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Global accessibility of groundwater remains highly uncertain

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Abstract

Groundwater is essential for maintaining healthy ecosystems and securing human access to freshwater. Here we show that current estimates of global groundwater accessibility by ecosystems and humans are highly uncertain. To quantify this uncertainty, we define three categories of accessibility and investigate four global groundwater models. Averaged across these models, we estimate that 23% [most deviating model: 71%] of the land area contains groundwater accessible to ecosystems and humans, 57% [29%] is accessible to humans only, and 20% [0.01%] is costly to access or inaccessible. We find that the uncertainty in estimating water table depth severely affects our ability to assess groundwater's crucial role in ecosystem health, global water supplies associated to food security, and human health, with possible implications for achieving multiple Sustainable Development Goals. To reduce this uncertainty, we outline three pathways towards (1) better global datasets, (2) alternative strategies for model evaluation, and (3) greater cooperation with regional experts.

Main

Groundwater makes up 99% of all non-frozen freshwater on our planet[1,2], sustaining ecosystems by providing water to vegetation[3,4], rivers, lakes, and wetlands[5–8]. Groundwater offers a relatively constant supply of freshwater to 43% of the world's irrigated agriculture[2,9] and safe drinking water to 3.7 billion people[2,9]. While surface water supply is increasingly fragile due to climate change[10], groundwater is assumed to remain a reliable source of freshwater[11]. Thus, groundwater is critical for ecosystem health, food supply, and access to clean drinking water – three of the Sustainable Development Goals (SDG) of the United Nations[2]. With a rapidly changing climate, increasing population, and economic growth, the importance of groundwater will likely increase[11]. However, the recent IPCC 6th assessment report[10] concluded that our knowledge of how climate change will affect groundwater is still poor. This lack of knowledge has at least three consequences critical to society.

(1) Terrestrial ecosystems provide vital services such as the supply of clean water[12] and are essential to the carbon cycle[13]. As vegetation may rely on groundwater directly or through capillary rise[4], knowledge about the depth of the groundwater table is a central building block in developing global carbon policy[14]. Recent studies showed that tropical forests may even change from carbon sinks to carbon sources due to water stress[15] and that global land cover changes affect rooting depth and thus carbon and water cycling[16].

(2) Groundwater is the sole source of drinking water for 2.5 billion people[2], but globally, wells are increasingly at risk of running dry[17]. Deeper wells may provide additional resources by accessing deeper lying aquifers[18], but (1) these wells will require more costly energy to build and operate[19,20], (2) water drawn from deeper aquifers might require desalinization[21,22] for human consumption as well as for agricultural uses[23,24], and (3) such wells are likely unsustainable because fossil groundwater replenishes much slower than it is pumped[19]. Cape Town's Day Zero[25] water crisis and the imminent crisis in Bangladesh[26] due to over-abstraction and arsenic contamination highlight the importance of groundwater in sustaining the human right to clean drinking water.

(3) Irrigated agriculture is the largest global user of groundwater by volume[2]. The increasing occurrence and intensity of heatwaves and droughts[10] lead to heightened irrigation demand[27], and non-renewable use already leads to widespread groundwater depletion[28]. Groundwater abstractions may aggravate water loss in rivers and wetlands as lowered groundwater levels potentially decrease the influx of water[29]. Regions like the Central Valley in California[30], the Mekong River Basin[31], and northwestern India[32] have overused their groundwater resources steadily, leading to widespread depletion of groundwater storage and land subsidence. The continuing expansion of agricultural area globally[33] will possibly aggravate the stress on groundwater resources.

A key variable to understand groundwater in all three contexts (ecosystems, drinking water supply, agriculture) is water table depth (WTD). Here we define WTD as depth from the land surface to the top of the saturated zone[34]. Groundwater can quickly become inaccessible for ecosystems if the WTD declines beyond the depth of vegetation roots[35] or below the bottom of rivers and lakes[8]. Humans may build wells reaching down to hundreds of meters[19], yet below a certain depth, reduced permeability will decrease groundwater yield[20] in addition to the already mentioned considerations regarding economic viability and sustainability. We define groundwater as accessible if the WTD is shallow enough to be used by ecosystems and/or humans. Notably, an "accessible" WTD does not mean that (financial) resources are in place to access this water and to transport it to its destination, that the water is of adequate quality, or that the hydrogeological configuration allows for abstraction.

Critically, despite groundwater's crucial role in the Earth system, we cannot yet provide robust information on current and potential future WTD, and thus accessibility, to inform global water policy. Without reliable knowledge of global WTD, it is unclear where international investments (e.g., through the World Bank) and global water policy (e.g., specialized UN agencies such as FAO) will be most needed and most impactful to safeguard this essential resource. This lack of knowledge threatens our ability to reach the SDGs of no poverty[36], zero hunger[37], clean water and sanitation[2], climate actions[10], and multiple sub-goals related to healthy ecosystems[4,8].

Observations of WTD inform us about the accessibility of groundwater, but, they are not available for every region of the world, show significant spatial biases, and come with unquantified uncertainties. In recent years, global groundwater models have emerged as an essential tool to provide a global picture of groundwater accessibility and its temporal evolution. However, the reliability of current models in support of water policy is highly debated within the community[38] and their estimates are challenging to evaluate[39]. Here we analyze and compare four global steady-state (non-time-dependent) groundwater models as well as available WTD observations. We chose both steady-state models and observations as they currently represent the most extensive available global dataset of simulated and observed long-term WTD[40].

Our analysis reveals that the worldwide accessibility of groundwater remains highly uncertain which impacts pivotal assessments and policy decisions. To reduce this uncertainty, we outline concrete pathways for water policy and future research: By (1) improving model evaluation, (2) compiling better datasets, and (3) making use of existing local knowledge, we will be able to provide more reliable assessments of global groundwater accessibility.

Global accessibility of groundwater and its uncertainty

Groundwater accessibility for ecosystems and humans varies globally

In the following sections, we use three categories of accessibility of groundwater: (1) accessible to ecosystems, (2) accessible for irrigation or drinking water supply, and (3) costly to access or inaccessible. Accessible to ecosystems implies that groundwater might also be a convenient human water source.

Globally, 96.9% of plants root no deeper than 10 m[35] and are projected to get shallower in agricultural areas[16]. We lack global data on groundwater connectivity to aquatic ecosystems, but two-thirds of US streams that potentially gain water from their surrounding aquifers lie in regions with water table depths no deeper than 10 m[7]. We thus use a WTD shallower than 10 m to define likely accessibility for ecosystems, noting that this generalization might not apply to specific local settings (e.g., because deep roots are likely under-sampled[35], vegetation may adapt to fluctuating water tables[41,42], and capillary rise delivers water above the water table[43]). We assume that with a groundwater table deeper than 10 m, surface water bodies (streams, lakes, wetlands) are likely not gaining and that vegetation will not have (direct) access to this groundwater[44,45]. Humans, on the other hand, can drill wells to access deeper groundwater, but these wells are often shallower than 100 m (the average well depth is 60 m[19] in the US and 46 m globally[17]) due to economic constraints[19,46]. Thus, we categorize regions with water tables deeper than 100 m as costly or inaccessible. Humans may also access shallow groundwater but sometimes chose not to due to contamination[47].

Following our definitions, 23% of global groundwater is accessible to ecosystems, 57% is accessible to humans, and 20% is too costly or inaccessible. These numbers are calculated from the ensemble mean estimates of four global groundwater models[35,48–50] (Fig. 1a, see Supplement and Methods). Shallow water tables accessible to ecosystems are located along coastlines and in regions with major aquifers, such as the Amazon Basin, the Central Valley aquifer, the Ganges-Brahmaputra Basin, and the Mississippi Alluvial Aquifer. Costly or inaccessible groundwater is mainly located in mountainous regions such as the Rocky

Mountains, the Andes, and the Himalayas. It is important to point out that the mean WTD shown here represents the long-term average (steady-state) of a natural world without human impacts (e.g., pumping). A consequence is a tendency to see shallower water tables because they do not include an anthropogenic fingerprint. For example, a shallow water table in the Central Valley aquifer, as shown in Fig. 1a, is reasonable in a steady-state simulation where no abstraction from groundwater was included.

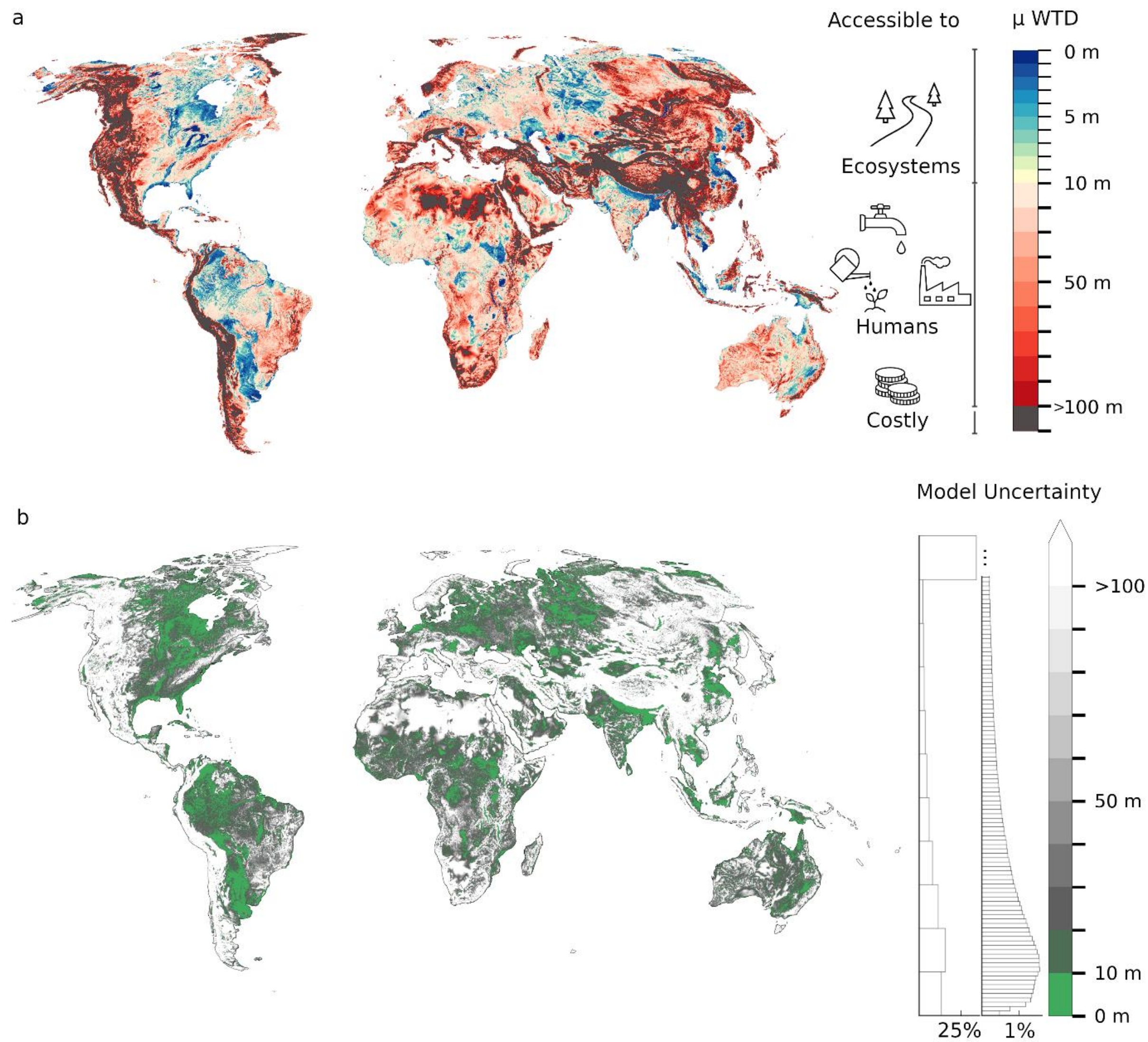

Figure 1. a) Ensemble mean (μ) of steady-state Water Table Depth (WTD) calculated using four steady-state global groundwater models without pumping and categorization into three accessibility categories: accessible by ecosystems, accessible by humans, and costly or inaccessible. b) Uncertainty in WTD (highest minus lowest value per grid cell), also represented by two histograms (based on number of grid cells not area) with a bin size of 1 m and 10 m. Blank spaces indicate areas with large uncertainties[51].

Global estimates of water table depth are highly uncertain

While the ensemble mean WTD shows patterns that agree with our conceptual understanding of groundwater processes, such as deeper water tables in drier or more mountainous regions[45], the inter-model differences are substantial. We show areas of considerable uncertainty as blank spaces[51] in Fig. 1b. For one-third of the global land area, the models show disagreements in WTD of more than 100 m. Green places depict where models tend to agree, with differences no more than 10 m, amounting to only 12% of the global land area. Areas of high agreement include the Central Valley aquifer, the Mississippi Alluvial Aquifer, and the Ganges-Brahmaputra Basin.

Model differences broadly reflect topography and are exceptionally high in mountainous regions, such as the Rocky Mountains, the Andes, and the Himalayas. But we also see significant differences in flatter regions with dry climates, such as the Sahara, South Africa, and Australia. While models generally agree that water tables are deeper in these regions (> 100 m), the models disagree on how deep, often by several hundreds of meters. There is a clear positive correlation between the depth of mean groundwater table and uncertainty (Spearman rank correlation ρ_s=0.96, p=0.00; see Fig. S2 Supplement). However, while the models agree more in regions with lower topographic slopes and shallower water tables, the uncertainty in these regions might be more consequential. Relative uncertainty (i.e., uncertainty in relation to the mean WTD, see Fig. S3 Supplement) is less correlated with topography and thus more strongly highlights flatter areas where models disagree (in relative terms), such as parts of the Amazon basin and the West-Siberian plain. In these flatter regions, a difference in water table depth of 5 m can have an immense impact on the accessibility of water for roots[35], capillary rise[43], and surface water connectivity[8].

Even though the smallest uncertainties are found in areas with shallow water tables (Fig. 1), they are large enough to have major implications on the outcomes of global assessments of groundwater accessibility. Here we analyze forests as a critical terrestrial ecosystem and carbon sink[14], population as a proxy for where groundwater might be important to domestic use and industry[46], and irrigated area as a proxy for the potential use of groundwater for agriculture[20]. Figure 2 translates the uncertainty in WTD into uncertainty of groundwater accessibility for forests, population, and irrigated areas (note that these classes are not mutually exclusive). It shows that the uncertainty is high for all three classes (forest, population, irrigation) and the three categories of accessibility. How many people live in areas of human-accessible groundwater (> 10 m and < 100 m) varies by 33.4%, and the uncertainty of how much irrigated land is in areas of ecosystem accessible (< 10 m) groundwater is 53.6%. That does not mean that forests, people, or agriculture are necessarily dependent on groundwater in these areas, but it highlights the large impact uncertainties have on such assessments.

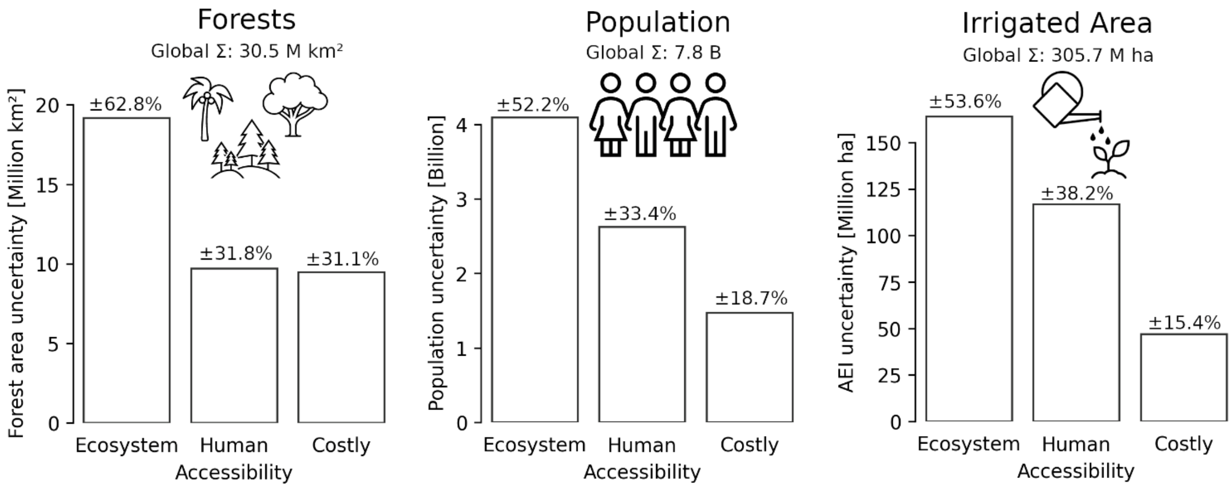

Figure 2. Forest area, population, and Area Equipped for Irrigation (AEI) uncertainties with respect to uncertain regions of three categories of groundwater accessibility. Each plot quantifies the uncertainty of how much forest, population, or irrigation is potentially located in areas of ecosystem, human, or costly accessible groundwater. For example, the global area covered by forest situated in regions with ecosystem-accessible groundwater (< 10 m) varies by 62.8% (compared to the global forest coverage) depending on what model estimate we use. The uncertainty of the categories is calculated based on the ensemble range (highest minus lowest value per grid cell). Percentages shown relate to the respective global sums of forest area, population, and AEI.

This high uncertainty directly affects our ability to provide critical global assessments and support decision-making. For example, assessing the likelihood of ecosystems losing connection to groundwater is pivotal for carbon policy and ecosystem protection. Mapping these ecosystems would indicate where ecosystem protection policy would provide the most significant impact. Furthermore, knowledge of where groundwater is potentially accessible for humans could guide decisions where a more in-depth investigation would yield the highest potential for projects that focus on using groundwater as a buffer for climate shocks such as droughts. By limiting our ability to support such decisions, we are ultimately jeopardizing our ability to reach multiple SDGs such as climate action (SDG 13), terrestrial ecosystems (SDG 15), and our ability to stay within planetary boundaries[52]. Securing safe access to drinking water for sanitation (SDG 6) and irrigation (SDG 2 zero hunger) while safeguarding groundwater from depletion requires us to make robust assessments of where water is potentially available and threatened.

Three pathways towards reduced uncertainty in groundwater accessibility

As discussed above, the current uncertainty in WTD compromises assessments of groundwater's crucial role in ecosystem health, global water supplies associated to food security, and human health. We discuss three concrete pathways to reduce this uncertainty, including (1) better global datasets, (2) alternative strategies for model evaluation, and (3) collection of local knowledge.

Better global datasets

Uncertainty in global water table depth does not only stem from model uncertainty but also from a lack of data. Currently, only one global scale observational dataset of WTD is available[40]. However, it is highly biased towards the USA, Europe, and Australia (see Supplement Fig. S11). Furthermore, there is a slight under-representation of observations in water-limited (i.e. rather dry) regions (59% vs. 66% global land area) compared to energy-limited (i.e. rather wet) regions, and a clear over-representation of low elevations (93% of observations are taken at surface elevations below 1000 m vs. 80% globally) and flat regions (96% of observations are flatter than 0.08m/m vs. 77% globally). Data availability is much worse if we relax the steady-state assumption since no consistent global scale time series of WTD are currently available. While models should correctly represent steady-state water table depth, their fit to trends is of pivotal interest as this would allow investigating the consequences of a changing climate and/or anthropogenic impacts.

Furthermore, we require improved hydrogeological data, global datasets on groundwater abstraction over time, and better datasets on groundwater recharge[39]. To this day, only one global permeability dataset is available[53,54] and no data product is available on global aquifer schematization. No global dataset on groundwater pumping exists, and abstractions can only be estimated[28,55]. Currently available global groundwater recharge estimates are highly spatially biased[56], and modeled recharge is highly uncertain[57].

Apart from the technical challenges of collating such global datasets, there are various reasons why these data are not yet available: (1) non-willingness to share data (groundwater being a politically important resource), (2) lack of resources (both in terms of financial resources and capacity), (3) duplicated, contradictory and/or non-existent mandates to collect groundwater data, (4) a general lack of sharing of data and information (even inside countries and institutions), and (5) poor data management without proper quality control and assurance[2]. Locally, groundwater level time series are available for many locations, but these data need to be collated by the scientific community and parties already active in data collection, i.e., the Global Groundwater Monitoring Network of the UNESCO centre IGRAC (International Groundwater Resources Assessment Centre) supported through the WMO Global Climate Observing System. Such an effort should ideally be in collaboration with other UN programs (e.g., UNICEF, UNEP, IHP) and supported scientifically through joint working groups with associations like the IAH (International Association of Hydrogeologists) and existing initiatives such as EGDI (European Geological Data Infrastructure). In this regard, groundwater needs to be recognized more prominently in SDG 6 (clean water and sanitation) and as a connecting building block among the SDGs[58], even though the UN has moved towards a recognition of groundwater in their recent report[2].

Alternative strategies for model evaluation

The large disagreement in WTD estimates across current models (Fig. 1 b) suggests that there is something to be learned from comparing models and modeling choices. We can learn from comparing the models with each other, with our expectations, and with available observations. Model evaluation is commonly performed against small-scale observations of WTD (often converted to hydraulic head)[35,40,49,50,59–61]. This, however, provides little insight into model disagreement, is limited to few (geographically biased) locations relative to the simulated domain, and suffers from commensurability issues[62].

As an alternative, we can evaluate global-scale groundwater models by investigating functional relationships between known drivers of groundwater flow and WTD[39,63,64], including how well the models reproduce these relationships in comparison to our current process understanding. Using the concept of water table ratio[45,65], we can conceptualize the water table as driven by four main natural factors: (1) climate (approximated by water-limited and energy-limited regions as an indicator for groundwater recharge; see Fig. 3b) (2) topography (approximated by topographic slope), (3) subsurface permeability, and (4) interactions with surface water bodies. We would, for example, expect deep water tables in dry, steep, highly permeable regions, far away from perennial streams. In the following, we briefly explore driver-WTD relationships between models and between models and the largest available dataset[40]. The median observed WTD[40] (5.5 m) is relatively shallow and thus closer to Reinecke[50] (8.2 m) and Fan[35] (8.6 m), while de Graaf[49] (37.8 m) and Verkaik[48] (24.4 m) simulate a deeper median WTD (see Supplement Table 2). The models also exhibit strong differences in how their WTD estimates relate to topographic slope and aridity (see Fig. 3). In agreement with our conceptual understanding[45], observations suggest deeper water tables in water-limited regions than in energy-limited regions (6.1 m vs. 4.9 m, respectively), and deeper water tables for steeper slopes (Spearman rank correlations are ρ_s=0.21 and 0.25, for water-limited and energy-limited regions, respectively). Deeper water tables in arid regions are estimated by Fan (15.0 m vs. 4.2 m), but not by Verkaik (24.4 m vs. 24.5 m), Reinecke (6.9 m vs. 10.7 m) and de Graaf (34.8 m vs. 45.2 m). The model of Fan shows medium correlations with slope (0.29 and 0.55), while the models of Reinecke (0.85 and 0.88), de Graaf (0.73 and 0.77), and Verkaik (0.69 and 0.92) show very high correlations with slope, particularly in energy-limited regions. We find weak inverse relationships between permeability and WTD for all models (ρ_s ranges between -0.25 and -0.09 and is slightly higher for energy-limited regions; see Supplement Table 3), while observations show no clear relationship. Models also differ in how WTD correlates with distance to perennial streams, but there is no consistent pattern (ρ_s between -0.19 and 0.38 for water-limited regions, and between -0.04 and 0.16 for energy-limited regions; see Supplement Fig. S8). In summary, we find topographic slope to be the dominant control in most models, while it is less pronounced in the observations.

Overall, these findings invite a more in-depth investigation to understand and explain inter-model and model-observation differences in the future[38,39]. Such a comparison would greatly benefit from a structured Model-Intercomparison Project (MIP) specifically focused on groundwater, comparable to the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)[66], to provide a consistent framework for model simulations (e.g., standardized forcing data, output resolution, and variable names)[38,39].

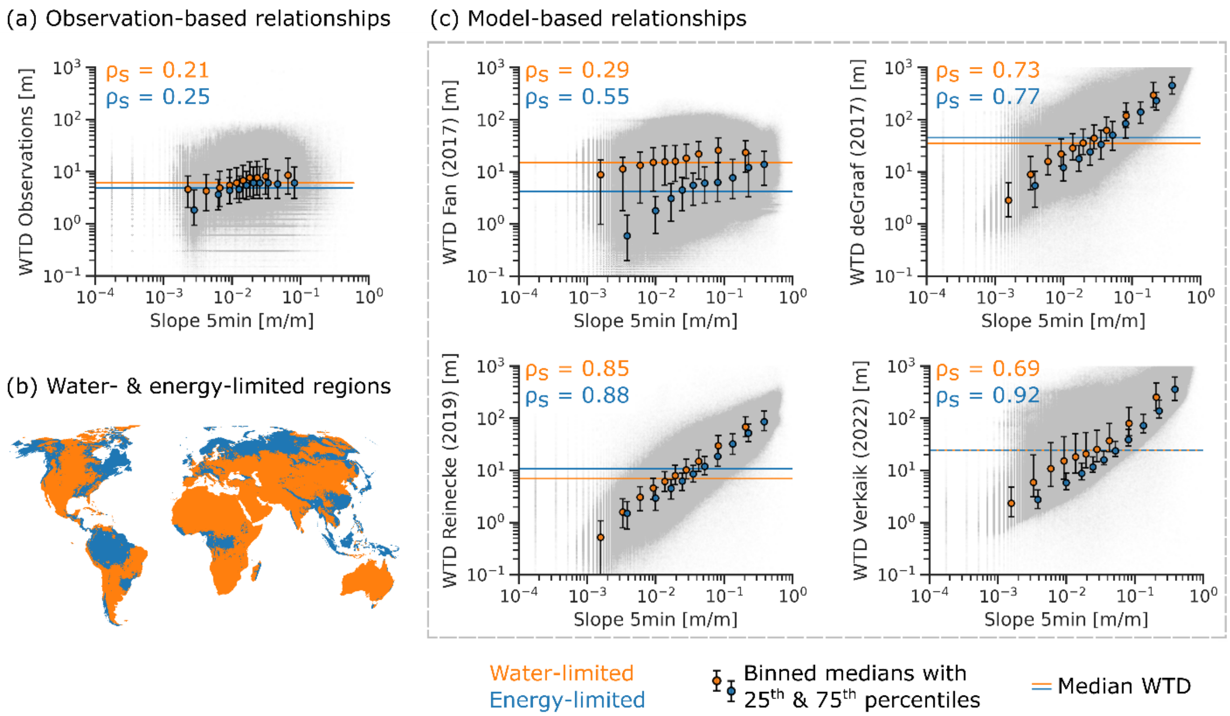

Figure 3. Relationship between topographic slope and observed (a) and simulated (c) WTD from four global models. (b) shows the location of water-limited (i.e. rather dry) and energy-limited (i.e. rather wet) regions. Spearman rank correlations shown in (a) and (c) are based on the point cloud, separated by aridity index. Bin averages are displayed as a visual aid and are separated based on the aridity index (orange and blue; see Methods for estimation). Topographic slope, aridity, and modeled WTD have been aggregated to a resolution of 5 arcmin. For the observations, the WTD values were compared with the 5 arcmin values of the grid cell in which the observations are located.

Collecting local knowledge of groundwater systems

Global models are (at least for now) considered unsuitable tools to answer regional-scale water management questions due to a lack of specific tailoring to local conditions, though they are often the only source of information in data-scarce regions. However, they would profit from existing regional knowledge about groundwater systems and how humans interact with these systems (i.e. pumping and managed aquifer recharge)[39]. Knowledge, for example, on preferential flow paths due to karst[67], volcanic rock, or deeply weathered soils (laterites)[68] is currently not embedded in any global dataset but available in regional models and expertise. Worldwide there are thousands of regional groundwater models in peer-reviewed articles and reports, often with accompanying data, and we have a rich base of expert knowledge within the heads of the many who built these models. This knowledge base could be harnessed to build powerful new data sets for ground-truthing[69] global results and for improving the representation of groundwater processes in global models[39].

A global database of existing local and regional groundwater models would offer many opportunities to improve our scientific understanding and facilitate the connection of the groundwater community globally[39]. Some national government organizations already openly share their groundwater models and all underlying data, for example, the USGS (US Geological Survey), the NHI (Netherlands Hydrological Instrument) and the GEUS (Geological Survey of Denmark and Greenland). A joint global collaboration between academics and national geological surveys, organized and supported by institutions such as the WMO, IGRAC, and IAH to create a globally accessible platform, would offer a powerful data portal. Such a platform of local models and knowledge could then be used to ground truth conceptual assumptions of global models and datasets. More than that, it would make existing local models more accessible to other nations and regions that could tailor model setups to their own local settings.

Groundwater accessibility information enables action on the SDGs

Knowledge of global groundwater accessibility is paramount to support effective action in reaching the SDGs of healthy ecosystems, climate action, clean water, and zero hunger. Without information on where to fund additional investigation or where policies for ecosystem protection are likely required, we are limiting our capabilities in reaching the SDGs. Terrestrial ecosystems such as forests have a natural ability to store carbon, which is crucial for climate change mitigation[10]. With improved knowledge of global groundwater accessibility and threats to it (i.e., unsustainable abstractions), the United Nations can better guide action in protecting ecosystem health and developing effective carbon policies. Knowledge of groundwater accessibility for humans will guide investments, e.g., of the World Bank, to regions that are projected to suffer from a lack of groundwater access. Such investments could involve more extensive local studies or support of local water infrastructure (such as new or deeper wells, water transportation, or alternatives such as surface reservoirs). Importantly, with better global models (including better representation of human impacts), we will be able to more robustly assess the impacts of climate change on global groundwater resources, filling a current gap in the IPCC reports. Climate change leads to changing precipitation patterns, increased droughts, and increased floods[10], affecting water availability[70] and global food security[71]. Information on where groundwater is accessible, abstracted, and potentially remains accessible for future irrigation will enable international parties like the FAO and the World Bank to guide programs on irrigation infrastructure and crop adaptation. To tackle these challenges, we need to know as much as possible about our most important freshwater source: groundwater.

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Author contributions statement

RR led the analyses and writing of the manuscript. TW and RR conceived the idea, SG and LS supported the analysis and development of the manuscript. SG led the analysis presented in Fig. 3. All authors reviewed the manuscript and provided suggestions on text and figures.

Data and Code availability:

The ensemble mean on 5 arcmin resolution including the uncertainty bounds can be accessed here: https://doi.org/10.5281/zenodo.7538161 CCby4.0.

The source code of the modeling framework of Reinecke et al.[50] can be accessed at:

http://globalgroundwatermodel.org

Competing interests: None.

Methods

Models

This analysis uses the outputs of four published global models: Verkaik[48], Fan[35], Reinecke[50], and de Graaf[49]. The models exclude Greenland and Antarctica. All models used here represent a global steady-state WTD which is not influenced by anthropogenic change, e.g. no pumping is implemented. The steady-state version of the models does not implement pumping as it represents an equilibrium state without a time component. Abstraction in such a model could lead to infinite depletion if the abstraction rate is larger than the sum of inflows and if no rules are defined at which water level pumping should stop. The models used here implement water abstractions in their transient version, however, before moving to a time-varying analysis they should first agree on a natural steady-state. For the calculation of the ensemble mean, model results were aggregated (resampling method = average) to a spatial resolution of 5 arcmin using GDAL. We chose not to calculate the ensemble median because of the low number (four) of models used here. The uncertainty range was computed by calculating: Max(WTD) - Min(WTD) for every grid cell of the ensemble. All assessments regarding relative area are calculated with the correct cell areas based on a global equal area projection.

Multiple reasons contribute to the differences between the four models investigated here, including (1) uncertainties in groundwater recharge estimates, (2) spatial resolution of the models, (3) model choices concerning the model parameterization, and (4) conceptual choices in model implementation (e.g., subsurface layering and assigned permeabilities). Groundwater recharge estimates (1) are highly uncertain[56,57,64,69], and their evaluation is challenging due to sparse observations associated with significant uncertainties[72]. The original spatial resolution (2) of Reinecke and de Graaf is similar (5 and 6 arcmins), whereas Verkaik and Fan use a higher resolution (30 arcsec). Given that the Verkaik model is, in principle, a higher resolution version of the model by de Graaf, comparing these two models indicates the impact of resolution on WTD (see also[61,73]). We find that aggregating to lower resolution has little effect on overall patterns of WTD (see Supplement Fig. S13), suggesting that model structure and forcing inputs might be more important than resolution (if no human impacts are considered). Regarding (3), different elevations of the bottom of surface water bodies[74], the inclusion of and assumptions regarding wetlands in arid areas (in the steady-state version[50]), and approaches to parameterize the conductance of the streambed[8,74] might impact modeled WTD. Lastly, some differences might be related to conceptual choices (4), such as the number of subsurface layers (two in Reinecke, de Graaf and Verkaik, 40 in Fan) or the assumption of decreasing permeability with depth (implemented by Fan and Reinecke).

Separation into three categories

We created water table accessibility categories based on global and large-scale datasets of rooting depth[35], potential groundwater-stream connectivity[7], and well depth[7] (see Supplement Fig. S1). The chosen categories such as rooting depth may not represent local systems. We assume a connectivity when surface water bodies are fed by groundwater, this excludes downward flow of surface water to the groundwater. The connectivity to lakes and rivers may also go beyond the chosen 10 m boundary for deeper lakes and streams.

Uncertainty impact assessment

Figure 2 uses three different data sources. Global tree cover data[75] on 30 m resolution was aggregated to 5 arcmin. The data representing the % coverage was then converted to area using the land mask covered by the model ensemble. Population data for the year 2020 (constrained version; https://hub.worldpop.org) on a 100 m resolution was aggregated (resampling method = sum) to 5 arcmin and cut to the land mask covered by the model ensemble. This resulted in a slight decrease of the global population as coastal areas are not as well represented by the coarser global model mask. Global irrigated areas on 5 arcmin resolution[76] were used to calculate the areas equipped for irrigation. The three 5 arcmin data products were spatially joined using GDAL with the calculated uncertainty range of the ensemble.

Model evaluation

WTD observations are from Fan et al. (2013)[40]. Aridity data are based on CHELSA data at 30 arcsec resolution[77]. Slope data are based on 250m slope data from the Geomorpho90m dataset[78] and elevation data (used in the Supplement) are based on 250m elevation data from[79]; both are based on the MERIT DEM[80]. For Figure 3, all rasters (aridity, slope, WTD from all models) were resampled to 5 arcmin resolution using GDAL (resampling method = median) and aligned to exactly overlay. Resampling may influence driver-WTD relationships as it smooths out variability. Overall, however, the patterns are only slightly affected (see Supplement). In Figure 3, each bin contains 10% of the data (spread evenly across all slope values). The correlations are calculated using all data points and are therefore unaffected by the bins, which are primarily there for visualization. Observational data used is possibly highly affected by water abstractions or return flows. The steady-state outputs of the models do not account for this anthropogenic impact.

Aridity was calculated by dividing potential evapotranspiration by precipitation (PET/P), both from CHELSA. Values below one indicate energy-limited, i.e. wetter, environments, values above on indicate water-limited, i.e. drier, environments.

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