

GROW-Qual: A global observational groundwater quality dataset linked to water table dynamics and Earth system variables

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Abstract

Groundwater underpins freshwater supply, food production and ecosystem health across the globe. Yet, groundwater levels and quality are increasingly threatened by overextraction, contamination, and climate change. Understanding how water table dynamics and quality are interlinked and affected by these pressures requires integrated observational groundwater datasets combined with Earth system variables that represent potential environmental drivers. Here we present *GROW-Qual*, a global dataset that standardises, harmonises and combines ~25 million groundwater quality observations across 92 constituents from 68 countries. Groundwater quality observations are linked to co-located water table timeseries (i.e. depth or level), in addition to a diverse range of contextual Earth system datasets spanning meteorological, hydrological, geophysical, biological and anthropogenic variables. *GROW-Qual* can support a broad range of applications, from empirical analysis to large-scale groundwater modelling, while its structural consistency with the companion river water quality dataset (*Caravan-Qual*) enables integrated study of groundwater-river water quantity and quality dynamics.

Background and summary

Groundwater is a fundamental component of the Earth system, underpinning freshwater supply, food production and ecosystem services across the globe¹. For example, groundwater is used by at least half of the global population for domestic purposes and accounts for ~43% of global consumptive irrigation use², with both the availability and quality of groundwater resources determining its suitability to meet human demands³. Beyond its role as a resource, groundwater sustains rivers flows worldwide⁴, supports groundwater-dependent ecosystems⁵, and mediates the exchange of water, solutes and energy between the subsurface and the broader hydrological cycle⁶.

Groundwater quantity and quality monitoring is therefore essential for understanding water system status, detecting and attributing changes and trends, and quantifying the effectiveness of management interventions⁷. This is especially relevant in the context of climate and socioeconomic change¹, which simultaneously drives greater dependence on groundwater to buffer drought impacts⁸ and mitigate water scarcity⁹, while also posing growing threats to groundwater availability (e.g. accelerated depletion¹⁰, altered recharge regimes^{1,11}), and quality (e.g. increased groundwater temperatures¹², pollutant accumulation and legacy effects in anthropogenic landscapes¹³).

Furthermore, groundwater quality is inextricably linked with water table dynamics. Changes in the water table (e.g. groundwater levels and recharge rates) can alter hydraulic gradients, flow paths, residence times and mixing, with consequences for the transport and transformation of dissolved constituents⁶. Water table dynamics can also modify the mobility and fate of nutrients and other solutes^{14,15}. For example, groundwater level decline in coastal aquifers can induce or exacerbate seawater intrusion and groundwater salinisation¹⁶⁻¹⁸, while climate driven changes in recharge¹¹ and groundwater temperature¹² can further influence groundwater flow and the biogeochemical processes that influence groundwater quality¹⁹.

Furthermore, as water and solutes can take decades to millennia to move through unsaturated and saturated groundwater pathways, the effects of anthropogenic pollutants, such as nutrients and pesticides from agricultural activities, may persist long after the polluting activity has stopped. This can produce considerable lag times between changes at the land surface and an observed groundwater quality response^{20,21}, for example with accumulated legacy nitrogen delaying improvements in groundwater quality even after reductions in nitrogen inputs on the land surface²².

In-situ groundwater quantity and quality monitoring records represent the primary source of data for characterising groundwater system behaviour and detecting trends, while also providing the foundation for calibrating and evaluating process-based and data-driven models and remote sensing approaches²³. Several international initiatives exist for standardising and disseminating groundwater data from national and regional monitoring networks worldwide, including the Global Groundwater Monitoring Network (GGMN)²⁴, hosted by the International Groundwater Resources Assessment Centre (IGRAC), and the global water quality database GEMSTAT operated by the Global Environmental Monitoring System for Freshwater programme (GEMS/Water) of the United Nations Environmental Programme (UNEP)²⁵. Beyond these international efforts, groundwater data is collected and disseminated by national and regional agencies (e.g. geological surveys, environmental protection agencies, water authorities), although these data are often inconsistent in formats, variable definitions and units, and overall remain largely inaccessible for global-scale analysis. Furthermore, these datasets are rarely integrated with contextual Earth system variables (e.g. climate, land cover, topography) that are fundamental to large-sample hydrology.

The global-scale integrated GROundWater package (*GROW*)²⁶ initiative seeks to address these issues for groundwater table dynamics, providing additional data harmonisation and quality control in addition to linking observed groundwater levels and depths to both static attributes (e.g. aquifer type, drainage density) and hydrometeorological time-series (e.g. precipitation, evapotranspiration). Yet, groundwater quality is currently not included in *GROW* or any other large-sample groundwater hydrology dataset. Given that groundwater quality is inextricably linked to water table dynamics, and furthermore influenced by similar drivers (e.g. recharge, abstraction, land use), harmonisation and integration of groundwater quality data within a unified dataset would be valuable for advancing our understanding of groundwater quality dynamics.

Here we present *GROW-Qual*, a harmonised global observational dataset that systematically integrates groundwater quality measurements with co-located measurements of groundwater levels and depths, in addition to contextual Earth system variables. The processing and structuring of this dataset closely mirrors that of *Caravan-Qual*²⁷, a global integration of stream water quality data into a large-sample hydrology dataset, and it is developed with a shared underlying philosophy of openness, extensibility and reproducibility. *GROW-Qual* is intended to serve multiple purposes, including: 1) to support large-scale assessments of groundwater quality status and trends; 2) to enable investigation of the drivers and controls

on groundwater quality across diverse hydrogeological, climatic, geographic and socioeconomic settings; 3) to provide benchmark data for the calibration and evaluation of groundwater quality models; 4) to advance process-informed understanding of groundwater quantity-quality dynamics; and 5) to facilitate the integration of groundwater quality into broader Earth system and hydrological modelling frameworks.

Methods

Groundwater quality data

Observational groundwater quality data in *GROW-Qual* is compiled from several existing global, regional and national databases, all of which have licenses that permit redistribution (see the licenses/ folder for full details), including:

1. Global: Global Groundwater Monitoring Network (GGMN)²⁴
2. Global: UNEP GEMS/Water Global Freshwater Quality Archive (GEMSTAT)²⁵
3. United States: Water Quality Portal (WQP)²⁸
4. Europe: NORMAN EMPODAT (EMPODAT)²⁹
5. Europe: Waterbase WISE State of Environment (Waterbase)³⁰
6. United Kingdom: Department for Environment, Food and Rural Affairs (UK-EA)³¹
7. Australia: Bureau of Meteorology (Aus-BOM)³²
8. India: National Water Data Portal (NWDP)³³

These sources include observations taken from groundwater wells across the globe, albeit with a heavy bias in both the number of observations and monitoring locations towards the contiguous United States, Europe, India, and Australia (Figure 1). Note that while groundwater quality observations may exist for other world regions, an inclusion criteria for *GROW-Qual* is that observations are freely available under open licenses that permit redistribution. Nevertheless, *GROW-Qual* is designed as an extendable and ‘living’ dataset that can be easily expanded with new observations and monitoring as more open-access datasets become available.

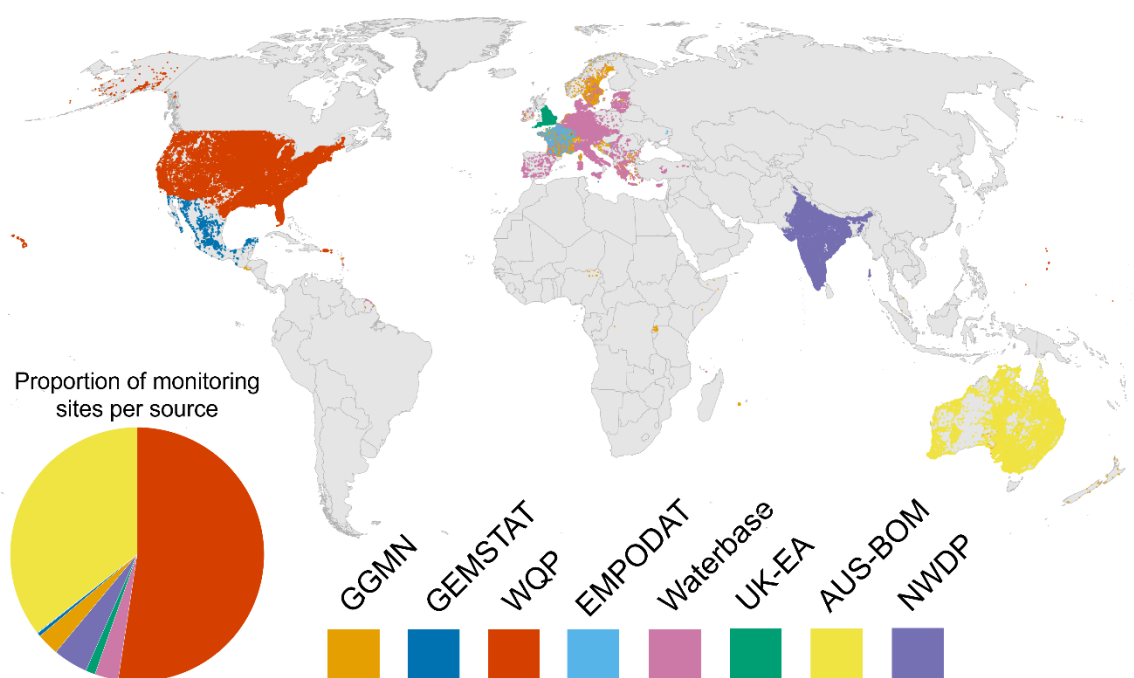


Figure 1. Spatial distribution of groundwater quality stations in *GROW-Qual*, disaggregated by source.

In total, 92 groundwater quality constituents were selected for inclusion in *GROW-Qual* (Figure 2, Table S1), covering a diverse range of physical, chemical and biological constituents that are both frequently monitored in groundwater systems and relevant for human water uses and environmental health²³. These constituents largely overlap with those in *Caravan-Qual*, the river water counterpart of *GROW-Qual*, with some additional constituents that are especially relevant in the context of groundwater systems included (e.g. uranium, sodium) and some constituents that are not (frequently) monitored in groundwater systems are excluded (e.g. Chlorophyll-*a*, particulate nutrient forms).

Groundwater quality observations were downloaded and processed following the methodology developed for *Caravan-Qual*²⁷, consisting of a pre-processing step (applied to the source groundwater quality datasets) and a post-processing step to harmonise all observations and monitoring locations into a unified dataset. Pre-processing involves steps to ensure sufficient geographical (i.e. latitude, longitude) and temporal (i.e. DD/MM/YYYY) information is included in the source data to enable inclusion in *GROW-Qual*, in addition to parameter code and unit harmonisation. Post-processing includes the assignment of a unique station identifier (“gwms_id”) based on unique coordinate pairs (to 5 decimal places), the removal of exact duplicate observations (identical gwms_id, date and observation), the

146 averaging of multiple unique observations taken at the same location on the same day
147 (identical gwms_id and date, but differing observation), the detection and flagging of
148 potential anomalous observations, and the processing of observations reported as below
149 detection limits in their source datasets. A complete description of these steps is provided in
150 the *Caravan-Qual* publication²⁷, while impact of the processing and harmonising procedures
151 on observational groundwater quality data in *GROW-Qual* is also provided (see Technical
152 Validation). Processed groundwater quality observations can be accessed through both the
153 core *GROW-Qual* dataset (i.e. *GROW-Qual.zarr*) and also in .csv format per constituent (see
154 Data Records).

155 Overall, the consistency in water quality constituents and processing methodologies between
156 *GROW-Qual* and *Caravan-Qual* makes the two datasets highly interoperable. This
157 interoperability opens new opportunities for the joint study of groundwater and surface water
158 dynamics across different world regions, such as linking groundwater quality and/or quality
159 to river water quantity and/or quality, without first needing to reconcile disparate datasets or
160 overcome barriers related to inconsistent variable definitions and units.

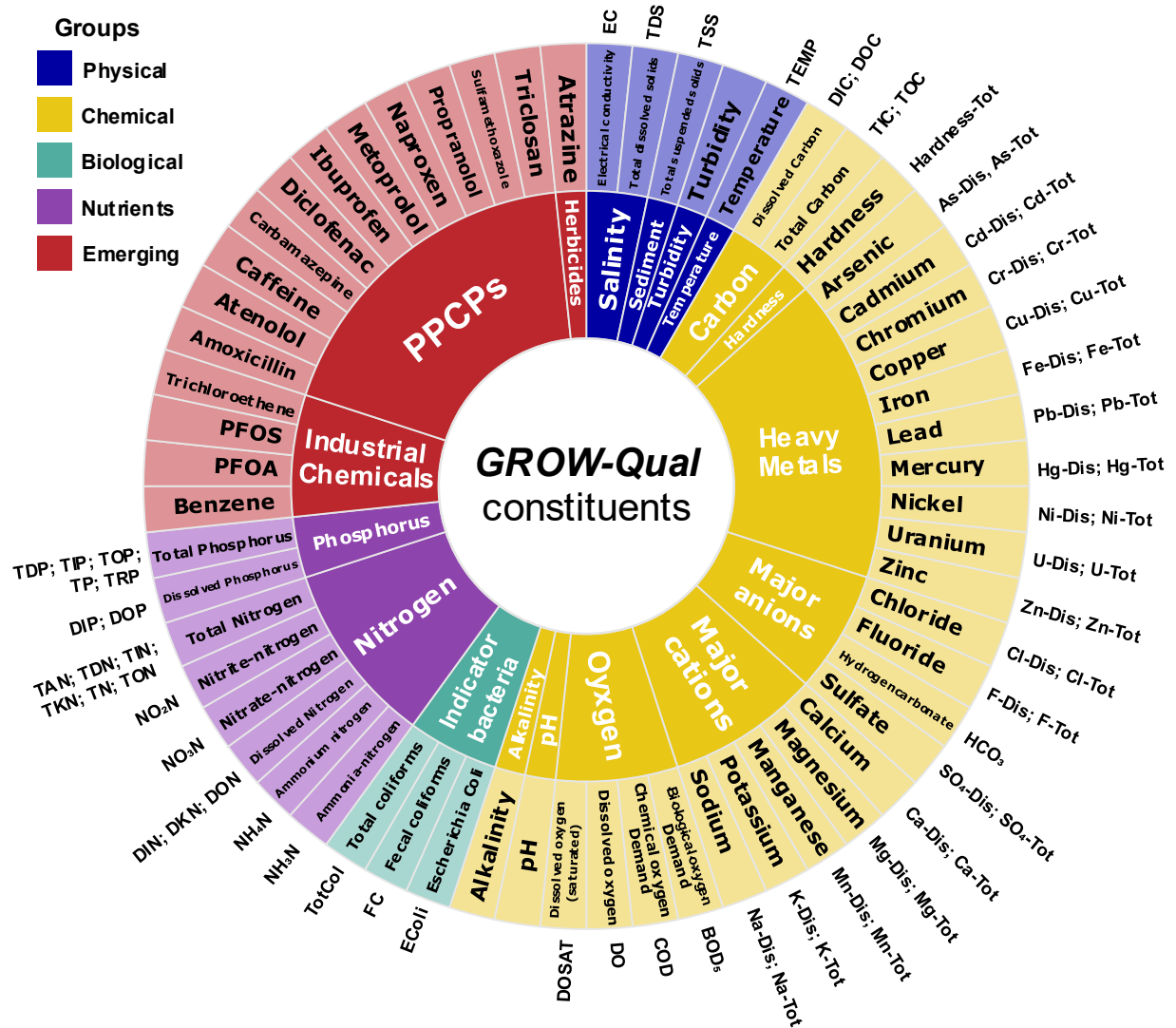


Figure 2. Overview of groundwater quality constituents included in the *GROW-Qual* dataset, including constituent codes, sub-groupings and groupings. A detailed list, including measurement units, is available in Supplementary Table S1.

Groundwater quantity data

Groundwater quantity observations included in *GROW-Qual* were derived from the Global Groundwater Monitoring Network (GGMN). GGMN is hosted via the Global Groundwater Information System (GGIS), and is created, maintained and developed by IGRAC. IGRAC's GGMN is designed as a 'network of networks', whereby in-situ groundwater monitoring data are collected from national and sub-national agencies responsible for monitoring programs. These data are collated and harmonised within a unified dataset, including an automatic flagging system for highlighting potentially erroneous data. The GGMN primarily contains groundwater quantity observations collected over medium to long timescales (years to

decades) and also comprises detailed metadata for the monitoring locations (e.g. coordinates, country, organisation), while retaining the original source and license for all data points. The GGMN is designed as a living dataset, updated regularly, and currently contains >130 million groundwater quantity observations from ~120,000 monitoring stations in 49 countries.

Observations provided by IGRAC are additionally processed through the global-scale integrated GROundWater package (*GROW*)³⁴, including additional steps for harmonisation and quality control, as well as the aggregation of time-series to daily, monthly or annual temporal resolutions. *GROW* additionally provides gap-filled versions of the groundwater time-series and links groundwater observations to associated well attributes and Earth system variables, including precipitation, potential evapotranspiration, hydrogeological and landscape characteristics. Full details of the procedures for quality control, temporal harmonisation, gap filling procedures and the derivation of Earth system variables are provided in the original *GROW* publication³⁴.

Groundwater quantity observations directly from GGMN are processed into the core *GROW-Qual* dataset (i.e. *GROW-Qual.zarr*), with both the original observations and associated station identifiers (i.e. “ggmn_id”) directly retained (see Data Records). Conversely, groundwater quantity observations additionally processed following the *GROW* approach are separated across three different datasets associated with the aggregated temporal resolution (i.e. *GROW_d.zarr*; *GROW_MS.zarr*; *GROW_YS.zarr*) and are indexed by “grow_id”. A linkage table provides the connections between the unique identifiers used for groundwater quality monitoring stations (“gwms_id”), GGMN stations (“ggmn_id”) and *GROW* stations (“grow_id”), enabling groundwater quality to be analysed alongside both the original GGMN observations and the harmonised *GROW* groundwater time series, with the procedure for linking groundwater quantity and quality stations described below.

Integrating groundwater quantity and quality observations

Groundwater wells with groundwater level and depth observations (ggmn_id, GROW_id) are spatially linked to groundwater quality monitoring stations (gwms_id) in *GROW-Qual* on the basis of a shared lithological unit from the Global Lithological Map (GLiM)³⁵ in combination with a (flexible) Euclidian distance threshold. GLiM is a globally applicable lithological dataset (comprising 1,235,400 unique polygons) assembled from 92 regional geological maps, which classifies rock type into 16 lithological classes. Lithology is used in *GROW-*

Qual as a first-order control on aquifer storage, transmissivity and residence time properties, on the logic that groundwater quantity and quality stations which are not directly co-located (i.e. sharing identically coordinates) may nonetheless be hydraulically and hydrochemically connected if situated within the same lithological setting. While simplistic, in the absence of more detailed and globally consistent subsurface information, this lithological-based approach represents a pragmatic solution for linking groundwater quantity and quality information for disparate sources and wells at global scale. More robust matching would require three-dimensional subsurface information to capture depth dependent lithological variations, including faults and confining layers that could potentially decouple groundwater quantity and quality signals within the same lithological unit, which is unfortunately not available globally. In addition to matching based on a shared lithological unit from GLiM, a Euclidean distance threshold can be applied to constrain matches to within a (user-defined) spatial extent.

For the purpose of visualisation in this manuscript, a distance threshold of 100m was set to show the linkages at global (Figure 3) and regional (Figure 4) scales, informed by the evaluation of the procedure used for linking groundwater quality and quantity stations (see Technical Validation).

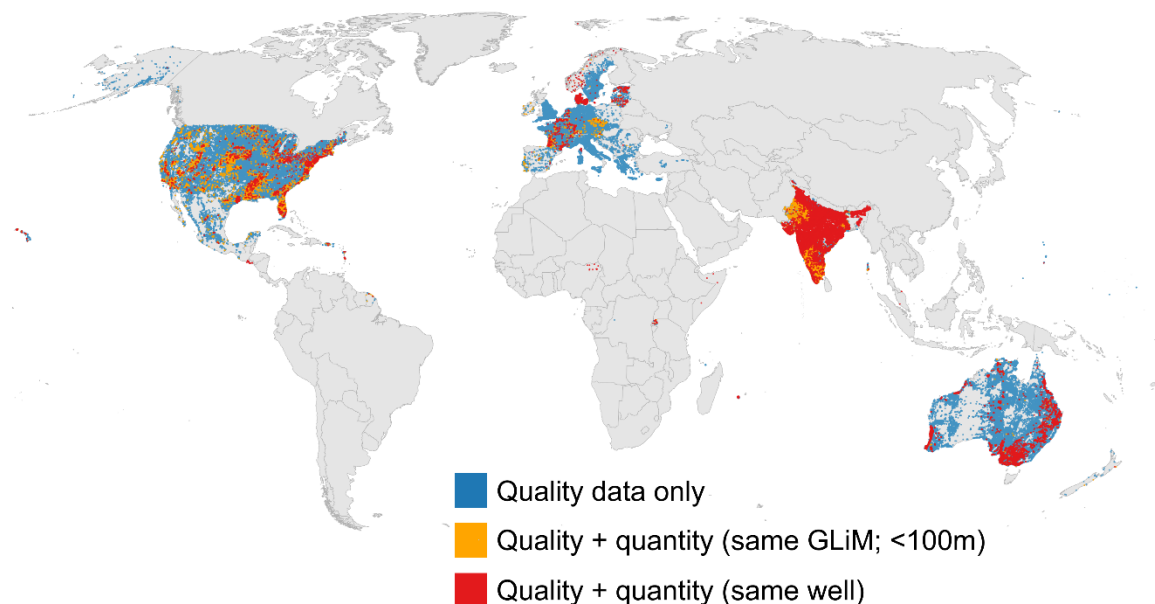


Figure 3. Spatial distribution of groundwater quality stations in *GROW-Qual*, excluding and including linkages to a groundwater quantity station (defined as either same well or at <100m distance and in the same GLiM lithological unit). Zoom-in panels for the four most densely monitored regions (i.e. contiguous United States, Western Europe, India and Australia) are displayed in Figure 4.

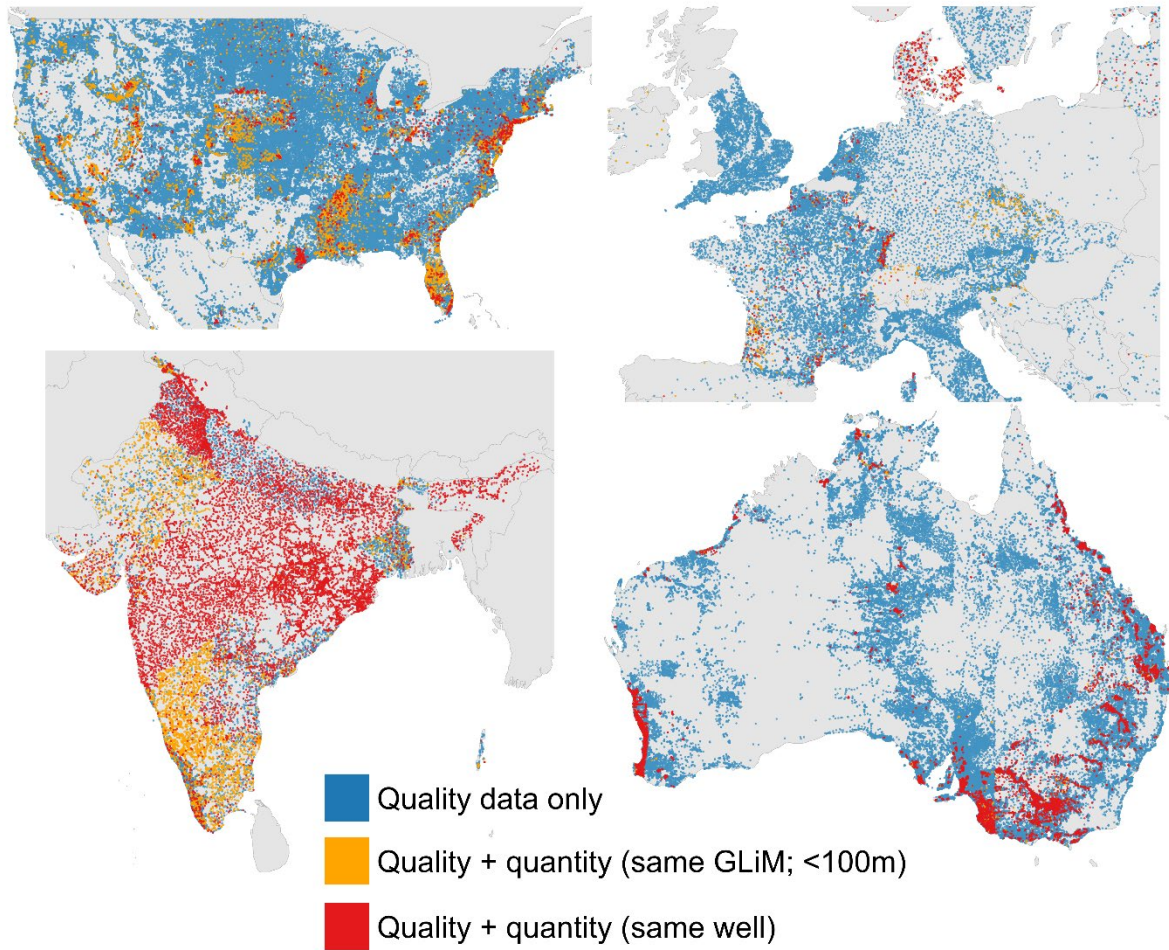


Figure 4. Spatial distribution of groundwater quality stations in *GROW-Qual*, excluding and including linkages to a groundwater quantity station (defined as either same well or at <100m distance and in the same GLiM lithological unit), in the four most densely monitored regions (i.e. contiguous United States, Western Europe, India and Australia).

In addition to the spatial matching of groundwater quality and quantity stations, the temporal overlap of observations is presented (Table 1). A groundwater quality observation was considered matched if a groundwater level or depth observation was available at the linked station (within a prescribed distance threshold) on the same day, within ± 1 month or within ± 1 year, so that overlap is quantified at three temporal scales and for various distance thresholds. As time series in *GROW* are pre-processed to daily, monthly or annual resolution, depending on data availability criteria, temporal matches between groundwater quality observations and quantity data *GROW* are only evaluated at the coarsest time step (i.e. ± 1 year). Overall, a relatively small proportion of groundwater quality observations had a matched groundwater level or depth observation, with coverage increasing with looser

temporal matching and greater distance thresholds, albeit at the potential expense of reliability (see Technical Validation).

Table 1. Proportion of groundwater quality observations matched with a groundwater quantity observation (i.e. level, depth) from the Global Groundwater Monitoring Network (GGMN) and *GROW* across different distance thresholds and temporal matching schemes (same day, same month and same year).

Distance (m)	GGMN			<i>GROW</i> *
	Same day (%)	±1 month (%)	±1 year (%)	±1 year (%)
<1	3.5	7.5	8.8	7.3
<100	4.6	11.1	13.1	13.5
<1000	5.3	12.8	15.7	16.2
<2500	6.3	14.9	18.5	18.9
<5000	7.8	17.5	22.0	21.7

*due to pre-processing of groundwater level/depth timeseries to an aggregated temporal resolution in *GROW* (daily, monthly or annual), temporal overlap with *GROW-Qual* only presented at the annual aggregation, which combines same-year matches irrespective of the native temporal resolution in *GROW*.

Deriving contextual Earth system variables

Contextual Earth system data is derived for all groundwater quality monitoring stations directly following the approach developed for and described by *GROW*³⁴. Here, groundwater monitoring locations are spatially linked to Earth-system datasets describing climate, hydrology, geology, topography, vegetation and anthropogenic influences. In total, 36 Earth system variables are included, derived from observation-based data, reanalysis data, or modelled data, which, depending on the variable and data source, can be either transient (Table 2) or static (Table 3).

In *GROW-Qual*, the *GROW* workflow is directly applied to groundwater quality monitoring locations, with transient Earth system variables indexed by monitoring station and time (“gwms_id” and “date”) and static Earth system variables indexed by monitoring station (“gwms_id” only). Transient variables were derived over a window spanning the full time period from the first to the last groundwater quality measurement. Additionally, the calendar year before each station’s first water quality observation and the full calendar year after its last was added, thereby providing at least one year of data on either side of the observed groundwater quality record. Overall, the inclusion of these Earth system variables provides consistent environmental context for analysing groundwater quality observations in relation to both time-varying forcing and the broader characteristics of the groundwater system.

275 **Table 2.** Overview of transient Earth system variables included in *GROW-Qual*, including
276 variable names and codes, units and data source.

Earth system variable	<i>GROW-Qual</i> variable code	Unit	Data source (source type)
Precipitation	precipitation_mswep_mm_year ⁻¹	mm/year	MSWEP V2 ³⁶ (multi-source)
	precipitation_gpcc_mm_year ⁻¹	mm/year	GPCC ³⁷ (Observation-based)
Potential Evapo-transpiration	potential_evapotranspiration_era5_m_m_year ⁻¹	mm/year	ERA5-Land ^{38,39} (Model)
	potential_evapotranspiration_gleam_mm_year ⁻¹	mm/year	GLEAM4 ⁴⁰ (model)
Actual Evapotranspiration	actual_evapotranspiration_mm_year ⁻¹	mm/year	GLEAM4 ⁴⁰ (model)
Interception loss	interception_mm_year ⁻¹	mm/year	GLEAM4 ⁴⁰ (model)
Air temperature	air_temperature_°C	°C	ERA5-Land ^{38,39} (Reanalysis)
Snow depth	snow_depth_m	m	ERA5-Land ^{38,39} (Model)
Days per year with snow cover	days_with_snow_cover_days_year ⁻¹	days/year	ERA5-Land ^{38,39} (Model)
NDVI	ndvi_ratio	-	1981-2013: AVHRR NDVI ⁴¹ ; 2014-2024: VIIRS NDVI ⁴² (Observation-based)
Leaf area index of low vegetation	lai_low_vegetation_ratio	-	ERA5-Land ^{38,39} (Model)
Leaf area index of high vegetation	lai_high_vegetation_ratio	-	ERA5-Land ^{38,39} (Model)
Total water withdrawal for industrial use	withdrawal_industrial_m3_year ⁻¹	m ³ /year	Wada <i>et al.</i> ⁴³ (Model)
Total water withdrawal for domestic use	withdrawal_domestic_m3_year ⁻¹	m ³ /year	Wada <i>et al.</i> ⁴³ (Model)
Fraction of urban areas	urban_area_fraction	-	Volkholz & Ostberg ⁴⁴ (Model)
Fraction of pastures	pastures_fraction	-	Volkholz & Ostberg ⁴⁴ (Model)
Fraction of rainfed cropland	cropland_rainfed_fraction	-	Volkholz & Ostberg ⁴⁴ (Model)
Fraction of irrigated cropland	cropland_irrigated_fraction	-	Volkholz & Ostberg ⁴⁴ (Model)
Fraction of forests and natural vegetation	forests_natural_vegetation_fraction	-	Volkholz & Ostberg ⁴⁴ (Model)

277 **Table 3.** Overview of static Earth system variables included in *GROW-Qual*, including
 278 variable names and codes, units and data source.

Earth system variable	<i>GROW-Qual</i> variable code	Unit	Data source (source type)
Koeppen-Geiger classification	koeppen_geiger_class	-	CHELSA v2.1 - kg0 ⁴⁵ (Downscaled Reanalysis)
Hydrobelt	hydrobelt_class	-	Meybeck et al. ⁴⁶ (Model + Observation-based)
Ground elevation	ground_elevation_merit_m_asl	m	MERIT DEM v1.0.3 ⁴⁷ (Observation-based)
Topographic slope	topographic_slope_degree	°	Geomorpho90m ⁴⁸ (Observation-based)
Rock type	rock_type_0-100_m_class	-	GLiM v1 ³⁵ (Observation-based)
Aquifer type	aquifer_type_class	-	WHYMAP WOKAM ⁴⁹ ; GLiM v1 ³⁵ (Observation-based)
Permeability for 0-100 m depth	permeability_0-100_m_m-2	m ²	GLHYMPS 2.0 ⁵⁰ (Observation-based)
Total porosity for 0-100 m depth	total_porosity_0-100_m_fraction	-	GLHYMPS ⁵¹ (Observation-based)
Soil texture class in topsoil (0-30 cm)	soil_texture_0-30_cm_class	-	HiHydroSoil v2.0 ⁵² (Model)
Soil texture class in subsoil (30-200 cm)	soil_texture_30-200_cm_class	-	HiHydroSoil v2.0 ⁵² (Model)
Saturated hydraulic conductivity of topsoil (0-30 cm)	soil_saturated_conductivity_0-30_cm_cm_d-1	cm/day	HiHydroSoil v2.0 ⁵² (Model)
Saturated hydraulic conductivity of subsoil (30-200 cm)	soil_saturated_conductivity_30-200_cm_cm_d-1	cm/day	HiHydroSoil v2.0 ⁵² (Model)
Distance between perennial streams	distance_perennial_streams_m	m	Cuthbert et al. ⁵³ (Observation-based, 0.1 cubic metres per second flow threshold)
Drainage density	drainage_density_m-1	m ⁻¹	HydroRivers ⁵⁴ ; BasinATLAS Level 9 ⁵⁵ (Observation-based)
Glacier cover in surface catchment	glacier_cover_fraction	-	BasinATLAS Level 9 ⁵⁵ (Observation-based)
Permafrost cover in surface catchment	permafrost_cover_fraction	-	BasinATLAS Level 9 ⁵⁵ (Model)
Average days per year with snow cover	days_with_snow_cover_average_days_year-1	days/year	ERA5-Land ^{38,39} (Model)
Groundwater dependent ecosystems	groundwater_dependent_ecosystems_class	-	Huggins <i>et al.</i> ⁵⁶ (Multi-source)
Main land use	main_landuse_class	-	Volkholz & Ostberg ⁴⁴ (Model)
Groundwaterscapes	groundwaterscapes_ID_class	-	Huggins <i>et al.</i> ⁵⁶ (Multi-source)

Data records

The *GROW-Qual* dataset⁵⁷ is provided in Zarr format, available at <https://doi.org/10.5281/zenodo.22638887>. The dataset is structured as follows:

- *GROW-Qual.zarr*:
 - **Dimensions:** time (daily timesteps from 1980-01-01 to 2025-09-30); gwms_id (groundwater quality monitoring station identifier); ggmn_id (groundwater quantity monitoring station identifier from GGMN).
 - **Station metadata:** spatial metadata per gwms_id (gwms_lat, gwms_lon, country_name, hydrobasin_level12) and ggmn_id (ggmn_lat, ggmn_lon).
 - **Observational data:** groundwater quality observations, detection limits and flags for multiple parameters (see constituent codes in Figure 2), indexed by gwms_id and time. Three groundwater quantity variables (groundwater depth below ground level, groundwater depth below the top of the well, and groundwater level elevation above sea level), indexed by ggmn_id and time.
 - **Earth system variables:** Transient variables (see Table 2) indexed by gwms_id and time, static variables (see Table 3) by gwms_id only, processed following the approach developed for *GROW*³⁴.
- *GROW.zarr*
 - **Dimensions:** time (daily timesteps for *GROW_d.zarr*; monthly for *GROW_MS.zarr*; annual for *GROW_YS.zarr*); grow_id (groundwater quantity monitoring station identifier from *GROW*).
 - **Station metadata:** spatial metadata per grow_id (grow_lat, grow_lon)
 - **Observational data:** Six groundwater quantity variables (groundwater depth below ground level, groundwater depth below the top of the well and groundwater level elevation above sea level; and gap-filled versions of these three variables), indexed by grow_id and time.
 - **Earth system variables:** Transient variables (see Table 2) indexed by grow_id and time, static variables (see Table 3) indexed by grow_id only.
- *linkages.parquet*
 - A metadata table (stored in Parquet format) that provides linkages between gwms_id, ggmn_id and grow_id, in addition to detailed metadata for efficient querying of the dataset.
- *gwms_site_info.csv*
 - Basic metadata for each groundwater quality monitoring sites, indexed by gwms_id.

Furthermore, processed water quality observations are provided as comma separated values per constituent (i.e. [constituent].csv), which include observations spanning the time period 1875 – 2026.

Data overview

GROW-Qual currently contains ~25 million groundwater quality observations from ~540,000 monitoring stations spanning the time period 1875 – 2026, of which approximately 15% are left-censored (below detection limits) and 4% were detected as potential outliers. The observations includes observations from across all major (inhabited) world regions, yet exhibits strong spatial bias towards Western Europe (~40% of total observations) and the United States (~37%), with extremely limited coverage across Southern Asia (excluding India) and East Asia & Pacific (excluding Australia) regions and effectively no coverage of Latin America & Caribbean (2.8%), Sub-Saharan Africa (0.4%) and the Middle East & North Africa (<0.01%) (Figure 3). These gaps do not necessarily reflect an absence of groundwater quality monitoring networks in these regions, but rather that these data may not be (currently) publicly accessible or otherwise available for inclusion in *GROW-Qual*.

In terms of the temporal distribution of observations, the number of observations has increased over time (with reporting lags responsible for the decline in recent years, due to e.g. internal quality assurance/quality control procedures of the monitoring agencies prior to data publication) (Figure 5a). Physical parameters are the most widely monitored individual constituents, with electrical conductivity (12%), water temperature (6%) and pH (6%) together accounting for approximately 24% of all groundwater quality observations, while some nutrient forms, particularly NO₃-N (6%) and NO₂-N (4%), are also widely monitored. In terms of constituent groupings, major cations (~19%), major anions (15%) and heavy metals (15%) also dominate in terms of number of observations, although these groupings include observations from across 10, 7 and 20 individual constituents respectively. Comparatively, the 11 constituents under the Pharmaceutical and Personal Care Products (PPCP) subgrouping combined constitute just 0.44% of total observations, of which ~97% are reported below detection limits.

Beyond biases in constituent coverage and geographic distribution, the representativeness of *GROW-Qual* also varies across different hydrogeological settings and climate conditions (Figure 5b-c). For example, observations are biased towards locations with recharge rates of 100-300mm/yr (as classified by spatial overlap with WHYMAP⁵⁸) and in temperate climates (as classified by spatial overlap with Köppen-Geiger⁴⁵).

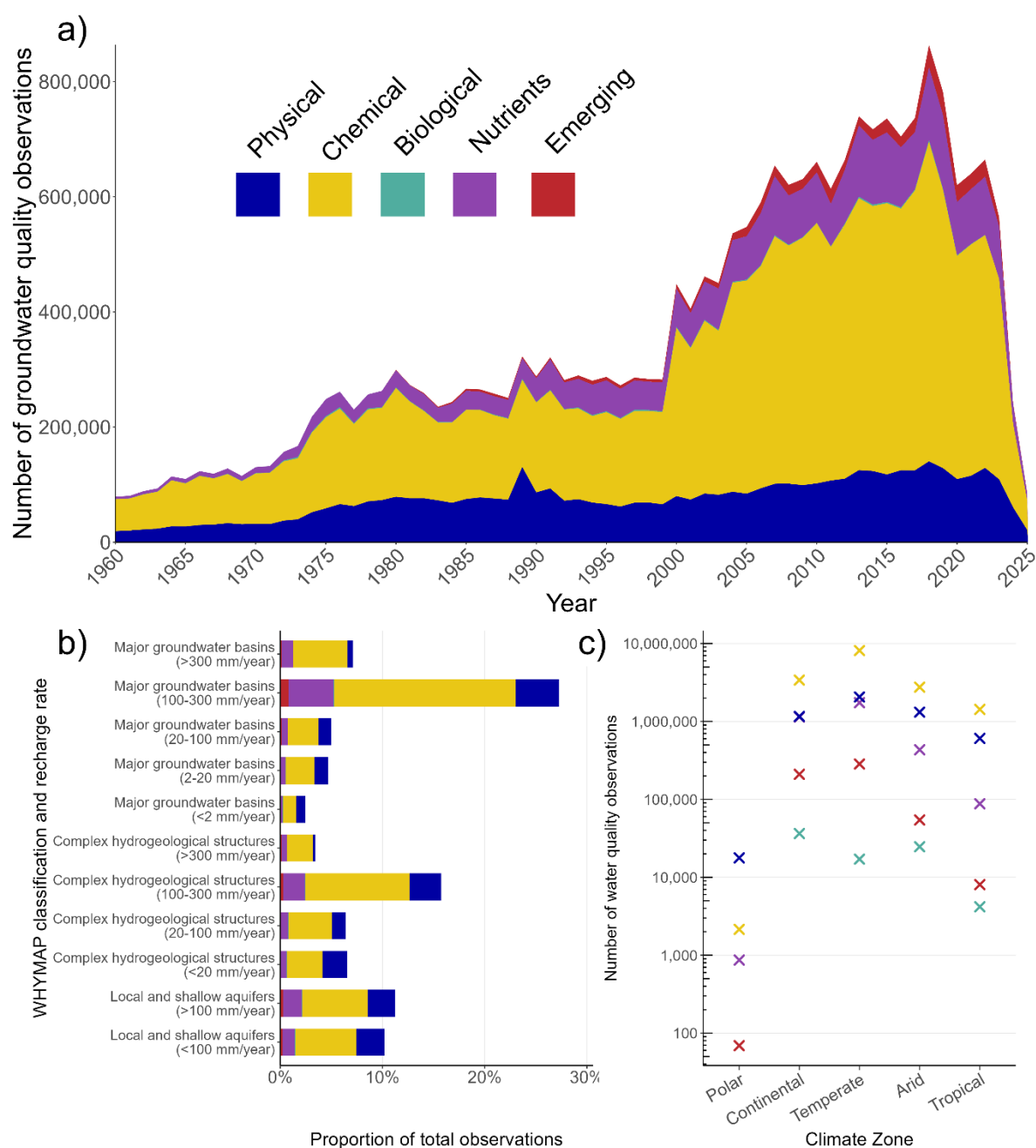


Figure 5. Temporal, hydrogeological and climatic distribution of groundwater quality observations in *GROW-Qual*. **a)** the number of groundwater quality observations per group from 1960-2025; **b)** the proportion of total observations aggregated based on their spatial overlap with each WHYMAP⁵⁸ classification of groundwater type and recharge rate; **c)** the number of water quality observations, aggregated per main Köppen-Geiger climate zone groupings⁴⁵.

Technical validation

Processing groundwater quality observations

Directly following the approach developed for river water quality observations in *Caravan-Qual*²⁷, extensive processing was applied to the raw groundwater quality observations in *GROW-Qual*. These steps include the removal of exact duplicate observations, in addition to outlier flagging and procedures for imputing observations reported at their Limit of Detection (LOD). Outlier flagging is based on plausible limits defined per water quality constituent (see `gwq_variable_list.csv`), termed “physical outliers”, while “statistical outliers” are detected only for groundwater quality monitoring stations with at least 10 observations of a constituent using the interquartile range method (IQR, with a threshold of 5xIQR). For observations reported in their source datasets as below detection limits (“<”), we process these either using Regression on Order Statistics (ROS) (for groundwater quality stations with at least 5 detected values and fewer than 50% of their time-series below detection limit) or otherwise using direct substitution with half of the reported detection limit. Statistics on the total number of observations within each water quality subgroup, in addition to the percentages of these which are flagged as either potential outliers or at LOD, is displayed (Figure 6).

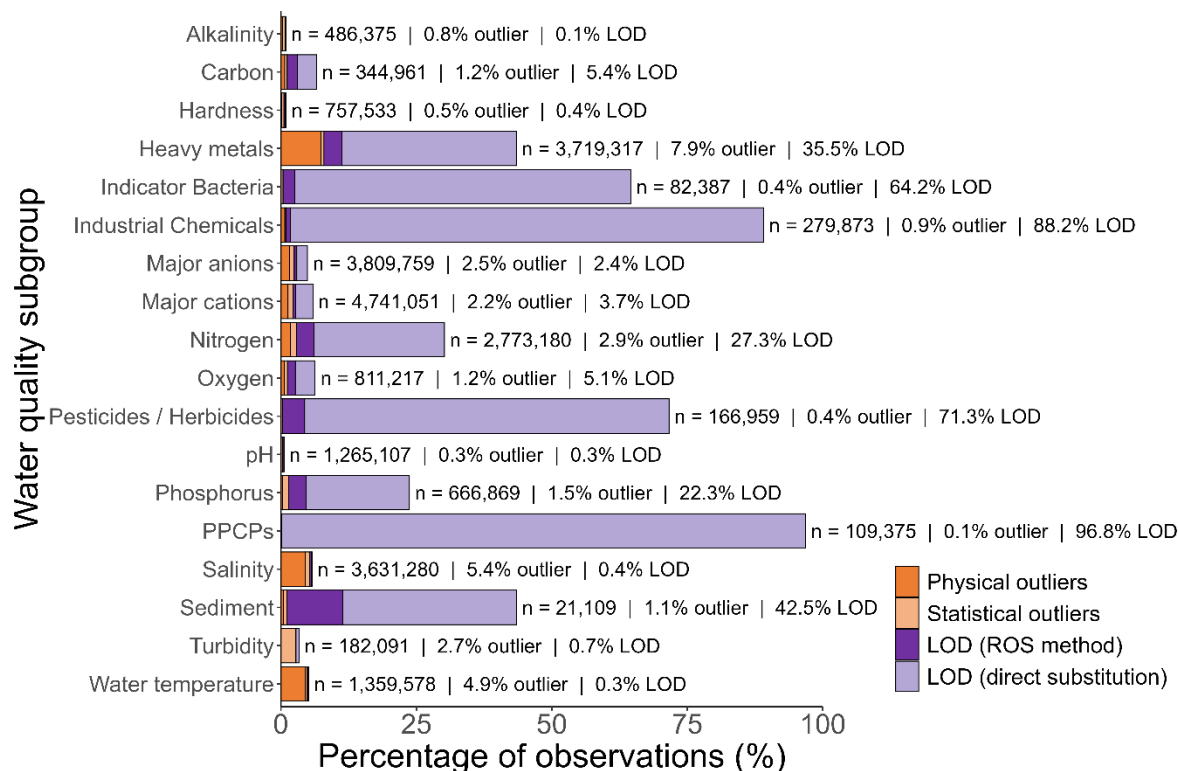


Figure 6. Summary statistics of flagged groundwater quality observations in *GROW-Qual*, identified as either: 1) potential outliers (physical or statistical); or 2) at Limit of Detection (LOD), which are subsequently processed using either direct substitution at half detection limit (i.e. LOD/2) or Regression on Order Statistics (ROS) depending on data availability. Note that all raw observations are also retained in *GROW-Qual* allowing users to applying their own filtering and processing criteria as desired.

After exact duplicate removal (i.e. same gwms_id, same date, same observation), *GROW-Qual* contains ~25 million observations, of which approximately 4% are flagged as potential outliers (3% physical, 1% statistical) and 15% are left-censored (i.e. flagged at LOD) with approximately 13% imputed using half detection limit and 2% using regression on order statistics. As with the river water quality observations in *Caravan-Qual*, observations reported at limit of detection were highly unequal across various constituent groups, at 97%, 88% and 71% for pharmaceuticals and personal care products (PPCPs), industrial chemicals and pesticides/herbicides, respectively.

Linking groundwater quality and quantity monitoring stations

As groundwater quality datasets rarely report water table depth or level, validating the spatial matching of groundwater quality and quantity stations in *GROW-Qual* is challenging. Where groundwater quantity information is provided in these datasets, it typically refers to the sampling or well screen depth, whereas GGMN and *GROW* primarily report depth to the water table. The two reported measurements are therefore not directly comparable.

However, the two can be used together as a first-order test of physical consistency. To this end, we used the sample depths reported alongside groundwater quality observations in the United States Water Quality Portal (WQP)²⁸ and compared them with the water table depth below ground level (bgl) at the matched GGMN station. Using the logic that groundwater quality samples must be taken at or below the water table, an observation was considered “physically consistent” if the sample depth was equal to or greater than the matched water table depth. Figure 7 shows the percentage of “physically consistent” water quality observations (top) and matched groundwater quality-quantity station pairs (bottom) as a function of the distance between matched stations, separately for each temporal match window (same day, ± 1 month or ± 1 year). Observed percentages are also compared against a chance baseline (obtained by comparing the sample depths reported alongside the water quality observation with randomly selected groundwater table depths from GGMN; averaged over 20 permutations), with results displayed for both all samples (Figure 7, left) and for shallow samples (≤ 30 m bgl) only (Figure 7, right).

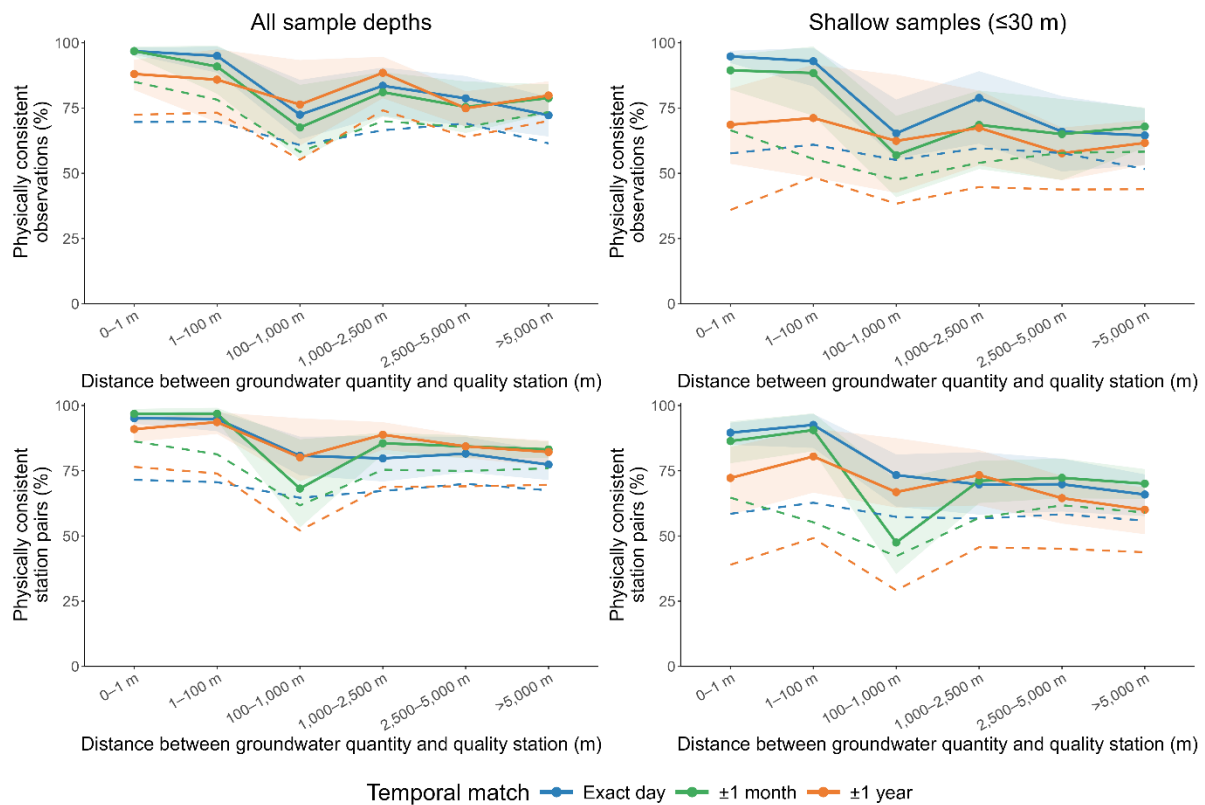


Figure 7. Physical consistency of matched GGMN groundwater table depths with sample depths reported alongside groundwater quality observations in WQP, as a function of distance between matched groundwater quality and quantity stations, for all samples (left) and shallow samples (≤ 30 m below ground level) only (right). Solid lines show the percentage of observations that are physically consistent (i.e. the sample depth reported in WQP was equal to or greater than the matched water table depth from GGMN; top panels) and the percentage of matched station pairs (i.e. unique combinations of water quality station and matched groundwater quantity station) that are physically consistent (bottom panels). Shaded bands display the 95% confidence interval of the percentage (percentile bootstrap, 1,000 resamples of matched GGMN stations). Dashed lines display the percentage expected by chance (i.e. if sample depths reported alongside the water quality observation were instead compared with a randomly selected groundwater table depth from GGMN). Colours show the finest available temporal match between the reported water quality observation (WQP) and depth to groundwater (GGMN), which is either the same day, ± 1 month or ± 1 year.

In total, 528,043 water quality observations in WQP had a reported sample depth matched to 2,176 GGMN stations, with groundwater table depths available on the same day for 180,864 observations, ± 1 month for 225,678 observations and ± 1 year for 121,501 observations. For all samples within 1 m distance (i.e. same well, often with shared USGS code), 97%, 97% and 88% of observations (and 95%, 97% and 91% of station pairs) are physically consistent for the same day, ± 1 month and ± 1 year respectively (Figure 7, left). For shallow samples (≤ 30 m bgl), 95%, 90% and 69% of observations (and 90%, 86% and 72% of station pairs) are

consistent within 1m distance between the groundwater quality and quantity station, exceeding the consistency expected by chance by 23-37 percentage points for observations and 22-33 percentage points for station pairs (Figure 7, right). Physical consistency remained high for station pairs matched between 1m and 100m, with 95%, 91% and 86% of all observations (and 95%, 97% and 94% of station pairs) consistent for same-day, ± 1 month and ± 1 year matches (Figure 7, left), and for 93%, 88% and 71% (93%, 91% and 81% of station pairs) of shallow samples (Figure 7, right). These are notably above the physical consistency that could be expected due to chance between 1 and 100m, at 70%, 78% and 73% for all samples and 61%, 56% and 49% for shallow samples only.

Physical consistency notably dropped for station pairs matched between 100 and 1000m, with 73%, 68% and 76% of all observations (and 81%, 68% and 80% of station pairs) consistent for same-day, ± 1 month and ± 1 year matches (Figure 7, left), and 65%, 57% and 62% (73%, 48% and 67% of station pairs) of shallow observations (Figure 7, right), with the gap in percentage points between observed and chance also shrinking. Beyond 1,000m, consistency did not systematically further decline and still often remained above the consistency expected by chance albeit with only modest differences in percentage points.

Together, these results show a step in agreement at around 100m, with matches within this distance being highly consistent with reported sample depths and a subsequent drop off beyond this distance. As matching groundwater quality and quantity stations within about 100m is well supported by our validation (based on US stations), we therefore use this threshold for display items in this manuscript (Figure 3; Figure 4). Matching at greater distances may still be useful and is therefore implemented as a user-defined choice in *GROW-Qual*, but nevertheless this should be done with caution and considering the validation results presented here. It should also be noted that agreement was substantially lower for looser temporal matches, even when groundwater quality and quantity observations are at the same location (e.g. 88% of observations matched at ± 1 year compared to 97% for same-day and ± 1 month within 1m). This is perhaps unsurprising, particularly in shallow samples, given seasonal and interannual variability in groundwater tables. Users should therefore carefully select both the distance and temporal window used to link groundwater quality and quantity observations appropriate to their own specific application.

Usage notes

- *GROW-Qual* contains groundwater quality observations spanning 1875 – 2026, which are available via the .csv files. The .zarr data store covers 1980-2025, a period over which 80% of groundwater observations were collected. Unless otherwise stated, summary statistics presented in this manuscript are with respect to the .csv files.
- While *GROW-Qual* is designed as a global resource, for example using globally applicable datasets in the derivation of Earth system variables, there are strong biases in the spatial distribution of groundwater data. These biases are largely unavoidable, reflecting the underlying availability of monitoring and reporting infrastructure. Users should keep this in mind when analysing and interpreting results. It is our hope that additional groundwater quantity and quality data will become freely and publicly accessible in the future, which given the extendable nature of *GROW-Qual* can be directly incorporated into the existing data structure.
- *GROW-Qual* serves primarily as a dataset for harmonising groundwater quantity and quality observations across multiple sources, alongside contextual Earth system data that may aid interpretation of the underlying drivers of these patterns. The underlying quality of the observations themselves are however largely dependent on the measurement, quality-control and reporting practices of the contributing monitoring institutes. While *GROW-Qual* includes some procedures for addressing data quality, such as the flagging of potential outliers, quantifying the impact of underlying sources of uncertainty (e.g. measurement error, transcription mistakes) fall outside the scope of this dataset.
- *GROW-Qual* is deliberately designed to share consistent variable definitions, units and processing methodologies with *Caravan-Qual*, which is in effect the river water quality counterpart to *GROW-Qual*. This shared structure facilitates interoperability between the two datasets, opening new opportunities for the joint study of groundwater and surface water dynamics across different world regions without the need for extensive preprocessing.
- A Jupyter notebook demonstrating a workflow for accessing and interacting with *GROW-Qual* is provided at: <https://github.com/SustainableWaterSystems/GROW-Qual>.

Data availability

GROW-Qual is available at: <https://doi.org/10.5281/zenodo.22638888>.

Code availability

All code used to produce the *GROW-Qual* dataset is available through Zenodo⁵⁷ (<https://doi.org/10.5281/zenodo.22638888>) and in a project homepage at: <https://github.com/SustainableWaterSystems/GROW-Qual>. The original *GROW* code is available through Zenodo³⁴ and in a project homepage at: <https://github.com/EarthSystemModelling/GROW/>.

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Author contributions

The research was conceptualized by E.R.J and M.T.H.v.V. E.R.J led the data acquisition, processing, analysis and interpretation, and wrote the manuscript. A.B. and R.R. provided input data and instructions for deriving the Earth system variables at the groundwater quality monitoring stations, and for the spatial matching of groundwater quantity and quality stations. A.R.P., N.G.O. and M.H. provided textual contributions. M.T.H.v.V. supervised the project and secured the funding. All authors contributed towards and approved the manuscript.

Competing interests

The contact author has declared that none of the authors has any competing interests.

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