John P. Wilson, Geographic Information and Analysis Center, Department of Earth Sciences, Montana State University, Bozeman, MT 59717-0348.

GIS-based Land Surface/Subsurface Modeling: New Potential for New Models?

ABSTRACT

Many soil erosion and non-point source pollution models have been combined with geographic information systems (GISs) to capitalize on the spatial analysis and display capabilities of these new software tools and provide regional soil erosion and non-point water quality assessments during the past decade. These models and the GIS software were developed by different groups of scientists (at different times and places) and the potential benefits and limitations of this integration warrant closer scrutiny. This paper addresses these data integration issues at two levels: (1) the input data requirements and role of GIS in providing these data for six popular land surface/subsurface models (USLE, ANSWERS, AGNPS, CMLS, LEACHM and TOPMODEL) are reviewed, and (2) the types of research that will be required to build stronger links between GIS and land surface/subsurface models and the potential for building new and improved GIS-based models in the future are examined. The effect of data resolution (i.e., the number and size of units used to represent model inputs) and input data estimation methods on model results is emphasized because: (1) the GIS-based applications vary widely in terms of the data structures and methods used to organize the spatially distributed model inputs, and (2) the development of new GIS-based methods for estimating model inputs will promote the development of new and improved environmental models.

INTRODUCTION

Mathematical models integrate existing knowledge into a logical framework of rules and relationships (Moore and Gallant 1991) and can be used to: (1) improve our understanding of environmental systems, that is, as a tool for hypothesis testing, and (2) provide a predictive tool for management (Beven 1989, Grayson et al. 1992). Many environmental models require spatially distributed inputs because solutions to accelerated soil erosion, non-point source pollution and other pervasive environmental problems involve changes in land use and management at the hillslope and catchment scales (Moore et al. 1993b). The paucity of input data at the preferred spatial resolution and difficulty of handling multiple inputs that vary in different ways across landscapes (i.e. the modifiable unit area problem) have emerged as major impediments to the successful application of models in environmental management.

Modern geographic information systems offer new opportunities for the collection, storage, analysis, and display of spatially distributed biophysical and socioeconomic data (Goodchild et al., 1993, 1996). Several soil erosion and non-point source pollution models have been 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 (e.g. Hession and Shanholtz 1988, Ventura et al. 1988, De Roo et al. 1989, Petach et al. 1991). The GIS is used to compile and organize the input data and/or display the model outputs in these applications, and the integration is achieved by passing data between the GIS and model of choice (e.g. Joao and Walsh 1992, Wilson et al. 1993) or by embedding the model in the GIS or a decision support system organized around the GIS (e.g. James and Hewitt 1992, Engel et al. 1993, Romanowicz et al. 1993). However, the GIS software, digital databases, and environmental models were developed by different groups of scientists (at different times and places) and the potential benefits and limitations of this integration warrant closer scrutiny (Moore et al. 1993b).

This paper critically reviews these data integration issues and explores the potential for building new and improved spatial models of land use systems and key environmental processes in the future. The paper is divided into two parts. The first part examines the input data requirements and role of GIS in providing these data for six popular land surface/subsurface models: the USLE (Wischmeier and Smith 1978), ANSWERS (Beasley and Huggins 1982), AGNPS (Young et al. 1987), CMLS (Nofziger and Hornsby 1986), LEACHM (Wagenet and Hutson 1989), and TOPMODEL (Beven and Kirkby 1979). The effect of data resolution (i.e. the number and size of units used to represent model inputs) and input data estimation methods on model results is emphasized because the GIS-based applications vary widely in terms of the data structures and methods used to organize the spatially distributed model inputs. The second part examines the types of research that will be required to build stronger links between GIS and land surface/subsurface models and the potential for building new and improved GIS-based models in the future.

Return to the abstract

RECENT GIS-BASED LAND SURFACE/SUBSURFACE MODELING APPLICATIONS

The descriptions of the six individual models which follow emphasize their input data requirements, how these data have been obtained or generated with a GIS, and the response of each model to variations in input data since the GIS-based applications vary widely in terms of the methods, scale, and data structures used to generate model inputs. The choice of scale is important because grid-scale parameters may not exist for some processes and they may not be related to point measurements in others (Binley et al. 1989, Goodrich and Woolhiser 1991).

The six models

- USLE
    - ANSWERS
        - AGNPS
            - CMLS
                - LEACHM
                    - TOPMODEL

USLE

The Universal Soil Loss Equation (USLE) is a simple multiplicative model that was derived from over 10,000 plot years of data (Wischmeier and Smith 1978). The factor values were recently updated following the analysis of thousands of new measurements (Renard et al. 1993) and a revised version of the model has been substituted in place of the original model for farm conservation planning in the United States (Glanz 1994). The USLE and Revised Universal Soil Loss Equation (RUSLE) can be written as:

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

where *A* is soil loss in tons per acre, *R* is the rainfall-erosivity factor, *K* is a soil erodibility factor, *L* is a slope length factor, *S* is a slope steepness factor, *C* is a cover-management factor, and *P* is a supporting practices factor. Land use and management are represented by *CP* and can be estimated from field observations or farm records (Wilson 1989, Busacca et al. 1993). *CP* may also, with some difficulty, be inferred from aerial photography or satellite imagery and ground-truth data (Stephens et al. 1985, Ventura et al. 1988, Fraser et al. 1995). Climate erosivity (*R*) can be computed directly from rainfall intensities and amounts. *R* varies on a regional scale. Soil erodibility (*K*) values have been measured or estimated for all mapped soil series as part of the county soil survey program in the United States. Soil series are mapped at scales of 1:15,000 to 1:20,000 in these surveys. The effects of topography and hydrology on soil loss are characterized by the combined *LS* factor. Soil loss predictions are more sensitive to slope steepness than slope length. Estimation of the *LS* factor poses more problems than any of the other factors in the USLE and is a particular problem in applying it to landscapes as part of a GIS (Wilson 1986, Renard et al. 1991, Moore and Wilson 1992, 1994).

Several attempts have been made to combine this model with a GIS and generate regional soil loss assessments. Hession and Shanholtz (1988) transformed the USLE into a raster-based model and combined it with the Map Analysis Package (Tomlin 1980) and a sediment delivery ratio to estimate sediment loadings to streams from agricultural land in Virginia's Chesapeake Bay. A single *R* was obtained from published maps and used for each county, *K* was obtained from county soil survey reports, *LS* was calculated for each cell by inserting slope length and the weighted cell slope into the appropriate USLE equations, *C* was determined from Landsat imagery and *P* was assumed to be constant and equal to unity. One hectare (100 m by 100 m) grid cells were used for all data except elevation. The majority rule was used to assign USLE factor values to cells for discontinuous data such as soil erodibility and the centroid value was assigned to each cell for continuous data such as the topographic factor. Elevation was sampled at a 4 ha cell resolution (200 m grid spacing) and slopes were determined by weighting the slope between each cell and its eight neighbors. The topographic factor was calculated at this coarse resolution and then interpolated to a 1 ha grid size because of (computer hardware?) cost constraints. A sediment delivery ratio was calculated for each agricultural land cell and combined with the USLE soil loss to estimate the sediment that reaches the stream.

Two other studies chose the polygon data structure of a vector GIS and treated the USLE as a zone-based model. Ventura et al. (1988) used a series of GIS polygon overlays and FORTRAN programs to estimate soil erosion in Dane County, Wisconsin. A seamless digital soil data layer for the entire county was prepared from 181 detailed soil maps and used to assign *R*, *K*, and *LS* factor values. Five land cover types were classified from a Landsat Thematic Mapper (TM) scene and combined with boundary information for Public Land Survey System (PLSS) quarter sections, incorporated areas, and wetlands to assign *C* and *P* factor values. These land cover and soil data layers were then overlaid and used to estimate soil erosion for the 500,000 polygons (0.4 ha average size) in Dane County labeled as row crop and hay/meadow cover types.

James and Hewitt (1992) used a series of ARC/INFO coverages and Arc Macro Language programs to build a decision support system for the Blackfoot River drainage in Montana. Their system was based on the Water Resources Evaluation of Nonpoint Silvicultural Sources (WRENSS) model which, in turn, incorporates a modified version of the USLE to estimate potential soil erosion. *R* was estimated from published maps and historic snow survey data, *K* values were estimated from a series of digital and paper USDA-Natural Resource Conservation Service (NRCS) and USDA-Forest Service (FS) soil survey maps, *LS* values were estimated from 3 arc-second digital elevation models (DEMs) using ARC/INFO's GRID module, and a land cover data layer was prepared from a Landsat TM scene. Some additional data processing was required because: (1) some of the soil survey source maps delineated NRCS soil series and others delineated FS land-type units at scales ranging from 1:250,000 to 1:24,000; (2) the topographic factor estimates were resampled to a larger cell size, stratified into classes, and converted into a vector format to ensure compatibility with the other model data layers; and (3) a generalized land cover data layer was generated without the benefit of extensive ground-truth data. The user interface that was developed as part of this decision support system allows data browsing and querying at the basin level and data modeling at the subwatershed level.

The GIS was used to transform the USLE into a semi-distributed model in these applications. However, there are a number of important assumptions embedded in the USLE that help to explain why the application of this model to landscapes is much more difficult than its application to soil loss plots. These key assumptions include: (1) sediment deposition (and soil losses and gains between neighboring areas) is not represented; (2) landscapes must be divided into uniform slope facets; and (3) runoff is generated uniformly over the catchment.

The first assumption represents a major practical problem because the USLE does not distinguish those parts of hillslope profiles experiencing net erosion and deposition. Cesium-137, a radioisotope by-product of atmospheric nuclear weapons testing programs, has been successfully used to document patterns of erosion and deposition in fields (Ritchie and McHenry 1990). Busacca et al. (1993), for example, used Cs-137 to measure net soil loss and gain at 143 locations in a 46 ha closed watershed in the Palouse region of northern Idaho and found that net erosion averaged 11.6 t ha^{-1} yr^{-1} from erosional areas (60% of the watershed) and that deposition averaged 18.6 t ha^{-1} yr^{-1} onto depositional areas (Figure 1). The USLE (and RUSLE) should only be applied to those parts of the landscape experiencing net erosion (Wischmeier 1976, Wilson 1986).

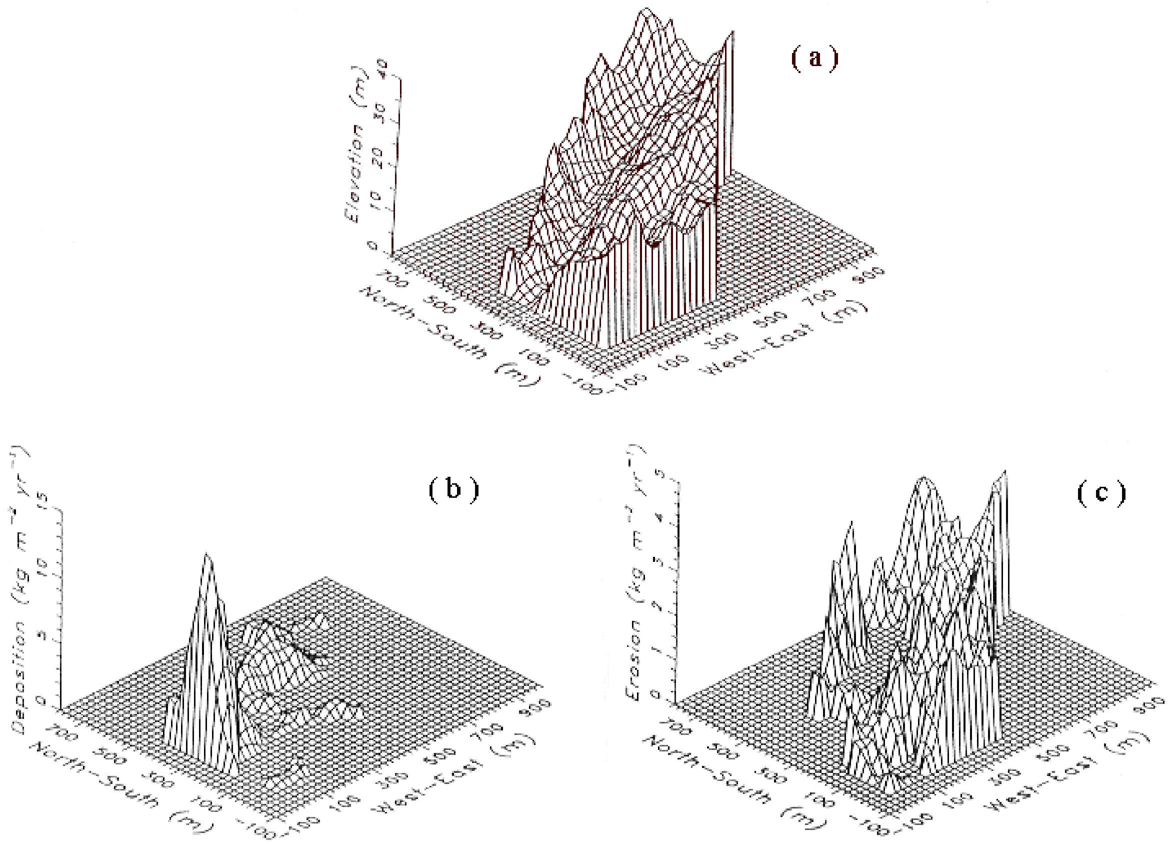

Figure 1 (a) Relative elevation of Palouse study site (15x vertical exaggeration), (b) soil deposition rates, and (c) soil erosion rates across study area based on kriged estimates (from Busacca et al. 1993, 365-366).

The final two assumptions are also important because they affect how the GIS divides the landscape into zones and how the attributes (model inputs) are aggregated (estimated) in each zone. The original USLE computed average soil loss along hillslope profiles that were defined with reference to a "standard" soil loss plot. These standard plots were 22.1 m long and planar in form although these conditions may not occur very often in natural landscapes (Moore and Wilson 1994). Foster and Wischmeier (1974) later divided irregular slopes into a series of uniform segments and modified the original USLE *LS* equations to calculate the average soil loss on these slope profiles. However, this method still requires the subdivision of landscapes into hillslope facets. Griffin et al. (1988) rewrote the original USLE to calculate erosion at any point in a landscape and thereby avoided this requirement. Their equation is much easier to implement than the original model, although the user must still distinguish those areas experiencing net erosion and deposition. This version also retains the 1-D structure of the original model and (similar to the original USLE and RUSLE models) cannot handle variations in runoff rates caused by spatially varying infiltration rates (Kinnell et al. 1995) and/or converging and diverging terrain (Moore and Wilson 1992, 1994, Wilson and Gallant 1996).

None of the GIS-based USLE applications discussed above mentioned the need to distinguish areas experiencing net erosion and deposition before applying this equation. It is not clear how they responded to this challenge (if at all) and the discussion about scale (i.e. size of raster cells and/or vector polygons used to compute soil loss) and the consequences of using source data compiled at different scales is also vague. These applications also used different slope gradient and length terms from those specified in the original model, assumed that runoff was generated uniformly across the landscape, and ignored the revised USLE proposed by Griffin et al. (1988) for estimating soil erosion at points (grid cells) in the landscape (Wilson 1996).

Repetto and Wilson (1996) calculated five sets of RUSLE *LS* values for a 2,900 km² catchment in southwest Montana and found that the magnitude and spatial pattern of LS varied greatly with data source (30 m and 3 arc-second USGS DEMs) and grid spacing (30, 100, and 200 m grid cells). The five DEMs used for this study were prepared with ANUDEM (Hutchinson 1989). This program automatically removes spurious pits within user-defined tolerances, calculates stream lines and ridge lines from points of locally maximum curvature on contour lines and (most importantly) incorporates a drainage enforcement algorithm to maintain fidelity with a catchment's drainage network (Hutchinson 1989, Moore et al. 1993b). *LS* values were grouped into five categories and the overall agreement between pairs of maps was defined as the percentage of cells that were assigned to the same *LS* classes. Table 1 lists the overall agreement values for different pairs of maps and shows that low levels of overall agreement (< 50%) were computed for each pair of maps.

Table 1. Overall agreement between RUSLE *LS* values at five mapping resolutions (%) (from Repetto and Wilson, 1996)

	Data source & map resolution				
Data source & map resolution	30m/ 30m	30m/ 100m	3 a-s/ 100m	30m/ 200m	3 a-s/ 200m
30 m DEM / 30 m spacing	---				
30 m DEM / 100 m spacing	31.3	---			
3 arc-second DEM / 100 m spacing	27.4	37.5	---		
30 m DEM / 200 m spacing	27.2	40.1	37.4	---	
3 arc-second DEM / 200 m spacing	26.9	38.7	42.6	49.3	---

ANSWERS

The Areal Nonpoint Source Watershed Environmental Response Simulation (ANSWERS) model was developed by Beasley and Huggins (1982) to simulate surface runoff and erosion in predominantly agricultural catchments. The model divides catchments into square elements (grid cells) and uses the connectivity of the cells (derived from slope aspect values) and the continuity equation to route flow to the catchment outlet (Beasley et al. 1982). Three erosion processes are considered: detachment of soil particles by raindrop impact, detachment of soil particles by overland flow, and transport of soil particles by overland flow. The quantity of erosion or deposition occurring within each cell is estimated based on the erodibility of the soil and land cover type of the cell, the rate of flow passing through the cell, and the quantity of sediment in the flow passing through the cell (Brown et al. 1993). A series of topographic (elevation, slope, aspect), soil (porosity, moisture content, field capacity, infiltration capacity, USLE *K* factor), land cover (percent cover, interception, USLE *CP* factor, surface roughness, retention), channel (width, roughness), and rainfall inputs are required for each element (De Roo et al. 1989).

The original version of ANSWERS was limited to 20 spatially homogeneous soil and land cover types because the input files had to be created by hand (Beasley and Huggins 1982, Beasley et al. 1982). The collection and organization of the input data in a GIS means that unique values can be used for each element and the level of spatial aggregation is determined by the size of the grid cells (De Roo et al. 1989, Joao and Walsh 1992). This fundamental change in data resolution and model organization will almost certainly alter the output of the model: De Roo et al. (1989), for example, found that ANSWERS predicted 46% more total runoff and 36% more soil loss when a GIS-based version of the model that divided the landscape into 4,275 0.01 ha (10 m by 10 m) grid cells was used in place of the original (lumped) model for a measured rainfall event in the Catsop catchment located in Limburg Province, Netherlands.

Brown et al. (1993) also examined the response of this model to variations in input data aggregation levels for a 2,100 ha catchment in the central piedmont of North Carolina. Five GIS data layers representing land cover, soil type, slope angle, slope aspect, and stream channels were prepared and used with a series of look up tables to derive model inputs for 23,629 0.1 ha (30 m by 30 m) grid cells (Joao and Walsh 1992). Soils, land cover, and slope angle coverages were then generalized by assigning the class value occupying the majority of the area within an aggregation unit to all cells within that unit at eight generalization levels (see Table 2 for details).

Table 2. Overall agreement between erosion and deposition at eight mapping resolutions (%) (from Brown et al. 1993, 507)

	Generalization level							
Generalization level	30	60	120	180	240	300	420	600
30	---							
60	84.8	---						
120	75.9	72.2	---					
180	65.7	66.5	67.7	---				
240	62.8	63.0	64.9	69.8	---			
300	61.2	61.3	62.6	66.2	69.7	---		
420	55.9	56.4	58.5	64.2	67.6	64.1	---	
600	53.8	54.7	56.5	60.0	64.4	62.6	69.3	---

Slope aspect and stream channel coverages were not generalized to maintain the connectivity of the hydrologic network. The patterns of semivariogram and fractal dimension plots were similar among soil and land cover parameters and indicated that the surface variation was more dependent on the pattern of polygon boundaries captured with the original data sources than on the actual attribute values represented by those polygons (land cover data were interpreted and digitized from 1:58,000-scale color aerial photographs and soils data were digitized from 1:15,480-scale NRCS maps for this study).

Brown et al. (1993) also implemented the ANSWERS model with each set of input data and a user-defined precipitation event to produce a series of erosion/deposition maps. Erosion and deposition were grouped into four categories and the overall agreement between pairs of maps was defined as the percentage of cells that were assigned to the same erosion/deposition classes. Table 2 lists overall agreement values for different pairs of maps and shows: (1) the best overall agreement occurred between model runs with low aggregation levels (30-60 m cell spacings); (2) overall agreement between maps decreased as resolution differences increased; (3) overall agreement decreased with increasing cell size (the 30 and 600 m runs were least similar for example). Percent area curves for erosion and deposition in the whole basin and along a stream corridor (reproduced in Figure 2) show that the break in the erosion and deposition estimates consistently occurred between the model runs with 120 m by 120 m and 180 m by 180 m input cells. This range of cell sizes corresponded to the sampling interval at which spatial dependance was maintained and would seem to indicate that smaller cell sizes (30-60 m on a side) were unnecessarily detailed given the input data. The effects of aggregation on model output was relatively minor to the 120 m by 120 m cell size and any cell size within this range (30 by 30-120 by 120 m) was likely to produce similar model results.

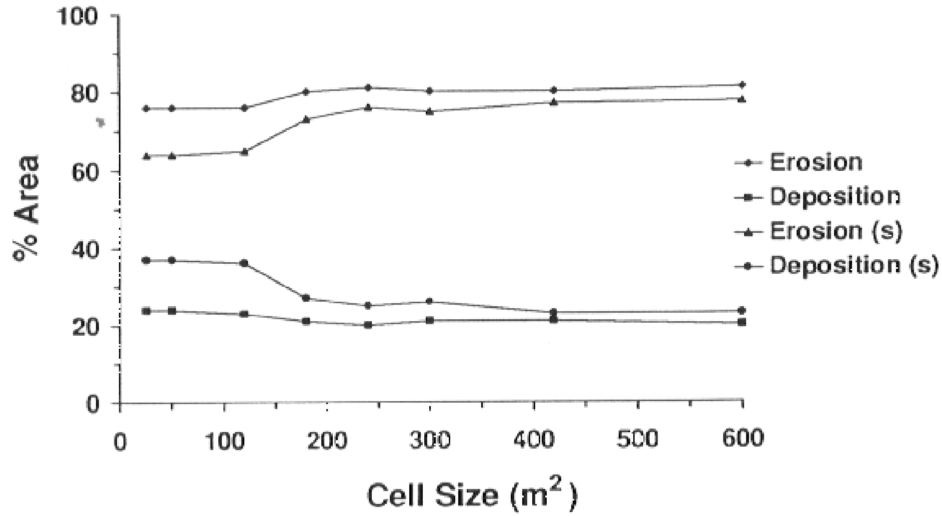

Figure 2. Percent area of erosion and deposition as affected by data aggregation. Curves are given for the basin as a whole and for all areas within 60 m of stream channels [indicated by (s)] (from Brown et al. 1993, 507).

De Roo et al. (1989) also conducted multiple ANSWERS model runs to evaluate the sensitivity of surface runoff and soil loss predictions to individual soil, land cover, and channel inputs. Topographic inputs were computed from a DEM and the other factor values were estimated from field (point) observations and/or geostatistical interpolation techniques (e.g. block kriging) at a 10 m grid spacing. One model run used average soil and land cover inputs to simulate a 20 minute, 20 mm storm in a 42.7 ha portion of the Catsop catchment (Table 3). Five values above and below the average values were chosen to represent possible values for soils and vegetation in the region and used in ten additional model runs. A simple sensitivity index was computed to describe the output variation $(RES_{11} - RES_1)$ around an average output (RES_6) as follows:

$$S_{(V1,V11)} = (RES_{11} - RES_1) \,/\, \mathrm{RES}_6 \qquad (2)$$

where RES_1 and RES_{11} are the results produced with the smallest and largest values used for each of the input variables. Table 3 shows that the model is very sensitive to the infiltration variables and antecedent soil moisture content. This is a potentially serious problem because: (1) these variables can be expected to vary through space and time; (2) measurement and interpolation of these variables is difficult and expensive; and (3) results from individual studies may be difficult to extrapolate to other rainstorms and/or catchments because the relationships between model inputs and outputs are non-linear and cannot be described by one type of function (Figure 3). The sensitivity of model outputs to these input variables can be expected to vary with the precipitation patterns, different rainfall-intensity distributions, and topography (relief, landforms, etc.) within the simulated catchment.

Table 3. Results of a sensitivity analysis of the ANSWERS model (from DeRoo et al. 1989, 256)

Variable	Range	Average Value	Sensitivity index Runoff	Soil Loss
TP (%)	40-50	45	-1.89	-1.79
FP (%)	50-70	60	0.24	0.26
FC (mm/h)	2-18	10	-3.98	-5.88

A (mm/h)	20-300	160	-10.83	-26.23
DF (mm)	5-155	80	-11.37	-25.21
P (--)	0.6-0.7	0.65	0.39	0.67
ASM (%)	40-90	65	10.15	22.32
K (--)	0.4-0.7	0.55	0	0.44
PIT (mm)	0-3	1.5	-1.67	-2.18
PER (%)	0-100	50	-1.05	-1.56
RC (--)	0.3-0.8	0.55	-2.11	-4.81
HU (mm)	30-180	105	-0.49	-1.19
N (--)	0.05-0.37	0.21	-2.62	-4.02
C (--)	0.1	0.5	0	1.79
WIDTH (m)	0.5-45	2.5	-0.06	-0.77
MAN. (--)	0.01-0.16	0.085	-0.09	-0.07
GRF (--)	0-0.001	0.0005	0.94	0.11

TP total porosity
FP field capacity
FC saturated infiltration capacity
A initial minus saturated infiltration capacity
DF infiltration control-zone depth
P infiltration constant
ASM antecedent soil moisture
K soil erodobility (USLE K)
PIT potential interception capacity
PER crop coverage
RC soil roughness coefficient
HU max roughness height
N Manning's n soil surface
C crop factor (USLE C*P)
WIDTH channel width
MAN Manning's n channel
GRF groundwater release fraction

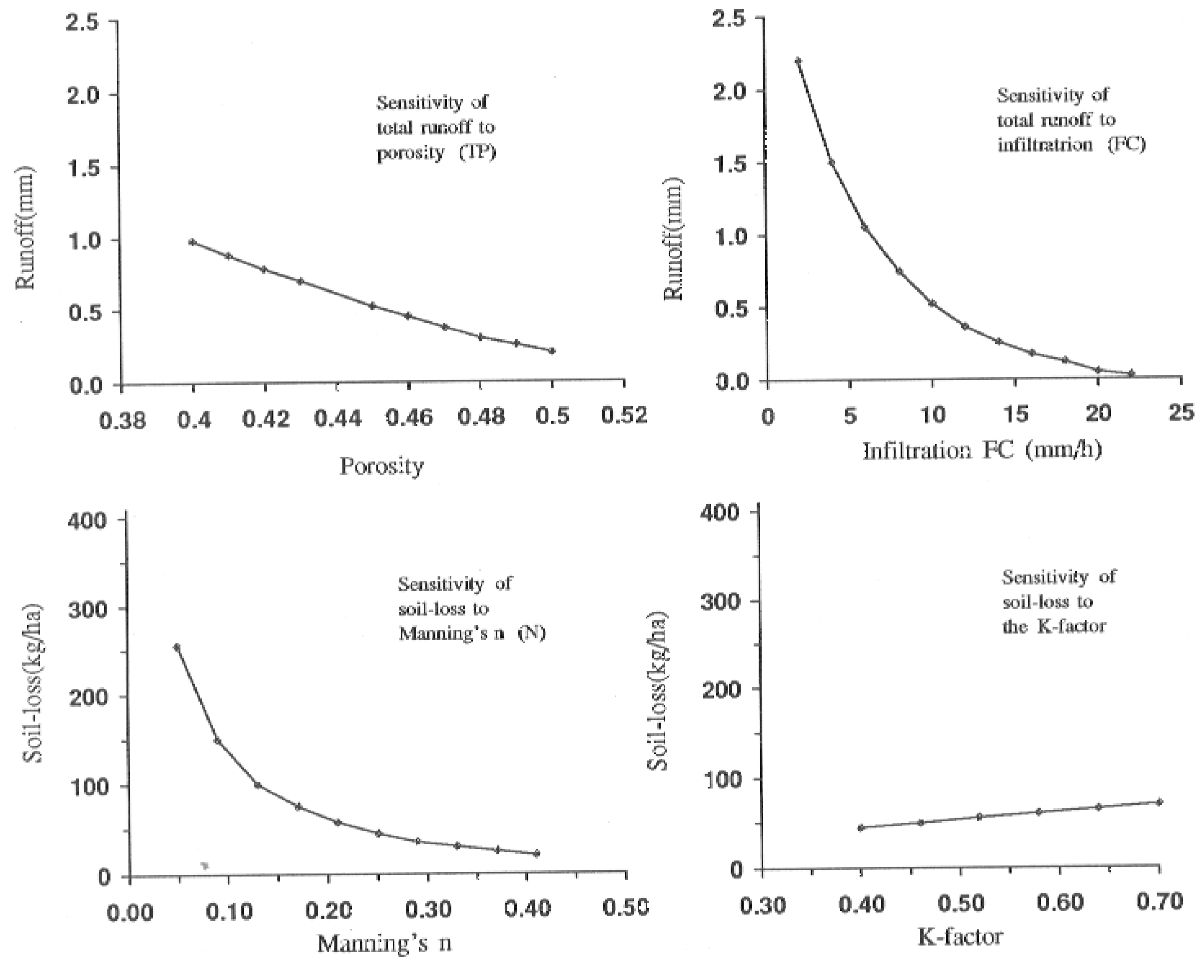

Figure 3. Sensitivity of selected ANSWERS model ouputs to input variables (from De Roo et al. 1989, 525)

AGNPS

The AGricultural NonPoint Source (AGNPS) model is an event-based model that simulates runoff, sediment, and nutrient transport from agricultural watersheds ranging in size from a few hectares to approximately 20,000 ha (Young et al. 1989). The model incorporates separate hydrology, erosion, sediment transport, and chemical transport modules which route water, sediments, and other contaminants through cells from the catchment boundary to the outlet in a stepwise fashion. The choice of cell size affects the time and labor required to run the model as well as model accuracy, and 16 ha (400 m by 400 m) grid cells are recommended for watersheds exceeding 800 ha. Runoff volumes are estimated with the USDA-NRCS curve number method and upland erosion is estimated with a modified version of the USLE (Young et al. 1987). Sediment transport and deposition are estimated with equations proposed by Foster et al. (1981) and Lane (1982) respectively, and the chemical transport component is based on relationships derived for CREAMS (Frere et al. 1980) and a feedlot evaluation model (Young et al. 1982). Several erosion (streambanks, streambeds, gullies, etc.) and nutrient sources (animal feedlots) are treated as point sources and added to contributions from diffuse sources. Model outputs can be obtained for each cell and/or at the watershed outlet.

Engel et al. (1993) linked AGNPS with the GRASS GIS as part of a decision support system to assist with the management of runoff, erosion, and nutrient movement in agricultural landscapes. The GIS was used to organize the input data and display the model results in this application. Terrain-based attributes (slope gradient, length, shape, aspect, upslope contributing area, etc.) represent approximately one-third of the input parameters required by this model and can be generated from DEMs. Panuska et al. (1991) used a series of contour- and grid-based terrain analysis methods and DEMs to generate a terrain-based parameter file that could be linked with AGNPS. They also examined the sensitivity of the slope, upslope contributing area, and maximum flow path length variables computed from different DEM structures for a range of element sizes on the 210 ha North Fork Cottonwood Creek catchment in southwestern Montana. The computed flow path lengths and contributing areas (but not slopes) varied with terrain analysis method and element (cell) size (Figure 4). Panuska et al. (1991) concluded that the adequacy of the DEM would depend on the characteristics of the terrain since the smallest cell size will only produce the most accurate representation of the terrain if the dimensions of the cells are greater than the horizontal resolution of the primary elevation data and the elevation differences between neighboring points are greater than the vertical resolution of the data. This result suggests that rolling terrain with small to moderate relief would be better represented by a coarser DEM than a dissected catchment with steep ridges and ravines.

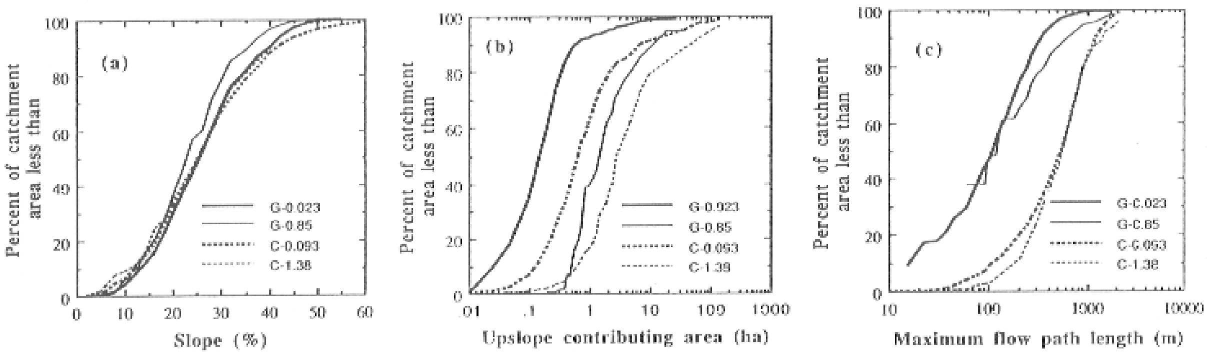

Figure 4. Examples of (a) slope, (b) upslope contributing area, and (c) maximum flow path length distributions calculated with (G) grid- and (C) contour-based DEMs and terrain analysis methods for a range of element sizes (from Panuska et al. 1991)

Garbrecht and Martz (1994) also used sensitivity analysis to examine the dependence of six drainage properties (critical source area, number of channel links, total channel length, mean channel link slope, watershed drainage density, and mean channel link direct drainage area) on DEM cell size. They started with a 30 m DEM in central Oklahoma and generated coarser DEMs by successive spatial averaging of the baseline DEM. Their results showed that a DEM would need to have a grid area of less than 5% of the network reference area (i.e. the mean area draining directly into the channel links) to reproduce important drainage features within 10% of the baseline reference values because the DEM cannot accurately reproduce drainage features that are at the same scale as the spatial resolution of the DEM. These results are similar to those of Panuska et al. (1991) to the extent they show that: (1) the grid size must be selected relative to the size of the features of interest, and (2) high-resolution DEMs are needed if small drainage features are important.

CMLS

The Chemical Movement through Layered Soils (CMLS) model was developed by Nofziger and Hornsby (1986, 1987) to interactively simulate chemical movement through soil with easily obtained soil, chemical, and weather inputs. CMLS divides the soil into as many as 20 layers and calculates the fraction of the applied chemical remaining in the entire soil profile and the position of the solute front at different times based on the piston displacement of water. The soil properties affecting chemical movement (bulk density, permanent wilting, field capacity water contents, and organic carbon content) may vary between layers but are assumed to be uniform within each layer. Two chemical properties (the partition coefficient normalized to soil-organic carbon and degradation half-life) and several climatic and cultural factors known to affect chemical movement (plant root depth, daily precipitation, irrigation, and evapotranspiration amounts) are also required by the model. Although this model was written primarily as a management and educational tool, its performance has been compared favorably with observed data and the predictions of several other pesticide fate models in several U.S. locations (Pennell et al.

1990, Inskeep et al. 1996). The CMLS model has also been combined with GIS to predict the threat to groundwater posed by current herbicide applications (e.g. Wilson et al. 1993) and several recent studies have examined the impact of data resolution and input data estimation methods on model outcomes. The problems are complicated in the U.S. because modern soil surveys report large ranges for most soil properties.

Foussereau et al. (1993) used bootstrapping to generate a series of pseudo-profiles of soils from pedon characterization data and evaluate the uncertainty of CMLS model predictions due to variability of soil input data beneath citrus groves in southwestern Florida. Their method is important because it shows how the variability of the major soils occurring in map units can be incorporated in groundwater pollution assessments. Five hundred pseudo-soil profiles were generated for each single-name soil map unit (known as consociations) from three or more actual pedon characterization data sets and combined with weather sequences predicted with the WGEN weather generator (Richardson and Wright 1984) to produce cumulative probability curves showing the fraction of applied pesticide leaching beyond the 1 m depth (Figure 5). At least three actual pedon characterization data sets were also used to generate pseudo-profiles for each of the named soils in multiple-named soil map units (i.e. soil associations or soil complexes) and the highest probability of exceedance (POE) of the U.S. EPA health advisory levels for specific pesticides was used as an estimator of the environmental risk on GIS maps showing these map units. Other soil inclusions that were not included in map unit names (although they may represent $\leq$25% of a single-name soil map unit) were not considered because map unit descriptions in soil survey reports usually contain only qualitative descriptions of these soils. Foussereau et al. (1993) did compile some transect data for three Florida map units that showed how a given map unit may have different types and percentages of soils from those provided in the soil map unit descriptions in soil survey reports. These discrepancies left them with continuing and difficult questions as to how they might incorporate these soils into their bootstrapping algorithm without creating hypothetical soil profiles that do not reflect the actual soils occurring in the landscape of interest.

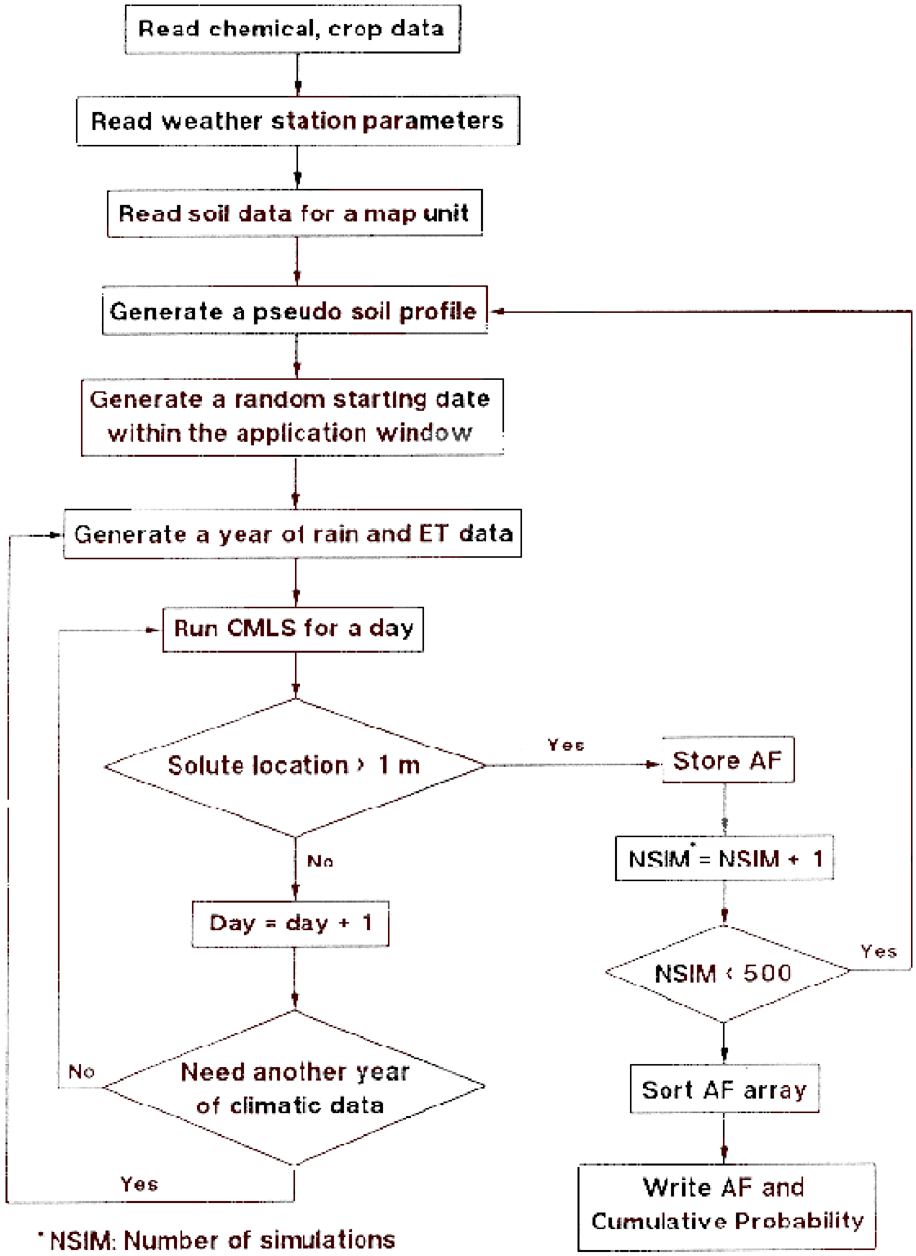

Figure 5. Flow chart of simulation procedure using pseudo-profile data, generated weather sequences, estimated evapotranspiration, and varying pesticide appllications (from Foussereau et al. 1993, 265).

Wilson et al. (1996) used the WGEN and CMLS models with two sets of soil and climate inputs to evaluate the impact of input data resolution on model predictions for a 320 km² study area in Teton County, Montana. The basic soil and climate inputs required by WGEN and CMLS were acquired from either: (1) the USDA-NRCS State Soil Geographic (STATSGO) database (Bliss and Reybold 1989); (2) the USDA-NRCS (County) Soil Survey Geographic (SSURGO) database (Reybold and TeSelle 1989); (3) the Montana Agricultural Potentials System (MAPS) database (which divides Montana into approximately 18,000 20 km² cells and stores more than 200 different land and climate characteristics for each of these cells) (Nielsen et al. 1990); and (4) a series of fine-scale monthly climate surfaces developed by the authors (0.55 km² cell size) using thin-plate splines, published climate station records and USGS DEMs (Custer et al. 1996) (Figure 6). Fifteen years of daily precipitation and evapotranspiration values were generated and combined with soil and pesticide inputs in CMLS to estimate the depth of picloram (4-amino- 3,5,6-trichloro-2-pyridinecarboxylic acid) movement at the end of the growing season for every polygon containing unique soil and/or climate inputs. The results showed that: (1) the mean depths of picloram movement predicted for the study area with the SSURGO soil and MAPS (coarse-scale) climate information and the two model runs using the fine-scale climate data were significantly different from the values predicted with the STATSGO soil and MAPS climate data (based on a new variable representing the differences between the depths of leaching predicted with the different input data by soil/climate map unit and testing whether the mean difference was significantly different from zero at the 0.01 significance level) (Table 4); and (2) CMLS identified numerous (small) areas where the mean center of the picloram solute front was likely to leach beyond the root zone when the county soils information was used (Figure 7). These results show how the CMLS model predictions vary with the choice of climate and soil inputs and why high resolution SSURGO soil information is needed if the goal is to identify those areas where potential chemical applications are likely to contaminate groundwater.

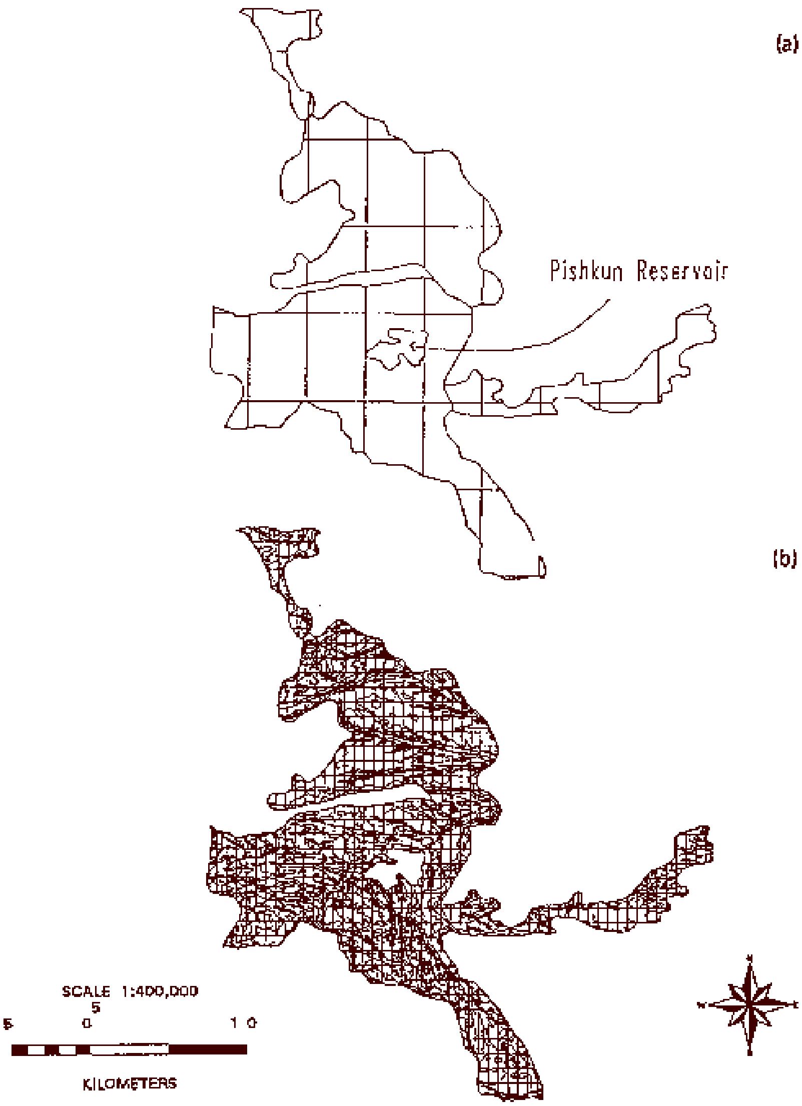

Figure 6. Maps of Teton County study area showing (a) MAPS climate cells overlaid on STATSGO soil mapping units, and (b) ANUSPLIN climate cells overlaid on SSURGO soil mapping units (from Wilson et al. 1996).

Table 4. T test results comparing MAPS/SSURGO, ANUSPLIN/STATSGO, and ANUSPLIN/SSURGO CMLS model prediction with MAPS/STATSGO CMLS model predictions (from Wilson et al. 1996).

Model run	Mean depth (cm)	Std. error	T	Prob > |T|
MAPS/SSURGO	2.52	0.43	5.80	0.0001
ANUSPLIN/STATSGO	-1.37	0.19	-7.12	0.0001
ANUSPLIN/SSURGO	1.65	0.47	3.49	0.0010

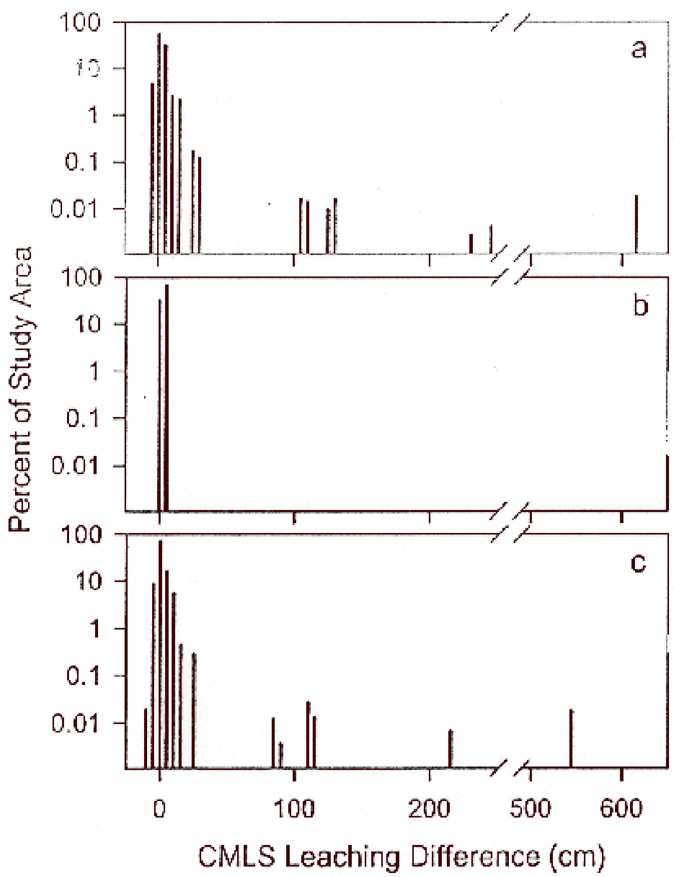

Figure 7. Histograms showing differences in predicted depth of solute movement for MAPS/STATSGO and (a) MAPS/SSURGO, (b) ANUSPLIN/STATSGO, and (c) ANUSPLIN/SSURGO data inputs (from Wilson et al. 1996).

Inskeep et al. (1996) compared predicted and observed pentafluorobenzoic acid (PFBA), 2, 6-difluorobenzoic acid (DFBA) and dicamba travel times at a single field site near Manhattan, Montana. CMLS and LEACHM (Wagenet and Hutson, 1989) predictions were generated using: (1) detailed site-specific measurements (both models); (2) conductivity and retentivity functions estimated from the SSURGO database (LEACHM model); and (3) volumetric water contents estimated from textural data in the SSURGO database and daily precipitation and evapotranspiration estimated with the WGEN weather generator and MAPS database (CMLS model). Comparison of observed and simulated mean travel times showed that: (1) both LEACHM and CMLS performed adequately with site-specific inputs (e.g. CMLS predicted mean travel times were within 3.5 to 38% of observed data over two growing seasons under a variety of crop and fallow conditions), and (2) the CMLS predictions were less sensitive to data input resolution than the LEACHM predictions due in part to the fact that CMLS provides an over-simplified description of transport processes. Inskeep et al. (1996) concluded that the use of the SSURGO and MAPS databases with CMLS may provide a reasonable approach for classifying the susceptibility of map units in terms of solute movement, although the potential applicability of this approach is limited to areas with digital copies of the SSURGO (selected counties scattered throughout the U.S.) and MAPS databases (Montana only).

LEACHM

The Leaching Estimation and CHemistry model (LEACHM) is a one-dimensional finite difference model designed to simulate the movement of water and solutes through layered and non-layered soil profiles (Wagenet and Hutson 1989). This is deterministic, mechanistic, research-oriented model with correspondingly greater input requirements than many simpler models (Inskeep et al. 1996). The model uses: (1) a variable time step based on allowable water content changes in the soil profile; (2) Darcy's law and the continuity equation to describe transient water flow; and (3) calculated water contents and fluxes to solve the convection-dispersion equation and describe the movement of solutes which can adsorb, volatilize, and degrade. The model also allows depth- and time-dependent root growth, water use (transpiration), and evaporation (Wagenet and Hutson 1989). LEACHM has been validated and used as a predictive tool at the plot and field scale (e.g. Wagenet and Hutson 1986, Wagenet et al. 1989), and several attempts have been made to combine this model with GIS databases for regional scale assessments of leaching behavior.

Petach et al. (1991) used LEACHM to simulate the movement of four chemicals through layered soils for a 70 km^2 study area near Albany, New York. The site was divided into 0.4 ha grid cells and a series of pedotransfer functions was used to relate soil physical properties to the mean and variance of the hydraulic properties occurring in each cell. The soils were classified into six hydraulic groups and LEACHM was executed 25 times using different combinations of soil hydraulic properties to represent the expected spatial variability in hydraulic properties. This approach generated estimates of the variability of chemical fluxes near the low end of the range published in the literature (although the simulated variability could well agree with field measured values if the process was extended to include other factors that affect chemical movement such as sorption and degradation) and the influence of the soil hydraulic properties on the estimated variability in leaching of both water and chemicals was approximately the same magnitude as the impact of the two precipitation years considered in this study.

The experience gained in the above study led to the development and application of a modified version of the pesticide version of LEACHM to a 300,000 km^2 study area encompassing the states of Connecticut, Maine, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont (Hutson and Wagenet 1993). This new model (LEACHA) replaced the Richards equation for water flow and the convection-dispersion equation for chemical transport with a mobile-immobile capacity model adapted from Addiscott (1977) and Nicholls et al. (1982). LEACHA divides the soil profile into horizontal layers and uses a daily time step to calculate fluxes and changes in water and chemicals for each layer. Soil attributes (mean clay content and bulk density values and the lowest (worst-case) organic carbon content) were obtained from the STATSGO database and water retention properties were estimated using regression equations developed by Rawls and Brakensiek (1982) which relate water retention to particle size, bulk density and organic matter data. The results in the New England application were mapped using four classes of leaching potential and showed that 60-84% of the variability in leaching could be explained by differences in soil organic carbon content (Hutson 1993). The other 16-40% of the variability was ascribed to differences in climate and parent material (Wagenet and Hutson 1996).

Overall, these results indicate why additional knowledge and documentation of precipitation and soil organic matter content patterns may be required to improve regional scale applications of LEACHA and other solute transport models. The precipitation inputs used by Hutson (1993) could have been improved using one of the new interpolation methods that predicts spatial patterns of precipitation based on published station records and DEMs (i.e. latitude, longitude, and elevation data) (e.g. Daly et al. 1994, Hutchinson 1995, Running and Thornton 1996). The soil organic carbon variable represents a more difficult problem because the soil organic matter data reported in published soil surveys are very generalized and may not reflect the soil organic matter conditions for the landscape unit being modelled (Wagenet and Hutson 1996).

TOPMODEL

TOPMODEL predicts the relative amount and spatial distribution of subsurface, infiltration excess, and saturation excess overland flow based on surface topography and soil properties (Beven and Kirkby 1979, Beven et al. 1984, Sivapalan et al. 1987, Quinn and Beven 1993). The model has been validated with rainfall-discharge data (e.g. Beven et al. 1984, Hornberger et al. 1985, Robson et al. 1993, Obled et al. 1994, Wolock 1995) and several recent studies have examined its applicability to water quality problems (Wolock et al. 1990, Robson et al. 1992). The continued popularity of TOPMODEL can be traced to its structural simplicity and parsimonious parameterization (Iorgulescu and Jordan 1994).

The model assumes a spatially uniform recharge rate and quasi-steady subsurface response to derive a function relating local soil moisture storage or water table depth to the topographic index (ln(*a*/tanß)) of a catchment:

$$S_i = S + m\{\lambda - \ln(a/\tan\beta)_i - (\delta - \ln(K_i))\} \qquad (3)$$

where S_i is the local soil moisture deficit, S is the mean soil moisture deficit of the catchment, m is a parameter that characterizes the decrease in hydraulic conductivity with soil depth, a is the drainage area per unit contour length, ß is the slope, K_i is the lateral transmissivity of the soil profile when the water table just intersects the surface, and λ and δ are the mean values of ln(*a*/tanß) and ln(*K*) for the catchment (Zhang and Montgomery 1994). Many applications ignore the soil transmissivity terms in (3) because the spatial pattern of soil transmissivity is seldom known and is often assumed to be constant over the catchment (Iorgulescu and Jordan 1994). S_i represents a negative soil moisture deficit so that $S_i = 0$ at complete saturation and $S_i > 0$ when a soil moisture deficit occurs. The mean soil moisture deficit of a catchment at time t, S_t, is calculated by:

$$S_t = S_{t-1} - (q_{t-1} - r)\Delta t \qquad (4)$$

where q is the total catchment runoff at time t - 1 divided by the catchment area, r is the net recharge rate into the soil column, and Δt is the time interval used for the model simulation. The soil moisture deficit at every point (grid cell) in the catchment is then computed using (3) and water is routed to the catchment outlet via: (1) subsurface runoff in areas with a soil moisture deficit larger than the precipitation added during a time step; (2) subsurface and infiltration excess overland flow in areas with rainfall intensities greater than the infiltration capacity; and (3) subsurface and saturation excess overland flow in areas with either a soil moisture deficit smaller than the incremental precipitation in a unit time step or that were saturated during the previous time step (Beven et al. 1984). The subsurface flow rate q_b of the catchment is calculated by:

$$q_b = \exp(-(\lambda - \delta))\exp(-S_t/m) \qquad (5)$$

and the saturation excess runoff q_0, which is the sum of the excess soil moisture and direct precipitation that falls on the saturated areas, is calculated by:

$$q_0 = (1/A_t)\int_{A_s}(-S_i/\Delta t + r)\,dA \qquad (6)$$

where A_s is the area of the catchment with surface saturation ($S_i \leq 0$) and A_t is the total area of the catchment. This approach means that predicted soil moisture patterns will follow the outline of the topographic index and the predicted saturated source area will expand and contract as the water balance of the model changes (Quinn et al. 1995). Total runoff q at each time step is the sum of subsurface and surface runoff (Beven and Kirkby 1979, Zhang and Montgomery 1994).

The ln(*a*/tanß) index was calculated manually using contour data in early applications of TOPMODEL and the advent of GIS and terrain analysis techniques has allowed this procedure to be automated (Quinn et al. 1995). However, several recent studies have demonstrated that the spatial pattern and statistical distribution of the topographic index varies with different grid resolutions and estimation procedures.

Zhang and Montgomery (1994) calculated slope, drainage area per unit contour length, and the topographic index for a series of depressionless square-grid DEMs at scales of 2, 4, 10, 30, and 90 m using the GRID tools in ARC/INFO and spot elevation data obtained from low-altitude aerial photographs. They found that the DEM grid size significantly affected both the computed topographic parameters and hydrographs for two study areas with moderate to steep relief in the western United States. The 10 m grid spacing provided a substantial improvement over the 30 m and 90 m data, but the 2 m and 4 m data provided only marginal additional improvement. This last result may be a function of the scale of the source data (spot elevations derived from low altitude aerial photography with a stereo digitizer at a density of approximately 10 m) and/or the method used to calculate drainage areas (i.e. the classical D8 algorithm discussed below). Moore (1996) showed that computed slope and topographic index values varied with grid size for a series of 22 square-grid DEMs with scales from 20 to 680 m in three 100 km² study areas in southeastern Australia. Quinn et al. (1995) computed drainage areas for a series of 5, 10, 25, and 50 m DEMs derived from a 1:10,000-scale contour map and found that: (1) small channels and catchment boundaries tend to become obscured or lost altogether as grid size increases, and (2) larger grid sizes exhibit a bias towards larger topographic index values. Zhang and Montgomery (1994) and Quinn et al. (1995) both concluded that DEMs of the order of 10 m or smaller were needed to capture the variability of the topographic form for hillslopes in their study areas, and the continued evolution and spread of modern Global Positioning System (GPS) tools may allow the collection of high resolution topographic data sets in some environments (Spangrud et al. 1995).

The choice of flow routing method may also affect the magnitude and spatial pattern of the computed topographic index values, and some programs provide multiple options. The TAPES-G user, for example, can select either the classical D8 algorithm (O'Callaghan and Mark 1984), the quasi-random Rho8 algorithm (Fairfield and Leymarie 1991), the multiple flow direction FD8/FRho8 algorithm (Freeman 1991, Quinn et al. 1991), or the stream-tube based DEMON algorithm of Costa-Cabral and Burges (1994) for calculating upslope contributing areas (Gallant and Wilson 1996).

The D8 algorithm allows flow from a node to only one of eight nearest neighbors based on the direction of steepest descent. The D8 algorithm tends to produce flow in parallel lines along preferred directions, which will only agree with the aspect when aspect is a multiple of 45°, and it cannot model flow dispersion (Moore et al. 1993a). However, this algorithm is used in ARC/INFO and remains the most commonly used algorithm notwithstanding these limitations. The Rho8 algorithm developed by Fairfield and Leymarie (1991) is a stochastic version of the D8 algorithm in which the expected value of the flow direction is equal to the aspect. This algorithm cannot model flow divergence (like the D8 algorithm), but it does simulate more realistic flow networks because long parallel flow paths are broken up at the cost of many more cells without upslope connection (Moore et al. 1993a).

The FD8 and FRho8 algorithms allow flow divergence or catchment spreading to be represented in upland areas above defined channels and use the D8 or Rho8 algorithms below points of channel initiation. The proportion of flow or upslope contributing area assigned to multiple downslope nearest neighbors above channels is determined on a slope-weighted basis using methods similar to those proposed by Freeman (1991) and Quinn et al. (1991). The FRho8 option gives much more realistic (smoother) distributions of contributing area and also eliminates D8's parallel flow paths (Quinn et al. 1991, Moore et al. 1993a, Wolock and McCabe 1994, Gallant and Wilson 1996). Because stream lines are usually quite well defined, the flow divergence (spreading) algorithm is usually best disabled in areas of high contributing area, and TAPES-G provides a threshold called the "maximum cross grading area" above which the simple D8 or Rho8 method is applied (Gallant and Wilson, 1996).

The DEMON algorithm generates flow in each pixel (source pixel) and follows it down a stream tube until the edge of the DEM or a pit is encountered. These stream tubes expand and contract in response to the DEM surface and thus naturally model both convergence and divergence. Costa-Cabral and Burges (1994) showed that: (1) the FD8/FRho8 algorithms can still generate errors in certain types of landscapes, and (2) the DEMON algorithm tends to delineate convergent and divergent flow areas more accurately than either the D8, Rho8, or FD8/FRho8 algorithms. Holmgren (1994) and Quinn et al. (1995) recently re-examined the multiple flow direction algorithms and suggested several modifications that may eliminate some of these problems. The fraction of contributing area passed from a cell to neighbor *i* in the initial multiple flow direction algorithms was given by:

$$f_i = S^p / \Sigma S^p \qquad (7)$$

where S is the slope from the central node to neighbor i and p is a positive constant. Freeman (1991) found that p = 1.1 produced the most accurate results for artificial conical surfaces and TAPES-G uses that value (Gallant and Wilson 1996). Recently, Holmgren (1994) reported that much higher values of p ranging from 6 to 8 may be more appropriate for many natural landscapes, and Quinn et al. (1995) showed that raising the power in (7) tends to give more of a single flow direction (Figure 8). The optimum solution will vary with the type of landscape and the grid size that is chosen.

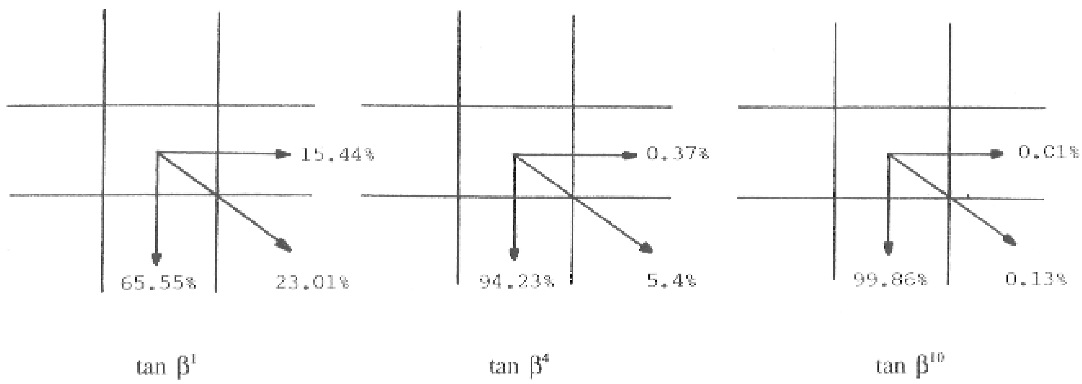

Figure 8. Effect of the flow apportioning routine when raising tanß to the power h (from Quinn et al. 1995, 170)

The choice of grid size and flow apportioning method will affect the runoff dynamics in TOPMODEL (Wolock and McCabe 1994, Quinn et al. 1995). The hydrograph predictions may not be affected because the changes in the magnitude and distribution of the topographic index will be offset by changes to the soil hydraulic conductivity and lateral transmissivity terms when the model is re-optimized. However, these changes will affect the pattern of variable source areas. These effects are complicated because channels represent subgrid features in many upland catchments and the methods used to handle the cells containing channels will have important consequences for the delineation of variable source areas in and around channels and channel heads (Quinn et al. 1995).

Morris and Heerdegen (1989) used the upslope contributing area as a threshold to initiate channels. Gallant and Wilson (1996) refer to this threshold as the maximum cross grading area in TAPES-G and they use it to switch from a multiple flow algorithm (in upland areas) to a single flow algorithm (in channel cells) for routing water to the catchment outlet. Quinn et al. (1995) have taken this idea further and suggested a new method for calculating the topographic index in grid cells containing a channel. They also compared the topographic index distributions for a series of successively smaller values of this channel initiation threshold (CIT) and found that unrealistic variable source area patterns were generated if the CIT was set incorrectly. They asked whether there is an optimum threshold for channel initiation and proposed using the CIT value which causes a rapid change in the magnitude and position of the peak value of the topographic index distribution function as this optimum value. Quinn et al. (1995) acknowledged that this CIT value may not represent the true position of the channels as measured in the field (cf. Dietrich et al. 1993, Prosser and Dietrich 1995), but argued that such a value could be defined for a particular grid resolution and that it was consistent with the aims of TOPMODEL and the assumptions of the analyses.

Quinn et al. (1995) also introduced a combined CIT and $(\tan\beta)^h$ index which assumed that: (1) the permanent channel can be identified, (2) the power factor used for flow apportioning starts with the full multiple flow direction algorithm near the catchment divide (i.e. h is equal to unity); and (3) this term changes in concert with the upslope contributing area to generate progressively straighter flows nearer the permanent channel. They proposed the following equation to model this downslope feedback effect:

$$d_i = cld \tan\beta^f \qquad (8)$$

h

where f = [($A/thresh$) + 1] , A = the current upslope area, *thresh* = the current CIT value chosen by the user, h = the adjustable power term, and *cld* = contour length. At low *A/thresh* the resulting power will be close to one and the multiple flow direction algorithm will be invoked. As the cells approach the specified CIT value a straighter flow direction will occur. The degree of straightening will depend on the value chosen for h and higher values of h will generate a faster change from multiple to single flow direction accumulation and tend to produce a stronger contrast in topographic index maps. Quinn et al. (1995) suggested choosing values for *thresh* and h that matched the pattern of the topographic index with field observations.

NEW POTENTIAL FOR NEW MODELS?

The descriptions of GIS-based modeling applications in the previous section offer little evidence that GIS software and databases have led to the development of new and/or improved land surface/subsurface models during the past decade. Most of the applications have simply used the GIS as a way to organize model inputs and display model predictions. The continued development of new terrain analysis methods for routing water flow across the landscape in conjunction with TOPMODEL represents a notable exception to this trend because the increasing availability of color displays afforded by GIS has accelerated the development and evaluation of these methods and led to improvements in TOPMODEL as well as the techniques themselves (Quinn et al. 1995). However, the relatively slow implementation of these new terrain analysis tools in commercial GIS packages (e.g. ARC/INFO still uses the classical D8 algorithm that represents the least preferred of the currently available algorithms) limits their availability and the opportunity to investigate their relevance to other field sites (and models).

Many of the GIS-based applications do show how difficult it is to generate reliable, location-specific estimates for key input variables and that the outputs of these models are very sensitive to small changes in the values of these input variables (e.g. De Roo et al. 1989, Brown et al. 1993, Wilson et al. 1996). This result suggests that additional work is needed to characterize the spatial variability of specific processes and properties occurring in landscapes. Two examples (one affecting the R factor and the other affecting the LS factor in the RUSLE) are reviewed here to illustrate recent developments and how these types of innovations might contribute to the development of improved land surface/subsurface models in the future.

The first example follows the proposal of Moore and Hutchinson (1991) and uses an index approach to characterize the spatial variability of the major hydrological and terrain factors affecting erosion. Moore and Wilson (1992, 1994) developed a simple dimensionless sediment transport capacity index (T_c) to predict the spatial pattern of soil loss potential that can be written as:

$$T_c = [\Sigma\ (\mu_i a_i / b_j) / 22.13]^m\ (\sin\beta_j / 0.0896)^n \qquad (9)$$

where μ_i is a weighting coefficient ($0 \leq \mu_i \leq 1$) that is dependent on the runoff generation mechanism and soil properties (i.e. infiltration rates), a_i is the area of the ith cell, b_j is the width of each cell, $ß_j$ is the slope in degrees, m and n are constants (0.6 and 1.3, respectively), and the i subscript refers to the set of i element indices which are hydrologically connected to cell j.

This equation was derived from the transport capacity limiting sediment flux in the Hairsine-Rose (Hairsine and Rose 1991, 1992a, 1992b), WEPP (Laflen et al. 1991a, 1991b), and catchment evolution (Willgoose et al. 1991) erosion theories (Moore et al. 1992). The index is equivalent to the length-slope factor in the Revised Universal Soil Loss Equation (Renard et al. 1991) for a two-dimensional hillslope, but it is simpler to use and conceptually easier to understand (Moore and Burch 1986a, 1986b). The index also distinguishes net erosion/deposition areas and accounts for different runoff producing mechanisms and soil properties using a spatially variable weighting function and it could be easily implemented within a raster-based GIS (Wilson and Gallant 1996).

The second example provides an alternative to the EI_{30} index used for the R factor in the USLE and RUSLE models. The product of storm rainfall kinetic energy (E) and the maximum rainfall intensity measured over 30 minutes (I_{30}) has been used as the R factor in the USLE throughout its history. However, this EI_{30} index does not consider variations in runoff rate that may result from differences in infiltration rates (Figure 9) and cause variations in erosion rates similar to those illustrated in Figure 10. Kinnell et al. (1995) examined erosion data from non-vegetated plots at Holly Springs, Mississippi and demonstrated that their $I_X E_A$ index is superior to the EI_{30} index because it accounts for the processes of detachment and transport better than the EI_{30} index. This $I_X E_A$ index, first proposed by Kinnell (1983), is based on the product of the excess rainfall rate (I_X) and the rate of expenditure of rain kinetic energy (E_A). Rainfall kinetic energies are computed from:

$$E_A = 1099I\,[1 - 0.72\exp(-1.27I)] \tag{10}$$

where E_A has units of ft-ton per acre per hour and I is rainfall intensity in inches per hour. This equation follows directly from the intensity-unit kinetic energy relationship used by Renard et al. (1993) in RUSLE (Kinnell et al. 1995). The excess rainfall term (I_X), which serves as a surrogate for the runoff rate (Q), is the difference between the rainfall intensity and infiltration rate (I_S). Spatially-variable estimates of I_X (and therefore the $I_X E_A$ index) could be obtained from a soils database (that included the infiltration rate as an attribute) and monthly values of I and/or I_S could be used in place of the EI_{30} index to predict the effects of different crops and cultivation practices on soil erosion (similar to the current model).

The $I_X E_A$ index is similar to the T_c index of Moore and Wilson (1992, 1994) in that it provides an opportunity to consider the effects of hydrology more directly within the USLE/RUSLE modeling environment than is currently possible (Kinnell et al. 1995). They are related to the extent that the $I_X E_A$ index can be used to help assign weights in (*9*) for landscapes dominated by Hortonian (infiltration-excess) overland flow. However, additional research is needed to evaluate the effects of using these alternative *R* and/or *LS* factors on *K* (which incorporates the effects of profile permeability) and the other RUSLE factors.

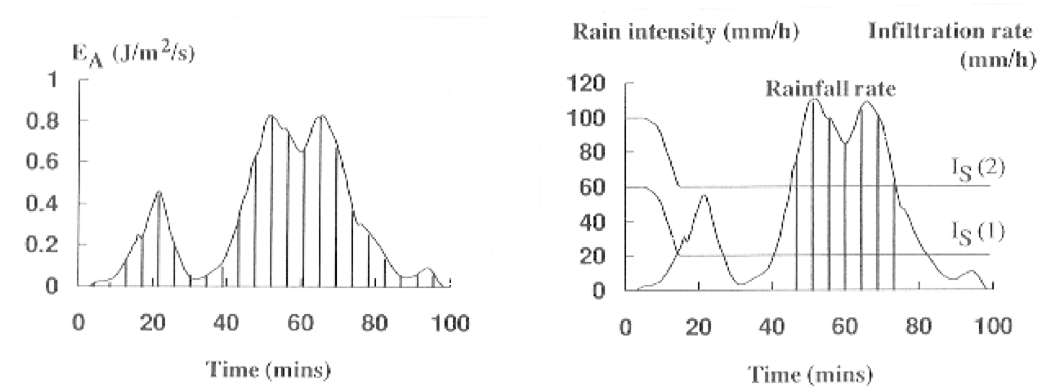

Figure 9. Schematic representation of EI_{30} index in relation to temporal variations in rainfall kinetic energy flux (E_A) and rainfall intensity. The EI_{30} for the event is given by twice the product of the shaded areas in Parts A and B, and examples of temporal variations in soil infiltration rate ($I_S(1)$, $I_S(2)$) that might apply under these circumstances are also shown in Part B (from Kinnell et al. 1995, 1450).

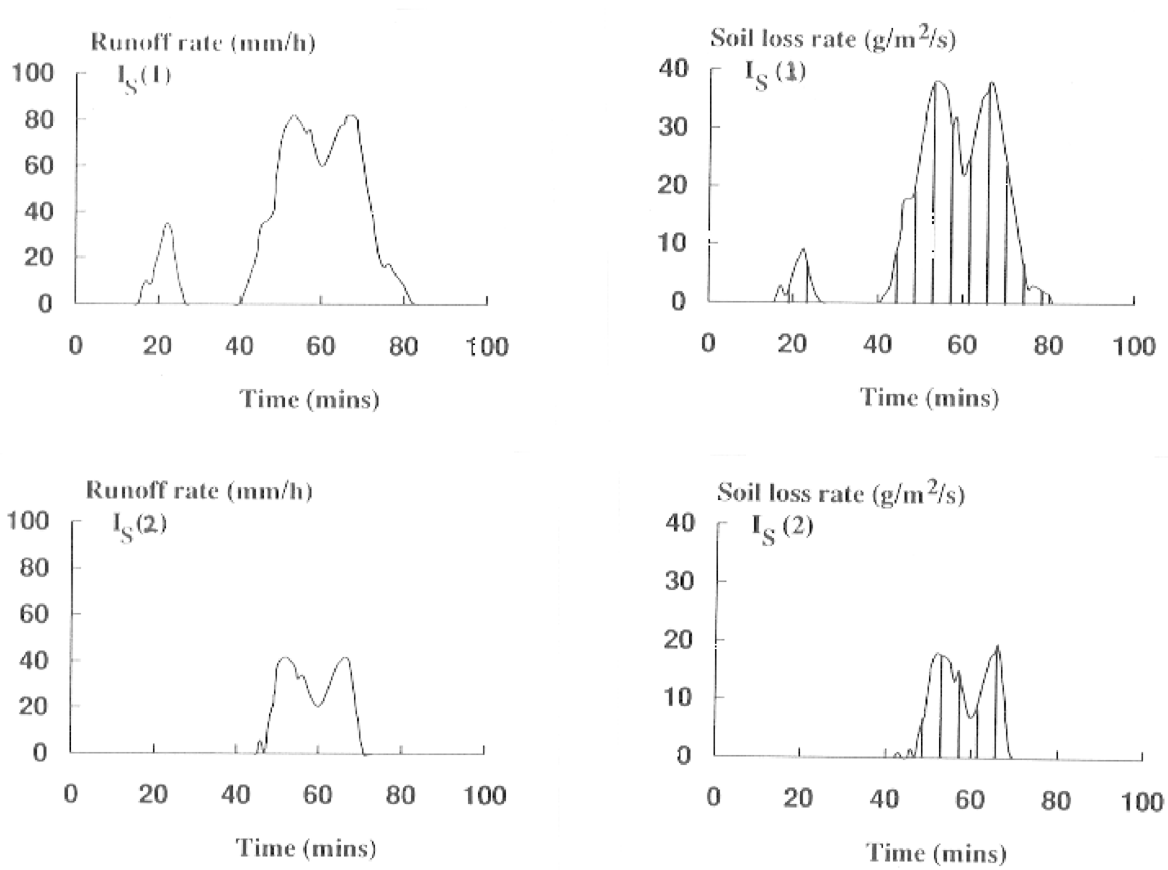

Figure 10. Possible variations in runoff and soil erosion resulting from the rainfall and infiltration conditions given in Figure 9 (from Kinnell et al. 1995, 1450)

The $I_X E_A$ index is similar to the *Tc* index of Moore and Wilson (1992, 1994) in that it provides an opportunity to consider the effects of hydrology more directly within the USLE/RUSLE modeling environment than is currently possible (Kinnell et al. 1995). They are related to the extent that the $I_X E_A$ index can be used to help assign weights in (*9*) for landscapes dominated by Hortonian (infiltration-excess) overland flow. However, additional research is needed to evaluate the effects of using these alternative *R* and/or *LS* factors on *K* (which incorporates the effects of profile permeability) and the other RUSLE factors.

The validation of GIS-based models may require additional data at the grid scale because grid-scale measurements may not exist for some model outputs and they may not be adequately described by point measurements in others. Repetto and Wilson (1996) recently computed the sediment transport index for the Palouse study site of Busacca et al. (1993) and found that the index could not predict the spatial pattern of net erosion and net deposition (see Figure 1 for diagrams showing patterns inferred from Cs-137 measurements). This result might be attributed to: (1) the failure of the model (and therefore the importance of factors other than topography in controlling the spatial patterns of erosion and deposition) (Quine and Walling 1993); (2) the failure of the 30 m DEM that was used as source data to capture the variability in the topographic form of the study area (see Zhang and Montgomery (1994) and Quinn et al. (1995) for similar claims), and/or (3) the failure of the Cs-137 point measurements to accurately represent the spatial patterns of soil erosion and deposition occurring at this level of spatial aggregation.

Overall, the GIS-based modeling experiences of the past ten years reiterate the need to develop new methods for collecting and characterizing the spatial variability of key processes and properties in landscapes, and the importance of modeling error and uncertainty in spatial databases and their effects on model predictions. Geographic information systems and related technologies (GPS receivers, remote sensing platforms, geostatistical techniques, etc.) can help with the collection and interpretation of these data and by doing so expedite the development of new and improved spatial models of key land surface/subsurface processes in future years.

REFERENCES CITED

Addiscott, T.M. (1977) A simple computer model for leaching in structured soils. *Journal of Soil Science* 28: 544-563.

Beasley, D.B., and Huggins, L.F. (1982) *ANSWERS (Areal Nonpoint Source Watershed Environmental Response Simulation) User's Manual* . Chicago: U.S. Environmental Protection Agency Report No. 905/9-82-001.

Beasley, D.B., Huggins, L.F., and Monke, E.J. (1982) Modeling sediment yields for agricultural watersheds. *Journal of Soil and Water Conservation* 37(2): 113-117.

Beven, K.J. (1989) Changing ideas in hydrology - the case of physically-based models. *Journal of Hydrology* 105: 157-172.

Beven, K.J., and Kirkby, M.J. (1979) A physically-based, variable contributing area model of basin hydrology. *Hydrological Sciences Bulletin* 24: 43-69.

Beven, K.J., Kirkby, M.J., Schofield, N., and Tagg, A.F. (1984) Testing a physically-based flood forecasting model (TOPMODEL) for three U.K. catchments. *Journal of Hydrology* 69: 119- 143.

Binley, A., Egly, J, and Beven, K.J. (1989) A physically-based model of heterogeneous hillslopes, 1. Runoff production, 2. Effective hydraulic conductivities. *Water Resources Research* 25: 1219- 1233.

Bliss, N.B., and Reybold, W.U. (1989) Small-scale digital soil maps for interpreting natural resources. *Journal of Soil Water Conservation* 44(1): 30-34.

Brown, D.G., Bian, L., and Walsh, S.J. (1993) Response of a distributed watershed model to variations in input data aggregation levels. *Computers and Geosciences* 19(4): 499-509.

Busacca, A.J., Cook, C.A., and Mulla, D.J. (1993) Comparing landscape-scale estimation of soil erosion in the Palouse using Cs-137 and RUSLE. *Journal of Soil and Water Conservation* 48(4): 361- 367.

Costa-Cabral, M., and Burges, S.J. (1994) Digital elevation model networks (DEMON): A model of flow over hillslopes for computation of contributing and dispersal areas. *Water Resources Research* 30(6): 1681-1692.

Custer, S.G., Farnes, P.E., Wilson, J.P., and Snyder, R.D. (1996) A comparison of hand and spline-drawn precipitation maps for mountainous Montana. *Water Resources Bulletin* 32(2): in press.

Daly, C., Neilson, R.P., and Phillips, D.L. (1994) A statistical-topographic approach to modeling the distribution of precipitation in mountainous terrain. *Journal of Applied Meteorology* 33(1): 140-158.

De Roo, A.P.J., Hazelhoff, L., and Burrough, P.A. (1989) Soil erosion modelling using ANSWERS and geographical information systems. *Earth Surface Processes and Landforms* 14: 517-532.

Dietrich, W.E., Wilson, C.J., Montgomery, D.R., and McKean, J. (1993) Analysis of erosion thresholds, channel networks, and landscape morphology using a digital terrain model. *Journal of Geology* 101(2): 259-278.

Engel, B.A., Srinivasan, R., and Rewerts, C. (1993) A spatial decision support system for modeling and managing agricultural non-point source pollution. pp. 231-237 in Goodchild, M.F., Parks, B.O. and Steyaert, L.T., eds., *Environmental Modeling with GIS*. New York: Oxford University Press.

Fairfield, J., and Leymarie, P. (1991) Drainage networks from grid digital elevation models. *Water Resources Research* 27(5): 709-717.

Foster, G.R., and Wischmeier, W.H. (1974)Evaluating irregular slopes for soil loss prediction. *Transactions of the American Society of Agricultural Engineers* 17(2): 305-309.

Foster, G.R., Lane, L.J., Nowlin, J.D., Laflen, J.M., and Young, R.A. (1981) Estimating erosion and sediment yield on field-sized areas. *Transactions of the American Society of Agricultural Engineers* 24(5): 1253-1262.

Foussereau, X., Hornsby, A.G., and Brown, R.B. (1993) Accounting for variability within map units when linking a pesticide fate model to soil survey. *Geoderma* 60:257-276.

Fraser, R.H., Warren, M.V., and Barten, P.K. (1995) Comparative evaluation of land cover data sources for erosion prediction. *Water Resources Bulletin* 31(6): 991-1000.

Freeman, G.T. (1991) Calculating catchment area with divergent flow based on a regular grid. *Computers and Geosciences* 17(3): 413-422.

Frere, M.H., Ross, J.D., and Lane, L.J. (1980) The nutrient submodel. pp. 65-87 in Knisel, W.G., ed., *CREAMS: A Field Scale Model for Chemicals, Runoff, and Erosion from Agricultural Management Systems* . Washington, D.C.: U.S. Department of Agriculture, Agricultural Research Service Conservation Research Report No. 26.

Gallant, J.C., and Wilson, J.P. (1996) TAPES-G: A grid-based terrain analysis program for the environmental sciences. *Computers and Geosciences* 22(4): in press.

Garbrecht, J., and Martz, L. (1994) Grid size dependency of parameters extracted from digital elevation models. *Computers and Geosciences* 20(1): 85-87.

Glanz, J. (1994) New soil erosion model erodes farmers' patience. *Science* 264: 1661-1662.

Goodchild, M.F., Parks, B.O., and Steyaert, L.T., eds. (1993) *Environmental Modeling with GIS* . New York: Oxford University Press.

Goodchild, M.F., Steyaert, L.T., Parks, B.O., Crane, M.P., Johnston, C.A., Maidment, D.R., and Glendinning, S., eds. (1996) *GIS and Environmental Modeling: Progress and Research Issues*. Fort Collins: GIS World, Inc.

Goodrich, D.C., and Woolhiser, D.A. (1991) Catchment hydrology. *Reviews of Geophysics, Supplement: U.S. National Report to the International Union of Geodesy and Geophysics* , 1987-1990, pp. 202-209.

Grayson, R.B., Moore, I.D., and McMahon, T.A. (1992) Physically-based hydrologic modeling: II. Is the concept realistic? *Water Resources Research* 26(10): 2659-2666.

Griffin, M.L., Beasley, D.B., Fletcher, J.J., and Foster, G.R. (1988) Estimating soil loss on topographically nonuniform field and farm units. *Journal of Soil and Water Conservation* 43, 326-331.

Hairsine, P.B., and Rose, C.W. (1991) Rainfall detachment and deposition: Sediment transport in the absence of flow-driven processes. *Soil Science Society of America Journal* 55(2): 320-324.

Hairsine, P.B., and Rose, C.W. (1992a) Modelling water erosion due to overland flow using physical principles: I. Sheet flow. *Water Resources Research* 28(1): 237-243.

Hairsine, P.B., and Rose, C.W. (1992b)Modelling water erosion due to overland flow using physical principles: II. Rill flow. *Water Resources Research* 28(1): 245-250.

Hession, W.C., and Shanholtz, V.O. (1988) A geographic information system for targeting nonpoint- source agricultural pollution. *Journal of Soil and Water Conservation* 43(3): 264-266.

Holmgren, P. (1994) Multiple flow direction algorithms for runoff modelling in grid-based elevation models: An empirical evaluation. *Hydrologic Processes* 8: 327-334.

Hornberger, G.M., Beven, K.J., Cosby, B.J., and Sappington, D.E. (1985) Shenandoah watershed study: Calibration of a topography-based, variable contributing area hydrological model to a small forested catchment. *Water Resources Research* 21: 1841-1850.

Hutchinson, M.F. (1989) A new procedure for gridding elevation and stream line data with automatic removal of spurious pits. *Journal of Hydrology* 106: 211-232.

Hutchinson, M.F. (1995) Interpolating mean rainfall using thin plate smoothing splines. *International Journal of Geographical Information Systems* 9(4): 385-403.

Hutson, J.L. (1993) Applying one-dimensional deterministic chemical fate models on a regional scale. *Geoderma* 60: 201-212.

Hutson, J.L., and Wagenet, R.J. (1993) A pragmatic field-scale approach for modeling pesticides. *Journal of Environmental Quality* 22: 494-499.

Inskeep, W.P., Wraith, J.M., Wilson, J.P., Snyder, R.D., and Macur, R.E. (1996) Input parameter and model resolution effects on solute transport predictions. *Journal of Environmental Quality* 25(3): in press.

Iorgulescu, I., and Jordan, J.-P. (1994) Validation of TOPMODEL on a small Swiss catchment. *Journal of Hydrology* 159: 255-273.

James, D.E., and Hewitt, M.J. (1992) To save a river: Building a resource decision support system for the Blackfoot River drainage. *GeoInfo Systems* 2(10): 36-49.

Joao, E.M., and Walsh, S.J. (1992) GIS implications for hydrologic modeling: Simulation of nonpoint pollution generated as a consequence of watershed development scenarios. *Computers, Environment, and Urban Systems* 16(1): 43-63.

Kinnell, P.I.A. (1983) The effect of kinetic energy of excess rainfall on soil loss from non-vegetated plots. *Australian Journal of Soil Research* 21(4): 445-453.

Kinnell, P.I.A., McGregor, K.C., and Rosewell, C.J. (1995) The IxEa index as an alternative to the EI30 erosivity index. *Transactions of the American Society of Agricultural Engineers* 37(5): 1449-1156.

Laflen, J.M., Elliot, W.J., Simanton, J.R., Holzhey, C.S., and Kohl, K.D. (1991a) WEPP: Soil erodibility experiments for rangeland and cropland soils. *Journal of Soil and Water Conservation* 46(1): 39-44.

Laflen, J.M., Lane, L.J., and Foster, G.R. (1991b) WEPP: A new generation of erosion prediction technology. *Journal of Soil and Water Conservation* 46(1): 34-38.

Lane, L.J. (1982) Development of a procedure to estimate runoff and sediment transport in ephemeral streams. pp. 275-282 in Walling, D.E., ed., *Recent Developments in the Explanation and Prediction of Erosion and Sediment Yield* . Wallingford: International Association of Hydrological Sciences Publication No. 137.

Moore, I.D. (1996) Hydrologic modeling and GIS. pp.143-148 in Goodchild, M.F., Steyaert, L.T., Parks, B.O., Crane, M.P., Johnston, C.A., Maidment, D.R., and Glendinning, S., eds., *GIS and Environmental Modeling: Progress and Research Issues*. Fort Collins: GIS World, Inc.

Moore, I.D., and Burch, G.J. (1986a) Physical basis of the length-slope factor in the Universal Soil Loss Equation. *Soil Science Society of America Journal* 50(5): 1294-1298.

Moore, I.D., and Burch, G.J. (1986b) Modelling erosion and deposition: Topographic effects. *Transactions of the American Society of Agricultural Engineers* 29(6): 1624-1630, 1640.

Moore, I.D., and Gallant, J.C. (1991) Overview of hydrologic and water quality modeling. pp. 1-8 in Moore, I.D., ed., *Modeling the Fate of Chemicals in the Environment* . Canberra: Centre for Resource and Environmental Studies, Australian National University.

Moore, I.D., and Wilson, J.P. (1992) Length-slope factors for the Revised Universal Soil Loss Equation: Simplified method of estimation. *Journal of Soil and Water Conservation* 47(5): 423-428.

Moore, I.D., and Wilson, J.P. (1994) Reply to "Comment on Length-slope factors for the Revised Universal Loss Equation: Simplified method of estimation" by George R. Foster. *Journal of Soil and Water Conservation* 49(2): 174-180.

Moore, I.D., Lewis, A., and Gallant, J.C. (1993a) Terrain attributes: Estimation methods and scale effects. pp. 189-

214 in Jakeman, A.J., Beck, M.B., and McAleer, M., eds, *Modelling Change in Environmental Systems*. New York: John Wiley and Sons.

Moore, I.D., Turner, A.K., Wilson, J.P., Jenson, S.K., and Band, L.E. (1993b) GIS and land surface-subsurface modeling. pp. 196-230 in Goodchild, M.F., Parks, B.O. and Steyaert, L.T., eds, *Environmental Modeling with GIS*. New York: Oxford University Press.

Morris, D.M., and Heerdegen, R.G. (1988) Automatically derived catchment boundaries and channel networks and their hydrological applications. *Geomorphology* 1(2): 131-141.

Nicholls, P.H., Walker, A., and Baker, R.J. (1982) Measurement and simulation of the movement and degradation of atrazine and metribuzin in a fallow soil. *Pesticide Science* 13: 484-494.

Nielsen, G.A., Caprio, J.M., McDaniel, P.A., Snyder, R.D., and Montagne, C. (1990) MAPS: A GIS for land resource management in Montana. *Journal of Soil and Water Conservation* 45(4): 450-453.

Nofziger, D.L., and Hornsby, A.G. (1986) A microcomputer-based management tool for chemical movement in soil. *Applied Agricultural Research* 1(1): 50-56.

Nofziger, D.L., and Hornsby, A.G. (1987) *Chemical Movement through Layered Soils Model Users Manual* . Gainesville: Florida Cooperative Extension Service, Institute of Food and Agricultural Sciences, University of Florida

Obled, Ch., Wendling, J., and Beven, K.J. (1994) The sensitivity of hydrological models to spatial rainfall patterns: An evaluation using observed data. *Journal of Hydrology* 159: 305-333.

O'Callaghan, J.F., and Mark, D.M. (1984) The extraction of drainage networks from digital elevation data. *Computer Vision, Graphics and Image Processing* 28: 323-344.

Panuska, J.C., Moore, I.D., and Kramer, L.A. (1991) Terrain analysis: Integration into the agricultural nonpoint source (AGNPS) pollution model. *Journal of Soil and Water Conservation* 46(1): 59- 64.

Pennell, K.D., Hornsby, A.G., Jessop, R.E., and Rao, P.S.C. (1990) Evaluation of five simulation models for predicting aldicarb and bromide behavior under field conditions. *Water Resources Research* 26: 2679-2693.

Petach, M.C., Wagenet, R.J., and DeGloria, S.D. (1991) Regional water flow and pesticide leaching using simulations with spatially distributed data. *Geoderma* 48: 245-269.

Prosser, I.P., and Dietrich, W.E. (1995) Field experiments on erosion by overland flow and their implication for a digital terrain model of channel initiation. *Water Resources Research* 31(11): 2867-2876.

Quine, T.A., and Walling, D.E. (1993) Use of caesium-137 measurements to investigate relationships between erosion rates and topography. pp. 31-48 in Thomas, D.S.G., and Allison, R.J., eds., *Landscape Sensitivity*. London: John Wiley and Sons.

Quinn, P.F., and Beven, K.J. (1993) Spatial and temporal predictions of soil moisture dynamics, runoff, variable source areas and evapotranspiration for Plynlimon, Mid-Wales. *Hydrological Processes* 7: 425-448.

Quinn, P.F., Beven, K.J., Chevallier, P., and Planchon, O. (1991) The prediction of hillslope paths for distributed hydrological modelling using digital terrain models. *Hydrological Processes* 5(1): 59-79.

Quinn, P.F., Beven, K.J., and Lamb, R. (1995) The ln(a/tanß) index: How to calculate it and how to use it within the TOPMODEL framework. *Hydrological Processes* 9: 161-182.

Rawls, W.J., and Brakensiek, D.L. (1982) Estimating soil water retention from soil properties. *Journal of the Irrigation Division, American Society for Civil Engineers* 108: 166-171.

Renard, K.G., Foster, G.R., Weesies, G.A., and Porter, J.P. (1991) RUSLE: Revised Universal Soil Loss Equation. *Journal of Soil and Water Conservation* 46(1): 30-33.

Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., and Yoder, D.C. (1993) Predicting Soil *Erosion by Water: A Guide to Conservation Planning with the Revised Universal Soil Loss Equation* . Washington, D.C.: U.S. Department of Agriculture, Agriculture Handbook No. 703.

Repetto, S., and Wilson, J.P. (1996) Identification of areas experiencing net erosion and deposition. In Wilson, J.P., and Gallant, J.C., eds, *Terrain Analysis Methods for the Environmental Sciences*. Cambridge: GeoInformation International (forthcoming).

Reybold, W.U., and TeSelle, G.W. (1989) Soil geographic data bases. *Journal of Soil and Water Conservation* 44(1): 28-29.

Richardson, C.W., and Wright, D.A. (1984)*WGEN: A model for generating daily weather variables* . Washington, D.C.: United States Department of Agriculture Report No. ARS-8.

Ritchie, J.C., and McHenry, J.R. (1990) Application of radioactive fallout Cesium-137 for measuring soil erosion and sediment accumulation rates and patterns: A review. *Journal of Environmental Quality* 19: 215-233.

Robson, A.J., Beven, K.J., and Neal, C. (1992) Towards identifying sources of subsurface flow: A comparison of components identified by a physically based runoff model and those determined by mixing techniques. *Hydrological Processes* 6: 199-214.

Robson, A.J., Whitehead, P.G., and Johnson, R.C. (1993)An application of a physically based semi-distributed model to the Balquhidder catchments. *Journal of Hydrology* 145: 357-370.

Romanowicz, R., Beven, K.J., and Moore, R. (1993) TOPMODEL as an application module within WIS. pp. 211-223 in Kovar, K. and Nachpaecel, H.P., eds., *Applications of Geographic Information Systems in Hydrology and Water Resources*. Wallingford: International Association of Hydrological Sciences Publication No. 211.

Running,S.W. and P.E. Thornton (1996) Generating daily surfaces of temperature and precipitation over mountainous terrain. pp. 93-98 in Goodchild, M.F., Steyart,L.T., Parks,B.O., Crane,M.P., Johnston,C.A., Maidment,D.R., and Glendinning,S. eds., *GIS and Environment Modeling: Progress and Research Issues*. Fort Collins: GIS World, Inc. (forthcoming).

Sivapalan, M., Beven, K.J., and Wood, E.F. (1987) On hydrologic similarity: 2, A scaled model of storm runoff production. *Water Resources Research* 23: 2266-2278.

Spangrud, D.J., Wilson, J.P., Nielsen, G.A., Jacobsen, J.S., and Tyler, D.A. (1995) Sensitivity of computed terrain attributes to the number and pattern of GPS-derived elevation data. pp. 285- 301 in Robert, P.C., Rust, R.H., and Larson, W.E., eds., *Site-Specific Management for Agricultural Systems*. Madison: American Society of Agronomy.

Stephens, P.R., MacMillan, J.H., Daigle, J.L., and Chilar, J. (1985) Estimating universal soil loss equation factor values with aerial photography. *Journal of Soil and Water Conservation* 40(1): 293-296.

Tomlin, C.D. (1980) *The Map Analysis Package*. New Haven: School of Forestry and Environmental Science, Yale University.

Ventura, S.J., Chrisman, N.R., Connors, K., Gurda, R.F., and Martin, R.W. (1988) A land information system for soil erosion control planning. *Journal of Soil and Water Conservation* 43(3): 230-233.

Wagenet, R.J., and Hutson, J.L. (1986) Predicting the fate of non-volatile pesticides in the unsaturated zone. *Journal of Environmental Quality* 15: 315-322.

Wagenet, R.J., and Hutson, J.L. (1989) *LEACHM: Leaching Estimation and Chemistry Model - A process based model of water and solute movement, transformations, plant uptake, and chemical reactions in the unsaturated zone*. Ithaca: Water Resources Institute, Cornell University.

Wagenet, R.J., and Hutson, J.L. (1996) Scale dependency of solute transport modeling/GIS applications. *Journal of Environmental Quality* 25(3): in press.

Wagenet, R.J., Hutson, J.L., and Biggar, J.W. (1989) Simulating the fate of a volatile pesticide in unsaturated soil:

A case study. *Journal of Environmental Quality* 18: 78-83.

Willgoose, G., Bras, R.L., and Rodriguez-Iturbe, I. (1991) A coupled channel network growth and hillslope evolution model: 1. Theory. *Water Resources Research* 27(7): 1671-1684.

Wilson, J.P. (1986) Estimating the topographic factor in the universal soil loss equation for watersheds. *Journal of Soil and Water Conservation* 41(3): 179-184.

Wilson, J.P. (1989) Soil erosion from agricultural land in the Lake Simcoe-Couchiching Basin, 1800-1981. *Canadian Journal of Soil Science* 69(2): 206-222.

Wilson, J.P. (1996) Spatial models of land use systems and soil erosion: The role of GIS. In Wegener, M., and Fotheringham, A.S. eds., *GIS and Spatial Models: New Potential for New Models?* London: Taylor and Francis (forthcoming).

Wilson, J.P., and Gallant, J.C. (1996) EROS: A grid-based program for estimating spatially-distributed erosion indices. *Computers and Geosciences* 22(4): in press.

Wilson, J.P., Inskeep, W.P., Rubright, P.R., Cooksey, D., Jacobsen, J.S., and Snyder, R.D. (1993) Coupling geographic information systems and models for weed control and groundwater protection. *Weed Technology* 7(1): 255-264.

Wilson, J.P., Inskeep, W.P., Wraith, J.M., and Snyder, R.D. (1996) GIS-based solute transport modeling applications: Scale effects of soil and climate databases. *Journal of Environmental Quality* 25(3): in press.

Wischmeier, W.H. (1976) Use and misuse of the universal soil loss equation. *Journal of the Soil and Water Conservation* 31(1): 5-9.

Wischmeier, W.H., and Smith, D.D. (1978) *Predicting Rainfall Erosion Losses: A Guide to Conservation Planning* . Washington, D.C.: U.S. Department of Agriculture, Agriculture Handbook No. 537.

Wolock, D.M. (1995) Effects of subbasin size on topographic characteristics and simulated flow paths in Sleepers River watershed, Vermont. *Water Resources Research* 31(8): 1989-1997.

Wolock, D.M., and McCabe, G.J. (1994) Comparison of single and multiple flow direction algorithms for computing topographic parameters in TOPMODEL. *Water Resources Research* 31(5): 1315- 1324.

Wolock, D.M., Hornberger, G.M., and Musgrove, T.M. (1990) Topographic effects on flow path length and surface water chemistry of the Llyn Brianne catchments in Wales. *Journal of Hydrology* 115:243-259.

Young, R.A., Onstad, C.A., Bosch, D.D., and Anderson, W.P. (1987) AGNPS, *Agricultural Nonpoint Source Pollution Model: A large watershed analysis tool*. Washington, D.C.: U.S. Department of Agriculture, Agricultural Research Service Conservation Research Report No. 35.

Young, R.A., Onstad, C.A., Bosch, D.D., and Anderson, W.P. (1989) AGNPS: A nonpoint source pollution model for evaluating agricultural watersheds. *Journal of the Soil and Water* Conservation 44(2): 168-173.

Young, R.A., Otterby, M.A., and Roos, A. (1982) A technique for evaluating feedlot pollution potential. *Journal of the Soil and Water Conservation* 37(1): 21-23.

Zhang, W. and D.R. Montgomery (1994) Digital elevation model grid size, landscape representation, and hydrologic simulations. *Water Resources Research* 30(4): 1019-1028.

Return to beginning of document

Wilson,J.P., GIS-based Land Surface/Subsurface Modeling: New Potential for New Models?

John P. Wilson
Geographic Information and Analysis Center
Department of Earth Sciences

Montana State University
Bozeman Montana MT 59717-0348