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# Crop-management Factor Calculation Using Weights of Spatio-temporal Distribution of Rainfall Erosivity

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**Abstract**

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Inappropriate integration of USLE or RUSLE equations with GIS tools and Remote Sensing (RS) data caused many simplifications and distortions of their original principles. Many methods of C and R factor estimation were developed due to the lack of optimal data for calculations according to original methodology. This paper focuses on crop-management factor evaluation (C) weighted by fully distributed form of rainfall erosivity factor (R) distribution throughout the year. We used high resolution (1-min) data from 31 ombrographic stations (OS) in the Czech Republic (CR) for monthly R map creation. All steps of the relatively time-consuming C calculation were automated in GIS environment with an innovative procedure of R factor weight determination for each agro-technical phase by land parcel geographic location. Very high spatial and temporal variability of rainfall erosivity within each month and throughout the year can be observed from our results. This highlights the importance of C factor calculation using a correctly presented method with emphasis on the geographic location of given land parcels.

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

The equations USLE (Wishmeier & Smith 1978) and RUSLE (Renard *et al.* 1997) are widely used and accepted methods over the world for calculating average annual soil loss. Development of geoinformation systems (GIS), remote sensing (RS) and distance monitoring technologies bring a lot of possibilities for integration with these equations as the USLE/RUSLE-GIS method. The greatest benefits include very accurate height data reached by LiDAR technology, on the other hand disproportion with accuracy of soil and vegetation data and discrepancies in rainfall erosivity calculation (Brychta & Janeček 2017) may cause large errors. The inappropriate integration with GIS and RS data may result in many simplifications and distortions. Many authors developed different methods of crop-management factor evaluation (C) and rainfall erosivity factor (R) estimation due to lack of optimal data for calculation according to original methodology. Approaches to C calculation can be divided into 7 groups based on:

(1) long-term monitoring of runoff plots (Wishmeier & Smith 1978; Schwetmann *et al.* 1987; Renard *et al.* 1997; Janeček *et al.* 2012b),
(2) defining subfactor values for soil loss ratio (SLR) calculation (Wishmeier & Smith 1978; Dissmeyer & Foster 1981; Renard *et al.* 1997),
(3) rainfall simulator application for C factor value determination (Parsons *at al.* 1994; Janeček *et al.* 1995, 2013a; Gacia-Orenes *et al.* 2009),
(4) land cover classification method and average values (Panagos *et al.* 2015a; Cebecauer *et al.* 2004),
(5) satellite multispectral data and vegetation indexes (De Jong 1994; Gilabert *et al.* 2000; Van der Knijff *et al.* 2000; Simeonakis & Darke 2004),
(6) regression and correlation analyses with climate data (Toman & Kadlec 2003),
(7) upscaling/extrapolation method (Zhao *et al.* 2013).

Groups 4–7 are useful mainly for global or regional scale. These methods lead to constant values for

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large areas, enable only low spatial and temporal resolution and do not reflect spatial and temporal variability of geographic location adequately. To increase spatial and temporal variability of group 4, linear regressions between vegetation spectral properties derived from multispectral satellite data (group 5) and field measurements (using group 2 or 3) were applied. For deriving spectral properties, mostly Normalized Difference Vegetation Index (NDVI) was used. Even though the correlation with NDVI was quite low (De Jong 1994; Tweddales *et al*. 2000), this method became very common. Gilabert *et al*. (2000) and Asis and Omasa (2007) used Linear Spectral Mixture Analysis (LSMA) which is more suitable for analysing mixed spectral information of soil and vegetation and gives a higher correlation with C factor values measured in the field (Asis & Omasa 2007). Group 5 methods enable multi-temporal observations (but limited due to cloudiness) which are necessary because C values change every year and even during the year. But C factor does not generally correlate with spectral properties universally for all crops because an important role is played by the effective fall height of rain drops which expresses also their kinetic energy (Jakubíková *et al.* 2006) and not only the amount of biomass. The USLE and RUSLE equations are methods for the calculation of average annual soil loss, therefore C factor should be calculated for multi-year crop rotations. Toman and Kadlec (2003) used linear regression between C and climatic regions of the Czech Republic, determined by annual temperature and rainfall totals, sums of temperature over 10°C, probability of dry growing seasons and moisture supply during the growing season. By using this method (group 6) C values for arable and non-arable agricultural land may be estimated. Zahao *et al*. (2013) used an upscaling method based on the extrapolation of small-scale information to a large scale (group 7). It is evident that groups 4–7 are dependent on field measurements using group 1–3 and its accuracy. According to original methodology by Wishmeier and Smith (1978) long-term data from runoff plots should be used for determining a soil loss ratio (SLR) between specific vegetation conditions and standard plot – black fallow (group 1). If the long-term monitoring data are not available, then the method from group 2 or 3 can be used. Group 2 method is based on determining subfactors for SLR calculation – canopy cover, ground cover and belowground effects (Wishmeier & Smith 1978), amount of bare soil and canopy, soil reconsolidation, organic content, fine roots, residual binding effect, on-site storage, steps, and contour tillage (only for forest conditions) (Dissmeyer & Foster 1981), prior land use, canopy cover, surface cover, surface roughness and soil moisture (Renard *et al*. 1997). For SLR measurement simulated rainfall can be utilized (group 3) according to Parsons *et al*. (1994) and Janeček *et al*. (1995, 2013a). The calibration of high rainfall intensity and rain drop size created by nozzle simulators is a specific problem of this method (Janeček *et al*. 2013a; Wiliams *et al*. 1998). The SLR data for each 15-day period (RUSLE) or 5 phenological phases (USLE) should be multiplied by weights of R factor percentage distribution throughout the year, calculated for a 15-day period (RUSLE) or monthly period (USLE). Due to low availability of these input data RUSLE has not found worldwide application and USLE still remains the most widely used method. In our research we focused on crop-management factor evaluation (C) weighted by rainfall erosivity factor (R) distribution throughout the year according to a geographic location. We used high-resolution (1-min) rainfall data from 31 ombrographic stations (OS) for monthly R map creation. We calculated R factor values for 31 ombrographic stations for each month and interpolated them to raster maps using a kriging method. All steps of relatively time-consuming C calculation were automated in GIS environment with an innovative procedure of R factor weight calculation for each agro-technical phase, determined by land parcel geographic location.

## MATERIAL AND METHODS

Agro-technical data from 11 localities where maize was planted and 1-min temporal resolution rainfall data from 31 ombrographic stations were collected. Geographic locations of used stations and maize areas are shown in Figure 1. Collected agro-technical operation data are documented in Table 3. We realize that 31 stations are not a sufficient number for interpolation and getting representative R values for every area in the CR but it is sufficient for presentation of the methodology of C factor calculation using weights of spatio-temporal distribution of rainfall erosivity. For this reason to reach representative values we chose all 11 maize localities for C calculation near ombrographic stations (Figure 1). Average monthly R and average annual R for 31 ombrographic stations were calculated. Monitored time periods of stations vary between 19 and 48 years with an average

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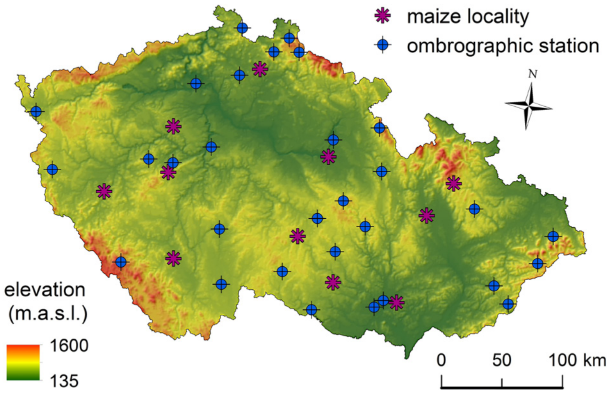


Figure 1. Spatial distribution of used ombrographic stations and maize localities in the CR

of 35.3 years. R for each rainfall event that fulfilled the total amount > 12.5 mm and simultaneously the intensity > 6.25 mm/15 min and was separated from other rainfall at least by a 6-hour interval (or less if the section was considered as one erosive rainfall) was calculated according to Janeček *et al.* (2013b) and Brychta and Janeček (2017) using equations (1–3):

$$R = E \times i_{30}/100 \tag{1}$$

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:

$$E = \Sigma_{i=1}^{n} E_i \tag{2}$$

where:

$E_i$ – kinetic energy of rainfall in the $i$-section ($n$ – number of sections):

$$E_i = (206 + 87 \log i_{si}) \times H_{si} \tag{3}$$

where:

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

$H_{si}$ – rainfall total in the $i$-section (cm)

According to the occurrence of erosive rainfalls in each month, average monthly R values were calculated for each month and the whole time period for all stations. Resultant R values were interpolated using an Ordinary kriging method and Geostatistical Wizard interface in GIS software package ArcGIS.10.2. Semivariogram models and parameters were chosen according to the best fitting to the empirical semivariogram and cross validation process results.

But for the purposes of C factor calculation we need average monthly percentage distribution of R throughout the year. These rasters were created simply using map algebra by calculation percentage of the annual average. Resultant rasters were integrated into a created GIS tool: STD C factor (Spatio-temporally distributed C factor) for C value

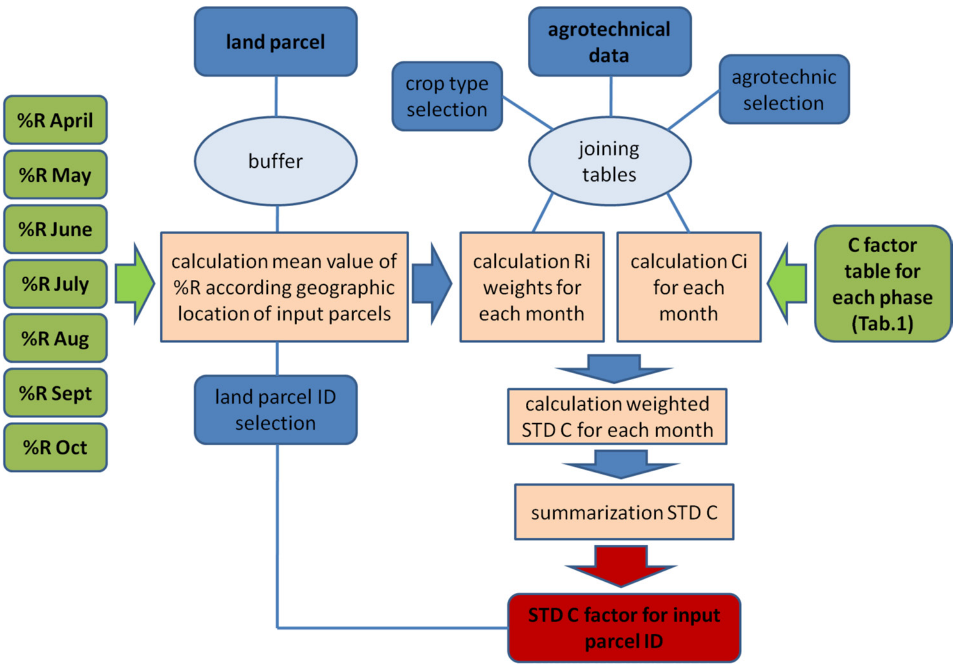


Figure 2. Structure of the Spatio-temporally distributed C (STD C) factor model
blue – required inputs; green – integrated datasets; light blue – basic processing; orange – C factor processing; red – output

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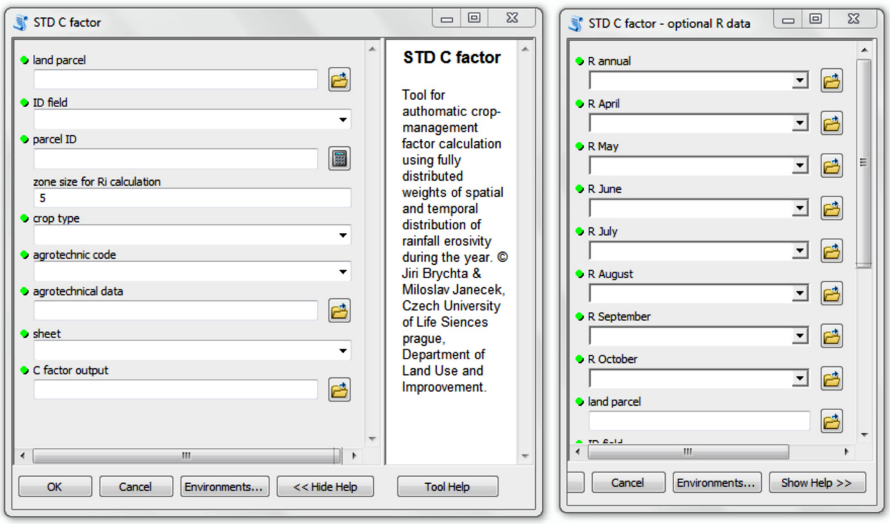
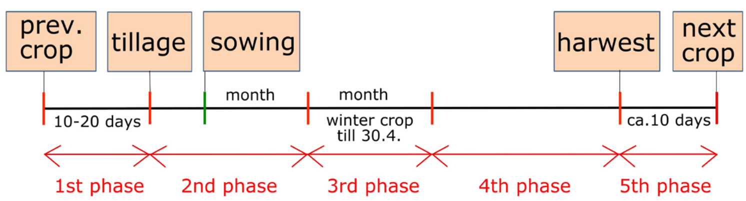



Figure 3. Model Spatio-temporally distributed C (STD C) user interface – version with default R data (left), optional R data (right)

calculation. The tool structure is shown in Figure 2 and its user interface in Figure 3. With awareness of the weaknesses of our R dataset, in particular a small number of stations, we created two versions of STD C factor GIS model – with integrated R data and with optional R data (see the user interface in Figure 3). For more information about advantages and disadvantages of all published R datasets available for the CR see Brychta and Janeček (2017). Among optional R data (annual and monthly R maps) the tool requires only two inputs – land parcel polygons (shapefile format) and a table with information about crop rotations (Excel table). The best way to obtain parcel data is the Land Parcel Identification System (LPIS) geodatabase (Trojacek & Kadlubiec 2004). We used principles of the original methodology by Wischmeier and Smith (1978) for C calculation according to 5 phases (Figure 4). These data must be included in the input table. Description of the required input XLS table is shown in Figure 4. The integrated rasters of average R distribution and two required inputs to STD C factor model were described above. There are also integrated tables and optional parameters which need to be described. As we can see in the user interface (Figure 3), crop type and agro-technique code selection is required. The crop type and agro-technique code can be selected according to Table 1 with C factor values for each phase in different crop rotations and used agro-technique according to Wischmeier and Smith (1978) and Janeček *et al.* (2012b) which are automatically joined. Other required options are ID field of input vector layer attribute table and identification number (ID) of land parcel polygon where the used crop rotation is located. For the input Excel file it is also necessary to choose which sheet contains the data (if there are




| phase | start | end |
|---|---|---|
| 1 | 10.8 | 31.8 |
| 2 | 1.9 | 30.9 |
| 2 | 1.10 | 10.10 |
| 3 | 11.10 | 31.10 |
| 3 | 1.4 | 30.4 |
| 4 | 1.5 | 31.5 |
| 4 | 1.6 | 30.6 |
| 4 | 1.7 | 31.7 |
| 5 | 1.8 | 10.8 |

Figure 4. The timeline of 5 phases and input table to the Spatio-temporally distributed C (STD C) factor model
In the input table each phase must be divided for each month – for example: (a) 2nd phase lasts from September 1 to October 10 and it must be inserted into two rows – part of September on the first row and part of October on the second row; (b) 3rd phase lasts from October 11 to April 30, part of October in the first row, from November to March no erosive rainfall occurred according to our results, that is why these months cannot be in the input table, April 1 to April 30 is in the second row

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Table 1. C factor values for 5 phases and different crop rotations and used agro-techniques (Janeček *et al*. 2012b)

<table>
<tr><th rowspan="2">Crop</th><th rowspan="2">code – crop rotation and used agro-technique</th><th colspan="6">C factor (SLR values) for each phase (Cp)</th></tr>
<tr><th>1</th><th>2</th><th>3</th><th>4</th><th>5</th><th>5m</th></tr>
<tr><td rowspan="6">Cereals, oilseeds</td><td>JP</td><td>0.5</td><td>0.55</td><td>0.3</td><td>0.05</td><td>0.2</td><td>0.04</td></tr>
<tr><td>JS</td><td>0.02</td><td>0.02</td><td>0.02</td><td>0.02</td><td>0.02</td><td>0.02</td></tr>
<tr><td>OP</td><td>0.65</td><td>0.7</td><td>0.45</td><td>0.08</td><td>0.25</td><td>0.04</td></tr>
<tr><td>OS</td><td>0.25</td><td>0.25</td><td>0.2</td><td>0.08</td><td>0.25</td><td>0.04</td></tr>
<tr><td>BP</td><td>0.7</td><td>0.75</td><td>0.5</td><td>0.08</td><td>0.25</td><td>0.04</td></tr>
<tr><td>BS</td><td>0.7</td><td>0.7</td><td>0.45</td><td>0.08</td><td>0.25</td><td>0.04</td></tr>
<tr><td rowspan="8">Maize, sunflower</td><td>M0P</td><td>0.7</td><td>0.9</td><td>0.7</td><td>0.35</td><td>0.7</td><td>0.4</td></tr>
<tr><td>OM0S</td><td>0.25</td><td>0.25</td><td>0.25</td><td rowspan="2">0.25</td><td rowspan="2">0.6</td><td rowspan="2">0.3</td></tr>
<tr><td>BM0S</td><td>0.7</td><td>0.7</td><td>0.5</td></tr>
<tr><td>M1P</td><td>0.7</td><td>0.9</td><td>0.7</td><td>0.35</td><td>0.7</td><td>0.4</td></tr>
<tr><td>OM1S</td><td>0.04</td><td>0.04</td><td>0.04</td><td>0.05</td><td>0.25</td><td>0.15</td></tr>
<tr><td>BM1S</td><td>0.3</td><td>0.25</td><td>0.2</td><td>0.2</td><td>0.4</td><td>0.3</td></tr>
<tr><td>PD</td><td>0.2</td><td>0.2</td><td>0.03</td><td>0.03</td><td>0.05</td><td>0.03</td></tr>
<tr><td>LD</td><td>0.05</td><td>0.05</td><td>0.05</td><td>0.05</td><td>0.15</td><td>0.1</td></tr>
<tr><td colspan="2">Potatoes, sugar beet, cabbage</td><td>0.65</td><td>0.8</td><td>0.65</td><td>0.3</td><td>0.7</td><td>-</td></tr>
<tr><td colspan="2">Alfalfa</td><td colspan="6">0.02</td></tr>
<tr><td colspan="2">Clover</td><td colspan="6">0.015</td></tr>
<tr><td colspan="2">Perennial grass, pasture</td><td colspan="6">0.005</td></tr>
</table>

J – after clovers; O – after cereals; B – after root crops and maize; P – sowing into ploughed field; S – sowing into stubble; M0 – straw of forecrop was harvested; M1 – straw of forecrop was left; PD – sowing into the turf of perennial ryegrass after herbicide application; LD – sowing into the turf of perennial forage after herbicide application; m – straw left (not harvested); for example: OM1Sm – after cereals, straw of forecrop was left, sowing into stubble, after harvest straw is left in the field

no other data in other sheets, it is generally Sheet 1). All model inputs and integrated datasets including the procedures of their creation were described. For better understanding of the structure of the model and principle of the method we will describe the complete procedure of input data transformation into the resultant parcel polygon with weighted C factor with the help of graphic schemes in Figure 5. The first input are LPIS blocks or manually vectorized land parcels, optional ID field and ID number of the used parcel polygon. According to a geographic location of selected land parcel, average monthly distribution of R (in %) throughout the year for each month is generated from the integrated rasters. A balancing zone of 5 km around the land parcels is generated to obtain representative values. The size of this area is a recommendation based on expert estimation according to rainfall condition variability in the CR but it was set as an optional input and can be chosen according to used R data and user assessment. All pixels contained in the created polygon (balancing zone) are averaged and using Python programming language and ArcGIS tools a table with all these values for each month is created. This is the first part of the model (left half in Figure 3 and 5). In the second part (right half in Figure 3 and 5) the crop rotation and used agro-technical operations are defined. At first the crop type and agro-technique code are selected by the user according to Table 1 (if there are missing crops or agrotechnology in Table 1, then SLR (Cp) values should be determined by methods of group 1–3 and has to be integrated into the source code of the STD C model). Next the Excel table with agro-technical data is inserted (Figure 2). C values for each month included in each phase are joined from integrated Table 1 and the number of days for each month contained in a given phase is calculated. The resultant weighted STD C factor value is calculated according to following equations (4–6):

$$\text{STD C} = \left(\sum_{i=4}^{n=10} \text{C}i\right)/y \tag{4}$$

$$\text{C}i = \text{R}i \times \text{C}p \tag{5}$$

$$\text{R}i = (\text{R}_d/Nm) \times Np \tag{6}$$

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where:

STD C – spatio-temporally distributed C factor

*i, n* – sequential number of months where erosive rainfalls were detected (April-October)

C*i* – C factor values for each month that occurs in a given phase

*y* – number of years

C*p* – C factor values (SLR – soil loss ratio between specific vegetation conditions and black fallow) for each phase (taken from Table 1)

R*i* – R factor weights for each month that occurs in a given phase

*N* – number of days that occurs in a given month and phase

$R_d$ – percentage distribution of R during the year (decimal number)

$N_m$ – number of days in a month (e.g. 31 for August, 30 for April etc.)

A detailed example of generating R*i* and C*i* for August and geographic location of land parcel is described in Figure 6. The resultant C factor value for a given land parcel will appear in the attribute table of the inputted shapefile. The STD C factor model was tested on 11 localities where maize was planted (Figure 1). The resultant STD C factor values confirm and highlight the revised presented methodology and C factor variability dependent on geographic location due to variability of R distribution throughout the year (Figure 9).

## RESULTS AND DISCUSSION

Due to the lack of optimal data many authors developed new methods of R factor estimation based on low temporal resolution data – yearly, monthly or daily, for different countries (Richardson *et al.* 1983; Renard & Freimund 1994; Mikhailova *et al.* 1997; Bodnila & Vidal 2011; Lee & Heo 2011; Hermando & Romana 2015). Rainfall intensity was not considered in these studies. The network of specific rain gauge recorders (ombrographs) is necessary for the application of a high resolution data approach, therefore this approach was used only in a few cases. The following authors used different erosive rainfall parameters of rainfall total and intensity which have to be fulfilled simultaneously (AND) or at least one of these parameters (OR). Angulo-Martinez *et al.* (2009) used rainfall total > 12.7 mm OR intensity > 6.35 mm/15 min according to Renard *et al.* (1997) in Spain, Janeček *et al.* (2006, 2012a, 2013b) used total >12.5 mm AND intensity > 12.5 mm/15 min for the Czech Republic, Hanel *et al.* (2016) used total > 12.7 mm OR intensity > 8.47 mm/20 min for the Czech Republic, Meusburger *et al.* (2012) used total > 12.7 mm OR intensity > 8.47 mm/20 min for Switzerland, Panagos *et al.* (2015b) used intensity > 12.7 mm OR intensity > 12.7 mm/30 min for Europe. Based on research performed by Janeček *et al.* (2006) we used verified parameters for the Czech Republic – total > 12.5 mm AND intensity > 6.25 mm

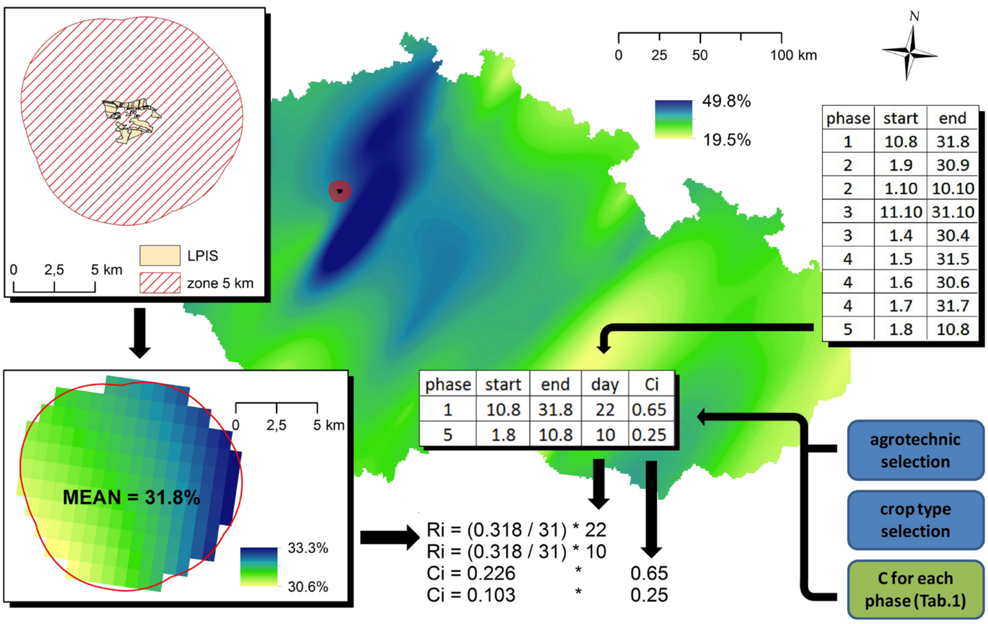


Figure 5. Generation of R*i* and C*i* for August according to the geographic location of land parcel and agrotechnical data
R*i*, C*i* – R and C factor for each month that occurs in a given phase

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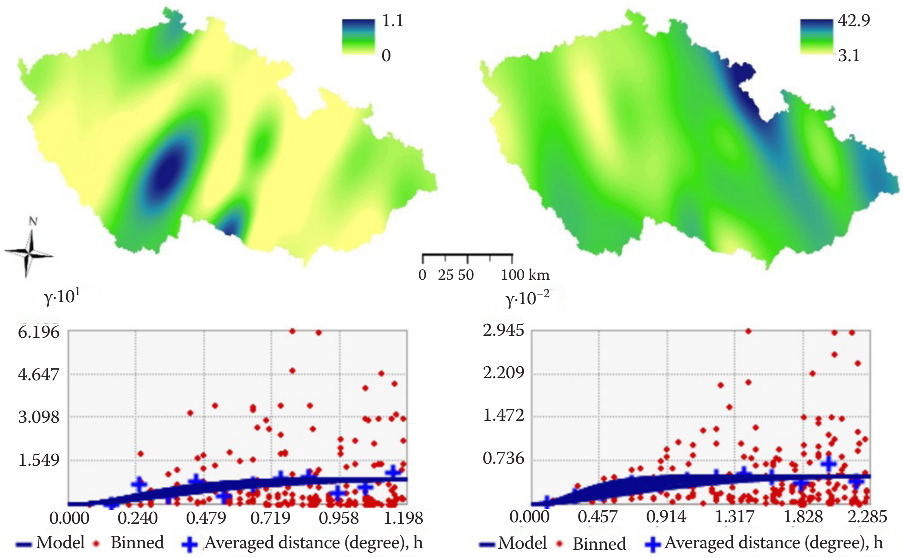


Figure 6. R factor values (MJ/ha·cm/h) for April (left) and July (right) interpolated using a kriging method with variograms below

per 15 min and methodology according to Janeček *et al*. (2012a, 2013b) and Brychta and Janeček (2017). Using these parameters we calculated R factor values for all ombrographic stations and R maps were interpolated using an Ordinary kriging method. An example of resultant R maps for April (month with the lowest R%) and July (month with the highest R%) with semivariograms are shown in Figure 6. Also other R maps can be used in the STD C model. Brychta and Janeček (2017) compared all available R datastets for the CR including calculation methods, interpolation methods and variables. Other information about interpolation methods was described by Hanel *et al.* (2016) using 96 stations (R dataset with the largest number of stations published for the CR so far). These authors used different methodologies of R calculation and also different interpolation methods with different variables. Therefore we used Ordinary kriging for our R dataset and set the R data as optional input. The representativeness of our R maps is illustrated in Figure 8. But the key point of this study is not methodology of R map creation but methodology of C factor calculation weighted by R factor distribution throughout the year determined by geographic location. This means that C factor is highly dependent not only on agro-technical dates defining the beginning of each of 5 phases but also on the spatio-temporal distribution of erosive rainfalls which can be highly different (Figure 6). Two types of semivariogram models best fit to empirical variograms – K-Bessel (Figure 6 left) and J-Bessel functions (Figure 6 right). For the calculation of weights of R distribution throughout the year it is necessary to create raster maps with values of long-term average monthly R distribution throughout the year. These rasters were created using map algebra and R maps with average monthly values within which erosive rainfall occurred (IV-X) and R map with average annual values. All maps were calculated using data from the whole period (19–48 years with an average of 35.3 years). The average percentage distribution of R values for each month reclassified using quantile classification method is shown in Figure 7. Very high spatial and temporal variability within each month and throughout the year can be observed from our results (Figure 7 and Table 2). This only highlights the importance of revised C-factor calculation using weights of spatio-temporal R factor distributions

Table 2. Statistics of resultant R factor distribution throughout the year (in %)

| Month | IV | V | VI | VII | VIII | IX | X |
|---|---|---|---|---|---|---|---|
| Min | 0 | 2.4 | 11.4 | 7.8 | 19.5 | 2.3 | 0 |
| Max | 2.8 | 15.7 | 38 | 70.2 | 49.8 | 12.7 | 2.6 |
| SD | 0.5 | 2.05 | 3.38 | 10.78 | 3.82 | 1.95 | 0.49 |
| Ø | 0.37 | 8.35 | 24.98 | 33.93 | 27.27 | 6.07 | 0.46 |
| Ø* | 1 | 11 | 22 | 30 | 26 | 8 | 2 |

IV–X – months; SD – standard deviation; Ø – mean; Q* – mean according to the currently valid methodology by Janeček *et al.* (2012b)

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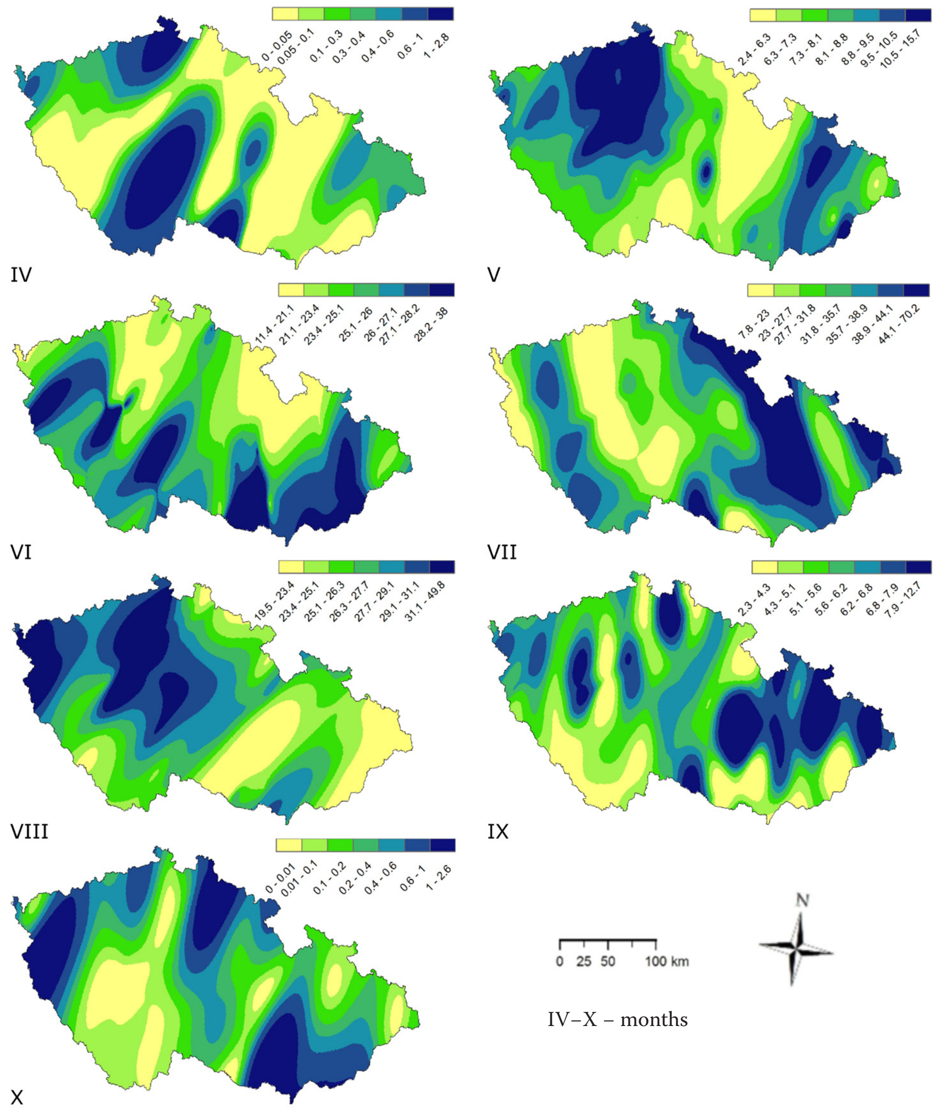


Figure 7. Long-term average monthly percentage R factor distribution throughout the year (in %) in the CR

throughout the year. This means that besides crop rotations, the geographic location of a given land parcel plays the main role.

We can notice from resultant values in Table 2 that average values are the highest for June-August. But we cannot generalize that this is a period with the highest water erosion risk for all places in the CR. The size of the CR approximately corresponds to areas in the USA for which the R values and R distribution throughout the year are generalized for USLE/RUSLE calculations (Table 2). Dates of agro-technical operations are another factor influenced by geographic location. We tested 11 maize localities in different parts of the CR where maize was planted (Figure 1). Collected agro-technical operation data and resultant R weights (average % R factor distri-

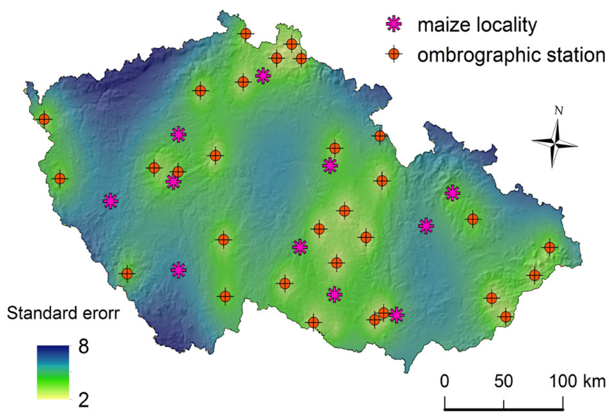


Figure 8. Representativeness of R map – yellow-green (can be used for C calculation), blue-dark blue (use with caution and zone for R*i* calculation > 5 km)

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Table 3. Resultant STD C factor values and percentage R distribution throughout the year for different parts of the CR according to local agrotechnical data for maize and local R factor weights

| Area | Agro-technical data tillage/sowing/harvest | % R for each month | | | | | | | STD C | C | diff (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | IV | V | VI | VII | VIII | IX | X | | | |
| 1 | 28.3./18.4./14.9. | 0.08 | 9.60 | 21.75 | 30.25 | 28.03 | 8.13 | 0.22 | 0.435 | 0.447 | 2.81 |
| 2 | 30.3./19.4./5.9 | 0.03 | 7.63 | 21.61 | 29.12 | 28.15 | 5.61 | 0.25 | 0.401 | 0.443 | 9.47 |
| 3 | 7.4./26.4./31.8. | 0.02 | 9.44 | 22.24 | 38.83 | 25.24 | 7 | 0.06 | 0.465 | 0.481 | 1.11 |
| 4 | 4.4/21.4/28.8. | 0.41 | 10.16 | 27.66 | 39.15 | 25.56 | 10.19 | 0.22 | 0.502 | 0.457 | 10.92 |
| 5 | 25.3./12.4./20.8. | 0.02 | 8.47 | 27.03 | 38.68 | 27.97 | 2.86 | 1.62 | 0.463 | 0.448 | 7.63 |
| 6 | 26.3./12.4./22.8. | 0.70 | 6.32 | 27.77 | 32.87 | 19.91 | 4.01 | 0.08 | 0.387 | 0.418 | 7.37 |
| 7 | 10.4./30.4/15.9. | 0 | 7.19 | 25.05 | 31.4 | 27.96 | 6.15 | 0.45 | 0.47 | 0.487 | 3.53 |
| 8 | 1.4./25.4./8.9. | 1.35 | 6.98 | 27.71 | 26.21 | 26.49 | 3.97 | 0.01 | 0.445 | 0.465 | 4.33 |
| 9 | 12.4/29.4/19.9 | 0.01 | 13.15 | 27.98 | 18.8 | 41.04 | 5.31 | 0 | 0.54 | 0.487 | 9.83 |
| 10 | 19.4./30.4./19.9. | 0.07 | 9.18 | 30.20 | 26.17 | 34.61 | 5.96 | 2.12 | 0.53 | 0.487 | 8.04 |
| 11 | 9.4./2.5./18.9. | 0.28 | 10.82 | 20.25 | 9.09 | 32.12 | 4.49 | 0.30 | 0.41 | 0.503 | 18.35 |

IV–X – months; STD C – spatio-temporally distributed C factor; C – calculation according to valid methodology (Janeček *et al.* 2012b), diff – difference between STD C and C in %

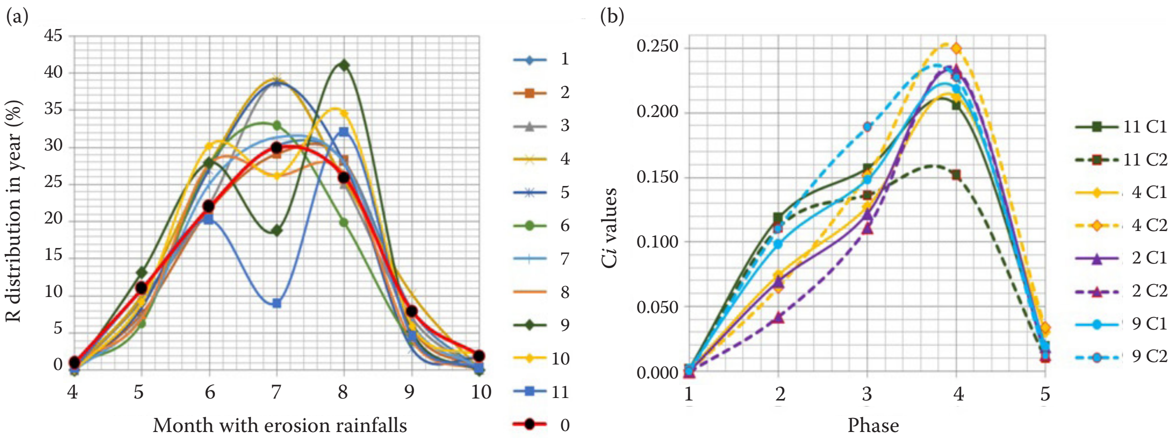


Figure 9. Variability of R distribution throughout the year for 11 areas and comparison with average values (O – red line) for the CR (a, left); comparison of $C_i$ values by original methodology (Wishmeier & Smith 1978; Janeček *et al.* 2012b) and by the presented STD C factor model (dashed line) for areas 2, 4, 9, 11 (b, right)

bution throughout the year for a given month) and C factor calculated using the STD C factor tool and by original methodology (Janeček *et al.* 2012b; Wischmeier & Smith 1978) are shown in Table 3. Resultant STD C factor values range from 0.387 to 0.54 and the difference from the original methodology varies from 1.1 to 18.35%. These results show high spatial variability which depends on rainfall erosivity distribution and agro-technical operation data. R distribution in 11 model localities throughout the year is compared with average values in the CR in Figure 9a. We can observe the largest difference in months with the highest occurrence of erosive rainfalls – July (varying from 9.09 to 39.15%) and August (varying from 19.01 to 41.04%). In Figure 9b we can see the comparison of $C_i$ values calculated by original methodology (Wischmeier & Smith 1978; Janeček *et al.* 2012b) and by the presented STD C factor model.

## CONCLUSION

In the presented research we highlighted the problems of currently used methods of C and R factor calculation and estimation. R factors for 31 ombrographic stations in the CR were computed. The

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long-term rainfall data (average 35.3 years) with 1 min temporal resolution were used. Resultant values show the high spatio-temporal variability of R values and their distribution throughout the year – tested on 11 different localities of the CR: July (varying from 9.09 to 39.15%) and August (varying from 19.01 to 41.04%). The relatively time-consuming C calculation was automated in the STD C factor GIS tool (version with integrated or optional R data) based on an innovative procedure of determination of R factor weights for each agro-technical phase by land parcel geographic location. The version with optional R data is universal and useful for all R maps created in the CR and also other countries (monthly R dataset for Europe by Ballabio *et al*. 2017). The variability of R distribution influenced C factor values by 1.1–18.35%. That is why the average values of R and its distribution should not be used for the whole territory of the CR (according to valid methodology by Janeček *et al*. 2012b) and similar size in the USA or Europe for USLE/RUSLE calculations.

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## References

Angulo-Martinez M., Lopez-Vincente M., Vincente-Serrano S.M., Bergueira S. (2009): Mapping rainfall erosivity at a regional scale: a comparison of interpolation methods in the Ebro Basin (NE Spain). Hydrology and Earth System Sciences, 13: 1907–1920.

Asis A.M., Omasa K. (2007): Estimation of vegetation parameter for modelling soil erosion using linear Spectral Mixture Analysis of Landsat ETM data. ISPRS Journal of Photogrammetry and Remote Sensing, 62: 309–324.

Ballabio C., Borrelli P., Spinoni J., Meusburger K., Michaelides S., Beguería S., Klik A., Petan S., Janeček M., Olsen P., Aalto J., Lakatos M., Rymszewicz A., Dumitrescu A., Tadić P., Diodato N., Kostalova J., Rousseva S., Panagos. P. (2017): Mapping monthly rainfall erosivity in Europe. Science of the Total Environment, 579: 1298–1315.

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

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 and Water Research, 12: 117–127.

Cebecauer T., Suri M., Hofierka J., Fulajtar E. (2004): Corine Land Cover in the context of soil erosion assessment at a regional scale. In: Workshop CORINE Land Cover 2000 in Germany and Europe and its Use for Environmental Applications, 20–21: 131–137.

De Jong S.M. (1994): Derivation of vegetative variables from a Landsat TM image for modelling soil erosion. Earth Surface Processes and Landform, 19: 165–178.

Dissmeyer G.E., Foster G.R. (1981): Estimating the cover-management factor (C) in the Universal Soil Loss Equation for forest condition. Journal of Soil and Water Conservation, 36: 235–240.

Garcia-Orenes F., Cerda A., Mataix-Solera J., Guerrero C., Bodi M.B., Arcenegui V., Zoronza R., Sempere J.G. (2009): Effects of agricultural management on surface soil properties and soil-water losses in eastern Spain. Soil and Tillage Research, 106: 117–123.

Gilabert M.A., Garcia-Harro F.J., Melia J. (2000): A mixture modelling approach to estimate vegetation parameters for heterogenous canopies in remote sensing. Remote Sensing and Environment, 72: 328–345.

Hanel M., Maca P., Basta 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.

Jakubíková A., Janeček M., Tippl M. (2006): Field determination of the specific input characteristics to calculate the value of C factor of time-variable crops for the Revised Universal Soil Loss Equation (RUSLE). Soil and Water Research, 1: 10–15.

Janeček M., Tippl M., Bohuslávek J. (1995): Using a rainfall simulator for monitoring soil protection effectiveness of planting variants of corn. Plant Production, 41: 485–490. (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., Květoň V., Kubatová E., Kobzová D. (2012a): Differention and regionalization of rainfall erosivity factor values in the Czech Republic. Soil and Water Research, 7: 1–9.

Janeček M. *et al.* (2012b): Protection of Agricultural Land from Erosion. Prague, VUMOP. (in Czech)

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

https://doi.org/10.17221/100/2017-SWR

Janeček M., Kubátová E., Procházková E. (2013b): Use of simulators in the rain erosion research. Vodní hospodářství, 63: 168–172. (in Czech)

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.

Meusburger K., Steel A.B., Panagos P., Montarella L., Alewell C. (2012). Spatial and temporal variability of rainfall erosivity factor for Switzerland. Hydrology and Earth System Sciences, 16: 167–177.

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

Panagos P., Borrellia P., Meusburger K., Alewellb Ch., Lugatoa E., Montanarellaa L. (2015a): Estimating the soil erosion cover-management factor at the European scale. Science of the Total Environment, 48: 38–50.

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

Parsons A.J., Abrahams A.D., Wainwright J. (1994): On determining resistance to interill overland flow. Water Resources Research, 30: 3515–3521.

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.

Richardson C.W., Foster G.R., Wright D.A. (1983): Estimation of erosion index from daily rainfall amount. Transactions of the ASAE, 26: 153–156.

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

Simeonakis E., Darke N. (2004): Monitoring desertification and land degradation over sub-Saharan Africa. International Journal of Remote Sensing, 25: 573–592.

Toman F., Kadlec M. (2003): Regionalization methods of agricultural land use expressed by C factor. Soil and Water, 2: 139–150. (in Czech)

Trojacek P., Kadlubiec R. (2004): Detailed mapping of agricultural plots using satellite images and aerial orthphoto maps. In: Goossens R. (ed.): Remote Sensing in Transition. Rotterdam, Millpress: 253–257.

Tweddales S.C., Eschlaeger C.R. Seybold W.F. (2000): An Improved Method for Spatial Extrapolation of Vegetative Cover Estimates (USLE/RUSLE C factor) using LCTA and Remotely Sensed Imagery. USAEC Report No. SFIM-AEC-EQ-TR-200011, ERD/CELR TR-00-7. Champaign, US Army of Engineer Reserach and Development Center, CERL.

Van Der Knijff J.M, Jones R.J.A., Montanarella L. (2000): Soil Erosion Risk Assessment in Europe. EUR 19044 EN, Joint Research Centre, European Soil Bureau.

Williams J.D. Wilkins D.E., McCool D.K., Baarstad L.L., Klepper B.L., Papendick R.I. (1998): A new rainfall simulator for use in low-energy rainfall areas. Applied Engineering in Agriculture, 14: 243–247.

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

Zhao W., Fu B., Qiu Y. (2013): An Upscaling Method for Cover-Management Factor and Its Application in the Loess Plateau of China. International Journal of Environmental Research and Public Health, 10: 4752–4766.

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