A Simple Model to Estimate Runoff Based on Daily Rainfall, Soil Properties, and the Seasonal Variability of Storm Intensity

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Problem Statement

Estimating daily runoff from little information such as daily precipitation and key soil properties. Useful for functional-type crop & soil models (DSSAT, SALUS). Ease the computational load in watershed-scale models linked to GIS.

Literature

1. The SCS curve number approach (USDA-SCS, 1985) was a simple, empirical method to estimate daily runoff from daily precipitation. It ignored the change of infiltration rate with time into the storm or the seasonal variability. Currently used in the DSSAT family of models (Jones et al., 1986).
2. Chou (1990) proposed a time-to-ponding approach that relates the infiltration capacity of the soil (and, indirectly, runoff) to time into the storm (Fig. 1). The amount that can infiltrate during a storm interval is calculated. Precipitation that cannot infiltrate, ponds. When ponding exceeds the ponding capacity of the soil (a function of slope and surface roughness), runoff is calculated. To implement this approach in DSSAT, two simplifying assumptions were necessary: (1) Daily precipitation falls in one storm starting at midnight;and (2) Curve A is an isosceles triangle (Gerakis and Ritchie, 1998). Seasonal changes to the shape of the storm are not considered. Simulation can be improved if assumptions 1 & 2 are relaxed, i.e., hourly precipitation data are used instead of assuming a storm shape. This is one of the two approaches to runoff simulation used in SALUS, if hourly rainfall is available..

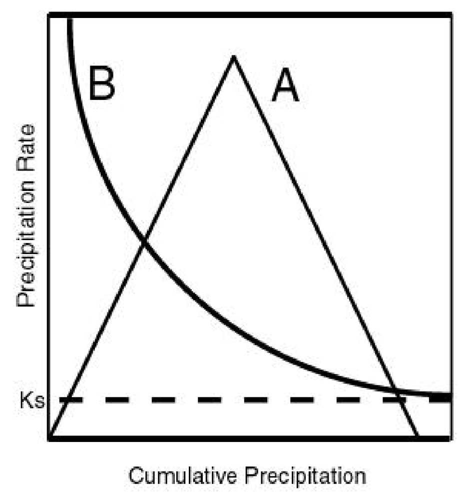

Figure 1. The time-to-ponding approach to infiltration. Curve A is the precipitation rate vs. cumulative precipitation. Curve B is the precipitation rate above which water ponds. Ks is the matrix saturated hydraulic conductivity of the top layer.

3. Another, more complex time-to-ponding approach is used by the WEPP model (Stone et al., 1995). Infiltration is computed using a mechanistic implementation of the Green-Ampt Mein-Larson model, and runoff is calculated as rainfall excess minus the ponding capacity of the soil. The problem is high uncertainty in the inputs.
4. The Root Zone Water Quality Model (Ma et al., 1998) predicts infiltration with the Green-Ampt equation. Too many inputs make this approach impractical for our functional-type models.
5. Because many weather stations collect only daily precipitation, and because there are lots of historical records of daily precipitation, the simplicity of the runoff curve approach is very appealing. Watershed scale hydrological models with many cells or overland flow elements can benefit from a simple, fast algorithm based on just daily rainfall and key soil properties (Basso, 2000).

Objective

To replace the SCS curve number and the time-to-ponding approaches with a modified runoff curve approach. Our improvement over the earlier SCS approach comes from the realization that storm intensity in many locations varies throughout the year. So, the same amount of rain may produce different runoff depending on time of the year. This approach is used in SALUS when only daily rainfall is available.

Method

1. We assume that runoff is proportional to daily rainfall for a soil of a given ponding capacity, antecedent water content, and macropore saturated hydraulic conductivity (Fig. 2). Sensitivity analysis using Chou's time-to-ponding model showed that the slope of the rainfall-runoff function is not sensitive to antecedent water content, because only a thin layer of top soil is involved in the infiltration/runoff calculation (percolation is simulated in another part of the model). We also assume that there is an upper limit to ponding capacity that depends on the slope of the land and surface roughness. So the only other factor to consider is macropore saturated hydraulic conductivity (KsMacro).

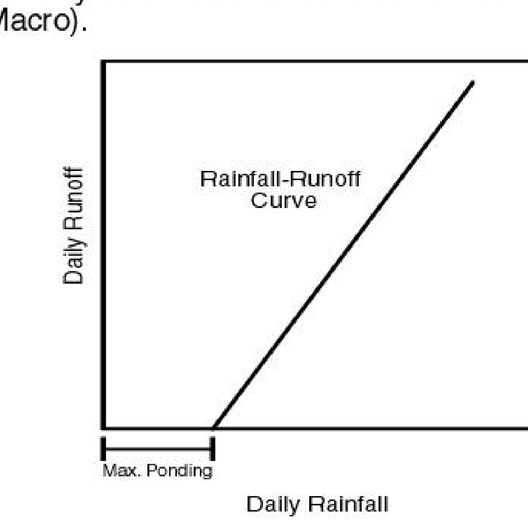

Figure 2. The daily rainfall vs. daily runoff curve.

2. The slope of the rainfall-runoff curve (Fig. 2) primarily depends on KsMacro. We assume that this slope is described by the model:

Runoff_Curve_Slope = exp (a KsMacro + b) =>

ln (Runoff_Curve_Slope) = a KsMacro + b [Eq. 1]

where KsMacro is the macropore saturated hydraulic conductivity, and a, b are estimation coefficients (Fig. 3).

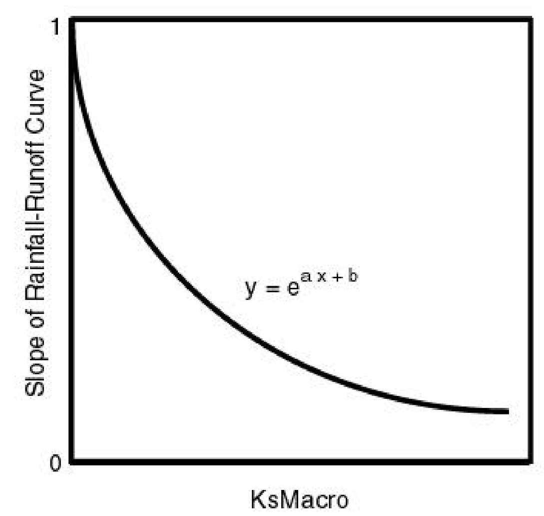

Figure 3. Slope of rainfall-runoff curve vs. KsMacro

3. The slope of the runoff curve depends on the time of the year, because storm intensity varies with season. Using up to 30 years of hourly rainfall data from the USA (NOAA/NREL, 1993) and the time-to-ponding runoff model, we simulated the slopes of several rainfall-runoff curves vs. KsMacro. Fig. 4 shows a set of these curves, one for each month, for one location (note log scale on y axis). With linear regression we obtain coefficient "a" from Eq. 1. Because coefficient "b" varies little and is not so critical anyway, we take it as constant equal to -0.3.

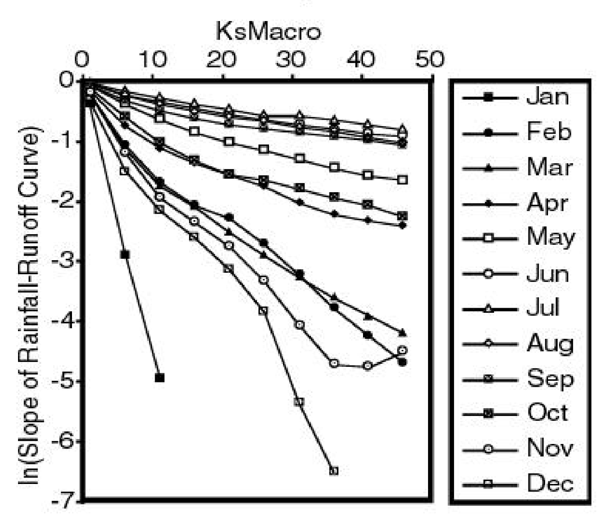

Figure 4. Logarithm of the slope of the rainfall-runoff curve simulated for a range of KsMacro.

4. Coefficient "a" (Eq. 1) is space-variable, too. We grouped similar values of the coefficient by region: N. Central USA, the ocean coasts, the Southern states, and the tropics (Puerto Rico and Hawaii). In every region, SALUS requires a set of 12 values, one for each month. These are stored as a table in the weather database. There are two ways to determine the array of the 12 coefficients:
5. If the area of interest is in the USA and territories, users can pick one of 230 weather stations for which there are up to 30 years of continuous hourly rainfall data. A utility program (NEAREST.EXE) can find the nearest weather station to the point of interest from latitude and longitude. Utility programs REFORMAT.BAT, MAKEHOUR.BAT, and HOUR2DAI.EXE clean up the data and convert them to DSSAT-friendly weather files. Program POND90.EXE runs the time-to-ponding model to derive the array of 12 coefficients.
6. If the area of interest if outside the USA and territories, the coefficients can be estimated from a time series of rainfall measured at short intervals. Fig. 5 is a plot of cumulative rain height vs. cum. rain hours for one year. The curve has 12 segments, one for each month. The slope of each segment is a function of the average storm intensity for that month, so it should bear some relation to coefficient "a" of Eq. 1. We plotted coefficient "a" against the slopes of the cumulative precipitation vs. cum. precipitation time curve for several weather stations (Fig. 6).

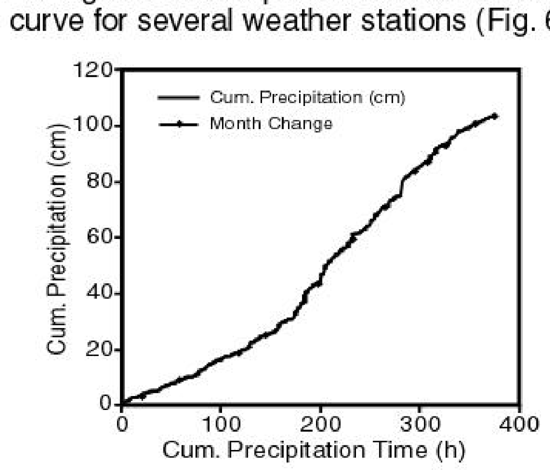

Figure 5. Cumulative precipitation vs. cumulative precipitation time for one year.

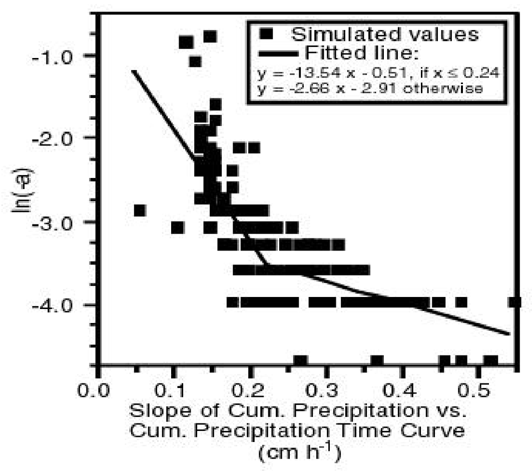

Figure 6. Approximating coefficient "a" from the slope of cum. precipitation vs. cum. precipitation time curve.

7. The KsMacro in Eq. 1 can be either measured, approximated from soil properties (Suleiman and Ritchie, In press) or simply calibrated for best fit (Ma et al., 1998; Risse et al., 1995a; Risse et al., 1995b; Stagnitti et al., 1992).

Calibration: Method

The simple runoff model was calibrated using the WEPP hillslope validation data set (NSERL, 2000). The method is outlined in Fig. 7.

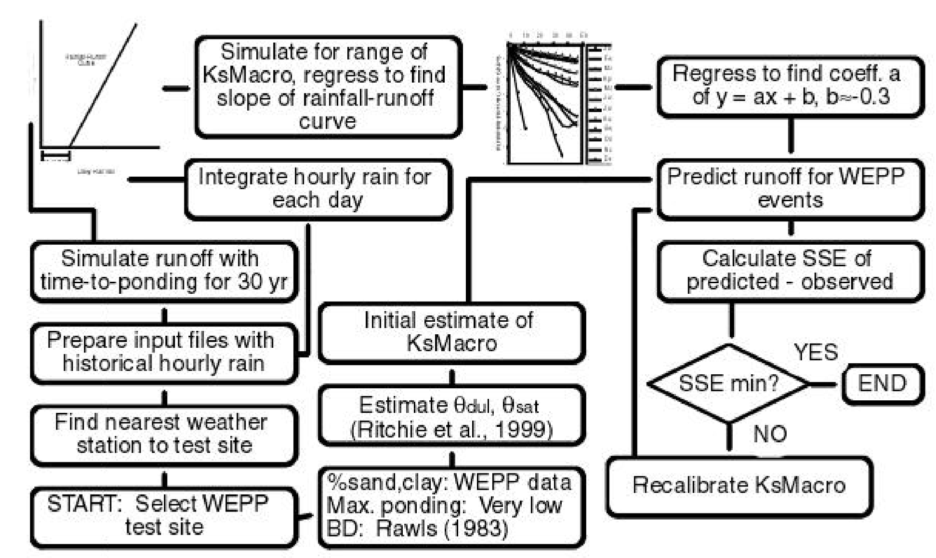

Figure 7. Calibration with WEPP Hillslope Data Sets: Method.

Calibration: Results and Discussion

1. Risse et al. (1995a) used 2,500 fallow events for validation of WEPP, whereas the data files posted on the internet (NSERL, 2000) contain only 1,150 events. Without knowing the reasoning for this reduction, our analysis is not directly comparable.
2. There probably were errors in the WEPP hillslope validation data files. In Tifton, on 28 Oct. 1959, a 9.98 cm rain reportedly produced only 0.15 to 0.08 cm runoff. In Pendleton, from 13 Feb. 1984 to 10 Apr. 1984 one plot produced no runoff, whereas its replicate produced 8.51 cm runoff.
3. In most sites, the KsMacro as calibrated with our model is in the same order of magnitude as the KsMacro calibrated by Risse et al. (1995a) using WEPP (Table 1).

Table 1. Comparison of model performance using the saturated hydraulic conductivity calibrated by Risse et al. (1995) versus the KsMacro calibrated using the simple model

WEPP Hillslope Validation Site	Latitude	Longitude	Nearest Weather Station	Distance (km)	% sand	% clay	Bulk Density	Risse Ks[1]	Risse RMSE[2]	Cal. Ks[3]	Cal. Max. Pond.[4]	Cal. RMSE[5]
Bethany, MO	40°15' N	94°02' W	Kansas City, MO	121	27.8	29.0	1.40	8.35	0.83	11-16	0.1	0.80
Castana, IA	42°04' N	95°49' W	Sioux City, IA	60	7.1	23.5	1.45	5.93	1.33	31-38	0.1	0.67
Geneva, NY	42°53' N	77°01' W	Rochester, NY	59	44.2	14.9	1.40	12.31	0.85	15	0.1	0.84
Guthrie, OK	35°24' W	97°36' W	Oklahoma City, OK	0	73.2	7.9	1.48	43.73	0.91	22-27	0.1	0.72
Holly Springs, MS	34°49' N	89°26' W	Memphis, TN	57	2.0	19.8	1.34	1.13	0.89	2-6	0.1	0.88
Madison, SD	44°02' N	97°10' W	Sioux Falls, SD	62	7.0	32.2	1.21	3.74	1.15	23-32	0.1	0.85
Morris, MN	45°35' N	95°55' W	Saint Cloud, MN	144	39.4	23.2	1.30	42.36	0.68	54-65	0.1	0.62
Pendleton, OR	45°41' N	121°31' W	Portland, OR	85	28.0	23.0	1.35	3.74	0.43	8-12	0.1	0.35
Presque Ile, ME	46°39' N	68°00' W	Caribou, ME	24	38.8	13.7	1.49	11.18	0.69	10	0.1	0.68
Tifton, GA	31°28' N	83°32' W	Macon, GA	138	87.0	5.7	1.58	49.66	1.71	21	0.1	1.29
Watkinsville, GA	33°32' N	83°06' W	Athens, GA	51	66.5	19.6	1.59	47.41	1.07	17-20	0.1	0.74

[1]Sat. hydraulic conductivity calibrated by Risse et al. (1995)
[2]Root Mean Square Error of the simple model when using Ks by Risse et al. (1995)
[3]Macropore saturated hydraulic conductivity calibrated using the simple model
[4]Maximum ponding capacity used for calibration of the simple model
[5]Root Mean Square Error of the simple model when using Ks calibrated using the simple model

4. A face-to-face comparison of our simple runoff model with WEPP would normally not be possible because WEPP is not a standalone infiltration/runoff model but includes other components for water balance, plant growth, residue decomposition, and soil consolidation. Yet, because validation plots were continuous cultivated fallow, we assume that the effect of the plant growth and residue decomposition components were insignificant. We compare runoff estimates from our model, WEPP and the SCS number approach in Tables 2 and 3. The values for WEPP and the SCS curve number are taken from Risse et al. (1995a). Model Efficiency (ME) is defined as 1 - [sum of squared deviations from observed] / [sum of squared deviations from the mean]. Fig. 8 shows the 95% confidence intervals for predictions with our simple runoff model.

Table 2. Performance statistics of simple model, WEPP, and the SCS curve number for validation sites (event basis).

		Simple Model			WEPP			SCS Curve Number		
Site	Measured Average Runoff	Average Runoff	Average Magnitude of Error	Model Efficiency	Average Runoff	Average Magnitude of Error	Model Efficiency	Average Runoff	Average Magnitude of Error	Model Efficiency
Bethany, MO	1.44±1.57	1.64±1.17	0.58	0.74	1.41±1.56	0.52	0.82	1.00±1.41	0.66	0.72
Castana, IA	1.15±0.85	1.18±0.55	0.50	0.39	1.01±0.92	0.46	0.48	1.18±1.00	0.55	0.10
Geneva, NY	0.79±1.11	1.03±0.82	0.60	0.41	0.67±1.02	0.41	0.73	0.60±1.05	0.51	0.58
Guthrie, OK	1.09±1.44	1.28±1.00	0.51	0.75	0.99±1.48	0.39	0.86	1.05±1.61	0.49	0.77
Holly Springs, MS	1.52±1.75	1.81±1.40	0.65	0.75	1.46±1.63	0.41	0.87	1.26±1.63	0.56	0.79
Madison, SD	0.81±1.17	1.04±0.60	0.63	0.47	0.71±0.95	0.39	0.77	0.67±0.83	0.45	0.69
Morris, MN	0.59±0.71	0.57±0.39	0.45	0.22	0.41±0.66	0.31	0.59	0.87±1.04	0.61	-1.06
Pendleton, OR	0.32±0.33	0.27±0.21	0.26	-0.12	0.22±0.31	0.21	0.06	0.18±0.28	0.25	-0.33
Presque Ile, ME	0.78±1.00	0.93±0.65	0.55	0.52	0.48±0.71	0.42	0.45	0.48±0.91	0.56	-0.25
Tifton, GA	1.91±1.73	2.00±1.20	0.88	0.44	1.78±1.64	0.71	0.67	2.11±2.02	0.88	0.24
Watkinsville, GA	1.05±1.40	1.21±1.09	0.52	0.72	1.27±1.56	0.42	0.84	1.19±1.60	0.56	0.74

Table 3. Performance statistics of simple model, WEPP, and the SCS curve number for validation sites (annual basis).

				Simple Model		WEPP			SCS Curve Number	
Site	n	Measured Average Runoff	Average Runoff	Average Magnitude of Error	Model Efficiency	Average Runoff	Average Magnitude of Error	Model Efficiency	Average Runoff	Average Magnitude of Error	Model Efficiency
Bethany, MO	10	15.73±7.02	17.87±5.09	2.96	0.72	23.1±5.2	5.2	0.28	17.5±4.9	6.8	-0.35
Castana, IA	12	8.60±4.49	8.88±3.82	1.49	0.81	9.5±4.6	2.1	0.78	12.5±5.0	2.6	0.59
Geneva, NY	10	7.63±4.83	9.96±3.19	3.42	0.34	17.2±5.0	5.2	0.57	7.9±4.0	9.3	-0.59
Guthrie, OK	15	12.36±8.92	14.49±7.15	3.11	0.83	14.1±7.4	2.6	0.83	7.8±4.4	7.7	-0.35
Holly Springs, MS	8	39.44±15.20	47.03±14.66	7.60	0.67	51.4±13.1	6.1	0.73	21.6±9.1	34.1	-5.76
Madison, SD	9	5.29±2.66	6.82±2.03	1.63	0.37	5.1±3.5	1.9	0.46	6.9±5.8	3.1	-0.75
Morris, MN	10	3.95±4.59	3.87±3.19	1.53	0.8	3.4±3.1	1.3	0.81	3.3±3.8	3.6	-0.23
Pendleton, OR	9	2.90±2.84	2.46±1.64	1.59	0.41	7.1±3.2	6.5	-0.87	6.0±2.4	4.5	-0.05
Presque Ile, ME	4	10.72±4.41	12.83±1.44	3.65	-0.01	7.5±4.8	3.9	0.52	8.9±4.4	4.8	0.19
Tifton, GA	8	15.48±11.07	16.27±8.43	3.43	0.84	23.1±9.0	7.8	0.37	13.5±7.9	15.5	-1.50
Watkinsville, GA	7	21.99±5.98	25.39±3.09	4.51	-0.11	39.8±15.6	5.6	0.86	39.5±18.6	5.3	0.88

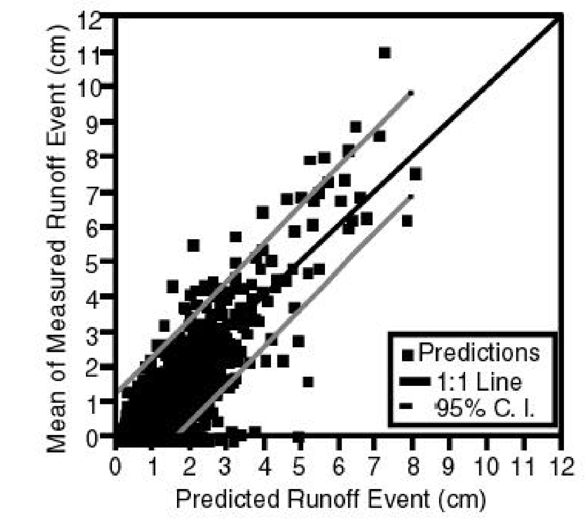

Figure 8. Ninety-five percent confidence intervals for predictions of the simple runoff model on an event basis.

5. On an event basis, our model performed worse than WEPP, except for the ME of one site (Presque Isle). This is expected because WEPP used detailed breakpoint data from tipping bucket rain gages to calculate storm shapes. WEPP validation runs calculated rainfall duration, time to maximum intensity, and relative peak intensity. In addition, WEPP has routines to calculate maximum ponding capacity (depression storage) from random roughness and the slope of the flow surface. In our validation runs, we always assumed a very low value for ponding capacity (0.1 cm), which may have overpredicted runoff.
6. On an annual basis, our model usually performed better than WEPP in terms of Average Magnitude of Error, and in many cases also in terms of Model Efficiency. Our model performed better than the SCS curve number in all cases except the ME of two sites, Presque Isle and Watkinsville.

Conclusions

1. We have found a simple alternative to the SCS curve number approach that accounts for the seasonal variation of storm intensity.
2. Incorporating the new runoff/infiltration model in SALUS has the added advantage that the tillage modifications of soil properties in SALUS will reflect on the simulation of infiltration and runoff. SALUS simulates changes in ponding capacity and KsMacro due to tillage, which in turn affect ponding, infiltration, and runoff.
3. Using cumulative rain vs. cumulative rain hours to estimate coefficient "a" in Eq. 1. is approximate. A more universal solution is required for regions where long-term hourly precipitation is not available.
4. Macropore saturated hydraulic conductivity is best calibrated, based on our experience and the relevant literature (Ma et al., 1998; Risse et al., 1995a; Risse et al., 1995b; Stagnitti et al., 1992).

Code Availability

The code that was used for model calibration and other related utilities are at http://nowlin.css.msu.edu/software/pond90.

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