Modeling Soil Erosion with ^{137}Cs

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Executive Summary

In order to develop landscape-scale estimates of soil erosion in Minnesota's agricultural landscapes, we conducted a broad survey study of ^{137}Cs in cultivated fields and uncultivated grassland reference sites located across the southern third of Minnesota. Because the only source of ^{137}Cs is nuclear fission and it binds tightly to soils, landscapes were "labeled" with ^{137}Cs during aboveground testing of nuclear weapons in the 1950s and 1960s. As a result of this, ^{137}Cs inventories can serve as an effective tracer for soil movement on decadal timescales. A ^{137}Cs conversion model was used to determine soil erosion rates for 107 locations in cultivated sites. Measured soil erosion rates ranged from 49 t ha^{-1} yr^{-1} (erosion) to -74 t ha^{-1} yr^{-1} (deposition). Based on these measured rates, regression models were developed with the goal of broadly predicting soil erosion rates based on topographic characteristics. Digital terrain attributes were calculated from LiDAR-derived (Light Detection And Ranging) digital elevation models and then used as predictor terms in regression model development. Resulting models showed that: (1) profile curvature, (2) planform curvature, and (3) slope steepness were significant model terms in predicting erosion rates for different Minnesota Major Land Resource Areas (MLRAs). The resulting regression models were able to explain 38% of the variability observed in measured soil erosion rates. When applied to cultivated landscapes, the regression models create maps of predicted long-term rates of soil erosion or deposition. These maps will be helpful to BWSR personnel, soil conservationists, and other local government unit personnel to help identify which portions of the landscape would benefit the most from perennial vegetation conservation practices. In a complementary manner, these maps may also be used to quantify the soil and water quality benefits of farmland enrollment into a conservation program (or, conversely, the environmental impact of converting perennially vegetated land for cultivation).

Introduction

Recent increases in corn and soybean prices have resulted, in the upper Midwest, in a shift toward increasing land managed for row crop production at the expense of perennial grasslands, including loss of CRP lands [*Wright and Wimberly*, 2013]. Under greater crop commodity prices, even marginally productive portions of the landscape can become profitable for farmers. The increase in cultivation on certain portions of the landscape can have detrimental impacts on soil and water quality through increased erosion. More specifically, landscape segments that are characterized by steep slopes and high curvature are especially prone to soil erosion [*Ritchie and McHenry*, 1990; *Wischmeier and Smith*, 1965; 1978]. While these ideas are well-established, resources to expand and apply them to broad portions of the landscape have been limited. In particular, wide availability of Digital Elevation Models (DEMs) has, until recently, been limited to products with a 30 m pixel resolution (or greater). While helpful in characterizing landscape-scale trends, this resolution was too coarse to produce a data product that could be meaningfully applied to many farm fields because important topographic features can often be smaller than 30 m. Subsequently, studies that showed the utility of including digital terrain attributes such as slope and curvature [*Hurst et al.*, 2012; *Moore et al.*, 1993; *Yoo et al.*, 2005] required site-specific surveys that contained sufficient detail but were limited in spatial scope.

More recently, Light Detection and Ranging (LiDAR) technology has advanced and become more affordable such that detailed DEMs are now becoming widely available for large areas. The State of Minnesota has been involved in coordinating and collecting statewide coverage of LiDAR data from 2010 through 2012 and those data products are now freely available. The MN LiDAR data have been used to produce digital elevation models with pixel resolutions of 1 and 3 meters and vertical accuracy of about 10 cm (root mean square error, county-specific values available at http://www.mngeo.state.mn.us/chouse/elevation/CVA_map_mn_lidar.pdf). The availability of these high-resolution DEMs provides the opportunity for a new assessment of soil erosion potential around Minnesota's farmland under row crop vs. grassland cover.

Detailed DEMs, however, only provide a portion of the information needed to assess land use impacts on soil erosion in the landscape. A separate measure of soil movement is also necessary to complement the DEMs and develop relationships suitable for quantifying topographic and land management effects on soil erosion. One method suitable for tracking soil erosion over time is measurement of ^{137}Cs activity in a variety of landscape positions, which can reflect different erosion (or deposition) history. ^{137}Cs is a radioactive isotope produced only as a result of high-yield thermonuclear reactions. In the 1950s and early 1960s, aboveground testing of thermonuclear bombs resulted in wide global distribution of ^{137}Cs (and other isotopes). Fallout of ^{137}Cs via dry and (mostly) wet deposition is locally homogenous (although larger regional and global patterns do exist due to differences in precipitation, [*Longmore*, 1982] and ^{137}Cs binds strongly to soil minerals [*Ritchie and McHenry*, 1990]. Because atmospheric testing of nuclear weapons ceased when the limited nuclear test ban treaty went into effect (October, 1963), the presence of ^{137}Cs in the soil profile can be used to interpret the movement of soil over an approximately 50-yr time span and help calculate long-term average erosion rates in agricultural soils when used in conjunction with ^{137}Cs data from nearby reference sites (perennial grasslands).

The goals of this study were to: (1) measure long-term average soil erosion rates for a variety of landscape positions across the predominantly-agricultural landscapes in the southern third of Minnesota, and (2), develop empirical models based on digital terrain attributes in order to expand soil erosion estimates to nearby similar croplands. It is the intent of this work that maps of long-term soil erosion rates can be used by local government units (LGUs) and Soil and Water Conservation District (SWCD) personnel to help identify landscape positions that are most prone to erosion as well as to quantify long-term (50-yr) average erosion rates. This information can help SWCD and LGU personnel identify priority locations for establishment (or maintenance) of CRP lands (or similar perennial cover) in order to protect Minnesota's soil and water resources while also helping to ensure more effective use of limited conservation funds.

Important Considerations

Results from this work are intended to be helpful for estimating long-term average erosion rates under cropland and grassland scenarios based on digital terrain attributes. More specifically, cropland scenarios reflect corn and soybean row crop agriculture, which dominates Minnesota's agricultural landscape. *Empirical models developed here do not attempt to account for differences in soil erosion that may result from agricultural management practices such as no-till, conservation tillage, or contour tillage (or other practices).* It is assumed that these practices varied and were not constant over the 50-yr time period that ^{137}Cs measurements encompass. *Because of differences in management practices, results presented here may differ from actual erosion/deposition rates on an individual farm*. Rather, these results are intended to estimate the average amount of soil erosion that would be prevented for a given landscape element if it were enrolled in a conservation program such as CRP (or otherwise managed in perennial vegetation).

Methods

Study Areas

Sites for this study were selected to include the Major Land Resource Areas [*USDA*, 2006] of Minnesota that are dominant in the agricultural lands comprising roughly the southern third of the state. Agricultural lands in the north western portion of the state (Red River Valley) were not included because of a history of land surface re-shaping to accommodate water drainage [*McCullough,* 2002] which precludes meaningful analysis of ^{137}Cs data.

Northern Mississippi Valley Loess Hills (MLRA 105) - Landscapes in MLRA 105 are bedrock-controlled. The bedrock consists of gently sloping strata of sandstones, dolomites, and limestones, with an occasional thin layer of shale. Streams are deeply incised in this karstic landscape. Although most or all of this area was glaciated at one time, intense erosion associated with periglacial conditions, has stripped away most of the glacial sediments. Thick (2.5 to 10 m) Peorian age loess now mantles the existing high relief landscape, often directly overlying bedrock. This landscape has a well-developed surficial drainage network, high relief, and virtually no closed depressions. Sediments that reach streams are transported out of the landscape. Presettlement vegetation was mainly hardwood forest on the slopes and either hardwood forest or prairie on the broader uplands.

Eastern Iowa and Minnesota Till Prairies (MLRA 104) - Landscapes in MLRA 104 (the northern extension of the Iowan Erosion Surface [*Ruhe et al.*, 1968]) are also relatively old and have well-developed surficial drainage. These landscapes are outside the boundary of the Wisconsinan glacial advance but were previously covered with a thick deposit of heavy Pre-Illinoisan clay-loam till. They have moderate relief and have developed a well-connected drainage network. Thin (0.5 to 0.75 m) Peorian age loess mantles these landscapes. The loess is somewhat sandier than that found in MLRA 105 to the east, but appears to be derived from the same western source [*Mason et al.,* 1994]. Presettlement vegetation in the region was mainly tall-grass prairie.

Central Iowa and Minnesota Till Prairies (MLRA 103) - Landscapes in MLRA 103 have developed mainly on glacial sediments associated with the Late Wisconsinan Des Moines Lobe advance. These sediments are generally loamy in texture. Because of the moderate relief and young age of these sediments, there has been little development of stream networks or other surficial drainage. Most of the landscape consists of closed depressions and a deranged drainage network. Presettlement vegetation in the area was dominated by prairie grasses with wetland vegetation present in the low-lying areas.

Consequently, sediments that are eroded from the uplands by tillage or water erosion are still retained within the landscape.

Rolling Till Prairie (MLRA 102A) - Landscapes in MLRA 102A have developed mainly on glacial moraines, outwash plains, terraces, and floodplain deposits. Much of the drainage in this MLRA is poorly organized and small depressions known as prairie pothole ponds and lakes are common. Most of the sediments eroded from upland areas are retained within the landscapes. Most of the landscape consists of closed depressions and a deranged drainage network. Similar to the Central Iowa and Minnesota Till Prairies, presettlement vegetation in the area was dominated by prairie grasses with wetland vegetation present in the low-lying areas.

A summary of sample location distribution is shown in Figure 1. Agricultural sites included UMN research and outreach center farms (Waseca, Lambteron, Morris) as well as private landowners identified via contacts with the MN Department of Agriculture and local Soil and Water Conservation Districts. In additional to agricultural sites, nearby grassland locations were selected to serve as reference points for ^{137}Cs data. The key criteria for these sites was that they have been under perennial grassland cover for at least the past 50 years as verified by a combination of approaches including historic air photos (going back to 1938), landowner knowledge, and DNR records (for Scientific and Natural Areas, SNAs). In total, 215 points were sampled across southern Minnesota, 107 cropland sites and 108 grassland sites.

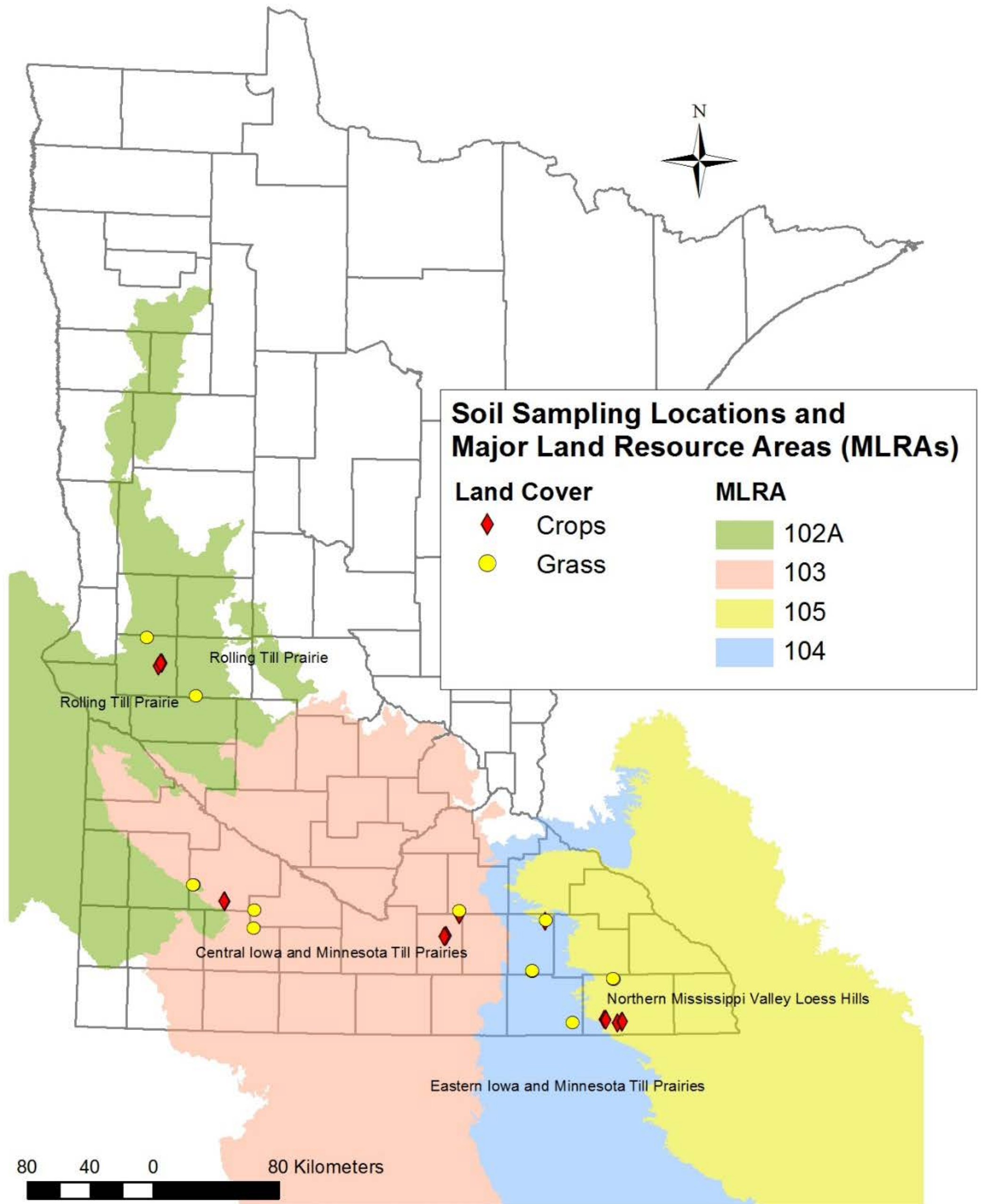

Figure 1. Minnesota Map showing the location of soil sampling locations with respect to Major Land Resource Areas across southern Minnesota. MLRA Numbers correspond with USDA designations and text above.

Soil Sample Collection

Field-sampling points were selected by inspecting the terrain attribute maps and identifying points that represented the range of attribute values present at a given site. In this manner, our sampling approach was targeted at representing the range of available terrain attribute values. Care was taken to select sampling points where terrain attribute values did not change abruptly from one pixel to the next in order to avoid sites that may be particularly sensitive to small differences in sample location. In the field, sampling points were located with a handheld GPS unit (accuracy was typically better than 3m, comparable to the pixel size of the 3m DEM used for model development). Soil samples were collected to 150 cm in the following depth increments: 0-5, 5-10, 10-15, 15-20, 20-25, 25-30, 30-40, 40-50, 50-75, 75-100, 100-125, and 125-150 cm. Samples in the upper 50 cm were collected by excavating a shallow pit (Figure 2) and then carefully collecting about 500 g of soil from each depth increment which was placed in a labeled plastic bag. At the same time a bulk density sample was collected from the same depth increment using a brass cylinder of known volume, which was pushed into the soil and then excavated.

A slide-hammer cylindrical corer (5 cm diameter, 30 cm long) with internal plastic sleeves (AMS, American Falls, Idaho, USA) was used to collect soil samples below 50 cm depth. Between sample increments, the hole was widened with a 7.0 cm diameter closed basket auger and then cleaned with a 7.0 cm diameter planer auger to prevent soil from above from contaminating the next sample. Sleeves were removed from the corer after sampling, capped on each end, labeled with the date, sample number, location, and depth, and placed in a labeled plastic zipper bag. Samples were stored with ice in coolers while in the field. Following transport to the laboratory, they were stored in a cold room until processed.

Figure 2. Photo showing sample collection increments for a typical soil pit. Pit face sampling was performed for the upper 50 cm. A multi-stage core sampler was used to collect samples to a depth of 150 cm.

Soil Sample Processing

Bulk Density

Sample bulk density was determined for each depth increment in the upper 50 cm (pit face sampling) by inserting a metal ring of known volume into soil and then carefully collecting the soil volume contained within the ring. Upon returning to the lab, soils were dried overnight at 105°C. Following drying, the soil was weighed, then sieved (2 mm) to remove root and rock fragments before calculating bulk density. Bulk density determined via the metal ring method for the 40-50 cm depth increment was assumed to be representative of bulk density for deeper soil depths (in order to avoid potential compaction effects on bulk density data that may have been introduced from the hand-driven hammer corer.

^{137}Cs and Soil Organic Carbon (SOC)

Soil samples for elemental and ^{137}Cs analyses were dried at 35°C overnight. Samples in plastic core sleeves were expelled prior to drying. Following drying, samples were hand-ground with a mortar and pestle and sieved (2 mm) to remove root and rock fragments before storage in either polycarbonate bottles or polyethylene Bags. For ^{137}Cs samples, a subsample of approximately 200-250 g was loosely packed to a depth of 1 cm center thickness in a Marinelli beaker, sealed with tape to prevent exchange of gasses with the atmosphere, and stored until analyzed. Prior to elemental analysis, carbonates were removed via HCl fumigation after methods described by [*Harris et al.*, 2001]. Briefly, samples were placed into plastic weigh-boats (following visual inspection to ensure no identifiable plant material was present) and wetted with milli-Q water (18MΩ or greater). Soils were then fumigated overnight in a dessicator with HCl vapor. The dessicator lid was opened and excess HCl vapor was allowed to dissipate for 2-3 hours in a fume hood before samples were moved to an oven and dried overnight at 40°C. Then, a known mass of sample was weighed for elemental analysis (organic C) via high-temperature combustion on a VarioMAX elemental analyzer (Elementar Americas Inc.) calibrated to glutamic acid standards. Elemental analyzer runs were interspersed with blanks and check-standards (glutamic acid). Mean deviation on duplicate samples was 0.05 %.

^{137}Cs activity measurement via gamma spectroscopy

Samples were measured for their ^{137}Cs content via gamma spectroscopy on a high purity germanium crystal detector (GX4018 coaxial, Canberra Industries, Inc.). Analysis time varied with sample depth and typically ranged from 8h (surface samples) to 24h (deep samples). Gamma spectra were energy- and efficiency calibrated based on an internally-prepared standard mixture of BL-5 uranium ore

(^{238}U series in secular equilibrium) combined with ^{137}Cs. The standard was mixed with deep loess parent material (no ^{137}Cs detectable) to achieve an activity of 5.122 to 5.430 Bq g^{-1} (depending on compound). Data were processed with the Genie2000 software and resulting sample activities are reported as Bq kg^{-1}. Minimum detectable activity (MDA) varied with acquisition time and sample activity and was determined for each sample individually. For data reported here, the mean MDA/signal ratio for samples collected from the soil surface was typically around 10%. Duplicate analyses of select samples showed mean difference of 0.06 Bq kg^{-1} with an average coefficient of variation of 3.7%.

Digital Terrain Attributes

Digital terrain attributes were calculated from LiDAR-derived digital elevation models (DEMs) available from the Minnesota Elevation Mapping Project:

http://www.mngeo.state.mn.us/committee/elevation/mn_elev_mapping.html

The final elevation product is available with cell sizes of both one and three meters. For this work, we opted to use the three-meter DEM as the base from which to determine digital terrain attributes. This decision was based on 1) the accuracy of the handheld GPS unit used for field work; 2) the observation that the one meter product tends to include more temporary features in crop lands such as tillage tracks from farm implements; and 3) preliminary results that show similar overall results between models based on both one- and three-meter DEMS. Three meter DEMs were used to calculate digital terrain attributes with the ArcGIS software package (v 10.2). Primary attributes (percent slope, profile curvature, and planform curvature) were calculated directly with available spatial analyst tools. Because of deranged drainage patterns and numerous internally drained areas common in MLRAs 102A and 103, we also explored DEM pits as an explanatory topographic feature.

Early efforts with digital terrain attribute modeling also included secondary attributes such as the Compound Topographic Index (CTI) and Stream Power Index (SPI). Preliminary results showed that these secondary terrain attributes did not substantially improve the predictive power of multiple regression models [*Dalzell et al,* 2011]. Further, the DEM software processing tool we employed (TauDEM; http://hydrology.usu.edu/taudem/taudem5/index.html) contained idiosnycracies that precluded its application for generating our final predictive models. These problems appeared to become worse when applied to larger DEMs such as the county-scale data used for this project. Because it was important that products from this work be applicable to broad portions of Minnesota's agricultural landscape, (as well as preliminary results that suggested their limited utility to improve predictive models) we ultimately opted to exclude secondary terrain attributes (SPI and CTI) from our analysis.

Estimation of Soil Erosion Rates (Proportional Model)

For each sampling pit, soil erosion/deposition rates were determined by comparing the ^{137}Cs inventory (whole profile) against the inventory of grassland sites. Differences in the ^{137}Cs inventory were converted to rates of soil movement based on a simple proportional model (PM) [*Walling et al.*, 2002]. The basic PM for estimating soil erosion based on ^{137}Cs inventories takes the form:

$$Y = 10\frac{BdX}{100T}$$

where:

Y = soil erosion rate (t ha^{-1} yr^{-1}; negative erosion indicated soil deposition)

B = bulk density of the soil (kg m^{-3})

d = the depth of cultivation (m)

X = percentage reduction in the ^{137}Cs inventory relative to a reference site: $(A_{ref}-A)/A_{ref}*100$

A_{ref} = ^{137}Cs reference inventory for undisturbed site (Bq m^{-2})

A = ^{137}Cs inventory for each sampling point (Bq m^{-2})

T = time elapsed since onset of ^{137}Cs accumulation (y)

For this study, the value of “d” was determined by inspecting ^{137}Cs distribution profiles of cultivated sites. Most sites showed soil mixing to a depth of 0.20 or 0.25 m. The value of “d’ was set to 0.225m. The bulk density (B) was determined based on the average measured value of samples in the upper 25 cm. A_{ref} was determined from ^{137}Cs profiles of samples collected at reference sites across the study area. While reference sites were selected based on criteria of no cultivation history and perennial vegetation cover over the past approximately 50 years, some ^{137}Cs profiles showed signs of disturbance and soil redistribution (in particular, several samples from a private hay field located in Dodge county). These sites were excluded from consideration as reference sites. The remaining sites were used to compute a mean total ^{137}Cs inventory value, which was 1989.7 Bq m^{-2}. The time since onset of ^{137}Cs accumulation (T) was set to reflect the difference between the timing of sample collection (2011) and the ratification of the nuclear test ban treaty of 1963 (48 y).

This model has the advantage of being mathematically straightforward and relatively easy to use. This model does not attempt to differentiate between erosion caused by water vs. tillage. Such models exist [*Li et al.*, 2010; *Walling et al.*, 2002], but rely on additional parameterization and a suite of assumptions that are beyond the scope of this work. Further, such models are not applied to study areas as large as employed in this study. However, given our application of these results to broader statewide trends (as opposed to a detailed study of one hillslope), we opted to use a simple model that could be easily applied without requiring estimates of additional parameters.

Statistical Analysis

Simple multiple linear regression analysis was applied to develop empirical relationships between terrain attributes and soil erosion rates determined based on ^{137}Cs inventories. Soil erosion rates were the model response variable while MLRAs (fixed effect) and digital terrain attributes were input as potential predictor variables. Interactions were also allowed between MLRAs and digital terrain attributes. Following initial model creation, non-significant terms were removed and the process was repeated. The end result was a set of four equations (one for each MLRA) to predict soil erosion rates based on digital terrain attributes. Statistical significance was determined at the $\alpha = 0.05$ level. In cases where p values are not provided in the text, statistical significance is neither assigned nor implied.

Before model creation, 25% of the samples were randomly selected (Microsoft Excel random number generator). Those samples were excluded from the model development exercise and used to validate the prediction expression.

Results

^{137}Cs profiles from undisturbed grassland sites showed generally the same distribution across all sample sites. After excluding profiles that showed evidence of soil disturbance, an average ^{137}Cs inventory was determined based on data from 30 pits (Figure 3). The average ^{137}Cs inventory of these sites was 1989.7 Bq m^{-2}; this was used as the value of A_{ref} to parameterize the Proportional Model.

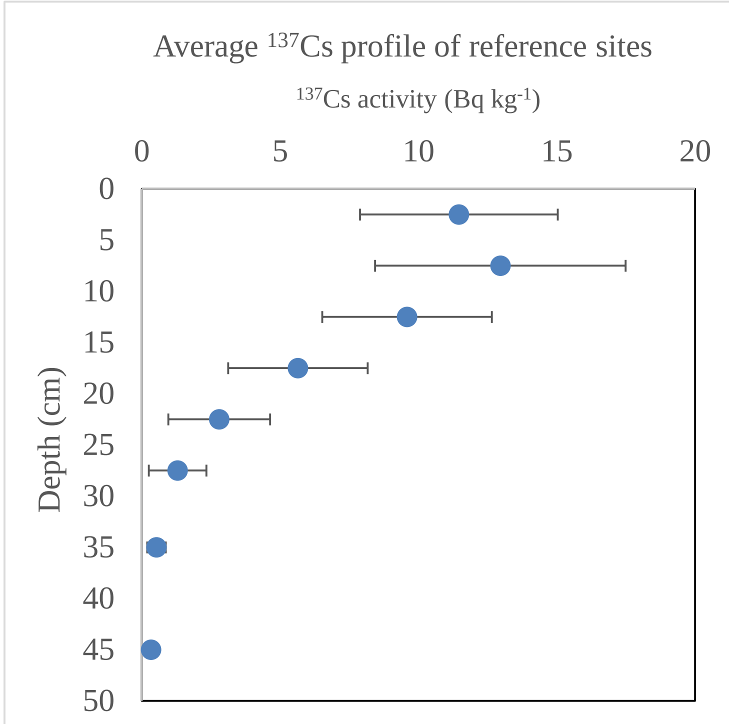

Figure 3. Average ^{137}Cs activity profile of grassland reference sites. The mean value of reference sites was used to parameterize the Proportional Model in order to estimate soil erosion rates based on ^{137}Cs inventories at cultivated sites.

Observed data showed that cropland soils had ^{137}Cs inventories that ranged from 467.3 (eroding sites) to 4079.8 Bq m^{-2} (depositional sites). In nearly all crop sites, the ^{137}Cs profile in the upper 20-25 cm was uniform, reflecting efficient mixing accomplished by agricultural tillage (Figure 4). Eroding sites exhibited overall depleted ^{137}Cs activities as deeper soils (unlabeled by ^{137}Cs) are incorporated into the tillage layer following erosion of previous topsoil. Depositional sites, by contrast, showed deep ^{137}Cs profiles, reflecting the previous positon of the soil surface and accumulation of soil eroded from upland sites.

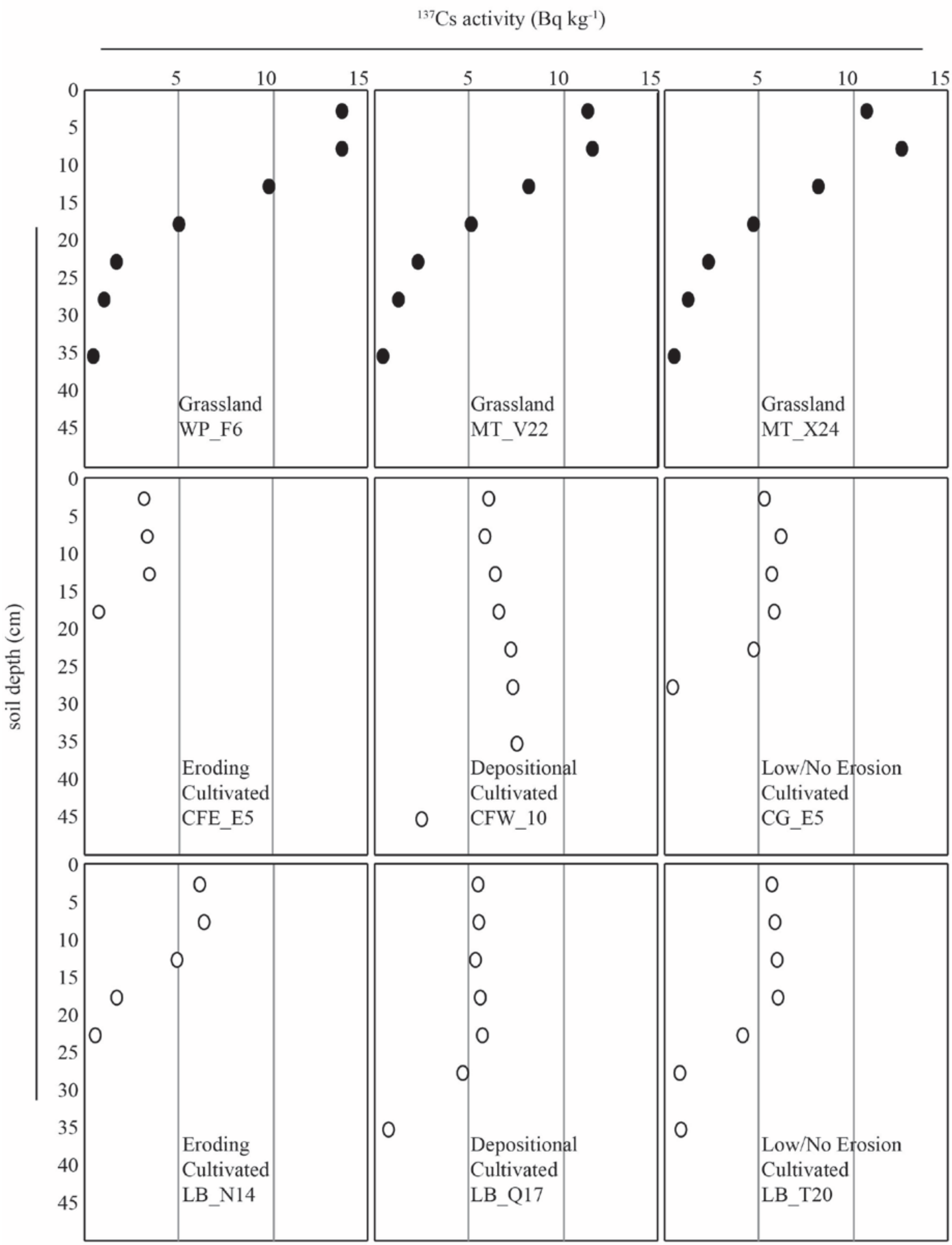

Figure 4. Representative ^{137}Cs profiles from grassland reference sites as well as cultivated sites reflecting different erosion/deposition histories.

The equations that resulted from multiple linear regression analysis showed significant terms for slope steepness, profile curvature, and plan curvature as well as differences in the prediction expression for each MLRA (below). Terms that differ between MLRAs are highlighted in bold.

Permanent Cover Reduction Models

MLRA 102A Rolling Till Prairie

Y = -31.39703+**10.14056**+(5.86678*Slope)+(-14.00313*ProCurve)+((Slope-5.38106)***-6.30051**)+((PlanCurv-(-0.08753))* **-35.43550**)+(28.55380*PlanCurv)

MLRA 103 Central Iowa and Minnesota Till Prairies

Y = -31.39703+**6.83722**+(5.86678*Slope)+(-14.00313*ProCurve)+((Slope-5.38106)***-5.82018**)+((PlanCurv-(-0.08753))* **-21.90729**)+(28.55380*PlanCurv)

MLRA 104 Eastern Iowa and Minnesota Till Prairies

Y = -31.39703+**-25.94160**+(5.86678*Slope)+(-14.00313*ProCurve)+((Slope-5.38106)* **13.83139**)+((PlanCurv-(-0.08753))***78.54040**)+(28.55380*PlanCurv)

MLRA 105 Northern Mississippi Valley Loess Hills

Y = -31.39703+**8.96382**+(5.86678*Slope)+(-14.00313*ProCurve)+((Slope-5.38106)***-1.71070**)+((PlanCurv-(-0.08753))***-21.19761**)+(28.55380*PlanCurv)

The prediction expression was able to explain 33% of the variability in the observed data (r^2 = 0.33). The 25% of samples reserved for the validation data set showed a similar agreement between observed and predicted values of soil erosion or deposition (Figure 5) with an r^2 value of 0.54. That comparison included two influential data points, however. When excluded, the regression between observed and predicted data was similar but the r^2 value decreased to 0.24. When applied to the all data points across the study area, r^2 agreement between observed and model-predicted soil erosion and deposition rates was 0.38 (Figure 5).

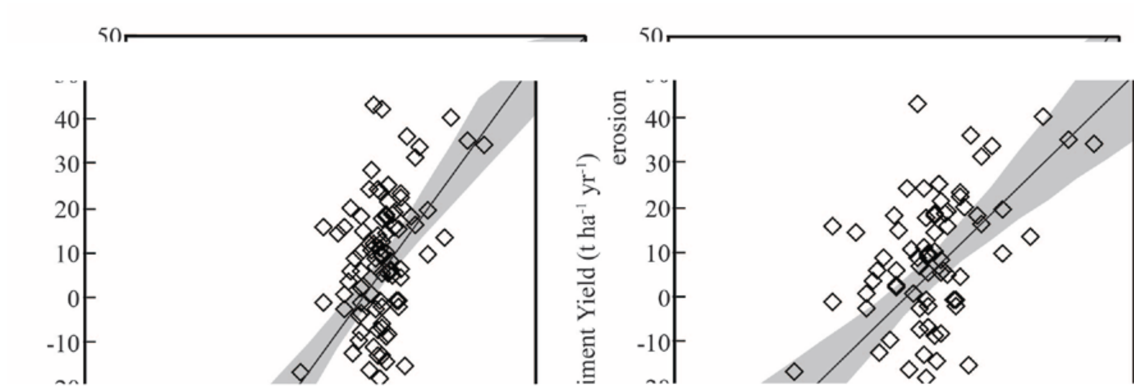

Figure 5. Results from a simple multiple linear regression model established to predict soil erosion rates from digital terrain attributes. The left panel shows the model applied only to the data points that were used to develop the model. The right panel shows all data points.

Discussion

The regression models developed for this study were able to predict 38% of the variability in observed soil erosion rates across the study area ($p < 0.0001$). Additional variability in the observed data that is not accounted for by the model is likely the result of several factors ranging from uncertainty in parameterization of the Proportional Model to differences in management practices across all study sites and MLRAs which would have produced different erosion rates over the past half-century (as well as random error introduced during sample and data collection). The models developed here are able to predict and quantify broad trends in soil erosion or deposition rates across a large portion of Minnesota's agricultural landscape.

Regression models were applied to each MLRA to generate maps that predict the long-term average soil erosion rates for the landscape under cultivated land use. A brief examination of a selected field in MLRA 105 is helpful for highlighting some of the uses and potential pitfalls of these data products (Figure 6). While there are some locally high areas of potential soil erosion within the field, most are near zero and the field-wide average soil erosion rate is 6.7 t ha^{-1} yr^{-1}. A widely applied estimate of tolerable soil loss is about 11 t ha^{-1} yr^{-1} [*Hudson*, 1995]. The depositional site located along the southern edge of the field (Figure 6) also highlights the importance of including additional information when considering locations for soil conservation practices. If that depositional site is situated along a ditch, it is likely that deposited sediment may be periodically re-mobilized and transported to receiving waterways during large storm events (something that is not considered by this model).

Based on the assumption that soil erosion (over decadal time-scales) is close to zero on perennially-vegetated landscapes, the soil erosion map can be used as a tool by BWSR staff, soil conservationists, or other interested parties as a method for estimating the amount of soil erosion that may be prevented for specific landscape segments when enrolled in conservation programs. Conversely, this map may also be used to predict the amount of erosion that may occur if conservation land is converted to cultivation. It is important to note that we did not perform this analysis for any forested landscapes and results of this analysis should not be applied to forest vs. cropland comparison without further development and testing.

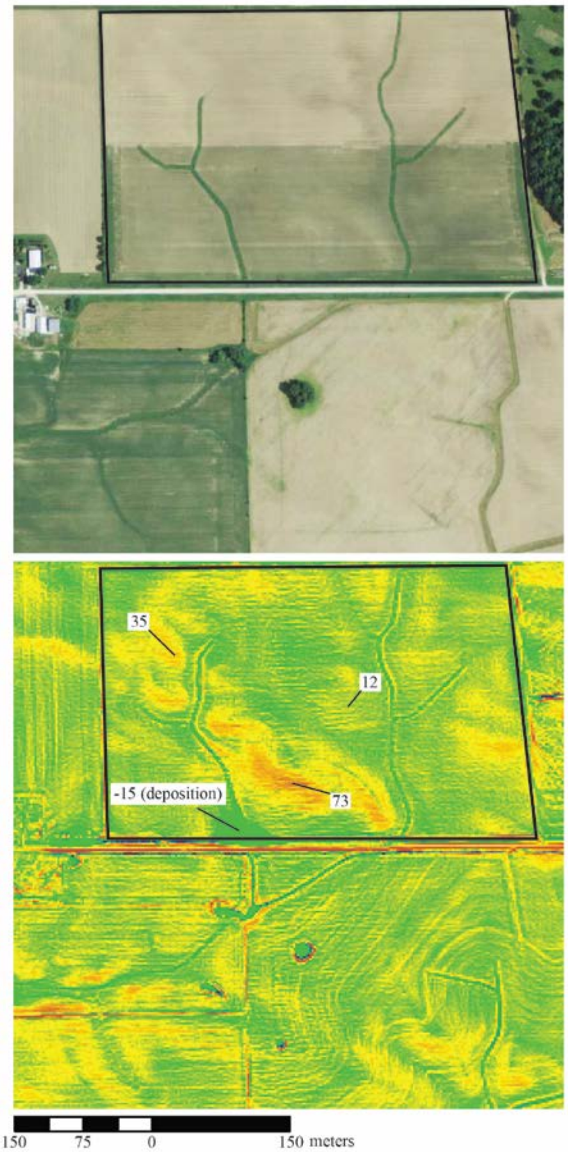

Figure 6. Example output of the multiple regression model for a selected farm field in MLRA 105. Based on digital terrain attributes, the model result shows localized areas of potentially high soil erosion rates while the overall field average erosion rate is 6.7 t ha^{-1} yr^{-1}.

Suggestions for Future Work

Model Refinement - A portion of the uncertainty unaccounted for by the regression model is likely to arise from differences in management practices across the agricultural sites used for this study. One potential way to quantify that uncertainty is to conduct more focused research on smaller sites with more uniform management practices. The UMN Research and Outreach centers are good candidates for this kind of inquiry and additional sampling is already underway as part of separate project. Ongoing analysis of additional future samples (in addition to those collected for this study) are likely to yield predictive regression models which are able to further constrain topographic effects on soil erosion under more specific sets of management practices. As further refinements are developed and become available, we will remain in communication with BWSR personnel to discuss the potential for improving existing conservation estimator projects. Additional refinement may be possible through application of more sophisticated conversion models to estimate soil erosion rates based on ^{137}Cs inventories. This effort would require more detailed information (or robust sets of assumptions) in order to parameterize the additional variables that are considered by these models.

Accounting for stream networks – The models developed from this study are based solely on predicting long-term soil erosion rates from digital terrain attributes. They do not account for the potential of downslope deposited sediment to be further re-mobilized into streams or rivers during large runoff events. Potential methods to account for this may include intersecting results from this soil erosion model with flow direction and flow accumulation information to highlight areas where high soil erosion occurs in close proximity to receiving waterways.

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Appendix A – Method for Determining Field-Average Erosion/Deposition Rates

This brief tutorial is intended to provide someone with basic GIS experience (and access to ArcMAP software with Spatial Analyst) the ability to compute field-average erosion/deposition rates based on the raster maps produced from this study.

Inputs:

1. Soil erosion/deposition raster for your county of interest (required)
2. Air Photo layer to help identify area of interest (optional but very helpful)

Outputs:

1. Shapefile of your area of interest
2. Raster showing the average predicted erosion/deposition rate for your area of interest.

Step 1. Manually delineate your field or area of interest.

- After identifying your field/area of interest, use the ArcMAP drawing tool to draw a polygon around your area. (Fig A-1)
- Using the ArcMAP "Draw" toolbar, select the draw polygon tool and create an appropriate polygon around your area. (Fig A-2)
- From the "Drawing" drop-down menu, select "Convert Graphics to Features" and add the exported data to the map as a layer. (Fig A-3)

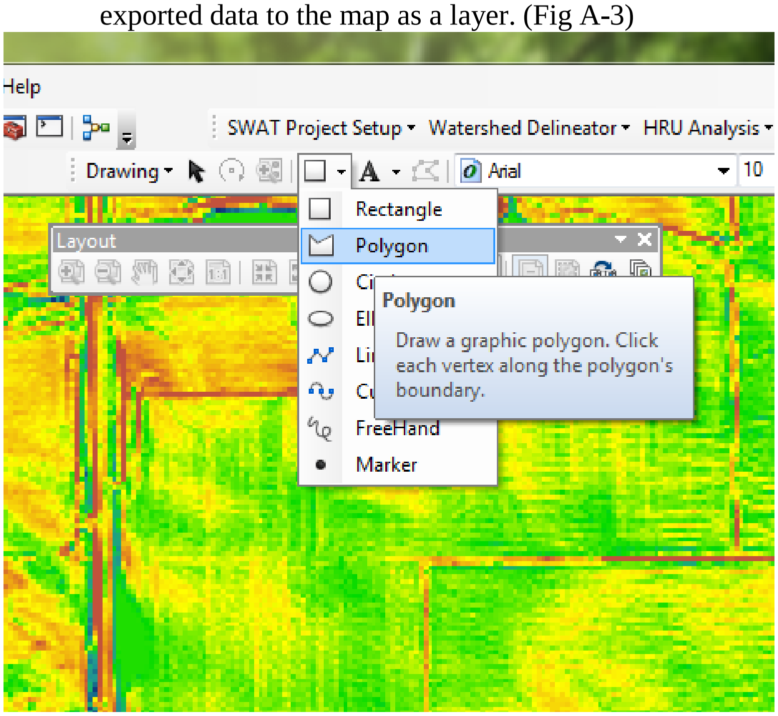

Figure A-1

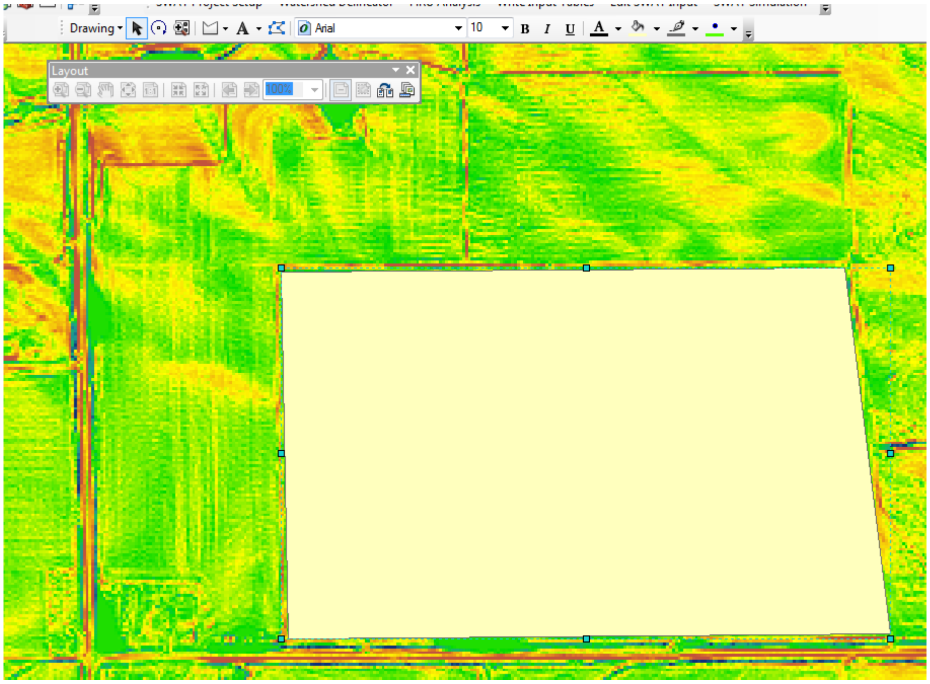

Figure A-2

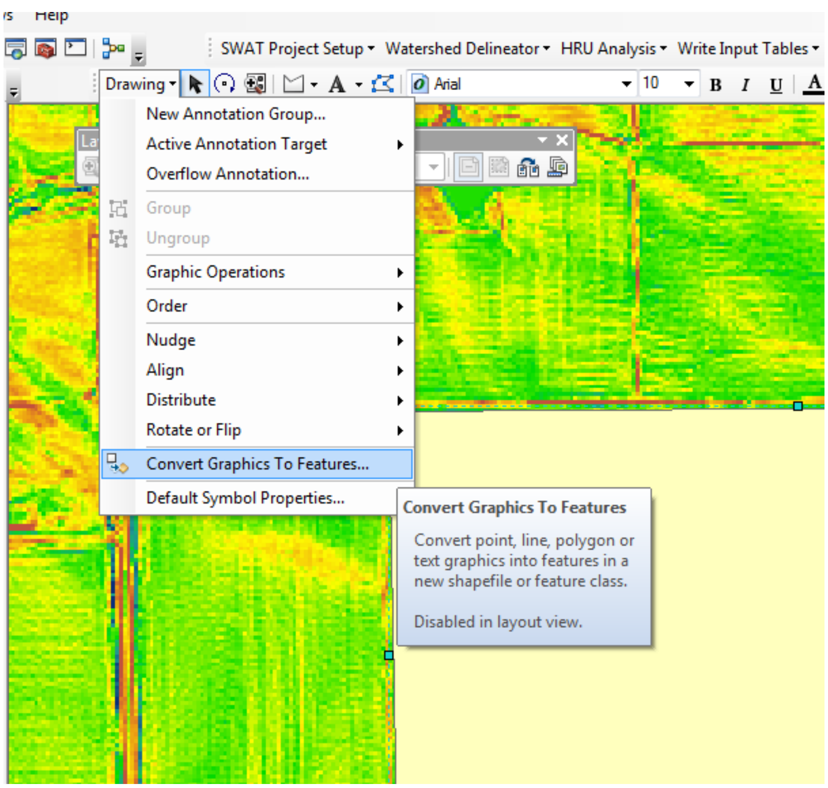

Figure A-3

Step 2. Perform zonal statistics.

- Launch the “zonal statistics” tool (Spatial Analyst -> Zonal -> Zonal Statistics). (Fig A-4)
- Input raster or feature zone data = the converted graphics (created in step 1 above)
- Zone field = name
- Input value raster = the soil erosion/deposition rate raster for your area.
- Output raster = select an appropriate location and file name.
- Statistics type = MEAN

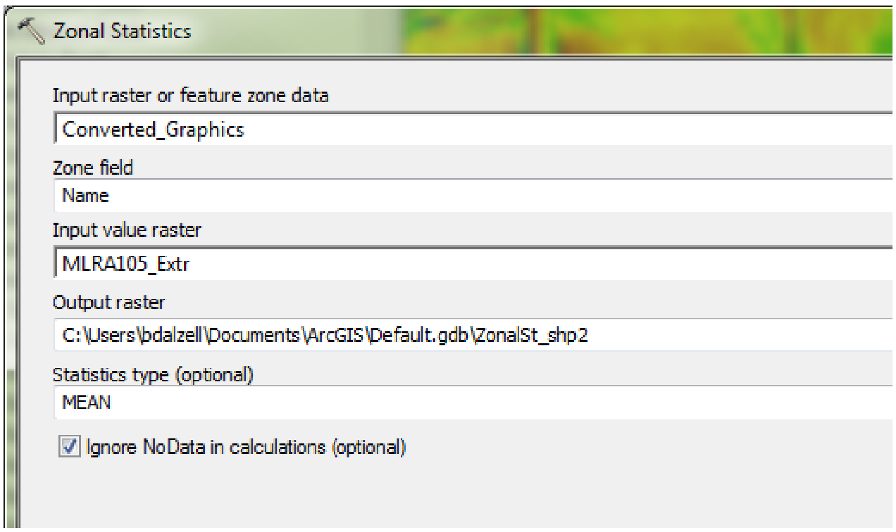

Figure A-4

The resulting raster should occupy the same extent as your field/area of interest. The raster will have only one value, which is the mean erosion/deposition rate for your area. (Positive values indicate erosion, negative values indicate deposition)