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Groundwaterscapes: A global classification and mapping of groundwater's large-scale socioeconomic, ecological, and Earth system functions

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Key points:

- Groundwaterscapes are presented as landscape units representing configurations of groundwater's social-ecological and Earth system functions
- Implements an iterative, two-stage self-organizing map methodology to derive groundwaterscapes (n = 18) at the global scale
- All large aquifer systems of the world contain multiple groundwaterscapes

Abstract

Groundwater is a dynamic component of the global water cycle with important social, economic, ecological, and Earth system functions. We present a new global classification and mapping of groundwater systems, which we call groundwaterscapes, that represent predominant configurations of large-scale groundwater system functions. We identify 18 groundwaterscapes, which offer a new lens to conceptualize, study, model, and manage groundwater. Groundwaterscapes are empirically derived using a novel application of sequenced self-organizing maps and capture grid cell level (5 arcminute) patterns in groundwater system functions, such as groundwater-dependent ecosystem type and density, storage capacity, irrigation, and integrated groundwater management. All large aquifer systems of the world are characterized by multiple groundwaterscapes, highlighting the pitfalls of treating these groundwater bodies as lumped systems in global assessments. We evaluate the distribution of Global Groundwater Monitoring Network wells across groundwaterscapes and find that industrial agricultural regions with strong groundwater management are disproportionately monitored, while several groundwaterscapes have next to no monitoring wells at all. This disparity undermines the ability to understand system dynamics across the full range of settings in which groundwater is found. We argue groundwaterscapes offer a conceptual and spatial tool to guide model development, hypothesis testing, and future data collection initiatives to better understand groundwater's embeddedness within social-ecological systems at the global scale.

Keywords:

Groundwater systems, Social-ecological systems, System classification, Archetype analysis, Self-organising maps

1 Introduction

Conceptual models and classification schemes of groundwater systems traditionally focus on physical attributes and hydroclimatic setting (Margat & van der Gun, 2013; Winter, 2001) and primarily serve in support of fundamental hydrogeological investigations (e.g., as system boundaries for trend analyses in Richey et al., 2015; Shamsudduha & Taylor, 2020). Yet, recent years have witnessed a marked shift beyond traditional hydrogeology as interdisciplinary studies are increasingly conducted on global groundwater systems in response to the era of "human domination over the water cycle" (Abbott et al., 2019) and in recognition of groundwater system interlinkages with social, economic, ecological, and Earth systems (Gleeson et al., 2020; Huggins et al., 2023a). Yet, there is currently no set of guiding principles nor a globally consistent classification scheme through which to consider global groundwater systems as embedded within social-ecological systems (see Table 1 for key terminology). Here, we conduct a first attempt at filling this gap by producing a global, spatially explicit classification of groundwater systems on the basis of groundwater's large-scale socioeconomic, ecological, and Earth system functions.

The understanding of groundwater systems as dynamic components of social-ecological systems is propelled by the large and growing evidence-base documenting the functions the resource provides across social, economic, ecological, and Earth systems (Foster et al., 2013; Gleeson et al., 2020; Kuang et al., 2024; Scanlon et al., 2023). For instance, groundwater provides ~40% of global irrigation water (Siebert et al., 2010) and is an important, strategic buffer against increasing climate variability (Scanlon et al., 2023; Taylor et al., 2013). Groundwater supports ecosystems around the world in the form of groundwater-dependent ecosystems (Kløve et al., 2011; Link et al., 2023), which can take the form of aquatic, terrestrial, or subsurface ecosystems and that offer services of both ecological and cultural significance (Kreamer et al., 2015). Economically, groundwater is used in mining, manufacturing, energy generation, and agriculture, while simultaneously holding tremendous relational values such as through offering “senses of place” in cultures around the world. From an Earth system perspective, groundwater can be dynamically coupled to the atmosphere (Haitjema & Mitchell-Bruker, 2005), land-surface (Maxwell & Kollet, 2008), oceans (Luijendijk et al., 2020), and lithosphere (Konikow & Kendy, 2005).

Understanding how these diverse functions co-occur is an important first step in developing a more integrated, system-of-systems understanding of groundwater at the global scale. There are a handful of system-spanning global groundwater classifications, such as nation-scale groundwater economies (Shah et al., 2007), or classifications that map the mode of interaction between groundwater and the atmosphere (Cuthbert et al., 2019a). These existing studies focus on pairwise system interactions. Yet, to our knowledge, no study to date has developed a global groundwater system classification using a holistic framing that considers groundwater’s socioeconomic and biophysical dimensions in equal depth nor includes as wide a set of groundwater functions as we do here. As groundwater systems evolve under global change (Kuang et al., 2024), having such a baseline system classification can be useful as a reference with which to track changes between groundwater and its connected systems.

Outside the groundwater literature, a wide collection of global social-ecological system typologies have been developed within recent decades. These studies include the development of global anthromes (Ellis & Ramankutty, 2008), land system archetypes (Václavík et al., 2013), dryland vulnerability patterns (Kok et al., 2016; Sietz et al., 2011), types of deforestation “frontiers” (Buchadas et al., 2022); and an even wider assortment of typologies at continental and regional scales (Beckmann et al., 2022; Rocha et al., 2020; Van Vliet et al., 2012; van der Zanden et al., 2016). Yet, we note that these underlying concepts and methods have yet to be applied in groundwater research.

A common motivation for these social-ecological system characterisations is the emerging discipline of archetype analysis and its associated goals (Eisenack et al., 2021). In the archetype literature, an archetype is understood as a “mental representation of relationships between attributes and processes that characterize systems" (Eisenack et al., 2019). Archetype analysis is explicitly sustainability-oriented and seeks to identify "recurrent patterns of [a] phenomenon of interest at an intermediate level of abstraction to identify multiple models that explain the phenomenon under particular conditions" (Oberlack et al., 2019). While there are a diversity of methods used to perform archetype analysis (Sietz et al., 2019), a "full" analysis typically consists of a configuration of attributes, an underlying theory to explain these configurations, and empirical cases where this theory holds (Oberlack et al., 2019). Indeed, many of the social-ecological system typologies referenced above explicitly use an archetype analysis language and framing.

In this study, we apply the recently developed framing of groundwater-connected systems (Huggins et al., 2023a) and implement a cluster analysis methodology consistent with spatial archetype analysis (Sietz et al., 2019) to develop a global typology of large-scale groundwater system functions. We focus on large-scale functions, which we understand as functions that broadly occur across regional extents (order ~10^4 km^2 and larger) and are conducive to global, systematic pattern identification. We name the clusters that emerge from this process as groundwaterscapes (Table 1). These groundwaterscapes offer a first step towards characterizing the predominant configurations and spatial patterns within groundwater's socioeconomic, ecological, and Earth system functions, which we believe can offer widespread potential uses and benefits across groundwater science and management.

Table 1. Key terminology.

Term	Definition
Social-ecological systems	Integrated systems formed by social and biophysical system interactions (Berkes & Folke, 1998). Social-ecological system science seeks to understand how society and the environment are intertwined and co-evolved systems.
Groundwater-connected systems	Systems that are formed through interactions between social, ecological, and Earth systems with physical groundwater systems. Groundwater-connected systems are understood as specific forms of social-ecological systems (Huggins et al., 2023a).
Groundwaterscapes	A landscape unit that represents a specific and broadly occurring configuration of groundwater-connected system functions. In this work, we empirically derive groundwaterscapes using global data sets representing the Earth system, ecosystems, food system, and water management system functions included in our conceptual model (Figure 1).

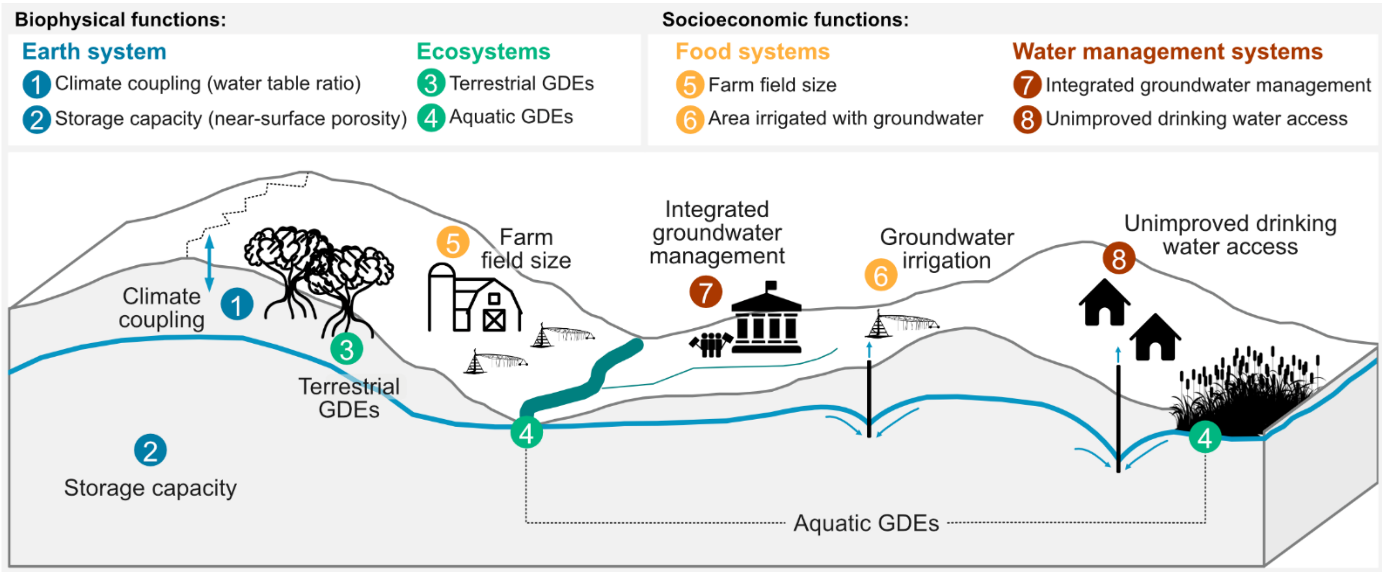


Figure 1. Groundwaterscape conceptual model, consisting of groundwater's large-scale Earth system, ecosystem, food system, and water management system functions. Maps of the input data representing these functions are shown in Figure 2.

2 Materials and methods

<u>2.1 Conceptual model</u>

Drawing on recent reviews of global groundwater systems (Gleeson et al., 2020; Lall et al., 2020; Scanlon et al., 2023), we identified four core systems that groundwater operates within across large spatial scales and that balance representation of biophysical and socioeconomic functions: Earth systems, ecosystems, food systems, and water management systems (Figure 1). We distinguish between biophysical and socioeconomic functions following the Social-Ecological Systems Framework (Ostrom, 2009), which argues for such a balanced approach when conceptualizing a social-ecological system (Binder et al., 2013). We included an equal number of functions per system (2) to ensure these systems were evenly represented in our analysis. To be included in our conceptual model, functions required a strong conceptual foundation in the large-scale groundwater literature and required global quantification in an existing data set. This number of input data sets (8) is within common ranges of input layer counts found in existing social-ecological system clustering studies and balances the parallel goals of including sufficient data to characterize our conceptual model while not being overly numerous to render the process of assessing and "disentangling" classification results intractable. Maps of all functions included in our conceptual model are shown in Figure 2.

For groundwater's *Earth system* functions (Figure 2a), which represent groundwater's interactions with the atmosphere, land, lithosphere, and oceans (i.e., Earth system components), we focus on groundwater's climate and storage functions. Groundwater is increasingly studied through an Earth system lens (Gleeson et al., 2020), and is recognized as a critical resource that affects overall Earth system resilience (Rockström et al., 2023). Water table depth is an important control on the land-atmosphere energy balance (Maxwell & Kollet, 2008). In areas with shallow water tables, groundwater is tightly coupled with land surface and energy processes (i.e., a bidirectional mode of interaction occurs with both groundwater recharge and evapotranspiration fluxes), and this coupling dissipates with deeper water tables and becomes recharge-dominated (i.e., a unidirectional mode). We use the water table ratio, a dimensionless criterion that classifies the mode of groundwater-climate interactions as bidirectional or unidirectional (Haitjema & Mitchell-Bruker, 2005) to represent groundwater's hydroclimatic function (Cuthbert et al., 2019a). Secondly, as the largest store of unfrozen freshwater globally, groundwater provides important storage functions (Gleeson et al., 2020). Net groundwater storage loss is a secondary contributor to global sea level rise (Konikow, 2011) while groundwater's large storage capacity also provides important retention and attenuation functions in the water cycle (Opie et al., 2020). Thus, groundwater naturally serves as an important control on hydrological processes such as drought (Van Lanen et al., 2013). As groundwater storage, particularly within depths that are dynamically connected to the Earth system, is challenging to quantify (Condon et al., 2020; Ferguson et al., 2021), we use shallow subsurface porosity (representative for depths on the order of 100m) as a proxy representation of groundwater storage capacity (Gleeson et al., 2014).

To represent groundwater's *ecosystem* functions (Figure 2b), we consider the type and density of groundwater-dependent ecosystems (GDEs). GDEs are terrestrial, aquatic, or subterranean ecosystems that rely on groundwater for some or all of their freshwater needs (Kløve et al., 2011). We focus on terrestrial and aquatic GDEs as these ecosystems are more closely coupled to land-surface processes, are better understood in contrast to subterranean GDEs, dominate conservation and management dialogues (Rohde et al., 2017; Saito et al., 2021), and have benefitted from recent global mapping efforts (Huggins et al., 2023b; Link et al., 2023). Terrestrial GDEs exist where root systems source groundwater and thus rely on the subsurface presence of groundwater while aquatic GDEs rely on surface expressions of groundwater and include rivers, streams, and wetlands.

Groundwater is a critical resource for a wide array of economic functions, including uses in mining, manufacturing, energy generation, and agriculture sectors. In this study, we focus exclusively on agriculture which is the dominant sectoral source of groundwater consumption globally (Giordano & Villholth, 2007; Wada et al., 2012). Thus, to reflect groundwater's *food system* functions (Figure 2c), we include the extent of areas irrigated with groundwater and dominant farm field size. Including groundwater irrigation patterns enables this analysis to differentiate regions based on agricultural reliance on groundwater. Secondly, though not often incorporated in groundwater studies, field size is a key attribute of agricultural systems that is associated with many functional differences in groundwater interactions, livelihoods, agricultural practices, and productivity (Meyfroidt, 2017). For instance, small scale farms, especially in developing countries, are less likely to have access to basic services, infrastructure, and mechanization (Meyfroidt et al., 2022), whereas large irrigated farms are generally associated with greater productivity and higher levels of economic development (Meyfroidt, 2017). Field size (which is related to farm size) (Graesser & Ramankutty, 2017; Lesiv et al., 2019) is additionally critical to consider in relation to land tenure and how this affects water and land management dynamics. For instance, a management area will have considerably more actors, a greater mosaic of land ownership, and thus a more complex management setting in regions with smaller farms in comparison to if the same area were covered by larger farms. Case studies have also identified that farm size is associated with participation rates in collaborative management processes (Amblard et al., 2023; Dobbin, 2020). Thus, incorporating field size is a pragmatic, coarse approach to represent qualitative differences in industrial versus smallholder agricultural systems.

Our inclusion of *water management system functions* (Figure 2d) is an effort to represent what actions are taken "within governance [frameworks] related to the development and protection of groundwater" (Villholth & Conti, 2018). Our included water management system functions aim to represent societal forms of interaction with groundwater resources expressed through policy measures, collective action, priority setting, and service provision. Inversely, societal interactions with groundwater systems form values and worldviews that in turn can shape water management practices. We first consider water management systems through the lens of integrated water resources management (IWRM). We use indicators from a global IWRM tracking initiative (UNEP, 2021) that explicitly relate to groundwater and represent the implementation level of dedicated groundwater management efforts. These indicators include measures of "basin/aquifer management plans", "basin/aquifer level organisations", and "aquifer management instruments". We note that it is not straightforward to quantify governance and management dimensions and the process of doing so is often contested (Thomas, 2010). For instance, these IWRM data we source were consolidated through multi-stakeholder processes, yet it is unclear how fidelitous these country-led summary results are to concrete, place-based governance frameworks and management actions. Regardless of these limitations, we view integrated groundwater management as a crucial component of our analysis whose inclusion ensures that groundwaterscapes reflect the broad scope of the groundwater-connected systems framing. Secondly, to consider the role of water management in relation to groundwater access, equity, and the domestic services of groundwater, we integrate fundamental data on the percentage of people that collect or use unimproved drinking water. This unimproved drinking water can come from many sources, including an unprotected dug well or spring, or alternatively from surface water sources such as a river, pond, or canal. However, data that disaggregate these sources of unimproved drinking water do not exist to the best of our knowledge. We view this indicator as a useful representation of groundwater's utilisation, or lack thereof, in supporting domestic activities and water security.

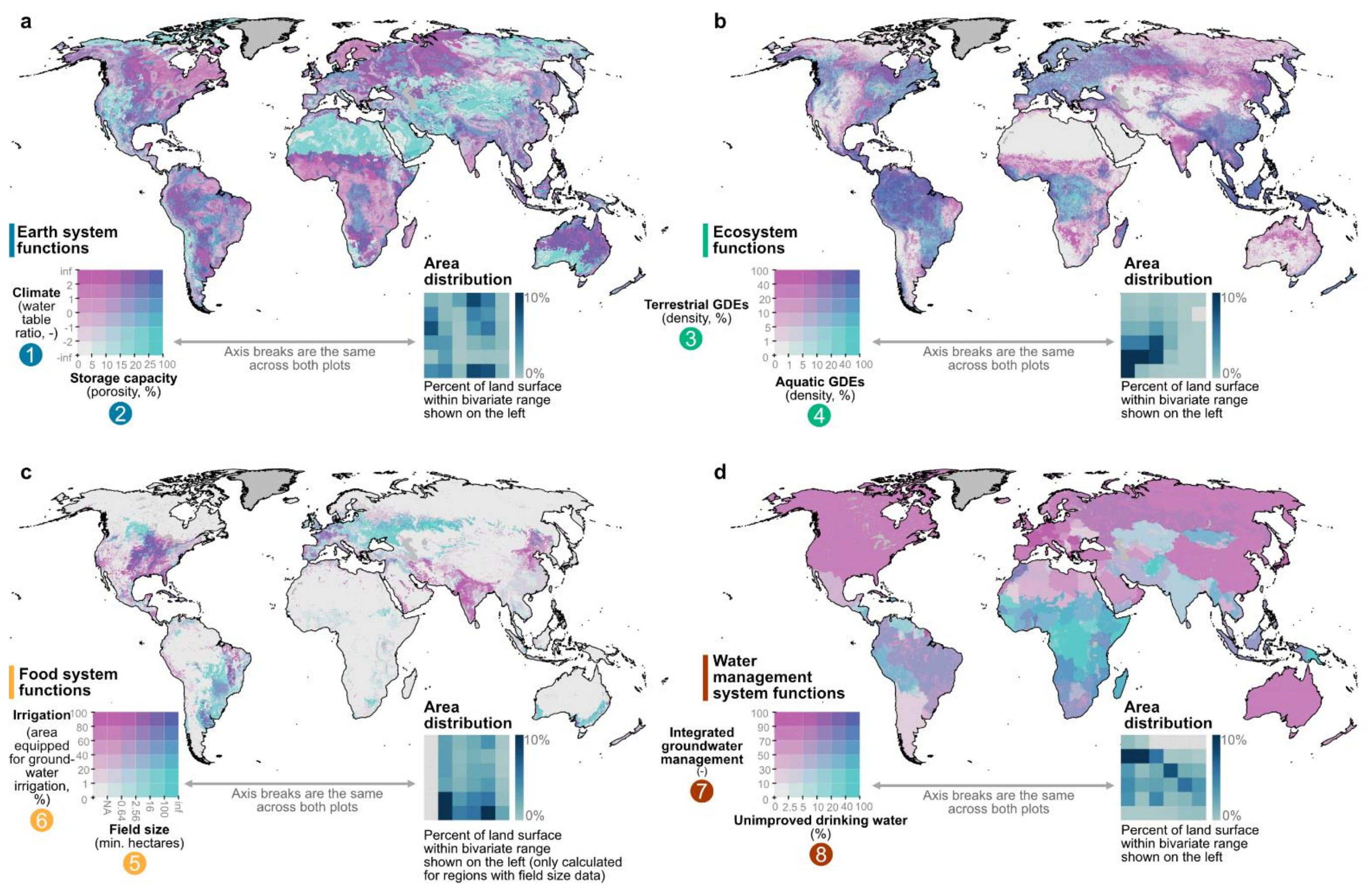


Figure 2. Exploratory mapping of groundwater's large-scale (a) Earth system, (b) ecosystem, (c) food system, and (d) water management system functions. Bivariate legends are numbered accordingly with the conceptual model show in Figure 1. The area distribution of each mapped bivariate relationship is shown by inset heatmaps which have the same axis breaks shown in each map's bivariate legend.

2.2 Spatial resolution and preprocessing

We conduct all analyses at 5 arcminute resolution (~10 km grids near the equator). This produces a moderate-resolution global groundwaterscape data product that balances the base resolutions of input data sets (Table 2) and is compatible with a wide array of global hydrological models (e.g., Burek et al., 2020; Sutanudjaja et al., 2018) and water-focussed social-ecological studies (e.g., Varis et al., 2019). Secondly, operating at the unit of grid cells rather than aquifers, basins, or administrative units enables analysis of groundwaterscape heterogeneity in these systems (see 2.4 Post hoc analysis).

All input data sets were preprocessed to generate a spatially harmonized raster stack at 5 arcminute resolution. Each raster layer was subsequently normalized such that grid cell distributions held the properties of zero mean and unit variance. Two exceptions were made for the water management system data which instead were normalized at the nation and watershed scale in correspondence with their respective derivation before rasterization. We subsequently applied feature clipping by setting minimum and maximum values at +/-2 standard deviations away from the mean to ensure that extreme outliers within individual data layers did not exert an outsized impact on groundwaterscape results. The study domain was defined by a common global earth mask (Wessel et al., 2019; Wessel & Smith, 1996) and further excluded Greenland and Antarctica given low data coverage across these regions. Sources, descriptions, and summaries of preprocessing steps for each data set are provided in Table 2.

Before performing the groundwaterscape derivation, we first evaluated the collinearity of the eight normalised input data sets (Figures S1) by calculating Pearson correlation coefficients on a random sample of 40,000 grid cells (~2% of all grid cells within study domain) to avoid impacts of spatial autocorrelation (cf. Beckmann et al., 2022; Václavík et al., 2013). There are moderate levels of collinearity ($r^2 \approx 0.5$) between certain inputs, such as between aquatic and terrestrial GDE density (Figure S2), but no correlation values were sufficiently high to require further modification when using common thresholds to evaluate detrimental levels of collinearity ($r^2 > 0.7$) (Dormann et al., 2013).

Table 2. Input data sets. Maps and histograms of each data set are shown in Figure S1.

Data set	Data source, information, and preprocessing
Water table ratio	**Data source**: Cuthbert et al. (2019b) **Persistent web-link**: https://doi.org/10.6084/m9.figshare.7393304.v8 **Spatial resolution**: 1 km **Temporal range**: Ca. 2000

	Harmonisation: Bilinear resampling to 5 arcminute resolution. **Additional preprocessing:** Regions with recharge <5 mm yr^{-1} were set to the minimum normalised value following Cuthbert et al. (2019a) who removed these regions given the variable's sensitivity to low recharge rates. We adopted this approach to reflect how arid regions typically have deep water tables with minimal evapotranspiration fluxes from groundwater. We used the same recharge data set (Döll & Fiedler, 2008) as used in Cuthbert et al. (2019a) to apply this mask.
Near-surface porosity	**Data source**: Gleeson (2018) **Persistent web-link**: https://doi.org/10.5683/SP2/DLGXYO **Spatial resolution**: Polygons with average size of ~14,000 km^2 **Temporal range**: N/A **Harmonisation:** Vector polygon rasterization to 5 arcminute resolution.
Groundwater-dependent ecosystem types (aquatic and terrestrial)	**Data source**: Huggins et al. (2023c) **Persistent web-link**: https://doi.org/10.5683/SP3/P3OU3A **Spatial resolution**: 30 arcsecond **Temporal range**: ca. 2015 **Harmonisation:** Area density calculated per 5 arcminute grid cell.
Area irrigated with groundwater	**Data source**: Siebert et al. (2013) **Persistent web-link**: https://www.fao.org/aquastat/en/geospatial-information/global-maps-irrigated-areas/latest-version/ **Spatial resolution**: 5 arcminute **Temporal range**: 2000 **Harmonisation:** None
Farm field size	**Data source**: Lesiv et al. (2018) **Persistent web-link**: https://pure.iiasa.ac.at/id/eprint/15526/ **Spatial resolution**: ~1 km **Temporal range**: ca. 2010-2016 **Harmonisation:** Modal resampling to 5 arcminute resolution.
Integrated groundwater management	**Data source**: IWRM Data Portal (UNEP, 2021) **Persistent web-link**: http://iwrmdataportal.unepdhi.org/ **Spatial resolution**: Nation scale **Temporal range**: 2020 **Harmonisation:** Vector polygon rasterization to 5 arcminute grids. **Additional preprocessing:** Countries without groundwater management sub-indicator data (n = 12) are assigned the data of their most-similar country with available water management data. We determine this country-to-country similarity using the Worldwide Governance Indicators database (Kaufmann & Kraay, 2023) and by calculating the Euclidean distance between country values reported for the year 2020. Countries missing data include Argentina, Brunei, Canada, Djibouti, Eritrea, Uruguay, Venezuela, and several small island nations which are outside of the defined study domain.
Unimproved drinking water access	**Data source**: World Resources Institute's Aqueduct Water Risk Atlas (Kuzma et al., 2023) **Persistent web-link**: https://www.wri.org/data/aqueduct-global-maps-40-data **Spatial resolution**: HydroBASIN Level 6 **Temporal range**: 2015 **Harmonisation:** Vector polygon rasterization to 5 arcminute resolution.

2.3 Iterative self-organizing maps to derive groundwaterscapes

Social-ecological system classification has no consensus methodology (Sietz et al., 2019) and can be approached from either top-down or bottom-up perspectives. Bottom-up classification begins with individual case studies and groups cases together based on similarity in system composition or behaviour. These approaches are contextually rich but can be geographically or contextually limited based on spatial extent or case study count and diversity. Conversely, top-down approaches begin with spatially distributed data sets and derive recurring patterns using a variety of approaches such rule-based classification or cluster analysis. Top-down approaches provide a wider and more consistent spatial coverage in comparison to bottom-up approaches but can be limited by the quality of data used to represent system attributes and by bias in the data selection process. Thus, top-down approaches are more common among regional to global scale assessments. However, the two methodologies may support each other in mixed-method processes (Sietz & Neudert, 2022), where bottom-up approaches can aid in ground-truthing insights derived from top-down methods (Eisenack et al., 2021).

Here, we use an iterative and sequential self-organizing map (SOM) methodology to derive groundwaterscapes. SOMs are a form of unsupervised artificial neural network that perform a unique type of data quantization (Kohonen, 2013). SOMs work by projecting an n-dimensional input data space onto a low dimensional (typically two-dimensional) grid of nodes, where each node contains an n-dimensional "codebook" vector representing a contiguous region in the input data space. Nodes with similar codebook vectors are located closer to each other in this low dimensional grid and dissimilar codebook vectors further apart. SOMs are thus a particularly powerful method for data exploration and visualization as the low-dimensional grid of nodes preserve the topology of the input data and as so have been widely used to address clustering problems (Flexer, 2001; Kohonen, 2013; Vesanto & Alhoniemi, 2000), including the classification of social-ecological systems (Beckmann et al., 2022; Jung et al., 2024; Levers et al., 2018; Václavík et al., 2013; van der Zanden et al., 2016). SOMs are further advantageous for clustering applications as they are less prone to identifying local optima relative to other approaches (Bação et al., 2005). Furthermore, as the method does not require the specification of any parameter thresholds to determine clusters, it is considered as a clustering method less prone (but not immune) to researcher bias (Sietz et al., 2019).

A common strategy to conduct SOM-based clustering is to perform cluster analysis on the generated set of codebook vectors as this approach has the additional benefit of identifying complex cluster structures (Taşdemir et al., 2012; Delgado et al., 2017). We implement a similar methodology in this study by following Delgado et al. (2017) and perform a two-staged clustering methodology that implements SOMs at both stages of the clustering process (Figure 3). The first stage of this methodology develops a two-dimensional SOM to generate a vector quantization of the input data space that is substantially smaller but topologically similar to the original input data. The second stage of this method uses the codebook vectors of the first stage SOM as input data and develops a one-dimensional SOM whose vector quantization derives the clusters we present as groundwaterscapes. In each stage of this methodology, we iterate across a wide range of SOM grid sizes and select the best performing size based on a set of performance metrics (see below). In recognition of the stochastic property of SOMs, we develop an ensemble of SOMs at each grid size and filter-out performance outliers to improve reproducibility (see below).

First stage SOM methods: For the first stage SOM iterations, we follow Delgado et al. (2017) and set the minimum SOM grid size (S *x* S) as: $S_{min} = \sqrt{2N^{0.4}}$, where *N* is the number of patterns in the input data, and set the maximum SOM grid size as $S_{max} = \sqrt{0.15N}$. We iterate from: S_{min} to S_{max} in increments of 2. In determining *N*, which was originally intended to represent the number of unique input data points (as in Delgado et al., 2017) to be infeasible at our spatial resolution (>2 million grid cells, thus 2 million input features) as the approach suggests grid sizes far greater than are commonly found in similar SOM applications in the literature. Thus, to pragmatically estimate *N*, we iteratively performed k-means clustering on our input data until 99% of the input data variation (within cluster sum of squares relative to total sum of squares) is represented by these clusters. This criterion was met at k = 12,000 clusters, and thus this *k* was then used to estimate the number of input data patterns (i.e., *N*) to set the ranges in our first stage SOM grid sizes (S_{min}= 10, S_{max}= 42). We generated 60 alternative SOM grids for each S from $S_{min}, S_{min} + 2, S_{min} + 4, \ldots, S_{max}$ (1020 total iterations). As this procedure was designed to guide identification of the optimal first stage SOM grid size, we deemed it unnecessary to conduct these iterations on the full input data (>2 million data points) and instead conducted these iterations on the synthetic representation of this data generated in our k-means cluster centers. This process identified S = 22 best balanced SOM-specific and general clustering performance metrics (see below). With this optimal grid size identified, we then developed 60 alternative SOMs at S = 22 using the full set of input features and selected the best performing iteration using performance metrics as described below. The codebook vectors from his best performing iteration generate a set of 484 features that reflect the underlying structure of the input data (Figure S3) and offer an intermediate classification level.

Second stage SOM methods: The codebook vectors from the selected first stage SOM became the input features for the second stage SOM iterations. Conversely to the two-dimensional first stage SOMs, we followed Delgado et al. (2017) and iterated across one-dimensional SOM grid sizes so that iterations that determine prime numbers of clusters can be evaluated. For these second stage SOMs, we set a minimum size (1 x S) of S_{min}= 2, and a maximum size of S_{max}= 30 following social-ecological archetype analysis guidelines (Eisenack et al. 2019). As the input feature space is considerably smaller in this second stage, we generate 120 alternative SOMs for each grid size S from S_{min}, $S_{min}+1, S_{min}+2$, …, S_{max}. We select the best-performing SOM from these iterations to represent the groundwaterscapes. The crisp (e.g. mutually exclusive) classification provided by this methodology (where each grid cell is associated with a single node in the selected first stage SOM, and each of these first stage SOM nodes is associated with a single node in the selected second stage SOM) enables a simple classification of geospatial grid cells to their respective groundwaterscape. Following Jung et al. (2024), we apply a modal filter with a 3x3 grid cell moving window to reduce minor speckling noise in the final groundwaterscape map.

SOM performance metrics: For the first stage SOMs, we calculated performance using the SOM-specific Kaski-Lagus error function (Kaski & Lagus, 1996) and the clustering-specific Davies–Bouldin index (Davies & Bouldin, 1979). The Kaski-Lagus error function combines aspects of quantization error (average squared distance between input features and their assigned codebook vector) and topographic error (an indicator of how well the input data's topography is preserved in the SOM based on the share of total input features whose assigned and second-closest SOM node codebook vectors are neighbours within the SOM node grid). Conversely, the Davies-Bouldin index is a measure of both the compactness of individual clusters and the separation between clusters. To compare these performance metrics across SOM iterations, we min-max normalized each metric so that each had an equal influence on the performance evaluation.

For the second stage SOM, we continued to use the same Kaski-Lagus error function and Davies-Bouldin Index and additionally included two more metrics. The first is the percentage of unexplained variation, which we were drawn to include based on our observation that there was significantly lower range of explained variance in the second stage SOMs at small grid sizes that were not captured by the Kaski-Lagus error function due to topographic performance trade-offs. This variation-based performance metric was thus equally weighted with the Kaski-Lagus error function when deriving the second stage SOM performance scores.

The second additional performance metric is a size preference metric that was included to quantitatively reflect our preference of identifying a manageable number of system classes (i.e., preferencing fewer clusters should performance metrics otherwise be similar). Our inclusion of this size preference metric stems from our observation that SOM results can show similar performance across a wide range of SOM grid sizes and thus could benefit from additional discrimination by explicitly embedding this size preference in our derivation methodology. To accomplish this, we superimpose a trapezoidal function (set to preference cluster counts that are equal to and greater than an a priori estimate of the best number of partitions in the data) and the logarithm of the number of clusters (set to preference a lower number of clusters, based on Varshney & Sun, 2013). This a priori best estimate of cluster partitions is determined by taking the median value across 30 different clustering indexes that estimate the optimal number of clusters in a data set (Charrad et al., 2014) and is an approach that has been used to inform previous social-ecological system clustering (Rocha et al., 2020). The result is a curve resembling a piecewise function with its minimum located at this a priori estimate (Figure S4). We do not use this size preference function on equal footing with the SOM- and cluster-specific performance metrics, but rather as an additional consideration in a sensitivity analysis to assist our decision-making process (see below). While other SOM-based studies take simpler approaches to identify the optimal number of clusters, such as visually identifying the “elbow” in the within-cluster sum of squares (Beckmann et al., 2022), we view our method as a more elaborate but reflective approach consistent with our underpinning values and objectives for this study.

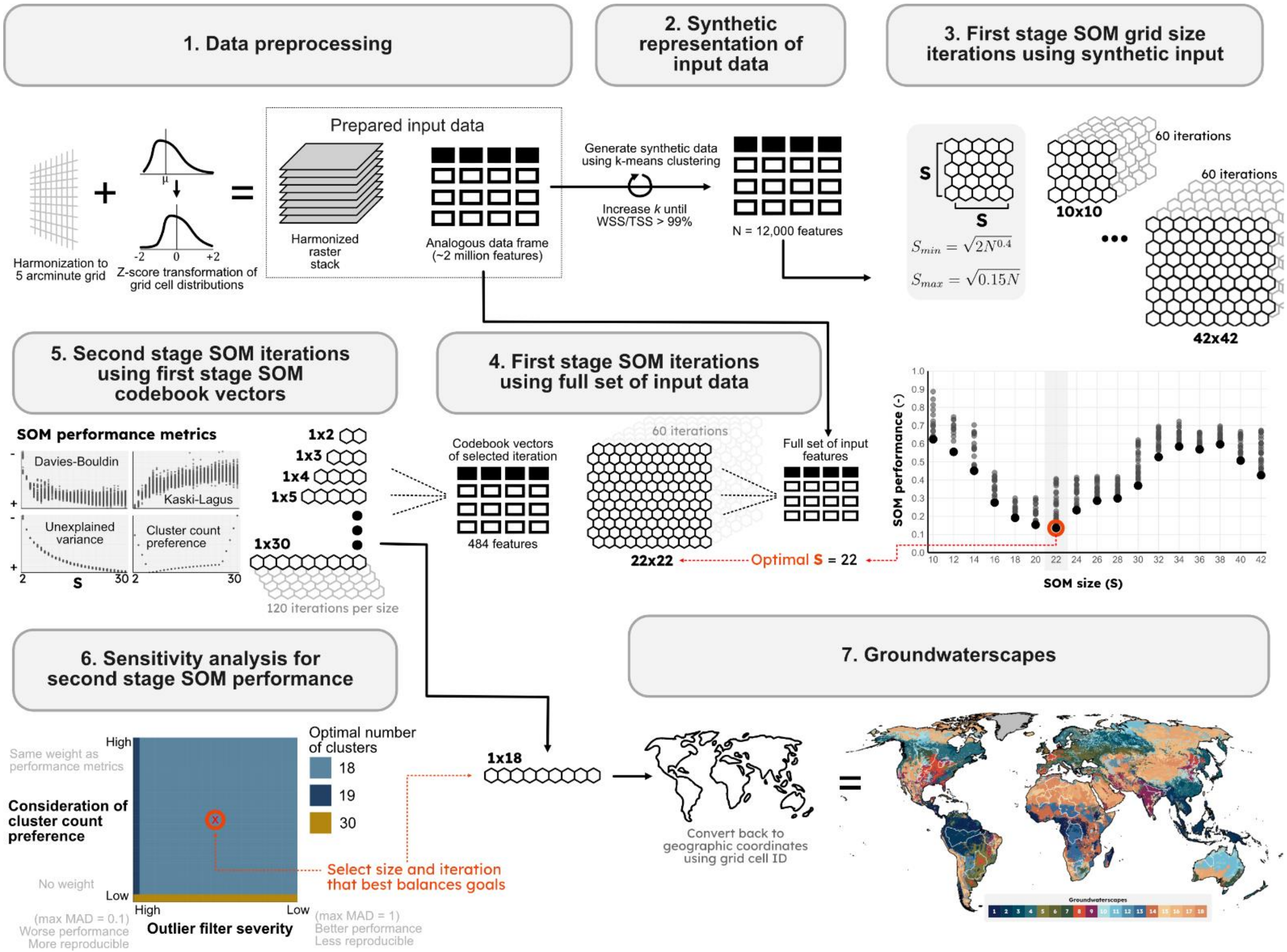
Reproducibility and sensitivity analyses: To increase the reproducibility of this approach given the stochastic nature of SOMs, we filter and remove performance outliers within SOM iterations at each SOM grid size. The threshold to detect outliers per SOM size is established using the median absolute deviation (MAD) of individual and combined performance metrics. We thus removed outlier iterations at each SOM size if any of the iteration’s individual performance metrics or integrated performance metric was outside the respective MAD from the size-specific median performance value. We found this approach to lead to highly reproducible SOM results across successive runs of our clustering scripts.

In our second stage SOM performance evaluation, we perform a bivariate sensitivity analysis to better understand possible trade-offs between study reproducibility, clustering performance, and cluster count preferences. To do this, we identify the best-performing SOM iteration while varying (i) the allowable limit of performance deviation and (ii) the weight given to the size preference function relative to the other performance metrics. The resulting matrix reveals the trade-offs embedded in this clustering process and enables the transparent selection across alternative local optimal iterations that best fit the needs of the study. 18 clusters are proposed across the majority of sensitivity analysis combinations (Figure 3, panel 6) and thus is selected as the optimal solution to this clustering problem.

2.4 Post hoc analysis

Within the large aquifer systems of the world (n = 37) (Richts et al., 2011), we calculated several landscape metrics to evaluate the spatial distribution of the groundwaterscapes. These metrics include the area distribution, Simpson's evenness index (Simpson, 1949), the contagion index (Riitters et al., 1996), marginal entropy, and relative mutual information (Nowosad & Stepinski, 2019) of groundwaterscapes. Simpson's evenness index is a diversity metric that represents if groundwaterscapes are evenly distributed within the aquifer (index is high) or if a few groundwaterscapes dominate the area (index is low). The contagion index is an aggregated metric that represents the likelihood that two adjacent grid cells belong to the same groundwaterscape. Marginal entropy measures the thematic complexity of groundwaterscapes within an aquifer, while relative mutual information has been shown as a useful approach to differentiate landscape patterns that otherwise show similar levels of thematic complexity (Nowosad & Stepinski, 2019). Calculating these metrics within the large aquifer systems of the world facilitates the exploration of spatial patterns of groundwaterscapes within these aquifer systems and can enable aquifer grouping based on their groundwaterscape composition.

Lastly, we compared the groundwaterscape map with the location of monitoring wells in the Global Groundwater Monitoring Network (GGMN) (IGRAC, 2024). While the GGMN is a participative initiative and thus does not reflect all monitoring wells worldwide, it is the best-available open global data set of groundwater monitoring well locations. To assess the coverage of monitoring wells across groundwaterscapes, we count the number of monitoring wells found within each groundwaterscape. We then calculate the proportion of monitoring wells found within each groundwaterscape and compare this frequency with each groundwaterscape's associated coverage of the global land surface.



409 **Figure 3. Groundwaterscape derivation methodology. Numbered panels denote individual components of the methodology.**

3 Results and discussion

3.1 Global groundwaterscapes

Our classification methodology generates a set of 18 groundwaterscapes (Figure 4). Each groundwaterscape represents a unique configuration of the Earth system, ecosystem, food system, and water management system functions included in our conceptual model. In Figure 4e, we visualize these unique function configurations for each groundwaterscape using radial plots representing the typical magnitude of each groundwater function.

We find groundwaterscapes to span spatially contiguous regions and capture broad patterns visible in individual groundwater functions (e.g., as shown in Figure 2). The largest groundwaterscape by surface area (GS17) represents arid and desert environments such as the Central Basin (USA) and the Gobi Desert (China) which have large storage capacities amid minimal other functions in jurisdictions with generally strong water management and collectively cover 9% of the land surface. By contrast, the smallest groundwaterscape (GS6) represents mosaic landscapes with agricultural regions and terrestrial GDEs, such as found across the South American Pampas, and is found across 2% of the land surface. Each groundwaterscape is described in Table 3 and the extent of individual groundwaterscapes are shown in Figure S5. Figure S6 shows the interquartile range of function magnitudes within each groundwaterscape to supplement the radial plots shown in Figure 4.

Groups of groundwaterscapes (Figure 4c, 4e) share overarching similarities but differ on a subset of functions. For instance, GS1 through GS4 are identified as landscapes that have extensive aquatic and terrestrial GDEs and have limited agricultural functions but are differentiated on the basis of their water management and Earth system functions. Out of the 18 groundwaterscapes, 13 describe non-agricultural regions (groundwaterscape groups I, II, III, and VI), while agricultural areas are described through five groundwaterscapes (groundwaterscape groups IV and V).

To substantiate finding that groundwaterscapes are spatially contiguous, we performed grid cell adjacency analysis (Figure S7). For each groundwaterscape, we find that any grid cell of a given groundwaterscape is most likely to neighbour with grid cells of the same groundwaterscape. Given that geographic location was not considered in our derivation methodology yet groundwaterscapes are found in contiguous patches suggests that our classification approach successfully identifies and reflects broad patterns in the groundwater functions included in our conceptual model. Yet, not every grid cell is represented in equal fidelity by this classification scheme as some grid cells have function configurations that more closely mirror their groundwaterscape model than others. To represent this “fit” of groundwaterscape classification, we plot the z-score of grid cell residual magnitudes per groundwaterscape (Figure S8). We find some regions to correspond tightly with their groundwaterscape representation such as the Amazon, central USA, Sudanian savanna, and Sahel. Other regions, such as the Congo basin have functional configurations that are relatively distant from their associated groundwaterscape model and could benefit from an investigation of “nested” groundwaterscapes (cf. Sietz et al., 2017) to further differentiate and describe systems in these regions. Using the intermediary codebook vectors produced through the first stage SOM (and as included in our data deposition) provide a subclassification of groundwaterscape that could be used for this purpose, however we leave such recursive groundwaterscape derivations and investigations for future study.

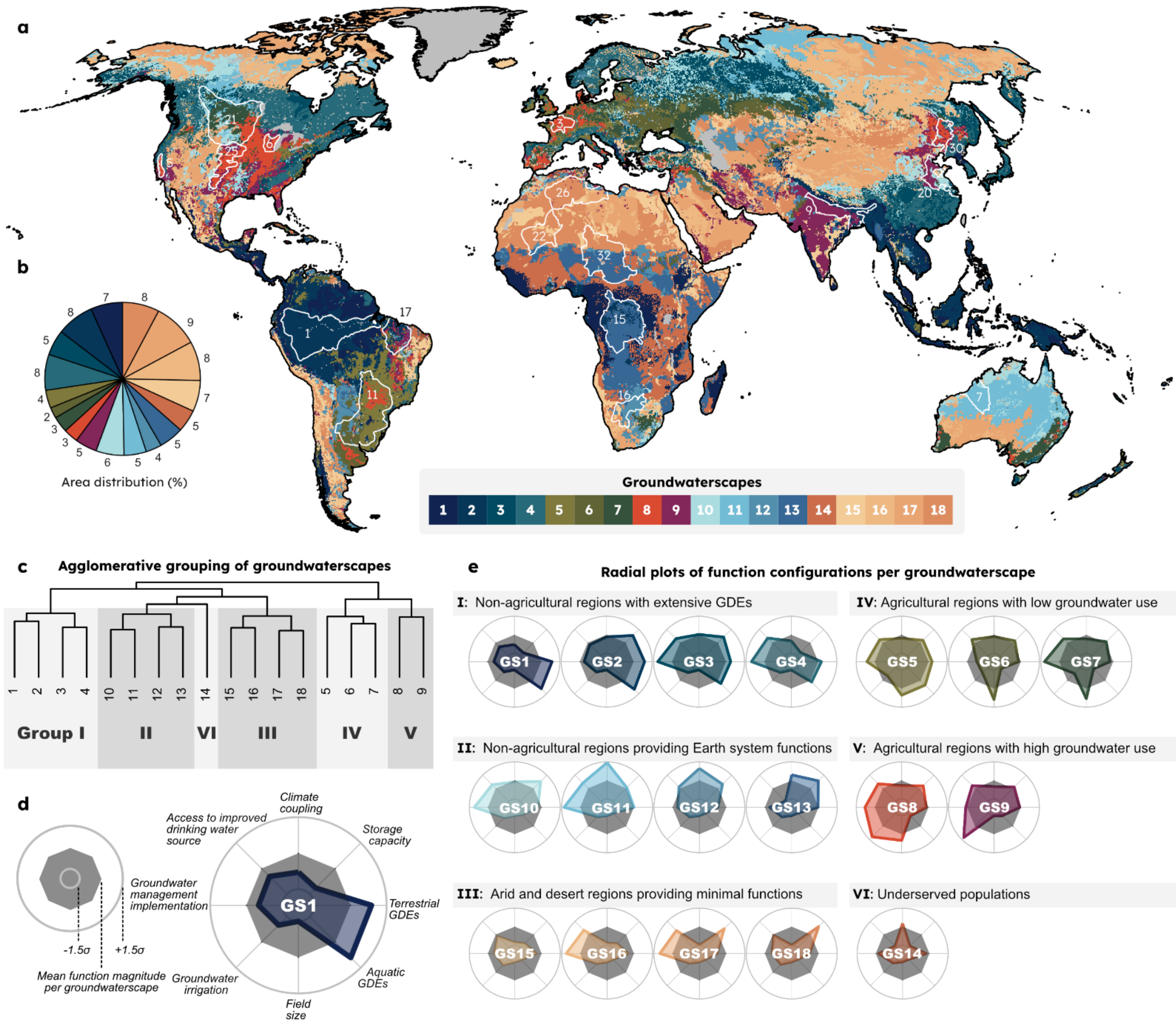


Figure 4. Global groundwaterscapes. (a) Map of the 18 derived groundwaterscapes. White polygon outlines represent large aquifer systems shown in subsequent figures. Annotated numbers correspond to aquifer IDs as used throughout the text. (b) Area distribution of groundwaterscapes. (c) Agglomerative grouping of groundwaterscapes. (d) Radial plot legend. (e) Radial plot of function magnitudes per groundwaterscape. Figure S6 shows the interquartile range of function magnitudes for each groundwaterscape.

Table 3. Groundwaterscape descriptions.

Groundwaterscape grouping	Additional descriptions specific to groundwaterscape	Example region
I: Non-agricultural, extensive terrestrial and aquatic groundwater-dependent ecosystems		
GS1	Small storage capacity	Eastern Madagascar
GS2	Large storage capacity	Amazon headwaters
GS3	Strong water management and large storage capacity	Western Siberia
GS4	Strong water management and small storage capacity	Eastern Canada boreal forest
II: Non-agricultural regions providing Earth system functions		
GS10	Strong water management and large storage capacity	Australian north coast
GS11	Strong climate coupling and water management	Australian outback
GS12	Strong climate coupling with limited water management	Botswana dry savanna
GS13	Limited water management, underserved populations, large storage capacity, and some terrestrial GDEs	Central Congo Basin
III: Arid and desert regions providing minimal functions		
GS15	Limited water management	Atacama Desert
GS16	Strong water management	Central Arabian Peninsula
GS17	Strong water management and large storage capacity	North American cold deserts
GS18	Limited water management and large storage capacity	Sahara
IV: Industrialized agricultural regions with low groundwater dependence		
GS5	Aquatic and terrestrial GDEs and some groundwater irrigation	Po River Basin
GS6	Limited water management	Pampas
GS7	Strong water management	Canadian Prairie
V: Agricultural regions with high groundwater dependence		
GS8	Industrial, large farms with strong water management	California Central Valley
GS9	Smallholder farming	Ganges River Basin
VI: Underserved populations		
GS14	Some terrestrial GDEs and climate coupling but otherwise limited functions	Burkina Faso

3.2 Groundwaterscapes facilitate social-ecological systems thinking on global groundwater

To illustrate how groundwaterscapes capture patterns across the underlying functions considered in our conceptual model, we zoom-in on five large aquifer systems and visualize the distribution of groundwaterscapes side-by-side with Earth system, ecosystem, food system, and water management system functions (Figure 5). For instance, we can observe how the Northern Great Plains Aquifer (Figure 5b) contains a mosaic of groundwaterscapes with GS7 (industrial agriculture with low-moderate groundwater use) dominating the central and western extents of the aquifer while GS8 (industrial agriculture with high groundwater use) is found across its southeastern regions. In addition to capturing this gradient in agricultural reliance on groundwater within the aquifer, the groundwaterscapes represent the extensive aquatic and terrestrial GDEs in the northeastern reaches of the aquifer through their assignment to GS4 (extensive GDEs with small storage capacity). We similarly demonstrate how this overlaying of system functions can visually explain the groundwaterscape maps for the Guarani Aquifer System, Northwestern Sahara Aquifer System, Ganges-Brahmaputra Basin, and North China Aquifer System (see in-figure annotations in Figure 5).

Characterizing groundwater systems in this way can facilitate investigation on interlinkages between these diverse groundwater functions. While hypothesis testing is beyond the scope of this classification study, we pose hypothetical lines of inquiry to exemplify this potential. For instance, how might the co-occurrences of extensive groundwater irrigation and low densities of GDEs have co-evolved under the setting of low to moderate levels of groundwater management across the Ganges-Brahmaputra Basin (Figure 5d)? Alternatively, how might the expansion of irrigated agriculture across the Northwestern Sahara Aquifer System increase the bi-directionality of groundwater-climate interactions and what might the implications of this be on ecosystems within these landscapes? And, how might regional variations in storage capacity within the Guarani Aquifer contribute to different realities regarding climate resilience in the agricultural sector across groundwater irrigating regions in the north and south of the aquifer?

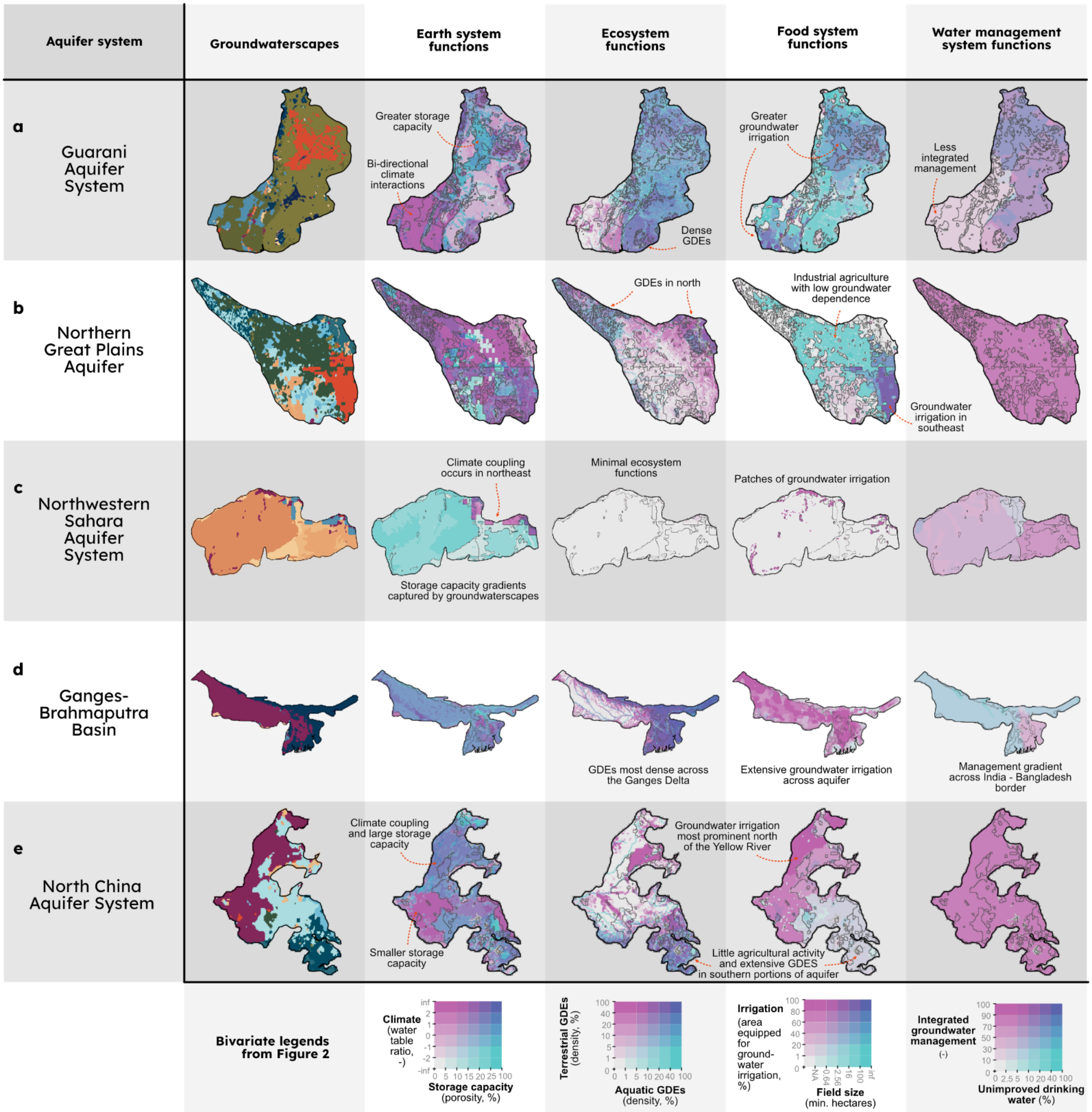


Figure 5. The multidimensional composition of groundwaterscapes. Columns represent spatial patterns in groundwaterscape distributions, Earth system functions, ecosystem functions, food system functions, and water management system functions for five case study aquifers: (a) the Guarani Aquifer System (Argentina, Brazil, Paraguay, Uruguay), (b) The Northern Great Plains Aquifer (USA, Canada), (c) the Northwestern Sahara Aquifer System (Algeria, Tunisia, Libya), (d) the Ganges-Brahmaptura Basin (Bangladesh, India, Nepal), and (e) the North China Aquifer System

(China). We provide a similar mapping of all 37 large aquifer systems of the world in Figures S9-S16.

Groundwaterscapes on their own cannot answer these questions. Yet, the groundwaterscapes can provide a spatial template of comparable units to evaluate particular system behaviours across a variety of system conditions. Given that generalising relationships in complex freshwater systems, such as biodiversity responses to environmental flow transgressions, has proven analytically challenging (Mohan et al., 2022), we hypothesize that integrating groundwaterscapes and their derivatives in similar investigations can provide an alternative template for analysis of these complex, interlinked systems where system behaviours and statistical relationships are investigated at the groundwaterscape level rather than globally.

3.3 Multiple groundwaterscapes in all large aquifers

All of the 37 large aquifer systems of the world contain multiple groundwaterscapes (Figure 6). The Amazon Basin (Brazil) and Canning Basin (Australia) are the least diverse of these large aquifer systems, with only two groundwaterscapes found within each system's borders (i.e., covering at least 1% of the aquifer's surface area). Conversely, the Karoo Basin (South Africa) and Maranhão Basin (Brazil) contain 10 and 12 groundwaterscapes, respectively. That 12 of the 18 groundwaterscapes are found within the Maranhão Basin highlights the region's exceptional groundwater system heterogeneity. That the Maranhão Basin and Amazon Basin are so proximal to each other (separated by <100 km at their nearest points) yet exist at opposite ends of this spectrum of groundwaterscape diversity underscore how the groundwaterscapes we derive offer counterintuitive insights.

We view our finding that every large aquifer system is characterized by multiple groundwaterscapes to be a fundamental insight that could have important implications for groundwater science. Treating these systems as homogeneous, lumped units, as is often the case in global groundwater assessments, severely underrepresents the functional heterogeneity that exists within each aquifer. Yet, as aquifer and groundwaterscape mapping are based on vastly different conceptual models, we foresee the potential to use these resources in tandem. It is possible for groundwaterscapes to span aquifers (as aquifers do not consider their overlying social-ecological and Earth system functions) and for aquifers to span groundwaterscapes (as groundwaterscapes do not account for lateral flow or the specific geology of the region and are derived uniquely per grid cell).

For example, understanding groundwater storage trends in the major aquifer systems of the world (e.g., as in Richey et al., 2015) could be strengthened by further specifying storage trends at the groundwaterscape unit within aquifers. It is well established that there are divergent groundwater storage trends within the High Plains (Ogallala) Aquifer, with pronounced depletion in its central and southern regions but groundwater storage gain in its northern regions (McGuire, 2017), yet taking a lumped-system approach moderates groundwater storage trend results across the entire aquifer. In contrast, evaluating the groundwater storage trends within groundwaterscapes within the Ogallala and for any other aquifer (Figure S9-S16) would support a more disaggregated specification of storage trends within aquifers while simultaneously facilitating thinking about the potential socioeconomic, ecological, and Earth system functions at risk due to hydrological change.

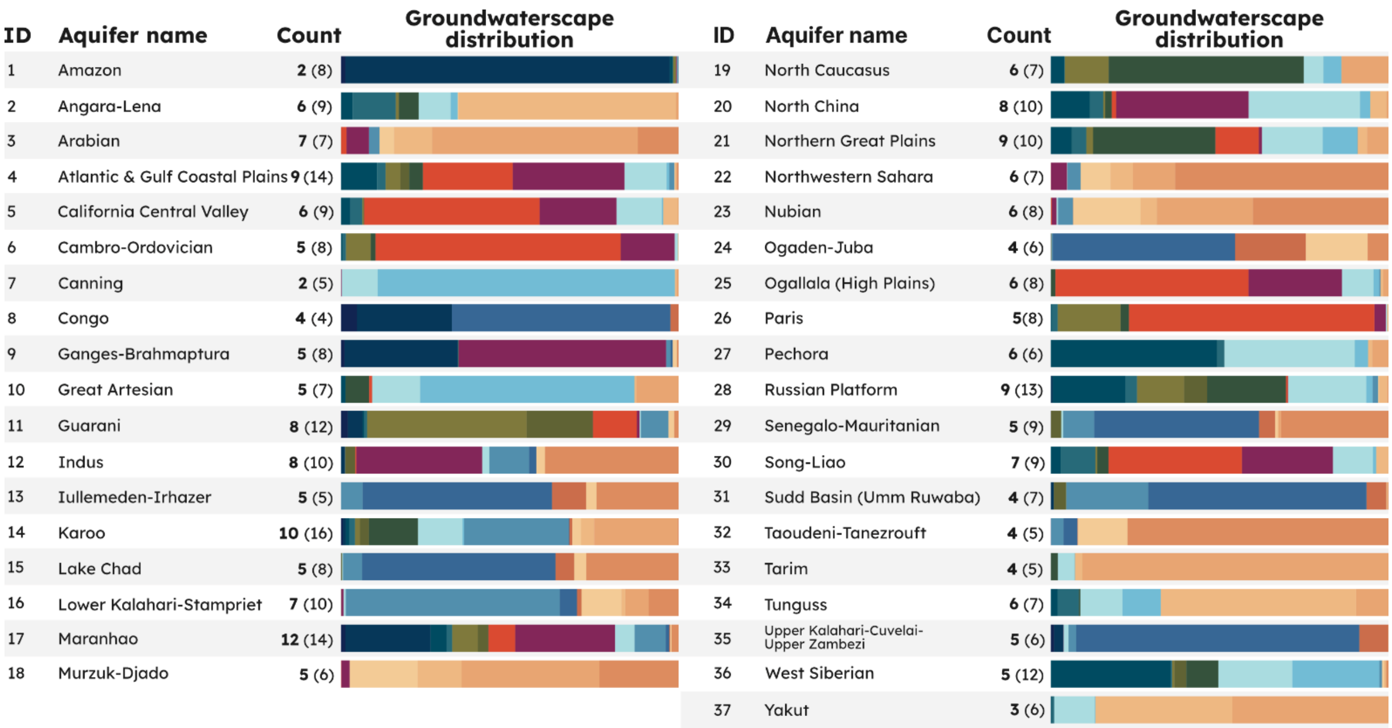


Figure 6. Groundwaterscape area distributions in the large aquifer systems of the world. Groundwaterscape counts are calculated based on those that cover a minimum threshold of 1% (and 0.1%) of the aquifer area.

Simply counting the number and areal distribution of groundwaterscapes within an aquifer provides an introductory but insufficient description of the groundwaterscape distribution within aquifer systems. For instance, although the Angara-Lena Basin (Russia) and Song-Liao Basin (China) both contain a similar number of groundwaterscapes within their boundaries (six and seven, respectively), it can be observed that one groundwaterscape is relatively dominant and covers a considerable combined area of the Angara-Lena Basin, whereas the seven groundwaterscapes within the Song-Liao Basin are more evenly distributed by area (Figure 6). Thus, we supplemented this analysis by computing several additional landscape metrics to further describe the spatial patterns of groundwaterscapes within aquifers (Figure 7). While similar analyses could be conducted across other units of organization (e.g., country borders, water management administrative regions, protected areas, ecological biomes, etc.), we continue our focus on the large aquifer systems as they represent a primary, well-known, and widely used global groundwater system classification.

There is a strong relationship between the Simpson's evenness index and the contagion index of groundwaterscapes within aquifers (Figure 7a). These metrics identify aquifers such as the Amazon Basin (Brazil) and Canning Basin (Australia) as among the least diverse and most contiguous in their groundwaterscape make-up, whereas the Song-Liao Basin (China) and Maranhão Basin (Brazil) are among aquifers with the greatest heterogeneity and diversity of groundwaterscapes. Given landscape indices such as the Simpson's evenness index and the contagion index are often correlated, plotting marginal entropy against relative mutual information is one proposed approach to differentiate and classify landscape patterns with weakly correlated indices (Nowosad & Stepinski, 2019). When applying this approach (Figure 7b), groundwaterscape patterns between aquifers that contain similar levels of evenness and contiguity can be differentiated. For instance, the Paris Basin (France) and Taoudeni-Tanezrouft Basin (Mali, Mauritania, and Algeria) show similar levels of evenness and contiguity (Figure 7a) yet the two basins can be differentiated on the basis of relative mutual information, with the Paris Basin having considerably less relative mutual information (Figure 7b). Such analytical approaches could be useful for applications that would benefit from grouping aquifers based on similarity in their groundwaterscape composition and landscape complexity.

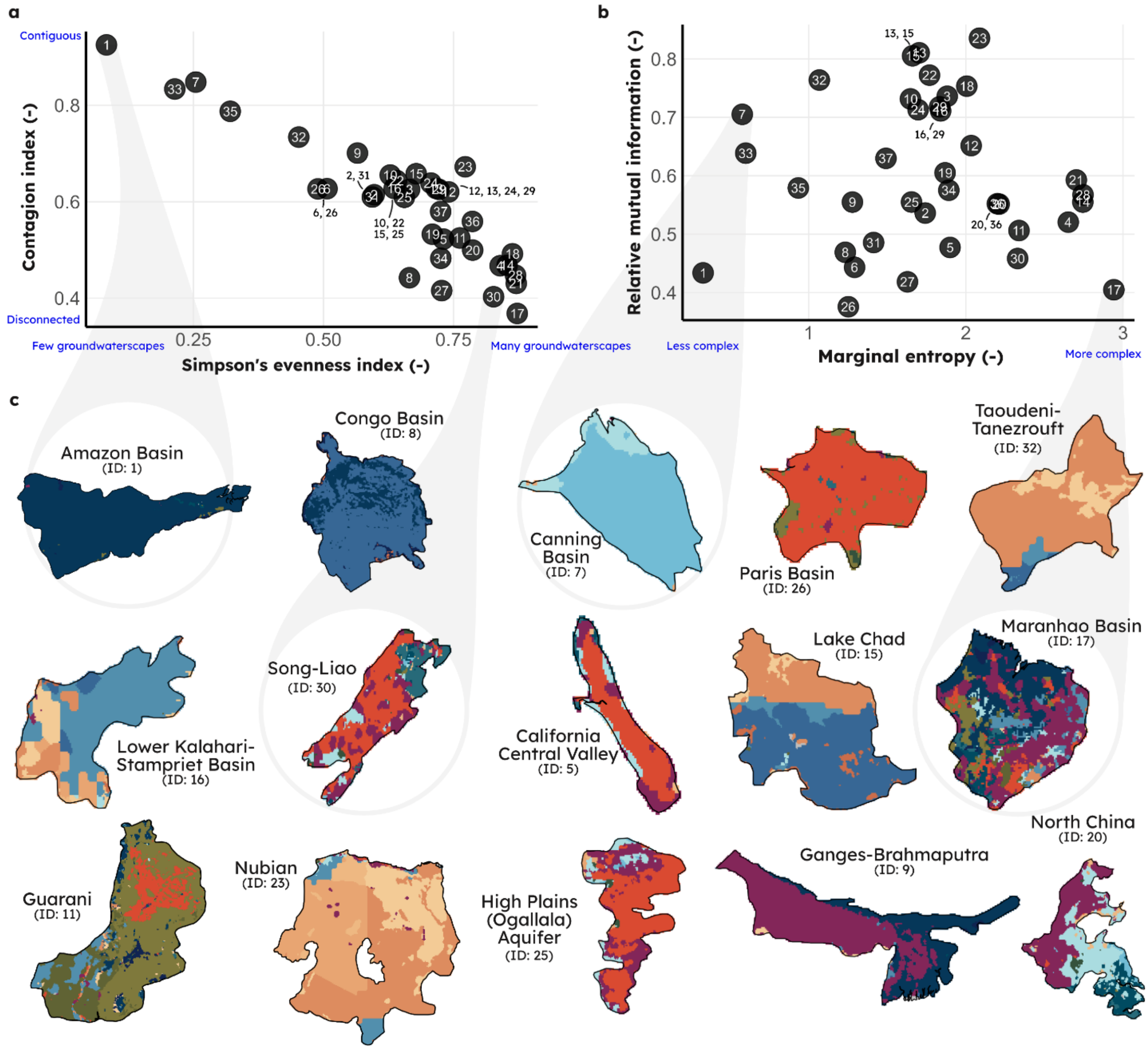


Figure 7. Landscape metrics of groundwaterscapes within the large aquifer systems of the world. (a) Plot of Simpson's evenness index (x-axis) and the contagion index (y-axis). (b) Plot of marginal entropy (x-axis) and relative mutual information (y-axis). (c) Groundwaterscape distributions within highlighted aquifers. Aquifer IDs correspond to the points labels in panels (a) and (b) and also correspond to the aquifer borders mapped in Figure 4. Inset maps are sized for visualisation and are not shown at a consistent scale.

3.4 Groundwaterscapes are not equally monitored

These groundwaterscapes offer an alternative conceptual model to understand, study, and manage global groundwater systems. To juxtapose this study with the influential concept of hydrologic landscapes, which hypothesize that hydrological systems behave as a function of land-surface form, geology, and climatic setting (Winter, 2001), we present groundwaterscapes as systems whose behaviour is a function of interacting Earth systems, ecosystem, agricultural system, and water management system processes. On this basis, groundwaterscapes are different and distinct systems to measure and study in comparison to physical groundwater systems.

We find a striking imbalance in the global groundwater monitoring well network distribution across groundwaterscapes (Figure 8a). Groundwaterscapes GS7 and GS8 (characterized by industrial agriculture and strong water management) benefit from >50% of all monitoring wells despite covering a combined 6% of the land surface (Figure 8b). Conversely, some groundwaterscapes have almost no representation in the observation network at all, such as GS12, GS13, and GS14 that combined have <1% of all monitoring wells within their extents yet cover over 14% of the land surface. These monitoring disparities thus intensify when normalizing by surface area (Figure 8c). As economic factors and management capacity influence the ability of jurisdictions to monitor their groundwater resources, it is not surprising that industrial agricultural groundwaterscapes dominate the monitoring network distribution. Yet, even within agricultural regions we see imbalances in monitoring. For instance, GS9 (groundwater-reliant smallholder agriculture) has about one quarter of the monitoring well density of GS7 and one-third of the density of GS8.

As observation instrumentation is one of the dimensions of the groundwater management data set included in our groundwatershed derivation, the biases we observe in the well network are not independent from our derivation methodology (i.e., it is expected that groundwaterscapes with lower groundwater management levels would have fewer observation wells). However, it remains that effective groundwater management depends on representative data (Curran et al., 2023), and therefore the biases and blind spots in global groundwater data collection undermine the ability to manage groundwaterscapes on a data-driven basis. In this way, the groundwaterscape concept can be a tool to prioritize data collection initiatives, and moreover to re-imagine what effective groundwater data collection entails in order to assemble more representative and capable sets of observations to understand change in groundwaterscapes.

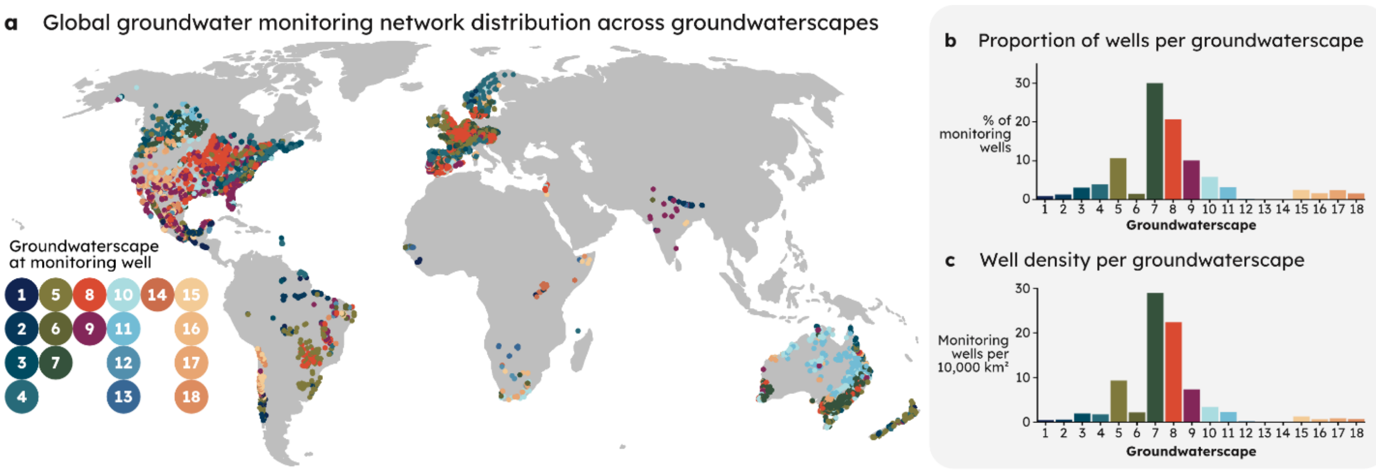


Figure 8. Distribution of the Global Groundwater Monitoring well network (GGMN) (IGRAC, 2024) across groundwaterscapes. (a) Map of GGMN wells coloured according to their groundwaterscape. (b) Proportion of GGMN wells found within each groundwaterscape. (c) GGMN well density per groundwaterscape.

3.5 Groundwaterscapes as a starting point

We present these groundwaterscapes as a plausible classification of global groundwater systems built on a function-oriented understanding of groundwater in social-ecological systems. Yet moreover, these groundwaterscapes represent a global mapping of the alternative conceptual model presented by the groundwater-connected systems framing (Huggins et al., 2023a) and thus support an overarching ambition to characterize, understand, and manage groundwater systems on the basis of the resource's role within social-ecological systems. Our perception is that debate on effective ways to proceed in this regard is far from settled and we expand on this reflection in a number of ways below.

In a practical sense, the groundwaterscapes are challenging to validate. This is not unique to this study and is a general problem across archetype analysis (Piemontese et al., 2022). This stems from the fact that social-ecological system typologies are conceptual constructs rather than physical entities (Oberlack et al., 2019) and thus cannot be directly measured. In the archetype analysis literature, a comprehensive validation procedure is proposed to consist of six dimensions (Piemontese et al., 2022) that span qualitative evaluations on the strength of conceptual framing, data fidelity, methodological robustness, the explicitness of study scope, empirical justification, and an evaluation of the potential application. As this study does not conduct a "full" archetype analysis and rather presents the groundwaterscapes as possible archetype 'candidates' for evaluation and future refinement, we do not foresee the need for the full set of proposed validation components to be incorporated here.

We perceive our study to follow "strong" validation guidelines by using a theory-grounded conceptual model to underpin our study, sourcing best-available, empirical global data sets that correspond closely with our conceptual model, and in implementing a robust and reproducible derivation methodology. We bound our study by acknowledging that the groundwaterscapes only represent the groundwater functions included in our conceptual model, and thus omit important functions that occur in coastal environments, small islands, permafrost regions, and urban settings. We also do not consider non-agricultural economic uses of groundwater and thus groundwater's role in mining, manufacturing, energy generation, and other industries is invisible to these groundwaterscapes. We also do not include consideration of groundwater quality or geochemical functions. We foresee the potential for adapted "groundwaterscapes" to address these conceptual limitations and readily welcome the pluralisation of the groundwaterscape concept.

There are important data limitations that provide further basis to view the groundwaterscapes through a critical lens. While we used the best-available data to represent each function included in our conceptual model, several of these data sets would benefit from further refinement. We used data layers for their most-recent year but some layers are now considerably dated (such as groundwater irrigation areas which correspond to the year 2000). Specific challenges to individual data sets include an opaque multi-stakeholder consolidation process underlying the development of the water management layer and a simple, inference-based mapping approach used to generate groundwater-dependent ecosystem data. Yet, we view these data limitations as sources for future groundwaterscape improvement, such as through updating existing data sets to more recent reference years (e.g., groundwater irrigation maps for the year 2020), refining methods (e.g., groundwater-dependent ecosystem maps), and disclosing data generation methods (e.g., in the case of stakeholder consolidated management data). We thus view our groundwaterscape results as a best-available representation of global groundwater systems functions given current data availability and note that our reproducible methodology enables the update of our groundwaterscape map following data improvements.

We perceive this groundwaterscape mapping study as a potential catalyst for wider application of social-ecological system concepts within the global-scale groundwater domain. For instance, global hydrological models, which are arcing towards visions of "physically-based continental Earth system models" (Bierkens, 2015), could benefit from parameterization and conceptual model development facilitated through the groundwaterscapes. The groundwaterscape concept can also be applied to support data collection strategies and as a spatial template to identify diverse case study locations for modelling or field work studies.

Groundwaterscapes can more generally be used to test hypotheses on groundwater-connected system behaviour. Thus, groundwaterscapes can support the application and development of middle range theories of change to groundwater science, which represent “contextual generalisations that describe chains of causal mechanisms explaining a well-bounded range of phenomena, as well as the conditions that trigger, enable, or prevent these causal chains” (Meyfroidt et al., 2018). Thus, an overarching potential of the groundwaterscape concept is to serve as a conceptual and analytical tool to facilitate investigations on causal processes connecting these complex and intertwined hydrological, social, ecological, and Earth systems.

4 Conclusion

We developed a global classification and mapping of groundwaterscapes which are landscape units with common configurations of eight large-scale (order of 10^4 km^2) functions of groundwater systems across Earth systems, ecosystems, food systems, and water management systems. We classified and mapped 18 groundwaterscapes across the global land surface using a two-stage, iterative self-organizing map methodology. Groundwaterscape groupings include non-agricultural regions with extensive groundwater-dependent ecosystems, non-agricultural regions providing Earth system functions, Arid and desert regions with minimal functions, agricultural regions with low groundwater use, agricultural regions with high groundwater use, and underserved populations. The groundwaterscapes provide a new lens to conceptualize, study, and manage groundwater systems worldwide. All large aquifer systems of the world contain multiple groundwaterscapes, highlighting the functional heterogeneity that is overlooked when these systems are treated as homogenous units in global analysis. We found a striking imbalance in global monitoring wells across groundwaterscapes with only two groundwaterscapes benefiting from over half of all monitoring wells while other groundwaterscapes contain next to no monitoring capacity. The groundwaterscapes can serve as a conceptual and spatial tool for the large-scale groundwater research community to engage more fully with the complex realities of groundwater system dynamics within social-ecological systems. Inspiring steps are being taken in this direction by multiple research groups, mainly oriented around developing pairwise system understandings with groundwater (e.g., groundwater-climate processes, groundwater-streamflow processes, groundwater- terrestrial ecosystem processes). This study is our attempt to begin the process of bringing together these research streams and make initial progress towards developing a more holistic, system-of-systems understanding of groundwater at the global scale.

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Open research

All analyses were conducted using the R project for statistical computing (R Core Team, 2023). R packages *kohonen* (Wehrens & Kruisselbrink, 2018), *aweSOM* (Boelaert et al., 2022), and *clusterSim* (Walesiak & Dudek, 2020) were used to develop and evaluate self-organising maps. Landscape metrics of groundwaterscapes within aquifer systems were computed using the *landscapemetrics* package (Hesselbarth et al., 2019). General spatial data processing was performed using *terra* (Hijmans, 2023). Plots were generated using *tmap* (Tennekes et al., 2018), *ggplot2* (Wickham, 2016), and *MetBrewer* (Mills, 2022) packages. Composite figures were assembled in Affinity Designer (https://affinity.serif.com/en-us/designer/).

Data used in this study, as listed in Table 2, include data sets of the water table ratio (Cuthbert et al., 2019b), groundwater recharge (Döll & Fiedler, 2008), near-surface porosity (Gleeson et al., 2018), groundwater-dependent ecosystems (Huggins et al., 2023c), groundwater irrigation (Siebert et al., 2013), farm field size (Lesiv et al., 2018), integrated groundwater management (UNEP, 2021; https://iwrmdataportal.unepdhi.org/), worldwide governance indicators (Kaufmann & Kraay, 2023), unimproved drinking water access (World Resources Institute, 2023), and groundwater monitoring well locations (IGRAC, 2024). A global land mask (Wessel et al., 2019) was used to establish the study domain.

Groundwaterscape data and scripts developed to produce all results will be deposited on Borealis (https://borealisdata.ca/) upon manuscript acceptance. Scripts are also available online at https://github.com/XanderHuggins/groundwaterscapes.

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