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Enhancing RUSLE to include runoff-driven phenomena

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Abstract:

RUSLE2 (Revised Universal Soil Loss Equation) is the most recent in the family of Universal Soil Loss Equation (USLE)/RUSLE/RUSLE2 models proven to provide robust estimates of average annual sheet and rill erosion from a wide range of land use, soil, and climatic conditions. RUSLE2's capabilities have been expanded over earlier versions using methods of estimating time-varying runoff and process-based sediment transport routines so that it can estimate sediment transport/deposition/delivery on complex hillslopes. In this report we propose and evaluate a method of predicting a series of representative runoff events whose sizes, durations, and timings are estimated from information already in the RUSLE2 database. The methods were derived from analysis of 30-year simulations using a widely accepted climate generator and runoff model and were validated against additional independent simulations not used in developing the index events, as well as against long-term measured monthly rainfall/runoff sets. Comparison of measured and RUSLE2-predicted monthly runoff suggested that the procedures outlined may underestimate plot-scale runoff during periods of the year with greater than average rainfall intensity, and a modification to improve predictions was developed. In order to illustrate the potential of coupling RUSLE2 with a process-based channel erosion model, the resulting set of representative storms was used as an input to the channel routines used in Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) to calculate ephemeral gully erosion. The method was applied to a hypothetical 5-ha field cropped to cotton in Marshall County, MS, bisected by a potential ephemeral gully having channel slopes ranging from 0·5 to 5% and with hillslopes on both sides of the channel with 5% steepness and 22·1 m length. Results showed the representative storm sequence produced reasonable results in CREAMS indicating that ephemeral gully erosion may be of the same order of magnitude as sheet and rill erosion.

KEY WORDS RUSLE; runoff; erosion; concentrated flow; sediment; ephemeral gully

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INTRODUCTION

The goal of this project was to enhance the RUSLE2 (Revised Universal Soil Loss Equation) model by using readily available monthly climate data to generate a representative series of runoff events, allowing expansion of RUSLE's conservation planning capabilities beyond erosivity-driven to runoff-driven phenomena, including examples such as ephemeral gully erosion or phosphorus transport. In order to understand this approach, it is important to understand the overall USLE (Universal Soil Loss Equation)/RUSLE/RUSLE2 family of models, especially their evolution in handling runoff.

The USLE (Wischmeier and Smith, 1965, 1978) summarized thousands of years of plot research and became widely used for conservation planning purposes on agricultural croplands, based on estimating the average annual soil erosion by water. This was an empirical model of simple structure that captured the main effects of rainfall intensity, soil type, topography, and management on sheet and rill erosion, with no attempt to account for sediment deposition nor gully erosion. In the early 1980s a program to develop technology to replace the USLE was initiated, resulting in the computer-based RUSLE model, documented in written form in 1997 (Renard *et al.*, 1997). RUSLE incorporated significant advances over the USLE and permitted application of soil erosion estimation for a great variety of crops and management practices beyond those in the original USLE data base. RUSLE was subsequently revised to include more advanced scientific and interface technology and was subsequently delivered as RUSLE2 in 2002 (Foster *et al.*, 2003; USDA-ARS, 2008). RUSLE2 is currently used by the United States Department of Agriculture-Natural Resources Conservation Service (USDA-NRCS) for conservation planning. RUSLE2 is a 'hybrid' model that computes sheet and rill erosion on a hillslope based on empirical equations driven by rainfall erosivity, but uses process-based equations driven by runoff estimates to determine sediment transport capacity, deposition, and sediment enrichment in clay and organic matter.

Estimation of runoff and the impact of management on runoff and its ability to carry sediment is probably the aspect that changed the most in the USLE/RUSLE/RUSLE2 evolutionary process, with evolution described in Table I. In the USLE, there was no runoff estimation and the slope length was defined as beginning at the top of the hillslope where runoff began, and extending down to where the sheet and rill flow reaches either a

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Table I. Evolution of the USLE/RUSLE family of models with respect to calculation and use of runoff estimates

Model	Delivery		Slope length down to	Runoff estimate	
	Initial	Updates		Based on	Used to calculate
USLE	1965 (Agricultural Handbook 282)	1978 (Agricultural Handbook 537)	Concentrated flow or deposition	None	None
RUSLE	1991 (initial software release)	1997 (Agricultural Handbook 703);	Concentrated flow or deposition caused by gradient	Index storm	*P* factor, critical slope length
RUSLE2	2004 (initial software release)	2010 (latest update; on-line documentation)	Concentrated flow	Index storm or daily values or representative storm sequence	Full CREAMS process-based transport/deposition

concentrated flow channel or a depositional area. The limit at the start of the depositional area was required because such deposition rarely occurred on the plots used to collect USLE data.

In RUSLE, the hillslope definition was expanded to include areas of deposition caused by management changes. This was accomplished by including some of the process-based routines used in Chemicals, Runoff, and Erosion from Agricultural Management Systems (CREAMS) (Foster *et al.*, 1980a,b). Runoff was estimated using a location-specific index storm approach (described in more detail in the following text) coupled to a user selected runoff index similar to a curve number (CN) (Renard *et al.*, 1997, Table 6–5). This index storm was used to determine critical slope length and to calculate *P* factors for such practices as contouring, grass strips, terraces, sediment basins, and subsurface drainage. However, deposition on concave slopes for management systems without contouring was still not considered.

In RUSLE2, this approach was extended to handle sediment deposition caused by changes in topography, and the simplified approach in RUSLE was expanded to include more of the CREAMS science. Hillslopes now reached from the top where runoff began down to a concentrated flow channel, and were conceived as being composed of three layers: topography, soil, and management. Allowing each of these layers to be segmented independently, RUSLE2 represented any complex one-dimensional hillslope as a series of segments comprising each unique combination of the slope steepness, soil, and management layers. With the CREAMS sediment transport and deposition equations available within every segment, RUSLE2 could now predict deposition due to both management changes and topographic concavity, considering both their impact on runoff generation and on overland flow transport capacity.

Like USLE and RUSLE, RUSLE2 assumed that sheet and rill erosion was linearly related to rainfall erosivity. Direct runoff values have never been part of the USLE/RUSLE detachment calculations because of, the good correlation between measured storm erosivity and unit plot erosion. This means that the impact of soil, topography, and management on runoff and the resulting impact of runoff on sheet and rill erosion are subsumed in the other RUSLE factors (K, soil erodibility; LS, topography; and CP, management impacts). There is strong evidence that knowledge of the actual runoff amounts can be used to increase the accuracy of USLE/RUSLE erosion estimates (Kinnell and Risse, 1998), but there is some question whether the accuracy is better if the runoff can only be estimated from rainfall values. This approach would also require recalculating all the other RUSLE factors to remove the subsumed runoff impacts mentioned earlier.

The approach of basing erosion solely on rainfall erosivity was not good enough for estimation of remote deposition occurring in areas with concave topography or high flow retardance. Therefore, RUSLE2 made runoff estimates using an index storm and time-varying estimates of the CN based on soil and management characteristics. This RUSLE2-calculated runoff was not used directly to estimate soil erosion, but rather to determine the following: if sediment transport capacity has been satisfied on a given slope segment; to predict sediment deposition within hillslope segments, channels, and impoundments; and to predict contour failure and backwater ponding upslope of barriers and buffer strips.

Currently, RUSLE2 does not predict erosion within concentrated flow channels. Although it has frequently been suggested that ephemeral gully erosion may be of a magnitude comparable to that of sheet and rill erosion (Poesen *et al.*, 2003), there is no database of ephemeral gully erosion observations comparable to the thousands of plot years of research that support the cropland sheet and rill erosion estimates calculated by USLE/RUSLE/RUSLE2. Therefore, most efforts to predict concentrated flow erosion in upland areas have involved application of algorithms that represent physical processes involved in detachment and transport (Foster *et al.*, 1980a; Hairsine and Rose, 1992; Street and Quinton, 2001; Gordon *et al.*, 2007).

The USLE calculations for time-varying phenomena were done on the basis of either annual values or a qualitatively defined ‘cropstage period’. In RUSLE, this was narrowed to half-month periods, which matched the available erosivity values. In RUSLE2 the calculations are done on a daily timestep; therefore, they need daily rainfall and erosivity values, which could come from measured daily values or daily values developed using a stochastic climate generator. Instead of this, in keeping with the desire for a general conservation planning model, RUSLE2 developers assumed that only monthly normal precipitation and erosivity values were available, so RUSLE2 climate databases included only monthly averages for precipitation, temperature, and erosivity density (erosivity per unit rainfall, MJ ha^{-1} h^{-1}, a measure of rainfall intensity), plus the location's 10-year 24-h precipitation amount ($P_{10\ \mathrm{year},24\ \mathrm{h}}$). The program then generated the necessary daily values by disaggregating the monthly data into daily values that preserved monthly totals, yet varied smoothly from day to day, resulting in small amounts of precipitation and erosivity every day of the year.

The daily disaggregation approach worked very well for the erosion estimates because of the linear relationship between erosivity and erosion seen in the original USLE plot data, but the small daily rainfall amounts would result in prediction of zero or very low runoff using the CN method. In order to get around this limitation for the transport/deposition calculations, RUSLE2 used a precipitation index storm taken as the location's $P_{10\ \mathrm{year},24\ \mathrm{h}}$. The ratio of sediment yield to erosion from the index storm falling on a given day was used to estimate the actual sediment yield as $\mathrm{SY}_i = \mathrm{A}_i \times \mathrm{SY}_{\mathrm{I}i}/\mathrm{A}_{\mathrm{I}i}$, where SY_i is the daily sediment yield, A_i is the daily erosion, and $\mathrm{SY}_{\mathrm{I}i}/\mathrm{A}_{\mathrm{I}i}$ is the ratio of sediment yield from the index storm to erosion from the index storm on that day. This approach essentially calculated a sediment delivery ratio for the slope on each day using the index storm erosion and yield, and then assumed that same ratio held for any storm size. It was thought that the uncertainty associated with this assumption was probably less than that associated with trying to estimate daily runoff. The other way of thinking of this approach is that the sediment yield calculated for the erosion and runoff from the index storm on that day was scaled by the ratio of each day's disaggregated erosivity to the erosivity of the $P_{10\ \mathrm{year},24\ \mathrm{h}}$ rainfall. Details on this approach can be found in the RUSLE2 documentation (USDA-ARS, 2008).

Through appropriate calibration, this approach provided reasonable and conservative estimates of sediment transport and sediment deposition suitable for conservation planning purposes. However, the runoff generated by assuming that $P_{10\ \mathrm{year},24\ \mathrm{h}}$ occurs every day was unrealistically high and was not appropriate for driving a physically based channel erosion model where the dimensions of the channel are important and vary through time, making it critical to have good estimates of the actual runoff rates. Therefore, a more realistic representative runoff event sequence was needed in order to drive hydraulically driven processes such as channel erosion.

The purpose of this paper is to describe new routines based solely on existing RUSLE2 database information that have been implemented in RUSLE2 (USDA-ARS, 2010) to calculate a representative sequence of daily runoff events suitable as inputs to physically based runoff-driven models, such as models to allow estimation of average annual channel (e.g. ephemeral gully) erosion, or models of phosphorus transport. In order to be considered successful, the resulting representative storm sequence must meet the following requirements: (1) in order to ensure that the erosion results are similar to those using the current daily disaggregated approach, (1a) the annual erosivity from these storms must be equal to the annual erosivity found in the database and (1b) the general erosivity patterns over the year for the two methods must match relatively well and (2) in order to ensure conservation of mass, the annual precipitation depths and patterns over the year for the two methods (current daily disaggregated and new representative storm sequence) must match. The method is validated through comparison to independent generated data and to measured field data, and use of the method in driving a runoff-based model is illustrated by coupling the RUSLE2 output for a hypothetical field to the channel erosion model used in CREAMS and Water Erosion Prediction Project (WEPP).

RUSLE2 DATABASE VALUES AFFECTING HYDROLOGY

In order to calculate average daily erosion and sediment delivery, RUSLE2 normally disaggregates monthly values of precipitation and erosivity into daily values. These climatic values do not affect the amount of biomass produced by a vegetation description, but they do affect the rates at which surface and subsurface residues and surface roughness degrade over time (USDA-ARS, 2008). The disaggregation procedure used to convert monthly to daily values is described in detail in section 3·1 of USDA-ARS (2008). As described there, this process conserves the monthly sum of values such as precipitation and erosivity, and the monthly average of values such as temperature and erodibility. These disaggregated values represent the best estimators of long-term average values and therefore have great utility.

As mentioned above, disaggregation of monthly values is not the only way that RUSLE2 can get daily values. Rather, daily precipitation and erosivity values can be a user-defined set, either entered by hand from 'real' measured data or pulled from a climate generator through the 'Single-storm erosivity' input option. In these latter two cases, discrete user-specified values are used to determine erosion and sediment delivery, but the other impacts of climate (e.g. residue decomposition and roughness degradation) are still based on the long-term disaggregated values to maintain the robustness of the approach, and because the results of these effects were calibrated against the USLE database to ensure a good fit to the large empirical database. In other words, RUSLE2 can do its calculations based on linkage to a climate generator, but use of the smoothed disaggregated average values is more robust and just as valid for conservation planning purposes (Yoder *et al*., 2007), except those purposes tied to runoff-driven calculations.

RUSLE2 management descriptions comprise combinations of operation and vegetation descriptions. Operations such as tillage, planting, or harvest take place on specified dates and affect hydrologically important properties such as surface roughness and residue cover. Vegetation descriptions specify growth timing and the amounts and types of residues produced. Residue characteristics include a biomass-cover relationship and a potential decay rate.

RUSLE2 soil descriptions primarily affect hydrology through the choice of soil hydraulic class and through textural effects on soil roughness created by tillage (USDA-ARS, 2008).

THE CN AND STORAGE INDEX

In order to understand the new approach to developing representative storms in RUSLE2, it is essential to understand the underlying CN runoff calculation. This starts with the storage index (S), sometimes called 'maximum retention', which is a transform of the CN (ASCE, 2009). Using SI units, S (mm) is calculated as:

$$S = \frac{(25400 - 254\ \mathrm{CN})}{\mathrm{CN}} \qquad (1)$$

Conceptually, CN can vary from 0 to 100, corresponding to S varying from ∞ to 0. When the 'initial abstraction' is taken as 0·2 S, and when S, precipitation P, and runoff Q, are in the same units, runoff is calculated as:

$$Q = \frac{(P - 0{\cdot}2S)^2}{P + 0{\cdot}8S} \qquad (2)$$

RUSLE2 internally calculates a CN based on soil, climate, and management descriptions, varying it on a daily basis due to changes in soil biomass, soil consolidation, soil roughness, and soil residue cover. However, the RUSLE2 CN does not vary through the year due to variation in the antecedent soil water content, because RUSLE2 does not include explicit water balance computations.

While use of the CN approach has received considerable criticism, including especially that CN results do not vary depending on the storm rainfall intensity (Garen and Moore, 2005; ASCE, 2009), most objections disappear when the objective of the model is long-term average behaviour, as is the case for this application in RUSLE2.

DATA TO DERIVE A REPRESENTATIVE RUNOFF EVENT SEQUENCE

Some erosion models use climate generators to predict stochastic series of input variables to drive the models (Bingner and Theurer, 2001; Meyer *et al*., 2008). Multiyear outputs of such models are then summarized to predict long-term averages or the likely magnitude of events with different probabilities of occurrence. Although RUSLE2 could take this approach through use of the daily precipitation/erosivity inputs described previously, in general RUSLE2 predicts long-term average sheet and rill erosion and the distribution of that erosion through a year or a rotation cycle. To be complementary, a RUSLE2 runoff-driven erosion estimate would need to be a long-term average of a highly variable sequence of events. Yu (2002) used a stochastic climate generator to derive RUSLE climate files. We took that one step further by using a stochastic model to generate the initial rainfall/runoff sets.

In order to meet the objective of developing a representative runoff event sequence based on the available database information, we needed a set of storm rainfall/runoff values. These could have been 'real' storm data collected from plots over years, but we chose to use the output of a stochastic model as the observations to derive the routines. These 'synthetic data' were used for several reasons: (1) we desired a general approach that could be used across the continental United States, which would allow application of the method to a wide range of users, (2) the data needed to represent a broad range of management and soil conditions at each location, in order to adequately demonstrate the impact of management and soil on runoff, and (3) the data needed to be for the plot/field scale modelled by RUSLE.

Generating long-term average runoff estimates using AnnAGNPS

We chose to use AnnAGNPS (version 3.5; Bingner and Theurer, 2001) as the stochastically driven model to generate our rainfall/runoff sets because AnnAGNPS and RUSLE use compatible management descriptions and both are operational models supported by available databases. Although AnnAGNPS and RUSLE2 both use CN methods to estimate runoff, the models differ considerably in their hydrology. AnnAGNPS uses measured or generated stochastic climatic input data with a sequence of wet and dry days and rainfall event sizes that vary from year-to-year. In contrast, for conservation planning purposes, RUSLE2 generally uses 30-year monthly mean rainfall disaggregated into a continuous series of daily rainfall values, and weather is assumed to be the same long-term normal every year. AnnAGNPS requires users to choose a base CN (NRCS, 2004) and daily adjusts that CN based on antecedent soil water conditions determined by water balance computations and planting and harvesting events; RUSLE2 calculates a CN internally based on soil, management, and climatic descriptions, and does not include an antecedent soil water content adjustment to the CN.

The AnnAGNPS and RUSLE2 input data for Goodwin Creek watershed in Panola County, MS, are compared in Figure 1. The AnnAGNPS input file was a 30-year synthetic Generation of Weather Elements for Multiple Applications (GEM) (Harmel *et al*., 2002) simulation based on weather statistics from Memphis, TN, and Greenwood, MS, combined with monthly estimates of dew point, sky cover, and wind speed interpolated to the Goodwin Creek watershed from maps in the AnnAGNPS Climate Atlas. In Figure 1A, the maximum rainfall occurring on each day during the simulation is plotted to demonstrate the stochastic nature of the

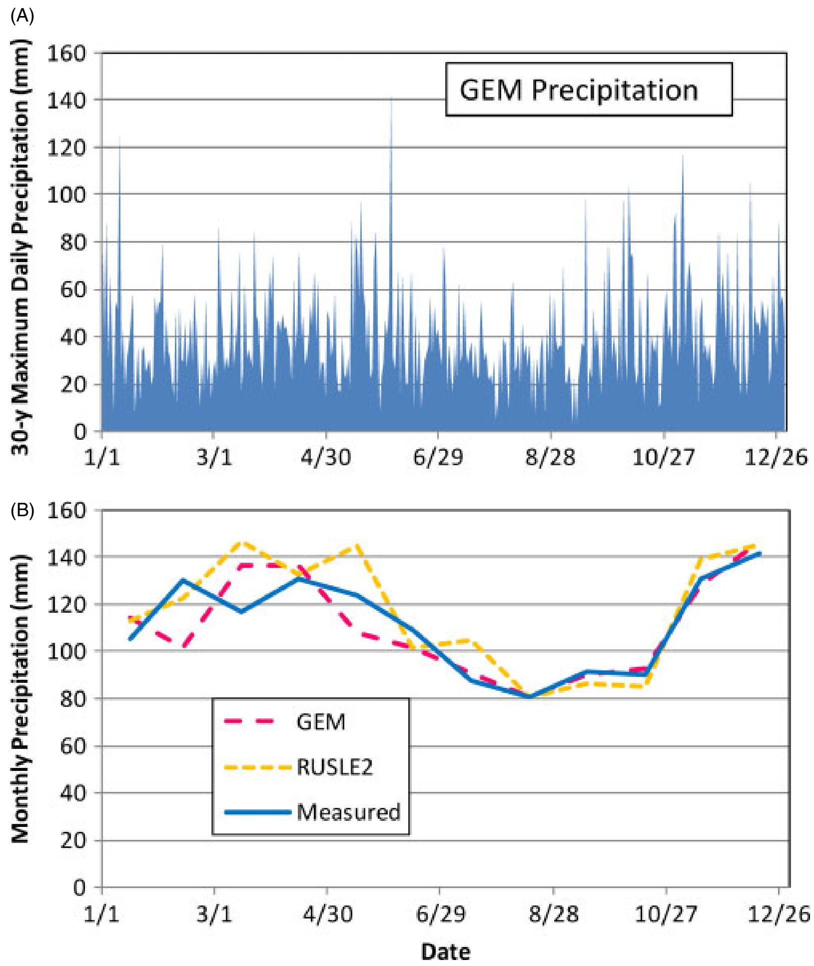

Figure 1. Daily maximum rainfall (A) in a 30-year GEM synthetic record for Panola County, MS and (B) comparison of measured (1981–2003) average monthly rainfall at Goodwin Creek Station #1, the 30-year monthly mean of the GEM record, and input values from the RUSLE2 database

AnnAGNPS inputs. However, the 12 monthly means of that record resemble the monthly rainfall files that are part of RUSLE2 database for Panola County, MS (NRCS, 2008), and both are similar to the monthly rainfall totals measured over 23 years (1982–2003) at gauging station #1 in the Goodwin Creek experimental watershed (Figure 1B).

AnnAGNPS was used to transform 30-year synthetic climate input files into a time sequence of runoff events for 30 US locations with annual precipitation from 191 to 1420 mm. At each location, a factorial combination of four soils (soil hydrologic classes A, B, C, and D) and four managements [tilled fallow, tilled maize (*Zea mays L.*), no-till (NT) maize, and pasture] were simulated. All the locations were in the continental United States between 30 and 48 °N latitude and 74 and 123 °W longitude. RUSLE2 climate databases (NRCS, 2008) were obtained from the same counties as the AnnAGNPS locations. In counties within the 11 western USA states that have multiple RUSLE2 climate files, sub county zones were selected so that average annual precipitation in the selected RUSLE2 climate file for each location differed by no more than 15% from that in the AnnAGNPS input data set. These combinations of locations/soils/managements were chosen to provide a wide range of applicability of the technique to the lower continental United States.

Results from four of the locations, selected to span a range of annual precipitation amounts and temperature regimes, were not used in the development of RUSLE2 prediction equations but were reserved to provide an independent assessment of prediction efficiency. This left 416 (26 locations, 4 soils, 4 managements) 30-year daily AnnAGNPS runoff series as the basis for developing regression relationships allowing prediction based on available RUSLE2 databases of: (1) long-term mean monthly runoff and (2) parameters to describe the frequency and statistical distribution of runoff events.

PREDICTING AVERAGE MONTHLY RUNOFF

Our technique for predicting monthly runoff values followed three steps. First, we sought to account for snowpack accumulation and melting by adjusting the RUSLE2 monthly precipitation values. Although snow pack accumulation and melting generally has minimal impact on rainfall erosivity because of the low precipitation intensities involved with snow, they can have a substantial impact on monthly runoff. Second, we used values from

Table II. ANOVA and coefficient estimates for predicting the ratio of S_i/S_A, the ratio of monthly to annual average S from RUSLE2 climate file parameters

Effect[a]	Numerator degrees of freedom	Denominator degrees of freedom	F Value[b]	Probability > F	Estimate
month	12	4932	661.32	<0·0001	—
dev$T_i\times$ month	12	4932	74.39	<0·0001	—
dev$Pa_i\times$ month	12	4932	162.85	<0·0001	—
$T_i\times$ month	12	4932	152.26	<0·0001	—
$Pa_i\times$ month	12	4932	162.47	<0·0001	—
Residual error	—	—	—	—	0.01366

	Coefficient estimates (C_{ij})											
Effect (X_j)	January	February	March	April	May	June	July	August	September	October	November	December
Month	0·46	0·43	0·51	0·91	0·90	1·66	2·26	3·02	1·80	1·33	0·40	0·54
dev$T_i\times$ month	−0·039	−0·051	0·064	−0·005	−0·037	−0·034	−0·069	−0·037	−0·035	−0·10	−0·080	−0·034
dev$Pa_i\times$ month	0·000	−0·001	−0·004	−0·001	−0·004	−0·005	−0·007	−0·007	−0·010	−0·002	−0·000	−0·000
$T_i\times$ month	0·012	0·017	0·017	0·013	0·011	−0·013	−0·033	−0·048	−0·025	−0·016	0·009	0·013
$Pa_i\times$ month	−0·004	−0·004	−0·002	−0·002	0·001	0·003	0·004	0·003	0·003	0·002	0·001	−0·002

The resulting regression relationship for each month i is of the form $S_i/i_A = C_{i1}\times X_1 + C_{i2}\times X_2 + \ldots + C_{i5}\times X_5$, where C_{ij} is the listed coefficient for effect j for month i, and X_j is the effect, for $j = 1-5$.
[a] Refer Nomenclature for definition of abbreviations.
[b] Ratio of effect mean square to residual error mean square; all statistical tests were made using partial sums of squares, which represent the contribution of each term to the model after considering all other terms so that the order of term addition does not influence the result.

the RUSLE2 climate database to predict monthly adjustments to the S (Equation (1)) that reflect seasonal variations in CN due to variations in antecedent soil water content. Third, we used the results of the first two steps and other information available in the RUSLE2 climate, soil, and management databases in multiple regression analysis to predict the average monthly runoff from the large pool of rainfall/runoff sets generated by AnnAGNPS.

Snowpack accumulation and melting

In limiting ourselves to the data available in the RUSLE2 climate database, snowpack accumulation was presumed to depend on precipitation and temperature values. These values were fit to the effect as modelled by AnnAGNPS, yielding adjusted RUSLE2 monthly precipitation amounts, Pa_i (mm), calculated by subtracting the predicted change in snowpack (δPs_i, mm) from the average monthly precipitation P_i (mm) available in the RUSLE2 climate database for each location. Precipitation was reduced when the snowpack increased, and increased when the snowpack decreased through the relationships:

$$\delta Ps_i = P_i \times [-0{\cdot}0735 + 0{\cdot}00851 \times T_i + \delta T_i \times (-0{\cdot}04386 + 0{\cdot}0061 \times T_i)],\ \ T_i \le 8 \quad (3)$$
$$\delta Ps_i = 0, \qquad T_i > 8$$
$$Pa_i = P_i - \delta Ps_i$$

where T_i is mean monthly temperature (°C) and δT_i is the change in T_i from the previous month ($\delta T_i = T_i - T_{i-1}$). The snowpack increases (δPs_i is positive) when δT_i is less than about −2 °C. If δT_i is positive, the snowpack melts and Pa_i is larger than P_i. If the absolute magnitude of δT_i is small, there is little gain or loss of snow pack. The main effect of T_i is to amplify the impact of δT_i. The temperature effect inside the brackets of Equation (3) is multiplied by the monthly precipitation, so effects are larger in wetter climates. For 30-year AnnAGNPS simulations at 26 locations, there were 104 location months with $T_i \le 8$ °C, and this four-parameter model predicted the average monthly AnnAGNPS changes in snowpack moderately well ($R^2 = 0{\cdot}65$, $n = 104$). Predicted δPs_i ranged from −31 to +43 mm, while the AnnAGNPS results ranged from about −69 to +51 mm, with two observations <−30 mm, and two above +30 mm. Thus, the adjustment shifted precipitation in the correct direction to capture important winter effects, but did not capture the entire effect for the highest snow locations (e.g. March in Portland, ME).

Monthly water balance adjustment to S (and CN)

Monthly values of the ratio of average monthly S_i, to that of its annual average, S_A, were calculated for 4992 combinations (26 locations, 4 soils, 4 managements, 12 months) from 30-year AnnAGNPS simulations. This 'S-ratio' (S_i/S_A) represents the seasonal variation in the S as reflected in the AnnAGNPS adjustment to the CN, which is based primarily on a daily soil water balance. We then used Proc Mixed (SAS, 1996) to develop a regression model to predict S_i/S_A from information already in the RUSLE2 climate database, including the monthly rainfall adjusted for snow effects. A 60 degree of freedom (12 monthly intercepts plus the interactions of 12 months with four parameters) regression model was highly significant ($R^2 = 0{\cdot}99$, $n = 4992$) and the resulting coefficient estimates, which are appropriate only to northern temperate regions, are presented in Table II. The monthly intercepts had the most predictive power, reflecting an increased S between June and October when antecedent conditions tend to be dry, and a decreased S from November to March. The four parameters modifying the effect of month were average temperature and snow-adjusted precipitation, and the deviations of these monthly values from their annual averages. These three parameters (month, temperature, and precipitation) are logical in defining the expected antecedent moisture impact on the CN, and therefore on the S_i value, as they have a clear correlation to sunlight and temperature—which in turn control evapotranspiration—and to rewetting of the soil.

Calculating average monthly runoff from RUSLE2 databases

A monthly runoff index parameter, q_i (mm), was calculated based on Equation (2) as:

$$q_i = \frac{(Pa_i - 0{\cdot}2S_R S_i/S_A)^2}{(Pa_i + 0{\cdot}8S_R S_i/S_A)} \tag{4}$$

where S_R is the average annual RUSLE2 S. The parameter q_i reflects a combination of soil, management, and climatic effects on runoff, and equals the runoff that would be predicted if the entire monthly precipitation fell as one storm.

A 22-parameter regression model using q_i and other information available in the RUSLE2 databases was fitted to average monthly AnnAGNPS runoff values (26 locations, 4 soils, 4 managements, 12 months), with the results shown in Table III. The regression model represented the AnnAGNPS average monthly runoff ($R^2 = 0{\cdot}90$, $n = 4992$) reasonably well. All retained terms were significant at $P < 0{\cdot}001$ after considering all other terms in the model. Significant terms included q_i, S_R and S_i/S_A, soil hydrologic group, precipitation, erosivity, temperature, and interactions and time differences between some of them. The first four of these terms represent the management and soil effects on the CN. The precipitation and erosivity values represent rainfall amounts and intensities. In RUSLE2 application, if the regression model predicted negative monthly runoff, that monthly runoff value was set to zero.

In examining the results of this portion of the process, Figure 2A illustrates the event runoff predicted by AnnAGNPS for the precipitation inputs shown in Figure 1A, while Figure 2B shows the average monthly runoff from the AnnAGNPS simulations and that calculated by the RUSLE2-based regression model for a hydraulic class C soil cropped to conventional tillage maize in Panola County, MS. Shown for comparison is the mean of a 22-year average monthly runoff measured at gauging station #1 of the Goodwin Creek experimental watershed. The pattern predicted by RUSLE2 is similar to the AnnAGNPS predictions and both vary slightly from to the measured data, which is to be expected as soils and land uses vary substantially within the 21 km^2 Goodwin Creek watershed (Kuhnle *et al*., 1996, 2008).

To test the ability of the RUSLE2 regression model to predict monthly runoff amounts outside the calibration data set, the results of the four validation locations (Table IV) were predicted for all 16 management and soil type combinations. Taking the AnnAGNPS values as observed data and RUSLE2 regression (Table III) predictions as modelled values, the Nash–Sutcliffe model efficiency coefficient (Moriasi *et al*., 2007) for monthly runoff amounts was 0·80 ($n = 768$).

Table III. Numerator degrees of freedom, F statistic, regression coefficients, and standard error estimates for predicting monthly runoff depth Q_i (mm) from the RUSLE2 databases

Effect[a] (X_{ij})	DF	F[b]	Soil	Coefficient (C_j)	SE
$q_i \times q_i$	1	314	—	0·00136	0·00008
$q_i \times$ SOIL	4	299	A	0·14604	0·01384
$q_i \times$ SOIL	—	—	B	0·20899	0·01397
$q_i \times$ SOIL	—	—	C	0·27213	0·01404
$q_i \times$ SOIL	—	—	D	0·31136	0·01417
$q_i \times S_i/S_A$	1	238	—	−0·14526	0·00941
T_i	1	82	—	−0·11496	0·01269
Pa_i	1	41	—	−0·05910	0·00921
$Pa_i \times E_i$	1	31	—	−0·01401	0·00254
$T_i \times E_i$	1	146	—	0·06636	0·00549
$Pa_i \times Pa_i$	1	181	—	0·00106	0·00008
$Pa_i \times R$	1	116	—	−0·00002	0·00000
EI30 $\times S_i/S_A$	1	12	—	−0·00483	0·00139
$S_R \times P_{10\ \mathrm{year},24\ \mathrm{h}} \times$ SOIL	4	20	A	−0·00006	0·00001
$S_R \times P_{10\ \mathrm{year},24\ \mathrm{h}} \times$ SOIL	—	—	B	−0·00005	0·00001
$S_R \times P_{10\ \mathrm{year},24\ \mathrm{h}} \times$ SOIL	—	—	C	−0·00000	0·00002
$S_R \times P_{10\ \mathrm{year},24\ \mathrm{h}} \times$ SOIL	—	—	D	−0·00004	0·00003
ΔT	1	102	—	0·13536	0·01338
ΔE	1	657	—	−2·04475	0·07979
ΔR	1	68	—	−0·02232	0·00271
R	1	400	—	0·00413	0·00021
$P_{10\ \mathrm{year},24\ \mathrm{h}}$	1	17	—	0·02445	0·00586

The first 13 degrees of freedom describe monthly variation, while the last nine degrees of freedom in the model determine a constant (baseline monthly runoff) for a given climate, management, and soil. The resulting regression relationship for each month i is of the form $Q_i = C_1 \times X_{i,1} + C_2 \times X_{i,2} + \ldots + C_{22} \times X_{i,16}$, where C_j is the listed coefficient for effect j, and X_{jj} is the effect for month i and effect number $j = 1 - 16$. When part of the effect is SOIL, the coefficient value used depends on the soil hydrologic group, so there are really four choices each for C_2 and C_{11}.

[a] Refer Nomenclature for definition of abbreviations

[b] Ratio of effect mean square to residual error mean square; all statistical tests were made using partial sums of squares, which represent the contribution of each term to the model after considering all other terms so that the order of term addition does not influence the result.

DETERMINING A REPRESENTATIVE RUNOFF EVENT SEQUENCE

Given estimates of monthly runoff calculated from regression results, there remains the problem of determining a suitable sequence of runoff events. This was approached by determining the mean number of events per year (EPY) and parameters characterizing the statistical distribution of runoff event sizes for each combination of location, soil, and management. Using these values and postulating that the largest event to be simulated in each RUSLE2 year would have a 1·0-year return period (RP), a sequence of events was calculated as described in the following text. The goal of this task was to develop a

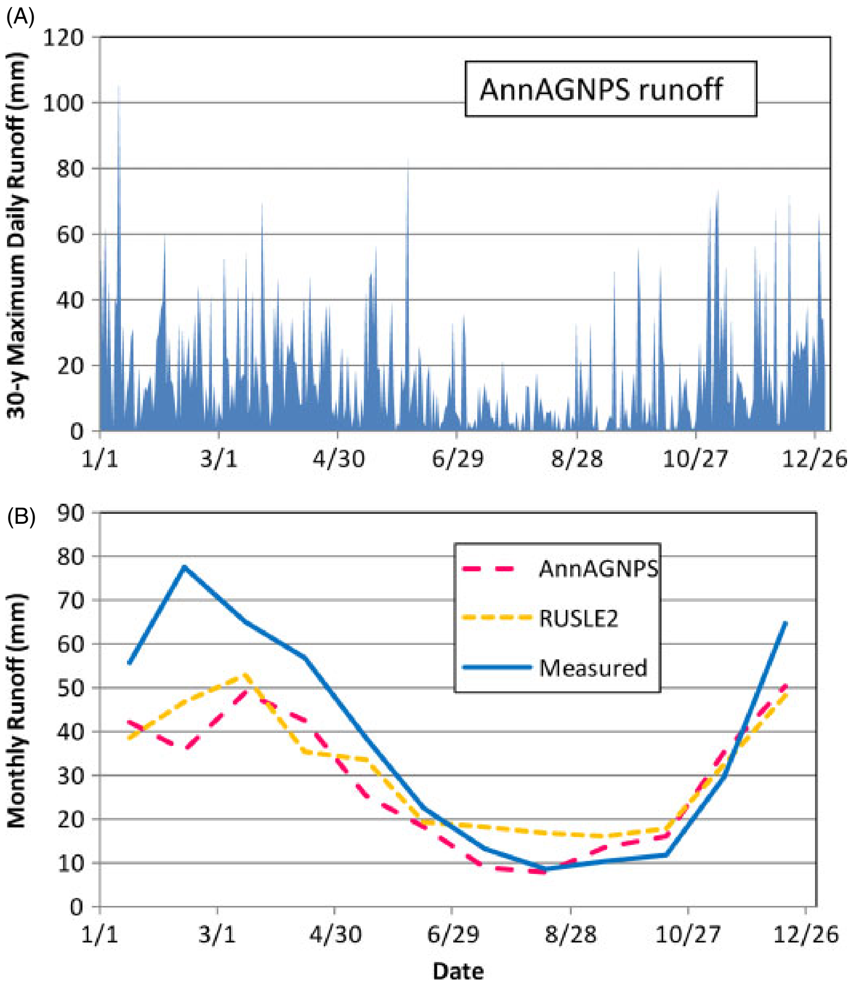

Figure 2. Maximum daily runoff (A) during a 30-year simulation predicted by AnnAGNPS from the precipitation shown in Figure 1A falling on conventional tillage maize grown on a hydraulic class 'C' soil in Panola County, MS, and (B) mean monthly runoff calculated from the AnnAGNPS record, calculated from RUSLE2 regression relationships (Table III), and measured runoff determined by hydrograph separation at Station #1 of the Goodwin Creek experimental watershed (Kuhnle *et al.*, 2008)

Table IV. RUSLE2 climate parameters for four locations that were used to test the ability of regression relationships to predict beyond the calibration data set

County State	Dare NC	Tulsa OK	Ingham MI	Spokane (R16–18) WA
T (°C)	16·5	15·2	8·4	8·5
P (mm)	1318	988	786	435
R (MJ mm ha^{-1} h^{-1})	5679	4422	1731	188
E (MJ ha^{-1} h^{-1})	4·1	4·1	1·9	0·5
$P_{10\ \text{year},24\ \text{h}}$ (mm)	191	155	86	46
ΔT (°C)	20·0	26·3	28·0	22·5
ΔP (mm)	62	92	57	35
ΔE (MJ ha^{-1} h^{-1})	4·8	5·6	4·2	0·8

Refer Nomenclature for definition of abbreviations.

storm sequence that would produce the correct amount of runoff distributed among a reasonable number of events, matching the total precipitation and erosivity defined in the RUSLE climate database, the temporal distribution of that precipitation through the year, and the runoff estimated by the rainfall/runoff set.

Estimate the number of runoff EPY for each location, soil type, and management

The average number of AnnAGNPS runoff EPY for each location, management, and soil type combination that had more than six runoff events within a 30-year AnnAGNPS simulation was fitted to a 24-parameter regression model based on information available in the RUSLE2 climate, soil, and management databases, with the results shown in Table V. The model accounted for most of the variability in the annual number of runoff events in the calibration data set ($R^2 = 0·98$, $n = 377$). All retained terms were significant at $P < 0·02$, and included S_R, soil hydrologic group, precipitation, erosivity, temperature, and interactions and time differences between some of these. The number of runoff events will clearly be a function of precipitation depth and intensity, as well as depending on soil characteristics, management influences, and temperature effects on antecedent moisture. In this case, the influence of management entered the model only through the parameter S_R and soil hydrologic group. In the RUSLE2 implementation, if the regression equation predicted less than four EPY, the number of

Table V. Numerator degrees of freedom, F statistic, regression coefficients, and standard error estimates for predicting the number of runoff EPY from the RUSLE2 databases

Effect[a]	DF	F[b]	Soil	Coefficient (C_j)	SE
$Pa \times Pa$	1	15	—	0·000029	0·000008
$P_{10\ \text{year},24\ \text{h}} \times S_R$	1	847	—	−0·001863	0·000110
SOIL	4	9	A	−21·286656	5·967795
SOIL	—	—	B	−18·734973	5·813829
SOIL	—	—	C	−15·549807	5·788602
SOIL	—	—	D	−10·747570	5·786878
$P_{10\ \text{year},24\ \text{h}} \times S_R \times$ SOIL	3	79	A	0·001424	0·000114
$P_{10\ \text{year},24\ \text{h}} \times S_R \times$ SOIL	—	—	B	0·001019	0·000122
$P_{10\ \text{year},24\ \text{h}} \times S_R \times$ SOIL	—	—	C	0·000655	0·000134
$P_{10\ \text{year},24\ \text{h}} \times S_R \times$ SOIL	—	—	D	0·000000	—
ΔT	1	21	—	1·398724	0·301712
$T \times \Delta T$	1	33	—	−0·052799	0·009247
R	1	13	—	0·021001	0·005840
ΔR	1	37	—	−0·300171	0·049659
$R \times \Delta R$	1	73	—	−0·000075	0·000009
E	1	129	—	20·351762	1·793082
ΔE	1	10	—	−5·131820	1·602032
$E \times \Delta E$	1	5	—	−0·685443	0·293896
$Pa \times$ SOIL	4	15	A	−0·032987	0·010837
$Pa \times$ SOIL	—	—	B	−0·024888	0·010698
$Pa \times$ SOIL	—	—	C	−0·019167	0·010598
$Pa \times$ SOIL	—	—	D	−0·017178	0·010581
$Pa \times E$	1	26	—	−0·034492	0·006779
$Pa \times T$	1	44	—	0·003171	0·000477
$Pa \times \Delta R$	1	66	—	0·000534	0·000066

The resulting regression relationship is of the form EPY $= C_1 \times X_1 + C_2 \times X_2 + \ldots + C_{16} \times X_{16}$, where C_j is the listed coefficient for effect j, X_j, for $j = 1 - 16$. When part of the effect is SOIL, the coefficient value used depends on the soil hydrologic group, so there are really four choices each for C_3, C_4, and C_{13}.
[a] Refer Nomenclature for definition of abbreviations
[b] Ratio of effect mean square to residual error mean square; all statistical tests were made using partial sums of squares, which represent the contribution of each term to the model after considering all other terms so that the order of term addition does not influence the result.

Table VI. Numerator degrees of freedom, F statistic, regression coefficients, and standard error estimates for predicting the scale parameter (σ) of a gamma distribution describing runoff event depth (mm) from the RUSLE2 databases

Effect[a]	DF	F[b]	Soil	Estimate	SE
$Pa \times Pa$	1	179	—	0·000025	0·000002
$i_R \times$ SOIL	4	12	A	0·002422	0·001617
$S_R \times$ SOIL	—	—	B	−0·002653	0·001646
$S_R \times$ SOIL	—	—	C	−0·004349	0·001842
$S_R \times$ SOIL	—	—	D	−0·008028	0·002239
$Pa \times S_R$	1	68	—	−0·000014	0·000002
$Pa \times$ SOIL	4	58	A	−0·004704	0·001673
$Pa \times$ SOIL	—	—	B	−0·003509	0·001667
$Pa \times$ SOIL	—	—	C	−0·002527	0·001660
$Pa \times$ SOIL	—	—	D	−0·001820	0·001656
$P_{10\ \text{year},24\ \text{h}}$	1	68	—	−0·126194	0·015254
R	1	58	—	0·009064	0·001186
E	1	202	—	6·696958	0·471168
$Pa \times E$	1	87	—	−0·014316	0·001531
$P_{10\ \text{year},24\ \text{h}} \times \Delta R$	1	56	—	0·000801	0·000107
$\Delta R \times \Delta T$	1	27	—	0·001534	0·000294
$R \times \Delta T$	1	16	—	−0·000038	0·000009
ΔT	1	80	—	0·323581	0·036278
ΔR	1	7	—	0·027311	0·010691
$Pa \times \Delta R$	1	108	—	−0·000166	0·000016
ΔE	1	150	—	−4·518450	0·368641
$E \times \Delta E$	1	89	—	0·762431	0·080661

The resulting regression relationship for each month i is of the form $\sigma = C_1 \times X_1 + C_2 \times X_2 + \ldots + C_{16} \times X_{16}$, where C_j is the listed coefficient for effect j, X_j, for $j = 1 - 16$. When part of the effect is SOIL, the coefficient value used depends on the soil hydrologic group, so there are really four choices each for C_2 and C_4.
[a] Refer Nomenclature for definition of abbreviations
[b] Ratio of effect mean square to residual error mean square; all statistical tests were made using partial sums of squares, which represent the contribution of each term to the model after considering all other terms so that the order of term addition does not influence the result.

EPY was set to four. The Nash–Sutcliffe model efficiency coefficient for predicting the average annual number of runoff events for all soil type and management combinations at the four locations not used in the calibration was 0·83 ($n = 64$).

Determine the gamma function scale and shape parameters describing daily runoff amounts

A gamma distribution is commonly used to fit rainfall data (Haan, 1977) and is generally defined by a scale parameter σ indicating something of the range of the values, and a shape factor α indicating the shape of the distribution. In this study, a gamma distribution was fit using Proc Univariate (SAS, 1996) to each runoff sequence with more than 6 runoff events within a 30-year AnnAGNPS simulation. Preliminary analysis indicated that for all location, soil, and management combinations the shape factor α was close to 0·5, so the gamma distribution scale parameter σ was estimated for all locations after specifying the shape parameter uniformly as 0·5. The resulting estimates of σ were then used as the dependent variable in a regression analysis conducted with Proc Mixed (SAS, 1996). The analysis resulted in a 22-parameter model ($R^2 = 0{\cdot}99$, $n = 377$) involving combinations and interactions of variables calculated from RUSLE2 databases (Table VI). All retained terms were significant at $P < 0{\cdot}01$, and included S_R, soil hydrologic group, precipitation, erosivity, temperature, and interactions and time differences between some of these. Because the resulting gamma function represented the distribution of runoff event depths given that a runoff event had occurred, we would expect that the results would be dominated by the precipitation values, which was the case, moderated by the primary factors controlling the resulting CN. In the RUSLE2 implementation, if the predicted scale parameter σ was <2 mm, σ for that location, soil, and management was set to 2 mm. The Nash–Sutcliffe model efficiency coefficient for predicting the gamma distribution scale parameter for all 16 combinations of soil and management at the 4 locations not used in the calibration was 0·83 ($n = 64$).

Determine the RP of the largest storm in a representative storm sequence

The default RP of the largest expected annual runoff event was set to 1·0 year. However, in the RUSLE2 implementation, this parameter can be varied by the user to investigate the effect of larger maximum events.

Determine the magnitude of the maximum annual runoff event

The size of a runoff event with a specified RP (year), was calculated as:

$$Q_{ev} = \Gamma^{-1}(Pr, \alpha) \times \sigma \quad (5)$$

where $Pr = 1 - 1/(\text{RP} \times \text{EPY})$ is the probability that an event will be smaller than the specified event within a gamma cumulative distribution function with shape parameter α and scale parameter σ, and Γ^{-1} indicates we are taking the inverse of the gamma function. Thus, for a 10-year RP at a location with 50 EPY, $Pr = 0{\cdot}998$; for a 1·0-year RP at a location with 50 EPY, $Pr = 0{\cdot}98$; and for a 1·0-year RP at a location with 25 EPY, $Pr = 0{\cdot}96$. As mentioned above, the maximum event was taken as the 1-year runoff event ($Q_{1\ \text{year},24\ \text{h}}$).

Determine the representative sequence of runoff events

To derive the sequence of significant runoff events, the monthly runoff estimates Q_i were disaggregated to daily runoff values using standard RUSLE2 procedures (USDA-ARS, 2008, section 3·1). The ratio of $Q_{1\ \text{year},24\ \text{h}}$ to the maximum daily runoff amount in the disaggregated runoff record was then termed R_Q and was used in two ways: (1) as a magnitude factor to convert daily runoff to representative event runoff, Q_{ev} and (2) as the basis for determining the period between representative runoff events. The number of events in the representative storm sequence was determined by rounding down the quotient of 365 days divided by R_Q, and then dividing 365 days by the resulting number of events. Taking the first event day as the date of maximum disaggregated daily runoff, the quotient was sequentially added, with each sum rounded down to determine event dates. On each event day, the depth of disaggregated daily runoff is multiplied by R_Q to calculate event runoff depth. This process resulted in the largest event being equal to $Q_{1\ \text{year},24\ \text{h}}$, and the sum of all events very closely approximating the AnnAGNPS results for annual runoff for the location, soil, and management.

Table VII shows the runoff parameter results for the four validation sites, comparing the input rainfall/runoff sets (in this case developed using AnnAGNPS) to the values resulting from the representative storm sequence as described previously. These results show very close matches, not only in the actual calculated runoff values, but even in the number of storms seen at the various locations.

Table VII. Thirty-year average AnnAGNPS averages and RUSLE2 regression predictions of CN, annual runoff, the gamma distribution scale factor, and the number of runoff events per for spring plow maize yielding 7 Mg ha^{-1} on a hydraulic class C soil at four locations that were not in the calibration data set

County State	Dare NC	Tulsa OK	Ingham MI	Spokane (*R*16–18) WA
	AnnAGNPS averages			
annual rainfall (mm)	1284	1078	739	433
Average CN	86	80	82	79
annual runoff (mm)	292	180	68	28
Gamma distribution σ (mm)	11·5	12·2	5·1	4·5
EPY (year^{-1})	50·7	29·7	26·0	12·5
	RUSLE2 storm sequence approach			
annual rainfall (mm)	1316	988	786	435
Average CN	87	85	83	77
annual runoff (mm)	311	192	72	35
Gamma distribution σ (mm)	11·6	9·9	3·6	3·7
EPY (year^{-1})	57·0	31·8	25·1	9·9

Determine precipitation amount of each event

Event precipitation amounts, P_{ev}, were calculated from event runoff by using the quadratic formula to solve Equation (2) for P, using an event S_{ev} defined as the product of the disaggregated daily S_{Ri} calculated from the RUSLE2 disaggregated CN, times the disaggregated S_i/S_A on the event date.

Determine the normal precipitation that occurs between runoff events

The normal precipitation between runoff events, P_{ei}, was determined by summing the disaggregated snowpack adjusted precipitation values between sequential runoff event dates.

Determine the event erosivity density multiplier

The ratio of normal rainfall between events to each event's precipitation was termed the erosivity density multiplier, $\text{edm}_{ev} = P_{ei}/P_{ev}$. Calculating EI30_{ev} by multiplying P_{ev} times the disaggregated daily erosivity density on the event day, E_{ev}, and edm_{ev} ensured that the sum of the rainfall erosivity for the representative event sequence would approximately equal the normal rainfall erosivity for the location. In this way, the annual sheet and rill erosion calculated for the representative event sequence will be shown to be very close to the normal RUSLE2 estimate.

CALCULATING EVENT SEQUENCE SHEET AND RILL EROSION

As RUSLE2 calculates sheet and rill erosion based on rainfall erosivity rather than runoff amounts, a procedure was needed to transform the runoff event sequence back into a sequence of rainfall erosivity events.

TEST CASE: RUNOFF AND EROSION FROM PLOTS AT HOLLY SPRINGS, MS

We demonstrate the procedure of calculating a runoff event sequence and using it to calculate sheet and rill erosion with RUSLE2 by representing the erosion plots reported and discussed in detail by Dabney *et al.* (2009). The plots were 22·1-m long hillslopes with 5% steepness cropped to conventional till (CT) or NT cotton from

Table VIII. Input climate data derived from RUSLE2 databases for Marshall County, MS, USA, and *P*a, the RUSLE2 rainfall adjusted for snowpack accumulation and melting

Annual data					
$P_{10\text{ year},24\text{ h (mm)}}$	T (°C)	P (mm)	R (MJ mm ha^{-1} h^{-1})	E (MJ ha^{-1} h^{-1})	Pa (mm)
145	15·5	1390	6360	4·7	1390

Month	T_i (°C)	P_i (mm)	EI30$_i$ (MJ mm ha^{-1} h^{-1})	E_i (MJ ha^{-1} h^{-1})	Pa$_i$ (mm)	Predicted[a] S_i/S_A
January	3·1	110	292	2·6	109	0·57
February	5·5	118	358	3·0	126	0·50
March	10·7	145	563	3·9	145	0·60
April	15·9	135	616	4·6	135	0·83
May	20·2	138	725	5·3	138	1·13
June	24·3	93	611	6·5	93	1·41
July	26·3	107	792	7·4	107	1·50
August	25·6	85	557	6·6	85	1·55
September	22·2	94	525	5·6	94	1·51
October	15·9	84	384	4·6	84	1·24
November	10·6	137	550	4·0	137	1·02
December	5·5	144	387	2·7	138	0·63
—	ΔT	—	—	ΔE	ΔP	—
—	23·2	—	—	4·8	61	

Refer Nomenclature for definition of abbreviations.
[a] Predicted antecedent soil water content adjustment to S based on the regression model reported in Table II.

1991 to 1997 in Marshall County, MS, USA. Table VIII summarizes the climate parameters for Marshall County, MS, USA, obtained from the RUSLE2 database. The climate of Marshall County, MS, was not part of the calibration data set, but it is similar to the climate of Panola County, MS, (Figure 1) which was part of the calibration data set. Comparison of the input monthly RUSLE2 precipitation data (Table VIII, column 3) with the snowpack adjusted Pa_i values (column 6) shows that in Marshall County, MS, snowpack adjustment resulted in only a slight decrease in effective precipitation during December and a slight increase during February.

Results reported are available in the 'storm sequence' tab of the 'ARS Science May 2010' template of the latest version of RUSLE2 (USDA-ARS, 2010). RUSLE2 predicted that the CN was higher for CT than for NT, and the regression models presented in Tables III, V, and VI predicted how tillage system affects runoff-related parameters (Table IX). The gamma distribution scale parameter σ varied depending on whether the long-term average RUSLE2 climate file or the actual weather observed during the 7-year study was used. Using long-term average weather, σ was 14·9 mm for CT *versus* 14·2 for NT. CT was predicted to have 48 runoff EPY compared to only 43 for NT. Of those events, 17 events spaced 22 days apart were considered to be significant events in CT, compared with 16 events spaced 23 days apart for NT. The peak runoff event occurred in December.

Table IX also reports predicted and observed annual average runoff, sheet and rill erosion, and sediment concentration values for CT and NT cotton. As reported by Dabney *et al*. (2009), using long-term average climate records RUSLE2 predicted sheet and rill erosion was 76% of measured annual averages for CT, and 114% of the measured value for NT. However, RUSLE2-predicted (like AnnAGNPS-predicted) runoff was lower than observed annual averages for both tillage systems, so sediment concentration estimates were higher than measured values. This discrepancy is discussed in the following text.

Predicting monthly runoff for the test case

Monthly runoff predictions and selected intermediate results are reported in the bottom section of Table IX. The monthly variation in the RUSLE2 S_{Ri}, values reflect the monthly changes to the CN calculated internally by RUSLE2 in response to management operations that affect surface roughness, surface residue cover, and soil biomass. For CT, the RUSLE2 CN goes down (S_{Ri} increases) after tillage in April, while for NT, S_{Ri} is highest during the winter after residue addition associated with the cotton harvest. It is noteworthy that the relative changes in S_{Ri} are smaller than, and out of phase with, the monthly variation in the S_i/S_A ratio that reflects antecedent soil water content effects (Table VIII). The product $S_{Ri}S_i/S_A$ reflects the combined influences of soil, management, and climate, including the water balance adjustment to the CN, and leads to the estimation of q_i and monthly runoff (using Table III).

Figure 3 A shows the monthly RUSLE2 precipitation and predicted and observed monthly runoff amounts from

Table IX. Runoff storm sequence parameter estimates based on normal RUSLE2 climate files or the 7-year average monthly rainfall measured during the study, measured 7-year annual average runoff and erosion, and monthly storm sequence runoff predictions for CT and NT cotton on hydraulic class C soil on a 5%, 22.1-m long plot in Marshall County, MS

	Annual results			
Tillage system	CT cotton		NT cotton	
Precipitation record	RUSLE2	7 year	RUSLE2	7 year
Average RUSLE2 CN	84	84	77	77
Storage index S_R (mm)	49	47	78	76
Gamma distribution σ (mm)	14·9	19·6	14·2	18.9
Runoff EPY (year^{-1})	48	37	43	32
Predicted $Q_{1\ \mathrm{year},24\ \mathrm{h}}$ (mm)	40	49	37	45
Gully EPY(year^{-1})	17	18	16	17
Period between gully events (days)	21·5	20·3	22·8	21.5
Day of peak runoff	12 December	17 March	9 December	9 April
RUSLE2 runoff (mm year^{-1})	349	293	290	230
RUSLE2 erosion (Mg ha^{-1} year^{-1})	44·5	63·4	6·1	9.2
RUSLE2 concentration (ppm)	13 000	21 600	2 110	3 980
Measured runoff (mm year^{-1})	619		378	
Measured erosion (Mg ha^{-1} year^{-1})	61.1		5.9	
Measured concentration (ppm)	9 870		1 570	

	Monthly predicted results for normal RUSLE2 climate input							
	CT cotton				NT cotton			
Month	S_{Ri} (mm)	$S_{Ri}S_i/S_A$ (mm)	q_i (mm)	Runoff (mm)	S_{Ri} (mm)	$S_{Ri}S_i/S_A$ (mm)	q_i (mm)	Runoff (mm)
January	43	25	93	39	85	49	81	34
February	42	21	110	50	86	43	100	44
March	41	24	130	56	87	51	110	48
April	38	31	110	40	86	71	84	30
May	67	75	71	21	76	86	65	20
June	60	85	25	11	73	100	20	11
July	53	79	35	11	71	110	24	9
August	47	74	22	12	68	110	12	11
September	45	69	31	11	71	110	17	9
October	44	55	35	14	77	95	20	11
November	43	44	95	31	82	84	70	23
December	44	27	120	51	86	54	100	44

CT and NT cotton. Comparison of predicted and observed monthly runoff patterns helps to explain the underestimation of annual runoff. As part of the discrepancy might be due to the differences between observed average rainfall patterns during the 7 year of observations and the long-term mean reflected in the RUSLE2 database, we also present observed 7-year average monthly rainfall and predictions based on measured rainfall amounts and measured erosivity density (Figure 3B). Using either long-term average or measured rainfall resulted in substantially underestimated runoff during the summer, which is a period of higher than average erosivity density (Table VIII). It may be that the RUSLE2 relationships underpredict runoff because the AnnAGNPS predictions upon which the regression relationships are based do not reflect the influence of rainfall intensity on CN, which is sometimes important (Hawkins, 1982; Hjelmfelt, 1991; Smith, 1997; Jain *et al*., 2006). The RUSLE2 monthly erosivity density values are directly proportional to the average monthly 30-min rainfall intensity (USDA-ARS, 2008) and thus reflect seasonal variation in rainfall intensity at a location. Therefore, we tested an adjustment to the S based on monthly erosivity density, E_i:

$$S_{ei} = \left(1 - \frac{(E_i - 3)}{14}\right)^3 \qquad \text{if } E_i > 3 \tag{6}$$

$$S_{ei} = 1 \qquad \text{if } E_i <= 3$$

The dimensionless factor S_{ei} is multiplicative with the adjustment reflecting antecedent water content, so an adjusted monthly S was calculated as $S_{ei}S_{Ri}S_i/S_A$. This modification reduced the S and increased predicted runoff when monthly erosivity density exceeded 3 MJ ha^{-1} h^{-1}. Applying this adjustment improved the agreement of measured and predicted monthly runoff (Figure 3C). When the S_{ei} adjustment was applied with observed rainfall (Figure 3D), the Nash–Sutcliff efficiency for predicted monthly runoff was 0·51 ($n = 24$).

Although the adjustment proposed as Equation (6) gives reasonable values over the range of erosivity

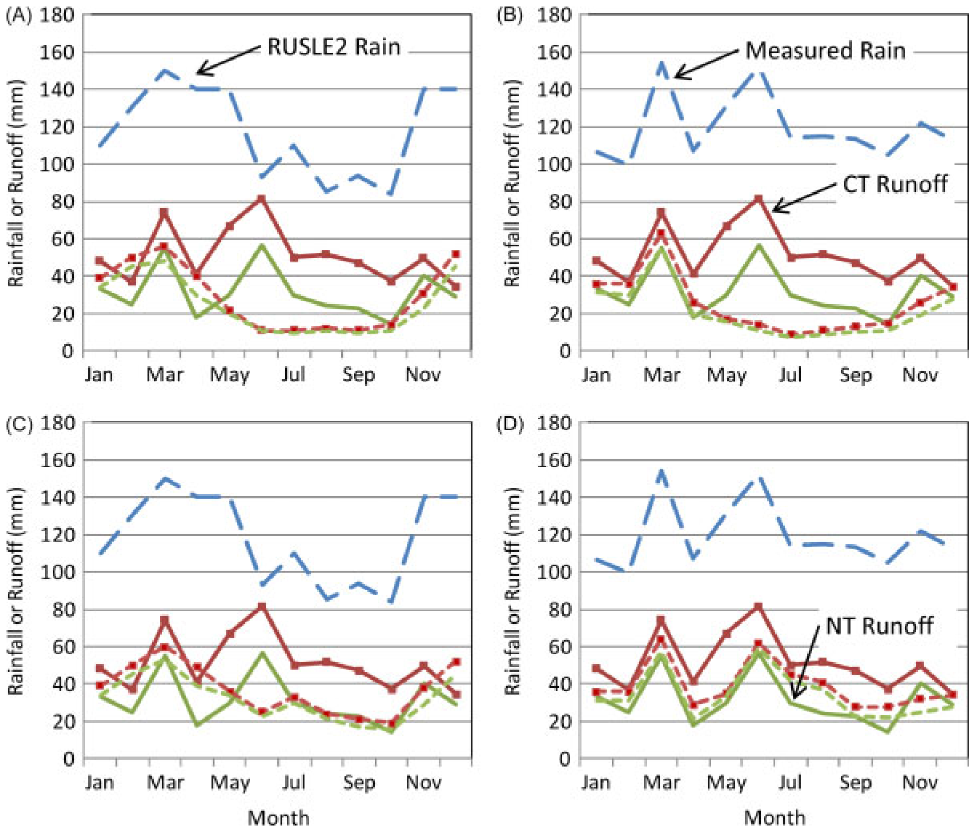

Figure 3. Monthly rainfall, measured average monthly runoff (solid lines), and predicted monthly runoff (dotted lines) at Holly Springs, MS for CT (square markers) and NT cotton: (A) predicted runoff based on RUSLE2 long-term average rainfall, (B) predicted runoff based on measured rainfall, (C) predicted runoff based on RUSLE2 rainfall with $S_{\mathrm{R}i}S_i/S_{\mathrm{A}}$ adjusted using S_{ei} from Equation (6), and (D) predicted runoff based on measured rainfall with $S_{\mathrm{R}i}S_i/S_{\mathrm{A}}$ adjusted using S_{ei} from Equation (6)

density values encountered in the RUSLE2 database, it is based on a limited data set and more testing is needed. The influence of rainfall intensity on infiltration/runoff partitioning is likely to vary with the amount of residue cover, the susceptibility of the soil to crusting, and other factors. The fact that the watershed level comparison in Panola County did not show an underprediction of summer runoff (Figure 1) suggests that a rainfall intensity adjustment may be more important at the plot scale than at the watershed scale. Nevertheless, the Holly Springs data set suggests that adjustment of predicted runoff based on rainfall intensity can improve model efficiency. Underestimation of extreme events by GEM may be another contributing factor as several studies have found that weather generators are better at predicting monthly means than at matching extreme events (Johnson *et al.*, 1996; Meyer *et al.* 2008).

Predicting a runoff event sequence for the test case

Figure 4A shows the disaggregated RUSLE2 erosivity density for Marshall County, MS and the disaggregated daily runoff amounts for CT cotton with and without the proposed S_{ei} adjustment. Although using the S_{ei} adjustment and actual measured rainfall data improved agreement with measured monthly runoff patterns, we chose the normal long-term average RUSLE2 rainfall to demonstrate estimation of a representative event sequence. Without the S_{ei} adjustment, the single

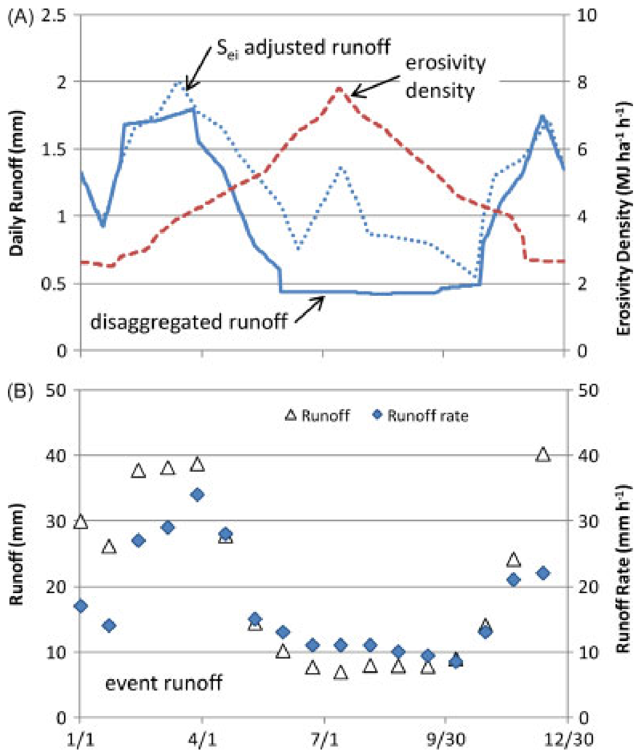

Figure 4. RUSLE2 disaggregated input erosivity density and predicted daily runoff with and without the S_{ei} (Equation (6)) adjustment (A), and the representative event sequence runoff amounts and rates (B) for CT cotton grown on hydraulic class C soil in Marshall County, MS, USA. The maximum runoff event depth is equal to $Q_{1\ \mathrm{year},24\ \mathrm{h}}$ (40 mm, Table IX)

Table X. Illustration of the predicted runoff event sequence for CT cotton grown on a hydraulic class C soil with a 5%, 22.1-m long slope in Marshall County, MS, USA:

Date	Event runoff (mm)	Event duration (min)	Runoff rate (mm h^{-1})	P_{ev} (mm)	E_{ev} (MJ ha^{-1} h^{-1})	edm_{ev}	$EI30_{ev}$ (MJ mm ha^{-1} h^{-1})	Sheet/rill erosion (Mg ha^{-1})	Concentration (g m^{-3})
7 January	27	110	15	48	2·7	2·1	270	1·2	4 420
31 January	31	97	19	52	2·8	1·6	240	1·1	3 570
25 February	37	81	27	58	3·3	1·9	370	1·9	5 120
21 March	40	73	32	61	4·0	1·8	450	2·2	5 550
14 April	31	61	30	56	4·5	2	500	4·9	16 100
9 May	19	57	20	62	5·3	1·8	590	7·4	40 100
2 June	10	47	13	51	6·2	2	650	8·1	80 900
26 June	9·9	41	14	51	6·6	1·4	490	4·3	43 300
21 July	9·8	38	15	48	7·4	1·8	640	3·2	32 300
14 August	9·8	44	13	47	7·1	1·5	500	1·7	17 000
7 September	10	48	12	46	5·7	1·5	380	2·4	23 900
2 October	11	58	11	43	5·0	1·8	390	2·5	22 800
26 November	11	65	10	41	5·2	1·5	330	1·4	12 400
19 November	26	69	23	58	4·3	1·8	440	2·8	10 700
14 December	41	110	22	64	2·6	1·8	290	1·7	4 130

Runoff depth (open triangles in Figure 2C), duration, and rate (filled triangles in Figure 2C); corresponding event precipitation (P_{ev}), disaggregated erosivity density (E_{ev}), erosivity density multiplier (edm_{ev}); and resulting rainfall erosivity ($EI30_{ev}$), event sheet and rill erosion, and apparent sediment concentration in runoff. Refer Nomenclature for definition of abbreviations.

largest daily disaggregated runoff value for CT cotton was 1·9 mm day^{-1} on 12 December. The ratio of $Q_{1\ year,24\ h}$ (40 mm, Table IX) to this maximum daily runoff value yielded $R_Q = 21{\cdot}5$ days, which is the magnitude factor for transforming disaggregated daily runoff values to event values. The number of EPY is determined by rounding down the quotient of 365 days divided by R_Q, yielding 17 events in this example. In order to determine the sequence of event dates (Table X), the time between events is determined by dividing 365 days by the number of events (17), and then sequentially adding the quotient (21·5 days) to the day of the first event, which is taken as the day of maximum runoff (12 December in this example). Each sum is rounded down to determine event dates, leading to intervals between events of either 21 or 22 days. On each event date, the value of disaggregated runoff (Figure 4A) was multiplied by the magnitude factor (21·5 days in this example) to calculate event runoff amounts. The event runoff predictions are illustrated with open triangles in Figure 4B, which are observed to follow the predicted monthly (Figure 3A) and disaggregated daily (Figure 4A) runoff patterns. The largest of the 17 events in the representative sequence has a runoff amount equal to $Q_{1\ year,24\ h}$ (40 mm), but there are several similarly sized ($4 > 37$ mm) events in the sequence. If the S_{ei} adjusted runoff had been used, the higher peak disaggregated daily runoff value (2·0 mm on 21 March) would have led to a larger set of events (18 EPY), but the size of largest event would have remained the same and equal to estimated $Q_{1\ year,24\ h}$.

In the CT cotton example, the sum of the sheet and rill event erosion estimates for the event sequence in Table X is 45·4 Mg ha^{-1} $year^{-1}$ and is within 3% of the 44·4 ha^{-1} $year^{-1}$ calculated by normal RUSLE2 procedures (Table IX), demonstrating that the event approach does not significantly alter hillslope erosion estimates.

The apparent sediment concentrations reported in Table X were determined from the RUSLE2 calculated event sheet and rill erosion and predicted event runoff. These values can serve as inputs to a channel erosion model.

LINKAGE WITH A RUNOFF-DRIVEN MODEL

As the procedure represented previously appears to provide good runoff and erosion results both for the validation RUSLE runs and a specific 'real world' test case, the remaining success criterion defined at the beginning was to show that the representative storm sequence could be used to drive an existing runoff-based model.

To demonstrate the ability to link RUSLE2 to a process-based, runoff-driven channel erosion model, we chose to use the well known CREAMS formulation (Foster *et al.*, 1980a) which is essentially the same theory used in the watershed version of WEPP (Ascough *et al.*, 1997) and in GeoWEPP (Renschler, 2003) to estimate channel and ephemeral gully erosion. In the CREAMS scheme, ephemeral gullies grow by first incising until they reach a non-erodible layer and then widening on top of that layer until the shear stress at the base of the channel sidewall is equal to the critical shear stress, τ_c, of the soil (Foster, 2005). Haan *et al.* (1994) provided a clear conceptual derivation of the channel erosion theory represented by the equations used in CREAMS. The theory is based on several assumptions: (1) that Manning's equation applies, (2) that the shear stress distribution around the cross section of a channel can be represented by a dimensionless distribution, (3) that the soil consists of a uniform erodible layer with characteristic erodibility and critical shear stress values overlying a non-erodible layer at a specified depth, (4) that potential detachment rate is proportional to excess shear stress, (5) that actual detachment is proportional to the unsatisfied transport capacity of a steady-state runoff rate, (6) that transport capacity can be determined by the set of equations proposed by Yalin (1963), and (7) that deposition occurs if sediment load exceeds transport capacity. In application, shear stress is calculated for an effective steady state runoff rate using channel slope, Manning's n, and channel dimensions to determine velocity and hydraulic radius, and the assumption that average shear stress is proportional to the product of slope, hydraulic radius, and the unit weight of water. Application of detachment/transport coupling relationships together with the assumption of a rectangular channel shape leads to the determination of an effective channel width during the incision phase that depends on critical shear stress but not on soil erodibility. The time to reach the non-erodible layer is determined (depending on available transport capacity and soil erodibility) and the total time of the event is divided into a period before reaching the non-erodible layer and a period after reaching the layer. After the non-erodible layer is reached, the channel widens, asymptotically approaching the width where shear stress at the toe of the channel bank is equal to the specified critical stress. This scheme allows application of a rapidly solved analytical calculation of soil loss at several cross sections down the channel. Two limitations of this approach are that the non-erodible layer remains forever non-erodible, and any deposition of sediment predicted from one event is neglected in subsequent erosion calculations

To drive CREAMS, representative event runoff depths had to be transformed into runoff rates. In RUSLE2, the duration of the $P_{10\ \mathrm{year},24\ \mathrm{h}}$ index storm is assumed to be 60 min. We modified this by multiplying this base duration by the ratio of the annual average erosivity density (4·7 MJ ha^{-1} h^{-1} in Marshall County, MS; Table VIII) to the daily disaggregated erosivity density on each event day. This adjustment was based on the logic that runoff occurs at higher rates during periods of the year with higher than average erosivity density. The result is illustrated in Figure 4B, where the solid diamonds (runoff rate mm h^{-1}) are higher than the open triangles (runoff amount per day) when $E_{\mathrm{ev}} > 4{\cdot}7$ and are lower than when $E_{\mathrm{ev}} < 4{\cdot}7$ MJ ha^{-1} h^{-1}.

PREDICTING EPHEMERAL GULLY EROSION: A HYPOTHETICAL EXAMPLE

We used CREAMS driven by the new RUSLE2 storm sequence to calculate potential ephemeral gully erosion for a hypothetical 5 ha field with a silt loam soil cropped to CT or NT cotton in Marshall County, MS, USA, with the field bisected by a potential ephemeral gully channel. Hillslopes on either side of the gully were modelled to represent the 22·1-m long CT and NT erosion plots simulated previously, so the length of the channel was about 1130 m. A non-erodible layer was assumed at 0·05-m depth. Computations were done at four ephemeral gully thalweg slopes (0·5, 1, 2, and 5%). Soil erodibility and critical shear stress, τ_c, values (Table XI) were estimated as the average of values suggested USDA-SCS (1992) for tilled and NT cropland.

Table XI. Predicted ephemeral gully erosion for a 1130-m channel with various thalweg gradients (s) with CT and NT cotton on hydraulic class C soil and 5% slope, 22.1-m long hillslopes on both banks in Marshall County, MS, USA

	Input parameters	
	CT cotton	NT cotton
Assumed erodibility (g N^{-1} s^{-1})	21	2·3
Assumed τ_c (Pa)	2·1	11
Non-erodible layer depth (m)	0·05	0·05
Initial top width (m)	0·03	0·03
	Annual channel erosion	
Gully, $s = 0{\cdot}005$ (Mg ha^{-1} year^{-1})	70·6	4·3
Gully, $s = 0{\cdot}01$ (Mg ha^{-1} year^{-1})	85·3	12·0
Gully, $s = 0{\cdot}02$(Mg ha^{-1} year^{-1})	93·8	17·1
Gully, $s = 0{\cdot}05$ (Mg ha^{-1} year^{-1})	103	21·9

Predicted event ephemeral gully and RUSLE2 sheet and rill erosion are illustrated in Figure 5. It may be noted that, rather than being associated mainly with the largest events, predicted ephemeral gully erosion was concentrated in the first significant runoff events following tillage. Total annual ephemeral erosion estimates are presented in Table XI exceeded average annual sheet and rill erosion (Table IX) in this hypothetical field for all cases where channel slope was at least 1%. As no long-term database ephemeral gully erosion rates are available for comparison with the simulations, the ephemeral gully erosion predictions discussed are regarded as conceptual. Their magnitude suggests that ephemeral gullies make an important contribution to field scale sediment delivery and underscores the need for more field measurements of this process.

SUMMARY AND CONCLUSIONS

RUSLE2 already uses runoff estimates to model transport and depositional processes on the hillslope as sediment moves through areas of higher flow retardance or lower steepness. It does this by routing runoff from an index storm down the slope every day to calculate a design sediment delivery ratio, then applying that ratio to the actual daily estimated erosion to derive a sediment delivery estimate. This approach enables reasonable and robust estimation of sediment delivery for the conservation planning process on the hillslope. This approach cannot be used, however, when estimating runoff-driven phenomena such as ephermal gully erosion or phosphorus transport, because in such cases the actual absolute runoff rate

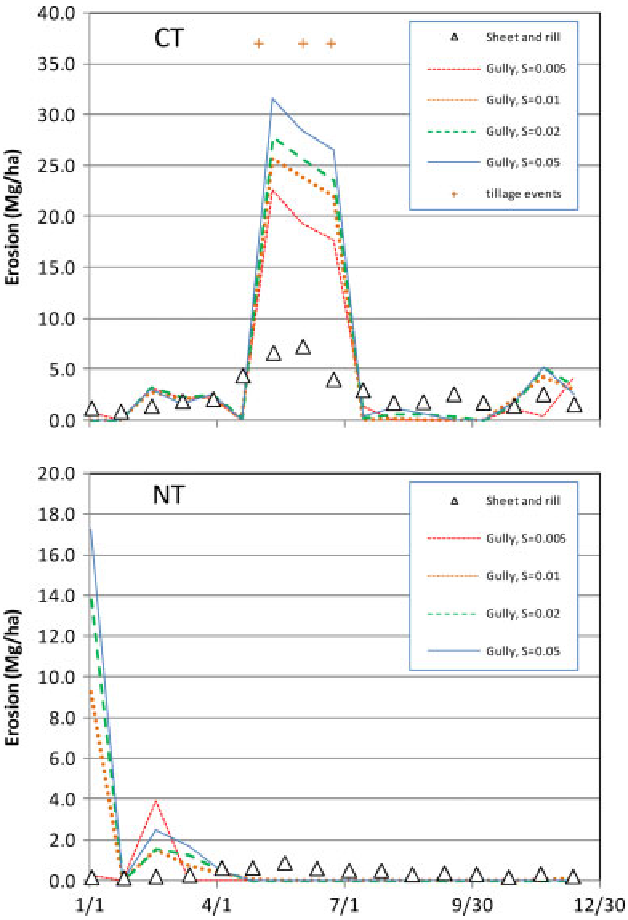

Figure 5. RUSLE2 predicted event sheet erosion for CT and NT cotton and predicted ephemeral gully erosion for channel grades of 0·005–0·05. Tillage events that refill the ephemeral gully in CT management are also shown

must be known to determine channel size and resultant flow velocities, shear stresses, sediment transport capacities, etc.

The objective of this study was to develop a process to provide an average annual representative runoff event series that could be put into RUSLE2 in place of the current daily disaggregated climate information. Event characteristics would be estimated based on information already available in the RUSLE2 climate database. The regression relationships to do this were generated using a series of rainfall/runoff data for extended periods in multiple locations across the continental United States. Actual data sets could have been used for this regression, but because such data sets are limited, the sets were generated using AnnAGNPS, which uses the GEM as a stochastic climate generator and a CN approach to estimate runoff.

Regression relationships developed using available RUSLE2 database information reliably approximated the mean monthly runoff, annual runoff event frequency, and a gamma distribution function scale parameter that characterized 30-year stochastic runoff predictions generated using the AnnAGNPS model. With these parameters, the size of the runoff event with any RP can be estimated, allowing RUSLE2 to be used in risk assessment calculations. By assuming that the largest in a series of runoff events that cause annual average ephemeral gully erosion had a 1-year RP and that the depths of the periodic runoff events were proportional to long-term average daily runoff amounts, the parameters were used to estimate the dates and sizes of a representative runoff event sequence within RUSLE2. The largest event in the sequence is equal to $Q_{1\text{ year},24\text{ h}}$ and the sum of all events approximates the annual runoff for any location, soil, and management combination. The validity of the procedure was tested by comparison to the input runoff values, comparison to current RUSLE erosion estimates, and by linking the representative event sequence hillslope runoff, sediment yield, and sediment size distribution to the CREAMS physically based channel erosion and sediment transport model, which produced reasonable results.

Comparison of predicted runoff amounts with plot observations suggested that the procedures developed may underestimate runoff during periods of higher than average rainfall intensity. A modified procedure was suggested that improved the fit to measurements at Holly Springs, but more testing is needed to determine the generality of the formulation. The general agreement between uncalibrated predictions and observations during winter months, and the correct trend in relative runoff amounts between CT and NT management, suggests that the AnnAGNPS and RUSLE2 models adequately represented the critical processes needed to reflect the effects of management alternatives on trends in runoff and erosion.

The methods presented provide a means of linking of runoff-driven phenomena such as ephemeral gully erosion with RUSLE2 as the sum of a location-specific representative sequence of runoff events.

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NOMENCLATURE

E —average annual erosivity density for a location (erosivity per mm of rainfall, MJ ha^{-1} h^{-1})

E_i —average monthly erosivity density (MJ ha^{-1} h^{-1})

ΔE —the range between the minimum and maximum monthly erosivity density (MJ ha^{-1} h^{-1})

E_{ev} —daily disaggregated erosivity density on the date of a runoff event (MJ ha^{-1} h^{-1})

$\mathrm{edm}_{\mathrm{ev}}$ —an erosivity density multiplier used with P_{ev} and E_{ev} to calculate $\mathrm{EI30}_{\mathrm{ev}}$ (dimensionless)

$\mathrm{EI30}_i$ —RUSLE2 monthly rainfall erosivity (MJ mm ha^{-1} h^{-1})

$\mathrm{EI30}_{\mathrm{ev}}$ —RUSLE2 rainfall erosivity on date of runoff event (MJ mm ha^{-1} h^{-1})

EPY —number of runoff events per year

Pr —$1-1/(\mathrm{RP} \times \mathrm{EPY})$ is the probability that an event will be smaller than the event with the specified RP

P —RUSLE2 average annual precipitation for a location (mm)

P_i —RUSLE2 monthly precipitation depth (mm)

$\delta P\mathrm{s}_i$ —monthly change in snow pack from the previous month (positive when the snowpack is increasing)

$P\mathrm{a}_i$ —RUSLE2 monthly precipitation depth after adjusting for snowpack ($P\mathrm{a}_\mathrm{i} = P_\mathrm{i} - \delta P\mathrm{s}_\mathrm{i}$, mm)

$\Delta P\mathrm{a}$ —the range between the minimum and maximum monthly snowpack adjusted precipitation

$\mathrm{dev}P\mathrm{a}_i$ —the deviation in monthly adjusted RUSLE2 precipitation from the location's average monthly adjusted precipitation

$P_{10\ \mathrm{year},24\ \mathrm{h}}$ —RUSLE2 10-year, 24-h precipitation depth for a location ('index storm', mm)

P_{ei} —normal snowpack adjusted precipitation expected between runoff event $i-1$ and event I (mm)

P_{ev} —event precipitation depth calculated from Q_{ev} (mm) and Sev

$Q_{1\ \mathrm{year},\ 24\ \mathrm{h}}$ —depth of a 24-h runoff event with an expected recurrence interval of 1 year (mm)

Q_{ev} —the event runoff depth (mm),

q_i —an index runoff depth defined through Equation (3) that equals the runoff that would be predicted if a month's precipitation fell as one storm (mm)

R —annual rainfall erosivity for a RUSLE2 location ($R = \Sigma\ \mathrm{EI30}_i$, MJ mm ha^{-1} h^{-1})

ΔR —the range between the minimum and maximum $\mathrm{EI30}_i$ (MJ mm ha^{-1} h^{-1})

RP —return period (year)

R_Q —the ratio of $\mathrm{Q}_{1\ \mathrm{year},\ 24\ \mathrm{h}}$ to the maximum daily disaggregated runoff amount (days)

s —channel grade

S —storage index, a transform of CN through Equation (1) (mm)

S_{ei} —a proposed adjustment to S defined through Equation (6) that reflects rainfall intensity effects on S (dimensionless)

S_{ev} —the S on the date of a runoff event

S_i/S_A —the ratio of average monthly to annual average S determined from AnnAGNPS results (dimensionless)

S_R —the annual average S corresponding to the average annual CN predicted internally by RUSLE2 for a given soil, management and climate combination (mm)

$S_{\mathrm{R}i}$ —the monthly S corresponding to the average monthly CN predicted internally by RUSLE2 for a given soil, management and climate combination (mm)

SOIL —the soil hydrologic class (A, B, C, or D)

T —average annual temperature for a RUSLE2 location (°C)

T_i —the average monthly RUSLE2 temperature (°C)

ΔT —the range between the minimum and maximum monthly temperature

$\mathrm{dev}T_i$ —the deviation of monthly RUSLE2 average temperature from annual mean temperature

δT_i —the change in T_i from the previous month ($\delta T_i = T_i - T_{i-1}$)

α —shape factor of a gamma distributions of runoff events for all location, soil, and management

σ —scale parameter of a gamma distribution (mm)

τ_c —critical shear stress of soil (Pa)

REFERENCES

ASCE. 2009. *Curve number hydrology, state of the practice*. Hawkins RH, Ward TJ, Woodward DE, Van Mullem JA (eds). American Society of Civil Engineers: Reston, VA; 106 pp.

Ascough JC, Baffaut C, Nearing MA, Liu BY. 1997. The WEPP watershed model: I. Hydrology and erosion. *Transactions of the American Society of Agricultural Engineers* **40**(4): 921–933.

Bingner RL, Theurer FD. 2001. AnnAGNPS: estimating sediment yield by particle size for sheet and rill erosion. In *Proceedings of the 7th Federal Interagency Sedimentation Conference*. Reno, NV; 25–29 March 2001, I-1–I-7.

Dabney SM, McGregor KC, Wilson GV, Cullum RF. 2009. How management of grass hedges affects their erosion reduction potential. *Soil Science Society of America Journal* **73**(1): 241–254.

Foster GR. 2005. Modeling ephemeral gully erosion for conservation planning. *International Journal of Sediment Research* **20**(3): 157–175.

Foster GR, Lane LJ, Nowlin JD, Laflen JM, Young RA. 1980a. A model to estimate sediment from field-sized areas. In *CREAMS: A Field-Scale Model for Chemicals, Runoff, and Erosion from Agricultural Management Systems*: Volume 1, *Model Documentation*, Knisel WG (ed.). 36–64. U.S. Department of Agriculture Conservation Research Report Number 26, 643 pp.

Foster GR, Lane LJ, Nowlin JD. 1980b. A model to estimate sediment from field-sized areas: selection of parameter values. In *CREAMS: A Field-Scale Model for Chemicals, Runoff, and Erosion from Agricultural Management Systems*: Volume 2, User Manual, Knisel WG (ed). 193–281. U.S. Department of Agriculture Conservation Research Report Number 26: Washington, D.C.; 643 pp.

Foster GR, Toy TJ, Renard KG. 2003. Comparison of the USLE, RUSLE1·06c, and RUSLE2, for application to highly disturbed land. In: *First Interagency Conference on Research in the Watersheds*, USDA-Agricultural Research Service: Washington, DC; 154–160.

Garen DC, Moore DS. 2005. Curve number hydrology in water quality modelling: uses abuses and future directions. *Journal of the American Water Resources Association* **41**: 377–388.

Gordon LM, Bennett SJ, Bingner RL, Theurer FD, Alonso CV. 2007. Simulating ephemeral gully erosion in AnnAGNPS. *Transactions of the ASABE* **50**(3): 857–866.

Haan CT. 1977. *Statistical Methods in Hydrology*, Iowa State University Press: Ames, IA; 378 pp.

Haan CT, Barfield BJ, Hayes JC. 1994. *Design Hydrology and Sedimentology for Small Catchments*. Academic Press: San Diego, CA.

Hairsine PB, Rose CW. 1992. Modeling water erosion due to overland flow using physical principles: 2. Rill flow. *Water Resources Research* **28**: 245–250.

Harmel RD, Johnson G, Richardson CW. 2002. The GEM experience: weather generator technology development in the USDA. *Bulletin of the American Meteorological Society* **83**: 954–957.

Hawkins RH. 1982. Interpretation of source-area variability in rainfall-runoff relations. In *Rainfall–runoff relationships*, Singh VP (ed.). Water Resources Publications: Fort Collins, CO; 303–324.

Hjelmfelt AT. 1991. Investigation of curve number procedure. *Journal of Hydraulic Engineering* **117**(6): 725–737.

Jain MK, Mishra SK, Suresh Babu P, Venugopal K, Singh VP. 2006. Enhanced runoff curve umber model incorporating storm duration and a nonlinear Ia-S relation. *Journal of Hydrologic Engineering* **11**(6): 631–635.

Johnson GL, Hanson CL, Hardegree SP, Ballard EB. 1996. Stochastic weather simulation: overview and analysis of two commonly used models. *Journal of Applied Methods* **35**: 1878–1896.

Kinnell PIA, Risse LM. 1998. USLE-M: Empirical modeling rainfall erosion through runoff and sediment concentration. *Soil Science Society of America Journal* **62**: 1667–1672.

Kuhnle RA, Bingner RL, Alonso CV, Wilson CG. 2006. Goodwin Creek Experimental Watershed - effect of conservation practices on sediment load. ASABE Paper No. 062069. St. Joseph, Mich.: ASABE.

Kuhnle RA, Bingner RL, Alonso CV, Wilson CG, Simon A. 2008. Conservation practice effects on sediment load in the Goodwin Creek Experimental Watershed. *Journal of Soil and Water Conservation* **63**(6): 496–503.

Kuhnle RA, Bingner RL, Foster GR, Grissinger EH. 1995. Effect of land use changes on sediment transport in Goodwin Creek. *Water Resources Research* **32**(10): 3189–3196.

Meyer CR, Renschler CS, Vining RC. 2008. Implementing quality control on a random number stream to improve a stochastic weather generator. *Hydrological Processes* **22**: 1069–1079.

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE* **50**: 885–900.

Poesen J, Nachtergaele J, Verstraeten G, Valentin C. 2003. Gully erosion and environmental change: importance and research needs. *Catena* **50**: 91–133.

Renard KG, Foster GR, Weesies GA, McCool DK, Yoder DC, Coordinators. 1997. *Predicting soil erosion by water: A guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). U.S. Department of Agriculture, Agricultural Handbook No. 703, 404 pgs*. (http://www.ars.usda.gov/SP2UserFiles/Place/64080530/RUSLE/AH_703.pdf, accessed 3 September 2008).

Renschler CS. 2003. Designing geo-spatial interfaces to scale process models: the GeoWEPP approach. *Hydrological Processes* **17**: 1005–1017.

SAS Institute. 1996. *SAS/STAT Software: Changes and enhancements through release 6.11*. SAS Inst., Cary, N.C.

Smith RE. 1997. Discussion: runoff curve number: has it reached maturity? *Journal of Hydrologic Engineering* **2**(3): 145–147.

Street L, Quinton JN. 2001. Development of an ephemeral gully erosion model: the role of undercutting in bank failure of small channels, 338–341. In *Proceedings of the International Symposium on Soil Erosion Research for the 21st Century, 3–5 Jan 2001, Honolulu, HI*, Ascough JC, Flanagan DC (eds). American Society of Agricultural Engineers: St. Joseph, MI; 713pp.

USDA-ARS. 2008. *Draft Science Documentation, Revised Universal Soil Loss Equation Version 2*. (http://www.ars.usda.gov/sp2UserFiles/Place/64080510/RUSLE/RUSLE2_Science_Doc.pdf, accessed 15 September 2009).

USDA-ARS. 2010. *RUSLE2 version 2·0·0·0*. http://www.ars.usda.gov/sp2UserFiles/Place/64080510/RUSLE/R2ARSSCIENCE.exe, accessed 26 May 2010).

USDA-NRCS. 2004. National Engineering Handbook, Part 630, Hydrology. Chapter 9, Hydrologic Soil-Cover Complexes (210-VI-NEH, July 2004). http://policy.nrcs.usda.gov/OpenNonWebContent.aspx?content=17758.wba. [accessed: 10 July 2010].

USDA-NRCS. 2008. Revised Universal Soil Loss Equation, Version 2 (RUSLE2), Official NRCS Database, ftp://fargo.nserl.purdue.edu/pub/RUSLE2/Climate_data/. [accessed: 8 October 2010].

USDA-SCS. 1992. *Ephemeral Gully Erosion Model (EGEM)*. Version 2.0, User Manual. U.S. Department of Agriculture, Soil Conservation Service: Washington, DC; 106.

Wischmeier WC, Smith DD. 1965. *Predicting rainfall-erosion losses from cropland east of the Rocky Mountains-A guide for selecting practices for soil and water conservation.* U.S. Department of Agriculture, Agricultural Handbook No. 282. (http://www.ars.usda.gov/SP2UserFiles/Place/64080530/RUSLE/AH_282.pdf, accessed 3 September 2008).

Wischmeier WC, Smith DD. 1978. *Predicting rainfall-erosion losses—A guide to conservation farming.* U.S. Department of Agriculture, Agricultural Handbook No. 537. (http://www.ars.usda.gov/SP2UserFiles/Place/64080530/RUSLE/AH_537.pdf, accessed 3 September 2008).

Yalin MS. 1963. An expression for bed-load transportation. *Proceedings of American Society of Civil Engineering* **89**(HY3): 221–250.

Yoder DC, Tyner JS, Balousek JD, Panuska JC, Buchanan JR, Kirsch, and KJ, Lyon JP. 2007. Conservation planning for construction sites. *Transactions of the ASABE* **50**(5): 1613–1618.

Yu B. 2002. Using CLIGEN to generate RUSLE climate inputs. *Transactions of the ASAE* **45**: 311–320.

