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Application of Web ERosivity Module (WERM) for estimation of annual and monthly R factor in Korea

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ABSTRACT

Soil erosion is a very serious problem from agricultural as well as environmental point of view. Various computer models have been used to estimate soil erosion and assess erosion control practice. Universal Soil Loss Equation (USLE) is one of the most frequently used soil loss estimation models which have been used in many countries around the world. Erosivity (USLE R-factor) is one of the USLE input parameters to reflect impacts of rainfall in computing soil loss. R factor for a specific rainfall event depends upon maximum rainfall intensity of specific period and kinetic energy of that event. Annual R factor is calculated as the sum of erosivities of such rainfall events that occurred. It is usually calculated from rainfall data having higher temporal resolution but the process of calculation is very tedious and also the higher temporal resolution data are not readily available in many parts of the world. Various regression models have been developed to estimate monthly R factor as well as annual R factor using monthly/yearly rainfall amount. However, it is rarely allowed to estimate R factor with higher accuracy using these models since they were developed from obsolete dataset and also only the rainfall amount was used for an input parameter without rainfall intensity. In this study, a web-based Erosivity estimation system (Web ERosivity Module-WERM) was developed to compute R factor using 10 min interval rainfall data. The model was then tested for 75 different cities in Korea using the rainfall data of 15 to 18 years from 1997 to 2014 obtained from Korea Meteorological Administration (KMA). Using the monthly rainfall data and R factor values obtained from the model, regression equation for 25 cities was developed to estimate monthly R factor from the monthly rainfall with amount and intensity of rainfall considered. The coefficient of determination (R^2) of the regression equation ranged from 0.75 to 0.92. This indicated that these regression equations can be used to estimate the value of R-factor from the monthly rainfall data with more than 75% accuracy. The WERM is very simple to use and it can be a very effective tool to compute R factor using higher temporal resolution rainfall data. Along with this, it is possible to calculate R factor using local daily rainfall with the help of regression equations which are available for 25 cities in South Korea till now.

1. Introduction

Global warming and climate change are the matter of concerns for climatologists and hydrologists. The hydrologic change is anticipated to be more aggressive as a result of rise in global air temperature, which consequently leads to change in current rainfall pattern (Christensen et al., 2015). Rainfall events with greater rainfall amount and rainfall intensity are anticipated to occur as per Intergovernmental Panel on climate change IPCC report report of IPCC (2013). As a result of frequent occurrence of greater intensity rainfall events, erosivity increases and top soil becomes more susceptible to soil erosion. Seven to 49% increase in annual rainfall erosivity was observed for East Tennessee, USA from 2010 to 2099 based on different greenhouse gas emission scenarios (Hoomehr et al., 2016). Soil erosion by water is one of the major problems all over the world from agricultural as well as environmental point of view. Soil erosion leads to a decrease in sustainability and productive capacity of agricultural land (Mullan, 2013). Many problems, such as increase in landslide phenomena, disturbance of ecosystem, loss of cultivable land, diffusion of toxic contaminant by the sediment inflow to rivers etc., arise due to soil erosion which consequently decrease agricultural productivity (Lee and Heo, 2011). Moreover, the quality of fertile soil is being deteriorated as a result of detachment and removal of top soil particles, which has led to decline in agricultural productivity in various places of the world. Likewise, soil erosion has affected ecosystem such as water quality and quantity, biodiversity, recreational activities etc. (Panagos et al., 2015). Thus, the

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world community has recognized soil erosion as a major problem and is giving more and more importance on protection and restoration of soil resources (Lal, 2003). Some effective best management practice should be implemented for the better sustainable management of soil erosion. Implementation of site-specific practice is not possible without estimation of accurate soil loss (Jeong et al., 2004). For this purpose, three different groups of models categorized as empirical, conceptual and physically-based models have been developed during the last few decades (De Vente and Poesen, 2005). These models are being used in order to assess current erosion condition and control practice implemented. One of such empirical models is Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1978). Similarly Agricultural Non-Point Source pollution Model (AGNPS) (Young et al., 1989) and Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998) are the few examples of conceptual models. Likewise, CREAMS: A field scale model for Chemicals, Runoff and Erosion from Agricultural Management System (Knisel, 1980), Water Erosion Prediction Project (WEPP) (Flanagan and Nearing, 1995) and European Soil Erosion Model (EUROSEM) (Morgan et al., 1998) are some of the examples of physically based models that have been developed and are being used. Empirical equations are still used to estimate soil erosion because of their simple structures and ease of application (Kim and Yun, 2008) with reasonable accuracy.

USLE is one of the most popular and widely used empirical erosion models to predict soil erosion. It is being used in many countries around the world especially at regional and national levels because of its simplicity and robustness (Park et al., 2010; Gitas et al., 2009). Despite its some drawbacks such as that it is not available to estimate gully and stream channel erosion since it considers only sheet and rill erosion and it considers single slope length for entire field (Wischmeier and Smith, 1978), the USLE model has been used around the world with six input parameters to calculate soil loss at a field scale (Gitas et al., 2009). The USLE input parameters can be enriched using recent technologies like detailed digital elevation model (DEM), satellite image data, management practices, soil layer depth survey, detailed soil information etc. Since the model performance relies entirely on the six input parameters, we need to evaluate them carefully and accurately (Eisazadeh et al., 2012). In South Korea, the USLE has been extensively used to predict soil erosion. The reason behind this is that the USLE parameters have already been well established over the years (Lim et al., 2005; Park et al., 2010). The USLE has been further improved with the help of additional research, experiments, data and newer resources to develop Revised Universal Soil Loss Equation (RUSLE) which has the same formula as USLE but has some improvements in determining factors (Renard et al., 1997).

Among these six USLE/RUSLE input parameters, the rainfall erosivity or R factor is a parameter to explain rainfall impacts on soil surface. It is the erosive capacity of rainfall to cause soil loss. When the other five factors are held to be constant, soil loss is seen to be directly proportional to total storm energy times maximum 30 min intensity (Renard et al., 1997). The product of total storm energy and maximum 30 min intensity is termed as R factor. In real, the factors that are affected by rainfall erosivity are amount, intensity, terminal velocity, drop size, and drop size distribution of rain (Blanco-Canqui and Lal, 2008). It is calculated as sum of product of Kinetic Energy and its maximum 30 min intensity of each rainfall storm in a year (Wischmeier and Smith, 1978; Renard and Freimund, 1994; Brown and Foster, 1987).

Specific kinetic energy of rainfall event can be expressed as volume-specific kinetic energy and time-specific kinetic energy (Kinnell, 1981; Rosewell, 1986). Time-specific kinetic energy can be obtained from volume-specific kinetic energy by multiplying it by rainfall intensity and some constant (Salles et al., 2002). Different kind of mathematical relations have been developed and proposed to describe relationship between kinetic energy and intensity of rainfall (Rosewell, 1986). Among which logarithmic model (Eq. (1)) proposed by Wischmeier and Smith (1978) and an exponential model (Eq. (2)) proposed by Kinnell (1981) are commonly used models.

$$KE = a + b \log I \tag{1}$$

$$KE = KE_{max}[1 - c.\exp(-d.I)] \tag{2}$$

Where KE is Kinetic energy, I is intensity of rainfall, a, b, c, and d are empirical constants and KE_{max} is a maximum unit energy (intensity approaching infinity) (Lim et al., 2005).

R factor is usually calculated from rainfall data having high temporal resolution but the process of calculation is very tedious. With the bulk amount of high temporal resolution rainfall data, it is not easy to calculate R factor manually using these empirical equations individually for each rainfall event and sum up. A web-based platform could be an effective tool in this case in order to save time and energy and get the accurate R factor value using these data within a couple of minutes. Moreover, measured higher temporal resolution data are not always readily available in many regions of the world (Blanco-Canqui and Lal, 2008). Therefore, R factor has been related with precipitation for quick and easy determination of its value for the sake of its accuracy. A long-term R factor was related to average annual precipitation for Switzerland by Meusburger et al. (2012) which explained the spatial variation of 53.4%. Monthly erosivity maps were developed along with seasonal erosivity density assessment and development of monthly R factor regression function for Greece based on high temporal resolution rainfall data by Panagos et al. (2016a) which showed that erosivity per precipitation amount were higher during the period of June to December. Likewise, monthly R factor for 1568 stations was recently calculated to update rainfall erosivity database at European scale (REDS) where July and August were found to be the month with highest number of intense erosive events in Europe (Panagos et al., 2016b).

Different researches have been conducted to estimate R factors in South Korea. Jung et al. (1983) estimated R factors from the rainfall data from 1964 to 1980 and derived a relationship between monthly/yearly R factor and monthly/annual precipitation for the city of Suwon, Korea. Eqs. (3) and (4) show monthly and yearly R factor equations by Jung et al. (1983).

$$\text{USLE annual R factor}: R = 0.0115X^{1.4947} \tag{3}$$

Where X is yearly rainfall amount (mm) and R is the yearly erosivity (MJ mm ha^{-1} h^{-1} $year^{-1}$)

$$\text{USLE monthly R factor}: R = 0.0378Y^{1.4190} \tag{4}$$

where Y is monthly rainfall amount (mm) and R is the monthly erosivity (MJ mm ha^{-1} h^{-1} $month^{-1}$).

Since these equations could not calculate variations of annual and monthly R factor values correctly for all the geographic regions of Korea, Jung et al. (1999) suggested correction coefficient of 0.595 for mountainous region and 1 or less for other non-mountainous regions (Park et al., 2010). However, these correction coefficient values could not explain variations in R factor values nationwide in Korea. Park et al. (2000) estimated R factor from the rainfall data of 53 stations from 1973 to 1996. For this estimation, hourly rainfall data were used, from which 30 min rainfall intensity cannot be estimated (Park et al., 2000). The average R-factor value of 158 locations in Korea was compiled and published by Jeong et al. (2004) which is suggested by Korean Ministry of Environment (2012). These values are calculated using inverse distance weight method based on one kilometer spatial unit from research of Jung et al. (1983) and Park et al. (2000) using the rainfall data of 24 years from 1973 to 1996 (Jeong et al., 2004). The USLE R factors based on 60-min-interval precipitation data from 60 meteorological sites covering entire Korea for 30 years from 1981 to 2010 was calculated by Park et al. (2011). Lee and Heo (2011) introduced a simplified way to calculate R factor based on monthly precipitation, also known as modified IAS (Institute of Agricultural Sciences) index. The relationship between precipitation and rainfall-runoff erosivity was analyzed and regression model was developed based on the data from 21 weather stations for over 25 years (Park et al., 2011). These erosivity factor equations are based on only rainfall amount data, however value of R factor also varies greatly with maximum 30 min intensity. So, regression equation considering rainfall amount, and maximum 30 min intensity would give better USLE R estimation. Moreover, the previous research on the R factor calculation for Korea used sixty minute interval rainfall data which cannot give the exact estimate of 30 min intensity. So it is necessary for new research using ten minute or finer interval rainfall dataset for the calculation of R factor in Korea. The R factor estimation using 10 min interval rainfall data is more precise but the values of R factors computed using these data are higher than that using 60 minute interval rainfall data since the finer time scale of rainfall data is, the greater the R factor will be (Yin et al., 2007; Panagos et al., 2016b).

Since climate change is having impact on the precipitation pattern, estimation of nationwide R factor for Korea using recent rainfall dataset is very much needed for present as well as future use. The process of calculation of R factor from ten minute interval rainfall data is very tedious and time consuming. Thus, development of web-based tool is one of the effective way to calculate R factor from rainfall data where user can input data of their study areas and obtain output of average annual R factor along with its detailed data of yearly and monthly values within a short time. The approach for this monthly R factor is very crucial since average annual R factor doesn't represent the real erosion potential as the rainfall distribution is not even all year-round as occurrence of 80% of total rainfall is observed only in rainy season. Moreover, the previous regression equations developed for R factors in Korea were based on merely rainfall amount. However, the R factor depends upon both energy and maximum-intensity. Since maximum intensity can be related somewhat to the order of the months, development of regression equation having two input parameters, i.e. rainfall amount and the order of the months will be efficient and helpful.

The objectives of this study are to

(a) Develop and apply Web ERosivity Module (WERM) which take input of 10 min interval rainfall data and give output average annual R factor along with detailed R factor of each year, month and rainfall event,
(b) Evaluate annual R factors for 75 synoptic weather station of Korea using recent rainfall data and create annual R factor map for whole Korea and
(c) Determine specific regression equation for monthly R factor of 25 location having two parameters: monthly rainfall amount and the order of month, ranging from 1 to 12.

2. Material and methods

2.1. Study area

The R factor was calculated from the rainfall data of the 75 rainfall gauge stations in Korea. Average annual R factor was computed for these stations along with determination of maximum 30 min intensity ($I30_{max}$) and the R factor for each month. Based on monthly R factor value and monthly rainfall data, regression model were developed for each weather station. Among these 75 stations, 25 stations having the greater R^2 values were selected for further study. Fig. 1 shows locations of 75 weather stations where 10 min interval rainfall data were available from the Korea Meteorological Administration (KMA) for the calculation of R factor. Fig. 1 also shows locations of 25 stations selected for this study on regression model among these stations.

2.2. Data

Ten minute interval rainfall data are supposed to be used as input in WERM. Ten minute interval data were used because the rainfall data can be achieved and provided in this format from the KMA for the users in Korea. For the prospective users of WERM outside Korea, if the data is not available in this format, rainfall data should be preprocessed into the desired ten minute interval format before uploading to the server.

Rainfall data for all the weather stations in this study were obtained from the Korea Meteorological Administration (2016). The rainfall data of 19 years from 1997 to 2015 were available in KMA for 38 stations. Similarly, recent 18 years rainfall data for 14 stations, 17 year data for 18 stations, 16 year data for 3 stations and 15 year rainfall data for 3 stations were available in KMA for our study. The data file were then formatted to have three columns of 'date', 'time', and 'rainfall data' before using it in WERM for computation of R factor.

2.3. USLE R-factor calculation

The first task for calculation of the R factor from existing ten minute interval rainfall data was to separate rainfall event (Panagos et al., 2015) from long-term rainfall dataset. There are especially three criteria for identification of erosive rainfall event. (i) Storm period with less than 1.3 mm (i.e. 0.0 in.) over six hours is used as a divider of a rainfall event (Renard et al., 1997; Wischmeier and Smith, 1978). (ii) The rainfall event less than 12.7 mm (0.5 in.) of amount was excluded in R factor calculation assuming insignificant rainfall to cause soil erosion unless (iii) there is 6.25 mm (0.25 in.) rainfall in 15 min. (Wischmeier and Smith, 1978; Renard et al., 1997; Panagos et al., 2015). The rainfall event of 12.7 mm threshold is considered as a precipitation event having erosive power which affects soil erosion (Panagos et al., 2015).

In this study, original USLE R-factor equation was used to determine average annual R factor values of 75 stations in Korea. R factor is the product of kinetic energy and maximum 30 min intensity of each rainfall event(Brown and Foster, 1987). Volume-based kinetic energy was used in this research to calculate the energy of rainfall. 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. (5):

$$R = \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{m}(E{\cdot}I30_{max})_k. \tag{5}$$

Where, R = average annual erosivity (MJ mm ha^{-1} h^{-1} year^{-1}), n = numbers of years, m = number of erosive rainfall events, E = total storm kinetic energy, and $I30_{max}$ = maximum of 30 min intensity. The total storm kinetic energy E (MJ ha^{-1}) was determined using Eq. (6):

$$E = \sum\nolimits_{k=1}^{n} e_k{\cdot}dk. \tag{6}$$

Where, e_k is unit rainfall energy (MJ ha^{-1} mm^{-1}) and dk is the rainfall volume (mm) during a time period of k. The unit rainfall energy (e_k) was again calculated using Eq. (7) below:

$$e_k = 0.119 + 0.0873\log(i_k). \tag{7}$$

Where, i_k is rainfall intensity during the time interval (mm/hr.). If the intensity of rainfall is greater than 76 mm per hour, the unit rainfall energy is taken as 0.283 MJ ha^{-1} mm^{-1} (Wischmeier and Smith, 1978; Renard et al., 1997).

2.4. Development of Web ERosivity Module (WERM)

WERM was developed based on Eqs. (5)-(7) from Agricultural Handbook number 537 (Wischmeier and Smith, 1978) to calculate the R factor. The program uses ten minute interval rainfall data accumulated

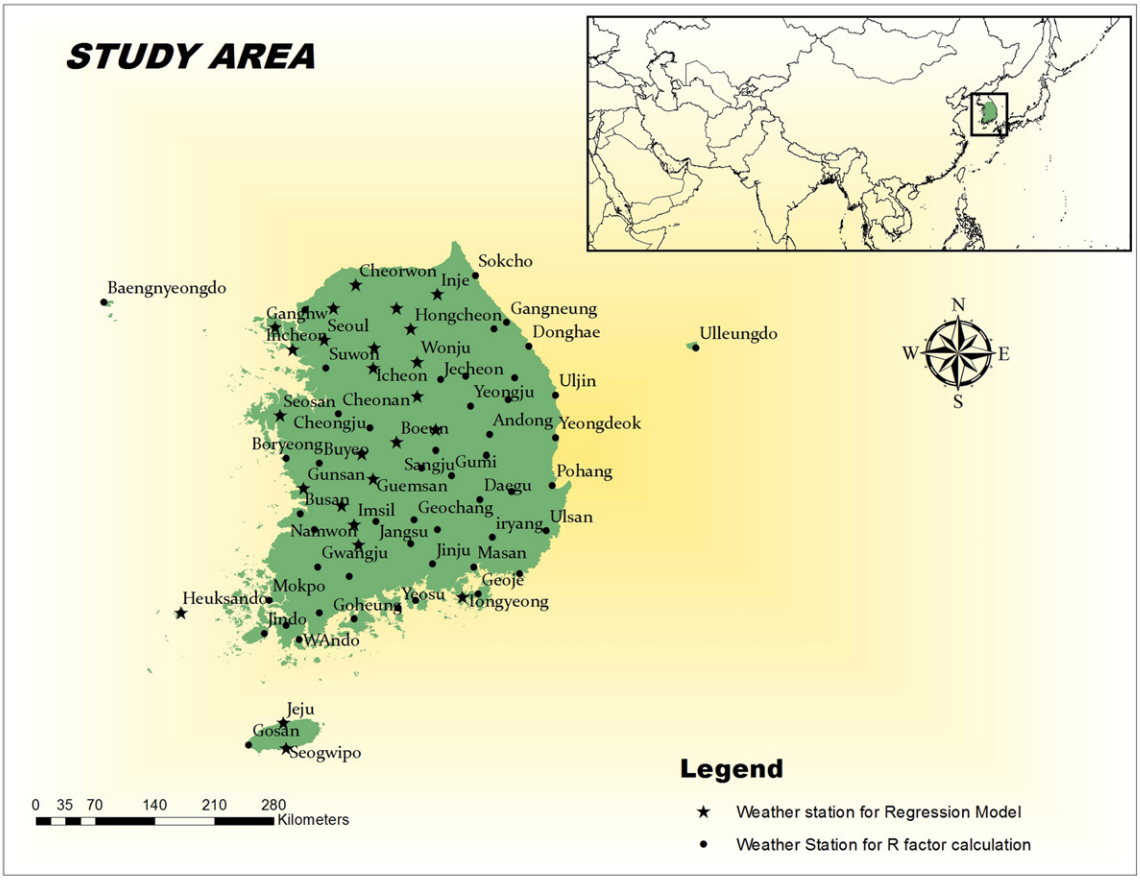

Fig. 1. Locations of weather stations used in the study.

for one day of entire time period as a text file. The input data has to be in the specified format in the increasing order of date and time. If the rainfall data for short period is missing, it can handle those missing rainfall data for R factor computation. The module is adjusted for those kinds of data and correct value can be achieved even if the data for some short period is absent. The module was developed using HTML, PHP, JavaScript, JQuery and HighChart. It provides yearly, monthly and event-based R-factor values instantly in the website and the output can be downloaded as a separate ASCII files for further analysis. Although standard minimum number of hours of no rainfall to separate one rainfall event from other is 6 h (Renard et al., 1997), this can be modified to consider different standards to explain rainfall pattern and policy in other countries. So, keeping this in mind, the module provides an option to select a minimum number of hours of no rainfall to be considered for separation of one rainfall event from another In the WERM input interface.

2.5. Development of Nationwide R factor map

Based on the R factor values calculated by the WERM, nationwide R factor map was developed using ArcGIS 10.1. The point R factor shape file was first created based on the R factor from 75 synoptic stations and spatial interpolation was performed using the inverse distance weighted (IDW) method. Although this method of IDW cannot simulate topographic effect and it just considers the distance between surrounding points for interpolation, it was used in our study because of its advantages such as it doesn't require assumption data and assessment of prediction error (Lam et al., 2015). Moreover, this method does not require preprocessing of data and it provides acceptable result in very short time (Tomczak, 1998). This method was also adopted by the Korean Ministry of Environment (2012) because of its simplicity in implementation. The IDW interpolation generic equation is given as Eq. (8): (Bartier and Keller, 1996).

$$Z_{x,y} = \frac{\sum_{i=1}^{n} z_i w_i}{\sum_{i=1}^{n} w_i} \tag{8}$$

Where, $z_{x,y}$ is the point which is to be predicted, z_i is the control value and w_i is the weight determining significance of z_i in interpolation process. w_i is related to inverse of distance to a power as given in Eq. (9)

$$w_i = d_{x,y}{}^{-\beta} \tag{9}$$

where, $d_{x,y}$ is the distance between $z_{x,y}$ and z_i and β is the exponent coefficient.

Eq. (8) can be rewritten as Eq. (10):

$$Z_{x,y} = \frac{\sum_{i=1}^{n} z_i d_{x,y}{}^{-\beta}}{\sum_{i=1}^{n} w_i}. \tag{10}$$

2.6. Development of monthly R estimation regression equation

Monthly R factor calculated from WERM was used to develop the regression equation for the calculation of monthly rainfall amount and order of month (i.e. the numbers 1 to 12 indicating each month). The R factor value calculated for each rainfall event was summed up for each month in order to obtain monthly value of R factor in the WERM. Regression models for 25 different cities were developed to calculate monthly R factor from monthly rainfall data and the order of months ranging from 1 to 12. The model was derived using the Curve Expert Professional (v.2.2.0) (Hyams, 2005) which offers more than 60 different models providing curve fitting result with various linear as well as nonlinear models. Out of different models provided, suitable model was selected for each equation based on the performance and rank given for each of them. The model and equation having higher correlation coefficient (r) and coefficient of determination (R^2) and giving non negative R factor value were selected as suitable model.

3. Result and discussion

3.1. Web ERosivity Module (WERM)

Web ERosivity Module (WERM) was developed based on the equation of Wischmeier and Smith (1978) which is very useful to calculate the value of R factor easily within a minute from the 10 min interval rainfall data. Anyone can access this module WERM from anywhere using following web address: (*http://www.envsys.co.kr/~werm/*). User can upload the input text file in the web interface as shown in Fig. 2. The option to select minimum number hour with no rainfall for the consideration of separation of rainfall event was provided in the interface. Default value of 6 h will be selected by default if user doesn't specify this.

User can view the value of average annual R factor computed by this WERM module from the input rainfall data of specified time period. Moreover, yearly, monthly and event-based values of R factor can be downloaded from the WERM website as separate text files. Likewise, we can see the relationship among monthly rainfall amount, monthly R factor and order of month in the form of three dimensional scatter plot as shown in the web interface in Fig. 3.

Beside this, the facility to view list of yearly, monthly and event-based R factor values as shown in Fig. 4 was provided in the website along with the provision of graphical interface for maximum 30 min intensity and R factor values. The bar graph showing temporal variation of monthly maximum 30 min intensity and monthly R factor was displayed in output web interface of the model as shown in Fig. 5.

3.2. Average annual R factor values of weather stations

Average number of erosive rainfall event per year was observed to be 24 with maximum of 50 rainfall events occurring in the year 1999 in Sancheong. The number of rainfall events in several dry months was observed to be 0 due to the absence of significant rainfall to cause soil erosion. Average number of events for the month of July and August were seen to be highest with 6.1 and 6.2 while December and January were seen to have the months having the least number of rainfall events with mean number of rainfall event of 0.4 each. The maximum number of rainfall events in a single month was observed to be 11 in August 1999 in Sangcheong. Similarly, the value of maximum 30 min intensities ($I30_{max}$) were found to be highest for August and lowest for January. The mean and standard deviation of $I30_{max}$ for August were observed to

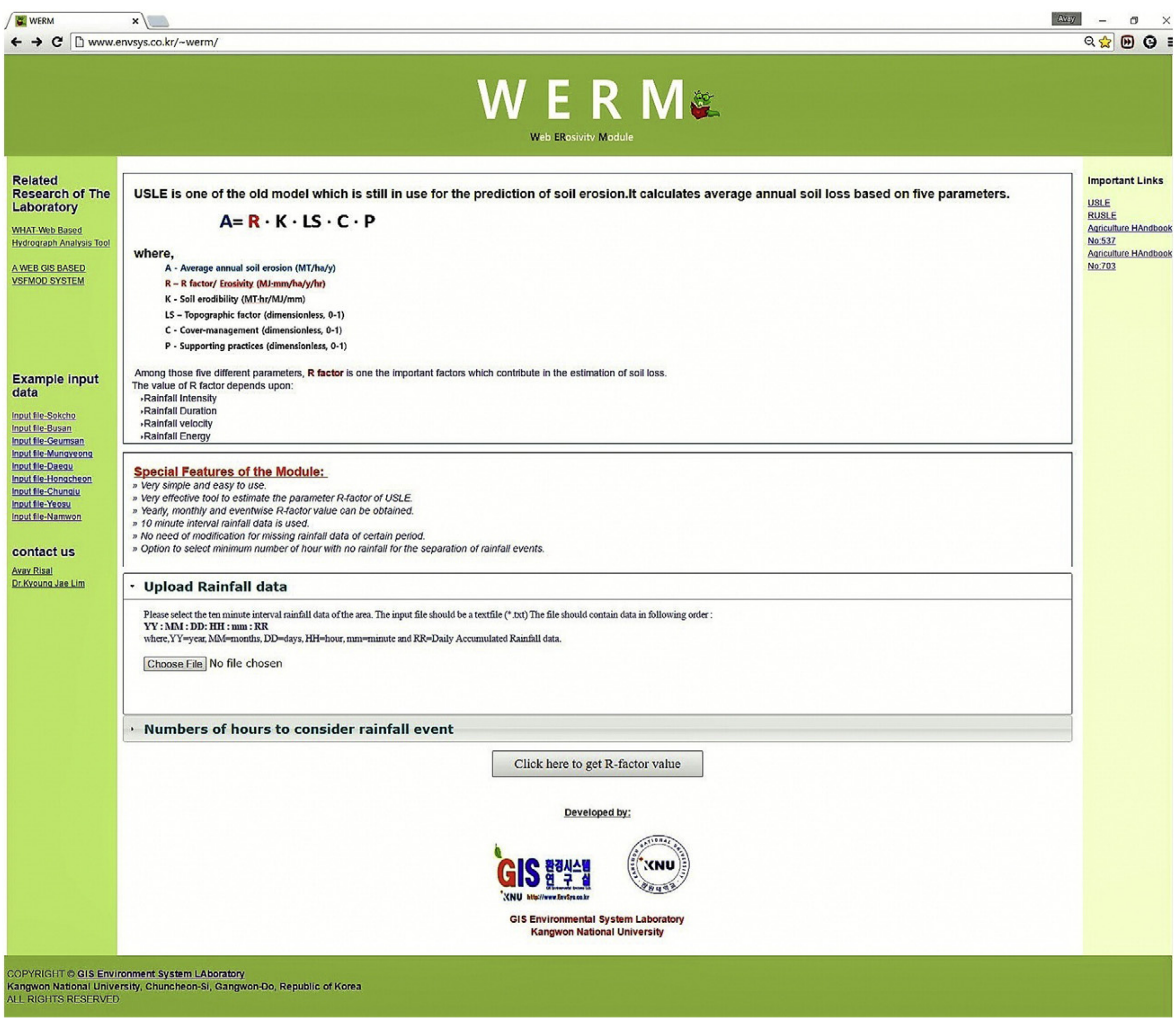

Fig. 2. WERM input interface.

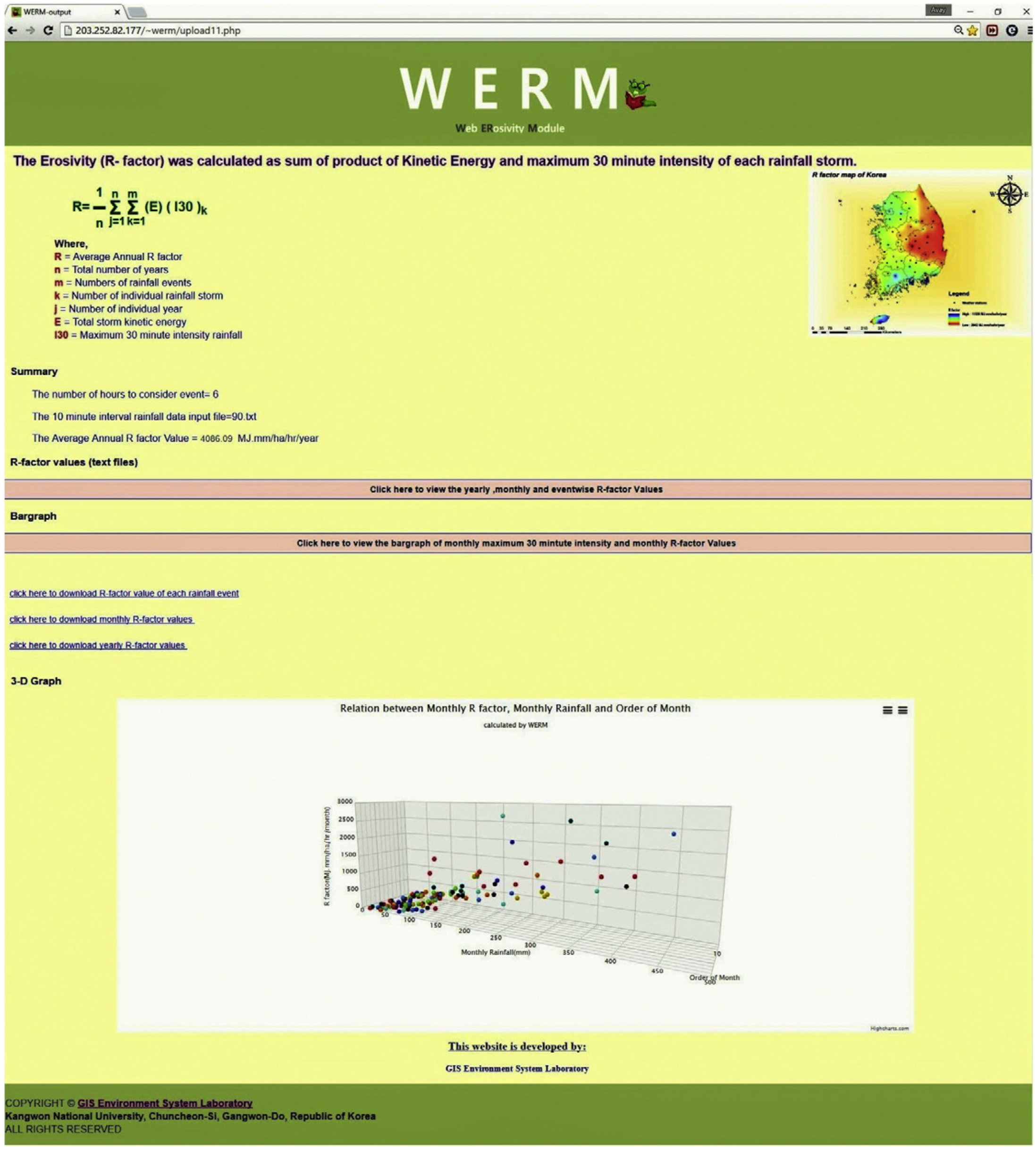

Fig. 3. WERM output interface.

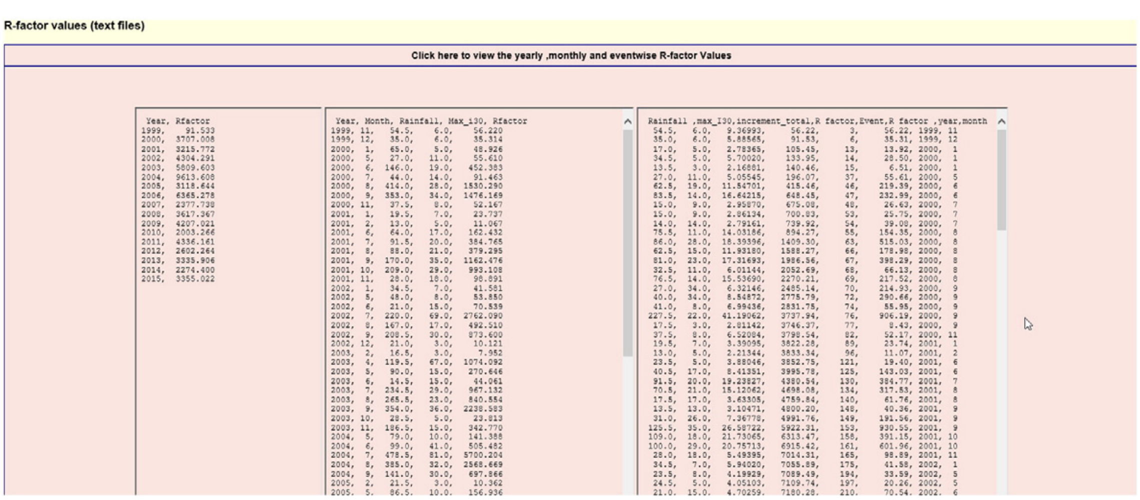

Fig. 4. List of yearly, monthly and event-based R factor values.

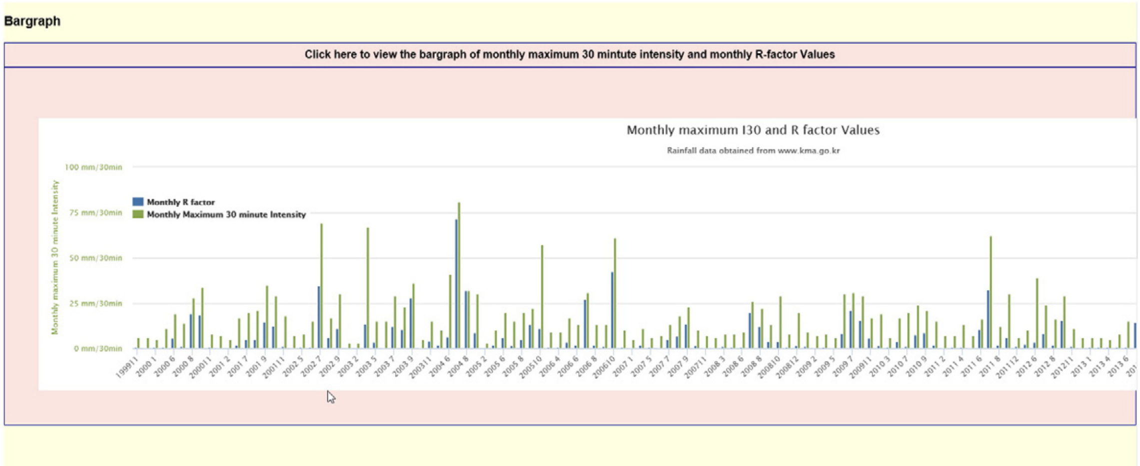

Fig. 5. Bar graph of monthly maximum 30 min intensity and monthly R factors over the period.

be 25.40 mm/h and 18.33 mm/h and those for January were found to be 10.36 mm/h and 9.077 mm/h. The greater standard deviation values show that the value of monthly $I30_{max}$ varies significantly every year since the rainfall pattern was not in uniform.

Average annual R factor for the 75 weather station was calculated from recent rainfall data of 15 to 19 years using the WERM and the values were compared with the existing R factor suggested by Korean Ministry of Environment based on the data from Park et al. (2000) and Jung et al. (1983) which were calculated from the rainfall data of 24 years from 1973 to 1996 (Jeong et al., 2004). Among the 75 stations for which R factor was calculated in this study, we cannot compare the R factor values for 8 stations which are not previously calculated and published by Korean Ministry of Environment. Table 1 shows the list of base period for calculation, new R factors and existing R factors along with their differences on their values for the 75 weather stations.

The minimum and maximum values of R factor calculated were 2942 MJ mm ha^{-1} h^{-1} yr^{-1} for Sancheong and 11,328 MJ mm ha^{-1} h^{-1} yr^{-1} for Baengnyeongdo respectively. The average R factor in Korea based on these stations was found to be 6189 MJ mm ha^{-1} h^{-1} yr^{-1} which is seen to have increased from the previous value of 4210 MJ mm ha^{-1} h^{-1} yr^{-1} (Jeong et al., 2004). The R factor values were seen to have increased for all the stations except for Donghae where the value of R factor has decreased by 12%. The maximum increase seen in new R factors from the existing R factor is 4731 MJ mm ha^{-1} h^{-1} yr^{-1} for Seogwipo which is 44% increase from previous value while the minimum increase is 302 MJ mm ha^{-1} h^{-1} yr^{-1} for Sokcho which is 7% higher than previous value. R factor values computed by WERM were found to be higher than the existing R factor values because these values were computed using 6o minute interval rainfall data and the value of R factor from finer time scale rainfall data is always higher than the value calculated from coarser time scale

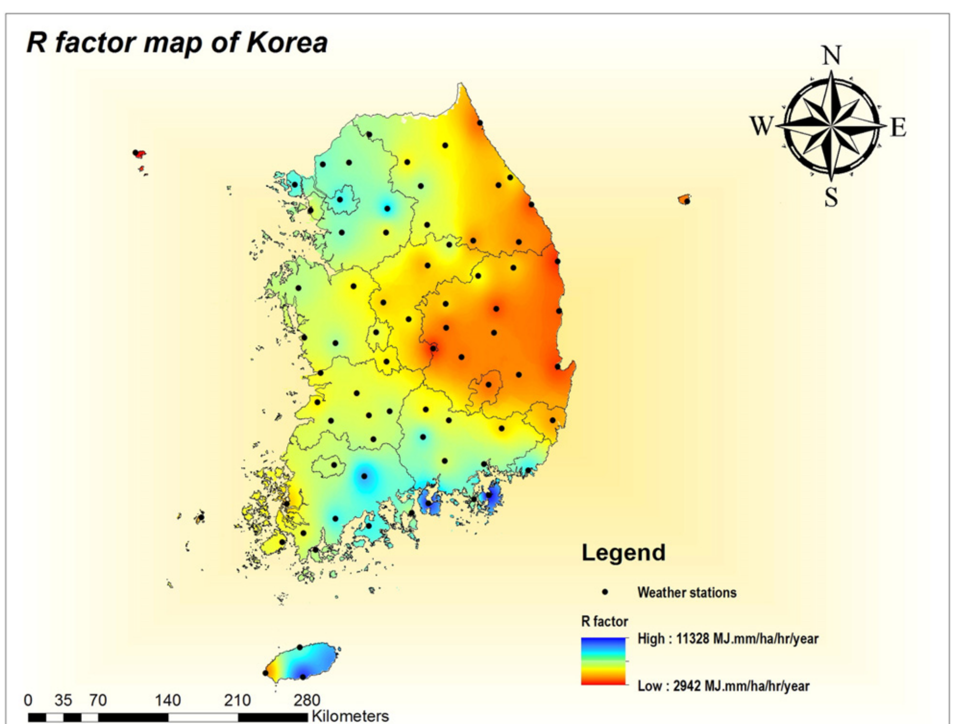

Fig. 6. R factor map of Korea.

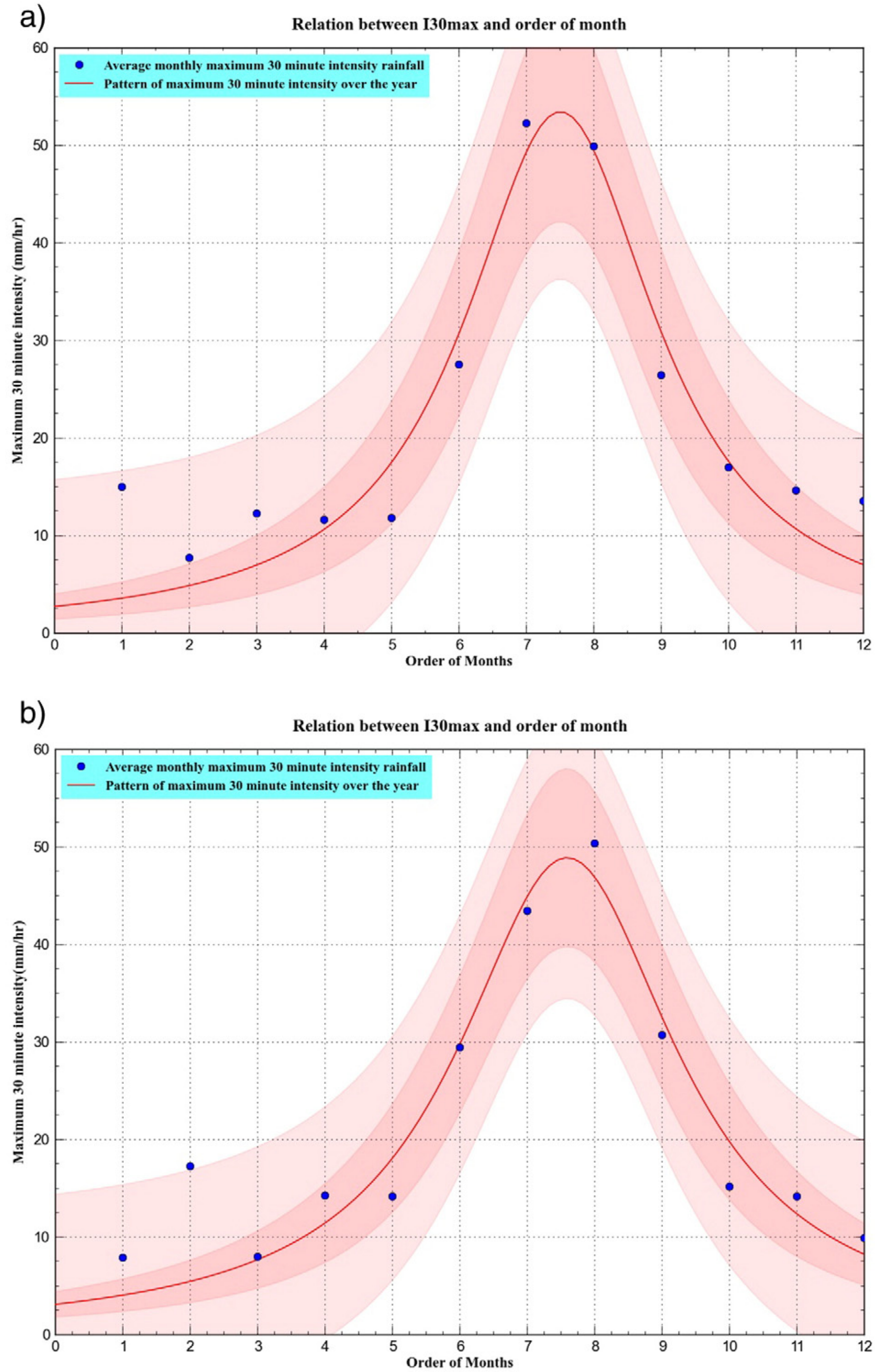

Fig. 7. (a) Relation between $I30_{max}$ and months for Hongcheon. (b) Relation between $I30_{max}$ and months for Boeun.

rainfall data (Yin et al., 2007; Panagos et al., 2016b). Moreover, the greater R factor value was due to increasing trend of rainfall intensity. Seogwipo was seen to have higher maximum 30 min intensity ($I30_{max}$) value frequently in recent decades as the values of 95, 102, 85, 95 and 92 mm per hour were observed in the years 2007, 2009, 2010, 2012 and 2015 because of which the average annual value was seen higher. This increase in value of R factor was also due to very high intensity rainfall that is occurring frequently in recent few decades. Sangcheong observed $I30_{max}$ of 189 mm per hour in the year 1998 and Suncheon observed 165 and 108 mm per hour in the year 1999 and 2011, respectively which contributed significantly in higher value of annual average R factor of those locations. Except for some year occurring typhoon and strong intense rainfall, generally the value of monthly maximum $I30_{max}$ ranges from 50 to 70 mm per hour in a year. On the other hand for the Donghae station, the only station in our study where R factor computed by WERM was seen to have a lower value than that suggested by Korean Ministry of Environment (2012). Monthly maximum $I30_{max}$ in the recent decade for this station was seen very low which ranged from 25 to 45 mm per hour. The greater $I30_{max}$ values of 97 and 71 mm/hr were observed only in the year 2003 and 2004 respectively.

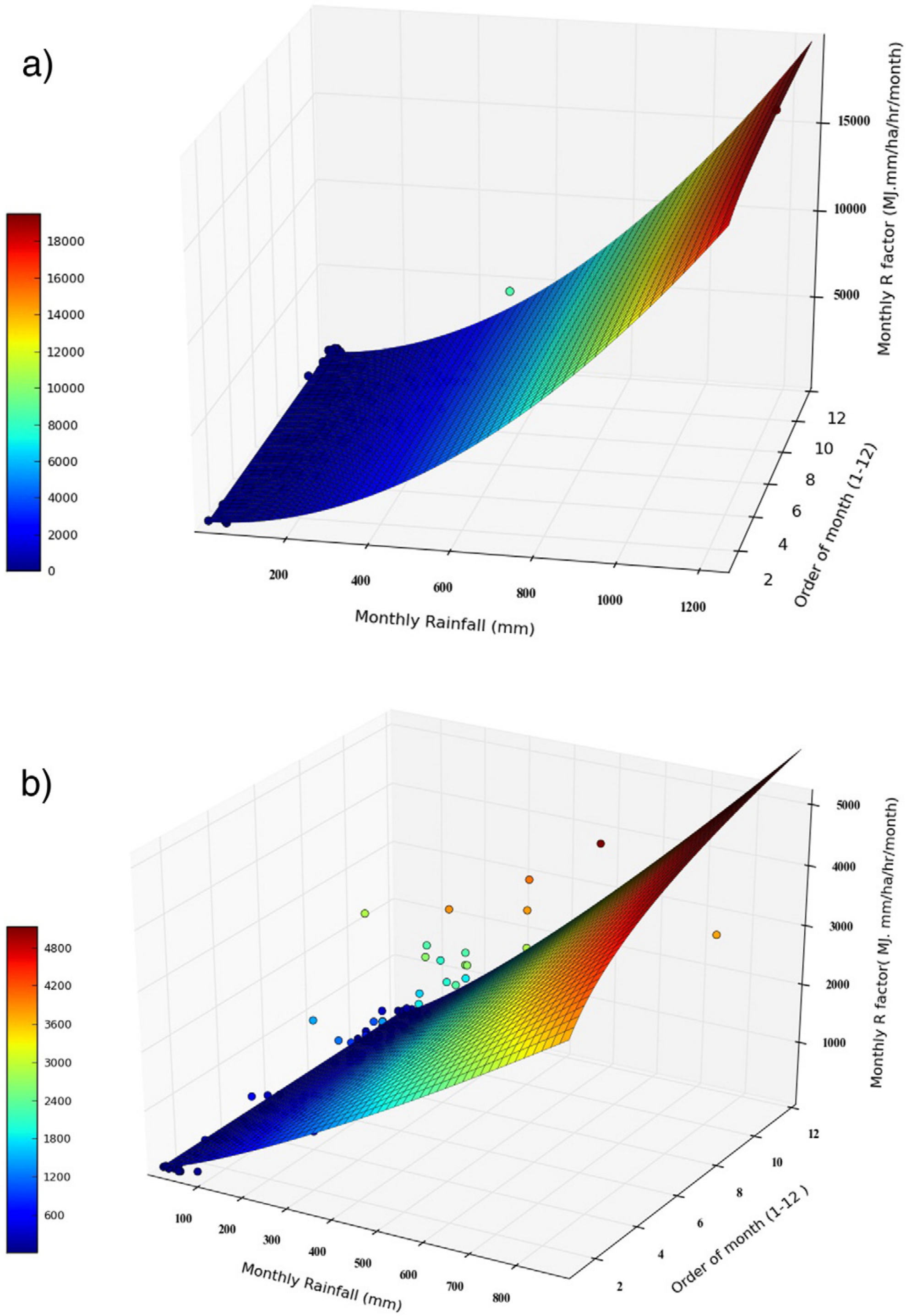

Fig. 8. (a) 3D graph of R factor for Hongcheon. (b) 3D graph of R factor for Boeun.

3.3. R factor map

On the basis of the values of R factor for the 75 locations in Korea calculated in this study, R factor map of whole Korea was prepared and presented in Fig. 2. For the preparation of this map, spatial interpolation of the available R factor values for these 75 locations was performed using inverse distance weighted (IDW) method in GIS. The stations were well distributed across the country and thus can be used for interpolation. This method has been proven to be a very effective tool for the preparation of nationwide erosivity map from representative R factor values of each station.

This R factor map (Fig. 6) shows that value of average annual R factor varies spatially. Eastern part of Korea was seen to have lower R factor values in comparison to that of western part. Comparatively higher erosivity values were observed at north-western part in Gyeonggido province and south-eastern part in Jeollanamdo and Chungcheongbukdo provinces of Korea whereas Chungcheongbukdo, Gyeongsanbukdo, and eastern part of Gangwondo province were seen to have lower R factor values. In jejudo, high variability in erosivity factor was seen as eastern part of Island including Jeju and Seogwipo stations have high R factor whereas western part of the island including Gosan station have lower erosivity factor. Western coastal area of Korea was observed to have

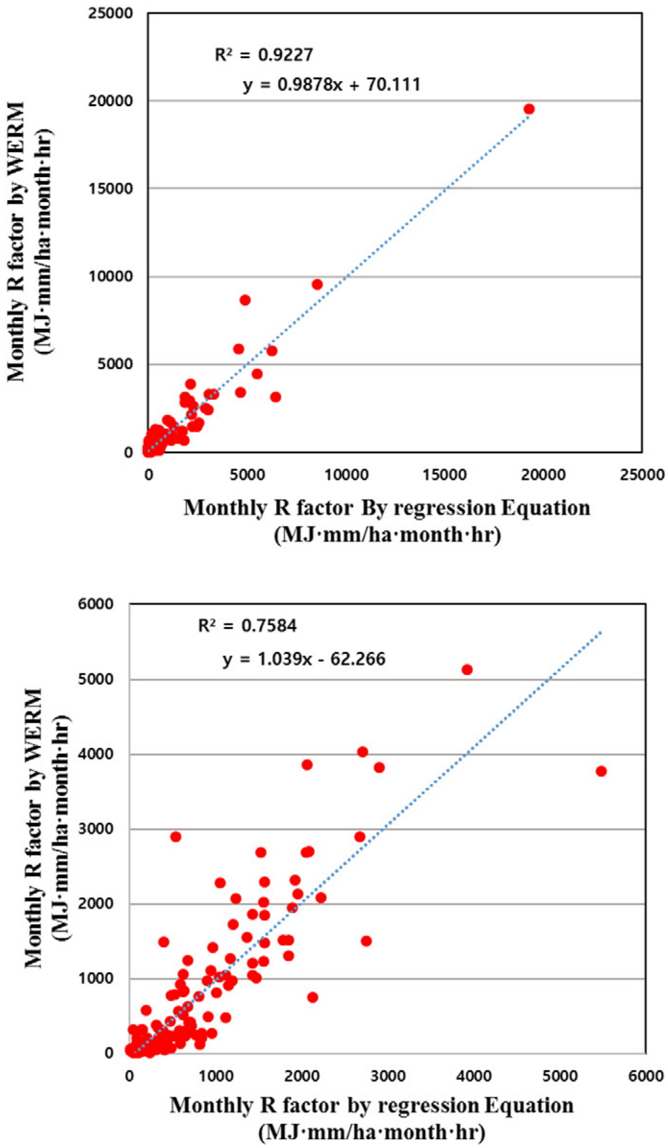

Fig. 9. Correlation graph for Hongcheon (up) and Boeun (down).

higher R factor than eastern coastal area. The lowest R factor values in the area of Nakdong River Basin, was mainly due to lower mean precipitation in the area. Moreover, the decreasing trend in rainfall intensity for 24 out of 187 weather stations in Korea (Chang et al. 2007) can be one of the reasons of lower R factor values in these locations. 18 out of these 24 stations were eventually located in Chungcheongbukdo, Gyeongsanbukdo, and eastern part of Gangwondo province which was also the reason for lower R factor in these locations.

Using this map, we can calculate the R factor of any location in Korea easily and calculate the soil loss using USLE. The R factor from this nationwide map gives better result than the previous R factor maps which were based on old dataset 60 min interval rainfall data.

3.4. Monthly R estimation equation

The average monthly R factor was computed from the monthly R factor values of 75 stations for 19 to 22 years. The average monthly R factor for the month of July was seen to be the greatest with the value of 1913 MJ mm/ha/h/month and standard deviation of 752 MJ mm/ha/h/month. Similarly, January was seen to have the lowest monthly R factor value of 139 MJ mm/ha/h/month and standard deviation of 263 MJ mm/ha/h/month. The R factor value for just 3 months from July to September contributes more than 75% of the total average annual R factor value of Korea since the average monthly R factor values for July, August and September were seen to be 1913, 1850 and 931 MJ mm/ha/h/month respectively.

Using the monthly R factor values computed from WERM and order of month, the specific regression model for 25 different locations were developed for the determination of monthly R factor. The order of the month has values from 1 to 12 as 1 for January, 2 for February and so on. The coefficient for the regression equations was derived using commercial software, Curve Expert Professional (v.2.2.0) (Hyams, 2005). Table 2 shows all the regression models for the selected 25 locations with their respective R^2 values.

Maximum 30 min interval rainfall ($I30_{max}$) is one of the key factors responsible for value of R factor. The relationship between average monthly maximum 30 min interval rainfall ($I30_{max}$) and the order of the months was analyzed. The 2 dimensional graph is plotted with the help of commercial software Curve Expert Professional (v.2.2.0) (Hyams, 2005). The value of this $I30_{max}$ is seen maximum in rainy season especially in July and August which was obvious because most of the rainfall occurs during this period. In the dry season the value of $I30_{max}$ is either zero or has a minimum value since there is no rainfall or very little rainfall. Thus, the value of $I30_{max}$ gradually increases from minimum in the starting months of the year to maximum up to July or August and again reduces to minimum value in the end of year which was represented by "Rational model" or "Reciprocal Quadratic" model. The graph for the locations of Hongcheon and Boeun that has the greatest and the lowest R^2 value of regression equation in our study is presented in Fig. 7(a) and (b) respectively.

In Fig. 7(a) and (b), average monthly maximum 30 min intensities were plotted against their respective months. For Hongcheon, as we can see in Fig. 7(a) the average monthly maximum $I30_{max}$ has the greatest value of 52 mm/h in July and the lowest value of 11.6 mm/h in April. Similarly for Boeun in Fig. 7(b), that average monthly maximum $I30_{max}$ was observed to have the highest value of 50.3 in August and the lowest value of 7 in January. The appropriate curve fitting this plot which was determined using Curve Expert (Hyams, 2005) shows the pattern of monthly maximum 30 min intensity over the year. The darker shaded region in Fig. 7(a) and (b) shows the confidence band that has 95% likelihood of containing true curve that fits our monthly maximum 30 min intensity data and the lighter shaded region shows the prediction band that has 95% likelihood of containing any future monthly maximum 30 min intensity data (Hyams, 2005).

Since the R factor varies greatly with $I30_{max}$ and $I30_{max}$ varies greatly with the order of the month, the order of month was taken as an input parameter of regression equation for the calculation of R factor. The three dimensional equation for the R factor was determined using commercial software Curve Expert Professional (v.2.2.0) (Hyams, 2005). Among different models provided by the software, Power model C ($y = ax_1^b + cx_2^d$) and power model E ($y = ax_1^b \cdot cx_2^d$) were found to be most suitable models which could explain the relationship between monthly R factor, monthly rainfall and order of months appropriately with greater R^2 values. The 3 dimensional graph is presented as in Fig. 8(a) and (b) for Hongcheon and Boeun respectively.

The R factor values were then determined from the regression equation using local monthly rainfall data and the order of month. The R factor thus calculated was then compared with the R factor value which was obtained from WERM. The correlation graph was plotted between the R factor from Regression model and the R factor from WERM, which is shown in Fig. 9 for Hongcheon and Boeun.

The coefficient of determination (R^2) of the correlation graph obtained for Hongcheon was found to have the greatest R^2 value of 0.92, whereas Boeun was found to have lowest R^2 value of 0.75 among our 25 weather stations. These regression equations can be used to estimate the value of monthly R factor with the help of local daily rainfall data with 75% or greater accuracy. As we can see from the figure above, the prediction of monthly R factor from monthly rainfall is much better for the lower R factor values than for the higher R factor values.

Table 1
List of new R factors, existing R factors and their difference for 75 locations of Korea.

Station number	Station name	Starting year	Ending year	Base period	New R factor	Existing R factor	Difference (%)
90	Sokcho	2000	2015	16	4086	3784	7
95	Cheoewon	1999	2015	17	7608	4440	42
98	Dongducheon	1999	2015	17	7905	4976	37
99	Munsan	2001	2015	15	7576	5301	30
100	Daegwallyeon	2001	2015	15	5043	–	–
101	Chuncheon	1999	2015	17	6144	4242	31
102	Baengnyeongdo	2000	2015	16	2942	–	–
105	Gangneung	1999	2015	17	5495	4111	25
106	Donghae	1997	2015	19	3553	3975	−12
108	Seoul	1999	2015	17	8348	5152	38
112	Incheon	1999	2015	17	6381	5557	13
114	Wonju	2000	2015	16	6678	4429	34
115	Ulleungdo	1999	2015	17	4078	–	–
119	Suwon	1999	2015	17	8147	4913	40
121	Yeongwol	1999	2015	17	4669	4032	14
127	Chungju	2001	2015	15	4834	4091	15
129	Seosan	1999	2015	17	7064	4982	29
130	Uljin	1999	2015	17	3377	3027	10
131	Cheongju	1997	2015	19	5137	4389	15
133	Daejeon	1999	2015	17	6271	4509	28
135	Chupungnyeon	1997	2015	19	3108	–	–
136	Andong	1999	2015	17	3746	3054	18
137	Sangju	2001	2015	15	3888	3186	18
138	Pohang	1999	2015	17	3556	2778	22
140	Gunsan	1999	2015	17	6242	4190	33
143	Daegu	1999	2015	17	4178	3062	27
146	Jeonju	1999	2015	17	6544	4259	35
152	Ulsan	1999	2015	17	4844	4276	12
155	Masan	2000	2015	16	7474	5417	28
156	Gwangju	1999	2015	17	6757	4615	32
159	Busan	1999	2015	17	8383	5496	34
162	Tongyeong	1999	2015	17	7273	5527	24
165	Mokpo	1999	2015	17	5247	3557	32
168	Yeosu	1999	2015	17	6970	5799	17
169	Heuksando	2000	2015	16	5128	–	–
170	WAndo	2000	2015	16	7464	5281	29
175	Jindo	2002	2015	14	6363	4674	27
184	Jeju	1999	2015	17	8034	4348	46
185	Gosan	2000	2015	16	4570	–	–
189	Seogwipo	1999	2015	17	10,766	6035	44
192	Jinju	1997	2015	19	6701	5238	22
201	Ganghw	1997	2015	19	8274	–	–
202	Yangpyeong	1997	2015	19	8651	4956	43
203	Icheon	1997	2015	19	6196	4762	23
211	Inje	1997	2015	19	5726	3367	41
212	Hongcheon	1997	2015	19	7177	4323	40
216	Taebaek	1997	2015	19	4229	3662	13
221	Jecheon	1997	2015	19	6621	4128	38
226	Boeun	1997	2015	19	5595	3875	31
232	Cheonan	1997	2015	19	5757	4646	19
235	Boryeong	1997	2015	19	6494	5230	19
236	Buyeo	1997	2015	19	7190	5104	29
238	Guemsan	1997	2015	19	5586	3934	30
243	Busan	1997	2015	19	5658	4111	27
244	Imsil	1997	2015	19	6352	3861	39
245	Jeongeup	1997	2015	19	6685	4245	36
247	Namwon	1997	2015	19	6718	4279	36
248	Jangsu	1997	2015	19	6769	4045	40
256	Suncheon	1997	2012	16	9420	5067	46
260	Jangheung	1997	2015	19	8316	5691	32
261	Haenam	1997	2015	19	6158	4785	22
262	Goheung	1997	2015	19	8339	6076	27
271	Bonghwa	1997	2015	19	5065	3431	32
272	Yeongju	1997	2015	19	5870	3752	36
273	Mungyeong	1997	2015	19	5136	3278	36
277	Yeongdeok	1997	2015	19	3704	2668	28
278	Uiseong	1997	2015	19	4255	2814	34
279	Gumi	1997	2015	19	4000	2728	32
281	Yeongcheon	1997	2015	19	4187	2723	35
284	Geochang	1997	2015	19	5755	3807	34
285	Hapcheon	1997	2015	19	6239	4145	34
288	Miryang	1997	2015	19	5282	3843	27
289	Sancheong	1997	2015	19	8097	5106	37
294	Geoje	1997	2015	19	11,328	7076	38
295	Namhae	1997	2015	19	10,799	–	–

Table 2
Regression equations and coefficient of determination for 25 stations.

Station number	Station name	Regression model	R^2
212	Hongcheon	$R = 0.027928P^{1.877257} \times M^{0.035298}$	**0.92**
201	Ganghw	$R = 0.000002P^{2.3510} \times M^{3.39209}$	**0.91**
108	Seoul	$R = 0.025638P^{1.67671} \times M^{0.757307}$	**0.90**
202	Yangpyeong	$R = 0.150650P^{1.599636} \times M^{0.077535}$	**0.88**
211	Inje	$R = 0.001917P^{1.908183} \times M^{1.261008}$	**0.88**
140	Gunsan	$R = 0.12092P^{1.6680} + 6.8367\ M^{1.127702}$	**0.87**
101	Chuncheon	$R = 0.009758P^{1.4863} \times M^{1.69049}$	**0.86**
146	Jeonju	$R = 0.119445P^{1.7191} \times M^{-0.100273}$	**0.85**
112	Incheon	$R = 0.291819P^{1.591707} \times M^{-0.23258}$	**0.84**
95	Cherwon	$R = 0.00115P^{1.65047} \times M^{2.326238}$	**0.83**
98	Dongducheon	$R = 0.09084P^{1.7294} \times M^{-0.11967}$	**0.83**
129	Seosan	$R = 0.3319P^{1.5138} + 0.2964\ M^{2.0677}$	**0.8**
133	Daejeon	$R = 0.2527P^{1.4575} \times M^{0.2518}$	**0.8**
189	Seogwipo	$R = 0.040442P^{1.598898} \times M^{0.7816}$	**0.8**
238	Guemsan	$R = 0.37805P^{1.290668} \times M^{0.47935}$	**0.79**
114	Wonju	$R = 0.289734P^{1.423463} \times M^{0.26482}$	**0.78**
127	Chungju	$R = 0.24249P^{1.3512} \times M^{0.50685}$	**0.78**
244	Imsil	$R = 0.058295P^{1.54611} \times M^{0.708547}$	**0.78**
247	Namwon	$R = 0.4253P^{1.32885} \times M^{0.357302}$	**0.77**
162	Tongyeong	$R = 0.000000073\mathrm{P}^{3.8771} + 192.943\ \mathrm{M}^{0.55414}$	**0.77**
184	Jeju	$R = 0.01806P^{1.77664} \times M^{0.6487}$	**0.76**
273	Mungyeong	$R = 0.230614P^{1.317071} \times M^{0.58916}$	**0.76**
169	Heukasano	$R = 0.011690P^{1.71941} \times M^{1.112783}$	**0.75**
203	Icheon	$R = 0.363415P^{1.472747} \times M^{-0.023684}$	**0.75**
226	Boeun	$R = 1.151644P^{1.188996} \times M^{0.186387}$	**0.75**

4. Conclusions

The WERM is very simple to use and provides convenience in R factor estimations using ten minute interval rainfall data within a minute. In addition, the users are able to obtain yearly, monthly and event based R factor of entire period of which the rainfall data has been used. The module does not request for the users to handle missing rainfall data as the module is adjusted for those kinds of data and correct value can be achieved even if the data for some short period is absent. Since the input for WERM is 10 min interval rainfall data, we cannot use this module for the rainfall data having time interval greater than 10 min. For the estimation of soil loss using USLE in Korea, the value of average annual R factor that is calculated and published for 75 different cities in this research gives the better value than previous R factor suggested by Ministry of Korea (Jeong et al., 2004). The R factor values published in this research are based on rainfall data of recent 15 to 19 years, whereas the values of previous R factors (Jung et al., 1983; Park et al., 2000) were determined by obsolete or outdated rainfall data from 1973 to 1996. The R factor map provided in this study which is based on recent dataset gives better result than previous R factor map based on *obsolete* dataset. Moreover the maximum 30 min intensity derived from ten minute interval rainfall data in this research is obviously more accurate than that estimated from hourly rainfall data by previous researchers. In absence of higher temporal resolution rainfall data, we can estimate the monthly R factor from local daily rainfall data using regression model developed in this study. The regression model can be used to estimate R factor with more than 75% accuracy. In addition to this, these regression equations can be used for the prediction of future R factor from predicted monthly rainfall amount using different climate change scenarios and thus erosion forecasting can be done(Sauerborn et al., 1999).

Since the R factor from this research is determined by recent rainfall data, the updated R factor is suggested to be used in future instead of the one suggested by Korean Ministry of Environment (2012) which is based on the old data from the research of Jung et al. (1983) and Park et al. (2000). This study can help the policy makers to update their guideline (Korean Ministry of Environment, 2012) regarding R factors values for Korea. Moreover, the monthly R factor is suggested to be used as far as possible instead of average annual R factor for the estimation of soil loss since more than 80% of rainfall occurs in the rainy season and the erosion potential then is very high compared to dry season. The R factors for three months from July to September contribute more than 75% of the total average annual R factor value of Korea. In such case, using the average annual R factor value can give misleading amount of soil loss especially when we are considering a smaller watershed or field based studies. But average monthly R factor value should not be used for the calculation of soil loss since we can see a lots of variability in the value of R factor on same months of different years. Due to the higher standard deviation for the average monthly R factors, it is suggested to calculate soil loss of each month of each year as far as possible using individual monthly R factor values. The monthly R factor values determined by the WERM can be very effective in such case. In the absence of 10 min interval rainfall data, Monthly R factor can be easily calculated for the 25 specific locations for Korea from regression equations using monthly rainfall data without running WERM.

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