A GIS-based Soil Erosion Risk Map for New Mexico

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Abstract

A soil erosion risk map was developed for the State of New Mexico using the Universal Soil Loss Equation (*USLE*), a fuzzy logic model (*FuzzyCell*) and *ArcGIS Desktop 9.3* software. Soil erosion was examined as a function of length-slope (*LS*) gradient, normalized difference vegetation index (NDVI), 2-yr, 6-hr precipitation levels ($_2P_6$), and soil erodibility (*K*). A color-coded erosion risk for New Mexico was developed showing that erosion risk varied between 0.05 and 0.87 on a scale of 0 (minimum) to 1 (maximum). This soil erosion risk map provides a visual perspective of potentially problematic areas for soil erosion within New Mexico. Although the data used in this study is specific to the State of New Mexico, the methodologies could be applied to other geographic regions.

Wischmeier (1959) developed the *Universal Soil Loss Equation* (*USLE*). Due to its ease of use and limited data input requirements, it is still a leading model for the estimation of soil erosion. *USLE* estimates soil erosion based on five empirical input variables: rainfall erosivity, soil erodibility, slope, land use cropping factor, and erosion prevention practice factor.

For this study, *USLE* is integrated into a Geographic Information System (GIS) along with publicly available data to generate a soil erosion risk map for New Mexico. Part of the difficulty with converting discrete data into a soil erosion risk map relates to the how discrete and ambiguous data are processed by computational systems. While the real world consists of fuzziness (ambiguous data), conventional GIS software only uses crisp data (yes/no choices or discrete data) as inputs. Shades of gray are present in the physical world (fuzzy logic), but only discrete data are used in traditional GIS environments (crisp logic). Both discrete data and fuzzy logic were used together to produce a soil erosion risk map.

Soil Erosion Model – Universal Soil Loss Equation (USLE)

USLE estimates annual soil loss, and it is based on five empirical input variables: rainfall erosivity, soil erodibility, length slope, land use cropping factor, and erosion prevention practice factor (Wischmeier, 1959). *USLE* is represented as:

$$A = K \times L \times S \times C \times R \times P \qquad (1)$$

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where A is average annual soil loss in metric ton/ha/yr, K is soil erodibility factor (metric ton·ha·hr/ha·MJ·mm), L is slope length factor (dimensionless), S is slope steepness factor (dimensionless), C is cover-management factor (dimensionless), R is rainfall erosivity factor (MJ mm/ha·hr·yr), and P is soil erosion prevention practice factor (dimensionless).

Four attributes were selected to represent the *USLE* parameters in Equation 1: soil erodibility (K), 1-dimensional length slope factor (LS), vegetative coverage (NDVI), and average precipitation ($_2P_6$). The soil erosion prevention practice factor (P) was not considered, and therefore assumed to be equal to 1.

Fuzzy Set Theory

Fuzzy logic allows for the management of uncertainty by simulating the human thinking process within a physical world. It provides a formal framework to process linguistic knowledge and its corresponding numerical data through membership (characteristic) functions. Membership certifies that a variable belongs to a class and the overall linguistic knowledge summarizes complex phenomenon, concepts, and outputs of human thinking process, while the numerical data are used for processing (Yanar and Akyürek, 2006).

Fuzzy logic is implemented within the *ArcGIS* environment as an extension to process uncertainty, and to imitate the human thinking process. An *ArcGIS* extension, *FuzzyCell*, was used to estimate the potential soil erosion risk within the State of New Mexico by processing the relationships between the contributing factors and soil transport.

Fuzzy set theory has been used for decades to reflect real physical world vagueness and uncertainty into binary systems. Fuzzy refers to computational vagueness and it represents any uncertain, imprecise, or ambiguous real world knowledge. Since most systems are designed to work with classic data sets, which denote a belonging to a set by 1 and not belonging to a set by 0; they are unable to reflect fuzzy information, which falls in between 1 and 0. Fuzzy logic was derived from the fuzzy set theory and is able to define vague linguistic forms of the memberships such as *high*, *medium* and *low*. Zadeh (1965) introduced fuzzy sets as classes of objects with a continuum of grades of memberships. His fuzzy set theory was based on the fact that the classes of objects encountered in the real physical world usually do not have precisely defined criteria of membership.

Kainz (2008) explained the human thinking process and language, stating that there are many uncertain and vague concepts, because human language is not binary, i.e., 0 or 1, black or white. The values in between, for example, 0.6 or gray, are said to be fuzzy. Fuzziness is an indication to what degree something belongs to a class. Any phenomenon that shows a degree of vagueness or uncertainty is in need of a proper expression, which is not possible using crisp sets of class boundaries.

According to Yen and Langari (1999) fuzzy models are capable of incorporating knowledge from human experts naturally and conveniently, while traditional models fail to do so. Fuzzy models are also capable of handling nonlinearity.

Liu (2009) argued that traditional multi-criteria decision-making methods do not provide the best decision support because they are ineffective at the modeling of qualitative human-thinking process. Fuzzy logic is broadly recognized as a tool that has the ability to compute with words, which is useful for modeling qualitative human thought process in the analysis of complex systems and decisions.

Fuzzy Logic Combined with *USLE*

Soil erosion can show a significant difference when linguistically formulated using fuzzy logic instead of estimated using classical soil erosion models. Yanar and Akyürek (2006) introduced fuzzy set theory into GIS. This integration allows users to obtain more flexibility and capability to effectively handle and process imprecise information about the real world. Using fuzzy logic, as a linguistic approach, they developed a fuzzy rule-based system called *FuzzyCell*.

As Tayfur (2003) stated, fuzzy rules, also known as *IF-THEN* rules, include two parts: the antecedent part of the rule, the part starting with *IF* up to *THEN*, and a consequent part, the part starting with *THEN* up to the end. For instance, *IF* the precipitation amount is high; the slope is very steep (high); the soil is compact (high); and NDVI is sparse (low), *THEN* the potential erosion risk is very significant (high).

Kainz (2008) defined membership function as an assignment to every element of the universe and a degree of membership to a fuzzy set. This membership value must be between 0 (no membership) and 1 (full membership), indicating to which degree an element belongs to the fuzzy set.

Mitra et al. (1998) developed a fuzzy logic model to study soil erosion in a relatively large watershed using a limited number of indicators. They worked on two different fuzzy logic rule bases. The first rule base included slope angle and land cover data as variables and the second rule base consisted of slope length, soil erodibility, and vegetation cover as input indicators. They came to the conclusion that fuzzy logic based soil erosion predictions were more successful than the USLE based calculations alone and the study based on three indicators was more accurate compared to the study with two indicators.

Tayfur et al. (2003) also claimed that experiments indicated the fuzzy model as a reliable sediment transport model. Ahamed (2000) compared soil loss calculated by the *USLE* and a *USLE* adapted fuzzy class membership approach. The comparison indicated that *USLE* based fuzzy approach showed more spatial variation in the regions with a soil erosion problem, while it showed no significant difference in areas without a soil erosion problem.

Software

The GIS-based software package used throughout this study is the Environmental Systems Research Institute's (ESRI) *ArcGIS Desktop 9.3*, as well as extensions, such as *ArcToolbox* and *ArcScene*. This *ArcGIS* application performs data-based manipulations such as spatial analysis, raster calculations, geoprocessing, and data merging. The fuzzy inference system that is implemented within *ArcGIS* was *FuzzyCell* (Yanar and Akyürek 2006). *FuzzyCell* allows eight

possible membership functions, inference methods for rule aggregation, operators for set operations, and defuzzification methods.

Site Description

The study area is the State of New Mexico located in the southwest region of the United States. New Mexico has a surface area of 121,412 square miles, is approximately 350 miles square, and lies between latitudes 32° and 37° N and longitudes 103° and 109° W.

New Mexico has a range of altitudes changing between 861-m and 4012-m with an average of 1749-m. The altitudes result in terrain slope values between 0 degrees and 77.2-degrees with an average of 6.5-degrees. On average, the level of precipitation within New Mexico ranges from a minimum of 0.77-inches to a maximum of 2.19-inches for a $_2P_6$ precipitation duration (2-yr frequency, 6-hr duration).

Data Sets

Four publicly available data sets for the State of New Mexico were used in this study: 1) United States Geological Survey (USGS) digital elevation maps (DEM); 2) USGS normalized difference vegetation index (NDVI); 3) 2-yr, 6-hr precipitation levels; 4) and soil erodibility (*K*). The soil erodibility (*K*) and DEM maps are 30 × 30-m resolution. The precipitation data is 800 × 800-m resolution and the vegetative index (NDVI) is 1000 × 1000-m resolution. When working with the GIS data sets, larger resolutions were downscaled to 30 × 30-m.

Digital Elevation Model (DEM) and LS Factor

For this macro-scale project, a 30-m DEM was used to quantify the topographical characteristics of New Mexico. The DEM data rendered in 3-D using *ArcScene* is presented in Figure 1.

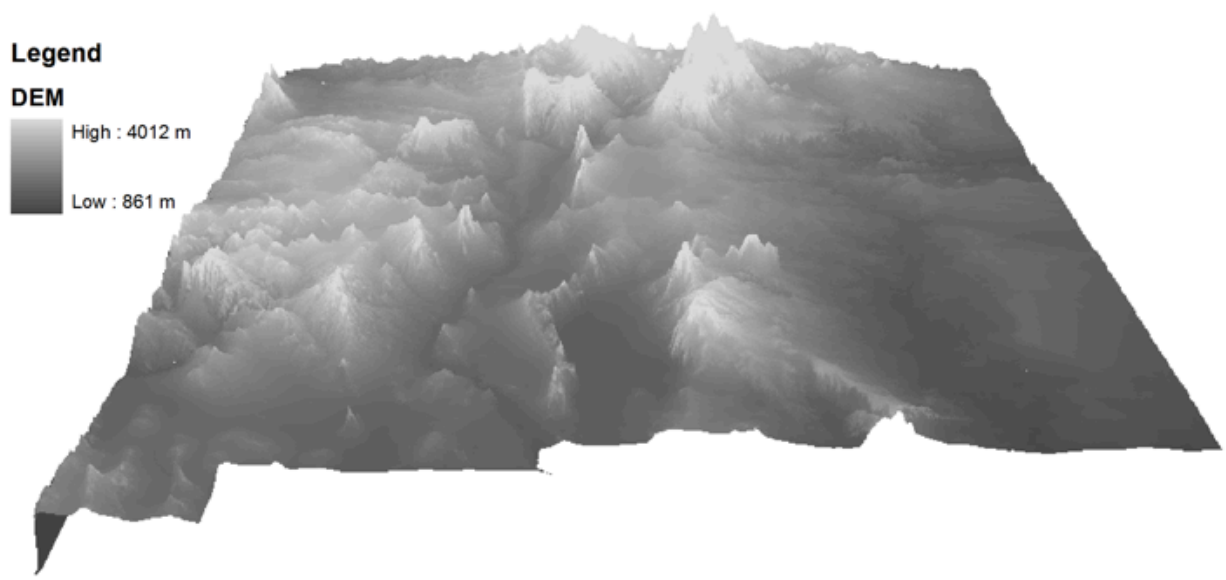

Figure 1. New Mexico Digital Elevation Map (DEM).

In this study, a 1-dimensional length-slope (*LS*) factor is evaluated and used as one of the contributing factors soil erosion risk rather than slope (Figure 2). *LS* provides a better identification of problematic areas affecting soil erosion risk. Detailed procedures for converting terrain slope into a length-slope factor are presented in Bulut, 2011.

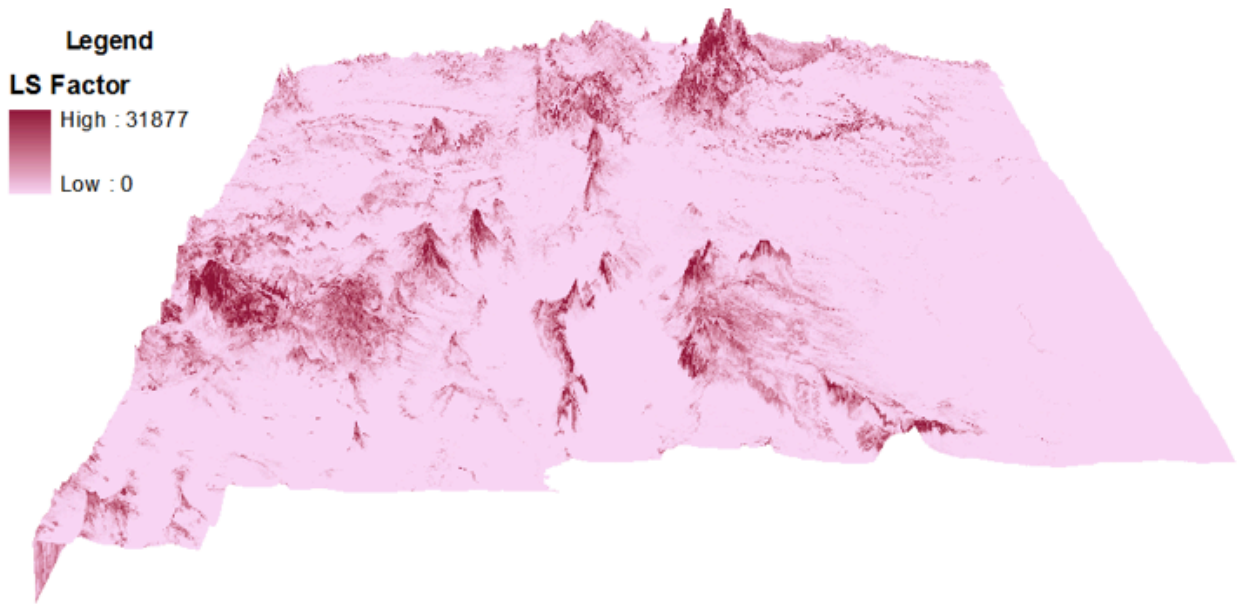

Figure 2. Length-Slope (*LS*) Factor for New Mexico

Normalized Difference Vegetative Index (NDVI)

The USGS defines the normalized difference vegetative Index (NDVI) as a standardized index of greenness. The differential in the reflections of different land coverage types under two spectral bands, red and infrared (IR), is monitored and the data are used to produce the NDVI data set. NDVI calculations are based on the fact that green plants absorb radiation in the visible range and they reflect radiation in the near IR range. Water stressed, diseased, or dead leaves become more yellow and reflect less radiation in the near IR range. Clouds, water, and snow reflect more radiation in the visible range than in the near IR range. Rock and bare soil show almost the same reflection in both the red and the near IR ranges. NDVI values vary between -1 and 1, where -1 represents clouds, water, and snow and 0 represents rock and bare soil. The NDVI process in the GIS environment creates a one-band, 8-bit image scaling output values of -1 to 1 to a scale from 0 to 255 (Lillesand and Kiefer, 1987). The NDVI raster data set representing the average maximum annual NDVI values from 1995-2009 is shown in Figure 3 based on this scaling. The lighter green shade represents the sparsely vegetated regions, while the darker shades of green represent heavily vegetated areas.

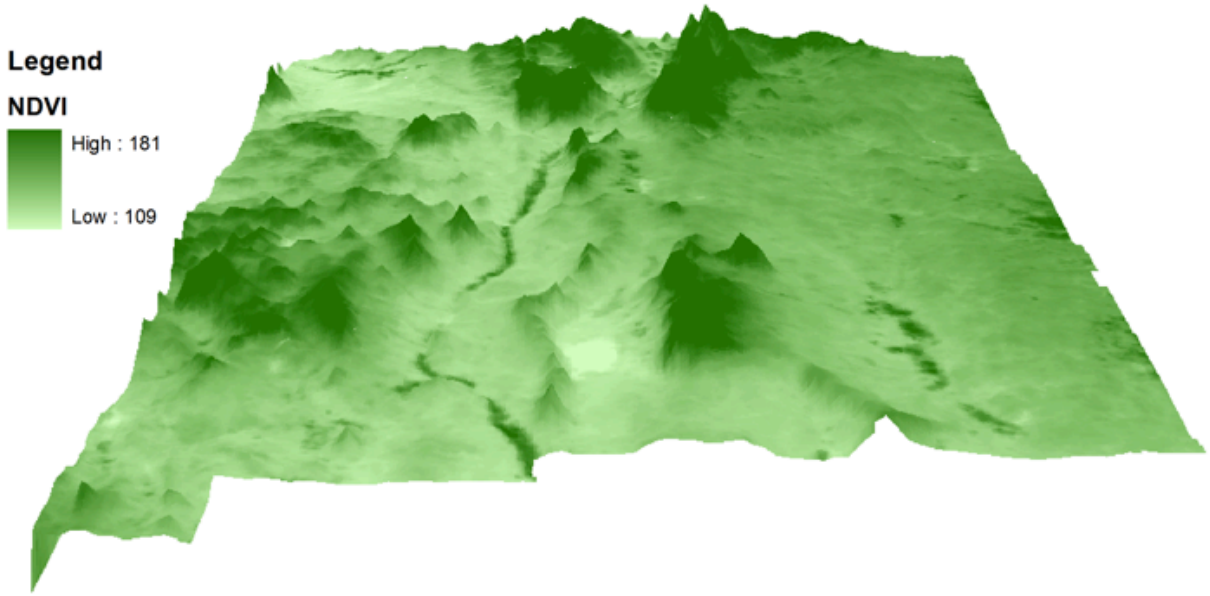

Figure 3. New Mexico Normalized Difference Vegetative Index Distribution.

Precipitation

Precipitation frequency data are prepared by the Hydrometeorological Design Studies Center (HDSC), a division of the National Oceanic and Atmospheric Administration (NOAA)'s National Weather Service. The related data set, including the New Mexico region, is obtained from the NOAA Atlas 14 (Volume 1) map of the semiarid southwest. Wischmeier and Smith (1978) suggested that the 2-yr, 6-hr precipitation ($_2P_6$), which is a 6-hour duration precipitation with a 2-year return period, represents a reasonable accuracy for rainfall erosivity for the western states. Rainfall erosivity indicates the erosion capacity of rainfall. The statewide $_2P_6$ precipitation map is displayed in Figure 4.

Figure 4. New Mexico 2-yr, 6-hr ($_2P_6$) Precipitation Distribution.

Soil Erodibility

The Soil Survey Geographic (SSURGO) and State Soil Geographic (STATSGO) are soil property databases produced by the Natural Resources Conservation Service (NRCS). Since the SSURGO data for New Mexico is not complete, the STATSGO data at a resolution of 30-m was selected for this study. The *K*-factor, or soil erodibility, is available in STATSGO, and for New Mexico, the values range between 0 and 0.64. Low *K*-values between 0.05 and 0.15 represent fine-textured soils which are resistant to detachment due to a high clay ratio. Coarse-textured soils, such as sandy soils, have also low *K*-values ranging from 0.05 to 0.2. The particles in coarse-textured soils are easily detached; however, these soils have high infiltration capabilities resulting in low runoff. Moderate *K*-values ranging from 0.25 to 0.45 correspond to medium-textured soils such as silty loam. This type of soil is moderately susceptible to particle detachment and generates moderate runoff rates. High silt content soil is particularly susceptible to erosion and has higher *K*-values in the range of 0.45 and 0.69. These particles are easily separated, causing large volumes of runoff (Weesies,1998). A soil erodibility distribution for New Mexico is shown in Figure 5. The outlined areas are for a *K*-factor equal to zero, denoting rock outcrops, or water (Soil Info, 2001). Hypothetically, a *K* equal to 0 is a totally resistant soil layer to erosion.

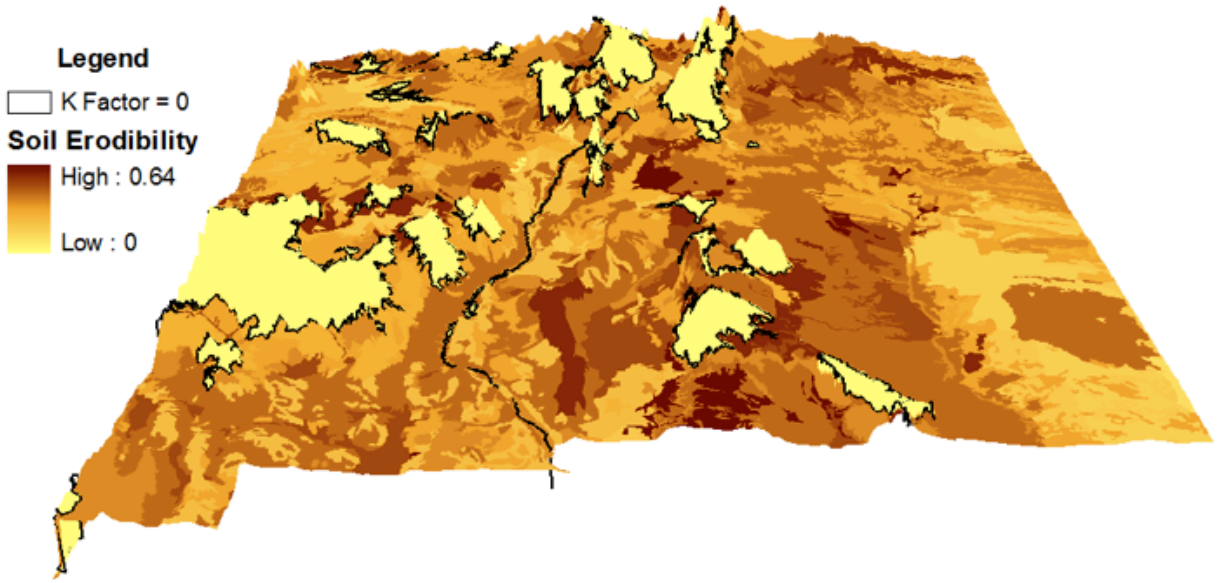

Figure 5. New Mexico Soil Distribution.

Development of the Soil Erosion Risk Map

The data sets for length-slope (*LS*), normalized difference vegetative index (NDVI), soil erodibility (*K*), and the 2-yr, 6-hr precipitation ($_2P_6$) were manipulated in the *ArcGIS* environment and supplied to *FuzzyCell* to generate a potential soil erosion risk map.

Application of Fuzzy Logic and FuzzyCell

Liu et al. (2009) outlined the four main steps necessary for fuzzy reasoning: computing compatibilities, truncating conclusions, aggregating truncated conclusions, and the defuzzification process.

The first step of fuzzy reasoning is compatibility computation, which designates a crisp value to each antecedent (the part starting with *IF* up to *THEN*). *FuzzyCell* operates on the input raster datasets pixel by pixel to generate an output. For each input variable (contributing factor) the tool reads its raw value for that pixel from the raster data and uses its membership function to calculate a membership value. After determining all four membership values, a fuzzy operator is applied to them to produce a single membership value. For this study, the trapezoidal-norm (t-norm) operator product is used, which forces the tool to draw conclusions sensitive to every input. *FuzzyCell* repeats this procedure and calculates a compatibility value for each rule.

Each indicator is considered to have three different membership functions (low, medium, and high) that quantify the grade of its membership. Since there are four indicators each having three different possible memberships, there are 3^4 or 81 *IF-THEN* rules that must be constructed. For instance: *IF* slope gradient is high (steepness), soil erodibility is high, NDVI is medium, and precipitation depth is high, *THEN* risk is very significant.

The second step of fuzzy reasoning is truncating conclusions. Once the compatibility for a rule is calculated, the membership function of the consequent part (from *THEN* up to end) is truncated by the compatibility value using a fuzzy implication operator, which is minimum (*MIN*) for this study.

The next step is aggregating truncated conclusions, which generates a new single fuzzy set representing the truncated conclusions for each rule. For this study, the maximum (*MAX*) aggregation operator is used to truncate the conclusions.

The last step is defuzzifying the overall conclusion to convert a fuzzy set back into a crisp (numerical) value. There are several defuzzification methods, such as the weighted average, maximum membership, average maximum membership, and center of gravity. In this study, the center of gravity method is employed (Tayfur et al. 2003), which takes the centroid of the area under the membership function curve of a fuzzy set as the result (Liu, 2009).

Fuzzy Membership and Parameter Cutoffs

A partially overlapping trapezoidal membership function was used for each indicator. Based on the study by Ahamed et al. (2000), cutoff values of 0.1, 0.3, and 0.5 were chosen for the soil erodibility distribution. Ahamed et al. (2000) also evaluated the *LS*-factor cutoff values for fuzzy memberships and suggested cutoff values as 0.5, 3.5, 9 and 16, respectively, for slope gradient classes of 0-5, 5-15, 15-30, and greater than 30%.

In order to calculate the NDVI cutoff values, *C*-factor cutoff values were assigned 0.2, 0.5, and 0.8 (Ahamed et al., 2000). NDVI values were then back calculated as 110, 125, and 145 using a NDVI-*C* factor relationship developed by van der Knijff et al. (1999).

The ${}_2P_6$ membership cutoff values were assigned as 0.63, 1.32, and 1.73 inches using the relationship developed by Wischmeier and Smith (1978) and *R*-factor cutoffs of 10, 50, and 90 as hundreds of ft·tonf ·in /ac·hr for low, medium, and high rainfall erosivity. This inverse method closely matched the minimum, average, and maximum ${}_2P_6$ data for New Mexico.

The soil erosion risk membership was defined so that it would scale the outcome from 0 to 1. A partially overlapping triangular membership function with cutoff values spanning seven fuzzy ranges was assumed. These soil erosion risk consequences were defined as *very insignificant (vi), insignificant (i), slightly insignificant (si), neutral (n), slightly significant (ss), significant (s) and very significant (vs)*. An example fuzzy reasoning process is presented in Figure 6, and the entire set of rules and membership classes are presented in Bulut (2011).

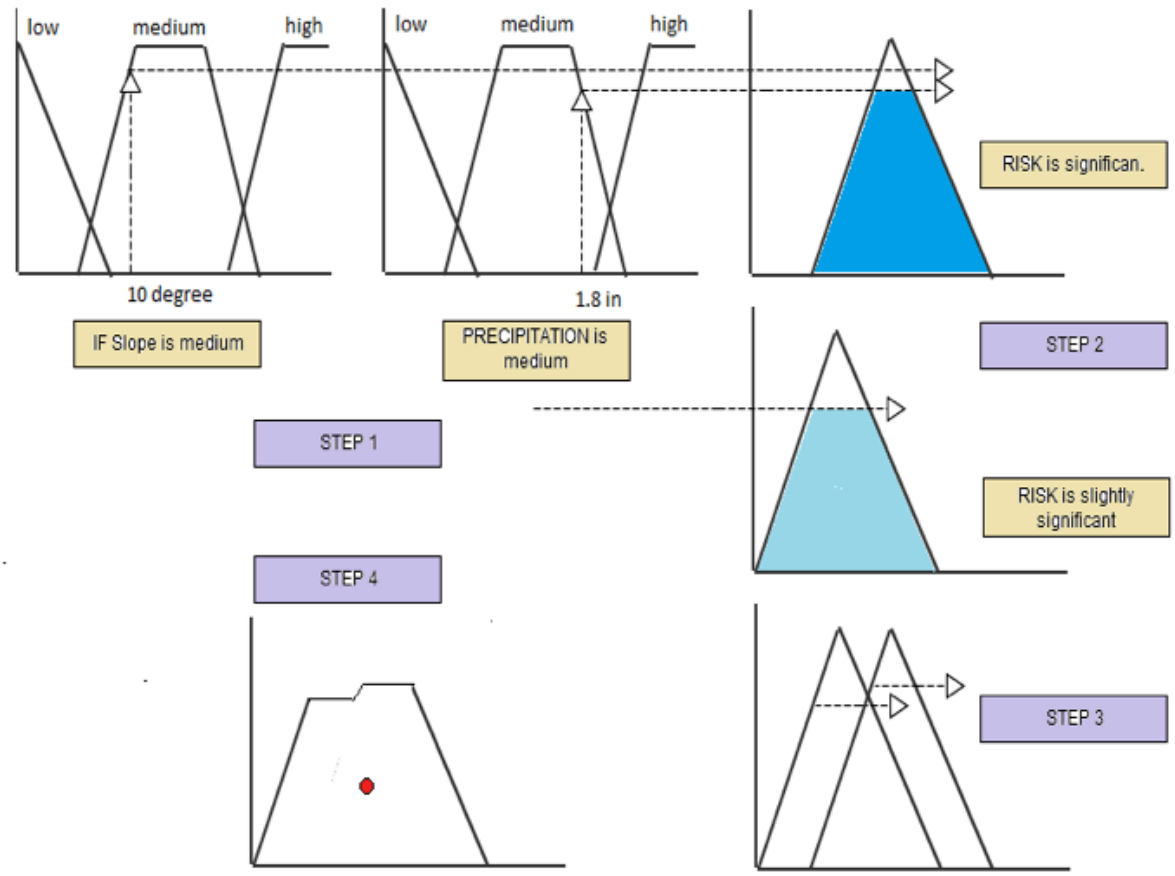

Figure 6. Fuzzy Reasoning Steps.

Soil Erosion Risk Map

The resulting soil erosion risk map based on the *LS*-factor is presented in Figure 7. The risk varied between 0.05 and 0.87 on a scale of 0 to 1. The red (high risk) to blue (low risk) color scale provides a visual perspective of potentially problematic areas.

With the superposition of individual rasters for NDVI, *LS*, *K*, and ${}_2P_6$, the combinations of one or more indicators can be interpreted that contribute to a given high or low erosion risk. For example, far northeast section of New Mexico shows moderate to high soil erosion risk. In this region, precipitation is high, soil erodibility is high, vegetative coverage is medium, and the terrain is flat. Along the eastern border, the soil erosion risk is low. Soil erodibility is low; however, the other three indicators are the same as above. The mid-south and southern regions show the highest erosion risk, having erodible soils, medium to dense vegetative cover, and low precipitation.

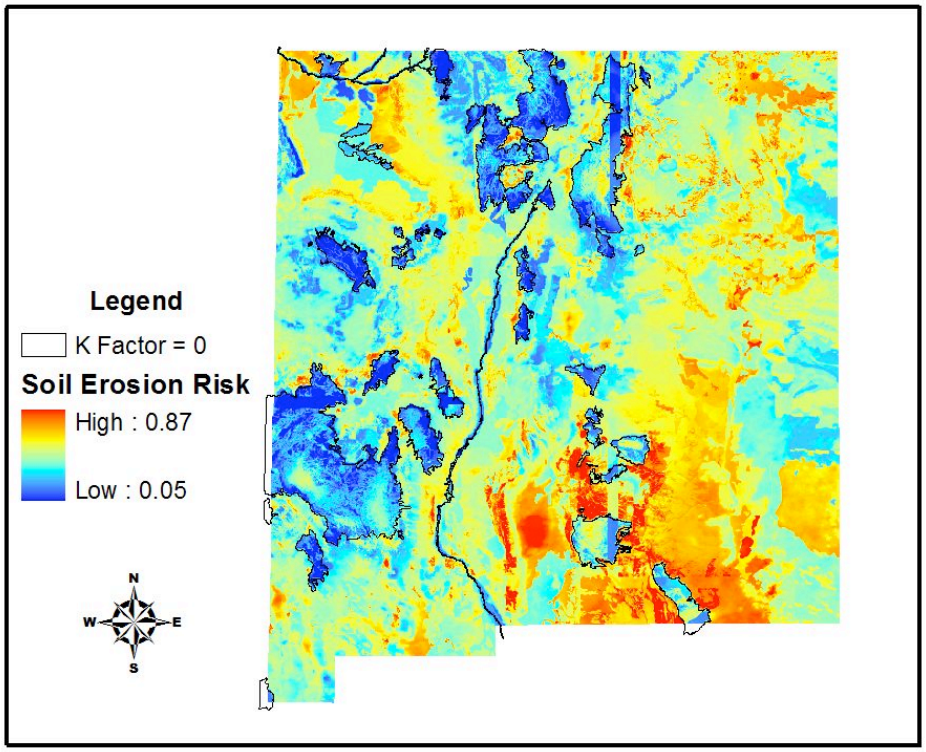

Figure 7. Soil Erosion Risk Map for New Mexico.

It is expected that low NDVI values result in high soil erosion risk, because there is not enough vegetation or land cover to inhibit soil movement. Steep slope gradients generally result in high soil erosion risk. Erodible soils are prone to detachment and movement by water during intense precipitation. The combinations of indicators and their dominance are complex and difficult to interpret, or generalize on a region by region basis.

The black framed areas in Figure 7 delineate areas there is either no soil erodibility data or the value is zero. This tends to bias those areas to have lower defuzzified soil erosion risk values. When the *K*-factor is zero, the membership function automatically becomes 1 (full belonging to low soil erodibility range). Since the defuzzification method used in this study is center of gravity, the outcome tends to be lower when one factor is zero. In addition, when soil erodibility is low, there are only 27 (3^3) rules left that can be applied to impact the outcome, depending on the pixel values of *LS*, NDVI and ${}_2P_6$. As evident in Figure 7, the black framed areas tend to have lower soil erosion risk (blue).

Conclusion

Quantifying the risk of soil erosion within a geographic region provides a useful engineering management and design tool. To this end, a soil erosion risk map was generated for the State of New Mexico. The method assumed that soil erodibility, precipitation, vegetation, and

topography were primary factors that contribute to soil erosion. Areas for soil erosion were identified based on a color scale from 0 (low risk) to 1 (high risk). The potential soil erosion risk map identified the most problematic areas are present in the south, northeast, and southeast of New Mexico.

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