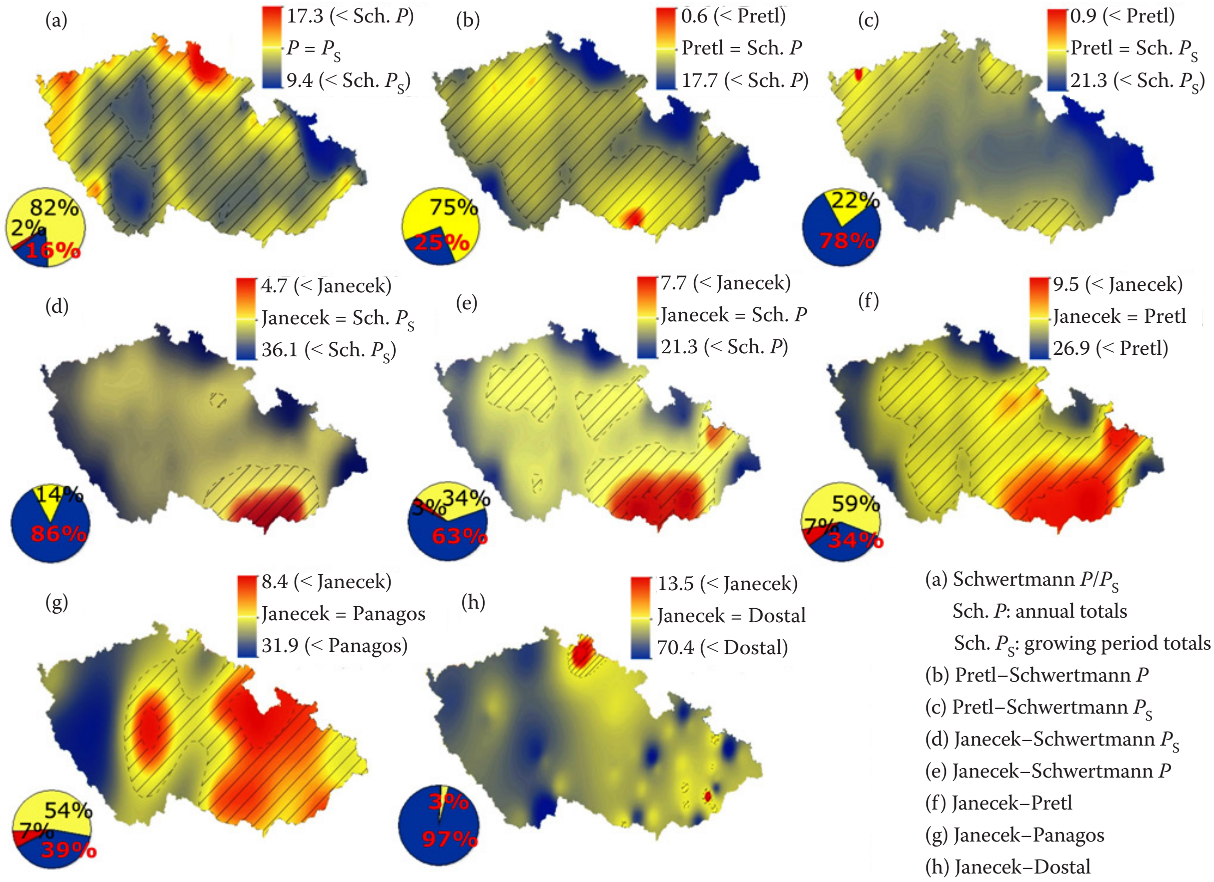

Figure 5. Differences in the rainfall erosivity factor (R) spatial distribution caused by different approaches
Schwertmann P/P_S – methodology according to Schwertmann *et al.* (1987); Sch. *P* – using average annual totals; Sch. P_S – using average growing period totals; Pretl – according to Pretl in Toman *et al.* (1993); Janecek – according to Janeček *et al.* (2012a, b, c, 2013); Panagos – according to Panagos *et al.* (2015); Dostal – according to Dostál *et al.* (2006)

latitude the correlation was not statistically significant ($|r| = 0.26 < r_{critical}$). To avoid distortion by unsatisfactorily confirmed covariates, the EBK method can be used. By this method were interpolated R values calculated according to Pretl in Toman *et al.* (1993), Schwertman *et al.* (1987), Dostál *et al.* (2006), Janeček *et al.* (2013), and Panagos *et al.* (2015) (Figure 4). The R values by Panagos *et al.* (2015) were considered with distortions caused by covariates. A spatial autocorrelation was found for all cases among R data set by Dostál *et al.* (2006) therefore the IDW method was used in this case (Figure 4e). The semivariogram model K-Bessel best fitted to empirical semivariograms and gave the smallest root-mean-square error (RMSE). Cross validation results are shown in Figure 4 and Table 2. All rasters

Table 3. Distortions of rainfall erosivity factor (R) spatial distribution caused by covariates

Covariate	Range	Ø	SD	RMSE	RF PM	% affecting R map	
						tolerance R = 5	tolerance R = 1
X	27.2–67.3	46.2	8.9	8.3	0.6*x* + 19.8	0	28
Y	28.6–66.9	46.3	8	8.9	0.46*x* + 26.96	18	61
Z	19.2–86.1	45.5	9.9	12	0.4*x* + 27.7	39	81
YZP	28.4–68.7	46	9.1	8.7	0.6*x* + 20.1	14	60

X – longitude; *Y* – latitude; *Z* – elevation; *P* – average annual rainfall total; SD – standard deviation; RMSE – root mean square error; RF PM – regression function of predicted and measured values

doi: 10.17221/176/2015-SWR

were compared using the tolerance limit 5 MJ/ha·cm/h to figure out differences in spatial distribution of R calculated using different erosive rainfall criteria and temporal resolution of rainfall data. The similarity with 1-min temporal resolution data approach according to the methodology by Janeček *et al.* (2012b, 2013) was tested (Figure 5, Table 2). An interesting finding is a very low similarity (14 and 34%) of R maps based on the methodology by Schwertmann *et al.* (1987) derived for the neighbouring territory of Bavaria. The best similarity (59%) gave the R based on the methodology by Pretl in Toman *et al.* (1993), even better than by Panagos *et al.* (2015) (54%). If the tolerance limit 1 MJ/ha·cm/h was used, the approach by Panagos *et al.* (2015) gave very low similarity (13.2%). The main reason is incorporating the covariates with no or very low correlation with R for the CR and using the precondition OR. Differences caused by precondition OR were confirmed by Janeček *et al.* (2006, 2012a). How covariates can affect R spatial distribution is demonstrated in Table 3 and Figure 6. Incorporating the elevation as covariate with no correlation with R can affect the resulting map (spatial distribution) by 81% and the longitude with high correlation by 28%. The lowest similarity (3%) gave R values by Dostál *et al.* (2006). The main reasons are using tipping rain gauges records with errors caused by intensive rainfalls, intensity criteria set at > 24 mm/h, and different time period – only 6 years which exhibits no spatial autocorrelation in resulting R values.

CONCLUSION

In evaluating the rainfall erosivity factor R, many distortions are caused by using precondition OR, different erosive rainfall criteria, short time period, tipping rain gauges errors, low temporal resolution rainfall data, the type of interpolation method, and inappropriate covariates. This study presents all approaches of R computation and estimation used in the CR. The differences in R spatial distribution caused by the used approaches were analyzed using the EBK method and GIS. A similarity with the highest temporal resolution data approach based on

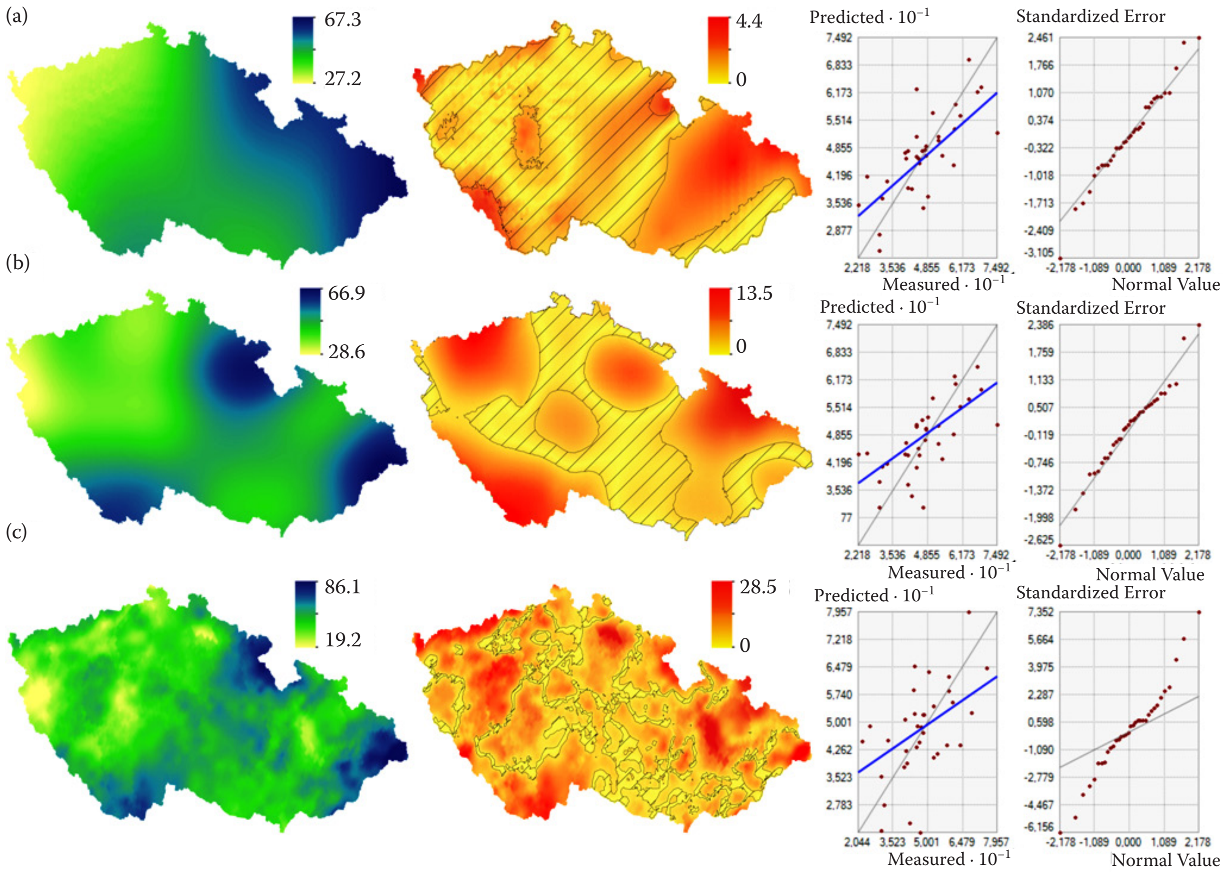

Figure 6. Distortions of the rainfall erosivity factor (R) spatial distribution caused by covariates (a) longitude, (b) latitude, (c) elevation

doi: 10.17221/176/2015-SWR

1-min rainfall data, precondition AND with rainfall intensity criteria > 6.25 mm/15 min were analyzed. Using low temporal resolution data approach (growing period rainfall totals) a 21% similarity was reached. That is why this approach cannot be recommended for the CR conditions. The approach using too short time periods with erosive rainfall intensity criteria > 24 mm/h and tipping rain gauges record exhibiting no autocorrelation in resulting R values dataset and kriging method cannot be used for interpolation. This approach exhibits almost no similarity but it was calculated for a different time period and affected by tipping rain gauges errors. The approach using 30-min data and precondition OR with a lot of incorporated covariates reached maximally 13.2% similarity. Results of verifying distortions by covariates for the CR conditions show a statistically significant correlation only for longitude and growing period totals. Incorporation of elevation, latitude and their combination with annual totals as covariates can affect the resulting R map (spatial distribution) by 60–81%. Covariates correlation depends on local conditions in individual countries and also on erosive rainfall criteria used for the R calculation. Therefore only covariates which exhibit high correlation with R can be recommended for incorporation in the cokriging method. Because of significant yearly variation of R factor values and not clearly confirmed methodology of R values calculation and their estimation at unmeasured places we recommend the R factor for agricultural land in the Czech Republic R = 40 MJ/ha·cm/h +/– 10% by geographic location in accordance with results by Janeček (2012b, 2013) based on processing 1-min temporal resolution rainfall data for the period 1971–2000 and 31 OS.

Acknowledgements. This work was supported by internal grant of Faculty of Environmental Sciences, Czech University of Life Sciences IGA FZP 20164213: Evaluation of the impact of assimilation area of vegetation in tropical and temperate zones on surface runoff and sediment transport using indexes NDVI and LAI, LiDAR and simulated rainfall.

References

Bonila A.C., Vidal L.K. (2011): Rainfall erosivity in Central Chile. Journal of Hydrology, 410: 126–133.

Dostál T. *et al* (2006): Partial Final Report of Project COST No. 1P04OC634.001 Methods and Ways of Predicting Surface Runoff, Erosion and Transport Processes in the Landscape. Prague, ČVUT. (in Czech)

Goovaerts P. (1999): Using elevation to aid the geostatistical mapping of rainfall erosivity. Catena, 34: 27–242.

Goovaerts P. (2000): Geostatistics in soil science: state-of-the-art and perspectives. Geoderma, 89: 1–46.

Hanel M., Máca P., Bašta P., Vlnas R., Pech P. (2016): Rainfall erosivity factor in the Czech Republic and its uncertainty. Hydrology and Earth System Sciences, 20: 4307–4322.

Hermando D., Romana G.M. (2015): Estimating the rainfall erosivity factor from monthly precipitation data in the Madrid region (Spain). Journal of Hydrology and Hydromechanics, 63: 55–62.

Janeček M. *et al.* (1992): Protection of Agricultural Land from Erosion. Prague, UVTIZ. (in Czech)

Janeček M., Kubátová E., Tippl M. (2006): Revised determination of the rainfall-runoff erosivity factor R for application of USLE in the Czech Republic. Soil and Water Research, 1: 65–71.

Janeček M., Kubátová E., Procházková E. (2012a): The influence of precipitation and rainfall intensity on soil loss by water erosion. Vodní hospodářství, 62: 134–137. (in Czech)

Janeček M., Květon V., Kubátová E., Kobzová D. (2012b): Differention and regionalization of rainfall erosivity factor values in the Czech Republic. Soil and Water Research, 7: 1–9.

Janeček M. *et al* (2012c): Protection of agricultural land from erosion, VUMOP, Prague. (in Czech)

Janeček M., Květoň V., Kubátová E., Kobzová D. (2013): Values of rainfall erosivity factor for the Czech republic. Journal of Hydrology and Hydromechanic, 61: 97–102.

Krása J. (2004): Evaluation of Erosion Processes in Large River Basins with the Support of GIS. [Ph.D. Thesis.] Prague, Czech Technical University in Prague, Faculty of Civil Engineering. (in Czech)

Krása J., Středová H., Dostál T., Novotný I. (2014): Rainfall erosivity research on the territory of the Czech Republic. In: Rožnovský J., Litschmann T. (eds): Mendel a Climatology, Brno, Sept 3–5, 2014.

Krivoruchko K., Gribov A. (2014): Pragmatic Bayesian kriging for nonstationary and moderately non-Gaussian data. In: Mathematics of Planet Earth. Proc. 15th Annual Conf. Int. Association for Mathematical Geosciences. Springer: 61–64.

Lee J.H., Heo J.H. (2011): Evaluation of estimation methods for rainfall erosivity based on annual precipitation in Korea. Journal of Hydrology, 409: 30–48.

Mikhailova E.A., Bryant R.B., Schwager S.J., Smith S.D. (1997): Predicting rainfall erosivity in Honduras. Soil Science Society of American Journal, 61: 273–306.

Moral F.J. (2010): Comparison of different geostatistical approaches to map climate variables: application to precipitation. International Journal of Climatology, 30: 620–631.

doi: 10.17221/176/2015-SWR

Panagos P., Ballabio C., Borrelli P., Meusburger K., Klik A., Rousseva S., Perčec Tadić M., Michaelides S., Hrabalíková M., Olsen P., Aalto J., Lakatos M., Rymszewicz A., Dumitrescu A., Beguería S., Alewell C. (2015): Rainfall erosivity in Europe. Science of the Total Environment, 511: 801–814.

Phillips D.L., Dolph J., Marks D. (1992): A comparison of geostatistical procedures for spatial analysis of precipitations in mountainous terrain. Agricultural and Forest Meteorology, 58: 119–141.

Pilz J., Spöck G. (2008): Why do we need and how should we implement Bayesian kriging methods. Stochastic Environmental Research and Risk Assessment, 22: 621–632.

Renard K.G., Freimund J.R. (1994): Using monthly precipitation data to estimate the R-factor in the revised USLE. Journal of Hydrology, 157: 287–306.

Renard K.G., Foster G.R., Weesies G.A., Mccool D.K., Yoder D.C. (1997): Predicting Soil Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). USDA Agriculture Handbook No. 703, Washington D.C., USDA-ARS.

Rogler H., Schwertmann U. (1981): Erosivitat der Niederschlage und Isoerodentkarte von Bayern. Zeitschrift für Kulturtechnik und Flurbereinigung, 22: 99–112.

Schwertmann U., Vogel W., Kainz M. (1987): Bodenerosion durch Wasser. Stuttgart, E. Ulmer Gmbh.

Sokolová I. (1992): Determining rainfall erosivity factor R for South Bohemian region. Pedologie a Meliorace, 28: 45–50. (in Czech)

Švehla F., Skořepa Z. (1995): Adjusting the data for determining the value of K and R factors in Wischmeier-Smith's formula. Pozemkové úpravy, 11: 12–13. (in Czech)

Toman F., Sanetrník J., Filip J. (1993): The influence of climatic conditions on the factor of erosion efficiency of torrential rains. In: Proc. Agro-meteorological Conference 93, Brno, Nov 25–26, 1993: 67–69. (in Czech)

Torri D., Borselli L., Guzzeti F. *et al*. (2006): Soil erosion in Italy: an overview. In: Boardman J., Poesen J. (eds): Soil Erosion in Europe. New York, Wiley: 245–261.

Van Der Knijff J.M., Jones R.J.A., Montanarella L. (2000): Soil Erosion Risk Assessment in Europe. Ispra, European Soil Bureau.

Wischmeier W.H., Smith D.D. (1978): Predicting Rainfall Erosion Losses – A Guide to Conservation Planning. USDA Agricultural Handbook No. 537, Washington D.C., USDA.

Received for publication October 7, 2015
Accepted after corrections August 19, 2016
Published online March 15, 2017