High resolution US water table depth estimates reveal quantity of accessible groundwater

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Groundwater is the largest accessible freshwater on Earth, yet its quantity and distribution remain unknown. Here, we develop a high-resolution (approximately 30 m) estimate of water table depth over the continental United States using machine learning that includes uncertainty. We estimate that there is 306,500 km³ (uncertainty range: 291,850–316,720 km³) of groundwater over North America. This represents our highest resolution estimate of accessible freshwater to date, supported by robust statistical performance. We calculate total and accessible groundwater storage, and results show that coarse resolution products are systematically biased in their estimates locally, where decisions are made, as well as at large scales. Our approaches are spatially extensive and locally relevant and thereby bridge a gap between remote sensing and point observations.

Groundwater has large spatial variability, which poses challenges for management

The vast majority of Earth's freshwater lies underground[1], yet its accessibility remains poorly defined. Water table depths, or how far water is from the surface, can vary greatly over short distances. Observations are helpful to detect local to global water table trends[2], and to estimate the total quantity of groundwater[3]. Prior studies have made great strides in simulating groundwater flow at a large scale[4,5] or using remote sensing to infer extraction[6,7]. However, national to global scale hydrological simulations that include pumping[8–10] are computationally and data expensive, typically at coarse resolution (greater than one square kilometer) and lacking uncertainty estimates. At the same time, remote sensing approaches cover only recent decades and have low resolution. Estimating actual water table depths (i.e., including anthropogenic impacts) at high resolution remains a challenge[11].

Groundwater systems are not a uniform reservoir and have significant spatial variability across multiple scales[12]. Water table depth is often portrayed as a subdued replica of topography[13], however, groundwater recharging at higher elevations can travel great distances laterally underground to topographic lows, also known as groundwater convergence. Groundwater can maintain shallow water table depth in areas of local convergence during dry conditions, the same way that baseflow supports streamflow[4,8]. These groundwater-land surface connections are of great importance to both watershed dynamics and ecosystem function[14] often helping to sustain vegetation through drought[15–17].

Shallow groundwater supports more than just ecosystems and streamflow. Local variability in water table depth can also challenge local users who rely on groundwater. For example, a center-pivot irrigation system in which a sprinkler is attached to a single groundwater well to water crops covers approximately 500 m² (Fig. 1). There are more than 14 million center pivots over a large agricultural region like the Ogallala[18] which covers an area of almost 500,000 km² (Fig. 1). Farmers make individual irrigation decisions at these local (500 m²) scales but collectively their actions impact major aquifers regionally that span several US states.

Existing remote sensing tools capture regional[19] to global water trends[6], but generally have very low spatial resolution (Fig. 1). For example, the widely used GRACE satellite data only has a native resolution between 200–500 km² practically closer to the latter[20]. At this resolution, they are unable to capture local groundwater patterns[21]. InSAR monitors ground deformation at higher resolution but does not provide reliable estimates of water storage in shallow aquifers, especially when they are unconfined[22]. Large-scale groundwater modeling has also advanced greatly in recent years[23]; however, this remains a computationally and data-intensive process, and grid resolutions are generally greater than one square kilometer[24]. This resolution is larger than features like an individual well[25] or a center pivot (Fig. 1), and can miss local groundwater convergence that happens at the hillslope scale. The existing

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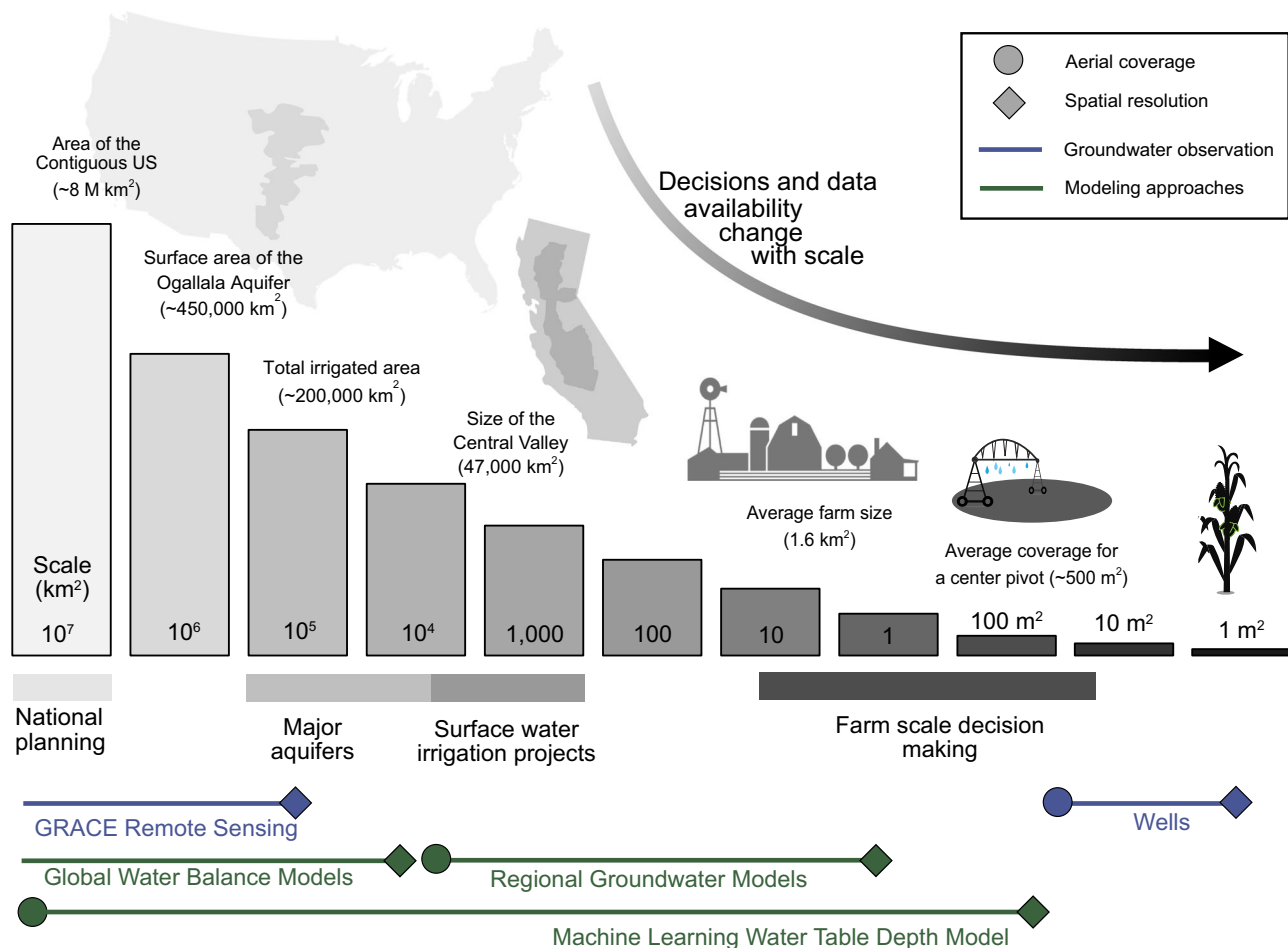
Fig. 1 | The scales of human and natural groundwater systems mismatch with remote sensing and models. There is an inherent mismatch between the scales at which national policy is set (~8 M km²), the extent of major aquifers and irrigation projects (~50 K km²), and the scale at which local irrigation decisions are made (~1 km²). Existing models and remote sensing data products are unable to capture this seven orders of magnitude range of scales, and while much progress is being made, gaps remain at important scales for agriculture. The machine learning approach presented here can seamlessly bridge these scales.

low-resolution approaches can provide insights into aquifer systems, but this information is of limited local use and is likely to be systematically biased because it over smooths topography and spatial variability[26,27].

Here we use a machine learning approach combined with a large (~1 M data point) dataset of groundwater observations (Fig. S1) and ten spatially gridded climatological and hydrogeological inputs at the finest resolutions available (ranging from 1 arc-second to 1 km; see SI section S1.1 and Fig. S2) to develop a high-resolution (one arc-second, approximately 30 m resolution) estimate of water table depth over the US (see S1.2). While this constitutes the most complete groundwater dataset available for the US, well measurements remain sparse and poorly distributed. There are major spatial and temporal gaps in observations (see discussion Section S1.1). Machine learning approaches have been widely applied in surface water hydrology to learn time series behavior for a point such as a stream gage location[28]. In contrast, given the spatial variability in water table depth, predictions of temporal evolution at a point such as a single well are often of limited value. What is needed is a high-resolution spatially extensive product that can combine all available observations and leverage our understanding of the primary drivers of groundwater configuration. Ensemble regression tree approaches, such as random forests, have been used effectively to map water contamination[29,30]. This work builds on the successes of national-scale water table depth estimation using random forests[31,32](see S1.2 for more information on training on randomly split datasets).

Results and Discussion
Machine learning sidesteps computational barriers to bridge scales

The water table depth product presented here was rigorously evaluated at the national (Fig. S3) and regional scale (Figure S12–S29) and provides the statistically most accurate estimate of water table depth to date for the US (see SI S1.2 and S2.1) with a Pearson Correlation Coefficient equal to 0.79 and a root mean square error equal to 14.94 m for the entire US, based on independent test dataset (see S1.2). This product is developed from observations that span a wide range in time (1914–2023) and reflect the pronounced anthropogenic signal of groundwater pumping[2]. Because we do not apply any adjustments to observations for pumping to accurately match the observed water table depths, the machine learning approach implicitly includes the pumping signal present in these observations. The magnitude and location of groundwater pumping are not well characterized nationally and were thus not provided as input to the model (Fig. S2). However, the good performance seen in highly pumped regions (Fig. S8) and when compared to only recently observed water table depths from 2024 (with a Pearson Correlation Coefficient of 0.85 and a root mean square error of 18.96 m; Fig. S10) suggests that a modern groundwater pattern that includes pumping is well represented by this approach. This study does not propose replacing physically based models with machine learning. Instead, our high-resolution data product is intended to complement other approaches to improve understanding of freshwater resources across the US.

Estimates demonstrate local variability and highlight the abundance of shallow groundwater

Our fine scale estimate of the quantity and accessibility of groundwater over the US highlights spatial variability that occurs over many scales (Fig. 2). In addition to areas of deeper groundwater, local groundwater convergence is evident, as are surface features like streams and reservoirs that are closely connected to groundwater (Fig. 2 see insets). Overall, the groundwater patterns shown in Fig. 2 are broadly consistent with regional patterns found in previous work[33,34], though with a more accurate statistical match for predicted and observed WTD across multiple metrics (S3), regions (S12–S29), including uncertainty (S5-S6). For example, deeper water table depths in the western US and shallower depths in the more humid eastern US (Fig. 2) with broad differences seen in climate and terrain consistent with model sensitivity to temperature, elevation, and precipitation (Fig. S4).

We combine our water table depth product (Fig. 2) with spatially variable estimates of porosity from previous literature to calculate total groundwater storage (see SI S1.3 and Table S1). We estimate a total groundwater storage of 306,500 km^3, with an uncertainty range of 291, 850 km^3 to 316, 720 km^3. This estimate includes all groundwater above a depth of 392 m (this depth is the deepest depth for which we have reliable porosity data[35], and roughly the limit of active circulation in the hydrologic cycle[36]).

Substantial previous work has been carried out to understand the total quantity of groundwater storage[1,3,37] and its quality[38,39]. One of the earliest total groundwater storage estimates calculated groundwater recharge as 25% of the precipitation that occurred from 1800-1960 to arrive at an estimate of 220,000 km^3 of storage in the US[40]. Subsequent estimates have generally assumed a constant fully saturated groundwater thickness and multiplied this by the land area and assumed porosity to calculate a storage volume[3,37,41,42]. Total groundwater storage for the US, based on these approaches, range from 400,000[41] to 1.9 M cubic kilometers (global estimates were scaled based on land area to get storage estimates for the US). The two key sources of variability in these estimates are (1) the assumed porosity and (2) the assumed groundwater thickness. For example, an early estimate assumed a thickness of 1000 m and a uniform porosity of 1%[41], whereas later estimates[3,42] used more complicated depth-dependent

porosity estimates and larger groundwater thicknesses of up to 2000 m. More recent work by Gleeson[3] incorporated spatial variability into the porosity mapping. Our results can be compared to these prior estimates by scaling the previous estimates to the 392 m depth used in this study. Using this approach, previous total storage estimates range from 159,559 km^3 (using a 1% porosity[41]), to 320,000 km^3 and 570,00 km^3 (using depth-dependent porosity[3,42]), to 257,000 km^3 (using spatially variable porosity[3]).

Our total storage estimate of 306,500 km^3 agrees well with these previous estimates. Differences in our results are caused by (1) differences in the porosity we use (refer to the SI for details on our hydrogeologic mapping) and (2) the fact that we do not assume a fully saturated water column and use water table depth in our storage estimates. The key advancement in our storage estimate is not the refinement of the total storage number, but rather the ability to evaluate storage with depth and to specifically quantify the presence of shallow groundwater. We find that roughly 40% of the land area in the CONUS domain has a water table depth that is shallower than 10 m, and 16% has water table depths shallower than 5 m. Given the link between shallow groundwater and streamflow[43], vegetation[14,16,44], and agriculture[21], understanding the quantity of groundwater storage that is expected to be closely connected to the land surface is critically important.

Previous work that assumed a fully saturated groundwater column cannot provide depth-dependent storage estimates beyond the relationship between storage and porosity. Gleeson et al.[3] did provide some initial insights into this issue by estimating the fraction of young groundwater that has been recharged in the last 50 years. They used Tritium tracers to calculate the fraction of modern groundwater occurring at different depths and estimated 20,000 km^3 of young groundwater (<50 years) in the US (adjusting based on area from their global estimate). Young groundwater is an important indicator of land surface interactions, but does not provide a direct estimate of storage with depth.

What is not available in prior estimates of continental groundwater storage are the multiscale local patterns that emerge over these regional trends (as illustrated in the Fig. 2 insets). We see similar patterns of local convergence around lakes and stream networks in both the eastern and western US. However, where water table depths are deeper, this convergence
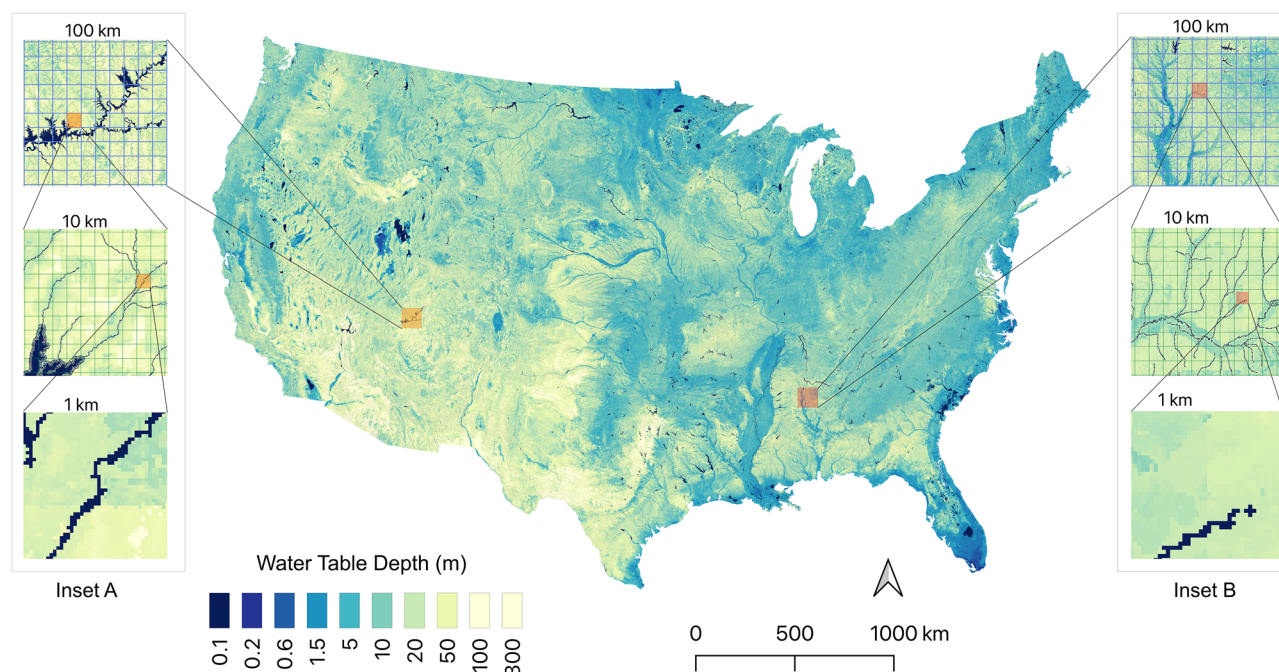

Fig. 2 | A machine learning approach can synthesize ~ 1 M water table depth observations with high-resolution data products to develop a fine-scale estimate of the quantity and accessibility of groundwater over the US. This product is national in scope and covers 7.3 M km^2 yet provides detail at one arc-second (~30 m) resolution. Insets A and B demonstrate these changes in scale, starting at a pixel 100 km on a side, scaling down to show the range of water table depths (WTD) present in even a 1 km cell. Note the log scale in this figure.

is much sharper with transitions from water table depths greater than 100 m to essentially 0 over the span of less than a kilometer. These patterns emphasize the importance of tools that can resolve hillslopes to really capture groundwater surface water connections and areas of shallow groundwater.

Low resolution estimates systematically underestimate accessible groundwater

Existing remote sensing products[6,45] have spatial resolutions of roughly 100 s of km, many global hydrologic models[11,46,47] have 10 km resolution, and national models have 1 km resolution. To compare our 30 m products to these existing frameworks, we systematically decrease the resolution used to estimate water table depths from 30 m to 100 km. There are visual changes in the groundwater patterns (Fig. 3A) with loss of resolution; local convergence zones disappear, and the density of the stream network decreases. These losses of spatial details systematically change both the total quantity of groundwater estimated at different resolutions (Fig. 3B) and the relative fraction of shallow groundwater (Fig. 3C).

The current storage estimates presented here build upon prior work and underline the importance of resolution. Total groundwater storage increases from 252,290 km³ in the lowest resolution (100 km) case to 306,500 km³ in our 30 m resolution product, indicating an 18% underestimation with the coarse resolution product. The storage estimates from the lowest two resolution cases (100 km, 10 km) both fall outside the uncertainty bounds, represented by the inter quartile range, of higher resolutions. The highest three resolutions (1 km-100 m-30 m) produce similar total storage, corroborating prior estimates[3,37] but also indicating that resolutions finer than 1 km are not necessarily needed to further enhance the estimates of total groundwater volume.

The relative fraction of shallow and deep groundwater also shifts systematically with resolution. (Fig. 3C). The very shallow water table depths (less than a meter) are not resolved at coarser resolutions, and shallow (less than five meters) depth estimates increase from 1% to 12% over the US as we refine resolution from 100 km to 30 m. A semivarogram analysis of water table depth over the CONUS for 100 km to 30 m resolutions demonstrates the information lost at different scales (Fig. S11).

This finding highlights a systematic underestimation of shallow groundwater areas in low-resolution products. Because shallow groundwater is closely connected to the land surface, both through surface water bodies and vegetation. Systematically underrepresenting shallow groundwater can lead to biased results if models are used to evaluate sensitivity to drought or flood[48].

Uncertainty in accessible groundwater estimates provides actionable information across scale

In addition to the median of the estimated water table depth (S1.2), we also produce a 300-member ensemble (Fig. S2, S5, S6). This ensemble provides an estimate of the uncertainty in this estimation (S1.2), which varies regionally and by land cover over the US (Fig. 4A, B). Uncertainty over the CONUS varies widely (Fig. 4B). Generally speaking, in relation to estimated water table depths, the interquartile range is higher in the more arid western US than the more humid east. There are also systematic differences in water table uncertainty based on land cover. The distribution of water table depths under crop land cover (Fig. 4A) is shallower and more certain than for the entire study domain. This is likely due to the fact that crops are often grown in flatter and low-lying areas, such as valleys, where the water table depths are shallower.

If we compare the 25th, 50th and 75th percentile estimates of water table depth over a portion of the high plains (Fig. 4C) we see the impact of this uncertainty. In this inset, the ranges for water table depth estimates vary with uncertainty (Fig. 4C). At the local scale the uncertainty can be large; the estimated water table might shift from shallow to deep because of the range in the 25th and 75th percentile estimates. The difference between medium and very deep water table depths has significant implications for water management. This illustrates the need for further work to reduce uncertainty in groundwater estimates with more subsurface observations. While our approach is the most statistically accurate groundwater estimate available, it should be noted that this data-driven approach is still limited by the available observations. In many locations, groundwater observations remain sparse in both space and time. The uncertainty shown here illustrates the need for (1)
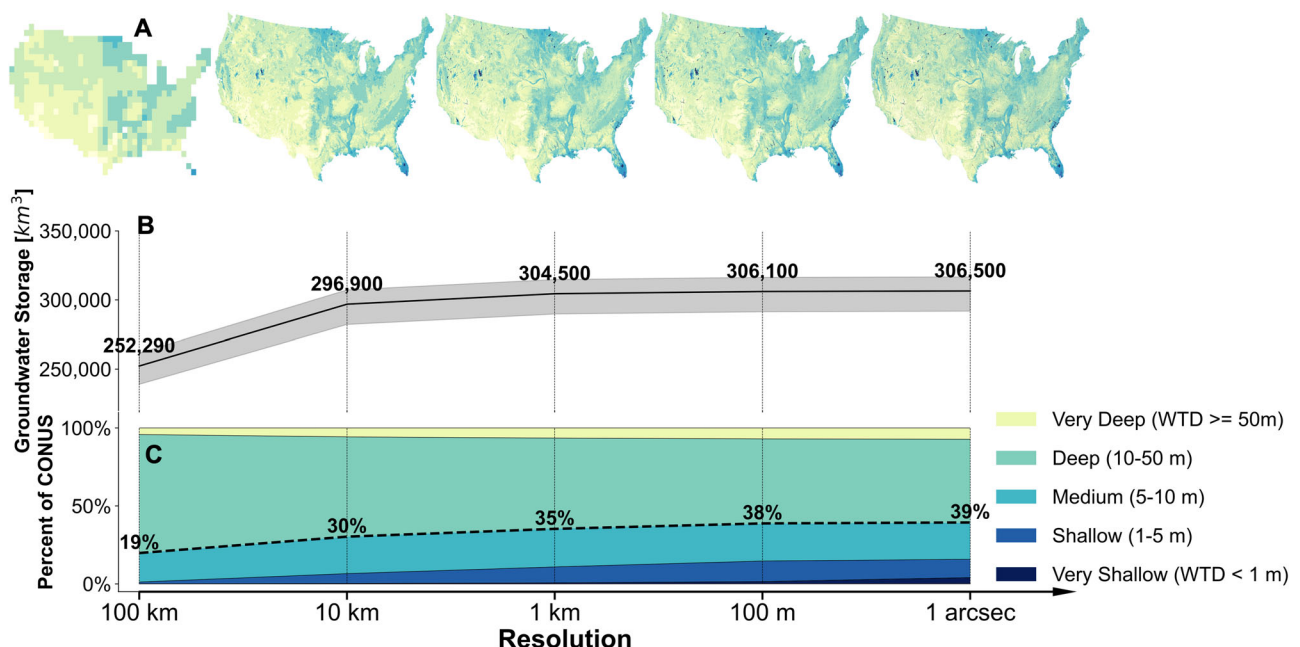

Fig. 3 | High resolution products are needed to resolve accessible groundwater. As resolution is systematically decreased (**A**) from 30 m to 100 km, detail is lost. This loss of detail impacts estimates of the amount of groundwater within the US (**B**), although these estimates stabilize at resolutions finer than 1 km. While the fractions of the US underlain with very deep groundwater (**C**) do not significantly change with resolution, the percentage of the US with shallow groundwater changes significantly as resolution increases to 30 m.
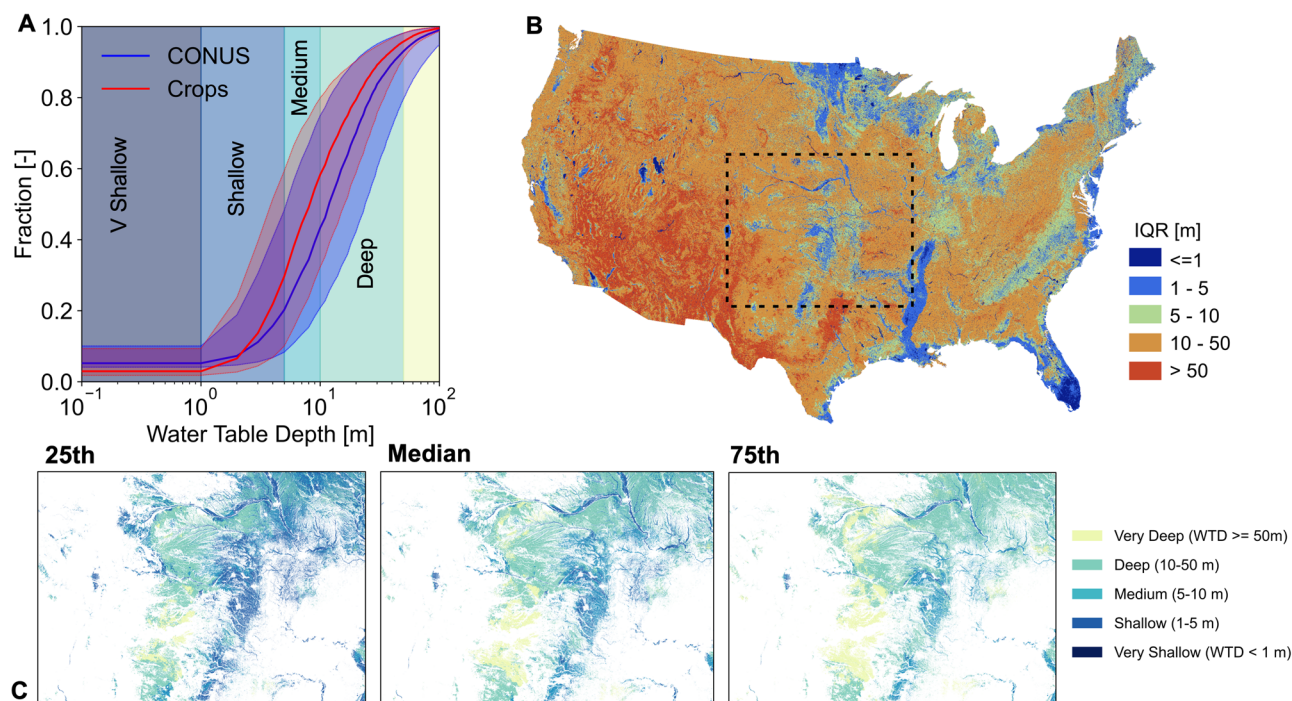
Fig. 4 | The distribution of groundwater under agricultural regions demonstrates the uncertainty in the national water supply used to sustain food production. When compared to the entire CONUS, cropland overlays shallower water table depths with lower uncertainty (**A**). The uncertainty in water table depth varies widely over the US (**B**) as shown by the inter-quartile range (IQR). In general, this uncertainty is lower in the eastern US and greater in the west. This uncertainty impacts our understanding of the security of water used to grow our food (**C**, inset location shown in (**B**) where large portions of agricultural regions might be underlaid by less accessible (very deep) water table depths.

expanded groundwater monitoring and (2) hybrid approaches that combine physically based modeling with data-driven solutions.

Despite the groundwater challenges we currently face[49] and the anticipation of future challenges[50], large-scale estimates of the quantity of groundwater can be connected to the local-scale water table depth to provide additional information critical in water management. The accessibility of groundwater under agricultural regions demonstrates the uncertainty in the national water supply used to sustain food production.

Methods

The complete methods for this work are presented in SI Section 1, including Figs. S1 to S11 and Tables S1 and S2, and are summarized briefly here. We developed a high-resolution water table depth (WTD) map for the contiguous United States using machine learning methods trained on over one million well observations. Long-term mean WTD measurements were compiled from three major groundwater databases spanning 1914-2023 and mapped to a 1 arc-second (~30 m) resolution grid, resulting in 726,828 grid cells with observations (Section S1.1). A random forest model with 300 decision trees was trained on 80% of these data using input variables including climatology (precipitation, temperature, PME), subsurface properties (hydraulic conductivity, soil texture), and topographic features (elevation, slope, distances to streams), achieving test performance of $r = 0.79$, RMSE = 14.94 m, and NSE = 0.62 (Section S1.2). The model generated WTD estimates across CONUS using the median of the tree predictions, with uncertainty quantified using 25th and 75th percentiles of tree outputs. Groundwater storage was then calculated by combining these WTD estimates with 10-layer porosity data from the ParFlow CONUS 2.0 platform, assuming a total subsurface depth of 392 m (Section S1.3). Additional validation was performed across 18 HUC2 basins (Section S2.1) and against independent (i.e., hold-out) observations in Arizona (Section S2.2).

Data availability

Code availability

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