Interactive comments on “Rainfall erosivity estimation based on rainfall data collected over a range of temporal resolutions” by S. Yin et al.

Anonymous Referee #1

The manuscript addresses an important topic, i.e. what temporal resolution is required for making accurate estimates of rainfall erosivity. This topic is of global interest, given the often non-existent or difficult-to-acquire quality rainfall datasets at high temporal resolutions. As much as I applaud therefore this effort, I do have a number of concerns with the current version of the manuscript. These are:

1. The authors rightly take the EI30 measure as the reference given its wide-spread use. However, they fail to discuss properly the kinetic energy component of this indicator, and the issues of measuring/estimating it. The kinetic energy of rainfall can be measured (e.g. with disdrometers), but given the non-availability of such measurements for most stations, mostly it is estimated based on empirical equations. The authors simply present equation (2) but fail to give a rationale for it. Other studies exist that compare various existing empirical relationships (e.g. van Dijk et al, 2002, Journal of Hydrology 261, 1-23 and see also Salles et al. 2002, Journal of Hydrology 257, 256-270), and should at least be discussed here.

Response:

We agree with the comment and we added an extensive discussion of kinetic energy of rainfall in the Introduction of the revised version, including the references suggested, as follows:

“*Kinetic energy (KE) is generally suggested to indicate the ability of a raindrop to detach soil particles from a soil mass (e.g., Nearing and Bradford, 1985). Since the direct measurement of KE requires sophisticated and costly instruments, several different estimating methods have been developed that estimate KE based on rainfall intensity (I) using logarithmic, exponential, or power functions. The original 1978 release of the USLE utilized a logarithmic function (Wischmeier and Smith, 1978) that was based on rainfall energy data published by Laws and Parsons (1943). Brown and Foster (1987) re-evaluated this relationship and recommended the use of an exponential relationship, which was subsequently used in RUSLE (Renard et al., 1997).*

McGregor et al. (1995) compared the KE equations used in the USLE and RUSLE with the results from the equation and data of McGregor and Mutchler (1976), which was developed based on 29 standard recording rain gauges in the Goodwin Creek Watershed in northern Mississippi, USA. The results showed that the annual erosivities predicted by the equation of McGregor and Mutchler (1976) and the USLE were almost identical, whereas the RUSLE predicted values that were about 8% lower. McGregor et al. (1995) suggested that the equation of Brown and Foster (1987) be modified, changing the value of the exponential function to -0.082 rather than -0.05 that was used in RUSLE. Foster (2004) used the 0.082 value in RUSLE2, as follows:

$$e_r = 0.29[1 - 0.72\exp(-0.082 i_r)] \qquad (1)$$

where e_r is the estimated unit rainfall kinetic energy (MJ ha^{-1} mm^{-1}) and i_r is the rainfall intensity (mm h^{-1}) at any given time within a rainfall event (usually taken as one minute for computational purposes, with average intensity representative of the time increment).

Other work has been done to evaluate the relationships between rainfall intensity and KE. After reviewing more than 20 exponential KE vs. I relationships based on natural rainfall data observed in a variety of climate classifications, van Dijk et al. (2002) derived:

$$\mathrm{e_r} = 0.283[1 - 0.52\exp(-0.042 i_r)] \qquad (2)$$

Salles et al. (2002) suggested using a power law KE_{time} vs. I expression wherein the constants of the power law were different for convective rain and stratiform rain types. It is, however, often difficult to define if a storm should be classified as convective or stratiform based on the breakpoint data alone. Breakpoint data is fine resolution information on time during a rainfall event with associated cumulative rainfall depth. The term breakpoint refers to times when there are detectible changes in rainfall intensity as shown by a change in the slope of the cumulative rainfall curve. It originates from the time that rainfall records were read from recording pen charts.

Preliminary analysis (not shown) of our data from China indicated that the van Dijk equation resulted on average in similar R values to those from RUSLE2, slightly lower R values compared to USLE, and much greater R values than given by RUSLE. The Salles et al. (2002) equations produced on average much greater values of erosivity than did all of the other equations. In general, the RUSLE2 value produced results in the mid-range of all of these equations."

2. It is not always very clear which erosivity values are taken as input for estimating the modelling error. E.g. if the authors refer to monthly, is this always "average monthly"? If so, why, and would it not be more useful to look at erosivity values for individual months? This would relate better to the ongoing discussion on ways forward for erosion monitoring (e.g. Vrieling et al, 2014 Global and Planetary Change 115, 33-43).

Response:

It was confusing. Instead of "monthly" and "yearly" when referring to individual months and years, we should have used "month" and "year", which we did in the revision. We revised, for example, to read: "*These were treated as observed values and summed to obtain the erosivity factors, R, for daily, month (individual month totals), year (individual year totals), average monthly, and average annual time scales."* Note that the mathematical definitions are presented in (for example for months) in (the original) equations 6 and 7 (equation numbers changed in the revision.)

$$\mathrm{R}_{\mathrm{month,y,m}} = \sum_{\mathrm{j=0}}^{\mathrm{J}} (\mathrm{EI}_{30})_{\mathrm{y,m,j}} \qquad (6)$$

$$\mathrm{R}_{\mathrm{ave\_month,m}} = \frac{1}{\mathrm{Y}} \sum_{\mathrm{y=1}}^{\mathrm{Y}} \mathrm{R}_{\mathrm{month,y,m}} \qquad (7)$$

where $(EI_{30})_{y,m,j}$ is the EI_{30} value for the jth event in the mth month of the yth year; $R_{month,y,m}$ is the R value for the mth month of the yth year; $R_{ave\_month,m}$ is the average R value for the mth month over the years of record.

We will clarify the definitions in the revision and add more discussion on Vrieling et al, 2014 Global and Planetary Change 115, 33-43.

3. In relation to the last point, I would encourage the authors to contribute to this discussion and (based on their results) give more concrete recommendations for ways forward. Currently the authors refer in a very general way to “users” in their conclusions. In my view, end-users are never those that want just to make an estimate of erosivity, but rather they need erosion estimates and possibly a monitoring framework, e.g. for planning purposes and impact evaluations. Adding a clearer opinion on how to move forward with erosivity analysis, including its embedding in mapping/monitoring frameworks, would be a welcome addition to this manuscript.

Response:

Absolutely correct! We have added a new section 3.5 Recommendations and applications:

“*The results of this study provide a multitude of options for dealing with the problem of variations in available temporal resolutions of rainfall data from across the world for developing erosivity maps and databases. We present a series of 21 potential equations for use in estimating erosivity at time scales from event to average annual using input data resolution ranging from maximum ten minute rainfall intensity to average annual rainfall amount. Of the 21 equations we can recommend the use of 17. Equations Month I, Year I, and Average Monthly I, which use only total rainfall amounts for the respective time scales, all had low ME values and poor prediction capability (Table 4). Annual III, which is a linear function of average annual rainfall and the maximum daily precipitation over the recording period, performed very poorly, with a negative ME value (Table 4).*

We found that using finer resolution data input produced better predictions of erosivity at a given output time scale. An exception was for the event-based models, where using I30 gave slightly better results than using I60 or I10. However, we also found that that using equations with the finest data resolution possible, and aggregating or summing results for finer erosivity time scales, gave the best results (Table 6). In other words, If one were interested in average annual erosivity, but had daily rainfall data available for using the Daily I model, then results are better using the Daily I model and summing results over the period of data record rather than using Average Monthly I-IV or Annual I-V models. It is also evident that predictions of erosivity using Daily I improve as the time scale increases. In other words, the predictions of average annual erosivity calculated by summing the daily values from Daily I give a higher level of fit than when using Daily I to estimate daily erosivity (Table 6).

Models in this study performed better or similar to models from previous research based on these independent validation data.”

4. While the research seems well-embedded in existing erosivity estimation efforts in China, in my view the authors could make a better link with other ongoing efforts in other areas that look at different temporal resolutions of rainfall data. I am thinking for example about Panagos et al (2015, Science of Total Environment 511, 801-814) who normalize R-factor estimates for Europe based on recording intervals. Although the authors focus on rainfall station data, another line of research (i.e. application of satellite rainfall estimates) should be acknowledged, i.e. work by Vrieling et al (2010 in Journal of Hydrology, and 2014 cited above), but also for China (Fan et al, 2013, Journal of Mountain Science 10(6): 1008-1017). This is especially relevant for end-users that require spatially-consistent information on soil erosion. In fact, a performance evaluation for the stations in the manuscript of erosivity estimated from satellite rainfall products could be a nice follow-up study for the authors (but probably not for this paper).

Response: We expanded and improved the Introduction to include discussion relative to:
Fan et al, 2013, Journal of Mountain Science 10(6): 1008-1017
Vrieling et al 2010 in Journal of Hydrology
Vrieling et al, 2014 Global and Planetary Change 115, 33-43
Panagos et al, 2015, Science of Total Environment 511, 801-814
Sadeghi, S. H. R., M. Moatamednia, and M. Behzadfar. 2011. Spatial and Temporal Variations in the Rainfall Erosivity Factor in Iran. J. Agr. Sci. Tech. (2011) Vol. 13: 451-464.
Sadeghi, S.H.R., and S. Tavangar. 2015. Development of stational models for estimation of rainfall erosivity factor in different timescales. Nat Hazards 77:429–443 DOI 10.1007/s11069-015-1608-y.
Oliveira, P.T.S., E. Wendland, and M.A. Nearing. 2012. Rainfall erosivity in Brazil: A review, Catena 100:139–147. http://dx.doi.org/10.1016/j.catena.2012.08.

5. Perhaps I misunderstood something in the paper, but it seems to me that the models are only evaluated for the temporal scale to which they are applied. In Tables 3 and 4, the event-based models are only evaluated on the basis of events modelled. While there is nothing wrong with that, I would also expect the models to be evaluated at the aggregate scale. I mean that EI30 estimated from event-based models should also be added up to monthly and yearly values, to evaluate if fine-scale temporal resolution data improves also the accuracy of aggregate erosivity measures.

Response: This is an extremely important comment!! It points out something that we forgot to address in our study. See the new Table 6. In fact the reviewer is entirely correct. Two important facts emerge: 1. When the models are applied at the aggregated scale their predictions get better. And 2. The models that use finer resolution of input data predict better for the same erosivity time scale compared to models using coarser resolution input data. Thank you!
Other comments:

- P4967L11: delete first "as"

Done

- P4967L19 and L28: it is unclear what authors mean with "breakpoint data"
"breakpoint data" defined and discussed in the revision as: "*Breakpoint data is fine resolution information on time during a rainfall event with associated cumulative rainfall depth. The term breakpoint refers to times when there are detectible changes in rainfall intensity as shown by a change in the slope of the cumulative rainfall curve. It originates from the time that rainfall records were read from recording pen charts*."

- P4967L22: change "to develop" into "by developing"
done

- P4968L14: "course" should read "coarse"
done

- P4968L23-24: strange sentence. This can be deleted as it is obvious that these intensities are "easy to calculate".
done

- P4970L10-11: “the eastern water erosion region of China”: it is unclear what is meant with this. changed to “*eastern half*”

- P4976L9-11: see also general point (2) above. The authors could also use all annual values for the stations (i.e. for all years) rather than just the average annual erosivity. see response to #2 above

- P4982L7: “Predication” should read “prediction”. However, the sentence is also un-clear. Rather state "Erosivity could not be predicted accurately in southwest China using rainfall amount as input." Even if rephrased in this way: what rainfall amount? Hourly? Daily, monthly, yearly? corrected and clarified

Anonymous Referee #2

“I fully agree with the first Reviewer. The results of such an interesting topic should be explored and compared with the recent scientific advancements in Erurope (Panagos et al., 2015) and in Africa (Vrieling et al., 2015).”

Response: Agreed: We added this to the manuscript Introduction. Dsicussions of Recommendations and applications. Includes discussions relative to:

Fan et al, 2013, Journal of Mountain Science 10(6): 1008-1017

Vrieling et al 2010 in Journal of Hydrology

Vrieling et al, 2014 Global and Planetary Change 115, 33-43

Panagos et al (2015, Science of Total Environment 511, 801-814)

Sadeghi, S. H. R., M. Moatamednia, and M. Behzadfar. 2011. Spatial and Temporal Variations in the Rainfall Erosivity Factor in Iran. J. Agr. Sci. Tech. (2011) Vol. 13: 451-464.

Sadeghi, S.H.R., and S. Tavangar. 2015. Development of stational models for estimation of rainfall erosivity factor in different timescales. Nat Hazards 77:429–443 DOI 10.1007/s11069-015-1608-y.

Oliveira, P.T.S., E. Wendland, and M.A. Nearing. 2012. Rainfall erosivity in Brazil: A review, Catena 100:139–147. http://dx.doi.org/10.1016/j.catena.2012.08.

Anonymous Referee #3

#1 The manuscript was reviewed. It was a very tough work to work on such huge quantity of data. It has tried to calibrate different models to estimate erosivity index with the help of rainfall data with different time scales for 18 stations mainly distributed in eastern China. However, it has no particular novelty. Considering all comments and suggestions annotated in the manuscript, it is subjected to major revision for acceptance.

Response: We think that this work is important and new. We note in the Introduction: “*Although several studies have been conducted on this topic in the past, no study used as comprehensive a data set collected over this wide geographic area of China to evaluate the wide range of erosivity time scales needed for erosion work, and utilizing such a wide range of temporal resolution rainfall data as the independent variable.*”

#2 In fact the research has no particular novelty but it contains a quite bit of energy and time which makes it investigatable.

Response: see immediately above

#3 Some quantitive results are missed from the abstract.

Response: Yes, it is difficult to summarize because there are just so many numbers. We tried to be a bit more quantitative as we could in the Abstract revision.

#4 Not adequately documented in reputed journals.

Response: Yes, unfortunately true. We de-emphasized the model in the revision. But nonetheless the model is very important in China. The model has been widely used in the application of soil conservation planning in China. There are some related publications in Chinese. It is a pity that the model has not been published in a reputable English Journal. Realizing it is not good for international communication, recently, Liu et al. are preparing an English manuscript about CSLE.

#5 This is not widely used model!!

Response: See #4 response

#6 I advise respected author to consult and clearly cite the following papers in different parts of the manuscript:
1)Sadeghi, S.H.R. and Hazbavi, Z., 2015. Trend analysis of the rainfall erosivity index at different time scales in Iran, Natural Hazards, 77: 383-404.
2)Sadeghi, S.H.R. and Tavangar, Sh., 2015. Development of stational models for estimation of rainfall erosivity factor in different timescales, Natural Hazards, 77:429-443.

Response: Agreed: We added discussions relative to:
Fan et al, 2013, Journal of Mountain Science 10(6): 1008-1017
Vrieling et al 2010 in Journal of Hydrology
Vrieling et al, 2014 Global and Planetary Change 115, 33-43
Panagos et al (2015, Science of Total Environment 511, 801-814)
Sadeghi, S. H. R., M. Moatamednia, and M. Behzadfar. 2011. Spatial and Temporal Variations in the Rainfall Erosivity Factor in Iran. J. Agr. Sci. Tech. (2011) Vol. 13: 451-464.
Sadeghi, S.H.R., and S. Tavangar. 2015. Development of stational models for estimation of rainfall erosivity factor in different timescales. Nat Hazards 77:429–443 DOI 10.1007/s11069-015-1608-y.
Oliveira, P.T.S., E. Wendland, and M.A. Nearing. 2012. Rainfall erosivity in Brazil: A review, Catena 100:139–147. http://dx.doi.org/10.1016/j.catena.2012.08.

#7 This is better to address international literatures instead of focusing Chinese ones mainly.

Response: Agreed. We will add discussions regarding the above papers, and we also discuss the work of Renard and Freidmund (USA), Bofu Yu (Australia), and some of the other climate change and erosion work.

#8 The necessity of applying different time scales has to be well explained, since neither such high resolution data are not available to be easily used for calculation of erosivity index nor these data are being used for erosion models universally used for soil erosion estimation.

Response: Yes. Both the Introduction and the Applications sections have added clarification regarding the need for different time scales of erosivity.

#9 It was mentioned 11 earlier!!!

Response: Yes, 11 calibration stations, 7 validation stations, 18 total stations.

#10 This is often called "common years"!!

Response: changed

#11 How accurate this criterion is??

Response: Although there were missing data in the information used, Data M were internally consistent in all comparisons reported. Therefore, it was believed 15% is acceptable.

#12 So, how did you incorporate the precipitation of this period???

Response: The data simply is not available for the months indicated in the northern areas. These are not considered to be erosive months in those locations.

#13 How it worked for China??

Response: We suppose here the reviewer means if the KE equation by Foster (2004) is suitable for China. If I understood right, I think the query is the same with the first comment raised by Reviewer 1. See response above.

#14 It has to be logically the average value of annual EI30. Rewrite it please. Though mathematically there may not be any difference between results.

Response: You are correct that there is no difference. We changed it to read per your suggestion.

#15 Hard to follow!!!

Response: Agreed. We rewrote and clarified the entire section. There is a lot of information here, and many, many variables. We tried to be meticulous in the revision to be sure that each variable is clearly explained. Nonetheless, it will take a careful read to get all the nuance, but we think that now it is all there.

#16 Why these models were selected??

Response: Basically we were trying to examine the Chinese models with the Chinese data, since those models were also based on smaller sets of Chinese data.

#17 Use similar acronyms throughout the manuscript.

Response: Agreed and corrected.

#18 Such subtitles are not common!! This is usually discussed in discussion.

Response: True. Subtitles are modified in the revision.

#19 They need to be finished. It means the equations have to be written in nice manner to be read and recognized easily.

Response: Yes, there are many equations in these tables. We are assuming that we will work with the journal for ensuring that the equations are properly displayed in the tables, as is normal.

#20 It does not look nice!! It has to be written capital as well.

Response: Changed.

#21 What about this area??? The entire stations are distributed in high receiving precipitation areas!!

Response: All the stations are located in the water erosion area in China. The northwestern part of China is mainly influenced by wind erosion.

#22 Bar charts are logically more acceptable for discrete data presentation.

Response: changed.

Rainfall erosivity estimation based on rainfall data collected over a range of temporal resolutions

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Abstract

Rainfall erosivity is the power of rainfall to cause soil erosion by water. The rainfall erosivity index for a rainfall event, EI_{30}, is calculated from the total kinetic energy and maximum 30 minute intensity of individual events. However, these data are often unavailable in many areas of the world. The purpose of this study was to develop models ~~that relate~~based on ~~more~~ commonly available rainfall data resolutions, such as daily or monthly totals, to rainfall erosivity. Eleven stations with one-minute temporal resolution rainfall data collected from 1961 through 2000 in the ~~eastern water-erosion areas~~eastern half of China were used to develop and calibrate 21 models. Seven independent stations, also with one-minute data, were utilized to validate those models, together with 20 previously published equations. ~~Results showed that~~ The models in this study performed better or similar to models from previous research to estimate rainfall erosivity for these data. ~~Prediction capabilities, as determined u~~Using symmetric mean absolute percentage errors and Nash-Sutcliffe model efficiency coefficients, ~~were demonstrated for the 41 models including those for estimating erosivity at event, daily, monthly, yearly, average monthly and average annual time scales~~we can recommend 17 of the new models that had with model efficiencies ≥0.59. Prediction capabilities were generally ~~generally~~ better using higher resolution rainfall data as inputs at a given erosivity time scale~~.~~. Also, using equations with the finest

data resolution possible, and aggregating or summing results for finer erosivity time scales, gave the best results. ~~For example, models with rainfall amount and maximum 60-min rainfall amount as inputs performed better than models with rainfall amount and maximum daily rainfall amount, which performed better than those with only rainfall amount. Recommendations are made for choosing the appropriate estimation equation, which depend on objectives and data availability.~~

1. Introduction

~~Soil erosion leads to land degradation and water pollution and also delivers sediment to streams and rivers, which increases the risks for flooding. Great efforts have been made in many parts of the world to reduce soil erosion by implementing biological, engineering, and tillage conservation practices.~~ Soil erosion prediction models are effective tools for helping to guide and inform soil conservation planning and practice. The most widely used soil erosion models used for conservation planning are derived from the Universal Soil Loss Equation (USLE) (Wischmeier and Smith, 1965, 1978). ~~These~~ These models include the USLE, the Revised USLE (RUSLE) (Renard et al., 1997), and RUSLE2 (Foster, 2004) ~~and the Chinese Soil Loss Equation (CSLE) (Liu et al., 2007)~~. ~~RUSLE is the official tool used by government conservation planners in the United States.~~ Adaptations of the USLE have also been developed for use in other parts of the world, including, for example, Germany (Schwertmann et al., 1990), Russia (Larionov, 1993), and China (Liu et al., 2002). ~~The~~ For example, the Chinese Soil Loss Equation (CSLE) was successfully utilized in the first national water erosion sample survey in China (Liu et al., 2013)~~.~~.

These models have in common ~~the~~ a rainfall erosivity factor (R), which reflects the potential capability of rainfall to cause soil loss from hillslopes, and which is one of the most important basic factors for ~~the above mentioned models~~estimating soil erosion. In its simplest form, the R factor is as an average annual value, calculated as a summation of event-based energy-intensity values, EI_{30}, for a location divided by the number of years over which the data was collected. EI_{30} is defined as the product of kinetic energy of rainfall and the maximum contiguous 30-min rainfall intensity during the rainfall event. It is the basic rainfall erosivity index that was developed by Wischmeier (1958) originally for the USLE, and is still widely used in other erosion prediction models (e.g., RUSLE, RUSLE2 ~~and CSLE~~), with some modifications and improvements. Wischmeier (1976) suggested that more than 20 years' rainfall data are needed to calculate average annual erosivity to include dry and wet periods.

Determination of the maximum contiguous 30-min rainfall intensity during the rainfall event is a relatively straightforward process, although it requires a temporally detailed rainfall record for a storm. Determination of the kinetic energy of a storm is more complex.

Kinetic energy (KE) is generally suggested to indicate the ability of a raindrop to detach soil particles from a soil mass (e.g., Nearing and Bradford, 1985). Since the direct measurement of KE requires sophisticated and costly instruments, several different estimating methods have been developed that estimate KE based on rainfall intensity (I) using logarithmic, exponential, or power functions. The original 1978 release of the USLE utilized a logarithmic function (Wischmeier and Smith, 1978) that was based on rainfall energy data published by Laws and Parsons (1943). Brown and Foster (1987) re-evaluated this relationship and recommended the use of an exponential relationship, which was subsequently used in RUSLE (Renard et al., 1997).

McGregor et al. (1995) compared the KE equations used in the USLE and RUSLE with the results from the equation and data of McGregor and Mutchler (1976), which was developed based on 29 standard recording rain gauges in the Goodwin Creek Watershed in northern Mississippi, USA. The results showed that the annual erosivities predicted by the equation of McGregor and Mutchler (1976) and the USLE were almost identical, whereas the RUSLE predicted values that were about 8% lower. McGregor et al. (1995) suggested that the equation of Brown and Foster (1987) be modified, changing the value of the exponential function to -0.082 rather than -0.05 that was used in RUSLE. Foster (2004) used the -0.082 value in RUSLE2, as follows:

$$e_r = 0.29[1 - 0.72\exp(-0.082 i_r)] \qquad (1)$$

where e_r is the estimated unit rainfall kinetic energy (MJ ha^{-1} mm^{-1}) and i_r is the rainfall intensity (mm h^{-1}) at any given time within a rainfall event (usually taken as one minute for computational purposes, with average intensity representative of the time increment).

Other work has been done to evaluate the relationships between rainfall intensity and KE. After reviewing more than 20 exponential KE vs. I relationships based on natural rainfall data observed in a variety of climate classifications, van Dijk et al. (2002) derived:

$$e_r = 0.283[1 - 0.52\exp(-0.042 i_r)] \qquad (2)$$

Salles et al. (2002) suggested using a power law KE_{time} vs. I expression wherein the constants of the power law were different for convective rain and stratiform rain types. It is, however, often difficult to define if a storm should be classified as convective or stratiform based on the breakpoint data alone. (Breakpoint data is fine resolution information on time during a rainfall event with associated cumulative rainfall depth. The term breakpoint refers to times when there are detectible changes in rainfall intensity as shown by a change in the slope of the cumulative rainfall curve. It originates from the time that rainfall records were read from recording pen charts.)

Preliminary analysis (not shown) of our data from China indicated that the van Dijk equation resulted on average in similar R values to those from RUSLE2, slightly lower R values compared to USLE, and much greater R values than given by RUSLE. The Salles et al. (2002) equations produced on average much greater values of erosivity than did all of the other equations. In general, the RUSLE2 value produced results in the mid-range of all of these equations.

The temporal resolution of rainfall data across the world varies greatly (Sadeghi et al., 2011; Sadeghi and Tavangar, 2015; Oliveira et al., 2012; Panagos et al., 2015), even within countries with extensive rainfall monitoring programs. In the United States, for example, intra-storm, temporally detailed data (historically taken on pen recording charts, now taken as one-minute digital data) are only available at limited stations, whereas daily data are common (Nicks and Lane, 1995; Flanagan et al., 2001). There is a need for developing models for application in all areas of the world in order to produce erosivity maps that can be used for evaluating soil erosion rates (e.g., Sadeghi et al., 2011, Sadeghi and Tavangar, 2015; Oliveira et al., 2012; Panagos et al., 2015).

In Europe, Panagos et al. (2015) undertook the task to develop an erosivity map for Europe based on data from 1541 precipitation stations with temporal resolutions of 5 to 60 min. To use data that had been reported at the different time resolutions they had to apply adjustment factors to the data, which they reported to have introduced some uncertainty into the estimations. Sadeghi and Tavangar (2015) evaluated various erosivity estimation indices, including Fournier (Fournier, 1960), modified Fournier (Arnoldus, 1977), Roose (1977) and Lo (Lo et al., 1985), using data from 14 stations in Iran. They evaluated annual, seasonal and monthly information. Similarly, the work in Brazil summarized by Oliveira et al. (2012) highlighted several studies that used various estimations of erosivity based on various types of data and interpolations.

Other innovative ways have been advanced to produce better mappings of erosivity, including the use of daily (Fan et al., 2013) or 3 hour (Vrieling et al., 2010 and 2014) data from the TRMM Multi-satellite Precipitation Analysis (TRMM).

~~The calculation of EI_{30} requires high-temporal resolution rainfall data, typically breakpoint data, which are often unavailable in many regions of the world where rainfall is recorded only at a daily resolution. E~~Other efforts to address this problem have been made by developing~~to develop~~ simpler methods to estimate rainfall erosivity by using daily (Richardson et al., 1983; Yu, 1998; Capolongo et al., 2008), monthly (Arnoldus, 1977; Renard and Freimund, 1994; Yu and Rosewell, 1996; Ferro et al., 1999), or annual rainfall data (Lo et al., 1985; Renard and Freimund, 1994; Yu and Rosewell, 1996; Bonilla and Vidal, 2011). ~~In general, more rainfall data with longer periods of record are available at these time scales than at sub-event temporal resolution.~~ Generally the technique has been to develop a simple empirical relationship using limited breakpoint data and then to extend the ~~analysis~~ analyses to wider areas and longer periods with coarser temporal resolution rainfall data ~~(~~(Angulo-Martinez and Begueria, 2012; Ma et al., 2014; Ramos and Duran, 2014; Sanchez-Moreno et al., 2014).

~~Potential future rainfall erosivity due to climate change has also been studied (Zhang et al., 2010; Shiono et al., 2013; Plangoen and Babel, 2014; Segura et al., 2014). Climate~~

~~change models (Global Circulation Models) do not predict the rainfall for daily, hourly, or sub-hourly time-scales that would be necessary to directly calculate erosivity. Some studies (Nearing, 2001; Zhang et al., 2010; Shiono et al., 2013; Plangoen and Babel, 2014; Segura et al., 2014), therefore, developed simpler methods based on lower temporal resolution rainfall data and then utilized climate model rainfall data as input to these models to conduct studies concerning climate change on rainfall erosivity and soil erosion. There are also studies reporting trends for rainfall erosivity based on longer series of observed breakpoint data in Europe (Verstraeten et al., 2006; Fiener et al., 2013) and the United States (Angel et al., 2005).~~

Several simpler models for estimating rainfall erosivity from ~~course~~ coarse resolution data have also been developed in China in specific areas, including the Loess Plateau (Wang, 1987; Sun, 1990), Fujian Province (Huang et al., 1992; Zhou et al., 1995) and Anhui Province (Wu, 1994). Wang et al. (1995) ~~first~~ developed a series of simplified equations at several time scales by utilizing ~~several~~ stations located in different areas of China. In China~~, specifically,~~ the specifications for surface meteorological observations by the China Meteorological Administration (China ~~M~~Meteorological Administration~~A~~, 2003) have required since the 1950s that the maximum 60 and 10 minute rainfall amounts, $(P_{60})_{day}$ and $(P_{10})_{day}$ be compiled, hence these data are readily available in China. The measurements were made using siphon-method, self-recording rain gauges. ~~Maximum~~ Because of this, there is an interest in China to utilize the maximum daily 10 and 60 minute rainfall intensities, $(I_{10})_{day}$ and $(I_{60})_{day}$~~-~~, to calculate erosivity~~are easy to calculate from the $(P_{60})_{day}$ and $(P_{10})_{day}$, also~~.

There have been several other research efforts to estimate erosivity based on Chinese data, many of which are published only in Chinese. These include ~~Other researchers then used data from more stations with longer series of rainfall records to develop erosivity estimation models with event rainfall and the maximum, contiguous 10-min intensity, I_{10}, in~~ an ~~event~~ daily or sub-daily models (Yin et al., 2007; Zhang et al., 2002a~~), daily rainfall and $(I_{10})_{day}$ (~~; Xie et al., 2001~~), daily rainfall (~~; Zhang et al., 2002b) and ~~,~~ monthly or annual ~~rainfall~~ models (Zhang and Fu, 2003)~~ and hourly rainfall (Yin et al., 2007)~~. Zhang and Fu (2003) compared five models for estimating annual average rainfall erosivity, including one model using daily rainfall (Zhang et al., 2002b) and four models using monthly or annual rainfall (Zhang and Fu, 2003). They demonstrated that the model using daily rainfall performed best and that there were no significant differences among the other four models. Xie et al. (2015) found that the daily erosivity model with information on $(I_{60})_{day}$ improved the daily EI_{30} index estimation significantly when compared with that using only daily rainfall totals. ~~The multiplication of daily rainfall and maximum $(I_{10})_{day}$ is used often in place of EI_{30}, due to the difficulty in obtaining the breakpoint data (Zhang et al., 2002b, Zhang and Fu, 2003), but availability of the maximum 10-min intensity data.~~

Renard and Freimund (1994) developed two power law models for the continental United States using average annual rainfall and a Modified Fournier Index reflecting seasonal variation in precipitation. Using data from 29 sites in southeastern Australia, Yu and Rosewell (1996) calibrated the two models developed by Renard and Freimund (1994) and recommended the model using average annual rainfall as input for the estimation of average annual erosivity because of similar model efficiency as compared with the model using the Modified Fournier Index and the ready availability of annual rainfall data.

~~Other temporal resolutions of erosivity are often required for soil erosion work in addition to average annual erosivity. For example, in the USLE (Wischmeier and Smith, 1965, 1978) and RUSLE (Renard et al., 1997), both average annual erosivity and its seasonal distribution, represented as half-monthly averages, are used. Event or daily erosivity can also be important in soil loss recurrence analyses and non-point source pollution assessment (Kinnell, 2000; Sun et al., 2009).~~

The objectives of this study were three-fold: (1) calibrate methods of estimating erosivity for time scales ranging from daily to average annual based on different temporal resolutions of rainfall data from 11 calibration stations with one-minute resolution data; (2) compare models in this study with those published in previous research, based on seven independent validation stations using the same data types; and (3) determine the most accurate methods, based on these data, for calculating different time scales of erosivity when different temporal resolutions of rainfall data are available. Note that, in this paper, we use the term "time scales" when discussing the erosivity values (equation outputs) and "resolution" (equation inputs) when referring to the rainfall input data, for clarity. Although several studies have been conducted on this topic in the past, no study used as comprehensive a data set collected over this wide geographic area of China to evaluate the wide range of erosivity time scales needed for erosion work, and utilizing such a wide range of temporal resolution rainfall data as the independent variable.

2. Data and Methods

2.1 Data

Data collected at 18 stations by the Meteorological Bureaus of Heilongjiang, Shanxi, Shaanxi, Sichuan, Hubei, Fujian, and Yunnan provinces and the municipality of Beijing were used (Fig.1, Table 1). These stations were distributed over the eastern ~~water erosion region~~half of China. One-minute resolution rainfall data (Data M) were obtained by using a siphon, self-recording rain gauge ~~to collect self-recording rain gauge observations~~. The data collection period began in 1971 for Wuzhai (53663) and Yangcheng (53975) in Shanxi Province and from 1961 for the remaining 16 stations. The data records ended in 2000 for all stations. Quality control of Data M was done to select the best observation years using the more complete data sets of daily rainfall totals, Data D, which were observed by simple rain gauges at the same stations. Data M was compared with Data D on a day-by-day basis, and those days with deviation exceeding a certain criterion were marked as questionable and were not used in this analysis (Wang et al., 2004). The criterion used was that the data were considered good when the absolute deviation between Data M and Data D was less than 0.5 mm when the daily rainfall amount was less than 5 mm and no more than 10% when the daily rainfall amount was greater than or equal to 5 mm. Data M in the earlier years of record tended to have more days with missing or suspicious observations. These totals of Data M and Data D were compared year-by-year to determine which years could be designated as "common" years for use in this study, with an effective year having a relative deviation for yearly rainfall amount of no more than 15%. There were at least 29 common years for all 18 stations, and seven stations had common years of at least 38 years (Table 1). Note that though there were missing data in the information used, Data D was only used for quality control purposes and the data used in the analysis, Data M, were internally consistent in that only the data from common years were used in all comparisons and evaluations reported.

Data M were used to calculate the ~~actual~~ event-based EI_{30} values as a function of the calculated kinetic energy and maximum 30 minute rainfall intensity (Foster, 2004). These were treated as observed values and summed to obtain the erosivity factors, R, for daily, month~~ly~~ (individual month totals), year~~ly~~ (individual year totals), average monthly (one value for each month at each station), and average annual (one value for each station) time scales. Total rainfall event depth values were also compiled into the other temporal resolutions of rainfall data, including correspondent daily, month~~ly~~, year~~ly~~, average monthly, and average annual resolutions. For the eight stations in the northern part of China (including stations in Heilongjiang, Shanxi, Shaanxi provinces and Beijing municipality), only the periods from May through September were used because the siphon, self-recording rain gauges were not utilized in the winter to avoid freeze damage. Percentages of precipitation during May through September to total annual precipitation varied from 75.6 to 89.2% for these eight northern stations. Data M for the full 12 month year were used from the remaining ten stations located in the southern parts of China.

Eleven stations, including Nenjiang, Wuzhai, Suide, Yan'an, Guangxiangtai, Chengdu, Suining, Neijiang, Fangxian, Kunming, and Fuzhou, marked with dots in Fig. 1, were used to calibrate the models (Table 1). The other seven stations, including Tonghe, Yangcheng, Miyun, Xichang, Huangshi, Tengchong, and Changting, marked with triangles in Fig. 1, were used to validate the models.

2.2 Calculation of the R factor at different time scales

Different time scales for RUSLE2 erosivity, R, including event, daily, month~~ly~~, year~~ly~~, average monthly, and average annual, were calculated based on the one-minute resolution data (Data M). Recall that "month" and "year" refer to individual months and years, and not averages. EI_{30} (MJ mm ha^{-1} h^{-1}) is the rainfall erosivity index for a rainfall event, where E is the total rainfall kinetic energy during an event and I_{30} is the maximum contiguous 30-min intensity during an event (Wischmeier and Smith, 1978). An individual rainfall event was defined as a period of rainfall with at least six preceding and six succeeding non-precipitation hours (Wischmeier and Smith, 1978). An erosive rainfall event was defined as one with rainfall amounts greater than or equal to 12 mm, following Xie et al. (~~2012~~2002). We used the equation ~~Using the equation~~ recommended by Foster (2004) for RUSLE2 to calculate the kinetic energy of the storms, which used Eq. 1 combined with: ~~,~~

$$E = \sum_{r=1}^{n} (e_r \cdot P_r) \quad (3)$$

where e_r is the estimated unit rainfall kinetic energy (from Eq. 1) for the r^{th} minute (MJ ha^{-1} mm^{-1}); P_r is the one-minute rainfall amount for the r^{th} minute (mm); r=1, 2,…, n represents each 1-min interval in the storm; and i_r is the rainfall intensity for the r^{th} minute (mm h^{-1}). The Foster (2004) equations were chosen because they are currently used for erosion assessment for RUSLE2 in the United States and for the CSLE in China, and it appears to give results similar to the original USLE and in the mid-range of other equations that have been developed, as was discussed in the Introduction.

Our evaluation included 4 models for events and one for daily erosivities. Event models were simply models to predict individual event erosivities, regardless of whether they occurred in one or more days, and regardless of whether more than one event occurred in a day. For the daily model, ~~rainfall storm energies were calculated as:~~

$$\cancel{E = \sum_{r=1}^{n} (e_r \cdot P_r) \quad (1)}$$

$$\cancel{e_r = 0.29[1 - 0.72\exp(-0.082 i_r)] \quad (2)}$$

~~e_r is the estimated unit rainfall kinetic energy for the r^{th} minute (MJ ha^{-1} mm^{-1}); P_r is the one-minute rainfall amount for the r^{th} minute (mm); r=1, 2,…, n represents each 1-min interval in the storm; and i_r is the rainfall intensity for the r^{th} minute, (mm h^{-1}).~~

~~R~~rainfall erosivity for each day, R_{day}, was calculated following the method by Xie et al. (2015). When a day had only one erosive event and this event began and finished during the same day, then

$$R_{day} = EI_{30} \quad (\cancel{3}4)$$

When more than one full rainfall event happened during one day, then

$$R_{day} = \sum_{i=1}^{n} E_{event\_i} \cdot (I_{30})_{event\_i}$$ ~~(4~~(5)

where n is the number of rainfall events during the day, and E_{event_i} and $(I_{30})_{event\_i}$ are the total rainfall energy and the maximum contiguous 30-min intensity, respectively, for the i^{th} event. When only one part of a rainfall event occurred during one day, then

$$R_{day} = E_{day\_d} \cdot (I_{30})_{event}$$ (~~5~~6)

where E_{day_d} is the rainfall energy generated by the part of rainfall occurred during the d^{th} day and $(I_{30})_{event}$ is the maximum contiguous 30-min intensity for the entire event. The remaining situations were calculated by combining Eqs. (~~4~~5) and (~~5~~6).

Month~~ly~~, ~~yearly~~year, average monthly, and average annual R values were summed from the event EI_{30} index by erosive storms that occurred during the corresponding period. They were calculated by using Eqs. (~~6~~7)-(~~9~~10).

$$R_{month,y,m} = \sum_{j=0}^{J} (EI_{30})_{y,m,j}$$ (~~6~~7)

$$R_{ave\_month,m} = \frac{1}{Y} \sum_{y=1}^{Y} R_{month,y,m}$$ (~~7~~8)

$$R_{year,y} = \sum_{m=1}^{12} R_{month,y,m}$$ (~~8~~9)

$$R_{ave\_annual} = \sum_{y=1}^{Y} R_{year,y}$$ (~~9~~10)

where Y is the number of years of record, $(EI_{30})_{y,m,j}$ is the EI_{30} value for the j^{th} event in the m^{th} month of the y^{th} year; $R_{month,y,m}$ is the R value for the m^{th} month of the y^{th} year; $R_{ave\_month,m}$ is the average R value for the m^{th} month over the years of record; $R_{year,y}$ is R value in the y^{th} year; and R_{ave_annual} represents average annual erosivity, correspondent to the annual average R-factor in ~~the~~ USLE-type models~~USLE~~ (MJ mm ha^{-1} h^{-1} a^{-1}).

2.3 Model calibration using different resolutions ~~for~~ of rainfall data

A total of 21 models were calibrated for different time scales of R, based on ~~different~~ varying resolutions of rainfall data (Table 2). Event amount P_{event} and peak intensity indices were derived based on the one-minute resolution data, including I_{10}, I_{30}, and I_{60}, which were the maximum contiguous 10-min, 30-min, and 60-min intensities, respectively, within an event. I_{10} and I_{60} were used because of their close correlation with the daily $(I_{10})_{day}$ and $(I_{60})_{day}$ values commonly reported by the Chinese Meteorological Administration (2003). Four event-based models were developed relating measured EI_{30} to estimated EI_{30} (Table 2). Similar models for the other time scales were also calibrated (Table 2). Data was organized in various ways. P_{day}, P_{month}, P_{year}, P_{ave_month}, and P_{annual} were the daily, (individual) month~~ly~~, (individual) year~~ly~~, average monthly, and average annual rainfall amounts, respectively, for a given station. $(P_{60})_{month}$ and $(P_{60})_{year}$ represented~~ed~~ maximum contiguous 60-min rainfall amount observed within a specific month or year, respectively. $(P_{60})_{month\_max}$ represented the maximum of ~~all~~ $(P_{60})_{month}$ values for each month of the year~~, or the single maximum contiguous 60-min rainfall amount that occurred in a month (from Jan. through Dec.)~~ over the entire period of record. The average of $(P_{60})_{month}$ values was $\overline{(P_{60})_{month}}$. Each station had 12 values of $(P_{60})_{month\_max}$ and $\overline{(P_{60})_{month}}$, one for each month of the year. $(P_{60})_{year\_max}$ was the maximum value of $(P_{60})_{year}$ and $\overline{(P_{60})_{annual}}$ was the average of $(P_{60})_{year}$ values. Each station had only one value for these two parameters. P_{1440} was daily rainfall amount and its related index, including $(P_{1440})_{month}$, $(P_{1440})_{year}$, $(P_{1440})_{month\_max}$, $\overline{(P_{1440})_{month}}$, $(P_{1440})_{year\_max}$, and $\overline{(P_{1440})_{annual}}$, which were defined in ~~a similar~~an analogous way as were ~~those~~ correspondent values for P_{60}.

The parameters were obtained station-by-station for calibration stations first and parameters for linear relationships were compared to determine if data from all stations could be pooled together to conduct the regressions (Snedecor and Cochran, 1989). Parameters for power-law models, including Month~~ly~~ I, Year~~ly~~ I, Average Month~~ly~~ly I, and Annual I (Table 2), were obtained by using the Levenberg-Marquardt algorithm (Seber and Wild, 2003). Note that models coded as “Annual” refer to annual averages.

2.4 Models published in previous research for comparison

~~A~~ In addition to the 21 new models presented here, ~~total of~~ 20 representative models developed using data from China in previous research were also compared (Table 3). For these models other variables were ~~calculated~~needed. P_{d12} was average daily erosive rainfall total and P_{y12} was average annual erosive rainfall total. $P_{5\text{-}10}$ represented the rainy season rainfall amount from May through October for a specific year. $P_{\geq 10year}$ was the summation of daily rainfall no less than 10 mm in a year and $P_{\geq 10annual}$ was the annual average for $P_{\geq 10year}$.

Models by Wang (1987) and Wang et al. (1995) utilized (m t cm ha^{-1} h^{-1} a^{-1}) as the units of R for comparison. A conversion factor of 10.2 was multiplied to convert R to (MJ mm ha^{-1} h^{-1} a^{-1}). Later, models by Wu (1994) and Zhou et al. (1995) utilized (J cm m^{-2} h^{-1} a^{-1}). Their conversion factor, 10, was multiplied to convert (J cm m^{-2} h^{-1} a^{-1}) to (MJ mm ha^{-1} h^{-1} a^{-1}).

2.5 Assessment of the models

After the 21 models in Table 2 were calibrated with the data from the 11 calibration stations, the performance for these models was assessed and compared with the performance of the previously published models listed in Table 3 using data from the seven validation stations. Symmetric mean absolute percentage error ($MAPE_{sym}$) and the Nash-Sutcliffe model efficiency coefficient (ME) were utilized to reflect the deviation of the calculated values from the observation data. $MAPE_{sym}$ is considered to be superior to MAPE, since it ~~can~~ corrects the problem of MAPE’s asymmetry and the possible influence by outliers (Makridakis and Hibon, 1995). $MAPE_{sym}$ was calculated as follows (Armstrong, 1985):

$$\mathrm{MAPE_{sym}} = \frac{100}{m}\sum_{k=1}^{m}\left|\frac{R_{sim}(k) - R_{obs}(k)}{(R_{sim}(k) + R_{obs}(k))/2}\right| \qquad (\cancel{10}11)$$

where R_{obs} is the measured rainfall erosivity for the k^{th} period of time, such as month~~ly~~, year~~ly~~, or annual, based on one-minute resolution rainfall data. R_{sim} is the estimated value for the same period using equations in Tables 2 or 3.

ME was calculated as follows (Nash and Sutcliffe, 1970):

$$ME = 1 - \frac{\sum_{k}^{m}[R_{sim}(k) - R_{obs}(k)]^2}{\sum_{k}^{m}[R_{obs}(k) - \overline{R_{obs}}(k)]^2} \quad (\cancel{11}12)$$

ME compares the measured values ~~on the line as~~to a perfect fit (1:1 line). Hence, ME is a combined measure of linearity, bias, and relative differences between the measured and predicted values. The maximum possible value for ME is 1. The higher the value the better the model fit. An efficiency of M*E* < 0 indicates the single value (the mean) for the measured data’s mean is a better predictor of the data than the model.

$MAPE_{sym}$ and ME were calculated ~~station by station~~based on all the data for the seven validation stations. ~~and their mean~~Individual values for all stations were also determined~~reported~~. ~~R_{obs} has only one value for each station for the annual average scale of R estimation, and hence ME was calculated based on simulations and observations for the seven stations.~~

3. Results and discussion~~s~~

3.1 Basic data results

Average annual rainfall ranged from 449.7 to 1728.1 mm, and average annual erosivity varied from 781.9 to 8258.5 MJ mm ha^{-1} h^{-1} yr^{-1} (Table 1). A total of 11,801 erosive events were used in the study. The eleven stations had 6,376 erosive events, which were used to calibrate the models, and the seven validation stations had 5,425 erosive events.

3.2 Validation and calibration for the new models ~~that use different resolutions of input data~~

Parameters, $MAPE_{sym}$, ME, and coefficients of determination, R^2, for calibration models are shown in Table 4. ~~Statistical tests showed data from all stations could not be pooled.~~

~~The r^2 for all event level models was greater than 0.92 (Table 4).~~ The model Event IV, with a combination of event rainfall amount P_{event} and $I_{30,}$ when I_{30} was divided into two categories, with a threshold of 15 mm h^{-1}, performed slightly ~~–~~be~~st~~tter in terms of the $MAPE_{sym}$ value than did Event II, which used the same variables but did not separate the rainfall events by intensity ~~(Table 4)~~. The performance of Daily I with daily rainfall amount and $(I_{10})_{daily}$ was similar with that for Event I with event rainfall amount and I_{10} ~~(Table 4)~~.

Using only total rainfall amount as input, ~~The power law~~the models for monthl~~y~~, yearl~~y~~, and average monthly~~, and annual~~ scales ~~(Monthly I, Yearly I, Average Monthly I and Annual I), with only total rainfall amount as input~~ were statistically significant, with~~had~~ determination coefficients R^2 greater than 0.66~~, which suggested the models were statistically significant~~ (Table 4 and Fig. 2). However, their capabilities in predicting ~~R~~ erosivity ~~with time scales intended for the models~~ were limited ~~or ineffective~~based on the ME values (Table 4).~~, with ME being 0.20, -0.83, -0.44 and 0.63 for Monthly I, Yearly I, Average Monthly I and Annual I, respectively.~~ Data from Tengchong and Xichang, located in the southwestern part of China, were ~~mainly~~ in part responsible for these low~~er~~ ME values. Table 5 shows the individual values of $MAPE_{sym}$ and ME for the seven validation stations, with average of each using all the stations and using only the five without Tengchong and Xichang. Results were much better without those two stations. ~~When these two stations were removed, the average ME for monthly scale of R increased to 0.59 for Monthly I, 0.37 for Yearly I, and 0.60 for Average Monthly I (Table 5).~~ The model Annual I, which use only average annual precipitation values, performed reasonably well, considering that the only input required was annual average precipitation (Table 4). If other information is available, other models performed better, but Annual I may be used if only average annual precipitation is available at a location.

In general, we found that the finer the temporal resolution of the rainfall input data, the better the models performed for a given erosivity time scale. ~~Seasonal variations by monthly and average monthly models (Fig. 3) and yearly variations by monthly and yearly models (Fig. 4) were demonstrated using Tonghe and Tengchong stations. Monthly I and Average Monthly I captured the general seasonal pattern for the Tonghe station (Figs. 3a and c), but the simulated peak value of monthly R was in July for the Tengchong station, which was not~~

~~consistent with observation. Monthly I and Yearly I captured the general year-to-year pattern for the Tonghe station (Figs. 4a and c), but they overestimated yearly erosivity for the Tengchong station (Figs. 4b and d). Monthly I and Yearly I also overestimated the yearly erosivity for the Xichang station. The reason for the overestimation for the Tengchong and Xichang stations was mainly due to two aspects: (1) the percentages of erosive rainfall amount to total rainfall at those stations were lower (71.9% and 76.9%, respectively), suggesting that more events occurred with small amount totals that do not generate soil loss (Table 5); and (2) the ratio for event EI~~$_{30}$~~ to event rainfall amount P was lower (3.6 and 4.1, respectively), inferring that rainfall intensity and erosivity generated by per amount of rainfall were both less than that of the other stations (Table 5). This result was consistent with that of Nel et al. (2013), which demonstrated that two models using annual average rainfall and average monthly rainfall substantially overestimated annual erosivity in the west coast and the Central Plateau of Mauritius, which also have a large amount of non-erosive rainfall. Rainfall erosivity reflected a combined effect of rainfall amount and rainfall intensity. Therefore, it was reasonable that rainfall amount could only explain part of rainfall erosivity variation at these stations.~~

Models that used some expression of maximum daily rainfall amount (Month~~ly~~ III, Year~~ly~~ III, Average Monthly III, Average Monthly V, Annual III, and Annual Model V) predicted the R factor better than those models with only total rainfall amount as input (Table 4), for a specific time scale. Models based on rainfall amount and maximum contiguous 60-min rainfall amounts (Month~~ly~~ II, Year~~ly~~ II, Average Monthly II, Average Monthly IV, Annual II, and Annual IV) generally performed better than corresponding models with rainfall amount and maximum daily rainfall amount (Month~~ly~~ III, Year~~ly~~ III, Average Monthly III, Average Monthly V, Annual III), except for Annual Model V, which performed well. The reason for that may be due to the fact that maximum contiguous 60-min rainfall amounts may have been more highly correlated with maximum contiguous 30-min intensity in an event as compared to just the maximum daily rainfall amount. The only annual average model that did not perform well was Annual III, which utilized $(P_{1440})_{year\_max}$, the maximum of $(P_{1440})_{year}$ values for each year over the entire period of record.

Tables 3 and 4 show the models only evaluated for the erosivity temporal scale that corresponds to the input data resolution. For example, the event-based models are only evaluated on the basis of events modelled. We also evaluated the models at the aggregate scale. For example, EI_{30} estimated from event-based models were summed up to month and year values, in order to evaluate if fine-scale temporal resolution data improves also the accuracy of aggregate erosivity measures (Table 6). Two important facts emerge. First, when the models are applied at the aggregated scale their predictions get better. Secondly, the models that use finer resolution of input data predict better for the same erosivity time scale compared to models using coarser resolution input data. This has important implications for model applications.

3.3 Seasonal variations of erosivity

Taking Tonghe and Tengchong as examples, it was ~~demonstrated~~ found that Month~~ly~~ II generated better results than Month~~ly~~ III, which performed better than Month~~ly~~ I, in estimating seasonal and yearly variations (Figs. 3a, b and Figs. 4a, b). Correspondingly, seasonal variations by Average Monthly II were closer to observations as compared to those by Average Monthly III and Average Monthly I (Figs. 3c and d). Year~~ly~~ II and Year~~ly~~ III ~~improved the~~produced better simulations of yearly variations compared with Year~~ly~~ I, especially for the Tengchong station (Figs. 4c, d).

Seasonal variations by monthly and average monthly models (Fig. 3) and yearly variations by month~~ly~~ and year~~ly~~ models (Fig. 4) were demonstrated using Tonghe and Tengchong stations. Month~~ly~~ I and Average Monthly I captured the general seasonal pattern for the Tonghe station (Figs. 3a and c), but the simulated peak value of monthly R was in July for the Tengchong station, which was not consistent with observation. Month~~ly~~ I and Year~~ly~~ I captured the general year-to-year pattern for the Tonghe station (Figs. 4a and c), but they overestimated yearly erosivity for the Tengchong station (Figs. 4b and d). Month~~ly~~ I and Year~~ly~~ I also overestimated the yearly erosivity for the Xichang station. The reason for the overestimation for the Tengchong and Xichang stations was mainly due to two aspects: (1) the percentages of erosive rainfall amount to total rainfall at those stations were lower (71.9%

and 76.9%, respectively), suggesting that more events occurred with small amount totals that do not generate soil loss (Table 5); and (2) the ratio for event EI_{30} to event rainfall amount P was lower (3.6 and 4.1, respectively), inferring that rainfall intensity and erosivity generated by per amount of rainfall were both less than that of the other stations (Table 5). This result was consistent with that of Nel et al. (2013), which demonstrated that two models using annual average rainfall and average monthly rainfall substantially overestimated annual erosivity in the west coast and the Central Plateau of Mauritius, which also have a large amount of non-erosive rainfall. Rainfall erosivity reflected a combined effect of rainfall amount and rainfall intensity. Therefore, it was reasonable that rainfall amount ~~could~~ only explained part of rainfall erosivity variation at these stations.

~~3.3~~3.4 ~~Comparisons with~~Evaluation of models from previous research with current models

Generally speaking, the more accurate the resolution of input data for models, the better was the performance of the model for estimating at the same temporal erosivity scale. For example, the models with daily rainfall amount and daily maximum 60-min or 10-min amount as inputs performed better than models with only daily rainfall amount as input. Similarly, results from models with maximum 60-min rainfall amount (Month II, Year II, Average Monthly IV, and Annual IV) were generally better than those with maximum daily rainfall amount (Month III, Year III, Average Monthly V, and Annual V, Fig. 5).

Wang et al. (1995) used a combination of event rainfall amount P_{event} and I_{10} for event scale models. The model using the I_{10} data was divided into two categories, with a threshold of 10 mm h^{-1}, performed best among the four models compared (Table 3). That model had similar performance with Event IV in this study (Table 4), which also divided the data by a rainfall intensity threshold.

There ~~are~~ were three kinds of daily scale models, according to the number and type of inputs required. Two models used daily rainfall amount (Zhang et al., 2002b and Xie et al., 2015), two models used daily rainfall amount and daily maximum 10-min intensity (Xie et al., 2001 and Daily I), and one model used daily rainfall amount and daily maximum 60-min intensity (Xie et al., 2015). The model with daily rainfall amount as input in Xie et al. (2015) performed better than that of Zhang et al., (2002b) (Table 3). Daily I, which used daily rainfall amount and daily maximum 10-min intensity as inputs in this study, performed better than the model in Xie et al., (2001). Models with an additional daily 10-min or 60-min intensity index performed better than those with only a total rainfall amount ~~index~~ (Table 3 and Table 4).

There ~~are~~ were generally four groups of models for month~~ly~~, year~~ly~~, average monthly, and annual scale models. The first group used linear regression (Sun et al., 1990; Wu, 1994; Zhou et al., 1995) or a power law function (Zhang and Fu, 2003; Month~~ly~~ I, Year~~ly~~ I, Average Monthly I, and Annual I) with only rainfall amount as input, so that the data required were relatively easy to collect. Models by Sun et al., (1990), Wu (1994) and Zhou et al. (1995), when they were used to estimate the monthly scale of R, had MAPE$_{sym}$ values of 8~~8~~6.7~~3~~, 60.~~9~~2 and 67.~~8~~3% and ME of -0~~1~~.63~~96~~, 0.~~53~~ 57 and 0.35~~8~~, respectively (Table 3). When they were used to estimate annual scale of R, there was a tendency of underestimation, especially for the stations with larger erosivity (Figs. 5a, b). Four models by Zhang and Fu (2003) overestimated the R factor, with MAPE$_{sym}$ varying between 34.6 and 60.8% and ME varying between -2.~~41~~ 11 to ~~-~~0.~~0~~1~~3~~0 (Table 3, Fig. 5), which suggested the models' abilities were limited. Two models by Zhang and Fu (2003) using the Modified Fournier Index generated ~~worse~~ poorer results ~~compared to~~than the model by Zhang and Fu (2003) using average annual rainfall as input (Table 3), which was consistent with the ~~result~~ findings of ~~of~~ Yu and Rosewell (1996). The power law models in this study, including Month~~ly~~ I, Year~~ly~~ I, Average Monthly I, and Annual I, tended to overestimate the R factor for the stations with larger erosivity (Fig. 5).

The second group of models (Wang et al., 1995, Month~~ly~~ II, Year~~ly~~ II, Average Monthly IV, Annual IV) used linear regression with rainfall amount (total rainfall or total rainfall with daily rainfall no less than 10 mm) and maximum 60-min rainfall as inputs. All these seven models generated statistically significant~~good~~ results, with MAPE$_{sym}$ for R with time scale intended for the model ranging from 11.5~~4~~ to 36~~5~~.0~~6~~% and ME from 0.80~~42~~ to 0.94 (Table 3 and Table 4; Fig. 5). ~~When these models were used to estimate annual R, the measured and predicted values were near the 1:1 line (Fig. 5).~~

The third group used linear regression with rainfall amount and maximum daily rainfall as inputs (Month~~ly~~ III, Year~~ly~~ III, Average Monthly V, Annual V), which generated reasonable results (Table 4) and a slightly overestimated annual R (Fig. 5). Overall they did not perform as well as did the models in the second group (Table 4).

The fourth group (Wang et al., 1995) used a combination of three indices, including rainfall amount, maximum 60-min rainfall amount, and maximum daily rainfall amount as inputs and generated good simulation results, however, there was no improvement compared with the two models by Wang et al., (1995) in the second group (Table 3). ~~was the performance of the model. For example, the models with daily rainfall amount and daily maximum 60-min or 10-min amount as inputs performed better than models with daily rainfall amount as input. Results from models with maximum 60-min rainfall amount (Monthly II, Yearly II, Average Monthly IV, and Annual IV) were generally better than those with maximum daily rainfall amount (Monthly III, Yearly III, Average Monthly V, and Annual V, Fig. 5).~~

~~If monthly rainfall data are available, there are several models from which to choose. For example, if only monthly rainfall amounts are available, Monthly I, Yearly I, Average Monthly I, and Annual I can be selected. Yearly, average monthly, and annual rainfall amounts can be first derived from monthly rainfall amount data and then used in the corresponding models to estimate the R factor. The prediction capabilities for seven validation stations for the four models; Monthly I, Yearly I, Average Monthly I, and Annual I, were very similar to each other (Table 5, Fig. 5). Similar results can be found among four models with maximum 60-min amount, including Monthly II, Yearly II, Average Monthly IV, and Annual IV, as well as the four models with maximum daily rainfall amount, including Monthly III, Yearly III, Average Monthly V, and Annual Model V. Therefore, users have the option to choose the simplest method for estimating the R factor. However, if seasonal variations are required, monthly and average monthly models may be utilized; whereas, yearly and annual models cannot satisfy the requirements. If yearly variations are required, monthly and yearly models may be utilized; whereas, average monthly, and annual models~~

~~cannot satisfy the requirements.~~

3.5 Applications and recommendations

The results of this study provide a multitude of options for dealing with the problem of variations in available temporal resolutions of rainfall data from across the world for developing erosivity maps and databases. We present a series of 21 potential equations for use in estimating erosivity at time scales from event to average annual using input data resolution ranging from maximum ten minute rainfall intensity to average annual rainfall amount. Of the 21 equations we can recommend the use of 17. Equations Month I, Year I, and Average Monthly I, which use only total rainfall amounts for the respective time scales, all had low ME values and poor prediction capability (Table 4). Annual III, which is a linear function of average annual rainfall and the maximum daily precipitation over the recording period, performed very poorly, with a negative ME value (Table 4).

We found that using finer resolution data input produced better predictions of erosivity at a given output time scale. An exception was for the event-based models, where using I_{30} gave slightly better results than using I_{60} or I_{10}. However, we also found that ~~that~~ using equations with the finest data resolution possible, and aggregating or summing results for finer erosivity time scales, gave the best results (Table 6). In other words, ~~I~~if one were interested in average annual erosivity, but had rainfall data available for using the Daily I model, then results are better using the Daily I model and summing results over the period of data record rather than using Annual I-V models. It is also evident that predictions of erosivity using Daily I improve as the time scale increases. In other words, the predictions of average annual erosivity calculated by summing the daily values from Daily I give a higher level of fit than when using Daily I to estimate daily erosivity (Table 6).

Models in this study performed better or similar to models from previous research based on these independent validation data.

~~If monthly rainfall data are available, there are several models from which to choose.~~

~~For example, if only monthly rainfall amounts are available, Monthly I, Yearly I, Average Monthly I, and Annual I can be selected. Yearly, average monthly, and annual rainfall amounts can be first derived from monthly rainfall amount data and then used in the corresponding models to estimate the R factor. The prediction capabilities for seven validation stations for the four models; Monthly I, Yearly I, Average Monthly I, and Annual I, were very similar to each other (Table 5, Fig. 5). Similar results can be found among four models with maximum 60-min amount, including Monthly II, Yearly II, Average Monthly IV, and Annual IV, as well as the four models with maximum daily rainfall amount, including Monthly III, Yearly III, Average Monthly V, and Annual Model V. Therefore, users have the option to choose the simplest method for estimating the R factor. However, if seasonal variations are required, monthly and average monthly models may be utilized; whereas, yearly and annual models cannot satisfy the requirements. If yearly variations are required, monthly and yearly models may be utilized; whereas, average monthly, and annual models cannot satisfy the requirements.~~

~~4. Conclusions~~

~~Rainfall erosivity is needed for using USLE-type soil erosion models. Considering the difficulties in obtaining breakpoint data to calculate the erosivity index, a series of 21 simpler methods using different resolutions of often readily available rainfall data were calibrated, based on 6,376 erosive events derived from one-minute resolution data from 11 stations. These models, plus 20 models from previous research, were evaluated by using 5,425 erosive events from the seven validation stations. The following conclusions are presented:~~

~~(1) Symmetric mean absolute percentage error ($MAPE_{sym}$) and the Nash-Sutcliffe model efficiency coefficient (ME) were presented for 41 models to reflect deviation of the simulation from the observation when different time scales for the R factor were estimated, including event/daily, monthly, yearly, average monthly, and annual scales. Models in this study performed better or similar with models from previous research.~~

~~(2) Predication capabilities for models with rainfall amount as inputs were limited in the geographic region of southwestern China, where the percent of erosive amount was lower and the ratio for event EI_{30} to event rainfall amount P was lower.~~

~~(3) Models with higher temporal resolution of input generally performed better. Models with rainfall amount and maximum 60-min rainfall amount as inputs performed better than models with rainfall amount and maximum daily rainfall amount, which performed better than those with only rainfall amount. Users can select different models to calculate rainfall erosivity, based on their available rainfall data and objectives. For example, if the user wants to estimate event scale EI_{30}, then they must choose an event model. However, if the objective is estimating average annual R, then there are many choices of models that use various resolutions of input rainfall data.~~

~~In summary, from the view of prediction accuracy, the event EI_{30} as originally calculated is considered the best indicator of rainfall erosivity for either erosivity distribution analysis or annual erosivity calculation. However, in the absence of breakpoint rainfall data users can select from the different methods presented here to calculate rainfall erosivity, based on availability of rainfall data and accuracy requirements.~~

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~~Tables~~

Table 1. Information for the 18 rainfall stations

Province	Station name	Lat. (°N)	Long. (°E)	Elevation (m)	Common years	No. of erosive events	Annual rainfall [3] (mm)	R [4] (MJ mm ha^{-1} h^{-1} a^{-1})
Heilongjiang[1]	Nenjiang	49.17	125.23	243.0	30	343	485.8	1368.7
	Tonghe[2]	45.97	128.73	110.0	38	471	596.2	1632.5
Shanxi[1]	Wuzhai	38.92	111.82	1402.0	30	289	464.0	781.9
	Yangcheng[2]	35.48	112.4	658.8	30	340	605.9	1503.3
Shaanxi[1]	Suide	37.5	110.22	928.5	29	256	449.7	992.8
	Yan’an	36.6	109.5	958.8	39	411	534.6	1233.7
Beijing[1]	Guanxiangtai	39.93	116.28	54.7	40	434	575.0	3188.1
	Miyun[2]	40.38	116.87	73.1	37	476	648.1	3575.0
Sichuan	Chengdu	30.67	104.02	506.1	39	717	891.8	3977.0
	Xichang[2]	27.9	102.27	1590.9	40	998	1007.5	3021.0
	Suining	30.5	105.58	279.5	33	654	932.7	4091.3
	Neijiang	29.58	105.05	352.4	39	826	1034.1	5097.9
Hubei	Fangxian	32.03	110.77	427.1	31	563	829.5	2298.4
	Huangshi[2]	30.25	115.05	20.6	32	898	1438.5	6049.4
Yunnan	Tengchong[2]	25.02	98.5	1648.7	36	1205	1495.7	3648.9
	Kunming	25.02	102.68	1896.8	33	747	1018.8	3479.0
Fujian	Fuzhou	26.08	119.28	84.0	39	1136	1365.4	5871.1
	Changting[2]	25.85	116.37	311.2	31	1037	1728.1	8258.5

[1] The eight stations in these provinces are located in the northern part of China and had one-minute resolution data collected from May through September. The remaining ten stations were based on data collected during the entire year.

[2] Seven validation stations (The other 11 stations were calibration stations.)

[3] Based on daily rainfall datasets collected during 1961-2000.

[4] R in this case is the average annual erosivity.

Table 2. New ~~M~~models calibrated

Model codes	Models	Model codes	Models
Event I	$EI_{30} = \lambda_1 P_{event} I_{10}$	Average Monthly I	$R_{ave\_month} = \alpha_3 P_{ave\_month}^{\beta_3}$
Event II	$EI_{30} = \lambda_2 P_{event} I_{30}$	Average Monthly II	$R_{ave\_month} = \lambda_{11} P_{ave\_month} (P_{60})_{month\_\max}$
Event III	$EI_{30} = \lambda_3 P_{event} I_{60}$	Average Monthly III	$R_{ave\_month} = \lambda_{12} P_{ave\_month} (P_{1440})_{month\_\max}$
Event IV	$EI_{30} = \lambda_4 P_{event} I_{30} \quad I_{30} < 15 mm/h$ $EI_{30} = \lambda_5 P_{event} I_{30} \quad I_{30} \geq 15 mm/h$	Average Monthly IV	$R_{ave\_month} = \lambda_{13} P_{ave\_month} \overline{(P_{60})_{month}}$
Daily I	$R_{day} = \lambda_6 P_{day} (I_{10})_{day}$	Average Monthly V	$R_{ave\_month} = \lambda_{14} P_{ave\_month} \overline{(P_{1440})_{month}}$
Month~~ly~~ I	$R_{month} = \alpha_1 P_{month}^{\beta 1}$	Annual I[1]	$R_{annual} = \alpha_4 P_{annual}^{\beta_4}$
Month~~ly~~ II	$R_{month} = \lambda_7 P_{month} (P_{60})_{month}$	Annual II	$R_{annual} = \lambda_{15} P_{annual} (P_{60})_{year\_\max}$
Month~~ly~~ III	$R_{month} = \lambda_8 P_{month} (P_{1440})_{month}$	Annual III	$R_{annual} = \lambda_{16} P_{annual} (P_{1440})_{year\_\max}$
Year~~ly~~ I	$R_{year} = \alpha_2 P_{year}^{\beta_2}$	Annual IV	$R_{annual} = \lambda_{17} P_{annual} \overline{(P_{60})_{annual}}$
Year~~ly~~ II	$R_{year} = \lambda_9 P_{year} (P_{60})_{year}$	Annual V	$R_{annual} = \lambda_{18} P_{annual} \overline{(P_{1440})_{annual}}$
Year~~ly~~ III	$R_{year} = \lambda_{10} P_{year} (P_{1440})_{year}$		

[1] Annual refers to Average Annual values of erosivity.

Table 3. Models published in previous research and their prediction capabilities determined using the validation stations-the symmetric mean absolute percentage errors, $MAPE_{sym}$, and Nash-Sutcliffe model efficiencies, ME.

Erosivity time scales	Models	Sources	$MAPE_{sym}$ (%) [1]	ME[2]
Event	$R_{event} = 10.2 \cdot (0.0247 P_{event} I_{30} - 0.17)$	Wang, 1987	30.6	0.97
	$R_{event} = 10.2 \cdot (0.025 P_{event} I_{30} - 0.32)$	Wang, 1987	28.8	0.97
	$R_{event} = 10.2 \cdot (1.70 \frac{P_{event} I_{30}}{100} - 0.136) \quad I_{30} < 10 mm\, h^{-1}$ $R_{event} = 10.2 \cdot (2.35 \frac{P_{event} I_{30}}{100} - 0.523) \quad I_{30} \geq 10 mm\, h^{-1}$	Wang et al., 1995	15.5	0.98
	$R_{event} = 0.1773 P_{event} I_{10}$	Zhang et al., 2002a	44.7	0.89
Daily	$R_{day} = 0.184 P_{day} (I_{10})_{day}$	Xie et al., 2001	44.9	0.91
	$R_{day} = \alpha\, P_{day}{}^{\beta}$ $\beta = 0.8363 + \frac{18.144}{P_{d12}} + \frac{24.455}{P_{y12}}, \ \alpha = 21.586 \beta^{-7.1891}$	Zhang et al., 2002b	74.6	0.69
	$R_{day} = 0.2686 [1 + 0.5412 \cos(\frac{\pi}{6} j - \frac{7\pi}{6})] P_{day}{}^{1.7265}$	Xie et al., 2015	63.7	0.71
	$R_{day} = 0.3522 P_{day} (P_{60})_{day}$	Xie et al., 2015	38.2	0.95
Month	$R_{month} = 10 \cdot 0.0125 P_{month}{}^{1.6295}$	Wu, 1994	60.2	0.57
	$R_{month} = 10 \cdot (0.3046 P_{month} - 2.6398)$	Zhou et al., 1995	67.3	0.35
Year	$R_{year} = 1.77 P_{5-10} - 133.03$	Sun et al., 1990	86.7	-0.63
	$R_{year} = 10.2 \cdot 0.272 (P_{year} (P_{60})_{year} / 100)^{1.205}$	Wang et al., 1995	31.8	0.80
	$R_{year} = 10.2 \cdot 1.67 (P_{\geq 10 year} (P_{60})_{year} / 100)^{0.953}$	Wang et al., 1995	18.9	0.87

	$R_{year} = 0.0534 P_{year}^{1.6548}$	Zhang and Fu, 2003	44.4	0.10
Average Annual	$R_{\mathrm{annual}} = 10.2 \cdot 0.009 \mathrm{P}_{\mathrm{annual}}^{0.564} \cdot \overline{(\mathrm{P}_{60})_{annual}}^{1.155} \cdot \overline{(\mathrm{P}_{1440})_{annual}}^{0.560}$	Wang et al., 1995	17.3	0.83
	$R_{\mathrm{annual}} = 10.2 \cdot 0.0244 \mathrm{P}_{\geq 10\mathrm{annual}}^{0.551} \cdot \overline{(\mathrm{P}_{60})_{annual}}^{1.175} \cdot \overline{(\mathrm{P}_{1440})_{annual}}^{0.376}$	Wang et al., 1995	12.0	0.86
	$R_{\mathrm{annual}} = 10.2 \cdot 2.135 (\mathrm{P}_{\geq 10\mathrm{annual}} \cdot \overline{(\mathrm{P}_{60})_{annual}} / 100)^{0.919}$	Wang et al., 1995	11.5	0.94
	$R_{annual} = 0.1833 F_F^{1.9957},\ F_F = \frac{1}{N} \sum_{i=1}^{N} \frac{\sum_{j=1}^{12} P_{i,j}^2}{\sum_{j=1}^{12} P_{i,j}}$	Zhang and Fu, 2003	55.9	-1.21
	$R_{annual} = 0.3589 F^{1.9462},\ F = (\sum_{j=1}^{12} P_{ave\_month\_j}{}^2) / P_{annual}$	Zhang and Fu, 2003	60.8	-2.11
	$R_{annual} = 0.0668 P_{annual}^{1.6266}$	Zhang and Fu, 2003	34.6	-0.03

[1] $MAPE_{sym}$ (%) is the symmetric mean absolute percentage error values for all the data across validation stations for R with time scale intended for the model.

[2] ME is the Nash-Sutcliffe model efficiency coefficient for all the data across validation stations for R with time scale intended for the model.

Table 4. Models calibrated in this study and their prediction capabilities determined using the validation stations-the symmetric mean absolute percentage errors, MAPE$_{sym}$, and Nash-Sutcliffe model efficiencies, ME.

Model codes	Models [1]	R^2 [2]	MAPE$_{sym}$ (%)	ME
Event I	$EI_{30} = 0.1547 P_{event} I_{10}$	0.92	34.5	0.91
Event II	$EI_{30} = 0.2372 P_{event} I_{30}$	0.98	29.3	0.98
Event III	$EI_{30} = 0.3320 P_{event} I_{60}$	0.94	35.8	0.96
Event IV	$R_{event} = 0.1592 P_{event} I_{30} \quad I_{30} < 15mm/h$ $R_{event} = 0.2394 P_{event} I_{30} \quad I_{30} \geq 15mm/h$	0.97	13.9	0.98
Daily I	$R_{day} = 0.1661 P_{day} (I_{10})_{day}$	0.92	38.4	0.91
Month I	$R_{month} = 0.1575 P_{month}^{1.6670}$	0.66	69.5	0.48
Month II	$R_{month} = 0.1862 P_{month} (P_{60})_{month}$	0.85	36.0	0.88
Month III	$R_{month} = 0.0770 P_{month} (P_{1440})_{month}$	0.65	55.2	0.69
Year I	$R_{year} = 0.5115 P_{year}^{1.3163}$	0.70	38.1	0.48
Year II	$R_{year} = 0.1101 P_{year} (P_{60})_{year}$	0.80	20.9	0.84
Year III	$R_{year} = 0.0502 P_{year} (P_{1440})_{year}$	0.54	28.9	0.59
Average Monthly I	$R_{ave\_month} = 0.0755 P_{ave\_month}^{1.8430}$	0.89	44.7	0.17
Average Monthly II	$R_{ave\_month} = 0.0877 P_{ave\_month} (P_{60})_{month\_max}$	0.94	23.5	0.88
Average Monthly III	$R_{ave\_month} = 0.0410 P_{ave\_month} (P_{1440})_{month\_max}$	0.87	30.1	0.73
Average Monthly IV	$R_{ave\_month} = 0.2240 P_{ave\_month} \overline{(P_{60})_{month}}$	0.98	22.9	0.88
Average Monthly V	$R_{ave\_month} = 0.1082 P_{ave\_month} \overline{(P_{1440})_{month}}$	0.94	31.4	0.79
Annual I	$R_{annual} = 1.2718 P_{annual}^{1.1801}$	0.89	25.6	0.63
Annual II	$R_{annual} = 0.0584 P_{annual} (P_{60})_{year\_max}$	0.92	15.4	0.91

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Annual III	$R_{annual} = 0.0253 P_{annual} (P_{1440})_{year\_max}$	0.92	22.5	-0.44
Annual IV	$R_{annual} = 0.1058 P_{annual} \overline{(P_{60})_{annual}}$	0.94	17.0	0.88
Annual V	$R_{annual} = 0.0492 P_{annual} \overline{(P_{1440})_{annual}}$	0.92	18.2	0.91

[1] Parameters of models for power law models, including α_1, β_1, α_2, β_2, α_3, β_3, α_4, β_4, α_5, β_5, were solved by pooling data from 11 stations together. Parameters for average annual scale models, including λ_{15}, λ_{16}, λ_{17}, λ_{18}, were calculated by fitting data from all calibration stations and for the remainder they were the average values of parameters for the 11 calibration stations. [2] R^2 is the coefficient of determination.

~~[2] ME is the Nash-Sutcliffe model efficiency coefficient for R with time scale intended for the model. ME was calculated based on simulations and observations for seven stations for the annual average scale of R estimation and was averaged for all seven stations for the other scales.~~

~~**Table 4. Models calibrated in this study and their prediction capabilities determined using symmetric mean absolute percentage errors and Nash-Sutcliffe model efficiency coefficients.**~~~~of parameters for the 11 calibration stations.~~

~~[2] r^2 is the coefficient of determination.~~

Table 5. Validation s~~-~~tation-averaged ~~S~~symmetric mean absolute percentage errors ($MAPE_{sym}$) and Nash-Sutcliffe model efficiency coefficients (ME) for R_{month} by Month~~ly~~ I, R_{year} by Year~~ly~~ I and R_{ave_month} by Average Monthly I models for seven validation stations and statistics on event rainfall amount and event EI_{30}.

Station name	R_{month} by Month I		R_{year} by Year I		R_{ave_month} by Average Monthly I		Percent of erosive amount (%)	EI_{30}/P
	$MAPE_{sym}$	ME	$MAPE_{sym}$	ME	$MAPE_{sym}$	ME		
Tonghe	70.2	0.73	30.9	0.47	29.5	0.93	71.2	4.8
Yangcheng	65.5	0.31	27.1	0.55	16.4	0.96	81.7	4.2
Miyun	52.0	0.71	45.1	-0.06	37.6	0.88	82.8	7.8
Xichang	77.5	0.47	45.4	-0.15	57.2	0.09	76.9	4.1
Huangshi	70.1	0.65	24.5	0.63	46.1	0.73	86.5	5.7
Tengchong	83.4	-2.01	66.6	-7.51	68.3	-6.98	71.9	3.6
Changting	52.0	0.54	20.9	0.26	35.2	0.30	88.4	6.1
Mean[1]	67.2	0.20	37.2	-0.83	41.5	-0.44	79.9	5.2
Mean[2]	62.0	0.59	29.7	0.37	38.7	0.60	82.1	5.7

[1] Averaged value for seven validation stations.

[2] Averaged value for five validation stations except Xichang and Tengchong.

Table 6. $MAPE_{sym}$ for the models when used to estimate longer time scales of erosivity.

Model codes	Models	Event & Daily	Month	Ave. monthly	Year	Annual
Event I	$EI_{30} = 0.1547 P_{event} I_{10}$	34.5	29.0	20.4	16.4	12.0
Event II	$EI_{30} = 0.2372 P_{event} I_{30}$	29.3	24.2	16.0	11.4	9.1
Event III	$EI_{30} = 0.3320 P_{event} I_{60}$	35.8	28.5	15.1	10.8	6.2
Event IV	$R_{event} = 0.1592 P_{event} I_{30} \quad I_{30} < 15 mm/h$ $R_{event} = 0.2394 P_{event} I_{30} \quad I_{30} \geq 15 mm/h$	13.9	11.0	7.0	6.4	4.7
Daily I	$R_{day} = 0.1661 P_{day} (I_{10})_{day}$	38.4	29.2	19.6	16.2	11.7
Month I	$R_{month} = 0.1575 P_{month}^{1.6670}$		69.5	46.7	39.4	28.7
Month II	$R_{month} = 0.1862 P_{month} (P_{60})_{month}$		36.0	19.9	18.6	13.1
Month III	$R_{month} = 0.0770 P_{month} (P_{1440})_{month}$		55.2	26.7	24.8	12.3
Year I	$R_{year} = 0.5115 P_{year}^{1.3163}$				38.1	23.5
Year II	$R_{year} = 0.1101 P_{year} (P_{60})_{year}$				20.9	14.3
Year III	$R_{year} = 0.0502 P_{year} (P_{1440})_{year}$				28.8	17.3

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Figures

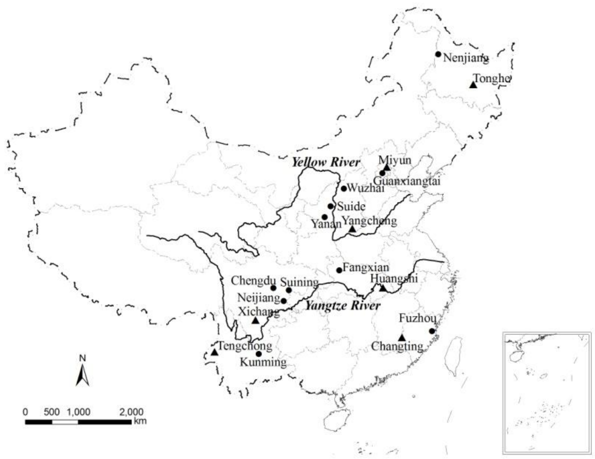


Fig. 1. ~~Distribution~~ Locations of the 18 stations with one-minute resolution rainfall data. Eleven stations marked with dots were used to calibrate 21 models. The other seven stations marked with triangles were used to validate models and conduct comparisons with previous research.

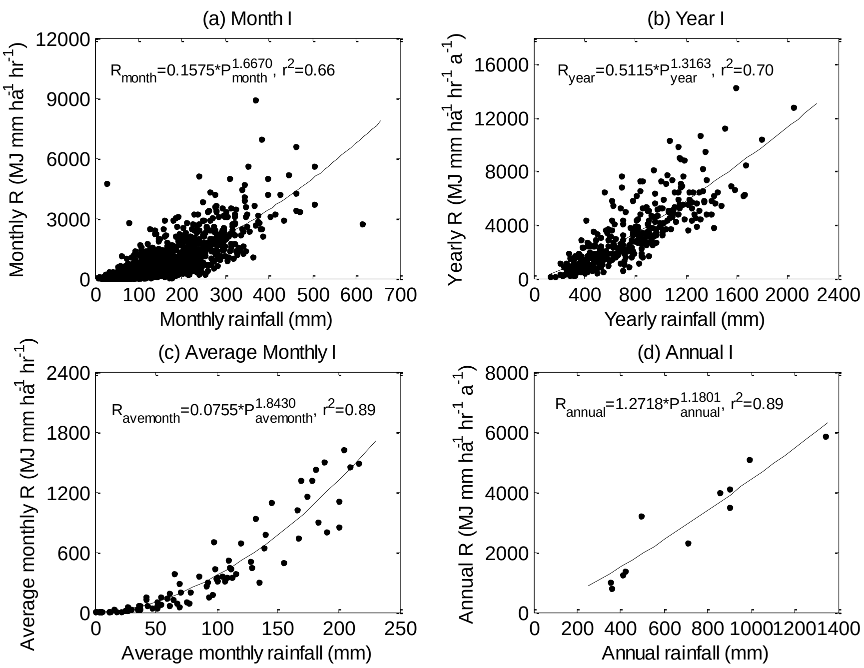


Fig. 2. Scatterplots for power law models using rainfall amount: (a) Month~~ly~~ I, (b) Year~~ly~~ I, (c) Average Monthly I, and (d) Annual I, based on the 11 calibration stations.

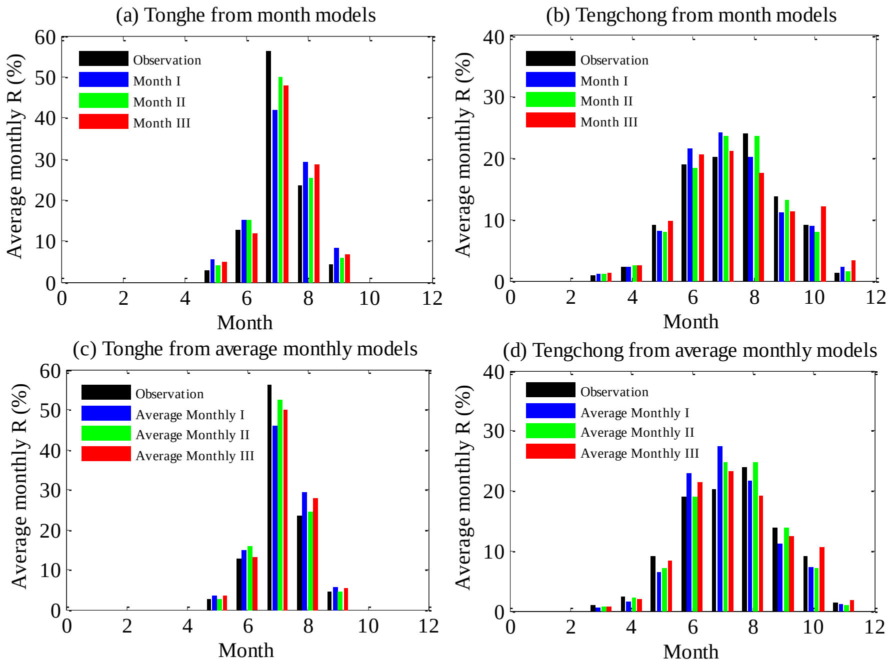
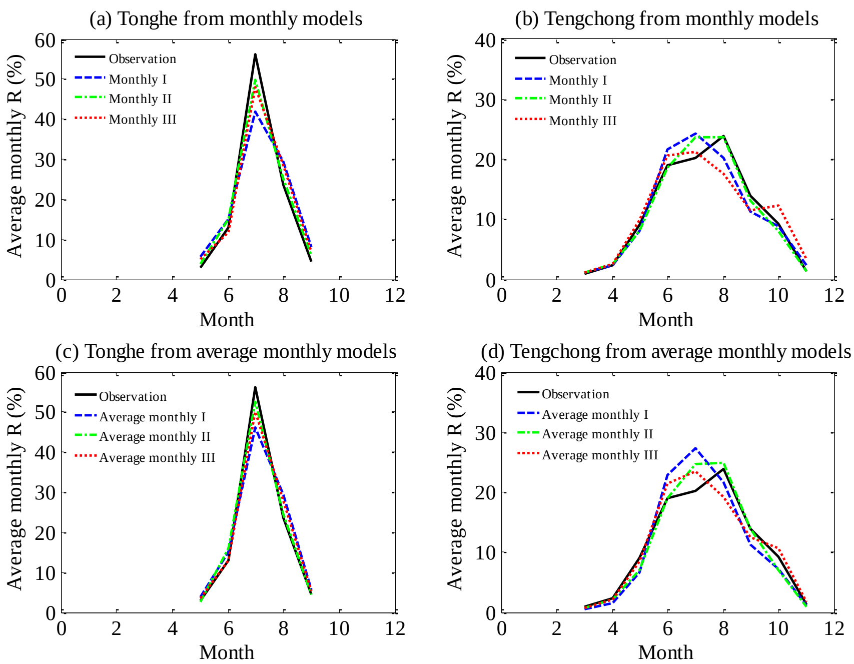


Fig. 3. Comparisons of average monthly R values between observation values calculated using one-minute resolution rainfall data and estimated values using month models (a, b) and average monthly models (c, d) for the Tonghe and Tengchong stations.



~~Fig. 3. Comparisons of average monthly R values between observation values calculated using one-minute resolution rainfall data and estimated values using monthly models (a, b) and average monthly models (c, d) for the Tonghe and Tengchong stations.~~

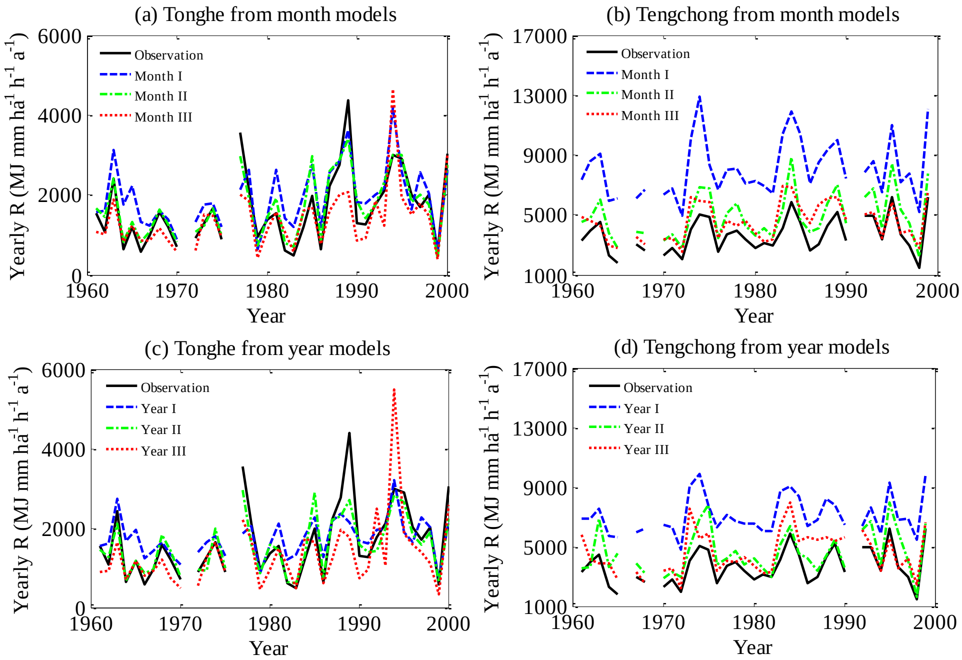


Fig. 4. Comparison of yearly R values between observation values calculated using one-minute resolution rainfall data and estimated values using month~~ly~~ models (a, b) and year~~ly~~ models (c, d) for the Tonghe and Tengchong stations. The years without marks were ineffective years.

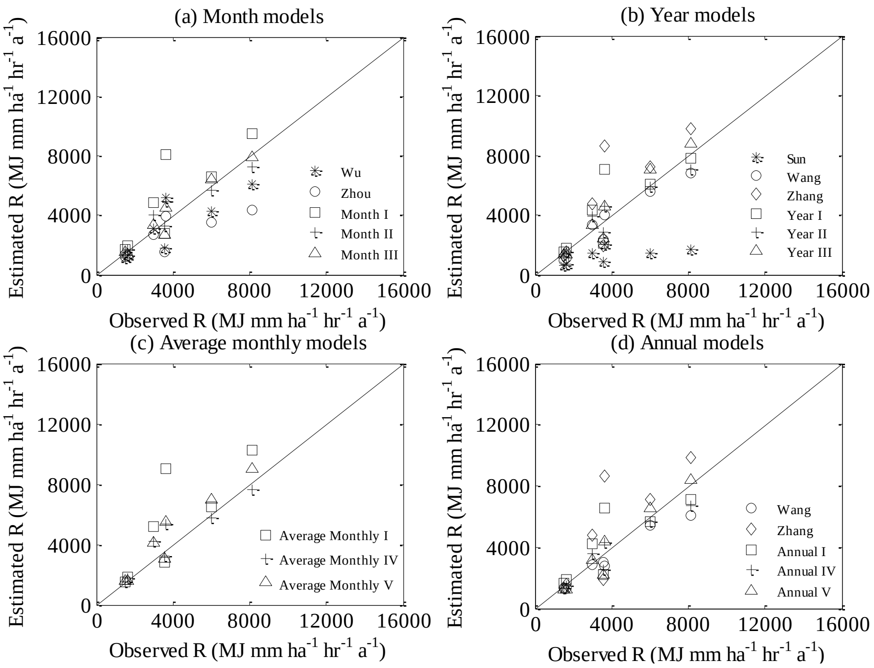


Fig. 5. Comparisons of the estimated R-factor value calculated based on (a) month~~ly~~, (b) year~~ly~~, (c) average monthly, and (d) average annual models using one-minute resolution data for the seven independent validation stations. Month~~ly~~ models included models in Wu (1994), Zhou et al. (1995), and Month~~ly~~ I, II, and III from this study. Year~~ly~~ models included models from Sun et al. (1990), Wang et al. (1995, the one with $MAPE_{sym}$ of 18.9%), Zhang and Fu (2003), and Year~~ly~~ I, II, and III from this study. Average monthly models included models from Average Monthly I, II, and III from this study. Average annual models included models from Wang et al. (1995, the one with $MAPE_{sym}$ of 11.5%), Zhang and Fu (2003, the one with $MAPE_{sym}$ of 34.6%), and Annual I, II, and III from this study.