Evaluation of the Relationship Between the RUSLE R-Factor and Mean Annual Precipitation

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Abstract

The first studies performed to measure and estimate soil erosion began in the early 1900s. By the 1940s, development of soil loss equations began in the Corn Belt. Walt Wischmeier and Dwight Smith introduced the Universal Soil Loss Equation (USLE) in 1965 and a revised version in 1978. The USLE became the standard equation used to estimate soil erosion from agricultural lands. Subsequent revised versions have been published, with the most commonly used one being the Revised Universal Soil Loss Equation (RUSLE) (Renard et al., 1997).

$$A = R*K*LS*C*P$$

Where A = soil loss in tons per acre per year

R = rainfall erosivity factor

K = soil erodibility factor

LS = slope length – gradient factor

C = crop/vegetation and management factor

P = support practice factor (contour farming, strip cropping, cross slope, etc.)

The rainfall erosivity factor (R) is defined as the average annual sum of individual storm erosion index values, EI_{30}, where E is the total storm kinetic energy per unit area, and I_{30} is the maximum 30 minute rainfall intensity. Calculation of the R-factor is a complex process and involves the collection of years of data. In addition, rainfall intensity data is not typically readily available for many parts of the globe. For these reasons, many attempts have been made to estimate the R-factor as a function of mean annual precipitation (P), a parameter that is available for most of the world. There are three major objectives of this paper:

- Establish geographic relationships between rainfall erosivity and mean annual precipitation in the conterminous United States, and compare them to previously published relationships.
- Determine the applicability and accuracy of these relationships.
- Determine the reasons for variability among geographic regions.

History of the USLE/RUSLE

The first studies on erosion and its effects on agricultural lands began in 1912 on an overgrazed farm in central Utah. 1929 marked the beginning of the Dust Bowl, a several year drought in the Great Plains that led to devastating dust storms caused by wind erosion. The damage caused by these storms led Congress to provide $160,000 in funding for soil erosion research. Using this money, ten stations were set up across the Midwestern U.S. to measure erosion and examine the factors affecting it. The main factors focused on were slope, slope length, types and rotations of crops, and conservations practices. From these studies, a large database of soil erosion and factors was created that would later be used in developing mathematical equations to estimate erosion. In 1933, the Soil Erosion Service (SES) was established as a part of President Roosevelt's "New Deal" program. The SES was later changed to the Soil Conservation Service (SCS) and became a permanent federal agency under the Department of Agriculture. In the 1940's, A.W. Zingg introduced the first mathematical equation to estimate soil erosion losses

$$A = C\,S^{1.4}\,L^{0.6}$$

Where A was average soil loss per unit area, C was a constant, S was percent land slope, and L was the length of the slope. In 1941, Dwight D. Smith introduced a conservation practice factor, P.

$$A = C\,S^{1.4}\,L^{0.6}P$$

In 1953, the Agricultural Research Service (ARS) began and many of the SCS employees that were involved in erosion research were transferred to the ARS. In the next year, 1954, the National Runoff and Soil Loss Data Center at Purdue University was created with Walt Wischmeier as its director. It became the central location for collection of soil loss data in the U.S. This data would be used in the development of equations to predict soil losses due to erosion. Over the next 11 years, Wischmeier, Smith and others compiled the data and analyzed it using early model computers. This culminated in the development of the Universal Soil Loss Equation (USLE), published in 1965 in USDA Agricultural Handbook 282. Over the next 13 years, Wischmeier and Smith would make improvements to the equation. The R-factor, which was initially only calculated for the Eastern half of the United States due to lack of intensity data in the West, would be extended to the Pacific Coast, using an empirical relationship found between R and the 2-yr, 6-hr rainfall depth. Also of note is the development of a soil erodibility nomograph (for the K-factor) in 1971, which used data from a large rainfall simulator study. In 1978, a revised version of the USLE equation would be published in USDA Agricultural Handbook 537. It would have the same form as the original, but with improvements made to the variables and a westward expansion.

$$A = RKLSCP$$

Where A = soil loss (tons per acre per year)

R = rainfall erosivity (hundreds of foot-ton-inches per acre per hour)

K = soil erodibility factor (ton-acre-hours per hundred foot-tons per inch)

LS = slope-length and gradient factor

C = crop/vegetation and management factor

P = support practice factor

Since 1978, many studies have been performed to improve upon the 1978 version of the USLE. Several revised versions have been published, with the Revised Universal Soil Loss Equation (RUSLE) being the most commonly used one today. Published by Renard and others in 1997, the RUSLE maintains the same form as the USLE equation. Each of the factors in the equation was revised to become more accurate. In addition to a revised R-factor equation, an increase in the number of rain gauges across the nation provided a denser and further-reaching data set. The R-factor map, or isoerodent map, was split into regions; each with more precisely calculated and displayed isoerodent lines than the original. Rainfall intensity data was now available in the West, so that the relationship between rainfall erosivity (R) and the 2-yr, 6-hr rain event would not be needed as an estimator any longer. A time-varying approach would now be used to calculate the soil erodibility factor (K). A sub-factor approach was developed for evaluation of the cover management factor (C). The slope-length and gradient factor (LS) was now calculated with a new and improved equation, and new conservation practice (P) values were introduced.

Literature Review

Using the data collected at the National Runoff and Soil Loss Data Center, Wischmeier and Smith developed an empirical formula for calculating rainfall erosivity (R). This was based on the analyses performed by their early model computers on over 10,000 plot-years of data. Wischmeier and Smith determined that the energy available to move sediment during a rainstorm is the product of the total amount of kinetic energy (E) contained within a storm, and the intensity (I) of the storm. This product became known as the *EI* parameter. The R-factor can be defined as the average annual sum of the *EI* parameters for all storms in a year. From the data analyses, they also determined that the maximum thirty minute intensity of the storm yielded the best results. The hyetograph shown below in **Figure 1** shows an example storm broken up into thirty minute increments, each with an approximated constant intensity.

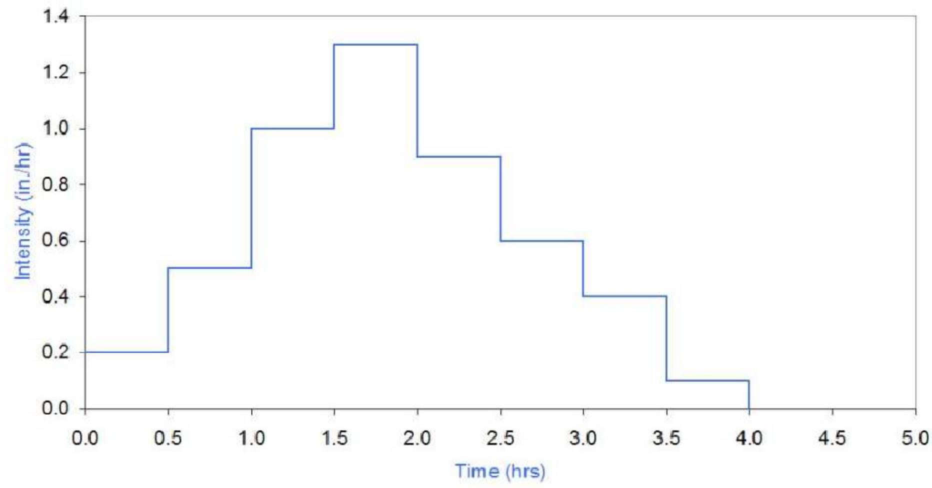

Figure 1- Example Storm Hyetograph

Wischmeier and Smith also developed the following empirical equation for determining E, the total amount of kinetic energy in a storm that would be used to initiate the motion of sediment particles:

$$E = 916 + 331 log_{10} I$$

Where E is in foot-tons per inch and I is the intensity of the storm in inches per hour. They found that for a given storm, energy did not increase with intensity above 3 inches per hour, so the maximum value used for I in this equation is 3.

After determining the E and I_{30} values for each individual storm over the period of record, they are to be multiplied by each other and then summed on a per-year basis. The average of these annual sums over the period of record is the R-factor.

$$R = \frac{1}{n}\sum_{j=1}^{n}\left[\sum_{k=1}^{m}(E)(I_{30})_k\right]_j$$

Where k is the number of the individual storm up to m, the total number of storms in a year, and j is the number of the year up to n, the total number of years over which data was collected.

In 1997, Renard and others published the Revised Universal Soil Loss Equation (RUSLE). With this came a new method for determining the R-factor. They would still use the *EI* parameter and the summation/averaging equation above. I_{30} would also be determined in the same manner as before. E, however, would be calculated using a new equation.

$$E = \sum_{k=1}^{m} e_r v_r$$

Where e_r is the rainfall energy per unit depth of rainfall per unit area (foot-tons per acre per inch), v_r is the depth of rainfall in inches for the r^{th} increment of a storm hyetograph which is divided into m parts, each with essentially constant rainfall intensity (in/hr). For each increment of the storm, e_r is determined using the following equation:

$$e_r = 1099\left[1 - 0.072^{(-1.27 i_r)}\right]$$

Where i_r is the approximated constant intensity over the time increment. The calculation of v_r is simply the product of intensity of the r^{th} increment and the length of the time of the r^{th} increment.

$$v_r = i_r t_r$$

Because many parts of the world still do not have detailed rainfall intensity data available, many studies have been performed to estimate the R-factor based on available rainfall data. In 1978, Bols performed an empirical study in Indonesia relating R to P (annual precipitation in mm). According to Teh (2011), this relationship is also applicable in Malaysia due to similar climatic conditions, and because annual precipitation data is easier to obtain than pluviographic data. R is in MJ*mm/(ha*hr) and P is annual precipitation in millimeters.

$$R = \frac{2.5P^2}{100(0.073P + 0.73)}$$

In January of 1997, Mikhailova, Bryant, Schwager, and Smith developed an equation relating their calculated R-factor to both mean annual precipitation and elevation in Honduras. In their research, they first established relationships between R-factor and each of the other two parameters. Their linear equation for R as a function of P is below where, again, R is in MJ*mm/(ha*hr) and P is annual precipitation in millimeters. Their relationship was very good, with an r^2 value of 0.86:

$$R = -3172 + 7.562P$$

In 2006, Torri et al. established a similar linear relationship between rainfall erosivity and annual rainfall (mm) in Italy. He found that the R-factor ($MJ*mm*ha^{-1}*hr^{-1}$) can be approximated by:

$$R = -944 + 3.08P$$

Renard and Fremund, in 1994, developed a power function to estimate the rainfall erosivity ($MJ*mm*ha^{-1}*hr^{-1}$) as a function of mean annual precipitation (mm) in the Continental U.S. Their equation (below) had an r^2 value of 0.81.

$$R = 0.04830P^{1.510}$$

Also using a power function, Yu and Rosewell established a relationship to estimate the R-factor ($MJ*mm*ha^{-1}*hr^{-1}$) based on mean annual precipitation (mm) in southeastern Australia in 1996. Their relationship was very good, with an r^2 value of 0.91.

$$R = 0.0438P^{1.61}$$

Table 1 below is a summary of the above equations.

Table 1 - Summary of previously developed relationships

Location	Equation
Indonesia (Bols, 1978) Malaysia (Teh, 2011)	$R = \frac{2.5P^2}{100(0.073P + 0.73)}$
Honduras (Mikhailova et al., 1997)	$R = -3172 + 7.562P$
Italy (Torri et al., 2006)	$R = -944 + 3.08P$
Conterminous U.S. (Renard, Fremund, 1994)	$R = 0.04830P^{1.510}$
S.E. Australia (Yu, Rosewell, 1996)	$R = 0.0438P^{1.61}$

Isoerodent Maps

Figure 2 is the isoerodent map developed by Wischmeier and Smith in 1965 for the conterminous United States. It can be seen that the Midwest has a fairly uniform spatial distribution of rainfall erosivity. In the Appalachian Mountains there is much more variability in the distribution. Because of the sporadic rainfall and lack of long-term recording-rain gage records available at the time, the western states were left off of this initial map. While detailed rainfall intensities were not available in the west, other rainfall data was. For the Western Plains and North Central States, researchers at Purdue found that there was reasonable accuracy in approximating the R-factor based on the 2-year, 6-hr rainfall amount. The updated map, seen in **Figure 3** was extended to the Pacific Coast in 1976 by using this relationship. The high level of climate variability in the West is very evident, as it is reflected in the rainfall erosivity.

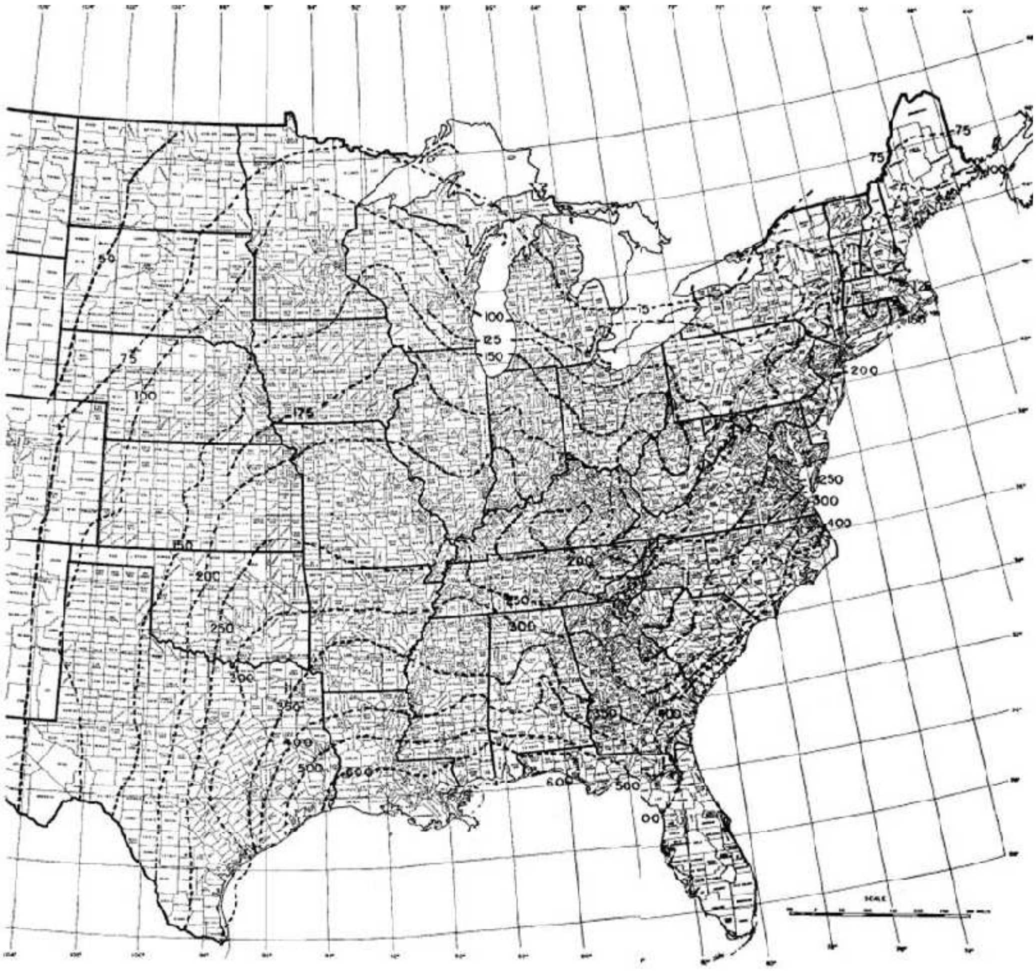

Figure 2 - Initial Isoerodent Map for the Eastern United States (Wischmeier, Smith 1965)

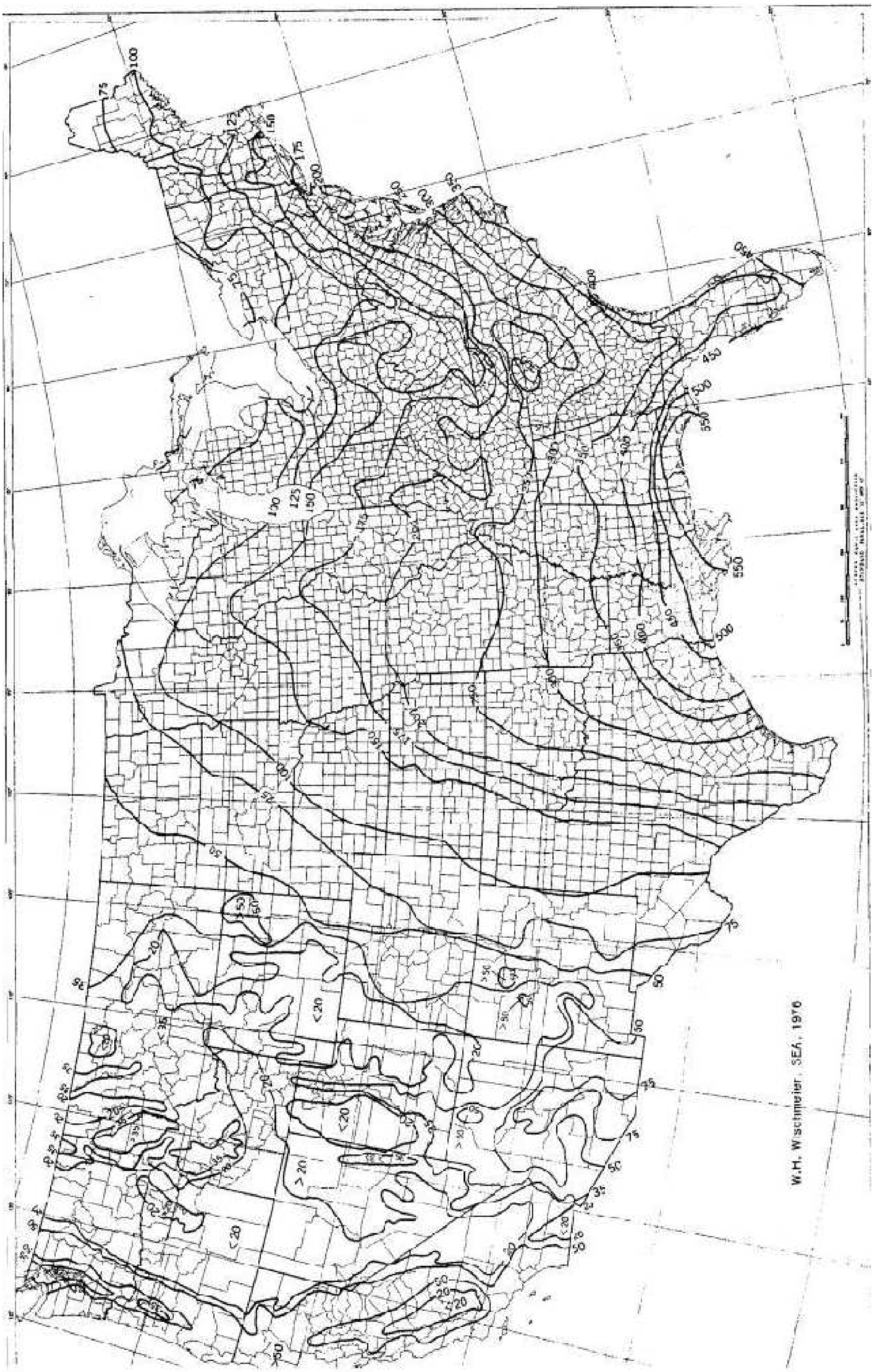

Figure 3 - Isoerodent Map for the Conterminous U.S. from Wischmeier and Smith (1976)

Using the updated formula for the R-factor from Renard (1997), new erosivity maps have been developed. These maps are divided into regions of the conterminous United States and were released by the EPA in 2001. **Figure 4** below is the map of Washington and Oregon. It is evident that this map is much more precise than the original maps released by Wischmeier and Smith. Notice that on the west coast, erosivity is very high, reaching values up to 340. The Cascade Mountains provide a barrier from precipitation for the eastern portions of the states. The effect of the mountains is reflected in the trends of the isoerodent lines in the central portions of the states. East of the mountains the erosivity is much lower, as expected, with an average value of around 10.

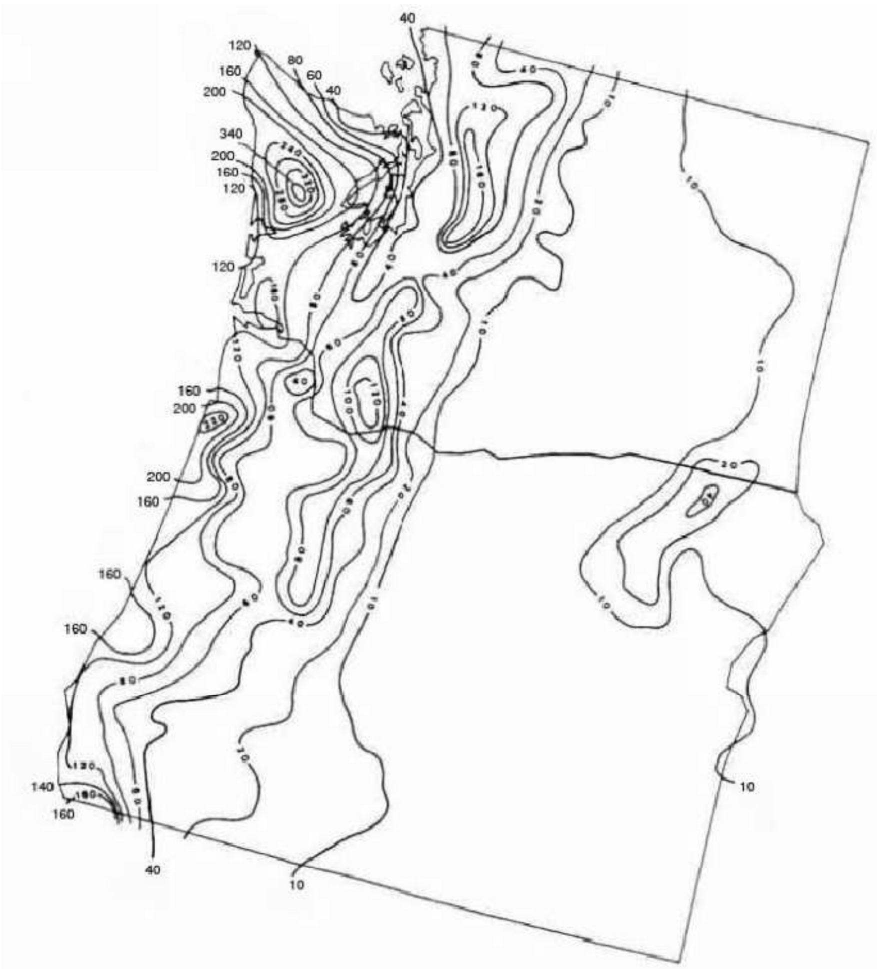

Figure 4 - Current Isoerodent Map for Washington and Oregon (EPA 2001)

Figure 5 is the current EPA isoerodent map for the state of California, published in 2001. The patterns seen here are very similar to those in Washington and Oregon. The Pacific Coast has the highest values, up to 180. There is a band running north and south in the North Central region of the state. This is the Sierra Nevada Mountains. Just like the Cascades to the north, the Sierra Nevadas shield the area to the east from precipitation. Southern California is much drier than Northern California, which is reflected in the isoerodent lines. In the Southeastern portion of the state is the Mojave Desert, which has extremely low values for R, below 10.

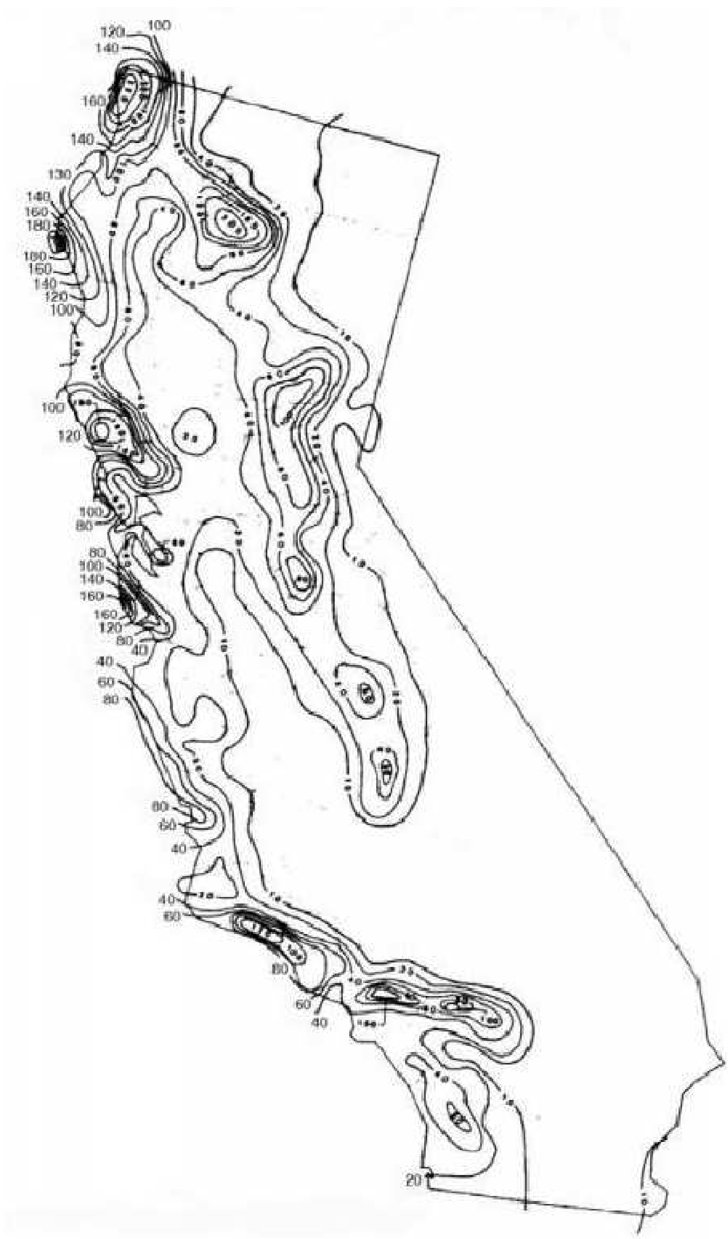

Figure 5 - Current Isoerodent Map for California (EPA 2001)

Figure 6 is the EPA (2001) isoerodent map for the Western United States. It contains Idaho, Montana, Wyoming, Nevada, Utah, Colorado, Arizona, and New Mexico. This is the most dynamic region of the Unites States with respect to elevation and climate. As expected, it also has the most dynamic spatial distribution of rainfall erosivity. For most of the higher elevations, the R-factor is around 10. This is because most of the precipitation in these areas is snow. While snow causes a considerable amount of erosion, the R-factor accounts only for erosion due to rainfall. In the USLE paper published in 1978, Wischmeier and Smith made an attempt to account for snow by altering the R-factor based on the annual amount of snowfall. This adjustment was not used in calculating the isoerodent lines, but rather the isoerodent lines are used to calculate the adjusted R-factor by adding to them the snowfall correction factor. The isoerodent lines are based solely on rainfall.

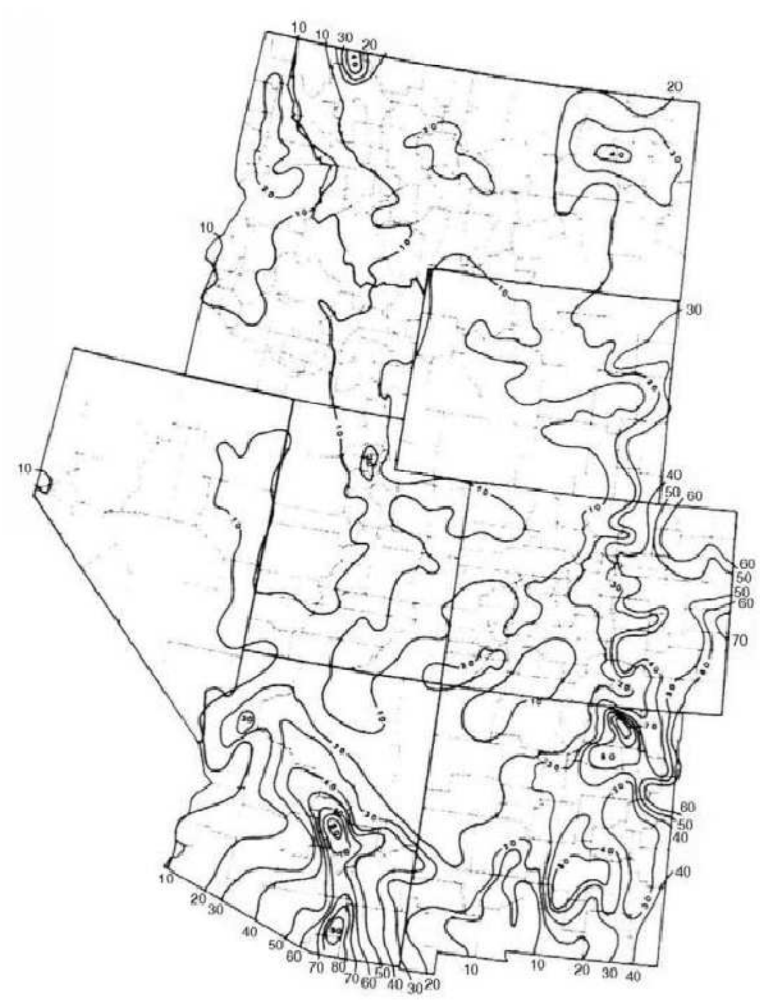

Figure 6 - Current Isoerodent Map for the Western United States (EPA 2001)

The Eastern United States (**Figure 7**) has a much more uniform distribution of rainfall erosivity than the other regions. The highest values are on the coast at the Gulf of Mexico, specifically in Louisiana, which receives a significant amount of rain, much of which falls during intense thunderstorms and hurricanes. The R-factor here is over 700. Values are also high along the southern portion of the Atlantic Coast due to the same processes, up to 600 at the southern tip of Florida. The Appalachian Mountains cause a "dip" in the isoerodent lines in eastern Tennessee, western North Carolina, eastern Kentucky, western Virginia, and West Virginia. This is because the mountains shield some of the weather coming from the Atlantic Coast and the Gulf of Mexico, and the high elevations here cause much of the precipitation to fall in the form of snow. West Texas is where rainfall erosivity is the lowest. This area is considered the arid Southwest. The lack of rainfall here causes a lack of rainfall erosivity.

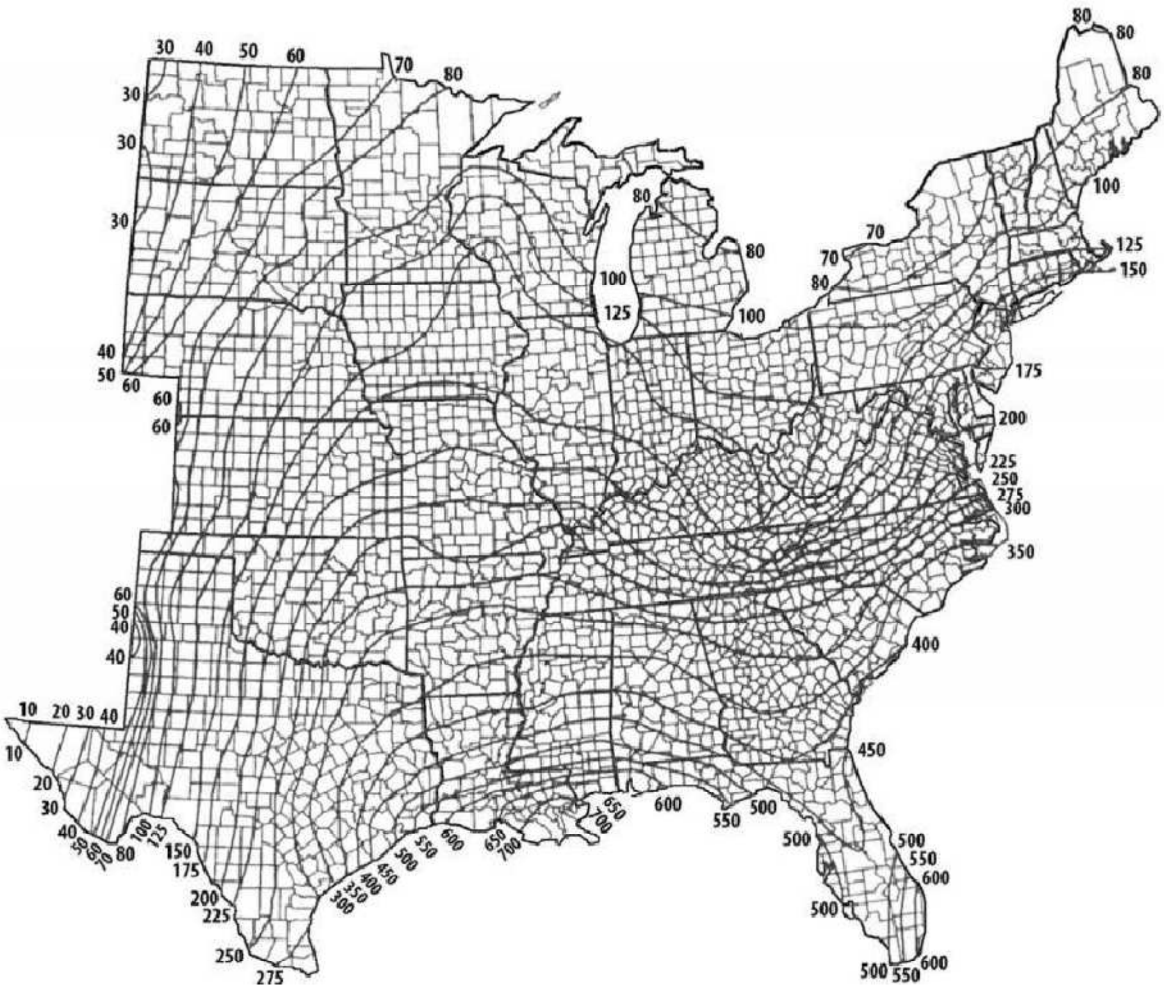

Figure 7 - Current Isoerodent Map for the Eastern United States (EPA 2001)

ArcGIS Processes

Because rainfall erosivity data is not available for download in an ArcGIS format, the maps in **Figures 4-7** were imported into ArcGIS as jpeg files. A shapefile was then created through a process called *heads-up digitizing*. The first step was to download a projected shapefile of the 48 conterminous states. Because the isoerodent maps are projected in Albers Equal Area Conic, the shapefile selected also had to be. After importing the states shapefile, each of the EPA isoerodent jpeg files was overlaid onto the map and the isoerodent lines were traced meticulously. It should be noted that although the isoerodent maps were labeled Albers Equal Area Conic, they did not line up properly. Each jpeg file had to be translated and/or rotated several times throughout the tracing process so that the two sets of data were approximately lined up for the given region being traced. After this process was complete, each line was assigned an R-factor by creating a field within the layer and manually inputting the associated value. **Figure 8** below shows the traced lines and the downloaded conterminous United States shapefile.

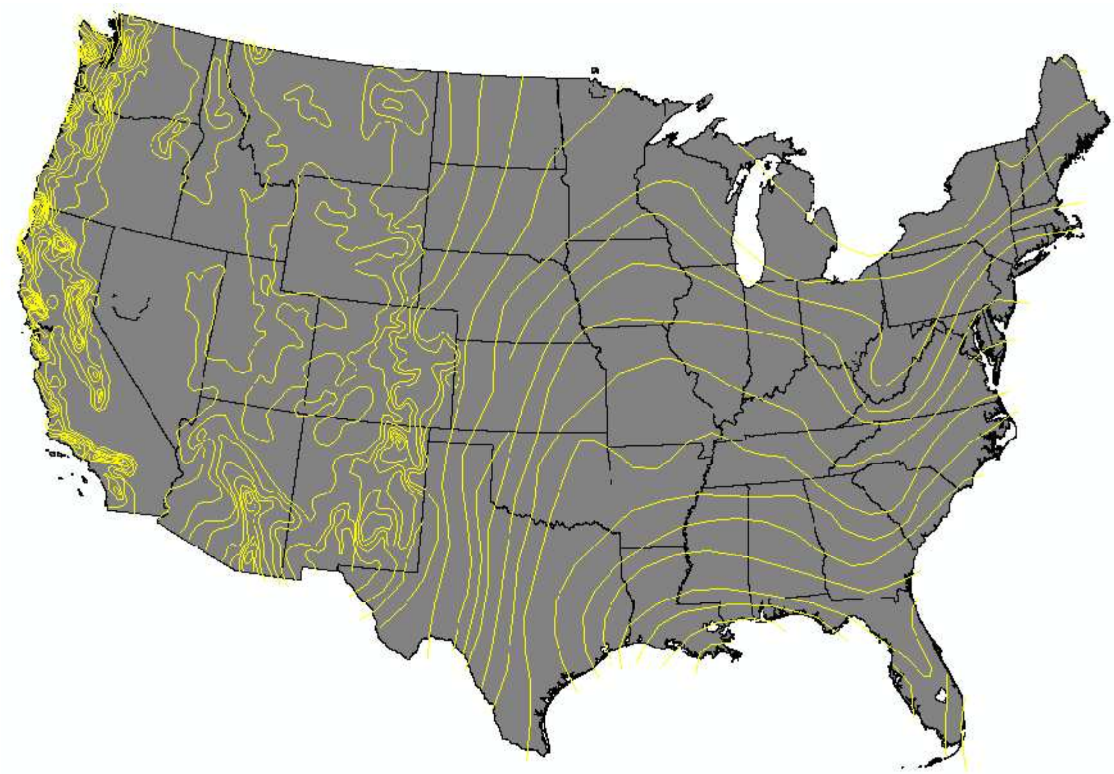

Figure 8 - Isoerodent Map for Conterminous United States Digitized in ArcGIS

The created isoerodent contours do not contain data between the lines. ArcGIS would be used to interpolate between those lines through raster creation. Using the *3D Analyst -> Raster Interpolation -> Topo to Raster* command under *Arc Toolbox*, a raster map of the R-factor was then created for the entire conterminous United States (see **Figure 9**). Now all points on the map had an associated rainfall erosivity that would later be used in data analysis. The lowest value for an isoerodent line on the maps was 10. Initially, the interpolation function assigned negative values to very small portions of the West. In order to avoid this, a minimum raster cell value of 5 was set, so that no cells were interpolated as being significantly lower than the published data. Small spots in Central Oregon, Northwestern California, and Southern California were affected by this boundary. This map gives a better visual representation of the rainfall erosivity's distribution across the U.S. than the isoerodent maps. Rather than reading off individual values from isoerodent lines and comparing with the values read from other parts of the country, one can immediately get an idea of how rainfall erosivity is distributed by looking at the raster image.

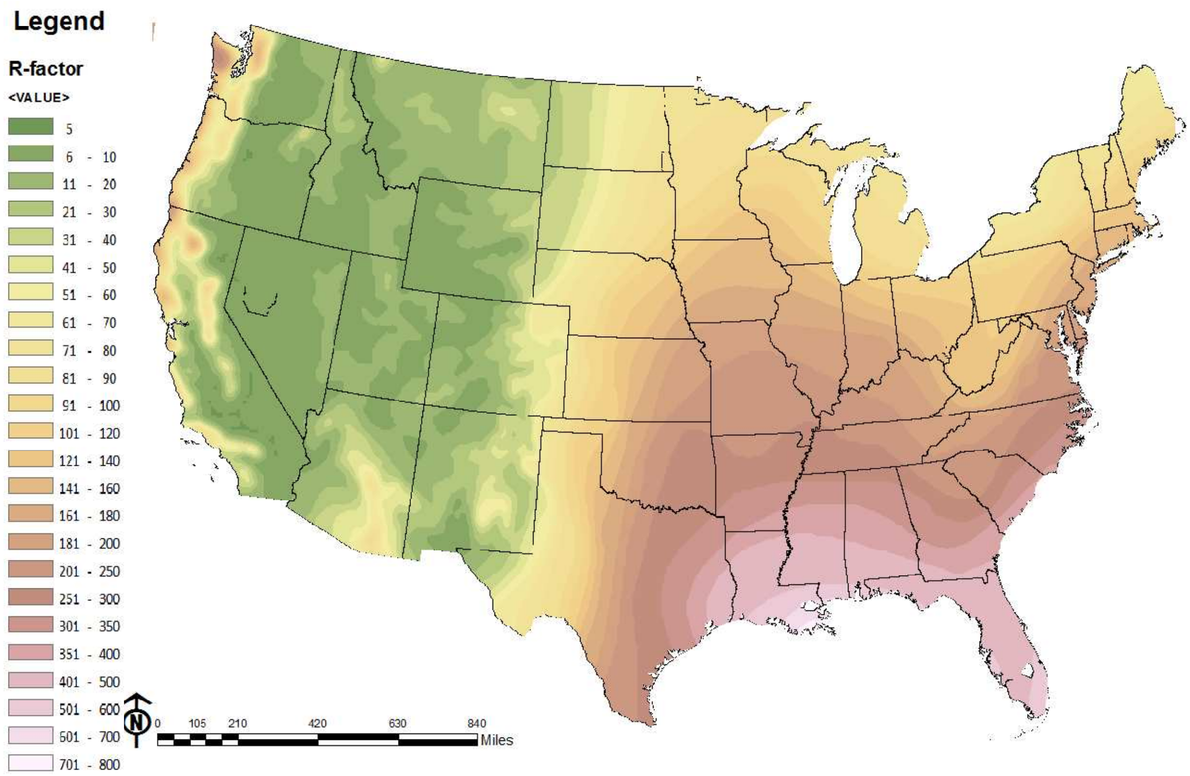

Figure 9 - Raster Map of the R-Factor for the Conterminous United States

After the rainfall erosivity (R) field was created, the next step was to create a field for mean annual precipitation (P). From www.nationalatlas.gov, the raw data was downloaded as a polygon shapefile. This data was mean annual precipitation in inches for the conterminous United States from 1961-1990. The shapefile was imported with the same projection as the data frame, so that it lined up directly with the data already in the ArcGIS file. Because this data was in polygon format, it had to be converted to a raster similar to the rainfall erosivity data. The *Arc Toolbox -> Conversion Tools -> To Raster -> Polygon to Raster* command was used to perform this operation. The polygon file and precipitation field were selected as the inputs and the precipitation raster was the output (**Figure 10**). The distribution of rainfall is somewhat similar to that of rainfall erosivity, with the highest values being in the Southeast and Northern Pacific Coast. However, while erosivity is clearly higher around the Gulf of Mexico than in the Northern Pacific Coast, mean annual precipitation is not. The highest values for precipitation are in the Western portions of Washngton, Oregon, and Northern California. The lowest values are in the Southwest, and in portions of the Rocky Mountains. Also in the Rocky Mountains are areas that receive a high amount of precipitation in the form of snow.

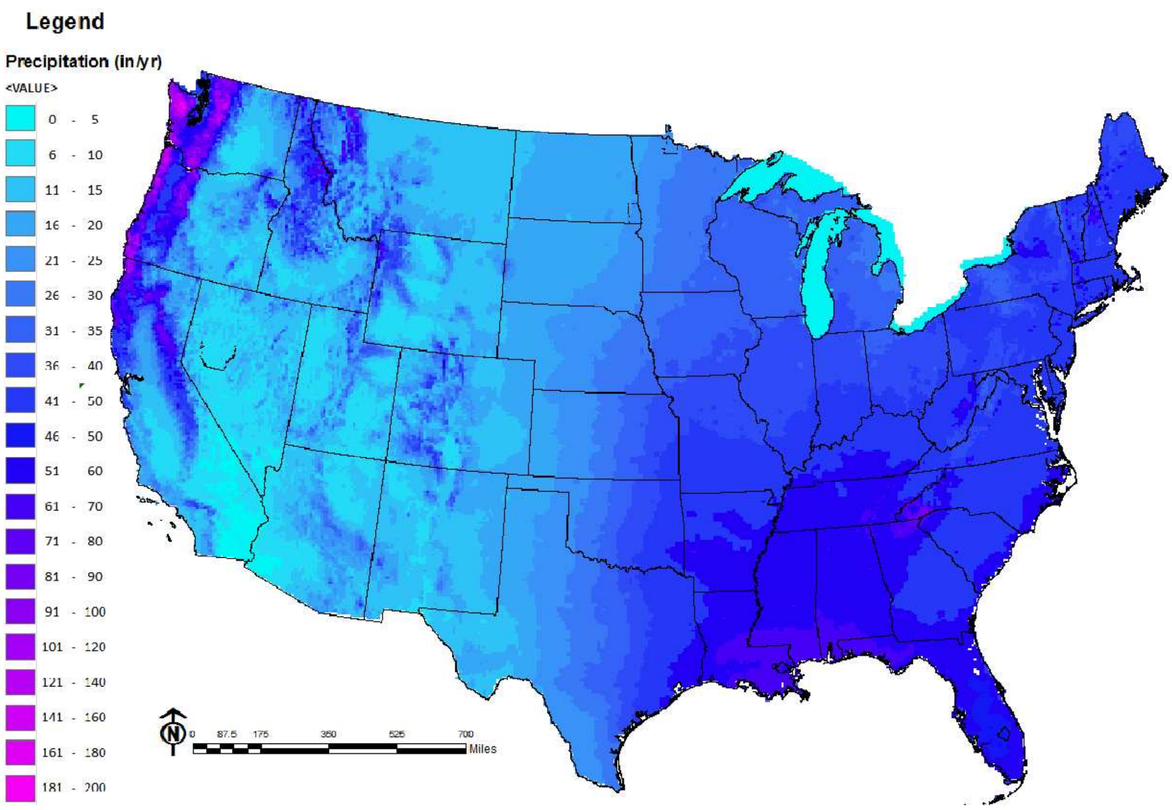

Figure 10 - Raster Map of Mean Annual Precipitation (in/yr) for Conterminous United States

Figure 11 below shows the isoerodent contours overlaid on the mean annual precipitation raster image. Using this map, comparisons between R and P can begin to be made. The general trends are similar, with high values in the Pacific Northwest and in the Southeast for both parameters. The Northeast seems to have an approximate median value for both R and P. The Rocky Mountains have a high variability of annual precipitation, but consistently low rainfall erosivity. This is expected, due to the high precipitation amounts being in the form of snow, which rainfall erosivity does not account for. Near the Pacific Coast, where precipitation values are high, erosivity also appears to be high, and where precipitation values are low, erosivity appears to be low. An initial assessment indicates that the Eastern United States, Washington and Oregon, and California will all have good relationships between R and P, while the Rocky Mountains will not. The region of the country where the two parameters appear to have the best relationship is a band running north and south in the Central U.S., including Texas, Oklahoma, Kansas, Nebraska, South Dakota, and North Dakota. The trends in the two parameters in the region just north of the Gulf of Mexico also seem to behave in a similar fashion.

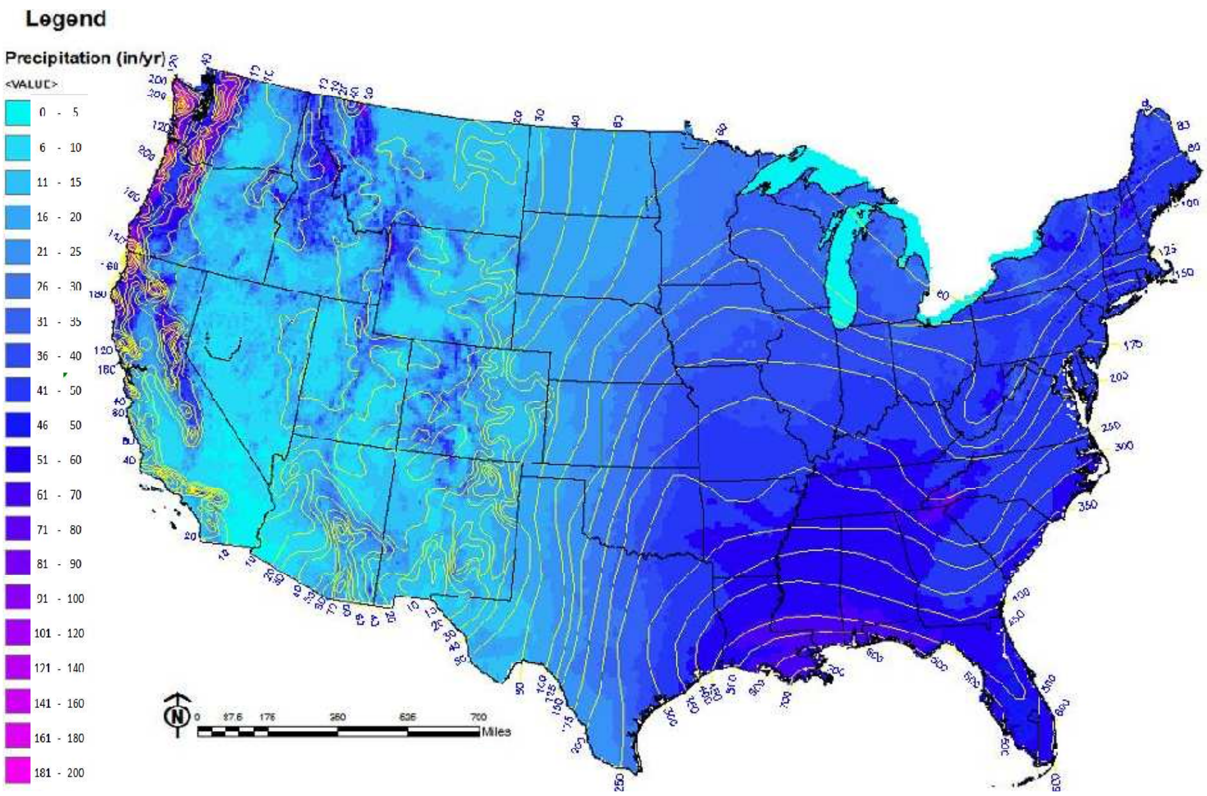

Figure 11 - Isoerodent Map Overlaid on the Precipitation Raster Map for Conterminous United States

Now that the two parameters had an entire field of data covering the conterminous United States, specific data points had to be created, each having an associated value for rainfall erosivity and mean annual precipitation. At this point the decision was made to split the map into regions matching the regions from the EPA isoerodent maps. These regions were chosen because of the initial assessment made based on the observed patterns in **Figure 11**. For each region, a new shape file layer was created and within that shape file, an arbitrary set of points was generated using the *sketch* tool under the *editor* toolbar. Points were placed so that all portions of each region were represented with no bias towards any particular part of the region. **Figure 12** shows the data point placement in the Washington/Oregon region. This process was repeated for each of the regions. Once each region had a set of data points created, each data point had to have a value assigned to it for each of the parameters. This was achieved through use of a command called *Surface Spot*, under *Arc Toolbox -> 3d Analyst -> Functional Surface* (**Figure 13**). This command creates a field within a feature class and assigns a value to each point in that field based on a surface. The value assigned to each point is the value from the designated field in the selected raster image at the location of the data point. If a data point is located at the intersection of multiple cells within the raster image, then ArcGIS interpolates a value, using a weighted average function. For each region, this process was repeated using the R-factor raster and the precipitation raster as input surfaces. Once completed, each set of data points now had an associated R and P, which could be viewed by right clicking on the layer name and selecting *Open Attribute Table* from the drop down menu. From this table, this data was copied and pasted into Microsoft Excel.

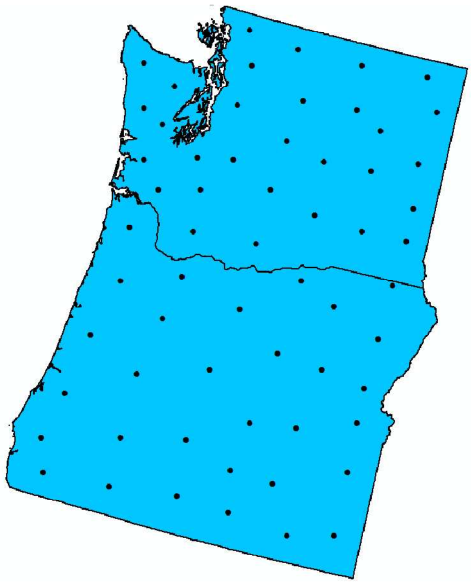

Figure 12 - Data Point Placement in Washington and Oregon

Figure 13 - Surface Spot Command

Data Analysis

Excel would be used to compile and plot the data, and then generate trendlines to approximate a relationship between the two parameters. It should be noted that the power functions generated approximate a homoschedastic relationship, while the actual data is heteroschedastic, with a larger range of values for the R-factor at high precipitation depths. For Washington and Oregon, the following power function trendline was generated:

$$R = 0.27P^{1.26}$$

On the plot below in **Figure 14**, it can be seen that the R-factor values range from approximately 5 up to 250, while the precipitation ranges from approximately 10 up to just over 100 inches per year. There is a visible trend and the trendline seems to approximate it well, with an r^2 value of 0.8224. Of the four regions, this one has the highest r^2 value, and therefore the most predictable rainfall erosivity based on mean annual precipitation.

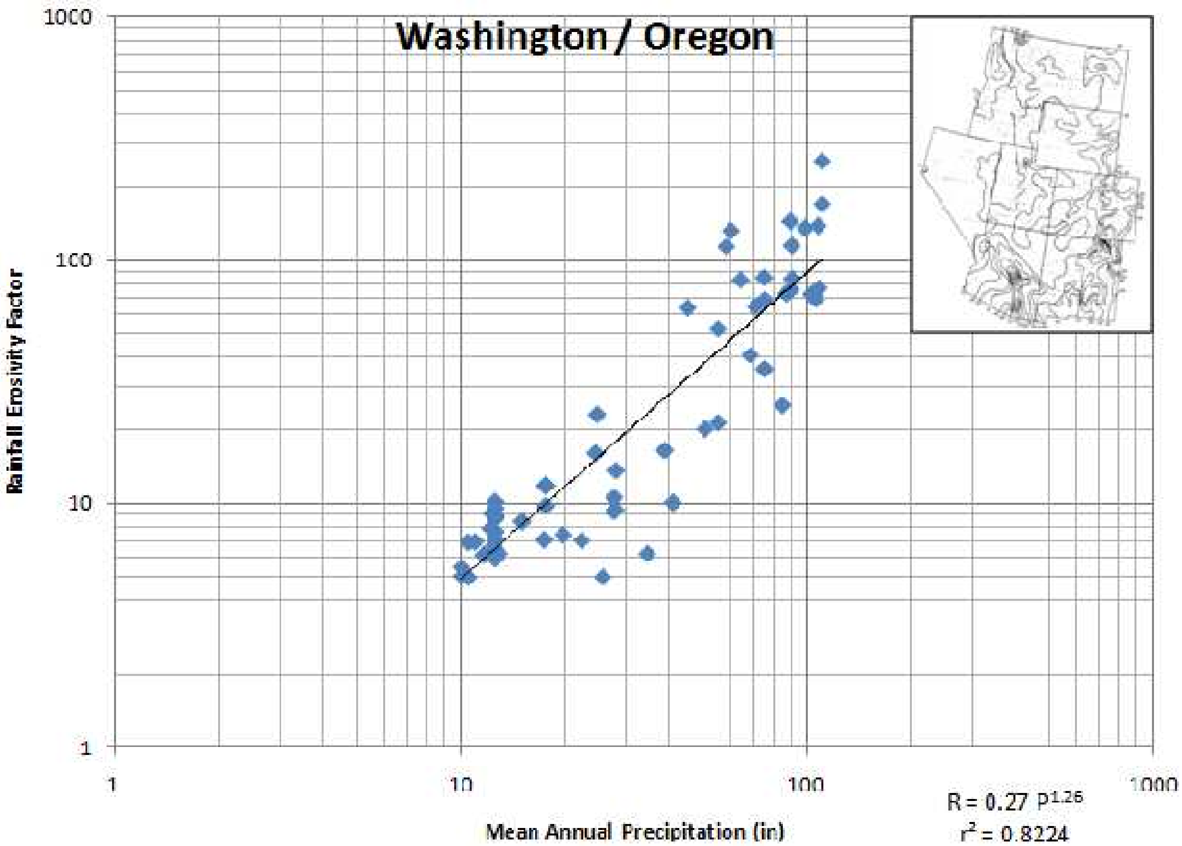

Figure 14 - Data Plot for Washington and Oregon

In California, the lower bound for rainfall erosivity is again around 5, while the upper bound is quite a bit lower than in Washington and Oregon, at just over 100. The rainfall range is from 5 inches per year up to just over 100 inches per year.The following power function trendline was generated by Excel:

$$R = 0.82P^{1.09}$$

The equation gives a fairly decent approximation of erosivity based on mean annual precipitation, although not as good as the equation for Washington and Oregon. This r^2 value for this function is significantly lower, at 0.606. There does appear to be a trend in the data that could be approximated with a step function, where $R \approx 7$ when P is below 20 inches per year, and $R \approx 100$ when P is above 20 inches per year. This is most likely because of the drastic and well defined variability in California's climate, with very wet regions on the Northwest coast and desert in the Southeast. See **Figure 15**.

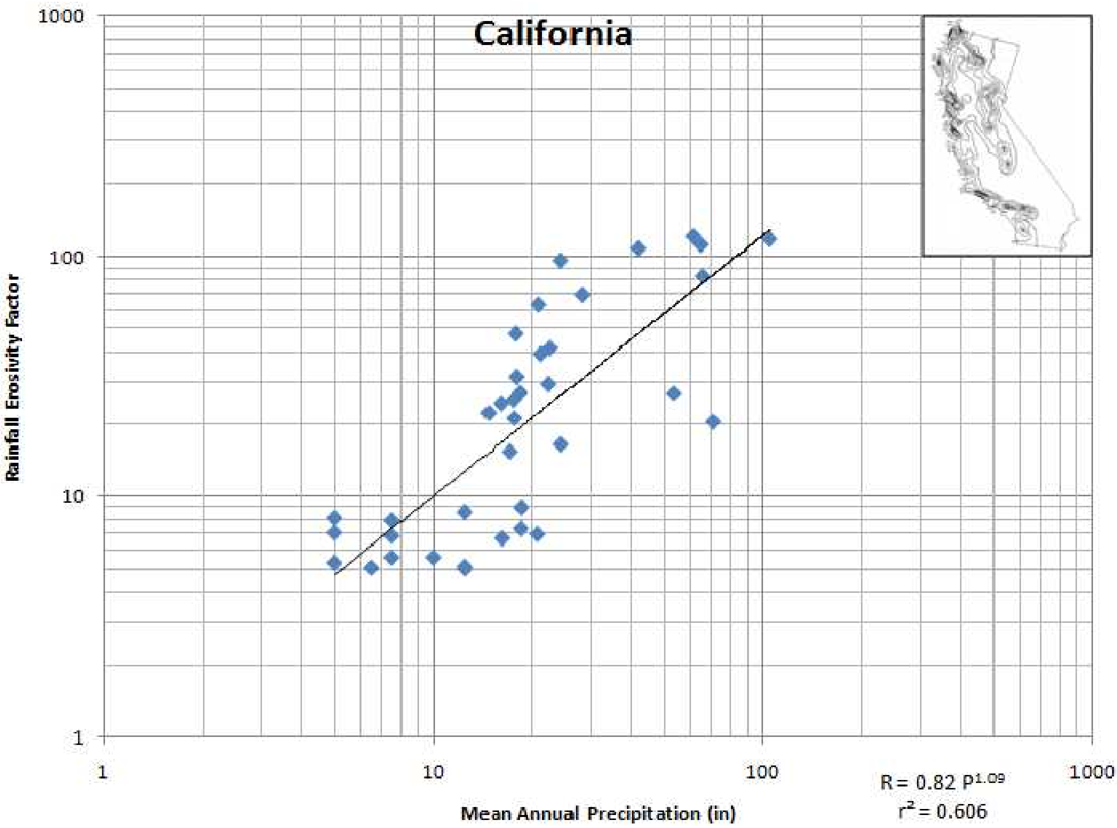

Figure 15 - Data Plot for California

In the Western United States, there is no recognizable relationship between rainfall erosivity and mean annual precipitation. The main cause for this is snow. The areas that receive the most annual precipitation receive it in the form of snow, not rain. This causes high P values and low R values. Still, a trendline was generated so that comparisons could be made with other regions and within this region:

$$R = 9.17P^{0.20}$$

As expected, the r^2 value for this function is extremely low, at 0.0176. This means that there is no identifiable relationship between R and P in the given data set. If annual snowfall were considered, a trendline could likely be generated that would yield a much better approximation of the R-factor. Another observation is that the USLE equation was developed for agriculture, based on data from farmland. Farmland is not common in these areas of high elevation where snowfall is high. See **Figure 16**.

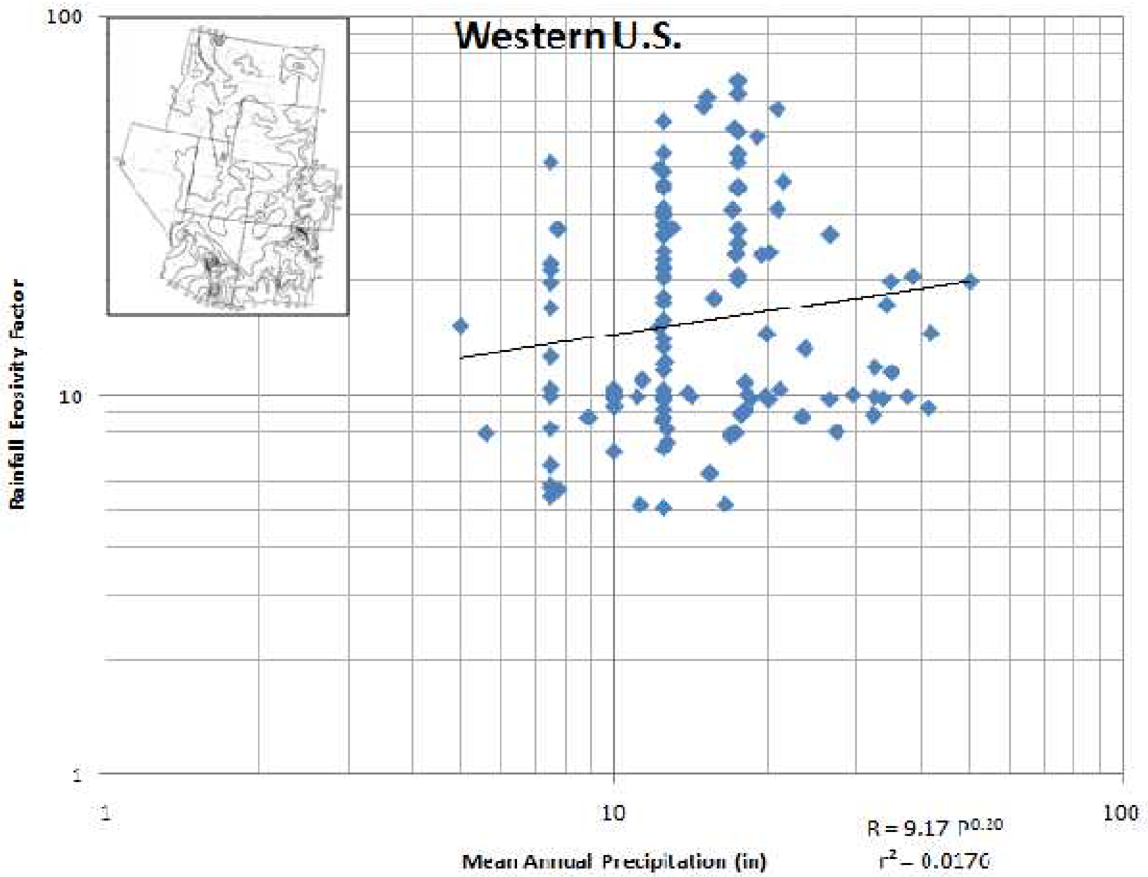

Figure 16 – Data Plot for the Western United States

The Eastern United States has much higher values for rainfall erosivity than the other three regions. The lowest value is just under 20, while the upper bound is approximately 700. This is because much of the rainfall in the Southeast comes in the forms of intense thunderstorms and hurricanes. The intensity of these storms causes the erosivity to be higher for a relatively lower precipitation depth. The power function generated to approximate the relationship between the two parameters is:

$$R = 1.24P^{1.36}$$

While the data appears to fit the trendline better than in the other regions, the r^2 value of 0.5727 is significantly lower than in Washington and Oregon, and slightly lower than in California. This is because the values for the R-factor are higher. The log-log plot reduces the visibility of variability in the upper regions of the plot. See **Figure 17**.

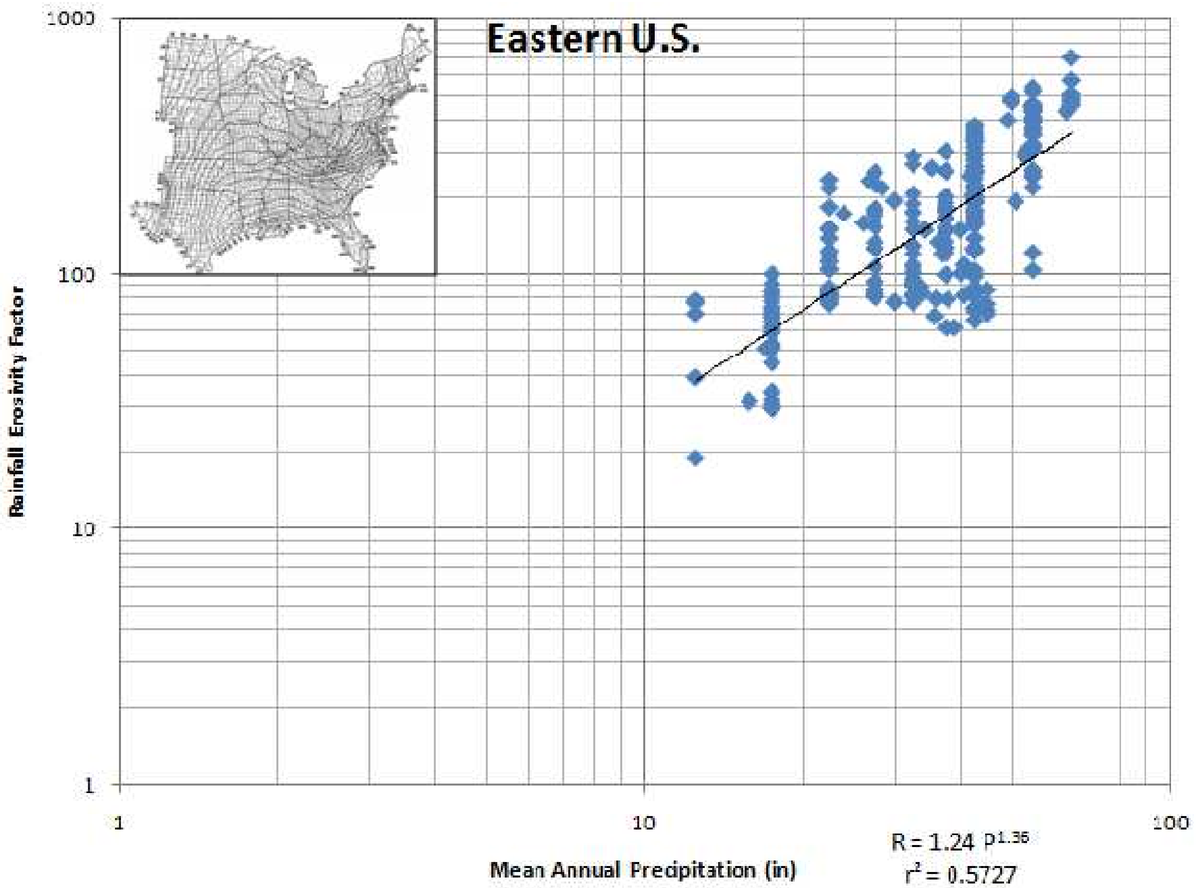

Figure 17 - Data Plot for the Eastern United States

Figure 18 shows all of the data points for the conterminous United States. Each region is displayed in a different color and the trendlines are shown. The highest R-factors occur in the Eastern United States, as expected based on the presence of intense thunderstorms and hurricanes there. California has the most extensive range of precipitation values, because of its climatic variability, with desert in the Southeast and abundant rain in the Nortwest. The Western United States have relatively low values for both R and P. Washington and Oregon have a wide range of both R and P due to the variable climate caused by the Cascade Mountain Range. The clear separation of the relationships suggests that regional analyses must be performed when predictting rainfall erosivity based on mean annual precipitation. If attempting to estimate R based on P for a region where the R-factor has not yet been calculated, the relationship must be chosen from an area with similar climate. Even then, the expected error will be significant.

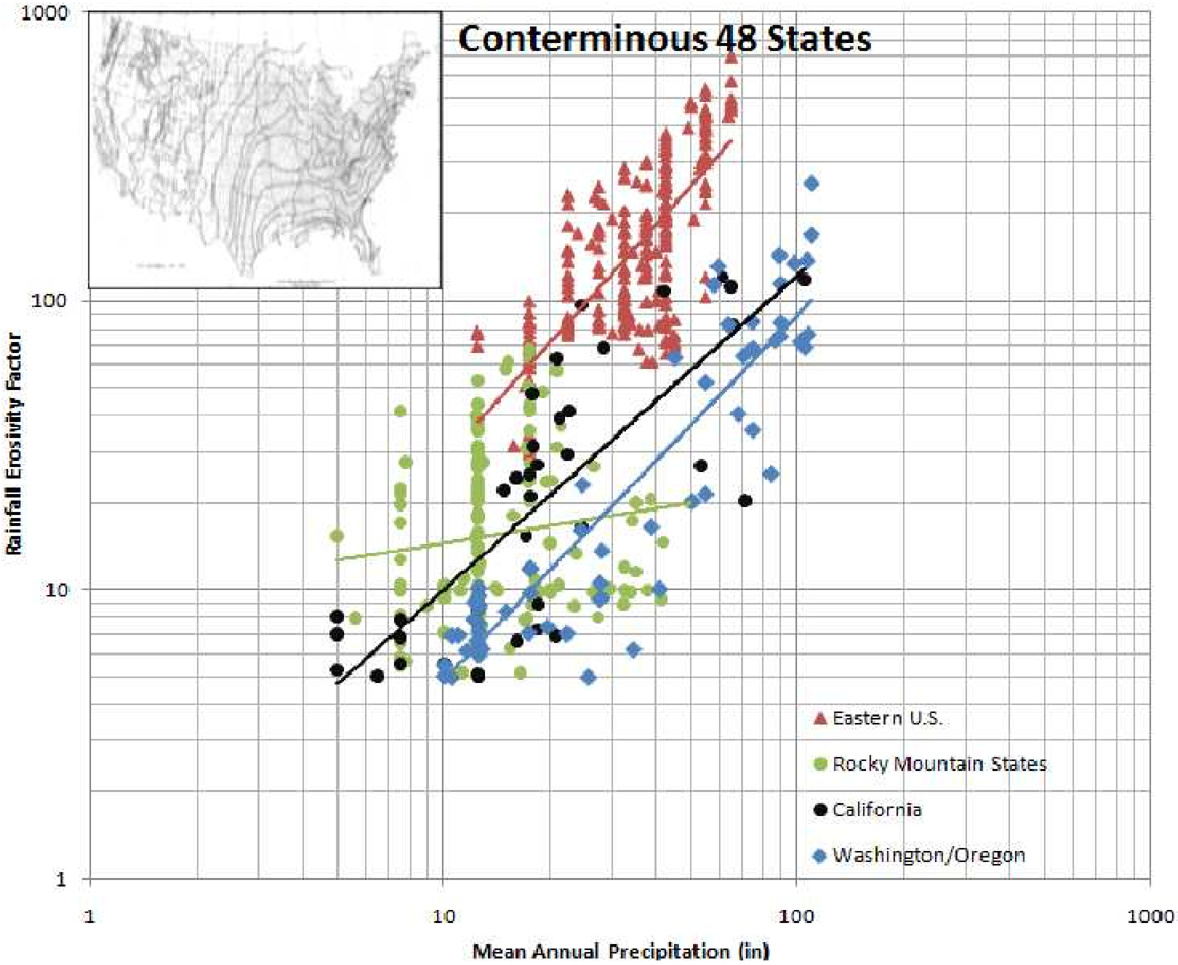

Figure 18 - Composite Data Plot for the Four Regions

Table 2 summarizes the relationships, using the following equation form:

$$R = aP^b$$

Where a is the scale factor and b is the shape factor. Without consideration of the Western United States, because of its inaccuracy, the average value for the shape factor, b, is 1.24. The values for the scale factor, a, are more highly variable and reflect climatic regional variability

Table 2 - Summary of the Regional Prediction Equations

Region	a	b	r^2
Washington/Oregon	0.27	1.26	0.82
California	0.82	1.09	0.61
Western U.S.	9.17	0.2	0.02
Eastern U.S.	1.24	1.36	0.57

Once the relationships were established, it was apparent that they contained a significant amount of error. In order to gain a better understanding of why and where this occurs, the error would have to be quantified and represented geographically. To quantify the error in each point, the following equation was used:

$$\%Error = 100 * \left(\frac{R_{predicted} - R_{actual}}{R_{actual}}\right)$$

Using this equation, at points where the trendline underestimates the R-factor, the error will be negative, and at points where the trendline overestimates the R-factor, the error will be positive. In order to represent the error geographically, ArcGIS was used to create maps of the error in each region. This was achieved by using the field calculator to calculate the predicted R-factor, based on the generated equation for each region (**Figure 19**). Once the field for the predicted R-factor was created, the error could be calculated also using the field calculator (**Figure 20**).

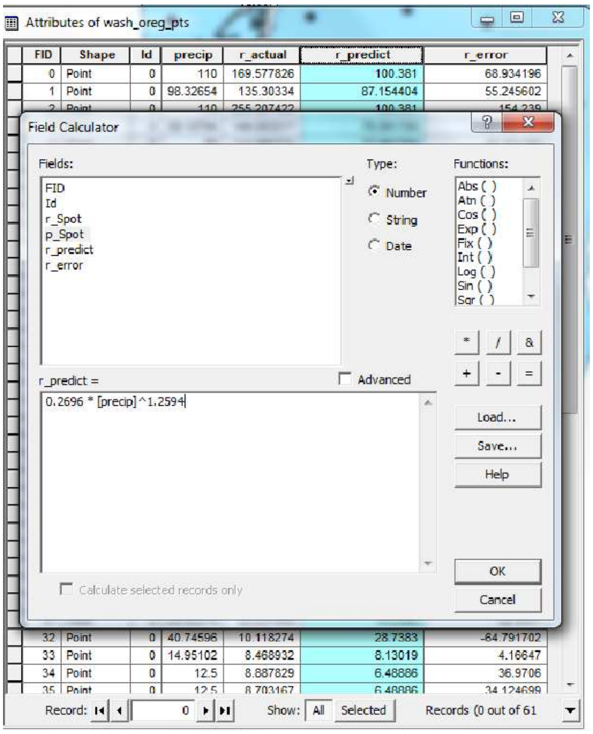

Figure 19 - Screen Shot of Predicted R Field Calculation

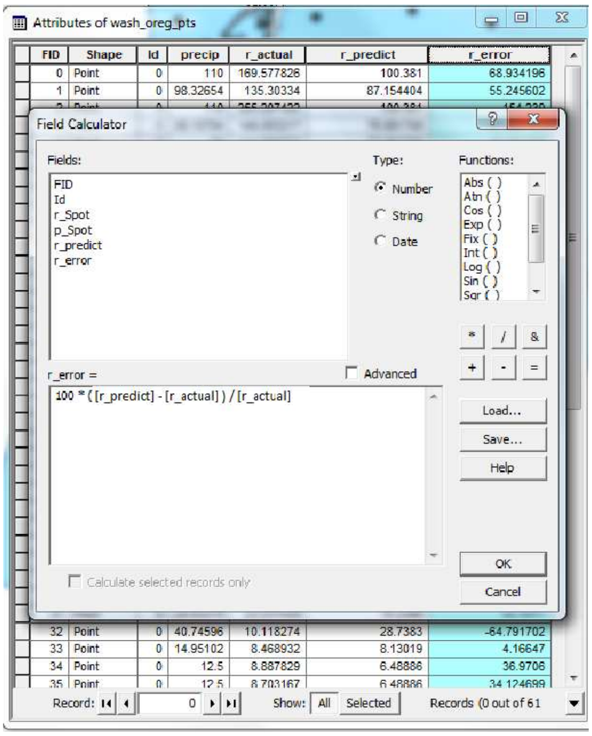

Figure 20 - Screen Shot of Error Field Calculation

Now that each region had a field created relating each data point to its percent error, a map could be created. These maps would be useful in helping to determine where and why the error occurs. In order to create these maps, the *3d Analyst -> Raster Interpolation -> Natural Neighbor* command was used. This command creates a raster image based on field values associated with point data. Because only exists at the data points in each region, this method introduced a zone of poorly interpolated data around the perimeter of the data point locations (**Figure 21**). To remedy this, the raster was cropped around the outer data points and a geostatistical tool called *Kriging* was used to smooth the image and extend it to the boundary of each region. The smoothing performed by the *Kriging* command would introduce a slight amount of error to the maps. This error would be insignificant, because the maps are simply for viewing the location of the overestimation and underestimation of the R-factor by the prediction equations, which was unaffected by the smoothing.

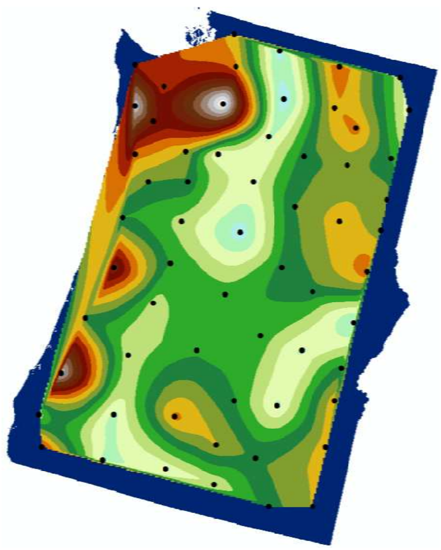

Figure 21 - %Error Raster with Poor Perimeter Interpolation

The Washington and Oregon error map is shown in **Figure 22**. Areas in green are where the prediction equation underestimates the R-factor, and areas in purple are where the R-factor is overestimated by the equation. As expected, the prediction equation underestimates the R-factor where rainfall is highest, near the Pacific Coast. The maximum error associated with this underestimation is about 64%. It overestimates the R-factor where snowfall is highest, in the Cascade Mountains. This is also expected due to the amount of snow that falls in the mountains. The maximum of the overestimation is about 215%. Interestingly, in the eastern portion of the state, where precipitation is very low, the prediction equation underestimates the rainfall erosivity. This is likely because while rainfall is low there, erosivity is high relative to the mountainous part of the region.

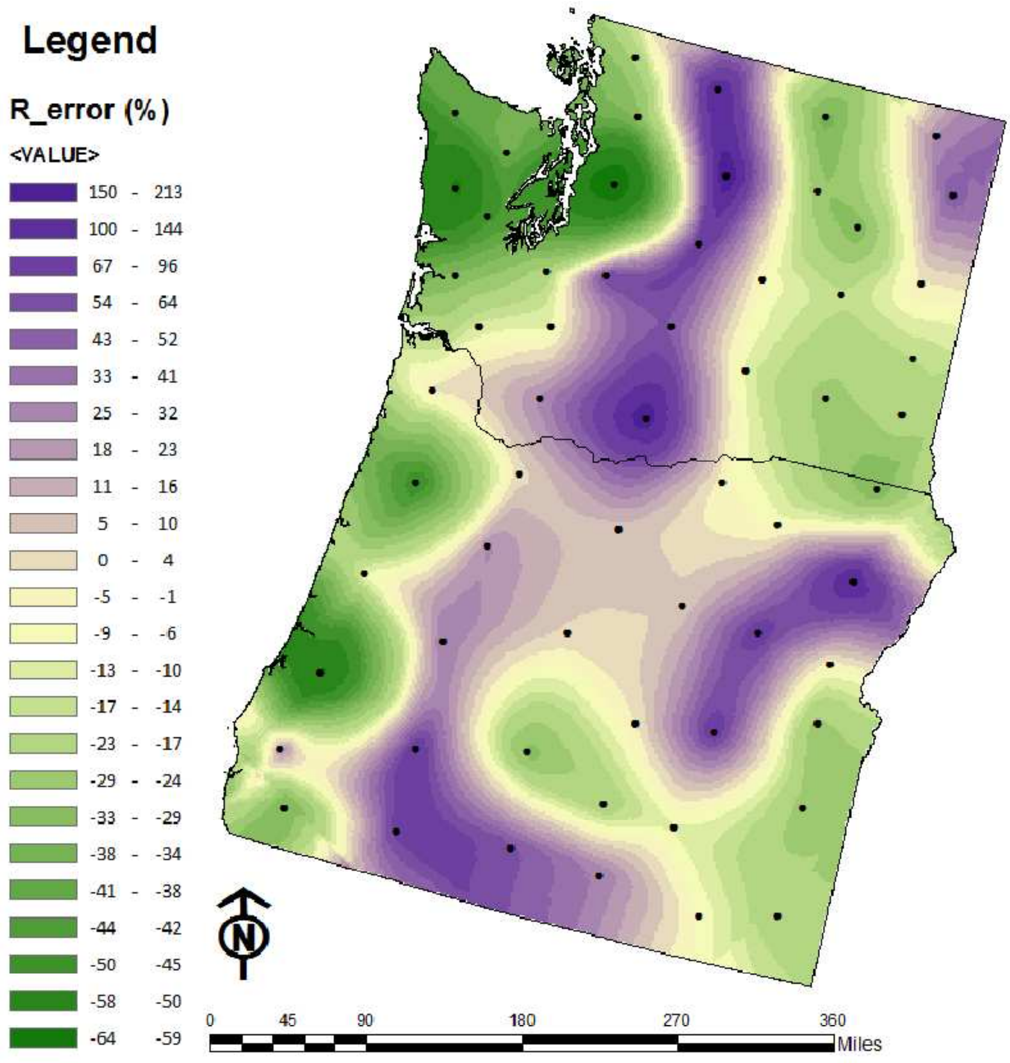

Figure 22 - Error Between Estimated and Actual R-Factors for Washington and Oregon

The mapped error for the state of California is shown below in **Figure 23**. As is the case in Washington and Oregon, the prediction equation here underestimates the rainfall erosivity near the Pacific Coast, where rainfall is most frequent and most intense. The maximum underestimation is significantly higher than in Washington and Oregon, at approximately 74%. This occurs just south of the San Francisco Bay. In the Cascade and Sierra Nevada Mountain Ranges, the rainfall erosivity is overestimated by the prediction equation. As in Washington and Oregon, this is due to the high amount of precipitation that falls in the form of snow, which does not contribute to rainfall erosivity. The largest magnitude of overestimation is about 260%, which occurs in the Sierra Nevada Range in the East-Central portion of the state. In the Mojave Desert (Southeastern California), the prediction equation appears to be fairly accurate. The reason for this is not so much what happens here, but what doesn't. There is no snow to skew the erosivity lower, and there is very little intense rainfall to skew the erosivity higher. Therefore, the R-factor's relationship with precipitation is not at either extreme.

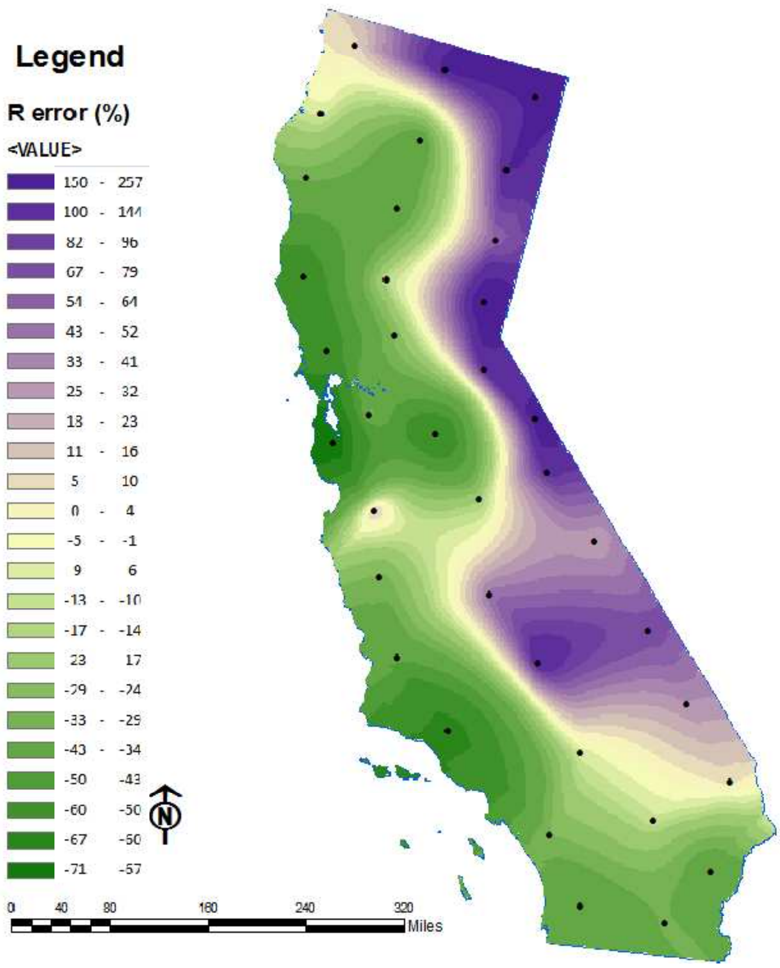

Figure 23 - Error Between Estimated and Actual R-Factors for California

The relationship between rainfall erosivity and mean annual precipitation is almost non-existent. The r^2 value associated with the generated trendline is 0.0176. While the equation does not accurately predict the R-factor, it can be used to get a visual representation of how R behaves relative to mean annual precipitation. There are three major geographic features present in this part of the country, all with different climates. They are the mountains (Rocky Mountains and Sierra Nevada), the arid Southwest (Mojave Desert), and the Great Plains in the East. **Figure 24** shows that in the mountainous parts of the region, the prediction equation overestimates the R-factor. Just like in Washington, Oregon, and California, this is due to the high percentage of the precipitation that falls here as snow, which doesn't affect rainfall erosivity. The maximum error for the overestimated area is approximately 200%. In the eastern part of the region is the Great Plains. Intense thunderstorms here raise the erosivity, causing the prediction equation to underestimate it, with a maximum error around 75%. In the Southwest, there is very little rain, but the rain that does fall typically comes in intense thunderstorms, causing the R-factor to be relatively high with respect to the mean annual precipitation. The maximum error here is also around 75%.

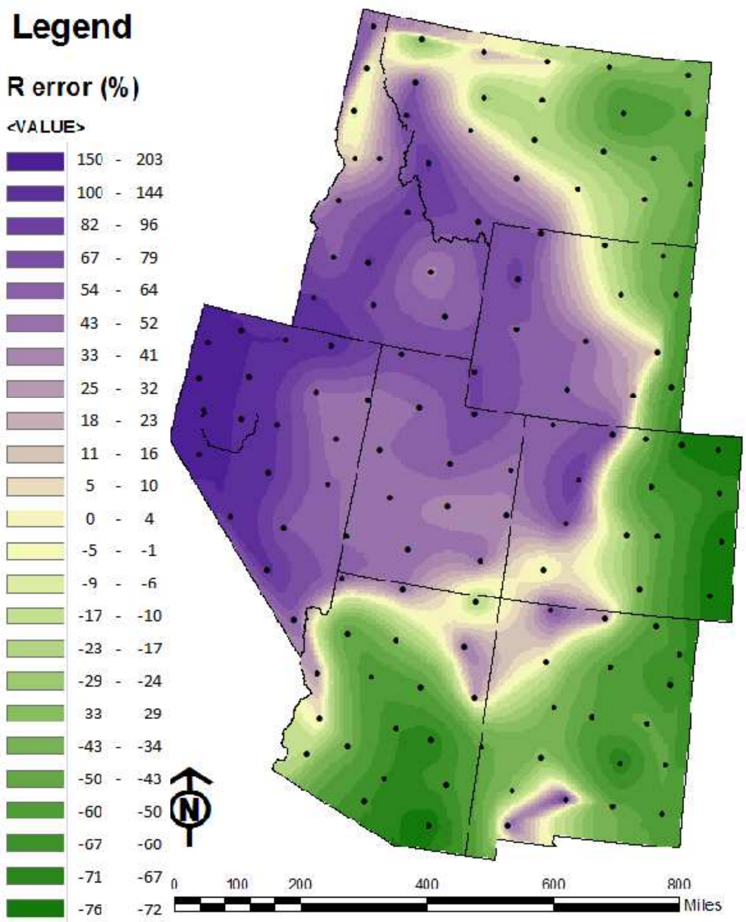

Figure 24 - Error Between Actual and Predicted R-Factors for the Western United States

Figure 25 shows the mapped error in the Eastern United States. The prediction equation here had an r^2 value of 0.5727. The Southeast experiences thunderstorms and even hurricanes near the Gulf of Mexico and along the Eastern Seaboard. These intense rains cause the erosivity to be high with respect to the amount of annual precipitation. Here, the prediction equation underestimates the R-factor. The maximum underestimation error of 63% occurs in the southern tip of Texas, where mean annual rainfall is low, but intense hurricanes are experienced. In the Northeast, much of the precipitation comes in the form of snow. Much like in other regions of the country, this causes the prediction equation to overestimate the R-factor. The overestimation extends as far south as eastern Tennessee, North Carolina, and even into northern Georgia. This coincides with the southern end of the Appalachian Mountains. The maximum overestimation error (200%) occurs in the northern part of Maine, where snow is most common. The area where the prediction equation is most accurate is in parts of the Midwest and between the central portion of the Eastern Seaboard and the Appalachian Mountains. These areas experience little snow and intense storms are also less prevalent.

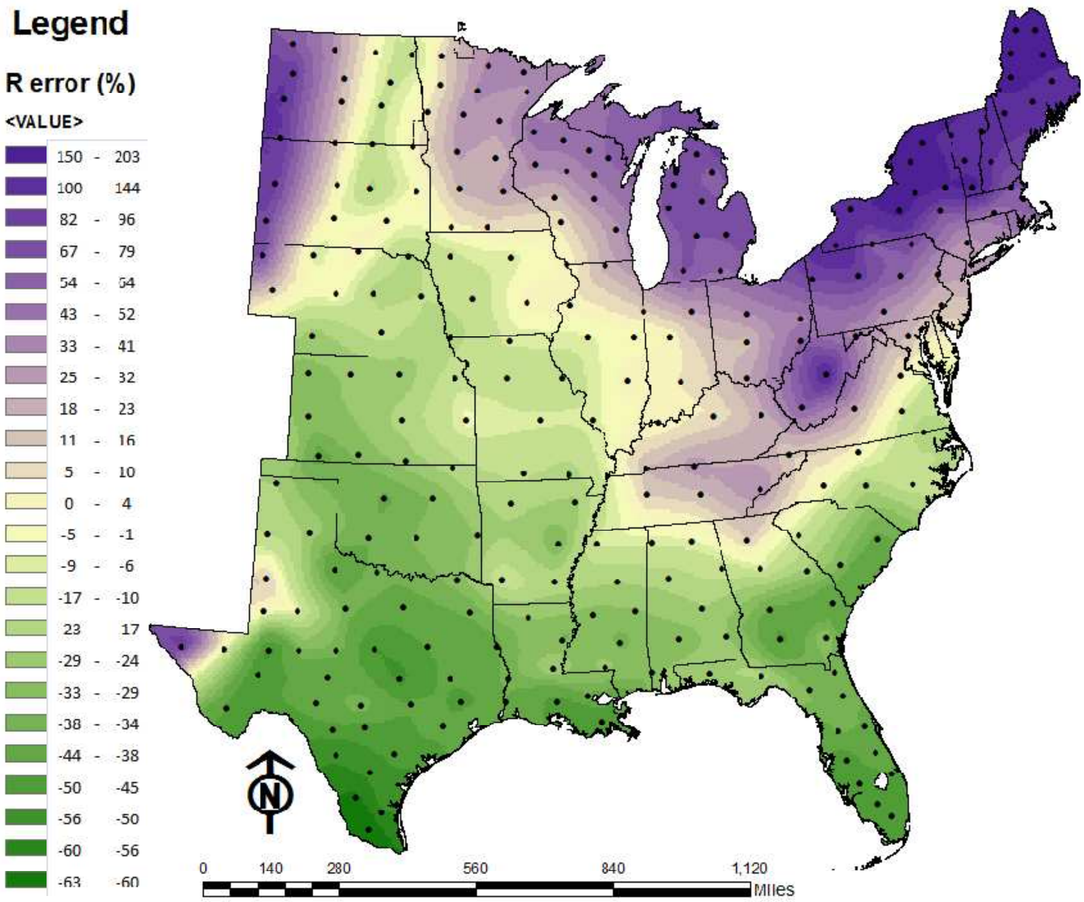

Figure 25 - Error Between the Actual and Predicted R-Factors in the Eastern United States

Comparisons with Other Relationships

In order to compare the relationships from this study to previously developed ones mentioned in the Literature Review, the first step was to plot each relationship. Because this study has used English units and previous studies have used the International System of Units (SI), unit conversion would be necessary.

$$\frac{1\ MJ*mm}{ha*hr}*\left(\frac{368.78\ ft-tons}{MJ}\right)*\left(\frac{1\ hundred\ ft-ton}{100\ ft-tons}\right)*\left(\frac{1\ in}{25.4\ mm}\right)*\left(\frac{1\ ha}{2.471\ ac}\right)$$
$$=.05876\left(\frac{hundred\ ft-ton*in}{ac*hr}\right)$$

Each of the five previously developed relationships is plotted below in **Figure 26**, along with the relationships from this study. **Table 3** shows R and P for each of the previously developed equations, in both English and SI units. The estimated R-Factor can range over an order of magnitude, depending on which relationship is used. This suggests that selection of a proper estimation is imperative.

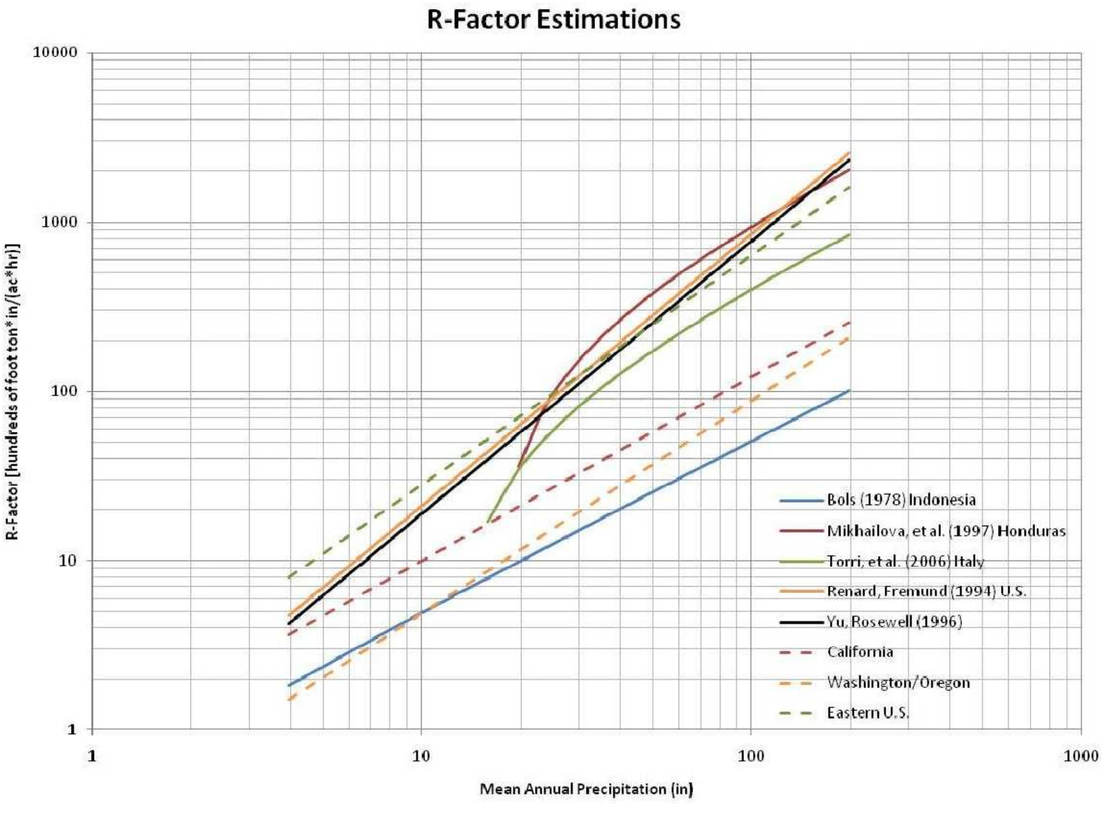

Figure 26 - Compilation of R-Factor Estimations

Table 3 - R and P for Previously Developed Equations in Both English and SI Units

		Bols (1978) Indonesia		Mikhailova, Bryant, Schwager, Smith (1997) Honduras		Torri, et al. (2006) Italy		Renard Fremund (1994) Continental U.S.		Yu, Rosewell (1996) Southeast Australia	
P (mm/yr)	P (in/yr)	R (SI)	R (English)	R (SI)	R (English)	R (SI)	R (English)	R (SI)	R (English)	R (SI)	R (English)
100	4	31	2	-2416	-142	-636	-37	80	5	73	4
200	8	65	4	-1660	-98	-328	-19	245	14	222	13
300	12	99	6	-903	-53	-20	-1	470	28	426	25
400	16	134	8	-147	-9	288	17	747	44	677	40
500	20	168	10	609	36	596	35	1070	63	970	57
600	24	202	12	1365	80	904	53	1435	84	1301	76
700	28	236	14	2121	125	1212	71	1839	108	1668	98
800	31	271	16	2878	169	1520	89	2280	134	2068	121
900	35	305	18	3634	214	1828	107	2756	162	2499	147
1000	39	339	20	4390	258	2136	126	3265	192	2961	174
1100	43	373	22	5146	302	2444	144	3807	224	3452	203
1200	47	408	24	5902	347	2752	162	4380	257	3972	233
1300	51	442	26	6659	391	3060	180	4982	293	4518	265
1400	55	476	28	7415	436	3368	198	5613	330	5090	299
1500	59	510	30	8171	480	3676	216	6273	369	5688	334
1600	63	545	32	8927	525	3984	234	6960	409	6311	371
1700	67	579	34	9683	569	4292	252	7673	451	6958	409
1800	71	613	36	10440	613	4600	270	8413	494	7629	448
1900	75	647	38	11196	658	4908	288	9178	539	8323	489
2000	79	682	40	11952	702	5216	306	9968	586	9039	531
2100	83	716	42	12708	747	5524	325	10783	634	9778	575
2200	87	750	44	13464	791	5832	343	11621	683	10538	619
2300	91	784	46	14221	836	6140	361	12483	734	11320	665
2400	94	819	48	14977	880	6448	379	13369	786	12123	712
2500	98	853	50	15733	924	6756	397	14277	839	12947	761
2600	102	887	52	16489	969	7064	415	15207	894	13791	810
2700	106	921	54	17245	1013	7372	433	16160	950	14654	861
2800	110	955	56	18002	1058	7680	451	17135	1007	15538	913
2900	114	990	58	18758	1102	7988	469	18130	1065	16441	966
3000	118	1024	60	19514	1147	8296	487	19148	1125	17364	1020
3100	122	1058	62	20270	1191	8604	506	20185	1186	18305	1076
3200	126	1092	64	21026	1236	8912	524	21244	1248	19265	1132
3300	130	1127	66	21783	1280	9220	542	22323	1312	20243	1189
3400	134	1161	68	22539	1324	9528	560	23422	1376	21240	1248
3500	138	1195	70	23295	1369	9836	578	24541	1442	22255	1308
3600	142	1229	72	24051	1413	10144	596	25680	1509	23287	1368
3700	146	1264	74	24807	1458	10452	614	26838	1577	24338	1430
3800	150	1298	76	25564	1502	10760	632	28016	1646	25405	1493
3900	154	1332	78	26320	1547	11068	650	29212	1716	26490	1557
4000	157	1366	80	27076	1591	11376	668	30427	1788	27592	1621
4100	161	1401	82	27832	1635	11684	687	31661	1860	28712	1687
4200	165	1435	84	28588	1680	11992	705	32914	1934	29847	1754
4300	169	1469	86	29345	1724	12300	723	34185	2009	31000	1822
4400	173	1503	88	30101	1769	12608	741	35474	2084	32169	1890
4500	177	1538	90	30857	1813	12916	759	36781	2161	33354	1960
4600	181	1572	92	31613	1858	13224	777	38105	2239	34555	2030
4700	185	1606	94	32369	1902	13532	795	39448	2318	35773	2102
4800	189	1640	96	33126	1946	13840	813	40808	2398	37006	2174
4900	193	1675	98	33882	1991	14148	831	42185	2479	38255	2248
5000	197	1709	100	34638	2035	14456	849	43580	2561	39520	2322

Conclusions

The following relationships were developed for the conterminous United States:

Washington and Oregon:

$$R = 0.27P^{1.26}$$

$$r^2 = 0.82$$

California:

$$R = 0.82P^{1.09}$$

$$r^2 = 0.61$$

Western United States:

$$R = 9.17P^{0.20}$$

$$r^2 0.02$$

Eastern United States:

$$R = 1.24P^{1.36}$$

$$r^2 0.57$$

Where R is rainfall erosivity (hundreds of foot-ton inches per acre per hour), and P is mean annual precipitation (inches). Without consideration of the Western United States, because of its lack of a good relationship, the shape factors in these power functions range from 1.09 to 1.36. This is relatively consistent. The scale factors in the power functions, however, have a broader range. This suggests that climate only affects the scale factor. The slopes of the power functions on a log-log plot are relatively consistent.

This trend remains when these relationships are compared with those developed for other parts of the world (**Figure 26**). The plots all seem to have a similar slope, because of consistent shape factors. However, they cover a wide range of R-factors for a given mean annual rainfall because of scale factor variability. The R-factor range can span an order of magnitude for a given mean annual precipitation. This high variability suggests that consideration of climate is imperative when choosing a relationship to estimate the R-factor for a region where it has not yet been calculated. The process through which precipitation falls seems to have the largest effect on the R-factor. Regions that receive their precipitation primarily in the form of snow will have a much lower scale factor in the power function. Areas that experience frequent, drizzling rainfalls, like the Pacific Northwest, will also have a small scale factor. Where hurricanes and intense thunderstorms occur, the R-factor will be relatively high for a given mean annual precipitation, resulting in a large scale factor in the estimation equation.

Even when climate is carefully considered in choosing a relationship to estimate the R-factor, a significant amount of error can be expected. For the region where the relationship was most accurate, Washington and Oregon, the error in R-factor estimation ranged from -65% to 230%. Application of an R-factor estimation is not recommended if a high level of accuracy is desired in the result of the USLE or RUSLE equation. Where the R-factor has been accurately calculated, the published value should be used. In areas where it has not been calculated, these estimations can yield a very approximate value.

Based on the maps in **Figures 22-25**, it appears that elevation may have a significant impact on rainfall erosivity, likely due to frequent snowfall in higher elevations. Future studies on estimating the R-factor should consider elevation and/or snowfall.

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