

# GPU-based high-performance computing for integrated surface - sub-surface flow modeling

Phong V. V. Le<sup>a</sup>, Praveen Kumar<sup>a,b,\*</sup>, Albert J. Valocchi<sup>a</sup>, Hoang-Vu Dang<sup>c</sup>

<sup>a</sup>*Department of Civil and Environmental Engineering, University of Illinois, Urbana, IL 61801, USA*

<sup>b</sup>*Department of Atmospheric Sciences, University of Illinois, Urbana, IL 61801, USA*

<sup>c</sup>*Department of Computer Science, University of Illinois, Urbana, IL 61801, USA*

---

## Abstract

The widespread availability of high-resolution lidar data provides an opportunity to capture micro-topographic control on the partitioning and transport of water for incorporation in coupled surface - sub-surface flow modeling. However, large-scale simulations of integrated flow at the lidar data resolution are computationally expensive due to the density of the computational grid and the iterative nature of the algorithms for solving nonlinearity. Here we present a distributed physically based integrated flow model that couples two-dimensional overland flow and three-dimensional variably saturated sub-surface flow on a GPU-based (Graphic Processing Unit) parallel computing architecture. Alternating Direction Implicit (ADI) scheme modified for GPU structure is used for numerical solutions in both models. Boundary condition switching approach is applied to partition potential water fluxes into actual fluxes for the coupling between surface and sub-surface models. The algorithms are verified using five benchmark problems that have been widely adopted in literature. This is followed by a large-scale simulation using lidar data. We demonstrate that the method is computationally efficient and produces physically consistent solutions. This computational efficiency suggests the feasibility of GPU computing for fully distributed, physics-based hydrologic models over large areas.

*Keywords:* Surface - sub-surface interactions, GPU computation, ADI scheme, finite difference, lidar

---

---

\*Corresponding author

*Email address:* [kumar1@illinois.edu](mailto:kumar1@illinois.edu) (Praveen Kumar)

## 1. Introduction

The interaction between surface and sub-surface flow is an important component of the hydrologic cycle (Winter et al., 1998; Sophocleous, 2002). Capturing these interactions in models is thus critical to predicting soil moisture states and the responses of ecohydrological processes to global change across various scales (Rodriguez-Iturbe, 2000). Several conjunctive hydrologic models have been developed to integrate surface and sub-surface flow and are being used to address a range of science questions (Paniconi & Wood, 1993; Morita & Yen, 2002; Panday & Huyakorn, 2004; Ivanov et al., 2004; Kumar et al., 2009; Camporese et al., 2010; Shen & Phanikumar, 2010). These models have evolved into a family of coupling schemes that can represent the relevant physical processes influencing hydrologic responses from small catchment to larger river basin scales (Maxwell et al., 2014). In addition, these conjunctive models are being coupled to vegetation-hydrology dynamics (Ivanov et al., 2008), solute transport (VanderKwaak & Sudicky, 1999; Weill et al., 2011), and land-surface and atmospheric models (Maxwell & Miller, 2005; Maxwell et al., 2007). However, existing models have not been applied to capture the micro-topographic controls revealed by light detection and ranging (lidar) digital elevation model (*l*DEM) data (Le & Kumar, 2014). The goal of this paper is to present numerical scheme suited for Graphic Processing Unit (GPU) based computation to enable studies using *l*DEM over large areas.

The increasing availability of high-resolution topographic data from lidar technique has offered new opportunities for broader exploration of the control of landscape variability at fine scales such as water and nutrient dynamics (Lefsky et al., 2002; Schwarz, 2010; Ussyshkin & Theriault, 2011; Le & Kumar, 2014) and to explore behavioral response (Kumar, 2011). Previous studies have shown that depressions arising from micro-topographic variability can have significant effects on streamflow generation (Dunne et al., 1991; Frei et al., 2010; Thompson et al., 2010; Loos & Elsenbeer, 2011), soil moisture dynamics (Simmons et al., 2011), and the surface - sub-surface flow interactions (Frei & Fleckenstein, 2014). Recent work has begun to identify and characterize the spatial distribution of topographic depressions as power laws for size and volume, using lidar data (Le & Kumar, 2014). Dynamics associated with these micro-topographic features need to be incorporated into conjunctive surface - sub-surface flow models to understand their impacts on the hydrologic and biogeochemical processes. This incorporation also leads to a significant increase in computational cost for numerical models due to the size of the computational grid and the iterative

31 nature of the algorithms in the coupled models.

32 A number of effort have contributed to the development of parallel formulation for some existing  
33 surface - sub-surface flow (Hwang et al., 2014; Kollet et al., 2010; Maxwell, 2013) and other coupled  
34 hydrologic systems (Gasper et al., 2014; Hammond et al., 2014). This has established the feasibility  
35 of high-resolution simulations at regional and continental scales. In addition, several studies have  
36 dealt with the computational scaling issues ranging from multi-cores to thousands of CPU cores  
37 on supercomputing systems (Gasper et al., 2014; Hammond et al., 2014; Kollet et al., 2010). This  
38 has also established the feasibility of high performance CPU computing for a range of applications  
39 for hydrologic modeling.

40 For the past few years, the graphics processing units (GPUs) have become increasingly pop-  
41 ular and an integral part of today’s mainstream computing systems (Owens et al., 2008). The  
42 increased capabilities and performance of recent GPU hardware in combination with high level  
43 GPU programming languages such as NVIDIA’s Compute Unified Device Architecture (CUDA)  
44 and Open Computing Language (OpenCL) has provided massively parallel processing power for  
45 numerically intensive scientific applications, and made general purpose GPU computing accessible  
46 to computational scientists. It also opens a possibility for simulations over larger computational  
47 grids, for example, detailed ecohydrologic modeling over large domains at lidar-data resolution and  
48 large-scale computational fluid dynamics (Vanka, 2013). In comparison with central processing  
49 units (CPUs), however, GPUs have a distinct architecture centered around a large number of fine-  
50 grained parallel processors (Kirk & Hwu, 2010). Therefore, numerical models must be specifically  
51 structured such that processes are executed concurrently across many fine-grained processors.

52 This study aims to present an integrated flow model that couples two-dimensional overland  
53 flow and three-dimensional variably saturated sub-surface flow on a GPU-based parallel computing  
54 architecture (GCS-flow). The goal is to support simulations over large areas using fine resolution  
55 /DEM to reveal flow and accumulation associated with microtopographic features. Because the  
56 programmable units of GPU follow a single-instruction multiple-data (SIMD) model, we use finite  
57 difference alternating direction implicit (ADI) approach for discretizing independent tridiagonal  
58 linear systems and efficiently solving the governing equations. Though ADI for multi-dimensional  
59 nonlinear problems has been rarely used in favor of fully implicit methods using Krylov-based  
60 solvers with preconditioning due to stability, its has advantages over Krylov solvers in terms of

61 scalability for large domains and computational cost as tridiagonal linear systems can be solved  
62 directly. **Since data parallelism in ADI is abundant, there is high potential for this scheme to be**  
63 **advantageous on the throughput-oriented design of GPU.**

64 The rest of the paper is organized as follows. In section 2, we provide an overview of the  
65 theory and numerical formulation of the GCS-flow model using ADI for GPU computing structure.  
66 Benchmark tests for model verification against other published solutions are presented in section 3.  
67 Results and analyses for simulations using lidar topographic data are shown in section 4. We  
68 demonstrate that the implemented model in GPU enables much faster execution than single-  
69 threaded performance in CPU. In section 5, the paper closes with the summary and discussion of  
70 the key points.

## 71 **2. Theory and numerical methods**

72 The theory of coupled surface - sub-surface flow has been an important area of research in the  
73 field of hydrology. Overview and details of the literature may be found in previous work (Paniconi  
74 & Wood, 1993; Morita & Yen, 2002; Panday & Huyakorn, 2004; Camporese et al., 2010; Sulis et al.,  
75 2010; Maxwell et al., 2014). We only provide a brief summary of the governing equations that form  
76 the basis for the set of coupled equations, the numerical method structured specifically for GPU  
77 architecture, and the coupling strategy between surface and sub-surface domains.

### 78 *2.1. Overland flow*

Overland flow is described by the depth-averaged flow equations commonly referred to as  
St. Venant equations that consist of a continuity (mass conservation) and two momentum equa-  
tions. The continuity equation is written as:

$$\frac{\partial h}{\partial t} + \nabla \cdot (\boldsymbol{\nu}h) + q_e + q_r = 0 \quad (1)$$

where  $h$  is water depth on the surface [ $L$ ],  $t$  is the time [ $T$ ],  $\boldsymbol{\nu}$  is depth averaged velocity vector [ $L T^{-1}$ ],  $q_e$  represents exchange fluxes between surface and sub-surface domains [ $L T^{-1}$ ], and  $q_r$  is a general source/sink term [ $L T^{-1}$ ] such as precipitation and evaporation. In diffusion flow, the momentum equations for overland flow reduce to:

$$S_{f,i} = S_n \quad (2)$$

79 where  $S_{f,i} = \partial H / \partial x_i$  are friction slopes [-],  $i$  stands for the  $x$ - and  $y$ -directions, and  $S_n$  is the slope  
80 of the water [-] computed as  $\sqrt{(\partial H / \partial x)^2 + (\partial H / \partial y)^2}$ . The term  $H = h + z$  is the water above a  
81 datum [ $L$ ] and  $z$  is ground elevation above a datum [ $L$ ] (Lal, 1998a,b).

Hromadka & Lai (1985) showed that Manning's equation can be used to establish a flow depth-discharge relationship:

$$\nu_i = -\frac{h^{2/3}}{n_b \sqrt{S_n}} \frac{\partial H}{\partial x_i} = -\frac{D}{h} \frac{\partial H}{\partial x_i} \quad (3)$$

in which  $D$  is the diffusion coefficient [ $L^2 T^{-1}$ ] and described by:

$$D = \begin{cases} \frac{h^{5/3}}{n_b \sqrt{S_n}}, & \text{for } |S_n| > S_{min} \text{ and } h > h_{min} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

where  $n_b$  is the Manning's coefficient [ $L^{-1/3} T$ ]. The condition  $h > h_{min}$  is used to facilitate wetting and drying, and  $S_{min}$  is used to maintain  $D$  within finite limits (Lal, 1998a). Using Equation (3), the governing continuity equation of the overland flow in two spatial dimensions can be expressed as:

$$\frac{\partial H}{\partial t} = \frac{\partial}{\partial x} \left( D \frac{\partial H}{\partial x} \right) + \frac{\partial}{\partial y} \left( D \frac{\partial H}{\partial y} \right) - q_e - q_r \quad (5)$$

82 where  $x$  and  $y$  are the horizontal coordinates [ $L$ ]. The term  $D$  is useful in linearizing and simplifying  
83 the diffusion flow equations. A variety of numerical algorithms can be used to solve the linearized  
84 diffusion overland flow equation (Lal, 1998a).

## 85 2.2. Variably saturated groundwater flow

The governing equation for variably saturated groundwater flow is represented on the basis of the mixed form Richards equation (Richards, 1931) as:

$$S_s \frac{\theta}{\phi} \frac{\partial \psi}{\partial t} + \frac{\partial \theta}{\partial t} = \nabla \cdot K(\theta) \left[ \nabla \psi + \hat{\mathbf{k}} \right] + q_s + q_e \quad (6)$$

86 where  $\psi$  is the sub-surface pressure head [ $L$ ],  $\theta$  is the soil moisture [-],  $\phi$  is the porosity [-],  $\hat{\mathbf{k}}$   
87 is the unit-upward vector,  $S_s$  is the specific storage coefficient [ $L^{-1}$ ],  $K$  is unsaturated hydraulic  
88 conductivity [ $L T^{-1}$ ],  $q_s$  is a general source/sink term representing pumping or injection [ $T^{-1}$ ], and  
89  $q_e$  represents the unit exchange fluxes between surface and sub-surface domains [ $T^{-1}$ ] The ratio  
90  $\theta/\phi$  is known as the degree of saturation.

The mixed form of the variably saturated flow equation has been shown to possess conservation property to maintain mass balance (Allen & Murphy, 1985; Celia et al., 1990). Different numerical

methods can be used for solving variably saturated groundwater flow (Huyakorn & Pinder, 1983). In the mixed form Richards formulation presented here, a closed-form model by van Genuchten (1980) is used to describe the constitutive relationships between  $\theta$ ,  $\psi$ , and  $K$ . The water retention curve is given by:

$$\Theta = \frac{\theta(\psi) - \theta_r}{\theta_s - \theta_r} = \left[ \frac{1}{1 + (\alpha\psi)^n} \right]^{1-1/n} \quad (7)$$

where  $\Theta$  is the relative saturation [-],  $\theta_r$  is residual water content [-],  $\theta_s$  is saturated water content [-] (often approximated by the porosity  $\phi$ ),  $n$  is the pore-size distribution [-], and  $\alpha$  is a parameter related to the inverse of the air entry suction [ $L^{-1}$ ]. The unsaturated hydraulic conductivity function is given by (Mualem, 1976):

$$K(\theta) = K_s \Theta^{\frac{1}{2}} \left[ 1 - \left( 1 - \Theta^{1-\frac{1}{n}} \right)^{1-\frac{1}{n}} \right]^2 \quad (8)$$

where  $K_s$  is the saturated hydraulic conductivity [ $L T^{-1}$ ] identified from soil physical properties.

### 2.3. Discretization and numerical implementation

The alternating direction implicit (ADI) method is used for numerical solutions in both surface and sub-surface flow models in GCS-flow. This approach has advantages over the fully implicit methods in terms of simplicity and cost (on a per iteration basis) because only tridiagonal linear systems are required to provide direct solutions. In addition, the discretization of ADI is more scalable ( $O[\mathcal{N}]$ ) than fully implicit approach ( $O[\mathcal{N}^d]$ ) as the problem dimensions increase, in which  $\mathcal{N}$  and  $d$  represent the size and the number of dimensions of the domain. An et al. (2011) have compared the performances between ADI and preconditioned conjugated gradient methods for multi-dimensional variably saturated flow implemented on CPU. They showed that ADI method is faster than fully implicit method while still yielding very similar results. However, the main disadvantage of ADI is the constrains in stability which requires smaller time steps than unconditionally stable fully implicit methods. ADI has better stability condition than explicit method without hard requirements on the time step. Morita & Yen (2002) showed the stability criterion of ADI for 2D overland flow,  $\xi_1 = D\Delta t (\Delta x^{-2} + \Delta y^{-2}) < 5$ , and 3D subsurface flow,  $\xi_2 = K\Delta t (\Delta x^{-2} + \Delta y^{-2} + \Delta z^{-2}) < 1.25$ , where  $\Delta x$ ,  $\Delta y$ ,  $\Delta z$  are the grid spacing in their respective directions and  $D$  and  $K$  are shown in Equations (5) and (6), respectively.

The mass balance condition with Crank-Nicolson type scheme forms the basis for the ADI formulation in overland flow. Using the ADI method, Lal (1998a) showed that the continuity

equation (1) for overland flow can be expressed in the following split formulation in sequence:

$$(1 - \delta_x)H_{i,j}^{n+\frac{1}{2}} = (1 + \delta_y)H_{i,j}^n - \frac{\Delta t}{2}(q_e + q_r) \quad (9a)$$

$$(1 - \delta_y)H_{i,j}^{n+1} = (1 + \delta_x)H_{i,j}^{n+\frac{1}{2}} - \frac{\Delta t}{2}(q_e + q_r) \quad (9b)$$

108 where  $n$  is the time step,  $(i, j)$  denotes spatial location,  $\delta_x$  and  $\delta_y$  are the standard second-  
 109 order centered differencing operators in  $x$  and  $y$  direction, respectively. In our model, the coupled  
 110 Equations (9) are solved as two 1-D problems for each row and column of the 2-D domain for  
 111 tridiagonal matrices at every half time step  $\frac{\Delta t}{2}$ . Linearized implicit methods use  $D$  values of the  
 112 previous time step (Lal, 1998a). Right-hand sides of these equation consist of entirely known  
 113 values at the time of computation. The detailed derivation and numerical form of Equations (9)  
 114 are presented in the Appendix A.

A simple mass-conservative numerical approach based on the backward Euler scheme associated with Picard iteration (Celia et al., 1990) is modified for 3-D sub-surface flow using the ADI method in this study. Because the relationship between  $\theta$  and  $\psi$  is highly non-linear, iterative calculation and linearization are needed to solve these systems. The backward Euler approximation for 3-D variably saturated groundwater flow can be written as:

$$\frac{S_s}{\phi}\theta^{n+1,m} \left[ \frac{\psi^{n+1,m+1} - \psi^n}{\Delta t} \right] + \left[ \frac{\theta^{n+1,m+1} - \theta^n}{\Delta t} \right] = \frac{\partial}{\partial x_i} \left( K^{n+1,m} \frac{\partial \psi^{n+1,m+1}}{\partial x_i} \right) - \frac{\partial K^{n+1,m}}{\partial x_3} + q_e + q_s = 0 \quad (10)$$

115 where  $m$  is the Picard iteration level. Values at level  $m$  are known while at level  $m+1$  are unknown.  
 116 Here  $x_i$  denotes spatial coordinates.

Using ADI, we sequentially solve Equation (10) at every  $\frac{\Delta t}{3}$  time step, keeping one direction implicit and the other two explicit. The implicit direction is then changed to the next direction (or axis), and so on until the next time step. The derivation and full numerical form of Equations (10) separated in  $x$ ,  $y$ , and  $z$  direction using ADI are presented in Appendix B. The iteration process to solve Equations (10) continues until the difference between the calculated values of the pressure head of two successive iteration levels become less than the user-defined tolerance for convergence:

$$|\psi^{n+1,m+1} - \psi^{n+1,m}| \leq \epsilon_\psi \quad (11)$$

117 Independent linear systems obtained from ADI for the two models are suitable for parallelizing in  
118 a large number of fine-grained processors in GPU devices.

#### 119 2.4. GPU Parallelization

120 We implement the integrated surface - sub-surface flow model on a GPU parallel computing  
121 structure. The model supports the use of different generations and types of CUDA-capable GPUs,  
122 which consists of a sequential *host* program that may execute parallel programs known as *kernels*  
123 on a parallel *device*. While data processing is performed on the host using C++ programming  
124 language, all model computation is executed in parallel on NVIDIA's GPUs (device) using CUDA  
125 programming language (Nickolls et al., 2008). CUDA virtualizes multiprocessors as blocks and  
126 processors as threads, which enables users to run a potentially large number of parallel threads  
127 and blocks across different generations of GPUs regardless of the number of physical processors  
128 (Zhang et al., 2010). Each thread runs the same scalar sequential program for solving tridiagonal  
129 linear systems (ADI solvers).

130 We sequentially solve the 2-D overland flow and 3-D sub-surface flow sub-models in parallel  
131 using these ADI solvers and couple them through an iterative strategy presented in the next  
132 section. More specifically, for each model we set up and solve simultaneously a large number  
133 of systems of  $n$  linear equations of the form  $Ax = b$ , where  $A$  is the tridiagonal matrix, and  $x$   
134 and  $b$  are vectors. This approach discretizes each governing equation for both sub-models into  
135 a number of independent tridiagonal linear systems which can be solved simultaneously using  
136 parallel cyclic reduction (PCR) method (Hockney & Jesshope, 1988) and the Thomas (TDMA)  
137 algorithm (Thomas, 1949). To efficiently solve these systems in parallel, we map the PCR solvers to  
138 the GPU's two-level hierarchical architecture with systems mapped to blocks and equations mapped  
139 to threads to utilize shared memory. If matrix size is small enough (i.e. in vertical  $z$  direction),  
140 TDMA solvers are mapped directly to threads to utilize local and register memory (Figure 1). The  
141 number of systems for large simulation domain we solve is usually far larger than the number of  
142 multiprocessors, so that all multiprocessors are fully utilized.

143 At the thread level, the total storage consists of five main vectors: three for the matrix diagonals,  
144 one for the right-hand side, and one for the solution vector. These five vectors store the data of all  
145 systems continuously, with the data of the first system stored at the beginning of the arrays, followed  
146 by the second system, the third system, and so on. For each system, we load the three diagonals



147 and right-hand side from global memory to register, local, or shared memories (Figure 1), solve  
148 and store the solution back to global memory on device. Therefore, global memory communication  
149 only occurs at the beginning and end of each time step in ADI solver. Other vectors (i.e. for  
150 the linearization of diffusion coefficients and van Genuchten relationship) can be generated in  
151 threads for the solutions of surface and sub-surface flow. As data is stored in global memory,  
152 no communication between CPU and GPU is needed as the direction (or axis) of calculation is  
153 changed.

#### 154 *2.5. Coupled surface - sub-surface formulation*

155 A boundary condition switching procedure (Paniconi & Wood, 1993; Camporese et al., 2010;  
156 Sulis et al., 2010; Camporese et al., 2014) is used for coupling the surface and sub-surface flow  
157 in GCS-flow model. Specifically, the boundary condition at any surface ground nodes of the sub-  
158 surface domain is allowed to switch between a Dirichlet and a Neumann type, depending on the  
159 saturation (or pressure head) state of that node. A Neumann (or specified flux) boundary condition  
160 corresponds to atmosphere-controlled infiltration or exfiltration with the flux equal to the rainfall or  
161 potential evaporation rate given by the atmospheric input data. In contrast, a Dirichlet (specified  
162 head) boundary condition is activated when the surface node reaches a threshold level of saturation  
163 (and ponding) or lower moisture deficit and the infiltration and exfiltration processes become soil-  
164 limited. This switching algorithm is applied for both rainfall and evaporation cases. We refer to  
165 previous studies (Camporese et al., 2010, 2014) for further details on boundary condition switching  
166 approach.

167 Flows between the sub-surface and overland flow domains are represented through the unit  
168 interactive flux  $q_e$  across ground surface in Equations (1) and (6). Through this term, the coupling  
169 strategy we used partitions potential (atmospheric) fluxes into actual fluxes across the land surface  
170 and changes in surface storage. In the surface model, the surface to sub-surface contribution  
171 and water depth are determined after solving the overland flow equation for subsequent input to  
172 the sub-surface flow equation, while the sub-surface to surface contribution is determined after  
173 solving the sub-surface flow equation for subsequent procedure for the solution of the coupled  
174 equation. The atmospheric fluxes are resolved only in subsurface model. The exchange of flux  
175 performed via the switching algorithm in the sub-surface module and the simple mass balance  
176 calculation in the surface module resolves the coupling in the model without the need to introduce

177 new parameters representing an exchange process or an interface property but still guarantees the  
178 necessary continuity of flux and pressure head at the ground surface (Camporese et al., 2010).

### 179 **3. GPU computing performance**

180 To demonstrate the efficiency of GPU computing for ADI approach, we compared the per-  
181 formance of iterative ADI solvers in 5 simulations for unsaturated sub-surface flow between a  
182 single-threaded sedec-core CPUs (16 Intel Xeon 2.67 GHz processors, written in C++) and each  
183 of two NVIDIA GPUs (Tesla C2070 and Tesla K40, written in CUDA C++). The simulation do-  
184 mains are isotropic, rectangular, and set at different dimensions ( $N_x \times M_y \times P_z$ ): (i)  $78 \times 78 \times 10$ ;  
185 (ii)  $128 \times 128 \times 16$ ; (iii)  $256 \times 256 \times 16$ ; (iv)  $512 \times 512 \times 16$ , and (v)  $1024 \times 1024 \times 16$ , where  
186  $N_x, M_y$ , and  $P_z$  are the numbers of soil layers or grids in  $x, y$ , and  $z$  directions, respectively. The  
187 mesh discretization and time stepping are identical for all 5 cases:  $\Delta x = 5 [m]$ ,  $\Delta y = 5 [m]$ ,  
188  $\Delta z = 0.2 [m]$ , and  $\Delta t = 0.05 [hr]$ . Simulations are run for 48 [hr]. Parameters for the closed-form  
189 equation for the soil water retention curve and unsaturated hydraulic conductivity function are  
190 obtained from previous study (Celia et al., 1990), where  $\alpha = 0.0335 [cm^{-1}]$ ,  $\theta_s = 0.368$ ,  $\theta_r = 0.102$ ,  
191  $n = 2$ ,  $K = 0.0332 [m/hr]$ . Initial and boundary conditions were taken as  $\psi(x, y, z, 0) = -5.0$   
192 [m],  $\psi(x, y, P_z, t) = \psi_{bottom} = -3.0 [m]$ ,  $\psi(x, y, 0, t) = \psi_{top} = -1.0 [m]$ , no-flow boundaries are  
193 used for horizontal flow, and no source and sink terms are included. While C2070 devices (second-  
194 generation) have 448 CUDA cores and deliver up to 515 gigaflops of double-precision peak perfor-  
195 mance, K40 devices (third-generation) are configured with 2,880 CUDA cores and deliver up to  
196 1,430 gigaflops of double-precision peak performance (NVIDIA Corporation, 2011).

197 Figure 2 shows the relative speed-up for solving ADI using tridiagonal matrix systems in two  
198 GPU devices over that in CPU. The average speed-up of the simulations for C2070 and K40 are  
199 26.3 and 83.2, respectively. The speedup comes from the ability of single instruction, multiple  
200 thread architecture (Kirk & Hwu, 2010) in GPUs to simultaneously execute thousands of linear  
201 systems solver. However, since each GPU core is clocked at as low as few hundreds *Mhz*, and  
202 latency due to fetching for matrix entries is limited by the memory subsystems, the speedup is not  
203 close to the number of GPU cores. Nevertheless, we achieve a performance typically seen in GPU  
204 computing (Lee et al., 2010). We also see a large difference between the two GPU generations in  
205 this comparison. The K40 device with improved architecture to accelerate computation, higher

206 theoretical peak-performance and number of processors is 3 to 6 times faster than the C2070 device.  
207 The discrepancy in performance is also found among the size of the computational grid. Larger  
208 domains of simulation tend to get better speed-up than smaller domains as the occupancy of GPUs  
209 processor is higher. Our scalable ADI solver implemented in this work is also expected to utilize  
210 the architecture improvement of next CUDA-capable GPU generations.

#### 211 4. Benchmark simulation tests

212 Due to the lack of an analytical solution for coupled surface - sub-surface flow, we use a set  
213 of benchmark test cases summarized below to compare our model with those published by others  
214 for verification. We use direct value comparison method (Bennett et al., 2013) for measuring the  
215 quantitative performance among models in all test cases. Detailed information about these tests  
216 can be found in previous work (Gottardi & Venutelli, 1993; Panday & Huyakorn, 2004; Kollet &  
217 Maxwell, 2006; Kumar et al., 2009; Sulis et al., 2010; Maxwell et al., 2014). The test cases include:  
218 (i) tilted V-catchment, (ii) infiltration excess, (iii) saturation excess, (iv) slab tests, and (v) re-  
219 turn flow. These involve simple geometries associated with other features (topography, hydraulic  
220 and hydrogeological properties, and atmospheric forcing), but with complex physical responses  
221 designed to thoroughly compare model behavior (Maxwell et al., 2014). The test cases also feature  
222 step functions of rainfall followed by a recession period. The response variables analyzed include  
223 domain outflow, saturation conditions, and location of intersection between the water table and  
224 land surface (Maxwell et al., 2014). Model parameters used for these tests are similar to the  
225 set shown in two inter-comparison studies by Maxwell et al. (2014) and Sulis et al. (2010) and  
226 presented in Table 1. To avoid confusion, we only select four representative models based on simi-  
227 larities and differences for comparison in this paper: ParFlow (Parallel Flow) - uses fully implicit  
228 finite difference method for numerical solution (Kollet & Maxwell, 2006); Cathy (Catchment HY-  
229 drology) - uses finite element method and the boundary condition switching approach for coupling  
230 strategy (Paniconi & Wood, 1993; Paniconi & Putti, 1994); tRIBS+VEGGIE (Triangulated Irreg-  
231 ular Network (TIN)-Based Real Time Basin Simulator) - uses an irregular spatial discretization  
232 and first-order exchange for coupling strategy (Ivanov et al., 2004); and PAWS (Process-based  
233 Adaptive Watershed Simulator) - uses asynchronous linking and couples 1-D Richard equation in  
234 unsaturated zone with saturated domain (Shen & Phanikumar, 2010). Additional comparisons for

235 similar tests from other available models can be found in previous studies (Maxwell et al., 2014;  
236 Qu & Duffy, 2007).

#### 237 4.1. Tilted V-catchment

238 The tilted V-catchment problem is a standard test case for the overland flow model. The  
239 domain consists of two inclined planar rectangles of width 800 [m] and length 1000 [m] connected  
240 together by a 20 [m] wide sloping channel as shown in Figure 3a & b. This test only considers the  
241 surface flow processes and is used to assess the behavior of the surface routing component without  
242 any contribution from the sub-surface by assuming that no infiltration occurs. The slope of the  
243 planes is 5% and the slope of the channel is 2%. The simulation consists of a 90 [min] rainfall  
244 event (at a uniform intensity of  $1.8 \times 10^{-4}$  [m/min]) followed by 90 [min] of recession (Figure 3c).

245 The comparisons of outflow result from GCS-flow with other four models in the tilted V-  
246 catchment test case are shown in Figure 3d. The GCS-flow model generally predicts quite similar  
247 behaviors to the four models selected. GCS-flow exhibits agreement with tRIBS-VEGGIE for  
248 rising limb, prediction of time to steady state, peak flow, and recession phases. However, the  
249 largest model differences during the rising phase are found in the predictions of GCS-flow and  
250 Parflow model. We have also found that outflow in GCS-flow occurs slightly earlier than all other  
251 models during the rising limb phase of the hydrograph. This discrepancy may be attributed to  
252 the time-splitting treatment of ADI for diffusive flow in comparison with other overland routing  
253 models. Nonetheless, there is a greater agreement among all models during the recession phase.

#### 254 4.2. Infiltration Excess

255 The infiltration excess tests aim to investigate the Hortonian runoff produced before complete  
256 saturation of the soil column. This is achieved by specifying homogeneous saturated hydraulic  
257 conductivity  $K_s$  smaller than the rainfall rate. We test the model with two different low values of  
258  $K_s$  as shown in Table 1. The domain is an inclined planar rectangle of width 400 [m] and length  
259 320 [m] (Figure 4a) with a uniform soil depth of 5 [m]. The slope of the planes in  $x$ -direction  
260 and  $y$ -direction are 0.05% and 0%, respectively. No-flow boundary is prescribed at bottom of the  
261 domain, and the initial water table is set at 1 [m] depth. A rainfall event 200 [min] in duration  
262 with a rate of  $3.3 \times 10^{-4}$  [m/min] was applied to generate runoff, followed by 100 [min] of recession  
263 period (Figure 4b). Model outflow is measured at the outlet of the grey strip of cells (Maxwell  
264 et al., 2014; Sulis et al., 2010).

265 Figure 4c shows the outflow rate of GCS-flow as a function of time from the infiltration excess  
 266 test as compared with other models. In general, the four models produce very similar hydrograph  
 267 behavior throughout all phases as well as the magnitude of the outflow for both values of  $K_s$ .  
 268 For the lower  $K_s$  test case, the largest difference in outflow is found again between GCS-flow and  
 269 Parflow during the rising limb phase. We observe that the outflow is larger than Parflow at the  
 270 beginning but the two models tend to converge at the end of the rising limb. This discrepancy is  
 271 similar to the overland V-catchment test case shown above. For the higher  $K_s$  test case, in which  
 272 overland flow is less dominant, the outflow obtained from GCS-flow is in better agreement with the  
 273 four models. However, we also see that the recession curve drops slightly faster than other models  
 274 and most discrepancy is with Parflow in the last 60 [min] of the simulation time. Associated with  
 275 overland flow, the sharper drop of the recession curve may be attributed to the infiltration that is  
 276 treated using ADI and boundary switching algorithm in GCS-flow model.

#### 277 4.3. Saturation Excess

278 The saturation excess tests are designed to investigate the Dunne runoff produced by ensuring  
 279 complete saturation of the soil column from below and the intersection of the water table with the  
 280 land surface. This is also achieved by specifying a homogeneous saturated hydraulic conductivity  
 281 ( $K_{sat} = 6.94 \times 10^{-4}$  [m/min]) which is larger than the rainfall rate (Table 1). Boundary conditions  
 282 and domain of simulation are the same as the infiltration excess test (Figure 4a). However, we run  
 283 the model for two different values of initial water table depth at: 0.5 [m] and 1.0 [m] as shown in  
 284 Table 1. The test case with water table depth near the ground is expected to produce runoff earlier  
 285 and will be associated with larger flow magnitude than the test with deeper water table level. As  
 286 in the previous test, a rainfall event 200 [min] in duration with a rate of  $3.3 \times 10^{-4}$  [m/min] was  
 287 applied to generate runoff, followed by 100 [min] of recession Figure 4b.

288 Figure 4d shows the outflow rate of GCS-flow as a function of time from the saturation excess  
 289 test and how it compares with other four models. We observe that the hydrograph produced from  
 290 GCS-flow model is in most agreement with tRIBS+VEGGIE and PAWS for both tests. In addition,  
 291 difference between GCS-flow and Cathy and Parflow is smaller than in the infiltration **excess** test,  
 292 especially for shallow water table case. Outflow occurs at very similar time for both shallow water  
 293 table tests ( $\sim 20$  [min]) and deep water table test ( $\sim 120$  [min]). Peak flow is also found in good  
 294 agreement with all models in the shallow test. For deep water table test case, GCS-flow is in largest

295 disagreement with Cathy during the rising limb. The difference in peak flow between GCS-flow  
296 and Cathy is about  $1.1 [m^3/min]$  (12%). This is quite surprising as the two models use the same  
297 boundary switching approach for calculating infiltration. But we note that Cathy has the lowest  
298 peak flow among all the models. The discrepancy may come from the numerical method used for  
299 both overland and subsurface flow in the models that need further investigations.

#### 300 4.4. Slab Test

301 The slab test illustrates the effect of spatial heterogeneity of soil hydraulic conductivity in  
302 the same domain as in the infiltration and saturation excess tests. In this simulation, the soil  
303 is generally uniform (with a  $K_s$  value of  $6.94 \times 10^{-4} [m/min]$ ) except for a 100- $m$  long, 0.05-  
304  $m$  thick, very low conductivity slab with  $K_s = 6.94 \times 10^{-6} [m/min]$  as shown in Figure 5a.  
305 The saturated hydraulic conductivity of the slab is designed to generate infiltration excess runoff  
306 while the hydraulic conductivity of the rest of the domain is large and will only generate surface  
307 runoff through saturation excess. Boundary conditions and domain of simulation are the same  
308 as the previous two tests, and water table is set at 1  $[m]$  depth. As in the infiltration excess  
309 case, a rainfall event 200  $[min]$  in duration with a rate of  $3.3 \times 10^{-4} [m/min]$  was applied to  
310 generate runoff, followed by 100  $[min]$  of recession (Figure 5b). We expect the combination of both  
311 infiltration excess and saturation excess runoff in outflow for this test.

312 The comparisons of outflow result from GCS-flow with other models in the slab test case are  
313 shown in Figure 5c. We found differences between the GCS-flow model and all others in this test.  
314 First, runoff occurs after 80  $[min]$  which is later than tRIBS+VEGGIE model but earlier than  
315 PAWS, Parflow, and Cathy models. Second, During the rising limb phase, the hydrograph curve  
316 from GCS-flow is quite smooth while ones produced from other models are quite flat. Finally,  
317 the peak flow from GCS-flow model is closer to Cathy model ( $1.1 [m^3/min]$ ) and lower than the  
318 other two models. Both GCS-flow and Cathy models are similar in using the boundary condition  
319 switching approach, which might explain this similarity in the response of runoff. During the  
320 recession phase, similar to other tests, outflow in GCS-flow model is in much better agreement  
321 with other models.

322 Snapshots of saturation profile obtained from GCS-flow model at: 0, 60, 90, and 150  $[min]$   
323 are presented in Figure 6. These moments of time, before the recession period, are chosen to  
324 show the complex physical responses of heterogeneous soil columns to infiltration, saturation, and

325 lateral unsaturated flow. While water table in soil columns with uniform  $K_s$  rises quickly due to  
326 saturation excess, water table in the soil columns with heterogenous  $K_s$  (slab on top) rises very  
327 slowly due to infiltration capacity limits. Lateral unsaturated flow is also observed due to gradient  
328 of moisture in the sub-surface. Saturation profile for other models can be found in Maxwell et  
329 al. (2014, see Figure 8). We also found some differences in saturation profiles among all models.  
330 These may likely be explained due to the different coupling strategies and numerical scheme for  
331 solving the models.

#### 332 4.5. Return flow

333 This test case uses the same hillslope domain as for the infiltration and saturation excess tests  
334 (see Figure 4a) but with much higher values of hydraulic conductivity ( $6.94 \times 10^{-2}[m/min]$ ) to  
335 allow rapid rise and fall of the water table. The water table is initially set at 0.5 [m] depth. Return  
336 flow is generated by an atmospheric forcing sequence formed by an initial 200 [min] rainfall event  
337 of uniform intensity  $1.5 \times 10^{-4}[m/min]$  followed by 200 [min] of evaporation at a uniform rate  
338 of  $5.4 \times 10^{-6}[m/min]$  (Figure 7a). Two hillslope inclinations are considered (0.5% and 5%) to  
339 highlight the effect of different characteristic times scales of the surface and subsurface processes  
340 (Maxwell et al., 2014; Sulis et al., 2010). The dynamics of return flow are evaluated by tracking  
341 the evolution of the intersection point between water table and the land surface. The model is also  
342 run with a uniform discretization comprising 100 vertical layers as done in other studies

343 Figure 7b&c show the intersection point between the water table and the land surface as  
344 a function of time for hillslope inclination of 0.5% and 5%, respectively. For the 0.5% slope  
345 case, in which infiltration and subsurface flow remain predominant, although the prediction of  
346 time for steady state is similar for all models, we observe that water table along the hillslope  
347 obtained from GCS-flow rises and intersects the ground more uniformly than other models. During  
348 evaporation phase, the recession of the water table is slower than other models, except for Cathy  
349 (sheet flow). For the 5% inclination case, in which the catchment drains faster, we do see more  
350 disagreements among GCS-flow and others during all rising, quasi-steady equilibrium, and recession  
351 phases. Specifically, the intersection point in GCS-flow are closer to the upslope point during steady  
352 state than others which implies that the moisture gradient resulting from the surface slope was not  
353 captured well in GCS-flow. This could be due to the discretization of finite difference in ADI for  
354 solving the variably saturated equation. This issue may also explain the uniform rising of water

355 table before reaching steady state in both cases. The recession of the water table is faster than the  
356 gentler-slope case and exhibits better agreement with PAWS and Parflow.

357 In general, the GCS-model performs quite similarly to other conjunctive models that have been  
358 published in literature. Although, we observe greater differences among models in more complex  
359 tests and owing to different numerical approach, all model are very consistent in more simple tests.  
360 These results support the rationale for the modeling scheme developed using GPUs for larger scale  
361 simulation presented in the next section.

## 362 5. Simulations with lidar data

363 We run the GCS-flow model for an observed topography in the Goose Creek watershed of  
364 the Sangamon River Basin, in central Illinois, USA (Figure 8). This watershed is intensively  
365 managed for agriculture and is part of the Critical Zone Observatory for Intesively Managed Land-  
366 scapes (<http://imlczo.org>). Lidar data used is available from the Illinois State Geological Survey  
367 (<https://www.isgs.illinois.edu>). The domain of simulation is  $6.6 \text{ km} \times 7.4 \text{ km}$  with  $2.0 \text{ m}$  soil depth.  
368 Topographic resolution of the simulation domain is  $1.2 \text{ m} \times 1.2 \text{ m}$  (Figure 8c). **This results in over**  
369 **35 million grid points on the surface and 350 million grid points over the entire subsurface domain.**  
370 At this high resolution, micro-topographic features can be observed on the land surface such as  
371 road-side ditches, small depressions, etc. Topographic gradient in the study site is quite small as  
372 elevation variation is very small (from 205 to 222 [m] above sea level, average slope  $\approx 0.25\%$ ). Soil  
373 physical properties are available from Soil Survey Geographic database (SSURGO) distributed by  
374 Natural Resources Conservation Service (<http://websoilsurvey.sc.egov.usda.gov>). The average val-  
375 ues of soil properties used in our simulation is follow:  $K_s = 0.0054 \text{ [m/min]}$ ,  $\theta_s = 0.37$ ,  $\theta_r = 0.10$ ,  
376  $\alpha = 3.35 \text{ [cm}^{-1}\text{]}$ , and  $n = 1.25$ .

377 Observed atmospheric forcing data obtained from nearby Bondville flux tower is used to drive  
378 the GCS-flow model. We use precipitation collected at  $30 \text{ min}$  intervals during a three week period  
379 in May 2005 for running the simulations (Figure 9a). Evaporation rate is assumed at constant rate  
380  $1 \text{ [mm/day]}$  for the domain. Initial soil moisture is set uniformly at 0.26 over the entire domain. In  
381 surface domain, no-flow boundaries are applied at the lateral boundaries. In sub-surface domain, we  
382 use a fixed boundary pressure head at  $-4 \text{ [m]}$  for the bottom and no-flow boundaries for the lateral  
383 interfaces. In term of computational efficiency, the simulation domain results in approximately 3.5



384  $\times 10^8$  unknowns (grid cells) for computation. The model takes about 19.6 [hr] on Tesla K40 GPUs  
385 for completion. Given using a single GPU device, this computational efficiency is significant and  
386 makes hydrologic simulations feasible over large areas.

387 A smaller area (900 m  $\times$  1080 m) within the simulation domain is chosen (red box in Figure 8c)  
388 to show for detailed illustration of the vertical variation of soil-moisture as impacted by micro-  
389 topographic features. The snapshot of overland spatial flow in this reduced area after 320 [h] is  
390 presented in Figure 9b. The model shows flow accumulation in topographic depressions and in the  
391 road-side ditches which carries significant flows in these agricultural landscapes. These features  
392 are often ignored in modeling with lower resolution and coarser computational grid. The profile  
393 of soil moisture over depth at the same time is shown in Figure 9c. While the top boundary of  
394 the domain is controlled by surface water availability and atmospheric fluxes, the low values of  
395 bottom boundary allow water to drain significantly to soil layers below the simulation domain.  
396 We however observe the positive correlation between micro-topographic depressions on the land  
397 surface and soil moisture distribution below-ground. Areas where water is accumulated due to low  
398 elevation on the landscape provide more moisture for infiltration than other area.

## 399 6. Conclusion

400 A formulation of coupled surface - sub-surface flow model using lidar-resolution topographic  
401 data that is implemented on GPU parallel computing architecture has been presented. The nu-  
402 merical solution for both overland flow and sub-surface flow model is based on the alternating  
403 direction implicit (ADI) method. While 2-D classic ADI is applied for overland flow model, an  
404 iterative ADI associated with Picard iteration approach is used for 3-D sub-surface model due to  
405 the non-linearity in the relationship in the mixed form of Richards equation. This approach com-  
406 bines benefits in simplicity and cost for computation because only tridiagonal linear systems are  
407 involved for providing direct solution and the ability to decompose into fine-grain tasks for GPU  
408 parallel structure. The model has been compared with others using several standard benchmark  
409 test cases. The results from benchmark tests generally show good agreements among all the model  
410 for a wide variety of benchmark test cases. Some model differences are found in complex tests due  
411 to different coupling strategies and numerical solution.

412 The GCS-flow model has been used to simulate an intensively managed landscape in the Goose

413 Creek watershed, Illinois, USA. The lidar-derived topographic data at 1.2  $m$  resolution is used  
 414 for detailed hydrologic simulation. Results presented indicate that this performance is faster than  
 415 CPU and has the potential to apply for detailed ecohydrologic modeling in large areas.

416 We suggest that future work should aim to expand this model to understand the dynamics  
 417 and linkages between soil moisture and microtopographic features on a range of applications in-  
 418 cluding ecohydrology, agriculture, etc. In addition, with rapid advances in GPU computing, the  
 419 model can be used as a starting point to explore: (i) possible alternative formulations (i.e. fully  
 420 implicit scheme, iterative methods) based improved computational libraries for GPU developed by  
 421 the community; (ii) new memory structures and capabilities released in the next GPU generations  
 422 for parallel computing in general and for hydrologic modeling in particular; and (iii) implementa-  
 423 tions and scaling behaviors of hydrologic and integrated flow modeling on multiple-GPUs. Such  
 424 efforts will lead to an improved understanding and a more robust generation of integrated surface-  
 425 subsurface flow modeling using high-performance GPU computing.

## 426 Appendix A: ADI discretization for 2D overland flow

The mass balance condition with Crank-Nicolson type scheme forms the basis for the ADI formulation in overland flow model. Following a study by Lal (1998a), the discretization of overland flow continuity equation may be written as:

$$H_{i,j}^{n+1} = H_{i,j}^n + \Delta t \left[ \alpha \frac{Q_{net}(H^{n+1})}{\Delta x \Delta y} + (1 - \alpha) \frac{Q_{net}(H^n)}{\Delta x \Delta y} - q_e - q_r \right] \quad (\text{A1})$$

in which  $\alpha$  is the weighting factor for numerical scheme ( $\alpha = 0.5$  for Crank-Nicolson),  $n$  is the time step,  $(i, j)$  denotes spatial location, and  $Q_{net} [L^3]$  is the net inflow to the cell as a function of potential head, computed as:

$$Q_{net} = D_{i+\frac{1}{2},j}(H_{i+1,j} - H_{i,j}) + D_{i-\frac{1}{2},j}(H_{i-1,j} - H_{i,j}) \\ + D_{i,j+\frac{1}{2}}(H_{i,j+1} - H_{i,j}) + D_{i,j-\frac{1}{2}}(H_{i,j-1} - H_{i,j}) \quad (\text{A2})$$

where  $D$  is diffusion coefficient [ $L^2 T^{-1}$ ] (See equation (4) in the main text). The spatial differencing operators used in the derivation are as follows:

$$\delta_x H_{i,j}^n = 0.5 \frac{\Delta t}{\Delta x \Delta y} \left[ D_{i+\frac{1}{2},j}(H_{i+1,j}^n - H_{i,j}^n) + D_{i-\frac{1}{2},j}(H_{i-1,j}^n - H_{i,j}^n) \right] \quad (\text{A3a})$$

$$\delta_y H_{i,j}^n = 0.5 \frac{\Delta t}{\Delta x \Delta y} \left[ D_{i,j+\frac{1}{2}}(H_{i,j+1}^n - H_{i,j}^n) + D_{i,j-\frac{1}{2}}(H_{i,j-1}^n - H_{i,j}^n) \right] \quad (\text{A3b})$$

After rearranging the unknown values to the left-hand side, Equations (A1) and (A2) can be now expressed using the standard second-order centered differencing operators as:

$$(1 - \delta_x - \delta_y)H_{i,j}^{n+1} = (1 + \delta_x + \delta_y)H_{i,j}^n - (q_e + q_r)\Delta t \quad (\text{A4})$$

By neglecting higher-order terms, Equation (A4) can also be split into sequences:

$$(1 - \delta_x)H_{i,j}^{n+\frac{1}{2}} = (1 + \delta_y)H_{i,j}^n - \frac{\Delta t}{2}(q_e + q_r) \quad (\text{A5a})$$

$$(1 - \delta_y)H_{i,j}^{n+1} = (1 + \delta_x)H_{i,j}^{n+\frac{1}{2}} - \frac{\Delta t}{2}(q_e + q_r) \quad (\text{A5b})$$

The ADI finite-difference expressions for the overland flow can be written as:

$$\begin{aligned} H_{i,j}^{n+\frac{1}{2}} - 0.5 \frac{\Delta t/2}{\Delta x \Delta y} \left[ D_{i+\frac{1}{2},j} \left( H_{i+1,j}^{n+\frac{1}{2}} - H_{i,j}^{n+\frac{1}{2}} \right) + D_{i-\frac{1}{2},j} \left( H_{i-1,j}^{n+\frac{1}{2}} - H_{i,j}^{n+\frac{1}{2}} \right) \right] = \\ H_{i,j}^n + 0.5 \frac{\Delta t/2}{\Delta x \Delta y} \left[ D_{i,j+\frac{1}{2}} (H_{i,j+1} - H_{i,j}) + D_{i,j-\frac{1}{2}} (H_{i,j-1} - H_{i,j}) \right] + (q_e + q_r) \frac{\Delta t}{2} \quad (\text{A6}) \end{aligned}$$

$$\begin{aligned} H_{i,j}^{n+1} - 0.5 \frac{\Delta t/2}{\Delta x \Delta y} \left[ D_{i,j+\frac{1}{2}} \left( H_{i,j+1}^{n+1} - H_{i,j}^{n+1} \right) + D_{i,j-\frac{1}{2}} \left( H_{i,j-1}^{n+1} - H_{i,j}^{n+1} \right) \right] = \\ H_{i,j}^{n+\frac{1}{2}} + 0.5 \frac{\Delta t/2}{\Delta x \Delta y} \left[ D_{i+\frac{1}{2},j} \left( H_{i+1,j}^{n+\frac{1}{2}} - H_{i,j}^{n+\frac{1}{2}} \right) + D_{i-\frac{1}{2},j} \left( H_{i-1,j}^{n+\frac{1}{2}} - H_{i,j}^{n+\frac{1}{2}} \right) \right] + (q_e + q_r) \frac{\Delta t}{2} \quad (\text{A7}) \end{aligned}$$

429 The coupled Equations (A6) and (A7) are solved as two 1D problems for each row and column  
430 of the 2D domain using the TDMA or PCR algorithms for tridiagonal matrices at half time step  
431  $\frac{\Delta t}{2}$ . Right-hand sides of these equation consist of entirely known values at the time of computation.  
432 The values of  $H_{i,j}^{n+\frac{1}{2}}$  are obtained from Equation (A6) in the first-half time step and then used to  
433 solve Equation (A7) in the second-half time step.

## 434 Appendix B: ADI discretization for 3D variably saturated sub-surface flow

The backward Euler scheme associated with Picard iteration is one of the most widely used time approximation for the Richards equation and applied in this study. The two terms in the left-hand side of the variably saturated sub-surface flow equation are approximated as:

$$S_s \frac{\theta}{\phi} \frac{\partial \psi}{\partial t} + \frac{\partial \theta}{\partial t} \approx \frac{S_s}{\phi} \theta_{i,j,k}^{n+1,m} \left[ \frac{\psi_{i,j,k}^{n+1,m+1} - \psi_{i,j,k}^n}{\Delta t} \right] + \left[ \frac{\theta_{i,j,k}^{n+1,m+1} - \theta_{i,j,k}^n}{\Delta t} \right] \quad (\text{B1})$$

Here,  $(i, j, k)$  denote spatial location in  $x$ ,  $y$ , and  $z$  directions, respectively,  $n$  and  $m$  denote the time and the Picard iteration levels, respectively. After Celia et al. (1990), moisture content at new time step and a new iteration level  $\theta_{i,j,k}^{n+1,m+1}$  is expanded using first-order truncated Taylor series, in terms of pressure-head perturbation, about the expansion point  $\psi^{n+1,m}$  as follow:

$$\theta_{i,j,k}^{n+1,m+1} = \theta_{i,j,k}^{n+1,m} + \left. \frac{d\theta}{d\psi} \right|_{i,j,k}^{n+1,m} (\psi_{i,j,k}^{n+1,m+1} - \psi_{i,j,k}^{n+1,m}) + O(\delta^2) \quad (\text{B2})$$

The specific water capacity function of the soil  $C(\psi)$  [ $L^{-1}$ ] is defined as:

$$C(\psi) = \frac{d\theta}{d\psi} \quad (\text{B3})$$

Using equation (B2) and (B3), the Equation (B1) can be expressed as:

$$S_s \frac{\theta}{\phi} \frac{\partial \psi}{\partial t} + \frac{\partial \theta}{\partial t} \approx \frac{S_s}{\phi} \theta_{i,j,k}^{n+1} \left[ \frac{\psi_{i,j,k}^{n+1,m+1} - \psi_{i,j,k}^n}{\Delta t} \right] + \frac{\theta_{i,j,k}^{n+1,m} - \theta_{i,j,k}^n}{\Delta t} + C_{i,j,k}^{n+1,m} \left[ \frac{\psi_{i,j,k}^{n+1,m+1} - \psi_{i,j,k}^{n+1,m}}{\Delta t} \right] \quad (\text{B4})$$

435 Rearranging and use the increment in iteration:  $\delta^m = \psi^{n+1,m+1} - \psi^{n+1,m}$ , the finite difference  
436 alternating direction implicit formulation at every  $\Delta t/3$  can be written as follow:

437 • Time splitting in  $z$  direction

$$\begin{aligned} & \left[ \frac{S_s}{\phi} \theta_{i,j,k}^{n+\frac{1}{3},m} + C_{i,j,k}^{n+\frac{1}{3},m} \right] \frac{\delta_{i,j,k}^m}{(\Delta t/3)} - \frac{1}{\Delta z^2} \left[ K_{i,j,k+\frac{1}{2}}^{n+\frac{1}{3},m} (\delta_{i,j,k+1}^m - \delta_{i,j,k}^m) - K_{i,j,k-\frac{1}{2}}^{n+\frac{1}{3},m} (\delta_{i,j,k}^m - \delta_{i,j,k-1}^m) \right] \\ & = \frac{1}{\Delta x^2} \left[ K_{i+\frac{1}{2},j,k}^{n+\frac{1}{3},m} (\psi_{i+1,j,k}^{n+\frac{1}{3},m} - \psi_{i,j,k}^{n+\frac{1}{3},m}) - K_{i-\frac{1}{2},j,k}^{n+\frac{1}{3},m} (\psi_{i,j,k}^{n+\frac{1}{3},m} - \psi_{i-1,j,k}^{n+\frac{1}{3},m}) \right] \\ & + \frac{1}{\Delta y^2} \left[ K_{i,j+\frac{1}{2},k}^{n+\frac{1}{3},m} (\psi_{i,j+1,k}^{n+\frac{1}{3},m} - \psi_{i,j,k}^{n+\frac{1}{3},m}) - K_{i,j-\frac{1}{2},k}^{n+\frac{1}{3},m} (\psi_{i,j,k}^{n+\frac{1}{3},m} - \psi_{i,j-1,k}^{n+\frac{1}{3},m}) \right] \\ & + \frac{1}{\Delta z^2} \left[ K_{i,j,k+\frac{1}{2}}^{n+\frac{1}{3},m} (\psi_{i,j,k+1}^{n+\frac{1}{3},m} - \psi_{i,j,k}^{n+\frac{1}{3},m}) - K_{i,j,k-\frac{1}{2}}^{n+\frac{1}{3},m} (\psi_{i,j,k}^{n+\frac{1}{3},m} - \psi_{i,j,k-1}^{n+\frac{1}{3},m}) \right] \\ & + \frac{K_{i,j,k+\frac{1}{2}}^{n+\frac{1}{3},m} - K_{i,j,k-\frac{1}{2}}^{n+\frac{1}{3},m}}{\Delta z} - \frac{S_s \theta_{i,j,k}^{n+\frac{1}{3},m}}{\phi(\Delta t/3)} \left[ \psi_{i,j,k}^{n+\frac{1}{3},m} - \psi_{i,j,k}^n \right] - \frac{\theta_{i,j,k}^{n+\frac{1}{3},m} - \theta_{i,j,k}^n}{(\Delta t/3)} \quad (\text{B5}) \end{aligned}$$

- Time splitting in  $x$  direction

$$\begin{aligned}
& \left[ \frac{S_s}{\phi} \theta_{i,j,k}^{n+\frac{2}{3},m} + C_{i,j,k}^{n+\frac{2}{3},m} \right] \frac{\delta_{i,j,k}^m}{(\Delta t/3)} - \frac{1}{\Delta x^2} \left[ K_{i+\frac{1}{2},j,k}^{n+\frac{2}{3},m} (\delta_{i+1,j,k}^m - \delta_{i,j,k}^m) - K_{i-\frac{1}{2},j,k}^{n+\frac{2}{3},m} (\delta_{i,j,k}^m - \delta_{i-1,j,k}^m) \right] \\
&= \frac{1}{\Delta x^2} \left[ K_{i+\frac{1}{2},j,k}^{n+\frac{2}{3},m} (\psi_{i+1,j,k}^{n+\frac{2}{3},m} - \psi_{i,j,k}^{n+\frac{2}{3},m}) - K_{i-\frac{1}{2},j,k}^{n+\frac{2}{3},m} (\psi_{i,j,k}^{n+\frac{2}{3},m} - \psi_{i-1,j,k}^{n+\frac{2}{3},m}) \right] \\
&+ \frac{1}{\Delta y^2} \left[ K_{i,j+\frac{1}{2},k}^{n+\frac{2}{3},m} (\psi_{i,j+1,k}^{n+\frac{2}{3},m} - \psi_{i,j,k}^{n+\frac{2}{3},m}) - K_{i,j-\frac{1}{2},k}^{n+\frac{2}{3},m} (\psi_{i,j,k}^{n+\frac{2}{3},m} - \psi_{i,j-1,k}^{n+\frac{2}{3},m}) \right] \\
&+ \frac{1}{\Delta z^2} \left[ K_{i,j,k+\frac{1}{2}}^{n+\frac{2}{3},m} (\psi_{i,j,k+1}^{n+\frac{2}{3},m} - \psi_{i,j,k}^{n+\frac{2}{3},m}) - K_{i,j,k-\frac{1}{2}}^{n+\frac{2}{3},m} (\psi_{i,j,k}^{n+\frac{2}{3},m} - \psi_{i,j,k-1}^{n+\frac{2}{3},m}) \right] \\
&+ \frac{K_{i,j,k+\frac{1}{2}}^{n+\frac{2}{3},m} - K_{i,j,k-\frac{1}{2}}^{n+\frac{2}{3},m}}{\Delta z} - \frac{S_s \theta_{i,j,k}^{n+\frac{2}{3},m}}{\phi(\Delta t/3)} \left[ \psi_{i,j,k}^{n+\frac{2}{3},m} - \psi_{i,j,k}^{n+\frac{1}{3},m} \right] - \frac{\theta_{i,j,k}^{n+\frac{2}{3},m} - \theta_{i,j,k}^{n+\frac{1}{3},m}}{(\Delta t/3)} \quad (B6)
\end{aligned}$$

- Time splitting in  $y$  direction

$$\begin{aligned}
& \left[ \frac{S_s}{\phi} \theta_{i,j,k}^{n+1,m} + C_{i,j,k}^{n+1,m} \right] \frac{\delta_{i,j,k}^m}{(\Delta t/3)} - \frac{1}{\Delta y^2} \left[ K_{i+\frac{1}{2},j,k}^{n+1,m} (\delta_{i+1,j,k}^m - \delta_{i,j,k}^m) - K_{i-\frac{1}{2},j,k}^{n+1,m} (\delta_{i,j,k}^m - \delta_{i-1,j,k}^m) \right] \\
&= \frac{1}{\Delta x^2} \left[ K_{i+\frac{1}{2},j,k}^{n+1,m} (\psi_{i+1,j,k}^{n+1,m} - \psi_{i,j,k}^{n+1,m}) - K_{i-\frac{1}{2},j,k}^{n+1,m} (\psi_{i,j,k}^{n+1,m} - \psi_{i-1,j,k}^{n+1,m}) \right] \\
&+ \frac{1}{\Delta y^2} \left[ K_{i,j+\frac{1}{2},k}^{n+1,m} (\psi_{i,j+1,k}^{n+1,m} - \psi_{i,j,k}^{n+1,m}) - K_{i,j-\frac{1}{2},k}^{n+1,m} (\psi_{i,j,k}^{n+1,m} - \psi_{i,j-1,k}^{n+1,m}) \right] \\
&+ \frac{1}{\Delta z^2} \left[ K_{i,j,k+\frac{1}{2}}^{n+1,m} (\psi_{i,j,k+1}^{n+1,m} - \psi_{i,j,k}^{n+1,m}) - K_{i,j,k-\frac{1}{2}}^{n+1,m} (\psi_{i,j,k}^{n+1,m} - \psi_{i,j,k-1}^{n+1,m}) \right] \\
&+ \frac{K_{i,j,k+\frac{1}{2}}^{n+1,m} - K_{i,j,k-\frac{1}{2}}^{n+1,m}}{\Delta z} - \frac{S_s \theta_{i,j,k}^{n+1,m}}{\phi(\Delta t/3)} \left[ \psi_{i,j,k}^{n+1,m} - \psi_{i,j,k}^{n+\frac{2}{3},m} \right] - \frac{\theta_{i,j,k}^{n+1,m} - \theta_{i,j,k}^{n+\frac{2}{3},m}}{(\Delta t/3)} \quad (B7)
\end{aligned}$$

440 Similarly, the coupled Equations (B5), (B6), and (B7) are solved as three 1D problems for  
441 each directions of the 3D domain using the TDMA or PCR algorithms for tridiagonal matrices at  
442 one-third time step  $\frac{\Delta t}{3}$ . Right-hand sides of these equation consist of entirely known values at the  
443 time of computation.

#### 444 Acknowledgement

445 We gratefully acknowledge support from Vietnam Education Foundation (VEF), Innovation  
446 grant from the Department of Civil and Environmental Engineering, Fellowship from the Com-  
447 putational Science and Engineering Program, and NSF Grants # EAR 1331906, CBET 1209402,  
448 EAR 1417444, and ICER 1440315

449 **Code availability**

450 Code available from server at: <https://github.com/HydroComplexity/GCSFlow>

451 **References**

452 **References**

- 453 Allen, M. B., & Murphy, C. (1985). A finite element collocation method for variably saturated flows in porous media.  
454 *Numerical Methods for Partial Differential Equations*, 1, 229–239.
- 455 An, H., Ichikawa, Y., Tachikawa, Y., & Shiiba, M. (2011). A new iterative alternating direction implicit (iadi)  
456 algorithm for multi-dimensional saturated/unsaturated flow. *Journal of Hydrology*, 408, 127 – 139.
- 457 Bennett, N. D., Croke, B. F., Guariso, G., Guillaume, J. H., Hamilton, S. H., Jakeman, A. J., Marsili-Libelli, S.,  
458 Newham, L. T., Norton, J. P., Perrin, C., Pierce, S. A., Robson, B., Seppelt, R., Voinov, A. A., Fath, B. D.,  
459 & Andreassian, V. (2013). Characterising performance of environmental models. *Environmental Modelling & Software*, 40, 1 – 20.
- 461 Camporese, M., Daly, E., Dresel, P. E., & Webb, J. A. (2014). Simplified modeling of catchment-scale evapotranspi-  
462 ration via boundary condition switching. *Advances in Water Resources*, 69, 95 – 105.
- 463 Camporese, M., Paniconi, C., Putti, M., & Orlandini, S. (2010). Surface-subsurface flow modeling with path-based  
464 runoff routing, boundary condition-based coupling, and assimilation of multisource observation data. *Water*  
465 *Resources Research*, 46.
- 466 Celia, M. A., Bouloutas, E. T., & Zarba, R. L. (1990). A general mass-conservative numerical solution for the  
467 unsaturated flow equation. *Water Resources Research*, 26, 1483–1496.
- 468 Dunne, T., Zhang, W., & Aubry, B. F. (1991). Effects of rainfall, vegetation, and microtopography on infiltration  
469 and runoff. *Water Resources Research*, 27, 2271–2285.
- 470 Frei, S., & Fleckenstein, J. (2014). Representing effects of micro-topography on runoff generation and sub-surface  
471 flow patterns by using superficial rill/depression storage height variations. *Environmental Modelling & Software*,  
472 52, 5 – 18.
- 473 Frei, S., Lischheid, G., & Fleckenstein, J. (2010). Effects of micro-topography on surface-subsurface exchange and  
474 runoff generation in a virtual riparian wetland – a modeling study. *Advances in Water Resources*, 33, 1388 – 1401.
- 475 Gasper, F., Goergen, K., Shrestha, P., Sulis, M., Rihani, J., Geimer, M., & Kollet, S. (2014). Implementation  
476 and scaling of the fully coupled terrestrial systems modeling platform (terrsypm v1.0) in a massively parallel  
477 supercomputing environment ? a case study on juqueen (ibm blue gene/q). *Geoscientific Model Development*, 7,  
478 2531–2543.
- 479 van Genuchten, M. T. (1980). A closed-form equation for predicting the hydraulic conductivity of unsaturated soils.  
480 *Soil Science Society of America*, 44, 892–898.
- 481 Gottardi, G., & Venutelli, M. (1993). A control-volume finite-element model for two-dimensional overland flow.  
482 *Advances in Water Resources*, 16, 277 – 284.

483 Hammond, G. E., Lichtner, P. C., & Mills, R. T. (2014). Evaluating the performance of parallel subsurface simulators:  
484 An illustrative example with pflotran. *Water Resources Research*, *50*, 208–228.

485 Hockney, R. W., & Jesshope, C. R. (1988). *Parallel Computers Two: Architecture, Programming and Algorithms*.  
486 (2nd ed.). Bristol, UK: IOP Publishing Ltd.

487 Hromadka, T., & Lai, C. (1985). *Solving the two-dimensional diffusion flow model*. volume 1. New York, U.S.A.,  
488 American Society of Civil Engineers.

489 Huyakorn, P. S., & Pinder, G. F. (1983). *Computational methods in subsurface flow*. Monograph Series. New York:  
490 Academic Press.

491 Hwang, H.-T., Park, Y.-J., Sudicky, E., & Forsyth, P. (2014). A parallel computational framework to solve flow and  
492 transport in integrated surface?subsurface hydrologic systems. *Environmental Modelling & Software*, *61*, 39 – 58.

493 Ivanov, V. Y., Bras, R. L., & Vivoni, E. R. (2008). Vegetation-hydrology dynamics in complex terrain of semiarid  
494 areas: 2. energy-water controls of vegetation spatiotemporal dynamics and topographic niches of favorability.  
495 *Water Resources Research*, *44*.

496 Ivanov, V. Y., Vivoni, E. R., Bras, R. L., & Entekhabi, D. (2004). Catchment hydrologic response with a fully  
497 distributed triangulated irregular network model. *Water Resources Research*, *40*.

498 Kirk, D. B., & Hwu, W.-m. W. (2010). *Programming Massively Parallel Processors: A Hands-on Approach*. (1st  
499 ed.). San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

500 Kollet, S. J., & Maxwell, R. M. (2006). Integrated surface–groundwater flow modeling: A free-surface overland flow  
501 boundary condition in a parallel groundwater flow model. *Advances in Water Resources*, *29*, 945 – 958.

502 Kollet, S. J., Maxwell, R. M., Woodward, C. S., Smith, S., Vanderborght, J., Vereecken, H., & Simmer, C. (2010).  
503 Proof of concept of regional scale hydrologic simulations at hydrologic resolution utilizing massively parallel com-  
504 puter resources. *Water Resources Research*, *46*.

505 Kumar, M., Duffy, C. J., & Salvage, K. M. (2009). A second-order accurate, finite volume–based, integrated hydrologic  
506 modeling (film) framework for simulation of surface and subsurface flow. *Vadose Zone Journal*, *8*, 873–890.

507 Kumar, P. (2011). Typology of hydrologic predictability. *Water Resources Research*, *47*.

508 Lal, A. (1998a). Performance comparison of overland flow algorithms. *Journal of Hydraulic Engineering*, *124*,  
509 342–349.

510 Lal, A. (1998b). Weighted implicit finite-volume model for overland flow. *Journal of Hydraulic Engineering*, *124*,  
511 941–950.

512 Le, P. V. V., & Kumar, P. (2014). Power law scaling of topographic depressions and their hydrologic connectivity.  
513 *Geophysical Research Letters*, *41*, 1553–1559.

514 Lee, V. W., Kim, C., Chhugani, J., Deisher, M., Kim, D., Nguyen, A. D., Satish, N., Smelyanskiy, M., Chennupaty,  
515 S., Hammarlund, P. et al. (2010). Debunking the 100x gpu vs. cpu myth: an evaluation of throughput computing  
516 on cpu and gpu. In *ACM SIGARCH Computer Architecture News* (pp. 451–460). ACM volume 38.

517 Lefsky, M. A., Cohen, W. B., Parker, G. G., & Harding, D. J. (2002). Lidar Remote Sensing for Ecosystem Studies.  
518 *BioScience*, (pp. 19–30).

519 Loos, M., & Elsenbeer, H. (2011). Topographic controls on overland flow generation in a forest -? an ensemble tree  
520 approach. *J. Hydrol.*, *409*, 94 – 103.

521 Maxwell, R. M. (2013). A terrain-following grid transform and preconditioner for parallel, large-scale, integrated  
522 hydrologic modeling. *Advances in Water Resources*, *53*, 109 – 117.

523 Maxwell, R. M., Chow, F. K., & Kollet, S. J. (2007). The groundwater–land-surface–atmosphere connection: Soil  
524 moisture effects on the atmospheric boundary layer in fully-coupled simulations. *Advances in Water Resources*,  
525 *30*, 2447–2466.

526 Maxwell, R. M., & Miller, N. L. (2005). Development of a coupled land surface and groundwater model. *Journal of*  
527 *Hydrometeorology*, *6*, 233–247.

528 Maxwell, R. M., Putti, M., Meyerhoff, S., Delfs, J.-O., Ferguson, I. M., Ivanov, V., Kim, J., Kolditz, O., Kollet, S. J.,  
529 Kumar, M., Lopez, S., Niu, J., Paniconi, C., Park, Y.-J., Phanikumar, M. S., Shen, C., Sudicky, E. A., & Sulis,  
530 M. (2014). Surface-subsurface model intercomparison: A first set of benchmark results to diagnose integrated  
531 hydrology and feedbacks. *Water Resources Research*, *50*, 1531–1549.

532 Morita, M., & Yen, B. C. (2002). Modeling of conjunctive two-dimensional surface-three-dimensional subsurface  
533 flows. *Journal of Hydraulic Engineering*, *128*, 184–200.

534 Mualem, Y. (1976). A new model for predicting the hydraulic conductivity of unsaturated porous media. *Water*  
535 *Resources Research*, *12*, 513–522.

536 Nickolls, J., Buck, I., Garland, M., & Skadron, K. (2008). Scalable parallel programming with cuda. *Queue*, *6*,  
537 40–53.

538 NVIDIA Corporation (2011). *NVIDIA CUDA C Programming Guide*.

539 Owens, J., Houston, M., Luebke, D., Green, S., Stone, J., & Phillips, J. (2008). Gpu computing. *Proceedings of the*  
540 *IEEE*, *96*, 879–899.

541 Panday, S., & Huyakorn, P. S. (2004). A fully coupled physically-based spatially-distributed model for evaluating  
542 surface/subsurface flow. *Advances in Water Resources*, *27*, 361 – 382. A Tribute to George F. Pinder.

543 Paniconi, C., & Putti, M. (1994). A comparison of picard and newton iteration in the numerical solution of multi-  
544 dimensional variably saturated flow problems. *Water Resources Research*, *30*, 3357–3374.

545 Paniconi, C., & Wood, E. F. (1993). A detailed model for simulation of catchment scale subsurface hydrologic  
546 processes. *Water Resources Research*, *29*, 1601–1620.

547 Qu, Y., & Duffy, C. J. (2007). A semidiscrete finite volume formulation for multiprocess watershed simulation. *Water*  
548 *Resources Research*, *43*.

549 Richards, L. A. (1931). Capillary conduction of liquids through porous mediums. *Physics*, *1*, 318–333.

550 Rodriguez-Iturbe, I. (2000). Ecohydrology: A hydrologic perspective of climate-soil-vegetation dynamics. *Water*  
551 *Resources Research*, *36*, 3–9.

552 Schwarz, B. (2010). Lidar: Mapping the world in 3d. *Nature Photonics*, *4*, 429–430.

553 Shen, C., & Phanikumar, M. S. (2010). A process-based, distributed hydrologic model based on a large-scale method  
554 for surface - subsurface coupling. *Advances in Water Resources*, *33*, 1524–1541.

555 Simmons, M. E., Ben Wu, X., & Whisenant, S. G. (2011). Plant and soil responses to created microtopography and  
556 soil treatments in bottomland hardwood forest restoration. *Restoration Ecology*, *19*, 136–146.

557 Sophocleous, M. (2002). Interactions between groundwater and surface water: the state of the science. *Hydrogeology*  
558 *Journal*, *10*, 52–67.



- 559 Sulis, M., Meyerhoff, S. B., Paniconi, C., Maxwell, R. M., Putti, M., & Kollet, S. J. (2010). A comparison of  
560 two physics-based numerical models for simulating surface water-groundwater interactions. *Advances in Water*  
561 *Resources*, *33*, 456–467.
- 562 Thomas, L. H. (1949). *Elliptic Problems in Linear Differential Equations over a Network*. Technical Report Columbia  
563 University.
- 564 Thompson, S. E., Katul, G. G., & Porporato, A. (2010). Role of microtopography in rainfall-runoff partitioning: An  
565 analysis using idealized geometry. *Water Resources Research*, *46*.
- 566 Ussyshkin, V., & Theriault, L. (2011). Airborne lidar: Advances in discrete return technology for 3d vegetation  
567 mapping. *Remote Sens.*, *3*, 416–434.
- 568 VanderKwaak, J., & Sudicky, E. (1999). Application of a physically-based numerical model of surface and subsurface  
569 water flow and solute transport. In F. Stauffer (Ed.), *ModelCARE 99 Proceedings of the International Conference*  
570 *on Calibration and Reliability in Groundwater Modeling: Coping with Uncertainty* (pp. 641–648). ETH Zurich,  
571 Zurich, Switzerland.
- 572 Vanka, S. P. (2013). 2012 Freeman Scholar Lecture: Computational Fluid Dynamics on Graphics Processing Units.  
573 *Journal of Fluids Engineering*, *135*, 061401+.
- 574 Weill, S., Mazzia, A., Putti, M., & Paniconi, C. (2011). Coupling water flow and solute transport into a physically-  
575 based surface-subsurface hydrological model. *Advances in Water Resources*, *34*, 128–136.
- 576 Winter, T. C., Harvey, J. W., Franke, O. L., & Alley, W. M. (1998). *Ground Water and Surface Water A Single*  
577 *Resource*. Technical Report 1139 US Geological Survey Circular.
- 578 Zhang, Y., Cohen, J., & Owens, J. D. (2010). Fast tridiagonal solvers on the gpu. *SIGPLAN Not.*, *45*, 127–136.

Table 1: Parameters values for the Test Cases

Parameters	V-catchment	Infiltration Excess	Saturation Excess	Slab Case	Return Flow
Horizontal mesh size, $\Delta x = \Delta y$ [m]	5	20	20	1	5
Vertical mesh size, $\Delta z$ [m]	<i>n/a</i>	0.2	0.2	0.05	0.05
Time step, $\Delta t$ [min]	0.1	0.1	0.1	0.1	0.1
Initial water table depth, $wt$ [m]	<i>n/a</i>	1.0	0.5, 1.0	1.0	0.5
Specific storage, $S_s$ [ $m^{-1}$ ]	<i>n/a</i>	$5 \times 10^{-4}$	$5 \times 10^{-4}$	$5 \times 10^{-4}$	$5 \times 10^{-4}$
Porosity, $\phi$ [-]	<i>n/a</i>	0.4	0.4	0.4	0.4
Saturated hydraulic conductivity, $K_{sat}$ [ $m \text{ min}^{-1}$ ]	<i>n/a</i>	$6.94 \times 10^{-5}$ $6.94 \times 10^{-6}$	$6.94 \times 10^{-4}$	$6.94 \times 10^{-4}$ $6.94 \times 10^{-6}$	$6.94 \times 10^{-2}$
Manning's coefficients, $n_b$ [ $m^{-\frac{1}{3}} \text{ min}$ ]	<i>n/a</i>				
- Hillslope	$2.5 \times 10^{-4}$	$3.31 \times 10^{-4}$	$3.31 \times 10^{-4}$	$3.31 \times 10^{-4}$	$3.31 \times 10^{-4}$
- Channel	$2.5 \times 10^{-3}$	<i>na</i>	<i>na</i>	<i>na</i>	<i>na</i>
Rainfall rate [ $m \text{ min}^{-1}$ ]	$1.8 \times 10^{-4}$	$3.3 \times 10^{-4}$	$3.3 \times 10^{-4}$	$3.3 \times 10^{-4}$	$1.5 \times 10^{-4}$
Evaporation rate [ $m \text{ min}^{-1}$ ]	0	0	0	0	$5.4 \times 10^{-6}$
x-direction slope, $S_x$ [%]	5.0	0.05	0.05	0.05	0.5, 5
y-direction slope, $S_y$ [%]	2.0	0	0	0	0
<i>vanGenuchten parameters</i>					
Alpha, $\alpha$ [ $cm^{-1}$ ]	<i>n/a</i>	1.0	1.0	1.0	1.0
Pore-size distribution, $n$ [-]	<i>n/a</i>	2.0	2.0	2.0	2.0
Residual water content, $\theta_r$ [-]	<i>n/a</i>	0.08	0.08	0.08	0.08
Saturated water content, $\theta_s$ [-]	<i>n/a</i>	0.4	0.4	0.4	0.4

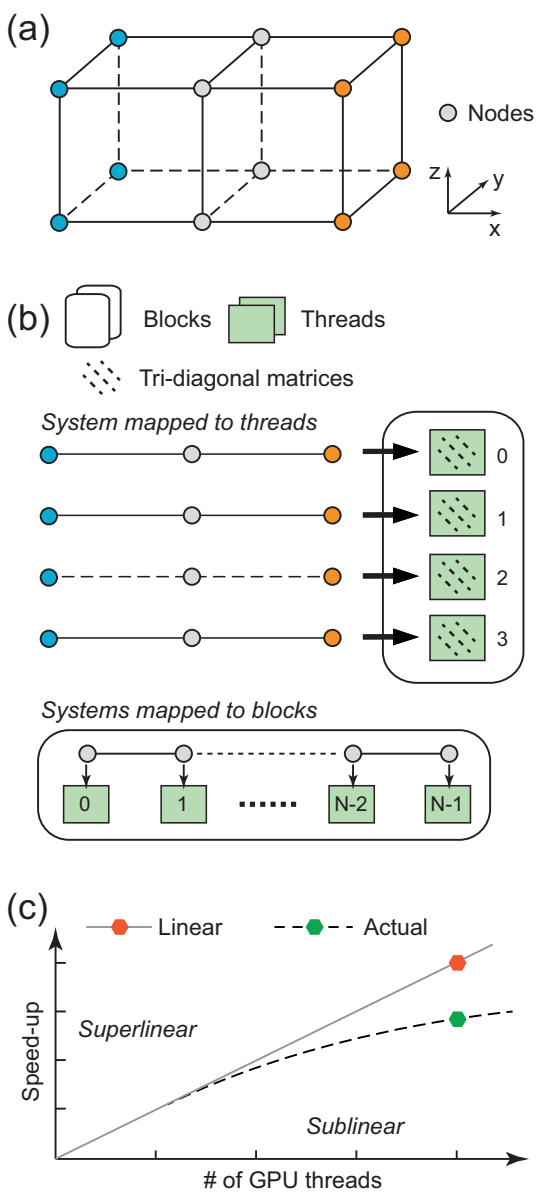


Figure 1: Parallel implementation of the ADI solvers in GPU computing. (a) Computational grid domain in three-dimensional space. (b) ADI approach discretizes the computational domain into 1-D problems involving independent tridiagonal linear systems. Each is assigned into a single thread (system mapped to threads) or block (system mapped to block) for numerical solution. A large number of fine-grained GPU processors can solve these systems in parallel. (c) Illustration of actual speed-up in GPU parallel computing. Thread synchronization is required at all time step, which reduces the speed-up from a linear trend for iterative ADI solver.

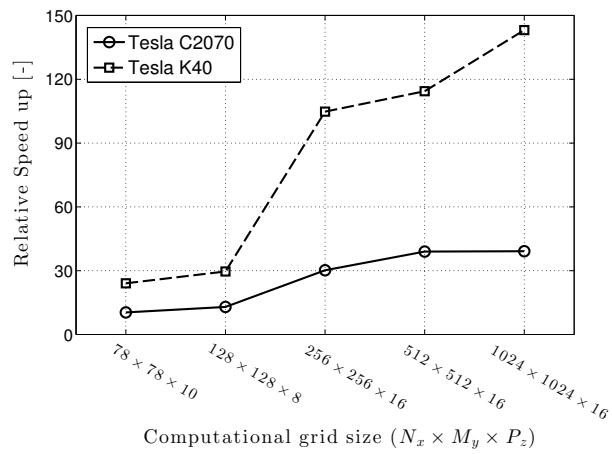


Figure 2: Relative speedup of the iterative ADI solver for tridiagonal matrix systems at different sizes of problem between GPUs (C2070 and K40) and CPUs (Xeon 2.67GHz). The speedup is the ratio between simulation time in CPU and in each GPU.

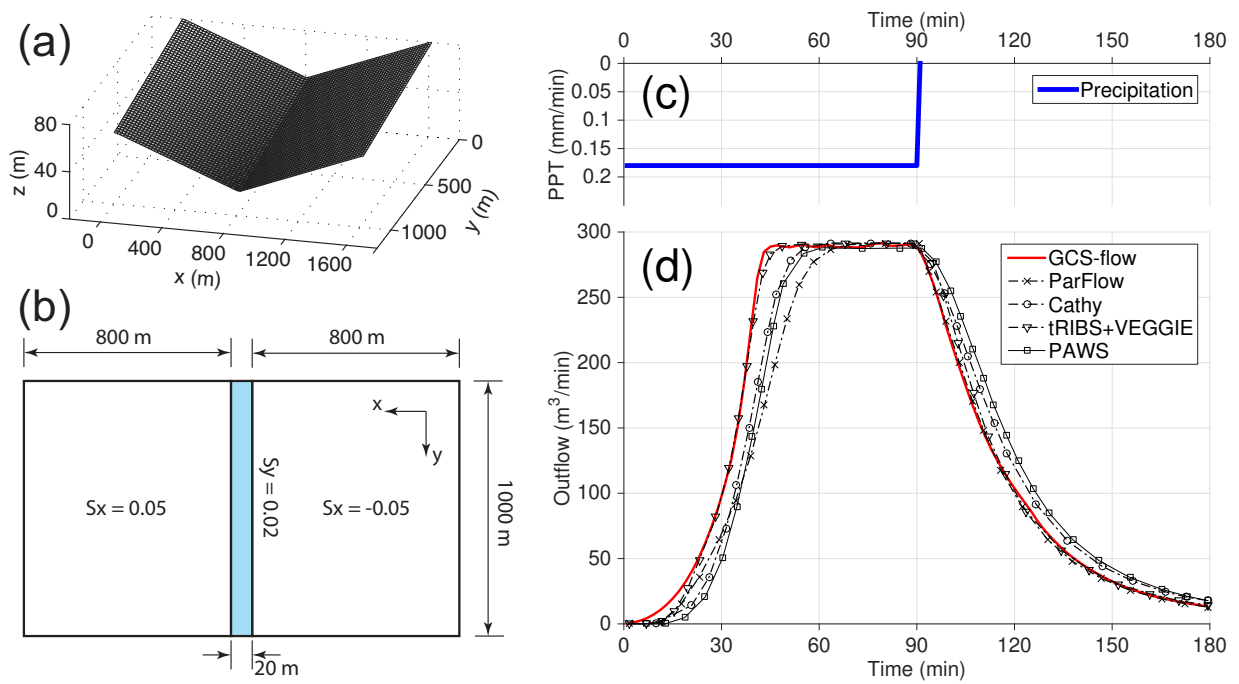


Figure 3: Benchmarking outflow response using a tilted V-catchment for overland and channel flow [after Sulis et al. (2010); Maxwell et al. (2014)]. (a) Tilted V-catchment domain - three-dimensional view. (b) Tilted V-catchment domain - top view. (c) Rainfall series consists of a uniform rainfall event from 0 to 90 [min] followed by 90 [min] of no rainfall. (d) Comparisons of overland and channel outflow at the outlet between GCS-flow and other models.

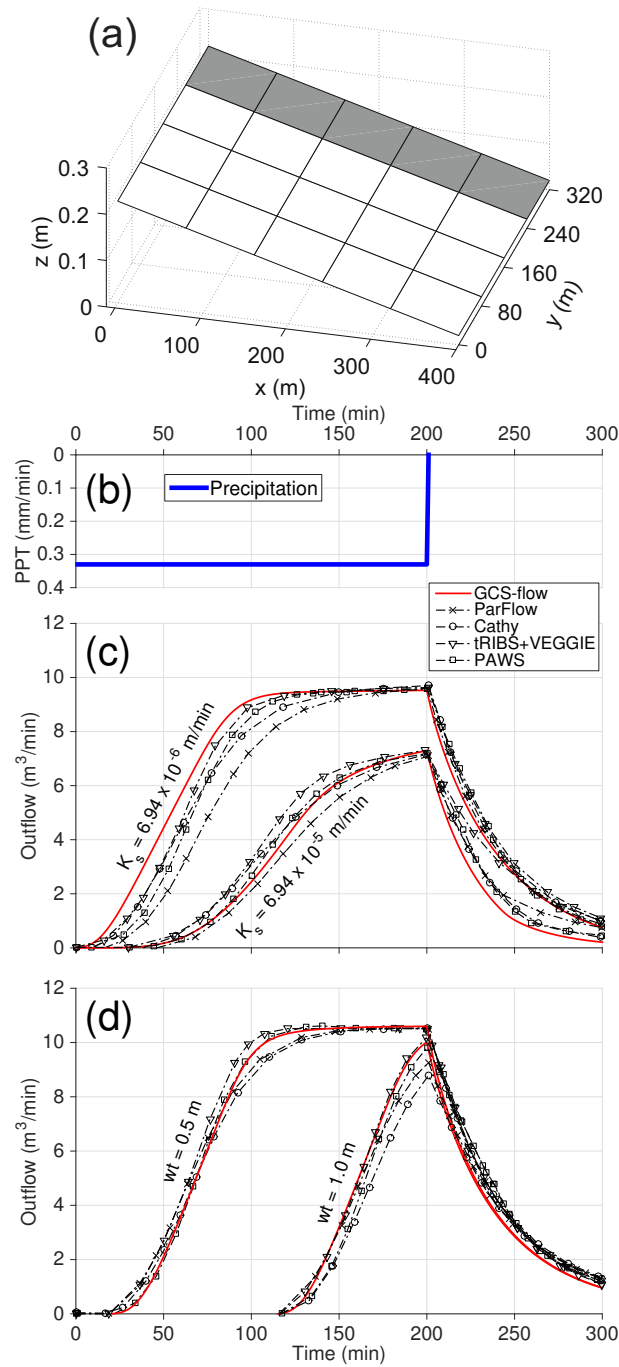


Figure 4: Benchmarking outflow response using homogeneous sloping tests [after Sulis et al. (2010); Maxwell et al. (2014)] (a) Illustration of the domain for sloping tests. Outflow is measured at the outlet of the grey strip of cells. (b) Rainfall series consists of a uniform rainfall event from 0 to 200[*min*] followed by 100[*min*] of no rainfall. (c and d) Comparisons of outflow at the outlet between GCS-flow and other models for two test cases: (c) Infiltration excess with two different values of hydraulic conductivity; and (d) Saturation excess with two different values of water table depth.

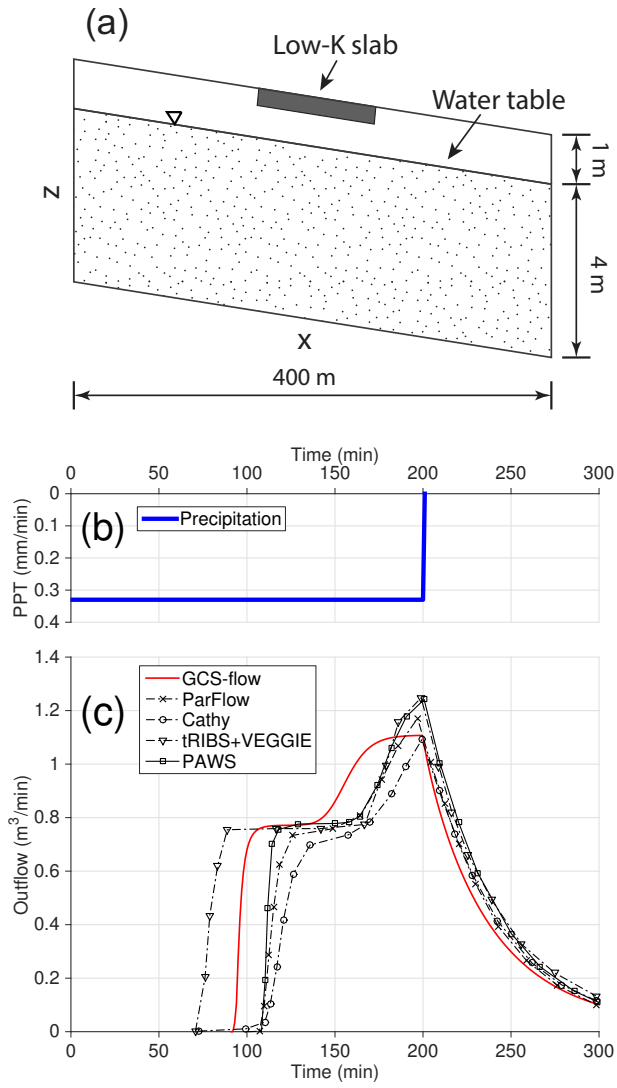


Figure 5: Benchmarking flow response using heterogeneous (slab) sloping tests [after Sulis et al. (2010); Maxwell et al. (2014)] (a) Domain and hydraulic conductivity distribution for slab test. (b) Rainfall series consists of a uniform rainfall event from 0 to 200 [min] followed by 100 [min] of no rainfall. (c) Comparison of outflow at the outlet between GCS-flow and other models.

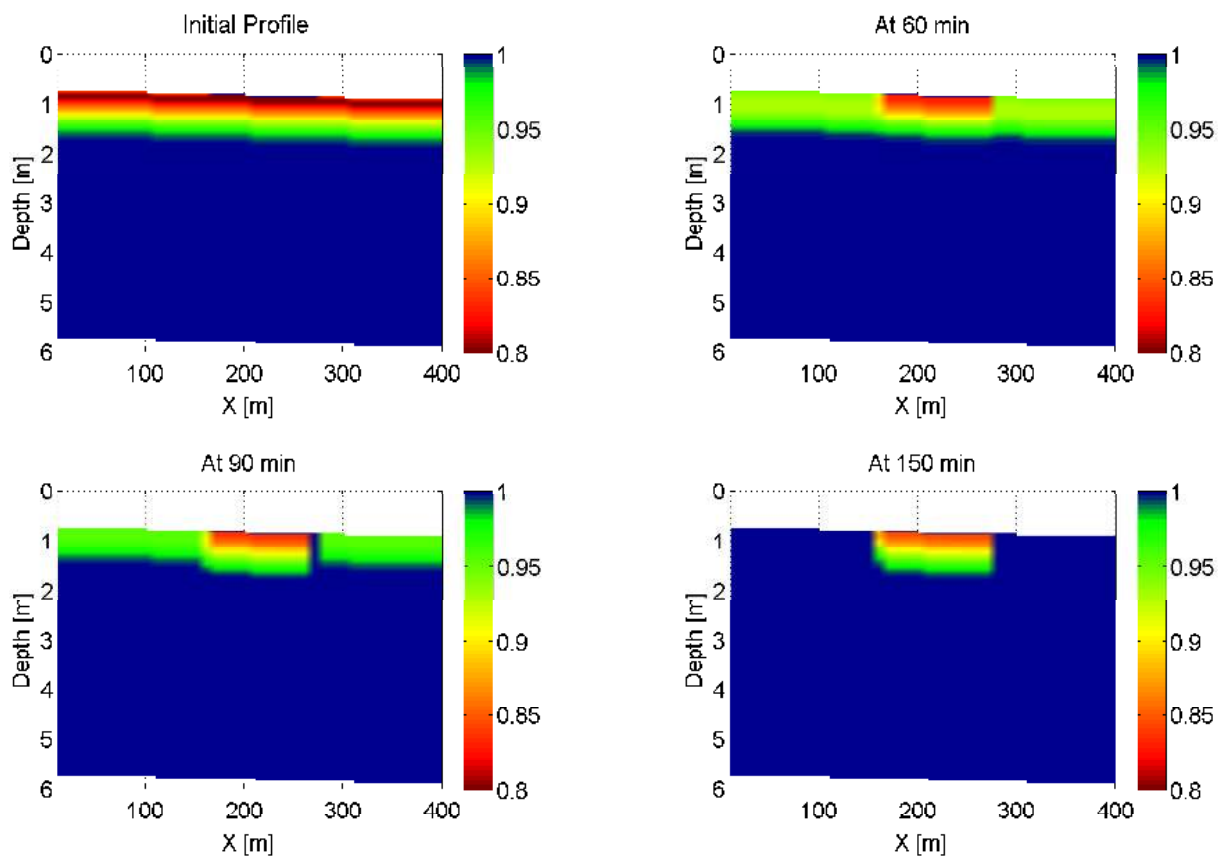


Figure 6: Saturation profile for the slab test at time 0, 60, 90, and 150 [min] obtained from GCS-flow model



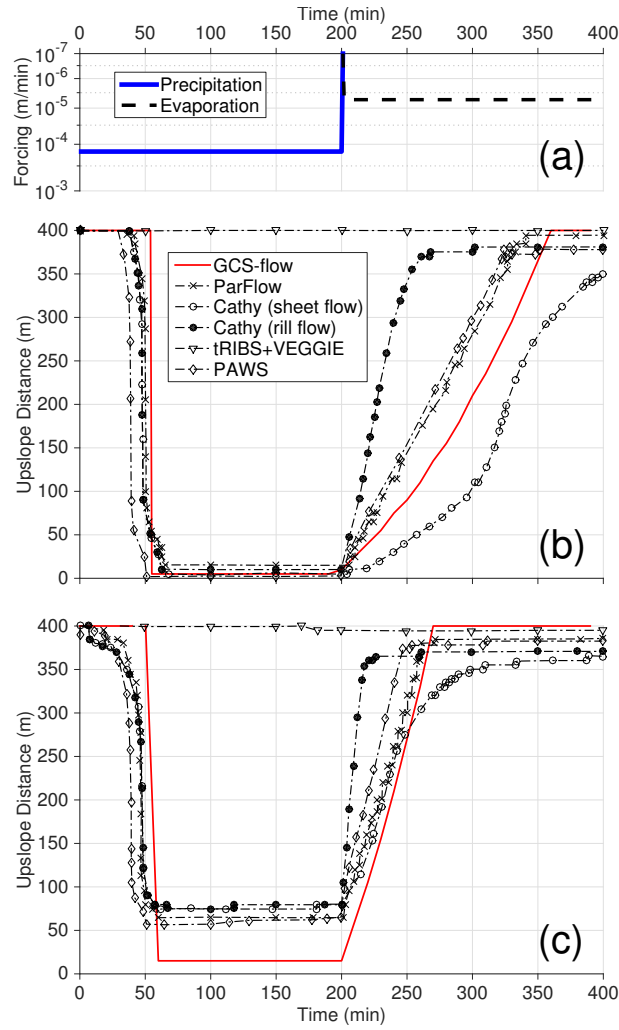


Figure 7: Benchmarking the evolution of the intersection point between the water table and the land surface [after Sulis et al. (2010); Maxwell et al. (2014)]. (a) Atmospheric forcing consist of a uniform rainfall event from 0 to 200 [min] followed by 200 [min] of uniform evaporation in log scale. (b, c) Simulation results for the return flow test using hillslope inclination of (b) 0.5% slope and (c) 5 % slope.

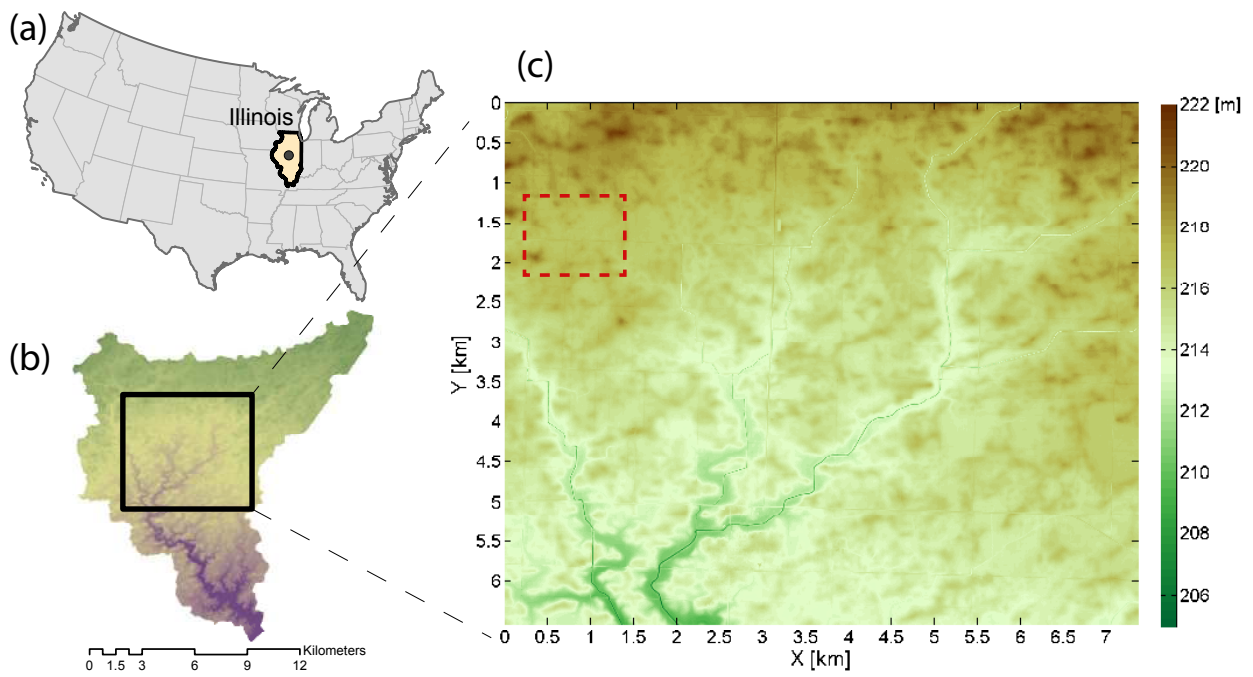


Figure 8: Area of simulation used to illustrate the GCS-flow model at lidar-data resolution. (a and b) Map of Goose Creek watershed of the Sangamon River Basin in central Illinois, USA. (c) Lidar data in Goose Creek watershed. Red rectangle shows the area used in illustration in [Figure 9](#).

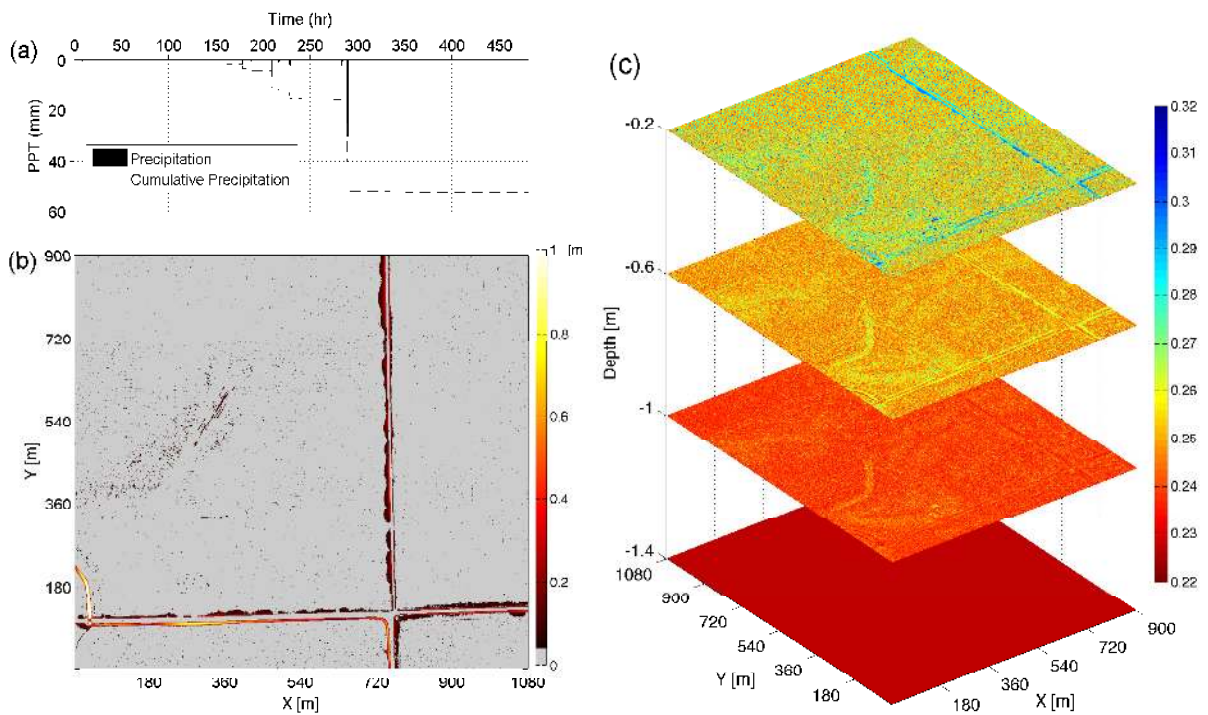


Figure 9: Profile of the spatial distribution of soil-moisture for the rectangle domain shown in [Figure 8c](#). (a) Precipitation time series used for the simulation period; (b) Water depth simulated on the study area by GCS-flow at 320 hr; and (c) Corresponding soil moisture profile at layers over depth simulated by GCS-flow at 320 hr