PLOT-SCALE RAINFALL-RUNOFF CHARACTERISTICS AND MODELING AT SIX SITES IN AUSTRALIA AND SOUTHEAST ASIA

B. Yu, C. W. Rose, K. J. Coughlan, B. Fentie

ABSTRACT. During major runoff events when most soil loss occurs, runoff is likely to dominate the rainfall-driven erosion processes. Thus accurate estimation of the runoff rate is critical to soil loss predictions. At plot scale, the Green-Ampt infiltration model is commonly assumed to be able to describe the temporal variation of the infiltration rate over a storm event. Field measurements of both rainfall intensity and runoff rate at 1-min intervals at six sites in the tropical and subtropical regions of Australia and Southeast Asia, however, strongly suggest that the apparent infiltration rate is closely related to the rainfall intensity and it is essentially independent of the cumulative infiltration amount, features not accord with the Green-Ampt infiltration equation. Furthermore, the storage effect and runoff rate attenuation are not negligible at the plot scale. With an initial infiltration amount to determine when runoff begins, an exponential distribution to describe the spatial variation in the maximum infiltration rate and a linear storage formulation to model the lag between runoff and rainfall, we were able to develop a satisfactory three-parameter model for the runoff rate at 1-min intervals within a storm event. Keywords. Infiltration variability, Runoff, Erosion.

Surface runoff plays a critical role in determining the rate of soil loss from agricultural lands. This is especially the case during large events with high stream power (Proffitt and Rose, 1991). In the USLE (Wischmeier and Smith, 1978), the effect of rainfall and runoff is encapsulated in a rainfall and runoff factor, known as the R-factor, to represent the climatic influence on soil erosion. As such, the R-factor cannot and should not be used to determine the soil loss on an event basis. In contrast, process-based water erosion models explicitly require the runoff rate in order to determine the rate of soil loss. For example, in WEPP (Water Erosion Prediction Project, Laffen et al., 1995), which represents a new generation of process-based erosion models, the User Requirement (Foster and Lane, 1987) suggests that the maximum information required to represent a design storm consists of (1) storm amount, (2) storm duration, (3) ratio of peak intensity to average intensity, and (4) time to peak. With these standard inputs of storm characteristics, WEPP uses the Green-Ampt infiltration model to determine runoff amount, and a kinematic wave model to determine the peak runoff rate (WEPP User Manual, USDA, 1995). The peak runoff rate is then assumed to be the steady-state runoff rate for erosion computations. In GUEST (Rose, 1993; Ciesiolkta et al., 1995), a theoretical expression is derived for sediment concentration at the transport limit by assuming a fraction of the stream power is used to raise sediment (against its immersed weight) at a rate corresponding to its deposition rate. This expression involves the instantaneous rate of runoff per unit area, Q, Rose (1993) and Ciesiolkta et al. (1995) give the theoretical basis for computing a single effective runoff rate for any runoff event, Q_e, defined as:

\[ Q_e = \left( \frac{\sum Q_i}{\sum Q} \right)^{1.25} \]

where the summation is for the duration of the runoff event. In both cases, runoff rates are needed to determine the rate of soil loss using physically based methodology. It is important therefore to predict runoff rates for given rainfall intensity, soil and topographical characteristics.

As part of a project (No. 8551) funded by Australian Centre for International Agricultural Research (ACIAR), both rainfall intensity and runoff rate were measured at 1-min intervals at five sites in Australia and Southeast Asia. The major aim of the project was to provide a methodology to allow scientists to make rational decisions about the effectiveness of various land management options in reducing soil erosion in the tropics and sub-tropics. Research outcomes from the project were published in a special issue of Soil Technology in 1995 (Vol. 8, No. 3). In a new project (No. 9201), new sites in Thailand and Australia were included, and additional rainfall and runoff data were collected with an explicit objective, among others, to develop hydrologic models to predict runoff rates from one-minute rainfall rates for a range of soil type, slope, slope length, and management practice in the tropical and subtropical regions of Australia and Southeast Asia. This article is one of the first attempts to meet these objectives.

In this article, plot-scale runoff processes are characterized and modeled in the context of soil erosion prediction using physically based methodology. We first
describe the field sites and the nature of rainfall and runoff data collected for the project. A simple hydrologic model is developed for runoff rates at 1-min intervals taking into account the spatial variation in the infiltration rate and the lag between rainfall excess and observed runoff rate.

EXPERIMENTAL SITES, AND RAINFALL AND RUNOFF DATA

All six sites are in tropical and sub-tropical regions of Australia and Southeast Asia (fig. 1). Table 1 provides general information on the location, climate, soil, and plot dimensions. Summer rainfall predominated at the two Australian sites with about 70% of rain occurring between November and April. Annual rainfall at Kemaman is the highest of the six sites studied. Seasonal rainfall at the site show a bimodal distribution with peaks in March and November. Rainfall for the six months between June and November at Los Baños accounts for about 77% of annual total, while rainfall at VISCA (Visayas State College of Agriculture, Baybay, Leyte, the Philippines) has two peaks in January and July, respectively. Rainfall at Nan in Thailand is highly seasonal with up to 87% of rainfall in the six months from April to September.

Soil texture was classified using the U.S. system (Soil Survey Staff, 1975), the site at Imbil being particularly stony with 44% of particles larger than 5 mm. Field experiments were carried out on hydrologically bounded plots with areas varying from 20 to 216 m² (see also table 1). Both rainfall intensity and runoff rate were measured using tipping bucket technology at one minute intervals. All of the tipping buckets were calibrated using a dynamic calibration method (Calder and Kidd, 1978; Ricchetti and Bailey, 1990) prior to the field trials. Details of recording equipment and measurements made were given elsewhere (Ciesiolka et al., 1995). Data management programs (Ciesiolka et al., 1995) were developed to convert data on tip rates into meaningful hydrologic data such as rainfall intensity (mm/h) and runoff rate (mm/h).

Data used in this article are from bare plots, kept virtually free from vegetation in order to provide reference data on soil and water loss to which the effectiveness of other management options are compared (Ciesiolka et al., 1995). Data on rainfall and runoff rates at 1-min intervals were prepared for the 30 largest storm events in terms of total rainfall from bare plots at the six sites. Rainfall intensity and runoff rate are continuous processes while the tipping bucket technology is discrete in nature. As a result, there is a fixed absolute sampling error depending on such factors as the bucket size, catchment area, and sampling interval. For given plot size and sampling equipment, the shorter the sampling interval the higher the sampling error (Yu et al., 1997). Implications of this sampling error for runoff modeling are discussed later in the article.

Figure 1—Locations of the six ACIAR sites from which data used in this article were gathered.

![Map of Australia and Southeast Asia showingLocations of the six ACIAR sites](image)

Table 1. Bare plot characteristics at the six sites in Australia and Southeast Asia

<table>
<thead>
<tr>
<th>Site</th>
<th>Country</th>
<th>Location</th>
<th>Soil Type</th>
<th>Soil Texture</th>
<th>Mean Annual Rainfall (mm)</th>
<th>Length (m)</th>
<th>Width (m)</th>
<th>Slope* (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Goomboorian</td>
<td>Australia</td>
<td>26°04'S, 152°48'E</td>
<td>Typic Eutropept</td>
<td>Sand</td>
<td>1 200</td>
<td>36</td>
<td>3</td>
<td>5</td>
</tr>
<tr>
<td>Imbil</td>
<td>Australia</td>
<td>26°26'S, 152°41'E</td>
<td>Lithic Eutropept</td>
<td>Loam</td>
<td>1 200</td>
<td>12.2</td>
<td>3.2</td>
<td>33</td>
</tr>
<tr>
<td>Kemaman</td>
<td>Malaysia</td>
<td>4°18'N, 103°19'E</td>
<td>Orthic Tropadul</td>
<td>Sand loam</td>
<td>3 500</td>
<td>5</td>
<td>4</td>
<td>17</td>
</tr>
<tr>
<td>Los Baños</td>
<td>Philippines</td>
<td>1°46'N, 121°12'E</td>
<td>Typic Tropadul</td>
<td>Clay</td>
<td>1 900</td>
<td>12</td>
<td>6</td>
<td>26</td>
</tr>
<tr>
<td>VISCA</td>
<td>Philippines</td>
<td>10°45'N, 124°45'E</td>
<td>Oxic Dystropept</td>
<td>Clay</td>
<td>2 200</td>
<td>11.9</td>
<td>6</td>
<td>50</td>
</tr>
<tr>
<td>Nan</td>
<td>Thailand</td>
<td>19°24'N, 100°45'E</td>
<td>Oxic Paleustult</td>
<td>Clay</td>
<td>1 200</td>
<td>36</td>
<td>6</td>
<td>Variable 12-50</td>
</tr>
</tbody>
</table>

* Each plot, though at different slope, was very approximately planar, but with unsurveyed natural irregularities in the 36 m length of plot.

OBSERVATIONS OF RAINFALL-RUNOFF CHARACTERISTICS—PLOT SCALE

Of over 2000 events for which rainfall intensity and runoff were recorded at 1-min intervals, we prepared 30 events at each site for data analysis and modeling. While we have examined a large number of events for each of the six sites with respect to rainfall-runoff characteristics described below, we select only one such event to note and highlight those most important characteristics on which model development in the next section is based.

Figure 2 shows rainfall intensity and runoff rate during a thunder storm in the early summer of 1992-1993 at the Goomboorian site. The storm lasted a little over three hours. The total rainfall and runoff amounts for the event were 54.4 mm and 26.3 mm, respectively. Both rainfall intensity and runoff rate are highly variable at a 1-min time scale (fig. 2a). It is also clear that averaging over an interval of 10 min, for example, can result in considerable loss of detail with respect to the temporal variation in rainfall intensity and runoff rate. For example, the first peak of 83 mm/h in rainfall intensity (fig. 2a), which occurred 10 min after the event commenced, is completely averaged out (fig. 2b). There is a measurable lag between peak runoff rate and rainfall intensity in figure 2a of about
one minute. Once data are aggregated at 10-min intervals, this lag is no longer discernible, as shown in figure 2b.

We define an apparent infiltration rate as the difference between the observed rainfall intensity and observed runoff rate. When this apparent infiltration rate is plotted against the rainfall intensity using the original 1-min data for the same event (fig. 3a), no simple relationship can be easily identified between them. Apart from the constraint that this apparent infiltration cannot be greater than rainfall intensity, there seems to be no upper limit as to the magnitude of this apparent infiltration rate. Although there is a considerable amount of scatter, figure 3a suggests that the apparent infiltration rate increases with the rainfall intensity. This scatter to some extent can be attributed to the lag between runoff and rainfall noted in the previous paragraph because the apparent infiltration rate would be larger when rainfall intensity is rising than when it is falling. When the lag is eliminated through data aggregation, the relationship between rainfall intensity and apparent infiltration rate becomes much clearer (fig. 3b). It can be seen that the apparent infiltration rate equals rainfall intensity when the latter is less than about 10 mm/h for this particular event. The apparent infiltration rate continues to increase as rainfall intensity increases although the rate of increase is reduced at high rainfall intensities. When runoff occurs, the apparent infiltration rate is a good indicator of the maximum infiltration rate or infiltration capacity at that time. There is little evidence in the data collected for the project to suggest that the apparent infiltration rate after runoff commences decreases significantly over time. In figure 2b, for example, the apparent infiltration rate (i.e., the difference between the two curves) for the fifth time interval is actually higher than that for the second interval although the rainfall intensity for both intervals is about the same. Significant correlation exists between rainfall intensity and apparent infiltration rate for all of the events we examined.

In summary, through inspection of a large number of events with respect to the rainfall-runoff characteristics, we found that the lag between runoff and rainfall is a significant feature even at plot scales. More importantly, we noted that the apparent infiltration rate is primarily a function of rainfall intensity. The model developed below attempts to capture these two essential features in the runoff hydrographs measured at the plot scales defined in table 1.

**Modeling Runoff Rates at Small Time Intervals**

At sufficiently small spatial scales, or for sufficiently large time intervals, the difference between rainfall intensity and infiltration rate, commonly known as excess rainfall rate, can be regarded as the runoff rate. For this project, plot length ranges from 5 m at Kemaman to 36 m at Nan and Goomborrian. Limited field observations (Ciesiolk, per. comm.) suggested that the overland runoff
velocity was about 0.1 to 0.2 m/s. Time of travel to the collecting device is, therefore, of the order 10^5 s, a time scale comparable with the time interval for which runoff rate was recorded. As a result, the lag between rainfall excess and the measured runoff rate needs to be taken into account as noted in the previous section. For this reason, the model has two separate but connected components. The first component addresses infiltration, and therefore the rainfall excess, and the second one deals with runoff routing down the slope length. Since the model was developed especially for small-scale runoff plots, the model is henceforth called SSRRM to stand for a Small Scale Runoff Routing Model.

INfiltration Component

All classic theories of infiltration, such as the Green-Ampt infiltration equation, suggest two distinct infiltration phases. Initially the infiltration rate is high and in excess of rainfall intensity due to the capillary effect. The maximum rate of infiltration decreases rapidly to reach the saturated hydraulic conductivity. For operational hydrologists, it has been a common practice to model the two phases of infiltration separately, an initial infiltration amount being followed by either a constant infiltration rate or an infiltration rate in proportion to the rainfall intensity. Pilgrim and Cordery (1993) reviewed these and other operational infiltration models in connection with flood estimation.

Most infiltration models describe a decrease over time in the maximum infiltration rate at a point in the landscape. Field measurements of hydraulic properties, including saturation hydraulic conductivity and steady-state infiltration rate, have all shown enormous spatial variability (Nielsen et al., 1973; Sharma et al., 1980; Loague and Gander, 1990) even at the plot scale. As rainfall intensity increases, the proportion of the surface with rainfall intensity being greater than the maximum infiltration rate would increase, hence the rainfall excess and surface runoff rate would increase. As a result, the apparent infiltration rate (the difference between rainfall and runoff) would increase as rainfall intensity increases. Dependence of the observed infiltration rate on rainfall intensity is strongly supported by the observed hydrologic data (see, for example, fig. 3). Hawkins (1982) reviewed a number of previous investigations and simulator-based field research and pointed out that the notion that observed infiltration rates vary positively with rainfall intensity was not well accepted by hydrologists and poorly accommodated in infiltration theory, and he also argued that representation of the spatial infiltration variability in probabilistic terms would have important implications for practical application and research.

To characterize the spatial variation of infiltration capacity, let f(I) be the frequency distribution of a spatially variable maximum infiltration rate, I. This maximum infiltration rate can be interpreted in the sense that for given rainfall intensity, I, at a given point within the plot, the actual infiltration rate, i, is no greater than I:

\[ i = \begin{cases} P & \text{if } I > P \\ I & \text{if } I \leq P \end{cases} \]

It follows that the rainfall excess at the point, r, is:

\[ r = \begin{cases} 0 & \text{if } I > P \\ P - I & \text{if } I \leq P \end{cases} \]

Thus for given rainfall intensity, the rainfall excess can be regarded as a function of the maximum infiltration rate which varies in space. This spatially variable rainfall excess because of the variable infiltration characteristics can be integrated to give an average rainfall excess for the plot, R:

\[ R = \frac{1}{A} \int_{\text{plot}} r \, da \]

\[ = \int_0^P r \, f(I) \, dl \]

\[ = \int_0^P (P - I) \, f(I) \, dl, \text{ since } r = 0 \text{ when } I > P \] (2)

where A is the plot area and da is the area increment. Implicit in this formulation for plot-averaged rainfall excess is the assumption that rainfall excess produced anywhere within the plot becomes measurable runoff at the plot outlet. In other words, we assume that run-on from less permeable areas to more permeable areas within the plot can be ignored. Integrating equation 2 by parts yields:

\[ R = \int_0^P F(I) \, dl \] (3)

where F(I) is the distribution function. Hence, if the distribution function and its parameter values are known, the rainfall excess rate for the plot can be uniquely determined for given rainfall intensity. A log-normal distribution has been used to describe the spatial distribution of the saturation hydraulic conductivity (Nielsen et al., 1973), and the steady-state infiltration rate (Sharma et al., 1980; Loague and Gander, 1990) while Hawkins (1982) and Hawkins and Cundy (1987) used an exponential distribution to describe the spatial variation of the maximum infiltration rate. For parameter-efficiency, we used a one-parameter exponential distribution to characterize the spatial variation of the maximum infiltration rate, i.e.:

\[ F(I) = 1 - e^{-I/I_m} \] (4)

Therefore, the rate of rainfall excess as a function of the rainfall intensity is given by:

\[ R = P - I_m(1 - e^{-P/I_m}) \] (5)
The parameter $I_m$ is the mean maximum infiltration rate across the field when saturation occurs everywhere and the entire plot generates runoff. It is the spatially averaged infiltration capacity, or the maximum possible infiltration rate, and it is distinct from the average actual infiltration rate during a storm event. An alternative interpretation of $I_m$ is that 100/e% or 37% of the plot has a maximum infiltration rate in excess of $I_m$. Figure 4 illustrates the relationship between rainfall intensity and apparent infiltration rate with an exponential spatial variation of the maximum infiltration rate (eq. 5).

In addition to this spatially averaged maximum infiltration rate, an initial amount of infiltration, $F_0$, is also assumed to occur prior to runoff.

**RUNOFF ROUTING COMPONENT**

The rainfall excess, $R$, is routed to the plot outlet using the kinematic wave approximation, for which the storage equation can be written:

$$\frac{dS}{dt} = R - Q$$

where $S$ is the equivalent depth of water stored on the soil surface. If we assume a linear relationship between flow rate and storage, with the storage written as $S = KQ$, then a constant lag between rainfall excess and runoff rate is implied. The storage equation 6 combined with the linearity assumption were shown to give an approximate analytical solution of the basic partial differential equation governing the overland flow (Rose et al., 1983). A variant of this linear approximation of the storage/discharge relationship, known as the Muskingum method, has been widely used for flood routing along natural stream channels (e.g., Chow et al., 1988). Let $Q_i$ and $R_i$ be the average runoff rate and rainfall excess rate for the time interval $i$, then the storage equation can be written in a discrete form:

$$K(Q_i - Q_{i-1}) = (R_i - Q_i)\Delta t$$

or

$$Q_i = \alpha Q_{i-1} + (1 - \alpha)R_i$$

where the parameter $\alpha$ is related to the lag, $K$, and time interval, $\Delta t$ by:

$$\alpha = \frac{K}{K + \Delta t}$$

Since velocity, and therefore the time of travel, varies as a function of the flow rate, one would expect that the lag reflecting storage to flow rate actually varies as a function of the flow rate as well. For this article, parameter $\alpha$ is assumed to be a constant within an event. A variable lag, thus variable $\alpha$, may be used in the future to determine whether use of a variable lag would improve model performance.

In summary, three model parameters have been chosen to describe the variation in the plot-scale runoff rate at small time intervals:

- $F_0$: The initial infiltration amount in mm before runoff occurs.
- $I_m$: A spatially averaged maximum infiltration rate in mm/h which could be achieved if the entire plot produces runoff.
- $\alpha$: A dimensionless routing parameter between 0 and 1 depending on the lag and the time interval.

Sub-surface flow at plot-scale is not considered in SSRM because contribution of sub-surface flow to soil erosion from bare plots is in most cases insignificant and can be ignored.

**PARAMETER ESTIMATION AND MODEL EVALUATION**

The three parameters, namely $F_0$, $I_m$, and $\alpha$ were estimated by minimizing the sum of squared errors, $SSE$, between the observed ($Q_i$) and modeled ($\hat{Q}_i$) runoff rates, where:

$$SSE = \sum_{i=1}^{N} (Q_i - \hat{Q}_i)^2$$

with $N$ the duration of the event in minutes. The Levenberg-Marquardt method (Press et al., 1992) was used for optimization purposes.

Model performance is measured by the coefficient of efficiency, $E$ (Nash and Sutcliffe, 1970), defined as:

$$E = 1 - \frac{\sum_{i=1}^{N} (Q_i - \hat{Q}_i)^2}{\sum_{i=1}^{N} (Q_i - \bar{Q})^2} = 1 - \frac{SSE}{\sum_{i=1}^{N} (Q_i - \bar{Q})^2}$$

where $\bar{Q}$ is the average of the observed runoff values.

Figure 4-The relationship between apparent infiltration rate and rainfall intensity assuming an exponential distribution for the maximum infiltration rate (the parameter $I_m$ is set to be 50 mm/h).
The coefficient of efficiency, $E$, is commonly used as a measure of model performance in hydrology (e.g., Loague and Freeze, 1985) and soil sciences (e.g., Risse et al., 1993). We opt for an overall fit between the observed and modeled hydrographs, not simply the commonly used indicators such as peak runoff rate and time to peak, because the whole population of runoff rates is important for soil erosion prediction purposes. In addition, by using this coefficient of efficiency we make it explicit that the process of minimizing the sum of squared errors is in effect to maximize this coefficient of efficiency (eq. 11). To further characterize the model performance, the standard error of modeled runoff rate in mm/h was also computed in order to compare with the sampling errors in the runoff rate measurements.

RESULTS

Of the 30 events for each site, the modeled hydrograph was fitted to the observed hydrographs for 10 randomly selected events. Averages of the estimated parameter values, model efficiency as a measure of the goodness of fit, and the standard error of the estimated hydrograph are summarized in table 2. The observed and modeled hydrographs are presented in figure 5a-f. They include one hydrograph for each site which exhibited a coefficient of efficiency closest to the site average (see table 2). From table 2 and figure 5a-f, a number of observations can be made.

The average model efficiency is high (at least 0.72), implying a good fit between the observed and modeled hydrograph in general. The standard error is small and of the same order of magnitude as the sampling error in peak runoff rates at 1-min interval (cf. table 2 in Yu et al., 1997). This suggests that the infiltration component of the model is plausible and the spatial variation of the maximum infiltration rate at the plot scale is a significant feature and should not be ignored. The lag between rainfall excess and runoff rate is not negligible at the 1-min sampling interval, although a constant lag for each event seems to be a reasonable assumption. Given that the model is simple, with only three parameters, there is a great potential for predicting runoff rates at 1-min intervals if rainfall data at comparable time resolution is available.

There is a considerable event to event variability in parameter values at all sites. For bare plots, the average coefficient of variation (CV) for the initial infiltration ($F_i$) is 0.7, ranging from 0.4 to 1.1. The average maximum infiltration rate ($I_{max}$) has an even greater variability (CV = 0.8, ranging from 0.5 to 2.4). Of the three parameters, the routing parameter $\alpha$ has least amount of variation between events, with CV in the range from 0.1 to 0.4 only. Investigations of the variability of the effective hydraulic conductivity for the Green-Ampt equation have shown that parameter variability over time is strongly influenced by factors such as soil crusting, event size and antecedent moisture conditions for plots under fallow conditions (Risse et al., 1995), with the effective surface cover as an additional factor for crop lands (Zhang et al., 1995a,b). They used regression techniques to identify and develop relationships that are based on these factors to represent the temporal variability of hydraulic conductivity. To estimate the parameters of the model proposed in this article for other locations, a similar approach can be adopted in future studies because one would expect that similar factors would influence the initial infiltration amount as well as the spatially averaged maximum infiltration rate in the current context. Unless the 1-min rainfall and runoff modeling is undertaken in a continuous mode, rather than on an event basis as reported here, it is, at this stage, not possible to isolate the effects of antecedent moisture conditions and soil crusting development to explain the event to event variation in estimated parameter values.

Table 2 also shows that the highest the gross runoff coefficient, $R_c$, defined as the ratio of total runoff to total rainfall, the better the model performance in terms of the coefficient of efficiency, $E$. The two sites with the highest $R_c$, Goomoorrang and Kemaman, also have the highest $E$ values (see also fig. 5a and 5c). The lowest coefficient of efficiency of the six sites at VISCA is associated with the extremely low runoff coefficient of the site. Figure 5e shows an event at VISCA with an $E$ value of only 0.62. Peak intensity was 95.8 mm/h during the event. Because of the high infiltration rate with the spatially averaged maximum infiltration rate estimated to be 693 mm/h, the peak runoff rate was only 5.9 mm/h and the runoff coefficient was 2.2% for the event. The sampling error at this site has a standard error of 1.7 mm/h (table 2 in Yu et al., 1997). Thus, the observed runoff rates would have considerable noise, resulting in a low coefficient of efficiency and a poor fit between the observed and modeled hydrographs (fig. 5e).

In summary, plot-scale runoff models need to take into account the spatial variation of the maximum infiltration rate, and the lag between rainfall intensity and runoff rate can be important at small time intervals. A simple exponential distribution of the maximum infiltration rate and a constant lag can satisfactorily describe the temporal variation of the runoff rate within an event for this data set. Modeling runoff rates at small time intervals is important because it helps understand the infiltration characteristics at each site, and identify predominant infiltration and runoff processes that need to be considered.

To determine soil loss on an event basis, runoff amount and the effective runoff rate given by equation 1, are needed. To test the predictive potential of the runoff routing model, the average parameter values (table 2) were used as a first approximation to predict the runoff amount and effective runoff rate for the remaining 20 events for each of the six sites. Runoff prediction was attempted in spite of considerable event-to-event variation in the estimated parameter values as table 2 amply shows. The overall standard error of estimated runoff amount was 9.3 mm and overall coefficient of efficiency was 0.56. Figure 6a shows a scatter plot of predicted runoff amount against measured runoff amount for the 120 site-events. Slightly better
prediction results were obtained for the effective runoff rate shown in figure 6b for which the overall standard error was 11.7 mm/h and the coefficient of efficiency was 0.62. The outlier in figure 6b is worth commenting on. For one event at the Imbil site, the measured effective runoff rate of 131.5 mm/h is 2.8 times as large as the predicted effective runoff rate. This particular event occurred on Christmas Eve of 1989. It was the most violent thunderstorm ever recorded at the site during the study period. The recorded peak runoff rate was 425 mm/h while the recorded peak rainfall intensity was only 246 mm/h. The latter was believed to be considerably less than the true peak rainfall intensity during the event (Ciesiolk, per. comm.), for two nearby pluviometers recorded peak intensity of about 360 mm/h. This observation highlights the need to always scrutinize the data for quality assurance purposes.

This prediction trial suggests that the runoff routing model has the potential to predict the required hydrologic variables for soil loss calculations. There is minimal bias (<1%) in both predicted runoff amount and the effective runoff rate, and the percent error decreases as the magnitude of runoff amount and effective runoff rate increases. This implies that the model performance does not deteriorate for large events when accurate prediction of soil losses is most needed, and so the model may be quite adequate for determining long-term soil losses for the site as far as
DISCUSSION AND CONCLUSION

In this article, we report observed runoff characteristics and how we have attempted to model the highly variable runoff processes at the plot scale. The objective was to develop a method whereby 1-min rainfall rate data can be used to predict 1-min runoff rates because the latter is the required hydrologic input for soil erosion prediction using the physically based methodology such as GUEST. Through the modeling exercise, we learned that the spatial variation of the infiltration characteristics at plot scale cannot be ignored and the spatial variability of the maximum infiltration rate can be approximated by an exponential distribution function. At plot scale, the time taken for water to run off the plot length is comparable with the time interval at which both rainfall and runoff data were logged. As a result, the lag between rainfall excess and observed runoff cannot be ignored. With SSRM, we were able to model three important aspects of the runoff processes at small temporal and spatial scales.

First, infiltration was separated into two distinct phases. No runoff occurs in the first phase because the maximum infiltration rate is usually quite high in the beginning of a rainfall event. Secondly, an exponential distribution was used to model the spatial variation in the maximum infiltration rate over the plot once runoff commences. The net result is that once runoff begins, the runoff rate is closely related to the rainfall intensity as was observed. Thirdly, a linear storage formulation was used to model the lag between rainfall excess of the plot and the observed runoff rate at the plot outlet. A total of three parameters, one for each of the three aspects of the runoff processes, were used to achieve parameter parsimony.

We fitted observed hydrographs at 1-min intervals for a total of 60 site-events and found that SSRM performed satisfactorily using a model efficiency measure and also a comparison between the standard error of estimates and the sampling error in the runoff measurements. While considerable event to event variations in the estimated parameter values are noted, we nonetheless attempted to predict the runoff amount and effective runoff rate, which are required for soil loss predictions with GUEST, using the average parameter values for each site. Prediction results for additional 120 site-events show that the average parameter values can be used as a first approximation for soil loss prediction purposes. Hydrological modeling in a continuous mode is also called for so that the temporal variation in the parameters can be adequately addressed.

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