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Global estimates of groundwater withdrawal trends and uncertainties

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Abstract

Groundwater, Earth's largest source of liquid freshwater, is essential for sustaining ecosystems and meeting societal demands. However, accurately quantifying global groundwater withdrawals remains a significant challenge due to inherent uncertainties in input data, sectoral allocation assumptions, and model parameterization. In this study, we analyze global groundwater withdrawals from 2001 to 2020 using a newly developed data-driven Global Groundwater Withdrawal (GGW) model and quantify uncertainties through Monte Carlo simulations. The GGW model integrates reported country-level data with global grid-based datasets to estimate annual withdrawals across domestic, industrial, and agricultural sectors at a 0.1° resolution. Our results indicate an average global groundwater withdrawal of 648 km^3 a^{-1}, with an uncertainty range of 465-881 km^3 a^{-1}. Agriculture accounts for 50% of total withdrawals, followed by domestic use at 34.5% and industrial use at 15.5%. Temporal analysis shows increasing groundwater withdrawal in 66% of the IPCC WGI reference regions over the 20 years, with a global average annual increase of 0.5% (varying regionally from 6.5% annual increase to 9% annual decrease). Comparison with previous studies highlights the impact of methodological choices and assumptions about groundwater withdrawal on the resulting global estimates. Our findings underscore the need for comprehensive uncertainty assessments and improved datasets. Expanding spatial coverage in underrepresented regions and enhancing temporal resolution, particularly for dynamic variables like irrigated areas, are crucial for more

accurate groundwater withdrawal assessments. These improvements will enable better management and conservation of this vital resource in the face of growing global demands and climate change impacts.

1. Introduction

Groundwater, a critical component of the global water cycle, sustains both natural ecosystems and human societies. It supports biodiversity directly as a habitat for subterranean life forms and indirectly by providing water to groundwater dependent ecosystems across various hydrogeological and climatic settings [1-3]. It provides essential social and economic needs for human populations through its reliable supply of freshwater. However, growing dependence on this resource, expected to peak around 2050 [4], presents challenges for sustainable management, particularly regarding quantification of groundwater withdrawals. Despite its importance, global groundwater withdrawal patterns and their associated uncertainties remain poorly understood due to inconsistent data availability, methodological differences, and limited direct observations.

Groundwater provides domestic freshwater for almost half of the world's population [5], particularly benefiting rural populations with limited access to other water sources. In the industrial sector, groundwater accounts for approximately 27% of total withdrawals [6], especially in areas where surface water is scarce. Agriculture, however, is the main consumer of groundwater, responsible for about 70% of global groundwater withdrawals [5, 7]. This agricultural dependence is particularly pronounced in countries like China, India, Iran, Pakistan, and the United States, which collectively account for a significant portion of global groundwater use for irrigation [8, 9].

In global-scale assessments, Global Hydrological Models (GHMs) and Land Surface Models (LSMs) are commonly used to simulate groundwater withdrawal across various sectors [10-14]. These models estimate domestic and industrial groundwater demand by calculating water use intensities based on national reference-year withdrawal data. The temporal evolution of these demands is adjusted using factors such as technological advancements, infrastructure changes, population growth, Gross Domestic Product (GDP), and electricity production [6, 15, 14]. Agricultural groundwater demand is usually modeled as a function of irrigation efficiency, crop calendars, irrigated area, crop types, and climatic conditions [16-18].

Existing global models often rely on complex methodologies and extensive data requirements, which can amplify uncertainties. Typically, these models estimate total water demand for each sector and calculate groundwater demand by either assessing the gap between total demand and available surface water resources [9] or applying fixed, sector- and cell-specific fractions of groundwater use to total demand [6]. In addition, methods such as estimating irrigation demand based on crop water requirements or using proxy indicators for economic activities add layers of complexity and increase the potential for propagated errors. In contrast, simpler models can achieve comparable results while offering clearer assessments of uncertainties [19, 20].

To address the challenges of data-intensive methodologies, propagated uncertainties, and computational complexity in existing global models, we developed a data-driven approach that provides a more transparent estimation of groundwater withdrawals across domestic, industrial, and agricultural sectors. By leveraging existing global datasets, our model directly estimates groundwater withdrawals at a grid level while simultaneously evaluating associated uncertainties.

The objectives of this study are threefold: first, to provide estimates of annual groundwater withdrawals for each sector over a 20-year period (2001-2020), identifying dominant groundwater users across different regions; second, to assess the temporal variability of groundwater withdrawals and pinpoint regions with increasing withdrawal rates; and third, to evaluate the uncertainties on the resulting groundwater withdrawal estimates.

2. Methods

The newly developed Global Groundwater Withdrawal (GGW) model is a data-driven framework developed to estimate annual groundwater withdrawal (*GWW*) across three main sectors: domestic, industrial, and agricultural. Implemented in Python, the model operates at a spatial resolution of 0.1° and is used here to estimate annual withdrawal from 2001 to 2020. Using nationally reported statistics, it calculates annual *GWW* for each country (c) and year (y) across the domestic ($GWW_{Dom,c,y}$), industrial ($GWW_{Ind,c,y}$), and agricultural ($GWW_{Agr,c,y}$) sectors. For countries lacking reported data, the model estimates withdrawals based on climatic and socioeconomic similarities to other countries (Supplementary, Section 1.1). These country-level estimates are subsequently downscaled to grid-level values for more detailed spatial analysis (Figure 1).

The primary input datasets include the country-level annual total groundwater withdrawal ($GWW_{Total,c,y}$) sourced from FAO AQUASTAT [21], and the sector-specific (s) fractions of groundwater withdrawal ($GWW_{Frac,s,c}$) derived from International Groundwater Resources Assessment Centre (IGRAC) [22]. We cross-referenced and updated the annual sector-specific groundwater withdrawal data for European countries using Eurostat sources [23].

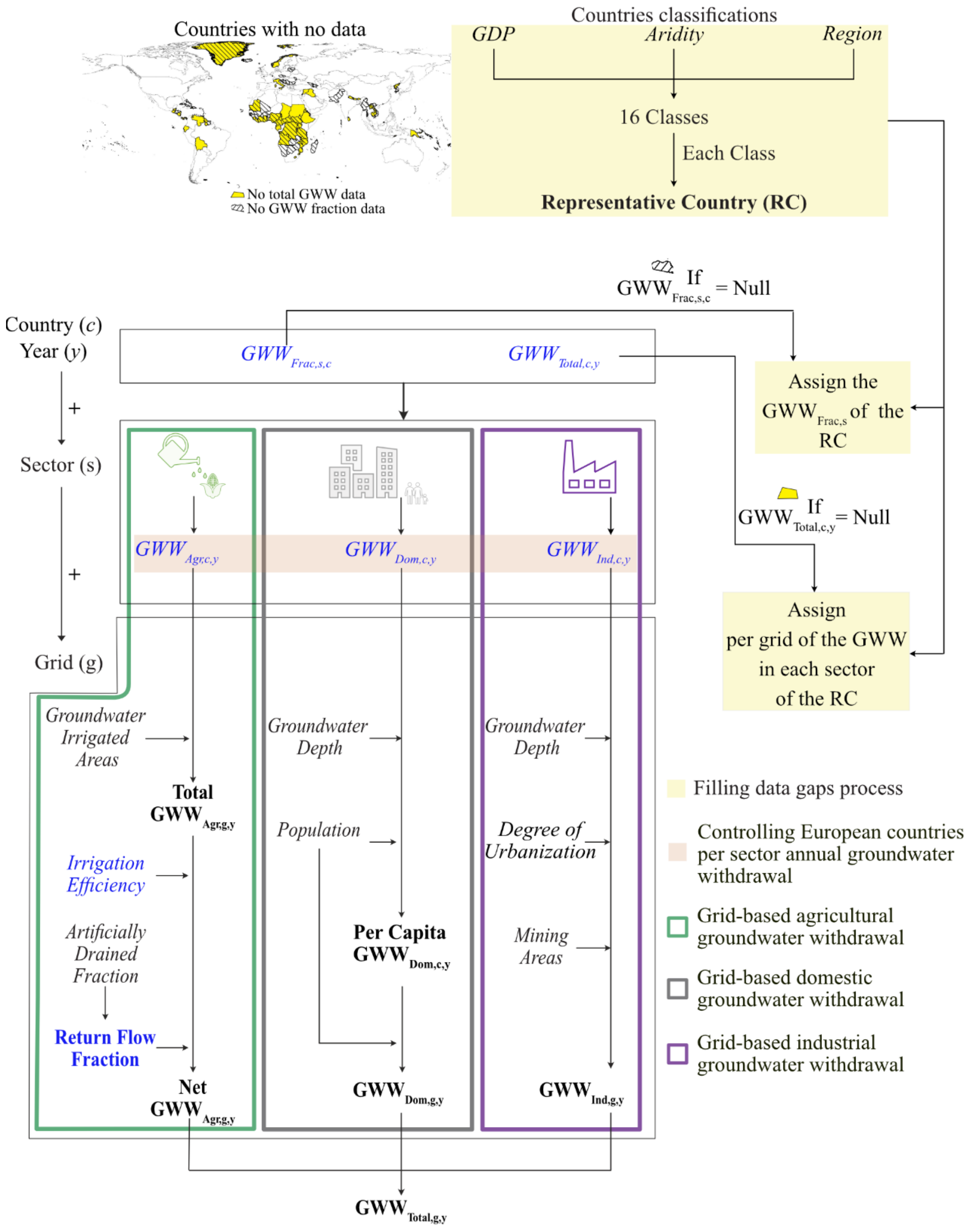

Figure. 1. Schematic representation of the data-driven Global Groundwater Withdrawal (GGW) Model. This diagram illustrates the methodology used to calculate annual groundwater withdrawal per domestic (*Dom*), industrial (*Ind*), and agricultural (*Agr*) sectors grid, including country classification and gap-filling techniques ($GWW_{total,c,y}$: Annual country groundwater withdrawals, $GWW_{Frac,s,c}$: per-sector country fraction of groundwater withdrawal). Inputs are presented in italic font, and elements considered in the uncertainty assessment are marked in blue.

2.1. Domestic groundwater withdrawal

Using nationally reported statistics [21, 22], the GGW model takes domestic groundwater withdrawals at the country level as its base input and calculates annual withdrawals at the grid level by integrating two key datasets: population and water table depth (*WTD*). Population and *WTD* are used to proportionally distribute country-level domestic groundwater withdrawal, reflecting both human demand and groundwater availability.

Population data are taken from the Gridded Population of the World, version 4 (GPWv4) dataset [24]. Here we assume that people do not use groundwater occurring more than 100 m below ground, as analyses reveal that most global wells are shallow, with only 10% exceeding this threshold. Thus, this study focuses on grids with *WTD* up to 100 meters to represent exploitable groundwater. The *WTD* data [25] are derived from the mean ensemble of four global groundwater models [26-29] that estimate global steady-state *WTD* (see Supplementary, Section 1.2).

2.2. Industrial groundwater withdrawal

To estimate global industrial groundwater withdrawal at the grid level, the model integrates three key datasets: degree of urbanization, mining locations, and *WTD*. Given the diversity of industries and the lack of global datasets identifying their exact locations, the degree of urbanization [30] is used as a proxy to identify areas likely to host water-demanding industries such as food processing, beverage production, paper manufacturing, and textiles [31, 32]. As in the domestic sector, only grids where *WTD* is up to 100 meters are considered (Supplementary, Section 1.3). Additionally, recognizing the substantial water requirements of mining activities, which are often located in remote regions [33], the model incorporates global mining locations [34].

2.3. Agricultural groundwater withdrawal

The agricultural groundwater withdrawal per grid is calculated by first estimating the total agricultural groundwater withdrawal ($Total\ GWW_{Agr,g,y}$) and then determining the net agricultural groundwater withdrawal ($Net\ GWW_{Agr,g,y}$). Unlike the domestic and industrial sectors, the agricultural sector calculation accounts for return flows to groundwater from irrigation activities. To estimate the total agricultural groundwater withdrawal, the model uses a global map of groundwater-irrigated areas [35], distributing each country's agricultural groundwater withdrawal ($GWW_{Agr,c,y}$) proportionally to its irrigated areas, resulting in $Total\ GWW_{Agr,g,y}$ for each grid.

The net agricultural groundwater withdrawal per groundwater-irrigated areas grid is then calculated using two key factors: irrigation efficiency (IE_c), a country-specific dataset [36] developed considering irrigation methods, management system, and conveyance system losses, and the return flow fraction to groundwater ($F_{r,gw}$). Irrigation efficiency is employed to calculate groundwater consumption in the agricultural sector per grid ($GWC_{Agr,g,y}$), derived as the product of IE_c and $Total\ GWW_{Agr,g,y}$. To account for higher return flows to surface water due to artificial drainage, the model incorporates the artificially drained fraction ($F_{d,irr}$) [37] and adopts a methodology similar to the WaterGAP global hydrological model [6]. The return flow fraction to groundwater is calculated as $F_{r,gw} = 0.8 – 0.6*F_{d,irr}$. Finally, $Net\ GWW_{Agr,g,y}$ is determined as:

$$Net\ GWW_{Agr,g,y} = Total\ GWW_{Agr,g,y} - F_{r,gw}(Total\ GWW_{Agr,g,y} - GWC_{Agr,g,y}) \tag{1}$$

2.4. Temporal trend and uncertainty assessment

To assess the temporal dynamics of global groundwater withdrawal (2001–2020), this study applies the pre-whitening Mann-Kendall (MK) test [38, 39] at the grid level, with results aggregated using the IPCC WGI reference regions (version 4) [40] (see Supplementary Section 1.4).

In addition, this study assesses epistemic and parametric uncertainties associated with model development and input data, primarily due to imbalances in data availability, quality, and gaps in system understanding. A major challenge for global groundwater models is the substantial regional variation in data coverage and quality, as well as measurement uncertainties. In addition, limited understanding of groundwater withdrawal processes - particularly the fraction of water withdrawn that returns to the source - introduces further uncertainty.

To address these uncertainties, we evaluate key input variables influencing sectoral withdrawals, including country-level annual total withdrawals, sector-specific fractions, European sectoral data, irrigation efficiency, and return flow fractions (blue variables in Figure 1). The uncertainty analysis employs Latin Hypercube Sampling (LHS) [41, 42], with 1000 model iterations, systematically varying key input parameters (Supplementary Sections 1.5 and 1.6). To assess spatial uncertainty distribution, relative uncertainty (*RU*) is used, defined as the ratio of the 90% confidence interval to the mean for each grid.

3. Results

3.1. Global distribution of groundwater withdrawal

The GGW model estimates an average global groundwater withdrawal of 648 $km^3\ a^{-1}$ for the period 2001 to 2020 (Figure 2(a)). Groundwater withdrawal of individual grid cells ranges from zero to 0.29 $km^3\ a^{-1}$. Half of the world's grid cells extract less than $5*10^{-6}$ $km^3\ a^{-1}$, typically in sparsely populated areas like central Australia and western China, or regions less reliant on groundwater. The top 25% of grid cells withdraw more than $1.35*10^{-6}$ $km^3\ a^{-1}$, highlighting regions with dense population centers, such as Indonesia, India, and eastern China, or regions heavily dependent on groundwater, including the Middle East, southern Europe, and part of the United States.

Based on the GGW model, agriculture accounts for 50% (324 km^3 a^{-1}) of the total global groundwater withdrawals. This dominance is particularly pronounced in countries such as India, Iran, Pakistan, the United States, and southern Europe (Figure 2(b) and (c)). Domestic use contributes 34.5% (224 km^3 a^{-1}) of total withdrawals, with a widespread global distribution and notable prominence in Southeast Asia. For instance, in Indonesia, 93% of total groundwater withdrawal supports domestic water supply. Industrial use accounts for a smaller share of withdrawals at 15.5% (100 km^3 a^{-1}) but is the predominant sector in specific regions. In parts of Europe, industrial demand outweighs other sectors; for example, 80% and 72% of total withdrawals in Estonia and Norway, respectively, are dedicated to industrial activities.

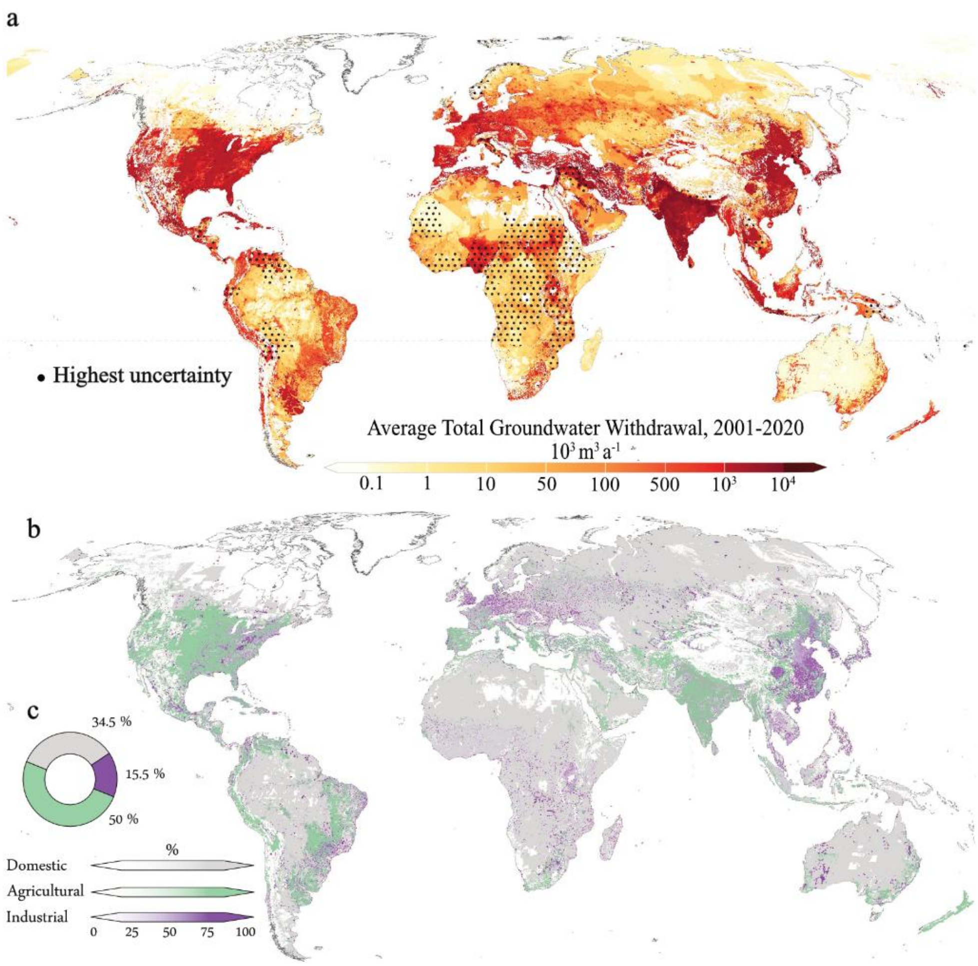

Figure. 2. Global distribution of groundwater withdrawal and dominant sectoral users (2001–2020): (a) Average total groundwater withdrawal, highlighting regions with the highest uncertainty with black dots, corresponding to countries with no reported data on annual total groundwater withdrawal (section 2.5 and Supplementary section 1.5). (b) Sectoral distribution of groundwater withdrawal percentages (domestic, industrial, and agricultural), where white indicates no groundwater withdrawal. (c) Pie chart illustrating the proportional contribution of each sector - domestic, industrial, and agricultural - to total groundwater withdrawal over the 20-year period.

3.2. Temporal dynamics of global groundwater withdrawal

An analysis of the temporal dynamics of total groundwater withdrawal reveals an average annual increase of $2.6*10^{-6}$ km^3 a^{-1} per grid. The temporal dynamic is calculated for the IPCC WGI reference regions and shows a range of declining withdrawal from -0.31 to increasing up to 1.11 km^3 a^{-1} (Figure 3(a) and Table SP1). Notably, 63% of regions exhibited statistically significant changes, with nearly two-thirds showing increased withdrawal.

Groundwater withdrawals have declined primarily in regions located in Australia and Europe. The largest absolute annual decreases were observed in East Asia (EAS) and Western and Central Europe (WCE), with decreases of 0.31 and 0.15 $km^3\ a^{-1}$, respectively. Similarly, South Australia (SAU) and Northern Europe (NEU) showed a significant decrease of 0.07 $km^3\ a^{-1}$.

Conversely, groundwater withdrawals increased in 66% of the regions, spanning diverse climatic zones. These include tropical regions such as South Asia (SAS) and Southeast Asia (SEA), as well as arid and semi-arid areas like West Central Asia (WCA) and the Sahara (SAH). Southeast Asia (SEA) recorded the highest annual increase, with domestic groundwater use rising by 1 km^3. In South Asia (SAS), the world's largest agricultural groundwater consumer (126 $km^3\ a^{-1}$), growth was primarily driven by increasing agricultural withdrawals, which rose by 0.6 $km^3\ a^{-1}$ per year.

When considering relative rates of change (calculated as the ratio of the annual trend to the 20-year average usage in each region), total withdrawal has increased globally at an average annual rate of 0.5%. The highest relative increase, 6.5% annually, was observed in Northeast South America (NES), while the most pronounced decline, 9% annually, occurred in Central, East, and South Australia (CAU, EAU, SAU). These relative rates highlight how regions with smaller baseline withdrawals can experience rapid growth, while high-usage areas may show smaller relative changes despite substantial absolute increases (for further details see Figure SP1 and Table SP1).

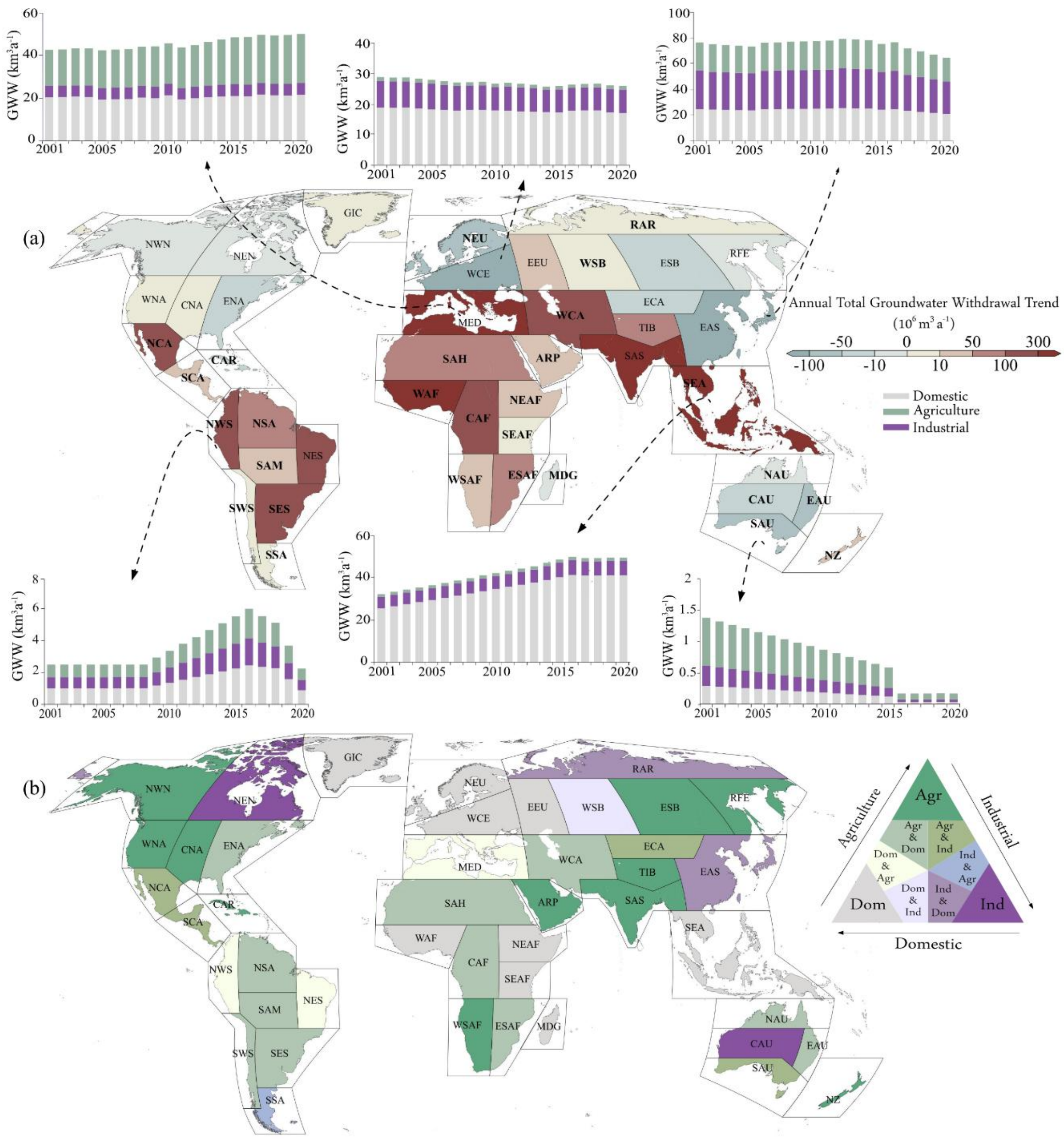

Figure 3. (a) The annual total groundwater withdrawal trend (10^6 m^3 a^{-1}) from 2001 to 2020 across IPCC WGI reference regions (version 4) based on the Mann-Kendall test. Each bar chart displays the annual groundwater withdrawals for domestic, agricultural, and industrial sectors. Regions with statistically significant trends are highlighted in bold text. (b) Regional classification of dominant groundwater withdrawal users. Regions are categorized into nine groups, based on the dominance of specific sectors. Single-sector dominance (agriculture, domestic, or industrial) is defined when a sector accounts for more than 60% of the total groundwater use. For IPCC WGI reference regions without single-sector dominance, the two most significant users are indicated in descending order of contribution, as shown in the ternary legend.

3.3. Assessing uncertainty in global groundwater withdrawal

The 20-year uncertainty assessment indicates that, on average, the total simulated withdrawal ranges between 465 $km^3\ a^{-1}$ and 881 $km^3\ a^{-1}$ (5th to 95th percentile range; Figure 4(d)). Sector-specific analyses reveal distinct ranges of uncertainty: domestic groundwater withdrawal spans 154-306 $km^3\ a^{-1}$, industrial withdrawal ranges from 65-142 $km^3\ a^{-1}$, and agricultural withdrawal varies between 225-463 $km^3\ a^{-1}$ (Figure 4(a)-(c)). Among these, the agricultural sector demonstrates the largest uncertainty, reflecting the combined influence of variability in country-level input data - common to all sectors - and additional factors specific to agriculture, such as irrigation efficiency and return flow fractions. This is consistent with agriculture's role as the dominant global groundwater user, which amplifies the effect of small changes in input parameters on overall uncertainty.

Excluding regions where no data on total groundwater withdrawal were reported - classified as areas of highest uncertainty - we assessed the global spatial distribution of relative uncertainty (*RU*) (Figure 4(e)). We found that only 0.5% of the global area exhibits very low ($RU < 0.05$) or low uncertainty ($0.05 \leq RU \leq 0.1$). In contrast, 9% of the global area falls under extreme uncertainty, and 29% is classified as having very high uncertainty.

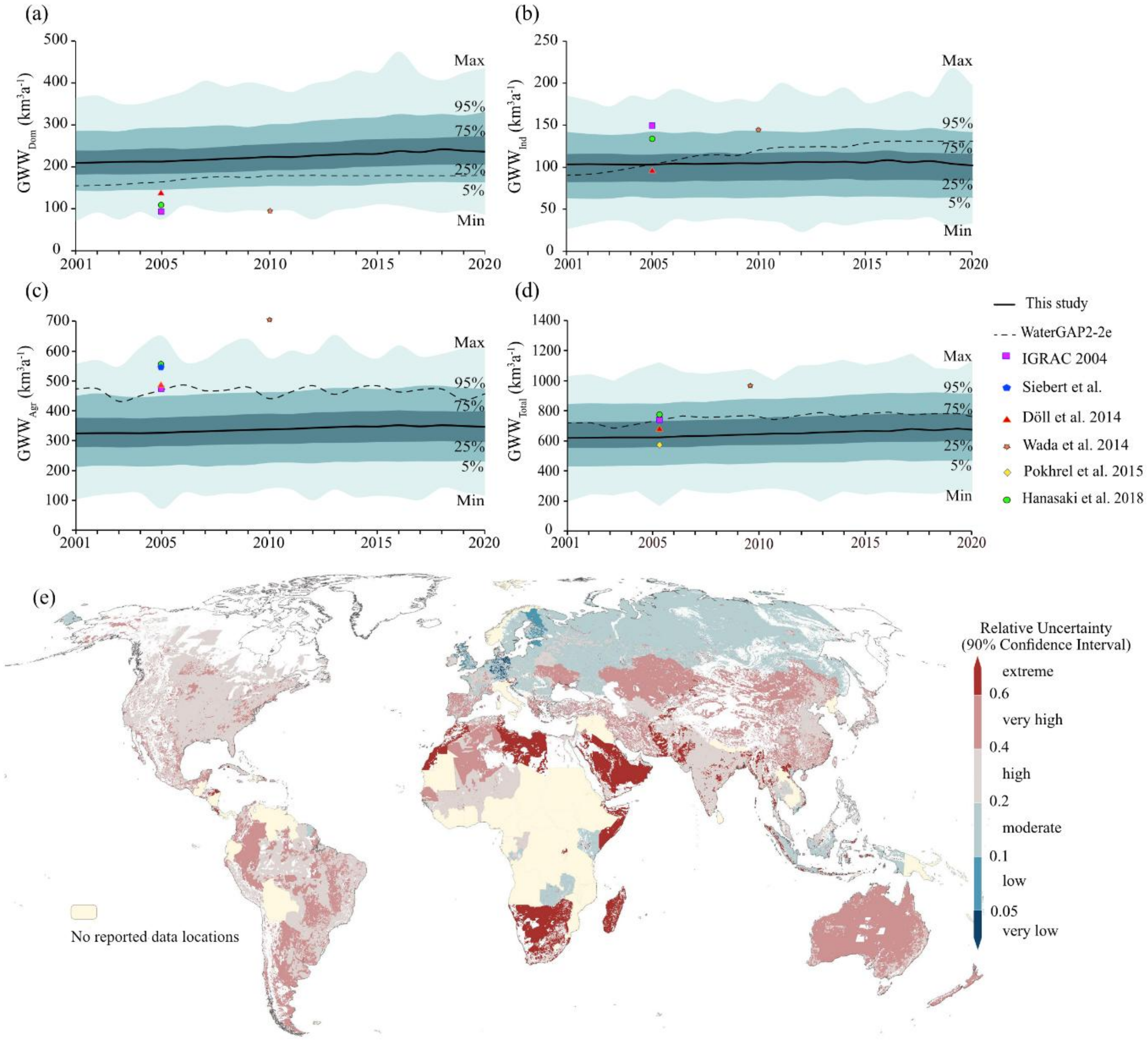

Figure 4. Temporal and spatial assessment of global groundwater withdrawal uncertainty (2001–2020) using the GGW model. Panels (a), (b), (c), and (d) depict the temporal uncertainty ranges for domestic (GWW_{Dom}), industrial (GWW_{Ind}), agricultural (GWW_{Agr}), and total (GWW_{Total}) groundwater withdrawals, respectively, with a comparison to estimates from previous studies (See Section 2.4 for details) [8, 43, 44, 13, 18, 22, 45]. Panel (e) illustrates the spatial distribution of relative uncertainty, categorized into six uncertainty levels ranging from very low to extreme.

4. Discussion

4.1. Regional dominant groundwater users

Determining the dominant groundwater user in each IPCC WGI reference region extends beyond factors like population or irrigated area density. Our findings show that groundwater use is influenced by sector-specific withdrawal fractions, population distribution, groundwater-irrigated areas, urbanization, and mining activities. Agriculture dominates in 27% of IPCC regions (Figure 3(b)), accounting for over 60% of total withdrawals, while domestic use leads in 20%. Although the industrial sector has the smallest global share, it is dominant in specific regions, such as Central Australia (CAU) and Eastern Asia (EAS), where mining and industrial demand are substantial. These results indicate that while agriculture remains the dominant groundwater consumer globally, domestic and industrial withdrawals can be significant in specific regions.

Beyond identifying IPCC regional dominant users, our analysis reveals the combination of factors also drives temporal variations in groundwater withdrawal patterns. Population growth and the changes in groundwater demand are decoupled (Figure SP2). This counterintuitive discovery challenges the common assumption that increasing populations inevitably lead to greater groundwater extraction. Instead, it points to a more nuanced reality where multiple factors - social, economic, technological, and environmental - converge to influence groundwater use patterns.

For instance, in Australia, groundwater withdrawal has declined despite population growth. This decline has been attributed to reduced reliance on groundwater, driven by increased surface water availability, and regulatory changes introduced in 2016, including volumetric limits on groundwater withdrawal, water trading mechanisms, and adaptive management strategies [46-48]. Conversely, in regions like Southeast Asia (SEA) and Western Africa (WAF), population growth continues to drive increases in groundwater withdrawal. For example, in Indonesia and Nigeria, rising domestic demand is closely tied to expanding populations.

Understanding the interplay between these regional groundwater withdrawal dynamics and variations in groundwater recharge is essential for crafting tailored water management strategies that safeguard groundwater resources while unlocking their potential to meet growing freshwater demands [49]. For example, in Africa - home to 13.6% of the world's population – contributes only 3.5% to global groundwater withdrawals (Supplementary Table SP3 and Figure SP3). This disparity underscores the untapped potential of groundwater resources in Africa, warranting further exploration [7]. In addition, the literature suggests that traditional groundwater management methods, such as improving irrigation efficiency or changing cropping patterns [50], should be complemented by innovative, region-specific measures, including incentive-based policies [51, 52], water markets [53], and awareness campaigns [4].

4.2. Methodological impacts on groundwater withdrawal estimates

Methodological choices and assumptions in the sectoral withdrawal calculations have a substantial impact on the estimates. The evaluated uncertainties are compared with previous global estimates [8, 43, 44, 13, 18, 22, 45] for each sector (Figure 4(a)-(b), Table SP2). While most previous studies fall within the uncertainty ranges determined here, there are notable differences in annual sectoral withdrawals due to differences in methodologies and data gap filling approaches (Supplementary Section 2.2 and 2.4 and Figure SP4).

For the domestic sector, the methodology for estimating groundwater demand varies across studies. Previous studies typically model domestic groundwater demand by incorporating socioeconomic indicators (e.g., GDP) alongside population data and adjustments for daily temperature variations [44, 45]. In contrast, the GGW model uses country-level reported data and addresses data gaps by employing a representative country approach (Supplementary, Section 1.1). This method, especially for countries with missing data like Nigeria, where large populations rely heavily on groundwater [7], influences the estimated values for domestic groundwater withdrawals.

The methodology employed in different studies also influences the temporal dynamics of estimations. This is evident when comparing industrial withdrawal of the GGW model and WaterGAP2.2e [45]. While both models report similar ranges for 2005, their simulations diverge over time. In the GGW model, the annual industrial groundwater withdrawal estimates remain relatively stable. In contrast, WaterGAP2.2e introduces temporal variability by incorporating factors such as manufacturing gross value added (GVA) and dynamically adjusting industrial groundwater estimates. This approach accounts for technological advancements and economic trends, using 2005 as a base year but the values are inconsistent with reported groundwater withdrawal.

In the agricultural sector, the impact of methodological differences is even more pronounced. Compared to previous studies, the GGW model consistently reports lower agricultural groundwater withdrawals (Figure 4(c)). In previous estimations, total agricultural water demand was estimated and allocated to groundwater based on surface water availability [44] or sectoral groundwater fractions [43, 45]. The GGW model, however, restricts groundwater use to explicitly groundwater-irrigated areas, leveraging the well-established linear correlation between irrigated areas and water withdrawals [54]. Furthermore, prior models incorporate factors such as climatic variables, cropping patterns, growing season lengths, and dynamically calculated surface water availability to estimate agricultural water demand - elements not included in the data-driven GGW modeling approach.

These comparisons highlight the influence of methodological choices on global groundwater withdrawal estimates and the uncertainties still associated with it. The variability among studies underscores the need to report uncertainty ranges rather than relying solely on point estimates.

Providing these ranges is essential for robust science and for identifying areas where data availability and methodologies require improvement.

4.3. Spatial variability and drivers of uncertainty

The highest uncertainty levels are mainly observed in areas with significant variability in reported total withdrawals or near river networks where the return flow fraction to groundwater shows substantial spatial variation (Figure 4(e)). These annual variations in reported groundwater withdrawals are due to a combination of factors, including changes in surface water availability, population dynamics, economic or technological developments, and climate change [7]. These areas of high variability indicate where future projections are likely to have greater uncertainty and should be considered in groundwater withdrawal projections, as historical variability often has greater uncertainty in projected trends.

4.4. Limitations

The GGW model provides an alternative for global-scale assessment of groundwater withdrawals by focusing on simplicity and transparency. However, its exclusive focus on groundwater without considering the potential contribution of surface water may be a limitation. The focus is consistent with the primary objective of the study, which is to estimate groundwater withdrawal directly, rather than inferring it as a fraction of total demand, which is a common approach in other global estimates. Notably, the availability of surface water does not necessarily translate into its prioritization for use. For instance, in Germany, despite abundant surface water resources, 71% of domestic freshwater demand is met by groundwater, highlighting a strong reliance on groundwater even in water-rich regions [55]. To enhance the plausibility of groundwater withdrawal estimates, proxies such as water table depth were used to ensure resource availability before allocation.

The GGW model is reliant on the applied methodology and the quality of input datasets. This dependence can lead to overestimations in densely populated urban regions, where domestic and industrial water use may primarily rely on surface water. Similarly, in the agricultural sector, the reliance on irrigated-area data may not fully capture regional differences, resulting in a more uniform distribution of agricultural groundwater withdrawals across the country, overlooking localized variability. To further illustrate the impact of these assumptions, we compared the GGW model results with the national data sets of the example countries (Supplementary Section 2.5 and Figures SP5-SP6). By incorporating uncertainty evaluations, the GGW model enables a cautious and uncertainty-aware interpretation of its outputs, striking a balance between computational feasibility and practical utility.

5. Conclusion

Based on combining per-country reported water usage values with data representing the groundwater fraction, this study presents a global groundwater withdrawal estimate from 2001 to 2020. The study highlights regional usage patterns and temporal variations, while also illuminating the complexities of estimating groundwater withdrawals and the uncertainties inherent in global groundwater assessments.

Uncertainty of model results varies widely among regions. The spatial variability of the calculated uncertainty indicates that regions with greater variability in historical withdrawal patterns have higher relative uncertainty. This variability is due to factors such as fluctuations in surface water availability, regulatory changes (e.g., Australia), population dynamics (e.g., Nigeria and Indonesia), and economic or technological developments. In addition, comparisons with previous studies show that the choice of methods used to calculate sectoral demand, to adjust for temporal dynamics, and to allocate groundwater within total water use have a direct impact on the results.

The identified uncertainty and its spatial variability can serve as a reference for groundwater withdrawal studies focusing on future developments, as regions with historically inconsistent patterns are more likely to have greater uncertainty in future estimates. Additionally, the compiled input datasets, sectoral grid-based groundwater withdrawal estimates, and calculated uncertainty ranges from this study provide training data to support machine learning applications in global groundwater withdrawal assessments.

Based on our findings, research on groundwater withdrawal should advance in two key data-related areas: First, improving data availability in regions with no reported groundwater withdrawal is essential. Uncertainty is highest in these areas due to reliance on assumptions without validation. Second, availability of temporally resolved datasets regarding irrigated areas with groundwater, irrigation efficiency, and groundwater withdrawal fractions - would enhance model estimations. Uncertainty assessments of global grid-based input datasets, including irrigated areas, population density, and mining locations would improve the uncertainty assessment of the withdrawal estimates substantially.

Our findings indicate that global groundwater withdrawals over the past 20 years range between 465-881 $km^3\ a^{-1}$. Despite uncertainties, our results show an average annual global increase of 0.5%, regionally rising up to 6.5% per year in 66% of the IPCC regions. These trends are shaped by a complex interplay of factors that also determine the dominant groundwater users in each region, extending beyond demographic trends to sector-specific demands. While agriculture remains the largest user of groundwater globally, our results highlight that it is not always the primary user since domestic and industrial sectors play a dominant role in certain regions. These findings emphasize the importance of context-specific groundwater management strategies tailored to regional needs.

Code availability

The source code of the GGW model is available under the GNU General Public License v3.0 at Zenodo (now it's available here, https://github.com/Global-Groundwater-Model/Global_Groundwater_Withdrawal_Model, later it will be submitted to Zenodo).

Data availability statement

All input datasets used in the development of the GGW model are available from the sources cited in this study. The primary outputs, including grid-based long-term average annual global groundwater withdrawal estimates for domestic, industrial, and agricultural uses, along with associated uncertainty ranges (5^{th} and 95^{th} percentile values), are available in the PANGAEA database (data is submitted, the DOI will be provided).

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CRediT authorship contribution statement

S. Nazari: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **R. Reinecke:** Co-supervision, Writing – review & editing, Methodology, Conceptualization. **N. Moosdorf:** Supervision, Writing – review & editing, Methodology, Conceptualization.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT, an AI language model developed by OpenAI, in order to improve the clarity of the writing. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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