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Hydrology and Earth System Sciences
Discussions

Technical note: Accounting for snow in the estimation of root-zone water storage capacity from precipitation and evapotranspiration fluxes

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Abstract. A common parameter in hydrological modeling frameworks is root-zone water storage capacity ($S_R[L]$), which mediates plant-water availability during dry periods and the partitioning of rainfall between runoff and evapotranspiration. Recently, a simple flux-tracking based approach was introduced to estimate the value of S_R (Wang-Erlandsson et al., 2016). Here, we build upon this original method, which we argue may overestimate S_R in snow-dominated catchments due to snow melt and evaporation processes. This matters for hydrological predictions under warming scenarios with decreased snowpack. We propose a simple extension to the method presented by Wang-Erlandsson et al. (2016), and show that the approach provides a more conservative minimum estimate of S_R in snow-dominated watersheds. This S_R dataset is available at 1 km resolution for the continental United States, along with the full analysis code, on Google Colaboratory and Earth Engine platforms. We highlight differences between the original and new methods across the rain-snow transition in the Southern Sierra Nevada, California, USA. As climate warms and precipitation increasingly arrives as rain instead of snow, the subsurface may be an increasingly important reservoir for storing plant-available water between wet and dry seasons; improved estimates of S_R will therefore better clarify the future role of the subsurface as a storage reservoir that can sustain forests during seasonal dry periods and episodic drought.

1 Introduction

Root-zone water storage capacity ($S_R[L]$) quantifies the maximum amount of subsurface water that can be stored for use by vegetation. This ecohydrological parameter plays a central role in the determination of plant community composition and drought resilience (Hahm et al., 2019a, b), runoff generation mechanisms (Botter et al., 2007; Salve et al., 2012), landslide triggering (Montgomery and Dietrich, 1994), landscape evolution (Deal et al., 2018), and the partitioning of precipitation into evapotranspiration and runoff (Porporato et al., 2004). Practically, *in situ* measurement of S_R at large spatial scales is infeasible, leading to the development of various methods for estimating S_R using remote sensing and model inversion approaches (de Boer-Euser et al., 2016; Gao et al., 2014; Wang-Erlandsson et al., 2016; Dralle et al., 2020). Although high-resolution maps of *soil* plant-available water storage capacity exist (Reynolds et al., 2000), such maps incompletely describe the water used by

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plants: there is considerable evidence of plant water uptake from depths below soil (Dawson et al., 2020; Schwinning, 2010). For example, roots can extend into and draw water from the bedrock vadose zone (rock moisture, *sensu* Rempe and Dietrich, 2018; Hahm et al., 2020) or groundwater (Miller et al., 2010; Lewis and Burgy, 1964). Within seasonally dry environments in particular, a significant volume of water accessed during the growing season can be derived from depths below mapped soils (Rose et al., 2003; Jones and Graham, 1993; Arkley, 1981). We emphasize that an accurate representation of S_R therefore should include not only moisture available within the soil, but also plant-accessible water below the soil.

S_R does not, however, include snowpack, which is an above-ground water storage reservoir. Conservatively estimating S_R in systems that currently receive a significant proportion of their precipitation as snow is particularly important given the ongoing shift from snow to rain under a warming climate, and the attendant heightened significance of subsurface water storage dynamics to plant ecosystems and streams. An existing, widely used method for estimating S_R (Wang-Erlandsson et al., 2016) does not account for snow melt and sublimation/evaporation dynamics, which may result in significant overestimation of this reservoir. We present an extension to the original method to ensure a conservative estimate of S_R in snowy areas. We describe the method details and highlight results from a rain-snow transition transect in the Southern Sierra Nevada, California, USA. We also provide a geotiff raster map of S_R across the continental United States at the 1 km pixel scale. Finally, we link to a Google Earth Engine (https://earthengine.google.com/) script written in Python (https://www.python.org/) within the Colab coding environment (https://colab.research.google.com/) to document application of the method, and to facilitate comparative analyses using other widely available and spatially distributed precipitation, snowcover, and actual evapotranspiration datasets.

2 Method

To estimate S_R, Wang-Erlandsson et al. (2016) compute a running root-zone storage deficit (more positive means larger capacity in the subsurface for storage) using differences between fluxes exiting (F_{out}) and entering (F_{in}) the root zone during a given time interval (typically equal to the sampling period of the remotely sensed evapotranspiration dataset). To obtain a conservative estimate of S_R (that is, a robust lower bound), it is important to make sure that F_{in} is not underestimated (when in doubt, assume all precipitation enters the rooting zone), and that F_{out} is not overestimated (when in doubt on the amount of F_{out} that contributes to increases in the root zone storage deficit, simply set $F_{out} = 0$). Accordingly, other (often difficult to measure at large spatial scales) fluxes exiting the rooting zone, such as leakage and runoff, are ignored when computing running storage deficits, as neglecting these fluxes results in a conservative estimate of S_R. Due to these simplifications, F_{in} and F_{out} are set equal to precipitation (P) and evapotranspiration (ET), respectively.

The original storage deficit tracking (and subsequent estimation of S_R) procedure presented by Wang-Erlandsson et al. (2016) is achieved through two steps. First, over a given time interval t_n to t_{n+1}, the accumulated difference ($A_{t_n \to t_{n+1}}$) between F_{out} and F_{in} is calculated as:

$$A_{t_n \to t_{n+1}} = \int_{t_n}^{t_{n+1}} F_{out} - F_{in} dt. \quad (1)$$

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Hydrology and Earth System Sciences Discussions
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Here, since the root-zone storage *deficit* is being calculated (and not actual storage), the incoming and outgoing fluxes have opposite signs from a conventional mass balance. A lower bound on the root-zone storage deficit at each time interval can then be calculated as the maximum value of 0 and the running sum of these accumulated differences:

$$D(t_{n+1}) = \max\left(0, D(t_n) + A_{t_n \to t_{n+1}}\right) \tag{2}$$

Finally, S_R is estimated as the maximum observed value of D.

The potential inaccuracy introduced by this original method that we explore here is that during periods when snowpack is present within the pixel, F_{in} may be underestimated (due to melting snow entering the rooting zone, for example, when precipitation is zero) and F_{out} from the root zone may be overestimated (due to attribution of sublimation/evaporation from the snow surface to a flux from the subsurface). As discussed above, both of these possibilities may lead to overestimation of S_R.

In the absence of spatially and temporally resolved information about snowmelt and sublimation dynamics, a simple and conservative way to correct for these potential errors is to continue to decrease the storage deficit as incoming precipitation arrives, and to set $F_{out} = 0$ during periods when snow cover (C, the fraction of the pixel covered in snow, which is reliably measured at large spatial scales via satellites) is present, thereby not counting evapotranspiration towards increasing the storage deficit during snowy periods. We therefore introduce a correction term for the outgoing flux in the calculation of the accumulated difference between outgoing and incoming fluxes during each time interval:

$$A_{t_n \to t_n+1} = \int\limits_{t_n}^{t_{n+1}} (1 - \lceil C - C_0 \rceil) \cdot F_{out} - F_{in}\, dt \tag{3}$$

where C_0 is some threshold below which it is assumed that snow cover is negligible, and $\lceil\cdot\rceil$ is the ceiling operator (rounding up to the nearest integer), returning a 1 if $C > C_0$ and 0 if $C \leq C_0$. The expression therefore effectively sets $F_{out} = 0$ whenever snow is present (or deemed not-negligible) in the pixel, providing a robust lower-bound estimate of S_R in the running storage deficit calculation.

2.1 Algorithm implementation and datasets

We implement the original and snow-corrected algorithm developed here using Google Earth Engine, accessed via a Google Colab notebook and the Python programming language's Earth Engine application programming interface. This readily enables i) access to distributed timeseries hydrological products (i.e., snowcover, evapotranspiration, and precipitation); ii) computation in the cloud and iii) a shareable script that can be quickly modified and executed by new users (see link at end of manuscript).

The algorithm requires precipitation and evapotransipration datasets to compute F_{in} and F_{out}, and a snow cover dataset to implement the proposed snow-correction step. We use Oregon State's PRISM daily precipitation product (https://developers.google.com/earth-engine/datasets/catalog/OREGONSTATE_PRISM_AN81d) (Daly et al., 2008, 2015), available at 2.5 arc minute resolution. For evapotranspiration, we use the Penman-Monteith-Leuning Evapotranspiration V2 product (https://developers.google.com/earth-engine/datasets/catalog/CAS_IGSNRR_PML_V2)(Zhang et al., 2019; Gan et al., 2018), available at an 8 day timestep and 500 m resolution, and sum the vegetation transpiration and soil evaporation bands to calculate total evapotranspiration from the subsurface (interception is not included, as it is not a flux that increases a subsurface moisture deficit). For the snowcover dataset, we use the Normalized Difference Snow Index (NDSI) snow cover band from the 500m MODIS/Terra data product (https://developers.google.com/earth-engine/datasets/catalog/MODIS_006_MOD10A1) (Hall et al., 2016), and set C_0 = 0.1 (snow cover is assumed negligible at less than $C_0 = 10\%$ pixel coverage; in this case, $C_0 = 10\%$ is also the resolution of the underlying snow cover dataset). We restrict our analysis to the temporal intersection of these three datasets (the 2003 to 2017 water years), reproject into WGS84 (EPSG:4326), and resample pixels using nearest-neighbor to a 32.34 arc-second pixel scale (approximately 1 km).

We mask out pixels from our analysis where we anticipate our method will fail to accurately estimate S_R, namely urban areas, open water, and croplands (which are typically subject to irrigation). To generate this mask, we use the 'LC_Type1' band from the 2001 year of the MODIS MCD12Q1 v6 landcover product (https://developers.google.com/earth-engine/datasets/catalog/MODIS_006_MCD12Q1) (Friedl and Sulla-Menashe, 2015). In some areas (e.g., deserts), dataset errors or unaccounted for inter-pixel flow result in unrealistic S_R estimates, as described by Wang-Erlandsson et al. (2016). Although Wang-Erlandsson et al. (2016) correct these potential errors by adding the long term average difference $ET - P$ to F_{in}, we choose to remove these areas entirely from our data product by masking out pixels where cumulative evapotranspiration over the study period exceeds cumulative precipitation. If needed, this correction method implemented by Wang-Erlandsson et al. (2016) can easily be added to the code notebook published alongside this manuscript.

3 Results

To demonstrate the impact of the method in snowy areas, we focus on a region of the Sierra Nevada in California, United States, where there exists a strong elevation-driven gradient in winter snow cover. Figure 1 illustrates three raster data layers derived from application of the new method. Figure 1a plots root-zone storage capacity calculated using the snow-correction method. Values range from near 0 mm over exposed bedrock outcrops in the High Sierra, to over 900 mm in the dense mid-elevation forests. Figure 1b shows the difference between S_R computed using the original method and the snow-corrected S_R. Figure 1c plots average winter (January through April) snow cover. As expected, the difference in Figure 1b is small in the lower, rain-dominated elevations, and larger in areas with snow cover. However, some areas with substantial snow cover show small differences between the methods. These are likely areas where S_{max} is small, coinciding with low-energy, exposed-bedrock locations at high elevations.

Figure 2 illustrates the full timeseries output of the snow-accounting and original methods at two locations, identified by white points in Figure 1. The location farther west is a 'low snow' location, with negligible snowfall (snow present less than 1% of the time) during the winter months, and the location to the east is a 'high snow' location, with snowcover present over 50% of the time during the winter months. Gray shading in all subplots indicates that greater than 10% of the pixel is covered

https://doi.org/10.5194/hess-2020-602
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Hydrology and Earth System Sciences
Discussions

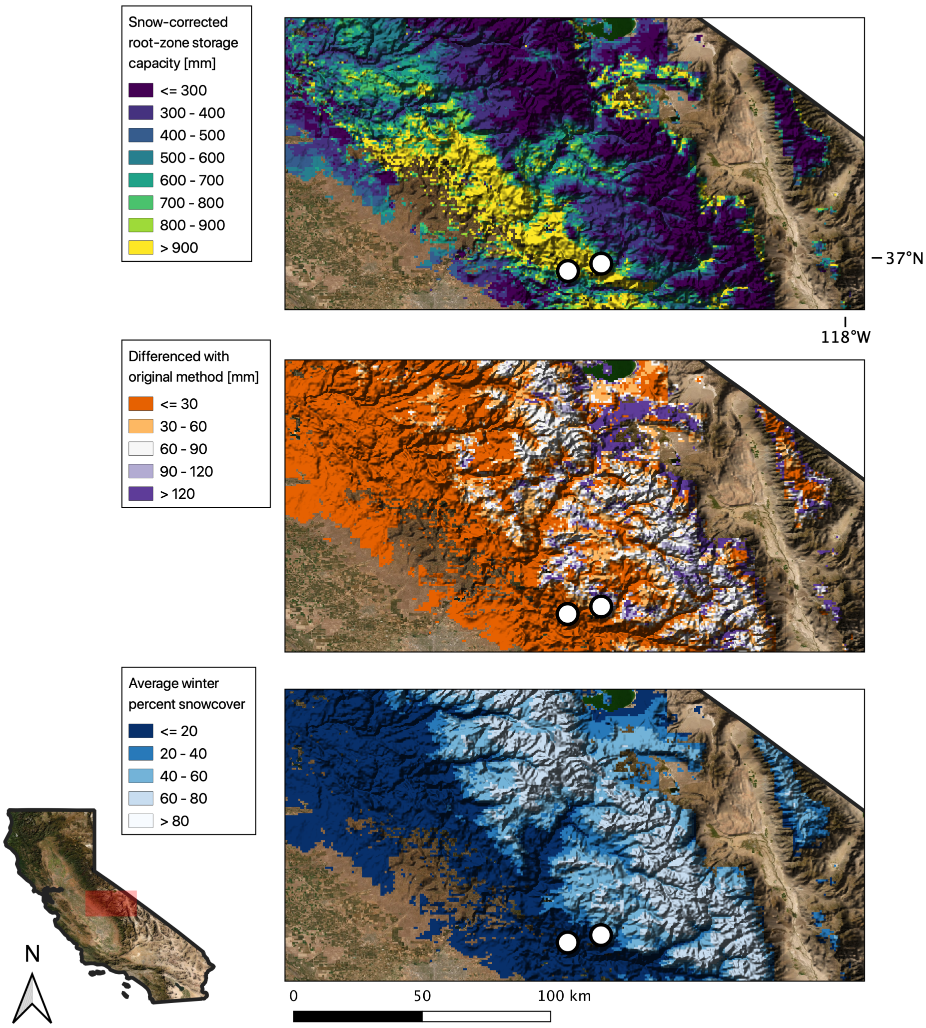

Figure 1. Maps of snow-corrected S_R (a), the difference between the original and snow-corrected S_R (b), and average winter (January - April) percent snow-cover (c) over a region of the Southern Sierra Nevada, California, USA. White points identify rain-dominated (western) and snowy (eastern) locations highlighted in Fig. 2

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in snow at that time point, during which evapotranspiration is set to zero in our method (lower panels). The top panels of Figure 2 plots storage deficits using the original and the snow-accounting methods, clearly demonstrating the divergence of deficit calculations between the two methods in the region with significant snow cover. In all instances, S_R is calculated as the maximum observed value of the storage deficit. In the high snow location using the original method, this leads to an estimated value of S_R that is approximately 50% larger than that calculated with the snow-accounting method.

https://doi.org/10.5194/hess-2020-602
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Hydrology and Earth System Sciences
Discussions

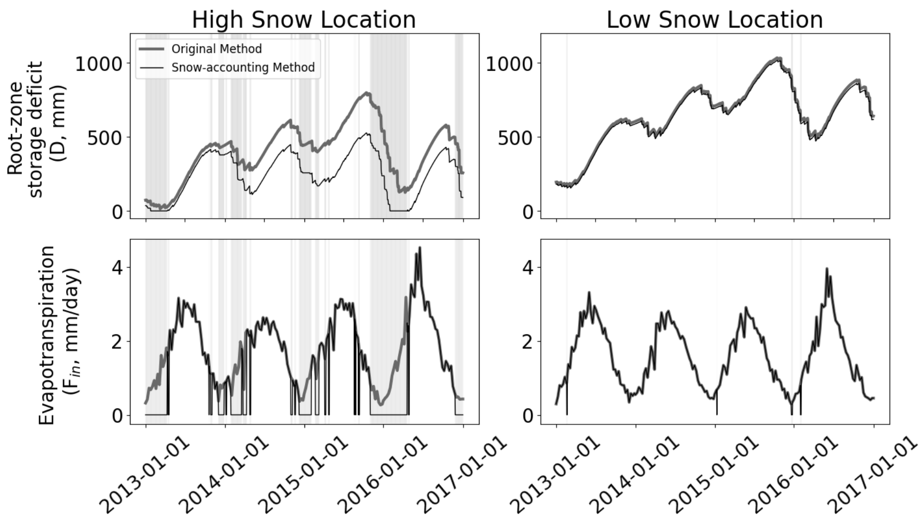

Figure 2. Storage deficit timeseries for representative 'high-snow' and 'low-snow' locations in the Sierra Nevada (locations mapped in Fig. 1) showing the difference between the original and snow-accounting methods. During snow-free periods (white background), deficits change identically (though there may be a vertical offset). During periods when snow is present (grey background), the new method prevents deficit growth, whereas the deficit may grow during snowy periods using the original method (e.g., Jan of 2015). The plot demonstrates how the original method may lead to a larger estimate of S_R (computed as the maximum value of D) in snow-dominated locations.

4 Discussion

Our proposed method for estimating S_R is a minimum estimate. Actual S_R should generally exceed estimated S_R values presented in our revised method, because some evapotranspiration occurs during times when snow cover is present. The snow-accounting method and the original method do not account for leakage, surface runoff, and upslope drainage in the calculation of F_{in}.

S_R in rain-dominated climates has been shown to impact drought resilience (Hahm et al., 2019a), and snow-rain transition elevations are increasing as the climate warms (Knowles et al., 2006). If precipitation arrives as rain rather than snow, the role of the subsurface in storing that water for plants will likely be amplified. Globally, mountainous snow-rain transition zones tend to coincide with forested areas, underscoring the importance of accurate estimates of S_R for prediction of forest sensitivity to climate variability in the future.

5 Conclusions

We argue that an existing method for estimating root-zone water storage capacity (S_R) will tend to overestimate S_R in snowy areas due to unaccounted for snow melt, evaporation, and sublimation processes. We provide a correction factor that relies on a widely available distributed percent snow cover dataset to provide a tighter lower bound estimate on S_R. Conservatively

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describing S_R is important because the role of the subsurface in storing water is likely to be amplified in a warming climate, in which more precipitation will fall as rain rather than snow.

6 Data and code availability

The Python code used to implement the algorithm described here with the Google Earth Engine is available and executable as a notebook hosted on Google Colab here: https://colab.research.google.com/drive/1R6WkxaG77-O2Q7hEaiCVMvuE_1oCf_6S?usp=sharing#scrollTo=dIgdaDTl8Jb5. The datasets used to calculate S_R are free and publicly accessible via the Earth Engine platform (see the links above in the Methods section above and the retrieval of the datasets within the code). The output S_R raster is available at Hydroshare: https://www.hydroshare.org/resource/ee45c2f5f13042ca85bcb86bbfc9dd37/.

Author contributions. All authors conceived of the project. D.N.D., W.J.H., and K.D.C. wrote code, D.N.D. and W.J.H. wrote the first manuscript draft, and all authors edited the manuscript.

Competing interests. The authors declare no competing interests.

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https://doi.org/10.5194/hess-2020-602
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References

Arkley, R. J.: Soil moisture use by mixed conifer forest in a summer-dry climate, Soil Science Society of America Journal, 45, 423–427, 1981.

Botter, G., Porporato, A., Rodriguez-Iturbe, I., and Rinaldo, A.: Basin-scale soil moisture dynamics and the probabilistic characterization of carrier hydrologic flows: Slow, leaching-prone components of the hydrologic response, Water resources research, 43, 2007.

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., Curtis, J., and Pasteris, P. P.: Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States, International Journal of Climatology: a Journal of the Royal Meteorological Society, 28, 2031–2064, 2008.

Daly, C., Smith, J. I., and Olson, K. V.: Mapping atmospheric moisture climatologies across the conterminous United States, PloS one, 10, e0141 140, 2015.

Dawson, T. E., Hahm, W. J., and Crutchfield-Peters, K.: Digging deeper: what the critical zone perspective adds to the study of plant ecophysiology, New Phytologist, 226, 666–671, https://doi.org/10.1111/nph.16410, 2020.

de Boer-Euser, T., McMillan, H. K., Hrachowitz, M., Winsemius, H. C., and Savenije, H. H. G.: Influence of soil and climate on root zone storage capacity, Water Resources Research, 52, 2009–2024, https://doi.org/10.1002/2015wr018115, 2016.

Deal, E., Braun, J., and Botter, G.: Understanding the role of rainfall and hydrology in determining fluvial erosion efficiency, Journal of Geophysical Research: Earth Surface, 123, 744–778, 2018.

Dralle, D. N., Hahm, W. J., Rempe, D. M., Karst, N. J., Anderegg, L. D. L., Thompson, S. E., Dawson, T. E., and Dietrich, W. E.: Plants as sensors: vegetation response to rainfall predicts root-zone water storage capacity in Mediterranean-type climates, Environmental Research Letters, https://doi.org/10.1088/1748-9326/abb10b, http://iopscience.iop.org/10.1088/1748-9326/abb10b, 2020.

Friedl, M. and Sulla-Menashe, D.: MCD12Q1 MODIS/Terra+ aqua land cover type yearly L3 global 500m SIN grid V006 [data set], NASA EOSDIS Land Processes DAAC, 10, 2015.

Gan, R., Zhang, Y., Shi, H., Yang, Y., Eamus, D., Cheng, L., Chiew, F. H., and Yu, Q.: Use of satellite leaf area index estimating evapotranspiration and gross assimilation for Australian ecosystems, Ecohydrology, 11, e1974, 2018.

Gao, H., Hrachowitz, M., Schymanski, S., Fenicia, F., Sriwongsitanon, N., and Savenije, H.: Climate controls how ecosystems size the root zone storage capacity at catchment scale, Geophysical Research Letters, 41, 7916–7923, 2014.

Hahm, W. J., Dralle, D. N., Rempe, D. M., Bryk, A. B., Thompson, S. E., Dawson, T. E., and Dietrich, W. E.: Low subsurface water storage capacity relative to annual rainfall decouples Mediterranean plant productivity and water use from rainfall variability, Geophysical Research Letters, 2019a.

Hahm, W. J., Rempe, D. M., Dralle, D. N., Dawson, T. E., Lovill, S. M., Bryk, A. B., Bish, D. L., Schieber, J., and Dietrich, W. E.: Lithologically controlled subsurface critical zone thickness and water storage capacity determine regional plant community composition, Water Resources Research, https://doi.org/10.1029/2018WR023760, 2019b.

Hahm, W. J., Rempe, D. M., Dralle, D. N., Dawson, T. E., and Dietrich, W. E.: Oak Transpiration Drawn From the Weathered Bedrock Vadose Zone in the Summer Dry Season, Water Resources Research, 56, e2020WR027 419, https://doi.org/https://doi.org/10.1029/2020WR027419, 2020.

Hall, D., Riggs, G., and Salomonson, V.: MODIS/Terra Snow Cover Daily L3 Global 500m Grid, Version 6, Boulder, CO: NASA National Snow and Ice Data Center Distributed Active Archive Center, 2016.

Jones, D. and Graham, R.: Water-holding characteristics of weathered granitic rock in chaparral and forest ecosystems, Soil Science Society of America Journal, 57, 256–261, 1993.

185 Knowles, N., Dettinger, M. D., and Cayan, D. R.: Trends in snowfall versus rainfall in the western United States, Journal of Climate, 19, 4545–4559, 2006.

Lewis, D. and Burgy, R. H.: The relationship between oak tree roots and groundwater in fractured rock as determined by tritium tracing, Journal of Geophysical Research, 69, 2579–2588, 1964.

Miller, G. R., Chen, X., Rubin, Y., Ma, S., and Baldocchi, D. D.: Groundwater uptake by woody vegetation in a semiarid oak savanna, Water Resources Research, 46, 2010.

Montgomery, D. R. and Dietrich, W. E.: A physically based model for the topographic control on shallow landsliding, Water resources research, 30, 1153–1171, 1994.

Porporato, A., Daly, E., and Rodriguez-Iturbe, I.: Soil water balance and ecosystem response to climate change, The American Naturalist, 164, 625–632, 2004.

195 Rempe, D. M. and Dietrich, W. E.: Direct observations of rock moisture, a hidden component of the hydrologic cycle, Proceedings of the National Academy of Sciences, 115, 2664–2669, 2018.

Reynolds, C., Jackson, T., and Rawls, W.: Estimating soil water-holding capacities by linking the Food and Agriculture Organization soil map of the world with global pedon databases and continuous pedotransfer functions, Water Resources Research, 36, 3653–3662, 2000.

Rose, K., Graham, R., and Parker, D.: Water source utilization by Pinus jeffreyi and Arctostaphylos patula on thin soils over bedrock, Oecologia, 134, 46–54, 2003.

Salve, R., Rempe, D. M., and Dietrich, W. E.: Rain, rock moisture dynamics, and the rapid response of perched groundwater in weathered, fractured argillite underlying a steep hillslope, Water Resources Research, 48, 2012.

Schwinning, S.: The ecohydrology of roots in rocks, Ecohydrology: Ecosystems, Land and Water Process Interactions, Ecohydrogeomorphology, 3, 238–245, 2010.

205 Wang-Erlandsson, L., Bastiaanssen, W. G. M., Gao, H., Jägermeyr, J., Senay, G. B., van Dijk, A. I. J. M., Guerschman, J. P., Keys, P. W., Gordon, L. J., and Savenije, H. H. G.: Global root zone storage capacity from satellite-based evaporation, Hydrology and Earth System Sciences, 20, 1459–1481, https://doi.org/10.5194/hess-20-1459-2016, 2016.

Zhang, Y., Kong, D., Gan, R., Chiew, F. H., McVicar, T. R., Zhang, Q., and Yang, Y.: Coupled estimation of 500 m and 8-day resolution global evapotranspiration and gross primary production in 2002–2017, Remote Sensing of Environment, 222, 165–182, 2019.