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Development of web-based WERM-S module for estimating spatially distributed rainfall erosivity index (EI30) using RADAR rainfall data

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ABSTRACT

Despite technological advances, soil erosion modeling is a very complicated process as the amount and rate of soil erosion vary considerably over space and time. Universal Soil Loss Equation (USLE) is one of the oldest and popular models used for soil loss estimation worldwide. USLE R-factor is one of the six input parameters accounting for the impact of rainfall amount and intensity on soil erosion in USLE. The USLE R factor is calculated by averaging annual long time rainfall erosivity index (EI30) values, computed by multiplying maximum rainfall intensity during 30 min periods and the kinetic energy of the rainfall. The gage rainfall data are used for the determination of such EI30 index, and one representative value is given for the entire area. Due to the spatial and temporal variability of rainfall pattern, the value may vary considerably over space and time. It is required to obtain the rainfall data over a surface (heterogeneous) rather than at a point (homogeneous) so that spatially distributed erosivity index values can be calculated. Even though RADAR can provide spatially and temporally distributed rainfall data, the process of manual erosivity index calculation for each raster pixel is very tedious, time-consuming and practically not feasible. To overcome these limitations, the web-based WERM-S module was developed to compute a spatial EI30 index from the 10-min interval spatial rainfall data. The WERM-S consists of three different Fortran modules (Convert Module, R-factor calculation module, and R-factor ASCII module). The Jaun-ri watershed was selected as the study area to test the module since the RADAR rainfall data was available for 2015. June, July, and August were found to be the months receiving the maximum amount of rainfall and the average erosivity indices for June, July and August were found to be 2096, 1002, and 993 MJ·mm/ha-hr-month, respectively. The maximum erosivity index for a pixel within the study area was observed to be 9821 MJ·mm/ha-hr-month for June 4382 MJ·mm/ha-hr-month for July and 6093 MJ·mm/ha-hr-month for August respectively. The higher value of standard deviations of 1850, 950 and 1115 MJ·mm/ha-hr-month for June, July, and August were observed respectively representing that the erosivity index of individual space widely deviated from the mean monthly erosivity index. Thus spatial erosivity index is suggested to be used over average annual R factor values to calculate soil loss using USLE. Furthermore, the WERM-S module can be a very useful tool to automatically calculate the spatially distributed rainfall erosivity index from 10-min interval RADAR rainfall data.

1. Introduction

Soil erosion modeling is considerably complicated process since erosion occurs diversely over space and time. There is a need of local and regional estimate of soil loss since erosion rate should be quantified for proper decision-making regarding appropriate control practice to be implemented (de Vente et al., 2008; Jeong et al., 2004). Various empirical, conceptual and physically-based computer models such as Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978), Agricultural Non-Point Source Pollution Model (AGNPS) (Young et al., 1989), Soil and Water Assessment Tool (SWAT)(Arnold et al., 1998), Water Erosion Prediction Project (WEPP) (Flanagan and Nearing, 1995), and European Soil Erosion Model (EUROSEM) (Morgan et al., 1998) have been developed over the last few decades and are in

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practice for the soil erosion estimation and erosion control assessment (De Vente and Poesen, 2005). USLE is one of the oldest and widely used empirical models, which has been applied in many countries around the world. It is extensively used in Korea since the input parameters have been well-established over the years (Lim et al., 2005; Park et al., 2010). USLE uses six input parameters namely erosivity (R) factor, erodibility (K) factor, topographic (LS) factor, cover management (C) factor and conservation practice (P) factor for the estimation of soil loss. Erosivity or R-factor is one of the six input parameters, which accounts for impacts of rainfall amount and intensity on soil erosion. Rainfall erosivity index (EI30) is one of important parameter required for calculation of the R-factor which is computed by multiplying maximum rainfall intensity during 30 min periods with the kinetic energy of the rainfall. A minimum of 20 years average value of such erosivity indices summed up for a year is termed as USLE/RUSLE R factor (Renard et al., 1997). Because of the spatial and temporal variability of rainfall pattern, such erosivity index also varies considerably over space and time which consequently affects the value of R factor and thus soil erosion amount. Besides, such event based erosivity indices summed up for a month to obtain monthly erosivity can be multiplied with other monthly USLE parameters to obtain the amount of monthly soil erosion for a watershed or field (Diodato, 2006).

The gage rainfall data have been used to determine yearly, monthly and event-based erosivity indices and such erosivity index values have been published for various weather stations in South Korea (Risal et al., 2016). Though the quality and source of error in rainfall data from rain gage can be determined easily, the rain gage provides a measure of rainfall at a point (Einfalt et al., 2004). Since soil erosion is the phenomena occurring over a particular area rather than at a point, soil loss amount needs to be calculated over the area. As USLE is used to estimate soil erosion, actual R-factor over the area rather than at a point is required. The R-factor derived from the gage rainfall data cannot accurately represent the spatial distribution of R-factor since rainfall distribution over the surface is not always uniform. The desirable spatially distributed R-factor can be determined using the spatial rainfall data and applied in USLE for the accurate estimation of soil loss amount. A case study was performed on prediction and uncertainty of soil loss using RUSLE by Wang et al. (2002) and found that R-factor had a considerable spatial and temporal variability even over a relatively smaller area.

For the determination of such spatially distributed R factor using rainfall erosivity index, spatial and temporal rainfall data are needed. RAdio Detection And Ranging (RADAR) is one of the possible sources for finer scale (spatial and temporal) rainfall data. In the areas where rain gages are sparsely distributed, the RADAR data are more suitable to estimate rainfall compared to the gaged data (Yang et al., 2004). The RADAR technology has been utilized in the field of hydrology for the last four decades for weather prediction. The basic principle of this technology is the measurement of the backscattered electromagnetic wave from rain particles in the direction of the RADAR station (Skolnik, 1962). The reflectivity (Z) of the backscattered radiation is proportional to the summation of sixth power of particle diameter (Wilson and Brandes, 1979). Rainfall is related to reflectivity by the following empirical relationship as given in Eq. 1 (Battan, 1973).

$$z = a \bullet R^{b} \tag{1}$$

where z is reflectivity in $mm^6\ m^{-3}$, R is rainfall amount in $mm\ hr^{-1}$, a and b are constants which depend on rain type and geographic locations (Austin, 1987). The widely used values of constants a and b in Eq. 1 are 200 and 1.6 respectively (Marshall and Palmer, 1948).

The rainfall data obtained from RADAR has been used in various hydrologic and meteorological studies by various researchers around the world (Lo Conti et al., 2015; Peleg et al., 2016; Noh et al., 2016). The RADAR rainfall was compared with actual rain gage data for two short storm events in Southern California in the USA and it was concluded that RADAR rainfall estimate could be used for storm event analysis with consideration of possible topographic interference (Espinosa et al., 2015). In a study by Fabry et al. (1994), rainfall with high spatial and temporal resolution was measured by RADAR for a small basin and it was reported that rainfall map at greater time resolution could capture the temporal evolution essential for optimal rainfall estimation with sufficient accuracy. These findings indicate that RADAR data can be used for deriving the spatial rainfall amount for small area for small time interval. Even though those desired rainfall data exists, the process of manual USLE R-factor calculation from rainfall erosivity index for each raster pixel (small area) is very tedious, time-consuming and practically impossible. There is a necessity of development of a module which can automatically compute spatial erosivity indices from the bulk of spatial rainfall data for the given period. The web-based tool is one of the effective ways for the calculation of such spatially distributed erosivity index from a number of rainfall (ASCII) data files for short time interval since users can access and use the web tool easily from anywhere.

The objectives of this study are to (a) develop the Web ERosivity Module-Spatial (WERM-S) module to calculate spatial rainfall erosivity index of each raster pixel (500 × 500 m resolution) from raw RADAR rainfall data (ASCII files for each 10 min interval) and (b) analyze the difference in rainfall erosivity indices derived from spatial RADAR rainfall data and rain gage data of three nearest stations.

2. Materials and methods

2.1. Study area

The Jaun-ri, a rural hilly watershed located in the Gangwon Province in South Korea, was selected as a study area to test our newly developed WERM-S module and thus estimate spatially distributed R-factor from spatial rainfall data. The watershed is located at the coordinate of 39°42′17″N latitude and 128°24′08″E longitude. The selected watershed is very vulnerable to soil erosion and has been designated as a nonpoint source pollutant hotspot area by the government of South Korea (Park et al., 2011). The R-factor with high spatial resolution is needed to estimate soil erosion accurately and introduce various best management practices in the study watershed. Moreover, the topography of the basin is very steep with a mean slope of 33.5%. The average annual temperature of the watershed is 8.35 °C with maximum and minimum annual precipitation of 2173 and 739 mm respectively for the period from 2010 to 2015 with an annual average precipitation of 1442 mm (KMA, 2016). The study watershed receives maximum rainfall in July and August with more than 50% of total annual precipitation concentrating during the period of these two months. The mean monthly precipitation was measured to be 424 and 212 mm in July and August respectively whereas the mean monthly precipitation of just 11 mm was observed in January. The maximum daily precipitation of 144 mm was observed on 27th July 2011. Similarly, the high amount of rainfall of 111 mm on 15th July 2013 and 95 mm on 15th August 2012 were observed to have occurred in our study area.

The watershed has two dominant land uses, namely forest and agricultural land. Out of total area of 24.89 ha, 23.83 ha (96.17%) is covered by forest, and the remaining 1.06 ha (3.83%) is covered by agricultural land (Park et al., 2011). The soil in the watershed is mostly sandy that is composed of 63% of sand, 28.2% of silt and 7.8% of clay. Extensive highland agricultural farming is performed in the downstream areas of the study watershed. The location of the study area is shown in Fig. 1.

2.2. Data

2.2.1. RADAR rainfall data

The rainfall data (ASCII files) with 10 min interval for 2015 were obtained using RADAR installed in Gwanak Mountain (located at

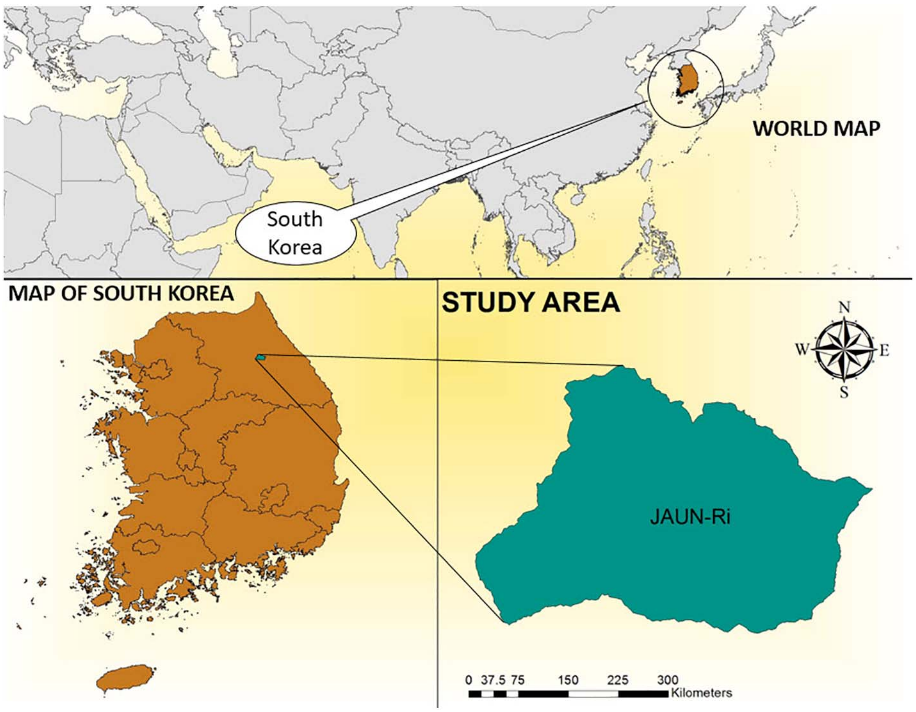

Fig. 1. Study area.

Table 1
Technical details of the RADAR.

Developer	Enterprise Electronics Corporation (EEC), Alabama, USA
Signal processor	EDRP-9
Software tool	EDGE 5.2.0-5
PRF(HZ)	322-1282
Peak power	850 kw
Transmission type	Klystron
Frequency	S-Band
Beam width	1.0°
Antenna gain	45 dB

Table 2
Summary of the RADAR data.

Station name	Gwanak San
longitude(°E)	126°57′49.46"
latitude(°N)	37°26′39.42"
elevation(m)	580
Total number of observations	13
Observation angles(°)	0.0, 0.4, 0.8, 1.2, 1.6, 2.0, 3.0, 4.2, 5.7, 7.5, 9.8, 12.5, 15.8
Maximum scan speed	36°/s
Operation scan speed	15°/s
Time interval(minute)	10

Gyeonggi-do) at an elevation of 580 m above mean sea level. The Gwanak RADAR (S-band single polarization RADAR) is one of the 11 KMA (Korea Meteorological Administration) RADAR networks that have an effective coverage area within the radius of 240 km from the radar station. The technical detail regarding the Gwanak RADAR is presented in Table 1:

The reflectivity observations were archived from the RADAR at every10 minute interval at a spatial resolution of 250 × 250 m, which were later resampled to the resolution of 500 × 500 m. The observed reflectivity was related to rainfall using the Eq. 2 (Marshall and Palmer, 1948).

$$z = 200 \bullet R^{1.6} \quad (2)$$

where z is reflectivity in mm^6/m^3, R is rainfall amount in mm/hr.

The summary of RADAR data obtained is provided in Table 2:

The RADAR data was obtained for the period from January 1, 2015, to December 31, 2015, in the form of ASCII Grid (ESRI Grid format) file. Each grid file contained rainfall data for 513 pixels (27 × 19 pixels) at 500 × 500 m resolution. Two types of reflectivity data, one recorded at the ground surface and other recorded at an elevation of 1.5 km from the ground surface were available for the same time interval. The data obtained from the reflectivity at an elevation of 1.5 km above earth surface which is also known as constant altitude plan position indicator (CAPPI) data are taken for this study since variation in the observation altitude can be eliminated using these CAPPI reflectivity data (Chumchean et al., 2006). One of the Quantitative precipitation estimation (QPE) data of Gwanak Mountain RADAR recorded at 2015/07/12 12:00 is presented in Fig. 2:

2.2.2. Rain gage rainfall data

Gage rainfall data for three nearby weather stations (Hongcheon, Inje, and Daegwallyeong) were obtained from the KMA (2016). The obtained data are in the form of the 10-min interval, and the Web ERosivity Module WERM (Risal et al., 2016) was used to generate monthly and event-based erosivity index for these stations. The detail about WERM is provided in the later section. The location of these three nearby rain gage stations along with their distances from the study area is presented in Fig. 3.

2.3. Universal Soil Loss equation (USLE) model

The USLE model is a popular model which has been widely used in many countries around the world for estimating the amount of soil loss. It uses six input parameters namely erosivity (R) factor, erodibility (K) factor, topographic (LS) factor, cover management (C) factor and conservation practice (P) factor for the estimation of soil loss. The USLE equation is given by Eq. 3:

$$A = R \times K \times LS \times C \times P \quad (3)$$

Though the USLE was initially applied for quantification of soil loss from agricultural land in the USA and the input parameters were

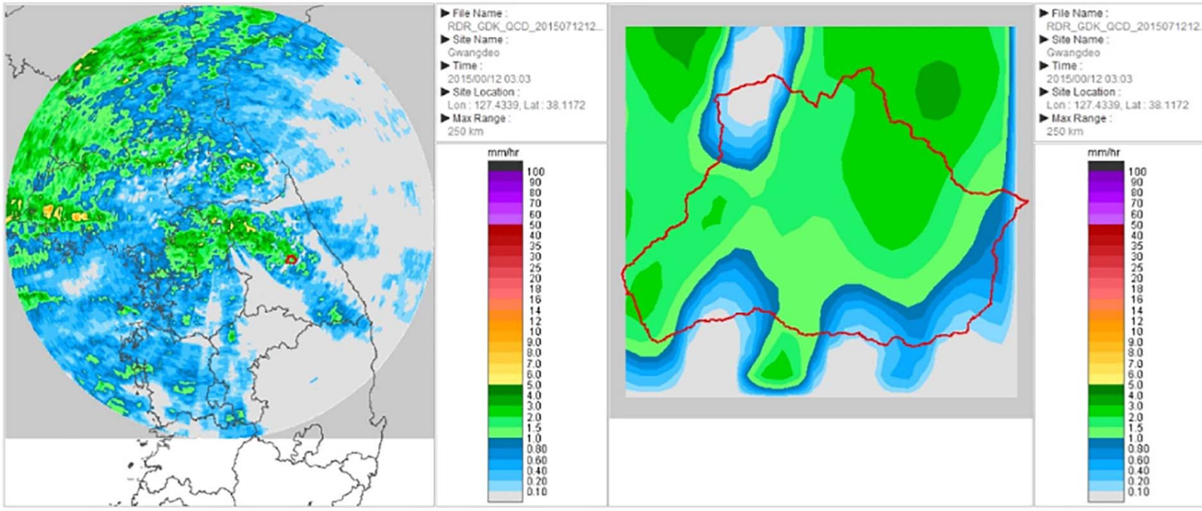

Fig. 2. CAPPI Precipitation Image of entire coverage (left), Juan watershed (Right).

determined for the USA conditions, it has been extended for estimation of soil erosion in many other countries (Kinnell, 2010). Moreover, the applicability of USLE has been increased after the development of GIS and remote sensing, which has contributed to the development of spatiotemporal USLE parameters. Specifically, USLE is extensively used in Korea since the input parameters have been well established over the years (Lim et al., 2005; Park et al., 2010).

2.4. Web ERosivity Module (WERM)

Web Erosivity Module (WERM) (http://www.envsys.co.kr/~werm/) is one of the useful tools to calculate R-factor values using the rainfall data from rain gage stations. It is based on the USLE equations from Agricultural Handbook number 537 (Wischmeier and Smith, 1978) and uses ten-minute interval rainfall data accumulated for one day of the entire period in the form of a text file as input. The input data for this module need to be in a specified format in an increasing order of date and time. The sample input data for several weather stations are available on the website, and they can be used to prepare the input file. The yearly, monthly and event-based R-factor values are calculated and displayed instantly on the website after the input file is uploaded in the module. Moreover, the output (text files containing yearly, monthly and event-based R-factor values) can be downloaded from the website for further analysis. Although the standard minimum number of hours without rainfall to separate one rainfall event from other is 6 h (Renard et al., 1997), this minimum number of hours with no rainfall can be modified according to rainfall pattern and as per need basis. Thus, the option of selecting a minimum number of hours of no rainfall is made available in WERM for separation of rainfall events and R-factor calculation.

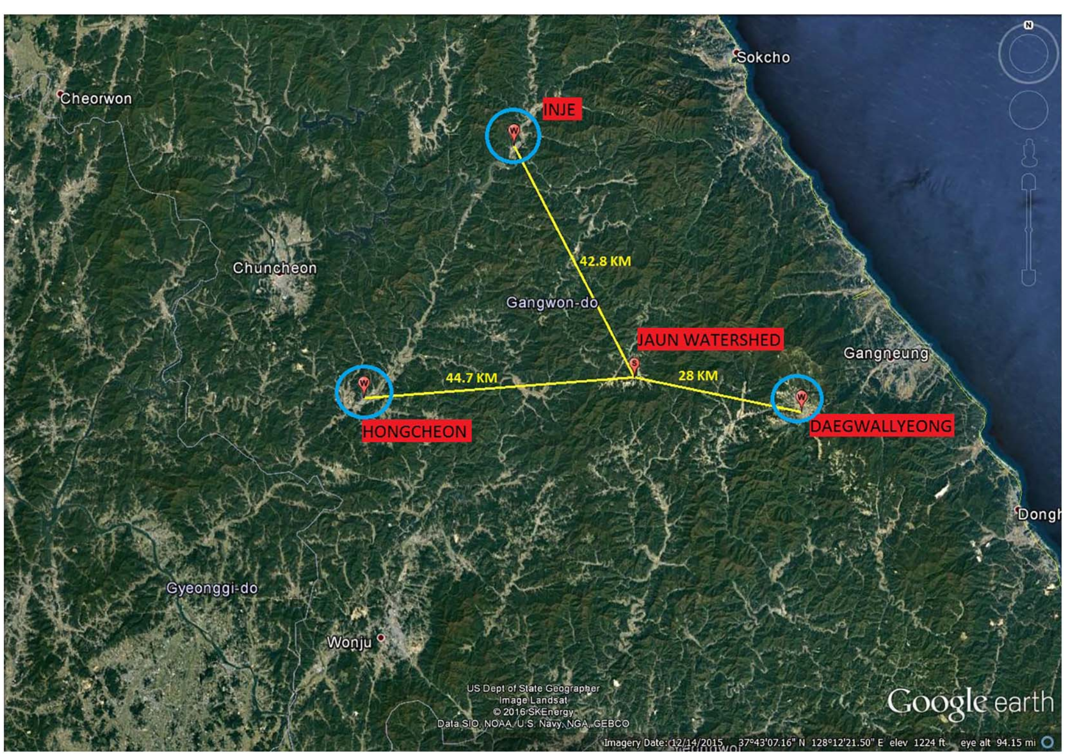

Fig. 3. Distance of rain gage stations from the Juan-ri watershed.

Fig. 4. WERM-S web interface.

3. Development of web ERosivity module-spatial (WERM-S)

The WERM-S model, developed in this study, consisted of three different modules namely "*convert module*", "*R-factor calculation module*", *and* "*R-factor ASCII module*". These three different modules are based on the distinct Fortran codes compiled separately on the Linux server using Intel Fortran compiler. The compiled executable files of these codes along with HTML, PHP, JavaScript, CSS, and Jquery are used to develop this web-based module and interfaces. The web interfaces of WERM-S (http://www.envsys.co.kr/~WERM-S/) is shown in Fig. 4.

Similarly, the interface of the three sub-modules of WERM_S along with the description of their required input files is presented in Fig. 5. The "*convert module*" first converts ASCII files of each 10-min interval RADAR rainfall data into several text files containing 10-min interval rainfall data of each pixel. The *R-factor calculation module* then calculates the erosivity index of each pixel from the rainfall data obtained from the convert module. Finally, the *R-factor ASCII module* converts back the erosivity index of each pixel into a single ASCII file so that the resulting spatially distributed map of the erosivity index can be visualized in ArcGIS interface.

3.1. Convert module

The main purpose of the *convert module* is to preprocess raw RADAR rainfall data in ASCII format into a format that can be used in the *R-factor calculation module* of WERM-S. These raw input data needs to be processed to separate erosive rainfall events and calculate event based R-factor for each raster pixel. Rainfall events separated by 6 h with insignificant amount for each pixel was used to separate one rainfall event from another. The R-factor formula is applied to each rainfall event. The detailed procedure for R-factor calculation is discussed in later section. For this conversion purpose, a Fortran code capable of automatic conversion of these 10 min interval rainfall (ASCII files) into

Fig. 5. Submodules of WERM_S.

each raster pixel's separate 10 min interval rainfall data (text files) was developed. Users need to keep all the input ASCII files into one folder and compress the folder into the .zip file before using it on the web interface. The compressed .zip file must be uploaded into the *convert module* along with the text file containing the name of each ASCII files through any web browser. The number of output text files from this convert module equals the total number of raster pixels present in the input rainfall ASCII files. The output of this module is the input for the *R-factor calculation module*.

3.2. R-factor calculation module

This module of WERM-S calculates the event-based erosivity index of each raster pixel of the input data (RADAR rainfall). It first separates erosive rainfall events and then estimates the event based erosivity index of each raster pixel. To identify and separate the erosive rainfall events, the three criteria were considered. For the first criterion, the storm period with less than 1.3 mm of rainfall for 6 h was used to divide one rainfall event from another (Renard et al., 1997; Wischmeier and Smith, 1978). The second criterion was that the rain events that are with less than 12.7 mm were not considered in the calculation as an insignificant rainfall to cause soil erosion. For the third criterion, the rainfall less than 12.7 mm was considered to cause erosion if there was an occurrence of continuous 6.25 mm rainfall for 15 min (Wischmeier and Smith, 1978; Renard et al., 1997; Panagos et al., 2015). Rainfall of 12.7 mm was considered as the threshold value that can cause soil erosion and thus used to specify erosive precipitation event (Panagos et al., 2015).

After the identification and differentiation of each erosive rainfall event, original USLE R-factor equation was applied to a rainfall event of each raster pixel. According to USLE R-factor equation, R-factor is the product of kinetic energy and maximum 30-min intensity of each rainfall event (Brown and Foster, 1987). The logarithmic model used by Wischmeier and Smith (1978) was used for the determination of kinetic energy in the process of calculation of R-factor. The R-factor was calculated by using Eq. 4:

$$R = \sum_{k=1}^{n} (E \bullet I30_{max})_k \tag{4}$$

where R is an average annual erosivity (MJ·mm/ha-hr-year), n is the

Table 3
Monthly rainfall amount and maximum 30-min intensity ($I30_{max}$) for 3 months.

Station name	Latitude	Longitude	June		July		August	
			Monthly precipitation (mm)	$I30_{max}$ (mm/hr)	Monthly precipitation (mm)	$I30_{max}$ (mm/hr)	Monthly precipitation (mm)	$I30_{max}$ (mm/hr)
Hongcheon	37.68	127.88	52	14	199	31	115	59
Inje	38.05	128.16	44	22	235	32	118	42
Daegwallyeong	37.68	128.76	88	23	133	23	309	49
Jaun-ri (RADAR)	39.70	128.40	185	44	303	35	239	31

number of erosive rainfall events, Eis the total storm kinetic energy and $I30_{max}$ are the maximum 30-min intensity in the erosive event. The total storm kinetic energy E (MJ/ha) used in above equation was determined using Eq. 5:

$$E = \sum_{k=1}^{n} e_k \bullet dk \tag{5}$$

where e_k is unit rainfall energy (MJ/ha-mm) and dk is the rainfall volume (mm) during a time period of k. The unit rainfall energy (e_k) used above in Eq. 3 was calculated using following Eq. 6:

$$e_k = 0.119 + 0.0873 \log\ (i_k) \tag{6}$$

where i_k is rainfall intensity during the time interval (mm/hr). If the intensity of rainfall is greater than 76 mm/hr, the unit rainfall energy is taken as 0.283 MJ/ha/mm (Wischmeier and Smith, 1978; Renard et al., 1997).

Event-based erosivity index for each raster pixel calculated using the above equations was then summed up for a month to generate a monthly erosivity index of each raster pixel. For this purpose, another Fortran code was developed which was capable of automatic calculation of event based and monthly erosivity index of each raster pixel. The output text files from the *convert module* are the input for the *R-factor calculation module*. The output of this module consists of a file containing the summation of event based erosivity index for the entire period and other files for monthly erosivity index along with individual event based erosivity index text files for each raster pixel. The monthly output erosivity index text files from this module are the input for the *R-factor ASCII module* which converts these individual monthly erosivity indices into a single monthly erosivity index in ASCII file format.

3.3. R-factor ASCII module

The main purpose of the R-factor ASCII module is the post processing of spatially distributed erosivity index values in order to display the result as a graph and analyze the values easily. The raw output data in the text files from the previous module were converted into a single ASCII file so that it would be possible for those result to be visualized graphically in the ArcGIS interface. For this, another separate Fortran code was developed which was capable of converting the input (monthly erosivity index) into the desired ASCII format.

4. Application of web ERosivity module-spatial (WERM-S)

The WERM_S module was applied for the Jaun-ri watershed to estimate spatially distributed erosivity index. The rainfall and erosivity index for individual raster pixel obtained from WERM_S were analyzed for the spatial variability of rainfall and erosivity index in the study area. Similarly, the monthly average erosivity index of the study area was compared with the monthly erosivity index values of three nearby weather stations (Hongcheon, Inje, and Daegwallyeong). The results of our study are discussed in following headings:

4.1. Comparison of RADAR rainfall data versus rain gage data of nearby stations

The average RADAR rainfall data of the study area was compared with the rainfall data of three nearby rain gage stations - Hongcheon, Inje, and Daegwallyeong. The Jaun ri received a high amount of rainfall in June, July, and August. Since these three months were seen to have significant amount of rainfall, the erosivity values of these three months have been discussed in detail. The average erosivity values of the other nine months are relatively very low compared to these three months. The erosivity index is dependent on not only rainfall amount but also the maximum of 30-min intensity rainfall ($I30_{max}$). Therefore, $I30_{max}$ was also considered for the comparison purpose. Though the total monthly rainfall amount for Hongcheon in August is seen relatively low as 115 mm, the erosivity index value is greater for this month since a severe rain storm was seen to have occurred with $I30_{max}$ of 59 mm/hr. The lowest $I30_{max}$ was observed as 14 mm/hr in Hongcheon for June. The precipitation amount and $I30_{max}$ of RADAR and three stations for June, July and August are presented in Table 3 and also shown in Fig. 6.

The gage rainfall data were measured at a point (local station) and they, along with average RADAR rainfall data, represent rainfall of the area surrounding weather stations assuming rainfall distribution over the surface was uniform.

4.2. Estimation of spatial erosivity index from RADAR rainfall data using WERM-S

Event based erosivity index for each raster pixel was calculated using RADAR rainfall data which were then summed up for a month to estimate the monthly erosivity index. Since three months June, July, and August were seen to have a significant amount of rainfall, the erosivity values for these three months have been discussed in detail. The average erosivity index for June was found to be 2092 MJ·mm/ha-hr-month, for July was 1000 MJ·mm/ha-hr-month and that for August was found to be 991 MJ.mm/ha-hour-month. The maximum erosivity indices were 9821, 4382 and 6093 MJ·mm/ha-hr-month for June, July, and August respectively. Similarly, the minimum erosivity index value of 28 MJ·mm/ha-hr-month for June, 34 MJ·mm/ha-hr-month for July and 49 MJ·mm/ha-hr-month for August was seen. The standard deviations for the erosivity index for different pixels were observed to be 1851 MJ·mm/ha-hr-month, 950 MJ·mm/ha-hr-month and 1115 MJ·mm/ha-hr-month for June, July and August respectively. The high standard deviation values indicate that the erosivity index for the raster pixel deviates greatly from the mean erosivity index for each month. The result also indicates that the use of average R-factor values may not be appropriate to be used in USLE for the determination of soil erosion since R-factor varies spatially as rainfall does. Moreover, USLE equation must be applied to each small area or each raster pixel so that it is possible to determine soil loss amount from each pixel rather than applying over the relatively large area. To apply USLE to each raster pixel, it is necessary to determine the input parameters for each pixel. Since R-factor is one of the six input parameters of USLE, WERM-S is a very effective tool for the determination of the desired pixel based erosivity index for calculation of USLE R factor using spatial and temporal RADAR rainfall

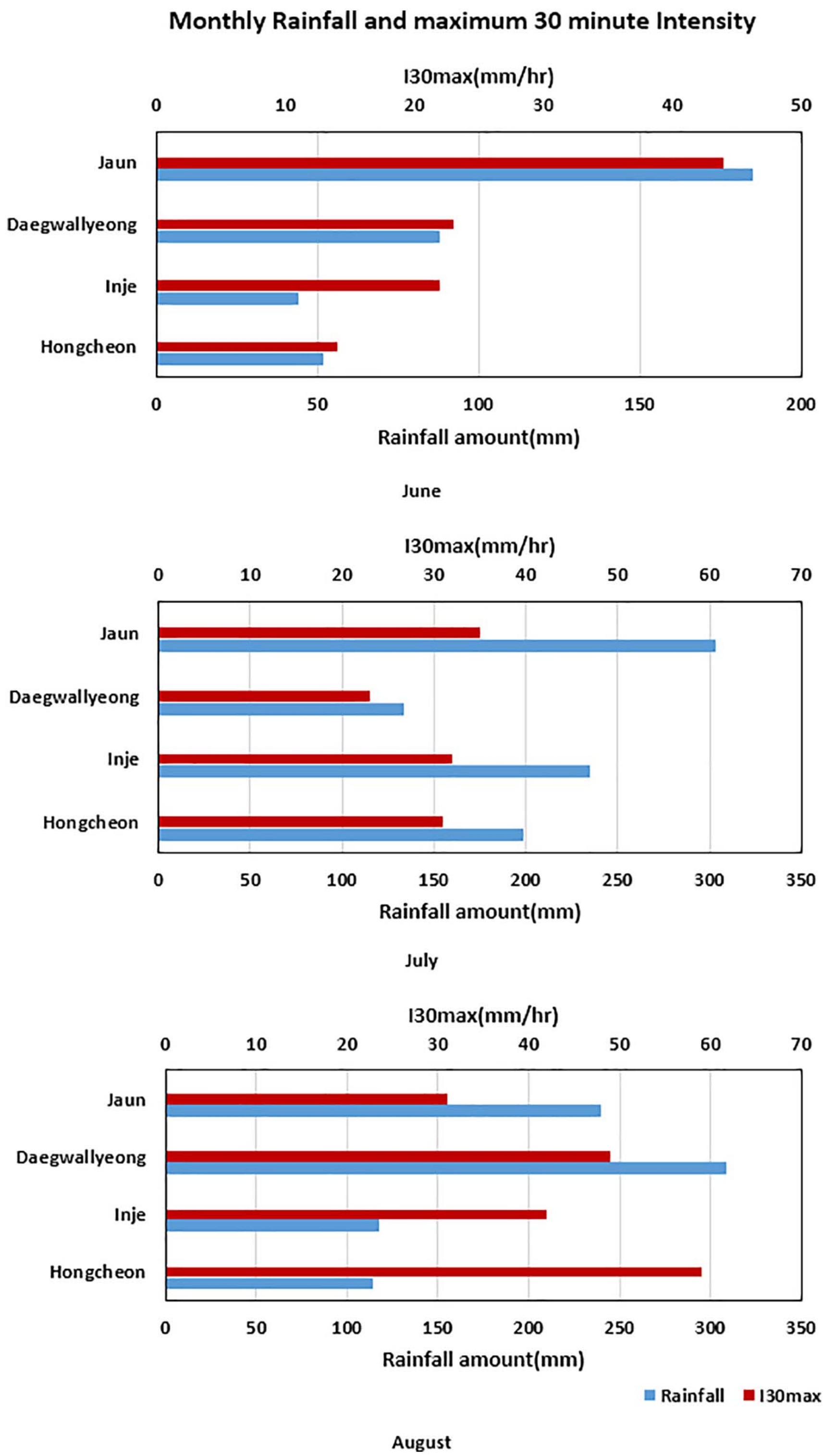

Fig. 6. Monthly rainfall and maximum 30-min intensity.

data.

The total erosivity index values of each pixel for three months (June, July, and August) of the study area are presented in Fig. 7. The blue bars show the erosivity index values of the individual pixel for June, green above the blue bar for July and red bars above the two bars represent an erosivity index for August. The horizontal dotted line is the average erosivity index value for the entire study area for those three months. As shown in Fig. 7, the erosivity index of individual pixels varied greatly from the mean erosivity index. This result indicates the necessity of using spatial R-factor in USLE over mean R-factor values or R-factor derived from gage rainfall data.

The erosivity index was also calculated from average RADAR rainfall data using WERM (Risal et al., 2016). The value of the monthly erosivity index and $I30_{max}$ derived from average RADAR rainfall data along with the monthly erosivity index and $I30_{max}$ of some individual raster pixels having extreme values are summarised in Table 4.

It was observed that erosivity index, as well as $I30_{max}$ values, varied significantly (Table 4). The erosivity index of pixel number 83 was computed to be 9821 MJ·mm/ha-hr-month in June whereas the value for pixel number 43 was estimated to be 28 MJ·mm/ha-hr-month for

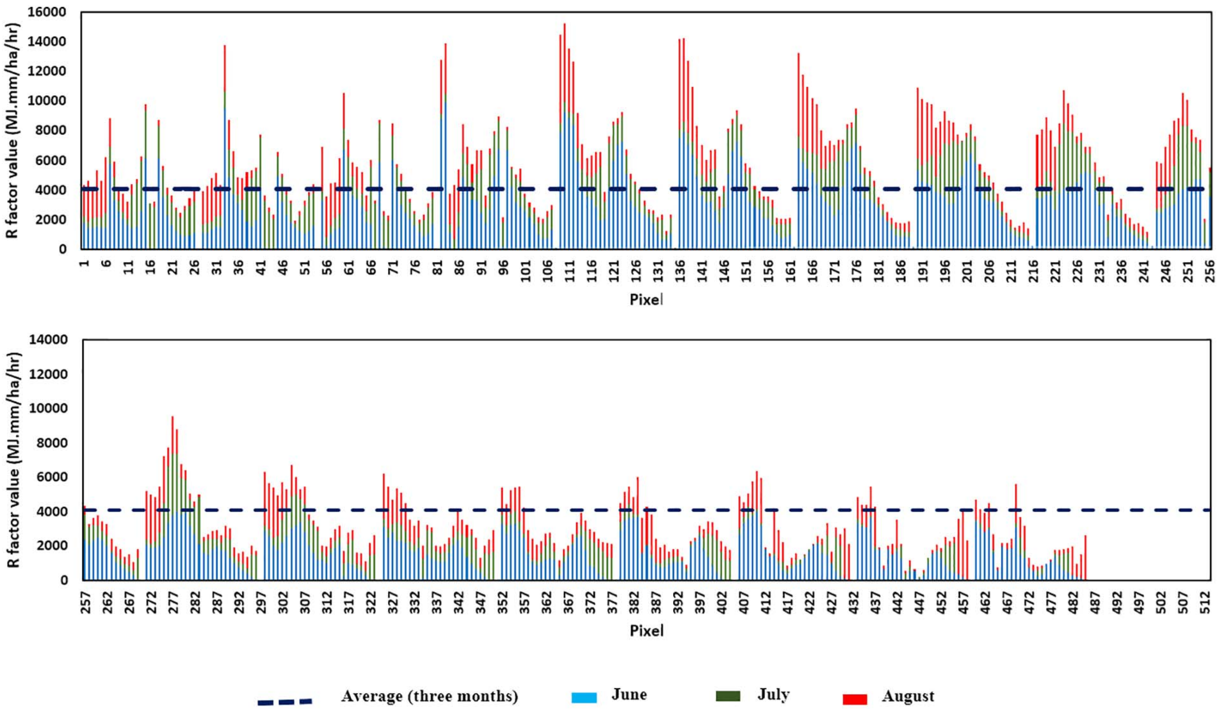

Fig. 7. Comparison of average and individual erosivity index of Jaun-ri for June, July and August.

the same month. In this condition, the mean erosivity index value of 295 MJ·mm/ha-hr-month from average RADAR cannot account for these extreme values.

For July, the erosivity index of pixel number 223 was computed to be 4382 MJ·mm/ha/hr/month and that for pixel number 412 was estimated to be just 34 MJ·mm/ha-hr-month. In the meantime, the mean erosivity index value computed from RADAR data was 648 MJ·mm/ha-hr.-month. Similarly, the variation in erosivity index for different pixel for August was seen to have scattered from 49 to 6093 MJ·mm/ha/hr/month, whereas the value of erosivity index derived from average RADAR rainfall was determined to be 432 MJ·mm/ha/hr/month which could not account for these extreme erosivity indices. The main factor responsible for the value of the erosivity index was $I30_{max}$ whose value varied from 8 to 181 mm/hr for June, 14 to 118 mm/hr for July and 14 to 91 mm/hr for August. $I30_{max}$ derived from average RADAR rainfall was found to be 44, 35 and 31 mm/hr for June, July, and August respectively.

Since erosivity index and $I30_{max}$ for individual pixels largely deviate from that derived from the average RADAR rainfall of each pixel, these average values are not suggested to be used in the USLE equation for soil loss estimates. Instead, individual R-factor values are recommended to be applied.

Individual erosivity index values for each raster pixel of the study area for each month were then converted to ASCII files as monthly erosivity index maps (Fig. 8)The monthly erosivity index map can be used directly along with the similar map of other input data of USLE- K, LS, C and P factors to determine the monthly soil loss map of the area. The erosivity index map also shows great variation in erosivity index values for the 12 months in 2015. These spatial erosivity index maps can be used to identify and apply best soil erosion practices at a finer scale.

The frequency distribution of erosivity index values for the month of June, July and August are presented in Fig. 9(a, b and c) respectively. It was observed that the erosivity index ranged from 100 to 1500 MJ-mm/ha-hr-month for majority of pixels for those three months. Only few pixels have very high erosivity index value. In general, it was observed that the erosivity index value was widely distributed. In this condition, the average value of the pixels may not give the best estimate

Table 4
Monthly Erosivity Index values from different average rainfall data.

Rainfall data source	June		July		August	
	$I30_{max}$ (mm/hr)	Erosivity (MJ·mm/ha-hr-month)	$I30_{max}$ (mm/hr)	Erosivity (MJ·mm/ha-hr-month)	$I30_{max}$ (mm/hr)	Erosivity (MJ·mm/ha-hr-month)
Average RADAR rainfall	44	295	35	648	31	432
Individual pixel (cell-223)	122	3877	118	4382	77	2257
Individual pixel (cell-136)	145	7346	28	599	91	6093
Individual pixel (cell-422)	60	1712	0	0	14	49
Individual pixel (cell-462)	87	2808	14	34	133	1100
Individual pixel (cell-83)	181	9821	35	578	98	3411
Individual pixel (cell-43)	8	28	74	2444	26	290

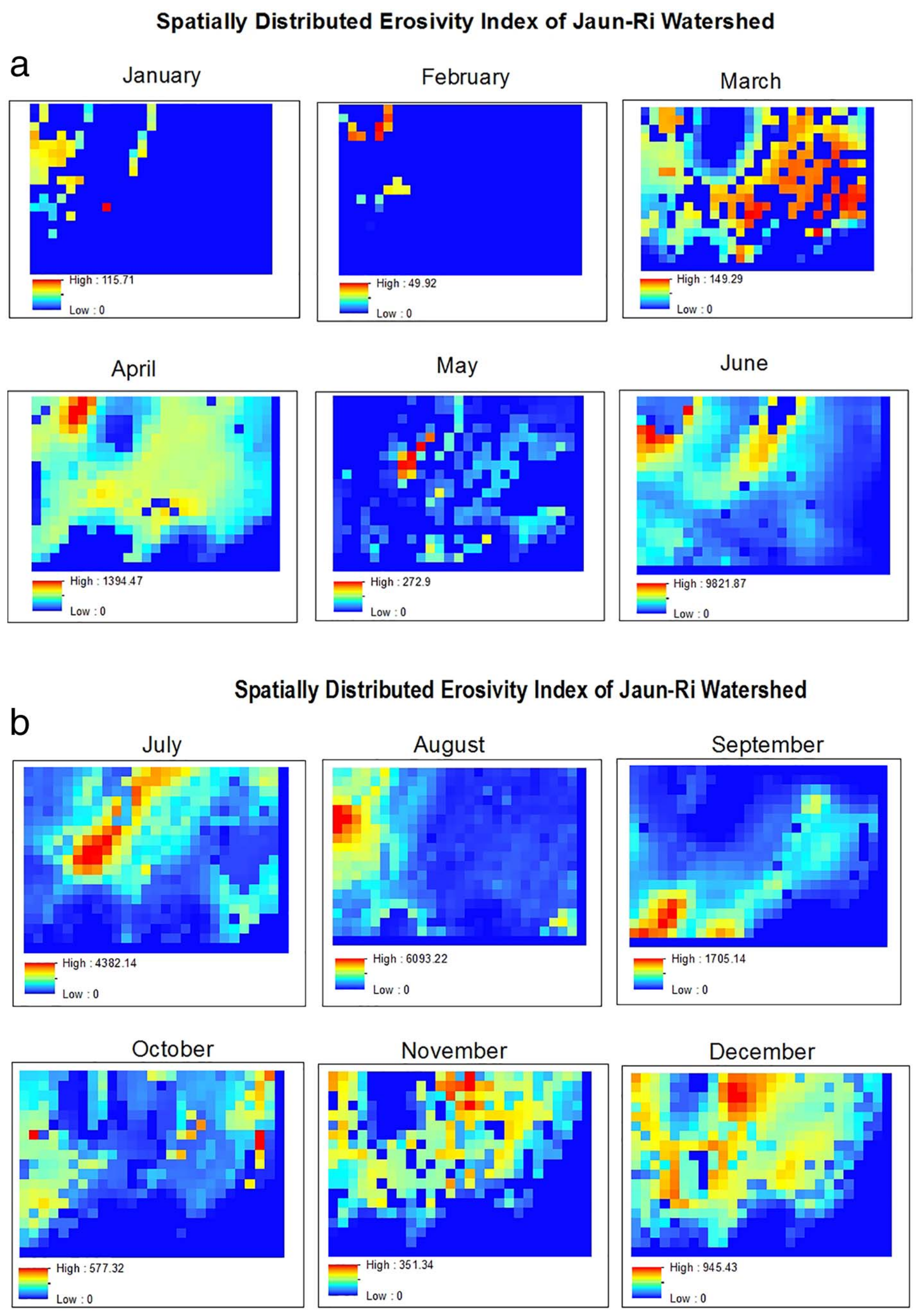

Fig. 8. (a): Spatially distributed monthly Erosivity Index values estimated using the WERM-S module (January to June)
(b): Spatially distributed monthly Erosivity Index values estimated using the WERM-S module (July to December).

of USLE R-factor. Thus, the R factor determined using spatial erosivity index are recommended to be applied in USLE instead of average annual R-factor.

4.3. Erosivity from radar and rain gage data

In order to show the significance of computed erosivity using RADAR data, the average erosivity of all the pixel of study area was compared with the erosivity from gage data for the watershed. The coefficient of regression (R^2) and Nash-Sutcliffe Coefficient (NSE) obtained from the analysis were 0.96 and 0.94 respectively as shown in Fig. 10. Similarly, the Root mean square error (RMSE) was found to be 0.074.The higher values of these indices indicates that erosivity computed from RADAR data can be applied in soil loss evaluation using USLE and can be useful for further research on soil erosion.

5. Conclusions and recommendations

The Web Erosivity Module Spatial (WERM_S) module developed in this study (http://www.envsys.co.kr/~WERM-S/) can be a convenient tool to calculate the spatially distributed erosivity index from input 10-min interval RADAR rainfall data (ASCII files). The monthly erosivity index derived in this study can be applied to obtain the monthly R factor and used along with other USLE input parameters- K, LS, C and P factors to determine the monthly soil loss map of the area.

Spatial erosivity indices are the better choice than average erosivity index derived from the rainfall data of representative weather station to generate detailed soil loss map. Due to the greater values of standard deviation for a monthly erosivity index of our study area, it was found that erosivity index of pixels varied significantly. Since Jaun-ri is very vulnerable to soil erosion, estimation of soil loss using spatial erosivity index map developed in this study can be more accurate than using R factor map derived from high-resolution gage rainfall data because gage

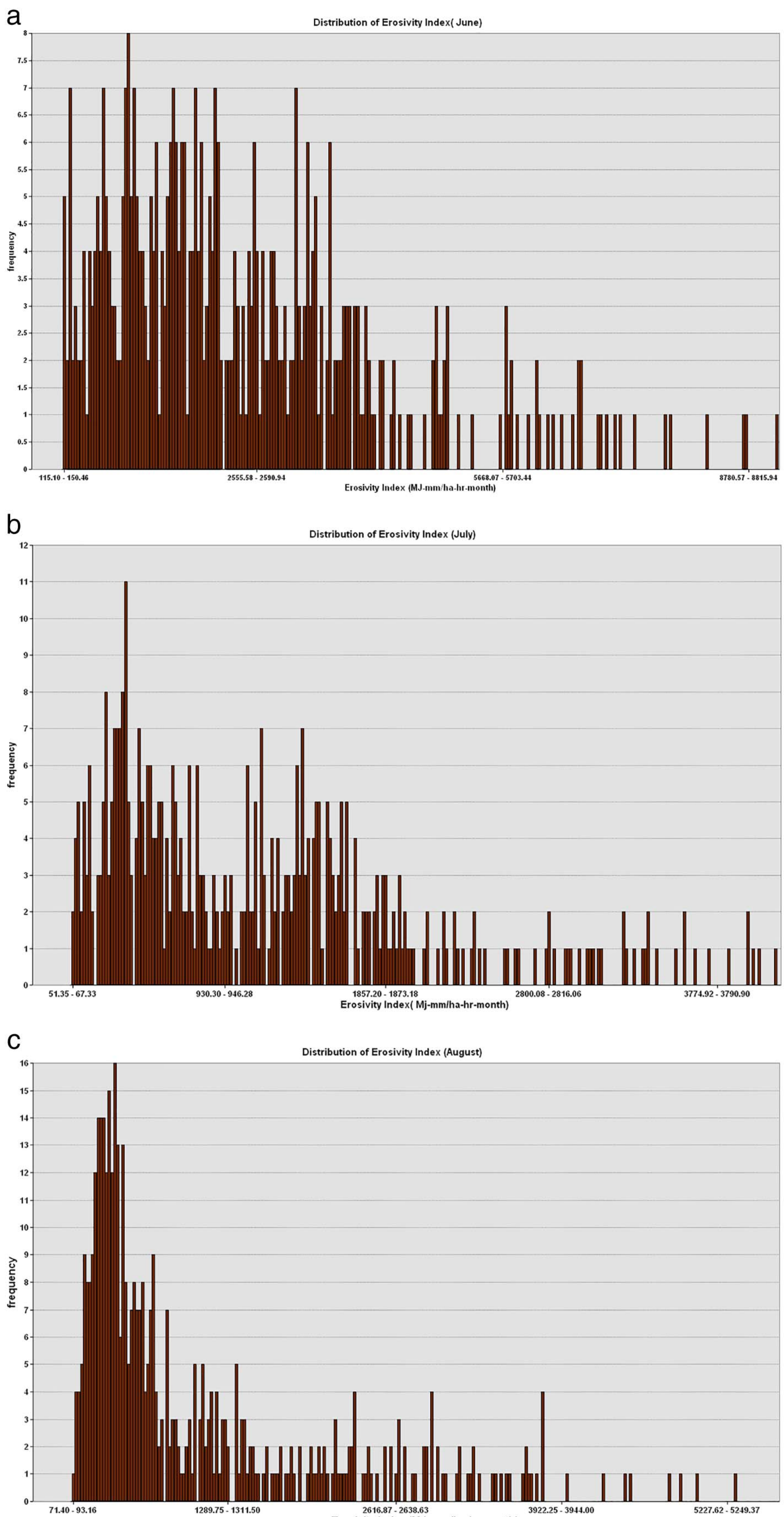

Fig. 9. (a): Histogram of Erosivity Index (June)
(b): Histogram of Erosivity Index (July)
(c): Histogram of Erosivity Index (August).

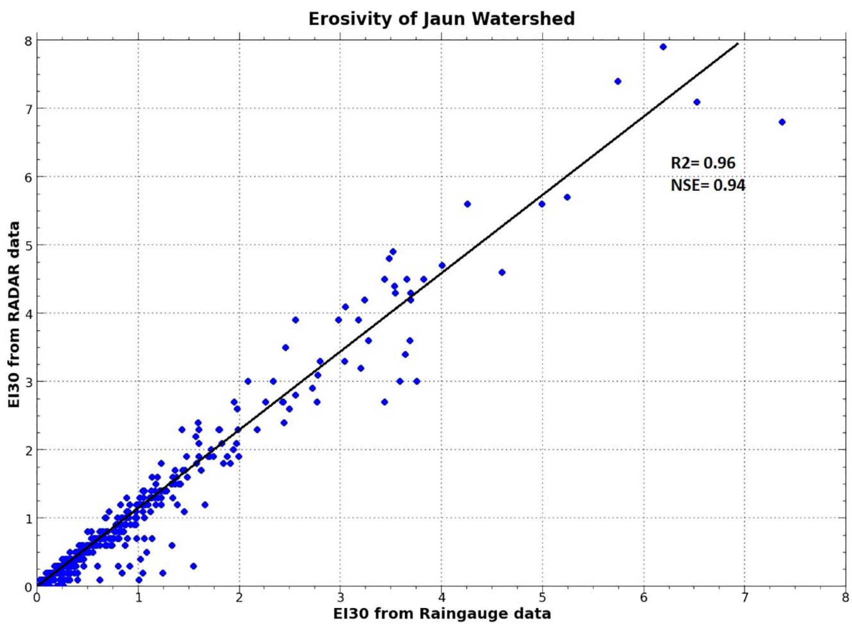

Fig. 10. Regression analysis of EI30 using RADAR and raingage data.

rainfall is the representative data of local station only. Therefore, the erosivity index derived from such limited rain gage data are not suggested to be used in USLE for soil loss estimates. Instead, the spatial erosivity map is suggested to be developed for such hot spot regions of soil erosion from the high-resolution RADAR or remote sensing data, if available using the web-based module before application of USLE to estimate soil erosion of that area accurately.

The spatially distributed erosivity index in high resolution for large areas can be computed using available RADAR reflectivity images from the existing RADAR networks using WERM_S module developed in this study. Moreover, apart from RADAR rainfall, remote sensing data such as tropical rainfall measuring mission (TRMM) and global precipitation mission (GPM) can be used in WERM_S in future if such data will be available in the desired temporal resolution (Yong et al., 2015). The monthly erosivity index thus derived can be used along with other USLE input parameters to calculate soil loss of each raster pixel and obtain accurate soil erodent map of hot spot soil erosion area.

Since the accuracy and reliability of spatially distributed erosivity index map depends upon the reliability of the radar rainfall data, there are some uncertainties in estimation of RADAR-rainfall due to attenuation of rain path and the lack of uniqueness in reflectivity to rainfall transformation (Krajewski and Smith, 2002; Anagnostou et al., 2010; Sorooshian et al., 2011). Moreover, the estimation of RADAR rainfall is affected by other factors such as calibration, blockage of electromagnetic waves, anomalous wave propagation, and ground clutter effect as a result of which uncertainty in RADAR rainfall data increases (Park et al., 2016; Marzano et al., 2004). Several error models such as precipitation uncertainties for satellite hydrology (PUSH) (Maggioni et al., 2014) and space-time error model (Hossain and Huffman, 2008) have been developed and proposed for quantification of uncertainty in RADAR rainfall. Such error models can be used for the RADAR rainfall data before using them in WERM-S module to improve the efficiency of resulting spatial erosivity maps.

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