Impact of connectivity on the modeling of overland flow within semiarid shrubland environments

Eva Nora Mueller,[1] John Wainwright,[2] and Anthony J. Parsons[2]

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[1] The objective of this study is the evaluation of the spatial variability and intrinsic connectivity features of model input parameters for the parameterization of process-based, spatially distributed overland flow models. Parameter scaling tools based on the statistical and geostatistical properties of an extensive field data set were developed. These allowed the reproduction of the spatial heterogeneity of model parameters associated with the soil- and vegetation-related properties of semiarid shrubland environments to a varying degree. The outcome of the study emphasizes that connectivity plays a fundamental role in the modeling of water fluxes within semiarid catchments. The larger the degree to which connected features are represented, the better the model performance. In contrast, the parameterization approaches that did not contain connected patterns of parameter values performed comparatively poorly. A spatially connected overland flow model therefore enabled the generation of realistic overland flow patterns that qualitatively resembles field surveys of overland flow generation not only at the outlet of the model domains but also within the catchments without the need of calibration.

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1. Introduction

[2] The spatial arrangement of hydrologically significant components of the landscape, such as infiltration, surface roughness and variations in gradient play an important role in the generation and movement of runoff and thus require consideration in the parameterization of spatially distributed overland flow models. Of particular significance is the degree of spatial association of these landscape components because, for example, where areas of low infiltration are connected to each other they provide connected pathways of runoff through the landscape. The term connectivity is frequently used to denote the extent to which these connected features are present in a hydrologically relevant spatial pattern [*Western et al.*, 2001]; that is, it describes a certain degree of spatial organization of parameter values. Examples of connected features include connected low values of flow resistance in barren, nonvegetated interrill areas, connected high values of hydraulic conductivity in aquifers leading to preferential flow [*Koltermann and Gorelick*, 1996], and connected band-shaped saturation zones in catchments [*Grayson et al.*, 1995]. This spatial association of hydrologically significant landscape components in the form of connected patterns is herein termed connectivity.

[3] Various hydrological modeling studies have shown that the adequate spatial representation of model parameters, specifically in regard to their connectivity features, can be critically important for the performance of a process-based, spatially distributed numerical rainfall-runoff model [*Bronstert and Bardossy*, 1999; *Merz and Bardossy*, 1998; *Grayson et al.*, 1995]. This study investigates the impact of connectivity on the process-based, spatially distributed modeling of overland flow generated by high-intensity, short-duration rainstorm events in shrubland environments of the Chihuahuan Desert, in the southwestern United States. The parameterization of spatially distributed models is a complex task and is further complicated by the heterogeneous nature typical of dryland shrublands with regard to the spatial distribution of their soil- and vegetation-related characteristics, which are at the same time often highly sensitive model parameters (see, for example, the modeling studies by *Parsons et al.* [1997] and *Howes* [1999]). It appears to be essential to include both the spatial heterogeneity of dryland settings as well as the intrinsic connectivity characteristics of shrubland environments implicitly in the parameterization approaches by developing parameter-scaling tools for the spatially correct interpolation, extrapolation and disaggregation of model input parameters.

[4] The following two research questions were formulated regarding parameterization and parameter scaling:

[5] 1. How does the spatial representation of parameter values influence the modeling outcome; that is, does an increase in the degree of the representation of spatial organization of model parameters improve the modeling results?

[6] 2. Is it possible to obtain realistic modeling results without the need for calibration; that is, by using solely the information derived from field plot studies in combination with adequate scaling tools to scale model parameters to the catchment scale?

[1]Institute of Geoecology, University of Potsdam, Potsdam, Germany.
[2]Sheffield Centre for International Drylands Research, Department of Geography, University of Sheffield, Sheffield, UK.

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[7] For this study it was hypothesized that if the spatial distribution and connectivity patterns of model parameters are preserved and thus the modeling scale corresponds to the observation scale of field or remotely sensed data (and the observation scale accurately resolves the physical processes in both space and time), and the process descriptions are correct, then the model outcome should be accurate and acceptable and not in need calibration.

[8] Calibration of the modeling results is problematic and often not desired, as calibrated models frequently give reasonable results at the outlet of a catchment, but not inevitably within the catchment [e.g., *Grayson and Blöschl*, 2000; *Senarath et al.*, 2000]. The main goal of this modeling exercise is a realistic reproduction of overland flow characteristics, not only at the outlet but for the entire catchment area, as this is a prerequisite for, for example, the adequate performance of spatially distributed sediment and nutrient transport models.

[9] Because of the general lack of measured data, the spatial distribution of runoff production is often not known. However, there are several studies with evidence that demonstrate that the production of overland flow in dryland shrublands is spatially very heterogeneous, as can be seen, for example, in the flow patterns in the photographs of Figure 1. Large-scale plot studies by *Scoging et al.* [1992] showed that overland flow is not generated uniformly over space, but concentrated within interplant spaces and within a complex network of rills and flow paths where large amounts of total overland flow was generated, whereas other areas, particularly around shrub patches, contributed only insignificant amounts to the overall runoff production. Therefore, in this study a model parameterization will be considered satisfactory if it both reproduces this spatial variability in runoff generation typical of dryland shrublands, and considers the above described connectivity requirements of the distribution of input model parameters.

2. Testing Data Sets and Study Area

[10] The modeling studies derived from different spatial representations of model input parameters were tested by comparing the simulated with observed discharge data. Observations are from instrumented semiarid shrubland catchments in the Jornada Experimental Range that comprises the Long-Term Ecological Research Site (LTER), Chihuahuan Desert. The Jornada Basin (32°31′N, 106°47′W) is situated ~40 km NNE of Las Cruces, New Mexico. Location experiences a semiarid to arid climate with a mean annual precipitation of 245 mm and a mean annual potential evapotranspiration of 2204 mm. The majority (65%) of the precipitation falls as intense, short-duration, convective summer storms with a duration of 20–30 min and intensities frequently exceeding 50–100 mm/h [*Wainwright*, 2006]. Dominant shrubland associations of the region are creosotebush (*Larrea tridentata*), honey mesquite (*Prosopis glandulosa*) and tarbush (*Flourensia cernua*).

[11] Testing data are available for water discharge and rainfall intensity for one rainstorm event in three representative, instrumented catchments within the three dominant shrublands (mesquite, tarbush and creosotebush shrubland) with an approximate size of 0.15 km^2 and average sine slope between 0.01 and 0.05. The mesquite catchment is located in the central northern part of the basin (32°41′N, 106°43′W) within a dune landscape with sandy soils. The creosotebush catchment is located at the lower piedmont slope in the central eastern part of the basin (32°39′N, 106°36′W) with gravelly sandy loamy soil. The tarbush catchment is located in the central part of the basin with fine-sandy loamy, occasionally heavily crusted soil (32°32′N, 106°41′W). These catchments exhibit features typical for the three shrubland types such as inherent soil structure, vegetation patterns and topographical location and slope characteristics.

[12] Each catchment terminates in a dam constructed to create a ponded water supply for stock ranched on the Jornada Experimental Range. Inside each of these stock ponds, stilling wells and pressure transducers were installed in 2001 to measure the changes of depth of the water level. Figure 2 shows a typical stock pond after a flow event. Data were recorded using a Druck Campbell PDCR1830 Pressure Transducer fitted to a CR510 data logger that registered depth records at 5-min intervals. Conversion to changes of water volume was made from a depth-volume relationship derived from high-resolution digital elevation models of the stock tanks using tacheometric surveys. Water discharge into the stock tanks is therefore given by the change of water volume divided by the measurement time interval of five minutes. A tipping bucket rain gauge is located adjacent to each stock tank. Data from these rain gauges are assumed to be valid for the catchments as a whole because of the relatively small size of the catchment relative to a typical runoff-producing storm event at the Jornada [*Wainwright*, 2006]. Table 1 summarizes the characteristics of the selected, representative rainfall storm events typical for the Jornada Basin and the corresponding discharge data of the testing data set for each shrubland catchment, which were used for modeling validation. Typical rainstorm events in the Jornada Basin, that lead to the generation of substantial overland flow during the summer monsoon months July and August and that are investigated in this study, are characterized by their short duration of normally less than one hour, their high rainfall intensities often exceeding 100 mm/h and their infrequent occurrence (only one to four storm events per year) [*Wainwright*, 2006]. As the storm events are highly localized, it was not possible use the same date for all three shrubland catchments. Instead, for each study catchment, an individual storm event was tested in this study with the specific dates as given in Table 1.

3. Modeling Approach

[13] The overland flow modeling approach is based on a kinematic wave approximation to the St. Venant equations for the routing of overland flow. Runoff is generated by a Hortonian infiltration submodel and the Darcy-Weisbach equation is used to rate the depth-discharge component of the kinematic wave model. The model uses a two-dimensional, finite difference grid with regular, rectangular cells for the spatial representation of model parameters. The model has previously been proven to describe overland flow processes and patterns of flow adequately in arid and semiarid environments by *Scoging et al.* [1992], *Smith et al.* [1995], *Parsons*

Figure 1. Photographs of overland flow concentrations during a runoff event in mesquite shrubland in the Jornada Basin in July 2002.

et al. [1997], and *Howes* [1999]. The continuity equation and the rating equation are given by

$$\frac{\partial q}{\partial x} + \frac{\partial d}{\partial t} = r - i \tag{1}$$

$$q = v \cdot d \tag{2}$$

where q is the discharge per unit width (mm^2/s), d is the flow depth (mm), r is the rainfall rate (mm/s), i is the infiltration rate (mm/s), v is the flow velocity (mm/s), and ∂x and ∂t are space and time increments. A finite difference solution (Euler backward difference form) is used to solve equation (1) numerically [after *Scoging*, 1992].

[14] Flow velocity v (mm/s) is calculated using the Darcy-Weisbach flow equation

$$v = \sqrt{\frac{8gdS}{f}} \tag{3}$$

where g is the gravitational constant (mm/s^2), S is the sine of the slope gradient (m/m), and f is the Darcy-Weisbach friction factor (dimensionless).

[15] Infiltration i (mm/s) is estimated using the *Smith and Parlange* [1978] model, which is suitable for simulating nonuniform rainfall and run-on infiltration:

$$i = \frac{K_{sat} e^{F/B}}{e^{F/B} - 1} \tag{4}$$

where K_{sat} is the saturated hydraulic conductivity (mm/s), F is the cumulative infiltration rate to present (mm), and B (mm) is a soil-moisture-storage parameter accounting for both capillary suction and initial moisture conditions. The suitability of this infiltration equation for describing infiltration rates in semiarid environments has been demonstrated by *Smith et al.* [1995] and *Howes* [1999]. The model allows complete or partial run-on to occur as a function of current infiltration rate and current water depth within individual model cells [*Wainwright and Parsons*, 2002]. The routing of overland flow and corresponding flow lines toward flow concentrations and thence to main rill networks are derived from a digital elevation model using vector analysis of height differences with simple steepest descent as described by *Scoging et al.* [1992] with flow being routed along four cardinal directions. The simulation time step is set to one second to account for the sudden changes of rainfall intensities during storm events, where rainfall intensities may reach more than 100 mm/h over very short time periods of several minutes that lead to the generation of substantial amounts of overland flow in time intervals of sometimes less than one minute [*Wainwright*, 2006].

[16] As the modeling studies concentrate on the influence of the small-scale variability of model input parameters on model behavior, a very small pixel resolution of 2 m is used for model domains of an approximate size of 0.2 km^2. This model resolution is small enough to describe the flow processes in rill and interrill areas adequately and at the same time large enough to avoid extensive computing times [*Parsons et al.*, 1997].

4. Scaling and Parameterization Approaches

4.1. Parameter Scaling of Saturated Hydraulic Conductivity and Friction Factor

[17] In general, the most sensitive parameters of the hydrological overland flow model are the K_{sat} parameter, the Darcy Weisbach friction factor and the slope estimates [*Wainwright and Parsons*, 2002]. While the latter is usually derived from digital elevation models, the first two parameters are normally derived from single point measurements

Figure 2. Typical stock tank with water discharge measurement equipment after an overland flow event in the Jornada Basin.

Table 1. Characteristics of the Representative Rainstorm and Overland Flow Events for the Three Instrumented Catchment With Characteristic Shrubland Vegetation

Catchment	Date	Total Rainfall, mm	Rainstorm Duration, min	Max. Rainfall Intensity, mm/h	Total Discharge, m^3	Peak Discharge, m^3/s
Tarbush	27 Jul 2002	25.5	42	105	1706	1.9
Mesquite	2 Aug 2002	27.7	45	172	1585	2.0
Creosote	20 Jul 2002	30.3	37	115	7474	3.3

of rainfall simulations at the plot scale in the field. The spatial distribution of K_{sat} and the friction factor are normally not known and are often neglected in the parameterization process. However, the observation scale of the two parameters in the field is often significantly different from the model scale in terms of data spacing, data extent and data support as has been discussed thoroughly in the corresponding hydrology scaling literature [e.g., *Blöschl and Sivapalan*, 1995]. Hence the point measurements of K_{sat} and friction factor require adequate transformation from the observation scale to the model scale. This study aims to develop adequate transformation tools and thus to include the spatial heterogeneity of model parameters into the parameterization process by applying appropriate scaling techniques to reproduce the intrinsic spatial parameter variations. For this purpose, the parameterization of the hydrological model is based on a field work integrated approach, which combines the efforts of a numerical modeling study with an extensive field campaign carried out by *Mueller* [2004] at the three shrubland catchments to obtain an enhanced understanding of the spatial distribution of hydrological properties and their connectivity patterns. As repeated performance of rainfall simulations in the field is costly, it was not possible for this study to carry out a large enough number of experiments that would have been necessary to obtain the spatial distribution of the two parameters. Therefore the average values of K_{sat} and the friction factor were derived from a survey of previously published field experiments as described below, whereas their spatial variations in form of their geostatistical properties were derived from surrogate parameters that were collected in a fieldwork campaign over a period of 7 months during the spring and summer of 2002 and 2003.

[18] Vegetation cover is an important control on the flow hydraulics, and thus on the spatial distribution of the friction factor [*Singh*, 1996]. It is therefore assumed that the friction factor varies significantly as a function of presence or absence of vegetation cover; hence the spatial distribution of vegetation cover was estimated as a surrogate for the spatial distribution of the friction factor. The average values of the friction factor were derived from the field studies of *Howes* [1999] and *Weltz et al.* [1992]. *Howes* [1999] carried out overland flow simulations by trickle-induced flow for friction factor estimation in the Jornada Basin and obtained a Darcy-Weisbach friction factor value of $\sim$1.0 [dimensionless] for bare intershrub areas. Following the recommendations after *Weltz et al.* [1992], who carried out rainfall simulation experiments at vegetated shrubland plots in the Chihuahuan Desert, a friction factor of 20.0 [dimensionless] is used to characterize vegetated surface cover. As a reasonable first approximation, the same parameter set of (20, 1) for the binary representation of vegetated and bare surface cover, respectively, is used to describe the friction factor for all shrub vegetation associations.

[19] The average values for the K_{sat} parameter for bare and vegetated surface covers were derived from rainfall simulation experiments after the field studies of *Parsons et al.* [2003], J. Herrick (Rainfall simulation experiments to estimate final infiltration rates on field plots in tarbush vegetation of the Joranda Basin, New Mexico, unpublished data set, 2001) and *Howes* [1999], who carried out rainfall simulations on 1–2 m^2 plots with high-intensity rainfall on bare and vegetated surface covers in mesquite, tarbush and creosote shrublands within the Jornada Basin (Table 2). Ponded infiltration experiments in the field with a single-ring infiltrometer were used as a surrogate for the spatial distribution and the geostatistical properties of the infiltration rate. Although ponded infiltration rates tend to be higher than the actual final infiltration rates of natural or simulated rainfall events, and therefore cannot be used directly as estimates for K_{sat}, it is assumed that both rates posses the same pattern of spatial continuity.

[20] The spatial field measurements for vegetation cover and ponded infiltration rate were carried out on a 60 m $\times$ 60 m field plot area within each of the three shrubland catchments with a total number of 108 sampling locations per plot. The field plots were subdivided into 30 m $\times$ 30 m, 10 m $\times$ 10 m and 3 m $\times$ 3 m rectangular cells; two sets of nine random locations have been chosen within the four 30 m cells, four sets of nine random locations in the 10 m cells, and six sets of random locations in the 10 m cells with nine sampling points lying on a 3 m $\times$ 3 m grid. Vegetation cover [%] was estimated for 1 m^2 plots using a vertical photograph method. A 35-mm SLR camera with a 35-mm lens was mounted on a 2-m-high tripod and used to take transparencies which were then scanned at a resolution of 1250 $\times$ 1900 pixels. The resulting digital images were categorized into shrub or grass cover or bare ground using the IDRISI software package. Ponded infiltration rate [mm/h] was measured using a single-ring infiltrometer with a diameter of 12.5 cm (equivalent to a support of $\sim$0.012 m^2) following the guidelines of *Herrick et al.* [2005] for monitoring grassland, shrubland and savannah ecosystems.

[21] The statistical properties of the friction factor and the K_{sat} values as derived from the above specified literature and the geostatistical properties (fitted models to the experimental semivariogram, range and sill values following the model definitions of *Olea* [1999]) of vegetation cover and ponded infiltration rate derived from the field survey as surrogate parameters for K_{sat} and the friction factor are summarized in Table 2. The following sections describe the scaling tools used for interpolation and extrapolation to

Table 2. Statistical and Geostatistical Characteristics of the Parameterization Data for the Three Shrubland Associations

	Mesquite	Tarbush	Creosotebush	Source[a]
Vegetation cover,%	21	20	23	
Saturated hydraulic conductivity				
$K_{sat,bare}$, mm/h	30	15	11	1, 2, 3
$K_{sat,\ verg}$, mm/h	153	40	33	1, 2, 3
$K_{sat.area\text{-}weighted}$, mm/h	55.8	26.0	16.0	
Ponded infiltration rate as surrogate				
Semivariogram model[b]	Gaussian	Gaussian	Gaussian	
Range, m	5.5	8.0	3.0	
Sill	0.7	0.78	0.43	
Nugget	0.3	0.22	0.57	
Friction factor				
f_{bare}, dimensionless	1	1	1	3
f_{verg}, dimensionless	20	20	20	4
$f_{area\text{-}weighted}$, dimensionless	6.1	9.4	5.4	
Vegetation cover as surrogate				
Semivariogram model[b]	Gaussian	Exponential	Gaussian	
Range, m	5.5	6.0	3.0	
Nugget	0.3	0.15	0.3	
Sill	0.7	0.75	0.7	

[a]Sources are 1, *Parsons et al.* [2003]; 2, J. E. Herrick (unpublished work, 2001); 3, *Howes* [1999]; 4, *Weltz et al.* [1992].
[b]Definition of semivariogram model according to *Olea* [1999].

develop parameterization approaches for the parameters K_{sat} and friction factor. The parameterization approaches differed in their degree and detail of spatial parameter representation, and thus incorporated connectivity patterns. In each case, the representation of slope is the same.

4.1.1. Scheme 1: Binary Approach

[22] The first parameterization approach is based on a binary approach which uses the spatial distribution of vegetation cover within the different shrubland associations to distribute the values for the saturated hydraulic conductivity and friction factor values. This approach is based on the fact that the connectivity of a hydrological system is strongly tied to the spatial distribution and possible fragmentation of vegetation cover [*Wu et al.*, 2000a, 2000b]. Patches of vegetation serve an important function of capturing and retaining limited resources of overland flow particularly in semiarid and arid ecosystems. Landscapes with an undisturbed vegetation cover retain and utilize these resources, whereas highly patchy landscapes tend to generate concentrated overland flow and soil erosion in a highly connected rill network [*Ludwig et al.*, 2002]. For this approach, Digital Orthophoto Quadrangles aerial photography from the year 1996 and provided by the U.S. Geological Survey with a ground resolution of 1 m was classified in patches with bare and vegetated surface covers.

4.1.2. Scheme 2: Area-Weighted Approach

[23] The second parameterization approach, called the area-weighted approach is a spatial simplification of the binary system approach as it assumes a spatially uniform distribution of model parameters. It uses the average fractions of vegetated and bare areas for the entire catchment area to calculate uniform, weighted parameters based on the two parameter sets derived from vegetated and bare surface covers. Thus the area-weighted approach does not contain any spatial variability, but is nonetheless employed in this study to compare this simple, spatial integration over spatial variations with the more sophisticated scaling approaches. The average fractions of vegetation cover for the individual modeling catchments are derived from the classification of the aerial photographs and are given by 27% for the mesquite site, 44% for the tarbush site and 23% for the creosotebush site. The weighting scheme is given by

$$X_{area\ weighted} = Fraction_{vegetation}\, X_{vegetated} + Fraction_{bare}\, X_{bare} \quad (5)$$

where X is the model input parameter.

4.1.3. Scheme 3: Unconditioned Gaussian Stochastic Simulation Approach

[24] The third approach is based on unconditioned Gaussian stochastic simulation of surface patterns based on the geostatistical properties of the two parameters. The models fitted to the experimental semivariograms of ponded infiltration rates and vegetation cover as surrogate parameters for K_{sat} and the friction factor as was summarized in Table 2 were used. The FORTRAN routine sgsim for sequential Gaussian simulation from GSLIB (Geostatistical Software Library [*Deutsch and Journel*, 1998]) was employed to produce equiprobable realizations of sequential Gaussian simulations. For this approach, five equally probably realizations were prepared for comparison with the other approaches.

4.1.4. Scheme 4: Conditioned Gaussian Stochastic Simulation Approach

[25] The fourth approach is based on conditioned Gaussian stochastic simulation. In contrast to the previous approach, this approach directly incorporates existing features of the connectivity pattern of the model parameters. This approach assumes that the generation of overland flow is significantly influenced by the distribution of individual shrubs and shrub patches in the form of a fragmentation of vegetation cover and the creation of connected pattern features resulting in the layout of the rill network. On the one hand, overland flow is slowed down within patches of high K_{sat} and friction factor values associated with vegetated areas. On the other hand, substantial overland flow is generated in bare areas with low K_{sat} and friction factor values in the

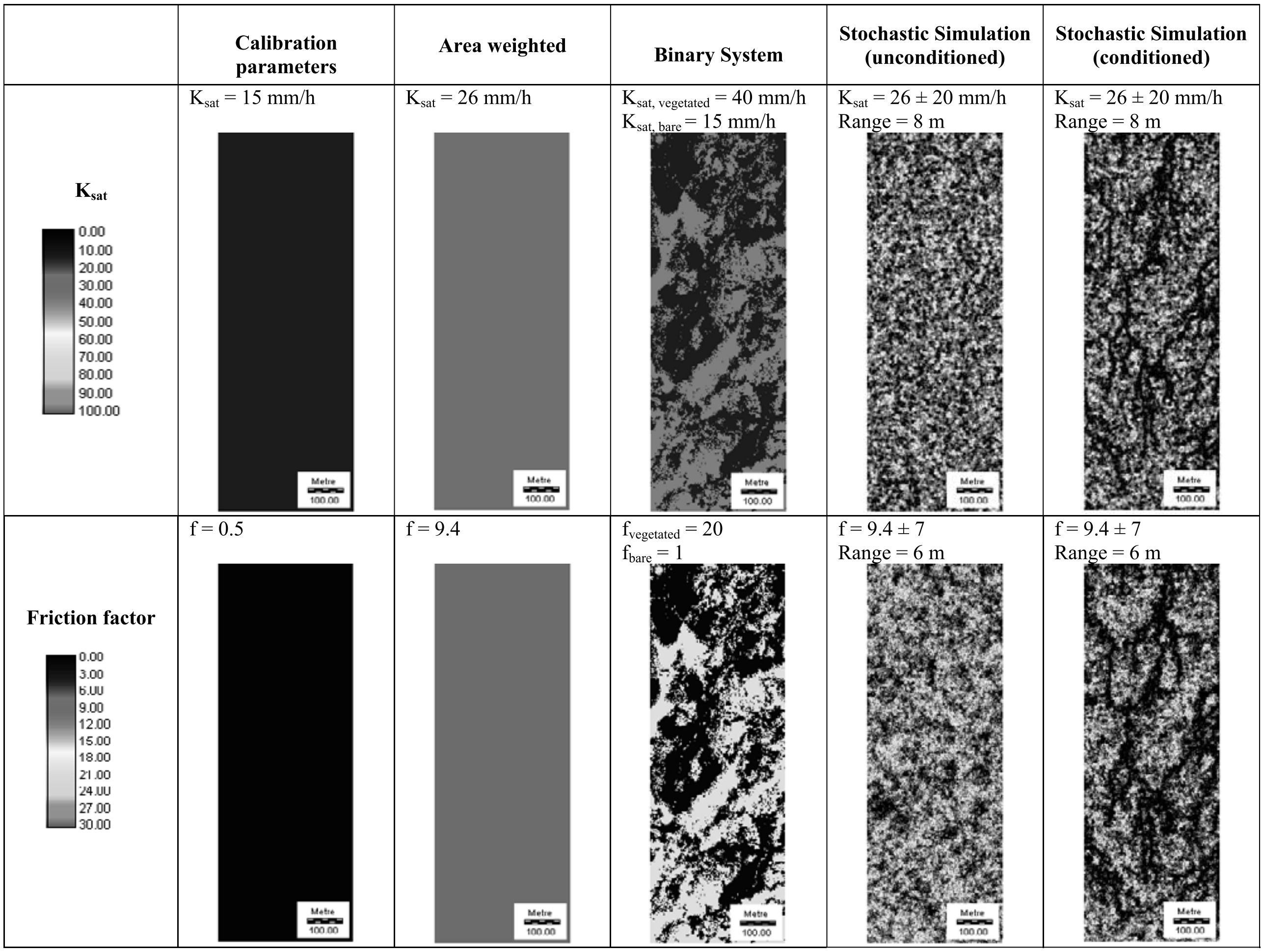

Figure 3. Representation of spatial parameterization approaches for the tarbush catchment.

vicinity of minor flow concentrations and rills which meander around the vegetation patches. These bare areas may form large, coherent patches, which are connected by the major rills of the rill network (depicted for the tarbush catchment on the right in Figure 3). To incorporate the hydrologic connectivity associated with the existence of the rill network, the following methodology is proposed to produce structured variability in the form of connectivity patterns for the K_{sat} and friction factor parameters. The realizations of the stochastic simulations are conditioned in accordance to the rill network locations of the three model domains. Within the major rill network, approximately a cell every 20 m was selected and the low parameter values of K_{sat} and the friction factor for bare surface covers as used for the binary system approach were assigned to this cell. As a rule of thumb, not more than one percent of the total number of model cells was conditioned, as excessive conditioning would affect the statistical properties of the realizations. When the GSLIB sgsim routine [*Deutsch and Journel*, 1998] is executed, the points in the local neighborhoods adjacent to the conditioning points are assigned similarly low values in accordance to the autocorrelation length given by the semivariogram model. As with the third approach, five equally probably realizations were prepared for comparison with the other approaches.

4.1.5. Scheme 5: Calibrated Approach

[26] The fifth approach is called the calibrated approach and is based on the best fit parameters for K_{sat} and the friction factor. This calibrated approach may be understood as the more or less traditional way of dealing with and overcoming poor model performance due to either the lack of field data for model parameterization, or to the negligence of scaling tools for the interpolation, extrapolation and disaggregation of model parameters. However, it should be recognized that this approach often leads to a faulty parameterization as it does not represent the spatial distribution of model parameters and is normally not based on K_{sat} and friction factor data measured in the field.

[27] For each catchment, the best fit parameters for K_{sat} and the friction factor were derived by comparing the simulated with the observed hydrographs. The main criteria for the fitting of these two parameters were the reproduction of the shape, magnitude and timing of peak discharge of the observed hydrographs at the outlets of the catchments and by optimizing a goodness of fit measure, in this case the *Nash and Sutcliffe* [1970] coefficient of efficiency measure. The derived calibrated values for K_{sat} and the friction factor are presented in Table 3. It is notable that the parameter values derived from the calibrated approach

Table 3. Best Fit Parameters for K_{sat} and Friction Factor After Calibration for the Simulated Runoff Events

Model Domain	Date	K_{sat}, mm/h	Friction factor f, dimensionless
Tarbush	27 Jul 2002	15	0.5
Mesquite	2 Aug 2002	35	0.5
Creosote	20 Jul 2002	10	0.5

differ markedly from the mean values as derived from the field measurements.

[28] Figure 3 exemplifies the five parameterization approaches for K_{sat} and the friction factor for the model domain at the tarbush site. Note that the same color scale was used for the illustrations of each parameter to aid comparability. It is noteworthy that all parameterization approaches, except the calibrated one, have the same areal average values for K_{sat} and the friction factor integrated over the individual, entire catchment areas. This equivalence is due to the fact that the area-weighted approach uses essentially the average values of the binary system approach, and stochastic simulation approaches were derived using a normal probability distribution based on the average area-weighted parameters. The various color patches clearly show the large differences of the uniformly and spatially distributed approaches and their spatial and quantitative compositions. For example, the unconditioned realization produces scattered patterns in the form of small islands of relatively high and low values. In contrast, the binary system approach and the conditioned stochastic simulation approach reproduce produces the large patches of high or low parameters values similar to the agglomeration of shrub patches and large patches of bare areas.

4.2. Parameter Scaling of the Slope Estimates

[29] Slope estimates for the parameterization of the Darcy-Weisbach flow equation and the routing of the rill network were derived from a digital elevation model (DEM) acquired by the U.S. Geological Survey in the year 2004 with a 10-m cell resolution. Slope values derived from digital elevation models are often underestimated due to smoothing over surface features. In the Darcy-Weisbach equation, sine slope has a reciprocal relationship with the friction factor. This implies that an underestimation of the slope is equivalent to an overestimation of the friction factor. The friction factor is known to be one of the most influential factors in runoff calculations [e.g., *Singh*, 1996], as it influences the shape of the hydrograph and the timing of peak runoff and at the same time affects total runoff. The correct estimation of slope is therefore crucial for the model performance as its underestimation may lead to a severe underestimation of peak and total discharge of water fluxes. To obtain a first approximation on the slope underestimation, slopes derived the 10-m DEM were compared to several high-resolution field surveys for slope estimates that were carried out at different locations within the Jornada Basin:

[30] 1. *Howes* [1999] produced a DEM for a creosotebush site within the Jornada Basin with a resolution of 0.5 m.

[31] 2. L. Cunningham (Topographical survey of field plots in tarbush vegetation of the Joranda Basin, New Mexico, unpublished data set, 2006) surveyed three 6 × 12 m plots with a resolution of 2 m within the tarbush catchment of this study.

[32] 3. *Rango et al.* [2000] carried out field surveys at a mesquite site in the central plain of the Jornada Basin in the vicinity of the mesquite catchment, using 100-m transects and a 0.5-m spacing of measurements.

[33] Precise locations and full data sets were accessible for all three field surveys. The comparison in Table 4 indicates that average sine slope is underestimated by 166% for the creosotebush site, 400% for the tarbush site and between 450% for the bare interspaces and 1700% for the dunes of the mesquite site. The large variation for the mesquite site is due to the detailed slope measurements of individual mesquite dunes in the field survey, which can reach heights up to 3 m.

[34] The field surveys give a strong indication that the average slope is underestimated in the 10-m USGS DEM by a scaling factor of 4.5 to 5 for areas in the central part of the Jornada Basin, and by a factor of 1.6 for the piedmont slopes. It is problematic to transfer the knowledge from a small number of field studies with a small extent to the catchment scale. Even so, the four field surveys were carried out at locations that were representative of the different vegetation associations. The area averages of the sine slopes without scaling are 0.03, 0.01, and 0.01 for the creosotebush, mesquite, and tarbush model domains, respectively. These estimates compare well to the underestimated sine slope values of the field surveys carried out in the corresponding vegetation associations as given in Table 4. As a reasonable first approximation, the underestimation of slope is therefore explicitly considered by using the scaling factors derived from these surveys for adjusting the underestimated slope estimates. Slope scaling is often neglected in the process of parameterization of overland

Table 4. Comparison of Slope Measurements Derived From Field Surveys and USGS 10-m DEM for the Various Locations Within the Jornada Basin

Study	Dominant Vegetation	Resolution, m	Extent of Survey	Sine Slope ± SD: From Field Surveys	Sine Slope ± SD: From 10-m DEM	Slope Scaling Factor[a]
Howes [1999]	creosote	1	889 m^2	0.05 ± 0.04	0.03 ± 0.02	166%
L. Cunningham (unpublished data set, 2003)	tarbush	2	72 m^2	0.04 ± 0.03	0.01 ± 0.005	400%
Rango et al. [2000]	mesquite	0.5	100 m	0.04 ± 0.04 (bare area)	0.01 ± 0.003	450%
				0.17 ± 0.08 (dunes)		1700%

[a]Corresponds to the percent underestimation of average sine slope.

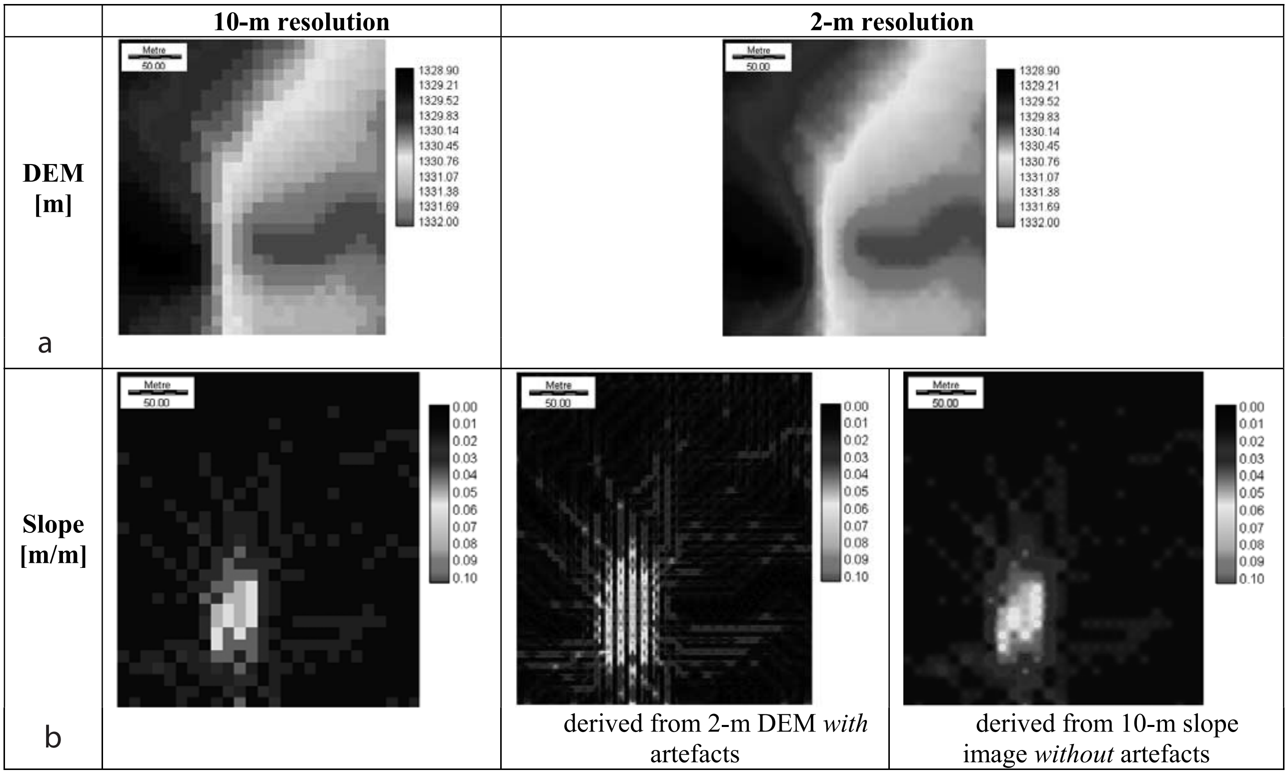

Figure 4. Disaggregation schemes of the digital elevation model from 10-m to 2-m resolution and corresponding slope distributions for 10-m and two different 2-m resolution scenarios for a section of the tarbush catchment.

flow models, which is linked to a lack of appropriate slope-scaling methods and rules. The above described approach should therefore to be understood as a novel and preliminary one that requires further testing and elaboration.

[35] Because the modeling studies are run on a 2-m resolution grid, the 10-m DEM had to be adequately disaggregated from the 10-m to the 2-m cell size. Automated procedures implemented by common GIS software such as Idrisi and ArcMap use the distance-weighted average routines to disaggregate digital elevation models, and thereby often introduce artifacts to the disaggregated DEM. To illustrate this point, Figure 4 compares the 10-m DEM with the 2-m DEM (Figures 4a, left, and 4a, right) and the slope estimates derived from the 10-m DEM (Figure 4b, left) and from the disaggregated 2-m DEM (Figure 4b, middle) that was created using a distance-weighted average routine (for a section of the tarbush catchment). The images show that the slope patterns related to the major rill network characteristics are preserved in the 2-m image in comparison to the 10-m slope image; however, the spatial distribution of slope of the 2-m image (Figure 4b, middle) is severely affected by a pattern of numerical artifacts. These numerical artifacts are characterized by a regular, quadrangular pattern of zero values that do not correspond to the slope estimates of the 10-m image. The erroneous zero slope values in Figure 4b (middle) cause severe numerical instability in the overland calculation when used for the calculation of the Darcy-Weisbach equation (equation (3)). To reduce the disaggregation errors in slope estimation, it is reasonable to disaggregate the slope distribution directly from the 10-m slope estimates, rather than first disaggregate the 10-m DEM to 2-m resolution and then calculate the slope from the disaggregated 2-m DEM. The spatially distributed slope estimates with a 2-m resolution as depicted in Figure 4b (right) are then used as input to the Darcy-Weisbach equation thus avoiding the introduction of artifacts derived from the disaggregated 2-m DEM.

[36] According to *Zhang et al.* [1999], it is currently not possible to disaggregate the existing spatial patterns of topography to a smaller scale. The uniform distribution of slope estimates is a considerable simplification of the true spatial pattern within a single 10×10m cell, but is assumed to be a sufficient first approximation as the piedmont slopes of the Jornada Basin and the central part of the basin are characterized by gently sloping interrill areas. The analysis of scaling properties and the development of scaling techniques for the disaggregation of DEMs calls for further investigation, but is beyond the scope of this study.

5. Modeling Results and Discussion

5.1. Evaluation of the Five Parameterization Schemes

[37] The five parameterization approaches were tested for several high-intensity rainfall events of the years 2002 and 2003. The results of a typical storm event (with rainfall characteristics and dates as summarized in Table 1) for each of the three shrubland catchments are presented here. Figure 5 provides an example that compares the simulated hydrographs for the tarbush catchment using each of the five parameterization approaches with the observed hydrograph for the rainstorm event on 27 July 2002. Table 5 comprises quantitative comparisons of observed and simu-

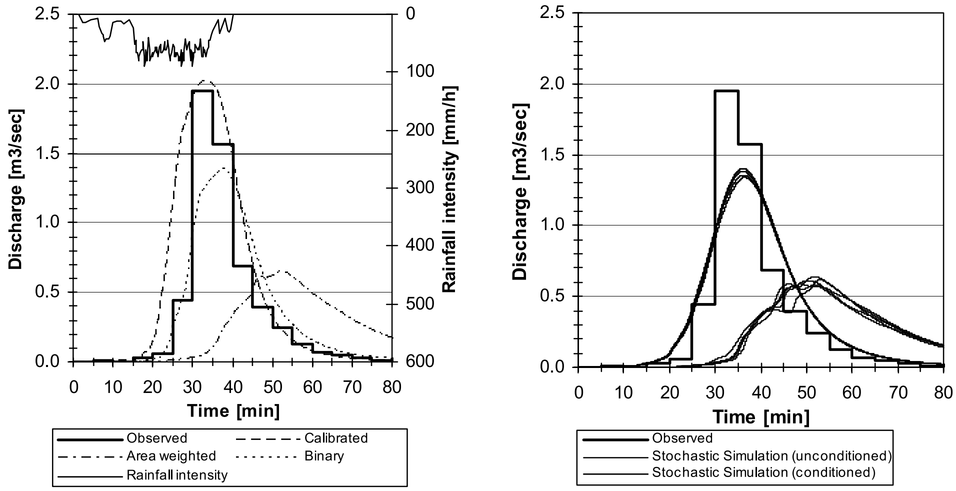

Figure 5. Hydrographs for the tarbush catchment (27 July 2002) using the calibrated, area-weighted average, binary system, unconditioned, and conditioned stochastic simulation parameterization approaches.

lated peak and total discharge and *Nash and Sutcliffe*'s [1970] coefficient of efficiency for all three model domains. A first visual inspection of the observed and simulated hydrographs at the outlet of the three model domains reveal that (1) the binary and conditioned approaches perform well with regard to peak and total discharge and the timing of peak discharge; (2) the calibrated hydrographs show the (seemingly) best overall performance; and (3) the area-weighted average approach and the unconditional stochastic simulation approach perform very similarly: both heavily underestimate peak and total discharge and show a delay in timing of the peak discharge.

[38] The *Nash and Sutcliffe* [1970] coefficient of efficiency (CE) measures for the calibrated parameterization approach as given in Table 5 are generally large for most of the events, ranging from 0.7 to 0.95, thus reflecting a good correspondence with observed discharge. This outcome is not surprising, as the two crucial parameters of the hydrological model were calibrated to obtain the best fit to the observed hydrographs. The calibrated parameterization approach apparently outperforms the other parameterization approaches in the reproduction of discharge characteristics at the outlet of the catchments. However, there are several major drawbacks to this parameterization approach. First, different parameter sets of the K_{sat} and friction factor parameters would have to be used for different rainstorm events, which drastically limited the portability of the model to other rainstorm events and therefore limit its use for the reliable estimation of water fluxes (as was tested for a range of different rainstorm events in the work by *Mueller* [2004]). Second, the K_{sat} and friction factor values employed for this parameterization approach deviate significantly from actual field measurements and which draws into question a realistic reproduction of overland flow characteristics within the interrill and rill areas of the entire catchment area. Third, from field observations it is known that overland flow generation is greatly influenced by the small-scale variability of soil and vegetation parameters, as, for example, described by *Scoging et al.* [1992], and that therefore a spatially uniform description of the model parameters is very unrealistic. In contrast, Figure 1 demonstrates the presence of flow paths in an overland flow event, illustrating concentrated flows in areas with low measured infiltration rates and friction factors meandering around vegetation

Table 5. Modeling Results for the Three Model Domains Within Tarbush, Creosotebush, and Mesquite Shrub

	Observed	Calibrated	Area-Weighted	Binary	Unconditioned	Conditioned
Tarbush						
Total, m^3	1706	2385	1299	1715	1150	1732
Peak, m^3/s	1.9	2.0	0.6	1.4	0.6	1.3
CE,[a] dimensionless	–	0.71	−0.09	0.85	−0.05	0.80
Creosote						
Total, m^3	7474	6450	4609	5045	4709	4913
Peak, m^3/s	3.3	3.5	2.2	2.8	2.2	2.6
CE,[a] dimensionless	–	0.93	0.21	0.76	0.28	0.75
Mesquite						
Total, m^3	1585	1805	83	1319	157	901
Peak, m^3/s	2.0	2.1	0.1	1.5	0.1	0.9
CE,[a] dimensionless	–	0.95	−0.31	0.90	−0.29	0.63

[a]CE, coefficient of efficiency.

patches that are characterized by high infiltration rates and friction factors.

[39] The area-weighted average approach severely underestimates the peak and total discharge and leads to a considerable delay of the timing of peak discharge in all simulation studies. The coefficients of efficiency for the area-weighted average approach are negative or close to zero in most cases, which signifies very poor model performance. The area-weighted approach is, in contrast to the calibrated approach above, based on field measurements. However, the modeling results demonstrate that it is not possible simply to average and thus scale over the small-scale variability and aggregate model parameters derived from vegetated and bare surface covers by taking their area-weighted average. A uniform description of input parameters is inadequate for the same reasons as were previously described for the calibrated approach above. This simple integration over the spatial small-scale variability of the K_{sat} and friction parameters and possibly their connectivity features is therefore inadequate for parameter aggregation.

[40] The binary system approach produces satisfying results overall for all catchments with coefficients of efficiency ranging between 0.76 and 0.90, however, all events underestimate the peak and total discharge. The general underestimation of the binary system approach may be partly explained by the possible presence of inadequate fits between the vegetation cover maps and the simulated rill network derived from the digital elevation models due to projection errors or faults of the two sets of remotely sensed data as well as the downscaling of the 10-m resolution to the 2-m resolution digital elevation model. An incorrect overlay of the two types of spatial data may cause overland flow in the main rill network to be simulated as flowing through supposedly vegetated areas characterized by large K_{sat} and friction factor values, which consequently leads to the calculation of larger infiltration rate and a deceleration of the flow velocity and therefore to a decrease of total discharge. An examination of the two data sets revealed that divergences exist for some parts of the catchments but which overall represents only a small proportion of the model domain. Another possible explanation for the underestimation is the fact that the binary system approach is not able to adequately reproduce the flow characteristics of locations where pathways of rills run under the canopy of shrubs or shrub patches; that is, the canopy cover possibly screens the location of existing rills. Both types of mismatches introduce errors into the representation of the system configuration and consequently to a decreased representation of connected patterns.

[41] For the calculations of the hydrographs calculated using the stochastic simulation approaches, five nearly equiprobable realizations were used for each parameter presentation. The corresponding five hydrographs for the tarbush domain are presented in the associated hydrograph plots in Figure 5. Visual inspection reveals that differences between hydrographs using different realizations are insignificant for both the unconditional and conditional cases.The hydrographs calculated with the unconditioned stochastic simulation approach show essentially the same characteristics in terms of peak and total discharge, timing and coefficient of efficiency as the area-weighted average approach for all catchments and runoff events. In this case, the hydrological system is chiefly governed by the statistical rather than the geostatistical properties of the K_{sat} and friction factor parameters. This result implies that by adding the geostatistical characteristics of the K_{sat} and friction factor parameters, and ergo its continuity description, does not influence or improve the model performance whatsoever. This result strongly suggests that not only the continuity but also the connectivity of a parameter space is important.

[42] The application of the conditioned rather than unconditioned stochastic simulation approach greatly improves the model performance: peak and total discharge increases and the timing of peak discharges improve substantially. In comparison to the unconditioned approach, the CE value increases from -0.29 to 0.63 for the mesquite catchment, from -0.05 to 0.8 for the tarbush catchment and from 0.28 to 0.75 for the creosotebush catchment.

[43] These results indicate that the geostatistical parameter characteristics and the reproduction of connectivity in the form of connected pattern features are of great importance for the performance of the hydrological model. Both the binary and the conditioned stochastic simulation approach enable the reproduction of pattern features of connected bands of high and low K_{sat} and friction factor values and yielded satisfactory model results. The increase of the hydrological connectivity from the unconditioned to the conditioned stochastic simulation approaches and from the area-weighted to the binary approach is echoed by an increase of peak and total overland flow; that is, the hydrological system becomes increasingly leaky which in turn enabled a better reproduction of observed hydrographs.

[44] The binary and the conditioned approach are in fact very dissimilar in the way they represent the parameter space. The former reproduces the effects of a discontinuity with discrete zones; that is, an abrupt change in the behavior of a parameter at the edge of the vegetation cover boundary. In contrast, the latter is characterized by a continuous, rather smooth spatial change of the small-scale variability of parameter values. Both approaches efficiently incorporate intrinsic connectivity patterns of high and small values for the K_{sat} and friction factor in the parameter distribution of the three shrubland associations. A smooth, continuous change of parameter values appears to be a more realistic representation of the variability of soil- and vegetation-related model parameters.

[45] However, the stochastic simulation approach does not work acceptably for the mesquite shrubland. The disadvantages of the stochastic simulation approach are threefold. First, stochastic simulation based on Gaussian sequential simulation requires the use of a normal probability distribution function. As many environmental data tend to follow lognormal rather than normal distributions [*Nielsen and Wendroth*, 2003], the higher K_{sat} and friction factor values are potentially overrepresented in the spatial reproduction of the parameter space using a normal distribution. In contrast, a lognormal distribution would favor the reproduction of smaller K_{sat} and friction factor values, which would result in an increase of overland flow generation. Second, the preparation of stochastic simulation images is costly as the geostatistical properties of the model parameters are often not known and need to be derived from labor-intensive field studies. Third, problems arise when

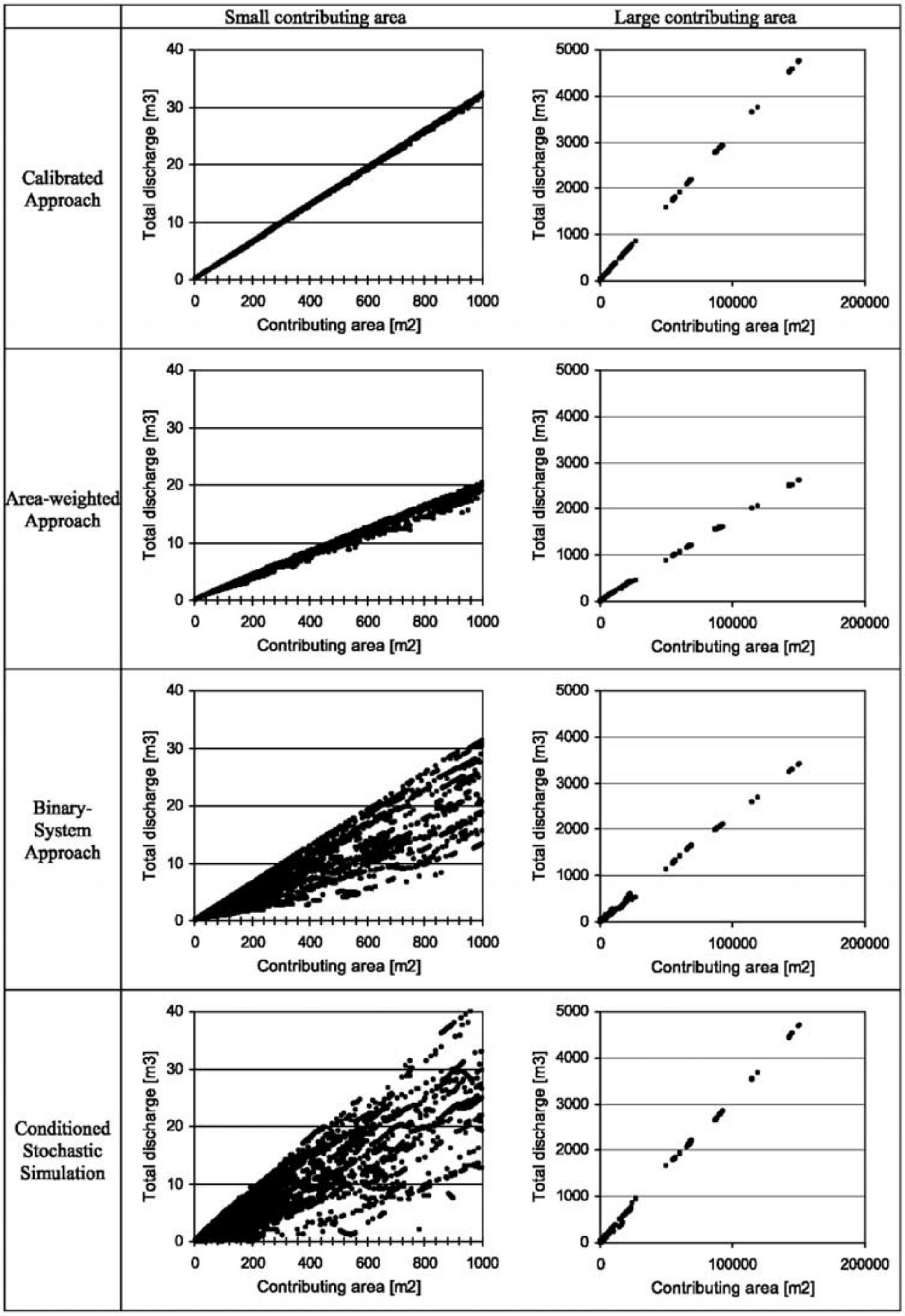

Figure 6. Spatial representations of total water fluxes versus contributing area of the tarbush model domain for the calibrated, area-weighted, binary, and stochastic simulation approaches.

this approach is applied to model domains that contain more than one vegetation association and its related parameter distributions. It is uncertain how to overlay the statistical and geostatistical properties of such parameters, for example, at vegetation boundaries, for example, between tarbush and creosotebush areas. Sophisticated geostatistical software libraries such as the GSLIB [*Deutsch and Journel*, 1998] do not contain any routines or even mathematical concepts for the stochastic simulation of mixed distributions. This issue substantially restricts the applicability of this approach to the flux estimation of real, dynamically changing landscapes. In comparison, the binary system approach is a conceptually cruder approach, but easier to parameterize. The main disadvantage of the binary system approach is the possible error introduced by an inadequate overlay of characteristics derived from the vegetation cover maps and the digital elevation model.

5.2. Evaluation of the Simulated Spatial Patterns of Overland Flow Generation

[46] The plots in Figure 6 give a comparison of the spatial representations of total water fluxes versus contributing area

(Figure 6 (left), <1000 m^2, and Figure 6 (right) <200,000 m^2) for the calibrated, area-weighted, binary and conditioned stochastic simulation approaches (showing results for the tarbush catchment). The plots signify that for the large-scale representation (area < 200,000 m^2), all four approaches yield an approximate linear relationship between contributing area and water flux, but at the small-scale representation (area < 1000 m^2), the binary and the stochastic simulation approaches show a much more complex distribution of water flux as a function of area. The two spatially uniform distributed cases (calibrated and area weighted) behave nearly linearly for the full range of contributing areas, whereas the spatially distributed cases (binary and stochastic simulation) exhibit large fluctuations of water fluxes (see particularly contributing areas smaller than 1000 m^2 in Figure 6). For this range of areas, the conditioned stochastic simulation approach is characterized by slightly larger fluctuations than the binary system approach. As pictured in the two photographs in Figure 1 and as previously shown through the detailed spatial measurements of flow depth in field studies by *Scoging et al.* [1992], overland flow is known to be heterogeneously distributed as a function of area. The two spatially distributed parameterization approaches appear to reproduce therefore a much more realistic picture of flow distributions than the uniform ones, although at the moment there are no independent spatial field measurements available to prove this point except through qualitative evidence of observations such as the observations of fresh trash lines or photographs taken directly after rainstorm events in the field. The results for the other model domains show qualitatively the same behavior, and are therefore not depicted separately.

6. Conclusion

[47] In answer to the research questions, the following can be stated from the modeling results: First, from the same field data sets (i.e., the same statistical properties), different scaling tools yielded very different parameterizations, resulting in different degrees of reproduction of spatial details and pattern of connectivity of model parameters, and thus modeling results. The more connectivity, in the form of connected pattern features, is included in the parameterization approach (as, for example, incorporated in the binary system and the conditioned stochastic simulation approaches), the better the modeling results. Second, it was possible to obtain satisfactory modeling results without the need for calibration, by using parameters derived from field measurements in combination with adequate scaling tools that retained the spatial pattern of connectivity and employed scaled slope estimates in the parameterization procedure. Many modelers take calibration of hydrological models for granted, but at the same time risk degrading the process description through excessive calibration of their underlying formula and parameters [*Grayson and Blöschl*, 2000; *Loague*, 1990]. Here, it was shown that a calibration of the model parameters, and thus disregarding the underlying connectivity pattern, has indeed a large effect on the spatial distribution of the overland flow generation, and leads to a faulty reproduction of spatial overland flow behavior for rill and interrill areas (as depicted in Figure 6).

[48] The outcome of the study is that connectivity plays a fundamental role in the appropriate parameterization and the modeling of water fluxes within semiarid catchments. The four parameterization approaches derived from the statistical and geostatistical properties of large field data set had one common characteristic; they all have the same overall areal average value for the K_{sat} and friction factor parameters. However, their different ability to incorporate small-scale variability had a crucial impact on model performance.

[49] The different parameterization approaches did not only influence the hydrographs at the outlet of the catchments, but also the simulated production of overland flow within the catchments. The binary system approach and the conditioned stochastic simulation approach succeeded in producing a realistic spatial variability of runoff generation. The binary system approach has the added advantage of being relatively easy to parameterize in comparison to the stochastic simulation approach which requires as input extensive spatial field data sets for the underlying geostatistical analysis. The generated runoff patterns of both approaches reflect the fragmentation of the landscape into surface patches that capture and retain water resources, and into surface areas that promote the water transport along a highly connected rill network.

[50] An overland flow model that produces appropriate spatial patterns of runoff is desirable not least because it is a necessary prerequisite to minimize error propagation for dependent modeling studies, such as the spatially distributed modeling of sediment and nutrient transport in overland flow. This paper has succeeded in identifying two candidate spatially distributed parameterization approaches that achieve this goal.

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E. N. Mueller, Institute of Geoecology, University of Potsdam, Karl-Liebknecht-Str. 24-25, D-14476 Potsdam, Germany. (enmue@uni-potsdam.de)

A. J. Parsons and J. Wainwright, Sheffield Centre for International Drylands Research, Department of Geography, University of Sheffield, Winter Street, Sheffield S10 2TN, UK.