

1 **Partitioning snowmelt and rainfall in the critical zone: effects of** 2 **climate type and soil properties**

3
4 John C. Hammond^{a*}, Adrian A. Harpold^b, Sydney Weiss^c, Stephanie K. Kampf^a

5
6 ^a Department of Ecosystem Science and Sustainability, Colorado State University, Fort Collins, CO 80523

7 ^b Department of Natural Resources and Environmental Science, University of Nevada, Reno, NV 89557

8 ^c College of Earth, Ocean, and Atmospheric Science, Oregon State University, Corvallis, OR 97331

9 * now at U.S. Geological Survey MD-DE-DC Water Science Center, Baltimore, MD, 21228

10 *Correspondence to:* John Christopher Hammond (john.christopher.hammond@gmail.com)

11 **Abstract**

12
13 Streamflow generation and deep groundwater recharge may be vulnerable to loss of snow, making it important to
14 quantify how snowmelt is partitioned between soil storage, deep drainage, evapotranspiration, and runoff. Based on
15 previous findings, we hypothesize that snowmelt produces greater streamflow and deep drainage than rainfall and
16 that this effect is greatest in dry climates. To test this hypothesis we examine how snowmelt and rainfall partitioning
17 vary with climate and soil properties using a physically based variably saturated subsurface flow model, HYDRUS-
18 1D. We developed model experiments using observed climate from mountain regions and artificial climate inputs
19 that convert all precipitation to rain, then evaluated how climate variability affects partitioning in soils with different
20 hydraulic properties and depths. Results indicate that event-scale runoff is higher for snowmelt than for rainfall due
21 to higher antecedent moisture and input rates in both wet and dry climates. Annual runoff also increases with
22 snowmelt fraction, whereas deep drainage is not correlated with snowmelt fraction. Deep drainage is less affected by
23 changes from snowmelt to rainfall because it is controlled by deep soil moisture changes over longer time scales.
24 Soil texture modifies daily wetting and drying patterns but has limited effect on annual water budget partitioning,
25 whereas increases in soil depth lead to lower runoff and greater deep drainage. Overall these results indicate that
26 runoff may be substantially reduced with seasonal snowpack decline in all climates, whereas the effects of snowpack
27 decline on deep drainage are less consistent. These mechanisms help explain recent observations of streamflow
28 sensitivity to changing snowpack and highlight the importance of developing strategies to plan for changes in water
29 budgets in areas most at risk for shifts from snow to rain.

39 1 Introduction

40

41 Snowmelt is the dominant source of streamflow generation and groundwater recharge in many high elevation and
42 high latitude locations (Regonda et al. 2005; Stewart et al. 2005; Earman et al., 2006; Clow, 2010; Jefferson, 2011;
43 Furey et al., 2012). Soils modulate the partitioning of snowmelt into subsurface storage, deep drainage, evaporative
44 losses and surface runoff. Snow persistence, the fraction of time with snow cover, shows declines around the globe
45 (Hammond et al., 2018b), and these snow losses may lead to changes in water input magnitude and timing (Harpold
46 et al., 2015; Musselman et al., 2017; Harpold and Brooks, 2018). As areas of “at risk snow” become more apparent
47 (Nolin and Daly, 2006), there is an urgent need for mechanistic studies that quantify the partitioning of snowmelt in
48 the critical zone among vapor losses, surface flow, and subsurface flow and storage (Brooks et al., 2015; Meixner et
49 al., 2016).

50

51 Changes in precipitation phase from snow to rain can modify hydrological partitioning by altering the timing and
52 rate of inputs. Daily snowmelt rates typically do not reach the extreme intensities of rainfall (Yan et al., 2018),
53 meaning that most areas (i.e. the Cascades) are predicted to receive more intense water inputs with more winter
54 rainfall, whereas some other areas (i.e. Southern Rockies) will likely experience a decline in input intensity with
55 snow loss (Harpold and Kohler, 2017). Warmer areas like the maritime Western U.S. may experience near complete
56 loss of snowpack as snow fully transitions to rain by the end of the 21st century (Klos et al., 2014). Unlike rainfall,
57 which is typically episodic, snow can accumulate over time and melt as a concentrated pulse of soil water input
58 (Loik et al., 2004). This means that at 7- to 30-day scales snowmelt inputs are of greater magnitude than rainfall
59 (Harpold and Kohler, 2017). Concentrated snowmelt can lead to a large proportion of runoff and deep drainage
60 (Earman et al., 2006; Berghuijs et al., 2014; Li et al., 2017). With climate warming, future snowmelt rates may be
61 reduced in many areas because earlier melt occurs when solar radiation is lower (Musselman et al., 2017). Along
62 with warmer temperatures, increasing atmospheric humidity is leading to more frequent mid-winter melt events in
63 humid regions, yet increased snowpack sublimation and/or evaporation in dry regions (Harpold and Brooks, 2018).
64 Given the considerable heterogeneity in climate, soils, topography, and vegetation across mountain ranges, the water
65 budgets of different locations respond unevenly to a loss of snow.

66

67 Water inputs from rain or snowmelt during periods of low potential evapotranspiration and high antecedent moisture
68 conditions are more likely to generate runoff and deep drainage (Molotch et al., 2009). Prior research has shown that
69 near-surface soil moisture response is closely related to snow disappearance (Harpold and Molotch, 2015; Webb et
70 al., 2015; Harpold et al., 2015) with strong links between snowmelt and soil moisture dynamics at multiple spatial
71 and temporal scales (Loik et al. 2004; Williams et al. 2009; Blankinship et al. 2014; Kormos et al., 2014; Harpold
72 and Molotch, 2015; Webb et al. 2015; Kampf et al. 2015). Earlier snow disappearance can lead to lower average
73 soil moisture conditions not as conducive to streamflow generation as later snowmelt (Kampf et al. 2015; Harpold,
74 2016). The effects of earlier snowmelt on soil moisture dynamics may also vary with precipitation after snowmelt.
75 Late-spring precipitation can overwrite the signal of earlier snowmelt timing on spring and summer soil moisture

76 (Liator et al., 2008, Conner et al., 2016), whereas a lack of spring and summer precipitation can cause effects of
77 earlier snowmelt on soil moisture to persist longer (Blankenship et al, 2014; Harpold, 2016). A transition to earlier,
78 slower, and lesser snowmelt may increase overall evapotranspiration losses (Kim et al., 2016; Foster et al., 2015;
79 Trujillo et al., 2012) while simultaneously decreasing the water use efficiency of conifer forests during snowmelt
80 (Knowles et al., 2018). However, even at a well-studied location in Colorado the projected effects of shifts from
81 snow to rain on tree water use and carbon uptake differ between modeling (Moore et al., 2008; Scott-Denton et al.,
82 2003) and observational studies (Hu et al., 2010; Winchell et al., 2017).

83
84 Both surface runoff and deep drainage are affected by soil texture, soil depth, rooting depth (Cho and Olivera, 2009;
85 Seyfried et al., 2005) and topography. These properties have limited variability over timespans of hydrologic
86 analysis and can produce temporally stable spatial patterns of soil moisture, where some parts of the landscape are
87 consistently wetter than others (Williams et al., 2009; Kaiser and McGlynn, 2018). Aspect modifies the snowpack
88 energy balance, leading to higher sustained soil moisture content on north-facing slopes compared to south-facing
89 slopes with the same input (in the northern hemisphere; Williams et al., 2009; Hinckley et al., 2014; Webb et al.,
90 2015; Webb et al., 2018). Landscape evolution may lead to deeper profiles and more deeply weathered rock due to
91 wetter conditions on north-facing slopes, making these slopes more conducive to deep drainage in some locations
92 (Hinckley et al., 2014; Langston et al., 2015).-Where soils are shallow, winter precipitation may exceed the soil
93 storage capacity, leading to both runoff generation and deep drainage (Smith et al., 2011). Deeper soil profiles have
94 greater storage capacity, which can sustain streamflow, even with snow loss; however, given consecutive years of
95 low input these profiles will be depleted of storage leading to lower flows (Markovich et al., 2016). Deeper soils can
96 also help sustain transpiration during the late spring and summer, when shallow soils have dried (Foster et al. 2016;
97 Jepsen et al., 2016). Streamflow can be insensitive to inputs under dry conditions, but respond rapidly once a
98 threshold soil moisture storage value is exceeded (McNamara et al., 2005; Liu et al., 2008; Seyfried et al., 2009).
99 McNamara et al. (2005) hypothesized that when dry-soil barriers are breached, there is sudden connection to
100 upslope soils, leading to delivery of water to areas that were previously disconnected. In their semi-arid study area,
101 such breaching of dry-soil barriers was only observed for periods of concentrated and sustained input from high-
102 magnitude spring snowmelt. Together, the complex interactions of soil properties, antecedent conditions, water
103 inputs, and evaporative demand make it challenging to determine how changes from snow to rain affect hydrologic
104 response even in idealized settings.

105
106 The goal of this study is to improve our understanding of how changes in precipitation phase from snow to rain
107 affect hydrological partitioning in a one-dimensional (1-D) representation of the critical zone. Partitioning of
108 precipitation input, P , can be into runoff, Q , defined as lateral export of water from the domain, evaporation, E ,
109 transpiration, T , deep drainage below the root zone, D , and storage within the soil root zone, ΔS . Throughout this
110 study, the term runoff refers to non-infiltrated input that exits the domain laterally due to infiltration or saturation
111 excess mechanisms. Over a given time increment, partitioning can be tracked using the water balance (equation 1).

113
$$P = Q + E + T + D + \Delta S \tag{1}$$

114

115 We address the questions: (1) Are snowmelt and rain partitioned differently between Q , ET , and D ? and (2) How is
116 snowmelt and rain partitioning affected by climate, soil type, and soil depth? We use a physically-based 1-D
117 modeling approach to address these questions and systematically test hypotheses about hydrologic response to snow
118 loss. **The 1-D modeling approach allows for isolated comparison of climatic and edaphic factors on input**
119 **partitioning; it is a simplified approach that neglects lateral redistribution of water.**

120

121 We hypothesize that reducing the fraction of precipitation falling as snow leads to lower runoff and deep drainage
122 because it reduces the concentration of input in time (Figure 1). Concentrated input during melt of a seasonal
123 snowpack often saturates soils, causing saturation excess runoff and deep drainage below the root zone (Hunsaker et
124 al., 2012; Kampf et al., 2015; Webb et al., 2015; Barnhart et al., 2016). Diffuse input over time reduces the
125 likelihood of saturation because it allows more water redistribution and evapotranspiration between inputs. We also
126 hypothesize that snowmelt is critical for runoff generation and deep drainage in dry climates and deep soils, where
127 snowmelt is the dominant cause of soil saturation (McNamara et al., 2005; Tague and Peng, 2013), whereas the
128 partitioning of rain and snowmelt may be more similar in wet climates and shallow soils, which are more frequently
129 saturated by either rain or snowmelt inputs (Loik et al., 2004) (Figure 1).

130

131 **2 Methods**

132

133 To evaluate soil moisture response to rainfall and snowmelt over a wide range of climate and soil conditions we
134 used HYDRUS-1D (Šimůnek et al. 1998), a physically-based finite element numerical model for simulating one-
135 dimensional water movement in variably saturated, multi-layer, porous media.

136

137 **2.1 Study design, site selection, and data sources**

138

139 We utilized daily input data from five United States Department of Agriculture Natural Resources Conservation
140 Service (NRCS) snow telemetry (SNOTEL) sites in each of three regions that span a wide range of climate and
141 snow conditions: the Cascades, Sierra Nevada, and Uinta mountains for a total of 15 sites. Daily rather than hourly
142 data were chosen to limit the effects of missing and incorrect values on the analyses. The three regions were chosen
143 to represent dominant climate types in the western U.S., and within each region, sites were selected to span a snow
144 persistence (SP) gradient, where SP is the mean annual fraction of time that an area is snow covered between Jan 1
145 and Jul 3 (Moore et al., 2015) (Figure 2a, Table 1).

146

147 With each climate scenario we simulated vertical profiles of volumetric water content (VWC), which were depth-
148 integrated to compute soil moisture storage (S). For these simulations deep drainage (D) is any flux of water
149 downward below the root zone. Runoff (Q) is any water that does not infiltrate into the soil, either because of

150 saturated conditions or because input rates exceed infiltration capacity. Evaporation (E) is direct evaporation from
151 the soil, and transpiration (T) is mediated by plant roots. For this study, these values are combined into
152 evapotranspiration (ET) to represent the bulk loss of water to the atmosphere.

153 Daily precipitation (P), snow water equivalent (SWE), and volumetric water content (VWC) at 5, 20, and 50 cm
154 were obtained for each SNOTEL site using the NRCS National Weather and Climate Center (NWCC, 2016) Report
155 Generator (Table 1). The records were quality controlled to ensure reasonable precipitation, SWE and VWC values
156 as in Harpold and Molotch (2015). Unrealistic values were removed (i.e. negative SWE, VWC below zero or above
157 unity); all daily VWC outside of three standard deviations from the mean were removed, and a manual screening
158 was performed on VWC data to identify shifts and other artifacts not captured by the first two automated
159 procedures. Daily potential evapotranspiration (PET) was extracted from daily gridMET (Abatzoglou, 2013) for the
160 4 km pixel containing each SNOTEL site. This product uses the ASCE Penman-Monteith method to compute PET.

161
162 We chose three SNOTEL sites (432 Currant Creek, 698 Pole Creek R.S., 979 Van Wyck) to represent soil profile
163 characteristics. While 365 of the 747 SNOTEL sites in the western U.S. have soil moisture sensors, only a fraction
164 of these sites have detailed soil profile data. The sites with soil profile data have information obtained from soil
165 samples taken in the soil pits and processed in the NRCS Soil Survey Laboratory in Lincoln, NE for texture, water
166 retention properties, and hydraulic conductivity. We obtained detailed soil profile data, in the form of pedon primary
167 characterization files from the NRCS, and selected profiles (Figure 2b, Table 2) that represent the range of soil
168 textures and hydraulic conductivity values present at SNOTEL locations. Each had detailed NRCS pedon primary
169 characterizations to depths greater than 100 cm and >15 years of daily soil moisture records at 5, 20 and 50 cm
170 depths.

171 **2.2 Simulations**

172
173 In HYDRUS-1D, we simulated water flow and root water uptake for a vertical domain 10 m deep (Figure 2b). The
174 domain was discretized into 500 nodes with higher node density near the surface (~0.15 cm for top 5 cm to ~5 cm
175 for the bottom of the profile). For the surface boundary, we used a time variable atmospheric boundary condition,
176 which allows specifying input (snowmelt and rain) and potential evapotranspiration (PET) time series. Runoff can
177 also be generated at the surface boundary. For the lower boundary, we allowed free drainage from the bottom of the
178 soil profile at 10 m. Surface soil water input was calculated by totaling snowmelt and rainfall input at the daily time
179 step from SNOTEL precipitation and SWE values. Melt was computed for any day when SWE decreased; if SWE
180 decreased, and the precipitation was greater than 0, total soil water input was assumed to be melt plus precipitation.
181 The atmospheric boundary condition requires PET, leaf area index (LAI), and a radiation extinction coefficient used
182 in the estimation and separation of potential evaporation and transpiration. We assigned a constant LAI of three, as
183 this value generally fits the mixed conifer forests (Jensen et al., 2011) where SNOTEL sites are installed. We
184 assumed a radiative extinction coefficient of 0.39, which is the default value. Root water uptake in the model was
185 estimated using Feddes parameters for a conifer forest (Lv, 2014: h1 0 cm, h2 0 cm, h3h -5,100 cm, h3l -12,800 cm,

186 h4 -21,500 cm, T_{plow} 0.5 cm/d, T_{phigh} 0.1 cm/d), with roots uniformly distributed from the soil surface to the
187 interface with a lower hydraulic conductivity layer, as we lacked any more detailed information on root distribution
188 or soil depth at these sites.

189
190 We created soil layers with depths and textures taken from the NRCS soil pedon measurements. From this
191 information we applied the neural network capability of HYDRUS-1D, which draws from the USDA ROSETTA
192 pedotransfer function model (Schaap et al., 2001), to determine soil hydraulic parameters. Using the NRCS pedon
193 primary characterizations we input percent sand, silt and clay, bulk density, wilting point, and field capacity. The
194 neural network model then estimates soil hydraulic parameters based on these inputs. Below the depth of the soil
195 pedon measurements, we configured the simulations to have a deep “bedrock” or regolith layer with lower saturated
196 hydraulic conductivity (K_s) but the same water retention parameters as the layer above. Any water entering this
197 lower layer is considered deep drainage. The hydraulic conductivity of this lower layer was set at one tenth that of
198 the layer above. This value was determined through iterative testing of K_s values (see Supplementary). We extended
199 the “bedrock” or regolith layer to 10 m depth to allow for deep drainage to occur without boundary effects that could
200 be caused by a shallower regolith. The initial VWC for all layers in each simulation was 0.2, and simulations were
201 run with a year of surface boundary condition inputs to establish initial conditions. We tested the simulation
202 configuration by comparing to observed VWC at 5, 20 and 50 cm depths for the three selected soil profile sites
203 (Figure S1, Table S1). Rather than force-fitting, our goal was to produce simulations with similar timing of wetting
204 and drying to observations. This approach is consistent with other studies using HYDRUS – 1D, which also started
205 with basic soils data and application of the ROSETTA pedotransfer function (Scott et al., 2000) and then calibrated
206 to observed water content measurements by adjusting permeability of the “bedrock” layer (Flint et al., 2008).

207
208 We applied climate scenarios from each of the 15 SNOTEL sites selected (Table 1) to each of the soil profiles to
209 examine how climate and soil type affect partitioning. We then conducted additional experiments to modify inputs
210 using just the loam profile. First to examine whether snowmelt and rainfall are partitioned differently, we changed
211 all precipitation to rain and compared the simulation output to those with the original climate data. **Second, to**
212 **examine the effects of input concentration, the temporal clustering of input through time, we artificially produced**
213 **intermittent input (four five-day periods of low magnitude) and concentrated input (one twenty-day period of high**
214 **magnitude) of the same annual total for one wet (559) and one dry (375) site using the loam profile (1056) for all**
215 **years of data.** Third, to examine how soil depth affects partitioning we altered the depth of rooting zones to 0.5, 1.5
216 and 2 times their original depth. For 0.5 depth scenarios, we replaced soil layers deeper than 0.5 times the original
217 depth with the bedrock/regolith layer. For 1.5x and 2x scenarios, the layer above bedrock/regolith was extended
218 downward, and the rooting zone extended to the new soil depth.

219
220
221
222

223 2.3 Analysis

224

225 Using the simulation results, we examined how rain and snowmelt were partitioned into soil storage (S), deep
226 drainage (D), evapotranspiration (ET), and runoff (Q). Daily soil storage is reported as the total soil water within the
227 rooting zone only, and D is any water passing below the rooting zone (106-127 cm depending on the soil profile).
228 We assessed partition components both in units of length (cm) and as ratios to total input (unitless, e.g. Q/P) at both
229 event and annual time scales.

230

231 To analyze hydrologic partitioning at event time scale we defined rainfall events as days with precipitation while
232 SWE equaled zero and snowmelt events for days with declining SWE and no simultaneous precipitation. To focus
233 on differences between rainfall and snowmelt, only events with entirely rainfall or entirely snowmelt input were
234 considered in this analysis; mixed events were excluded, though mixed input accounts for an average of 47% of
235 annual input across all sites and years (Table S6). Events could last as long as the conditions were continuously
236 satisfied, and only those followed by at least five days of no input were used in analysis. Total depths of each
237 variable were computed for each defined event time period. Input rain and snowmelt were summed over the event
238 time period, and response variables (Q, ET, D) also included the day after the event ended to account for lag in event
239 response. Antecedent S for each event was determined by taking the root zone storage from the day prior to the first
240 event input.

241

242 At the annual scale, soil water input and partitioning components (rain, snowmelt, Q, ET, D) were totaled for each
243 year, and the change in water year storage (ΔS) determined by subtracting the values of S at the end of the year from
244 the value at the beginning of the year. In addition to ΔS , mean saturation (Sat) at each observed depth was calculated
245 as the average annual VWC divided by soil porosity. We use mean saturation (Sat) as an alternative to change in
246 water year storage (ΔS) because mean saturation is much easier to quantify at a field site than root zone storage, and
247 this extends the application of our study to other areas with daily VWC data. Sat also provides a measure of soil
248 water conditions throughout the year as opposed to ΔS , which represents only changes between the start and end of
249 the water year.

250

251 To characterize climate conditions at the mean annual scale, each site was classified as dry (precipitation deficit,
252 $PET > P$) or wet (precipitation surplus, $PET < P$). This separation by aridity index is based on our hypothesis that the
253 influence of concentrated snowmelt is greater in dry climates than in wet climates (Hammond et al, 2018a). We also
254 report the maximum SWE and snowmelt fraction as the annual total snowmelt divided by annual total input.
255 Following the methods for computing the precipitation concentration index (PCI), which represents the continuity or
256 discrete nature of input through time (Martin-Vide, 2004; Raziei et al., 2008; Li et al., 2011), we computed the input
257 concentration index (ICI) using snowmelt and rain input. When calculated with daily data on an annual basis, PCI
258 commonly ranges between 0 and 100, where higher values correspond to precipitation that is irregularly spaced in
259 time and low values correspond to precipitation evenly distributed throughout the year (Cortesi et al., 2012). Our use

260 of the terms input concentration and the input concentration index refer to the temporal clustering of input in time,
261 and do not refer to the intensity of melt. Pearson correlation tests were conducted between explanatory variables (P ,
262 PET, P/PET , peak SWE, average melt rate, and ICI) and dependent variables (Q , ET , D , mean saturation at 100 cm:
263 Sat100).

264
265 Using both the event and annual results, we examined (1) whether partitioning of rainfall input differed from that of
266 snowmelt input, and (2) how partitioning was affected by climate, soil texture, and soil depth. For question 1, we
267 tested for differences in event partitioning between input type (rain or snowmelt) and differences in annual
268 partitioning between historical and all rain scenarios using ANOVA. For question 2, we tested for differences in
269 annual partitioning between climate (wet, dry) and soil depth groupings, also using ANOVA. Additionally, for
270 question 2 we tested the pairwise difference in linear regression slopes using the regression with interaction test in
271 JMP (SAS-based statistical software) to determine whether the rate of change between explanatory and response
272 variable differed by climate or soil depth grouping. By comparing the slopes of regressions run on standardized data,
273 it is possible to assess the influence of independent variables on dependent variables in different groupings. In this
274 study, we use this test to assess the influence of snowmelt fraction of input and input concentration index on runoff
275 and deep drainage response for all, wet and dry groupings as well as soil texture groupings.

276

277 3 Results

278

279 Simulations for each of the 15 climate scenarios exhibit substantial variability at the annual scale in precipitation
280 (P), runoff (Q), and deep drainage (D) (Figure 3). All regions have a wide range of annual P , but overall the highest
281 P was in the Cascades region and lowest in the Uinta. The wide range of climate conditions simulated allows for an
282 evaluation of climate effects on Q , ET , D , and Sat100 (Table S3). Annual precipitation (P) is positively correlated
283 with runoff (Q , $r=0.97$), deep drainage (D , $r=0.92$), and Sat100 ($r=0.73$) (Table S3). The relationship is linear for Q
284 but nonlinear for D and Sat100. Sat100 plateaus at ~250 cm P with further P partitioned to Q instead of D .
285 Evapotranspiration (ET) has the weakest correlations with P ($r=0.08$) of all partitioned components. Q/P increases
286 with P up to around 250 cm of P , and D/P increases with P up to around 100 cm (Figure 3). ET/P decreases with
287 precipitation, whereas $\Delta S/P$ is unrelated to P . At values of P greater than around 300 cm, all variables have
288 relatively consistent values even as P increases.

289

290 3.1 Snowmelt vs rainfall and climatic influences on partitioning

291

292 Our first research question asks whether snowmelt and rainfall are partitioned differently. At the event scale, input
293 rates are significantly greater on average for snowmelt than for rainfall in each of the three regions and for the full
294 dataset (ANOVA $p<0.0001$, mean snowmelt 1.1 cm/d, mean rainfall 0.9 cm/d, Figure 4), though rainfall events have
295 a higher maximum input rate (maximum snowmelt 8.0 cm/d, maximum rainfall 14.7 cm/d). Snowmelt events tend to
296 occur on wetter soils, as estimated by antecedent soil moisture storage for the rooting zone (ANOVA $p<0.0001$,

297 mean S for snowmelt 56.6 cm, mean S for rainfall 48.2 cm). Average runoff ratios (Q/P) are higher for snowmelt
298 than for rainfall (ANOVA $p < 0.0001$, mean Q/P snowmelt 0.20, mean Q/P rainfall 0.03), whereas ET/P is lower for
299 snowmelt as compared to rainfall (mean snowmelt 0.24, mean rainfall 0.40). Deep drainage responses are affected
300 by longer time scales than single events, so we did not include these in the event analysis. This event analysis only
301 considered binary snowmelt or rainfall events.

302
303 At the annual scale, input at all sites is a mixture of rain and snowmelt. To examine the importance of snow to
304 partitioning, we used snowmelt fraction, defined as the fraction of snowmelt to total precipitation, and input
305 concentration index (ICI). Snowmelt fraction and snow persistence are generally positively correlated with ICI at
306 dry sites in the Uinta and Sierra, but this correlation declines with wetter sites in the Cascades (Figure S7). Q/P
307 increases with snowmelt fraction ($r = 0.41$), most noticeably where snowmelt fraction is > 0.5 , and increases with ICI
308 ($r = 0.80$) (Figure 5). The ranges of Q/P are higher in wet than in dry climates, though dry climates show greater rates
309 of change with increasing snowmelt fraction and input concentration (Table S4). D/P is somewhat correlated with
310 snowmelt fraction ($r = 0.20$) and ICI ($r = 0.43$). D/P ranges are higher in wet than in dry climates, and many years in
311 dry climates do not generate D . ET/P is not related to snowmelt fraction and generally declines with ICI ($r = -0.75$).
312 Ranges are lower for wet climates, where greater input is partitioned to Q and D .

313
314 We then compared the hypothetical scenarios where we treated all precipitation as rain to snow-dominated historical
315 scenarios. All rain leads to significantly lower Q/P ($p < 0.0001$, all rain mean 0.17; historical mean 0.31) for both wet
316 and dry sites (Table 3, Figure 6). This partly relates to lower near-surface saturation in all rain scenarios. The mean
317 fraction of annual runoff from saturation excess is 88% when all input is rain as compared to 97% with historical
318 rain and snow input. All rain also leads to higher ET/P for dry sites ($p < 0.0001$, all rain mean 0.95; historical mean
319 0.83); lower D/P for dry sites (all rain mean 0.01; historical mean 0.03), and higher D/P at wet sites ($p = 0.011$, all
320 rain mean 0.14; historical mean 0.12) (Table 3, Figure 6).

321
322 Another effect of snow loss can be a decrease in input concentration. Experimental scenarios with constant P
323 separated into intermittent and concentrated inputs for a wet site (375) and a dry site (559) show that increasing
324 input concentration leads to significantly greater Q/P in the dry site ($p < 0.05$, intermittent mean 0.54, concentrated
325 mean 0.68, Table 3, Figure 6) but no significant difference in the wet site. In contrast, D/P is significantly greater
326 ($p < 0.0001$) for the concentrated input scenarios for both dry and wet sites, as no deep drainage is produced with
327 intermittent input. ET/P is significantly lower in concentrated input scenarios, with a greater difference in dry
328 climates ($p = 0.004$, mean intermittent 0.80 vs. concentrated 0.66) than in wet climates ($p = 0.013$, mean intermittent
329 0.34 vs. concentrated 0.28).

330
331
332
333

334 3.2 Soil property influences on partitioning

335

336 Soil stores water that may later be partitioned into Q , ET , and D . Using Sat100 as an indicator of soil moisture
337 storage, Figure 7 displays the relationships between Q/P , D/P and ET/P vs Sat100 as separated by climate type, soil
338 texture, and root zone depth. Sat100 has strong relationships with Q/P , D/P , and ET/P for all, wet, and dry sites
339 (Figure 7, Table S5). Q/P is generally low (Figure 7a, <0.3) until Sat100 is greater than >0.5 . D/P in the simulations
340 also increases with Sat100, and many simulation years have limited D when Sat100 <0.5 . ET/P generally decreases
341 with saturation for Sat100 values >0.5 .

342

343 When these same relationships are separated by soil texture rather than wet/dry climate (Figure 7b, Table S5), the
344 response patterns are similar between soil types except for the sandy loam profile, which displays higher Q/P and
345 D/P than the loam and sandy clay loam profiles at similar Sat100 levels. Differences between responses by soil
346 texture are more evident at sub-annual time scales (Figure 8a). For the example time period shown in Figure 8a, the
347 100 cm depth in loam and sandy clay loam profiles wet up each spring during snowmelt 5 days prior to the sandy
348 loam profile, and they generated deep drainage earlier and on more occasions than sandy loam due to higher water
349 retention. The latter soils ultimately reached the highest annual D/P values at higher Sat100 values, leading to more
350 runoff generation via saturation excess, whereas the drier conditions in sandy loam led to more infiltration excess
351 runoff. While this example time period and site displays noticeable differences in cumulative response between soil
352 textures, when the data for all sites and years are combined few significant differences in annual partitioning
353 between soil textures emerge (Figures 6,7).

354

355 To assess the influence of soil profile depths on partitioning, we altered the loam soil profile to be 0.5x, 1.5x and 2x
356 times its original depth (Figure 6, Table 3). For historical input, Q/P and D/P are greatest for the 0.5x depth
357 scenario, and Q/P declines significantly with deeper soils for both dry and wet sites ($p<0.0001$), with the greatest
358 declines between 0.5x and 1x (original) depth. D/P declines significantly between 0.5x and 1x depth, then increases
359 slightly for all sites with subsequent increases in depth to 1.5x and 2x (Figure 6, Table 3). Q/P and D/P differences
360 by depth are significant between 0.5x and 1x depth, but not for all subsequent depth comparisons for all, wet and dry
361 site classifications (Table 3). In pairwise comparisons between depth scenarios Q/P is only significantly different
362 between 0.5x and 1x depth categories ($p<0.0001$). Changes in ET/P with soil depth are not significant according to
363 ANOVA tests.

364

365 Figure 8b displays daily time series of surface runoff, deep saturation, deep drainage, and cumulative deep drainage
366 during an example period for the four different soil root zone depth scenarios. The shallowest rooting zone of 0.5x
367 original depth produces the greatest surface runoff as well as cumulative deep drainage throughout the example
368 period. Each depth reaches and remains at saturation for different amounts of time, with the shallowest profile
369 reaching saturation earliest and remaining saturated longest, but also decreasing more rapidly to the lowest ending
370 saturation. The deepest profile takes the longest to increase Sat100, not reaching as high a peak, yet remaining

371 higher at the end of the period. Deep drainage begins earliest for the shallowest depth scenario, though reaching a
372 lower daily flux than the original depth. Deep drainage from the 1x 1.5x and 2x original depth scenarios lag behind
373 the 0.5x scenario following the same succession as their Sat100 patterns. These patterns in daily Sat100 and deep
374 drainage result in the highest cumulative deep drainage for the shallowest scenario.

375

376 **4 Discussion**

377

378 **4.1 Snowmelt as an efficient runoff generator and factors accentuating snowmelt efficiency**

379

380 The initial hypotheses for this study were that runoff and deep drainage would be greater from snowmelt than
381 rainfall, and that snowmelt is more important to generating runoff and deep drainage in deep soils and dry climates
382 than in shallow soils and wet climates. Our results indicate that snowmelt is an efficient runoff generator, though not
383 necessarily an efficient generator of deep drainage. Deep drainage is less affected by input type because it is
384 controlled by deep soil moisture patterns over longer time scales. Soil texture modifies daily wetting and drying
385 patterns but has limited overall effects on annual partitioning, whereas increases in soil depth decrease runoff and
386 increase deep drainage. Overall these results indicate that runoff may be substantially reduced with seasonal
387 snowpack decline in all climates, whereas the effects of snowpack decline on deep drainage are less consistent. We
388 expand on these key findings in the paragraphs below and suggest that areas in dry watersheds with storage similar
389 to peak SWE may be most likely to experience reductions in deep drainage with continued slow loss.

390

391 Multiple lines of evidence confirm snowmelt as a more efficient runoff generator on average than rainfall. At event
392 scale runoff efficiency was elevated for snowmelt because of the 22% greater input rate and 17% wetter soils than
393 rainfall. This is consistent with previous studies showing that snowpack development and subsequent melt tend to
394 occur when soils are at elevated moisture contents due to lower *ET* (Liu et al., 2008; Williams et al., 2009; Bales et
395 al., 2011). The effects of snowmelt vs. rainfall are weaker at annual time scales (Figure 5, Table S3) because these
396 longer time periods include a combination of snow, mixed, and rainfall inputs in contrast to the event analysis in
397 which we analyzed only events that were exclusively snowmelt or rainfall-dominated. Forcing all input into the
398 extreme case of all rain produces 67% declines in runoff efficiency (Dry: 0.13 vs. 0.04; Wet: 0.46 vs. 0.29) (Table 3,
399 Figure 6), likely because the input becomes less concentrated in time for the all rain scenario, allowing more *ET*. We
400 also hypothesized that the effects of changing snowpacks would be greatest in dry climates, where soil saturation is
401 less frequent. However, simulations suggest that both wet and dry climates are as likely to show reduced surface
402 runoff with declining snow water inputs.

403

404 The effects of snow loss on *D* were not as consistent across our simulations as the effects on *Q*. Prior research has
405 demonstrated strong seasonality in groundwater recharge, attributable to thresholds in input intensity (Jasechko and
406 Taylor, 2015) and seasonal differences in evapotranspiration (Jasechko et al., 2014; Jasechko et al., 2017). We had
407 hypothesized based on additional research (Hunsaker et al., 2012; Langston et al., 2015; Barnhart et al., 2016; Li et
408 al., 2017; Hammond et al., 2018a) that input concentration along with evapotranspiration seasonality, would be the

409 primary reason for elevated Q and D from snowmelt relative to rainfall. In this study, changes from snow to rain
410 both increased and decreased D/P (Figure 6, Figure S2), and D/P was not correlated with either snowmelt fraction or
411 ICI in wet climates. In general, Q/P was greater than D/P , and the D/P response to changing input was weaker
412 because S mediates the connection between input and D . In the 1D model Q is affected by infiltration rate and near-
413 surface storage and can more rapidly respond to input changes. In the simulations shown here once subsurface
414 storage is zero, D will plateau, and Q will increase with further input due to the saturation excess mechanism.
415 Although these processes were simulated in 1-D, they are consistent with observations of saturation excess overland
416 flow documented in the elevation bands of many SNOTEL sites (Newman et al., 2004; Eiriksson et al., 2013;
417 Kampf et al., 2015). In wet climates, D/P is less affected by input type because conditions are more likely to be wet,
418 regardless of whether input is snow or rain. D/P is more affected by changes from snow to rain in dry climates,
419 likely because of the role that concentrated snowmelt can play in allowing water to reach the base of the soil
420 column.

421
422 Soil texture and depth generally did not change partitioning at the annual time scale as much as the varying climate
423 scenarios (Figure 6), with the exception of changes in the shallowest soils (1x depth to 0.5x depth results in 12% Q
424 increase, 180% D increase). D/P generally increased with increasing soil depth, demonstrating the importance of
425 lower boundary conditions to shallow versus deep partitioning. Altering soil profile depth and the associated root
426 zone depth produced the largest effects on Q/P and D/P from 0.5x to 1x depth. The responsiveness of fluxes to
427 changes in soil depth from 0.5-1x may relate to storage capacity relative to input. The soil depths ranged from 106-
428 127 cm, which with a porosity of 0.4 gives a storage capacity of 42-51 cm, large enough to store the mean annual
429 precipitation in some dry watersheds. When this storage was reduced by half to 21-25 cm, it is smaller than the
430 mean annual precipitation at the wetter sites, increasing the likelihood of soil saturation that leads to D and Q .
431 Consequently, the change in profile depth from 0.5 m to 1 m represents a shift from annual input greatly exceeding
432 profile storage, to storage approximately accommodating annual input. At the sites used in this study, mean annual P
433 ranged from 0.8 to 11.3 times the storage of the 1x soil profile, and peak SWE ranges from 0.1 to 5.9 times the
434 storage. Prior field-based studies have also documented SWE that is similar in magnitude to the maximum amount
435 of water storage in the upper meter of soil (Bales et al. 2011) and have shown that reducing soil depth increases
436 surface runoff and deep drainage (Smith et al., 2011).

437
438 Focusing on the influence of soil texture, simulations indicate that shorter durations of deep drainage for the coarser
439 sandy loam compared to the finer texture soils are offset by higher rates of flux during deep drainage in the coarser
440 profile (Figure 8a). Similarly, lower likelihood of surface saturation in the sandy loam soil compared to other soils is
441 offset by greater likelihood of infiltration excess runoff. Therefore, in this 1-D approach, soil depth exerts a stronger
442 control on annual total input partitioning to Q and D , whereas soil texture has limited effect on annual partitioning
443 but can affect the timing of partitioning and water availability during different times of year. In natural landscapes,
444 texture differences can result in spatially variable soil moisture (Williams et al. 2009; Kaiser and McGlynn 2018).
445 Combined variations in soil texture and depth within a watershed may result in significant differences in soil

446 moisture storage across the basin (Bales et al, 2011), resulting in substantial differences in response throughout a
447 watershed. The distribution of soil water storage capacity across the watershed likely exerts a strong control on
448 locations where surface runoff, streamflow generation, and deep drainage are most efficiently generated especially
449 in dry watersheds where soil moisture is generally low except during snowmelt (Atkinson et al., 2002; Seyfried et
450 al., 2009). Additionally, unsaturated soil water storage may be the dominant control on streamflow activation during
451 dry periods, while total input depth is the dominant control on streamflow generation during wetter periods (Farrick
452 and Branfireun, 2014). Combining the role of soil storage capacity in space and time, areas in dry watersheds with
453 storage similar to peak SWE may be most likely to experience reductions in deep drainage with continued slow loss.

454

455 **4.2 Limiting assumptions**

456

457 Given the complex nature of soil water movement in heterogeneous mountain topography, this study makes several
458 assumptions and simplifications. The simulations do not include the intricacies of vegetation water use, assuming a
459 static leaf area index (LAI) with root uptake controlled only by PET and soil moisture, and we assume free drainage
460 from the bottom boundary of the modeled domain. Changing static LAI has a substantial effect on soil moisture
461 dynamics (Chen et al., 2014), though model performance to match simulated and observed soil moisture does not
462 necessarily improve with the assimilation of dynamic LAI values (Pauwels et al., 2007). Incorporating site specific
463 constant LAI from field measurements or remotely sensed data may have improved model performance especially
464 during spring green up and fall senescence and is recommended for future site specific studies. The water balance in
465 hydrologic models can be highly sensitive to the method chosen to represent root uptake and plant water use (Gerten
466 et al., 2004), and hydrologic models generally poorly capture or replicate the interactions between soil, vegetation
467 and atmospheric properties that combine to control plant water use (Gómez-Plaza et al., 2001; Gerten et al., 2004;
468 Zeng et al., 2005). In addition, we did not allow for frozen soils in our simulations, but this can be a strong influence
469 on soil input partitioning in places where snow depth was <50 cm and incapable of insulating the soil (Slater et al.,
470 2017).

471

472 Additionally, simulations are generally wetter than measured water contents; therefore, the representation of
473 partitioning shown here displays relative response between climates and soil profiles rather than absolute
474 quantification of these partitioned components. The profile depths we simulated represent the minimum likely soil
475 depth, as the collection of the pedon reports was limited by the depth of refusal for sample collection. Shallow soil
476 profiles can also lead to a wet bias in simulations, and this can artificially elevate saturation excess flow leading to
477 our observations of greater Q/P than D/P in most site-years. Our modeled domain included an extended “bedrock”
478 or regolith layer to 10 m depth to allow for deep drainage without lower boundary effects. The choice of lower
479 boundary condition affects the simulation of soil moisture and water balance partitioning with free drainage
480 generally resulting in lower soil moisture, evapotranspiration and runoff than with a no-flux boundary condition
481 controlled by an impervious layer or fluctuating water table (Chen et al., 2018). We created a domain much deeper
482 than the soil zone to minimize this boundary condition effect; effects of lower boundary conditions are generally

483 seen in deeper layers of the soil profile and during transition periods between soil water input events when capillary
484 rise can influence transpiration and deep drainage (Leterme et al., 2012; Brantley et al., 2017). Though a no-flux
485 boundary condition may be appropriate for sites where relatively shallow water tables exert a strong influence on
486 soil moisture dynamics, the inclusion of a no-flux lower boundary for the sites in this study would have made
487 simulations wetter, furthering the difference between observed and modeled VWC.

488
489 Sub-daily dynamics in snow melt and ET are not captured by our use of a daily time step. We chose to model soil
490 water response to rainfall and snowmelt at the daily time step due to better data quality, but processes affecting
491 partitioning of these inputs take place at sub-daily scales. Comparisons of results from simulations using daily vs
492 hourly input demonstrate similar timing of response, but greater cumulative surface runoff from hourly simulations
493 and greater cumulative deep drainage from daily simulations (Table S2). The short hourly time period allows for
494 higher intensity input, which causes infiltration excess overland flow, whereas daily input is of lower intensity,
495 allowing for greater deep percolation. Additionally, SNOTEL sites do not have measured values of PET, so we
496 relied on a modeled 4km gridded product (Abatzoglou, 2013), which may better represent some sites than others. It
497 was beyond the scope of this study to perform a sensitivity analysis of PET data source.

498
499 Hydrologic response in hillslopes and catchments is not fully captured in the 1-D modelling approach. Water
500 partitioned into Q and D in a 1-D model may not represent the same Q and D observed at a stream: Q generated at a
501 point location may infiltrate downslope; D may also emerge downslope to supply streamflow rather than
502 remaining in the deep subsurface. Topography affects both soil moisture and snow patterns (Western et al., 2004;
503 Liator et al., 2008; Williams et al., 2009; Brooks et al., 2015), and it leads to lateral surface or subsurface flow,
504 which can be important in redistributing water downslope along the soil snow interface (Webb et al., 2018) and
505 within the shallow subsurface (Kampf et al., 2015, Kim et al., 2016). Lateral redistribution of water thus leads to
506 spatially variable patterns of input, storage, runoff generation, and ET at the hillslope to watershed scales (Brooks et
507 al., 2015). While simulating only vertical flow is reasonable for SNOTEL sites located in relatively flat forest
508 openings, 1-D simulations will tend to be biased wet because they do not allow any lateral redistribution. A
509 progression of the work shown here would be to simulate 3-D flow (ex. Weiler et al., 2007; Seyfried et al., 2009)
510 and examine the spatial variability in effects of snow loss. For example, a decline in deep drainage near a ridge line,
511 where flow paths are predominantly vertical could reduce subsurface flow emergence at downslope locations, and
512 this decreased groundwater emergence may reduce ET in areas where vegetation is reliant on the emergence of
513 deeper flow paths.

514
515 The simulations used here only allow for matrix flow, excluding macropore flow, for a simplified representation of
516 soil water movement. Preferential flow though the profile can enhance deep drainage relative to surface runoff,
517 which is another potential reason why soil moisture simulations were biased wet. 60-80% of deep drainage has been
518 shown to occur as preferential rather than interstitial flow (Wood et al., 1997; Jaynes et al., 2001; Sukhija et al.,
519 2003), although the amount of preferential flow varies substantially between climates and soils. The magnitudes of

520 fluxes in our simulations are consistent with observation studies, however, lending more confidence to the simplified
521 modeling approach. Simulated annual D/P for dry climates (~ 0.05) is similar to values reported from observations
522 (Wood et al., 1997). The simulated Q/P ($\sim 0.0-0.9$) vs snowmelt fraction plots from HYDRUS-1D simulations
523 follow the same general increasing pattern ($r = 0.41$) as observed Q/P ($\sim 0.0-1.0$) vs SP in Hammond et al., 2018a (r
524 $= 0.39$).

525
526 Future work could examine the potential sensitivity of the results to these limiting assumptions, In particular,
527 researchers could examine the extent to which adding spatially and temporally varying vegetation processes and/or
528 preferential flow pathways would change water balance partitioning. Simulations could expand to two dimensions to
529 examine how downslope affects partitioning from ridgelines to valley bottoms or to three dimensions to examine
530 effects of flow convergence and exfiltration in hillslope hollows. Because of the complexity of subsurface
531 properties, this work would also benefit from more information about the hydraulic properties of the deep subsurface
532 below the measured soil pedons. This could be linked with model analyses examining how both subsurface
533 properties and boundary conditions affect the simulations.

534

535 **5 Conclusions**

536

537 This study helps to explain the mechanisms that lead to greater runoff from snowmelt. At event scale snowmelt
538 generates more runoff because it tends to have a greater input rate and occurs on wetter soils than rainfall. Seasonal
539 snowmelt elevates runoff in both wet and dry climates. Deep drainage can also decline with loss of snow, but it has a
540 weaker response because soil storage buffers the impacts of snow loss. Soil properties can mediate the effects of
541 snowmelt to rainfall changes, with soil depth having a greater effect than texture on input partitioning, particularly
542 where soil water storage is less than mean annual precipitation. Soils that are shallower than observed soil depths
543 generate the greatest runoff and deep drainage, indicating that shallow soils may show the largest changes in
544 partitioning as input transitions from snowmelt to rainfall. Increasing soil depth above observed depths gradually
545 reduces surface runoff while increasing deep drainage. Soil texture modifies short-term timing of soil moisture and
546 runoff generation, but these effects are not large enough to alter the annual response of different soil types to
547 changes in snow. The 1-D simulations provide basic hypotheses for hydrologic partitioning under changing
548 snowmelt that should be further explored with 2-D or 3-D hydrological models and direct observations. Although
549 more work is necessary to translate these findings to watershed-scale streamflow response, the findings highlight the
550 importance of precipitation phase shifts on runoff generation and groundwater recharge.

551

552 **Author Contributions**

553 JH, AH and SK designed the experiments and JH and SW carried them out. JH and SW performed the simulations.
554 JH conducted statistical analyses on model outputs. JH prepared the manuscript with contributions from all co-
555 authors.

556 **Competing interests**

557 The authors declare that they have no conflict of interest.

558 **Acknowledgements**

559 This research was supported by the US National Science Foundation: NSF EAR 1446870.

560

561 **References**

562 Abatzoglou, J. T.: Development of gridded surface meteorological data for ecological applications and modelling,
563 Int. J. Climatol., doi:10.1002/joc.3413, 2013.

564

565 Atkinson SE, Woods RA, Sivapalan M.: Climate and landscape controls on water balance model complexity over
566 changing timescales. *Water Resources Research* 38(12): 1314, DOI:10.1029/2002WR001487, 2002.

567

568 Bales, R. C., Hopmans, J. W., O'Geen, A. T., Meadows, M., Hartsough, P. C., Kirchner, P., Hunsaker, C. T. and
569 Beaudette, D.: Soil Moisture Response to Snowmelt and Rainfall in a Sierra Nevada Mixed-Conifer Forest, *Vadose*
570 *Zo. J.*, 2011.

571

572 Barnhart, T. B., Molotch, N. P., Livneh, B., Harpold, A. A., Knowles, J. F. and Schneider, D.: Snowmelt rate
573 dictates streamflow, *Geophys. Res. Lett.*, doi:10.1002/2016GL069690, 2016.

574

575 Berghuijs, W. R., Woods, R. A. and Hrachowitz, M.: A precipitation shift from snow towards rain leads to a
576 decrease in streamflow, *Nat. Clim. Chang.*, doi:10.1038/nclimate2246, 2014.

577

578 Blankinship, J. C., Meadows, M. W., Lucas, R. G. and Hart, S. C.: Snowmelt timing alters shallow but not deep soil
579 moisture in the Sierra Nevada, *Water Resour. Res.*, doi:10.1002/2013WR014541, 2014.

580

581 Brantley, S. L., Lebedeva, M. I., Balashov, V. N., Singha, K., Sullivan, P. L., and Stinchcomb, G.: Toward a
582 conceptual model relating chemical reaction fronts to water flow paths in hills. *Geomorphology*, 277, 100-117,
583 2017.

584

585 Brooks, P. D., Chorover, J., Fan, Y., Godsey, S. E., Maxwell, R. M., McNamara, J. P. and Tague, C.: Hydrological
586 partitioning in the critical zone: Recent advances and opportunities for developing transferable understanding of
587 water cycle dynamics, *Water Resour. Res.*, doi:10.1002/2015WR017039, 2015.

588

589 Broxton, P. D., Harpold, A. A., Biederman, J. A., Troch, P. A., Molotch, N. P., and Brooks, P. D.: Quantifying the
590 effects of vegetation structure on snow accumulation and ablation in mixed-conifer forests. *Ecohydrology*, 8(6),
591 1073-1094, 2015.

592

593 Chen, M., Willgoose, G. R., and Saco, P. M.: Spatial prediction of temporal soil moisture dynamics using
594 HYDRUS-1D. *Hydrological Processes*, 28(2), 171-185, 2014.

595

596 Chen X D, Liang X, Xia J, and She D X.: Impact of lower boundary condition of Richards' equation on water,
597 energy, and soil carbon based on coupling land surface and biogeochemical models. *Pedosphere*.28(3): 497-510,
598 2018.

599

600 Cho, H. and Olivera, F.: Effect of the spatial variability of land use, soil type, and precipitation on streamflows in
601 small watersheds, *J. Am. Water Resour. Assoc.*, doi:10.1111/j.1752-1688.2009.00315.x, 2009.

602

603 Clow, D. W.: Changes in the timing of snowmelt and streamflow in Colorado: A response to recent warming, *J.*
604 *Clim.*, doi:10.1175/2009JCLI2951.1, 2010.

605

606 Conner, L. G., Gill, R. A., and Belnap, J.: Soil moisture response to experimentally altered snowmelt timing is
607 mediated by soil, vegetation, and regional climate patterns. *Ecohydrology*, 9(6), 1006-1016, 2016.

608

609 Cortesi, N., González-Hidalgo, J. C., Brunetti, M., and Martín Vide, J.: Daily precipitation concentration across
610 Europe 1971-2010. *Natural Hazards And Earth System Sciences*, 2012, vol. 12, p. 2799-2810, doi:10.5194/nhess-
611 12-2799-2012, 2012.

612

613 Earman, S., Campbell, A. R., Phillips, F. M. and Newman, B. D.: Isotopic exchange between snow and atmospheric
614 water vapor: Estimation of the snowmelt component of groundwater recharge in the southwestern United States, *J.*
615 *Geophys. Res. Atmos.*, doi:10.1029/2005JD006470, 2006.

616

617 Eiriksson, D., Whitson, M., Luce, C. H., Marshall, H. P., Bradford, J., Benner, S. G., Black, T., Hetrick, H. and
618 Mcnamara, J. P.: An evaluation of the hydrologic relevance of lateral flow in snow at hillslope and catchment scales,
619 *Hydrol. Process.*, doi:10.1002/hyp.9666, 2013.

620

621 **Farrick, K. K. and Branfireun, B. A.: Soil water storage, rainfall and runoff relationships in a tropical dry forest**
622 **catchment. *Water Resources Research*, 50(12), 9236-9250, 2014.**

623

624 Flint, A. L., Flint, L. E. and Dettinger, M. D.: Modeling Soil Moisture Processes and Recharge under a Melting
625 Snowpack, *Vadose Zo. J.*, doi:10.2136/vzj2006.0135, 2008.

626

627 Furey, P. R., Kampf, S. K., Lanini, J. S. and Dozier, A. Q.: A Stochastic Conceptual Modeling Approach for
628 Examining the Effects of Climate Change on Streamflows in Mountain Basins, *J. Hydrometeorol.*, doi:10.1175/jhm-
629 d-11-037.1, 2012.

630

631 Gerten, D., Schaphoff, S., Haberlandt, U., Lucht, W. and Sitch, S.: Terrestrial vegetation and water balance -
632 Hydrological evaluation of a dynamic global vegetation model, *J. Hydrol.*, doi:10.1016/j.jhydrol.2003.09.029, 2004.

633

634 Gómez-Plaza, A., Martínez-Mena, M., Albaladejo, J. and Castillo, V. M.: Factors regulating spatial distribution of
635 soil water content in small semiarid catchments, *J. Hydrol.*, doi:10.1016/S0022-1694(01)00483-8, 2001.

636

637 Hammond, J. C., Saavedra, F. A. and Kampf, S. K.: How Does Snow Persistence Relate to Annual Streamflow in
638 Mountain Watersheds of the Western U.S. With Wet Maritime and Dry Continental Climates?, *Water Resour. Res.*,
639 doi:10.1002/2017WR021899, 2018.

640

641 Hammond, J. C., Saavedra, F. A. and Kampf, S. K.: Global snow zone maps and trends in snow persistence 2001–
642 2016, *Int. J. Climatol.*, doi:10.1002/joc.5674, 2018.

643

644 Harpold, A. A. and Kohler, M.: Potential for Changing Extreme Snowmelt and Rainfall Events in the Mountains of
645 the Western United States, *J. Geophys. Res. Atmos.*, doi:10.1002/2017JD027704, 2017.

646

647 Harpold, A. A.: Diverging sensitivity of soil water stress to changing snowmelt timing in the Western U.S., *Adv.*
648 *Water Resour.*, doi:10.1016/j.advwatres.2016.03.017, 2016.

649

650 Harpold, A. A. and Brooks, P. D.: Humidity determines snowpack ablation under a warming climate, *Proc. Natl.*
651 *Acad. Sci.*, doi:10.1073/pnas.1716789115, 2018.

652

653 Harpold, A. A. and Molotch, N. P.: Sensitivity of soil water availability to changing snowmelt timing in the western
654 U.S., *Geophys. Res. Lett.*, doi:10.1002/2015GL065855, 2015.

655

656 Harpold, A. A., Molotch, N. P., Musselman, K. N., Bales, R. C., Kirchner, P. B., Litvak, M. and Brooks, P. D.: Soil
657 moisture response to snowmelt timing in mixed-conifer subalpine forests, *Hydrol. Process.*, doi:10.1002/hyp.10400,
658 2015.

659

660 Hinckley, E. L. S., Ebel, B. A., Barnes, R. T., Anderson, R. S., Williams, M. W. and Anderson, S. P.: Aspect control
661 of water movement on hillslopes near the rain-snow transition of the Colorado Front Range, *Hydrol. Process.*,
662 doi:10.1002/hyp.9549, 2014.

663

664 Hu, J., Moore, D. J. P., Burns, S. P. and Monson, R.: Longer growing seasons lead to less carbon sequestration by a
665 subalpine forest, *Glob. Chang. Biol.*, doi:10.1111/j.1365-2486.2009.01967.x, 2010.
666

667 Hunsaker, C. T., Whitaker, T. W. and Bales, R. C.: Snowmelt Runoff and Water Yield Along Elevation and
668 Temperature Gradients in California's Southern Sierra Nevada, *J. Am. Water Resour. Assoc.*, doi:10.1111/j.1752-
669 1688.2012.00641.x, 2012.
670

671 Jasechko, S., Birks, S. J., Gleeson, T., Wada, Y., Fawcett, P. J., Sharp, Z. D., McDonnell, J. J., and Welker, J. M.:
672 The pronounced seasonality of global groundwater recharge, *Water Resour. Res.*, 50, 8845–8867, doi:10.1002/
673 2014WR015809, 2014.
674

675 Jasechko, S., and Taylor, R. G.: Intensive rainfall recharges tropical groundwaters. *Environmental Research*
676 *Letters*, 10(12), 124015, 2015.
677

678 Jasechko, S., Wassenaar, L. I., and Mayer, B.: Isotopic evidence for widespread cold-season-biased groundwater
679 recharge and young streamflow across central Canada. *Hydrological processes*, 31(12), 2196-2209,
680 <https://doi.org/10.1002/hyp.11175>, 2017.
681

682 Jaynes, D. B., Ahmed, S. I., Kung, K.-J. S. and Kanwar, R. S.: Temporal Dynamics of Preferential Flow to a
683 Subsurface Drain, *Soil Sci. Soc. Am. J.*, doi:10.2136/sssaj2001.6551368x, 2010.
684

685 Jefferson, A. J.: Seasonal versus transient snow and the elevation dependence of climate sensitivity in maritime
686 mountainous regions, *Geophys. Res. Lett.*, doi:10.1029/2011GL048346, 2011.
687

688 Jepsen, S. M., Harmon, T. C., Meadows, M. W. and Hunsaker, C. T.: Hydrogeologic influence on changes in
689 snowmelt runoff with climate warming: Numerical experiments on a mid-elevation catchment in the Sierra Nevada,
690 USA, *J. Hydrol.*, doi:10.1016/j.jhydrol.2015.12.010, 2016.
691

692 Kaiser, K. and McGlynn B. L.: Nested scales of spatial and temporal variability of soil water content across a
693 semiarid montane catchment, *Water Resources Research*. DOI: 10.1029/2018WR022591, 2018.
694

695 Kampf, S., Markus, J., Heath, J. and Moore, C.: Snowmelt runoff and soil moisture dynamics on steep subalpine
696 hillslopes, *Hydrol. Process.*, doi:10.1002/hyp.10179, 2015.
697

698 Kim, J. H., Hwang, T., Yang, Y., Schaaf, C. L., Boose, E., and Munger, J. W.: Warming-Induced Earlier Greenup
699 Leads to Reduced Stream Discharge in a Temperate Mixed Forest Catchment. *Journal of Geophysical Research:*
700 *Biogeosciences*, 123(6), 1960-1975, 2018.
701

702 Kim, J., Mohanty, B.P.: Influence of lateral subsurface flow and connectivity on soil water storage in land surface
703 modeling, *J. Geophys. Res. Atmos.*, 121, doi:10.1002/2015JD024067, 2016.
704

705 Klos, P. Z., Link, T. E., & Abatzoglou, J. T.: Extent of the rain-snow transition zone in the western US under
706 historic and projected climate. *Geophysical Research Letters*, 41(13), 4560-4568, 2014.
707

708

709 Knowles, J. F., Molotch, N. P., Trujillo, E., & Litvak, M. E. (2018). Snowmelt-driven trade-offs between early and
710 late season productivity negatively impact forest carbon uptake during drought. *Geophysical Research Letters*,
711 45(7), 3087-3096.
712

713 Kormos, P. R., Marks, D., McNamara, J. P., Marshall, H. P., Winstral, A. and Flores, A. N.: Snow distribution, melt
714 and surface water inputs to the soil in the mountain rain-snow transition zone, *J. Hydrol.*,
715 doi:10.1016/j.jhydrol.2014.06.051, 2014.
716

717 Langston, A. L., Tucker, G. E., Anderson, R. S. and Anderson, S. P.: Evidence for climatic and hillslope-aspect
718 controls on vadose zone hydrology and implications for saprolite weathering, *Earth Surf. Process. Landforms*,
719 doi:10.1002/esp.3718, 2015.

720
721 Leterme, B., Mallants, D., and Jacques, D.: Sensitivity of groundwater recharge using climatic analogues and
722 HYDRUS-1D. *Hydrology and Earth System Sciences*, 16(8), 2485-2497, 2012.
723
724 Li, D., Wrzesien, M. L., Durand, M., Adam, J. and Lettenmaier, D. P.: How much runoff originates as snow in the
725 western United States, and how will that change in the future?, *Geophys. Res. Lett.*, doi:10.1002/2017GL073551,
726 2017.
727
728 Li, X., Jiang, F., Li, L. and Wang, G.: Spatial and temporal variability of precipitation concentration index,
729 concentration degree and concentration period Xinjiang, China, *Int. J. Climatol.*, doi:10.1002/joc.2181, 2011.
730
731 Litaor, M. I., Williams, M. and Seastedt, T. R.: Topographic controls on snow distribution, soil moisture, and
732 species diversity of herbaceous alpine Vegetation, Netwot Ridge, Colorado, *J. Geophys. Res. Biogeosciences*,
733 doi:10.1029/2007JG000419, 2008.
734
735 Liu, F., Parmenter, R., Brooks, P. D., Conklin, M. H. and Bales, R. C.: Seasonal and interannual variation of
736 streamflow pathways and biogeocheical implications in semi-arid, forested catchemnts in Valles Caldera, New
737 Mexico, *Ecohydrology*, doi:10.1002/eco.22, 2008.
738
739 Loik, M. E., Breshears, D. D., Lauenroth, W. K. and Belnap, J.: A multi-scale perspective of water pulses in dryland
740 ecosystems: Climatology and ecohydrology of the western USA, *Oecologia*, doi:10.1007/s00442-004-1570-y, 2004.
741
742 Lv, L.: Linking montane soil moisture measurements to evapotranspiration using inverse numerical modeling. Utah
743 State University, 2014.
744
745 M Foster, L., A Bearup, L., P Molotch, N., D Brooks, P. and M Maxwell, R.: Energy budget increases reduce mean
746 streamflow more than snow-rain transitions: Using integrated modeling to isolate climate change impacts on Rocky
747 Mountain hydrology, *Environ. Res. Lett.*, doi:10.1088/1748-9326/11/4/044015, 2016.
748
749 Markovich, K. H., Maxwell, R. M. and Fogg, G. E.: Hydrogeological response to climate change in alpine
750 hillslopes, *Hydrol. Process.*, doi:10.1002/hyp.10851, 2016.
751
752 Martin-Vide, J.: Spatial distribution of a daily precipitation concentration index in peninsular Spain, *Int. J. Climatol.*,
753 doi:10.1002/joc.1030, 2004.
754
755 McNamara, J. P., Chandler, D., Seyfried, M. and Achet, S.: Soil moisture states, lateral flow, and streamflow
756 generation in a semi-arid, snowmelt-driven catchment, *Hydrol. Process.*, doi:10.1002/hyp.5869, 2005.
757
758 Meixner, T., Manning, A. H., Stonestrom, D. A., Allen, D. M., Ajami, H., Blasch, K. W., Brookfield, A. E., Castro,
759 C. L., Clark, J. F., Gochis, D. J., Flint, A. L., Neff, K. L., Niraula, R., Rodell, M., Scanlon, B. R., Singha, K. and
760 Walvoord, M. A.: Implications of projected climate change for groundwater recharge in the western United States, *J.*
761 *Hydrol.*, doi:10.1016/j.jhydrol.2015.12.027, 2016.
762
763 Molotch, N. P., Brooks, P. D., Burns, S. P., Litvak, M., Monson, R. K., McConnell, J. R. and Musselman, K.:
764 Ecohydrological controls on snowmelt partitioning in mixed-conifer sub-alpine forests, *Ecohydrology*,
765 doi:10.1002/eco.48, 2009.
766
767 Moore, D.J., Hu, J., Sacks, W.J., Schimel, D.S. and Monson, R.K.: Estimating transpiration and the sensitivity of
768 carbon uptake to water availability in a subalpine forest using a simple ecosystem process model informed by
769 measured net CO₂ and H₂O fluxes. *Agricultural and Forest Meteorology*, 148(10), pp.1467-1477, 2008.
770
771 Moore, C., Kampf, S., Stone, B. and Richer, E.: A GIS-based method for defining snow zones: application to the
772 western United States, *Geocarto Int.*, doi:10.1080/10106049.2014.885089, 2015.
773
774 Musselman, K. N., Clark, M. P., Liu, C., Ikeda, K. and Rasmussen, R.: Slower snowmelt in a warmer world, *Nat.*
775 *Clim. Chang.*, doi:10.1038/nclimate3225, 2017.

776
777 National Water and Climate Center [NWCC]: Report Generator 2.0, [10/01/2003-09/30/2015]. Portland, Oregon,
778 USA, 2016.
779
780 Newman, B. D., Wilcox, B. P. and Graham, R. C.: Snowmelt-driven macropore flow and soil saturation in a
781 semiarid forest, *Hydrol. Process.*, doi:10.1002/hyp.5521, 2004.
782
783 Nolin, A. W. and Daly, C.: Mapping “At Risk” Snow in the Pacific Northwest, *J. Hydrometeorol.*,
784 doi:10.1175/jhm543.1, 2006.
785
786 Pauwels, V. R. N., N. E. C. Verhoest, G. J. M. De Lannoy, V. Guissard, C. Lucau, and P. Defourny: Optimization of
787 a coupled hydrology–crop growth model through the assimilation of observed soil moisture and leaf area index
788 values using an ensemble Kalman filter, *Water Resour. Res.*, 43, W04421, doi:10.1029/2006WR004942, 2007.
789
790 Raziei, T., Bordi, I. and Pereira, L. S.: A precipitation-based regionalization for Western Iran and regional drought
791 variability, *Hydrol. Earth Syst. Sci.*, doi:10.5194/hess-12-1309-2008, 2008.
792
793 Regonda, S. K., Rajagopalan, B., Clark, M. and Pitlick, J.: Seasonal cycle shifts in hydroclimatology over the
794 western United States, *J. Clim.*, doi:10.1175/JCLI-3272.1, 2005.
795
796 Schaap, M. G., Leij, F. J. and Van Genuchten, M. T.: Rosetta: A computer program for estimating soil hydraulic
797 parameters with hierarchical pedotransfer functions, *J. Hydrol.*, doi:10.1016/S0022-1694(01)00466-8, 2001.
798
799 Scott, R. L., Shuttleworth, W. J., Keefer, T. O. and Warrick, A. W.: Modeling multiyear observations of soil
800 moisture recharge in the semiarid American Southwest, *Water Resour. Res.*, doi:10.1029/2000WR900116, 2000.
801
802 Scott-Denton, L.E., Sparks, K.L. and Monson, R.K.: Spatial and temporal controls of soil respiration rate in a high-
803 elevation, subalpine forest. *Soil Biology and Biochemistry*, 35(4), pp.525-534, 2003.
804
805 Šejna, M., Saito, H., Sakai, M. and Genuchten, M. T. van: The Hydrus-1D Software Package for Simulating the
806 Movement of Water, Heat, and Multiple Solutes in Variably Saturated Media., 2008.
807
808 Seyfried, M. S., Schwinning, S., Walvoord, M. A., Pockman, W. T., Newman, B. D., Jackson, R. B. and Phillips, F.
809 M.: Ecological control of deep drainage in arid and semiarid regions, in *Ecology.*, 2005.
810
811 Seyfried, M. S., Grant, L. E., Marks, D., Winstral, A. and McNamara, J.: Simulated soil water storage effects on
812 streamflow generation in a mountainous snowmelt environment, Idaho, USA, *Hydrol. Process.*,
813 doi:10.1002/hyp.7211, 2009.
814
815 Šimůnek, J., M. Šejna, and van Genuchten M.: The HYDRUS-1D software package for simulating the one-
816 dimensional movement of water, heat, and multiple solutes in variably saturated media. Version 1.0. IGWMC-TPS-
817 70. Golden, Colo.: Colorado School of Mines, International Ground Water Modeling Center, 1998.
818
819 Slater, A. G., Lawrence, D. M. and Koven, C. D.: Process-level model evaluation: A snow and heat transfer metric,
820 *Cryosphere*, doi:10.5194/tc-11-989-2017, 2017.
821
822 Smith, T. J., Mcnamara, J. P., Flores, A. N., Gribb, M. M., Aishlin, P. S. and Benner, S. G.: Small soil storage
823 capacity limits benefit of winter snowpack to upland vegetation, *Hydrol. Process.*, doi:10.1002/hyp.8340, 2011.
824
825 Stewart, I. T., Cayan, D. R. and Dettinger, M. D.: Changes toward earlier streamflow timing across western North
826 America, *J. Clim.*, doi:10.1175/JCLI3321.1, 2005.
827
828 Sukhija, B. S., Reddy, D. V., Nagabhushanam, P. and Hussain, S.: Recharge processes: Piston flow vs preferential
829 flow in semi-arid aquifers of India, *Hydrogeol. J.*, doi:10.1007/s10040-002-0243-3, 2003.
830
831

831 Tague, C. and Peng, H.: The sensitivity of forest water use to the timing of precipitation and snowmelt recharge in
832 the California Sierra: Implications for a warming climate, *J. Geophys. Res. Biogeosciences*, doi:10.1002/jgrg.20073,
833 2013.

834

835 Varhola, A., Coops, N. C., Weiler, M., and Moore, R. D.: Forest canopy effects on snow accumulation and ablation:
836 An integrative review of empirical results. *Journal of Hydrology*, 392(3-4), 219-233., 2010.

837

838 Webb, R. W., Fassnacht, S. R. and Gooseff, M. N.: Wetting and Drying Variability of the Shallow Subsurface
839 Beneath a Snowpack in California's Southern Sierra Nevada, *Vadose Zo. J.*, doi:10.2136/vzj2014.12.0182, 2015.

840

841 Webb, R. W., Fassnacht, S. R. and Gooseff, M. N.: Defining the Diurnal Pattern of Snowmelt Using a Beta
842 Distribution Function, *J. Am. Water Resour. Assoc.*, doi:10.1111/1752-1688.12522, 2017.

843

844 Webb, R. W., Fassnacht, S. R. and Gooseff, M. N.: Hydrologic flow path development varies by aspect during
845 spring snowmelt in complex subalpine terrain, *Cryosphere*, doi:10.5194/tc-12-287-2018, 2018.

846

847 Williams, C. J., McNamara, J. P. and Chandler, D. G.: Controls on the temporal and spatial variability of soil
848 moisture in a mountainous landscape: The signature of snow and complex terrain, *Hydrol. Earth Syst. Sci.*,
849 doi:10.5194/hess-13-1325-2009, 2009.

850

851 Wood, W. W., Rainwater, K. A. and Thompson, D. B.: Quantifying Macropore Recharge: Examples from a Semi-
852 Arid Area, *Ground Water*, doi:10.1111/j.1745-6584.1997.tb00182.x, 2005.

853

854 Yan, H., Sun, N., Wigmosta, M., Skaggs, R., Hou, Z. and Leung, R.: Next-Generation Intensity-Duration-Frequency
855 Curves for Hydrologic Design in Snow-Dominated Environments, *Water Resour. Res.*,
856 doi:10.1002/2017WR021290, 2018.

857

858 Zeng, X., Zeng, X., Shen, S. S. P., Dickinson, R. E. and Zeng, Q. C.: Vegetation-soil water interaction within a
859 dynamical ecosystem model of grassland in semi-arid areas, *Tellus, Ser. B Chem. Phys. Meteorol.*,
860 doi:10.1111/j.1600-0889.2005.00151.x, 2005.

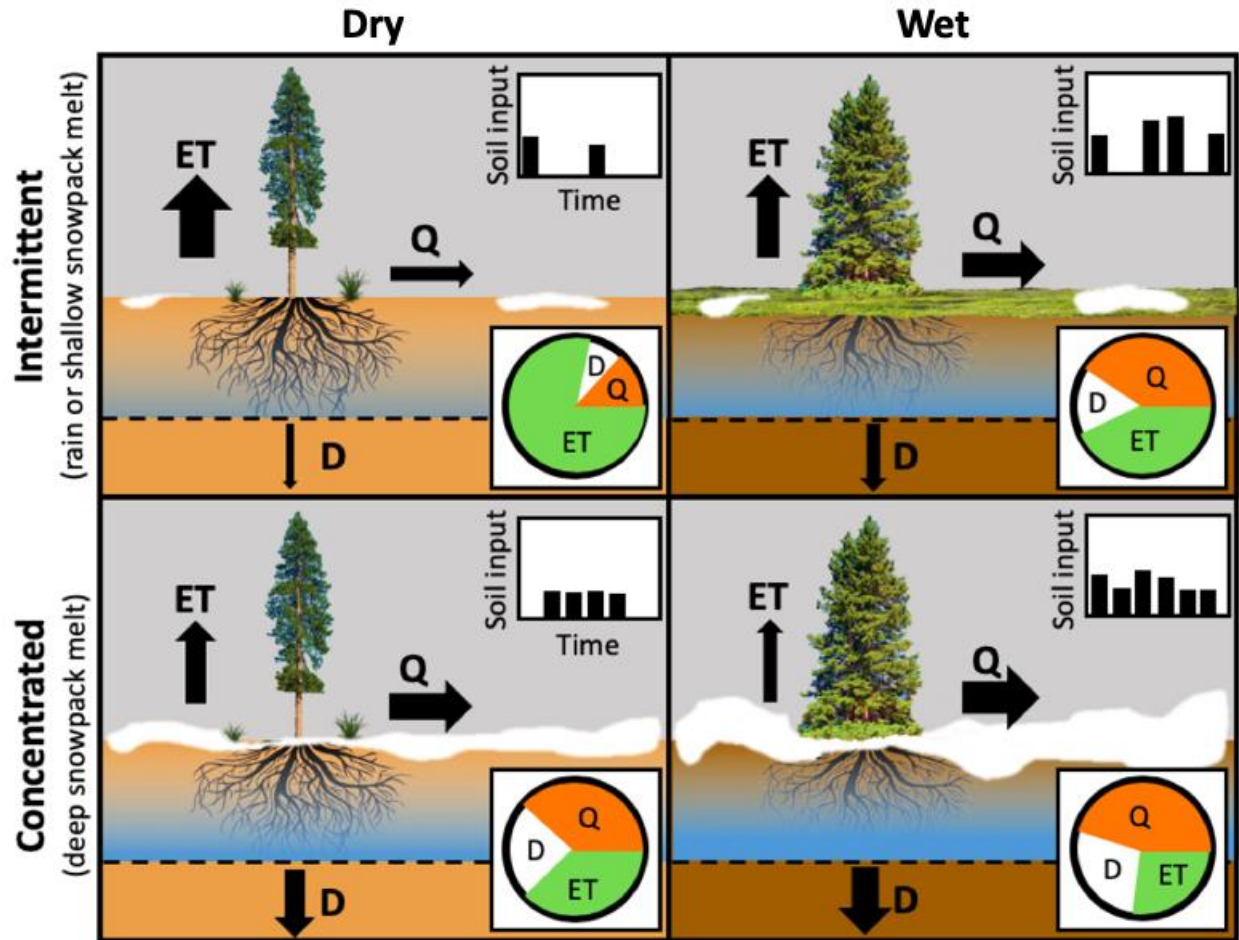
861

862 Zheng, Z., Kirchner, P. B., and Bales, R. C.: Topographic and vegetation effects on snow accumulation in the
863 southern Sierra Nevada: a statistical summary from lidar data. *The Cryosphere*, 10(1), 257-269, 2016.

864

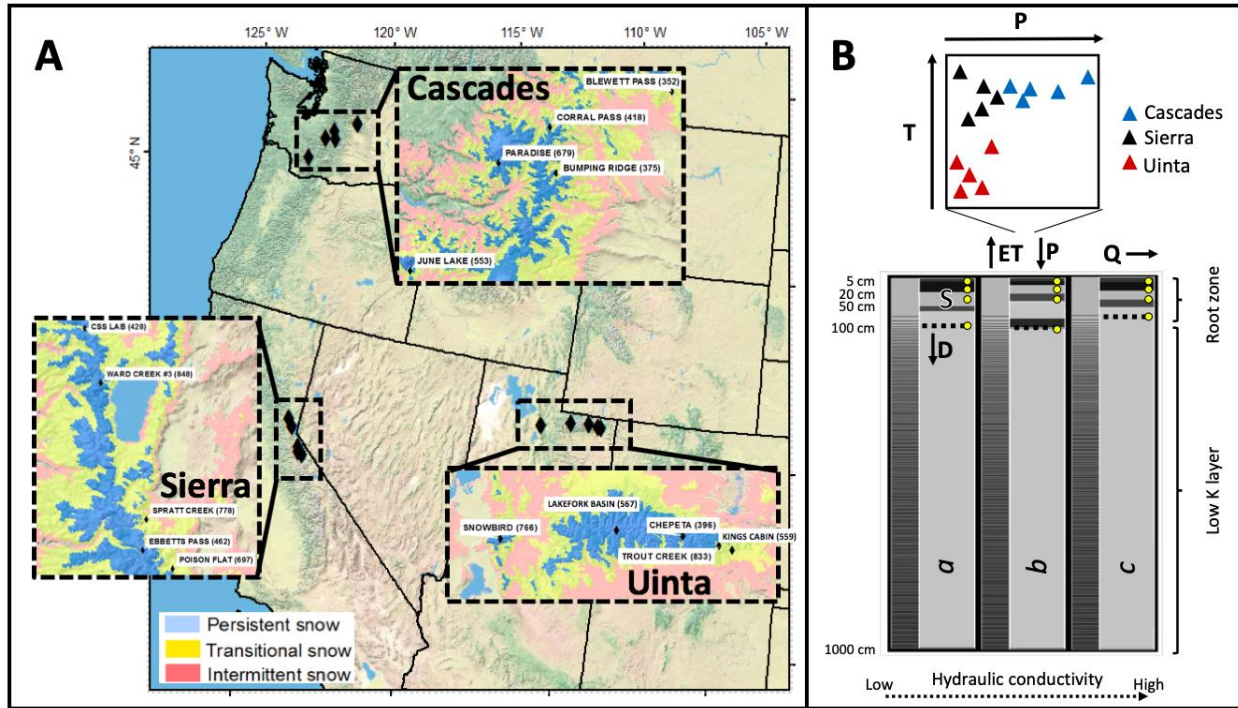
865

866



867

868 Figure 1. Conceptual illustration of study hypotheses indicating the importance of concentrated snowmelt
 869 input (bottom panels) versus intermittent input (top panels) for runoff generation. The wet climate (right-
 870 hand panels) generates more runoff (Q) and deep drainage (D) and less evapotranspiration (ET) compared to
 871 the dry climate (left-hand panels). In both climates, concentrated input can increase both Q and D because it
 872 is more likely to allow soil saturation than intermittent input, which allows ET during periods of drying. The
 873 concentrated input from snowmelt leads to greater increases in Q and D in the dry climate than in the wet
 874 climate because snowmelt is the most likely cause of soil saturation in dry climates.
 875

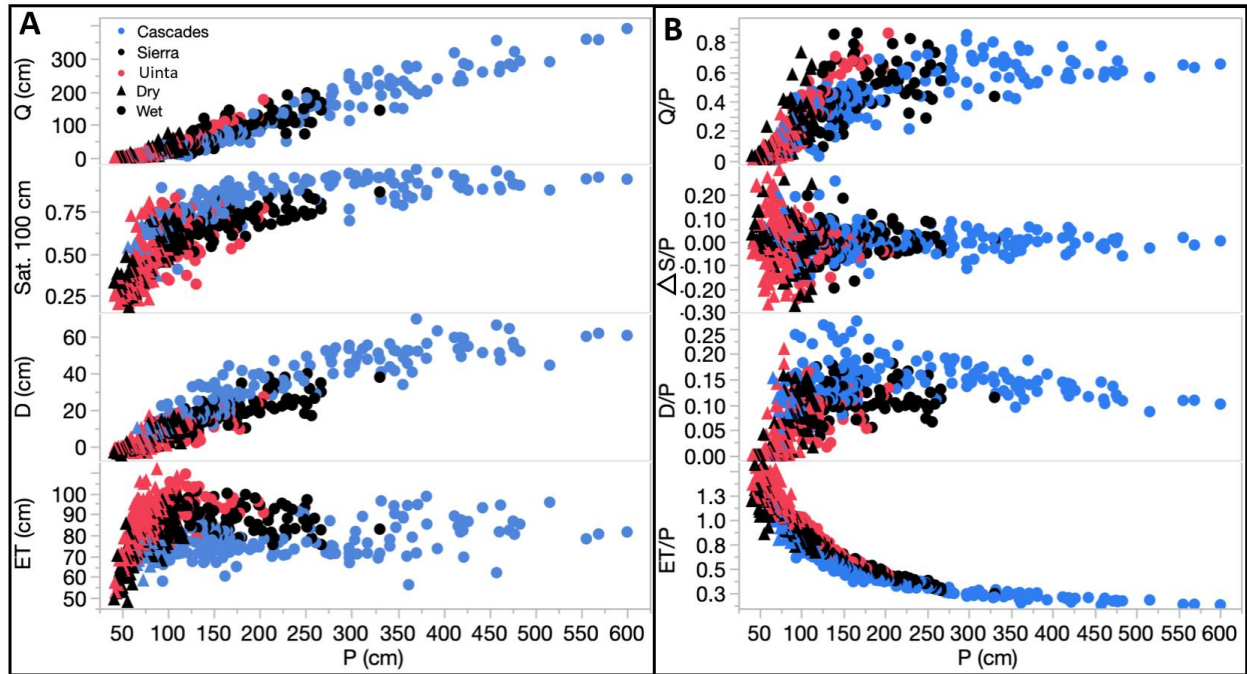


876

877 Figure 2. (A) SNOTEL sites utilized for climate scenarios in this study with insets displaying snow zones
 878 classified by mean annual snow persistence (Moore et al., 2015). (B) Modeling domain layout with yellow
 879 points showing 5, 20 and 50 cm depths where volumetric water content time series were used for model
 880 calibration. Deepest yellow point is the depth where time series were extracted to calculate deep saturation.
 881 Symbols in the graph above the discretized soil profile represent the range of climate scenarios used plotted
 882 by mean annual precipitation (P) and mean annual temperature (T), and the three soil profiles below
 883 represent the soil parameter sets labeled with italicized capital letters (*a*) loam (*b*) sandy clay loam (*c*) sandy
 884 loam. Different layers in each soil profile are represented as shades of gray, shading does not indicate any
 885 property of the soil layer.

886

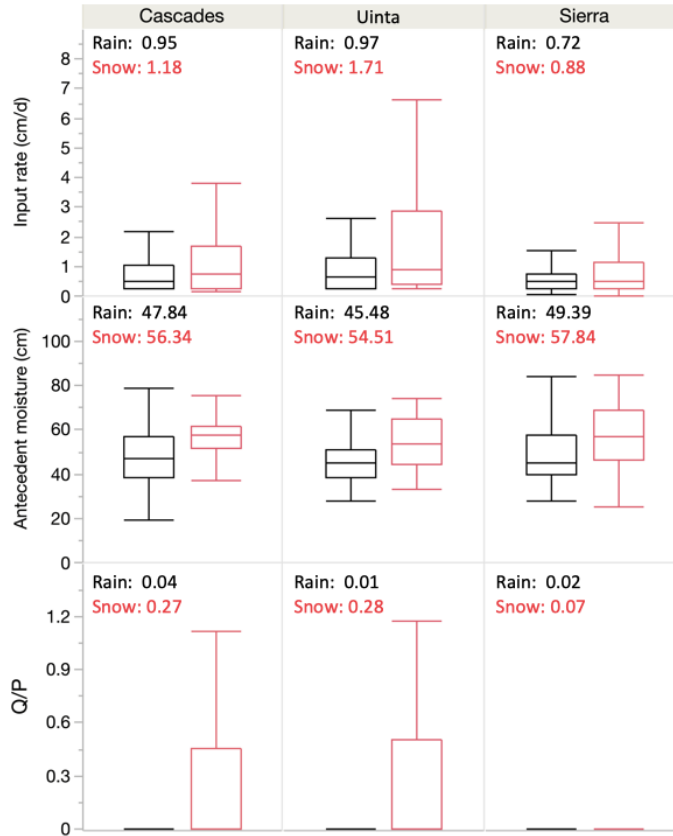
887



888

889 **Figure 3. A) Annual runoff (Q), mean saturation at 100 cm depth (Sat100), deep drainage (D) and**
 890 **evapotranspiration (ET) vs annual precipitation (P) classified by region and climate type. B) Q/P , $\Delta S/P$, D/P**
 891 **and ET/P vs P classified by region and climate type. Dry sites $P/PET \leq 1$, Wet $P/PET > 1$. Data from historical**
 892 **input scenarios for soil profile 1056, loam.**
 893

894



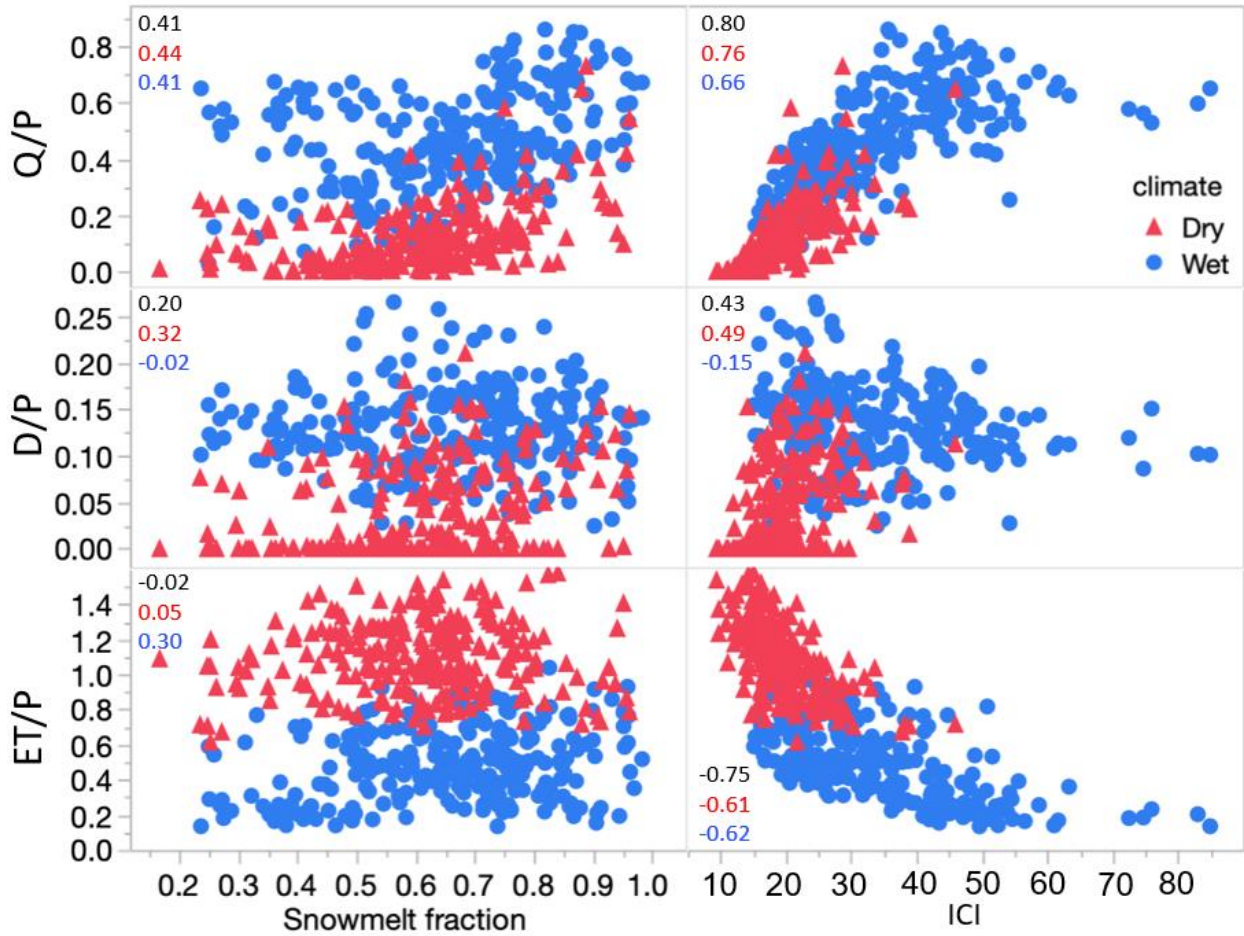
895

896 Figure 4. Boxplots of event input rate (cm/d) (top), antecedent soil moisture storage (S , cm) (middle) and
 897 event runoff ratio (Q/P , bottom) by region and event type (rain black, snowmelt red). Text in each subplot
 898 gives mean values. All ANOVA comparisons between values for rain and snowmelt have p-values <0.0001.
 899 Results from historical simulations on loam profile.

900

901

902



903

904

905

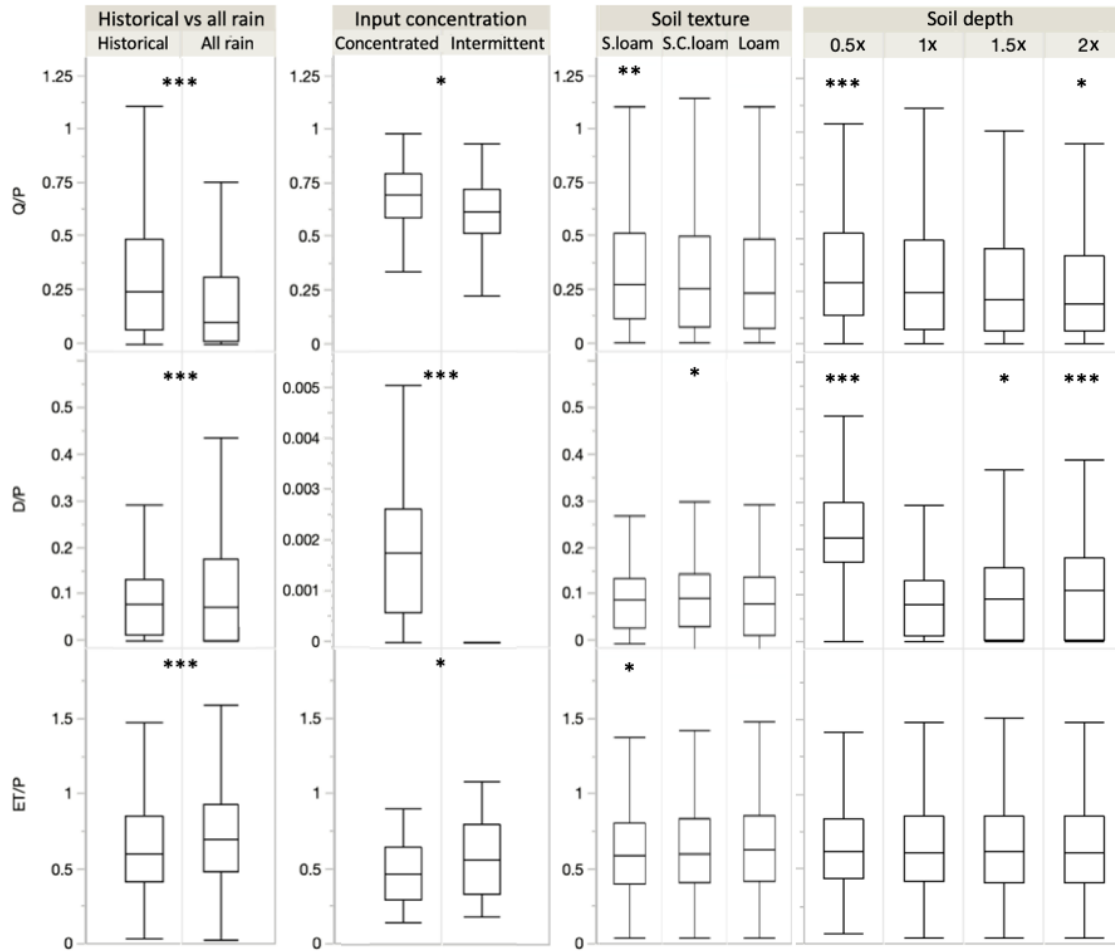
906

907

908

909

Figure 5. Ratio of runoff (Q), deep drainage (D) and evapotranspiration (ET) to input (P) vs. snowmelt fraction of input and input concentration index (ICI) at the annual time scale. Data from historical simulations on loam profile. Dry sites $P/PET < 1$, Wet $P/PET > 1$. Correlation values between explanatory and dependent variables displayed in each panel colored by all (black), dry (red) and wet (blue) classifications. Correlation values also shown in Table S4.

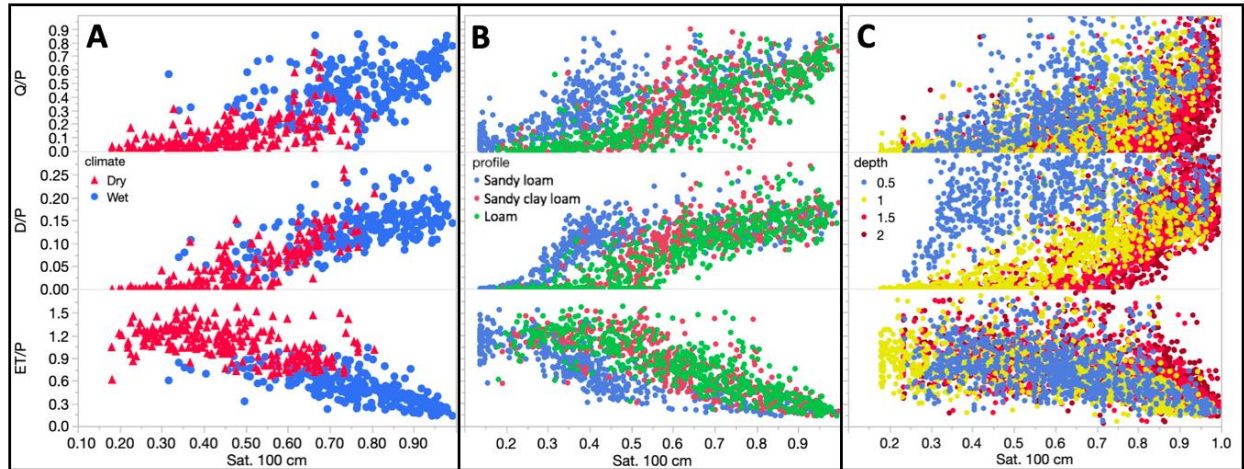


910

911 **Figure 6. Boxplots of Q/P , D/P and ET/P for four different experiments: historical vs all rain input on loam**
 912 **soil and constant 1x depth, intermittent vs concentrated input on loam soil and constant 1x depth, different**
 913 **soil textures with constant 1x depth, and different soil depths all with loam soil texture. Asterisks denote**
 914 **significance of ANOVA tests between groupings. P-value of ANOVA, * <0.05 , ** <0.01 , *** <0.001 . Boxplots**
 915 **correspond with values in Table 3. Soil texture and soil depth scenarios are compared to 1x depth and loam**
 916 **texture profile for ANOVAs.**

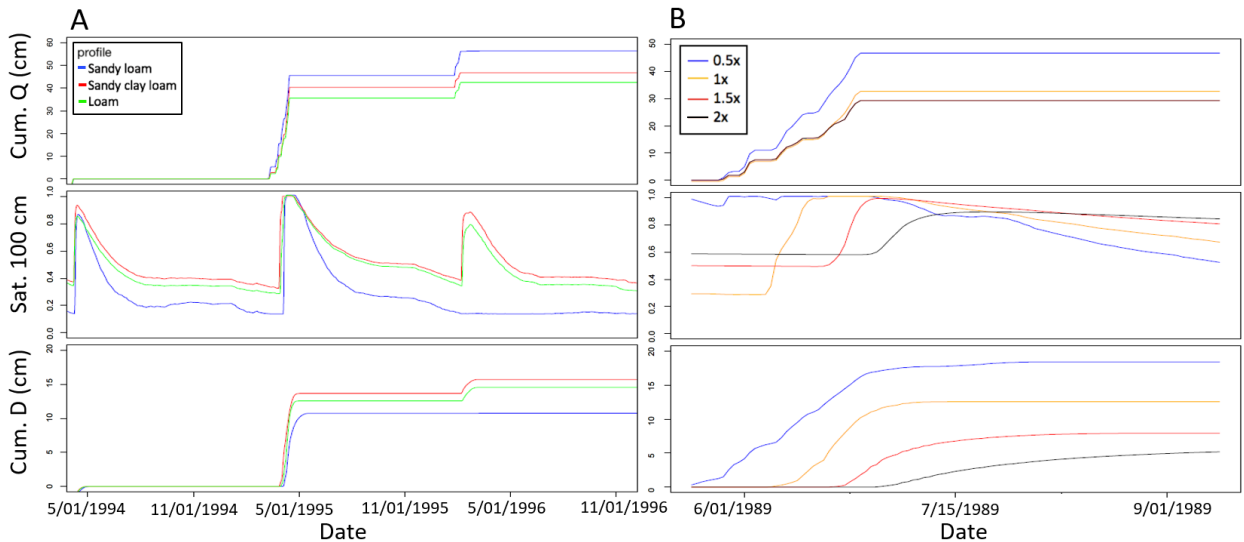
917

918



919

920 Figure 7. A) Annual surface runoff (Q), deep drainage (D) and evapotranspiration (ET) as a fraction of
 921 annual precipitation (P) vs annual mean saturation at 100 cm depth (Sat100) and classified by climate on
 922 the loam profile, Dry sites $P/PET \leq 1$, Wet $P/PET > 1$. B) The same variables displayed in A but classified by
 923 soil texture on three different soil profiles. C) The same variables in A but classified by root zone depth on
 924 four different profiles of differing root zone depth. All simulations use historical input.
 925



926

927 Figure 8. (A) daily time series of cumulative runoff (Q), saturation at 100 cm depth (Sat100), and cumulative
 928 deep drainage (D) for SNOTEL site 698 input on SNOTEL site 515 (sandy loam), 1049 (sandy clay loam) and
 929 1056 (loam) profile. (B) daily series for the same variables plotted for four depth scenarios 0.5x, 1x 1.5x and
 930 2x original rooting zone depth.

Table 1. SNOTEL station properties including the start and end of data records, site elevation, and mean annual climatic characteristics: precipitation (*P*), temperature (*T*), snow persistence (*SP*, %), and aridity index (*P/PET*).

SNOTEL ID	Region	State	Start	End	Elevation (m)	P (cm)	T (C)	SP	P/PET
352	Cascades	WA	1981	2015	1292	90	6.3	54	0.8
553	Cascades	WA	1982	2015	1049	433	6.9	65	4.4
375	Cascades	WA	1978	2015	1405	146	4.9	69	1.8
679	Cascades	WA	1980	2015	1564	263	4.8	77	4.9
418	Cascades	WA	1981	2015	1768	158	3.6	83	1.9
778	Sierra	CA	1980	2015	1864	69	8.0	53	0.7
697	Sierra	CA	1980	2015	2358	98	3.8	63	0.6
428	Sierra	CA	1981	2015	2089	180	6.0	72	1.3
848	Sierra	CA	1978	2015	2028	197	5.9	74	1.3
462	Sierra	CA	1978	2015	2672	142	4.0	78	1
559	Uinta	UT	1979	2015	2659	74	1.4	60	0.6
833	Uinta	UT	1979	2015	2901	70	1.5	69	0.7
396	Uinta	UT	1981	2015	3228	81	-0.1	76	0.9
567	Uinta	UT	1980	2015	3342	98	0.0	86	0.9
766	Uinta	UT	1989	2015	2938	157	3.2	87	1.3

Table 2. Soil profile properties derived from NRCS pedon reports and ROSETTA (Ros.) neural network. Columns are SNOTEL site, soil profile horizon, depth range of horizon, rock percent of sample volume, organic carbon percent of sample volume, sand percent of sample weight, silt percent of sample weight, clay percent of sample weight, Db_{33} bulk density of soil sample desorbed to 33kPa, Θ_{33} volumetric water content at field capacity, Θ_{1500} volumetric water content at wilting point, soil texture, residual volumetric water content Θ_r , saturated volumetric water content Θ_s , pore size distribution parameter α , and K_s saturated hydraulic conductivity. The lowest horizon K_s value was calibrated. Soil textures abbreviated as follows: sandy loam (SL), sand (S), loamy sand (LS), sandy clay loam (SCL), loam (L). SNOTEL 515, Harts Pass, WA, SNOTEL 1049, Forestdale Creek, CA, SNOTEL 1056, Lightning Ridge, UT.

Site	Hor.	Depth (cm)	rock % vol	organic C % vol	sand % wt	silt % wt	clay % wt	Db_{33} g cm^{-3}	Θ_{33}	Θ_{1500}	Text.	Ros. Θ_r	Ros. Θ_s	Ros. α (1/cm)	Ros. K_s (cm/d)
515	A1	0-15	9	9	53.5	35.6	10.9	0.63	0.41	0.14	SL	0.06	0.62	0.009	17.4
515	A2	13-38	8	8	57.6	35.3	7.1	0.64	0.47	0.14	SL	0.05	0.60	0.011	20.5
515	2Bw1	38-61	27	3	73.1	22.1	4.8	0.86	0.3	0.08	SL	0.04	0.55	0.032	15.1
515	2Bw2	61-81	55	1	81	11	8	1.46	0.16	0.09	LS	0.05	0.40	0.036	5.49
515	Cd	81-106	7	1	91.3	4.1	4.6	1.52	0.14	0.05	S	0.05	0.38	0.033	17.4
515	Cd	106-1000	7	1	91.3	4.1	4.6	1.52	0.14	0.05	S	0.05	0.38	0.033	1.74
1049	A	0-9	10	7	52.6	25.2	22.2	0.94	0.40	0.14	SCL	0.08	0.55	0.014	5.17
1049	Bt1	9-20	14	2	48.6	25.4	26	1.13	0.30	0.14	SCL	0.08	0.50	0.014	2.13
1049	Bt2	20-43	14	1	52.9	23.8	23.3	1.24	0.32	0.12	SCL	0.07	0.47	0.016	1.74
1049	Bt3	43-63	21	1	53.4	24	22.6	1.19	0.33	0.13	SCL	0.07	0.48	0.015	2.18
1049	Bt4	63-77	19	1	55.5	25.9	18.6	1.39	0.32	0.12	SL	0.06	0.42	0.017	1.22
1049	Bt5	77-110	11	0	52.4	30.2	17.4	1.21	0.39	0.13	SL	0.06	0.45	0.013	2.22
1049	Bt5	110-1000	11	0	52.4	30.2	17.4	1.21	0.39	0.13	SL	0.06	0.45	0.013	0.22
1056	A	0-10	11	3	36.1	48.8	15.1	1.17	0.30	0.12	L	0.06	0.44	0.010	2.41
1056	A	10-38	7	2	35.3	49.5	15.2	1.27	0.28	0.11	L	0.06	0.41	0.006	1.47
1056	Bt1	38-76	6	2	36	48.6	15.4	1.25	0.30	0.10	L	0.06	0.42	0.006	1.59
1056	Bt2	76-89	16	1	39.3	46	14.7	1.26	0.34	0.09	L	0.06	0.41	0.007	1.54
1056	2B	89-127	6	2	36.3	48.2	15.5	1.18	0.24	0.09	L	0.06	0.44	0.006	2.23
1056	2B	127-1000	6	2	36.3	48.2	15.5	1.18	0.24	0.09	L	0.06	0.44	0.006	0.22

Table 3. Mean values of unitless response variables Q/P , D/P , and ET/P compared by climate type for four hypothetical scenarios: (1) historical vs all rain input, (2) intermittent vs concentrated input, (3) historical input on sandy loam, sandy clay loam, and loam profiles, (4) historical input on 0.5x, 1x, 1.5x and 2x original rooting zone depth. Dry sites $P/PET \leq 1$, Wet $P/PET > 1$. All scenarios in the table besides those explicitly altering soil texture use the loam profile (1056). Asterisks denote the significance of ANOVA tests between groupings of simulations and arrows show the direction of change relative to the base scenario: historical input on 1x depth profile with loam texture. P-value of ANOVA, * <0.5 , ** <0.01 , * <0.001 . Boxplots correspond with values in Table 3.**

Experiment	Scenario	Climate	Q/P	D/P	ET/P
Historical vs. all rain	Historical	All	0.31	0.09	0.66
		Wet	0.44	0.12	0.51
		Dry	0.13	0.03	0.83
	All rain	All	0.19↓***	0.12↑	0.73↑**
		Wet	0.28↓***	0.14↑*	0.55↑
		Dry	0.04↓***	0.01↓***	0.95↑***
Intermittent vs. concentrated ²	Intermittent	All	0.59	0.00	0.58
		Wet	0.64	0.00	0.34
		Dry	0.54	0.00	0.80
	Concentrated	All	0.68↑*	0.002↑***	0.48↓*
		Wet	0.68↑	0.002↑***	0.28↓*
		Dry	0.68↑*	0.002↑***	0.66↓**
Soil texture	Loam (L)	All	0.31	0.09	0.66
		Wet	0.44	0.12	0.51
		Dry	0.13	0.03	0.83
	Sandy loam (SL)	All	0.35**↑	0.09	0.63↓*
		Wet	0.05↓	0.13↑	0.51↓
		Dry	0.19↑*	0.05↑	1.01↓* ¹
	Sandy clay loam (SCL)	All	0.32↑	0.10↑*	0.65↓
		Wet	0.48↑	0.14↑	0.52↑
		Dry	0.14↑	0.06↑	1.08↓ ¹
Soil depth	0.5x	All	0.35↑***	0.25↑***	0.67↑
		Wet	0.54↑***	0.28↑***	0.53↑*
		Dry	0.17↑**	0.22↑***	0.80↓*
	1x	All	0.31	0.09	0.66
		Wet	0.44	0.12	0.51
		Dry	0.13	0.03	0.83
	1.5x	All	0.29↓	0.10↑*	0.67↑
		Wet	0.46↑	0.16↑*	0.51
		Dry	0.09↓	0.03	0.84↑
	2x	All	0.27↓*	0.11↑***	0.66
		Wet	0.44	0.18↑***	0.51
		Dry	0.09↓	0.04↑	0.84↑

¹Values of $ET/P > 1$ indicate root uptake from soil storage for years with low input (Figure S5).

²For a dry site (375) and a wet site (559). Intermittent simulations have annual total input separated into four five-day periods, whereas concentrated input simulations have all input in twenty-day period of high magnitude.