In the past several decades, field studies have shown that woody plants can access substantial volumes of water from the pores and fractures of bedrock\(^2\)–\(^5\). If, like soil moisture, bedrock water storage serves as an important source of plant-available water, then conceptual paradigms regarding water and carbon cycling may need to be revised to incorporate bedrock properties and processes\(^5\)–\(^6\). Here we present a lower-bound estimate of the contribution of bedrock water storage to transpiration across the continental United States using distributed, publicly available datasets. Temporal and spatial patterns of bedrock water use across the continental United States indicate that woody plants extensively access bedrock water for transpiration. Plants across diverse climates and biomes access bedrock water routinely and not just during extreme drought conditions. On an annual basis in California, the volumes of bedrock water transpiration exceed the volumes of water stored in human-made reservoirs, and woody vegetation that accesses bedrock water accounts for over 50% of the aboveground carbon stocks in the state. Our findings indicate that plants commonly access rock moisture, as opposed to groundwater, from bedrock and that, like soil moisture, rock moisture is a critical component of terrestrial water and carbon cycling.

**Results and discussion**

**Bedrock water sustains transpiration**

Over 45% of the wooded land area across the CONUS is underlain by shallow (<1.5 m deep) bedrock (Fig. 1). These areas are distributed across a broad range of environments (Fig. 2), consistent with previous mapping of the distribution of weathered bedrock across the CONUS\(^3\). A compilation of field studies reporting rooting into bedrock (locations shown as pink and green in Fig. 2b) confirms that roots penetrate bedrock across a broad range of plant species, climates and rock types globally (Methods). To quantify where bedrock water is routinely accessed by woody vegetation, we calculated a lower bound on the volume of bedrock water accessed by plants in a given water year \((D_{\text{bedrock},Y})\) bedrock water storage deficit in water year \(Y\) ) for areas where woody vegetation overlies shallow bedrock. The spatial distribution of \(D_{\text{bedrock},Y}\) is mapped in Figs. 2, 3 (Methods, Extended Data Fig. 1). In locations shown in black in Fig. 2, \(D_{\text{bedrock},Y}\) is zero in all years, meaning that soil water storage capacity is insufficient to explain the observed evapotranspiration (ET). However, in many areas across the CONUS, soil water storage capacity is insufficient to explain ET (that is, \(D_{\text{bedrock},Y}\) is commonly greater than zero; pink and green in Fig. 2), and, therefore, bedrock must supply water for transpiration. Green areas, where \(D_{\text{bedrock},Y}\) is greater than zero across all study years, indicate routine use of bedrock water for transpiration. These locations host substantial aboveground biomass. For example, woody vegetation that withdraws bedrock water for ET on an annual basis (green in Fig. 2) accounts for over 50% of California’s aboveground carbon stocks\(^19\) (587 Tg of carbon) (Extended Data Fig. 2a).

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We calculate a bedrock root-zone water storage capacity, \( S_{\text{bedrock}} \), which is defined as the largest storage used by woody vegetation over a multiyear time window (2003–2017) that cannot be accounted for by soil water storage capacity (Methods, Extended Data Fig. 5). \( S_{\text{bedrock}} \) as a percentage of total root-zone storage capacity is reported in Fig. 4, which shows that bedrock water storage often constitutes the majority of total storage capacity in the root zone.

In some locations, the magnitude of \( D_{\text{bedrock}} \) is relatively consistent across different years, and consequently similar to \( S_{\text{bedrock}} \) indicating that plants withdraw similar amounts of bedrock water each year. However, in other locations, such as the southern Sierra Nevada in California and the Edwards Plateau in Texas, \( S_{\text{bedrock}} \) is often larger than \( D_{\text{bedrock}} \) (Extended Data Figs. 3, 5), indicating that the storage capacity of plant-accessible water in bedrock is much greater than the storage that is withdrawn in a given year. Under these conditions, bedrock may have a central role in plant response to multiyear drought because bedrock water is progressively drawn down to explain the observed ET.

Bedrock water serves as a reservoir for transpiration in locations hosting high aboveground biomass (Extended Data Fig. 2a) across a range of biomes and Köppen climate types, including humid climates (Extended Data Fig. 6). The largest measurements of \( S_{\text{bedrock}} \) are associated with arid, semiarid and Mediterranean climate types and evergreen forests, savannas and shrublands (Extended Data Fig. 6, Extended Data Table 1). Bedrock water storage may be particularly important in semiarid shrublands, Mediterranean savannas and Mediterranean needleleaf forests (Extended Data Table 1).

Rock moisture commonly accessed

Locations where field studies document plant use of unsaturated bedrock water storage (that is, rock moisture) coincide with locations where we calculate positive median \( D_{\text{bedrock}} \) (Fig. 3b, Extended Data Fig. 7). This corroborates our use of \( D_{\text{bedrock}} \) as an indicator of ecosystem access to bedrock water stores. Field studies reporting greater than 50% of annual ET derived from rock moisture are shown in Fig. 3b. Some of these sites do not meet our analysis criteria (Methods) and are consequently masked (designated with superscripts in Fig. 3b, Extended Data Fig. 7). This is another indication that our reported values are underestimates of the spatial extent of bedrock water use, and thus the volume of bedrock water accessed (Methods). Although bedrock water storage volumes measured at these sites are calculated using very different methods from those employed here, there is general agreement between \( D_{\text{bedrock}} \) (shown as blue bars in Fig. 3b) and field measurements of bedrock water storage accessed by plants (shown as circles in Fig. 3b).

Bedrock water storage used by plants can commonly occur in the form of rock moisture (Fig. 3b, Extended Data Fig. 7); however, \( D_{\text{bedrock}} \) and \( S_{\text{bedrock}} \) do not discriminate between rock moisture (unsaturated) and bedrock groundwater (saturated). Even in field settings, partitioning plant water use between the unsaturated and saturated zones remains challenging, yet the distinction between them is germane to mechanistically modelling biogeochemical and hydraulic processes. Rock moisture use has been confirmed under circumstances that might commonly be attributed to groundwater use. For example, Hahm et al. have shown that oaks relied on rock moisture to sustain dry season transpiration at an oak savannah site where groundwater remains within 3 m of the surface throughout the year. Insensitivity of ET to extended drought is another tool used to attribute groundwater as a transpiration source; however, storage capacity in the unsaturated zone can produce similar insensitivity of ET to drought. These circumstances suggest that misattribution of rock moisture as groundwater is likely, and that rock moisture use by woody plants may be common.
Fig. 2 | Bedrock water use by woody plants is spatially extensive and can be routine. a, The occurrence of bedrock water withdrawal by woody plants in the CONUS from 2003 to 2017. Coloured areas indicate the extent of woody vegetation where bedrock is encountered within the upper 1.5 m. This area is divided into four colours reflecting locations where the annual bedrock water storage deficit ($D_{\text{bedrock}}$) is greater than zero for every year of the study (green), $D_{\text{bedrock}}$ is greater than zero for at least one year of the study (pink), $D_{\text{bedrock}}$ is not greater than zero for any years of the study (black) and $D_{\text{bedrock}}$ is not reported because our analysis criteria are not met (grey; Methods). An annual $D_{\text{bedrock}}$ value of greater than zero in a given location indicates that the withdrawal of bedrock water is necessary to explain observed ET (Methods). Landcover data were sourced from the USGS NLCD40 and depth to bedrock from the USDA gNATSGO41. b, Global map showing the locations of field studies where rooting into bedrock has been reported (blue) and where rock moisture (that is, bedrock water in the unsaturated zone) has been observed or measured as a contribution to ET (orange). The vector map was generated in Python with data from the literature review (Methods).

Fig. 3 | Magnitude of bedrock water contribution to ET across Texas, California and field studies. a, Magnitude of annual bedrock water storage deficit ($D_{\text{bedrock}}$) across California (top) and Texas (bottom) for the years 2011 and 2017, which represent high variation in $D_{\text{bedrock}}$. $D_{\text{bedrock}}$ for all of the CONUS is shown in Extended Data Fig. 3. b, Soil water storage capacity ($S_{\text{soil}}$, brown) and median $D_{\text{bedrock}, 2003-2017}$ (blue) across sites where previous studies report that over 50% of ET is derived from rock moisture, that is, bedrock water storage in the unsaturated zone. The volume of bedrock water use reported for each study is shown as closed circles (minimum estimates) or open circles (maximum estimates) where available. Site locations are shown at the bottom. Asterisks denote locations where soil depths are greater than 1.5 m (ref. 41), and thus are masked from maps reporting $D_{\text{bedrock}}$ or $S_{\text{bedrock}}$. References for field studies: 1, refs. 2,3, 2, refs. 3,21, 3, refs. 4,43, 4, refs. 5,44,45, 5, refs. 6,46, 6, refs. 7,47,48, 7, refs. 1,50. Data in b are from the literature review (Methods).
Implications of bedrock water uptake

Although it has long been recognized that woody plants root into bedrock\(^\text{22}\), the widespread and routine transpiration of bedrock water reported here suggests that the dynamics of bedrock water storage may be as fundamental to understanding terrestrial water and carbon cycling as soil moisture. Across the western United States in particular, large volumes of water are stored in bedrock and released back into the atmosphere on an annual basis. For example, our deficit analysis suggests that in California alone, 20 km\(^3\) (16.2 million acre-feet) of water can be extracted from bedrock by woody plants annually. This is approximately equal to the volume of water stored in all of the state’s reservoirs combined\(^\text{23}\), and about three times the state’s annual domestic water use\(^\text{24}\). Although our study is limited to the CONUS, bedrock water use by woody vegetation has also been documented in a wide range of environments globally\(^\text{25–32}\).

Investigation of biological and hydraulic processes in the bedrock rhizosphere is a frontier research area\(^\text{33}\). New studies are needed to clarify the role of bedrock water storage under projected shifts in global precipitation regimes, including the stability or vulnerability of ecosystem carbon storage, water-limited conditions\(^\text{37}\). Thus, the availability of bedrock water storage may be key to predicting large-scale vegetation dynamics, including the stability or vulnerability of ecosystem carbon storage, under climate change.

Long-term, intensive monitoring studies are increasingly documenting mechanisms by which roots in bedrock impact ecosystem function\(^\text{31}\), groundwater and stream chemistry\(^\text{32}\), and rates of soil production and weathering\(^\text{3}\). Although bedrock water storage in the humid eastern USA may be largely undetectable via a deficit-based water balance, substantial circulation of water in bedrock may be occurring. This could lead to largely unmeasured drivers of carbon cycling\(^\text{7}\). Thus, bedrock water storage dynamics are likely key to understanding the sensitivity of carbon, water and latent heat fluxes to changes in climate.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, extended data, supplementary information, acknowledgements, peer review information; details of author contributions and competing interests; and statements of data and code availability are available at https://doi.org/10.1038/s41586-021-03761-3.

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Methods

Literature compilation of rooting in bedrock
Available English-language published evidence of rooting into bedrock is included in our literature compilation, which builds on several past compilations. Each entry includes information about rooting, climate, soil and bedrock properties. A subset of sites report use of rock moisture by vegetation. For these entries, where possible, we report estimates of the contribution of rock moisture to evapotranspiration, as well as any estimates of plant-available soil and rock moisture water storage capacities (Fig. 3b, Extended Data Fig. 7).

Landcover and soil datasets
To determine woody landcover, we used the evergreen, deciduous, mixed forest and shrub/scrub landcover classes reported by the United States Geological Survey (USGS) National Land Cover Database (NLCD) at 30-m resolution. To determine areas underlain by bedrock within 1.5 m of the surface, and the available soil water storage capacity for those areas, we use the United States Department of Agriculture (USDA) Gridded National Soil Survey Geographic Database (gNATSGO) product at 90-m resolution. gNATSGO data are generated using soil data from field surveys and subsequent laboratory analysis. These surveys are occasionally repeated and the newest data are validated against historical surveys before replacement in the official nationwide database.

To determine where bedrock underlies shallow soils, we use the gNATSGO product, which reports depths of soil restrictive layers for the classifications of lithic, densic and paralithic bedrock. Our calculation of bedrock water storage considers only areas where bedrock has been encountered within 1.5 m of the surface (Fig. 1, Extended Data Fig. 1). The 1.5 m depth is chosen because soil water storage capacity (S\text{soil}) is only available across the CONUS to 1.5 m depth. Although bedrock water may be accessible to plants in areas with greater than 1.5 m soil depth, we exclude these areas because we cannot quantify S\text{soil} there. We note that in practice, the interface between soil and bedrock has not been systematically mapped and the terminology used for defining that interface can be inconsistent. The contact between soils and underlying bedrock can also be gradational and challenging to determine in the field. For example, saprolite, which can be defined as highly weathered bedrock that retains the original fabric of the rock, is often, but not always designated as a ‘C’ or ‘Cr’ horizon by the gNATSGO soil survey, and thus categorized as a soil in our study. Therefore, S\text{soil} can include saprolite.

We estimate S\text{soil} as the ‘soil available water storage’ (AWS) reported by the gNATSGO database (Extended Data Fig. 2b). This AWS product is calculated as the storage volume, in units of depth, between field capacity (−1/10 bar or −1/3 bar) and wilting point (−15 bars) and is measured for each soil layer until contact with a bedrock restrictive layer. For each layer within a given soil profile, gNATSGO reports a high, low and median value of AWS, which they take a thickness weighted average of to generate three estimates of profile total AWS. Here we use the highest reported value to represent the AWS of any given layer to avoid underestimating soil water storage. As the AWS product does not account for water stored between field capacity and saturation in soils, we tested the sensitivity of our results to the inclusion of this excess water by reporting S\text{bedrock} and median D\text{bedrock} for a hypothetical test case of double S\text{soil} (Extended Data Fig. 8). We double S\text{soil} to approximate the volume of water between field capacity and saturation. Doubling of S\text{soil} necessarily reduces the magnitudes of S\text{bedrock}; however, the spatial area of positive S\text{bedrock} is reduced by only 35%, indicating that underestimation of soil water storage capacity by a factor of two would still lead to a large volume of bedrock water use across the CONUS.

Masking procedure
We employ three masking criteria to constrain our analyses to places where (i) woody landcover occupies at least 75% of the 500-m pixel, (ii) all soils within the 500-m pixel are underlain by bedrock and less than 1.5 m deep, and (iii) total evapotranspiration is less than total precipitation from 2003 to 2017 (Extended Data Fig. 1). The first two masking criteria restrict our calculations to places where water storage deficits could be explained by water extraction by woody plants from bedrock, because bedrock is near the surface and woody plants are present. The third masking criterion is employed to remove locations where outputs exceed inputs over long timespans, indicating either errors in fluxes or unmeasured fluxes entering the rooting zone, such as fog, dew, irrigation or lateral flow in soils. Bedrock water storage could be accessed in areas that do not meet these criteria, and indeed, there are several studies that report plant use of bedrock water in locations that are masked (Fig. 3b, Extended Data Fig. 7). However, in locations where our masking criteria fail to account for fog, dew or lateral inputs of water, bedrock water storage capacity may be overestimated (Methods).

Calculation of root-zone water storage capacity and maximum annual root-zone storage deficit
Here we use a statistically interpolated precipitation data product (Oregon State’s PRISM daily precipitation) and a remotely sensed evapotranspiration product (Penman–Monteith–Leuning Evapotranspiration V2) to estimate the minimum magnitude of root-zone water storage capacity (S\text{root}) following the method developed by Dralle et al., which adapts the original method of S\text{drought} estimation from Wang-erlandsson et al. to account for the presence of snow. All raster processing was conducted using the Google Earth Engine Python application programming interface (API).

The method takes a mass-balance approach and is therefore broadly applicable, not requiring place-based soil or plant-community parameterization. Specifically, the technique tracks a root-zone storage deficit (D) as a running, integrated difference between water fluxes exiting (F\text{out}) in units of length per time (L/T) and entering (F\text{in}) the root zone, here taken to be evapotranspiration (ET) and precipitation (P), with F\text{out} = ET and F\text{in} = P. This is accomplished by first computing the accumulated difference between F\text{out} and F\text{in} over a given time interval t\text{n} to t\text{n+1}:

\[ A_{t_n\rightarrow t_{n+1}} = \begin{cases} 0 & \text{if } C \geq C_0 \\ \int_{t_n}^{t_{n+1}} F_{\text{in}} - F_{\text{out}} \, dt & \text{if } C < C_0 \end{cases} \]

where C\text{drought} is the threshold percentage of areal snow cover deemed non-negligible, here chosen as 10%. This avoids attributing evapotranspiration from snowmelt recharge into the rooting zone to unreplicated water storage depletion. Snow data are acquired from the Normalized Difference Snow Index (NDSI) snow cover band from the 500-m MODIS/Terra data product.

With this, the root-zone storage deficit at any given time is defined iteratively as:

\[ D(t_{n+1}) = \max(0, D(t_n) + A_{t_n\rightarrow t_{n+1}}) \]

Following these equations, D at any given time represents a lower bound on the volume of water that plants have used that must have been withdrawn from root-zone storage without replenishment by precipitation. The deficit is effectively ‘reset’ to zero during wet periods, because the updated D(t\text{n+1}) equals the maximum of 0 and the previous deficit plus the current difference between outgoing and incoming fluxes. Over the course of a year or many subsequent seasonal cycles, the maximum value of D represents the largest amount of subsurface water storage space that must have been used to supply ET.

Here we report two deficit-related quantities: the observed maximum root-zone storage deficit in water year Y (D\text{max,Y}) and the maximum root-zone storage deficit over the period of record (2003–2017), taken as a lower bound on the actual root-zone storage capacity, S\text{root}} D\text{max,Y} is
calculated for a given water year \( Y \) (that is, from 1 October in year \( Y - 1 \) to 30 September in year \( Y \)) first by assuming the root-zone storage deficit on 1 October is zero, then tracking that deficit through to the end of the water year. \( D_{\text{max,}Y} \) is the maximum value of the deficit time series over that water year. The procedure for computing \( S \) is similar, but the deficit time series is computed over the period of record. That is, \( D \) is taken to be zero on 1 October 2003 and is tracked continuously until 30 September 2018. \( S \) is then taken to be the maximum value of this multiyear deficit time series. Importantly, \( S \) and \( D_{\text{max}} \) are conservative lower estimates of water storage capacity and do not account for all possible withdrawal (see Assumptions and limitations of deficit-based calculations of bedrock water storage).

### Bedrock root-zone water storage capacity and annual bedrock root-zone water storage

To quantify the root-zone storage capacity that cannot be accounted for by soil water storage capacity, \( S_{\text{bedrock}} \), we subtract the soil water storage capacity from \( S \), making sure to bound \( S_{\text{bedrock}} \) at zero:

\[
S_{\text{bedrock}} = \begin{cases} 
0 & \text{if } S_{\text{soil}} \geq S \\
S - S_{\text{soil}} & \text{if } S_{\text{soil}} < S 
\end{cases}
\]

We perform a similar calculation to quantify the annual bedrock root-zone water storage capacity, \( D_{\text{bedrock,}Y} \), which is the maximum annual root-zone storage deficit that cannot be accounted for by soil water storage capacity:

\[
D_{\text{bedrock,}Y} = \begin{cases} 
0 & \text{if } S_{\text{soil}} \geq D_{\text{max,}Y} \\
D_{\text{max,}Y} - S_{\text{soil}} & \text{if } S_{\text{soil}} < D_{\text{max,}Y} 
\end{cases}
\]

To attribute \( D_{\text{bedrock,}Y} \) and \( S_{\text{bedrock}} \) to transpiration of bedrock water by woody plants, we assume that evaporation is restricted to the soil layer, such that evaporation fluxes are accounted for by subtraction of \( S_{\text{soil}} \) from \( D_{\text{max}} \) or \( S \). Note that we use the highest AWS value reported. Therefore, \( S_{\text{bedrock}} \) and \( D_{\text{bedrock,}Y} \) are conservative lower bounds, as we use the upper bound on \( S_{\text{soil}} \) and the lower bound on \( S \) and \( D_{\text{max,}Y} \), respectively. The sensitivity of \( S_{\text{bedrock}} \) to \( S_{\text{soil}} \) is discussed above in ‘Landcover and soil datasets’.

### Assumptions and limitations of deficit-based calculations of bedrock water storage

The methods we use to estimate the spatial pattern and magnitude of bedrock water use will provide a lower bound on bedrock water storage capacity, because (1) we employ a deficit-based water balance, (2) we use the largest available estimate of soil water storage capacity, and (3) we use masking criteria to exclude areas where alternative mechanisms might reasonably account for evapotranspiration. Here we explore the assumptions and limitations of our approach.

Deficit-based calculations of root-zone storage yield lower-bound estimates because they rely on fluxes to infer storage dynamics. That is, deficit-based methods cannot ‘detect’ the presence of a storage element if that storage does not supply a flux over the period of record of the flux datasets. For this reason, actual root-zone storage capacity will always exceed deficits measured through water-balance methods. Thus, in the absence of systematic error, the deficit is a lower bound on storage capacity. In addition, we make an assumption that bedrock water storage is only accessed when soil water storage is exhausted. If bedrock water is accessed at the same time as soil water storage, then our water balance calculation would result in additional underestimation of bedrock water storage capacity.

We assume that tracking the fluxes of precipitation \( (F_{\text{prec}}) \) and evapotranspiration \( (F_{\text{evap}}) \) into and out of a pixel, respectively, results in a lower-bound estimate of root-zone water storage deficit. In addition to the reasons listed elsewhere, this is also because the deficit is minimized by ignoring any fluxes out of the pixel that occur by mechanisms other than evapotranspiration, such as downward drainage or runoff. We acknowledge that not all precipitation entering the root zone leaves as evapotranspiration; however, by imposing that \( F_{\text{evap}} \) is represented by evapotranspiration alone, the deficit represents a lower bound on root-zone storage capacity. Including any additional fluxes in \( F_{\text{out}} \) would act to increase the deficit. As drainage is challenging to quantify, we follow deficit-based calculation methods (for example, Wang-Erlandsson et al.\(^{43}\)) and do not attempt to quantify it. Instead, we report the lower bound of root-zone storage, which occurs when \( F_{\text{out}} \) occurs by evapotranspiration only.

Underestimating input fluxes (\( F_{\text{in}} \)) leads to overestimating \( S_{\text{bedrock}} \) and \( D_{\text{bedrock,}Y} \), as \( F_{\text{out}} \) could be underestimated where fog, dew, irrigation or lateral flow (across pixels) is important. Fog and dew may be important sources of water, but are probably only important in a small subset of the areas where we report \( S_{\text{bedrock}} \) and \( D_{\text{bedrock,}Y} \). By masking locations where evapotranspiration exceeds precipitation over long time periods, we exclude locations where additional inputs to the root zone are required to explain the observed evapotranspiration data. However, lateral transport of water in the subsurface could still occur without causing evapotranspiration to exceed precipitation in the long term, in which case \( S_{\text{bedrock}} \) and \( D_{\text{bedrock,}Y} \) would be overestimated. By removing entire 500-m pixels where any soils exceed 1.5 m depth, we tend to exclude convergent parts of the landscape, which can have thicker soils. These areas are the most likely to experience lateral inputs of water into the root zone. Nonetheless, additional research is needed to constrain lateral water flows within hillslopes to better understand water availability to plants.

Systematic errors in the data products used in our water balance could lead to overestimation of storage. One limitation of the deficit method is that it relies on taking the integrated (summed) difference between precipitation (\( F_{\text{in}} \)) and evapotranspiration (\( F_{\text{evap}} \)) such that error in either flux will accumulate and could be large relative to small deficit estimates. \( S_{\text{bedrock}} \) across the CONUS is shown in Extended Data Fig. 5. We compare this result to bedrock water storage deficit estimates obtained using the root-zone water store capacity (\( S \)) dataset of Wang-Erlandsson et al.\(^{44}\) (who used different \( P \) and ET data products at a coarser spatial resolution) shown in Extended Data Fig. 9. The patterns of bedrock water storage capacity remain similar, which suggests that the general spatial trends and magnitudes in bedrock water storage are robust to choices in input data products.

As remotely sensed ET and \( P \) datasets and in situ measurements of bedrock water storage become available, such datasets could be used to create increasingly accurate estimates of bedrock water use following the workflow presented here.

### Data availability

All of the datasets generated in this study are available in the Hydroshare repository at https://doi.org/10.4211/hs.a2f0d5fd10f4cd169a3465f72ca6f3\(^{15}\). The precipitation data are available from the PRISM Climate Group\(^{46}\) at https://prism.oregonstate.edu/. The evapotranspiration data are available from Penman–Monteith–Leuning Evapotranspiration V2 (PML_V2)\(^{47}\) at https://github.com/gee-hydro/gee_PML. The snow cover data are available from NASA's MODIS/Terra Snow Cover Daily\(^{48}\) at https://nsidc.org/data/MOD01A1/. The snow data are available from the USDA's gNATSGO\(^{49}\) database at https://www.ncrs.usda.gov/wps/portal/ncrs/detail/soils/survey/geo?cid=nrcsrpdr1464625 and in the Hydroshare repository. The landcover data are available from the USGS's National Land Cover Database\(^{50}\) at https://www.usgs.gov/cyberscience/eros/science/national-land-cover-database?qt-science_center_objects=0#qt-science_center_objects. The biome data are available from NASA’s MODIS/Terra + Aqua Land Cover Type Yearly\(^{51}\) at https://lpdaac.usgs.gov/products/mcd12q1v006/. The Köppen climate data are available at https://people.eng.unimelb.edu.au/mpeel/koppen. html. The above ground biomass\(^{52}\) data are available at https://daac.ornl.
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gov/VEGETATION/guides/Global_Maps_C_Density_2010.html. With the exception of the gNATSGO and aboveground biomass data, all of the raster datasets are accessible via Google Earth Engine\(^2\). Google Earth Engine access URLs can be found in the code accompanying this study (see Code Part 2, Section 1). Source data are provided with this paper.

Code availability

Codes are available from https://github.com/erica-mccormick/widespread-bedrock-water-use or https://doi.org/10.5281/zenodo.4904036.

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Author contributions

E.L.M. led the data acquisition and analysis and coordinated the manuscript preparation. E.L.M. and D.M.R. drafted the initial manuscript. D.N.D., K.D.C. and E.L.M. led the data acquisition and analysis and coordinated the process, and approved the final version. D.M.R. conceptualized and led the study. E.L.M. and D.M.R. drafted the initial manuscript. D.N.D., K.D.C. and E.L.M. led the data acquisition and analysis and coordinated the process, and approved the final version. D.M.R. conceptualized and led the study.

Competing interests

The authors declare no competing interests.

Additional information

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Extended Data Fig. 1 | Flow chart of the methodology for bedrock storage deficit and capacity calculations. Workflow for the calculation of total and annual bedrock water storage deficits ($S_{\text{bedrock}}$ and $D_{\text{bedrock}}$, respectively). Data products (solid thick border) are reported with their spatial resolution. Calculations and thresholds are reported in white boxes (Methods). Masking procedures exclude areas where output fluxes significantly exceed input fluxes (top right) and include areas where woody vegetation is established on shallow soils (middle right). These masks are applied to the water budget calculation (left and bottom) to arrive at conservative estimates of $S_{\text{bedrock}}$ and $D_{\text{bedrock}}$, at the CONUS scale.
Extended Data Fig. 2 | Maps of soil and aboveground carbon input products used in this study. a, Aboveground carbon sourced from Spawn et al.\(^\text{19}\) (Mg ha\(^{-1}\)). b, Soil available water storage capacity (mm) for the CONUS. Soil available water storage sourced at 90-m resolution from the USDA gNATSGO\(^\text{41}\) product and provided for the upper 1.5 m (Methods).
Extended Data Fig. 3 | Annual bedrock water storage deficit for four years across the CONUS. a–d, Annual bedrock water storage deficit, $D_{\text{bedrock}}$, for 2011 (a), 2014 (b), 2015 (c) and 2017 (d).
Extended Data Fig. 4 | Median annual bedrock water storage deficit constitutes more than a quarter of mean annual precipitation in some places. The magnitude of median $D_{\text{bedrock}}$ divided by mean annual precipitation shown as a percent for California (left) and Texas (right). Mean annual precipitation was calculated in Google Earth Engine\textsuperscript{42} in the Google Colaboratory environment using the PRISM Daily Spatial Climate Data set ANSl data product\textsuperscript{16,37}. 
Extended Data Fig. 5 | Bedrock water storage capacity across the CONUS, California and Texas. The distribution of bedrock water storage capacity, $S_{\text{bedrock}}$, for locations meeting masking and calculation criteria. Where $S_{\text{bedrock}}$ is greater than zero, bedrock water storage is needed to explain observed ET (Methods).
Extended Data Fig. 6 | Distribution of bedrock water storage capacity varies by Köppen climate type and biome. **a**, Boxplots show median, interquartile range and 1.5 times the interquartile range of $S_{\text{bedrock}}$ across Köppen climate type (left) and biome (MODIS landcover classifications) (right) for locations which meet analysis criteria (Methods). The number of pixels in each category is given above each box. The 25th percentile is non-zero for many biomes and climates. **b**, Maps indicating the locations associated with each climate (left) and biome (right). Biome and climate subgroups with less than 2,000 km$^2$ are excluded. Summary statistics of groupings are presented in Extended Data Table 1. Post hoc tests (Kruskal–Wallis and Dunn’s tests) reveal statistically significant differences ($P < 0.001$) of median $S_{\text{bedrock}}$ between all climate group pairings and between all biome group pairings. Boxplots and statistical analyses were processed using the Google Earth Engine Python API.
Extended Data Fig. 7 | Soil and bedrock water storage capacity at locations where rock moisture use by plants has been documented. Soil water storage capacity $S_{\text{soil}}$ (brown) and median $D_{\text{bedrock,2004-2017}}$ (blue) for locations with documented plant use of rock moisture, that is, bedrock water storage from the unsaturated zone. Superscripts denote locations that are masked, for not being classified as woody vegetation ($\dagger$), having soil depth greater than 1.5 m (*) or because the cumulative 2003–2017 evapotranspiration exceeds precipitation (†) (Methods, Extended Data Fig. 1). Data were sourced from the literature review (Methods). References for field studies: refs. 20,69,70,71,72,73,74,75,76,77,78,79,80.
Extended Data Fig. 8 | Comparison of $S_{\text{bedrock}}$ and median $D_{\text{bedrock}}$ to calculations using double the published soil water storage capacity values.

a, Bedrock water storage capacity ($S_{\text{bedrock}}$) assuming soil water storage capacity ($S_{\text{soil}}$) is double that reported by gNATSGO$^4$ to account for the possibility of soils providing water to ET at saturation, which is commonly estimated as double field capacity. 

b, $S_{\text{bedrock}}$ without doubling of $S_{\text{soil}}$.

c, d, Median annual bedrock water storage deficit, $D_{\text{bedrock}}$, 2003–2017, with doubled (c) and original (d) $S_{\text{soil}}$. 
Extended Data Fig. 9 | Bedrock water storage capacity calculated with published values of root-zone storage capacity. a, b, Two versions of bedrock water storage capacity ($S_{\text{bedrock}}$) are calculated using root-zone storage capacity ($S_{\text{r}}$) published by Wang-Erlandsson et al. at a 0.5° (roughly 50 km) resolution with input and output fluxes from Climatic Research Unit Time Series version 3.22 (CRU TS3.22) (a) and Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) (b). To arrive at $S_{\text{bedrock}}$, $S_{\text{root}}$ is subtracted from the maximum $S_{\text{r}}$ reported in Wang-Erlandsson et al.
**Extended Data Table 1 | Median bedrock water storage capacity for combinations of biomes and Köppen climate types**

| Köppen Climate                  | Biome                          | Median $S_{\text{bedrock}}$ | Mean $S_{\text{bedrock}}$ | Standard Deviation | Area km² |
|---------------------------------|--------------------------------|------------------------------|-----------------------------|---------------------|----------|
| Semi Arid (BSk)                 | Shrubland (<2m Height)         | 113                          | 133                         | 98                  | 99253    |
| Humid Subtropical & Oceanic (Cf)| Deciduous Broadleaf Forests    | 120                          | 124                         | 69                  | 71399    |
| Humid Continental (Db)          | Deciduous Broadleaf Forests    | 0                            | 18                          | 35                  | 59536    |
| Mediterranean (Csb)             | Evergreen Needleleaf Forests   | 154                          | 182                         | 130                 | 53710    |
| Humid Continental (Db)          | Woody Savannas                 | 112                          | 117                         | 78                  | 26369    |
| Humid Continental (Dsb)         | Shrubland (<2m Height)         | 133                          | 149                         | 105                 | 24719    |
| Arid (BWK)                      | Shrubland (<2m Height)         | 101                          | 116                         | 83                  | 23596    |
| Humid Continental & Subarctic (Df)| Deciduous Broadleaf Forests    | 53                           | 70                          | 65                  | 23462    |
| Humid Subtropical & Oceanic (Cf)| Shrubland (<2m Height)         | 410                          | 439                         | 199                 | 23313    |
| Semi Arid (BSk)                 | Open Shrublands                | 173                          | 185                         | 97                  | 19065    |
| Humid Subtropical & Oceanic (Cf)| Woody Savannas                 | 100                          | 132                         | 184                 | 18115    |
| Humid Subtropical & Oceanic (Cf)| Savannahs                      | 609                          | 495                         | 342                 | 14636    |
| Humid Continental (Dsb)         | Woody Savannas                 | 179                          | 197                         | 116                 | 13979    |
| Humid Continental (Dsb)         | Evergreen Needleleaf Forests   | 154                          | 163                         | 112                 | 13044    |
| Humid Continental (Df)          | Savannas                       | 144                          | 153                         | 82                  | 12694    |
| Mediterranean (Cs)              | Mixed Forests                  | 0                            | 4                           | 21                  | 10758    |
| Mediterranean (Cs)              | Woody Savannas                 | 343                          | 399                         | 212                 | 10204    |
| Humid Subtropical & Oceanic (Cf)| Mixed Forests                  | 100                          | 100                         | 67                  | 10162    |
| Mediterranean (Cs)              | Woody Savannas                 | 260                          | 287                         | 179                 | 10149    |
| Mediterranean (Csb)             | Evergreen Needleleaf Forests   | 367                          | 398                         | 159                 | 9954     |
| Humid Continental (Dsb)         | Savannahs                      | 183                          | 212                         | 149                 | 9397     |
| Semi Arid (BSk)                 | Woody Savannas                 | 139                          | 166                         | 124                 | 9376     |
| Subarctic (Dfc)                 | Shrubland (<2m Height)         | 97                           | 107                         | 74                  | 8898     |
| Semi Arid (BSk)                 | Savannahs                      | 208                          | 246                         | 159                 | 8277     |
| Mediterranean (Csb)             | Evergreen Broadleaf Forests    | 192                          | 232                         | 191                 | 7646     |
| Mediterranean (Cs)              | Shrubland (<2m Height)         | 300                          | 376                         | 304                 | 7431     |
| Mediterranean (Cs)              | Savannahs                      | 403                          | 508                         | 300                 | 7058     |
| Humid Continental (Df)          | Evergreen Needleleaf Forests   | 107                          | 114                         | 64                  | 6963     |
| Semi Arid (BS)                  | Shrubland (<2m Height)         | 587                          | 591                         | 210                 | 6670     |
| Subarctic (Dfc)                 | Woody Savannas                 | 119                          | 132                         | 71                  | 5986     |
| Mediterranean (Csb)             | Shrubland (<2m Height)         | 182                          | 246                         | 225                 | 5765     |
| Humid Continental & Subarctic (Df)| Shrubland (<2m Height)         | 157                          | 168                         | 84                  | 5288     |
| Mediterranean (Csb)             | Savannahs                      | 279                          | 366                         | 296                 | 4929     |
| Subarctic (Dfc)                 | Savannahs                      | 123                          | 124                         | 58                  | 4670     |
| Humid Continental & Subarctic (Df)| Woody Savannas                 | 31                           | 58                          | 75                  | 4402     |
| Arid (BWK)                      | Open Shrublands                | 168                          | 180                         | 93                  | 4148     |
| Mediterranean (Csb)             | Mixed Forests                  | 112                          | 120                         | 106                 | 3404     |
| Desert & Arid (BW)              | Open Shrublands                | 271                          | 277                         | 102                 | 3202     |
| Oceanic (Cfb)                   | Deciduous Broadleaf Forests    | 55                           | 63                          | 53                  | 2978     |
| Humid Continental & Subarctic (Dfs)| Shrubland (<2m Height)         | 129                          | 139                         | 74                  | 2931     |
| Mediterranean (Cs)              | Open Shrublands                | 271                          | 284                         | 160                 | 2828     |
| Oceanic (Cfb)                   | Evergreen Needleleaf Forests   | 65                           | 72                          | 64                  | 2671     |
| Semi Arid (BS)                  | Open Shrublands                | 298                          | 338                         | 190                 | 2396     |
| Semi Arid (BSk)                 | Evergreen Needleleaf Forests   | 169                          | 225                         | 220                 | 2200     |

Median $S_{\text{bedrock}}$ and standard deviation for combinations of biomes and Köppen climate types ranked from high to low median $S_{\text{bedrock}}$. The area represented by each biome and climate is reported. Areas less than 2,000 km² are excluded. Bedrock water storage may be particularly important in semiarid shrublands, Mediterranean savannas and Mediterranean needleleaf forests.