Assessment of Soil Erosion Risk within a Subwatershed using GIS and RUSLE with a Comparative Analysis of the use of STATSGO and SSURGO Soil Databases

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Abstract

Land degradation and subsequent soil erosion and sedimentation play a significant role in impairing water resources within subwatersheds, watersheds and basins. Using conventional methods to assess soil erosion risk is expensive and time consuming. Geographic Information Systems (GIS), coupled with the use of an empirical model to assess risk, can identify and assess soil erosion potential and estimate the value of soil loss. The objectives of this project are to: 1) assess soil erosion risk within a Zumbro River subwatershed in southeastern Minnesota using GIS and the Revised Universal Soil Loss Equation (RUSLE), 2) comparatively analyze the use and scaling effect of STATSGO and SSURGO soil databases with RUSLE and 3) assess the sensitivity and scaling effect of estimated soil loss to model variables. Soil, land use, digital elevation, flow accumulation and climatic data are used to generate RUSLE variables. This empirical soil erosion model estimates soil loss values by tons/acre/year and assesses the spatial distribution of soil erosion risk within the entire subwatershed. By comparing soil loss estimates, spatial distribution and variable sensitivity from the RUSLE model using STATSGO soil data and SSURGO soil data, it is possible to compare the responses of both soil databases. Nonparametric regression shows the level of relatedness between STATSGO and SSURGO RUSLE model outputs at the subwatershed scale. Correlation coefficients (R^2) of 0.914, 0.928, and 0.922 for 10, 30, and 50 meter resolutions respectively highlight the significance of the relationship. At high to very high levels of estimated soil erosion loss the relatedness between STATSGO and SSURGO-based RUSLE model outputs lessened. Of the LS, K, and C model variables investigated, the C variable (cover management) exhibited a greater level of relatedness to RUSLE model outputs than the other variables at 10, 30 and 50 meter resolutions but not enough to be significant.

Introduction

Agricultural land in the U.S. is losing invaluable soil faster than it can be replenished because of erosion and the detachment and movement of soil particles. Soil erosion is one of the major non-point pollution sources in many watersheds (Wang and Cui, 2005).

Soil loss from agricultural lands

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is estimated to be in the billions of tons per year. It is also estimated that more than 6 million metric tons of nitrogen fertilizer and over 100,000 metric tons of pesticides are applied to crop fields in the Midwest alone (Porter et al, 2001). Soil erosion, sedimentation, and the subsequent conveyance of fertilizers, pesticides, and herbicides play a significant role in impairing water resources within subwatersheds and watersheds.

Yet conventional methods to survey land and assess soil erosion are costly and time consuming. Mapping soil erosion using GIS can easily identify areas that are at potential risk of extensive soil erosion and provide information on the estimated value of soil loss at various locations (Yusof and Baban, 1999).

By effectively predicting soil erosion, it is possible to: develop sound land-use practices as they relate to earth disturbing activities, estimate the efficiency of best management practices required to prevent excess sediment loading, and identify target areas for conservation funds or research (Hickey et al, 2005).

Several soil erosion and non-point source pollution models have been developed, modified, and combined with GIS software to take advantage of these new capabilities and provide regional soil erosion and non-point water quality assessments during the past decade (Wilson, 2003). Among these models is the Revised Universal Soil Loss Equation (RUSLE).

An inherent variable in the RUSLE model, which will be described in further detail later in this paper, is the use of soils data to generate erosion risk estimates. Several soil databases are available for use and they include the State Soil Geographic (STATSGO), Soil Survey Geographic (SSURGO), National Resources Inventory (NRI), Food and Agriculture Organization Soil Map of the United Nations/World Soil Classification (FAO), and other local and state soil databases developed by local governments and state natural resource agencies.

The two most commonly available soil databases for soil erosion risk modeling and watershed assessment are STATSGO and SSURGO (Gowda and Mulla, 2005). Both were developed by the U.S. Department of Agriculture (USDA) Natural Resource Conservation Service (NRCS). For both of these databases, maps are produced from different intensities and mapping scales, and each database is linked to attribute data for each soil and map unit.

The STATSGO soil database was developed primarily for regional, multistate, state, basin, and multicounty resource planning. STATSGO data are not detailed enough for planning at the county scale or smaller. STATSGO soil maps are compiled by generalizing more detailed SSURGO soil databases and utilizing generalized county soil maps (USDA NRCS, 1994).

The SSURGO soil database in contrast provides a more detailed level of soils interpretation and resolution and was developed primarily for much smaller scale resource planning activities including those at the county, township, farm, ranch, and land parcel level. This soil database is an excellent source for determining erodible areas, assisting in developing appropriate erosion control practices and developing land use assessments (USDA NRCS, 1994).

For those researchers and resource managers that decide to utilize the USDA NRCS soil databases for modeling and assessment, availability of the databases may drive which databases are used. Figure 1, a map from the USDA NRCS, depicts the status of SSURGO soil database development by counties in Minnesota. As evident in Figure 1, one can see SSURGO is only available, as of August 2006, for 68 of Minnesota's 88 counties. Minnesota's current status is similar to what is found throughout the eastern and Midwestern U.S. with many counties still in the planning, development or review phases for SSURGO soil database establishment. The status of states and counties in the western U.S. is more incomplete with many areas that have not begun the planning and development phases of SSURGO establishment. National SSURGO coverage is planned for completion by 2008.

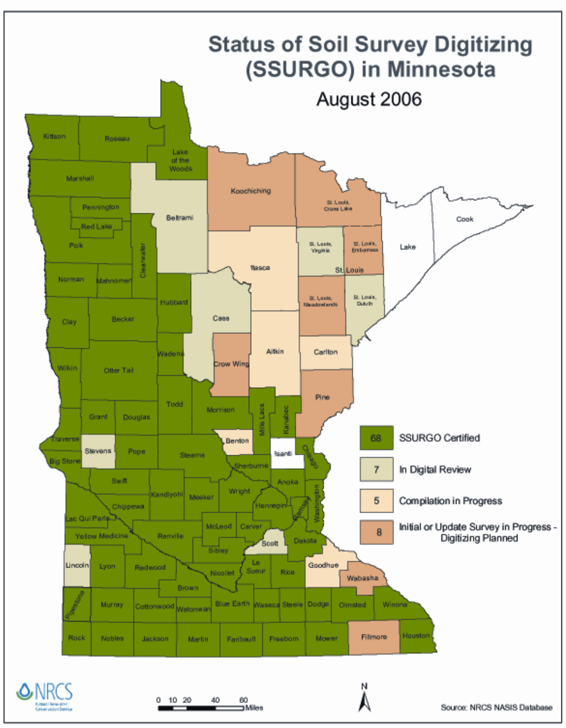

Figure 1. Minnesota map depicting the status of SSURGO soil database development by county as of August 2006. Source: USDA NRCS.

Researchers and resource managers who often use USDA NRCS soil databases have 1) begun using SSURGO when available, 2) combine SSURGO and STATSGO when conducting assessments at the regional scale and SSURGO is not available over the entire project area, or 3) continue utilizing STATSGO even when SSURGO is available as an option.

Researchers and resource managers, when considering which soil databases to utilize, must consider the benefits and drawbacks for each database based on project objectives and scale of research. It is also important to understand the effects of spatial scale at which soil databases are developed prior to choosing a database with which to work (Gowda and Mulla, 2005).

If choice of database is not an option, or different databases must be stitched together (Hickey et al, 2005), what kind of impact, if any, will result based on model outputs? With respect to comparing soil attributes of STATSGO and NRI databases, it was demonstrated that there was disagreement for selected soil properties. This result implies risk assessment and ecosystem modeling outputs can be influenced by the selection of data sources (Ding et al, 1999).

Additionally, differences in runoff and soil properties can be attributed to the differences in the spatial resolution of the data sets (Levick et al, 2004). It was demonstrated that when evaluating alternative agricultural management practices that a STATSGO-based model predicted annual nitrate losses consistently higher than that for SSURGO data and that a SSURGO-based model predicted annual phosphorous losses consistently higher than that for STATSGO data (Gowda and Mulla, 2005). On the other hand, it was demonstrated that the integration of a FAO soil database into a watershed hydrologic model produced results comparable to the results produced when calculated using both STATSGO and SSURGO soils data (Levick et al, 2004).

Because the determination of potential soil erosion risk can differ depending upon what data sources are used, it is difficult for resource managers to identify critical areas and apply appropriate management techniques. Consequently, a comparison of the most commonly available soil databases is needed. This project seeks to compare the STATSGO and SSURGO soil databases to determine their relatedness.

Methods

Empirical Model

The Universal Soil Loss Equation (USLE), developed by Wischmeier and Smith in 1978, is the most frequently used empirical soil erosion model worldwide and was later modified into a revised Universal Soil Loss Equation model by including improved means of computing soil erosion factors (Shi et al., 2002). These improved means for computing soil erosion factors generally fit into two categories: incorporation of new/better data and consideration of selected erosion processes. The inclusion of these factors into RUSLE has "the potential for broader prediction improvements" (Sonneveld and Nearing, 2003; Jones et al, 1996).

The RUSLE model can predict erosion potential on a cell-by-cell basis, which is effective when attempting to identify the spatial pattern of soil loss present within a large region. GIS can then be used to isolate and query these locations to identify the role of individual variables in contributing to the observed erosion potential value (Shi et al, 2002).

RUSLE computes average annual erosion from cover slopes as (Renard et al, 1997):

$$A = R * K * L * S * C * P$$

Where:

A = computed average annual soil loss in tons/acre/year
R = rainfall-runoff erosivity factor
K = soil erodibility factor
L = slope length factor
S = slope steepness factor
C = cover management factor
P = conservation practice factor

In examining the RUSLE variables the equation can be broken down into two parts: 1) environmental variables and 2) management variables (Hickey et al, 2005). The environmental variables include the R, L, S and K factors. These variables remain relatively constant over time. The management variables include the C and P factors and may change over the course of a year or less.

Model Limitations

There are several limitations to the RUSLE model and they appear to be in three main categories: 1) the research location in which RUSLE is applied, 2) limitations inherent in the mathematical calculations and 3) limitations in scale.

Research Location Limitations

RUSLE was designed primarily for agricultural regions. Soil-erosion potential as identified in non-agricultural regions may be inconsistent (Hickey et al., 2005). Further, RUSLE has had limited application outside of the U.S. In one study using data that was collected on natural runoff plots located primarily in the eastern half of the U.S., the RUSLE model did not outperform the USLE in its prediction accuracy (Sonneveld and Nearing, 2003).

Limitations in Mathematical Calculations

The environmental variables used in RUSLE are relatively constant over the timescale of tens of years (at a minimum), while the management variables may change over the course of a year or less. Consequently, it is difficult to obtain current and accurate management variable coverage (Hickey et al., 2005).

Several algorithms are required when processing data for input into RUSLE. Each of those algorithms may accentuate existing errors in data. Because RUSLE requires six input data layers to be multiplied together, the errors inherent in each layer are similarly multiplied, contributing to an even greater error in the derived soil loss values (Shi et al., 2002) Consequently, results of calculations should only be used in a comparative sense, and not to calculate sediment loads unless further validation or correction of the data occurs (Hickey et al., 2005).

Limitations in Scale

The erosion processes which are considered by RUSLE are often driven by relatively small features. Therefore, any output should be treated as qualitative, not quantitative, and the pattern of erosion, or vulnerability, should be examined (Hickey et al., 2005).

Project Site

The Zumbro River Watershed, (Figure 2), is approximately 1,513 $mi.^2$ in size and is one of 12 watersheds that make up the Lower Mississippi River Basin in southeastern Minnesota. The Zumbro River Watershed lies in Dodge, Goodhue, Olmsted, Rice, Steele and Wabasha Counties. The Watershed itself is made up of 91 subwatersheds that range in size from 5.45 $mi.^2$ to 51.21 $mi.^2$.

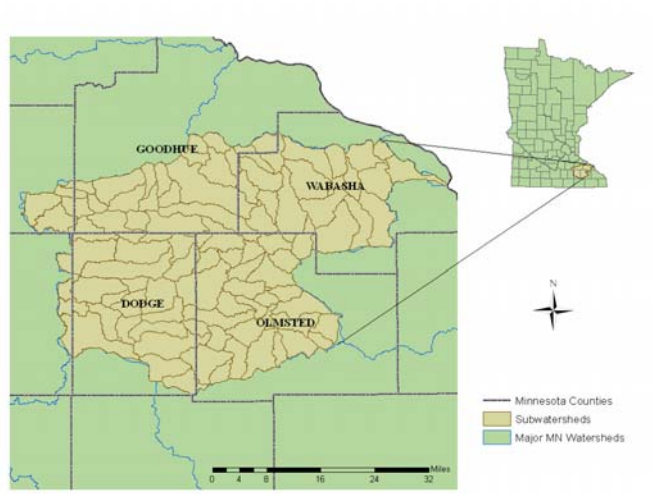

Figure 2. The Zumbro River Watershed and its associated 91 subwatersheds in southeastern Minnesota.

Many of the 91 subwatersheds that make up the Zumbro River Watershed have not been named. The subwatershed chosen as the project site for this research has not been named and for the purposes of this project and paper is considered the Zumbro River subwatershed.

The Zumbro River subwatershed, (Figure 3), is approximately 17.80 $mi.^2$ (11,391.57 ac., 4610.11 ha.) in size. The subwatershed lies entirely in Olmsted County, north of Rochester, Minnesota.

The Zumbro River subwatershed was chosen as the project site for this research due to: 1) the availability of spatial and tabular STATSGO and SSURGO soils data for Olmsted County, 2) diverse land cover that includes natural lowland and wetland, conifer and deciduous forests, pasture, hay, and row crops and 3) topographic variation in elevation and slope.

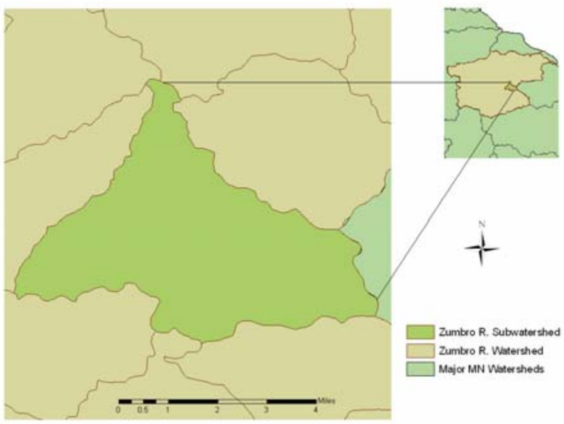

Figure 3. The Zumbro River subwatershed project site.

Data

Data needed for this research project include:

- Soil data
- Elevation data
- Land cover data
- Rainfall/precipitation data
- Conservation practices data
- State, county, watershed and subwatershed boundary data

The spatial and tabular State Soil Geographic (STATSGO) database and the spatial and tabular Soil Survey Geographic (SSURGO) database, established by the USDA NRCS, provided the soil data needed to generate the K factor (soil erodibility).

Digital elevation models (DEM) with a 30 meter resolution, established by the U.S. Geological Survey (USGS), provided the elevation data needed to generate the L and S factors (slope length and slope steepness).

Land cover digital data for the subwatershed was obtained from the Minnesota Land Cover Classification System (MLCCS), established by the Minnesota Department of Natural Resources (MDNR). This data, along with land cover and agriculture tabular data obtained from the USDA NRCS, was used to generate the C factor (cover management).

Rainfall/precipitation data was obtained from the USDA Agriculture Handbook Number 537 (Wischmeier and Smith, 1978). This information source provided the R factor (rainfall-runoff erosivity) for the Zumbro River subwatershed project site.

Data for the P factor (conservation practices) within the subwatershed were not available. Potential sources for the data were investigated and included county land conservation departments, Farm Service Agency (FSA), MDNR, and USDA NRCS. An established and routinely used protocol for addressing this lack of data will be utilized to control P factor in RUSLE model replications.

Data for the state, county, watershed, and subwatershed boundaries were obtained from the MDNR and the U.S. Fish and Wildlife Service (USFWS). The digital data provided the necessary information to develop locator and project site maps and additionally provided the boundary framework to develop, clip, and analyze subwatershed data.

Analysis

To address the project's objectives, a GIS was developed to generate two separate RUSLE models, each using either the STATSGO or SSURGO soil databases and each model being calculated at a 10, 30, and 50 meter (cell size) spatial resolution to investigate scaling effects. Environmental Systems Research Institute (ESRI) software was used for these purposes.

ArcCatalog was used to manage, manipulate, reproject, create, and delete the data layers for this project. ArcMap was used to view, develop, edit, query, and analyze the project's data layers while ArcToolbox was used in the development of the spatial data because of its geoprocessing functionality.

The projection used for this study was NAD83, UTM, Zone 15N. To ensure all spatial data obtained from data sources was in the correct projection, and to better understand the data overall, metadata from each data source was examined carefully.

In the ArcMap environment, three data frames were created to better manage each RUSLE model and their subsequent outputs for analysis. The first data frame housed the data layers and RUSLE model calculations that used the STATSGO soil database. The second data frame housed the same data layers and RUSLE model calculations that used the SSURGO soil database. The third data frame housed the RUSLE outputs for each model including the necessary data for further analysis.

RUSLE Spatial Data

For both RUSLE models, Minnesota state, county, watershed, and subwatershed spatial data, in the form of polygon shapefiles, were added to the ArcMap environment. Prior to adding these Minnesota shapefiles to ArcMap, ArcCatalog was used to reproject any data layers not in NAD83, UTM, Zone 15N to this correct projection. These shapefiles included the two most important data layers, the polygon shapefile for the Zumbro River Watershed and the shapefile for the Zumbro River subwatershed project site.

The spatial and tabular data layers for the Minnesota DEM and the MLCCS land cover were added to the ArcMap environment. Additionally, the data layers for the STATSGO and SSURGO soil databases were added to each respective model. Again, prior to adding these data layers, the Project feature from Data Management Tools was used to reproject any layers not projected in NAD83, UTM, Zone 15N.

Spatial data for the SSURGO soil database was obtained as a polygon shapefile. The spatial data for the STATSGO soil database, on the other hand, is an older soil database system and was obtained as an interchange file (.e00). Import71, a stand alone utility from ArcView GIS that converts an ArcInfo interchange file to a more current coverage, was used to convert the STATSGO .e00 file to a coverage. The STATSGO coverage was then converted to a shapefile and added to the project.

The DEM, MLCCS, STATSGO, and SSURGO data layers for the state of Minnesota needed to be clipped to the Zumbro River subwatershed project site. To accomplish this, the Clip feature tool was used to clip the DEM, MLCCS, STATSGO, and SSURGO data layers to the subwatershed polygon.

Data layers for the R factor and P factor also needed to be created. Each layer was created as a shapefile and clipped to the subwatershed project site and added to the ArcMap environment for each RUSLE model. The shapefiles were created so that each shapefile represented a single polygon that would be represented by a single value.

To further prepare the spatial data for modeling, the data layers would need to be converted from features to raster. The MLCCS, STATSGO, SSURGO, R factor, and P factor vector shapefiles were converted to raster format. This was completed using the Convert Features to Raster function within the Spatial Analyst extension. The output grids, as seen in Figures 4-8 (10 meter spatial resolution), were generated at cell sizes of 10, 30, and 50 meters.

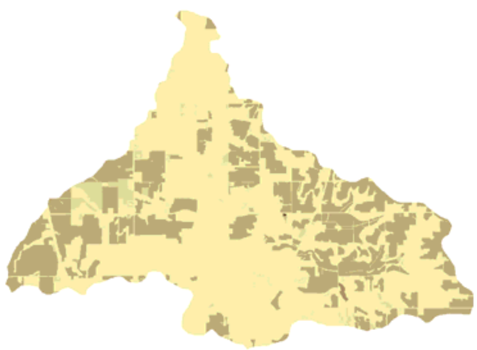

Figure 4. MLCCS grid (10 meter cell size) representing C factor (cover management) values.

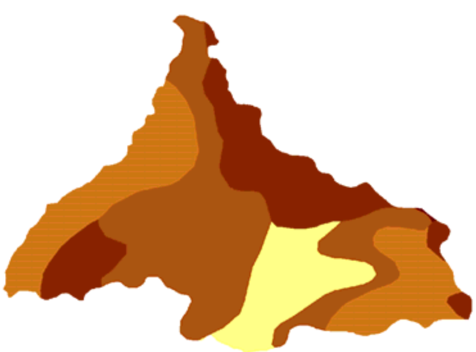

Figure 5. STATSGO grid (10 meter cell size) representing K factor (soil erodibility) values.

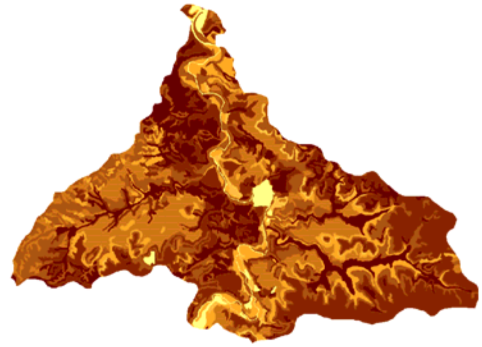

Figure 6. SSURGO grid (10 meter cell size) representing K factor (soil erodibility) values.

Figure 7. R factor grid (10 meter cell size) representing the rainfall-runoff erosivity value.

Figure 8. P factor grid (10 meter cell size) representing the conservation practice value.

With all the subwatershed layers in raster format, the last step was to generate a slope grid and a flow accumulation grid from the DEM. To create the slope grid, the Slope function feature was used. The output slope grid, as seen in Figure 9 (10 meter spatial resolution), was generated at cell sizes of 10, 30, and 50 meters. The flow accumulation grid was constructed using the ArcGIS extension, ArcHydro Tools, which was downloaded from the University of Texas at Austin Center for Research in Water Resources website.

Figure 9. Slope grid (10 meter cell size).

The Fill Sink feature under Terrain Preprocessing was used to fill in sinks within the DEM and create an output grid. This output grid was then used to determine flow direction using the Flow Direction feature. The flow direction output grid was then used to determine flow accumulation using the Flow Accumulation feature. The output flow accumulation grid, as seen in Figure 10 (10 meter spatial resolution), was generated at cell sizes of 10, 30, and 50 meters.

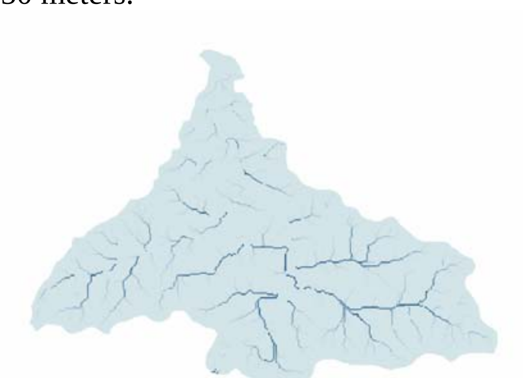

Figure 10. Flow accumulation grid (10 meter cell size).

With this last step, the raster grids for the subwatershed, MLCCS, STATSGO, SSURGO, R factor, P factor, slope, and flow accumulation were ready to be included in both RUSLE models at each of the three scales.

RUSLE Attribute Data

Prior to converting the MLCCS, STATSGO, SSURGO, R factor, and P factor vector data layers into raster grids, a new field needed to be added to each layer's attribute table. The new field added to the MLCCS attribute table housed the C factor values for each land cover polygon in the subwatershed.

Table 1 highlights land cover types and their associated C factor values (soil erodibility based on cover

Table 1. A sample of the 83 MLCCS land cover classifications and associated C factor values in the Zumbro River subwatershed.

Minnesota Land Cover Classification System (MLCCS)

Land Cover Type	CFactor
Cattail marsh permanently flooded	0.001
Coniferous forest	0.001
Cultivated herbaceous vegetation	0.320
Deciduous forest	0.002
Deciduous shrubland	0.025
Fruit trees on upland soils	0.110
Floodplain forest	0.010
Floodplain forest swamp white oak subtype	0.015
Grassland with sparse deciduous trees	0.010
Hydric soils-row cropland	0.470
Lowland hardwood forest	0.001
Maple-basswood forest	0.002
Medium-tall grassland	0.012
Medium-tall grassland altered/non-native dominated	0.015
Mixed coniferous-deciduous forest	0.001
Mixed coniferous-deciduous woodland	0.002
Oak forest with 4% to 10% impervious cover	0.004
Oak forest	0.002
Oak forest dry subtype	0.002
Oak woodland-brushland	0.005
Paulstrine open water	0.000
Planted or maintained grasses	0.140
Planted or maintained grasses with sparse tree cover	0.100
Planted, maintained or cultivated deciduous trees	0.070
Sand gravel pits with 0% to 10% impervious cover	0.000
Unconsolidated material (soil, sand and ash)	1.000
Upland coniferous forest	0.001
Upland coniferous woodland	0.001
Upland deciduous forest	0.002
Upland deciduous shrubland	0.005
Upland deciduous woodland	0.002

management) for a sampling of the 83 cover types found in the Zumbro River subwatershed using MLCCS. The C factor is a numerical value from 0 to 1 in which cover management values closer to 0 are less prone to soil erodibility. The C factor values were derived from a combination of data gathered from the USDA NRCS Minnesota office and several other soil erosion studies conducted in comparable climates and environments (i.e. Minnesota, Wisconsin, and New York).

The new field added to both the STATSGO and SSURGO attribute tables housed the K factor values for each soil unit in the subwatershed. Table 2 highlights STATSGO soil units and their associated K factor values (soil erodibility). For the Zumbro River subwatershed there are 9 soil polygons. Table 3 highlights SSURGO soil units and their associated K factor values. For the Zumbro River subwatershed there are 1,396 soil polygons.

The K factor is a numerical value from 0 to 1 in which soil erodibility values closer to 0 are less prone to soil erosion. The K factor values, including a diversity of other soil property characteristics, are found in separate tabular data that were added to the ArcMap environment, queried and joined to the spatial data layers attribute tables based on common fields.

Lastly, a new field was added to each of the R and P factor attribute tables in ArcMap. To reiterate, each spatial data layer consists of a single polygon that fits the entire extent of the subwatershed. The R factor (rainfall-runoff erosivity) value for the entire Zumbro River watershed is 140. Due to the lack of availability of conservation practice (P factor) information for the Zumbro River subwatershed, a value of 1 was added to the attribute table's new field. As mentioned, this is a technique used by researchers and resource managers that lack conservation practice information for their models and simply remove this variable from having any impact on the model.

Table 2. USDA NRCS STATSGO soil units and associated K factor values in the Zumbro River subwatershed.

State Soil Geographic (STATSGO) Soil Database

Polygon ID	Soil Type	KFactor
49785	MN240	0.3440
49787	MN216	0.3240
50152	MN221	0.3730
50155	MN225	0.3340
49803	MN212	0.3030
50157	MN216	0.3240
50158	MN228	0.1840
50159	MN214	0.2950
50160	MN240	0.3440

Table 3. A sample of the 1,396 USDA NRCS SSURGO soil units and associated K factor values in the Zumbro River subwatershed.

Soil Survey Geographic (SSURGO) Soils Database

Polygon ID	Soil Type	Soil Name	KFactor
400776	42E	Salida	0.2000
400731	244C	Lilah	0.2400
400812	516A	Dowagiac	0.2800
400773	401D	Mt. Carroll	0.3200
400778	465	Kalmarville	0.2800
400726	209A	Kegonsa	0.3200
400733	251F	Marlean	0.2800
400771	401C	Mt. Carroll	0.3200
400717	173F	Frontenac	0.3200
400731	244C	Lilah	0.2400
400778	465	Kalmarville	0.2800
400813	516B	Palms	0.2800
400731	244C	Lilah	0.2400
400789	476C	Frankville	0.3200
400778	465	Kalmarville	0.2800
400816	593D	Elbaville	0.3200
400734	251G	Marlean	0.2800
400724	19	Chaseburg	0.3700
400772	401C2	Mt. Carroll	0.3200
400814	516C	Dowagiac	0.2000

RUSLE Modeling

With the C, K, R, and P factor values now added to the attribute tables and the MLCCS, STATSGO, SSURGO, R factor, P factor, slope, and flow accumulation layers converted from features to raster, the stage is now set to begin calculating both RUSLE models at each designated scale.

The remaining factor of LS (slope length and slope steepness) was calculated using the slope and flow accumulation grids generated earlier. The longer the slope length the higher amount of cumulative runoff and the steeper the slope the higher the runoff velocity which contributes to erosion.

The original equation to calculate the LS factor was an empirical equation published in the USDA Agriculture Handbook No. 537 (Wischmeier and Smith, 1978). The equation has undergone some minor changes including the equation published by Moore and Burch in 1986.

The LS empirical equation used for this project is:

$$LS = (\text{Flow Accumulation grid} * \text{cell size} / 22.13)^{0.4} * (\text{Sin}(\text{Slope grid} * 0.01745) / 0.0896)^{1.4} * 1.4$$

The Raster Calculator in the Spatial Analyst extension of ArcMap was used to calculate the LS grid. The Raster Calculator expression of the equation above was:

LS = Pow([Flow Accumulation grid] * 10 / 22.13, 0.4) * Pow(Sin[Slope grid] * 0.01745) / 0.0896, 1.4) * 1.4

The output LS grid, as seen in Figure 11 (10 meter spatial resolution), was generated at cell sizes of 10, 30, and 50 meters.

The Raster Calculator was again used to calculate both RUSLE model grids to determine potential soil erosion risk in the Zumbro River subwatershed.

Figure 11. Slope length and steepness grid (10 meter cell size).

The first iteration of the RUSLE model was:

A = R * K * LS * C * P

Where:

A = computed average annual soil loss in tons/acre/year
R = rainfall-runoff erosivity grid
K = soil erodibility grid (STASGO)
LS = slope length and steepness grid
C = cover management grid (MLCCS)
P = conservation practice grid

The second iteration of the RUSLE model was:

A = R * K * LS * C * P

Where:

A = computed average annual soil loss in tons/acre/year
R = rainfall-runoff erosivity grid
K = soil erodibility grid (SSURGO)
LS = slope length and steepness grid
C = cover management grid (MLCCS)
P = conservation practice grid

When comparing models, both model variables except for the K factor (STATSGO and SSURGO) are identical, thereby controlling model calculations and allowing for a comparative analysis of the STATSGO and SSURGO soil databases.

Comparative Analysis

With both RUSLE models calculated using STATSGO and SSURGO soil databases at 10, 30, and 50 meter resolutions (cell sizes), the resulting output grids are ready to be sampled for comparison. Once sampled, XLSTAT and SPSS software were used to statistically analyze the data.

STATSGO vs. SSURGO: Estimated Soil Loss (A) and Scaling Effect

In comparing the degree of similarity and relatedness between STATSGO and SSURGO RUSLE models, the area and cell counts for each reclassified attribute class were compared between soil databases. In addition, the resulting RUSLE cell values for both models at each scale, A (tons/acre/year), were sampled within the subwatershed and compared using regression analysis.

Sensitivity and Scaling Effect of Estimated Soil Loss (A) to Model Variables

In comparing estimated soil losses (A) to variables for both RUSLE models, the cell values for the C, K, and LS grids were separately sampled at each scale and compared, using regression analysis, to their respective RUSLE cell output values.

Sampling

Simple random sampling was the technique used to sample the Zumbro River subwatershed. This technique was employed so that every cell in the subwatershed grid had an equal chance of being selected. Simple random sampling is probably the best method to ensure a bias-free sample for self contained units when data is available for all grid cells. It has several drawbacks, including high variance, sampled data not spatially balanced, and the potential for an increased probability that as the number of sampled data increases the greater the chance the sampled data does not provide a good representation of the entire population of grid cells (Theobald et al, 2005).

Hawth's Analysis Tools for ArcGIS was used to create a point shapefile of randomly selected points for the subwatershed. The Generate Random Points feature under Sampling Tools was used to create the point shapefile.

To determine the sampling size needed to effectively sample the subwatershed, the following equation from PennState Cooperative Extension was employed:

$$n = \frac{\dfrac{P[1-P]}{\dfrac{A^2}{Z^2} + \dfrac{P[1-P]}{N}}}{R}$$

Where:

n = sample size required
N = population size (number of cells)
P = estimated degree of variance (i.e., 0.5 for 50-50, 0.3 for 70-30)
A = precision desired, margin of error (i.e., 0.03, 0.05, 0.1 for 3%, 5%, 10%)
Z = based on confidence level: 1.96 for 95% confidence, 1.6449 for 90%, and 2.5758 for 99%
R = estimated response rate

For the purposes of this study, the variables include:

n = sample size required
N = 461,017 raster cells
P = 60-40 = 0.4
A = 5% = 0.05
Z = 95% confidence level = 1.96
R = 1

So the sampling size equation for this study looks like:

$$n = \frac{\dfrac{0.4[1-0.4]}{\dfrac{(0.05)^2}{(1.96)^2} + \dfrac{0.4[1-0.4]}{461017}}}{1}$$

where n = 368.499 = 369 for sample size required to adequately sample the subwatershed.

The sample size of 369 was used in the Generate Random Points feature in Hawth's Analysis Tools extension to create a shapefile containing 369 randomly placed points in the subwatershed. This point shapefile (Figure 12) was used to overlay with the RUSLE and model variable grids at each scale to collect cell values for comparative analysis. A total of 8,856 cell values were sampled.

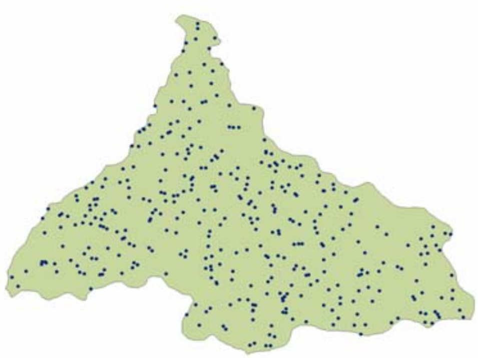

Figure 12. Random sampling points shapefile created by Hawth's Analysis Tools.

Results

Assessment of Soil Erosion Risk within the Zumbro River Subwatershed

Raster maps of the R, K, LS, C, and P grid layers were integrated within the ArcGIS environment to generate composite maps of estimated erosion loss within the subwatershed project site.

In all, six RUSLE empirical models were generated. Three models were run using the STATSGO soil database and associated K values at 10, 30, and 50 meter resolutions respectively. The remaining three models were run using the SSURGO soil database and associated K values also at 10, 30, and 50 meter resolutions respectively. The resulting six RUSLE subwatershed maps, Figures 19-24, can be found in Appendix A. The RUSLE maps were each overlaid onto a hillshade raster layer, created using the Spatial Analyst extension in ArcMap, to better visualize subwatershed topography.

Each RUSLE map was then reclassified into six categories of estimated erosion loss. The erosion loss categories were developed using previous RUSLE model reclassifications from temperate U.S. regions as a guide.

Table 4 provides an example of the estimated erosion loss categories used (and their soil loss values) for reclassification and the resulting cell count, proportion, and acreage for each erosion category. The resulting six reclassified RUSLE models at 10, 30, and 50 meter resolutions can be found in Appendix B (Figures 25-30).

Table 4 shows two-thirds of the cells that make up each raster layer fall within the Very Low Erosion category where estimated soil loss is less than 3 tons/acre/year. Within the U.S., 3 tons/acre/year is considered an acceptable loss. An evaluation of the maps reveals a significant proportion of these cells occur in the north, central and southern regions of the subwatershed, where more open water, wetlands, natural uplands, forests, and hay/forage cover types occur.

Table 4. Examples of two RUSLE models reclassified into six estimated erosion loss categories and subsequent count, proportion, and acreage results. Soil loss, A, is in tons/acre/year.

Reclass RUSLE STATSGO (10 meter)

ObjectID	Value	Erosion Risk	Soil Loss (A)	Count	Proportion (%)	Area (acres)
0	1	No Erosion	0	36532	7.92	902.73
1	2	Very Low Erosion	0 to 3	302547	65.64	7475.82
2	3	Low Erosion	3 to 6	38969	8.45	962.91
3	4	Moderate Erosion	6 to 15	47765	10.36	1100.25
4	5	High Erosion	15 to 100	34363	7.45	849.09
5	6	Very High Erosion	> 100	841	0.18	20.77
			Total	461017	100	11391.57 (4610.11 ha.) (17.80 sq. mi.)

Reclass RUSLE SSURGO (10 meter)

ObjectID	Value	Erosion Risk	Soil Loss (A)	Count	Proportion (%)	Area (acres)
0	1	No Erosion	0	40069	8.69	990.09
1	2	Very Low Erosion	0 to 3	304585	66.07	7526.19
2	3	Low Erosion	3 to 6	40017	8.68	988.81
3	4	Moderate Erosion	6 to 15	45122	9.79	1114.95
4	5	High Erosion	15 to 100	30485	6.61	753.27
5	6	Very High Erosion	> 100	739	0.16	18.26
			Total	461017	100	11391.57 (4610.11 ha.) (17.80 sq. mi.)

High to very high estimated soil loss tends to occur more in the western and eastern regions of the subwatershed. Within this landscape mosaic a greater proportion of the subwatershed's row crops are found.

What is interesting is that the central and eastern regions of the subwatershed have greater slope and topography. Parts of the eastern region exhibit moderate to very high estimated erosion loss, possibly due to the density of agricultural lands like row crops and areas with moderately exposed soils, combined with topography. When parts of the western region that have moderate to very high estimated erosion loss are examined, you have a greater agricultural presence but significantly reduced topography.

The inherent benefit of natural lowland and upland cover types and hay/forage practices becomes very evident if one examines the north, central, and southern regions of the subwatershed and reveals that regardless of significant slope and topography, minimal erosion is estimated.

Comparative Analysis of the Use and Scaling Effect of STATSGO and SSURGO

In examining the level of agreement or disagreement between a STATSGO-based RUSLE model and a SSURGO-based RUSLE model at 10, 30, and 50 meter resolutions, the cell counts, proportions, and acreages of the reclassified maps are first considered. Three histograms, Figures 13-15, compare acreages and soil databases at each resolution.

The histograms reveal that the cell count, proportion of each erosion category from the total, and acreage are very similar between the RUSLE models that utilized STATSGO and SSURGO at each resolution. In addition to the similarity so far observed between the soil databases, there is also a trend at

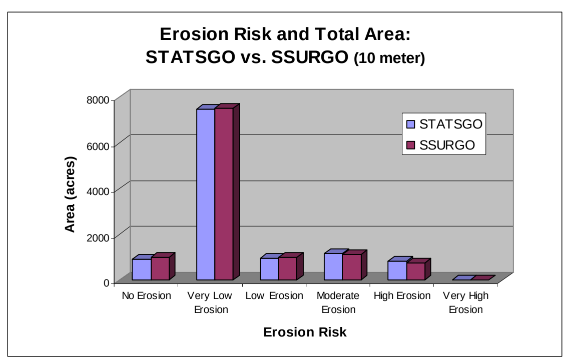

Figure 13. STATSGO vs. SSURGO: total area of estimated soil loss, by erosion category, at 10 meters resolution.

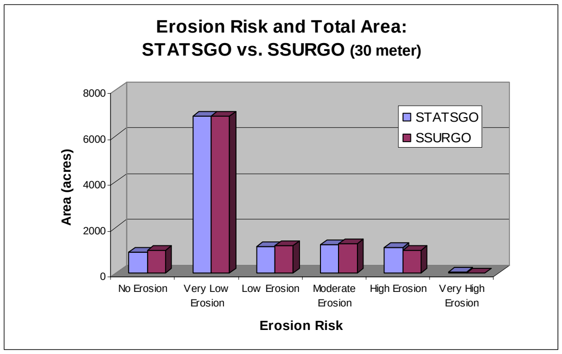

Figure 14. STATSGO vs. SSURGO: total area of estimated soil loss, by erosion category, at 30 meters resolution.

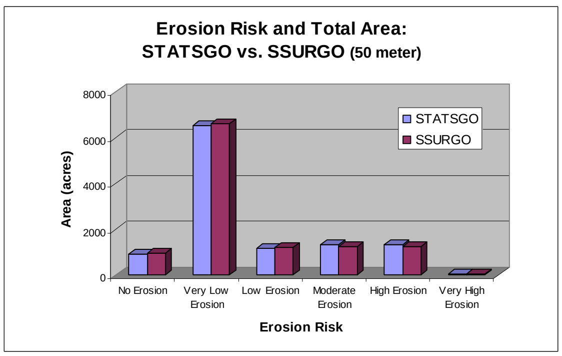

Figure 15. STATSGO vs. SSURGO: total area of estimated soil loss, by erosion category, at 50 meters resolution.

each resolution in which calculated erosion values (A) from SSURGO-based RUSLE models score slightly lower, on average, in their estimations of soil loss. This can be seen from the basic statistics, specifically the means, for each RUSLE model in Table 5.

Table 5. Basic statistics for STATSGO and SSURGO-based RUSLE models at 10, 30 and 50 meter resolutions.

STATSGO and SSURGO Statistics for RUSLE Raster Layers (10, 30 and 50 meters)

	Minimum	Maximum	Mean	Std. Dev.
STATSGO (A)				
10 meter	0	441.59	4.23	10.78
30 meter	0	556.79	5.49	13.52
50 meter	0	373.97	6.71	16.32
SSURGO (A)				
10 meter	0	474.97	3.96	10.44
30 meter	0	598.88	5.15	13.11
50 meter	0	469.04	6.28	15.66

Lastly, a regression analysis was conducted to better understand the relatedness between STATSGO and SSURGO soil databases with respect to their estimation of soil erosion loss. Regression analysis is often used to model relationships between variables, determine the degree of the relationship, and can be used to make predictions based on the models.

Before using regression analysis, it must first be determined what type of regression is needed based on the available data. Linear (parametric) regression assumes the data are continuous, independent, normally distributed, and the variance is equal (homoskedastic). Semiparametric regression assumes the data are not normally distributed and preserves the simplicity of parametric regression while employing the flexibility of nonparametric regression. If the data are known not to be normally distributed, nonparametric regression would be better suited for analysis because it does not make assumptions about the frequency distribution of the variables and is much more flexible so as to more likely detect the relatedness between the data.

The data is known to be continuous and independent so the data must be tested for normality to help make the final determination on which type of regression to run. The lack of normality in data, including the presence of outliers, can falsely impact the correlation coefficient, R^2, if normality is assumed incorrectly and linear (parametric) regression is used.

Using the Shapiro-Wilk, Anderson-Darling, Lilliefors and Jarque-Bera tests for the data sampled from each grid at 10, 30, and 50 meter resolutions, the presence or absence of normality in the data could be examined.

Scientific data from many disciplines exhibit strong nonconformity to parametric models (Yang, 2006). So it came as little surprise that each test calculated that the sampled data was not normally distributed, therefore strongly suggesting that for the sampled data, a nonparametric regression technique is the most suitable to detect the degree of relatedness.

The Robust Lowess nonparametric regression technique was used to determine the relatedness between STATSGO-based RUSLE samples and SSURGO-based RUSLE samples. Regression results have shown that estimated erosion loss values for STATSGO and SSURGO-based RUSLE models at 10, 30, and 50 meter resolutions are related. The correlation coefficient (R^2) is 0.914, 0.928, and 0.922 for 10, 30, and 50 meter resolutions respectively. The Robust Lowess regression for each scale can be seen in Figures 16-18.

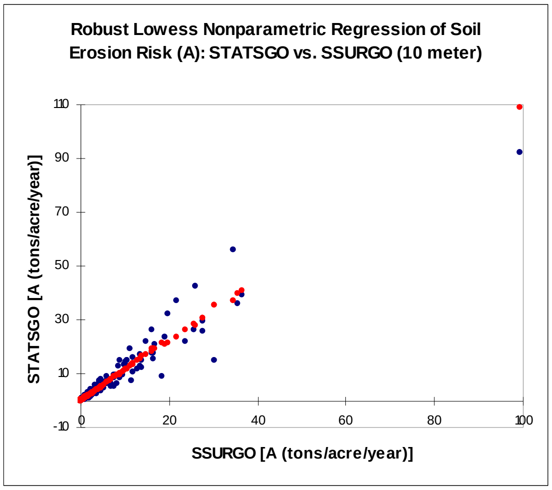

Figure 16. STATSGO vs. SSURGO: Robust Lowess nonparametric regression for soil erosion risk (A) at 10 meters resolution. R^2 = 0.914 (blue: soil grid data, red: nonparametric regression).

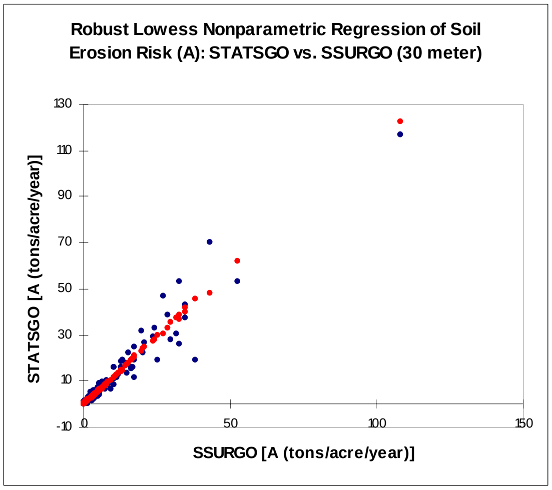

Figure 17. STATSGO vs. SSURGO: Robust Lowess nonparametric regression for soil erosion risk (A) at 30 meters resolution. R^2 = 0.928 (blue: soil grid data, red: nonparametric regression).

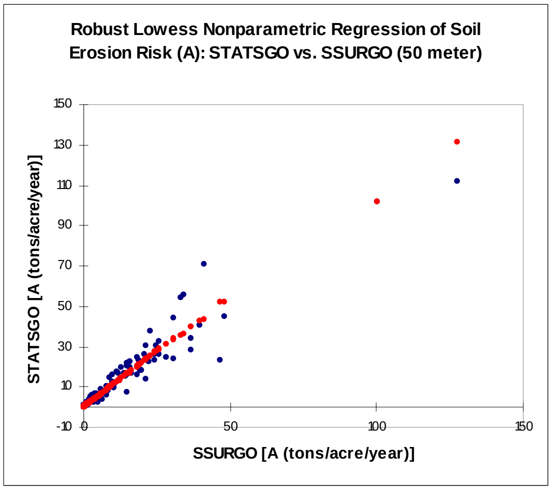

Figure 18. STATSGO vs. SSURGO: Robust Lowess nonparametric regression for soil erosion risk (A) at 50 meters resolution. R^2 = 0.922 (blue: soil grid data, red: nonparametric regression).

For every RUSLE value calculated using the STATSGO soil database, there is a high degree of confidence that the estimated erosion loss value will be similar to the value calculated using the SSURGO soil database and vice versa. An important note to make, however, is that when examining Figures 16-18, the relatedness of low to moderate estimated erosion values between RUSLE models is greater but for high to very high estimated erosion loss values the relatedness is less. These high erosion values are what drive the correlation coefficient down from 1 to 0.918, 0.928, and 0.922 for 10, 30, and 50 meter resolutions respectively.

Assessment of Sensitivity and Scaling Effect of Estimated Soil Loss to Model Variables

In examining the level of sensitivity between the model variables, LS, K, and C to estimated soil loss (A) at 10, 30, and 50 meter resolutions, the same principle behind using nonparametric regression analysis to determine relatedness is used as the section above. This includes lack of normality in conjunction with data being continuous and independent. Here, it is assumed that the greater the variable sensitivity to estimated soil erosion loss the greater the relatedness.

Table 6 below provides the coefficients of correlation (R^2) for each sampled model variable regressed against its corresponding RUSLE model at 10, 30, and 50 meter resolutions. The Lowess nonparametric regression technique was used for this analysis of relatedness. In all, 18 nonparametric regressions were run.

Table 6 suggests the model variables LS (slope length and steepness) and K (soil erodibility) are not related to their corresponding A values for either models that use STATSGO and SSURGO at any scale. For this project, LS and K variables do not seem to provide a highly significant and direct impact on RUSLE model outputs.

Table 6. The correlation coefficients (R^2) of model variables to estimated soil erosion loss (A) for each RUSLE model at 10, 30, and 50 meter resolutions using Lowess nonparametric regression.

Lowess Nonparametric Regression Correlation Coefficients

10 Meters					
STATSGO (A)	LS	0.07	SSURGO (A)	LS	0.066
	K	0.003		K	0.045
	C	0.493		C	0.489
30 Meters					
STATSGO (A)	LS	0.056	SSURGO (A)	LS	0.044
	K	0.002		K	0.049
	C	0.426		C	0.411
50 Meters					
STATSGO (A)	LS	0.05	SSURGO (A)	LS	0.057
	K	0.007		K	0.013
	C	0.514		C	0.516

The model variable C (cover management) has a greater relatedness to RUSLE model outputs at each scale than LS and K, but not what would be deemed a significant relationship. For STATSGO-based RUSLE models the R^2 is 0.493, 0.426, and 0.514 at 10, 30, and 50 meter resolutions respectively. For SSURGO-based RUSLE models the R^2 is 0.489, 0.411, and 0.516 at 10, 30, and 50 meter resolutions respectively. It would seem that the C factor, which includes land cover types and associated soil exposure, may play a slightly greater role in determining estimated soil erosion loss for this project but not at a significant level.

Conclusion

The RUSLE empirical model was applied six times to the Zumbro River subwatershed during this study. The variables, R, LS, C, and P were identical for each model except for K (soil erodbility). Three models used the STATSGO soil database at 10, 30, and 50 meter resolutions and the remaining three models used the SSURGO soil database also at 10, 30, and 50 meter resolutions.

The spatial distribution and estimated erosion loss values within the subwatershed were significantly related when comparing STATSGO and SSURGO-based RUSLE models at each resolution. Relatedness of estimated erosion loss values (A) between the soil databases at each resolution, however, was greater for very low to moderate soil losses and lessened dramatically for high to very high soil losses. The mean A (tons/acre/year) for the STATSGO-based RUSLE models were 4.23, 5.49, and 6.71 for 10, 30, and 50 meter resolutions respectively. The mean A for the SSURGO-based RUSLE models were 3.96, 5.15, and 6.28 for 10, 30, and 50 meter resolutions respectively.

For this study, the C model variable was more related to each corresponding A than the other variables but not at a significant level. This infers that in the subwatershed, the C variable, cover management, is a better indicator for resulting RUSLE outputs, A. It is generally accepted that ground cover is the most important factor in the soil erosion process, especially when considering surface cover, canopy cover, surface roughness and prior land use (Yazidhi, 2003).

Based on literature searches, additional assumptions would have led to the LS variable, slope length and steepness, as another good indicator for estimations of soil loss (Lee and Lee, 2006; Liu et al, 2000). In these two cited research projects in Korea and China, areas under study occurred on steeper slopes than what is found in the Zumbro River subwatershed but it may be that the sampling method used here did not recognize any potentially existing relationship between LS and A.

This study demonstrates that GIS is a valuable tool in assessing soil erosion modeling and in assisting the estimation of erosion loss at the subwatershed scale. But there are limitations that must be taken into account prior to modeling including the quality of data and the spatial resolution used.

The RUSLE model exemplifies that spatial resolution is sensitive to the estimations of erosion so caution must be taken when selecting grid size. When considering soil erosion modeling at scales much smaller than the subwatershed level (i.e. townships, parcels, etc.), it is recommended that soil databases chosen be more complex than STATSGO. Lastly, caution must also be practiced with data since minor errors can exponentially increase and skew results thereby compromising the implementation of conservation practices, education, and funds to address soil erosion issues.

Acknowledgements

I would like to take this opportunity to thank Dr. David McConville, Mr. John Ebert, and Mr. Patrick Thorsell in the Department of Resource Analysis for their assistance and ongoing support for this project and during my tenure at Saint Mary’s University.

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Appendix A. RUSLE models and estimated soil erosion loss (tons/acre/year) using STATSGO and SSURGO soil databases at 10, 30 and 50 meter cell sizes. Hillshading added for topographic visualization.

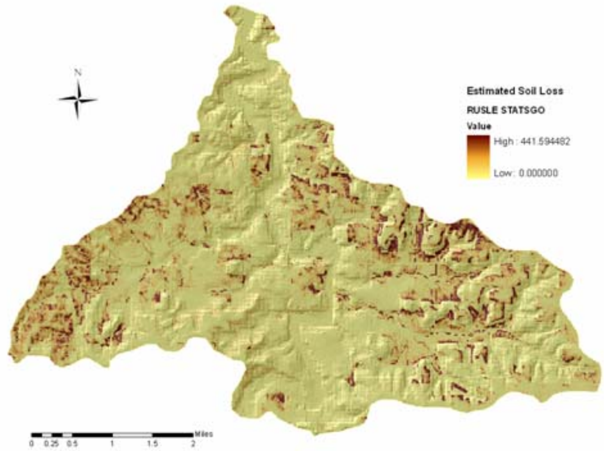

Figure 19. Estimated soil erosion loss at 10 meters resolution using STATSGO.

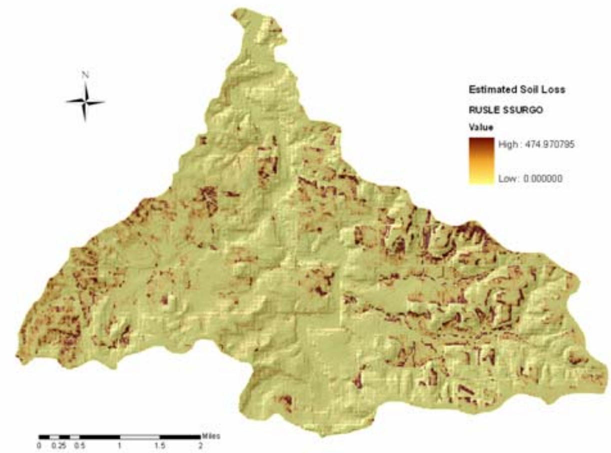

Figure 22. Estimated soil erosion loss at 10 meters resolution using SSURGO.

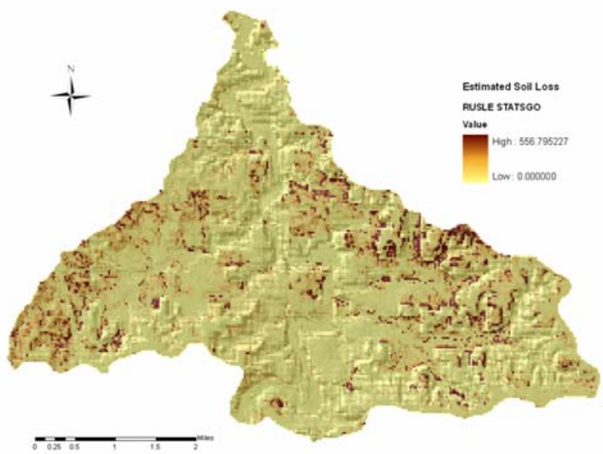

Figure 20. Estimated soil erosion loss at 30 meters resolution using STATSGO.

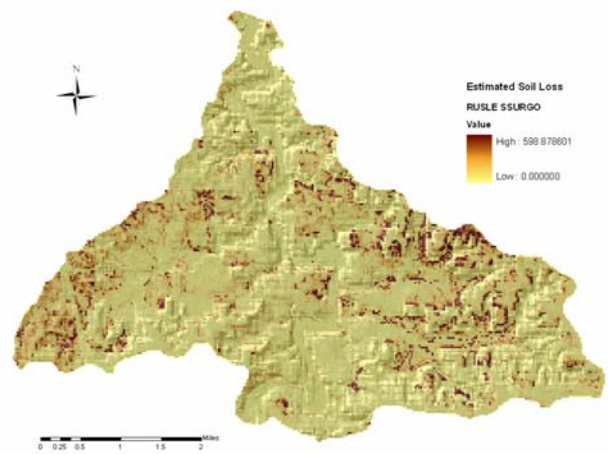

Figure 23. Estimated soil erosion loss at 30 meters resolution using SSURGO.

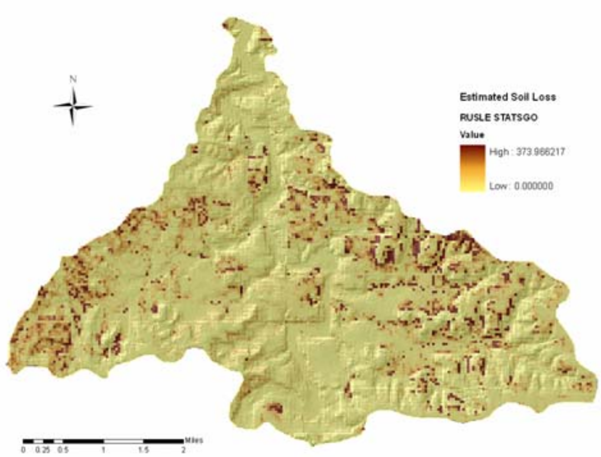

Figure 21. Estimated soil erosion loss at 50 meters resolution using STATSGO.

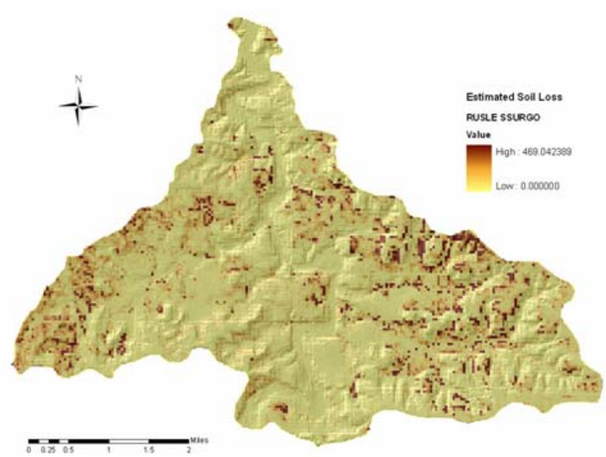

Figure 24. Estimated soil erosion loss at 50 meters resolution using SSURGO.

Appendix B. Reclassified RUSLE models and categorized soil erosion loss using STATSGO and SSURGO soil databases at 10, 30 and 50 meter cell sizes.

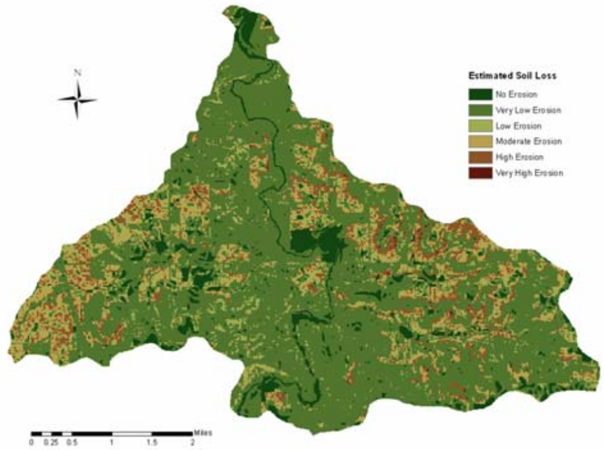

Figure 25. Reclassified RUSLE model at 10 meters resolution using STATSGO.

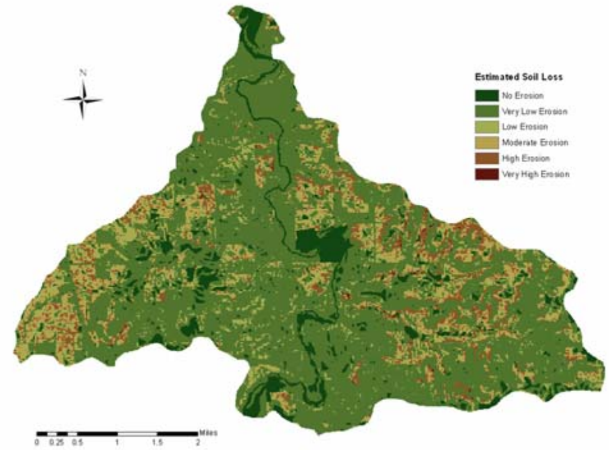

Figure 28. Reclassified RUSLE model at 10 meters resolution using SSURGO.

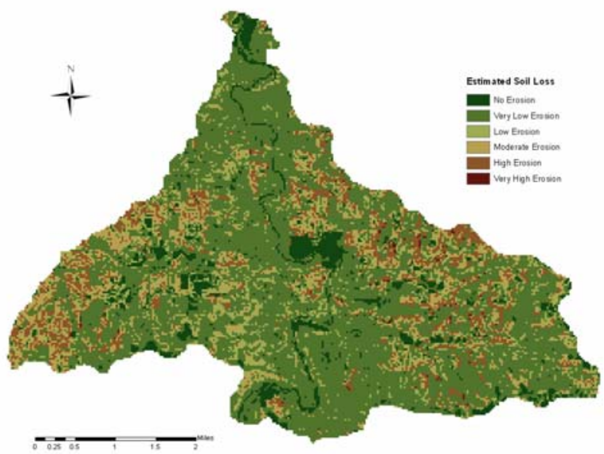

Figure 26. Reclassified RUSLE model at 30 meters resolution using STATSGO.

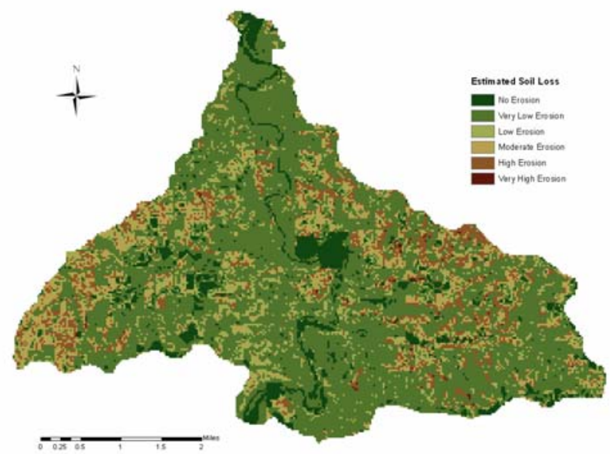

Figure 29. Reclassified RUSLE model at 30 meters resolution using SSURGO.

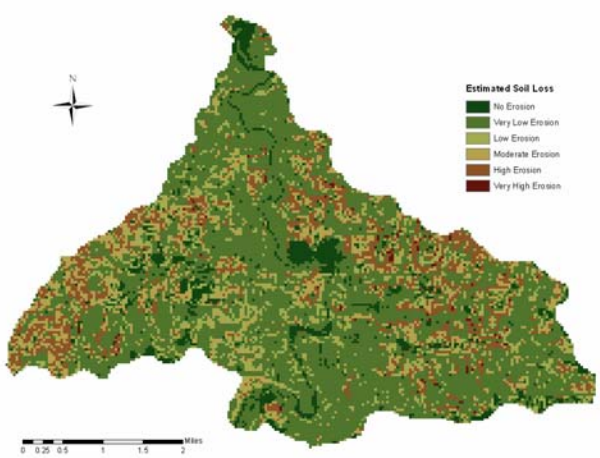

Figure 27. Reclassified RUSLE model at 50 meters resolution using STATSGO.

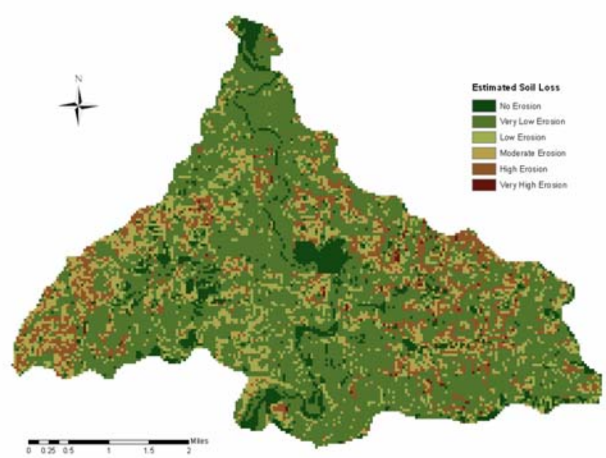

Figure 30. Reclassified RUSLE model at 50 meters resolution using SSURGO.