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# RUSLE Model Description and Database Sensitivity

K. G. Renard* and V. A. Ferreira

## ABSTRACT

Water quality modeling generally requires estimates of the amount of eroded material entering water courses. This information is necessary because sediment often transports adsorbed chemicals. Numerous models have been developed to assist with assessment of this problem. These models often contain some modification of the Universal Soil Loss Equation (USLE). A recently initiated effort to improve USLE technology has produced a computer-based model, RUSLE (Revised USLE), which employs new relationships to estimate values of the six factors in the equation. Three input databases are required: climatic data, crop data, and field operations data. Although numerous specific entries for these data are contained in the program, in many cases users must supplement or modify the supplied data. Results of a sensitivity analysis help users tailoring the databases to specific conditions.

Advances in natural resource modeling have been dramatic in the past several decades. Many of these have coincided with the rapid developments in computer technology and specifically, the development of personal computers. These developments have allowed increasingly complex quantitative descriptions of soil hydrology or "models." The model label has been used as a title, accusation, or compliment, and carries certain connotations depending on the bestower of the title (Wagenet, 1988). Some have looked askance at modelers, and have questioned both the motive of the modeling effort as well as the ability of the modeler to deal with the complexity of natural systems. Yet without the developments in analytical models we only have limited ability to address more complex questions being posed by society in dealing with conservation and environmental management problems.

Water quality of runoff from upland sources can change greatly from season to season and may even fluctuate during a given day. Such changes reflect natural stream discharge cycles, meteorologic conditions, and fluctuations due to agricultural practice changes. Such changes also may influence biological activity. In addition to natural changes, water quality changes may reflect flow abstractions for water supply as well as agricultural, urban, and industrial waste inputs. The many cause–effect relationships are difficult to emulate without analytic models. Recently, considerable progress in hydrologic modeling was reported in a symposium arranged and edited by DeCoursey (1988).

Heretofore, water management has been primarily a question of water quantity. Interest in water quality arose with increased water degradation and the decrease in water supplies of acceptable quality. To properly address water quality, it is necessary to understand the parameters directly connected to the uses of concern and to analyze the associated conditions.

Interaction between water quantity and quality is inevitable for any water management effort. Furthermore, it may be easier for technical, financial, and political reasons to maintain an acceptable water quality than to restore it following degradation. Thus, water quality should be of concern to everyone dealing with water resources.

Upland surface water quality problems have historically emphasized on-farm erosion control and downstream sediment damage. In the last two decades, this emphasis has changed to include emphasis on the fate of agricultural chemicals. Because many agricultural chemicals move through the system adsorbed on sediment, this paper focuses on the erosion modeling process. Conservation planning activities of many natural resource agencies (e.g., SCS, BLM, FS, and many state agencies) have relied on the USLE (Wischmeier and Smith, 1978). The USLE, as a stand-alone model or combined in a subroutine in models such as SWRRB (Williams, 1975), EPIC (Williams et al., 1983), ANSWERS (Beasley et al., 1980), and AGNPS (Young et al., 1989), is widely used to evaluate the impact of alternative management practices on soil erosion. Recent improvements in the USLE technology have created new opportunities in model development and erosion prediction, leading to the development of the RUSLE.

This paper (i) describes the RUSLE model, and (ii) reports on sensitivity analyses with the databases in the model.

## RUSLE

Wischmeier (1976) explained that the USLE contains parameters which are recognized as universally affecting erosion. Given the data available with which to identify the model terms, the technology can be successfully used to address conservation planning in most environments. Recent efforts by USDA and university cooperators has led to the RUSLE (Renard et al., 1991), which builds on the USLE technology to produce a new model. The RUSLE retains the same six factors of the USLE, but the equations used to produce the factors differ significantly. Furthermore, because of the complexity of the equations used to quantify the factors, RUSLE has been computerized to facilitate the calculations.

In both the USLE and RUSLE the fundamental equation is

$$A = RKLSCP \qquad [1]$$

where $A$ is the computed annual soil loss; $R$ is the rainfall–runoff erosivity factor; $K$ is a soil erodibility factor; $LS$ is a topographic factor combining slope length, $L$, and slope steepness, $S$; $C$ is a cover-management factor; and $P$ is a supporting practices factor.

### *R* Factor

Of the RUSLE factors, $R$ is the one most exactly computed from available data, namely, from rainfall amount and intensity. The factor represents the driving force of sheet and rill erosion. Differences in $R$ correspond to variations in the climate's erosivity.

One of the major improvements in RUSLE was a greatly

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**Abbreviations:** USLE, Universal Soil Loss Equation; RUSLE, Revised Universal Soil Loss Equation; SLR, soil loss ratio; WEPP, water erosion prediction project.

improved isoerodent map of the western USA (USDA RUSLE Handbook, 1993, unpublished data). Data from more than 1000 locations were used to produce the new map. Another change involves $R$-factor values for areas with flat slopes in regions of long, intense rainstorms. The RUSLE accounts for ponded water on the soil, reducing the erosivity of raindrop impact. Finally, an equivalent $R$ approach was developed for use in the small-grain farming areas of the Pacific Northwest to reflect the combined effect of thawing soil and rain on either snow or partly frozen soil.

### *K* Factor

The $K$ factor is an indicator of the inherent soil erodibility under the standard conditions of the USLE unit plot maintained in continuous fallow. Users have little difficulty choosing a $K$-factor value because the USDA, Soil Conservation Service[1] has identified values for major mapping units. The site-specific $K$ value may be different from the $K$ value given in soil survey information because of soil variability within a mapping unit.

The USLE erodibility nomograph is the most commonly used procedure for estimating $K$ values, but it does not apply for some soils. Erodibility data from around the world were used to develop a RUSLE equation to estimate $K$ as a function of an average soil particle diameter. The $K$ values for the volcanic soils of Hawaii are estimated with a special algorithm (El-Swaify and Dangler, 1976).

Of greatest significance is that RUSLE varies $K$ seasonally. Seasonal variability is highest in the spring with soil fluffing from freeze–thaw actions and lowest in midfall and winter because of rainfall compaction and/or frozen soil. Instantaneous $K$ estimates are made from equations relating $K$ to the frost-free period and the annual $R$ factor. Weighting the instantaneous $K$ estimate in proportion to the EI (kinetic energy times maximum 30-min rainfall intensity) for semimonthly periods provides a weighted average annual $K$ value. The RUSLE also accounts for rock fragments in and on the soil surface. Rock fragments on the surface are treated as surface cover in the $C$ factor, while rock in the soil profile of coarse-textured soils is assumed to reduce permeability and, in turn, increase runoff. This latter effect is reflected in the $K$ value.

### *L* and *S* Factors

Most RUSLE users have more questions about the $L$ factor than any other factor. This is because of the judgment involved in choosing a slope length. Attention given to the $L$ factor is not generally warranted because soil loss estimates are less sensitive to slope length than to most other factors. The RUSLE uses four separate slope length relationships. Three are functions of slope steepness as in the USLE, and of the susceptibility of the soil to rill erosion relative to interrill erosion. A separate slope length relationship was developed specifically for the dryfarmed cropland region of the Pacific Northwestern USA.

Soil loss is much more sensitive to slope steepness than to changes in slope length. The RUSLE has a more nearly linear slope steepness equation than the USLE. On steep slopes, RUSLE-computed soil loss is about one-half that predicted by USLE. The RUSLE also provides a slope steepness relation for short slopes subject primarily to interrill erosion, and a steepness relationship for the Palouse region of the Pacific Northwest.

In most applications, a slope estimated as a single plane with the USLE can be a poor representation of the field topography. Complex slopes can be readily represented by a series of segments in RUSLE to provide a better estimate of the topographic effect.

### *C* Factor

The $C$ factor is very important in soil loss estimation because it represents conditions that can be modified by management to reduce erosion. The $C$ values are weighted averages of soil loss ratios (SLR's) that represent the ratio of soil loss for a given condition at a given time to the corresponding soil loss under conditions of a unit plot. Thus, the SLR's vary during the year as management and cover conditions change. To compute $C$, SLR's are weighted according to the erosivity distribution for semimonthly periods during a year. In RUSLE, a subfactor method is used to compute SLR's as a function of five subfactors given by the equation

$$C = PLU\ CC\ SC\ SR\ SM \quad [2]$$

where $PLU$ is the prior land use subfactor, $CC$ is the canopy subfactor, $SC$ is the surface cover subfactor, $SR$ is the surface roughness subfactor, and $SM$ is the soil moisture subfactor (used in the Pacific Northwest Palouse area).

Subfactor values $PLU$ and $SR$ represent the within-soil effect and are calculated from the amount of biomass that accumulates in the soil from roots and incorporation of crop residue. The RUSLE computes biomass decomposition on and in the soil using a residue decomposition model. Surface ground cover effects on erosion have been observed to vary greatly in research studies. The $SC$ factor is computed with a negative exponential coefficient times the percentage of ground cover. The coefficient is increased as the tendency for rill erosion to dominate over interrill erosion increases. Guidelines are presented in the computer program to select the appropriate coefficient value. Crop canopy ($CC$) accounts for the role of plants in intercepting the energy of raindrops and allowing their reformation and drip from the crop canopy. The soil moisture subfactor (SM) used in the small grain farming areas of the Pacific Northwest represents the role of soil moisture withdrawal and replenishment in affecting rainfall excess and erosion hazard. Erosion potential rises with increased soil water content.

The subfactor approach in RUSLE permits application and development of SLR's where values are not available from previously published experimental analyses. The SLR's can be determined from some fundamental crop and tillage measurements. Data are needed to reflect canopy and residue characteristics, and root mass in the upper 4 in. (100 mm) of the soil profile. Tillage measurements are needed to indicate the percentage of soil disturbed, random roughness and the amount of residue incorporated. Thus, the user must specify the crops in a rotation and the dates of operations, such as tillage, planting, and harvest. The computer program then calculates SLR's, rotation, and average annual $C$ factor.

[1] Data published in *Soil Survey Reports* available through USDA-SCS field offices.

Grazing effects on rangeland, pasture, and meadow are reflected in the effects of canopy height, ground cover, and root biomass. In RUSLE, ground cover is given as 1.0 minus the amount of bare soil, reflecting the addition of rock and stone cover in addition to vegetative litter.

### *P* Factor

The *P* factor values are the least reliable of the RUSLE factor values because of the absence of experimental data to reflect the many combinations of conditions encountered. The *P* factor primarily represents how surface conditions affect flow paths and flow hydraulics.

In RUSLE development, data have been analyzed to evaluate the effect of contouring. The results have been interpreted to give contouring factor values as a function of ridge height, furrow grade, and erosivity. New *P*-factor values have been developed to account for the effect of terraces in causing deposition within the terrace channel. Buffer strips and a broader array of strip-cropping conditions also have been developed which require the user to postulate infiltration changes between strips. Conservation practice values for rangelands also are presented which require estimation of the time to reconsolidation following disturbance as well as infiltration changes as a function of cover and roughness. Some of the practice values on crops and rangeland are slope dependent.

All of the *P*-factor improvements were developed using fundamental detachment and transport theory based on flow hydraulics and sediment transport such as developed in CREAMS (Knisel, 1980; Foster et al., 1981). Field experimental data were then used to select parameter values for fundamental hydraulic and transport relationships.

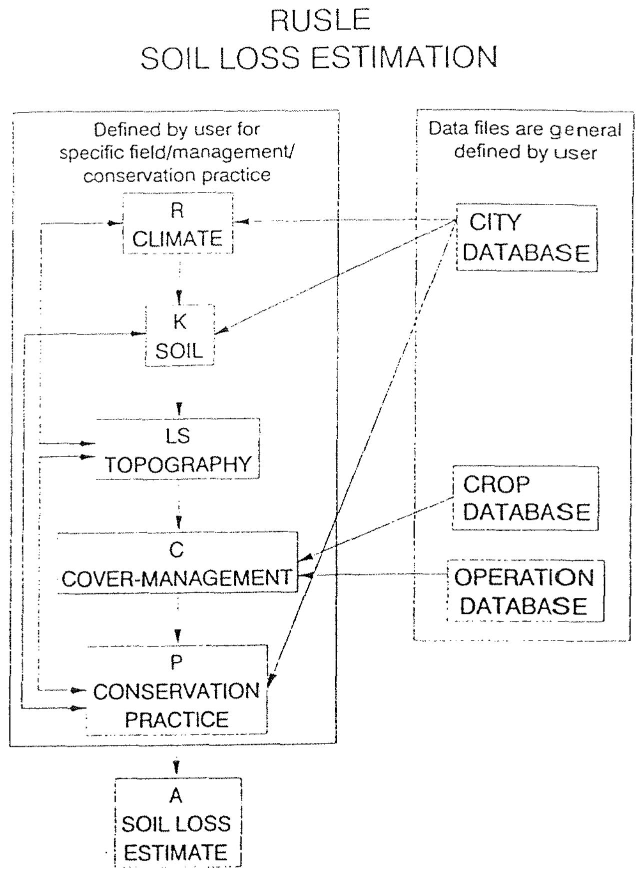


**Fig. 1. The RUSLE logic flow for a typical soil loss calculation.**

## The Revised Universal Soil Loss Equation Computer Program

Figure 1 illustrates the RUSLE logic flow for a typical soil loss calculation. The left-hand portion of the figure is where specific field-management/conservation-practice information is input by the user. The right-hand box contains the general program-supplied database sets called by the user representing the CITY DATABASE (climate data), CROP DATABASE (plant data representing above- and belowground characteristics) and OPERATIONS DATABASE (farming and soil disturbing factors).

Figures 2, 3 and 4 illustrate the data contained in the CITY, CROP, and OPERATIONS DATABASE sets, respectively. Because the information contained in these sets is general, the user may need additional sets or may need to modify an existing set to make it better describe a specific site where a soil loss estimate is required. Prior to either making these modifications or developing a new data set, the user of RUSLE technology needs to have an idea of how sensitive a specific soil loss estimate is to individual parameters. Thus a sensitivity analysis was performed to illustrate how changes in a specific parameter value affect the output.

## Sensitivity Analysis

### Background

Several approaches are available for performing sensitivity analysis. Lane and Ferreira (1980) defined sensitivity as the rate of change in an output variable as a result of the change of an input factor. Sensitivity analysis is useful in formulation, calibration, and verification of water resource models (McCuen and Snyder, 1986).

Meier et al. (1971) indicated that the sensitivity of a model's responses to variations in input data can be used to indicate the relative importance of various types of input information. Emphasis can then be placed on developing and refining those data which have the greatest influence on model output. In other words, given limited resources which will be used for data collection and data preparation, sensitivity analyses can be conducted to define how best to expend the effort.

A sensitivity analysis should be designed in accordance with the range of expected errors in gathering field data under different conditions. It is a systematic means of examining the response of a model independent of errors in parameter estimation or field data. This makes it possible to examine, in an objective manner, the rationality of the model as well as the effect of input errors on model output (McCuen, 1973).

Sensitivity analysis attempts to rank parameters based on their contribution to overall changes in model predictions. However, in most hydrologic applications, large variances in measurements are the rule and deterministic sensitivity analysis may be less useful. Much has been written about sensitivity analysis and the techniques used are generally grouped in two categories, deterministic approaches and stochastic approaches.

The primary assumption in the deterministic approach is that the response surface of the output variable of

```
    FILE        EXIT        HELP        SCREEN
---------------< Create/Edit City Database Set TEST 0.20 >---------------

 city code: 13001    city: CHICAGO                        state: IL
 total P: 33.3"      EI curve #: 101         Freeze-Free days/year: 192
 elevation: 607      10 yr EI: 100                         R factor: 140
 ---- Mean P ----------- Tav (deg. F) ------------ %EI -------- %EI ----
      1: 1.6             1: 26                     1: 0          13: 39
      2: 1.31            2: 27.65                  2: 0          14: 52
      3: 2.59            3: 36.25                  3: 0          15: 63
      4: 3.66            4: 48.95                  4: 1          16: 72
      5: 3.15            5: 60                     5: 2          17: 80
      6: 4.08            6: 70.5                   6: 3          18: 87
      7: 3.63            7: 75.6                   7: 4          19: 91
      8: 3.53            8: 74.15                  8: 6          20: 94
      9: 3.35            9: 66.1                   9: 9          21: 97
     10: 2.28           10: 55.05                 10: 14         22: 98
     11: 2.06           11: 39.85                 11: 20         23: 99
     12: 2.1            12: 29.1                  12: 28         24: 100

-----------------< F7 Saves, Esc Returns to CITY Main Menu >-------------
F10 Tab  Esc F1   F2  F7   Del
CMD FUNC esc help clr save del
```

Fig. 2. Sample of data contained in the CITY DATABASE.

interest is effectively linear within the small region of the parameter space explored by perturbations. The nominal values chosen for this analysis are usually those considered to give the best model predictions for a particular situation. A local sensitivity analysis is analogous to determining the partial derivative for each output variable with respect to each parameter. Performing a sensitivity analysis by increasing or decreasing each parameter by a fixed percentage of some nominal value assumes that each parameter is equally important.

The purpose of a stochastic sensitivity analysis is to assess the effect that a parameter has on an output variable over the range of parameter values that are likely to be exhibited. The range of parameter values is often based on a frequency distribution that is characteristic of each parameter. Stochastic sensitivity analysis attempt to partition the variance observed in an output variable among the parameters. Because of statistical and computational limitations, partitioning is often limited to producing an ordered list of parameters to which the outputs are sensitive.

Tiscareño-Lopez (1991) presented a synopsis of sensitivity analysis techniques. He used a Monte-Carlo method in his stochastic approach to illustrate changes in model predictions caused by changes in the Water Erosion Prediction Project (WEPP) Watershed model parameters for applications in semiarid rangeland watersheds.

## Methodology

Herein, parameters and variables of the three databases of RUSLE were systematically varied and the change in predicted soil loss (*A*) (% change in output resulting from a % change in input) analyzed. *Parameters* are defined here as single, fixed values. *Variables* are values

```
    FILE        EXIT        HELP        SCREEN
---------------< Create/Edit Crop Database Set TEST 0.17 >---------------
          crop: corn                        category: 1
res. @ harv. (lb/A): 7280    row spacing (in): 30   plant pop. (#/A): 25000
surf. res. decomp. cons.: 0.01200        sub. res. decomp. cons.: 0.01200
res. at 30% cover (#/A): 950    at 60% cover: 2400    at 90% cover: 6050
 days   root mass  canopy   fall    | days   root mass  canopy   fall
  of    #/Ac (in   cover    height  |  of    #/Ac (in   cover    height
growth   top 4")    (%)     (ft)    | growth  top 4")    (%)     (ft)
0       0          0        0       | 180    0          0        0
15      0          0        0       | 195    0          0        0
30      92         10       0.5     | 210    0          0        0
45      180        50       1       | 225    0          0        0
60      272        80       1.7     | 240    0          0        0
75      544        100      2.5     | 255    0          0        0
90      544        100      3       | 270    0          0        0
105     0          0        0       | 285    0          0        0
120     0          0        0       | 300    0          0        0
135     0          0        0       | 315    0          0        0
150     0          0        0       | 330    0          0        0
165     0          0        0       | 345    0          0        0
-----------------< F7 Saves, Esc Escapes to CROP Main Menu >-------------
F10 Tab  Esc F1   F2  F5   F7   Del
CMD FUNC esc help clr jump save del
```

Fig. 3. Sample of data contained in the CROP DATABASE.

```
    FILE        EXIT        HELP        SCREEN
 ------------< Create/Edit Field Operation Database Set TEST 0.17 >------------

         field operation: cult.; row
 Effect #1: 2   % disturb.:85    roughness:0.6   % cov. left:70    depth:4
 Effect #2: 1
 Effect #3: 1
 Effect #4: 1
 Effect #5: 1
                                     1. no effect
                                     2. soil surface disturbed
                                     3. current crop residue added to surface
                                     4. other residue added to surface
                                     5. residue removed from field
                                     6. current crop harvested
                                     7. crop growth begins
                                     8. current crop is killed
                                     9. call in a new crop growth set

 -------------------< F7 Saves, Esc Returns to OP Main Menu >------------------
 F10 Tab  Esc F1   F2  F5   F6   F7   Ins Del
 CMD FUNC esc help clr jump list save ins del
```

**Fig. 4. Sample of data contained in the OPERATIONS DATABASE.**

that change in space or time. Examples of RUSLE parameters are plant characteristics and freeze-free days per year. Variables include precipitation and temperature, which are contained in the city database as sets of monthly average values, and root mass and canopy cover, which are time varying and are described by semimonthly periods.

Unlike simpler models, RUSLE has the capability of responding in unexpected ways to input modifications. Changes in some parameters affect the value of others, thus either offsetting or magnifying the resulting change in predicted soil loss. It also is possible to change a single parameter which in turn changes entire groups of others. This study demonstrates several such model response characteristics. Knowledge of such behavior is useful to users, just as general sensitivity information is useful.

It is stressed that sensitivity analysis results are site- and condition-specific. This analysis gives users an understanding of model responses, but the results should be expected to vary at different sites and under other conditions. Users are encouraged to test their situations similarly, particularly with respect to program input with known uncertainties.

## Base Run

This study employed RUSLE Test Version 20 (we do not anticipate any major changes before the first official version is released). An initial RUSLE simulation was deemed the "base run." Base run database input is illustrated in Figs. 2, 3, and 4. Sensitivity analysis was then performed by changing parameter and variable values from their base values. Conditions chosen for the base run (Table 1) were corn under conventional tillage in the Chicago, IL, area. Base corn (*Zea mays* L.) parameters were from the CORN DATABASE set, as shown in Fig. 3. Table 2 describes the field operations (values from the OPERATIONS DATABASE) and the base-run operations schedule.

The program calculated the following RUSLE factor values: $R = 140$, $K = 0.297$, $LS = 0.716$, $C = 0.086$, and $P = 0.883$; the computed annual soil loss is $A = 2.26$ tons acre$^{-1}$ (5.07 t ha$^{-1}$).

## Model Response to CITY DATABASE Perturbations

The first parameter tested is the city code, a numerical identifier. Changing this code redefines the entire set of variables and parameters in the city database; i.e., we changed cities and all their attributes while holding the crop and operation attributes constant. Figure 5 illustrates the effect of using five different city codes, chosen for proximity to Chicago. It is apparent that this database contains information to which the model is very sensitive; Milwaukee and Indianapolis yielded results that represented changes of over 30% from the base Chicago run. Further tests on individual parameters and variables within the city database explain these differences.

Table 1. Base run data.†‡

| Location | Soil | Topographic data for 3 slopes 1 | 2 | 3 |
|---|---|---|---|---|
| Chicago, IL | A Tama soil, surface texture—silt, hydrologic soil group C, $K_{est}$ = 0.042 metric SI units (and 0.32 English units) from nomograph | | (slope) % | |
| | | 5 | 3.5 | 3 |
| | | | (Length) m | |
| | | 41.3 (125 ft) | 30.5 (100 ft) | 41.3 (125 ft) |

† Cover management, field operations are shown in Table 2.
‡ Conservation practice and contouring information: moderate ridges 7.6 to 10.2 cm (3 to 4 in.) height, furrow grade = 2%, and cover/roughness code 6, no cover and/or minimum roughness.

Table 2. Field operations schedule, base run.

| Date | Operation | Disturbance | Roughness | Cover left | Depth |
|---|---|---|---|---|---|
| | | % | cm (in.) | % | cm (in.) |
| 10 April | Fertilizer application | 20 | 1.27 (0.50) | 90 | 10 (4) |
| 15 April | Tandem risk | 100 | 1.91 (0.75) | 50 | 10 (4) |
| 28 April | Field cultivator | 100 | 1.77 (0.70) | 75 | 10 (4) |
| 28 April | Spike harrow | 100 | 0.76 (0.30) | 80 | 10 (4) |
| 28 April | Row planter | 20 | 1.52 (0.60) | 85 | 10 (4) |
| 25 October | Harvest | 0 | 0.76 (0.30) | 100 | 0 (0) |

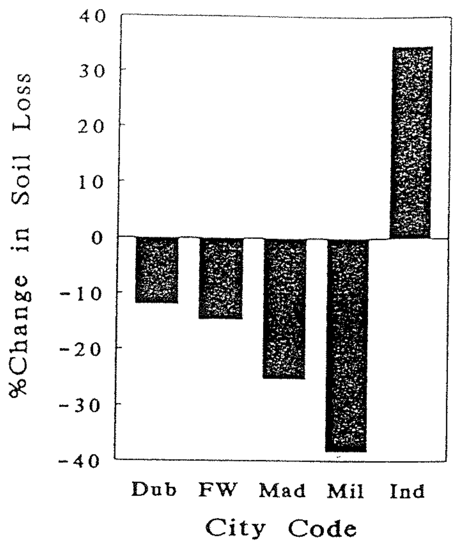


**Fig. 5. Result of changing the city code from 13 001 (Chicago, IL) to 15 002 (Dubuque, IA), 14 002 (Ft. Wayne, IN), 49 003 (Madison, WI), 49 004 (Milwaukee, WI), and 14 003 (Indianapolis, IN).**

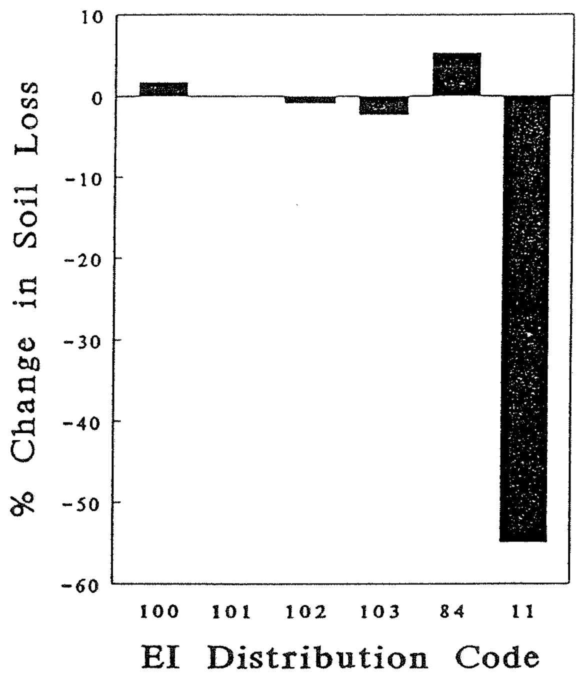


**Fig. 6. Effect of changing EI distribution code.**

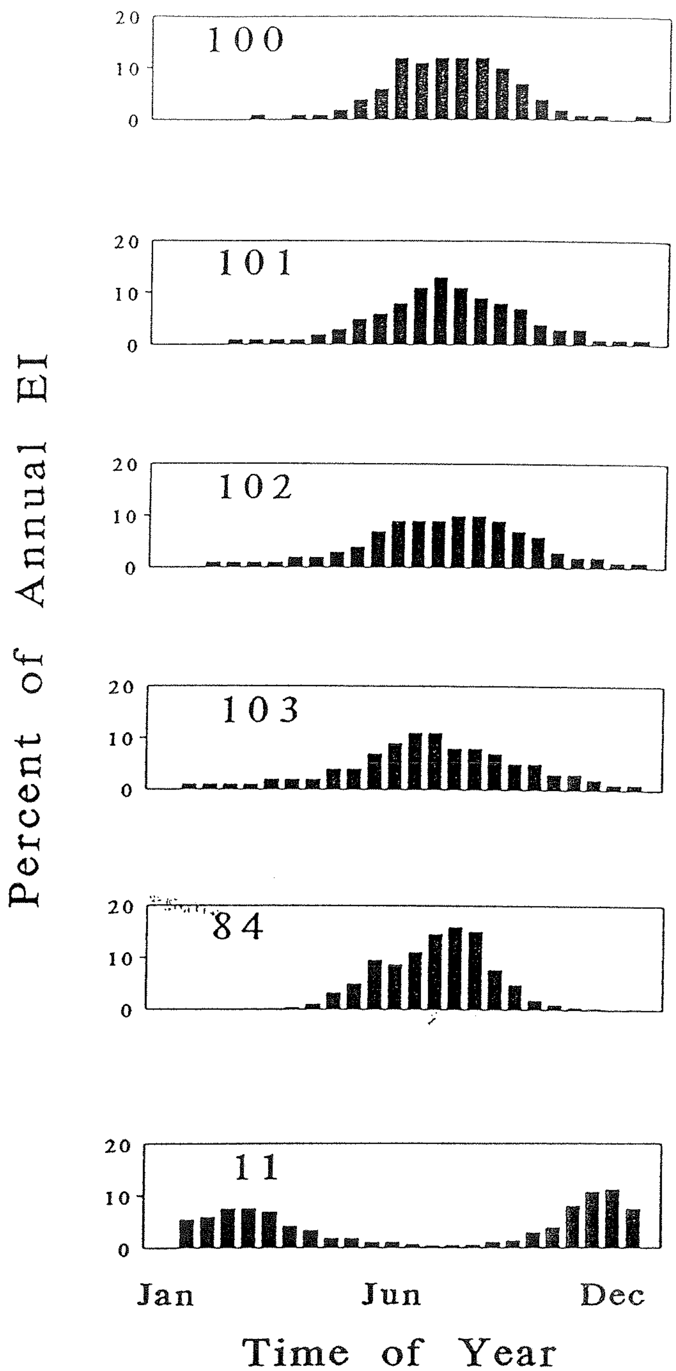


**Fig. 7. Annual time series of EI distributions.**

The EI (storm kinetic energy times 30-min maximum intensity summed over a year is defined as *R*) distribution code represents sets of 24 semimonthly values (% of the annual *R* factor). The code for Chicago, 101, was replaced by nearby codes 100, 102, and 103. Readers are referred to the RUSLE Handbook (pending) for a U.S. map of EI distribution codes. Results indicated very little change in predicted soil loss—less than 3% in Fig. 6 for the cited codes. The code for the Denver area, 84, was then substituted for contrast. There was still little change; again, the resulting soil loss was within about 5% of the base. A code from the West Coast, 11 (near San Francisco) was then tested. Results from the EI code exercise are illustrated in Fig. 6, clearly showing that any nearby EI codes yield fairly similar results. Yet the San Francisco distribution caused the model to predict about 50% less soil loss for the same base conditions. Figure 7 shows the six EI distributions, plotted as annual time series. Both the Midwest/Great Plains and West Coast distributions have distinct high and low periods, but these occur in different seasons. The West Coast rains occur during the winter, and are less intense than either the Great Plains or Midwest rains. Those storms producing the greater soil loss in the Midwest and Great Plains occur during the period of management disturbances such as plowing and cultivating, when the soil is most vulnerable to erosion. Thus, RUSLE is sensitive to EI distribution, but reasonably close estimates produce consistent results.

Two variables in the CITY DATABASE are precipitation and air temperature. These were each varied from base values for the Chicago database by as much as ±20% in 5% increments. All values of each variable were permuted at once, modifying the entire variable array instead of the 24 values independently. The temperature values are strikingly more important to the resulting soil loss estimates than precipitation (Fig. 8), and represent the effect of temperature on residue decomposition. Different results might be experienced in arid areas or in very humid areas. The RUSLE users are encouraged to make their own sensitivity evaluations for the crop and climate they are working with.

We then varied the CITY DATABASE parameter "freeze-free days" ±20%, in 5% increments. The freeze-free days are used in the calculation of the time varying soil erodibility. The program responded reasonably to negative variations, showing only a moderate sensitivity (−10% change in response to a 20% parameter reduction) (Fig. 9). The RUSLE showed no sensitivity above the base value of 192 freeze-free days because the time-varying soil erodibility term is assumed to have an upper limit.

Also shown in Fig. 9 is the RUSLE response to variation of the *R* factor. Given that this is one of the direct RUSLE factors, the result might be unexpected. Examination of Eq. [1] indicates that any change in *R* should yield an identical change in response, whereas the response is about half that expected. This is because *R* factor changes result in RUSLE modification of the *K* factor and the *C* factor in addition to direct effect on the soil loss estimation (Fig. 10).

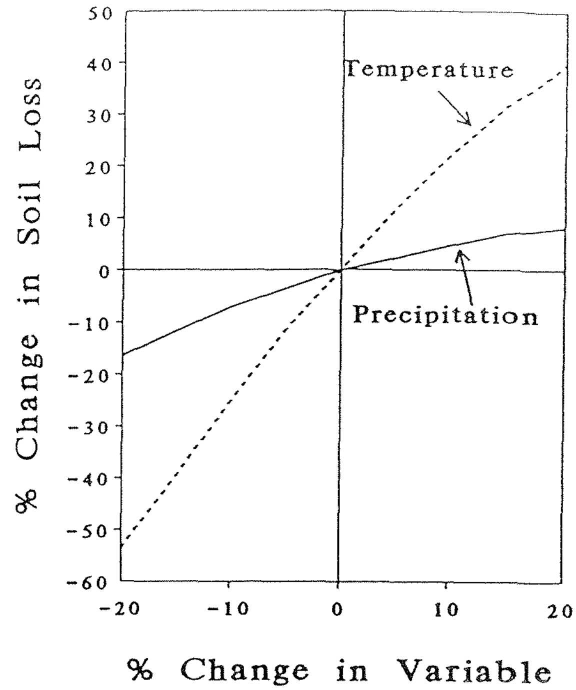


**Fig. 8. Effect of changes in precipitation and temperature in CITY DATABASE.**

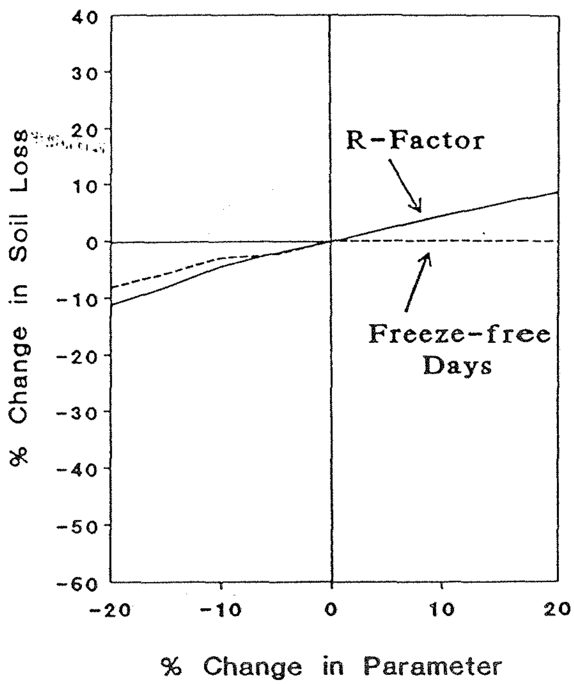


**Fig. 9. Effect of changes in *R* factor on freeze-free days parameters in CITY DATABASE.**

### Model Response to CROP DATABASE Perturbations

The base crop, corn, was modified to test model sensitivity to various CROP DATABASE parameters and variables. The first parameter tested was residue at harvest. As shown in Fig. 11, resulting soil losses varied inversely with changes in residue amount. The magnitude of change is nearly equal (20% reduction in this parameter results in near 20% reduction in computed soil loss).

Residue amounts at 30, 60, and 90% cover were varied as a set. Changing these amounts changes the amount of residue and in turn the SC and SR subfactors in the *C* factor. Figure 11 shows a direct relationship between changes in residue amounts and changes in soil loss (*A*), with a 20% variable change resulting in only 4% variations in soil loss. The residue decomposition rate caused directly proportional changes in soil loss of about half the change in parameter; i.e., a −20% change in rate resulted in about −10% change in soil loss (Fig. 11).

Also directly related to changes in soil loss are changes in fall height, the distance waterdrops fall from the vegetation, as shown in Fig. 12. Changes in fall height affect the CC. Though about half as sensitive as residue at harvest, fall height is over twice as sensitive as changes in residue amounts at 30, 60, and 90% cover.

Percentage canopy cover was shown to be an important variable with inverse effects. As illustrated in Fig. 12, soil loss changes from the base varied from 39% to −6% with −20% and 20% changes in this parameter, respectively. The interactions are complex and nonlinear. Root mass also caused inversely proportional changes in soil loss predictions, but of much smaller magnitude than percentage canopy cover. Figure 12 also shows the changes in soil loss resulting from changes in root mass. This parameter affects the canopy cover subfactor as does the previous term.

It should be noted that the canopy cover in this example is relatively sensitive, possibly because there was little surface cover with this conventional tillage scena-

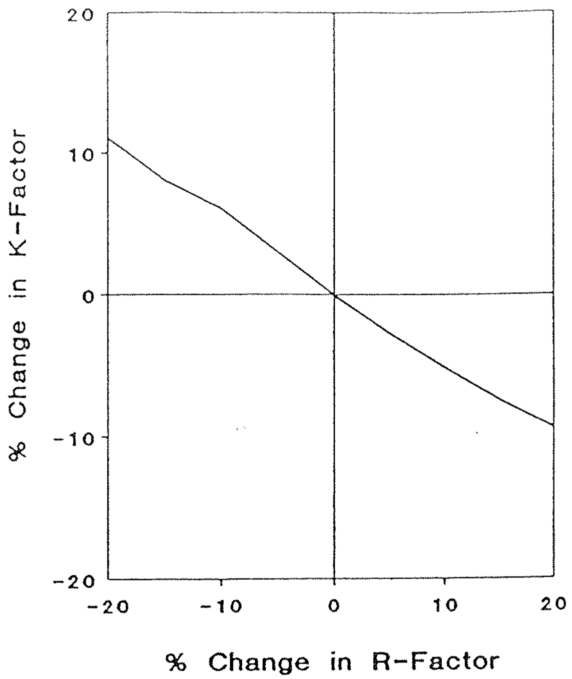


Fig. 10. Inverse effect of $R$ factor changes on $K$ factor.

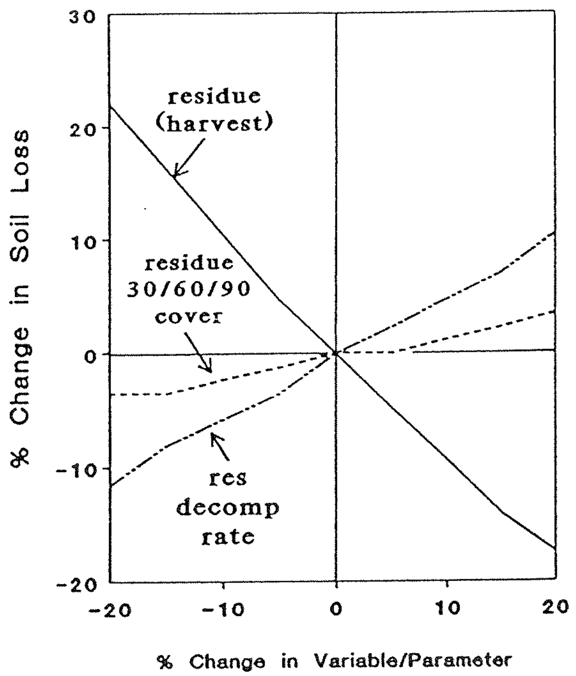


Fig. 11. Results of varying CROP DATABASE parameters and variables: harvest residue, residue decomposition, and residue amounts at 30, 60, and 90% cover.

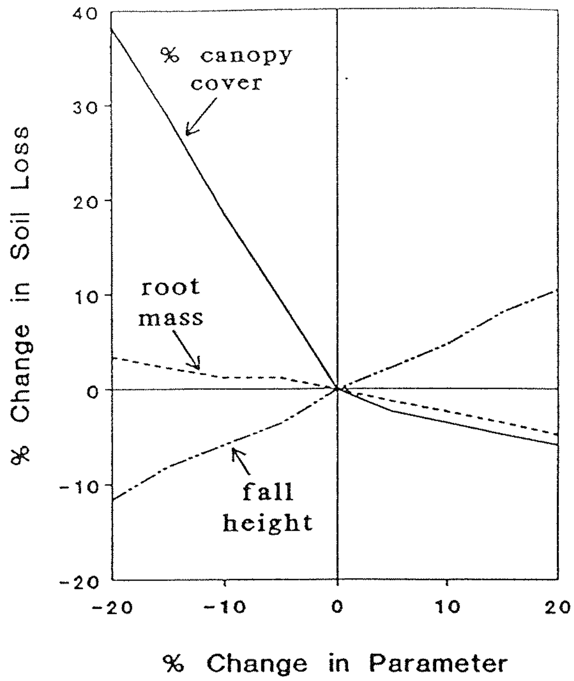


Fig. 12. Results of perturbations of CROP DATABASE parameters: percentage canopy cover, root mass, and canopy/drop fall height.

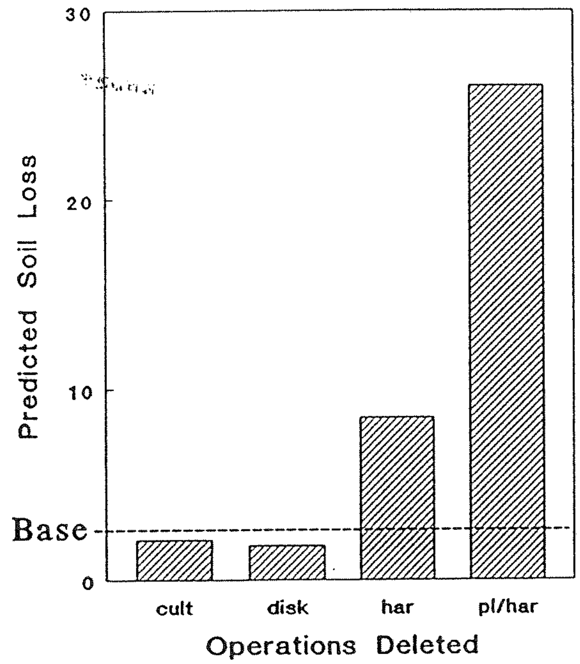


Fig. 13. Effects of deletions of cultivator (cult), disk (disk), harvest (har), and both planting and harvest (pl/har) operations.

rio. Had a no-till rotation been used, the residue on the surface would have probably "swamped" the canopy effect. Thus, the complexity of the subfactor approach to calculating $C$ factors in RUSLE requires careful consideration of the equations involved for specific crop and climatic conditions.

Plant population and row spacing are information parameters in RUSLE, included to permit later development of a plant growth subroutine. Perturbations of these parameters cause no change in predicted soil loss values in RUSLE.

### Model Response to OPERATIONS DATABASE Perturbations

Sensitivity analysis of individual values in this database may be particularly misleading because other temporal conditions greatly affect response. Operations in a sequence may alter the effects of subsequent or earlier operations. Because the $C$ factor for semimonthly intervals is multiplied by the percentage of EI in the interval, the specific operation may be effective for only a small part of the year. For example, we modified the roughness, percentage of area disturbed, percentage residue left, and depth of disturbance parameters within the row planter operation. Percentage of area disturbed changes caused minimal change in predicted soil loss. Roughness and depth change results were on the order of 1%. Percentage cover changes caused changes in calculated soil loss from 4 to −5%, varying inversely with parameter changes.

The same exercise was then performed perturbing the parameters of the spike harrow operation. Similar results were obtained.

These results should not lead one to infer model insensitivity to operations parameters. This is an obvious example of other conditions masking the effects of these parameters. In this case, the planting and cover of a corn crop mitigated effects of previous disk, cultivator, and harrow operations. To illustrate, we deleted operations from the schedule (Table 2), as though the farmer skipped an operation or stopped working midseason. Figure 13 shows the results, as compared to the base run results. Eliminating either the cultivator or disk operation reduced soil loss slightly. The impact of plants is apparent when either the harvest or both planting and harvest are deleted. Eliminating plants increased the predicted soil loss from the base value of 2.3 to 25.8 tons acre$^{-1}$ (5.2–57.8 t ha$^{-1}$. Results on the same order of magnitude were also achieved by deleting all operations following the cultivator and by eliminating all after the disk.

## SUMMARY AND CONCLUSIONS

The RUSLE model is a useful tool to assist in making field-management decisions that affect soil loss. In this study, a sensitivity analysis on parameters and variables in the CITY, CROP and OPERATIONS DATABASES discovered a range from minimal sensitivity to extreme sensitivity. For the case of corn grown under conventional tillage in the Chicago, IL, area, moderate sensitivity (10–40% change in prediction resulting from 20% change in a variable) was found for city code, precipitation, temperatures, $R$ factor, harvest residue, fall height, and percentage canopy cover. Only slight sensitivity (<10%) was found for reasonably nearby EI distribution codes, freeze-free days, root mass, and residue at 30, 60, and 90% cover. An EI distribution code from a dramatically different climate caused large changes in soil loss (magnitude of change more than 50% from the base). While many parameters and variables exhibited nearly linear response, freeze-free days and percentage canopy cover responses were nonlinear. Results of changing such field operation parameters as percentage of area disturbed, roughness, depth, and residue left were shown to be masked by later operations and plant growth. Insensitivity under the base conditions cannot be extrapolated to other conditions, as was shown by eliminating several field operations.

It is stressed that such a sensitivity analysis produces valuable information to help users determine which parameters and variables to put effort and resources into. Model users are encouraged to perform a simple sensitivity analysis such as these for their unique situation.

Surface water quality has historically meant soil erosion and sedimentation in rivers and reservoirs. Adsorbed agricultural chemical transported from upland areas has become a concern in recent decades. Incorporating RUSLE in more comprehensive models, such as EPIC and AGNPS, should permit more complete problem resolutions.

## REFERENCES

Beasley, D.B., L.F. Huggins, and E.J. Monke. 1980. ANSWERS: A model for watershed planning. Trans. ASAE 23:938–944.

DeCoursey, D.G. (ed.). 1988. Proceedings of the International Symposium on Water Quality Modeling of Agricultural Non-Point Sources, Parts 1 & 2. U.S. Dept. of Agric., Agric. Res. Svc. ARS-81, June 1990.

El-Swaify, S.A., and E.W. Dangler. 1976. Erodibilities of selected tropical soils in relation to structural and hydrologic parameters. p. 105–114. *In* Soil erosion: Prediction and control. Soil Conserv. Soc. Am., Ankeny, IA.

Foster, G.R., L.J. Lane, J.D. Nowlin, J.M. Laflen, and R.A. Young. 1981. Estimating erosion and sediment yield on field-sized areas. Trans. ASAE 24:1253–1262.

Knisel, W.G. (ed.). 1980. CREAMS—A field scale model for chemical, runoff, and erosion from agricultural management systems. USDA Cons. Res. Rep. no. 26. USDA, Washington, DC.

Lane, L.J., and V.A. Ferreira. 1980. Sensitivity analysis. p. 113–158. *In* W.G. Knisel (ed.) CREAMS—A field scale model for chemical, runoff, and erosion from agricultural management systems. USDA Conserv. Res. Rep. no. 26. USDA, Washington, DC.

McCuen, R.H., and W.H. Snyder. 1986. Hydrologic modeling statistical methods and application. Prentice Hall, New York.

McCuen, R.H. 1973. The role of sensitivity analysis in hydrologic modeling. J. Hydrol. 18:37–53.

Meier, W.L., A.O. Weiss, C.D. Puentes, and J.C. Moseley. 1971. Sensitivity analysis: A necessity in water planning. Water Resour. Bull. 7:529–542.

Renard, K.G., G.R. Foster, G.A. Weesies, and J.P. Porter. 1991. RUSLE: Revised universal soil loss equation. J. Soil Water Conserv. 46:30–33.

Tiscareño-Lopez, M. 1991. Sensitivity analysis of the WEPP watershed model. M.S. thesis. Univ. Arizona, Tucson.

Wagenet, R.J. 1988. Modeling soil hydrology: Perspectives, perils, and directions. p. 1–9. *In* J.J. Campbell (ed.) Proc. 1988 Int. Symp: Modeling Agricultural, Forest, and Rangeland Hydrology. St. Joseph, MI. 12 to 13 December. ASAE Publication 07–88. ASAE, St. Joseph, MI.

Williams, J.R. 1975. Sediment routing for agricultural watershed. Water Resour. Bull. 11:965–974.

Williams, J.R., K.G. Renard, and P.T. Dyke. 1983. EPIC—A new method for assessing erosion's effect on soil production. J. Soil Water Conserv. 38:381–383.

Wischmeier, W.H. 1976. Use and misuse of the universal soil loss equation. J. Soil Water Conserv. 31:5–9.

Wischmeier, W.H., and D.D. Smith. 1978. Predicting rainfall erosion losses. USDA Agric. Handb. 537. U.S. Gov. Print. Office, Washington, DC.

Young, R.A., C.A. Onstad, D.D. Bosch, and W.P. Anderson. 1989. AGNPS: A nonpoint source pollution model for evaluating agricultural watersheds. J. Soil Water Conserv. 44:168–173.