The influence of I30 on erosivity-J

P.I.A. Kinnell[1]

[1]Affiliation not available

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An I_{30} focused approach to estimating event erosivity in Australia

P.I.A. Kinnell, University of Canberra, Australia.

Email: peter.kinnell@canberra.edu.au

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Abstract

Storm erosivity in the Universal Soil Loss Equation is given by the product storm kinetic energy and the maximum intensity measured using a 30-minute window. In some locations short term rainfall data are not available to determine these two parameters well. Here it is shown that the estimated energy per unit quantity of rain for the rain that falls during the time the maximum 30-min rainfall amount is measured can be used to predict event erosivity at many locations in Australia. There may be merit in using this approach elsewhere where a lack of short-term rainfall data prevent event erosivity from being predicted accurately.

Keywords: soil erosion; soil loss prediction; Universal Soil Loss Equation; storm erosion

1. Introduction

The Universal Soil Loss Equation (USLE (Wischmeier and Smith, 1965; Wischmeier and Smith, 1978)) is an empirical model (Alewell et al., 2019) that was originally designed to predict long term average annual soil losses (mass/area/time) from field sized areas. It was later revised (Revised Universal Soil Loss (RUSLE (Renard et al., 1997)) to take advantage of new knowledge gained after the USLE was developed in the 1960s and 1970s. Later RUSLE2 (USDA, 2008) was developed to enable USLE technology to apply to complex land management systems that are beyond the capacity of the USLE and the RUSLE.

USLE based models operate mathematically in two steps. In the first step, the average annual soil loss on the "unit" plot (A_1) is predicted by the product of the rainfall runoff factor (R) and the soil "erodibility" factor (K)

$$A_1 = R\,K \tag{1}$$

The unit plot is defined as a 22.1 m long bare fallow area on a 9 % slope with cultivation up and down the slope. In the second step, A_1 is multiplied by factors related to slope length (L), slope gradient (S), crops and crop management (C) and soil conservation practice (P) to predict the soil loss for an area which differs from the unit plot situation (A),

$$A = A_1\,L\,S\;\;C\,P \tag{2}$$

R is defined at the average annual sum of the product of storm kinetic energy (E_s) and the maximum 30-minute intensity observed during the rainstorm (I_{30}).

$$R = Y^{-1}\sum_{n=1}^{N_s}(E_s\,I_{30})_n \tag{3}$$

where N_s is the number of effective rainstorms in Y years. In the USLE, rain showers of less than 12.5 mm (0.5 in) were omitted in the calculation of R unless at least 6.25 mm (0.25 in) of rain fell in 15 min. A period of 6 hours with less than 1.27 mm (0.05 in) was used as a storm separator. This rule is applied in RUSLE2 but all events were considered in the RUSLE.

When R is determined using Eq. 3, I_{30} (mm h^{-1}) is usually a measured value and is given by twice the maximum amount of rain that falls in a 30-minute window. E_s (MJ ha^{-1}) is seldom determined directly but is calculated from the relationship between kinetic energy per unit quantity of rain (ε) and rainfall intensity (I). The equation adopted in RUSLE2 is

$$\varepsilon_k\; = 0.29\;(1 - 0.72\;\exp\;(-0.082\;I_k\;) \tag{4}$$

where ε has units of MJ mm^{-1} ha^{-1} and I has units of mm hr^{-1} and k is a period of time during the rain storm. Storm energy is then computed using

$$E_s = \sum_{k=1}^{N_t} \varepsilon_k \, V_k \tag{5}$$

where N_t is the total number of periods in the rainstorm and V_k is the amount (mm) of rainfall in the *kth* period. Other equations have been observed to exist in many geographic locations but Eq. 4 has been used outside the USA including Australia. Rainfall data collected over short time intervals ensure the accurate determinations of E_s (Tu et al., 2023; Zhu et al., 2019). Rainfall data collected over a 6 min time interval at many locations in Australia are considered suitable. Once E_s has been determined, EI_{30} for a rainfall event can be calculated by

$$EI_{30} = E_s \, I_{30} \tag{6}$$

The procedure for determining EI_{30} for a rainfall event using Eqs 3 to 6 requires high resolution rainfall data in order to predict EI_{30} and R values with high precision. In many locations in the world, appropriate data is not available to do this. In this technical note, an approach to estimating event erosivity in Australia focussing on I_{30} is considered as a means of estimating spatial variations in R in Australia when only data on storm rainfall amount and I_{30} exists.

2. Theory

It follows from Eq. 6 that a linear relationship exists between EI_{30} and I_{30} if E_s is constant at a location. However, E_s is known to vary in space and time. Even so, it has been observed (Lal, 1976; Mannaerts and Gabriels, 2000) that, at some locations, E_s varies directly with event rainfall amount (V_s , mm). When this occurs, EI_{30} can be predicted at a location by

$$EI_{30} = b_1 \, V_s \, I_{30} \tag{7}$$

where b_1 is an empirical coefficient that varies between locations because of geographic differences in the synoptic conditions that dominate the production of rain. Figure 1 shows how Eq. 7 can predict EI_{30} values at two widely spaced locations in Australia. The data presented in Figure 1 was obtained using historic 6-minute rainfall data collected by Australian Bureau of Meteorology. It is clear from the fact that b_1 for Darwin is 1.22 times the b_1 for Adelaide, that b_1 is influenced by climate. Adelaide has a Mediterranean Climate while Darwin is in the Tropics.

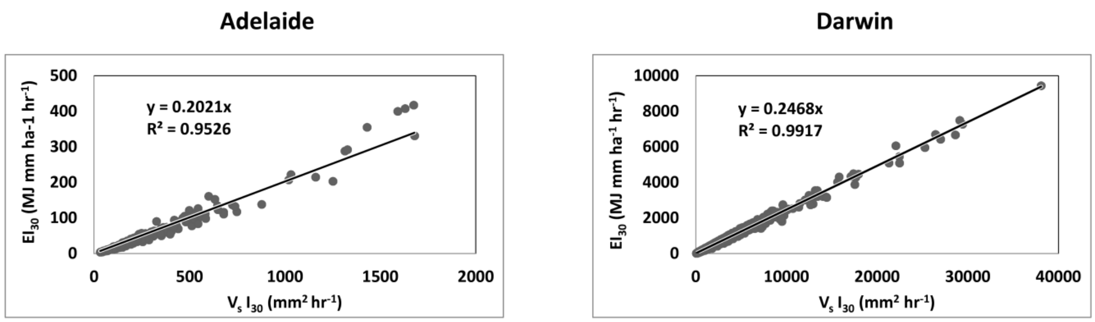

Figure 1: Relationships between *EI_{30}* and *$V_s I_{30}$* at Adelaide and Darwin obtained from 6-minute rainfall data collected by Australian Bureau Meteorology from 1967-2004 at Adelaide and 1953-1995 at Darwin.

Although b_1 can be considered to be a regression coefficient, using regression analysis to determine b_1 does not guarantee to predict the same average annual R value as observed at a location. b_1 can be calibrated to predict the same average annual R value as observed at a location by

$$b_1 = \frac{\sum_{n=1}^{N_{em}} (V_s\ I_{30s}\ \varepsilon_s)_n}{\sum_{n=1}^{N_{em}} (V_s\ I_{30s}\ )_n} \tag{8}$$

where N_{em} is the number of erosive storms where V_s > 12.6 mm. Figure 2 illustrates how b_1 determined using Eq.8 varied for 42 Australian locations where the Australian Bureau of Meteorology has collected 6-miute rainfall data for over 70 years up to 2010. The locations are listed by latitude so that the most northern location is first and the most southern location is last. As to be expected from the influence of high intensity rainfall, the highest values of b_1 occur in the tropics. The ratio for the highest b_1 to the lowest b_1 is 1.42.

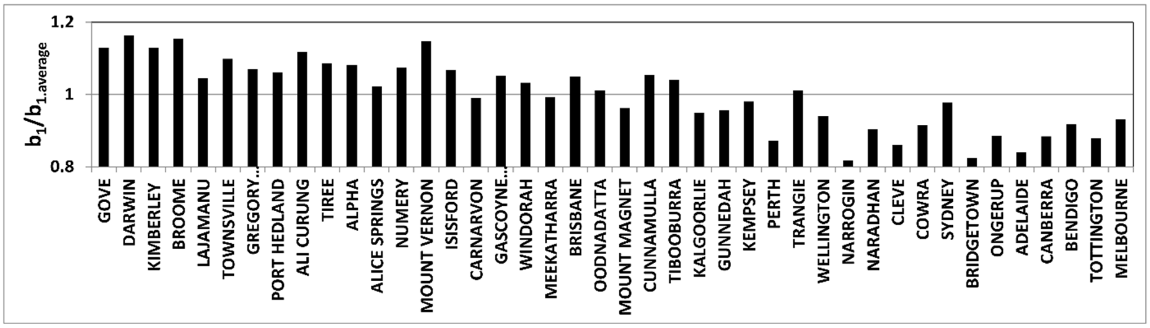

Figure 2. Values of the ratio of b_1 to its average at a number of locations in Australia where 6-min rainfall data is recorded by the Australian Bureau of Meteorology.

In addition to Eq. 6, EI_{30} can be calculated by

$$EI_{30} = V_s\, I_{30}\, \varepsilon_s \tag{9}$$

where ε_s is the kinetic energy per unit quantity of rain for the storm. ε_s is given by

$$\varepsilon_s = E_s\, V_s^{-1} \tag{10}$$

Consequently, variations in b_1 between geographic locations occur because Eq. 7 does not include direct consideration of the kinetic energy per unit quantity of the rain falling during the event.

Given that I_{30} is a measure of rainfall intensities sustained over a period of 30 minutes where a large proportion of the rainfall for an event tends to occur in some cases, arguably, ε_s may be well correlated with I_{30} in some way. Figure 3 shows that ε_s is non-linearly related to I_{30}. A power relationship is apparent for Adelaide but not for Darwin. In both cases, values of ε_k were determined using Eq. 4 and there is a tendency for many storms to have values of ε_s close to 0.29 MJ ha^{-1} mm^{-1} at Darwin because of the dominant influence of high intensity rainfall on ε_s at that location. Consequently, if only data on V_s and I_{30} are available, it is apparent that a simple empirical equation involving I_{30} cannot account for the effect of climate on b_1.

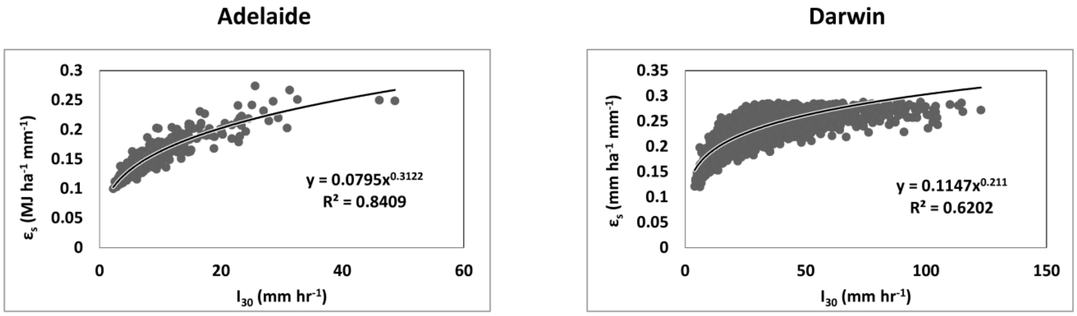

Figure 3. Relationships between storm rainfall energy per unit quantity of rain and I_{30} for rains producing more than 12.5 mm at Adelaide and Darwin

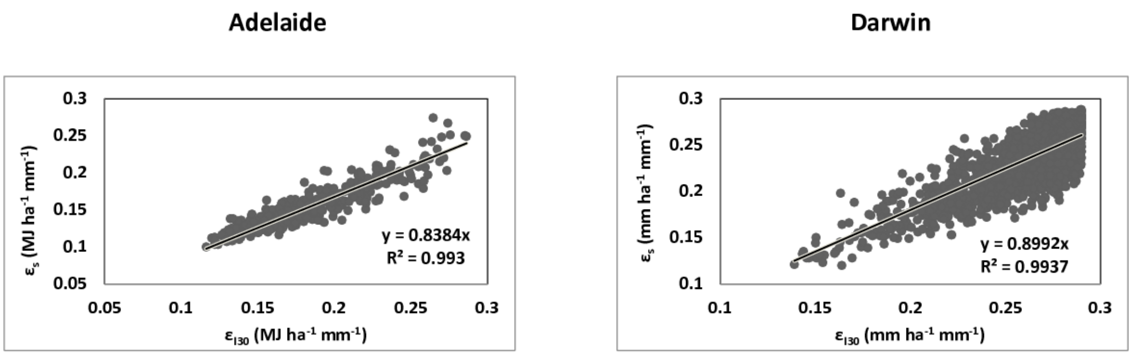

Figure 4. Relationships between storm rainfall energy per unit quantity of rain and rainfall energy per unit quantity of rain when I_{30} is recorded for rains producing more than 12.5 mm at Adelaide and Darwin.

The total amount of rainfall kinetic for a storm energy includes the amount of rainfall kinetic energy that occurs during the 30 minutes when the maximum amount of rain in 30 mins occurs. Consequently, it is possible that ε_s is directly related to the kinetic energy per unit quantity of the rain that falls during the period when I_{30} is measured (ε_{I30}) at some locations when ε_{I30} is calculated using the equation

$$\varepsilon_{I30} = 0.29\,(\,1 - 0.72\exp(-0.082\,I_{30}) \qquad (11)$$

Figure 4 show that this is the case at both Adelaide and Darwin. Regression analysis confirmed this finding at all the 42 locations considered here. It follows from this, that

$$EI_{30} = \beta\, V_s\, I_{30}\, [\, 0.29 - 0.72\, \exp(-0.082\, I_{30})\,] \qquad V_s => 12.6\, mm \qquad (12)$$

Regression analysis was undertaken to determine β values for all the 42 locations considered here

3 Results

Although β can be considered to be a regression coefficient, like b_1, using regression analysis to determine β does not guarantee to predict the same average annual R value as observed at a location. β can be calibrated to predict the same average annual R value as observed at a location by

$$\beta = \frac{\sum_{n=1}^{N_{em}} (V_s\, I_{30s}\, \varepsilon_s)_n}{\sum_{n=1}^{N_{em}} (V_s\, I_{30s}\, \varepsilon_{I30})_n} \qquad (13)$$

where N_{em} is the number of erosive storms where V_s > 12.6 mm. Fig. 5 illustrates how β determined using Eq.13 varied for the 42 Australian locations being considered. The spatial variation in β is much smaller than that for b_1. Consequently, β is much less influenced by the climate variations in Australia than b_1. The spatial variation is small enough for the average value of β to be used to estimate EI_{30} values at most of the locations considered. Consequently, using a single value of β in Eq. 12 may have a place in predicting spatial variations in R in Australia when only data on I_{30} and storm rainfall amount exists.

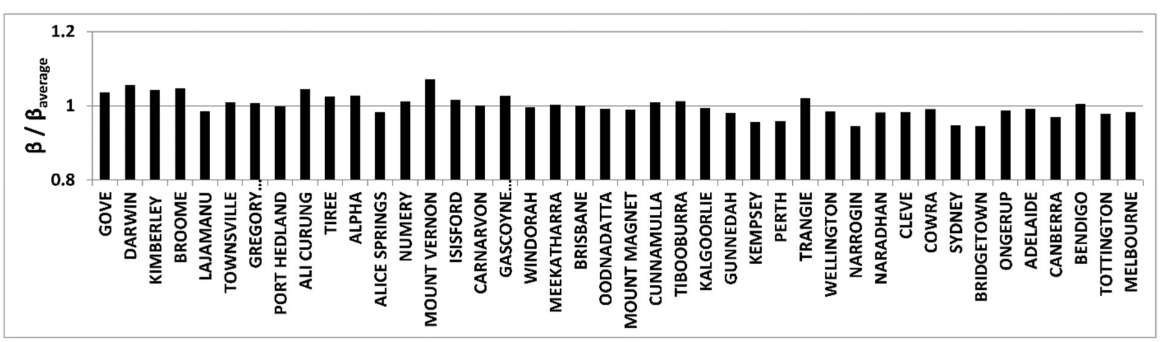

Figure 5. Values of the ratio of β to its average at a number of locations in Australia where 6-min rainfall data is recorded by the Australian Bureau of Meteorology

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4. Discussion

Spatial variations in R are important when USLE based technology is applied at a country or regional scale. It is common to use R values obtained at a number of different locations to map spatial variations in R at a country or regional scale using GIS techniques. One technique used involves a power relationship between daily EI_{30} (EI_{30d}) and daily rainfall (Yu and Rosewell, 1996),

$$EI_{30d} = \alpha\,[\,1 + \eta\cos(2\,\pi\,j - \varpi)\,]V_d^{b2} \tag{14}$$

where V_d is daily rainfall, α, $b2$, η and ω are model parameters. The primary parameters for a location are α and $b2$ and they are inversely related to each other. The term with the squared brackets deals with seasonal changes in erosivity on a monthly basis assuming it follows a sinusoidal form. j represents the month as a number from 1 (Jan) to 12 (Dec). ω is a number between 1 and 12 divided by 12 and is set to determine the month when EI_{30d} is most affected by a value of daily rainfall. α and $b2$ can be spatially mapped (Yang and Yu, 2015). It follows from Eq.12 and the data presented in Figure 5 that, if data on both V_s and I_{30} are available, reasonably good estimates of EI_{30} for erosive events can be obtained assuming that the average value of β (0. 833) observed for the locations examined is applied at all locations in Australia. Not only can R be predicted for a location using Eq 12 to obtain the storm EI_{30} values, Eq. 12 can also be used to predict seasonal variations in erosivity required for accounting for the interaction with cropping and crop management on the C factor in Eq. 2. Short term values of R in the RUSLE and RUSLE2 involve disaggregation of monthly R values. In this respect, Figure 6 shows monthly values of erosivity (R_m) for erosive events predicted using Eq. 12 with $\beta =$ 0. 833 in comparison with the observed values at 4 widely separated locations in Australia. These 4 locations have different climates. Perth in western Australia and Adelaide in southern Australia have a Mediterranean climate. Perth receives considerably more rain than Adelaide. Darwin in northern Australia has a tropical climate while Sydney in eastern Australia has a humid subtropical climate.

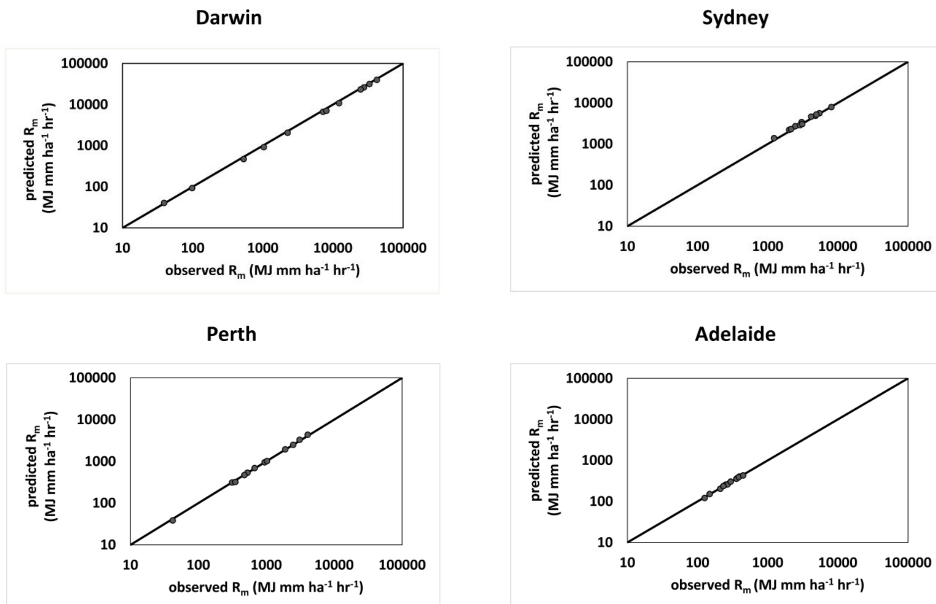

Figure 6. Relationships between monthly R values (R_m) and observed monthly R values obtained using Eq.12 with β = 0.833 at 4 widely spaced locations in Australia.

Obviously, where the temporal resolution of rainfall data at a sub 30-minute level exists, storm EI_{30} values can be determined with E_s values calculated using Eqs. 4 and 5. However, there are situations where data on rainfall amount and I_{30} are available without sub 30-minute data (Panagos et al., 2015) where determining EI_{30} values using Eq.12 may be practical. Also, rainfall data can be produced using climate generators. For example, Yu (2002) developed a method for predicting both I_{30} and storm energy for CLIGEN generated rainfalls. CLIGEN is able to reproduce daily rainfall and related storm patterns representing monthly statistics of historical records (Baffaut et al., 1996). The algorithms used by Yu over predicted R values in the USA by a relatively constant factor so that EI_{30} values predicted by those algorithms could, in general, be multiplied by 0.576 to predict R at locations in the USA. Arguably, Eq. 12 can be used as an alternative to the approach adopted by Yu. Assuming that β = 0. 833 can be used as a first approximation in the USA,

$$EI_{30} = b_3\, \beta\, V_{s.CG}\, I_{30.Yu}\, [\, 0.29\, (1.0.72 \exp(-0.082\, I_{30.Yu}\,)] \quad , V_{s.CG} > 12.6\, mm \qquad (15)$$

where $V_{s.CG}$ is event rainfall amount predicted by CLIGEN, $I_{30.Yu}$ is I_{30} for the event generated by Yu method, and b_3 is an empirical coefficient used to match R to the value of R allocated for RUSLE2. With values of b_3 varying from 0.601 to 0.788 (Table 1), applying Eq. 15 at 9 locations in the USA where Kinnell (2019) applied CLIGEN as a weather generator for RUSLE2 indicated that

I_{30} values predicted by the Yu method were too high. b_3 tends to increase slightly with the value of R allocated for RUSLE2 (Figure 7A) with Presque Isle appearing to be an exception to the rule. Figure 7B shows the relationship between EI_{30} values predicted using the algorithms for E_s and I_{30} presented by Yu (2002) and the values of EI_{30} predicted using Eq. 15 at Holly Springs where b_3 = 0.689 and EI_{30} values predicted by the Yu method when adjusted by a factor of 0.600 rather than 0.576 as suggested by Yu.

Table 1

location	state	county	R (MJ mm/(ha hr))	b_3
Bethany	MO	Brooke	3330	0.655
Castana	IA	Monona	2650	0.635
Geneva	NY	Ontario	1380	0.601
Guthrie	OK	Logan	3800	0.656
Holly Springs	MS	Marshall	6360	0.689
Madison	SD	Lake	1330	0.601
Presque Isle	ME	Aroostook	1230	0.738
Tifton	GA	Tilt	7110	0.788
Watkinsville	GA	Oconee	5050	0.684
Average				0.672

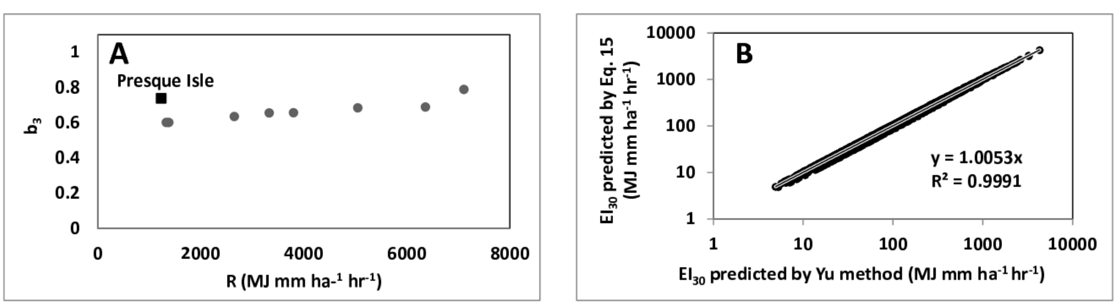

Figure 7: (A) The relationship between b_2 values obtained for the 9 locations in the USA and *R* factor values allocated by RUSLE2. (B) The relationship between EI_{30} values predicted at

Holly Springs by Eq.15 using b_3 = 0.689 and EI_{30} value predicted by the Yu method using an adjustment factor of 0.600 as opposed to 0.576 suggested by Yu.

The data presented here using Eq. 15 with CLIGEN is qualitative because β = 0.833 has not been verified for the USA. An analysis for the values of β in the USA is not possible using the rainfall data in the USLE database because the EI_{30} values given in the USLE database were calculated using

$$\varepsilon_k = 0.119 + 0.0873 \log10 \left(i_k\right) \qquad , i_k < 76\ mm/hr^{-1} \qquad (16a)$$

$$\varepsilon_k = 0.288 \qquad , i_k \geq 76\ mm\ hr^{-1} \qquad (16b)$$

not Eq.4. The original rainfall data used to determine EI_{30} values using Eq. 16 in the USLE database are not available.

Concerns have been raised about that validity of using I_{30} as an independent variable in determining erosivity in USLE based models for storms across a wide geographical and climatic range, where rainfall events may last from less than an hour to more than a day (Dunkerley, pers comm, Sept 2022). While the relative duration of the rain in the 30 minutes when I_{30} is determined may be small for large duration storms and large for short duration storms, the amount of rain kinetic energy when the maximum amount of rain in 30 minutes is recorded relative to amount rain kinetic energy for the storm is the factor being considered in the development of Eq.12. Eq.12 works well in Australia because there is a strong correlation between the amount of rain kinetic energy when the maximum amount of rain in 30 minutes is recorded relative to amount rain kinetic energy for the storm in rainstorms at locations in Australia. It is probably that a strong correlation between the amount of rain kinetic energy when the maximum amount of rain in 30 minutes is recorded relative to amount rain kinetic energy for the storm in rainstorms exists at locations in other parts of the world.

1. Conclusion

Generally, in order to predict EI_{30} values well, values of storm rainfall amount, I_{30} and the storm energy per unit quantity of rain need to be known (Eq.8). There can be situations where storm rainfall and I_{30} data are available but not data to determine storm kinetic energies. However, it has been shown here that when I_{30} is known, the storm energy per unit of rainfall that occurs when I_{30} is measured can be estimated using Eq.10. This enables variations in the storm energy per unit quantity of rain at a location to be estimated using the equation

$$EI_{30} = \beta V_s I_{30} [0.29 - 0.72 \exp(-0.082 I_{30})] \qquad V_s > 12.6mm \qquad (12)$$

where β is an empirical factor that is determined by

$$\beta = \frac{\sum_{n=1}^{N_{em}} (V_s I_{30s} \varepsilon_s)_n}{\sum_{n=1}^{N_{em}} (V_s I_{30s} \varepsilon_{I30})_n} \qquad (13)$$

Although β varies between locations, the spatial variation in Australia is not great so that the β = 0.833 enables monthly values of R to be predicted reasonably well in many places in Australia. Eq. 12 works well in Australia because there is a strong correlation between the amount of rain kinetic energy when the maximum amount of rain in 30 minutes is recorded and the amount of rain kinetic energy for the storm in rainstorms at locations in Australia. It is probably that a strong correlation between the amount of rain kinetic energy when the maximum amount of rain in 30 minutes is recorded and the amount of rain kinetic energy for the storm in rainstorms exists at locations in other parts of the world. There may be merit in using the approach elsewhere where there is a lack of short-term rainfall data to determine EI_{30} values more accurately. How useful Eq.12 might be in determining the effects temporal variations in climate at a given location is a matter for future study.

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