Development and testing of a terrain-based hydrologic model for spatial Hortonian Infiltration and Runoff/On

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Received 24 June 2006; received in revised form 28 September 2007; accepted 29 September 2007
Available online 7 January 2008

Abstract

Efficient numerical simulation of process interactions between infiltration and Hortonian runoff is needed to evaluate patterns of internal state variables and fluxes within a watershed. A fully distributed rainfall–runoff model was developed for event-based studies of space–time watershed processes. A routing hierarchy was defined over the watershed using the D-infinity contributing area algorithm. Computation of ponding time was included to handle variable run-on and rainfall intensity. The Green–Ampt model was adopted to calculate surface infiltration, and the kinematic wave model was used to route Hortonian runoff and channel flow. The model can handle input rainfall, soil parameters, and other properties that vary in space and time. The model was tested first against analytical solutions for idealized overland planes. After a sensitivity analysis to identify the most significant parameters, it was then calibrated and verified using rainfall and streamflow data from the USDA-ARS Walnut Gulch experimental watershed in Arizona, USA. The coefficients of efficiency for runoff volume, peak flow, and time to peak flow with respect to calibration/validation are 0.95/0.65, 0.85/0.09, and 0.69/0.88, respectively. Example applications of the model show its potential for simulating internal states and fluxes. The open-source model is provided for space–time simulation and scaling of event-based Hortonian runoff and infiltration.

Keywords: Infiltration; Hortonian runoff; Model development; Calibration; Model testing

Software availability

Program title: Hortonian Infiltration and Runoff/On (HIRO2)
Download website: http://arsagsoftware.ars.usda.gov/ (click on “AgSoftware”, then “HIRO2”)
Program language: Fortran 77
Hardware requirements: PC (depending on the number of pixels in the watershed, recommend 2.0+ GHz CPU, at least 1 GB RAM)
Operating System requirements: Windows 2000, XP, UNIX, or Linux
Cost: Free, no technical support.

1. Introduction and literature review

Various levels of physically based, distributed hydrological models have been developed for different purposes. Before discussing the available alternatives, one might ask, “Why build a new model?” To answer this question, we need to state the purpose and specific requirements. The present model was developed to investigate space–time scaling of infiltration during rainfall events over small to medium-sized catchments (e.g., Meng et al. (2006) simulated a 15 km² catchment at 30 m resolution). For this purpose, the model needed to: (1) be grid-based with at least 128 × 128 pixels; (2) allow variable rainfall in space and time; (3) simulate infiltration excess at each pixel; (4) route overland flow and allow infiltration of run-on; (5) output infiltration rate, cumulative infiltration, and runoff at each pixel; and (6) be numerically efficient to allow multiple realizations per rainfall event without excessive

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run-time. Although some existing models meet some of these criteria, none were found to be adequate for our purposes.

Similar hydrological models with distributed infiltration and runoff can be classified as fully three-dimensional (3D), flow-path based (but not grid-based), and representative area or hydrologic response unit (HRU) models. The first two classes allow runoff from upslope areas to become run-on to lower areas and possibly infiltrate (Nahar et al., 2004), whereas the HRU approach routes any runoff directly to channels. Fully 3D models (e.g., InHM (VanderKwaak and Loague, 2001; Loague et al., 2005)) and quasi-3D gridded models (e.g., CASC2D (Downer et al., 2002b) and GSSH (Downer et al., 2002a)) were determined to be too computationally intensive. More recently developed models, TACD (Uhlenbrook and Sieber, 2005), and HRU models (e.g., InHM (VanderKwaak and Loague, 2001; Loague et al., 2005)) and quasi-3D gridded models (e.g., Casc2D (Downer et al., 2002b) and GSSH (Downer et al., 2002a)) were determined to be too computationally intensive. More recently developed models, TACD (Uhlenbrook and Sieber, 2005), and AFFD (Moretti and Montanari, 2007), simulate quasi-3D runoff using cascading reservoirs based on the D8 flow-path algorithm (see our discussion of flow routing in the next paragraph). Quasi-3D models based on non-gridded flow paths include Thales (Grayson et al., 1995), Topog (Vertessy et al., 1993), and KINEROS (Woolhiser et al., 1990). Finally, HRU-type models, such as PRMS (Leavesley et al., 1983) and SWAT (Neitsch et al., 2002) or SWIM (Krysanova et al., 2007), do not simulate interactions between hillslope areas due to run-on. Twelve distributed hydrology models have been compared in terms of streamflow simulation (Reed et al., 2004; Smith et al., 2004), and the debate over model complexity in hydrology is a topic of ongoing discussion (Loague and VanderKwaak, 2004; Uhlenbrook and Sieber, 2005). Furthermore, various tools are becoming available for delineating subcatchment areas and aiding model setup (e.g., Gyllenhammar and Gumbricht, 2005; Miller et al., 2007).

Accurate delineation of flow network and drainage area is fundamental to the modeling of surface water hydrology. Several flow routing algorithms are available that can define flow paths in a watershed by determining flow direction and division at each digital elevation model (DEM) pixel such as D8 (O’Callaghan and Mark, 1984), multiple flow direction (MFD) (Freeman, 1991; Quinn et al., 1991), two directional edge-centered routing (2D-Lea) (Lea, 1992; Costa-Cabral and Burgos, 1994), two directional block-centered Routing (2D-Jensen) (Jensen, 1996), and D∞ (Tarboton, 1997) flow-path algorithms. Among these algorithms, D∞ provides an excellent approach to: (1) calculate a continuous flow direction, overcoming the limitation of D8 to only eight possible directions; and (2) partition flow from a single DEM pixel to one or two adjacent pixels based on the direction of the maximum downward slope, which reduces dispersion problems relative to MFD. Endreny and Wood (2003) examined the spatial congruence of observed and DEM-delineated overland flow network and ranked D∞ as one of the most accurate routing algorithms. Erskine et al. (2006) compared five flow routing algorithms and showed that contributing areas computed with D∞ fell between the other algorithms. Based on the above observations, the D∞ algorithm was chosen to determine the flow paths and the routing sequence of the pixel hierarchy in this rainfall—runoff model.

Here, the goal is to develop and test a fully distributed Hortonian rainfall—runoff model that incorporates an advanced flow-path algorithm, employs physical models for the computation of ponding time and infiltration, and routes overland flow and channel flow at the pixel level (e.g., 30 m). Notably, the routing of overland flow includes the dynamics of run-on from upslope areas affecting infiltration dynamics in space and time. The rainfall—runoff model can be applied to event-based studies of watershed processes, such as the spatial-temporal development of infiltration and runoff fields.

2. Model formulation and description

A physically based, distributed rainfall—runoff model, called HIRO2 (Hortonian Infiltration and Runoff/On), has been developed for event-based space—time studies of watershed processes. It consists of the following basic elements: flow-path scheme, ponding time computation, infiltration computation, hillslope overland flow routing, and channel flow routing. Some of the main features of HIRO2 are:

1. Input rainfall, soil parameters, and other watershed properties can vary in space and/or time down to pixel scale.
2. Hillslope and channel areas are delineated from DEM data using the D∞ flow algorithm.
3. Flow paths in the watershed are determined based on the D∞ flow algorithm. Thus flow is allowed to diverge and converge at any pixel (except that divergence is not allowed for channel pixels).
4. A routing hierarchy is defined from flow paths. Routing starts from the pixels at the top of the hierarchy and cascades down to pixels at the bottom of the hierarchy at each time step.
5. Infiltration is computed at each pixel using the Green—Ampt model. The source of water for infiltration includes both rainfall and run-on from upslope areas.
6. The ponding-time model can handle variable rain rate. Run-on is also taken into account in the computation of ponding time.
7. Hortonian runoff is routed pixel by pixel using a kinematic wave model for both hillslope overland flow and channel flow.
8. Infiltration rate, cumulative infiltration, water depth, and runoff (hydrograph) at any pixel and at any time can be written to output files in ASCII format. This feature makes HIRO2 a useful tool for the simulation of internal states and fluxes.
9. An implicit finite difference scheme is applied to solve the routing equations numerically.

Although the model simulates dynamics at individual pixels, such details of the simulations should be treated with caution. Distributed parameters are rarely identifiable down to the pixel scale due to a paucity of data for parameter estimation and distributed response testing. Instead, spatial patterns of infiltration and run-off may be analyzed statistically to test scaling relationships (e.g., Meng et al., 2006) that could not be tested empirically. While simulation of spatial and temporal details are illustrated below, inference in space and time is left for future research.

2.1. Flow-path and channel delineation

The D∞ flow algorithm (Tarboton, 1997) is used to determine flow direction at each DEM grid pixel. The direction of the maximum slope is based on eight triangular facets. Flow from this pixel goes to only one downslope pixel if its flow direction is cardinal or diagonal. Otherwise, flow is apportioned into two downslope pixels based on the flow angle. The watershed area contributing to each pixel can then be calculated based on flow directions of all its upslope pixels. A threshold contributing area can also be defined, and any pixels with contributing area larger than the threshold value are defined as channel pixels.
Since a one-dimensional routing scheme and an implicit finite difference method are employed, it is essential to determine the flow paths and the routing sequence pixel by pixel. This is accomplished with the aid of flow direction at each pixel. After flow paths are determined, routing can proceed in order. At each time step, infiltration and excess runoff are calculated first at pixels that cannot have any inflow from neighboring pixels. The next set of pixels only receive inflows from the first set of pixels, i.e., pixels that have already been simulated. This cascading procedure proceeds until infiltration and runoff are simulated at all pixels. Then, time advances one step and the same computational procedure is repeated until the end of the time period of interest.

2.2. Ponding-time computation

Smith and Parlange (1978) developed a formula to calculate ponding time which, in principle, suits any rainfall pattern:

\[ \int_0^b R(t)dt = M \left[ \frac{S[\theta_i]}{K_s} \right] \ln \left[ \frac{K_s}{K_t} \right] \]  

(1)

(note: Eq. (1) is modified from the original form based on personal communication with Smith) where \( R(t) \) is rainfall rate at time \( t \); \( t_p \) is ponding time; \( M = 0.5; K_s \) is effective hydraulic conductivity, and \( S[\theta_i] \) is soil sorptivity at initial soil moisture content, \( \theta_i \), such that \( S[\theta_i] = 2(\theta_i - \theta_s)K_s(\psi) \), where \( \theta_s \) is soil porosity, and \( \psi \) is wetting front suction. Broadbridge and White (1987) improved Eq. (1) by changing its coefficient \( M \) from 0.5 to the range 0.5 \( \leq M \leq 0.66 \) with an average value of 0.55. The computation of ponding time in this study is based on Eq. (1) with \( M = 0.55 \). For the case of instantaneous ponding, the Smith–Parlange infiltration model is exactly the form of Green–Ampt (Smith and Parlange, 1978, Eq. (27)). This implies that the two approaches are similar for infiltration after ponding. Several rainfall–runoff events are used to check the ponding times computed using the two infiltration models. The results show that the differences between the times are insignificant. Combining with the check on the available water supply (Section 2.3, Eq. (3)), there is essentially no difference in the infiltration and runoff processes no matter which model is used to calculate ponding time.

Run-on (inflow from neighboring pixels) is an important water source for infiltration and runoff. Run-on is included in HIRO2 for the computation of ponding time. Excess rainfall from upslope pixels is routed to the pixel under study. Run-on is taken to be the water depth corresponding to the inflow \( dh \) divided by the time increment \( dt \). The final form of the formula for calculating ponding time used in this work is Eq. (1) with \( R(t) \) replaced by \( [R(t) + dh/ dt] \) and \( M = 0.55 \).

2.3. Green–Ampt infiltration

Infiltration excess (Hortonian) runoff is the mechanism for runoff generation in HIRO2 where overland flow reaches its maximum intensity exceeds infiltration rate. The Green–Ampt model is adopted for the computation of infiltration capacity:

\[ i_c(t) = \begin{cases} \frac{R(t) + dh(t)}{K_s} & \text{for } t \leq t_p \\
\frac{K_s}{K_t} \left[ h(t) + R(t)dt/2 + \psi(\theta - \theta_s) \right] / I(t) & \text{for } t > t_p \end{cases} \]

(2)

where \( I(t) \) is cumulative infiltration at time \( t \). The actual infiltration rate is taken as the minimum of the infiltration capacity and the available water supply rate, i.e.,

\[ i(t) = \min \left[ i_c(t), R(t) + \frac{dh(t)}{dt} \right] \]

(3)

2.4. Hillslope overland flow routing

The kinematic wave model is used for hillslope overland flow routing where the friction and gravity forces balance each other, and the acceleration and pressure terms are neglected. Combining the kinematic wave model with Manning’s equation, an equation with discharge \( Q \) as the only dependent variable can be derived (e.g., Chow et al., 1988, Chapter 9). It is given by:

\[ \frac{dQ}{dt} + 5 \left( \frac{S[\theta_i]}{K_s} \right) \frac{Q^{1/3}}{\left( \frac{nB^{3/2}}{S_0^{1/2}} \right)^{1/3}} = \frac{5}{3} \left( \frac{S[\theta_i]}{K_s} \right) \frac{Q^{2/3}}{\left( \frac{nB^{3/2}}{S_0^{1/2}} \right)^{1/3}} - q = 0 \]

(4)

where \( x \) and \( t \) represent one-dimensional distance and time, respectively; \( S_0 \) is slope; \( n \) is Manning roughness coefficient; \( W \) is wetted perimeter which is taken to be pixel width \( (B) \) for overland flow; and \( q \) is lateral inflow per unit length. The surface water depth, \( h \), for overland flow is

\[ h = \frac{1}{B} \left( \frac{nB^{3/2}}{S_0^{1/2}} \right)^{1/3} Q^{1/3} \]

(5)

To numerically solve Eqs. (4) and (5), an implicit finite difference scheme is used because of its stability and capability to handle relatively large time steps. The numerical approximations to Eqs. (4) and (5) are

\[ \frac{\Delta t}{\Delta x} \left[ \frac{5}{3} \left( \frac{nB^{3/2}}{S_0^{1/2}} \right)^{1/3} \left( Q_i^{1/3} + Q_i^{1/3} \right)^{-1/3} \right] \left( Q_i^{1/3} + Q_i^{1/3} \right)^{-2/3} = \frac{5}{3} \left( \frac{S[\theta_i]}{K_s} \right) \left( \frac{nB^{3/2}}{S_0^{1/2}} \right)^{1/3} \left( Q_i^{1/3} + Q_i^{1/3} \right)^{-2/3} + \frac{\Delta t}{\Delta x} \left( q_i^{1/3} + q_i^{1/3} \right) \]

(6)

and

\[ h_i^{1/3} = \left[ \frac{nB^{3/2}}{S_0^{1/2}} \right]^{1/3} Q_i^{1/3} \]

(7)

where \( Q_i^{1/3} \) is the discharge of pixel \( i \) at time step \( j \). The initial condition is \( Q_0^{1/3} = 0 \) for all pixels in the study area. The boundary condition for a watershed is zero inflow from outside the watersheds. Fig. 1 shows the flowchart of hillside overland flow routing.

2.5. Channel flow routing

The same kinematic wave model used for overland flow routing is applied to channel flow routing with some modifications as elaborated below.

(i) The term \( B \) in Eq. (6) is replaced with the perimeter \( P_l \) of pixel \( i \) at time step \( j \) (Woolhiser et al., 1990):

\[ P_l = B + h_i^{1/3} \left( \frac{1}{S_L} + \frac{1}{S_R} \right) \]

(8)

where \( B \) is the bottom width of a trapezoidal channel; \( S_L \) is the slope of the channel left bank and \( S_R \) of the channel right bank.

(ii) The surface water depth takes the form

\[ h_i^{1/3} = \frac{B}{C} + \sqrt{\left( \frac{B}{C} \right)^2 + 2 \left( \frac{P_l^{3/2}}{S_L} \right)^{1/3} \left( Q_i^{1/3} \right)} \]

(9)

where

\[ C = \frac{1}{S_L} + \frac{1}{S_R} \]

(10)

(iii) The term \( Q_i^{1/3} \) in Eq. (6) becomes the inflow from the immediate upstream channel pixel(s) instead of the summation of inflows from all the immediate upslope pixels.

(iv) In addition, all inflows to a channel pixel \( i \) from pixels other than channel pixels are added to the excess rainfall rate of pixel \( i \) as lateral inflow \( q_i \) in Eq. (6).

HIRO2 does not include base flow, and channel flow routing starts as soon as excess runoff occurs. Thus HIRO2 is mainly suitable for watersheds where streamflow is intermittent. Fig. 2 shows the flowchart of channel flow routing.
2.6. Input/output data formats

Grid DEM data are required for the delineation of watershed and channels as well as the designation of flow paths and routing hierarchy. Terrain data are also used to calculate the slope at each pixel. Rain rate at each pixel and at each time step serves as input to HIRO2. Other inputs include saturated hydraulic conductivity, initial soil moisture content, porosity, wetting front suction and Manning’s roughness coefficient.

The internal states and fluxes involved in the computation of infiltration and runoff processes can be output at any or all time steps, including surface infiltration rate, cumulative infiltration, runoff, and surface water depth. All input and output variables in HIRO2 are in ASCII format.

3. Model testing with analytical solutions

HIRO2 was first tested against analytical solutions for idealized overland flow over uniform plane catchments whose overall length in the direction of flow is \( L \). The surface roughness, slope, and rainfall regime were assumed invariant in space and time. In all of the numerical experiments in this section the following parameters were set as follows: Manning’s \( n = 0.01 \), slope = 0.01, and rainfall rate \( R = 10 \) cm/h. Analytical solutions exist for hydrographs in such an idealized hillslope based on the kinematic wave assumption (e.g. Eagleson, 1970, Chapter 15).

Fig. 3 shows the hydrographs obtained at \( x = L \) with no infiltration \( (i = 0) \) based on both the analytical solution and the numerical solution using HIRO2. Fig. 3a represents the case when \( t_r > t_c \), where \( t_r \) is the storm duration and \( t_c \) is the time of concentration, i.e. the time when flow from the farthest point in the watershed reaches the outlet. Fig. 3b shows the case when \( t_r < t_c \). In both cases, agreement between the analytical and numerical solutions is very good with slight numerical
dispersion at the beginning or ending parts of steady runoff. Fig. 4 displays the hydrographs when a constant infiltration ($i = 5$ cm/h) is present. Again, there is good agreement between the analytical and the numerical results with the exception of some numerical dispersion (Fig. 4a). This verifies the overland flow routing component of HIRO2 and the correctness of the software code.

4. Model testing methods and site description

Next, HIRO2 was calibrated and validated using rainfall and channel streamflow data collected at the USDA-ARS Walnut Gulch experimental watershed (Goodrich, 1990). This section discusses various aspects of the calibration on the Walnut Gulch watershed.

4.1. Walnut Gulch subwatershed 11 (WG11)

The watershed used for the HIRO2 model calibration is subwatershed 11 (30°44’32”N, 109°59’35”W) of the Walnut Gulch Experimental Watershed (WG11) near Tombstone, Arizona. WG11 is located in a semiarid area with ephemeral streams and two stock ponds (Fig. 5). It has an area of 635 ha excluding the ponds’ contributing areas. The area contributing to the two stock ponds was excluded from the study area due to the insignificant contribution the ponds spillage makes to the event runoff at the watershed outlet (SWRC, 1993). The major soil type is sandy loam and the vegetation is mainly desert shrub and grass (SWRC, 1993). The drainage network of the watershed consists of three major branches that are either incised channels with sandy bottom or broad swales with sandy loam soil (Woolhiser et al., 1990).
The delineation of WG11 was based on a set of 7.5-min data with 30-m DEM resolution produced by the U.S. Geological Survey (http://edc.usgs.gov/products/elevation/dem.html). As shown in Fig. 5, the delineated boundary closely approximates the measured boundary. The threshold for defining the channel network in WG11 was set to be 22.5 ha. This results in a channel network that closely resembles the measured channel network (Meng, 2005).

There are nine weighing-type recording rain gages within WG11 and one supercritical flume with a capacity of 170 m$^3$/s at its outlet. Breakpoint rainfall data for the rain gages have been recorded by the USDA-ARS since the 1960s. Runoff data were also measured by the flume at the outlet and were initially available from August 1968 to October 1977. This period of record becomes a limiting factor in our choice of rainfall—runoff events for calibration at the early stage of this study. It was not until the validation stage that more runoff data became available from July 1963 to August 2003.

### 4.2. Spatial parameter estimation

The distributed nature of HIRO$_2$ requires that the input parameters be defined down to grid pixels and, for dynamic parameters, at each time step. Due to the lack of detailed measurements of most input parameters, they have to be estimated through techniques such as spatial interpolation and empirical equations.

#### 4.2.1. Rain rate

Ordinary kriging is used to estimate the space—time rain rate field from measurements at the rain gage stations. Kriging relies on the spatial dependence structure among the measurements in the form of a variogram to estimate values at any point in the watershed. Since rain rate usually has a rather strong spatial dependency at small scales, ordinary kriging is an appropriate method. Variograms of the rain rate fields were estimated by (ASCE, 1990):

\[
\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [R(\bar{x}_i) - R(\bar{x}_0)]^2
\]

where $\bar{x}$ denotes a vector; $R(\bar{x}_0)$ is measured rain rate at point $\bar{x}_0$; $|h|$ is the average distance between pairs of data points belonging to a distance group; $N(h)$ is the number of pairs of data points belonging to the distance group represented by $h$. A linear (i.e., nonstationary) variogram model was used to fit the data:

\[
\gamma(h) = \omega h
\]

where $\omega$ is the slope at the origin and $h$ is distance. The choice of a linear variogram model is supported by available rainfall

![Kinematic wave hydrograph for rainfall, $R = 10\text{ cm/h}$](image)

![Kinematic wave hydrograph with rainfall, $R = 10\text{ cm/h}$, and infiltration, $i = 5\text{ cm/h}$](image)
measurements. For example, Fig. 6 shows the variograms of rain fields at three different times for the rain event of September 13, 1975. They display reasonably well-defined linear trends for $h < 2700$ m ($90$ cell widths $\times 30$ m/cell). Thus, $h < 2700$ m was used in the estimation of $\omega$ for each rain field, which is appropriate given the relatively high density of rain gages.

4.2.2. Porosity and Manning’s roughness coefficient

Porosity $\phi$ was first estimated from soil texture. WG11 is dominated by sandy loam soil type with wide, sand-bed incised channels (Goodrich, 1990). Based on Rawls and Brakensiek (1985), the porosity was initially set to be 0.453 for all overland and swale pixels and 0.437 for incised channels. Porosity was assumed to be spatially constant for each soil type (sandy loam or sand), but initial $\phi$ values for each soil type were modified by a uniform multiplier $M_\phi$ during calibration. This approach reduces the degrees of freedom for spatial parameter estimation. Thus, initial estimates of $\phi$ were used to determine the relative difference between soil types and to constrain the range of feasible calibration values based on the multiplier $M_\phi$, where $0.5 < M_\phi < 0.8$ was the range explored here. The value of $M_\phi = 0.5$ corresponds to $\phi = 0.23$, which is the minimum expected for a gravely sandy loam with up to 20% gravel by volume (Andreu et al., 1997, Table 3).

The vegetation cover on WG11 is composed of 20% desert brush and 80% grassland. Manning’s $n$ was initially set to 0.06 for brush areas and 0.035 for grassland areas (Chow et al., 1988, Chapter 2). Similar to porosity, the initial $n$ values were modified by a uniform multiplier $M_n$ during calibration ($0.6 < M_n < 1.2$). Manning’s $n$ for the channel pixels was taken from a data set provided by David Goodrich (personal communication). The minimum $n$ for channels was 0.025, the maximum was 0.04, and the average value was 0.033. The values of the Manning’s $n$ for channels were fixed and remained unchanged during calibration.

4.2.3. Saturated hydraulic conductivity

The spatial estimation of the saturated hydraulic conductivity $K_s$ is more complicated than other parameters. Goodrich (1990) carried out an extensive study on WG11 and divided the watershed into six categories based on soil composition and vegetation (Table 1). To represent the spatial variability of $K_s$, a lognormal distribution was assumed for each of the four areas with $K_s$ categories A, B, C, and D (Fig. 7). No correlation structure was incorporated in the lognormal distribution, i.e. the $K_s$ field was assumed to be independent from pixel to pixel. This assumption is justified by the fact that the typical correlation length for $\ln(K_s)$ is from about 5 to 20 m (Rao S. Govindaraju, personal communication) which is less than the pixel size (30 m) used in this study. With given mean, coefficient of variation, and the number of pixels in

Fig. 5. Delineated subwatershed 11 of Walnut Gulch Experimental Watershed (WG11).

Fig. 6. Semi-variograms of rain fields from the rain event on September 13, 1975.
each category, the same number of lognormally distributed $K_s$ values are generated and sequentially assigned to the pixels. The channels, corresponding to categories E and F, are assumed to have constant $K_s$. The $K_s$ values given in Table 1 are the initial estimates for mean values of the $K_s$ for each area, and the coefficient of variation for each area was initially assumed to be 1.0 for all areas (Goodrich, 1990). Since the effect of ground cover was already incorporated, $K_s$ was assumed to be equal to the effective hydraulic conductivity, $K_e$.

When the mean $K_s$ values of the lognormally distributed $K_s$ in each of the six regions from Goodrich (1990) were applied to HIRO2, intense rain in certain areas always resulted in serious overestimates of the runoff volume, while heavy rain in some other areas led to underestimates of the runoff volume. This sensitivity of runoff volume to spatial rainfall variability called for the individual adjustment of $K_s$ value for each classified area. Individual classes were adjusted to fit runoff from storms where rainfall was localized primarily over one area. Therefore, a new two-step approach was adopted, where the six $K_s$ categories were tested individually to determine modified $K_s$ values first. During global calibration, a uniform multiplier $M_{K_s}$ was applied to all of the modified $K_s$ values. Since the same (single) $K_s$ field was applied to the entire calibration and validation event set, some discussion is warranted about the ergodicity of the $K_s$ field. Four lognormal distribution series were generated to represent the $K_s$ from the four overland $K_s$ categories. These series were created from some uniform random numbers generated by a pseudorandom number generator, Mersenne Twister (MT), which generates high quality random numbers with a period of $2^{19937} - 1$. Since uniform random numbers are white noise with good ergodicity, it is expected that the $K_s$ field is also ergodic and the results of this study are not dependent on the particular $K_s$ field chosen herein.

### 4.2.4. Initial soil water content

Initial soil water content $\theta_i$ was estimated from information on soil properties and rainfall and runoff histories prior to the rain event. Because WG11 is a semiarid rangeland where the average soil condition is fairly dry, $\theta_i$ was set to range from the residual soil water content $\theta_r$ to field capacity $\theta_f$. The initial soil water content is thus,

$$\theta_i = \theta_r + \frac{\theta_f - \theta_r}{d}$$

(13)

where $d \geq 1$ is a factor estimated based on rain history. This factor is proportional to the dryness of the soil, with $d = 1$ corresponding to $\theta_i = \theta_r$ and $d = \infty$ corresponding to $\theta_i = \theta_f$. The incised channels on WG11 usually have sandy bottoms, while the overland plane and swales have a sandy loam soil type. Thus, incised channels are typically drier than other parts of the watershed. This phenomenon is reflected in the estimated values of $d$ (Meng, 2005).

### 4.2.5. Other hydrological parameters

Field capacity, residual soil moisture content and wetting front suction are some of the parameters used in the computation of infiltration. Because of the lack of field measurements for these parameters, they were derived from $K_s$ through regression relations. The infiltration parameters for 10 soil textures (Rawls and Brakensiek, 1985) were used to obtain the regression relations (sand is excluded from the regression). Values of $\theta_i$ were set equal to soil moisture content at $-33$ kPa, and $\theta_f$ equal to soil moisture content at $-1500$ kPa. This approach addresses the spatial variability of these parameters.

### 4.3. Error evaluation methods

Model calibration and validation are evaluated using standard statistical metrics for both individual runoff time series and for event characteristics across all calibration or validation events.

#### 4.3.1. Metrics for individual runoff events

The primary evaluation measure is the coefficient of efficiency, $E$ (Nash and Sutcliffe, 1970):

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

(14)

where $\hat{Q}_i$ is the simulated streamflow (or other variable of interest), $Q_i$ is the observed streamflow, and $\overline{Q}$ is mean of $Q_i$ for
$i = 1$ to $N$ measurement times (or events). Note that $E$ without subscripts is defined by Eq. (14) for each runoff event, whereas other measures of model efficiency across multiple events will be introduced below. If a model predicts observed variables perfectly, $E = 1$. If $E < 0$, the model’s predictive power is worse than simply using the average of observed values. When $E$ is used to evaluate discharge from a single event, a slight shift in the timing of simulated hydrograph from the observed one could reduce $E$ dramatically. As noted by Goodrich (1990), clock errors in hydrograph observations could easily be 8—10 min. This warrants a timing adjustment in the simulated hydrographs just to gain a sense of how well the simulations agree with the observations without any possible contamination of timing error in the data record. Thus, in addition to the regular $E$ value, a time shift was used below to obtain improved, alternative values of $E$. The time shift is dependent on the individual calibration or validation event, and the time shift that gave the highest $E$ for the event was used. Both the original $E$ and the $E$ with time shift were tabulated as part of the calibration and validation results. Besides human (clock) errors, some other reasons for the time shifts in simulated hydrographs are inaccuracies associated with antecedent soil moisture conditions and rainfall distributions. In particular, Fig. 8 compares the observed hydrograph of the rainfall—runoff event on August 21, 1973 at the outlet of WG11 with simulated hydrographs under different initial soil moisture conditions. The wet antecedent soil leads to a slightly earlier onset of runoff event compared to the dry soil, but a time shift is required to align simulated and measured hydrograph peaks, while fitting the total runoff mass.

The second measure is the relative error that reflects mass conservation:

$$e(\%) = \frac{\sum_{D,t} R - \sum_{D,t} Q - \sum_{D,t} i}{\sum_{D,t} R} \times 100$$

where $\sum_{D,t}$ represents the summation over space and time; $R$ is rainfall; $Q$ is runoff; and $i$ is infiltration rate. Note that evaporation and transpiration are not considered in the simulated runoff events. A small relative error indicates that the model conserves mass well.

Another statistic included in the analysis is the Root Mean Squared Error (RMSE)

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (Q_i - \hat{Q}_i)^2}$$

Like $E$, the RMSE is sensitive to a shift in the timing between the simulated hydrograph and the observed one. In addition, visual inspections of the simulated hydrographs and comparisons of the calibration quantities in the form of scatter plots are provided below.

4.3.2. Metrics for ensembles of calibration/validation runoff events

Similarly, model efficiency was evaluated for three hydrograph characteristics (total volume, $V$, peak streamflow rate, $Q_p$, and time to peak, $T_p$) over all calibration or validation events. The corresponding efficiency values for $V$, $Q_p$, and $T_p$ are $E_V$, $E_{Q_p}$, and $E_{T_p}$, respectively, where $Q$ in Eq. (14) is replaced by the event characteristic of interest and $N$ is the number of calibration or validation events. Due to the limited number of events ($N = 5$ for calibration and 21 for validation), one or two poorly simulated events can dramatically decrease the model efficiency measure.

5. Hydrograph sensitivity analysis, calibration and validation results

Five rainfall—runoff events at WG11 were used for this part of the study based on data quality and data availability. The events were also chosen to cover a range of runoff volumes and peak flow rates. Table 2 lists the five rainfall—runoff events along with some detailed information about the characteristics of the events.

5.1. Sensitivity analysis

A sensitivity study was performed to identify the most important calibration parameters. Before the sensitivity analysis was conducted, a set of calibration parameters was adjusted until a good fit was found between the simulated and the observed hydrographs for a rainfall—runoff event on August 12, 1971. The calibration parameters include porosity $\phi$, coefficient of variation of $K_s$, Manning’s $n$, wetting front suction, initial soil water content, field capacity, and residual soil water content. This set of model parameters (hereafter denoted as “base parameters”) was applied to five test events and the

---

2 By fixing the mean but varying the coefficient of variation, a set of $K_s$ fields can be generated which have a lognormal distribution (except in the channels) with the same mean, the same seed for generating the lognormally distributed $K_s$ field, but different coefficients of variation, i.e. standard deviation. These $K_s$ fields can then be used to evaluate the effect of coefficient of variation of $K_s$ on the watershed model.
resulting values of runoff volume \((V)\), peak flow \((Q_p)\), and times to peak flow \((T_p)\) were taken as the base values for sensitivity analysis. The base parameters with \(\pm 20\%\) perturbations were then applied to the five events to test the marginal sensitivity of the three runoff variables \((V, Q_p, T_p)\) to each of the calibration parameters. The perturbation level of \(20\%\) was chosen to keep the parameters within their physical ranges and still produce responses in the three runoff variables for sensitivity analysis. Table 3 gives the Root Mean Squared Differences (RMSD) between the base values and the model results with \(\pm 20\%\) perturbations in each model parameter. RMSD is defined as

\[
\text{RMSD} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (x_i - y_i)^2}
\]

where \(x\) and \(y\) are two variables being compared, \(m\) is the number of samples. In this case, \(m = 5\) for the five events in Table 2.

Runoff volume, peak flow, and time to peak flow can all be important hydrologic variables. The sensitivity analysis (Table 3) demonstrates that \(\phi\) and \(K_s\) play dominant roles in HIRO2 for simulating \(V\), while Manning’s \(n\) becomes important for predicting \(Q_p\) and \(T_p\). A regression analysis on \(K_s\) and \(\phi\) values of the USDA 11 soil classes yielded an \(R^2\) value of 0.068, i.e., the two parameters are essentially uncorrelated. The calculated correlation coefficient of the \(K_s\) and Manning’s \(n\) data used in this work is \(-0.37\), and of \(\phi\) and \(n\) is \(0.17\). The relatively high correlation between \(K_s\) and Manning’s \(n\) is caused by about \(25\%\) bushy area (high Manning’s \(n\)) coinciding with an area of low \(K_s\). Since the majority of the overland area has a single Manning’s \(n\) value and hence uncorrelated \(K_s\) and Manning’s \(n\), there is not a significant risk of potential over-parameterization. The correlation between \(\phi\) and Manning’s \(n\) is low — indicating that the two variables are relatively independent of each other.

### 5.2. Parameter calibration

During calibration, the three uniform multipliers \(M_\phi\), \(M_n\) and \(M_K\) were varied systematically to test the watershed responses in each calibration event. The search ranges of the multipliers were set such that the calibration parameters have physically meaningful values. The criteria for choosing multipliers are for the calibration parameters to produce the best possible coefficient of efficiency for \(V\), and good coefficients of efficiency for \(Q_p\) and \(T_p\) within the search ranges. Thus, the calibration procedure ensures the following priority: \(E_V > E_{Q_p} > E_{T_p}\). Fig. 9 shows some of the contour plots of the coefficient of efficiency for the three calibration variables \((V, Q_p, T_p)\) in the multiplier space. Since the multiplier space is three-dimensional, one dimension (i.e. multiplier) is fixed in each of the 2D plots in Fig. 9 to show the contour of the other two multipliers. There are totally nine plots to accommodate the contours of three pairs of multipliers for each of the three calibration variables. It is noted that there are far more contour plots in the searched multiplier space than shown in Fig. 9. Based on the priority given to the calibration variables, an optimal set of multipliers was chosen: \(M_K = 1.5\), \(M_\phi = 0.55\), and \(M_n = 1.0\). The modified \(K_s\) and global optimum values for the six regions after employing the chosen multiplier are given in Table 4. The following statistics were derived from the model results when the optimal multipliers were applied to the five calibration rainfall—runoff events.

#### 5.2.1. Coefficient of efficiency

The following coefficients of efficiency were obtained for the five calibration events.

- **Runoff volume**: \(E_V = 0.95\)
- **Peak flow rate**: \(E_{Q_p} = 0.85\)
Time to peak: $E_{r_p} = 0.69$

The corresponding RMSE values are:

Runoff volume: $\text{RMSE}_V = 0.41$ mm
Peak flow rate: $\text{RMSE}_Q = 2.87 \text{ m}^3/\text{s}$
Time to peak: $\text{RMSE}_{t_p} = 12.06$ min

The coefficient of efficiency of 0.95 for $V$ is very good considering all the uncertainties involved in the field data for the watershed. The coefficients of efficiency for peak flow (0.85) and time to peak flow (0.69) are also acceptable. Scatter plots of the three calibration variables for the five events are shown in Fig. 10. The coefficients of efficiency for temporal discharge, $E_Q$, from individual events are given in Table 5.

5.2.2. Mass conservation

In addition to the $E_V$ statistic above, which is a measure of overall mass conservation, Table 5 shows the mass relative errors for each of the calibration events. The mass relative errors
for most of the rainfall—runoff events are less than or equal to 4.5% except for event 5 which is 7.8%. Such small errors also indicate that HIRO2 conserves mass well in most cases.

5.2.3. Time series plots

Fig. 11 displays the simulated hydrographs of the five calibration events along with the corresponding observed hydrographs at the outlet of WG11 and hyetographs at Rain Gage 90 (RG90). RG90 is located in the center part of WG11 (Fig. 5) and is usually representative of the rainfall events at WG11.

Of the five \( E \) values shown in Table 5, three (Events 1, 4, and 5) range between 0.31 and 0.69. This is caused primarily by a shift in the timing of the simulated hydrographs from the observed ones (Fig. 11). These values increased to between 0.86 and 0.98 after the simulated hydrographs are adjusted in time to match the observed hydrographs (Table 5). The worst \( E \) value of 0.06 obtained for event 3 (9/24/1974) combined with a low mass balance error indicates a timing problem, but it could not be improved substantially using a uniform time shift of 9 min. This event has the smallest runoff volume among the five events used for calibration (Table 2). The poor simulation results for this runoff event could be caused by one or both of the following: (1) errors in the calibration data, and (2) the model’s inability to capture runoff dynamics when there is little rainfall (i.e., threshold phenomena). Fortunately, the large rainfall—runoff events are most important from the point of view of watershed management (Goodrich, 1990). Overall, the above coefficients of efficiency are considered satisfactory for the calibration set.

5.3. Validation runs

The validation set is composed of 21 rainfall—runoff events between 1966 and 1988 (Table 6). An effort was made to use the same validation events as Goodrich (1990), so that the latter can serve as a benchmark for this study. However, two of Goodrich’s (1990) validation events were used for calibration in early stage of this work. Hence, the first two calibration events from Goodrich’s (1990) research were included here to make up the 21 validation events. The validation set covers a wide range of event sizes, initial conditions, and hydrograph types. The coverage of the events is considered good enough to capture the general behavior of the model and help with the understanding of how well the model can reproduce measured events.
5.3.1. Model efficiency

Applying the optimal parameter set obtained from calibration to the validation events, the following statistics were derived from the model results for the validation set.

Runoff volume: $E_V = 0.65$
Peak flow rate: $E_{Q_p} = 0.09$
Time to peak: $E_{T_p} = 0.88$

The corresponding RMSE values are:

Runoff volume: RMSE$_V = 1.06$ mm
Peak flow rate: RMSE$_{Q_p} = 4.15$ m$^3$/s
Time to peak: RMSE$_{T_p} = 3.42$ min

As expected, the runoff volumes and the peak flows from the 21 validation events have smaller $E$ values than for the calibration set, while the times to peak show better results. Table 7 lists the $E$ from each validation event. The important effect of time shifts in the hydrographs is also observed in the validation events as shown in Table 7. The value of $E$ increased significantly for most events after the timing of hydrographs was adjusted to better match the observed streamflow rates. Fourteen out of the 21 events have $E > 0.5$ after the time adjustment, and the maximum relative error is 6.35%, showing fairly good results for validation cases. Even after applying

Fig. 11. Observed and simulated hydrographs of calibration set at WG11 and the hyetograph at Rain Gage 90 (located in the central part of WG11): (a) event 1, 8/5/1968, (b) event 2, 8/12/1971, (c) event 3, 9/24/1974, (d) event 4, 8/21/1973, and (e) event 5, 9/6/1976. Time $t = 0$ in all graphs corresponds to the time when rainfall started on WG11.
the best time shifts, events 16, 18, and 21 have negative values of $E$, indicating that the simulations are worse than using the average measured runoff volume. Similar to calibration event 3, these events have very small runoff volumes which are the cause of the weak performance by HIRO2.

To have a reference for the model performance, Table 8 compares the calibration and validation results described here with those of Goodrich (1990). Goodrich calibrated and verified the KINEROS model (Woolhiser et al., 1990) using data from Walnut Gulch including data from WG11. While the majority of the validation events overlap between the two studies, the two calibration sets are completely different. Thus, this comparison is meant to be a general reference rather than a precise assessment of the differences between the two studies. Compared with Goodrich’s (1990) results, the coefficients of efficiency from this study show that the HIRO2 model performs well, particularly for model validation. This gives a degree of confidence in the model for event-based studies of watershed processes.

### 5.3.2. Mass conservation

The mass relative errors of the validation events are given in Table 7. Similar to the calibration events, the validation set also has mass relative errors below 5.0% except one event.

### 5.3.3. Hydrographs and scatter plots

The best and the worst predicted hydrographs from the validation set are shown in Fig. 12 along with the hyetographs at

Table 6

<table>
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<tr>
<th>Event #</th>
<th>Event date</th>
<th>Rain starting</th>
<th>Rain ending</th>
<th>Runoff starting</th>
<th>Runoff ending</th>
<th>Rain duration (min)</th>
<th>Runoff volume (mm)</th>
<th>Peak flow (m³/s)</th>
<th>Peak time (min)</th>
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<td>14:46</td>
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<td>9.28</td>
<td>49</td>
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<td>13:53</td>
<td>13:24</td>
<td>16:05</td>
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<td>10.53</td>
<td>53</td>
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<tr>
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<td>1:36</td>
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Table 7

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<th>Time shift (min)</th>
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Table 8

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<th>KINEROS</th>
<th>HIRO2</th>
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<td>CV of $K_s$</td>
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<tr>
<td>Variables used in calibration &amp; validation</td>
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<td>Volume, peak flow, time to peak flow</td>
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<td>Calibration $E_{Qv}$</td>
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<tr>
<td>Calibration $E_{Tv}$</td>
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<td>Validation $E_{Tv}$</td>
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</table>

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RG90. The goodness of fit is determined based on the discharge coefficient of efficiency \( E \). The rainfall—runoff event on July 27, 1976 has the best-fitted hydrograph with an \( E \) of 0.90 (0.97 after time adjustment), and the event on August 20, 1988 has the worst fitted hydrograph with an \( E \) of \(-18.29\) (\(-8.49\) after time adjustment).

Fig. 13 displays the scatter plots of the three calibration variables along with their respective coefficients of efficiency. Fig. 13 reveals that the multipliers for \( K_s \), \( f \) and Manning’s \( n \) as chosen from the calibration will generally lead to overestimation of runoff volume with small rainfall—runoff events and overestimation of peak flow at high flow, even though the overall statistics remain acceptable.

Fig. 13c also demonstrates the importance of timing adjustment for hydrographs in the above statistical analyses. Two outliers are shown in this figure which, with further investigation, appear to be timing errors in the data record. The two events are on September 20 and September 26 of 1983. In both cases, rain gages near flume 11 (1–1.5 km away) accumulated 1.1–4.6 cm of rain within 15–80 min. However, measured runoff at flume 11 did not start until 30–80 minutes after the bulk of each rainfall event had ceased. Thus, clock and/or human error seems to be a reasonable explanation.

6. Simulation of internal states and fluxes

As a distributed model, HIRO2 has a wide range of potential applications from spatial mapping of watershed processes to studying the connections between these processes and their driving factors such as topography and space—time rainfall. The following examples illustrate the use of HIRO2 for estimating internal watershed state variables and fluxes.

6.1. Spatial mapping of watershed processes

Fig. 14 shows interpolated rain fields and the simulated surface infiltration, runoff and cumulative infiltration fields for
the rainfall—runoff event on July 27, 1976 on WG11 at 25 and 50 min from the onset of rainfall. The images not only show spatial distributions of the variables but also reveal the temporal progression of watershed processes. At 25 min, the spatial infiltration rate (Fig. 14b) is a combined result of high rain intensity (Fig. 14a) and large infiltration capacities at the early stages of infiltration while the soils are relatively dry. Infiltration in the incised channels is much higher than in the rest of the watershed because of concentrated flow and the large infiltration capacity associated with the sandy channel bed. At 25 min, channel flow is present, especially at upstream reaches, but is still weak (Fig. 14c). The cumulative infiltration is small except in the incised channels (Fig. 14d). By 50 min, however, infiltration rates on the hillslopes...
(Fig. 14f) become much weaker as a result of the subsiding rain and the wet conditions. However, most of the incised channels sustain very large infiltration rates due to significant run-on from upslope. Spatial mapping of the runoff field at 50 min (Fig. 14g) reveals a well-developed channel network with increased channel runoff going downstream. Compared with 25 min, the cumulative infiltration field at 50 min (Fig. 14h) has increased considerably both in the channels and upslope areas.

6.1.1. Relating Hortonian runoff to topography

As demonstrated in Fig. 14c and g, streamflow in channels is considerably larger than overland flow on hillslopes. This observation leads to the hypothesis that certain properties of Hortonian runoff are controlled by topography, because streamflow is largely defined by the channel network and channels are a prominent feature of topography. Meng (2005) studied the multiscaling properties of Hortonian runoff using HIRO2 and found that channel streamflow, rather than overland runoff, dominates the spatial scaling characteristics of Hortonian runoff.

6.1.2. Significance of upslope run-on to cumulative infiltration patterns

HIRO2 explicitly models run-on from upslope, which is often important for predicting spatial infiltration patterns. Fig. 15 demonstrates this point by showing the difference field between the cumulative infiltration fields simulated with and without run-on from the event on July 27, 1976 on WG11 at 50 min after rainfall started. While run-on makes little to no impact on the cumulative infiltration at hillslope areas, it plays a significant role in the channels, where the maximum difference is 30 mm, i.e. more than 10% of the maximum cumulative infiltration value.

6.2. Spatial statistical distributions of infiltration and runoff

An advantage of HIRO2 over lumped rainfall-runoff models is its capability to output the spatial distributions of the modeled quantities at any given moment during the event. The output data can then be used to generate a picture of the spatial and temporal distributions of the watershed processes. Fig. 16 demonstrates this point by showing the cumulative distribution functions (CDFs) of the simulated infiltration rate, runoff, and cumulative infiltration fields from the event on July 27, 1976 at 25 and 50 min after the rain started at WG11.

An intrinsic shortcoming of a lumped conceptual/statistical model is that internal states and processes of the watershed can only be described as lumped quantities or statistical distributions, at best. On the contrary, it is very convenient in HIRO2 to output the time series of a quantity at any point of interest in the watershed. For instance, Fig. 17 displays the infiltration capacity, simulated infiltration rate and runoff at an overland pixel, thus showing the temporal infiltration capacity and effective infiltration rate due to the variable available water supply rate (rain rate plus run-on). The coordinate of the pixel used in Fig. 17 is (2310, 2010). It is an overland pixel located in the upper part of WG11 (refer to Fig. 5). Such temporal dynamics can be visualized spatially as illustrated for only two synoptic views in Fig. 14.
In addition to spatial patterns, lumped statistical behavior of variability within a gaged catchment may be analyzed. For example, the variable infiltration capacity (VIC) model (Wood et al., 1992), originally named Xinanjiang model (Singh, 1995), assumes that infiltration capacity, and thus runoff, vary statistically within a catchment. The fraction of the catchment that is saturated is a function of the infiltration capacity and the catchment wetness. Precipitation over the area catchment that is saturated is a function of the infiltration capacity and the catchment wetness. Precipitation over the area will only infiltrate in the fraction that is not saturated and produces direct runoff in the portion that has reached saturation (i.e., saturation excess mechanism). The VIC model assumes uniform precipitation which fills the spatial infiltration capacities based on its calibrated CDF. Instead, HIRO2 accepts variable infiltration as input and simulates space—time process interactions associated with Hortonian runoff.

Simulation results from HIRO2 can be analyzed statistically in a manner analogous to the VIC model. For example, the CDF in Fig. 16b shows that about 88% of the area of WG11 did not produce runoff at 25 min. The area producing runoff increased to about 18% at 50 min — revealing that more area had exceeded the infiltration capacity as more precipitation fell on the watershed. As expected, infiltration rates (Fig. 13a) decreased with time over the catchment as Hortonian runoff developed, and cumulative infiltration over time (Fig. 13b) exceeded zero at all locations. The cumulative infiltration represents a change in profile soil water storage during the event.

7. Summary and final remarks

The development, calibration and validation of a new model for event-based spatial Hortonian Infiltration and Runoff/On (HIRO2) were presented, along with examples of how the model can be used for space—time analyses. The main features of HIRO2 are: (1) input rainfall, soil parameters, and other watershed properties can vary in space and/or time down to pixel scale; (2) hillslope and channel areas are delineated from grid DEM data using the D∞ flow algorithm; (3) flow paths in the watershed are determined based on the D∞ flow algorithm, such that flow can diverge or converge at any pixel (except that divergence is not allowed for channel pixels); (4) infiltration is computed at each pixel using the Green—Ampt model, where the source of water includes both direct rainfall and run-on from upslope areas; (5) the ponding-time model handles variable rain rate and dynamic run-on in the computation of ponding time; (6) Hortonian runoff is routed using a kinematic wave model for both hillslope overland flow and channel flow; (7) infiltration rate, cumulative infiltration, water depth, and runoff (hydrograph) at any pixel and at any time can be written to output files in ASCII format for post-analyses of internal states and fluxes; and (8) an efficient implicit finite difference scheme is used to solve the routing equations numerically.

A particular niche for HIRO2 was identified as an event-based distributed watershed model that includes the effects of run-on during infiltration along both convergent and divergent flow paths. Computational efficiency was another major reason for developing new model to address multiple space—time scenarios at high resolutions. Currently, it is limited to the simulation of storm events, but it would be feasible to extend HIRO2 to continuous simulation. The source code and batch processing methods are provided for model developers and users.

The resolution of the DEM data used for this work was 30 m due to data availability. At this resolution, it is likely that some of the local run-on effect was not captured. However, it should be stressed that HIRO2 can be applied to a different grid size depending on the purpose of the study.

Application of the existing model includes multifractal scaling of simulated infiltration and runoff. Meng et al. (2006) have used HIRO2 to relate space—time scaling of infiltration to multifractal soil hydraulic conductivity and rainfall, showing how the spatial infiltration patterns reflect different controls over time during runoff events. Future application of HIRO2 will focus on the factors controlling space—time patterns of runoff. Other investigators may use the model to explore new problems of theoretical and practical interest.

Acknowledgements

This work was part of the Specific Cooperative Agreement (SCA) between the USDA Agriculture Research Service and Colorado State University. Funds provided by the SCA project “Quantifying Space—Time Variability in Agricultural Landscapes” are appreciated. We also thank Rose Shillito and David Goodrich for providing data from the USDA-ARS Walnut Gulch experimental watershed. Pre-submission peer reviews by Drs. Rao Govindaraju and George Leavesley, and two anonymous journal peer reviews are appreciated.

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