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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, 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 (≈10 km). 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 44 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]. Groundwater provides humans with essential social and economic needs and is a reliable freshwater supply. However, despite the continuously growing dependence on groundwater for irrigation, drinking water, and industrial use, which is expected to peak around 2050 [4], quantifications of groundwater withdrawal (GWW) remain uncertain. 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, reported to be 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].

Human water use has increasingly been recognized as an essential component of the global water cycle [10]. Global hydrological models (GHMs) and land surface models (LSMs) simulate GWW across various sectors [11–14], and integrated assessment models extend these analyses by endogenizing water demand within coupled energy, land, and economic systems, thereby capturing feedbacks between human activities and water use [4, 15–17]. GHMs and LSMs estimate domestic and industrial groundwater demand using nationally reported GWW data for a base year and model its change over time. The models' temporal evolution of these demands is typically driven by exogenously provided variables, such as technological advancements, infrastructure development, population growth, gross domestic product (GDP), and electricity production [12, 14, 18]. Agricultural groundwater demand is usually modeled as a function of irrigation efficiency (IE), crop calendars, irrigated area, crop types, and climatic conditions [19–21].

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 complexity and increase the potential for propagated errors. In contrast, simpler models can achieve comparable results while offering clearer assessments of uncertainties [22, 23]. However, they may lack the ability to capture complex interactions or region-specific drivers, which are represented by more detailed, data-intensive models.

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 transparent estimation of GWW across domestic, industrial, and agricultural sectors. By leveraging existing global datasets, our model directly estimates GWW at a grid level while simultaneously evaluating associated uncertainties.

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

2. Methods

The developed Global Groundwater Withdrawal (GGW) model is a data-driven framework designed to estimate annual GWW across three main sectors: domestic, industrial, and agricultural. In this study, withdrawal refers to the volume of groundwater abstracted from aquifers to meet sectoral demands [24].

The GGW model relies on two primary national-level datasets: (1) annual total GWW ($GWW_{Total,c,y}$) sourced from FAO AQUASTAT [24], and (2) sector-specific (s) fractions of GWW ($GWW_{Frac,s,c}$) derived from International Groundwater Resources Assessment Centre [25]. We cross-referenced and updated the annual sector-specific GWW data for European countries using Eurostat sources [26].

The model is implemented in Python and uses these national-level datasets to calculate annual sectoral withdrawals for each country (c) and year (y): domestic ($GWW_{Dom,c,y}$), industrial (including mining) ($GWW_{Ind,c,y}$), and agricultural ($GWW_{Agr,c,y}$) (figure 1). Given that livestock water use accounts for approximately 1% of total global water withdrawals [12] and is generally assumed to rely on surface water [27], the withdrawal fraction for livestock purposes is considered to be negligible. Using the national-level datasets, the GGW model applies a sector-specific downscaling approach to estimate domestic, industrial, and agricultural withdrawals at a spatial resolution of 0.1° (≈10 km). Importantly, this downscaling approach only redistributes water use spatially and does not change the total amount of water used at the country level.

For countries lacking reported data, the model estimates withdrawals using a classification-based gap-filling approach that groups countries based on climatic (aridity index), socioeconomic GDP, and regional similarities. This classification enables the assignment of representative values from similar countries to fill missing data (supplementary, section 1.1).

2.1. Domestic GWW

Using nationally reported statistics, the model uses domestic GWW at the country level as its base input and calculates annual domestic GWW at the grid level

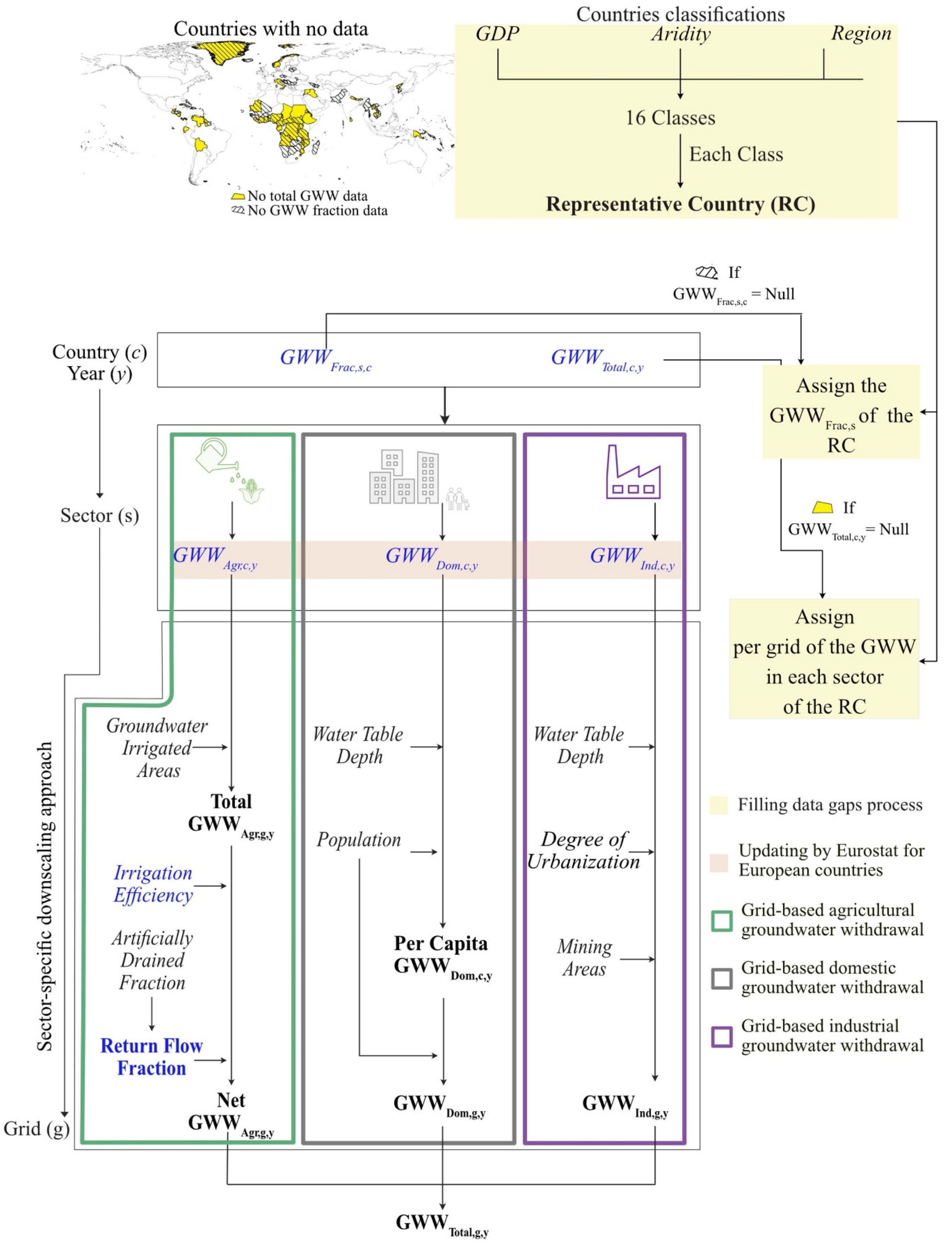

Figure 1. Schematic representation of the data-driven Global Groundwater Withdrawal (GGW) Model. This diagram illustrates the methodology used to estimate annual groundwater withdrawal for domestic (Dom), industrial (Ind), and agricultural (Agr) sectors at the grid level. Country-level data ($GWW_{total,c,y}$: annual country groundwater withdrawals [24], $GWW_{Frac,s,c}$: per-sector country fraction of groundwater withdrawal [25]) are used and downscaled to 0.1° resolution using sector-specific spatial proxies (e.g. population, irrigated area). The figure also shows country classification and gap-filling techniques. Inputs are presented in *italic* font, and elements considered in the uncertainty assessment are marked in blue.

by integrating two key datasets: population and water table depth (WTD). Population and WTD are used to proportionally distribute country-level domestic GWW, reflecting both human demand and groundwater availability.

Population data are taken from the Gridded Population of the World, version 4 (GPWv4) dataset [28]. A maximum WTD of 100 m is used to indicate accessible groundwater. While groundwater can be extracted from depths greater than 100 m [29], most wells are shallower due to economic and technical constraints [30–32]. The global average well depth is approximately 46 m [32], and around 60 m in the United States [30]. In addition, this threshold is consistent with categories proposed by Reinecke *et al.* [33], who identify <100 m WTD as potentially accessible for irrigation and domestic use. Therefore, this study distributes domestic groundwater extraction only on grids with WTD below 100 m to represent accessible groundwater. The WTD data are derived from the mean ensemble of four global groundwater models [34–37] that estimate global steady-state WTD (supplementary, section 1.2).

2.2. Industrial GWW

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, and considering the established correlation between urban centers and the distribution of industrial activities [38, 39], we use the degree of urbanization as a proxy to identify areas likely to host water-demanding industries such as food processing, beverage production, paper manufacturing, and textiles [40, 41].

The degree of urbanization is derived from the Global Human Settlement Layers dataset [42], which categorizes grid cells into eight settlement typologies based on population density and the proportion of built-up land (supplementary, section 1.3). As in the domestic sector, only grids where WTD is up to 100 m are considered. Additionally, recognizing the substantial water requirements of mining activities, which are often located in remote regions [43], the model incorporates global mining locations [44].

2.3. Agricultural GWW

The agricultural GWW per grid is calculated by first estimating the total agricultural GWW (Total $\text{GWW}_{\text{Agr,g,y}}$) and then determining the net agricultural GWW (Net $\text{GWW}_{\text{Agr,g,y}}$), defined as the portion of groundwater not returned to the groundwater system. To estimate the total agricultural GWW, the model distributes each country's agricultural GWW ($\text{GWW}_{\text{Agr,c,y}}$) proportionally to its groundwater-irrigated areas [45], resulting in *Total* $\text{GWW}_{\text{Agr,g,y}}$ for each grid.

Return flows from irrigation are then estimated using the return flow fraction to groundwater ($\text{F}_{\text{r,gw}}$), which represents the proportion of non-consumed irrigation water that percolates back into the aquifer. To account for enhanced return flow to surface water in areas with artificial drainage systems, the model incorporates the artificially drained fraction ($\text{F}_{\text{d,irr}}$) [46]. This dataset is provided at a 5′ resolution and includes values ranging from 0 to 100%, enabling spatial differentiation of drainage conditions across agricultural areas. The GGW applies a method adapted from the WaterGAP GHMs [6], and $\text{F}_{\text{r,gw}}$ is estimated as $\text{F}_{\text{r,gw}} = 0.8\text{–}0.6^{*}\text{F}_{\text{d,irr}}$.

To calculate net agricultural GWW, two key parameters are considered: $\text{F}_{\text{r,gw}}$ and IE_{c}. The country-specific IE dataset used here [47] accounts for a combination of partial efficiencies, specifically: conveyance efficiency, field application efficiency, and a management factor representing distribution and scheduling effectiveness. First, the groundwater consumption by crops ($\text{GWC}_{\text{Agr,g,y}}$) is estimated as the product of IE_{c} and Total $\text{GWW}_{\text{Agr,g,y}}$, and then Net $\text{GWW}_{\text{Agr,g,y}}$ is calculated as follows:

$$\text{Net GWW}_{\text{Agr,g,y}} = \text{Total GWW}_{\text{Agr,g,y}} - \text{F}_{\text{r,gw}} \times \left(\text{Total GWW}_{\text{Agr,g,y}} - \text{GWC}_{\text{Agr,g,y}}\right) \quad (1)$$

2.4. Temporal trend and uncertainty assessment

To assess the temporal dynamics of global GWW (2001–2020), this study applies the pre-whitening Mann–Kendall test [48, 49] at the grid level, a non-parametric test commonly used to detect trends in time series data (see supplementary section 1.4). The results are then aggregated to the IPCC WGI reference regions (version 4) [50] by calculating the average change in GWW across all grid cells within each region. This method provides a regionally representative trend and offers climatic and geographical coherence. It also enhances the relevance of the findings for climate adaptation planning and water resource policy frameworks [51].

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 GWW 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,

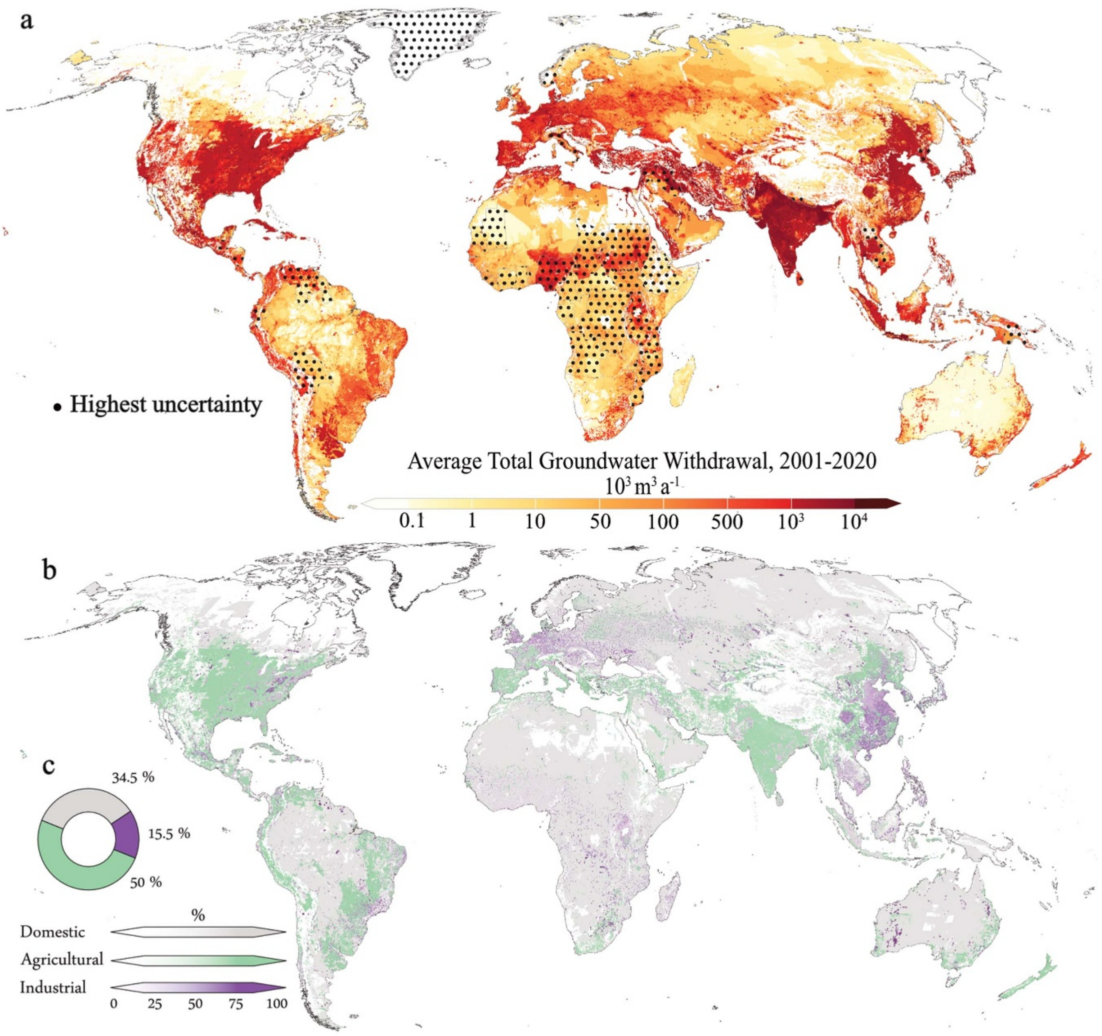

Figure 2. Global distribution of groundwater withdrawal and dominant sectoral users (2001–2020): (a) average total groundwater withdrawal, highlighting regions with the highest uncertainty with black dots, corresponding to countries with no reported data on annual total groundwater withdrawal (section 2 and supplementary section 1.1). (b) Sectoral distribution of groundwater withdrawal percentages (domestic, industrial, and agricultural), where white indicates no groundwater withdrawal. (c) Pie chart illustrating the contribution of each sector, domestic, industrial, and agricultural to total groundwater withdrawal over the 20-year period.

including country-level annual total withdrawals, sector-specific fractions, European sectoral data, IE, and return flow fractions (blue variables in figure 1). The uncertainty analysis employs Latin hypercube sampling [52, 53], 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 GWW

The GGW model estimates an average global GWW of 648 km^3 a^{-1} for the period 2001–2020 (figure 2(a)). GWW 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 GWW. This dominance is particularly pronounced in regions such as India, Iran, Pakistan, the United States, and southern Europe (figures 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. Industrial use accounts for a smaller share of withdrawals at 15.5%

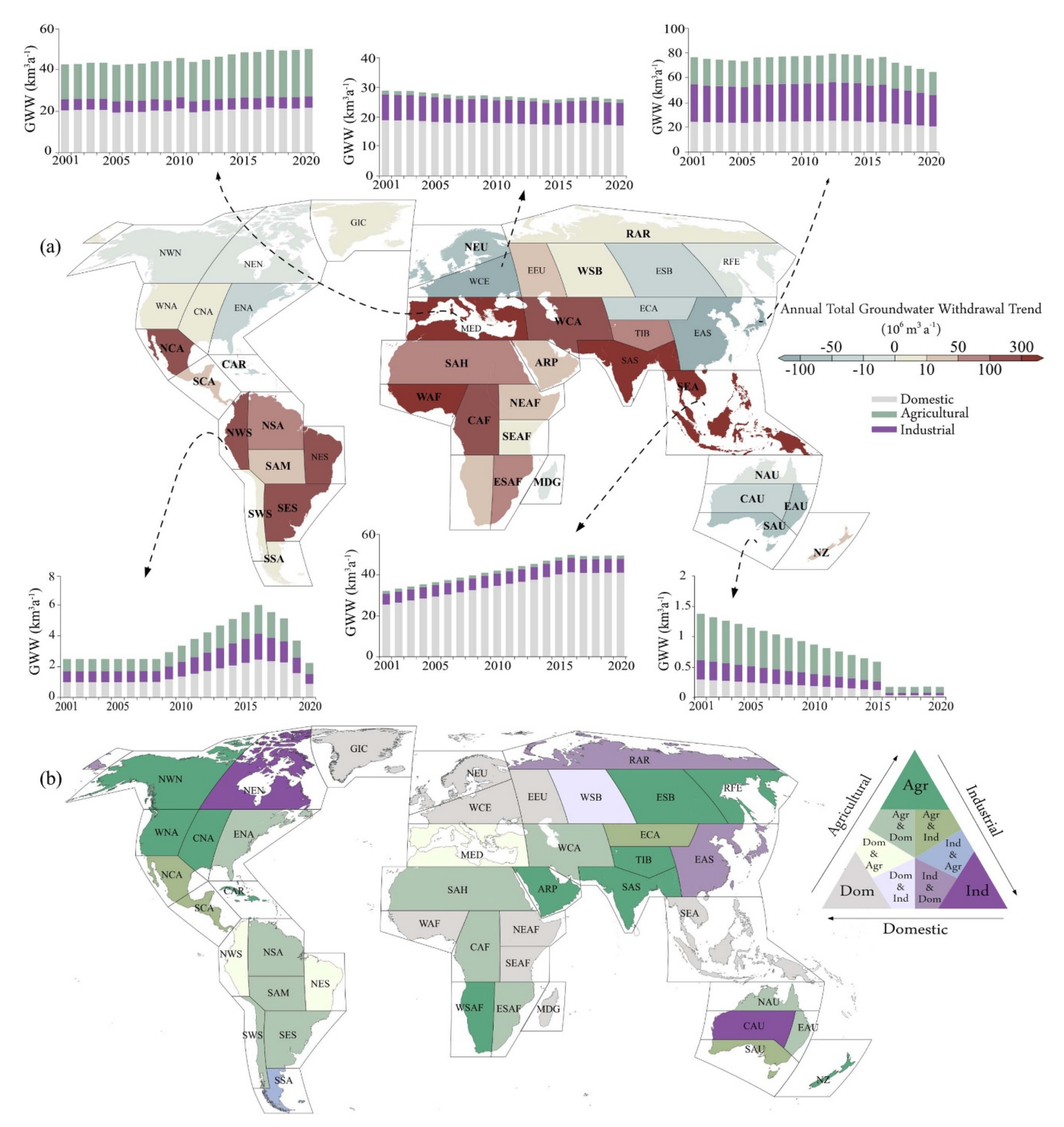

Figure 3. (a) The annual total groundwater withdrawal trend (10^6 m^3 a^{-1}) from 2001 to 2020 across IPCC WGI reference regions (version 4) [50] based on the Mann–Kendall test. Each bar chart displays the annual groundwater withdrawals for domestic, agricultural, and industrial sectors. Regions with 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 (agricultural, 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.

(100 km^3 a^{-1}) but is the predominant sector in some 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.

3.2. Temporal dynamics of global GWW

An analysis of the temporal dynamics of total GWW reveals an average annual increase of $2.6{*}10^{-6}$ km^3 a^{-1} per grid over the 20 modeled years. The temporal dynamic is calculated for the 44 IPCC WGI reference regions and shows a range of withdrawal from declining by 0.31 km^3 a^{-1} 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 of those showing increased withdrawal.

GWW has 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, GWW 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

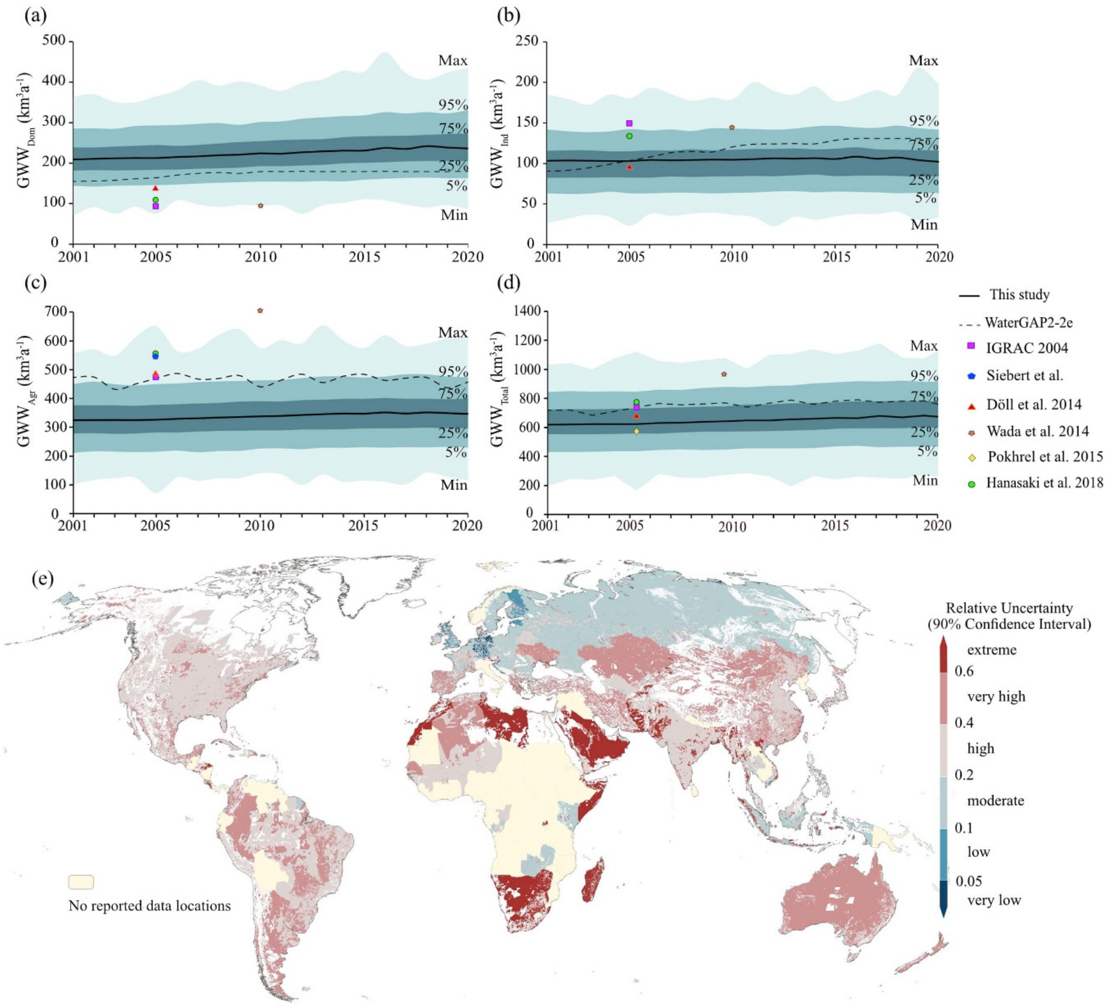

Figure 4. Temporal and spatial assessment of global groundwater withdrawal uncertainty (2001–2020) using the GGW model. Panels (a)–(d) depict the temporal uncertainty ranges for domestic (GWW_{Dom}), industrial (GWW_{Ind}), agricultural (GWW_{Agr}), and total (GWW_{Total}) groundwater withdrawals, respectively, with a comparison to estimates from previous studies (see section 2.4 for details) [8, 21, 25, 27, 54–56]. Panel (e) illustrates the spatial distribution of relative uncertainty, categorized into six uncertainty levels ranging from very low to extreme.

areas like West Central Asia (WCA) and the Sahara (SAH). Southeast Asia (SEA) recorded the highest annual increase, with domestic groundwater use rising on average by 1 $km^3\ a^{-1}$. 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 SP3, SP4 and table SP1).

3.3. Assessing uncertainty in global GWW

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 withdrawal spans from 154 to 306 $km^3\ a^{-1}$, industrial withdrawal ranges from 65–142 $km^3\ a^{-1}$, and agricultural withdrawal varies between 225 and 463 $km^3\ a^{-1}$ (figures 4(a)–(c)). Of these sectors, agriculture demonstrates the greatest uncertainty. This reflects the combined influence of variability in country-level input data, which is common to all sectors, as well as additional factors specific to agriculture, such as IE and return flow fractions. This is consistent with the role of agriculture 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 GWW were reported, classified as areas of highest uncertainty, we assessed the global spatial distribution of RU (figure 4(e)). We found that only 0.5% of the global area exhibits very low ($RU < 0.05$) or low uncertainty ($0.05 \leqslant RU \leqslant 0.1$). In contrast, 9% of the global area falls under extreme uncertainty, and 29% is classified as having very high uncertainty.

4. Discussion

4.1. Regional dominant groundwater users

The dominant groundwater user in each IPCC WGI reference region is determined 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 dominates in 20%. Although the industrial sector has the smallest global share, it dominates withdrawal in individual 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 largest groundwater consumer globally, domestic and industrial withdrawals can dominate in specific regions.

Often, it is a combination, not individual factors that drive temporal variations in GWW patterns. For instance, population growth and the changes in groundwater demand appear to be decoupled (figure SP5). This counterintuitive observation challenges the common assumption that increasing population leads to greater groundwater extraction. Instead, it points to a more nuanced reality in which social, economic, technological, and environmental factors converge to influence groundwater use patterns.

For instance, in Australia, GWW 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 GWW, water trading mechanisms, and adaptive management strategies [57–59]. Conversely, in regions like Southeast Asia (SEA) and Western Africa (WAF), population growth continues to drive increases in GWW.

Understanding the interplay between these regional GWW dynamics and variations in groundwater recharge is key to developing water management strategies that both protect resources and meet growing demand [60]. For example, Africa, home to 13.6% of the world's population, contributes 3.5% to global GWW (supplementary table SP3 and figure SP6). 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 IE or changing cropping patterns [61], should be complemented by innovative, region-specific measures, including incentive-based policies [62, 63], water markets [64], and awareness campaigns [65].

4.2. Methodological impacts on GWW estimates

Methodological choices in the sectoral withdrawal calculations have a substantial impact on the estimates. The evaluated uncertainties are compared with previous global estimates [8, 21, 25, 27, 54–56] (figures 4(a) and (b), table SP2). While most previous studies fall within the uncertainty ranges determined here, there are notable differences in annual sectoral withdrawals due to variations in methodologies and data gap-filling approaches.

For the domestic sector, previous studies typically modeled groundwater demand by incorporating socioeconomic indicators (e.g. GDP) alongside population data and adjustments for daily temperature variations [54, 56]. In contrast, the GGW model uses country-level annually 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.

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 [56]. While both models report similar ranges for 2005 ($\approx$103 km^3 a^{-1}), their simulations diverge over time. In the GGW model, the annual industrial GWW estimates remain relatively stable. In contrast, WaterGAP 2.2e uses 2005 as a base year and dynamically adjusts industrial groundwater estimates by accounting for technological advancements and economic trends, incorporating indicators such as manufacturing gross value added.

In the agricultural sector, the impact of methodological differences is even more pronounced. Compared to previous studies, the GGW model consistently reports lower agricultural withdrawals (figure 4(c)). In previous estimations, total agricultural water demand was estimated and allocated to groundwater based on surface water availability [54] or sectoral groundwater fractions [27, 56]. The GGW model, however, restricts groundwater use to explicitly groundwater-irrigated areas, leveraging the found linear correlation between irrigated areas and water withdrawals [66]. Furthermore, prior models incorporate factors such as climatic variables, cropping patterns, and growing season lengths, elements not included in the GGW modeling approach.

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 scientific conclusions 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 spatial variation (figure 4(e)). These annual variations in reported GWW are caused by changes in surface water availability, population dynamics, economic developments, 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 GWW projections, as historical variability often has greater uncertainty in projected trends.

4.4. Limitations

The GGW model provides an alternative framework for global-scale assessment of GWW by prioritizing simplicity and transparency. However, its exclusive focus on groundwater, without accounting for surface water contributions, limits its scope. This design choice aligns with the primary objective of the study: to estimate sectoral and spatial patterns of GWW based on nationally reported totals. Rather than estimating total water demand and partitioning it between sources, the GGW model uses reported national GWW values and distributes them across sectors and grid cells using sector-specific fractions and spatial proxy data.

To better represent the accessibility of groundwater and improve the spatial allocation of withdrawals, WTD was included in the modeling framework using a fixed threshold of 100 m WTD. While the simplification was necessary due to the lack of direct groundwater accessibility data, it may not fully reflect regional hydrogeological variability. Yet, it is consistent with literature and empirical well depth distributions [30, 32, 33].

The GGW model relies on the applied methodology and the quality of input datasets. One limitation is lack of the temporal resolution in some inputs, such as sector-specific fractions, which are treated as static. This limits the model's ability to fully capture temporal shifts in sectoral groundwater use at the national level. We have addressed this limitation through the uncertainty analysis, where variability in these fractions was incorporated to reflect plausible temporal changes.

This dependence on available datasets can also lead to overestimations in densely populated regions, where domestic and industrial water use may primarily rely on surface water. Similarly, in the agricultural sector, relying on data from irrigated areas may not fully capture regional differences. This can result in a more uniform distribution across the country that overlooks 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 SP8 and SP9).

5. Conclusion

This study presents global estimates of GWW from 2001 to 2020 by integrating country-reported values with sector-specific fractions and spatial proxy data. Our findings show that global GWW over the past two decades ranged between 465 and 881 $km^3\ a^{-1}$, with an average annual increase of 0.5%. In two-thirds of IPCC regions spanning all climatic zones, GWW increased. However, some regions with decreasing withdrawal warrant closer examination to determine if their experiences can serve as examples of successful water conservation policies.

Regions with greater historical variability in GWW also show higher RU in our estimates. The compiled input datasets, grid-based sectoral withdrawal estimates, and uncertainty ranges from this study can serve as training data for machine learning applications in global groundwater assessments. These estimates can also serve as inputs for large-scale studies examining groundwater depletion.

Given the increasingly high resolution of models used to assess the impacts of climate change, there is a need to reduce the significant uncertainties in representing the effects of human water use on the hydrologic cycle. Future research on GWW should focus on two areas: first, enhancing data availability in regions with limited reporting and expanding access to temporally resolved datasets, especially for groundwater-irrigated areas, IE, and sectoral withdrawal fractions. Second, including uncertainty assessments for critical input datasets, such as irrigated area maps, population density, and mining locations, would further improve global withdrawal estimates.

Data availability statement

All input datasets used here are available from the sources cited. The primary outputs, including grid-based long-term average annual global groundwater withdrawal estimates for domestic, industrial, and agricultural uses, along with uncertainty ranges (5th and 95th percentile values), are available in the PANGAEA database [67].

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Code availability

The source code of the GGW model is available under the GNU General Public License v3.0 at Nazari [68].

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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