SENSITIVITY OF RUSLE TO DATA RESOLUTION: MODELING SEDIMENT DELIVERY IN THE UPPER LITTLE TENNESSEE RIVER BASIN

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Abstract. Data resolution influences the magnitude and variability of erosion and sedimentation estimates from geographic information system (GIS) representations of the Revised Universal Soil Loss Equation (RUSLE). We implemented a GIS version of RUSLE for the Upper Little Tennessee River Basin in Macon County, North Carolina. When raster layers depicting elevation, land cover, and soil erodibility were coarsened in resolution, sediment load estimates differed by two orders of magnitude. Model output from low resolution data (285m x 285m pixels) captured less than 10% of the variability of model output from 30m data. We further quantified the importance of soil and land cover data resolution on model output. State Soil Geographic (STATSGO) soil erodibility factors were, on average, 34% (range -23% to 662%; s.d. 43%) greater than the same factors taken from the Soil Survey Geographic (SSURGO) database. Model results based on STATSGO were not tightly correlated with estimates based on SSURGO data. Linear regressions were weak but significant (R^2 approximately 0.50 in all cases) for comparisons of model output based on lowered cover factor resolutions. Before applying similar models in a management context, analysts should calibrate model output with in situ sediment loading or soil loss measurements because input data resolution and accuracy have significant influences over model output.

INTRODUCTION

The Universal Soil Loss Equation (USLE; Wischmeier and Smith 1978) and the Revised USLE (RUSLE; Renard 1997) provide simple methods to assess complex erosion and sedimentation problems. During the past two decades, variations of USLE have been used to simulate erosion within watersheds (McNulty and Sun 1998; Banasik 1986) and over large areas (Fernandes 1994; Morgan and Nalepa 1982). The U.S. Environmental Protection Agency has proposed a number of sediment Total Maximum Daily Load (TMDL) documents for streams in Georgia using modified versions of the USLE implemented within Geographic Information Systems (GIS) software. Our methods are very similar to those being used to set policy throughout Georgia.

USLE and RUSLE were originally developed for field-based estimation, not regional-scale modeling (Trimble and Crosson 2000). The fundamental difference between GIS modeling and field-based implementations of RUSLE is in the derivation of input parameters. GIS data impose constraints on how those parameters are measured. Since raw data for any one of the six USLE or RUSLE parameters (Equation 1) may come from a number of sources, analysts and decision makers should understand sources of error introduced by a given data source. We ask, what is the effect of data resolution on model output? The answer has direct implications for appropriate choices of data to be used with GIS-based RUSLE models and, ultimately, for decisions based on those models' results.

Our objective in this paper is to quantify the effects of data resolution on simulated upland soil delivery to streams using our GIS implementation of RUSLE. First, we examined the performance of the entire model when all data layers' resolutions were reduced simultaneously. Second, we compared model output when Soil Survey Geographic (SSURGO) data were replaced with coarser scale State Soil Geographic (STATSGO) soil data. Third, we analyzed the impact of land cover factor resolution on model output.

STUDY AREA AND METHODS

We examined the 966 km^2 portion of the Upper Little Tennessee River Basin that falls entirely within Macon County, North Carolina. Terrain is variable, with steep slopes in the headwaters and a broad alluvial valley containing the main stem of the river. Elevation varies between 552 and 1647 m and has a mean value of 879 m. In 1993, the catchment was 89% forested, 9% agriculture, and 2% developed (Herman et al. 1996). The region has been the focus of numerous studies on land use (Wear and Bolstad 1998) and

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

A: Average annual soil loss (ton / acre / yr); converted to annual metric tonnes per watershed.

R: Erosivity (hundreds of ft *tonf *in *acre^{-1} *yr^{-1}) (Wischmeier and Smith 1978); held constant.

K: Soil erodibility factor as proportion of erosion on a unit plot; SSURGO or STATSGO maps converted to 30m resolution grid for reference data and for model runs that compared SSURGO and STATSGO.

L: Slope length factor; proportion of erosion relative to a unit plot; each pixel in DEM; assumed intermediate rill:interrill ratio (see Renard 1997 for details).

S: Slope factor; proportion of erosion relative to unit plot; from 30m DEM for reference data.

C: Cover factor; proportion of erosion relative to clean-tilled, continuous-fallow state (Wischmeier and Smith 1978; EPA 2000). Land cover by Hermann (1996).

P: Practice factor; ratio of soil loss with a specific support practice to corresponding loss with uplope and downslope tillage; data not available; set equal to 1 for simulations.

Equation 1. RUSLE model structure (Renard 1997) and source data descriptions.

ownership patterns (Turner et al. 1996). Many stream ecosystem studies have been conducted in the study area in association with the Coweeta Long Term Ecological Research program. The Coweeta basin lies in the southern portion of our study area.

We used RUSLE to estimate soil loss on a per-pixel basis throughout the study area. The RUSLE model (Equation 1) consists of six factors whose interpretations and parameter ranges are detailed in Renard (1997). SSURGO K-values were from the Macon County Soil Survey (Devereux 1929; Digitized Soil Survey courtesy Macon County Mapping Department). STATSGO data (USDA 1991) were converted to a 30m grid. L and S factors were calculated based on digital elevation model data (30m resolution except for first set of analyses). Land cover data (30m; Hermann 1996) were attributed with cover factor (C) values (Wischmeier and Smith 1978; EPA 2000). We defined the P factors as "1" for all model simulations because spatial data describing practice factors were not available. Units were converted from ton*acre^{-1}*yr^{-1} to metric tonne annually exported from catchments directly contributing to each stream segment. Stream segments were defined as the section of stream, based on 1:24,000 hydrography, between an upstream and a downstream tributary or junction. Sediment load was calculated for the area directly contributing to each stream segment.

RUSLE does not include a hydrologic component, so we defined an overland transport function. Moore and Wilson (1996) found RUSLE LS factors to be tightly correlated with dimensionless overland sediment transport capacities. Thus the maximum allowable soil loss for a given cell was set to the quantity R*L*S. If the accumulated soil loss at any cell exceeded that maximum allowable soil loss, the difference was subtracted (deposited) before further delivery down the slope. This accumulation function continued to the lowest elevation in each stream segment's catchment. That sum defined a given stream segment's unique sediment load contribution.

We conducted numerous comparisons of model estimates of each stream segment's upland-derived sediment load. First, we ran the model with all data represented by 30 m resolution grids; K-factors were from Devereux (1929). These "reference model" results were considered to be the most reliable of the scenarios examined. Subsequently, each data layer was simultaneously aggregated from 45 m to 285 m in 15 m increments. Model output from each coarser resolution was regressed against the reference model output defined above. We quantified the relationship between explanatory power (R^2) and data resolution using logistic regression. Transformed (logit model) R^2 values from each of the 17 linear regressions were regressed against respective pixel sizes. Slope and intercept parameters from the 17 independent linear regressions were also regressed against pixel size. The second set of analyses quantified the effect on model output of coarser scale soil data. We used linear regression to compare the log-transformed results obtained with STATSGO data to the log-transformed model output obtained with the reference data (based on SSURGO data). All data layers were represented by 30m resolution grids. We back-transformed both sets of results for presentation purposes. The third set of analyses examined the independent effect of land cover resolution on model estimates. We ran the algorithm using land cover factors aggregated from 30 m to 285 m in 15 m increments. Other layers remained at their original 30m resolution. Linear regression was used to compare each of the coarser resolution outputs against the reference data set.

RESULTS

The model was sensitive to data resolution when pixel size was increased for all input data layers

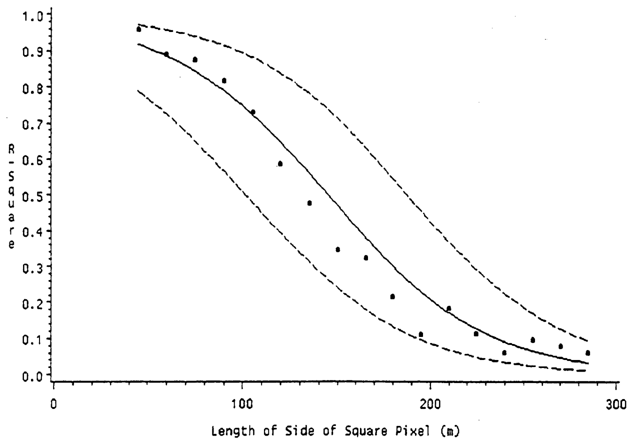

Figure 1. Explanatory power decreased with aggregation of all input data layers. 95% confidence intervals shown with dashed lines.

$$\beta_0 = 9.0 * d \; ; \; R^2 = 0.94 \quad \text{(a)}$$

$$\beta_1 = 0.05 * d \; ; \; R^2 = 0.80 \quad \text{(b)}$$

d is the length of one side of a pixel

β_0 is the intercept term for pixels of length d.

β_1 is the slope term obtained with pixel length d.

Equation 2. Coarser resolution data yielded lower predictions than reference data. Both the (a) intercept and (b) slope terms were positively correlated with cell size.

simultaneously. Simulations based on 30m resolution reference data (Equation 1) yielded predictions that were, on average, 2 to 300 times the values obtained when base layer resolution was decreased. The strength of the relationship between model outputs from coarsened and reference data grew weaker with larger pixel sizes; that is, R^2 values decreased monotonically with resolution (Figure 1; R^2=0.94). When input data were represented by 100 m x 100 m pixels, model output explained less than 75% of the variation in the reference model output. Model output from cells larger than 180 m x 180 m explained less than 20% of the variation in model output from the reference model output. Intercept (Equation 2a) and slope coefficients (Equation 2b) each increased with pixel size. In summary, model outputs yielded high variability and lower predictions when the resolution of all data layers was simultaneously lowered (larger pixels); these observations are based on comparisons to model output from higher resolution, reference model results.

Coarser soil and land cover factors had the opposite effect. Lower resolution soil data led to higher predictions of sediment delivery to streams, relative to

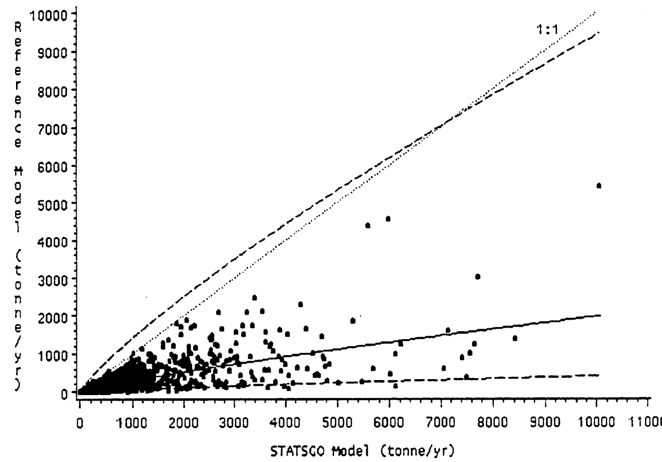

Figure 2. Log-log regression results for reference vs. STATSGO data. Dotted lines are upper and lower 95% confidence intervals; 1:1 relationship shown as a fine line.

the reference model results. On a pixel by pixel (30 m) basis, STATSGO K-values were, on average, 34% (range: -23% to 662%; standard deviation 43) greater than SSURGO data; therefore, the model using STATSGO data produced higher values than the reference model. Those two sets of model output were significantly related (R^2 = 0.974) when they were both log-transformed, but there was considerable scatter in the relationship (Figure 2).

Land cover analyses provided a similar set of results. Land cover factors (C in Equation 1) aggregated to 285 m x 285 m were up to 468 times larger than cover factors mapped with 30 m pixels. Coarser cover factor grids led to predictions that were higher and more variable when compared to model output from reference data. Linear regressions had R^2 values between 0.48 and 0.50; slopes ranged from 0.31 to 0.32, well below a 1:1 relationship. Loss in precision was considerable in aggregating from 30 m to 45 m but was not substantially worsened by subsequent aggregations.

DISCUSSION AND CONCLUSION

When all data sets (soil, digital elevation model, and land cover factors; Equation 1) were aggregated simultaneously, model results were substantially lower than when the model was run with the highest resolution data (all data with 30 m pixels and with SSURGO). In contrast, STATSGO and aggregated land cover data both led to higher sediment delivery predictions. We infer that the combined L*S factor decreased substantially when pixel size was increased.

Most analysts have access to 30 m DEMs comparable to ours, so we did not quantify the importance of DEM resolution to the L and S factors.

USDA states that STATSGO data may not be appropriate for analyses within counties (1991). STATSGO data provide generalized soil information at a scale of 1:250,000. In STATSGO, map units are aggregated, so soil K-values are not spatially explicit. SSURGO or field surveys provide more reliable data for spatially explicit studies. SSURGO data portray map unit composition based on field traverses and photo interpretation at scales from 1:12,000 to 1:63,600. SSURGO data are not commonly available in digital form, so EPA uses STATSGO for its sediment TMDLs in Georgia, despite STATSGO's resolution limitations. If STATSGO data must be used, sediment load estimates will generally be greater than estimates made using the same methods and SSURGO data. Although there is a statistically significant (log-log) relationship between model outputs based on SSURGO and STATSGO, sedimentation estimates within any given catchment may differ by an order of magnitude (Figure 2). Analysts must be aware of the variability in the relationship between model output derived from these two sources of soil K-values. Policy makers may require in situ measurements and calibration data before making site-specific recommendations based on models that use STATSGO data.

The land cover factor is arguably the most sensitive of the RUSLE components (Yoder et al. 1998). Land cover data with pixels larger than 30 m on a side led to over-estimation and substantial scatter in regressions with model results from reference data. Our study area is highly forested and relatively homogeneous, so this effect might be more severe in a fragmented landscape. Accuracy, precision, and resolution vary based on mapping techniques, so further research would be required to guide planners in proper techniques for mapping cover factors. Analysts must consider land cover accuracy, precision, and resolution and their implications for modeled sediment load estimates when using USLE or RUSLE in a GIS.

We demonstrated four main points pertinent to GIS implementations of RUSLE for stream sedimentation estimation. First, simultaneous coarsening of all data layers leads to lower model predictions. Second, model results based on STATSGO are generally higher than model results based on SSURGO soil erodibility (K) factors. Third, land cover data from imagery with pixels larger than 30 m x 30 m may also yield higher model results in forested, Blue Ridge Province watersheds. Fourth, all simulations produced unexplained scatter when comparing outputs to the reference model output; therefore, model estimates of sedimentation to a given stream are not necessarily comparable using different source data. Analysts, planners, and managers should be aware that the data they use largely determine the precision of RUSLE results obtained from a GIS.

GIS versions of RUSLE or USLE are simple to implement and provide objective means of comparing the potential impact of land use management on stream sedimentation. If management decisions are to be based on such modeling, those decisions should be supported by local observations of stream channel conditions and processes, watershed land use, and management practices. The model itself has too many sources of uncertainty to be the sole basis for regulatory actions.

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