

# Resistance schemes in shallow overland flow along a hillslope covered with patchy vegetation

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## Key Points:

- Roughness effects in non-kinematic overland flow can be approximated using a kinematic wave approximation
- The sensitivity of hydrological predictions to the depth-velocity scaling exponents closing the friction slope is small
- Parameterizing the ‘scale’ of roughness remains a key source of uncertainty

14 **Abstract**

15 Parameterizing the effects of surface roughness on flow resistance remains a major  
 16 challenge in modeling overland flow using physics-based descriptions such as the Saint  
 17 Venant equations (SVE). This challenge has prompted the development of a large number  
 18 of roughness schemes relating the properties of a rough surface, the bulk velocity and  
 19 resistance, yet it is often unclear which of these schemes should be used to represent a  
 20 given land surface, particularly on heterogeneous surfaces. Since it is often necessary to  
 21 calibrate any given roughness scheme to flow on a given surface, modelers need to under-  
 22 stand the sensitivity of their predictions to the choice of roughness scheme, post cal-  
 23 ibration. Here, we focus on hillslope-scale predictions made with the SVE: the water bal-  
 24 ance partitioning between runoff and infiltration, the hillslope hydrograph, and the dis-  
 25 charge velocity. We develop an approach to calibrate roughness schemes to each other,  
 26 by undertaking the calibration under equilibrium flow conditions and imposing the kine-  
 27 matic wave approximation at the outlet. This approach yields analytical relationships  
 28 between the parameters of two roughness schemes applied to the same hillslope and dis-  
 29 charge. We apply this approach to a sensitivity analysis of hydrological predictions re-  
 30 sulting from the choice of five commonly used roughness schemes. The results suggest  
 31 that, once calibrated, there is minimal prediction sensitivity to the choice of scheme across  
 32 a wide range of rainfall conditions. Operationally, these results mean that the param-  
 33 eterization of any selected roughness scheme is more important for predicting the hy-  
 34 drological behavior than the selection of a particular scheme.

35 **1 Introduction**

36 Overland flow is ubiquitous in locations with low soil permeability, such as moun-  
 37 tainous, arid, urban or agricultural landscapes (Descroix, Viramontes, Estrada, Barrios,  
 38 & Asseline, 2007; Dunne, 1983; Li, Sivapalan, Tian, & Harman, 2014). Overland flow  
 39 occurs at the expense of infiltration and is responsible for soil erosion and flash flood-  
 40 ing (Abrahams, Parsons, & Wainwright, 1994; Bracken, Cox, & Shannon, 2008). The oc-  
 41 currence, depth, velocity, and time evolution of overland flow during and after storms  
 42 is therefore relevant to land managers, practitioners, scientists, and engineers (Cantón  
 43 et al., 2011; Hallema, Moussa, Sun, & McNulty, 2016). In dryland environments, over-  
 44 land flow occurs on patchily-vegetated landscapes with spatially varying infiltration prop-  
 45 erties, roughness and slopes.

46 The most general physical equations with which to represent flow in such environ-  
 47 ments are the Saint Venant (or shallow water) equations (SVE). These equations com-  
 48 bine the continuity equation with the conservation of momentum, and are shown here  
 in their one-dimensional form for illustration:

$$\frac{\partial h}{\partial t} + \frac{\partial}{\partial x}(Uh) = p - i, \quad (1)$$

$$\frac{\partial U}{\partial t} + U \frac{\partial U}{\partial x} + g \frac{\partial h}{\partial x} + g(S_f - S_o) + \frac{U(p - i)}{h} = 0, \quad (2)$$

46 where  $h$  is the water depth at location  $x$  and time  $t$ ,  $U$  is the depth-averaged velocity,  
 47  $S_o$  and  $S_f$  are the bed- and friction- slopes, and  $g$  is the gravitational acceleration. The  
 48 boundary conditions are rainfall  $p$  and infiltration losses  $i$  that can vary with  $x$  and  $t$ .

49 The SVE do not form a closed system of equations, and users must specify a clo-  
 50 sure model for the friction slope  $S_f$ , which represents the net effects of bed and other  
 51 shear stresses (e.g. presence of obstructions) on the flow. The closure model takes the  
 52 form of a resistance formulation (colloquially, a ‘roughness scheme’) that describes  $S_f$   
 53 in terms of the modeled flow variables (i.e.  $h$  and  $U$ ), subject to constraints based on

54 the genesis of frictional resistance to flow. Roughness schemes must be defined even if  
 55 the full SVE is simplified to the dynamic or kinematic wave equations.

56 Resistance formulations for overland flow capture the effects of two sources of friction:  
 57 (i) friction imposed by shear created when the flow traverses the land surface (known  
 58 as bed friction) and (ii) friction produced when solid bodies such as soil, rocks, vegeta-  
 59 tion stems and leaves obstruct or protrude into the flow. Because these solid bodies may  
 60 be present across some or all of the water column, they are often referred to as distributed  
 61 roughness elements. Early work in hydraulics developed numerous resistance formula-  
 62 tions to describe bed shear stresses (Gauckler, 1867; Manning, Griffith, Pigot, & Vernon-  
 63 Harcourt, 1890), which have been elaborated on and extended to distributed roughness  
 64 elements by subsequent studies of the flow boundary layer (e.g. Brutsaert, 2005; Cheng  
 65 & Nguyen, 2010; Katul, Poggi, & Ridolfi, 2011; Kirstetter et al., 2016; Migler et al., 2011;  
 66 Wang, Huai, Thompson, & Katul, 2015). A subset of these schemes is summarized in  
 67 Table 1, and their derivation is reviewed in supporting information Text S1. Note that  
 68 these schemes are presented in their one-dimensional form for simplicity, but implemented  
 69 in two-dimensions in the model presented here.

70 Despite the differing sources of friction addressed by the roughness schemes, the  
 71 forms of the resistance equations in Table 1 share a number of common features. For ex-  
 72 ample, all of the equations can be represented as a dimensionless Froude number ( $Fr^2 \sim$   
 73  $\frac{U^2}{ghS_f}$ ) that depends either on the roughness properties of the surface, the bulk or elemen-  
 74 tal Reynolds number ( $Re \sim Uh/\nu$ , where  $\nu$  is the kinematic viscosity, and where  $h$  can  
 75 be replaced by an element-based lengthscale where appropriate), or both (see support-  
 76 ing information Text S1). As such, these resistance schemes are inherently power-law ex-  
 77 pressions linking  $U$  to  $h$  via an exponent and a scaling coefficient, whose function, loosely,  
 78 is to set the magnitude of frictional resistance (such as  $n$  in Manning's equation). The  
 79 exponents are independent of any calibration, and their impacts on resistance vary be-  
 80 tween roughness schemes. Even after the scaling parameters are calibrated, different rough-  
 81 ness schemes may result in different predictions because their exponents differ.

82 The purpose of this technical note is to quantify the consequences of selecting dif-  
 83 ferent roughness schemes for flow prediction on a synthetic dryland hillslope, in which  
 84 vegetation cover is generally patchy but can vary from uniformly absent to completely  
 85 vegetated. Such a hillslope provides an example of a landscape on which the 'best' choice  
 86 of roughness scheme is ambiguous. This ambiguity arises from the sparse, patchy dis-  
 87 tribution of vegetation, and the shallow but disturbed nature of the flow. We address  
 88 two questions:

89 (i) How can different roughness schemes be simply calibrated against each other on biph-  
 90 alic, heterogeneous landscapes, to facilitate inter-comparison of predictions? and  
 91 (ii) Following such calibration, how sensitive are the hydrological predictions made on  
 92 these landscapes to the selection of a roughness scheme?

93 Answering these basic methodological questions offers guidance regarding the likely  
 94 sensitivity of predictions to the choice of roughness scheme.

## 95 2 Methods

### 96 2.1 A framework for cross-comparison

97 <sup>c1</sup>Despite the common non-dimensional scaling that lies behind the roughness  
 98 schemes (see supporting information Text S1), the derived resistance equations embed  
 99 distinct ways to conceptualize a rough surface, and distinct parameterizations of the

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<sup>c1</sup> *Text added.*

**Table 1.** Summary of the relations between the dimensionless Froude number  $Fr^2 = U^2/gS_f h$  and friction factor  $f$ , as well as the resulting conveyance equation, where  $\alpha$  is a general resistance parameter. To compare to the published forms,  $S_f = S_o$ , which is the kinematic wave approximation to the momentum balance (Equation 2) in the SVE.

Name	Resistance equation	Conveyance equation	References
Bed resistance equations			
Darcy-Weisbach	$Fr^2 = \frac{8}{f}$	$U = \frac{1}{\alpha} h^{1/2} S_o^{1/2}$	Brutsaert (2005)
		$\alpha = \sqrt{\frac{f}{8g}}$	Cea, Legout, Darboux, Esteves, and Nord (2014)
Poisseuille	$Fr^2 = \frac{Uh}{3\nu}$	$U = \frac{1}{\alpha} h^2 S_o$	Brutsaert (2005)
		$\alpha = \frac{3\nu}{g}$	Kirstetter et al. (2016)
Manning	$Fr^2 = \frac{h^{1/3}}{n^2 g}$	$U = \frac{1}{\alpha} h^{2/3} S_o^{1/2}$	Brutsaert (2005)
		$\alpha = n$	Smith, Cox, and Bracken (2007)
Transitional /	$Fr^2 = \frac{8}{a\epsilon}$	$U = \frac{1}{\alpha} h S_o^{1/2}$	Brutsaert (2005)
Mixed-flow		$\alpha = \frac{a\epsilon}{8g}$	Horton (1938)
Distributed drag equations			
Cylinder array	$Fr^2 = \frac{2(1-\phi)}{C_d \mu D h}$	$U = \frac{1}{\alpha} \sqrt{S_o}$	Cheng and Nguyen (2010)
		$\alpha = \sqrt{\frac{C_d \mu D}{2g(1-\phi)}}$	Tanino and Nepf (2008)
Poggi	$Fr^2 = \frac{1}{\beta^2} \exp\left(\frac{-H_c}{\beta^2 L_c}\right)$	$U = \frac{1}{\alpha} h^{1/2} S_o^{1/2}$	Katul et al. (2011)
		$\alpha = \frac{\sqrt{\beta}}{g} \exp\left(\frac{H_c}{2\beta^2 L_c}\right)$	
Depth-dependent Manning	$Fr^2 = \frac{h}{n_o^2 g h_o^{2/3}}$	$U = \frac{1}{\alpha} h S_o^{1/2}$	Mügler et al. (2011)
		$\alpha = n_o h_o^{1/3}$	Jain, Kothyari, and Raju (2004)

100 surface features. In order to ask whether predictions are sensitive to the choice of a  
 101 scheme, the predictions made using different schemes need to be placed within a com-  
 102 mon framework to enable cross-comparison. Here, we develop such a framework via an  
 103 analytical calibration procedure.

104 Cross-comparison of schemes is facilitated by the similarities in their mathemat-  
 105 ical form when expressed in terms of the kinematic conveyance equation (the third col-  
 106 umn in Table 1) relating the flow velocity to the flow depth, the bed slope, and a range  
 107 of other parameters, which can be lumped together as a single factor  $\alpha$  (Brutsaert, 2005;  
 108 Lighthill & Whitham, 1955).

$$109 \quad U = \frac{1}{\alpha} h^m S_o^\eta. \quad (3)$$

110 where  $\alpha$  and  $m$  are generalized coefficients describing the surface roughness and flow regime,  
 111 respectively, discussed in greater detail below.

112 The units and physical interpretation of  $\alpha$  are scheme-specific, but in general,  $\alpha$   
 113 increases with increasing surface roughness. The flow regime (laminar, transitional, tur-  
 114 bulent), which sets the value of  $b$  in the generalized  $f \sim a\epsilon^b$  expression, emerges in Equa-  
 115 tion 3 as  $m$ . Figure 1 illustrates how surface roughness  $\alpha$  and flow regime  $m$  affect the  
 116 relation between  $U$  and  $h$  for a fixed hillslope gradient,  $S_o$ .

117 To compare predictions made by the schemes, the values of  $\alpha$  used in each scheme  
 118 must be chosen to minimize the differences in their predictions for a common situation.  
 119 If one scheme is treated as a reference, then this selection problem is essentially one of  
 120 calibration. To enable the use of an analytical framework, we assume that the conveyance  
 121 equation above applies at hillslope scales, even on the potentially complex hillslopes con-  
 122 sidered later. With this assumption, the calibration problem admits analytical solutions  
 123 for homogeneous hillslopes, if flow conditions are calibrated to each other at the hills-  
 124 slope outlet (as outlined in Section 2.2). We then consider how this method can be adapted  
 125 to patchily vegetated slopes, assuming that there is a known resistance equation that ap-  
 126 plies to bare sites on those slopes. We outline this method in Section 2.3. With the  $\alpha$   
 127 values selected to minimize disagreement between schemes, remaining differences in flow  
 128 predictions can be attributed to the unique physics implied by each resistance scheme,  
 129 which alters the relationship between flow velocity and depth (for example, the distinc-  
 130 tions seen between the curves in Figure 1 panel A).

131 <sup>c5</sup>We use a coupled Saint Venant - Richards equation model to evaluate the dif-  
 132 ferences in predicted hillslope-scale hydrology associated with different roughness schemes  
 133 <sup>c6</sup> <sup>c7</sup>following calibration of their roughness coefficients to each other (Section 2.4). We  
 134 undertake this evaluation for a wide and realistic range of storm and hillslope scenar-  
 135 ios.

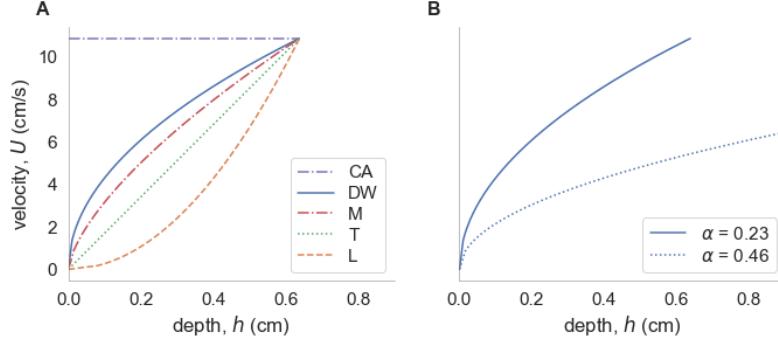
## 136 2.2 Calibration strategy for homogeneous slopes

137 We start with the problem of determining a roughness parameterization that will  
 138 relate two different roughness schemes for the same rain intensity on a common slope.  
 139 To proceed to an analytical solution, we consider the idealized situation of a hillslope  
 140 exposed to constant rainfall  $p$  on which infiltration occurs at a constant rate given by  
 141 the hydraulic conductivity  $K_s$ .

<sup>c5</sup> OC: A coupled Saint Venant - Richards equation model is then used

<sup>c6</sup> ST: after their

<sup>c7</sup> OC: kinematic conveyance equations have been calibrated to reference flow conditions



**Figure 1.** Illustration of the independent roles of the selection of a roughness scheme ( $m$ ) and its parameterization ( $\alpha$ ) on the predicted kinematic relation between velocity and depth. <sup>c3</sup> (A) illustrates how the selection of a roughness scheme implies a  $U - h$  scaling relation for each roughness scheme, independent of the value of  $\alpha$  (for each scheme,  $\alpha$  has been calibrated to preserve flow properties between schemes at the outlet, as described in Section 2.2). <sup>c4</sup> Conversely, (B) shows Darcy Weisbach flow on landscapes with two different values of  $\alpha$ .

Under steady-state conditions, the kinematic conveyance equations in Table 1 specify the relationships between discharge, velocity and stage. Additionally, at the hillslope outlet, discharge must be balanced by hillslope-scale rainfall inputs, such that on a per-unit-hillslope width basis:

$$q_o = Uh = L(p - K_s), \quad (4)$$

where  $L$  is the hillslope length and  $q_o$  is the flow rate at the outlet per unit width. We now consider that two different conveyance equations could be used to describe this flow:

$$U_1 = \frac{1}{\alpha_1} h_1^{m_1} S_o^{\eta_1} \quad (5)$$

$$U_2 = \frac{1}{\alpha_2} h_2^{m_2} S_o^{\eta_2} \quad (6)$$

Given that our interest is in representing hillslope-scale hydrological responses (which are evaluated at the hillslope outlet), we specify that the flow variables at the outlet should be conserved between the schemes, such that  $U_1 = U_2$  and  $h_1 = h_2$  at the outflow point.

Firstly, an expression for the flow depth at the outlet in the first scheme can be written as a function of the hillslope discharge  $q_o$ :

$$h_1 = \frac{q_o}{U_1} \quad (7)$$

$$= q_o \alpha_1 S_o^{-\eta_1} h_1^{-m_1}. \quad (8)$$

Rearranging:

$$h_1 = (\alpha_1 q_o S_o^{-\eta_1})^{1/(m_1+1)}. \quad (9)$$

Substituting Equation 9 into Equation 5:

$$U_1 = \frac{1}{\alpha_1} S_o^{\eta_1} (\alpha_1 q_o S_o^{-\eta_1})^{m_1/(m_1+1)}, \quad (10)$$

which simplifies to:

$$U_1 = \left( \frac{S_o^{\eta_1} q_o^{m_1}}{\alpha_1} \right)^{1/(m_1+1)}. \quad (11)$$

146 Because  $\alpha_1$  is known,  $U_1$  in Equation 11 is also known. The same logic means that the  
 147 outlet velocity  $U_2$  in the second roughness scheme can be written in the same form, and  
 148 rearranged to isolate the roughness term  $\alpha_2$ :

$$\alpha_2 = \frac{S_o^{\eta_2} q_o^{m_2}}{U_2^{m_2+1}}. \quad (12)$$

149 At this point, we require the outlet velocities to be equal between the two schemes, and  
 150 combine Equations 11 and 12 to obtain an analytic expression for  $\alpha_2$  in terms of the scal-  
 151 ing exponents of the roughness expressions (i.e.  $m_1$  and  $m_2$ ), the equilibrium discharge  
 152  $q_o$ , and the roughness parameter of the first scheme  $\alpha_1$ :

$$\alpha_2 = [\alpha_1^{m_2+1} S_o^{\eta_2(m_1+1)-\eta_1(m_2+1)} q_o^{m_2-m_1}]^{1/(m_1+1)}. \quad (13)$$

153

c1

154 This approach effectively calibrates the two schemes to each other at the outlet,  
 155 for a given hillslope and rainfall rate. The calibration quantifies an  $\alpha_2$  that produces equiv-  
 156 alent flow at the outlet to the reference scheme with  $\alpha_1$ , for a given set of storm and land-  
 157 scape parameters. The same result is obtained if the derivation proceeds by requiring  
 158  $h_1 = h_2$  at the outlet, as expected given the constraint that  $q_o$  is the same for both schemes.

159 The dependence of Equation 13 on slope length and rainfall rate (via  $q_o$ ) <sup>c2 c3</sup>re-  
 160 fects the fact that the calibrated  $\alpha_2$  absorbs differences in prediction that arise from dif-  
 161 ferences in  $m$  and  $\eta$  between the schemes, and thus depends on the  $h$  and  $U$  associated  
 162 with equilibrium flow. The calibrated  $\alpha_2$  is therefore not an independent description of  
 163 the surface roughness, but rather, a parameterization that is adjusted for the magnitude  
 164 of the flow and the differences in resistance that emerge between roughness schemes for  
 165 that flow.

166 Because the schemes are forced to agree at the outlet, differences in predicted  $U$   
 167 and  $h$  values will emerge at other locations on the hillslope. Thus, this calibration ap-  
 168 proach is appropriate for evaluating differences in hillslope-average flow properties af-  
 169 ter adjusting the roughness parameters <sup>c4</sup>( $\alpha$ ) to minimize those differences under equi-  
 170 librium flow conditions. Differences between schemes during unsteady conditions or at  
 171 other locations on the hillslope are not minimized by this approach. <sup>c5</sup> However, the  
 172 analytic tractability of the approach renders it attractive, as it requires no additional  
 173 model runs to calibrate  $\alpha_2$ . An alternative calibration approach would be to conduct  
 174 multiple model runs to achieve near-exact agreement over one assessment metric (e.g.  
 175 infiltration fraction), and assess the quality of the match over a different set of assess-  
 176 ment metrics (e.g. hydrograph NRMSE,  $t_{rise}$  and  $U_{max}$ ); however, such an approach  
 177 would require multiple model runs for storm and hillslope case, which would be com-  
 178 putationally more demanding and lacks theoretical underpinning.

<sup>c1</sup> *OC*: The same result is obtained if the derivation proceeds by requiring  $h_1 = h_2$  at the outlet, as expected given the constraint that  $q_o$  is the same for both schemes.

<sup>c2</sup> *ST*: implicitly accounts for

<sup>c3</sup> *ST*: Text added.

<sup>c4</sup> *OC*: Text added.

<sup>c5</sup> *OC*: However, the analytic tractability of the approach renders it attractive relative to other optimization approaches for  $\alpha_2$  that would require multiple model runs.

179 **2.3 Calibration strategy for patchy hillslopes**

180 We now extend the calibration strategy from homogeneous hillslopes (described in  
 181 the previous section), to patchy landscapes, addressing the additional complexity of flow  
 182 processes on these landscapes. To simplify the process, we consider a hillslope that can  
 183 be represented as a binary mosaic of vegetated and bare soil areas <sup>c6</sup>(see Figure 2). In-  
 184 infiltration rates are assumed to be low in bare areas due to the formation of surface crusts  
 185 (Assouline, 2004; Assouline et al., 2015) and higher under vegetation cover due to root  
 186 activity and protection of the soil surface against rain-splash by the canopy (Thompson,  
 187 Harman, Heine, & Katul, 2010). Roughness characteristics are similarly determined by  
 188 whether the surface is bare or vegetated. To further simplify the approach, we assume  
 189 that the bare sites are impermeable and have known roughness. <sup>c7</sup>The spatial pattern  
 190 of bare and vegetated sites is described by the vegetation cover fraction  $\phi_V$  and a char-  
 191 acteristic length-scale  $\sigma$  describing the spatial correlation of the patches (see supporting  
 192 information Figure S1 for a summary of the methods used to generate the vegetation  
 193 patterns).

194 While the impermeable bare soil areas are always sources of runoff, the vegetated  
 195 patches may function as runoff sources or sinks, depending on the values of  $p$  and  $K_s$ .  
 196 This requires adjustment to the calibration approach, <sup>c1</sup>which is achieved by separately  
 197 considering 3 cases:  $p$  greater than, approximately equal to, and less than  $K_s$ . <sup>c2</sup>Because  
 198 the heterogeneous land surfaces are two-dimensional, the calibration approach uses a  
 199 one-dimensional approximation, with the vegetation fields summarized by one-dimen-  
 200 sional statistics (e.g. vegetation fraction and characteristic patch length). Lastly, inter-  
 201 ception losses by the vegetation have been ignored here but could be readily accommo-  
 202 dated by adjusting  $p$ .

203 **2.3.1 Case 1: Rainfall intensity greater than hydraulic conductivity**

204 In this case, the entire hillslope is a runoff source. Vegetated patches generate runoff  
 205 at the rate  $p - K_s$ , and bare soil areas generate runoff at the rate  $p$ . For the purpose  
 206 of predicting hillslope-average outcomes, we can treat the hillslope as a homogeneous sur-  
 207 face, provided that we adjust the discharge at the outlet  $q_o$  to account for the different  
 208 surface types. To do this, we approximate  $q_o$  as:

$$q_o = L[p(1 - \phi_V) + (p - K_s)\phi_V], \quad (14)$$

209 and Equation 13 is otherwise unchanged.

210 **2.3.2 Case 2: Rainfall intensity less than hydraulic conductivity**

211 In this situation, runoff is generated on the bare soil patches, but the vegetated patches  
 212 act as sinks into which some or all of the runoff infiltrates. The effect of the vegetated  
 213 areas acting as sinks is that the fraction of the hillslope generating runoff is reduced to  
 214 a maximum of  $1 - \phi_V$ . In the most extreme case, only the patches that are immediately  
 215 adjacent to the hillslope outlet generate runoff (the so-called ‘directly connected areas’  
 216 (Alley & Veenhuis, 1983; Booth & Jackson, 1997; Lee & Heaney, 2003; Leopold, 1968)).

<sup>c6</sup> OC: Text added.

<sup>c7</sup> OC: The proportion of bare and vegetated sites is described by the vegetation cover fraction  $\phi_V$  and the characteristic length-scale of the bare patches,  $L_B$ , describing the spatial correlation of the patches.

<sup>c1</sup> OC: which we approach

<sup>c2</sup> OC: Although the heterogeneous land surface is two-dimensional, the calibration approach uses a one-dimensional approximation.

To account for this, we consider the behavior of runoff generated by an individual representative bare soil patch. We apply the calibration approach at the bottom boundary of this patch. Thus,  $q_o$  in Equation 13 is replaced with:

$$q_o = L_b p. \quad (15)$$

where  $L_b$  is the mean along-slope length of the bare soil areas.

### 2.3.3 Case 3: Rainfall intensity equal to hydraulic conductivity

For the situation where  $p = K_s$ , either patch or hillslope-scale calibration approaches could be used. Patch-scale calibration would be expected to produce better results for outcomes related to runoff generation from individual bare soil patches, for example, the shape of the the rising limb of the hydrograph, when transient dynamics associated with individual patch responses might dominate. Hillslope-scale calibration would be expected to produce better results close to the equilibrium conditions of the whole hillslope.

## 2.4 Testing the homogeneous calibration approach

One clear limitation of the calibration approach adopted here is that it assumes steady-state, kinematic flow conditions. These assumptions may not be valid during the unsteady conditions that often prevail during individual rainstorms<sup>c1</sup> so we used a coupled Saint Venant equation (SVE) - Richards equations model to explore the effects of unsteady, non-kinematic flow; specifically, we compared the hillslope-scale hydrological predictions made using five different roughness schemes. <sup>c2</sup>The model couples the 2D SVE solver used by Bradford and Katopodes (2001) to the 1D Richards equation solver developed by Celia, Bouloutas, and Zarba (1990) <sup>c3</sup>(see supporting information Text S2 for model details, soil parameters, and validation simulations). <sup>c4</sup>To enable inter-comparison, we designated Manning's equation with  $n=0.1$  as a 'reference scheme', and calibrated the other four schemes to it, using the homogeneous hillslope approach outlined in Section 3.2. We then assessed the disagreement between predictions made using the calibrated (non-Manning) and reference (Manning) schemes. The roughness schemes tested were the cylinder array, Darcy-Weisbach, transitional and laminar schemes listed in Table 1. We note that although the laminar Poiseuille equation lacks a free parameter, flume studies of laminar flow over natural surfaces have observed  $\alpha$  values ranging 6-40 times the Poiseuille coefficient,  $\alpha = 3\nu/g$  (Dunkerley, 2001; Pan, Ma, Wainwright, & Shangguan, 2016), presumably due to variations in the bed configuration and inundation depths.

To assess the viability of Equation 13 across a range of scenarios, we chose two representative hillslope gradients ( $S_o = 0.01$  and  $0.1$ ) and five effective rainfall intensities ( $p - K_s = 1, 2, 3, 4, 4.9$  cm/hr; with  $p = 5$  cm/hr and  $K_s = 0.1, 1.0, 2.0, 3.0, 4.0$  cm/hr), as summarized in Table 2. To avoid unsteady infiltration behavior, we assumed that the soil was initially saturated with  $i = K_s$ , provided there was sufficient water at the surface to supply this infiltration rate. We used the coupled Saint Venant - Richards equation model to simulate a 30 minute rainstorm for all of the parameter combinations listed in Table 2. For each simulation, the model predicts the two-dimensional overland flow

<sup>c1</sup> OC: Text added.

<sup>c2</sup> OC: We addressed this with a model that

<sup>c3</sup> Model details, soil parameters, and validation simulations are presented in supporting information Text S1.

<sup>c4</sup> OC: We used this coupled Saint Venant equation - Richards equation model to assess the disagreement between hillslope-scale hydrological predictions made using a reference roughness scheme - specifically Manning's equation with  $n = 0.1$  - and four other schemes calibrated to this reference condition using the homogeneous hillslope approach outlined in Section 3.2

**Table 2.** Parameters for the SVE model simulations, including both homogeneous and patchy hillslope. Where multiple parameters are listed, the cases were run factorially to explore all parameter combinations. For laminar, transitional, Darcy-Weisbach and cylinder array schemes,  $\alpha_2$  values were obtained with the calibration approach outlined in Section 2.3, using Manning's equation with  $n = 0.1$  as the reference scheme for vegetated areas. For bare soil areas in the patchy hillslopes, Manning's equation with  $n = 0.03$  was applied for all simulations.

Variable	Symbol	Values
<i>All simulations</i>		
Slope gradient (%)	$S_o$	1%, 10%
Roughness scheme	$m$	Laminar, Transitional, Manning, Darcy-Weisbach, Cylinder Array
Domain size	$L_x, L_y$	50 m $\times$ 25 m
Storm duration	$t_r$	30 minutes
<i>Homogeneous hillslope simulations</i>		
Hydraulic conductivity	$K_s$	0.1, 1, 2, 3, 4 cm/hr
Rainfall intensity	$p$	5 cm/hr
<i>Patchy hillslope simulations</i>		
Hydraulic conductivity (vegetated)	$K_s$	3 cm/hr
Rainfall intensity	$p$	1.5, 3.0, 4.5 cm/hr
Vegetation fraction	$\phi_V$	0.2, 0.5, 0.8
Standard deviation of the spatial kernel	$\sigma$	1, 5

depth and velocity, the runoff hydrograph, and a map of the cumulative infiltration depth. Hydrological outcomes were compared between roughness schemes using four error assessment metrics, as described in Section 2.6. <sup>c5</sup> Anticipating that this range of scenarios will produce non-kinematic flow conditions, we assessed (i) the 'kinematic-ness' of the flow (that is, how well the flow fields are described by the kinematic wave approximation), and (ii) whether non-kinematic flow conditions are correlated with larger calibration errors (see supporting information Text S3).

## 2.5 Testing the calibration approach for patchy hillslopes

To test the calibration method on patchy hillslopes, we generated a variety of synthetic vegetation patterns <sup>c1</sup> on a 50  $\times$  25 m gridded domain, following the approach outlined in Crompton, Sytsma, and Thompson (2019). <sup>c2</sup> We created multiple patterns spanning a range of vegetation fractions ( $\phi_V$ ) and patch correlation lengthscales ( $\sigma$ ), as detailed in Table 2 <sup>c3</sup> and illustrated in supporting information Figure S1.

<sup>c4</sup>

<sup>c5</sup> OC: Text added.

<sup>c1</sup> OC: Text added.

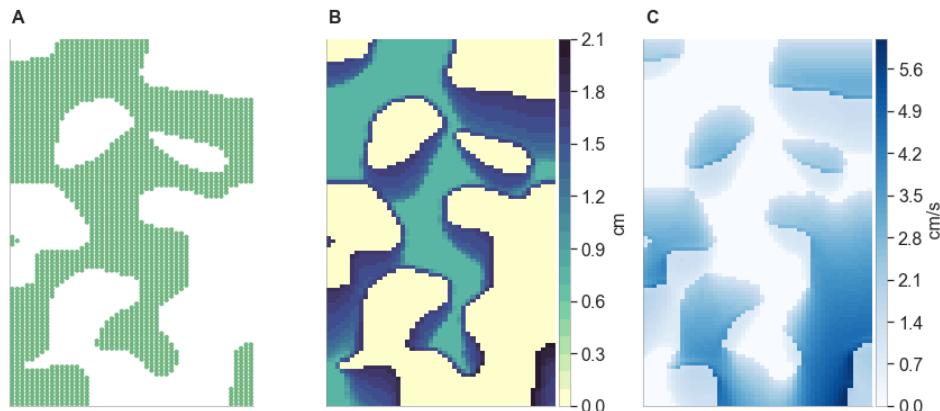
<sup>c2</sup> OC: Text added.

<sup>c3</sup> OC: Text added.

<sup>c4</sup> OC: ~~on a 50  $\times$  25 m gridded domain consisting of 0.5  $\times$  0.5 m grid cells. To generate the patterns, we drew a random number from a uniform distribution (0,1) for each grid cell. We prescribed a vegetation~~

267 We parameterized the Saint Venant - Richards equation model by treating all bare  
 268 soil areas as impermeable, with fixed roughness described by Manning's equation with  
 269  $n = 0.03$ . As in the homogeneous simulations, the reference roughness scheme for all veg-  
 270 etated patches was Manning's equation with  $n = 0.1$ . For each combination of rough-  
 271 ness scheme and hillslope parameters (slope,  $\phi_V$ , and rainfall intensity), we obtained  $\alpha_2$   
 272 from Equation 13, using the hillslope-scale  $q_o$  for all  $p \geq K_s$  cases and the patch-scale  
 273  $q_o$  for all  $p < K_s$  cases. We ran the model for factorial combinations of the rainfall in-  
 274 tensities, patterns of vegetation cover, and hillslope gradients listed in Table 2. Illustra-  
 275 tive model results from the Saint Venant - Richards equation model are presented in Fig-  
 276 ure 2, showing a vegetation pattern (panel A), cumulative infiltration depth (panel B)  
 277 and maximum overland flow velocity (panel C).

278 As a robustness check <sup>c1</sup>, we ran the same simulations with the converse calibra-  
 279 tion approach, where hillslope-scale calibration was replaced by patch-scale, or vice versa  
 280 (note that the hillslope-scale approach is not viable where  $p(1 - \phi_V) + (p - K_s)\phi_V <$   
 281 0). Comparison between the results obtained with patch- and hillslope-scale approaches  
 282 are included in supporting information <sup>c2</sup>[Figures S3-S5, which compare the performance](#)  
 283 [of the patch and hillslope-scale matching approaches. For each rainfall scenario, a larger](#)  
 284 [range of calibration errors is observed for patch-scale matching, which we attribute to](#)  
 285 [our estimation of the 'characteristic' lengthscale as the hillslope-mean bare soil patch](#)  
 286 [length.](#)



**Figure 2.** Domain set-up and computed outcomes. (A) map of the spatially random veg-  
 etation field with  $\phi_V = 0.5$  and  $\sigma = 5$  (green circles indicate vegetated  $0.5 \times 0.5$  m cells). (B)  
 Infiltration map and (C) maximum overland flow velocity resulting from a 30 min duration storm  
 with intensity  $p = 1.5$  cm/hour.

fraction as  $\phi_V$ , and classified cells as vegetated (1) or bare (0) around this value. The resulting binary domain was convolved with a symmetrical bivariate Gaussian kernel with standard deviation  $\sigma$  `scipy`. We again binarized the results around a value selected to preserve  $\phi_V$ . The use of the symmetrical kernel results in isotropic patterns, in which there is no systematic bias in patch properties associated with direction. We created multiple patterns spanning a range of values in  $\phi_V$  and  $\sigma$ , as illustrated in Figure 3 and detailed in Table 3. To provide a more intuitive summary of patch length scales, we computed the mean, along-slope patch lengths of the vegetated and bare sites,  $L_v$  and  $L_b$ , obtaining values in the range 2.5–30 m.

<sup>c1</sup> OC: on our reasoning in developing the calibration approach for patchy landscapes

<sup>c2</sup> OC: Text S3.

287 **2.6 Metrics to evaluate the sensitivity to scheme selection**

288 To assess the sensitivity of hydrological predictions to the choice of a roughness scheme  
 289 post calibration, we developed four quantitative metrics. For each of these metrics, we  
 290 computed the difference<sup>c3</sup><sub>s</sub> between model simulations<sup>c4</sup> parameterized with the refer-  
 291 ence scheme (Manning's equation) and<sup>c5</sup> those parameterized with the calibrated schemes.  
 292

293 These metrics were:

- 294 1. The hillslope-averaged water balance partitioning, as measured by the infiltration  
 295 fraction  $IF$ , the ratio of the hillslope mean infiltration depth to the rainfall depth.
- 296 2. The maximum overland flow velocity,  $U_{max}$ .
- 297 3. The rising time of the hillslope hydrograph, <sup>c1</sup> $t_{rise}$  estimated as the time at which  
 298 the hydrograph reached 80% of the maximum discharge obtained from the refer-  
 299 ence simulation.
- 300 4. The hydrograph shape, <sup>c2</sup>computed as a normalized root mean squared error  
 301 (NRMSE), where the normalizing factor is the maximum discharge from the  
 302 reference simulation.

303 <sup>c3</sup>We refer to these differences in hydrological predictions made using different  
 304 roughness schemes as 'calibration errors'

305 <sup>c4</sup>

## 3 Results

### 3.1 Homogeneous hillslopes

307 The homogeneous hillslope cases<sup>c5</sup> were used to to assess the effectiveness of the  
 308 analytical calibration approach in preserving hillslope-scale hydrological behavior<sup>c6</sup> (as  
 309 quantified by the error metrics listed in Section 2.6) across different roughness schemes.  
 310 <sup>c7</sup>The calibration errors are presented in Figure 3, which summarizes the differences in  
 311 infiltration fraction  $IF$ , hydrograph characteristics, and  $U_{max}$  between<sup>c8</sup> the calibrated  
 312 simulations and the reference Manning's equation simulations.

313 Numerical instabilities occurred in laminar simulations with  $K_s \leq 1.0$  cm/hr, and  
 314 these simulations were therefore not used in the analysis. <sup>c9</sup>These instabilities are in-  
 315 herent to the numerical scheme used for solution, which does not use additional sta-  
 316 bilizing techniques such as adding diffusion (Zarmehi, Tavakoli, & Rahimpour, 2011).  
 317 There are systematic differences in the errors across roughness schemes: the Darcy-Weisbach  
 318 and transitional formulations are most similar to the Manning predictions following cal-  
 319 ibration, and the laminar and cylinder array schemes are most different. This pattern  
 320 reflects variation in the differences between each conveyance equation's  $m$  exponent and

<sup>c3</sup> Text added.

<sup>c4</sup> OC: using the

<sup>c5</sup> Text added.

<sup>c1</sup> OC: Text added.

<sup>c2</sup> OC: normalized by the maximum discharge from the reference simulation.

<sup>c3</sup> Text added.

<sup>c4</sup> OC: Differences in univariate metrics between schemes were computed as simple differences, and differences in the hydrographs were computed as a normalized root mean squared error (NRMSE).

<sup>c5</sup> OC: provide a means

<sup>c6</sup> OC: Text added.

<sup>c7</sup> OC: Error metrics measuring differences in this behavior are presented in Figure

<sup>c8</sup> OC: the calibrated and reference Manning's equation simulations

<sup>c9</sup> OC: Text added.

321 Manning's equation ( $m = 2/3$ ). These differences are larger for the laminar ( $m = 2$ )  
 322 and cylinder array ( $m = 0$ ) schemes than for the Darcy-Weisbach ( $m = 1/2$ ) and trans-  
 323 sitional ( $m = 1$ ) schemes. However, the practical implications for prediction differences  
 324 are small: <sup>c10</sup>the standard deviation of the prediction differences is 1.1% for  $IF$ , 2.3%  
 325 for  $U_{max}$ , 6.1% for  $t_{rise}$  and 3.4% for the hydrograph NRMSE. Hydrograph NRMSE  
 326 reflect the different shapes of the hydrographs (e.g., Figure 3, Panels E and F), which  
 327 are unlikely to be important in practical applications. The results suggest that Equation  
 328 13 provides <sup>c11</sup>an effective means to parameterize different roughness schemes to  
 329 represent equivalent flow conditions, allowing for objective inter-comparison <sup>c12</sup>and as-  
 330 essment of the discrepancy between the physics implicit to each roughness scheme.

331 To estimate the differences in prediction between the most disparate schemes, we  
 332 also undertook a pairwise comparison between all schemes. We note, however, that all  
 333 simulations are calibrated to Manning's equation, so this pairwise comparison does not  
 334 represent the errors that would be generated by direct calibration of the compared schemes  
 335 to each other. Supporting information Table S4 displays the mean pairwise calibration  
 336 error for each assessment metric, with the range of values in parentheses. The predic-  
 337 tion differences are, unsurprisingly, greatest for the comparison between cylinder array  
 338 and laminar schemes.

339 To assess whether the differences in prediction were statistically significant, we used  
 340 the Wilcoxon signed-rank test of the null hypothesis that the mean difference in predicted  
 341 hydrological outcomes between two schemes is equal to 0. For each possible pairwise com-  
 342 bination of roughness schemes, and for the 4 hydrological assessment metrics, we obtained  
 343  $p$ -values less than 0.02, and therefore conclude that the sensitivity of the results to the  
 344 choice of roughness scheme is statistically significant.

### 345 3.2 Patchy hillslopes

346 Differences in predictions between the reference and calibrated simulations for patchy  
 347 hillslopes reflect errors associated with the adaptation of the homogeneous calibration  
 348 procedure to patchy hillslopes, in addition to those arising from the calibration pro-  
 349 cedure itself. Further, on patchy hillslopes, departures from kinematic conditions at patchy  
 350 boundaries potentially add an additional source of error. The fraction of the hillslope  
 351 held in common between all cases (the bare sites), however, acts to reduce the magni-  
 352 tude of the differences between cases. The resulting differences between reference and  
 353 calibrated simulations are shown in Figure 4, which summarizes the differences in  $IF$ ,  
 354  $U_{max}$  and hydrograph characteristics for all cases. The hillslope-scale calibration approach  
 355 was used for the  $p = 3.0$  and  $4.5$  cm/hr rainfall cases, and the patch-scale approach was  
 356 used for the  $p = 1.5$  cm/hr cases. <sup>c5</sup>

357 The paired simulations show close agreement: <sup>c6</sup>the standard deviation of the pre-  
 358 diction differences are 1.1% for  $IF$ , 2.3% for  $U_{max}$ , 6.0% for the hydrograph NRMSE,  
 359 and 3.3% for  $t_{rise}$ . In absolute units and grouped by scheme, the median  $U_{max}$  dif-  
 360 ferences range from -0.3 cm/s (cylinder array) to 0.3 cm/s (laminar), and the median  
 361  $t_{rise}$  errors range from -0.2 min (cylinder array) to 0.6 min (laminar). The hydrograph

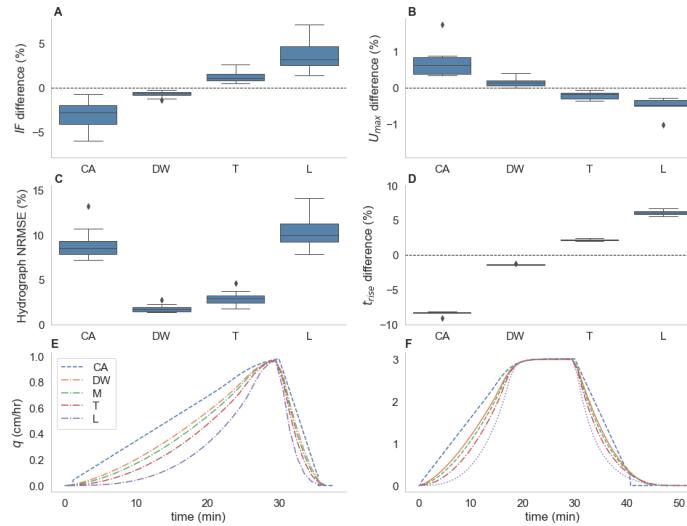
<sup>c10</sup>OC: simulations differ by less than 6% for  $IF$  and 2% for  $U_{max}$  in all cases. The hydrograph rising  
times differ by less than 9.1% in all cases, and the hydrograph NRMSE are less than 14%.

<sup>c11</sup>OC: a viable

<sup>c12</sup>OC: Text added.

<sup>c5</sup>OC: Numerical instabilities affected the laminar simulations with 20% vegetation cover and  $p \geq 3$   
cm/hr, and these simulations were excluded from the analysis.

<sup>c6</sup>OC: the  $IF$  differences are less than 4.3%, and the  $U_{max}$  differences are less than 7.4% (1.7 cm/hr in  
absolute units). The differences in  $t_{rise}$  are less than 3.4 minutes in all cases. The hydrograph NRMSE are  
less than 12% across schemes, and less than 4% for the Darcy-Weisbach and transitional schemes



**Figure 3.** <sup>c3</sup>Box-plots show the differences between each of the non-Manning roughness scheme simulations (cylinder array, CA; Darcy-Weisbach, DW; transitional, T; and laminar, L) and its paired Manning simulation: (A) the infiltration fraction  $IF$ , (B) the maximum velocity  $U_{max}$ , (C) the hydrograph rising time  $t_{rise}$ , and (D) the NRMSE between hydrographs. <sup>c4</sup>Panels (E) and (F) show the simulation hydrographs with the largest NRMSE and differences  $t_{rise}$ , respectively : (E)  $K_s = 4.0$  cm/hr and  $S_o = 0.01$ , and (F)  $K_s = 2.0$  cm/hr and  $S_o = 0.01$ .

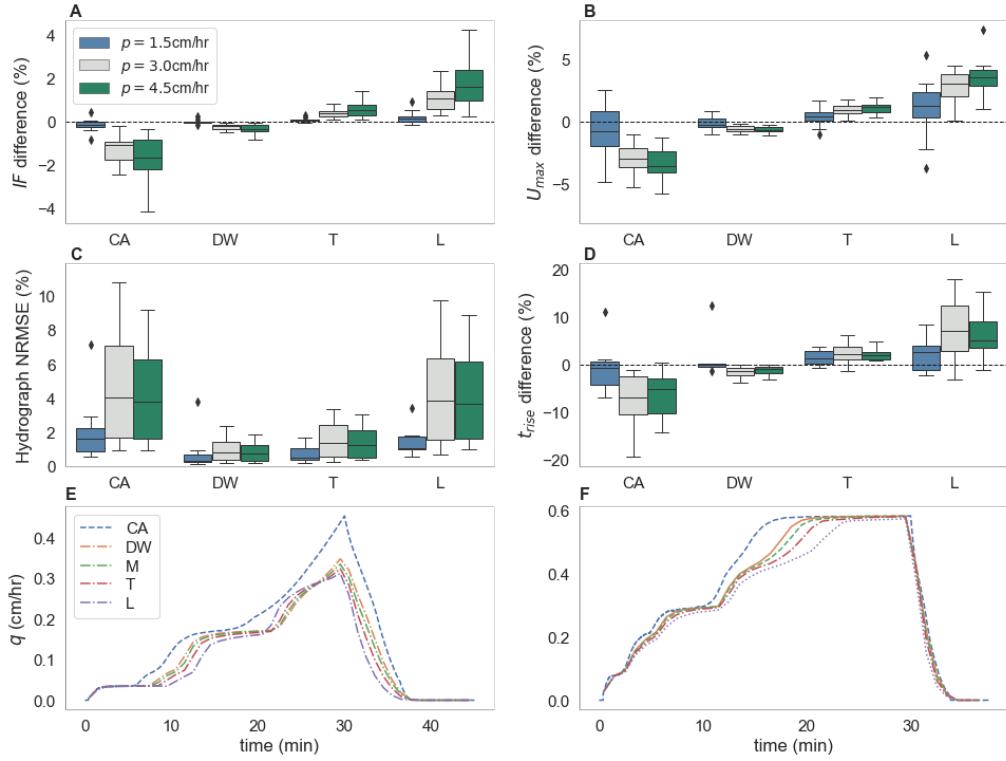
NRMSE are again larger than the other metrics, due to the differently shaped hydrographs. Overall, these errors are comparable to those produced on homogeneous slopes, and suggests that the additional sources of error in these simulations are compensated for by the use of identical roughness schemes for bare soil sites. The results shown in Figure 4 suggest that the sensitivity of hydrological predictions to the choice of roughness scheme for vegetated surfaces is small, provided the roughness parameters are appropriately calibrated. Similarly to the homogeneous hillslopes, the disagreement between schemes is greatest where the difference between the  $m$  exponents in the conveyance equations is largest.

As with the homogeneous hillslopes, we undertook a pairwise comparison between all schemes. Supporting information Table S5 displays the mean pairwise calibration error for each assessment metric, with the range of values in parentheses, again showing the greatest differences between cylinder array and laminar schemes.

We used the Wilcoxon signed-rank test for each of the 4 hydrological metrics and the 10 possible pairwise scheme combinations. We obtained  $p$ -values less than  $1 \times 10^{-5}$  for all cases, indicating statistically significant sensitivity of the results to the choice of roughness scheme.

#### 4 Discussion and Conclusions

The results demonstrate the efficacy of a simple kinematic framework to calibrate roughness schemes against each other in order to represent a common flow environment for the case of shallow, rainfall-induced overland flow on natural hillslopes. The key value of the approach is that by imposing kinematic assumptions, calibration can be achieved analytically for both homogeneous or patchily vegetated hillslopes, as demonstrated by comparison of numerical simulations that have been analytically calibrated to represent



**Figure 4.** Box-plots show the differences between each of the non-Manning roughness scheme simulations (cylinder array, CA; Darcy-Weisbach, DW; transitional, T; and laminar, L) and its paired Manning simulation: (A) the infiltration fraction  $IF$ , (B) the maximum velocity  $U_{max}$ , (C) the hydrograph rising time  $t_{rise}$ , and (D) the NRMSE between hydrographs.

Panels (E) and (F) show the simulation hydrographs with the largest NRMSE and difference in  $t_{rise}$ , respectively.

equivalent flow conditions. The calibrated equations make highly comparable hydrologic predictions for the same hillslope and storm conditions, regardless of the specific roughness schemes selected. This suggests that SVE flow predictions are more sensitive to the value of the roughness coefficient  $\alpha$  than to differences in the functional form of the resistance equation, provided the schemes are calibrated to a common flow condition, produced by the same rainfall forcing on the same hillslope. This agreement is likely a consequence of the relatively constrained range of velocity and depth values that arise during rain-induced shallow overland flow. Thus, these results should not be extrapolated to situations with deeper or more variable flow regimes. Similarly, the model results presented here assume that the Saint Venant - Richards equation model adequately represents overland flow dynamics, and that the features of the flow that were omitted - including explicit treatment of emergent roughness elements and microtopography - would not significantly alter the findings. This assumption seems reasonable in light of the agreement between our modeling findings and the experimental results obtained by Cea et al. (2014), who compared high resolution flow simulations with experimental flow data generated on  $1 \times 1 \text{ m}$  plaster moulds. Like us, they found strong agreement between flow predictions made with different roughness schemes, once those schemes were calibrated.

The hydrological outcomes predicted by the different roughness schemes, as reported in Figures 3 and 4, are not indistinguishable. The differences in predictions, however, are smaller or comparable to measurement uncertainties reported in empirical hydrolog-

406       ical studies, including in estimated rainfall rates (e.g. rain gauge under-catch results in  
 407       systematic under-estimates in the range 5–16%, McMillan, Krueger, & Freer, 2012); in  
 408       flow velocities (e.g. on the order of 3.0 cm/s using Large Scale Particle Image Velocime-  
 409       try, Cea et al., 2014, larger than the calibration errors associated with velocities here);  
 410       and in discharge data (e.g. approximate uncertainty in runoff derived from stage mea-  
 411       surements at plot scales range from 10–20%, Krueger et al., 2009; Turnbull, Wainwright,  
 412       & Brazier, 2010). Thus, the selection of a roughness scheme is unlikely to produce er-  
 413       rors that could be readily distinguished from experimental noise. We note that uncer-  
 414       tainties associated with field observations are rarely quantified in the literature (Brazier,  
 415       Krueger, & Wainwright, 2014; Turnbull et al., 2010), precluding a more comprehensive  
 416       analysis.

417       This study has presented an analytic approach by which to parameterize different  
 418       roughness schemes to represent common hillslope surface conditions. We have shown that  
 419       the kinematic wave approximation provides a suitable framework for calibrating rough-  
 420       ness parameters, as evidenced by the close agreement between the various schemes in  
 421       the simulation results. With a common representation of the surface roughness (via pa-  
 422       rameterization of  $\alpha$ ) important hydrological outcomes, including the water balance par-  
 423       titioning, flow velocity and runoff hydrograph, display only minor sensitivity to the se-  
 424       lection of a roughness scheme. Consequently, choosing the correct roughness scheme ap-  
 425       pears less significant than correctly parameterizing any selected scheme. Despite this prac-  
 426       tical implication, the results here do not assist in determining the correct roughness value  
 427       for a given scheme. Thus, roughness parameterization remains an open question, sub-  
 428       ject to ongoing research.

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 435       Svoray and Shmuel Assouline for helpful comments on the draft.

436       The source code for the SVE model is hosted openly on GitHub:

437       <https://github.com/octavia-crompton/SVE-R>. The SVE solver is in Fortran, and Python  
 438       wrapper scripts are provided to interface with Fortran. Jupyter notebooks are provided  
 439       to visualize the results for selected examples. Model output is available from the authors  
 440       on request.

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