

1 A high resolution simulation of groundwater and surface water over most of the continental US
2 with the integrated hydrologic model ParFlow v3

3
4 Reed M Maxwell^{1*}, Laura E Condon¹, Stefan J Kollet²

5 ¹*Hydrologic Science and Engineering Program, Integrated GroundWater Modeling Center, Department*
6 *of Geology and Geological Engineering, Colorado School of Mines, Golden, Colorado, USA*

7 ²*Centre for High-Performance Scientific Computing in Terrestrial Systems, Institute for Bio- and*
8 *Geosciences, Agrosphere (IBG-3), Research Centre Jülich, Jülich, DE*

9
10 *correspondence to: Reed M Maxwell, rmaxwell@mines.edu

11
12 **Abstract**

13 Interactions between surface and groundwater systems are well-established theoretically and
14 observationally. While numerical models that solve both surface and subsurface flow equations
15 in a single framework (matrix) are increasingly being applied, computational limitations have
16 restricted their use to local and regional studies. Regional or watershed-scale simulations have
17 been effective tools for understanding hydrologic processes; however there are still many
18 questions, such as the adaptation of water resources to anthropogenic stressors and climate
19 variability, that can only be answered across large spatial extents at high resolution. In response
20 to this ‘grand challenge’ in hydrology, we present the results of a parallel, integrated hydrologic
21 model simulating surface and subsurface flow at high spatial resolution (1km) over much of
22 continental North America (~6,300,000 km²). These simulations provide integrated predictions
23 of hydrologic states and fluxes, namely water table depth and streamflow, at very large scale and
24 high resolution. The physics-based modeling approach used here requires limited
25 parameterizations and relies only on more fundamental inputs, such as topography,
26 hydrogeologic properties and climate forcing. Results are compared to observations and provide
27 mechanistic insight into hydrologic process interaction. This study demonstrates both the
28 feasibility of continental scale integrated models and their utility for improving our
29 understanding of large-scale hydrologic systems; the combination of high resolution and large
30 spatial extent facilitates analysis of scaling relationships using model outputs.

31 **Introduction**

32 There is growing evidence of feedbacks between groundwater, surface water and soil
33 moisture that moderate land-atmospheric energy exchanges, and impact weather and climate
34 (Maxwell et al. 2007; Anyah et al. 2008; Kollet and Maxwell 2008; Maxwell and Kollet 2008;
35 Jiang et al. 2009; Rihani et al. 2010; Maxwell et al. 2011; Williams and Maxwell 2011; Condon
36 et al. 2013; Taylor et al. 2013). While local observations and remote sensing can now detect
37 changes in the hydrologic cycle from small to very large spatial scales (e.g. Rodell et al. 2009),
38 theoretical approaches to connect and scale hydrologic states and fluxes from point
39 measurements to the continental scales are incomplete. In this work, we present integrated
40 modeling as one means to address this need via numerical experiments.

41 Though introduced as a concept in the literature almost half a century ago (Freeze and
42 Harlan 1969), integrated hydrologic models that solve the surface and subsurface systems
43 simultaneously have only been a reality for about a decade (VanderKwaak and Loague 2001;
44 Jones et al. 2006; Kollet and Maxwell 2006). Since their implementation, integrated hydrologic
45 models have been successfully applied to a wide range of watershed-scale studies (see Table 1 in
46 Maxwell et al. 2014) successfully capturing observed surface and subsurface behavior (Qu and
47 Duffy 2007; Jones et al. 2008; Sudicky et al. 2008; Camporese et al. 2010; Shi et al. 2013),
48 diagnosing stream-aquifer and land-energy interactions (Maxwell et al. 2007; Kollet and
49 Maxwell 2008; Rihani et al. 2010; Condon et al. 2013; Camporese et al. 2014), and building our
50 understanding of the propagation of perturbations such as land-cover and anthropogenic climate
51 change throughout the hydrologic system (Maxwell and Kollet 2008; Goderniaux et al. 2009;
52 Sulis et al. 2012; Mikkelsen et al. 2013).

53 Prior to this work, computational demands and data constraints have limited the
54 application of integrated models to regional domains. Advances in parallel solution techniques,
55 numerical solvers, supercomputer hardware, and additional data sources have only recently made
56 large-scale, high-resolution simulation of the terrestrial hydrologic cycle technically feasible
57 (Kollet et al. 2010; Maxwell 2013). As such, existing large scale studies of the subsurface have
58 focused on modeling groundwater independently (Fan et al. 2007; Miguez-Macho et al. 2007;
59 Fan et al. 2013) and classifying behavior with analytical functions (Gleeson et al. 2011).
60 Similarly, continental scale modeling of surface water has utilized tools with simplified
61 groundwater systems that do not capture lateral groundwater flow and model catchments as
62 isolated systems (Maurer et al. 2002; Döll et al. 2012; Xia et al. 2012), despite the fact that
63 lateral flow of groundwater has been shown to be important across scales (Krakauer et al. 2014).
64 While much has been learned from previous studies, the focus on isolated components within
65 what we know to be an interconnected hydrologic system is a limitation that can only be
66 addressed with an integrated approach.

67 The importance of groundwater-surface water interactions in governing scaling behavior
68 of surface and subsurface flow from headwaters to the continent has yet to be fully characterized.
69 Indeed, one of the purposes for building an integrated model is to better understand and predict
70 the nature of hydrologic connections across scales and throughout a wide array of physical and
71 climate settings. Arguably, this is not possible utilizing observations, because of data scarcity
72 and the challenges observing 3D groundwater flow across a wide range of scales. For example,
73 the scaling behavior of river networks is well known (Rodriguez-Iturbe and Rinaldo 2001), yet
74 open questions remain about the quantity, movement, travel time, and spatial and temporal
75 scaling of groundwater and surface water at the continental scale. Exchange processes and flow

76 near the land surface are strongly non-linear, and heterogeneity in hydraulic properties exist at all
77 spatial scales. As such, a formal framework for connecting scales in hydrology (Wood 2009)
78 needs to account for changes in surface water and groundwater flow from the headwaters to the
79 mouth of continental river basins. We propose that integrated, physics-based hydrologic models
80 are a tool for providing this understanding, solving fundamental non-linear flow equations at
81 high spatial resolution while *numerically* scaling these physical processes up to a large spatial
82 extent (i.e. continental scale).

83 In this study, we simulate surface and subsurface flow at high spatial resolution (1 km)
84 over much of continental North America (6.3M km²), which is itself considered a grand
85 challenge in hydrology (e.g. Wood et al. 2011; Gleeson and Cardiff 2014). The domain is
86 constructed entirely of available datasets including topography, soil texture and hydrogeology
87 This simulation solves surface and subsurface flow simultaneously and takes full advantage of
88 massively parallel, high-performance computing. The results presented here should be viewed as
89 a sophisticated numerical experiment, designed to diagnose physical behavior and evaluate
90 scaling relationships. While this is not a calibrated model that is intended to match observations
91 perfectly, we do verify that behavior is realistic by comparing to both groundwater and surface
92 water observations.

93 The paper is organized as follows: first a brief description of the model equations are
94 provided including a description of the input variables and observational datasets used for model
95 comparison; next model simulations are compared to observations in a number of ways, and then
96 used to understand hydrodynamic characteristics and to describe scaling.

97
98

99 **Methods**

100 The model was constructed using the integrated simulation platform ParFlow (Ashby and
101 Falgout 1996; Jones and Woodward 2001; Kollet and Maxwell 2006) utilizing the terrain
102 following grid capability (Maxwell 2013). ParFlow is a physically based model that solves both
103 the surface and subsurface systems simultaneously. In the subsurface ParFlow solves the mixed
104 form of Richards' equation for variably saturated flow (Richards 1931) in three spatial
105 dimensions given as:

$$106 \quad S_s S_w(h) \frac{\partial h}{\partial t} + \phi S_w(h) \frac{\partial S_w(h)}{\partial t} = \nabla \cdot \mathbf{q} + q_r(x, z) \quad (1)$$

107 where the flux term \mathbf{q} [LT^{-1}] is based on Darcy's law:

$$108 \quad \mathbf{q} = -\mathbf{K}_s(\mathbf{x}) k_r(h) [\nabla(h + z) \cos \theta_x + \sin \theta_x] \quad (2)$$

109 In these expressions, h is the pressure head [L]; z is the elevation with the z -axis specified as
110 upward [L]; $\mathbf{K}_s(\mathbf{x})$ is the saturated hydraulic conductivity tensor [LT^{-1}]; k_r is the relative
111 permeability [-]; S_s is the specific storage [L^{-1}]; ϕ is the porosity [-]; S_w is the relative saturation [-
112]; q_r is a general source/sink term that represents transpiration, wells, and other fluxes including
113 the potential recharge flux, which is enforced at the ground surface [T^{-1}]; and θ [-] is the local
114 angle of topographic slope, S_x and S_y , in the x and y directions and may be written as
115 $\theta_x = \tan^{-1} S_x$ and $\theta_y = \tan^{-1} S_y$. Note that we assume that density and viscosity are both
116 constant, although ParFlow can simulate density and viscosity-dependent flow (Kollet et al.
117 2009). The van Genuchten (1980) relationships are used to describe the relative saturation and
118 permeability functions ($S_w(h)$ and $k_r(h)$ respectively). These functions are highly nonlinear and
119 characterize changes in saturation and permeability with pressure.

120 Overland flow is represented in ParFlow by the two-dimensional kinematic wave
 121 equation resulting from application of continuity conditions for pressure and flux (Kollet and
 122 Maxwell 2006):

$$123 \mathbf{k} \cdot (-\mathbf{K}_s(\mathbf{x})k_r(h) \cdot \nabla(h + z)) = \frac{\partial \|h, 0\|}{\partial t} - \nabla \cdot \|h, 0\| \mathbf{v}_{sw} + \lambda q_r(\mathbf{x}) \quad (3)$$

124 In this equation \mathbf{v}_{sw} is the two-dimensional, depth-averaged surface water velocity [LT^{-1}] given
 125 by Manning's equation; h is the surface ponding depth [L] the same h as is shown in Equation 1.
 126 Note that $\|h, 0\|$ indicates the greater value of the two quantities in Equation 3. This means that
 127 if $h < 0$ the left hand side of this equation represents vertical fluxes (e.g. in/exfiltration) across
 128 the land surface boundary and is equal to $q_r(\mathbf{x})$ and a general source/sink (e.g. rainfall, ET) rate
 129 [LT^{-1}] with λ being a constant equal to the inverse of the vertical grid spacing [L^{-1}]. This term is
 130 then entirely equivalent to the source/sink term shown in Equation 1 at the ground surface where
 131 \mathbf{k} is the unit vector in the vertical, again defining positive upward coordinates. If $h > 0$ then the
 132 terms on the right hand side of Equation 3 are active water that is routed according to surface
 133 topography (Kollet and Maxwell 2006).

134 The nonlinear, coupled equations of surface and subsurface flow presented above are
 135 solved in a fully-implicit manner using a parallel Newton-Krylov approach (Jones and
 136 Woodward 2001; Kollet and Maxwell 2006; Maxwell 2013). Utilizing a globally-implicit
 137 solution allows for interactions between the surface and subsurface flow system to be explicitly
 138 resolved. While this yields a very challenging computational problem, ParFlow is able to solve
 139 large complex systems by utilizing a multigrid preconditioner (Osei-Kuffuor et al. ; Ashby and
 140 Falgout 1996) and taking advantage of highly scaled parallel efficiency out to more than $1.6 \times$
 141 10^4 processors (Kollet et al. 2010; Maxwell 2013).

142 ParFlow solves saturated subsurface flow (i.e. groundwater), unsaturated subsurface flow
143 (i.e. the vadose zone) and surface flow (i.e. streamflow) in a continuum approach within a single
144 matrix. Thus, complete non-linear interactions between all system components are simulated
145 without *a priori* specification of what types of flow occur in any given portion of the grid.
146 Streams form purely based on hydrodynamic principles governed by recharge, topography,
147 hydraulic conductivity and flow parameters, when water is ponded due to either excess
148 infiltration (surface fluxes exceed the infiltration capacity, e.g. Horton 1933) or excess saturation
149 (subsurface exfiltration to the surface system, e.g. Dunne 1983) for further discussion see Kirkby
150 (1988) and Beven (2004) for example. Groundwater converges in topographic depressions and
151 unsaturated zones may be shallow or deep depending upon recharge and lateral flows.

152 The physically based approach used by ParFlow is similar to other integrated hydrologic
153 models such as Hydrogeosphere (Therrien et al. 2012), PIHM (Kumar et al. 2009) and CATHY
154 (Camporese et al. 2010). This is a distinct contrast to more conceptually-based models that may
155 not simulate lateral groundwater flow or simplify the solution of surface and subsurface flow by
156 defining regions of groundwater or the stream-network prior to the simulation. In such models,
157 groundwater surface water interactions are often captured as one-way exchanges (i.e. surface
158 water loss to groundwater) or parameterized with simple relationships (i.e. functional
159 relationships that impose the relationship between stream head and baseflow). The integrated
160 approach used by ParFlow eliminates the need for such assumptions and allows the
161 interconnected groundwater surface water systems to evolve dynamically based only on the
162 governing equations and the properties of the physical system. The approach used here requires
163 robust numerical solvers (Maxwell 2013; Osei-Kuffuor et al. 2014) and exploits high-
164 performance computing (Kollet et al. 2010) to achieve high resolution, large extent simulations.

165 **Domain Setup**

166 In this study, the model and numerical experiment was directed at the Continental US
167 (CONUS) using the terrain following grid framework (Maxwell 2013) for a total thickness of
168 102m over 5 model layers. The model was implemented with a lateral resolution of 1 km with
169 $n_x=3342$, $n_y=1888$ and five vertical layers with 0.1, 0.3, 0.6, 1.0 and 100 m discretization for a
170 total model dimensions of 3,342 by 1,888 by 0.102 km and 31,548,480 total compute cells. The
171 model domain and input data sets are shown in Figure 1. All model inputs were re-projected to
172 have an equal cell-size of 1 x 1 km as shown in Figure 1. Topographic slopes (S_x and S_y) were
173 calculated from the Hydrosheds digital elevation model (Figure 1b) and were processed using the
174 r.watershed package in the GRASS GIS platform. Surface roughness values were constant 10^{-5}
175 [$\text{h m}^{-1/3}$] outside of the channels and varied within the channel as a function of average watershed
176 slope. Over the top 2 m of the domain, hydraulic properties from soil texture information of the
177 Soil Survey Geographic Database (SSURGO) were applied and soil properties were obtained
178 from Schaap and Leij (1998). Note that two sets of soil categories were available. The upper
179 horizon was applied over the top 1m (the top three model layers) and the bottom one over the
180 next 1 m (the fourth model layer). These soil types were mapped to their corresponding category
181 in the property database and those values were used in the model simulation (e.g. saturated
182 hydraulic conductivity, van Genuchten relationships). Figures 1a and c show the top and bottom
183 soil layers of the model. The deeper subsurface (i.e. below 2 m) was constructed from a global
184 permeability map developed by Gleeson et al. (2011). These values (Gleeson et al. 2011) were
185 adjusted to reduce variance (Condon and Maxwell 2013; Condon and Maxwell 2014) and to
186 reflect changes in topography using the e-folding relationship empirically-derived in (Fan et al.

187 2007): $\alpha = e^{-\frac{50}{f}}$ where $f = \frac{a}{(1+b*\sqrt{S_x^2+S_y^2})}$. For this analysis $a=20$, $b=125$ and the value of 50

188 [m] was chosen to reflect the midpoint of the deeper geologic layer in the model. Larger values
189 of α reduce the hydraulic conductivity categorically, that is by decreasing the hydraulic
190 conductivity indicator values in regions of steeper slope. Figure 1e maps the final conductivity
191 values used for simulation. Below the deeper geologic layer, the presence of impermeable
192 bedrock was assumed. This assumption oversimplifies regions that have weathered or fractured
193 systems that contribute to regional flow and aquifer systems deeper than 100 m. These
194 assumptions are necessitated by lack of data at this scale, not limitations of the model simulation.
195 Note that this complex subsurface dataset is assembled from many sources and is subject to
196 uncertainty: heterogeneity within the defined geologic types, uncertainty about the breaks
197 between geologic types and parameter values assigned to these types. There are breaks across
198 dataset boundaries, commonly at State or Province and International political delineations. The
199 fidelity and resolution of the source information used to formulate this dataset also changes
200 between these boundaries yielding some interfaces in property values.

201 All input datasets are a work in progress and should be continually improved. However,
202 we feel it is important to continue numerical experiments with the data that is currently available,
203 while keeping in mind the limitations associated with every model input. Shortcomings in
204 hydrogeological data sets reflect the lack of detailed unified hydrogeological information that
205 can be applied in high resolution continental models. This constitutes a significant source of
206 uncertainty, which needs to be assessed, quantified and ultimately reduced in order to arrive at
207 precise predictions. Still, it should be noted that the purpose of this work is to demonstrate the
208 feasibility of integrated modeling to explicitly represent processes across many scales of spatial
209 variability using best available data. By focusing on large-scale behaviors and relationships we
210 limit the impact of uncertain inputs.

211 No-flow boundary conditions were imposed on all sides of the model except the land
212 surface, where the free-surface overland flow boundary condition was applied. For the surface
213 flux, a Precipitation-Evapotranspiration (P-E, or potential recharge) field, shown in figure 1d,
214 was derived from products developed by Maurer et al. (2002). They developed a gridded
215 precipitation field from observations and simulated evaporation and transpiration fluxes using
216 the VIC model. We calculate the average difference between the two from 1950-2000 and apply
217 all positive values as potential recharge (P-E) (negative values were set to zero). The model was
218 initialized dry and the P-E forcing was applied continuously at the land surface upper boundary
219 (q_r in equation 1) until the balance of water (difference between total outflow and P-E) was less
220 than 3% of storage. For all simulations a nonlinear tolerance of 10^{-5} and a linear tolerance of 10^{-10}
221 were used to ensure proper model convergence.

222 While this study employs state of the art modeling techniques, it is important to note that
223 the numerical simulation of this problem required significant computational resources.
224 Simulations were split over 128 divisions in the x -direction and 128 in the y -direction and run on
225 16,384 compute-cores of an IBM BG/Q supercomputer (JUQUEEN) located at the Jülich
226 Supercomputing Centre, Germany. These processor splits resulted in approximately 2,000
227 unknowns per compute core; a relatively small number, yet ParFlow's scaling was still better
228 than 60% efficiency due to the non-symmetric preconditioner used (Maxwell 2013). The reason
229 for this is the special architecture of JUQUEEN with only 256MB of memory per core and
230 relatively slow clock rate. Additionally, code performance was improved using efficient
231 preconditioning of the linear system (Osei-Kuffuor et al.). The steady-state flow field was
232 accomplished over several steps. Artificial dampening was applied to the overland flow
233 equations early in the simulation during water table equilibration. Dampening was subsequently

234 decreased and removed entirely as simulation time progressed. Large time steps (10,000h) were
235 used initially and were decreased (to 1h) as the stream network formed and overland flow
236 became more pronounced with reduced dampening. The entire simulation utilized
237 approximately 2.5M core hours of compute time, which resulted in less than 1 week of wall-
238 clock time (approximately 150 hours) given the large core counts and batch submission process.

239 Model results were compared to available observations of streamflow and hydraulic head
240 (the sum of pressure head and gravitational potential). Observed streamflow values were
241 extracted from a spatial dataset of current and historical U.S. Geological Survey (USGS) stream
242 gages mapped to the National Hydrography Dataset (NHD) (Stewart et al., 2006). The entire
243 dataset includes roughly 23,000 stations, of which just over half (13,567) fall within the CONUS
244 domain. For each station, the dataset includes location, drainage area, sampling time period and
245 flow characteristics including minimum, maximum, mean and a range of percentiles (1, 5, 10,
246 20, 25, 50, 75, 80, 90, 95, 99) compiled from the USGS gage records. For comparison, stations
247 without a reported drainage area, stations not located on or adjacent to a river cell in ParFlow,
248 and stations whose drainage area were not within twenty percent of the calculated ParFlow
249 drainage area were filtered out. This resulted in 4,736 stations for comparison. The 50th
250 percentile values for these stations are shown in Figure 2a. Note that these observations are not
251 naturalized, i.e. no attempt is made to remove dams and diversions along these streams and
252 rivers, however some of these effects will be minimized given the longer temporal averages.
253 Hydraulic head observations of groundwater at more than 160,000 locations were assembled by
254 Fan et al. (Fan et al. 2007; Fan et al. 2013). Figure 2b plots the corresponding water table depth
255 at each location calculated as the difference between elevation and hydraulic head. Note that

256 these observations include groundwater pumping (most wells are drilled for extraction rather
257 than purely observation).

258

259 **Results and Discussion**

260 Figures 3 and 4 plot simulated streamflow and water table depth, respectively, over much
261 of continental North America, both on a log scale for flow (Figure 3) and water table depth
262 (Figure 4). Figure 3 shows a complex stream network with flow rates spanning many orders of
263 magnitude. Surface flows originate in the headwaters (or recharge zones) creating tributaries that
264 join to form the major river systems in North America. Note, as discussed previously that the
265 locations for flowing streams are not enforced in ParFlow but form due to ponded water at the
266 surface (i.e. values of $h > 0$ in the top layer of the model in Equations 1-3). Overland flow is
267 promoted both by topographic convergence, and surface and subsurface flux; however, with this
268 formulation there is no requirement that all potential streams support flow. Thus, the model
269 captures the generation of the complete stream network without specifying the presence and
270 location of rivers in advance, but rather by allowing channelized flow to evolve as a result of
271 explicitly simulated non-linear physical processes.

272 The insets in Figure 3 demonstrate multiscale detail ranging from the continental river
273 systems to the first-order headwaters. In Figure 4, water table depth also varies over five orders
274 of magnitude. Whereas aridity drives large-scale differences in water table depth (Figure 1d), at
275 smaller scales, lateral surface and subsurface flow processes clearly dominate recharge and
276 subsurface heterogeneity (see insets to Figure 4). Water tables are deeper in the more arid
277 western regions, and shallower in the more humid eastern regions of the model. However, areas
278 of shallow water table exist along arid river channels and water table depths greater than 10m

279 exist in more humid regions. Note that this is a pre-development simulation, thus, results do not
280 include any anthropogenic water management features such as groundwater pumping, surface
281 water reservoirs, irrigation or urbanization—all of which are present in the observations. Many
282 of these anthropogenic impacts have been implemented into the ParFlow modeling framework
283 (Ferguson and Maxwell 2011; Condon and Maxwell 2013; Condon and Maxwell 2014).
284 Although anthropogenic impacts clearly influence water resources, a baseline simulation allows
285 for a comparison between the altered and unaltered systems in future work.

286 Next we compare the results of the numerical experiment to observations. As noted
287 previously, this is not a calibrated model. Therefore, the purpose of these comparisons is to
288 evaluate model behavior and physical processes against observations not to generate input
289 parameters. Figure 5 plots observed and simulated hydraulic head and streamflow for the dataset
290 shown in Figure 2. Hydraulic head (Figure 5a) is plotted (as opposed to water table depth) as it
291 is the motivating force for lateral flow in the simulation; it includes both the topography and
292 pressure influences on the final solution. We see a very close agreement between observations
293 and model simulations, though given the large range in hydraulic heads the goodness of fit may
294 be influenced by topography. Additional metrics and comparisons are explored below.
295 Simulated streamflow (Figure 5b) also agrees closely with observations. There is some bias,
296 particularly for smaller flows (which we emphasize by plotting in log scale), which also exhibit
297 more scatter than larger flows, and are likely due to the 1km grid resolution employed here.
298 Larger flows are more integrated measures of the system and might be less sensitive to resolution
299 or local heterogeneity in model parameters. We see this when linear least squared statistics are
300 computed where the R^2 value increases to 0.8.

301 Figure 6 plots histograms of predicted and observed water table depth (a), hydraulic head
302 (b), median (50th percentile) flow and 75th percentile flows (c-d). The hydraulic head shows
303 good agreement between simulated and observed (Figure 6b). While hydraulic head is the
304 motivation for lateral flow and has been used in prior comparisons (e.g. Fan et al 2007) both
305 observed and simulated values are highly dependent on the local elevation. Figure 6a plots the
306 water table depth below ground surface, or the difference between local elevation and
307 groundwater. Here we see the simulated water table depths are shallower than the observed,
308 something observed in prior simulations of large-scale water table depth (Fan et al 2013). The
309 observed water tables may include anthropogenic impacts, namely groundwater pumping, while
310 the model simulations do not and this is a likely cause for this difference. Also, because
311 groundwater wells are usually installed for extraction purposes there is no guarantee that the
312 groundwater observations are an unbiased sample of the system as a whole. Figure 6c plots the
313 steady-state derived flow values compared to median observed flow values and Figure 6d plots
314 these same steady-state simulated flows compared to the 75th percentile of the observed transient
315 flow at each station. While the ParFlow model provides a robust representation of runoff
316 generation processes, the steady-state simulations average event flows. We see the model
317 predicts greater flow than the 50th percentile observed flows (Figure 6c) and good agreement
318 between the model simulations and the 75th percentile observed flows (Figure 6d). This
319 indicates a potentially wet bias in the forcing, which might also explain the shallower water table
320 depths.

321 Figures 7 and 8 compare observed and simulated flows and water table depths for each of
322 the major basin encompassed by the model. Water tables are generally predicted to be shallower
323 in the model than observations with the exception of the Upper and Lower Colorado which

324 demonstrate better agreement between model simulations and observations than other basins.
325 These histograms agree with a visual inspection of Figures 2b and 4 which also indicate deeper
326 observed water tables. Figure 8 indicates that simulated histograms of streamflow also predict
327 more flow than the observations. This might indicate that the P-E forcing is too wet. However,
328 a comparison of streamflow for the Colorado Watershed, where water table depths agree (Figure
329 8 e and g) and flows are overpredicted (Figure 7 e and g), indicates a more complex set of
330 interactions than basic water balance driven by forcing.

331 To better diagnose model processes, model inputs are compared with model simulation
332 outputs over example regions chosen to isolate the impact of topographic slope, forcing and
333 hydraulic conductivity on subsurface-surface water hydrodynamics. We do this as a check to see
334 if and how this numerical experiment compares to real observations. It is important to use a
335 range of measures of success that might be different from that used in a model calibration where
336 inadequacies in model parameters and process might be muted while tuning the model to better
337 match observations. Figure 9 juxtaposes slope, potential recharge, surface flow, water table
338 depth, hydraulic conductivity and a satellite image composite also at 1km resolution (the NASA
339 Blue Marble image, (Justice et al. 2002)) and facilitates a visual diagnosis of control by the three
340 primary model inputs. While the model was run to steady-state and ultimately all the potential
341 recharge has to exit the domain as discharge, the distribution and partitioning between
342 groundwater and streams depends on the slope and hydraulic conductivity. Likewise, while
343 topographic lows create the potential for flow convergence, it is not a model requirement that
344 these will develop into stream loci. Figure 9 demonstrates some of these relationships quite
345 clearly over a portion of the model that transitions from semi-arid to more humid conditions as
346 the North and South Platte River systems join the Missouri. As expected changes in slope yield

347 flow convergence, however, this figure also shows that as recharge increases from west to east
348 ($X > 1700$ km, panel c) the model generally predicts shallower water tables and greater stream
349 density (panels d and e, respectively). Conversely, in localized areas of decreased P-E (e.g. 700
350 $< Y < 900$ km specifically south of the Platte River) water tables increase and stream densities
351 decrease. The satellite image (panel f) shows increases in vegetation that correspond to
352 shallower water tables and increased stream density.

353 Hydraulic conductivity also has a significant impact on water table depth and stream
354 network density. In areas of greater recharge in the eastern portion of Figure 9c, regions with
355 larger hydraulic conductivity (panel b) show decreased stream network density and increased
356 water table depths. This is more clearly demonstrated in Figure 10 (a region in the upper
357 Missouri) where, except for the northeast corner, recharge is uniformly low. Slopes are also
358 generally low (panel a), yet hydraulic conductivities show a substantial increase due to a change
359 in datasets between state and country boundaries (panel b, $X > 1250$ km, $Y > 1400$ km). The
360 relative increase in hydraulic conductivity decreases hydraulic gradients under steady state
361 conditions and generally increases water table depth, which in turn decreases stream network
362 density. This change in hydraulic conductivity yields a decrease in the formation of stream
363 networks resulting in an increase in water table depth. Thus, hydraulic conductivity has an
364 important role in partitioning moisture between surface and subsurface flow, also under steady-
365 state conditions. While mass balance requires that overall flow must be conserved, larger
366 conductivity values allow this flow to be maintained within the subsurface while lower
367 conductivities force the surface stream network to maintain this flow. In turn, stream networks
368 connect regions of varying hydrodynamic conditions and may result in locally infiltrating
369 conditions creating a losing-stream to recharge groundwater. This underscores the connection

370 between input variables and model predictions, an equal importance of hydraulic conductivity to
371 recharge in model states and the need to continually improve input datasets.

372 Finally, the connection between stream flow and drainage area is a classical scaling
373 relationship (Rodriguez-Iturbe and Rinaldo 2001), which usually takes the power law form
374 $Q=kA^n$, where Q is volumetric streamflow [L^3T^{-1}], A is the contributing upstream area [L^2] and k
375 [LT^{-1}] and n are empirical constants. While this relationship has been demonstrated for
376 individual basins and certain flow conditions (Rodriguez-Iturbe and Rinaldo 2001), generality
377 has not been established (Glaster 2009). Figure 11a plots simulated streamflow as a function of
378 associated drainage area on log-log axes, and Figure 11b plots the same variables for median
379 observed streamflow from more than 4,000 gaging stations. While no single functional
380 relationship is evident from this plot, there is a striking maximum limit of flow as a function of
381 drainage area with a continental scaling coefficient of $n = 0.84$. Both Figures 11a and b are
382 colored by aridity index (AI), the degree of dryness of a given location. Color gradients that
383 transition from blue (more humid) to red (more arid) show that humid basins fall along the
384 maximum flow-discharge line, while arid basins have less discharge and fall below this line. For
385 discharge observations (Figure 11b) the same behavior is observed, where more humid stations
386 fall along the $n=0.9$ line and more arid stations fall below this line. Essentially this means that in
387 humid locations, where water is not a limiting factor, streamflow scales most strongly with
388 topography and area. Conversely arid locations fall below this line because flow to streams is
389 limited by groundwater storage.

390 The model presented here represents a first, high-resolution integrated simulation over
391 continental-scale river basins in North America using the best available data. However, primary
392 input datasets are used (potential recharge, subsurface properties and topography), which clearly

393 require improvement. For example, higher resolution simulations are feasible, given that the
394 ParFlow model exhibits better than 80% parallel efficiency for more than 8 billion compute cells.
395 This could improve the surface and subsurface prediction; although, we do not expect the form
396 of the scaling relationships as shown in Figure 11 to change with an increase in resolution.
397 Higher resolution simulations would require higher resolution parameter fields that do not exist
398 at this time. Similarly, model lower boundaries (i.e. the overall thickness of the subsurface)
399 could be extended given information about deeper hydrogeologic formations and their properties.
400 The model domain could be expanded to larger spatial extent, either over more of continental
401 North America, coastlines, or even globally. Thus, the study strongly motivates improved,
402 unified input and validation data sets for integrated hydrologic models at the continental scale,
403 similar to data products available to the atmospheric sciences.

404 **Conclusions**

405 Here we present the results of an integrated, multiphysics-based hydrologic simulation
406 covering much of Continental North America at hyperresolution (1km). This numerical
407 experiment provides a consistent theoretical framework for the analysis of groundwater and
408 surface water interactions and scaling from the headwaters to continental scale (10^0 - 10^7 km²).
409 The framework exploits high performance computing to meet this grand challenge in hydrology
410 (Wood et al. 2011; Gleeson and Cardiff 2014; Bierkens et al. 2015). We demonstrate that
411 continental-scale, integrated hydrologic models are feasible and can reproduce observations and
412 the essential features of streamflow and groundwater. Results show that scaling of surface flow
413 is related to both drainage area and aridity. These results may be interrogated further to
414 understand the role of topography, subsurface properties and climate on groundwater table and

415 streamflow, and used as a platform to diagnose scaling behavior, e.g. surface flow from the
416 headwaters to the continent.

417 These presented results are a first-step in high resolution, integrated, continental-scale
418 simulation. We simulate an unaltered, or pre-development scenario of groundwater and surface
419 water flows under steady-state conditions. As such, the discussion focuses on the physical
420 controls of groundwater surface water interactions and scaling behavior; however there are
421 obvious limitations to this scenario and these simulations. Clearly reservoir management,
422 groundwater pumping, irrigation, diversion and urban expansion all shape modern hydrology.
423 Work has been undertaken to include these features within the ParFlow framework at smaller
424 scales (Ferguson and Maxwell 2011; Ferguson and Maxwell 2012; Condon and Maxwell 2013;
425 Condon and Maxwell 2014) and an important next step is to scale the impacts out to the
426 continent.

427 Additionally, the steady-state simulation does not take into consideration temporal
428 dynamics or complex land-surface processes, also important in determining the quantity and
429 fluxes of water. These limitations can all be addressed within the current modeling framework
430 but require transient simulations and additional computational resources. Model performance is
431 also limited by the quality of available input datasets. As noted throughout the discussion,
432 existing datasets are subject to uncertainty and are clearly imperfect. As improved subsurface
433 characterization becomes available, this information can be used to better inform models and
434 fully understand the propagation of uncertainty in these types of numerical experiments (e.g.
435 Maxwell and Kollet 2008; Kollet 2009). However, while the magnitudes of states and fluxes may
436 change with improved datasets, the overall trends and responses predicted here are not likely to
437 change. While there are always improvements to be made, these simulations represent a critical

438 first step in understanding coupled surface subsurface hydrologic processes and scaling at
439 continental scales resolving variances over four for orders of spatial scales.

440 This study highlights the utility of high performance computing in addressing the grand
441 challenges in hydrological sciences and represents an important advancement in our
442 understanding of hydrologic scaling in continental river basins. By providing an integrated
443 model we open up a useful avenue of research to bridge physical processes across spatial scales
444 in a hydrodynamic, physics-based upscaling framework.

445

446 **Code Availability**

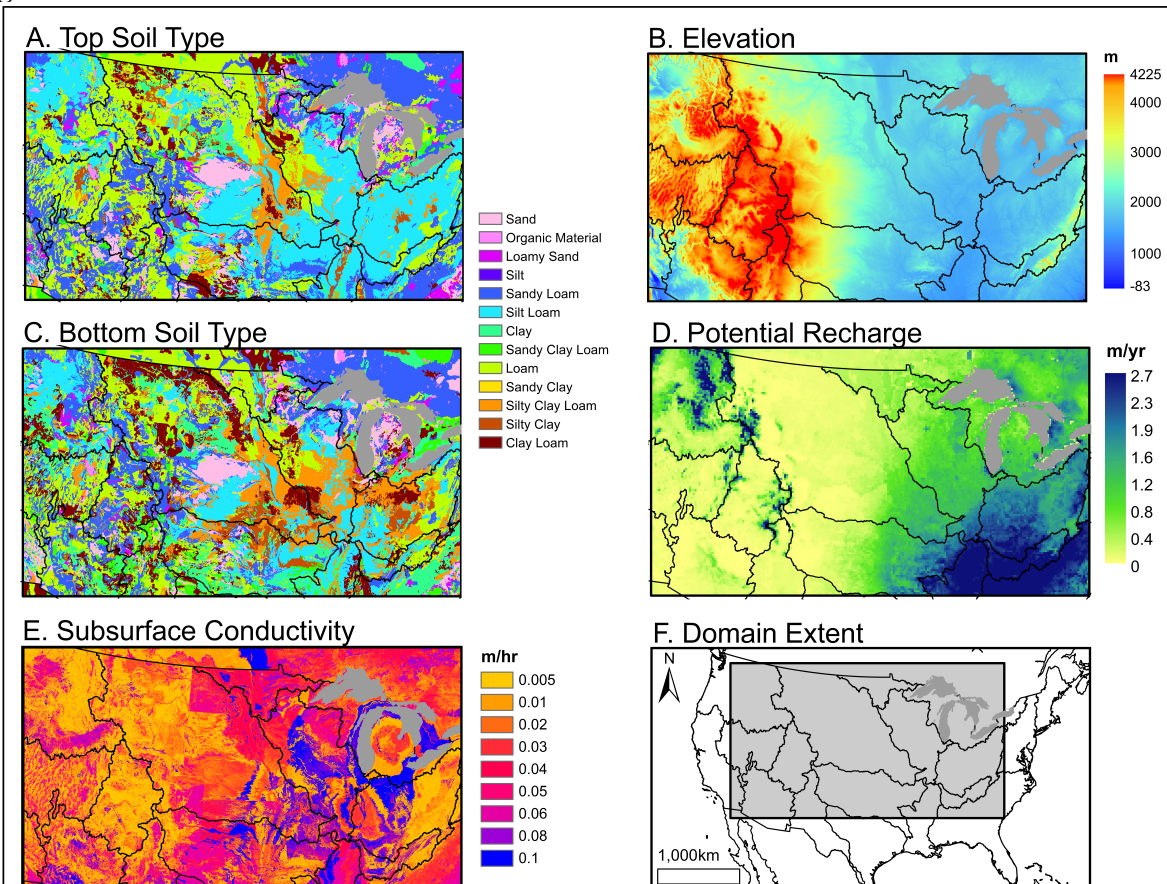
447 ParFlow is an open-source, modular, parallel integrated hydrologic platform freely available via
448 the GNU LPGL license agreement. ParFlow is developed by a community led by the Colorado
449 School of Mines and F-Z Jülich with contributors from a number of other institutions. Specific
450 versions of ParFlow are archived with complete documentation and may be downloaded¹ or
451 checked-out from a commercially hosted, free SVN repository; v3, r693 was the version used in
452 this study. The input data and simulations presented here will be made available and may be
453 obtained by contacting the lead author via email.

454

¹ http://inside.mines.edu/~rmaxwell/maxwell_software.shtml

455

456 **Figures**



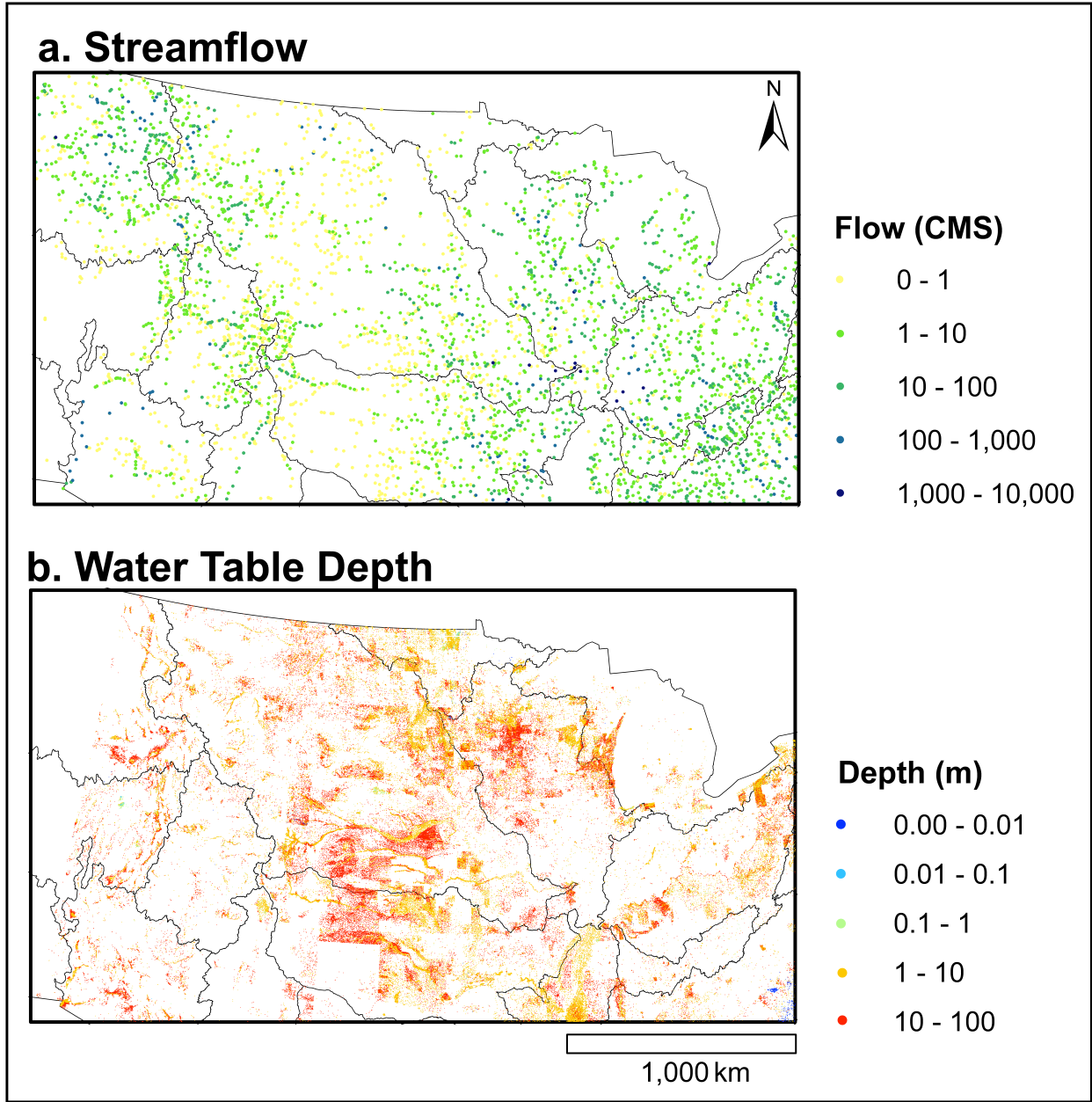
457

458 Figure 1. Maps of top soil type (applied over the top 2 m of the model) (a), elevation (masl) (b),

459 bottom soil type (c), potential recharge, P-E, (m/y) (d), saturated hydraulic conductivity (m/h,

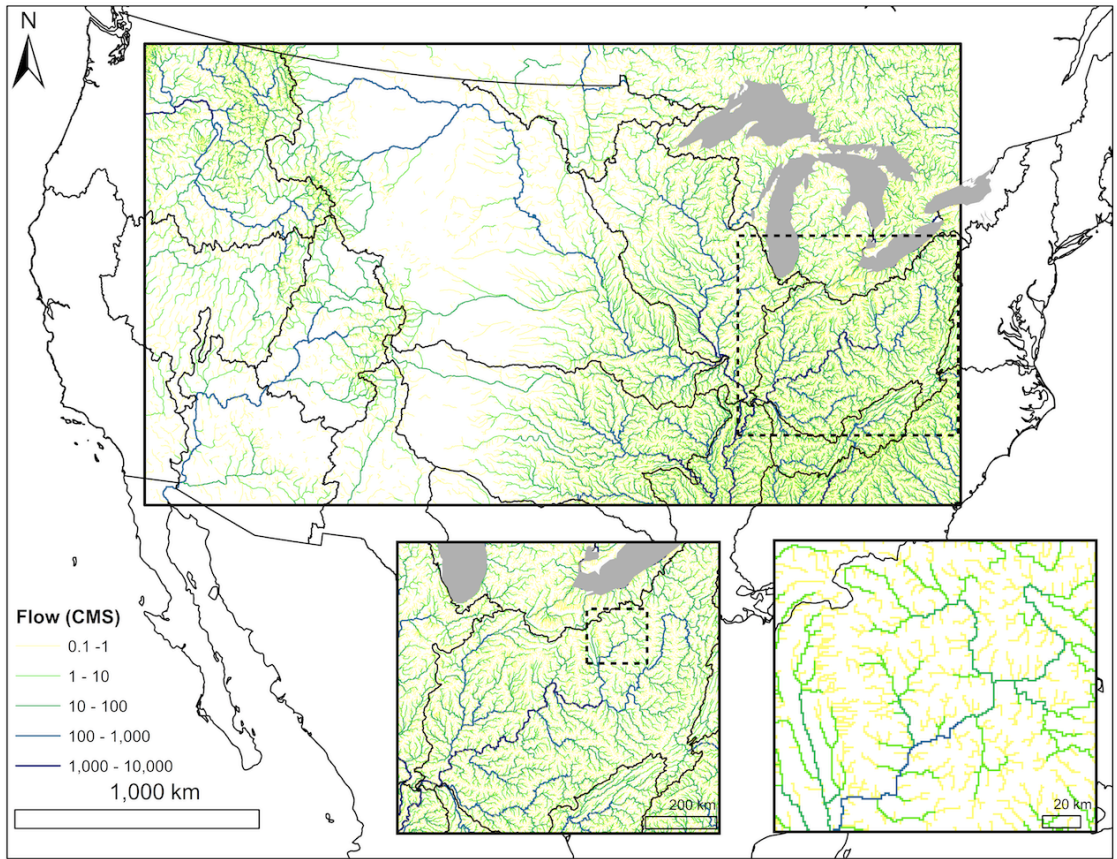
460 applied over the bottom 100 m of the model) (e) over the model domain (f).

461

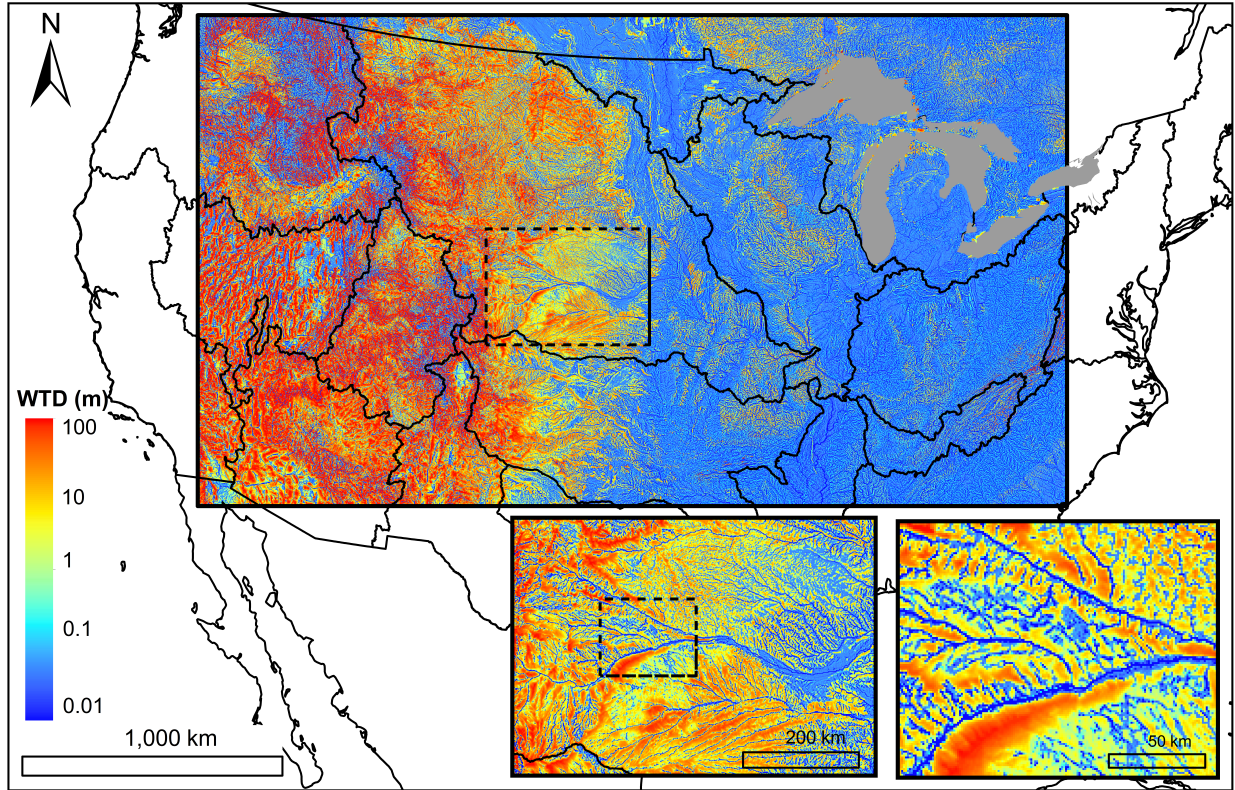


462
463
464

Figure 2. Plot of observed streamflow (a) and observed water table depth (b).

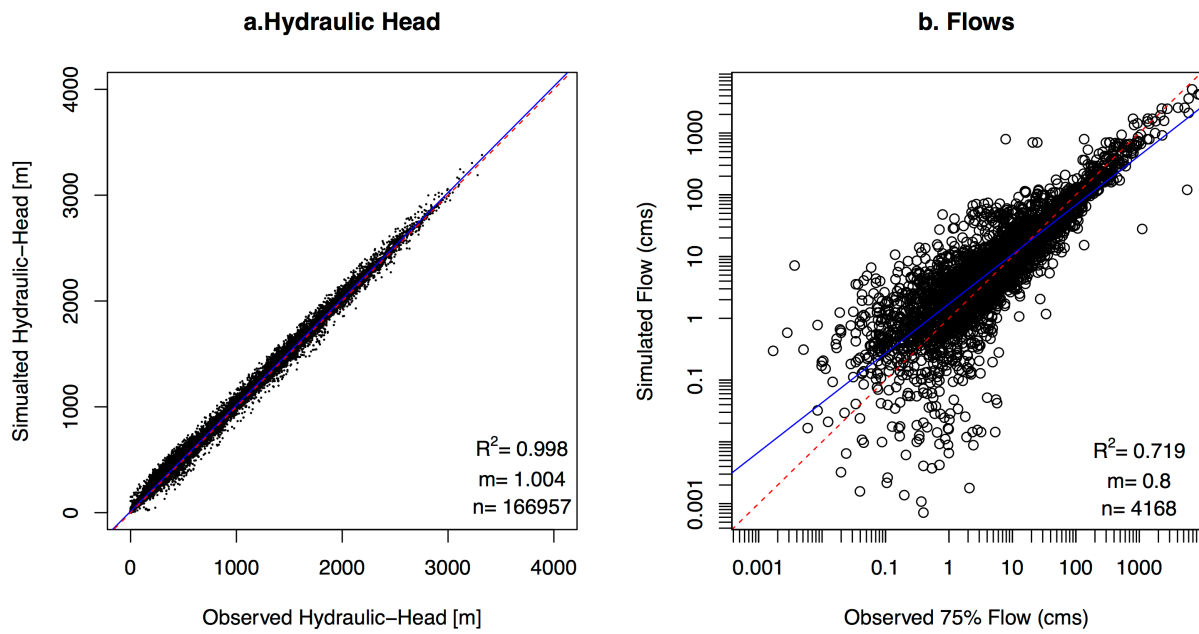


465
 466 Figure 3. Map of simulated surface flow (m^3/s) over the CONUS domain with two insets
 467 zooming into the Ohio river basin. Colors represent surface flow in log scale and line widths
 468 vary slightly with flow for the first two panels.
 469



470
471
472
473
474

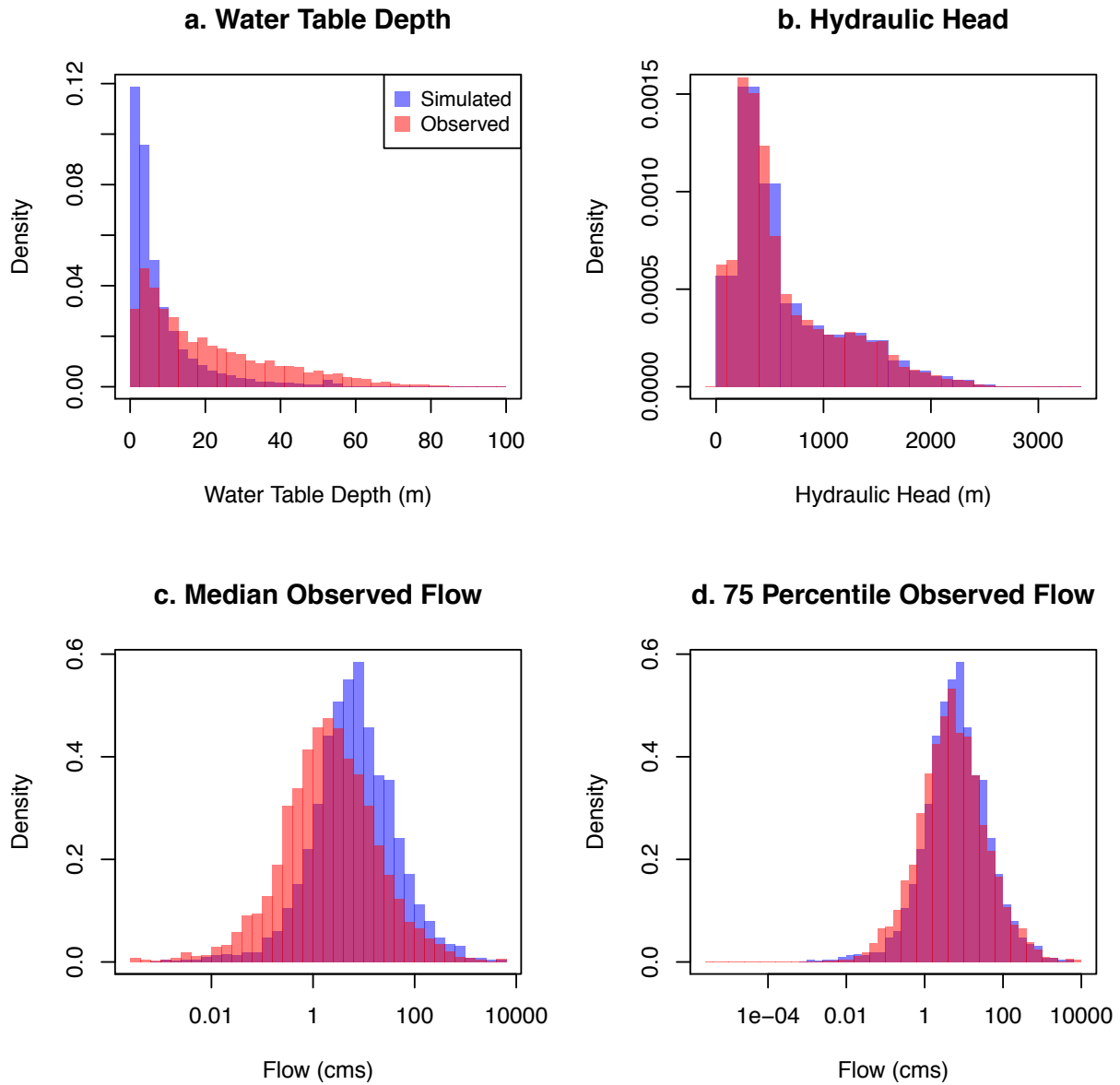
Figure 4. Map of water table depth (m) over the simulation domain with two insets zooming into the North and South Platte River basin, headwaters to the Mississippi. Colors represent depth in log scale (from 0.01 to 100m).



475

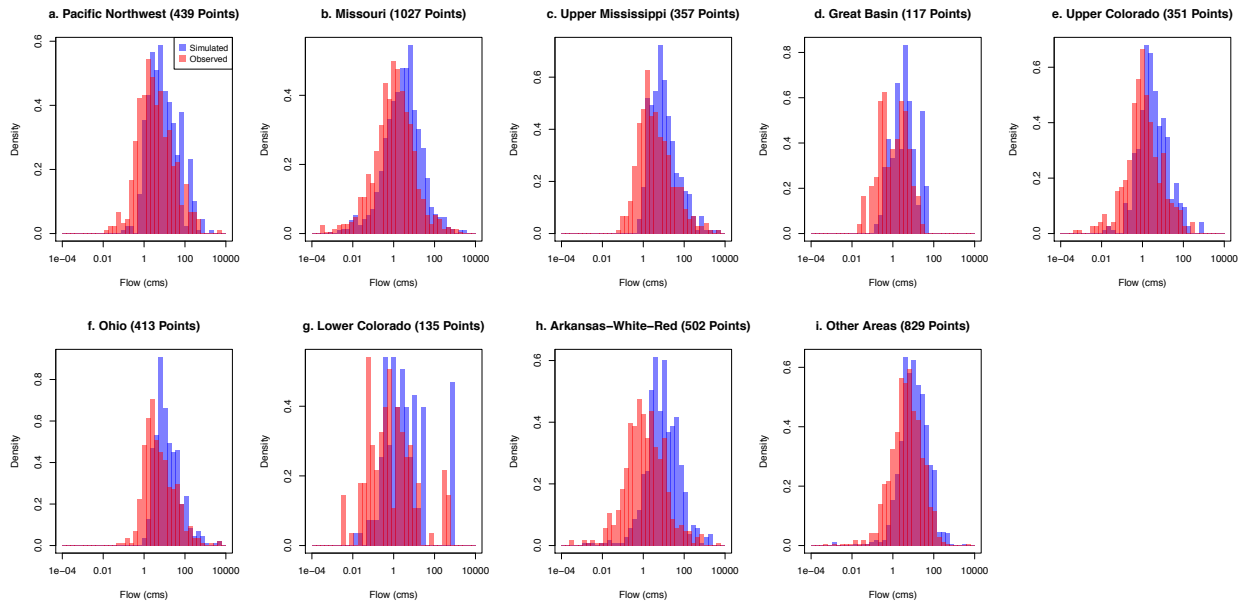
476 Figure 5. Scatterplots of simulated v. observed hydraulic head (a) and surface flow (b).

477



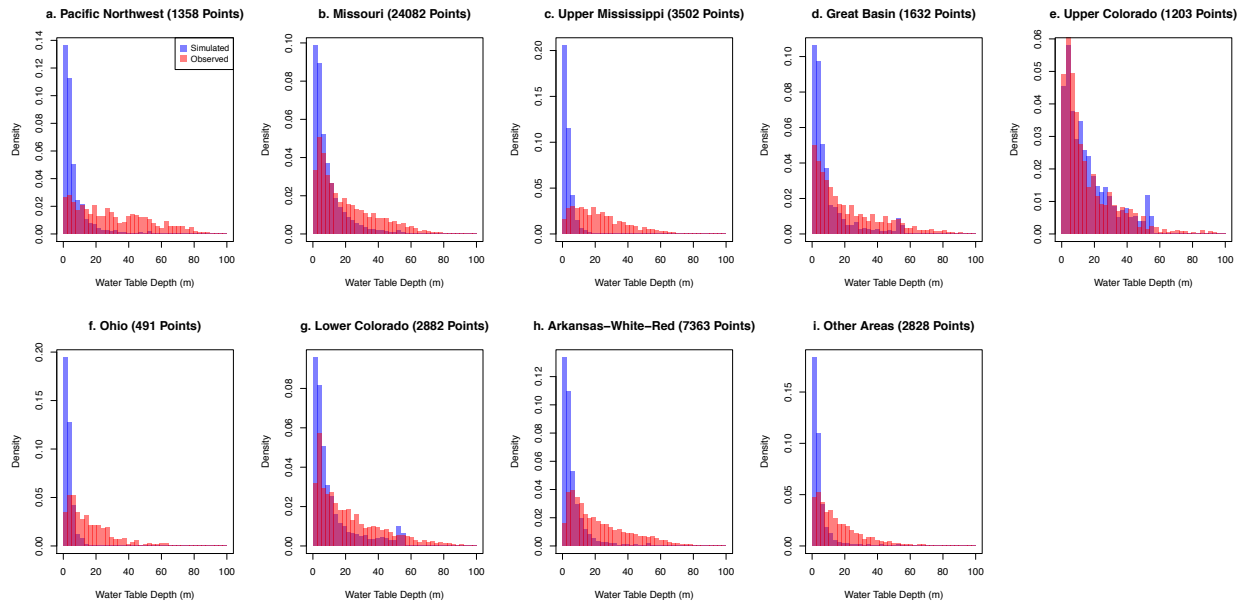
478
 479 Figure 6. Histograms of simulated and observed water table depth (a), hydraulic head (b),
 480 median observed flow (c) and 75th percentile observed flow (d).
 481

482
483



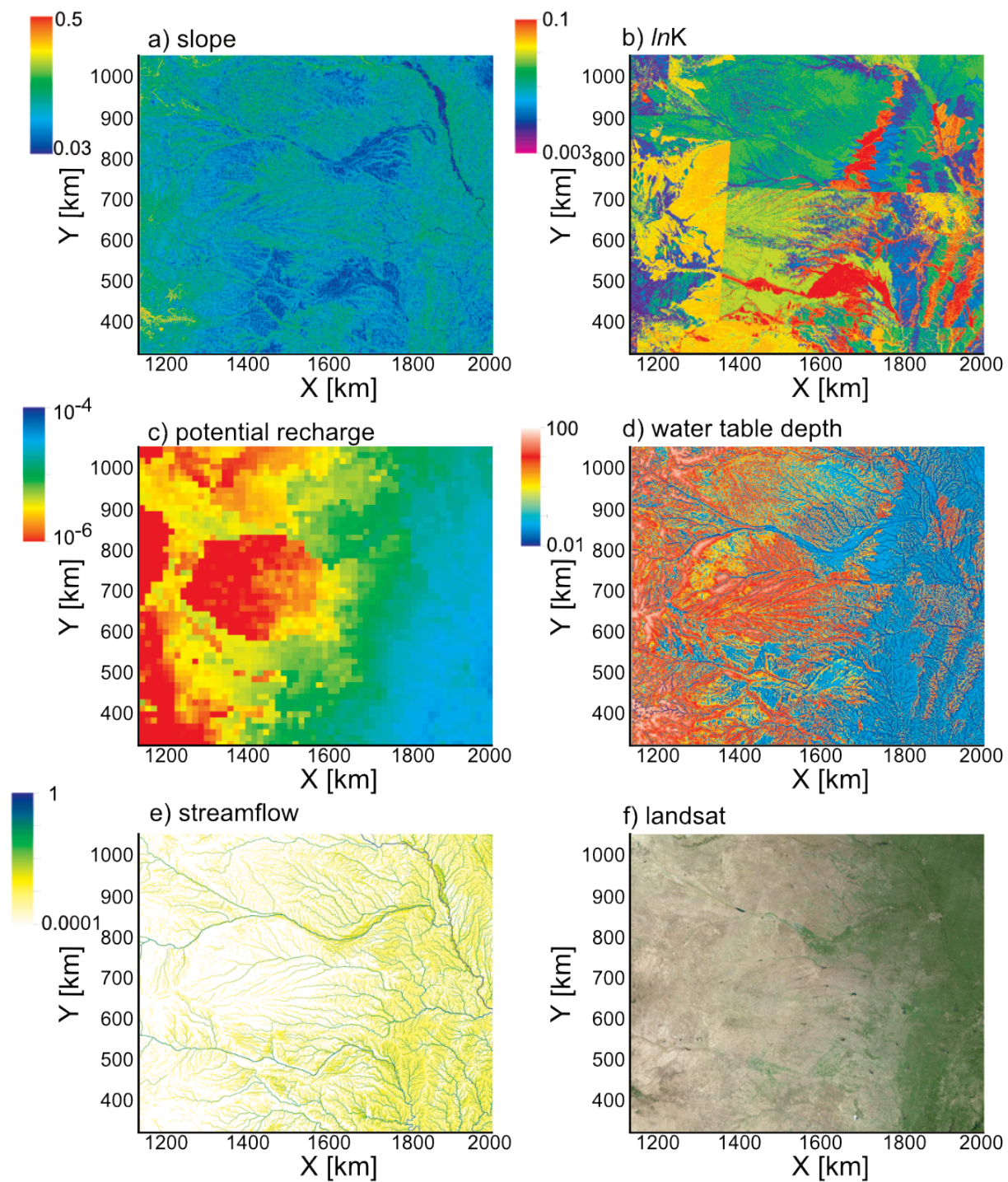
484
485
486

Figure 7. Distributions of observed and simulated streamflow by basin as indicated.

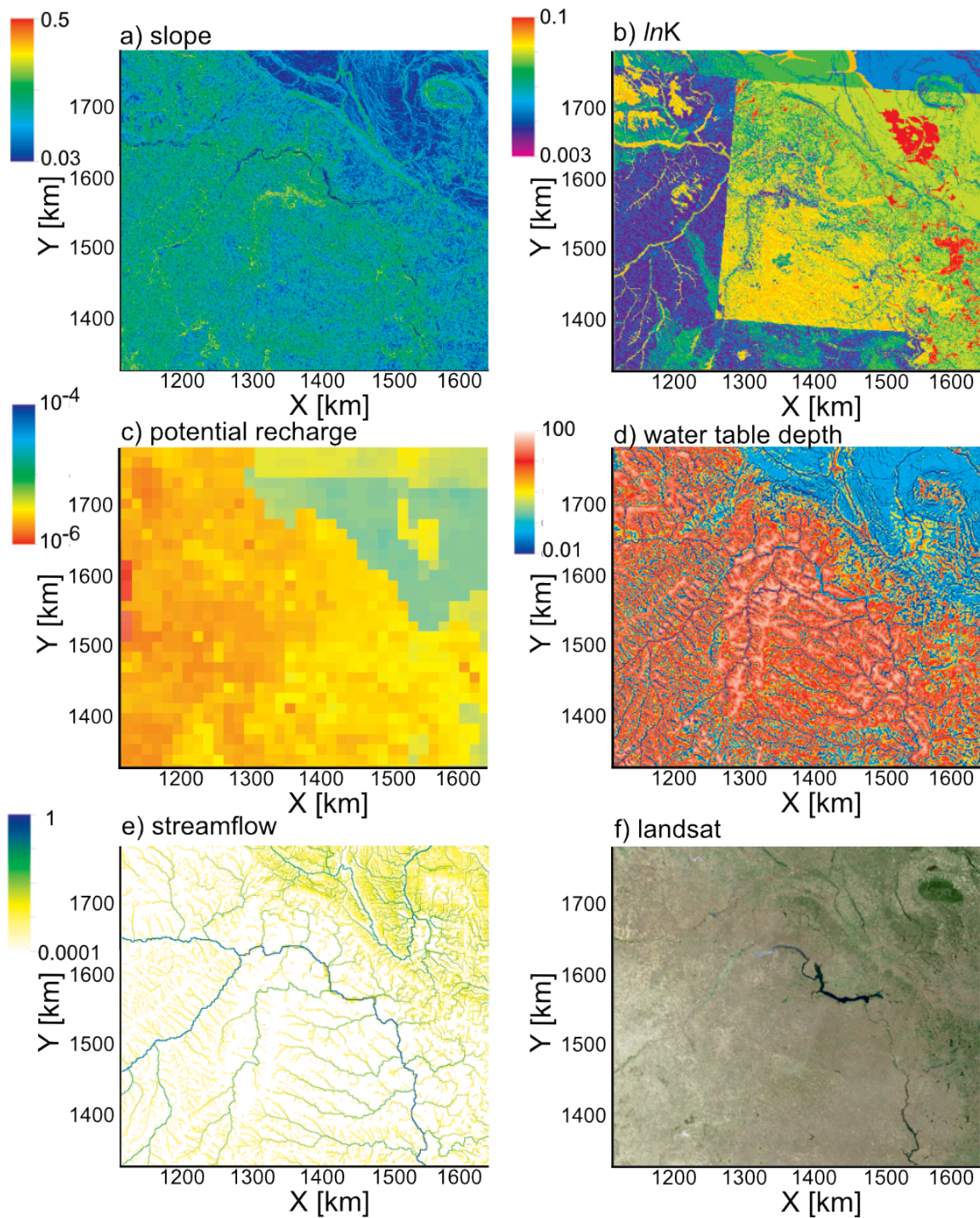


487
488

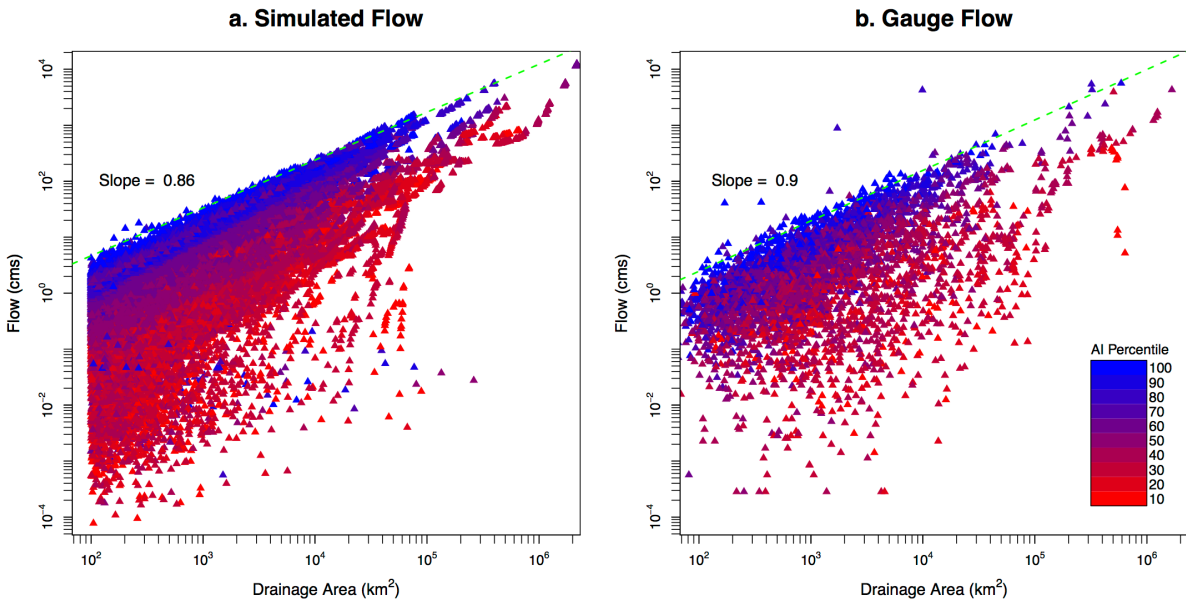
Figure 8. Distributions of observed and simulated water table depth by basin as indicated.



489
 490 Figure 9. Plots of topographic slope (a), hydraulic conductivity (b) potential recharge (c), water
 491 table depth (d), streamflow (e) and satellite image (f) for a region of the model covering the
 492 Platte River basin.
 493



494
 495 Figure 10. Plots of topographic slope (a), hydraulic conductivity (b) potential recharge (c), water
 496 table depth (d), streamflow (e) and satellite image (f) for a region of the model covering the
 497 Upper Missouri basin.



498
 499 Figure 11. Plots of scaling relationships for simulated and median observed surface flow. Log-
 500 scale plots of surface flow as a function of contributing drainage area derived from the model
 501 simulation (a) and observations (b). Individual symbols are colored by aridity index (AI) with
 502 blue colors being humid and red colors being arid in panels (a) and (b).
 503
 504
 505

506
507
508
509
510
511
512
513
514
515
516
517
518
519
520
521
522
523
524
525
526
527
528
529
530
531
532
533
534
535
536
537
538
539
540
541
542
543
544
545
546
547
548
549
550

References

- Anyah, R. O., C. P. Weaver, G. Miguez-Macho, Y. Fan and A. Robock (2008). "Incorporating water table dynamics in climate modeling: 3. Simulated groundwater influence on coupled land-atmosphere variability." Journal of Geophysical Research-Atmospheres **113**(D7): 15,
- Ashby, S. F. and R. D. Falgout (1996). "A parallel multigrid preconditioned conjugate gradient algorithm for groundwater flow simulations." Nuclear Science and Engineering **124**(1): 145-159,
- Beven, K. (2004). "Robert e. Horton's perceptual model of infiltration processes." Hydrological Processes **18**(17): 3447-3460,
- Bierkens, M. F. P., V. A. Bell, P. Burek, N. Chaney, L. E. Condon, C. H. David, A. de Roo, P. Döll, N. Drost, J. S. Famiglietti, M. Flörke, D. J. Gochis, P. Houser, R. Hut, J. Keune, S. Kollet, R. M. Maxwell, J. T. Reager, L. Samaniego, E. Sudicky, E. H. Sutanudjaja, N. van de Giesen, H. Winsemius and E. F. Wood (2015). "Hyper-resolution global hydrological modelling: What is next?" Hydrological Processes **29**(2): 310-320, 10.1002/hyp.10391
- Camporese, M., C. Paniconi, M. Putti and S. Orlandini (2010). "Surface-subsurface flow modeling with path-based runoff routing, boundary condition-based coupling, and assimilation of multisource observation data." Water Resources Research **46**(2): W02512, 10.1029/2008wr007536
- Camporese, M., C. Paniconi, M. Putti and S. Orlandini (2010). "Surface-subsurface flow modeling with path-based runoff routing, boundary condition-based coupling, and assimilation of multisource observation data." Water Resour. Res. **46**(2): W02512, doi: 10.1029/2008wr007536
- Camporese, M., D. Penna, M. Borga and C. Paniconi (2014). "A field and modeling study of nonlinear storage-discharge dynamics for an alpine headwater catchment." Water Resources Research **50**(2): 806-822, 10.1002/2013wr013604
- Condon, L. E. and R. M. Maxwell (2013). "Implementation of a linear optimization water allocation algorithm into a fully integrated physical hydrology model." Advances in Water Resources **60**(0): 135-147, <http://dx.doi.org/10.1016/j.advwatres.2013.07.012>
- Condon, L. E. and R. M. Maxwell (2014). "Feedbacks between managed irrigation and water availability: Diagnosing temporal and spatial patterns using an integrated hydrologic model." Water Resources Research **50**(3): 2600-2616, 10.1002/2013wr014868
- Condon, L. E., R. M. Maxwell and S. Gangopadhyay (2013). "The impact of subsurface conceptualization on land energy fluxes." Advances in Water Resources **60**(0): 188-203, <http://dx.doi.org/10.1016/j.advwatres.2013.08.001>
- Döll, P., H. Hoffmann-Dobrev, F. T. Portmann, S. Siebert, A. Eicker, M. Rodell, G. Strassberg and B. R. Scanlon (2012). "Impact of water withdrawals from groundwater and surface water on continental water storage variations." - **59**, **160**(- 0): - 156,
- Dunne, T. (1983). "Relation of field studies and modeling in the prediction of storm runoff." Journal of Hydrology **65**(1, 3): 25-48, [http://dx.doi.org/10.1016/0022-1694\(83\)90209-3](http://dx.doi.org/10.1016/0022-1694(83)90209-3)
- Fan, Y., H. Li and G. Miguez-Macho (2013). "Global patterns of groundwater table depth." Science **339**(6122): 940-943, 10.1126/science.1229881

551 Fan, Y., G. Miguez-Macho, C. P. Weaver, R. Walko and A. Robock (2007). "Incorporating
552 water table dynamics in climate modeling: 1. Water table observations and equilibrium
553 water table simulations." Journal of Geophysical Research-Atmospheres **112**(D10): -,
554 Ferguson, I. M. and R. M. Maxwell (2011). "Hydrologic and land–energy feedbacks of
555 agricultural water management practices." Environmental Research Letters - **6**(- 1),
556 doi:10.1088/1748-9326/6/1/014006

557 Ferguson, I. M. and R. M. Maxwell (2012). "Human impacts on terrestrial hydrology: Climate
558 change versus pumping and irrigation." Environmental Research Letters **7**(4): 044022,
559 Freeze, R. A. and R. L. Harlan (1969). "Blueprint for a physically-based, digitally-simulated
560 hydrologic response model." Journal of Hydrology **9**: 237-258,
561 Glaster, J. C. (2009). "Testing the linear relationship between peak annual river discharge and
562 drainage area using long-term usgs river gauging records." Geological Society of
563 America Special Papers **451**: 159-171, 10.1130/2009.2451(11)

564 Gleeson, T. and M. Cardiff (2014). "The return of groundwater quantity: A mega-scale and
565 interdisciplinary “future of hydrogeology”?" Hydrogeology Journal: **4**, 10.1007/s10040-
566 013-0998-8

567 Gleeson, T., L. Marklund, L. Smith and A. H. Manning (2011). "Classifying the water table at
568 regional to continental scales." Geophysical Research Letters **38**(L05401): 6,
569 10.1029/2010GL046427

570 Gleeson, T., L. Smith, N. Moosdorf, J. Hartmann, H. H. Dürr, A. H. Manning, L. P. H. van Beek
571 and A. M. Jellinek (2011). "Mapping permeability over the surface of the earth."
572 Geophysical Research Letters **38**(2): L02401, 10.1029/2010gl045565

573 Goderniaux, P., S. Brouyère, H. J. Fowler, S. Blenkinsop, R. Therrien, P. Orban and A.
574 Dassargues (2009). "Large scale surface, subsurface hydrological model to assess
575 climate change impacts on groundwater reserves." Journal of Hydrology **373**(1, 2):
576 122-138, <http://dx.doi.org/10.1016/j.jhydrol.2009.04.017>

577 Horton, R. E. (1933). "The role of infiltration in the hydrologic cycle." Transactions-American
578 Geophysical Union **14**: 446-460,

579 Jiang, X., G. Y. Niu and Z. L. Yang (2009). "Impacts of vegetation and groundwater dynamics
580 on warm season precipitation over the central united states." Journal of Geophysical
581 Research **114**: 15,

582 Jones, J. E. and C. S. Woodward (2001). "Newton-krylov-multigrid solvers for large-scale,
583 highly heterogeneous, variably saturated flow problems." Advances in Water Resources
584 **24**(7): 763-774,

585 Jones, J. P., E. A. Sudicky, A. E. Brookfield and Y. J. Park (2006). "An assessment of the tracer-
586 based approach to quantifying groundwater contributions to streamflow." Water Resour.
587 Res. **42**, 10.1029/2005wr004130

588 Jones, J. P., E. A. Sudicky and R. G. McLaren (2008). "Application of a fully-integrated surface-
589 subsurface flow model at the watershed-scale: A case study." Water Resources Research
590 **44**(3): W03407, 10.1029/2006wr005603

591 Justice, C. O., J. R. G. Townshend, E. F. Vermote, E. Masuoka, R. E. Wolfe, N. Saleous, D. P.
592 Roy and J. T. Morisette (2002). "An overview of modis land data processing and product
593 status." Remote Sensing of Environment **83**(1, 2): 3-15,
594 [http://dx.doi.org/10.1016/S0034-4257\(02\)00084-6](http://dx.doi.org/10.1016/S0034-4257(02)00084-6)

595 Kirkby, M. (1988). "Hillslope runoff processes and models." Journal of Hydrology **100**(1, 3):
596 315-339, [http://dx.doi.org/10.1016/0022-1694\(88\)90190-4](http://dx.doi.org/10.1016/0022-1694(88)90190-4)

597 Kollet, S. J. (2009). "Influence of soil heterogeneity on evapotranspiration under shallow water
598 table conditions: Transient, stochastic simulations." Environmental Research Letters **4**(3):
599 9,

600 Kollet, S. J., I. Cvijanovic, D. Schüttemeyer, R. M. Maxwell, A. F. Moene and B. P. (2009).
601 "The influence of rain sensible heat, subsurface heat convection and the lower
602 temperature boundary condition on the energy balance at the land surface." Vadose Zone
603 Journal **8**(4): 12,

604 Kollet, S. J. and R. M. Maxwell (2006). "Integrated surface-groundwater flow modeling: A free-
605 surface overland flow boundary condition in a parallel groundwater flow model." Advances in Water Resources **29**(7): 945-958,
606

607 Kollet, S. J. and R. M. Maxwell (2008). "Capturing the influence of groundwater dynamics on
608 land surface processes using an integrated, distributed watershed model." Water
609 Resources Research **44**(W02402): 18, doi:10.1029/2007WR006004

610 Kollet, S. J., R. M. Maxwell, C. S. Woodward, S. Smith, J. Vanderborght, H. Vereecken and C.
611 Simmer (2010). "Proof of concept of regional scale hydrologic simulations at hydrologic
612 resolution utilizing massively parallel computer resources." Water Resources Research
613 **46**(W04201): -, Doi 10.1029/2009wr008730

614 Krakauer, N. Y., H. Li and Y. Fan (2014). "Groundwater flow across spatial scales: Importance
615 for climate modeling." Environmental Research Letters **9**(3): 034003,

616 Kumar, M., C. J. Duffy and K. M. Salvage (2009). "A second order accurate, finite volume
617 based, integrated hydrologic modeling (fihm) framework for simulation of surface and
618 subsurface flow." Vadose Zone Journal,

619 Maurer, E. P., A. W. Wood, J. C. Adam, D. P. Lettenmaier and B. Nijssen (2002). "A long-term
620 hydrologically based dataset of land surface fluxes and states for the conterminous united
621 states*." Journal of Climate **15**(22): 3237-3251, 10.1175/1520-
622 0442(2002)015<3237:althbd>2.0.co;2

623 Maxwell, R. M. (2013). "A terrain-following grid transform and preconditioner for parallel,
624 large-scale, integrated hydrologic modeling." Advances in Water Resources **53**: 109-117,
625 <http://dx.doi.org/10.1016/j.advwatres.2012.10.001>

626 Maxwell, R. M., F. K. Chow and S. J. Kollet (2007). "The groundwater-land-surface-atmosphere
627 connection: Soil moisture effects on the atmospheric boundary layer in fully-coupled
628 simulations." Advances in Water Resources **30**(12): 2447-2466, Doi
629 10.1016/J.Advwatres.2007.05.018

630 Maxwell, R. M. and S. J. Kollet (2008). "Interdependence of groundwater dynamics and land-
631 energy feedbacks under climate change." Nature Geosci **1**(10): 665-669,

632 Maxwell, R. M. and S. J. Kollet (2008). "Quantifying the effects of three-dimensional subsurface
633 heterogeneity on hortonian runoff processes using a coupled numerical, stochastic
634 approach." Advances in Water Resources **31**(5): 807-817,

635 Maxwell, R. M., J. D. Lundquist, J. D. Mirocha, S. G. Smith, C. S. Woodward and A. F. B.
636 Tompson (2011). "Development of a coupled groundwater-atmospheric model." Monthly
637 Weather Review doi: **10.1175/2010MWR3392**(139): 96-116,

638 Maxwell, R. M., M. Putti, S. Meyerhoff, J.-O. Delfs, I. M. Ferguson, V. Ivanov, J. Kim, O.
639 Kolditz, S. J. Kollet, M. Kumar, S. Lopez, J. Niu, C. Paniconi, Y.-J. Park, M. S.
640 Phanikumar, C. Shen, E. A. Sudicky and M. Sulis (2014). "Surface-subsurface model
641 intercomparison: A first set of benchmark results to diagnose integrated hydrology and
642 feedbacks." Water Resources Research **50**(2): 1531-1549, 10.1002/2013wr013725

643 Miguez-Macho, G., Y. Fan, C. P. Weaver, R. Walko and A. Robock (2007). "Incorporating
644 water table dynamics in climate modeling: 2. Formulation, validation, and soil moisture
645 simulation." *Journal of Geophysical Research-Atmospheres* **112**(D13): -,
646 Mikkelsen, K. M., R. M. Maxwell, I. Ferguson, J. D. Stednick, J. E. McCray and J. O. Sharp
647 (2013). "Mountain pine beetle infestation impacts: Modeling water and energy budgets at
648 the hill-slope scale." *Ecohydrology* **6**(1): 64-72, 10.1002/eco.278
649 Osei-Kuffuor, D., R. M. Maxwell and C. S. Woodward "Improved numerical solvers for implicit
650 coupling of subsurface and overland flow." *Advances in Water Resources*(0),
651 <http://dx.doi.org/10.1016/j.advwatres.2014.09.006>
652 Osei-Kuffuor, D., R. M. Maxwell and C. S. Woodward (2014). "Improved numerical solvers for
653 implicit coupling of subsurface and overland flow." *Advances in Water Resources* **74**(0):
654 185-195, <http://dx.doi.org/10.1016/j.advwatres.2014.09.006>
655 Qu, Y. and C. J. Duffy (2007). "A semidiscrete finite volume formulation for multiprocess
656 watershed simulation." *Water Resources Research* **43**(W08419): 18,
657 doi:10.1029/2006WR005752
658 Richards, L. A. (1931). "Capillary conduction of liquids in porous mediums." *Physics* **1**: 318-
659 333,
660 Rihani, J. F., R. M. Maxwell and F. K. Chow (2010). "Coupling groundwater and land surface
661 processes: Idealized simulations to identify effects of terrain and subsurface
662 heterogeneity on land surface energy fluxes." *Water Resour. Res.* **46**: 1-14,
663 doi:10.1029/2010WR009111
664 Rodell, M., I. Velicogna and J. S. Famiglietti (2009). "Satellite-based estimates of groundwater
665 depletion in india." *Nature* **460**(7258): 999-1002,
666 Rodriguez-Iturbe, I. and A. Rinaldo (2001). *Fractal river basins: Chance and self-organization*,
667 Cambridge University Press.
668 Schaap, M. G. and F. J. Leij (1998). "Database-related accuracy and uncertainty of pedotransfer
669 functions." *Soil Science* **163**(10): 765-779,
670 Shi, Y., K. J. Davis, C. J. Duffy and X. Yu (2013). "Development of a coupled land surface
671 hydrologic model and evaluation at a critical zone observatory." *Journal of*
672 *Hydrometeorology* **14**(5): 1401-1420, 10.1175/jhm-d-12-0145.1
673 Sudicky, E., J. Jones, Y.-J. Park, A. Brookfield and D. Colautti (2008). "Simulating complex
674 flow and transport dynamics in an integrated surface-subsurface modeling framework."
675 *Geosciences Journal* **12**(2): 107-122, 10.1007/s12303-008-0013-x
676 Sulis, M., C. Paniconi, M. Marrocu, D. Huard and D. Chaumont (2012). "Hydrologic response to
677 multimodel climate output using a physically based model of groundwater/surface water
678 interactions." *Water Resources Research* **48**(12): W12510, 10.1029/2012wr012304
679 Taylor, R. G., B. Scanlon, P. Doll, M. Rodell, R. van Beek, Y. Wada, L. Longuevergne, M.
680 Leblanc, J. S. Famiglietti, M. Edmunds, L. Konikow, T. R. Green, J. Chen, M. Taniguchi,
681 M. F. P. Bierkens, A. MacDonald, Y. Fan, R. M. Maxwell, Y. Yechieli, J. J. Gurdak, D.
682 M. Allen, M. Shamsudduha, K. Hiscock, P. J. F. Yeh, I. Holman and H. Treidel (2013).
683 "Ground water and climate change." *Nature Clim. Change* **3**(4): 322-329,
684 Therrien, R., E. Sudicky, Y. Park and R. McLaren (2012). *Hydrogeosphere: A three-dimensional*
685 *numerical modelling describing fully-*
686 *integrated subsurface and surface flow and transport. User guide. Waterloo, Ontario, Canada,*
687 *Aquanty Inc.*

688 van Genuchten, M. T. (1980). "A closed-form equation for predicting the hydraulic conductivity
689 of unsaturated soils." Soil Science Society of America Journal **44**(5): 892-898,
690 VanderKwaak, J. E. and K. Loague (2001). "Hydrologic-response simulations for the r-5
691 catchment with a comprehensive physics-based model." Water Resources Research
692 **37**(4): 999-1013,
693 Williams, J. L. and R. M. Maxwell (2011). "Propagating subsurface uncertainty to the
694 atmosphere using fully-coupled, stochastic simulations." Journal of Hydrometeorology,
695 doi:10.1175/2011JHM1363.1
696 Wood, B. D. (2009). "The role of scaling laws in upscaling." Advances in Water Resources
697 **32**(5): 723-736, <http://dx.doi.org/10.1016/j.advwatres.2008.08.015>
698 Wood, E. F., J. K. Roundy, T. J. Troy, L. P. H. van Beek, M. F. P. Bierkens, E. Blyth, A. de Roo,
699 P. Döll, M. Ek, J. Famiglietti, D. Gochis, N. van de Giesen, P. Houser, P. R. Jaffé, S.
700 Kollet, B. Lehner, D. P. Lettenmaier, C. Peters-Lidard, M. Sivapalan, J. Sheffield, A.
701 Wade and P. Whitehead (2011). "Hyperresolution global land surface modeling: Meeting
702 a grand challenge for monitoring earth's terrestrial water." Water Resources Research
703 **47**(5): W05301, 10.1029/2010wr010090
704 Xia, Y., K. Mitchell, M. Ek, B. Cosgrove, J. Sheffield, L. Luo, C. Alonge, H. Wei, J. Meng, B.
705 Livneh, Q. Duan and D. Lohmann (2012). "Continental-scale water and energy flux
706 analysis and validation for north american land data assimilation system project phase 2
707 (nldas-2): 2. Validation of model-simulated streamflow." Journal of Geophysical
708 Research: Atmospheres **117**(D3): D03110, 10.1029/2011jd016051
709
710