DEVELOPMENT OF A REGIONAL MODEL TO CALCULATE RAINFALL EROSIVITY FACTOR BY USING READILY AVAILABLE RAINFALL DATA

a study report

by

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ABSTRACT

Land degradation is a pervasive environmental and economic challenge of present time in the developing countries. Soil erosion caused by water is considered as one of the major type of land degradation. So estimation of soil loss due to erosion and detection of erosion prone areas are utmost important of present time for agricultural planning and various other land management planning. Revised universal soil loss equation (RUSLE) is a well-known empirical method of soil loss calculation. In this method the annual average soil loss of an area is calculated by multiplying five factors, viz. rainfall erosivity factor (R), soil erodability factor (K), slope length and steepness factor (LS), cover management factor (C) and conservation practice (P) factor. Among the factors of RUSLE, the calculation of Rainfall erosivity factor as per RUSLE handbook needs very high temporal resolution pluviographic rainfall data for a very long period (about 15-20 years). But in a developing country like India it is very difficult to find such long term high resolution rainfall data. So, in this study some multiple linear regression (MLR) models for calculating rainfall erosivity factor using readily available rainfall data were tried to develop with the help of half hourly rainfall data of Guwahati. These models performed reasonably well in predicting the rainfall erosivity factor as compare to other existing methods. The MLR models will contribute in filling the gap of not having a regional formula for calculating rainfall erosivity factor for this region. Eight multiple linear regression models were developed and two of them were selected for future use after considering various criteria. The rainfall erosivity factor of a year is the annual summation of a parameter called EI30 of each storm event occurs in that year. In the present study, the models were tried to relate monthly EI30 values with various other monthly parameters. In the process of developing the models the long term Rainfall Erosivity Factor of Guwahati was also calculated.

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1.1 General

Land degradation is one of the most serious global environmental problems of modern time, threatening agricultural areas at an alarming rate. Land degradation happens when natural or anthropogenic processes reduce the quality of land by decreasing the ability of land to support crops, livestock and organisms. One of the major land degradation is soil erosion (Miller, 2006). Water is the most common cause for soil erosion, which is accelerated by poor land use and land management practices adopted in the upland areas of watersheds, incorrect methods of tillage, unscientific agricultural practices etc. (Arekhi et al., 2012).

Revised universal soil loss equation (RUSLE) is a well-known empirical method of soil loss calculation. In this method the annual average soil loss of an area is calculated by multiplying five factors, viz. rainfall erosivity factor (R), soil erodability factor (K), slope length and steepness factor (LS), cover management factor (C) and conservation practice (P) factor. Among which the calculation of Rainfall erosivity factor as per RUSLE handbook needs very high temporal resolution pluviographic rainfall data for a very long period. But in a developing country like India it is very difficult to find such long term high resolution rainfall data. There are some daily or monthly rainfall data based rainfall erosivity factor calculation method for various other countries and for some other parts of India. But rainfall pattern of those countries and those parts of India do not match with this region and, moreover those methods were very old, so use of those equation may result in inaccurate estimation of rainfall erosivity. The accurate estimation of rainfall erosivity factor is very important to have better modelling result of soil erosion (Renard, 1994). So there is a need of having a regional rainfall erosivity factor calculation method based on readily available rainfall data. Having such a method is also important because even when sufficient pluviographic data are available, the calculation of the factor is difficult because of its complicated and tedious computational procedure. In this study an effort was made to develop multiple linear regression models to calculate the rainfall erosivity factor using readily available daily or monthly rainfall data.

1.2 Rainfall Erosivity Factor (R)

Rainfall erosivity is defined as the aggressiveness of rain to cause erosion (Lal,2001). The rainfall and runoff erosivity factor (R) of the Universal Soil Loss Equation (USLE) (Wischmeier 1959, Wischmeier and Smith 1958) was derived from research data from many sources. The data indicate that when factors other than rainfall are held constant, soil losses from cultivated fields are directly proportional to a rainstorm parameter : the total storm energy (E) times the maximum 30-min intensity (I₃₀). The sum of the EI₃₀ values of the storm events for a given period is a numerical measure of the erosive potential of the rainfall within that period. The average annual total of the storm EI₃₀ values in a particular locality is the rainfall erosivity factor (R) for that locality (Renard et al., 1997).

The energy of a rainstorm is a function of the amount of rain and of all the storm's component intensities. The median raindrop size generally increases with greater rain intensity (Wischmeier and Smith, 1958), and the terminal velocities of free-falling water drops increase with larger drop size (Renard et al., 1997). Since the energy of a given mass in motion is proportional to velocity squared, rainfall energy is directly related to rain intensity. The relationship, based on the data of Laws and Parsons (1943), is expressed by the equation

$$e = 916 + 331 \log_{10} i \qquad i \le 3 \text{ inch. } h^{-1}$$

$$e = 1074 \qquad i > 3 \text{ inch. } h^{-1} \qquad (1.1)$$

where 'e' is kinetic energy in ft.tonf.acre⁻¹.inch⁻¹, and 'i' is intensity in inch.h⁻¹ (Wischmeier and Smith, 1958). A limit of 3 inch.h⁻¹ is imposed on 'i' because median drop size does not continue to increase when intensities exceed 3 inch.h⁻¹ (Renard et al., 1997).

Brown and Foster in the year 1987 used a unit energy relationship of the form to relate energy with rainfall intensity.

$$e_r = e_{max} \times 1 - a \times \exp(-b.i) \tag{1.2}$$

where, e_{max} = a maximum unit energy as intensity approaches infinity

a and b = coefficient

 e_r = energy in MJ.ha⁻¹.mm⁻¹ and

 $i = \text{Rainfall intensity in mm.h}^{-1}$

Brown and Foster (1987) in their analysis recommended a value of 0.29, 0.72 and 0.05 for e_{max} , *a* and *b* respectively.

Then rainfall erosivity factor (R) can be calculated as

$$R = \frac{\int_{i=1}^{j} (EI_{30})_i}{N}$$
(1.3)

where $(EI_{30})_i = (EI_{30})_i$ for storm i, j = number of storms in an N year period.

Now, $E = \begin{pmatrix} k \\ r=1 \end{pmatrix} e_r v_r$ in MJ.ha⁻¹ and I_{30} = maximum 30 min intensity (mm/hr) where v_r is the rainfall volume (mm) during the r^{th} time period of a rainfall event divided in k parts.

As per the RUSLE handbook (Renard, 1997) rainfall event of less than 0.5 inch or 12.7 mm were omitted from the erosion index computations, unless at least 0.25 inch or 6.35 mm of rain fell in 15 min and a storm period with less than 0.05 inch or 1.27 mm over 6 hr was used to divide a longer storm period into two storms.

Later Renard et al. (1997) mentioned in RUSLE handbook that all the future calculations should be made using equation given by Brown and Foster (1987), especially in countries other than USA.

Now for calculating R factor by the above methods high resolution pluviographic rainfall data have to be present in the target area for a long period (about 15 to 20 years), only then the calculation of E and I30 is possible. Due to unavailability of such high resolution data in many regions of the world researchers proposed some simplified method to evaluate R factor which generally correlate R factor with the monthly or annual rainfall or combination of both.

The prime objective of this study is to develop a regional formula for calculating rainfall erosivity factor using readily available rainfall data. So this chapter will include a discussion on past researches on development of various formulae for calculating rainfall erosivity factor in different parts of the world as well as in India using readily available data. To develop a rainfall erosivity factor calculation model based on readily available data many researchers tried to use various parameters. Most of the researchers used annual precipitation to predict rainfall erosivity (Stocking and Elwell, 1976, Bergsma et al., 1996, Yang et al. 2003, Torri et al., 2006, Xin et al., 2010). But as per Bhuyan et al. (2002) use of annual precipitation ignores the bimodal variability of rainfall within the year and even the regional seasonality which in some cases are necessary for two or more parallel analyses for specific seasons. Mati et al. (2000) developed two different regression models for R factor with annual rainfall data after separating the data into two groups based on the location of stations in a particular agro-climatic zone to bring in the effects of seasonality. Natalia (2005) developed two regression models, one for the wet and the other for the dry season using the pluviographic data of Colombian Andes (1987– 1997). Loureiro and Coutinho, (2001) developed multiple linear regression models relating monthly EI30 values with monthly rainfall for days where rainfall exceeds 10 mm (rain10) instead of mean monthly rainfall, and monthly number of days where rainfall exceeds 10 mm (days10) instead of simple rain duration for the Algarve region of Portugal.

Above all Modified Fornier Index is an index which has been most widely used for calculating rainfall erosivity factor. In 1960 Fornier developed an index

Fornier Index,
$$I_F = \frac{P_m^2}{P}$$
 (2.1)

where P_m is the maximum monthly rainfall depth (mm) and P (mm) is the annual rainfall.

Since Fournier's index does not consider the monthly rainfall distribution during the year, it does not always increase when the number of erosive rainfalls in the year

increases (Ferro et. al. 1999). To avoid this particuler drawback Arnoldus (1980) proposed a modified Fournier Index as follows

$$F = \frac{\frac{12}{i=1}P_i^2}{P}$$
(2.2)

where P_i is the rainfall depth in the month i (mm)

For regions in which no pluviograhic data is available, Arnoldus (1980) showed that the MFI provided a good approximation of R factor. The relation is given as follows

$$R = 1.735 \times 10^{(1.5 \times \log_{10} \frac{12}{i=1} \frac{P_i^2}{P} - 0.8188)}$$
(2.3)

For the present study the monthly EI30 value will be tried relate with MFI, Rain10, Days10 and monthly rainfall.

In India also many researchers tried to develop such models by relating the annual average precipitation with R factor (Singh, 1981; Rambabu et al., 1978). The equations are R=79+0.363 AAP (Singh ,1981) for entire India, R=22.8+0.64 AAP (Rambabu et al.,1978) for Dehradun, R=81.5+0.375 AAP (Rambabu et al. 1978) for Jharkhand, where AAP is the annual average precipitation.

3.1 Materials

The half hourly rainfall data of Guwahati for almost 19 years (1996-2016) were manually extracted from pluviograph at the office of IMD Guwahati. The data for the years 2011 and 2012 were not available due to some technical problem. The data extraction was a very tedious work. The daily rainfall data was also collected from IMD Guwahati station.

3.2 Methodology

The EI30 value of each erosive rainfall event was calculated by the method given by Eq. 1.3 (Brown and Foster, 1987).

In the present study the EI30 values for a month were added and generated a series of monthly EI30 value for all the months available in the half hourly rainfall data. The monthly EI30 parameter was named as $EI30_{month}$. Taking this $EI30_{month}$ parameter as dependent variable, a multiple linear regression model was tried to develop, the details of which is given in 5.5.

$$y = b_1 X_1 + b_2 X_2 + \dots + b_k X_k + \varepsilon$$
 (3.1)

This is called as the multiple linear regression model. The parameters b_1, b_2, \dots, b_k are the regression coefficients associated with X_1, X_2, \dots, X_k respectively and ε is the random error component reflecting the difference between the observed and fitted linear relationship.

In multiple linear regression analysis, the operation procedure is divided into three basic steps, namely: Specification, Calibration and Validation. In the specification stage, model and predictors are selected. In calibration stage the relation between dependent and independent variables is obtained and the accuracy of the model is checked in the validation stage.

Guwahati is a major city of the north east India, often considered as the gateway to the North-East Region (NER) of the country and is the largest city within the region. Geographically the present Guwahati area lies in both the sides of the mighty Brahmaputra. The area extends from 26°10' to 26°17' N latitude and from 91°46' to 91°77' E longitude. It covers a geographical area of about 358 km². Guwahati's climate is mildly sub-tropical with warm, dry summer from April to late May, a strong monsoon from June to September and cool, dry winter from late October to March. The city's average yearly temperature is recorded at 24° Celsius (76°F). December, January and February are the coldest and June, July, August and September are the hottest months. Average yearly precipitation is 161.3 cm (63.5 inches) with an average number of 77.3 rainy days. June and July are the wettest months. The average elevation of the plain area of Guwahati is 54.17 meter above the mean sea level. Land use pattern as a part of areal personality of Greater Guwahati is introduced here. The land use pattern of Guwahati is though generally controlled by the naturally created physical features such as hills, plains, etc the river Brahmaputra and other flowing streams and water bodies, forests and marshy areas, beels etc, it is also influenced by the growing pressure of population in the area. Alluvial soil, red soil, sandy soil, lateritic soil etc. are some of the soil found in the area.

5.1 Calculation of Rainfall erosivity factor of Guwahati

Rainfall erosivity factor is a key input for Revised Universal Soil Loss Equation. It is also used as an input in various water quality modelling and sediment yield studies (Lee et al., 2008). In spite of its necessity in various studies, it is less investigated in this region. This may be due to the requirement of high resolution rainfall data or the tedious evaluation process. As per the literatures, the rainfall erosivity for Guwahati was calculated once in the year 2004 by using only 1 year hourly rainfall data (Sarma et al., 2004). In this study the Rainfall erosivity factor of Guwahati has been calculated by using 12 years half hourly rainfall data with the help of Eq. 3.3 as per RUSLE handbook (Renard, 1997). The Rainfall erosivity factor is found as 7924 MJ.mm/ha.h.yr. The sample calculation of EI30 of a storm event is given in Appendix 2.

5.2 Parameter selection for model development

In this study an effort was made to develop multiple linear regression models using the $EI30_{month}$ i.e the monthly sum of EI30 value of all the storm events occur in a month, as dependent variable and some other hydrological parameters as independent variable. The hydrological parameters used in this study were taken from various literature and correlation of these parameters with actual $EI30_{month}$ values were checked with the help of Pearson Correlation Coefficient. All the parameters were found to be positively correlated. The selected parameters are

- i. Rain10 (Morgan,1986; Loureiro and Coutinho,2001) : It is the monthly rainfall for days with rainfall greater than 10mm.
- ii. Days10 (Morgan,1986; Loureiro and Coutinho,2001) : It is the number of days in a month with rainfall greater than 10mm.
- iii. Modified Fornier Index (MFI) (Arnoldus, 1980) : The expression for MFI is given as

$$MFI = \frac{12}{i=1} \frac{P_i^2}{P}$$
(5.1)

where P_i is the monthly rainfall of i^{th} month and P is the annual rainfall of that year. In this study $\frac{P_i^2}{P}$ value of each month was calculated and used as a parameter in the models.

iv. Rain_{month} (Morgan,1986; Loureiro and Coutinho,2001) : It is the monthly rainfall considering all the rainfall events.

The Pearson Correlation Coefficient for each parameter with $EI30_{month}$ value is given in Table 5.1. Pearson correlation coefficient is a measure of the linear correlation between two variables and is defined as the covariance of two variables divided by the product of their standard deviations. It can have values ranges from -1 to 1, where 1 represents total positive linear correlation, 0 represents no correlation and -1 represents total negative correlation.

Table 5.1			Pearson
correlation	Parameter	Pearson Correlation Coefficient	 coefficient for
various	Rain10	0.808559	parameters
	Days10	0.691780	—
	MFI	0.792252	
	Rain _{month}	0.817632	_

From the above table it can be observed that all the parameters are positively correlated and $Rain_{month}$ being the highest correlated parameter. Following are the plots showing the temporal variation of all the selected independent variables with $EI30_{month}$.

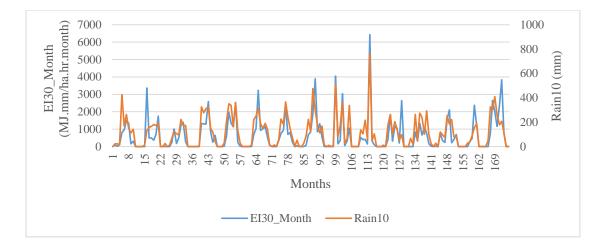


Figure 5.1 : Temporal variation of $EI30_{month}$ and Rain10

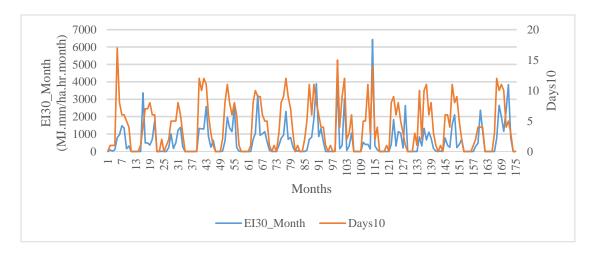


Figure 5.2 : Temporal variation of $EI30_{month}$ and Days10

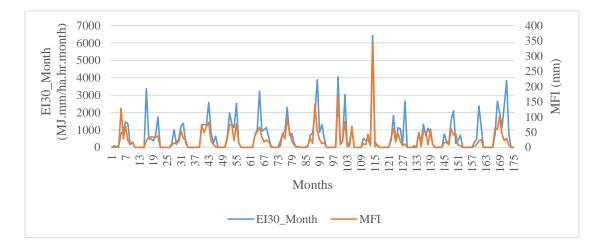


Figure 5.3 : Temporal variation of EI30month and MFI

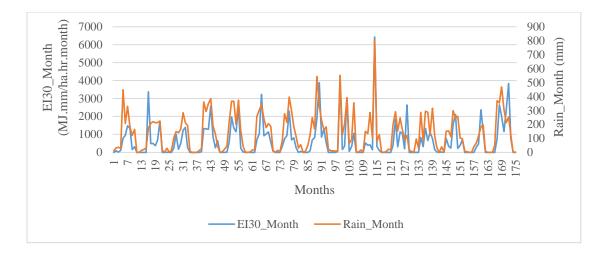


Figure 5.4 : Temporal variation of EI30month and Rainmonth

For preparing the series of independent variables 15 years (1996-2010) data were used. MATLAB computer programming was used to calculate the parameters from that large dataset. Among the 15 years data, 5 months data were omitted during model development as EI30 value for those months could not be calculated due to data insufficiency. Among the rest of the months, 129 month's data were used for calibration and almost 25% i.e 45 month's data were used for validation of the models. The calculated values of all the parameters (both dependent and independent) are shown in Table 5.2, Table 5.3, Table 5.4, Table 5.5 and Table 5.6.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual R Factor
1996	0.00	89.57	16.19	104.00	793.89	953.31	1480.21	1342.84	152.78	310.56	0.00	0.00	5243.359
1997	0.00	0.00	0.00	3364.71	489.93	494.80	368.60	692.89	1746.96	0.00	0.00	7.71	7165.601
1998	0.00	0.00	240.97	1008.03	172.50	490.87	N/A	1224.63	1384.14	274.73	0.00	0.00	N/A
1999	0.00	0.00	0.00	37.14	1323.75	1303.30	1282.54	2587.16	864.76	251.02	645.49	0.00	8295.143
2000	0.00	0.00	14.12	577.56	1964.01	1350.35	1142.43	2517.36	233.38	18.78	0.00	0.00	7817.998
2001	0.00	0.00	0.00	688.96	1038.56	3225.98	926.64	1017.82	1139.56	568.14	59.22	0.00	8664.881
2002	0.00	0.00	343.26	752.48	940.11	2297.70	694.53	806.49	258.71	0.00	45.41	0.00	6138.697
2003	0.00	0.00	74.61	688.25	821.66	1885.56	3885.18	854.51	1309.50	546.12	0.00	0.00	10065.38
2004	0.00	0.00	42.29	4043.86	155.88	346.71	3029.51	50.83	312.98	1054.86	0.00	0.00	9036.928
2005	0.00	0.00	522.94	396.48	413.92	147.40	N/A	6423.35	323.32	102.91	0.00	0.00	N/A
2006	0.00	0.00	0.00	405.23	1832.48	307.88	1136.86	1057.76	205.01	2639.38	0.00	0.00	7584.586
2007	0.00	0.00	0.00	837.25	313.74	1335.51	658.98	1107.36	767.85	159.47	15.61	0.00	5195.758
2008	17.24	0.00	774.22	348.09	236.26	1551.64	2106.22	222.68	392.20	701.09	0.00	0.00	6349.642
2009	0.00	0.00	0.00	288.67	N/A	470.81	N/A	N/A	2372.87	1196.97	0.00	0.00	N/A
2010	0.00	0.00	0.00	765.69	2645.21	2015.70	1159.45	2361.92	3831.57	753.98	0.00	0.00	13533.51

Table 5.2: EI30_{month} (MJ.mm/ha.h.month) values calculated from 15 years half hourly rainfall dataset of IMD Guwahati station

N/A = Data not available

Rainfall Erosivity Factor = $\frac{\sum Annual R factor}{12}$ = 7924.29 MJ.mm/ha.h.yr

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1996	0.0	22.6	23.3	13.0	424.0	172.5	261.9	151.2	111.1	141.6	0.0	0.0
1997	0.0	0.0	12.2	132.9	157.5	165.4	180.7	171.8	192.7	0.0	0.0	24.8

Table 5.3 : Rain10 (mm) values calculated from the 15 years daily rainfall dataset of IMD Guwahati station

1998	0.0	12.2	69.4	123.4	106.4	94.7	192.5	222.1	174.1	172.8	0.0	0.0
1999	0.0	0.0	0.0	0.0	326.2	276.7	310.0	327.2	150.3	117.4	42.7	0.0
2000	Jan	Feb	Mar	2001.4	349.77	338.3	1641.3	3625	1\$699	29ct	<u>8</u> .9v	<u>8</u> .65
2889	0.0	0.10	11 ¹ .4	220.0	250.8	318.6	188.5	149.4	189.8	$14\frac{4}{5.0}$	13.4	0.0
2002	12.3	0.0	58.1	225.4	182.3	366.5	241.6	147.3	75.2	0.0	52.2	0.0
2003	0.0	26.5	87.1	223.3	127.7	476.0	294.1	178.8	112.1	167.7	12.7	0.0
2004	10.7	0.0	0.0	511.7	82.5	172.2	359.6	26.3	64.3	336.8	0.0	0.0
2005	0.0	0.0	136.2	103.0	216.6	63.1	119.4	767.6	46.6	104.9	0.0	0.0
2006	0.0	11.0	0.0	176.4	263.9	102.2	205.0	143.8	52.8	96.9	0.0	0.0
2007	0.0	66.7	18.7	263.3	49.2	274.2	239.0	101.1	293.0	99.6	22.6	0.0
2008	28.0	0.0	119.2	95.4	76.3	253.0	184.6	221.0	80.8	84.0	0.0	0.0
2009	0.0	0.0	27.5	38.0	144.2	89.4	350.9	282.6	154.8	188.1	0.0	0.0
2010	0.0	0.0	48.8	326.0	302.0	410.3	259.6	178.5	206.7	116.0	0.0	0.0

Table 5.4 : Days10 (days) values calculated from the 15 years daily rainfall dataset of IMD Guwahati station

1997	0	0	1	4	7	7	8	6	6	0	0	2
1998	0	1	2	5	5	5	11	8	6	3	0	0
1999	0	0	0	0	12	10	12	11	6	3	1	0
2000	0	0	2	8	11	8	6	8	6	1	0	0
2001	0	0	1	8	10	9	9	6	5	5	1	0
2002	1	0	3	8	9	12	9	7	3	0	1	0
2003	0	2	5	11	6	11	8	6	4	4	1	0
2004	1	0	0	15	4	9	12	2	3	6	0	0
2005	0	0	5	5	11	3	4	14	2	4	0	0
2006	0	1	0	8	9	6	8	5	3	1	0	0
2007	0	3	1	10	2	10	11	6	8	3	1	0
2008	1	0	6	6	4	11	8	9	5	2	0	0
2009	0	0	1	2	4	4	12	11	4	4	0	0
2010	0	0	3	12	10	11	10	4	5	3	0	0

Table 5.5 : MFI (mm) values calculated from the 15 years daily rainfall dataset of IMD Guwahati station

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
			· · ·	· · · · ·			V	Â		I	

1996	0.000	0.628	0.845	0.521	128.337	27.632	69.652	21.495	9.418	17.350	0.000	0.000
1997	0.000	0.295	0.668	21.774	31.880	35.373	33.305	33.274	37.039	0.108	0.008	0.620
1998	0 j@0 0	0 F@\$ 7	6 M 971	1 4.95 0	1 2/97 5	17.6889	44 .5 46	5 2.99 0	2 9.69 4	2 4.25 3	0.1033	02000
1999	0.000	0.000	0.097	0.372	72.777	47.870	67.862	82.649	19.959	9.414	1.097	0.000
2000	0.000	0.288	1.137	26.874	74.608	73.837	22.436	77.234	14.100	1.034	0.002	0.000
2001	0.000	0.153	0.213	37.510	51.715	66.710	32.742	17.845	23.922	19.532	0.124	0.000
2002	0.000	0.012	4.409	45.827	27.611	94.025	52.126	19.906	7.730	0.602	1.779	0.000
2003	0.000	1.110	7.009	29.952	13.360	142.201	53.730	25.738	12.245	16.104	0.221	0.077
2004	0.000	0.039	0.065	167.319	8.734	23.141	84.361	2.331	4.436	69.094	0.008	0.000
2005	0.000	0.008	12.063	9.579	43.049	5.819	16.307	342.947	3.244	8.565	0.004	0.000
2006	0.000	0.363	0.246	30.410	63.245	17.729	45.860	19.866	5.812	10.789	0.190	0.034
2007	0.000	5.559	0.535	49.446	3.644	52.103	49.619	9.078	60.073	8.482	0.624	0.000
2008	0.000	0.008	15.678	15.989	8.516	60.303	40.579	45.320	7.190	6.429	0.043	0.016
2009	0.000	0.000	1.098	2.838	24.617	9.183	99.437	69.874	21.534	25.413	0.035	0.000
2010	0.000	0.000	1.168	63.860	58.551	102.596	43.918	21.237	29.859	6.841	0.002	0.002

Table 5.6: Rain_{month} (mm) values calculated from the 15 years daily rainfall dataset of IMD Guwahati station

1996	10.2	31.3	36.3	28.5	447.4	207.6	329.6	183.1	121.2	164.5	0.0	0.0
1997	14.3	20.0	30.1	171.9	208.0	219.1	212.6	212.5	224.2	12.1	3.3	29.0
1998	0.5	12.2	103.2	149.1	140.8	164.4	260.8	284.3	213.0	192.5	7.1	0.0
1999	0.0	0.0	13.2	25.8	360.9	292.7	348.5	384.6	189.0	129.8	44.3	0.9
2000	4.6	22.8	45.3	220.2	366.9	365.0	201.2	373.3	159.5	43.2	1.7	0.6
2001	2.1	16.4	19.4	257.2	302.0	343.0	240.3	177.4	205.4	185.6	14.8	0.0
2002	14.6	4.5	85.8	276.6	214.7	396.2	295.0	182.3	113.6	31.7	54.5	0.0
2003	6.2	48.0	120.6	249.3	166.5	543.2	333.9	231.1	159.4	182.8	21.4	12.6
2004	10.7	8.4	10.9	551.5	126.0	205.1	391.6	65.1	89.8	354.4	3.7	0.6
2005	16.6	3.8	150.6	134.2	284.5	104.6	175.1	803.0	78.1	126.9	2.8	0.0
2006	6.7	22.0	18.1	201.3	290.3	153.7	247.2	162.7	88.0	119.9	15.9	6.7
2007	0.0	96.1	29.8	286.6	77.8	294.2	287.1	122.8	315.9	118.7	32.2	0.0
2008	39.5	3.5	152.1	153.6	112.1	298.3	244.7	258.6	103.0	97.4	8.0	4.8
2009	0.0	0.6	40.8	65.6	193.2	118.0	388.3	325.5	180.7	196.3	7.3	0.0
2010	0.4	0.0	50.0	369.7	354.0	468.6	306.6	213.2	252.8	121.0	1.8	2.2

5.3 Handling of missing data

In a set of hydrological time series data, it is generally seen that some data are not available due to various reasons. In most of the cases people approximate this missing data with the help of various interpolation methods. In the present study an effort was made to relate the monthly EI30 value with days10, rain10, MFI and Rain_{month}. The calculation of EI30 needs half hourly data and calculation of days10 needs daily data and MFI and Rain_{month} needs monthly rainfall data. In the set of our hydrological data it was observed that, for some of the days half hourly data were not available, but for those days daily data were available. If in those days the daily rainfall value was greater than 10 mm then those days were omitted during the calculation of days10, rain10, MFI and Rain_{month}. In the present study as we are trying to relate, one monthly hydrological parameter with four other monthly hydrological parameters for a particular month through multiple linear regression, so the above method is enough to get a less erroneous result. However there were seven months in the half hourly rainfall data where more than 50% data were missing. So the monthly parameters calculated using the data of those months were not considered in the multiple linear regression model.

5.4 Performance Evaluation

To assess model performance these evaluation statistics are selected (Krause and Boyle, 2005; Moriasi et al., 2007): 1) Coefficient of determination (R^2) (Eq. 5.2) and 2) Nash-Suttcliffe efficiency (NSE) (Eq. 5.3).

 R^2 describes the degree of collinearity between simulated and observed data and ranges from 0 to 1, where 0 indicates no correlation and 1 represents perfect correlation. R^2 estimates the efficiency of model simulation in replicating the variance of observed values (Krause and Boyle, 2005; Moriasi et al., 2007).

$$R^{2} = \left[\frac{\sum_{i=1}^{n} \left(v_{i}^{obs} - \overline{Y_{obs}} \right) \left(v_{i}^{sim} - \overline{Y_{sim}} \right)}{\sqrt{\sum_{i=1}^{n} \left(v_{i}^{obs} - \overline{Y_{obs}} \right) \left(\sqrt{\sum_{i=1}^{n} \left(v_{i}^{sim} - \overline{Y_{sim}} \right)} \right)}\right]^{2}$$

(5.2)

where Y_i^{sim} is the *i*th simulated value for the variable being evaluated; Y_i^{obs} is the *i*th observation for the variable being evaluated.

NSE gives the residual variance relative to the measured data variance, it ranges between $-\infty$ to 1. It indicates how well the simulated output matches the observed data along a 1:1 line (Arnold et al., 2012). Values ranging between 0 and 1 are seen as satisfactory levels of performance (Moriasi et al., 2007). Value ≤ 0 implies that the mean of the observed data series is a better predictor than the simulated value (Krause and Boyle, 2005).

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n} \left(\sum_{i=1}^{obs} - Y_{i}^{sim} \right)}{\sum_{i=1}^{n} \left(\sum_{i=1}^{obs} - \overline{Y_{obs}} \right)} \right]$$

(5.3)

5.5 Results and Discussion

Various combination of the selected parameters were used to develop four different multiple linear regression models.

Model 1:

In model 1, two parameters were used to predict the monthly EI30 value. Loureiro and Coutinho (2001), used these two parameters in their study to predict monthly EI30 value and got a very good result with $R^2 = 0.89$ in the Algarve region of Portugal. That is why combination of these two parameters were examined first. After performing multiple linear regression by taking these two parameters as independent variable and EI30_{month} as dependent variable, we got the model as

$$EI30_{month} = 10.09 \text{ Rain}10 - 133.189 \text{ Days}10$$
(5.4)

From the above model it can be observed a positive relation between $EI30_{month}$ and Rain10 and a negative relation between $EI30_{month}$ and Days10. In other words it can be said that more amount of rainfall occur in lesser number of days yields higher EI30 value.

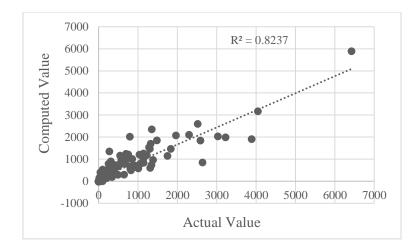


Figure 5.5 : Computed Vs. Actual value of EI30_{month} (MJ.mm/ha.h.month) value during calibration of Model 1

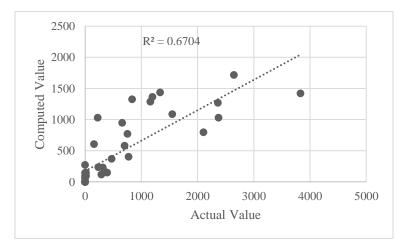


Figure 5.6 : Computed vs. Actual value of EI30 (MJ.mm/ha.h.month) value during validation of Model 1

Model 2:

In Model 2, one more parameter called MFI was added along with the parameters used in Model 1. The MFI i.e Modified Fornier Index is a widely used index for the calculation of Rainfall Erosivity Factor (Arnoldus,1980; Renard et al.,1994; Coutinho and Tomas, 1994). In India also this factor is used to calculate the rainfall erosivity factor. Recently some researchers from IIT roorkee used this index to prepare rainfall erosivity factor map of India (Tiwari et. al., 2016). The generated model is

$$EI30_{month} = 9.21 Rain10 - 120.596 Days10 + 1.95 MFI$$
(5.5)

In this model also the Rain10 is positively related with the the $EI30_{month}$ and Days10 is negatively related with $EI30_{month}$ and the newly added MFI also showed a positive relation.

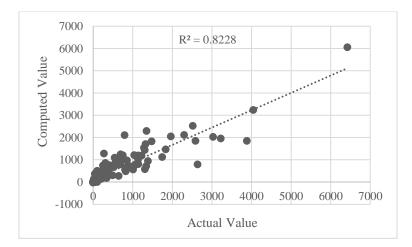


Figure 5.7 : Computed Vs. Actual value of EI30 (MJ.mm/ha.h.month) value during calibration of Model 2

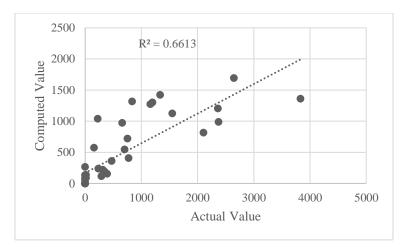


Figure 5.8 : Computed Vs. Actual value of EI30 (MJ.mm/ha.h.month) value during validation of Model 2

Model 3:

In Model 3, MFI of model 2 is replaced by $Rain_{month}$. As in the Pearson Correlation Coefficient analysis $Rain_{month}$ was found to have highest correlation with $EI30_{month}$. So this parameter was introduced in the model to see the performance in predicting the monthly EI30. The generated model is

$$EI30_{month} = 7.063 Rain10 - 152.059 Days10 + 3.203 Rain_{month}$$
(5.6)

In this model the Rain10 and Days10 showed same relation with $EI30_{month}$ as previous models. The Rain_{month} showed a positive relation with $EI30_{month}$.

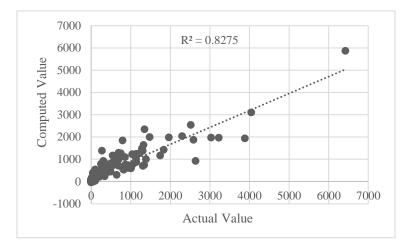


Figure 5.9 : Computed Vs. Actual value of EI30 (MJ.mm/ha.h.month) value during calibration of Model 3

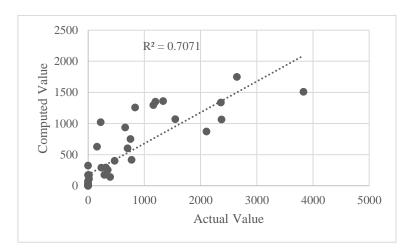


Figure 5.10 : Computed Vs. Actual value of EI30 (MJ.mm/ha.h.month) value during validation of Model 3

Model 4:

In model 4 only $Rain_{month}$ is used, the purpose of developing this model was to approximate the EI30 value when the daily rainfall is not available for a region. MFI was not used because it was giving less R^2 value. The model is

$$EI30_{month} = 5.158 Rain_{month}$$
(5.7)

But this model is strictly not advisable if daily data are available for a region. As in this model $EI30_{month}$ is expressed in terms of only one parameter, so it should be used if only monthly data are available to get a rough idea of $EI30_{month}$ value.

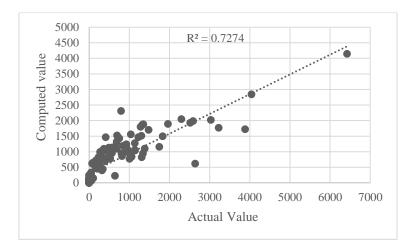


Figure 5.11 : Computed Vs. Actual value of EI30 (MJ.mm/ha.h.month) value during calibration of Model 4

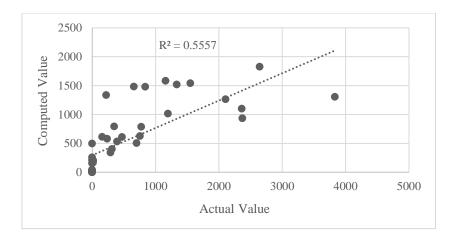


Figure 5.12 : Computed Vs. Actual value of EI30 (MJ.mm/ha.h.month) value during validation of Model 4

The statistical parameters evaluated for performance analysis of all the models are shown in Table 5.7.

Sl. No.	Model	Calibration		Validation		
		R^2	NSE	R^2	NSE	
1	Model 1	0.8237	0.8124	0.6704	0.6613	
2	Model 2	0.8228	0.8111	0.6613	0.6527	
4	Model 3	0.8275	0.8153	0.7071	0.6950	
5	Model 4	0.7274	0.7185	0.5557	0.5432	

Table 5.7: Performance evaluation of all the models using various statistical measures

Table 5.8 : Long term rainfall erosivity factor (R) calculated by the models

Sl			Computed	Actual R	Percentage
No.	Models		R factor	Factor	of Error
			(MJ.mm/	(MJ.mm/	(%)
			ha.h.yr)	ha.h.yr)	
1	EI30 _{month} = 10.09 Rain10 -	Calibration	7402.59	7924.29	-6.58
	133.189 Days10	Validation	6408.53		-19.13
2	EI30 _{month} = 9.21 Rain10 -	Calibration	7337.67		-7.403
	120.596 Days10 + 1.95	Validation	6296.88		-20.54
	MFI				
3	EI30 _{month} = 7.063 Rain10 -	Calibration	7617.77		-3.87
	152.059 Days10 + 3.203	Validation	6551.02		-17.33
	Rain _{month}				
4	$EI30_{month} = 5.158 Rain_{month}$	Calibration	8504.67		7.32
		Validation	7588.72		-4.23

During calibration of the models it was observed that the $EI30_{month}$ value of August, 2005 was 6423.35 MJ.mm/ha.h.yr, which is almost 60% higher than the second highest value (4043.86 MJ.mm/ha.h.yr). Therefore, scope of improving the model by considering 6423.35 MJ.mm/ha.h.yr as an outlier was also explored. Results obtained for this case is shown below:

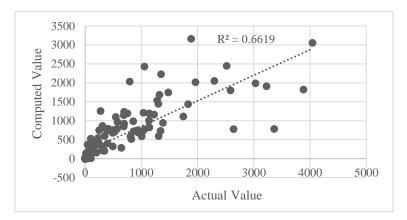


Figure 5.13 : Computed Vs. Actual value of EI30month (MJ.mm/ha.h.month) value during calibration of Model 5

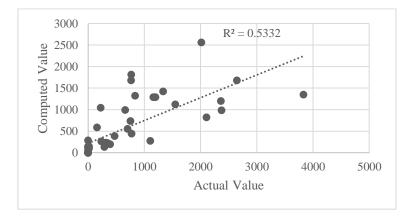


Figure 5.14 : Computed Vs. Actual value of EI30month (MJ.mm/ha.h.month) value during validation of Model 5

Model 6 : $EI30_{month} = 9.91 Rain10 - 114.968 Days10 - 2.56 MFI$

(5.9)

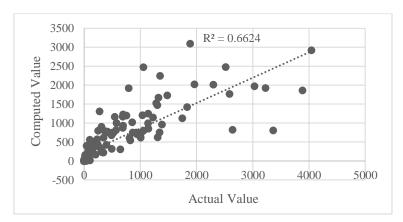


Figure 5.15 : Computed Vs. Actual value of EI30_{month} (MJ.mm/ha.h.month) value during calibration of Model 6

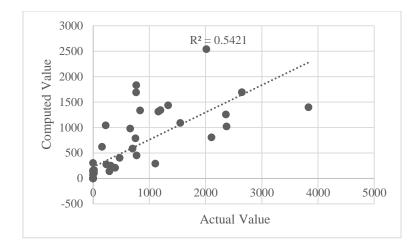


Figure 5.16 : Computed Vs. Actual value of EI30_{month} (MJ.mm/ha.h.month) value during validation of Model 6

Model 7 : $EI30_{month} = 5.933 Rain10 - 127.602 Days10 + 3.365 Rain_{month}$ (5.10)

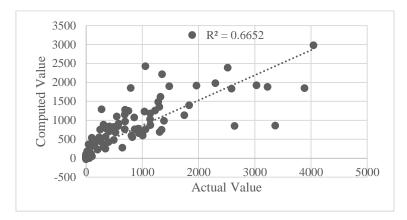


Figure 5.17 : Computed Vs. Actual value of EI30_{month} (MJ.mm/ha.h.month) value during calibration of Model 7

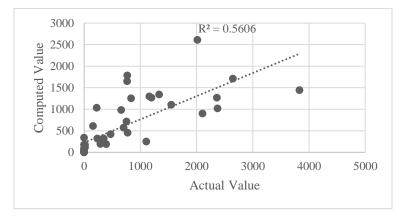


Figure 5.18 : Computed Vs. Actual value of EI30_{month} (MJ.mm/ha.h.month) value during validation of Model 7

Model 8 : EI30_{month} = 4.755 Rain_{month}

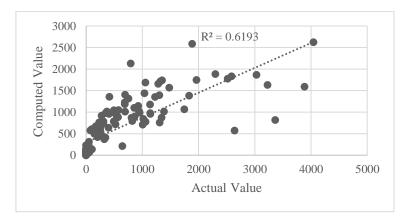


Figure 5.19 : Computed Vs. Actual value of EI30_{month} (MJ.mm/ha.h.month) value during calibration of Model 8

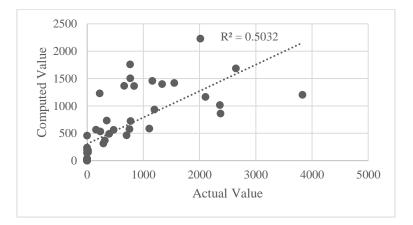


Figure 5.20 : Actual Vs. Simulated value of EI30_{month} (MJ.mm/ha.h.month) value during validation of Model 8

The statistical parameters evaluated for performance analysis of all the models are shown in Table 5.9.

 Table 5.9 : Performance evaluation of all the modified models using various statistical measures

Sl. No.	Model	Calibration		Validation		
		R^2	NSE	R^2	NSE	
1	Model 5	0.6619	0.6613	0.5332	0.5231	
2	Model 6	0.6624	0.6622	0.5420	0.5342	
3	Model 7	0.6652	0.6651	0.5606	0.5524	
4	Model 8	0.6193	0.6138	0.5032	0.5010	

Sl			Cor	nputed	Actual R	Perc	entage
No.	Models		R	factor	Factor	of	Error
			(MJ	ſ.mm/	(MJ.mm/	(%)	
			ha.ł	n.yr)	ha.h.yr)		
1	EI30 _{month} = 9.15 Rain10 -	Calibration	741	7.04	7924.29	-6.40)
	108.59 Days10	Validation	749	6.49		-5.39	9
2	EI30 _{month} = 9.91 Rain10 -	Calibration	748	4.07		-5.5	5
	114.97 Days10 – 2.56 MFI	Validation	761	7.61		-3.8	7
3	EI30 _{month} = 5.933 Rain10 -	Calibration	760	6.12		-4.0	1
	127.602 Days10 + 3.365	Validation	763	8.47		-3.60)
	Rain _{month}						
4	EI30 _{month} = 4.755 Rain _{month}	Calibration	801	4.81		1.14	
		Validation	836	4.62		5.55	
5	$R = 1.735 \times 10^{(1.5 \times \log_1)}$	₀ MFI –0.8188)	121	1.491		-84.′	71
	Given by Arnoldus (1977) a	nd used in India					
	by Prasannakumar et al. 20	11, Rahaman et					
	al. 2015, Shit et al., 2015)						
6	R=79+0.363 AAP*		692	.971		-91.2	26
	Given by Singh G. (1981)	gave for entire					
	India, used by Ramu et al., 2	015					
7	R=22.8+0.64 AAP*		110	5.28		86.0	5
	Given by Rambabu et	al. (1979) for					
	Dehradun						
8	R=81.5+0.375 AAP*		715	.77		-90.9	97
	Given by Rambabu et	al. (1979) for					
	Jharkhand, recently used b	y Jaiswal et al.					
	(2014)						
9	R=0.07397 MFI ^{1.847}		243	9.123		-69.2	22
	Given by Renard et al. (1994	4)					
	D- Annual Average Precinita						

Table 5.10 : Comparison of our models with some already existing models

*AAP= Annual Average Precipitation

By observing the Table 5.9 it is clear that the models did not perform so well in predicting monthly EI30 values. However if we observe Table 5.10 then it can be seen that all the models are showing very low percentage of error in the calculation of long term Rainfall erosivity factor (R), both during calibration and validation phase. In the monthly scale the computed values of $EI30_{month}$ for some months are though varying significantly from the actual value of $EI30_{month}$ for the corresponding months, the effects of fluctuations tend to average out over extended periods. As computation of R is always done with long term data series, the present models can still be considered for calculating long term rainfall erosivity factor R, using daily rainfall data.

Both during calibration and validation, Model 7 was the best with maximum R^2 and NSE value. And from the Table 5.10 also it can be observed that Model 7 is showing lowest percentage of error during the calculation of long term rainfall erosivity factor. So it is justified to use Model 7 in future studies if required. Model 8 was developed to calculate EI30_{month} if daily rainfall is absent for a station. As performance of Model 8 was not so good, and as the independent variable is also one here, so sometime it may give highly erroneous results.

In Table 5.10, Rainfall erosivity factor of this region, calculated by various existing models using the same rainfall data sets are also shown. From the Table 5.10 it can be observed that all the existing equations are heavily underestimating the rainfall erosivity factor value. This may be due to some high intensity rainfall events occur in this region, and one more reason may be the set of data they used. As all the models developed long ago, and various rainfall parameters are changing over the time. However in this study as recent rainfall data are used to develop the equations so it may be advantageous to use this models for present time.

6.1 Conclusion

In this study multiple linear regression models were developed to calculate the rainfall erosivity factor with readily available daily or monthly rainfall data. The model showed good performance result during validation. Though the model was developed using the high resolution rainfall data of Guwahati, it is expected to perform well for other part of this region also as the rainfall pattern is almost similar. This model will contribute in filling the gap of not having a regional formula for calculating rainfall erosivity factor of this region.

6.2 Scope for future work

In this study only the linear relationship of various parameters are examined to predict the rainfall erosivity factor. Though the multiple linear regression model showed reasonably good result, but nonlinear model may perform better than those. So developing a nonlinear model with inclusion of more parameters may be a scope for future work.

In the present study 15 years high resolution data of only one raingauge station was considered. However to have a knowledge of spatial variation of rainfall erosivity, more number of raingauge stations are required. So developing the model using the data of more than one station considering more number of years may be another scope for future work.

Arekhi, S., Bolourani, A.D., Shabani, A., Fathizad, H. and Ahamdy-asbchin, S., 2012. Mapping soil erosion and sediment yield susceptibility using RUSLE, Remote Sensing and GIS (Case study: Cham Gardalan Watershed, Iran).

Advances in Environmental Biology, 6(1): 109–124.

- Arnold, J. G., R. Srinivasan, R. S. Muttiah, and J. R. Williams, 1998. Large area hydrologic modeling and assessment part I: model development, *J. Am. Water Resour. Assoc.*, 34(1), 73–89.
- Arnoldus, H.M.J., 1980. An approximation of the rainfall factor in the Universal Soil Loss Equation. In: De Boodt, M., Gabriels, D. (Eds.), Assessment of Erosion. Wiley, Chichester, UK, 127-132
- Bergsma, E., Charman, P., Gibbons, F., Humi, H., Moldenhauer, W.C., Panichapong, S., 1996. Terminology for Soil Erosion and Conservation. *International Society of Soil Science (ISSS)*, UK.
- Bhuyan, S.J., Prasanta, K.K., Janssen, K.A., Barnes, P.L., 2002. Soil loss predictions with three erosion simulation models. *Environmental Modelling* & Software 17, 137–146.
- Coutinho, M.A., Tomas, P.P., 1994. Comparison of Fournier with Wischmeier rainfall erosivity indices. In: Rickson, R.J. (Ed.), *Conservation Soil Resources, European Perspectives*. CAB International, Wallingford.
- Ferro V., Giordano G. & Iovino M., 1991. Isoerosivity and erosion risk map for Sicily, *Hydrological Sciences Journal*, 36:6, 549-564
- Fournier, F., 1960. Climat et erosion. Presses Universitaires de France, Paris. Haan, C. T., Barfield, B. J. & Hayes, J. C. (1994). Design Hydrology and Sedimentology for Small Catchments. Academic Press, New York.
- Krause, P., and D. P. Boyle, 2005, Advances in Geosciences Comparison of different efficiency criteria for hydrological model assessment, *Adv. Geosci.*, 5(89), 89–97.
- Lal R., 2001. Soil degradation by erosion. *Land Degrad Dev* 12(5):519–539.

- Lal, R., 1977. Analyses of factors affecting rainfall erosivity and soil credibility. *In: Soil Conservation and Management in the Humid Tropics* (ed. D. J. Greenland & R. Lai), Wiley, Chichester, West Sussex, UK.
- Lee, J., Jung, Y., Oh, K., Heo, J., 2008. A study on estimation of rainfall erosivity in RUSLE. In: Proceedings of 2008 Conference on Korean Water Resources Association, Gyeongju, Korea, pp. 1324–1328.
- Louriero, 2001. A new procedure to estimate the RUSLE EI₃₀ index based on monthly rainfall data and applied to the Algarve region, Portugal, *Journal of Hydrology*, 250, 12-18.
- Mati, B.M., Morgan, R.P.C., Gichuki, F.N., Quinton, J.N., Brewer, T.R., Liniger,H.P., 2000. Assessment of erosion hazard with the USLE and GIS: a casestudy of the Upper Ewaso Ng'iro North basin of Kenya. JAG 2 (2), 78–86.
- Miller, G.T., 2006 Environmental Science: Working with the Earth. 11th ed. Belmont, CA: Thompson Brook/Cole.
- Morgan, R.P.C., 1986. Soil Erosion and Conservation. Longman Group, Essex, UK.
- Moriasi, D. N., J. G. Arnold, M. W. Van Liew, R. L. Binger, R. D. Harmel, and T. L. Veith ,2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations, *Trans. ASABE*, 50(3), 885–900.
- Natalia, H., 2005. Spatial modeling of soil erosion potential in a tropical watershed of the Colombian Andes. *Catena* 63 (1), 85–108.
- Prasannakumar, V., Vijith, H., Abinod, S., and Geetha, N., 2012. Estimation of soil erosion risk within a small mountainous sub-watershed in Kerala, India, using Revised Universal Soil Loss Equation (RUSLE) and geo-information technology. *Geoscience Frontiers*, 3(2): 209–215.
- Rahaman S., Aruchamy S., Jegankumar R., Ajeez S., 2015. Estimation of annual average soil loss, based on rusle model in kallar watershed, bhavani basin, Tamilnadu, india, ISPRS Annals of the Photogrammetry, *Remote Sensing and Spatial Information Sciences*, Volume II-2/W2, 2015 Joint International Geoinformation Conference 2015, 28–30 October 2015, Kuala Lumpur, Malaysia.

- Ram Babu, Tejwani, K.G., Agarwal, H.C. and Bhusan, L.S., 1978. Distribution of Erosion Index and Iso – erodent maps of India. *Indian J. Soil Conservation*, 6 (1): 1-12.
- Renard, K. G., Foster, G. R., Weesies, G. A., McCool, D. K. and Yoder, D. C., 1997. Predicting Soil Erosion by Water: a Guide to Conservation Planning with the Revised Universal Soil Loss Equation (RUSLE). Agriculture Handbook Number 703, Washington, DC: US Department of Agriculture.
- Renard, K. G., & Freimund, J. R., 1994. Using monthly precipitation data to estimate the R-factor in the revised USLE. *Journal of Hydrology*, 157(1-4), 287-306.
- Shit P., Nandi A., Bhunia G., 2015. Soil erosion risk mapping using RUSLE model on jhargram sub-division at West Bengal in India, *Model. Earth Syst. Environ.* 1:28.
- Singh, G., Ram Babu and Chandra, S., 1981. Soil Loss Prediction Research in India. Bulletin Nos.T-12/D-9. Central Soil and Water Conservation Research and Training Institute, Dehradun.
- Stocking, M.A., Elwell, H.A., 1976. Rainfall erosivity over Rhodesia. Trans. Inst. British Geographers (New Ser.) 1 (2), 231–245.
- Tiwari H., Rai S., Kumar D., Sharma N., 2016. Rainfall erosivity factor for India using modified Fourier index. *Journal of Applied Water Engineering* and Research, 4 (2), 83-91
- Torri, D., Borselli, L., Guzzetti, F., Calzolari, M.C., Bazzoffi, P., Ungaro, F., Bartolini, D., Salvador Sanchis, M.P., 2006. Italy. In: Boardman, J., Poesen, J. (Eds.), Soil Erosion in Europe. John Wiley & Sons Ltd., Chichester, United Kingdom, pp. 245–261.
- Wischmeier, W.H. and Smith, D.D., 1978. Predicting Rainfall-Erosion Loss: Agricultural Research Service Handbook No. 282, Washington, D.C., USDA
- Xin, Z., Yu, X., Li, Q., Lu, X.X., 2010. Spatiotemporal variation in rainfall erosivity on the Chinese Loess Plateau during the period 1956–2008. Reg. Environ. Change 11 (1), 149–159.
- Yang, D., Kanae, S., Oki, T., Koike, T., Musiake, K., 2003. Global potential soil erosion with reference to land use and climate change. *Hydrol. Proc.* 17, 2913–2928.

APPENDIX : 1

Photographs during data extraction and Laboratory experiment



Figure : During half hourly data extraction at the office of IMD Guwahati

APPENDIX : 2

The sample calculation of EI30 is shown below from a rainfall event occurring on 22 June, 2002.

Chart Reading		For each in				
	Cummulative	Intensity				
Time	Rainfall	Amount (mm)	(mm/hr)	I30	E	EI30i
18:30	1	1	2		0.10107	4.548148
19:00	1.25	0.25	0.5		0.021589	0.971497
19:30	2	0.75	1.5		0.072215	3.249692
20:00	2.5	0.5	1		0.045692	2.056124
20:30	4.5	2	4		0.238098	10.71441
21:00	27	22.5	45		6.029834	271.3425
21:30	44.5	17.5	35		4.44003	199.8014
22:00	48	3.5	7		0.500014	22.50063
22:30	62.5	14.5	29	45	3.494815	157.2667

 $EI30 = \sum EI30i = 672.45 \text{ MJ.mm/ha.h}$