

# Considerable gaps in our global knowledge of potential groundwater accessibility

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## Main Manuscript for

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### This PDF file includes:

Main Text  
Figures 1 to 4

34 **Abstract**

35 At what depth groundwater can be found below the land surface is key to understanding whether it is  
36 potentially accessible to ecosystems and humans, or what role it plays in the water cycle. Knowledge of  
37 ground-water table depth (WTD) exists at regional scales in many places, but a bottom-up knowledge  
38 aggregation to obtain a coherent global picture is exceptionally challenging. Uncertainty in global-scale  
39 WTD knowledge severely affects our ability to assess groundwater's future role in a water cycle altered by  
40 changes in climate, land use, and human water use. Global groundwater models offer a top-down pathway  
41 to gain this knowledge. However, we find them highly uncertain: four models investigated show WTD  
42 disagreements of more than 100 m for one-third of the global land area. Averaged across the models, we  
43 estimate that 23% [most deviating model: 71%] of the land area contains shallow groundwater potentially  
44 accessible to ecosystems and humans, <10m depth, 57% [29%] is potentially accessible to humans through  
45 pumping, 10-100m, while 20% [0.01%] is potentially too costly to access or inaccessible, >100m.  
46 Depending on the model, +-63% of global forest coverage and +-54% of irrigated land is inside areas of  
47 potentially ecosystem-accessible water, and +-33% of the global population lives in areas with potentially  
48 human-accessible groundwater. These results add significant uncertainties to any global-scale analysis,  
49 which will not significantly reduce without dedicated efforts. We outline three pathways to reduce this  
50 uncertainty through better global datasets, alternative strategies for model evaluation, and greater  
51 cooperation with experts.

52 **Significance Statement**

53 Global knowledge about groundwater is vital to assess its role in the global water cycle and how it will be  
54 impacted by future climate, water use, land use and population change. While regional groundwater  
55 knowledge is available in places, this is not the case everywhere in the world, and collating very different  
56 regional datasets is challenging. Global models offer an alternative perspective at the global scale, but we  
57 show here that they are still highly uncertain. As the scientific community already uses these models and  
58 their outputs, it is crucial to understand, consider, and address their limitations. To do so, we suggest three  
59 pathways to collect additional knowledge and improve currently available models.

60

61 **Main Text**

62

63 **Introduction**

64 Groundwater makes up 99% of all non-frozen freshwater on our planet(1, 2), sustaining ecosystems by  
65 providing water to vegetation(3, 4), rivers, lakes, and wetlands(5–8), and being a pivotal ecosystem by itself  
66 (9). Groundwater offers a relatively constant supply of freshwater to 43% of the world's irrigated  
67 agriculture(1, 10) and safe drinking water to an estimated 3.7 billion people(1, 10). While surface water  
68 supply is increasingly fragile due to climate change(11), groundwater is assumed to remain a reliable source  
69 of freshwater(12). Thus, groundwater is a critical element for ecosystem health by sustaining flow in surface  
70 water bodies and directly supplying vegetation, agriculture, and access to clean drinking water. With a  
71 rapidly changing climate, increasing population, and economic growth, the importance of groundwater will  
72 likely increase(12). However, the recent IPCC 6th assessment report concluded that "limitations in the  
73 spatio-temporal coverage of groundwater monitoring networks, abstraction data and numerical  
74 representations of groundwater recharge processes continue to constrain understanding of climate change  
75 impacts on groundwater"(11). This lack of knowledge has consequences in at least three critical aspects  
76 relevant to society: the accessibility of groundwater for terrestrial ecosystems, as drinking water, and for  
77 agricultural use.

78 Terrestrial ecosystems provide vital ecosystem services such as the supply of clean water(13), and they  
79 are essential to the carbon cycle(14). Groundwater is often connected to surface water bodies such as  
80 wetlands and supplies them with freshwater, which may sustain terrestrial ecosystems during dry periods  
81 (5). Knowledge of groundwater table depth is central in determining whether this connection exists and how

82 fragile it might be to changing conditions. For example, recent work showed that a substantial amount of  
83 streams in the US are likely losing their water to groundwater already(6). Groundwater may also supply  
84 freshwater to coastal ecosystems through submarine groundwater discharge, and knowledge of the  
85 hydraulic gradient towards the coast is necessary to determine the potential influxes of salt water into  
86 coastal aquifers(15). As vegetation may rely on groundwater directly or through capillary rise(3), knowledge  
87 of the depth of the groundwater table is a central building block in developing global carbon policy(16).  
88 Recent studies showed that tropical forests may change from carbon sinks to carbon sources due to water  
89 stress(17), and that global land cover changes affect rooting depth and, thus, carbon and water cycling(18).  
90 Furthermore, groundwater systems themselves are important ecosystems, providing living space to a  
91 multitude of organisms. Groundwater depth is an essential indicator in determining potential groundwater  
92 ecosystem richness and is central in determining the connectivity to surface ecosystems(9).

93 Groundwater is the sole source of drinking water for 2.5 billion people today (1), but many of these wells  
94 are increasingly at risk of running dry(19). Deeper wells may provide additional resources by accessing  
95 deeper-lying aquifers(20), but (i) these wells will require more costly energy to build and operate(21, 22),  
96 (ii) water drawn from deeper aquifers might require desalinization(23, 24) for human consumption as well  
97 as for agricultural use(25, 26), and (iii) they likely to be less productive as the aquifer becomes less  
98 permeable with depth(22). If groundwater is pumped continuously causing a long-term WTD decline, we  
99 may experience groundwater depletion and complete loss of freshwater resources. Importantly,  
100 groundwater contamination can be a more important factor in restricting sustainable groundwater supplies  
101 than depletion(27), and historical context in assessing depletion is essential(28). Groundwater depletion is  
102 a global crisis(29), and examples like Cape Town's Day Zero(30) water crisis highlight the importance of  
103 groundwater in sustaining the human right to clean drinking water.

104 Irrigated agriculture is by far the largest global user of groundwater by volume(1). The increasing  
105 occurrence and intensity of heatwaves and droughts(11) leads to heightened irrigation demand(31), while  
106 non-renewable use already leads to widespread groundwater depletion(32). Groundwater abstractions may  
107 aggravate water loss in rivers and wetlands as lowered groundwater levels potentially decrease the influx  
108 of water of even led to losing conditions(33). Regions like the Central Valley in California(29), the Mekong  
109 River Basin(34), and northwestern India(35) have overused their groundwater resources steadily, leading  
110 to widespread depletion of groundwater storage and subsequent land subsidence. The continuing global  
111 expansion of agricultural areas (36) will further aggravate the stress on groundwater resources.

112 A key variable to understand groundwater in all three contexts (ecosystems, drinking water supply,  
113 agriculture) is water table depth (WTD). Here we define WTD as depth from the land surface to the top of  
114 the saturated zone(37). Groundwater can quickly become inaccessible for ecosystems if the WTD declines  
115 beyond the depth of vegetation roots(38) or below the bottom of rivers and lakes(5). Humans may build  
116 wells reaching down to hundreds of meters(22), yet below a certain depth, reduced permeability will  
117 decrease groundwater yield(21) in addition to the already mentioned considerations of economic viability  
118 and sustainability. We define groundwater as potentially accessible if the WTD is shallow enough to be  
119 used by ecosystems and/or humans. Notably, a potentially accessible WTD does not mean that (financial)  
120 resources are in place to access this water and to transport it to its destination, that the water is of adequate  
121 quality, or that the hydrogeological configuration allows for abstraction.

122 Understanding the role of groundwater in the terrestrial water cycle is a key component in understanding  
123 how Earth system dynamics may change with human interventions on continental and planetary scales  
124 (39). Through its connection to streams, wetlands, and lakes, understanding WTD enables us to  
125 understand, for example, how streamflow will be affected by climate change and groundwater  
126 abstractions(5), and how it will affect sea level rise and water available for atmospheric circulation. Critically,  
127 despite groundwater's crucial role in the Earth system, we cannot yet provide a robust global picture of  
128 current and potential future WTD, and thus potential accessibility. While other global products, such as  
129 GRACE(29), exist to determine the global state of groundwater, WTD remains central in validating and  
130 calibrating these products. Furthermore, GRACE measures total storage changes rather than actual

131 storage, and requires additional hydrological model output to create a spatially coarse product of  
132 groundwater storage change estimates. Without reliable knowledge of WTD at the global scale, it is unclear  
133 where international investments (e.g., through the World Bank) and global water policy (e.g., specialized  
134 UN agencies such as the FAO) will be most needed and most impactful to safeguard this essential resource.

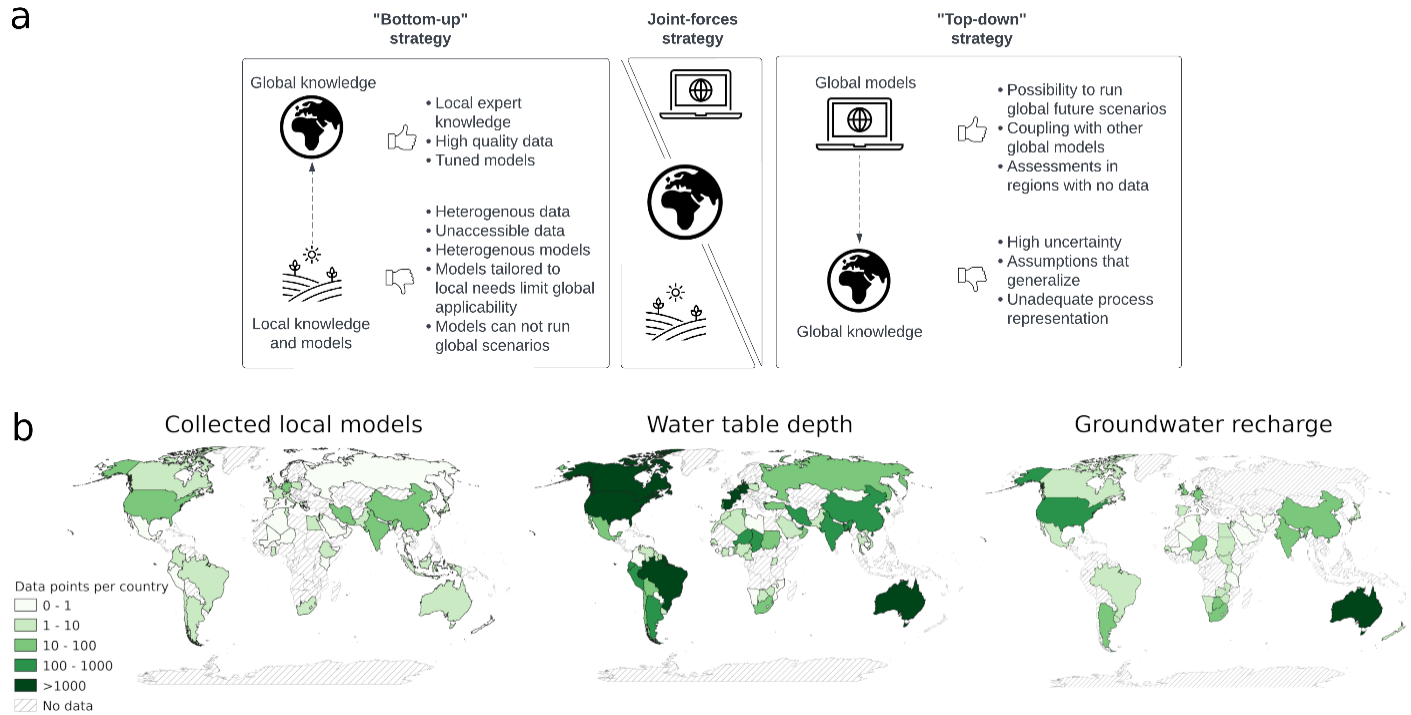
### 135 **Bottom-up and top-down strategies to assess potential groundwater availability at the global scale**

136 Two strategies may be used to obtain global-scale knowledge of groundwater accessibility (Fig. 1a): a  
137 bottom-up strategy that assembles regional data where they exist, and a top-down strategy that uses global  
138 groundwater models.

139 Advantages of the bottom-up strategy include its use of available regional observations and/or models that  
140 are specifically tailored to a region (e.g. a single aquifer system), as well as the possibility to include  
141 knowledge from local experts. However, it is not straightforward to synthesize these diverse sources to  
142 obtain a coherent global picture of groundwater accessibility and it will unavoidably contain large gaps (Fig.  
143 1b). Current global datasets show significant spatial biases as data is either not available for a region (e.g.,  
144 due to non-available resources or lack of local relevance) or is difficult or impossible to collect/access.  
145 Datasets might also be organized very differently and show distinctive differences on either side of  
146 administrative boundaries(40). There is also a lack of digital infrastructure to easily access these data  
147 (though it might be available for specific regions(41)) and other private or political interests prevent sharing  
148 of data. For example, Jasechko et al.(19) amassed 39 million groundwater level data points globally, but  
149 due to licensing or personal interests are not allowed to share it with the scientific community, apart from  
150 those datapoints already made public by national services. In addition to observations, regional models  
151 encode existing knowledge(42). However, they are not readily usable for global impact assessments as  
152 their approaches and assumptions differ widely (e.g., CVHM(43) and C2Vsim(44) in California are two  
153 models for the same regions that are based on very different perceptual models(45) e.g., on how to  
154 represent hydrogeology and human impacts). Global assessments of climate impact would entail the almost  
155 impossible task of running hundreds or thousands of regional models (if available) forced by an ensemble  
156 of climate models and socio-economic pathways (only on a relatively coarse spatial resolution)  
157 simultaneously. In addition, the analysis and interpretation of results would be an equally difficult task due  
158 to a lack in standardization of model setups (process representations, use of input data etc.).

159 In recent years, global groundwater models have emerged as a top-down strategy to obtain a global picture  
160 of groundwater resources and their temporal evolution. However, the reliability of current models for  
161 supporting water policy is highly debated within the community(46), and model estimates are challenging  
162 to evaluate given the data limitations discussed(40) (e.g., data biases affect our ability to evaluate and  
163 calibrate the models). Nevertheless, they are already broadly applied in different communities; for example,  
164 the results of Fan et al. (47) are used to conduct regional studies on groundwater accessibility for vegetation  
165 in the Amazon(48) or are included in datasets like the HydroATLAS(49).

166 Here we argue that both strategies are necessary and ultimately intertwined to improve global-scale  
167 knowledge and to critically assess the current status of the top-down approach. Increased community  
168 efforts in collecting existing knowledge will ultimately improve global models, and, even if global models are  
169 not yet fully able to reproduce regional conditions, they are capable of carrying out global impact  
170 assessments that are not otherwise possible to achieve(3, 5, 38, 50). Below, we analyze the current state-  
171 of-the-art by analyzing and comparing four global steady-state (non-time-dependent) groundwater models  
172 as well as available WTD observations. We chose steady-state models and observations as they currently  
173 represent the most extensive available global dataset of simulated and observed long-term WTD(47).  
174 Additionally, we would assume steady-state to be the simplest to simulate given that time varying factors  
175 such as changing climatic conditions are not taken into account. Any disagreement found in these  
176 simulations provide a baseline of what uncertainty can be expected for more complex model setups.



177

178 **Figure 1.** (a) Strategies to obtain global-scale groundwater knowledge, and (b) current available regional  
 179 data. Data of local groundwater models are based on a global database of regional groundwater  
 180 models(42), the water table depth data is taken from Fan et al.(47), and the groundwater recharge  
 181 observations from Moeck et al. (51).

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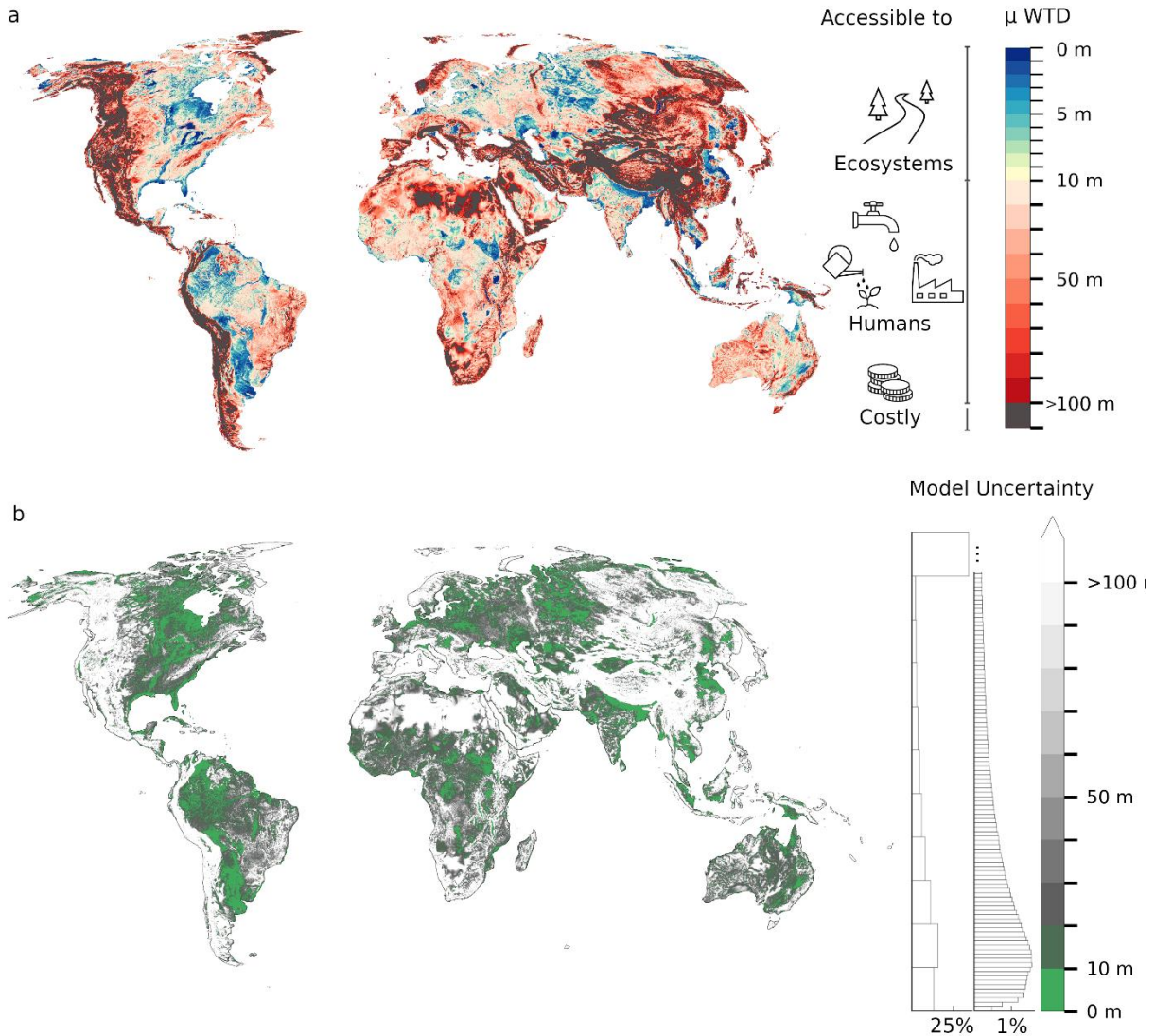
### 183 **Global variation of potential groundwater accessibility for ecosystems and humans**

184 In the following sections, we define three categories of potential groundwater accessibility: (i) potentially  
 185 accessible to ecosystems, (ii) potentially accessible for irrigation or drinking water supply, and (iii) costly to  
 186 access or inaccessible. Potentially accessible to ecosystems implies that groundwater might also be a  
 187 convenient human water source. We base these categories on an average WTD as a first order estimate,  
 188 recognizing that water tables may fluctuate seasonally up to multiple meters (52, 53). Locally, accessibility  
 189 of groundwater is not only controlled by WTD but also by geological setup (54), water quality (55), available  
 190 infrastructure (56, 57), available equipment (58), monetary resources (59), and applied policies (28).

191 Globally, 96.9% of plants root no deeper than 10 m(38) and are projected to become shallower due to  
 192 agricultural activities(18). We lack global data on groundwater connectivity to aquatic ecosystems, but two-  
 193 thirds of US streams that potentially gain water from their surrounding aquifers lie in regions with water  
 194 table depths no deeper than 10 m(6). We thus use a WTD shallower than 10 m to define accessibility for  
 195 ecosystems, noting that this generalization might not apply to specific local settings (e.g., because deep  
 196 roots are likely under-sampled(38), vegetation may adapt to fluctuating water tables(60, 61), and capillary  
 197 rise delivers water above the water table(62)). We assume that with a groundwater table deeper than 10  
 198 m, surface water bodies (streams, lakes, wetlands) are likely not gaining and that vegetation does not have  
 199 (direct) access to this groundwater(50, 63). Humans, on the other hand, can drill wells to access deeper  
 200 groundwater, but these wells are mostly shallower than 100 m (the average well depth is 60 m(22) in the  
 201 USA and 46 m globally(19)) due to economic constraints(22, 64). Thus, we categorize regions with water  
 202 tables deeper than 100 m as costly or inaccessible. Humans may also access shallow groundwater (below  
 203 10 m). We acknowledge that both thresholds are somewhat arbitrary; they primarily indicate where

204 groundwater is very deep or very shallow, which will impact accessibility and provides a useful first order  
205 estimate.

206 Following our definitions, we find that on average 23% of global groundwater is potentially accessible to  
207 ecosystems, 57% is potentially accessible to humans, and 20% is potentially costly or inaccessible. These  
208 numbers are calculated from the ensemble mean estimates of four global groundwater models(38, 65–67)  
209 (Fig. 2a, see Supplement and Methods). Shallow water tables accessible to ecosystems are located along  
210 coastlines and in regions with major aquifers, such as the Amazon Basin, the Central Valley aquifer, the  
211 Ganges-Brahmaputra Basin, and the Mississippi Alluvial Aquifer. Costly or inaccessible groundwater is  
212 mainly located in mountainous regions such as the Rocky Mountains, the Andes, and the Himalayas. The  
213 latter shows the limits of the coarse spatial representation used in the models (5 arcminutes), which may  
214 not be able to simulate local groundwater systems in topographically very diverse regions, even if  
215 groundwater provide a vital influx to streams in mountainous regions. It is important to remember that the  
216 mean WTD shown here represents the long-term average (steady-state) of a natural world without human  
217 impacts (e.g., pumping). A consequence is a tendency to see shallower water tables because they do not  
218 include an anthropogenic fingerprint(47). For example, a shallow water table in the Central Valley aquifer,  
219 as shown in Fig. 2a, is reasonable in a steady-state simulation if no groundwater abstraction is included. In  
220 general, due to their spatial resolution and limited global data to parameterize the models (for details see  
221 section Alternative strategies for model evaluation), all models used are not able to reproduce local  
222 convergence of groundwater(40).



223

224 **Figure 2.** (a) Ensemble mean ( $\mu$ ) of steady-state Water Table Depth (WTD) calculated using four steady-  
 225 state global groundwater models with categorization into three categories of potential accessibility: by  
 226 ecosystems, humans, and costly or inaccessible. (b) Uncertainty in WTD (highest minus lowest value per  
 227 grid cell), also represented by two histograms (based on number of grid cells not area) with a bin size of 1  
 228 m and 10 m. Blank spaces in the map indicate areas with large uncertainties(45).  
 229

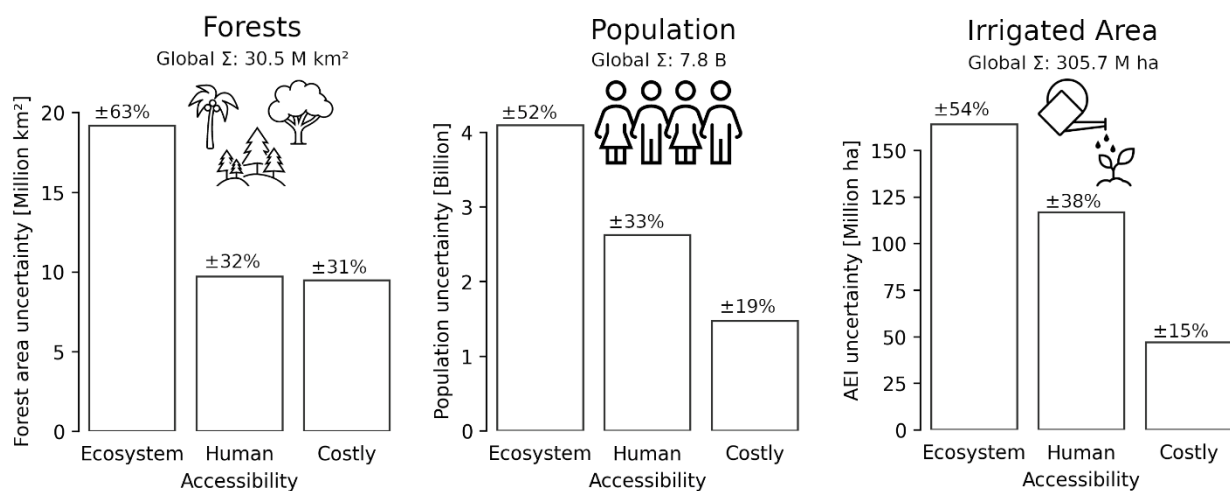
230 **Global estimates of water table depth are highly uncertain**

231 While the ensemble mean WTD broadly shows patterns that agree with our general conceptual  
 232 understanding of groundwater processes, such as deeper water tables in drier or more mountainous  
 233 regions(63), the inter-model differences are substantial. We show areas of considerable uncertainty as  
 234 blank spaces(45) in Fig. 2b. For one-third of the global land area, the models show disagreements in WTD  
 235 of more than 100 m. Green places depict where models tend to agree in absolute terms, with differences  
 236 no more than 10 m, amounting to only 12% of the global land area. Areas of high agreement include the  
 237 Central Valley aquifer, the Mississippi Alluvial Aquifer, and the Ganges-Brahmaputra Basin.



238 Model differences broadly reflect topography and are exceptionally high in mountainous regions, such as  
 239 the Rocky Mountains, the Andes, and the Himalayas. But we also see significant differences in flatter  
 240 regions if they are located in dry climates, such as the Sahara, South Africa, and Australia. While models  
 241 generally agree that water tables are deeper in these regions ( $> 100$  m), the models strongly disagree on  
 242 how deep, often by several hundreds of meters. There is a strong positive correlation between the depth of  
 243 the mean groundwater table and uncertainty (Spearman rank correlation  $\rho_s=0.96$ ,  $p=0.00$ ; see  
 244 Supplement). However, while the models agree more in regions with lower topographic slopes and  
 245 shallower water tables, the uncertainty in these regions might be more consequential. Relative uncertainty  
 246 (i.e., uncertainty in relation to the mean WTD, see Supplement) is less correlated with topography and thus  
 247 more strongly highlights flatter areas where models disagree (in relative terms), such as parts of the  
 248 Amazon basin and the West-Siberian plain. In these flatter regions, a difference in water table depth of 5  
 249 m can have an immense impact on the accessibility of water for roots(38), capillary rise(62), and surface  
 250 water connectivity(5). Regions like the Central Valley aquifer of the Ganges-Brahmaputra Basin are also  
 251 some of the regions where the largest human utilization of groundwater resources can be found(68), i.e.  
 252 where the steady-state assumption is least likely to hold.

253 Even though the smallest uncertainties are found in areas with shallow water tables (Fig. 2), they are large  
 254 enough to have major implications on the outcomes of global assessments of groundwater accessibility.  
 255 Here we analyze forests as a critical terrestrial ecosystem and carbon sink(16), population as a proxy for  
 256 where groundwater might be important to domestic use and industry(64), and (current) irrigated area as a  
 257 proxy for the potential use of groundwater for agriculture(21). Figure 3 translates the uncertainty in WTD  
 258 into uncertainty of potential groundwater accessibility for forests, population, and areas equipped for  
 259 irrigation (note that these classes are not mutually exclusive and are different from the defined potential  
 260 accessibility classes). It shows that the uncertainty is high for all three classes (forest, population, irrigation)  
 261 and all three categories of potential accessibility. We find that the global area covered by forest located in  
 262 regions with ecosystem-accessible groundwater ( $< 10$  m) varies by 63% (compared to the global forest  
 263 coverage) depending on what model estimate we use. How many people live in areas of potentially human-  
 264 accessible groundwater ( $> 10$  m and  $< 100$  m) varies by 33%, and the uncertainty of how much irrigated  
 265 land is in areas of potentially potential ecosystem accessible ( $< 10$  m) groundwater is 54%. We do not  
 266 suggest that forests, people, or agriculture necessarily depend on groundwater in these areas, but it  
 267 highlights the potential lack of robustness of any subsequent application of these simulations without  
 268 considering these uncertainties.



269  
 270 **Figure 3.** Uncertainties associated with, forest area, population, and area equipped for irrigation (AEI) with  
 271 respect to uncertain regions of three categories of potential groundwater accessibility. Each plot quantifies  
 272 the uncertainty of how much forest, population, or irrigation is potentially located in areas of ecosystem,  
 273 human, or costly accessible groundwater. For example, the global area covered by forest situated in regions

274 with potentially ecosystem-accessible groundwater (< 10 m) varies by 63% (compared to the global forest  
275 coverage) depending on what model estimate we use. The uncertainty of the categories is calculated based  
276 on the ensemble range (highest minus lowest value per grid cell). Percentages shown relate to the  
277 respective global sums of forest area, population, and AEI.

278

279 This large uncertainty directly affects our ability to provide critical global assessments and support decision-  
280 making. For example, assessing the likelihood of ecosystems losing connection to groundwater is pivotal  
281 for carbon policy and ecosystem protection(9, 69). Mapping these potentially fragile ecosystems would  
282 indicate where ecosystem protection policy would provide the most impact(69). By limiting our ability to  
283 support such decisions, we are ultimately jeopardizing our ability to achieve multiple SDGs such as climate  
284 action (SDG 13), terrestrial ecosystems (SDG 15), and our ability to stay within planetary boundaries(39).

285 The uncertainty shown here also affects scientific experiments we can conduct with these models and it  
286 contextualizes existing studies. It is the first time these four models are analyzed and compared directly,  
287 and thus provides an important foundation for subsequent research. Previous studies focused on individual  
288 global groundwater models and applied sensitivity experiments to demonstrate that their conclusions are  
289 not sensitive to key uncertainties (5, 70). Our results suggest that future analyses would benefit from  
290 expressing uncertainty more widely using multiple models while utilizing sensitivity analysis strategies to  
291 consider both current and potential future conditions (71).

292

### 293 **A strategy of joint-forces towards reduced uncertainty in global groundwater knowledge**

294 The uncertainty in WTD estimated by global models currently compromises assessments of groundwater's  
295 crucial role in ecosystem health, in global water supply for food security, and in human health. We discuss  
296 three concrete pathways to reduce this uncertainty, including (i) better global datasets, (ii) alternative  
297 strategies for model evaluation, and (ii) joint gathering of regional knowledge.

298

#### 299 **Better global datasets**

300 Uncertainty in global water table depth not only stems from model uncertainty but also from a lack of data  
301 which translates into an inability to parameterize, evaluate, or calibrate global models(40). Thus, the  
302 challenges of the bottom-up strategy (e.g., in combining available data) limit our capability to pursue the  
303 goals of the top-down strategy (Fig. 1).

304 Currently, only one global-scale observational dataset of WTD is available(47). However, it is highly biased  
305 towards the USA, Europe, and Australia (see Supplement Fig. 1). Furthermore, there is a slight under-  
306 representation of observations in water-limited (i.e. rather dry; PET/P > 1; see methods) regions (59% vs.  
307 66% of the actual global land area) compared to energy-limited (i.e. rather wet; PET/P < 1; see methods)  
308 regions, and a clear over-representation of low elevations (93% of observations are taken at surface  
309 elevations below 1000 m vs. 80% globally) and flat regions (96% of observations are in regions flatter than  
310 0.08m/m vs. 77% globally). Data availability is much worse if we go beyond the steady-state assumption  
311 since no consistent global-scale time series dataset for WTD is currently available. While models should  
312 correctly represent steady-state WTD, their fit to trends is of pivotal interest as this would allow investigating  
313 the consequences of a changing climate and/or anthropogenic impacts(5).

314 Furthermore, we require improved hydrogeological data, global datasets on groundwater abstraction over  
315 time, and better datasets on groundwater recharge(40). To this day, only one global permeability dataset  
316 is available(72, 73) and no data product is available on global aquifer schematization. No global dataset on  
317 groundwater pumping exists, and abstractions can only be estimated(32, 74). Currently available global

318 groundwater recharge estimates are highly spatially biased(75), and modeled recharge is highly  
319 uncertain(76).

320 Apart from the technical challenges of collating such global datasets, there are various reasons why this  
321 data is not yet available: (i) non-willingness to share data (groundwater being a politically important  
322 resource, scientific imperialism of data collectors) and a general lack of sharing of data (even inside  
323 countries and institutions)(19), (ii) lack of resources (both in terms of financial resources and capacity)(1),  
324 (iii) duplicated, contradictory and/or non-existent mandates to collect groundwater data, (iv) poor data  
325 management without proper quality control and assurance(1), and (v) data simply not existing because  
326 there is no motivation to collect it, for example, in regions where population is sparse. Locally, groundwater  
327 level time series are available for many locations. However, these data need to be collated by the scientific  
328 community and/or parties already active in data gathering, i.e., the Global Groundwater Monitoring Network  
329 of the UNESCO centre IGRAC (International Groundwater Resources Assessment Centre) supported  
330 through the WMO Global Climate Observing System. Such an effort should ideally be in collaboration with  
331 other UN programs (e.g., UNICEF, UNEP, IHP) and supported scientifically through joint working groups  
332 with associations like the IAH (International Association of Hydrogeologists) and existing initiatives such as  
333 EGDI (European Geological Data Infrastructure). In this regard, groundwater needs to be recognized more  
334 prominently in SDG 6 (clean water and sanitation) and as a connecting building block among the SDGs(77),  
335 even though the UN has moved towards a recognition of groundwater in their recent report(1). Furthermore,  
336 local capacity-strengthening needs to be recognized as a vital aspect in generating data and a willingness  
337 to share local expertise.

### 338 **Alternative strategies for model evaluation**

339 The large disagreement in WTD estimates across current models (Fig. 2 b) suggests that there is something  
340 to be learned from comparing models and modeling choices. We can learn from comparing the models with  
341 each other, with our expectations, and with available observations(40). Model evaluation is commonly  
342 performed against small-scale observations of WTD (often converted to hydraulic head)(38, 47, 65, 66, 78–  
343 80). This approach, however, provides little insight into the reasons for model disagreement, is limited to  
344 few (geographically biased) locations relative to the simulated domain, and suffers from commensurability  
345 issues(81).

346 As an alternative, we can evaluate global-scale groundwater models by investigating so-called functional  
347 relationships between known drivers of groundwater flow and WTD(40, 71, 82), including how well models  
348 reproduce these relationships in comparison to our current process understanding. For example, using the  
349 concept of water table ratio(63, 83), we can conceptualize the water table as driven by four main natural  
350 factors: (i) climate (approximated by water-limited and energy-limited regions as an indicator for  
351 groundwater recharge; see Fig. 4b) (ii) topography (approximated by topographic slope), (iii) subsurface  
352 permeability, and (iv) interactions with surface water bodies. We would, for example, expect deep water  
353 tables in dry, steep, highly permeable regions, far away from perennial streams.

354 In the following, we briefly explore driver-WTD relationships between models and between models and the  
355 largest available dataset(47). The median observed WTD(47) (5.5 m) is relatively shallow and thus closer  
356 to Reinecke(65) (8.2 m) and Fan(38) (8.6 m), while de Graaf(66) (37.8 m) and Verkaik(67) (24.4 m) simulate  
357 a deeper median WTD (see Supplement). The models further exhibit strong differences in how their WTD  
358 estimates relate to topographic slope and aridity (see Fig. 4). In agreement with our conceptual  
359 understanding(63), observations suggest deeper water tables in water-limited regions than in energy-  
360 limited regions (6.1 m vs. 4.9 m, respectively), and deeper water tables for steeper slopes (Spearman rank  
361 correlations are  $\rho_s=0.21$  and  $0.25$ , for water-limited and energy-limited regions, respectively). Deeper water  
362 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),  
363 Reinecke (6.9 m vs. 10.7 m) and de Graaf (34.8 m vs. 45.2 m). The model of Fan shows medium  
364 correlations with slope (0.29 and 0.55), while the models of Reinecke (0.85 and 0.88), de Graaf (0.73 and  
365 0.77), and Verkaik (0.69 and 0.92) show high correlations with slope, particularly in energy-limited regions.  
366 We find weak inverse relationships between permeability and WTD for all models ( $\rho_s$  ranges between -0.25

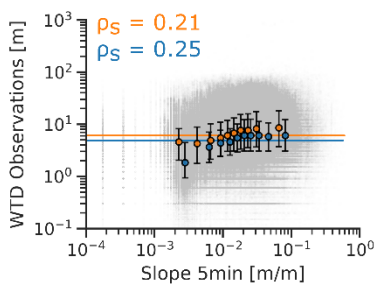
367 and -0.09 and is slightly higher for energy-limited regions; see Supplement), while observations show no  
 368 clear relationship. Models also differ in how WTD correlates with distance to perennial streams, but there  
 369 is no consistent pattern ( $\rho_s$  between -0.19 and 0.38 for water-limited regions, and between -0.04 and 0.16  
 370 for energy-limited regions; see Supplement). In summary, we find topographic slope to be the dominant  
 371 control in most models, while it is less pronounced in the observations.

372 Multiple reasons contribute to the differences between the four models investigated here, including (i)  
 373 uncertainties in groundwater recharge estimates, (ii) spatial resolution of the models, (iii) model choices  
 374 regarding model parameterization, and (iv) conceptual choices in model implementation (e.g., subsurface  
 375 layering and assigned permeabilities). Groundwater recharge estimates (i) are highly uncertain(75, 76, 82,  
 376 84), and their evaluation is challenging due to sparse observations associated with significant  
 377 uncertainties(85). The original spatial resolution (ii) of Reinecke and de Graaf is similar (5 and 6 arcmins),  
 378 whereas Verkaik and Fan use a higher resolution (30 arcsec). Given that the Verkaik model is, in principle,  
 379 a higher resolution version of the model by de Graaf, comparing these two models indicates the impact of  
 380 resolution on WTD (see also(78, 86)). We find that aggregating to lower resolution has little effect on overall  
 381 patterns of WTD (see Supplement), suggesting that model structure and forcing inputs might be more  
 382 important than resolution (if no human impacts are considered). Regarding (iii), different elevations of the  
 383 bottom of surface water bodies(70), the inclusion of and assumptions regarding wetlands in arid areas (in  
 384 the steady-state version(65)), and approaches to parameterize the conductance of the streambed(5, 70)  
 385 might impact modeled WTD. Lastly, some differences might be related to conceptual choices (iv), such as  
 386 the use of Darcy on very coarse spatial resolutions (leading to unrealistic gradients (78) and thus possibly  
 387 to the strong relation to slope), number of subsurface layers (two in Reinecke, de Graaf and Verkaik, 40 in  
 388 Fan), or the assumption of decreasing permeability with depth (implemented by Fan and Reinecke).

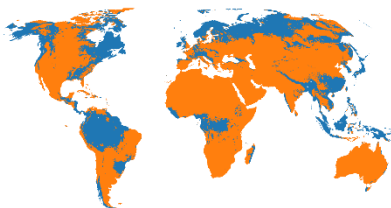
389 Overall, these findings invite a more in-depth investigation to understand and explain inter-model and  
 390 model-observation differences in the future(40, 46). Such a comparison would greatly benefit from a  
 391 structured Model-Intercomparison Project (MIP) specifically focused on groundwater, comparable to the  
 392 Inter-Sectoral Impact Model Intercomparison Project (ISIMIP)(87), to provide a consistent framework for  
 393 model simulations (e.g., standardized forcing data, output resolution, and variable names)(40, 46).

394

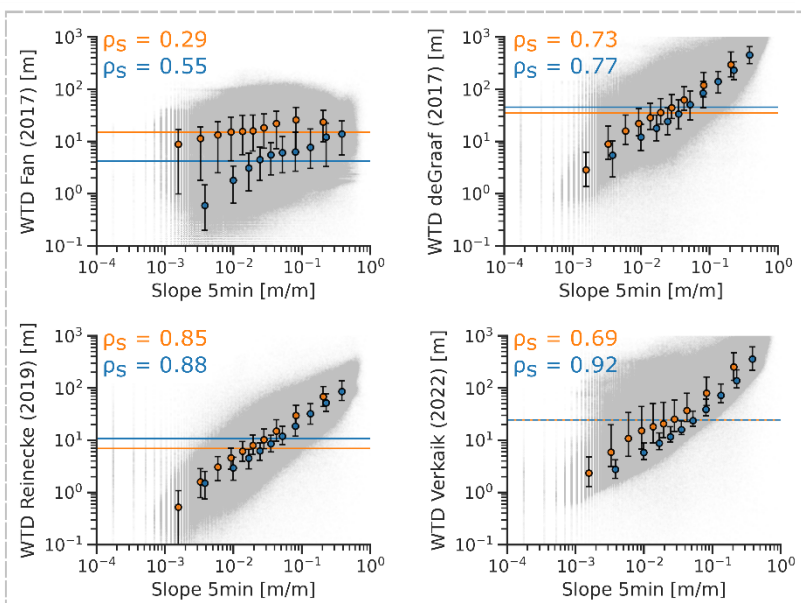
(a) Observation-based relationships



(b) Water- & energy-limited regions



(c) Model-based relationships



Water-limited      Binned medians with 25<sup>th</sup> & 75<sup>th</sup> percentiles      Median WTD  
 Energy-limited

395

396 **Figure 4.** Relationship between topographic slope and (a) observed as well as (b) simulated WTD from  
397 four global models. (b) Location of water-limited (i.e. rather dry) and energy-limited (i.e. rather wet) regions.  
398 Spearman rank correlations shown in (a) and (c) are based on the point cloud, separated by aridity index.  
399 Bin averages are displayed as a visual aid and are separated based on the aridity index (orange and blue;  
400 see Methods for estimation and Supplement for a global map). Topographic slope, aridity, and modeled  
401 WTD have been aggregated to a resolution of 5 arcmin. For the observations, the WTD values were  
402 compared with the 5 arcmin values of the grid cell in which the observations are located.

403

#### 404 **Gathering regional knowledge of groundwater systems**

405 Global models are (at least for now) considered unsuitable tools to answer regional-scale water  
406 management questions due to a lack of specific tailoring to local conditions, though they are often the only  
407 source of information in data-scarce regions. Also, combining them with existing observations is challenging  
408 because of the immense spatial scale differences(88). However, they would profit from existing regional  
409 knowledge about groundwater systems and how humans interact with these systems (i.e. pumping and  
410 managed aquifer recharge)(40). Knowledge, for example, on preferential flow paths due to karst(89),  
411 volcanic rock, or deeply weathered soils (laterites)(90) is currently not embedded in any global dataset but  
412 available in regional models and expertise. Even though a global map of carbonate rock regions is available  
413 (91) it has not yet been included in any global groundwater model. Worldwide, thousands of regional  
414 groundwater models have been published in peer-reviewed articles and reports, often with accompanying  
415 data, and we have a rich base of expert knowledge within the heads of those who built these models. This  
416 knowledge base could be harnessed to build powerful new data sets for ground-truthing(84) global results  
417 and for improving the representation of groundwater processes in global models(40). First efforts have been  
418 made to build community portals to collect such information(42).

419 A global database of existing local and regional groundwater models would offer many opportunities to  
420 improve our scientific understanding and facilitate the connection of the groundwater community  
421 globally(40). Some national government organizations already openly share their groundwater models and  
422 all underlying data, for example, the USGS (US Geological Survey), the NHI (Netherlands Hydrological  
423 Instrument) and the GEUS (Geological Survey of Denmark and Greenland). A joint global collaboration  
424 between academics and national geological surveys, organized and supported by institutions such as the  
425 WMO, IGRAC, and IAH to create a globally accessible platform, would offer a powerful data portal. Bringing  
426 this information onto one platform would already yield the opportunity for standardization (e.g., data formats  
427 and terminology) and community exchange; additional conferences and workshops could strengthen the  
428 latter to facilitate knowledge exchange and the development of methods to analyze the data. Such a  
429 platform of local models and knowledge could then be used to ground truth conceptual assumptions of  
430 global models and datasets. More than that, it would make existing local models more accessible to other  
431 nations and regions that could tailor model setups to their own local settings. The goal of such a platform  
432 and other global data collection efforts always needs be a partnership of local communities that search for  
433 a shared understanding and not a “harvesting” of knowledge through the global-scale research community.

434

#### 435 **Global-scale knowledge of groundwater table depth is necessary but not yet available**

436 Groundwater is a pivotal source of freshwater for terrestrial ecosystems, it functions as an ecosystem,  
437 provides drinking water to humans, and remains a reliable source for irrigation during drought periods. To  
438 assess how global change (e.g., climate change, land use change, water abstractions) affects our water  
439 cycle and potentially freshwater sustainability, we require a global perspective on groundwater. However,  
440 we are currently lacking a coherent and robust global knowledge base to provide this perspective. With  
441 improved knowledge of global groundwater accessibility and threats (i.e., unsustainable abstractions), the  
442 United Nations could better guide action in protecting ecosystem health and developing effective carbon

443 policies. Importantly, with better global models (including better representation of human impacts), we  
444 would be able to assess impacts of climate change on global groundwater resources more robustly, filling  
445 a current gap in the IPCC reports. Information on where groundwater is accessible, abstracted, and  
446 potentially remains accessible for future irrigation will enable international organizations like the FAO and  
447 the World Bank to guide programs on irrigation infrastructure and crop adaptation. To reach these goals,  
448 we need to acknowledge that current global-scale groundwater models must be improved and work jointly  
449 to compile existing local knowledge into global knowledge shared across communities.

450

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453 of the Alexander von Humboldt Professorship endowed by the German Federal Ministry of Education and  
454 Research (BMBF). We thank Ying Fan Reinfelder for her helpful remarks on an early draft.

455

## 456 **Data and Code availability:**

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

459 The source code of the modeling framework of Reinecke et al.<sup>45</sup> can be accessed at:

460 <http://globalgroundwatermodel.org>

461

462 **Competing interests:** None.

463

464

## 465 **Methods**

### 466 **Models**

467 This analysis uses the outputs of four published global models: Verkaik(67), Fan(38), Reinecke(65), and  
468 de Graaf(66). The models exclude Greenland and Antarctica. All models used here represent a global  
469 steady-state WTD which is not influenced by anthropogenic change, e.g. no pumping is implemented. The  
470 steady-state version of the models does not implement pumping as it represents an equilibrium state  
471 without a time component. Abstraction in such a model could lead to infinite depletion if the abstraction rate  
472 is larger than the sum of inflows and if no rules are defined at which water level pumping should stop. The  
473 models used here implement water abstractions in their transient version, however, before moving to a  
474 time-varying analysis they should first agree on a natural steady-state. For the calculation of the ensemble  
475 mean, model results were aggregated (resampling method = average) to a spatial resolution of 5 arcmin  
476 using GDAL. We chose not to calculate the ensemble median because of the low number (four) of models  
477 used here. The uncertainty range was computed by calculating: Max(WTD) - Min(WTD) for every grid cell  
478 of the ensemble. All assessments regarding relative area are calculated with the correct cell areas based  
479 on a global equal area projection.

### 480 **Separation into three categories**

481 We created water table accessibility categories based on global and large-scale datasets of rooting  
482 depth(38), potential groundwater-stream connectivity(6), and well depth(6) (see Supplement). The chosen  
483 categories such as rooting depth may not represent local systems. We assume a connectivity when surface

484 water bodies are fed by groundwater, this excludes downward flow of surface water to the groundwater.  
485 The connectivity to lakes and rivers may also go beyond the chosen 10 m boundary for deeper lakes and  
486 streams.

#### 487 **Uncertainty impact assessment**

488 Figure 2 uses three different data sources. Global tree cover data(92) on 30 m resolution was aggregated  
489 to 5 arcmin. The data representing the % coverage was then converted to area using the land mask covered  
490 by the model ensemble. Population data for the year 2020 (constrained version; <https://hub.worldpop.org>)  
491 on a 100 m resolution was aggregated (resampling method = sum) to 5 arcmin and cut to the land mask  
492 covered by the model ensemble. This resulted in a slight decrease of the global population as coastal areas  
493 are not as well represented by the coarser global model mask. Global irrigated areas on 5 arcmin  
494 resolution(93) were used to calculate the areas equipped for irrigation. The three 5 arcmin data products  
495 were spatially joined using GDAL with the calculated uncertainty range of the ensemble.

#### 496 **Model evaluation**

497 WTD observations are from Fan et al. (2013)(47). Aridity data are based on CHELSA data at 30 arcsec  
498 resolution(94). Slope data are based on 250m slope data from the Geomorpho90m dataset(95) and  
499 elevation data (used in the Supplement) are based on 250m elevation data from(96); both are based on  
500 the MERIT DEM(97). For Figure 3, all rasters (aridity, slope, WTD from all models) were resampled to 5  
501 arcmin resolution using GDAL (resampling method = median) and aligned to exactly overlay. Resampling  
502 may influence driver-WTD relationships as it smooths out variability. Overall, however, the patterns are only  
503 slightly affected (see Supplement). In Figure 3, each bin contains 10% of the data (spread evenly across  
504 all slope values). The correlations are calculated using all data points and are therefore unaffected by the  
505 bins, which are primarily there for visualization. Observational data used is possibly highly affected by water  
506 abstractions or return flows. The steady-state outputs of the models do not account for this anthropogenic  
507 impact.

508 Aridity was calculated by dividing potential evapotranspiration by precipitation (PET/P), both from CHELSA.  
509 Values below one indicate energy-limited, i.e. wetter, environments, values above one indicate water-limited,  
510 i.e. drier, environments. Using other data products, approaches and thresholds to calculate aridity will  
511 produce different aridity maps, however this will not substantially change the fact that we, for example,  
512 expect deeper water tables in regions which tend to be water-limited.

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