

High Impact Targeting (HIT) Background

The Great Lakes Watershed Management System (GLWMS) employs the High Impact Targeting (HIT) approach (www.iwr.msu.edu/hit2) to model erosion and sediment loading. HIT utilizes the Revised Universal Soil Loss Equation (RUSLE) (Renard et al. 1997) to estimate annual soil erosion, and the Spatially Explicit Delivery Model (SEDMOD) (Fraser 1999) to estimate the percentage of eroded soil that is delivered to the stream network in a given year. The product of RUSLE and SEDMOD is an estimate of sediment loading to streams in a given year. These calculations are performed within a GIS raster (grid) environment, so RUSLE, SEDMOD, and sediment loading are calculated for each 10-meter pixel on the landscape. With each user-generated land cover change scenario, the GLWMS adjusts the underlying RUSLE and SEDMOD parameters accordingly, re-runs the models, and reports the estimated changes in erosion and sediment loading.

In the sections below, we describe how those initial parameters were estimated (Figure 1).

RUSLE

The Revised Universal Soil Loss Equation (RUSLE) is a standard tool for soil erosion analysis. The equation has gone through several iterations, beginning with the Universal Soil Loss Equation (USLE) in 1965 (Wischmeier and Smith 1965, 1978), the Modified Universal Soil Loss Equation (MUSLE) (Williams and Berndt 1976) for watershed scale storm event calculations, RUSLE (Renard et al. 1997), and the development of NRCS's RUSLE 2 software package (http://fargo.nserl.purdue.edu/rusle2_dataweb/RUSLE2_Index.htm). For various reasons, particularly that the HIT modeling utilized by the Sediment Calculator estimates erosion on a pixel-by-pixel basis, IWR employs RUSLE as described by Renard et al.

In estimating annual erosion, RUSLE employs a K-factor to represent a particular soil's erodibility. Values can range from 0.02 for muck soils to 0.5 for soils of high silt content (<http://www.iwr.msu.edu/rusle/kfactor.htm>). To assign a K-factor value to each pixel we first downloaded NRCS SSURGO Soil Surveys of each county in the study area from the NRCS Soil Data Mart (<http://soildatamart.nrcs.usda.gov/>). Next, we utilized the Soil Data Viewer extension for ArcMap (<http://soils.usda.gov/sdv/download.html>) to extract surface layer *Kfact* (rock-free K-factor) values from each survey's database and link them to soil map units. Lastly, we rasterized the map units so that the K-factor values aligned with the other input rasters of the analysis.

RUSLE's R-factor represents annual rainfall intensity, and is typically averaged over a 30-year period (<http://www.iwr.msu.edu/rusle/rfactor.htm>). Values in Michigan can range from 75 to 135. We utilized

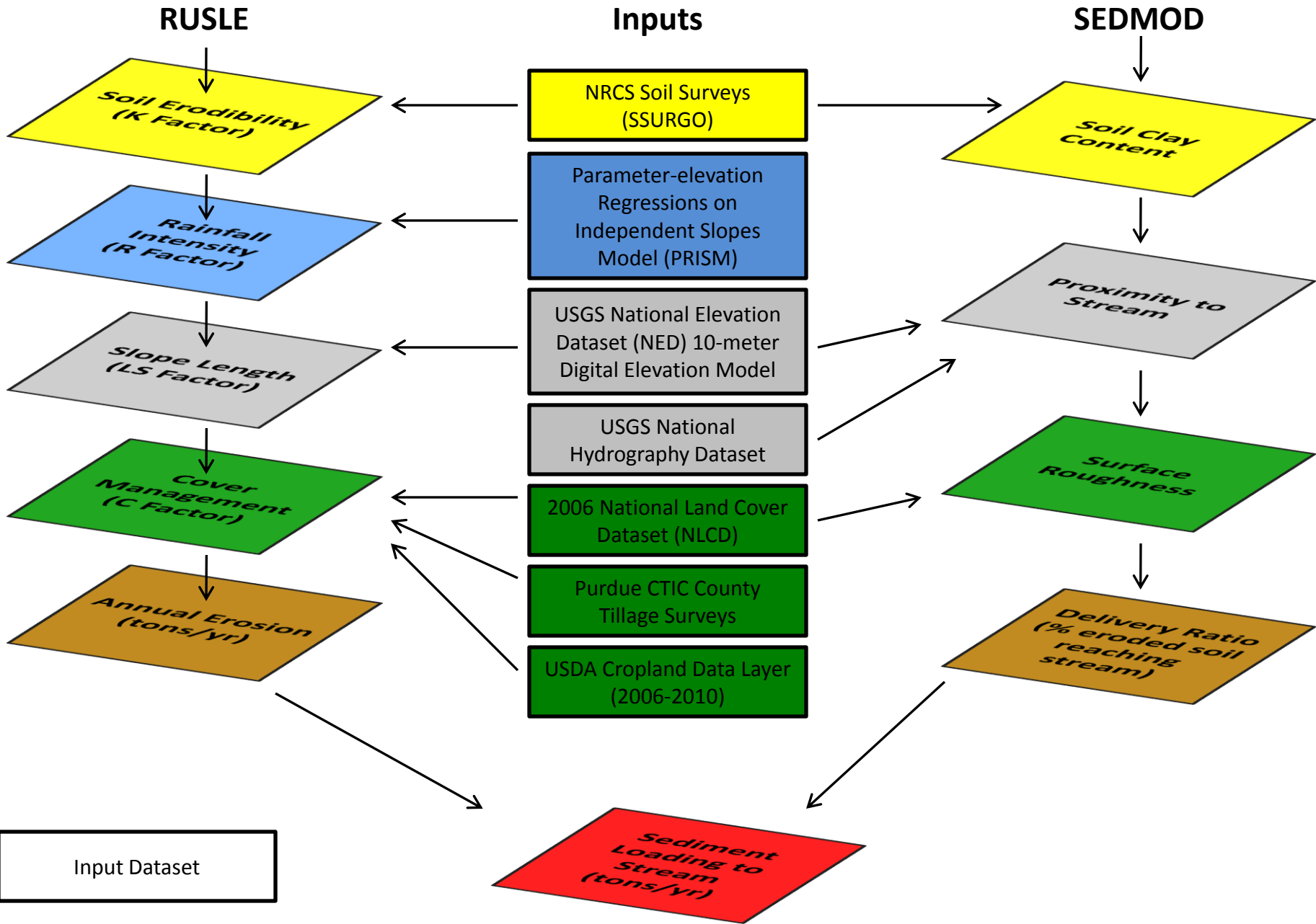


Figure 1

estimates of R-factor generated by the PRISM Climate Group at Oregon State University (<http://www.prism.oregonstate.edu/>).

RUSLE's LS-factor represents the effect of slope and slope-length on erosion. Values can range from 0 on flat slopes to values over 50 on very long and very steep slopes. To estimate the LS-factor, we employed an automated approach put forth by Robert Hickey (<http://www.onlinegeographer.com/slope/slope.html> - version 4 AML) that relies on a DEM. We utilized a 10-meter DEM from downloaded from USGS National Elevation Dataset (<http://ned.usgs.gov>) and modified Hickey's code for use with a Python scripting environment (upon which the Calculator and HIT models are based).

The majority of data pre-processing for calculating RUSLE in HIT, and therefore for estimating erosion and sediment reductions in the Calculator, is devoted to representing the RUSLE C-factor. The C-factor represents the impact of land-cover and cover management on erosion. Values can range from 0 for an impervious surface such as concrete (which RUSLE was not designed for), to 0.06 for a no-tilled field of corn, to 0.7 for a crop that does not provide much soil cover, such as sugar beets, to 1.0 for a continuously fallow and exposed soil. NRCS offices in various states have produced RUSLE technical guides that contain C-factor tables that list appropriate values for different crops under certain conditions. The key variables in selecting a value from these tables for a particular area are the crop-type grown the previous year, and the tillage practice employed for the year in question. An excerpt from the MI-NRCS RUSLE guide is provided on the following page.

IWR utilized four data sources in estimating C-factor for each pixel in the study area: the 2006 National Land Cover Dataset (NLCD), the USDA Cropland Data Layer (CDL) from 2006-2010, The Conservation Technology Information Center (CTIC) crop-residue surveys from 2000-2004, and the MI-NRCS RUSLE Technical Guide. The approach is presented visually in Figure 2 below. Based upon a review of literature and on-line reports, we identified C-factor values for various land cover classes, which we assigned to the corresponding classes in the study-area's land cover raster as coded by the NLCD. For pixels coded as row-crop agriculture in NLCD (code 82), we utilized the four sources mentioned above to estimate a C-factor. First, we referenced the most recent year of the CDL (2010) to identify the crop-type at the pixel in question. Next, we referenced the preceding year CDL (2009) to determine the crop rotation. With this information, we stored C-factor values for the identified rotation under three tillage scenarios (no-till, mulch-till, and conventional-till) based on the MI-NRCS RUSLE Technical Guide's tables. C-factor values were similarly stored for the preceding years through 2007. Next, to factor in the tillage practice applied to each crop, we consulted CTIC crop residue surveys (which recorded tillage at a county level) for the county in which the pixel in question resided. The CTIC surveys were gathered in the years 2000, 2002, and 2004; though it adds to the overall model uncertainty, we assume the tillage trends for the county over that three year period remained constant. Next, we applied the fractions of each crop's tillage practices to generate a weighted C-factor for each year. We repeated the process for the three previous years, and averaged a final C-factor across the four weighted C-factors.

For example, in Figure 2 the pixel in question is represented as corn in the 2010 CDL. The previous year CDL represents the pixel as soy. We then look to the MI-NRCS RUSLE Technical Guide and select C-

SINGLE YEAR 'C' VALUES

ZONE 102C

TECHNICAL GUIDE
SECTION
State-wide
WATER-34CG.80

CROP SEQUENCE

CORN, GRAIN	PLOW TILLAGE		* FALL MULCH TILLAGE * SPRING MULCH TILLAGE % cover								RIDGE TILL		NO - TILLAGE % cover					STRIP TILL
	FP	SP	<10	10	20	30	40	50	60	cover	C	<10	10	20	30	40	90	cover - C
AFTER:																		
y 1	0.23	0.14	0.22									-	-	-	-	-	-	-
			.17*									0.04	0.03	0.03	0.02	-		
Alfalfa y 2		0.26	0.25	0.23	0.2													
			.23*	.22*	.19*													
Cabbage	0.43	0.38	0.39	-	-							-	-	0.23	0.21	0.18		
			.36*	.32*	.25*							-	-	-	-	-		
Cabbage X	-	0.21	.19*	.16*	.13*	.10*						-	-	-	-	-		
												-	-	0.05	0.04	-		
Corn, grain	0.33	0.29	0.27	0.25	0.2	0.18	0.15	0.12	0.11	30% -	0.17	-	-	-	-	-	0.08	
			.25*	.24*	.20*	.15*	.14*	.11*	.10*	40% -	0.16	0.07	0.05	-	-	-	-	D
Corn silage	0.46	0.47	0.44	0.38						2% -	0.42	0.27	0.25	-	-	-	-	
			.44*	.37*								-	-	-	-	-	-	
Corn silage X	-	0.3	-	-	-	-	-	-	-			0.11	0.09	0.08	0.06	-		
					.19*	.16*	.11*	.09*	-			-	-	-	-	-		
Cucumbers	-	0.55	-	-	-	-	-	-	-			-	-	-	-	-		
Cucumbers X	-	0.37	-	-	-	-	-	-	-			-	-	-	-	-		
			.32*	0.29	.26*	.22*						0.18	0.15					
Grain Sorghum	0.34	0.31	0.28	0.25	0.22	0.18	0.16			20% -	0.21	-	-	-	0.11	0.09		
			.28*	.25*	.21*	.17*	.15*			30% -	0.19	0.06	-	-	-	-		
Oats	0.38	0.34	0.3	0.28	0.22	0.17	0.14	0.11				-	-	-	-	-	0.09	
			.29*	.27*	.22*	.17*	.14*	.11*				0.08	0.07	-	-	-	-	
Potato	0.52	0.53	0.5									0.49	-	-	-	-		
			.52*									-	-	-	-	-		
Potato X	-	0.3	-	-	-	-	-	-	-			-	-	-	-	-		
					.22*	.18*						-	.13*	.11*	-	-		
Snap beans	0.54	0.52	0.51									0.34	0.23					
			.51*									-	-	-	-	-		
Snap beans X	-	0.3	-	-	-	-	-	-	-			-	-	-	-	-		
			.27*	.23*								0.14	0.12	0.09				
Soys - 30in	0.42	0.38	0.39	0.33	0.26					20% -	0.27	-	0.2	0.17	-	-		
			.35*									-	-	-	-	-		
Soys - 30in X	-	0.28	.22*	.21*	.17*	.14*						-	-	-	-	-		
												0.1	0.08	0.06	0.05	-		
Soys - 7in	0.44	0.38	0.39									-	0.2	0.17				
			.36*									-	-	-	-	-		
Sugar beets	0.4	0.4	0.39									0.34	0.32					
			.37*									-	-	-	-	-		
Sugar beets X			.23*	.18*	.15*	.12*						-	-	-	-	-		
												-	0.08	0.06				
Sunflowers	0.38	0.34	0.33	0.29								-	-	-	0.1	-		
			.32*	.26*								-	-	-	-	-		
Tomato	0.46	0.42	0.41	-								-	0.34	-	-	-		
			.41*	.35*								-	-	-	-	-		
Tomato X			.27*	.25*	.22*	.20*	.16*	.14*	.11*			-	-	-	-	-		
												-	-	-	-	-		
Wheat	0.32	0.29	0.27	0.23	0.17	0.14	-	-	-			-	-	-	0.11	0.09	-	-
			.25*	.22*	.17*	.14*	.10*	.08*	.07*			-	0.04	0.04				

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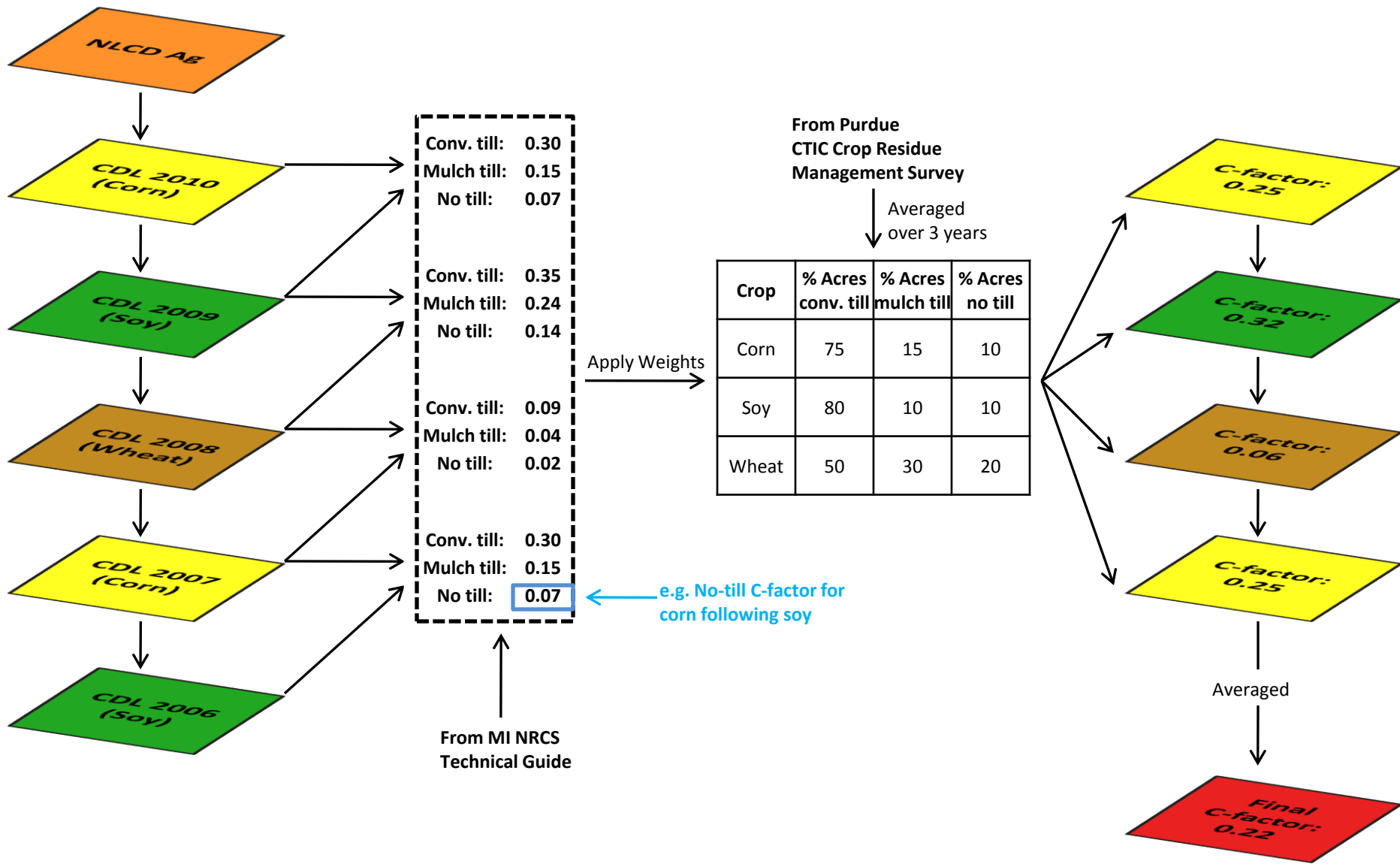


Figure 2

factors for the three tillage practices (0.30, 0.15, and 0.07 for conventional, mulch, and no till respectively). Next we look to the CTIC survey data to see what fraction of corn acres in the pixel's county were under each tillage practice. We see that 75% of corn acres in the pixel's county were under conventional tillage, with 15% under mulch till, and 10% no tilled. Weighting of the C-factors by these fractions leads to a 2010 C-factor estimate of 0.25. We repeat the process for 2009, 2008, and 2007 (not 2006, since we don't have a preceding crop year) and average the 4 weighted C-factors for a final estimate for the pixel of 0.22.

With estimates of each RUSLE factor generated for each pixel in the study area, we multiplied the values together to yield an estimate of annual erosion within each pixel. However, the RUSLE equation reports erosion in tons/acre/year, whereas each pixel corresponds to an area of 100m² (for a 10m x 10m pixel resolution). Therefore we adjust the initial RUSLE calculation by dividing by 40.47 (1 acre 4,047 m²).

SEDMOD

The Spatially Explicit Delivery Model (SEDMOD) (Fraser 1997) estimates the percentage of eroded soil that reaches the stream network on an annual basis. The model is run within a raster (grid) environment, with soil, elevation, land cover, and stream locations serving as the primary inputs. The model's general approach is to, for each pixel in the study area, identify the path to the stream network (determined from a digital elevation model and stream location), note the pixel's proximity to the stream network, note the soil clay content and surface roughness along the path (based on soil surveys and land cover input), and apply a user-defined weighting to these data to yield a delivery ratio. Pixel's close the stream network, along relatively smooth flow paths with high clay content will have high delivery ratios. On average, delivery ratios range from 10-20%.

As seen in Figure 1, the data sources for SEDMOD are basically the same as those for RUSLE. The same pre-processing that yielded the RUSLE K-factor rasters produced the pixel clay content for SEDMOD. The DEM used to estimate the RUSLE LS-factor was also used to simulate surface water flow-direction and calculate each pixel's proximity to the stream network. Manning's *n* surface roughness values were identified in literature and linked to the NLCD classes used in the C-factor processing.

What the Sediment Calculator does in the background

The Sediment Calculator allows the user to simulate a land-cover change within a user-defined area, re-run HIT based on that change, and view the changes in erosion and sediment loading. The focus on land-cover change means that only model input parameters that are adjusted are those derived from land cover: RUSLE C-factor and SEDMOD surface roughness. Each land-cover change or management practice option within the Calculator is linked to a particular C-factor and surface roughness value. These values were based on literature reviews and technical guides, and are provided for guidance; they are by no means definitive estimates of C-factor or surface roughness values for the land cover classes

and/or practices. Users have the options to specify their own parameter values (including the other RUSLE factors) if they feel they have a better estimate.

Once a user has digitized an area of interest and a land-cover scenario, they can re-run HIT for the defined area. Instead of re-running HIT for the entire watershed, an affected area is first identified. This area represents all uplands affected by the land-cover change. For example, changing an entire field to grass does not only reduce erosion on the field itself (due to grass' very low C-factor value and high surface roughness value), it reduces the amount of eroded soil reaching the stream network from the upland pixels that drain through those cells. This is due to the fact that the surface along the flow-paths for these upland cells just got rougher and more likely to trap sediment. An example of an affected area is shown in Figure 3.



Figure 3: Affected area in the Sediment Calculator.

Using Figure 3 as an example, the C-factor and surface roughness values for the pixels in green are changed accordingly. RUSLE is re-calculated for the affected area, though any change is only realized with the green area. SEDMOD is re-run for the affected area, with delivery ratios changing throughout the affected area, based on the change to surface roughness within the green area. The new RUSLE and SEDMOD calculations yield new estimates of erosion and sediment loading, which can then be compared to the baseline condition modeled by IWR, or to another land-cover scenario selected by the user.

HIT uncertainty

HIT is a relatively simple sediment loading model when compared to more popular models, such as SWAT (<http://swatmodel.tamu.edu/>) and AnnAGNPS (<http://www.ars.usda.gov/Research/docs.htm?docid=5222>) which require significantly greater user input. This simplicity makes HIT's estimates more uncertain than those from the aforementioned models, but facilitates its automation and implementation as a dynamic web-based modeling tool.

There are several key sources of HIT's uncertainty in estimating erosion and sediment loading. First, HIT's erosion model (RUSLE) is only focused on sheet erosion from agricultural lands. RUSLE does not account for stream-bank, wind, or ephemeral gully erosion; each of which can be significant in different regions of the country. Due to this fact, HIT's estimates of sediment loading, and the Calculator's estimates of sediment reductions, are likely conservative. RUSLE's focus on agricultural lands means that it does not identify urban areas as threats to stream water quality. Second, SEDMOD only estimates the percentage of eroded soil reaching the stream network; therefore, HIT does not model in-stream dynamics such as routing or deposition. Lastly, as a spatially explicit model, HIT's identification of high-risk pixels is significantly affected by the spatial accuracy of its model inputs. For example, several misclassified agricultural pixels in the land cover input may not significantly alter a sediment loading estimate in a spatially lumped model like SWAT, where estimates are made at watershed scales. However, in HIT, such a misclassification could cause a high-risk area to go unidentified.

IWR has coordinated efforts to measure HIT's uncertainty. To evaluate HIT's primary spatial output, the location of high-risk fields, conservation district technicians in three piloted Michigan watersheds (the Maple, Raisin, and Pigeon-Wiscoggin) visited over 200 farm fields and assessed HIT's characterization of the landscape. Roughly 70% of the time HIT correctly classified the landscape as either *high-risk* or *not at risk*. To evaluate HIT's watershed scale estimates of sediment loading (the summation of pixel values across watersheds), the technicians took samples from a small sub-set of streams (15) across the three watersheds and sent them to Michigan's DEQ for analysis. Rankings of HIT's sediment values among the sampled stream catchments were not correlated with rankings of observed total suspended solid rates. The lack of a relationship between the HIT and DEQ rankings could be attributed to the small sample size, or the afore-mentioned model limitations; additional samples are needed for a more conclusive analysis. You can read more about these evaluation efforts at <http://www.hydra.iwr.msu.edu/iwr/cv/proposals/publications/documents/2009/CIG-FinalReport.pdf> .

These evaluations indicate that HIT's primary strength is in identifying specific high-risk locations for erosion and sediment loading. Estimates of annual erosion or sediment loading should be used for relative comparisons between areas, not for precision.

References

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