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Groundwaterscapes: A Global Classification and Mapping of Groundwater's Large-Scale Socioeconomic, Ecological, and Earth System Functions

Xander Huggins[1,2,3], Tom Gleeson[1,4], Karen G. Villholth[5], Juan C. Rocha[6], and James S. Famiglietti[2,7]

[1]Department of Civil Engineering, University of Victoria, Victoria, BC, Canada, [2]Global Institute for Water Security, University of Saskatchewan, Saskatoon, SK, Canada, [3]International Institute for Applied Systems Analysis, Laxenburg, Austria, [4]School of Earth and Ocean Sciences, University of Victoria, Victoria, BC, Canada, [5]Water Cycle Innovation (Pty) Ltd., Bela-Bela, South Africa, [6]Stockholm Resilience Centre, Stockholm University, Stockholm, Sweden, [7]School of Sustainability, Arizona State University, Tempe, AZ, USA

Key Points:

- Groundwaterscapes are presented as landscape units representing configurations of groundwater's social-ecological and Earth system functions
- A two-stage self-organizing map clustering method is implemented to derive 15 groundwaterscapes at the global scale
- All large aquifer systems of the world contain multiple groundwaterscapes

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

X. Huggins,
xander.huggins@ubc.ca

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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 and map 15 groundwaterscapes which offer a new lens to conceptualize, study, model, and manage groundwater. Groundwaterscapes are derived using a novel application of sequenced self-organizing maps that capture patterns in groundwater system functions at the grid cell level (∼10 km), including groundwater-dependent ecosystem type and density, storage capacity, irrigation, safe drinking water access, and national governance. 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 are disproportionately monitored, while several groundwaterscapes have next to no monitoring wells. This disparity undermines the ability to understand system dynamics across the full range of settings that characterize groundwater systems globally. We argue that 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.

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) and Shamsudduha and 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, Cuthbert, et al., 2020; Gleeson, Wang-Erlandsson, et al., 2020; Huggins, Gleeson, Castilla-Rho, et al., 2023). 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, Cuthbert, et al., 2020; Gleeson, Wang-Erlandsson, 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 (GDEs) (Kløve et al., 2011; Link et al., 2023), which can take the form of

Table 1
Key Terminology

Term	Definition
Social-ecological systems	Integrated systems formed by social and biophysical system interactions (Berkes & Folke, 1998). Investigations that use social-ecological system framings seek 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, Gleeson, Castilla-Rho, et al., 2023)
Groundwaterscapes	Landscape units with specific and broadly occurring configurations 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) but groundwaterscapes could be defined with other methods and data

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 relational values such as through offering senses of place and contributing to cultural identity (Griebler & Avramov, 2015; Moggridge & Thompson, 2021). 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 or 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 variety of global social-ecological system typologies have been developed in 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); and an even wider assortment of typologies at continental and regional scales (Beckmann et al., 2022; Rocha et al., 2020; van der Zanden et al., 2016; Van Vliet et al., 2012). Yet, these underlying concepts and methods have yet to be applied to groundwater systems.

The emerging field of archetype analysis is a central, driving force behind these social-ecological system characterizations (Eisenack et al., 2021). In this 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 many methods have been 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, Gleeson, Castilla-Rho, et al., 2023) 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 function configurations. We focus on large-scale functions, which we understand as functions that broadly occur across regional extents (on the order of 10^4 km^2 and larger) and that are conducive to global, systematic pattern identification. We

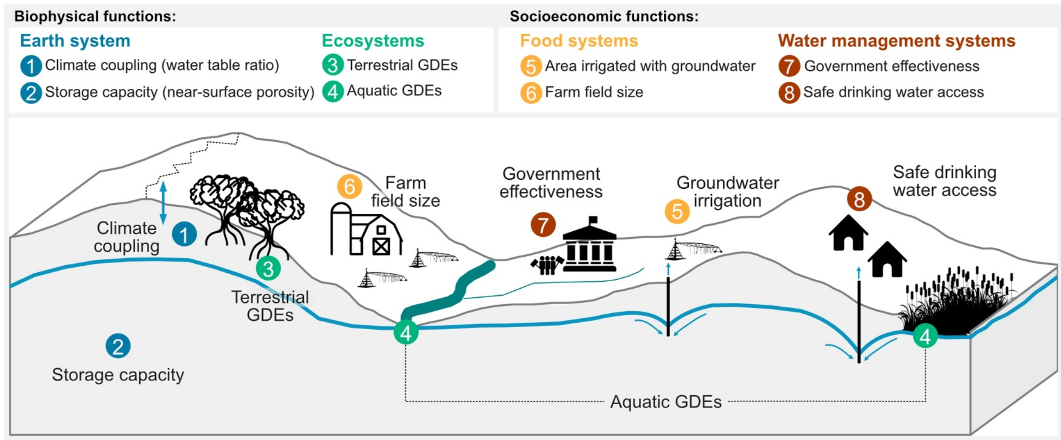

Figure 1. Conceptual model of groundwaterscape elements, consisting of groundwater's large-scale Earth system, ecosystem, food system, and water management system functions. Maps of the input data representing these functions are shown in Figure 2.

name the clusters that emerge from this process as groundwaterscapes (Table 1). These groundwaterscapes offer a first step toward characterizing the predominant configurations and spatial patterns within groundwater's socioeconomic, ecological, and Earth system functions, which we believe can provide widespread potential uses and benefits across groundwater science and management.

2. Materials and Methods

2.1. Conceptual Model

Drawing on recent reviews of global groundwater systems (Gleeson, Cuthbert, et al., 2020; Gleeson, Wang-Erlandsson, et al., 2020; Lall et al., 2020; Scanlon et al., 2023), we identified four core systems that groundwater interacts with at 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 (2) per system to ensure even representation in our analysis. In order to be included in our conceptual model, individual 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 the range of input layer counts commonly found in existing social-ecological system clustering studies. We found this number of input layers to include 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 the system 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, Cuthbert, et al., 2020; Gleeson, Wang-Erlandsson, 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). Second, as the largest store of unfrozen freshwater globally, groundwater provides important storage functions (Gleeson, Cuthbert, et al., 2020; Gleeson, Wang-Erlandsson, et al., 2020). Net groundwater storage loss is a secondary

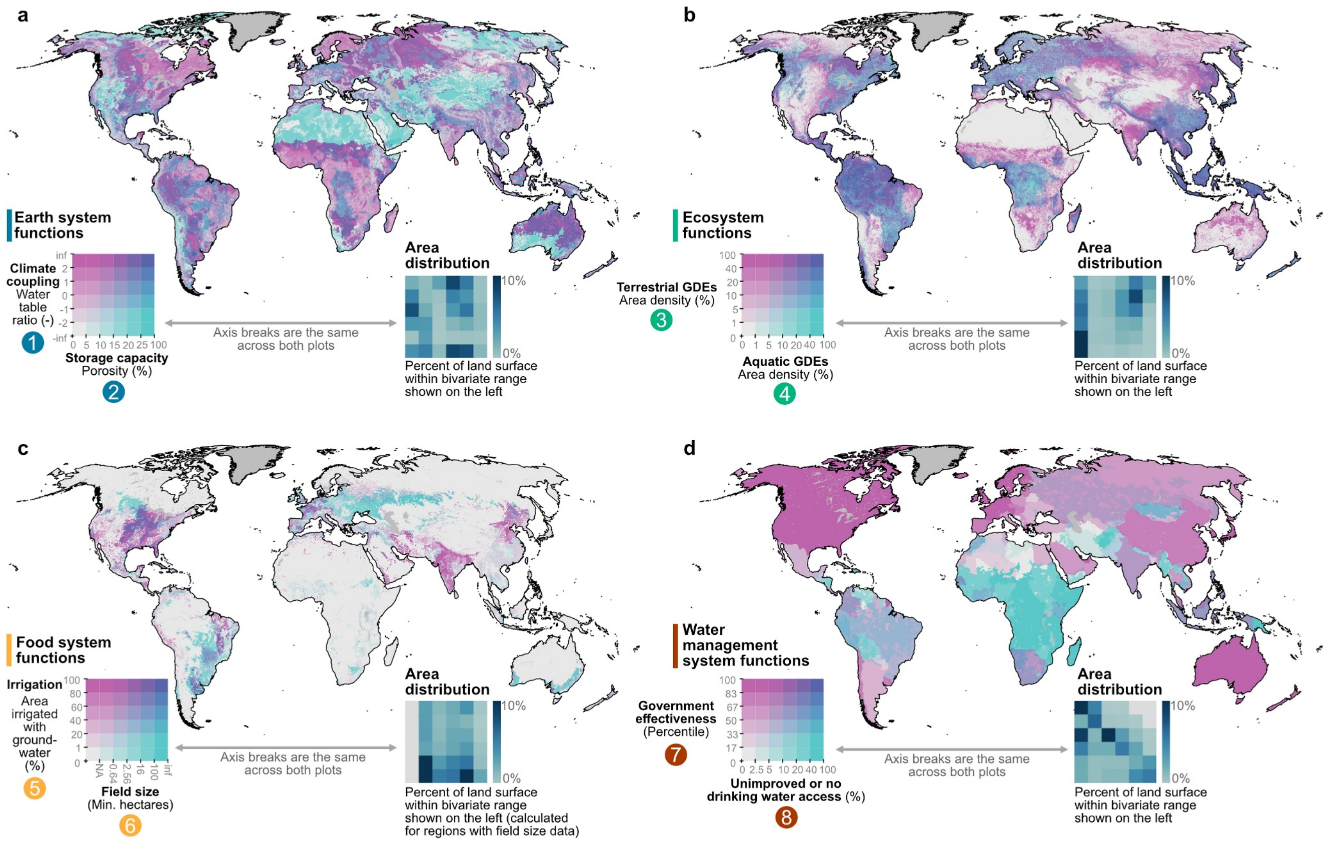

Figure 2. Exploratory mapping of groundwater's large-scale (a) Earth system, (b) ecosystem, (c) food system, and (d) water management system functions. Bivariate legends are numbered accordingly with their conceptual model element show in Figure 1. The area distribution of each mapped bivariate relationship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

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 at 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 100 m) 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 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 relative to subterranean GDEs, dominate conservation and management dialogs (Rohde et al., 2017; Saito et al., 2021), and have benefitted from recent global mapping efforts (Huggins et al., 2023b; Link et al., 2023; Rohde et al., 2024). 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 primary sector driving groundwater consumption globally (Giordano & Villholth, 2007; Wada et al., 2012). Thus, to reflect groundwater's *food system* functions (Figure 2c), we consider the extent of areas irrigated with groundwater and farm field size. Including groundwater irrigation patterns enables this analysis to differentiate regions based on agricultural reliance on groundwater. Second, 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).

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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 important in relation to land tenure and 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 and dynamics 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. In the absence of a global data set on groundwater or water governance and management, we use a general indicator of nation-scale government effectiveness as proxy representation of national water governance. Thus, we consider general government effectiveness to be a foundation of good water governance, which reflects the quality of public services, the degree of independence from political pressures, the quality of policy formulation and implementation, and the credibility of government commitment to these policies (Kaufmann & Kraay, 2023). In incorporating this government effectiveness layer, we follow Varis et al. (2019) who used this same data set to characterize the governance dimension of social adaptive capacity within river basins in a global analysis. We note that initial steps are being taken to monitor groundwater governance directly (e.g., https://iwrmdataportal.unepdhi.org/), however the process of comprehensively generating and validating these data globally remains an on-going challenge that prevents their inclusion in this study. More broadly, it is not straightforward to quantify governance and management dimensions and the process of doing so is often contested (Thomas, 2010). Furthermore, water governance frameworks, organizations, and actions will vary sub-nationally depending on local and regional hydrological and political context. Thus, our inclusion of national government effectiveness informs on the general governance setting but sub-national variations in governance are invisible to this study. Despite these limitations, we view the inclusion of this governance dimension as a crucial component of our analysis that ensures this first assessment of groundwaterscapes reflects the broad scope of the groundwater-connected systems framing and creates a baseline that can be refined in future studies.

Second, to consider the role of groundwater management in relation to safe water 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. 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 utilization, or lack thereof, in supporting domestic activities and water security.

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 map 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 freshwater-focused social-ecological studies (e.g., Gain et al., 2016; Varis et al., 2019). Second, operating at the unit of 5 arcminute grid cells rather than aquifers, basins, or administrative units enables analysis of groundwaterscape heterogeneity in these systems (see Section 2.4).

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 were normalized at the nation and watershed scale to match the scale at which they were respectively derived, before rasterization was conducted. We subsequently applied feature clipping by setting minimum and maximum values at ±2 standard

Table 2
Input Data Sets

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 **Harmonization:** Bilinear resampling to 5 arcminute grids **Additional preprocessing:** Regions with recharge <5 mm yr^{-1} were set to the minimum normalized 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 an average size of ∼14,000 km^2 **Temporal range**: N/A **Harmonization:** Vector polygon rasterization to 5 arcminute grids
Groundwater-dependent ecosystem types (aquatic and terrestrial)	**Data source**: Huggins et al. (2023a) **Persistent web-link**: https://doi.org/10.5683/SP3/P3OU3A **Spatial resolution**: 30 arcsecond **Temporal range**: ca. 2015 **Harmonization:** 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 **Spatial resolution**: 5 arcminute **Temporal range**: 2005 **Harmonization:** 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 **Harmonization:** Modal resampling to 5 arcminute grids
Government effectiveness	**Data source**: Worldwide governance indicators (Kaufmann & Kraay, 2023) **Persistent web-link**: www.govindicators.org **Spatial resolution**: Nation scale **Temporal range**: 2020 **Harmonization:** Vector polygon rasterization to 5 arcminute grids
Safe 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 **Harmonization:** Vector polygon rasterization to 5 arcminute grids

Note. Maps and histograms of each data set are shown in Figure S1 in Supporting Information S1.

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 & Smith, 1996; Wessel et al., 2019) 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 normalized input data sets 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 correlation ($r \approx |0.5|$) between certain inputs, such as between aquatic and terrestrial GDE density and between government effectiveness and safe drinking water access (Figure S2 in Supporting Information S1), but no correlation coefficients were sufficiently high to require further modification when using common thresholds to evaluate detrimental levels of collinearity ($r > |0.7|$) (Dormann et al., 2013).

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 behavior. 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). 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 (Delgado et al., 2017; Taşdemir et al., 2012). 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 a set of alternative of SOMs at each grid size and filter-out performance outliers to improve reproducibility (see below).

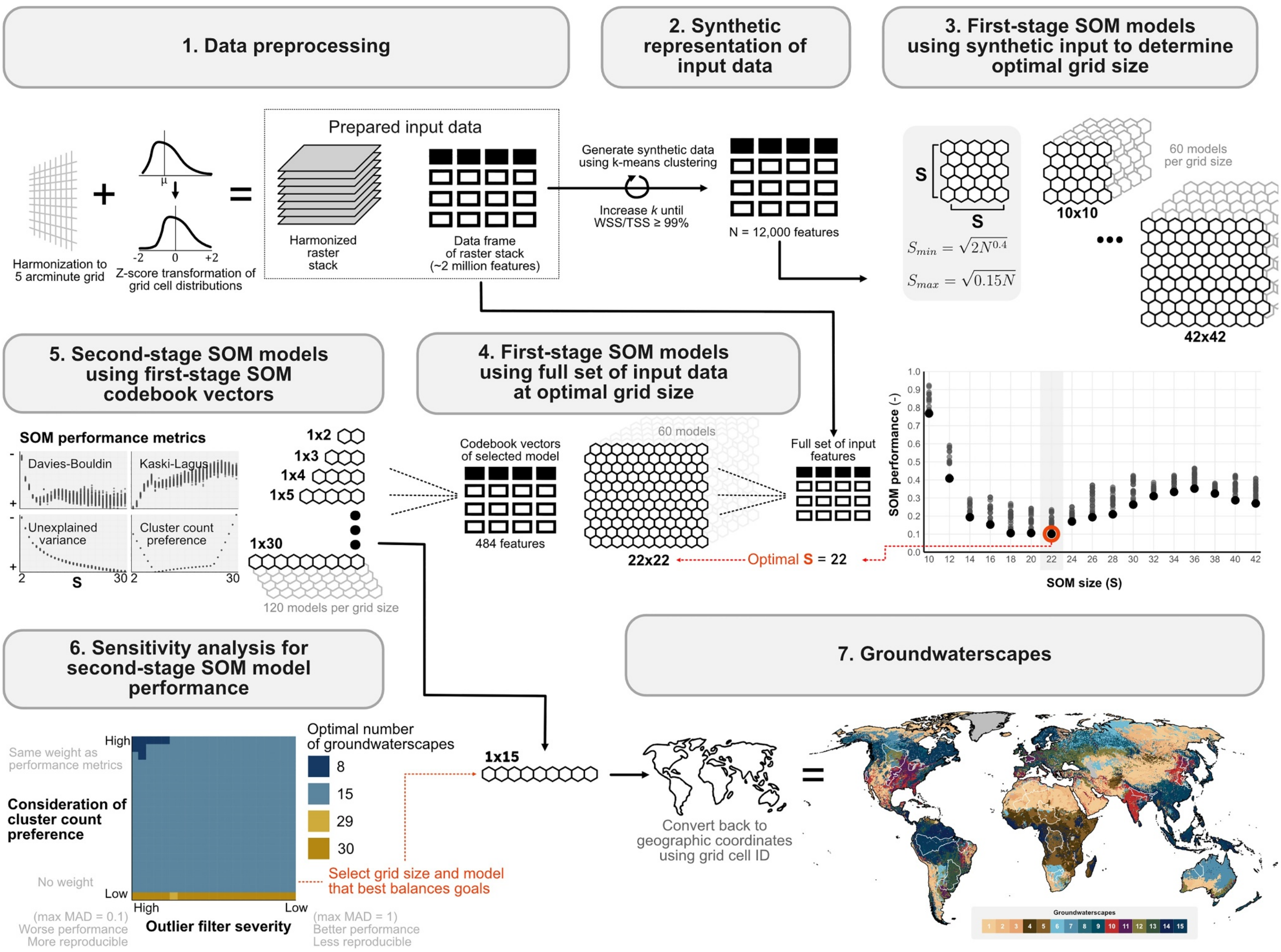

Figure 3. Groundwaterscape derivation. Numbered panels denote individual method components.

First-stage SOM methods: For the first-stage SOM iterations, we follow Delgado et al. (2017) and set the minimum SOM grid size ($S \times S$) 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. Determining N, originally intended to represent the number of unique input data points (as in Delgado et al., 2017), required modification as this approach was infeasible at our spatial resolution (>2 million grid cells, thus 2 million input features) as it 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 used to estimate the number of patterns in the input data (i.e., N) which then set the range of first-stage SOM grid sizes ($S_{\min} = 10$, $S_{\max} = 42$). We generated a set of 60 alternative SOM models for each S from $S_{\min}$, $S_{\min} + 2$, $S_{\min} + 4$, …, $S_{\max}$ (1,020 SOM models across all grid sizes). As this procedure was designed to guide identification of the optimal first-stage SOM grid size, we deemed it unnecessary to develop these SOMs on the full input data (>2 million data points) and instead conducted this step using the synthetic representation of the data space generated by our k-means cluster centers. This process identified the SOM grid size $S = 22$ best balanced SOM-specific and general clustering performance metrics (see below). With this optimal grid size identified, we then developed a set of 60 alternative SOMs at $S = 22$ using the full set of input features and selected the best performing model using performance metrics as described below. The codebook vectors from his best performing model yield a set of 484 features that reflect the underlying structure of the input data (Figure S3 in Supporting Information S1) 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 models. During this second stage, we followed Delgado et al. (2017) and iterated across one-dimensional SOM grid sizes so that models that determine prime numbers of clusters can be evaluated. For these second stage SOMs, we set a minimum size ($1 \times S$) of $S_{\min} = 2$, and a maximum size of $S_{\max} = 30$ following the upper limit of classes to identify as recommended for archetype analysis (Eisenack et al., 2019). As the input feature space is considerably smaller in this second stage, we generate a set of 120 alternative SOM models for each grid size S from $S_{\min}$, $S_{\min} + 1$, $S_{\min} + 2$, …, $S_{\max}$ (3,480 SOM models across all grid sizes). The best-performing SOM model from this set produces the groundwaterscapes presented in this study. The crisp (e.g., mutually exclusive) classification provided by our method (where each grid cell is associated with a single node in the selected first-stage SOM model, and each of these first-stage SOM nodes is associated with a single node in the selected second stage SOM model) enables a simple reclassification of geospatial grid cells to their respective groundwaterscape.

SOM performance metrics: For the first-stage SOM models, 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 neighbors 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. The SOM model with the minimum combined performance score is selected as the best-performing model.

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 in Supporting Information S1). We do not use this size preference function with equal weighting to 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 alternative SOM models at each 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 models for each grid size if any of the SOM'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 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 across the set of alternative models while varying (a) the allowable limit of performance deviation and (b) 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 a transparent selection among alternative optimal models to best fit the needs of the study. As 15 clusters are proposed across the majority of sensitivity analysis combinations (Figure 3, panel 6), a second-stage SOM model of grid size 1×15 was selected as the optimal solution to this clustering problem.

2.4. Post Hoc Analysis

We calculated several landscape metrics to evaluate the spatial distribution of the groundwaterscapes within the large aquifer systems of the world (Richts et al., 2011). 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 complexity (Nowosad & Stepinski, 2019). Calculating these metrics within the large aquifer systems of the world facilitates the exploration of spatial patterns of groundwaterscapes in 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 data set of global groundwater monitoring well locations. To assess the coverage of monitoring wells across groundwaterscapes, we calculated both the number of monitoring wells found within each groundwaterscape as well as the monitoring well area density per groundwaterscape.

3. Results and Discussion

3.1. Global Groundwaterscapes

Our classification method identifies and maps a set of 15 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. These characteristic configurations of function magnitudes are visualized for each groundwaterscape using radial plots (Figures 4d and 4e).

We find that groundwaterscapes span spatially contiguous regions and capture broad patterns visible in the individual and underlying groundwater functions (e.g., as shown in Figure 2). The largest groundwaterscape by surface area (GS1) 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 and covers 18% of the land surface assessed in this study (Figure 4b). By contrast, the smallest groundwaterscape (GS11) represents industrial agricultural regions dependent on groundwater and is found in the American Midwest, California's Central Valley, Argentinian Pampas, the Paris Basin, and in Northeastern China and covers 3% of the land surface. All of the remaining groundwaterscapes cover between 5% and 9% of the land surface (Figure 4b). Groundwaterscapes are described individually in Table 3 and the extent of individual groundwaterscapes are mapped in Figure S5 in Supporting Information S1. Figure S6 in Supporting Information S1 shows the interquartile range of function magnitudes within each groundwaterscape to supplement the radial plots shown in Figure 4.

We group the 15 groundwaterscapes into seven groups (Figure 4e), as guided by agglomerative clustering (Figure 4c), to provide a simplified version of this classification scheme and to enable easier interpretation of groundwaterscape descriptions and differences. Groundwaterscape groups share overarching similarities but

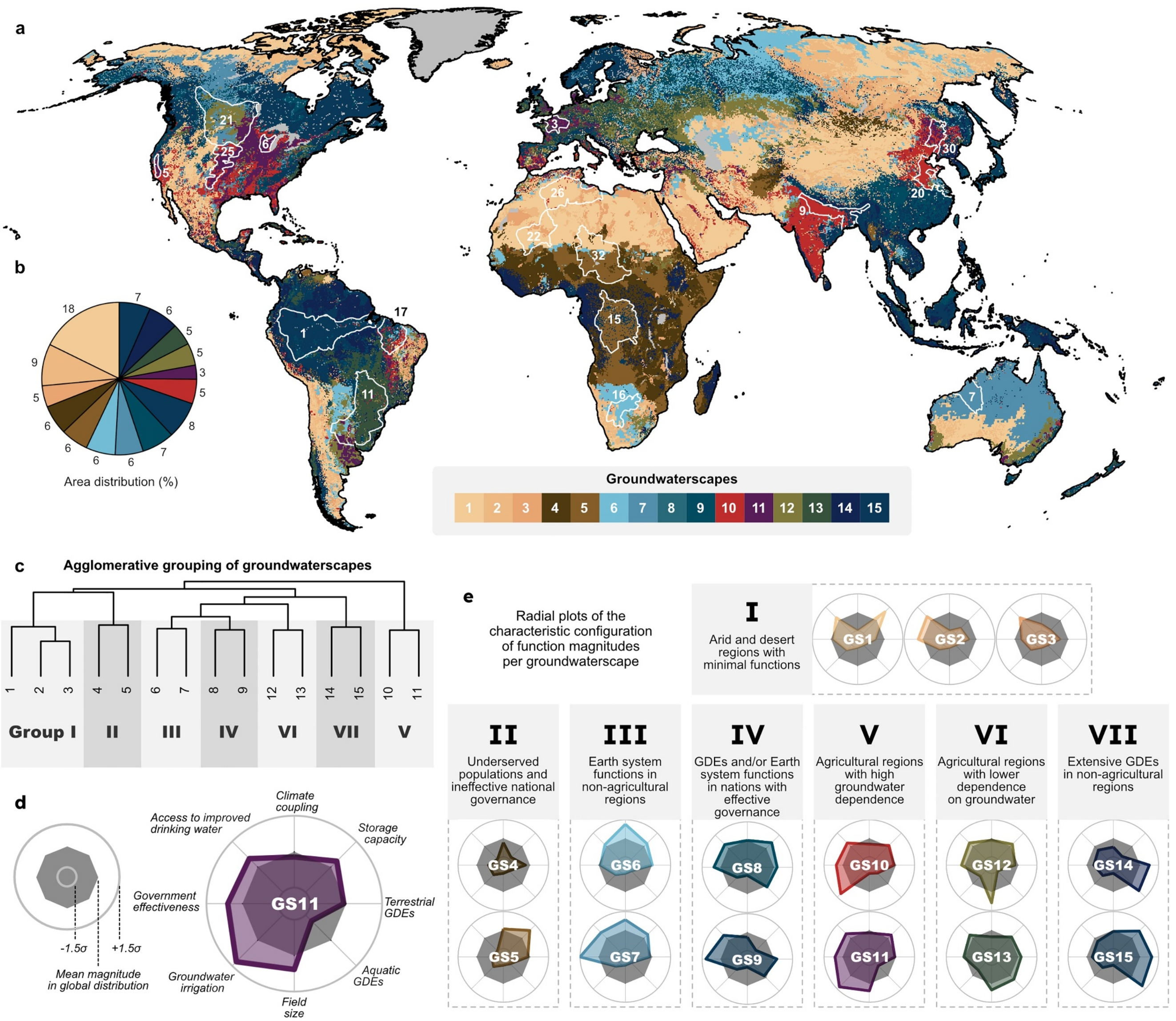

Figure 4. Global groundwaterscapes. (a) Map of the 15 derived groundwaterscapes. White polygon outlines and annotated numbers represent aquifer systems and aquifer IDs that are shown in subsequent figures. (b) Area distribution of groundwaterscapes. (c) Agglomerative grouping of groundwaterscapes. (d) Radial plot legend. (e) Radial plot of function magnitudes per groundwaterscape. Figure S6 in Supporting Information S1 shows the interquartile range of function magnitudes for each groundwaterscape.

differ on a subset of functions. For instance, GS14 and GS15 (group VII) are identified as landscapes that have extensive aquatic and terrestrial GDEs, limited agricultural functions, and generally ineffective national governance but differ in storage capacity. Similarly, GS10 and GS11 (group V) are characterized as agricultural regions dependent on groundwater irrigation, yet GS10 is characterized by smallholder farms whereas GS11 is characterized by large-scale, industrialized agriculture. Of the 15 groundwaterscapes, 11 describe non-agricultural regions (groups I–IV, VII), while agricultural areas are described by four groundwaterscapes (groups V and VI).

We find that any grid cell of a given groundwaterscape is most likely to neighbor with grid cells of the same groundwaterscape (Figure S7 in Supporting Information S1). 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 and contiguous 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

Table 3
Groundwaterscape Descriptions

Groundwaterscape group	Additional descriptions of individual groundwaterscapes	Example region
I: Arid and desert regions with minimal functions		
GS1	Large storage capacity	Sahara
GS2	Small storage capacity and moderately effective national governance	Arabian Peninsula
GS3	Small storage capacity and ineffective national governance	Northern Libya
II: Underserved populations and ineffective national governance		
GS4	Some terrestrial GDEs amid generally limited functions	Great Rift Valley
GS5	Large storage capacity, moderate climate coupling, and some terrestrial GDEs	Congo Basin
III: Earth system functions in non-agricultural regions		
GS6	Some terrestrial GDEs	Siberia
GS7	Effective national governance and some terrestrial GDEs	Northern Australia, Northern Canada
IV: Moderate GDEs and/or Earth system functions in nations with effective governance		
GS8	Large storage capacity and moderate climate coupling	Eastern China
GS9	Small storage capacity and very effective national governance	Scandinavia
V: Agricultural regions with high groundwater dependence		
GS10	Smallholder farming and moderately effective national governance	Ganges basin
GS11	Large farms with effective national governance	California Central Valley
VI: Agricultural regions with lower dependence on groundwater		
GS12	Moderate climate interactions, few aquatic GDEs, large farms	Canadian Prairie
GS13	Large farms situated among GDEs	Southeastern Brazil
VII: Extensive GDEs in non-agricultural regions		
GS14	Small storage capacity, underserved populations, and ineffective national governance	Eastern Madagascar
GS15	Large storage capacity, large range in underserved populations, and ineffective national governance	Amazon Basin

than others. To represent this "fit" of groundwaterscape classification at the grid cell level, we plot the Z-score of grid cell residual magnitudes per groundwaterscape (Figure S8 in Supporting Information S1). We find that some regions correspond tightly with their groundwaterscape model, such as the Amazon, central USA, and the Greater Sahel region. Other regions, such as the Congo basin have functional configurations with relatively large residuals from their associated groundwaterscape model and could benefit from an investigation of "nested" groundwaterscapes (cf. Sietz et al., 2017) to further differentiate and describe groundwater systems in these regions. Using the intermediary codebook vectors produced through the first-stage SOM provide a sub-groundwaterscape classification that could be used for this purpose. However, we leave such recursive groundwaterscape derivations and investigations for future study.

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 look to 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 GS12 (industrial agriculture with low-moderate groundwater use) characterizing the central and western extents of the aquifer and GS11 (industrial agriculture with high groundwater use) found across its southeastern regions. In addition to reflecting the gradient in agricultural reliance on groundwater within the aquifer, the groundwaterscapes also capture the aquatic and terrestrial GDEs in the northeastern reaches of the aquifer through assignment to GS9 (moderate GDEs with small storage capacity). We similarly illustrate how this overlaying of system functions can visually confirm and clarify groundwaterscape maps for the Guarani Aquifer System, Northwestern Sahara Aquifer System, Ganges-Brahmaputra Basin, and North China Aquifer System (see

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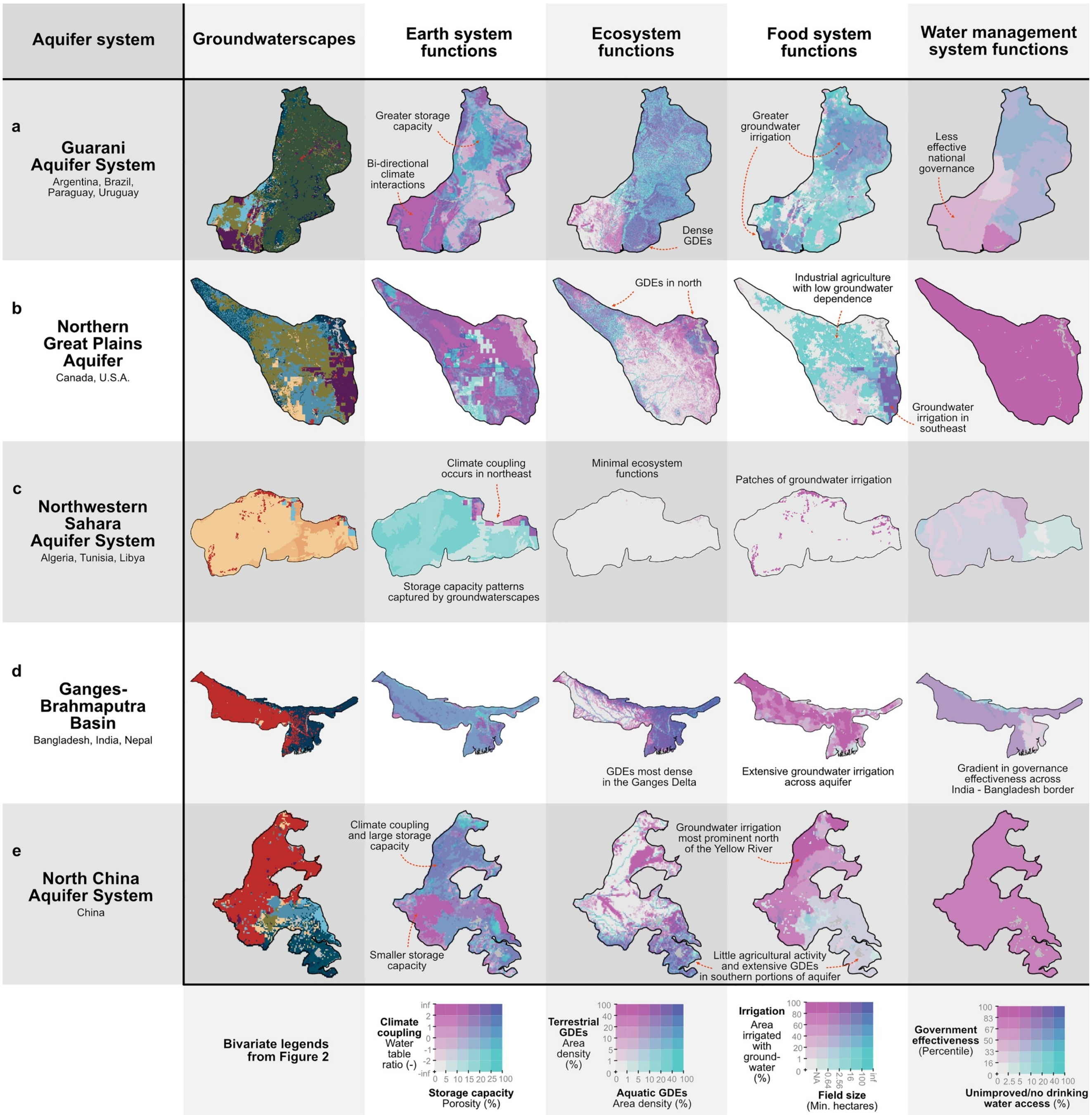

Figure 5. The multidimensional composition of groundwaterscapes. Columns represent spatial patterns in groundwaterscape distributions, Earth system functions, ecosystem functions, food system functions, and water management system functions for five aquifers: (a) the Guarani Aquifer System, (b) The Northern Great Plains Aquifer, (c) the Northwestern Sahara Aquifer System, (d) the Ganges-Brahmaputra Basin, and (e) the North China Aquifer System. We provide a similar mapping of all 37 large aquifer systems of the world in Figures S9–S16 in Supporting Information S1.

in-figure annotations in Figure 5). Below, we further explore and discuss the fidelity of the groundwaterscape maps by briefly placing global results in relation to recent regional descriptions of the greater Sahel region (Rohde et al., 2024) and California's Central Valley (USA) (Huggins, Gleeson, Castilla-Rho, et al., 2023).

The Greater Sahel region is characterized by a challenging intersection of food and water insecurity, cultural diversity, social instability, and weak governance. In these drylands, groundwater crucially sustains terrestrial GDEs that support biodiversity and offer refuge for pastoralists during drought (Rohde et al., 2024). In our mapping, the region is predominantly characterized by groundwaterscape group II (GS4 and GS5: underserved populations and ineffective national governance). Moderate terrestrial GDE densities are represented in both of these groundwaterscapes, a result that is consistent with the prevalence of these ecosystems in the Sahel relative to more extensive GDE landscapes in humid climates, such as across the Amazon and Indonesia. The groundwaterscapes thus broadly reflect the underutilized role of groundwater in the Sahel to support rural water and food security and the challenges of accomplishing development goals in a region with fragile institutions. Yet, local-scale dynamics such as the linkages between GDEs and pastoral livelihoods are invisible to our global groundwaterscapes.

California's Central Valley is one of the most productive agricultural regions in the USA and worldwide. Here, industrial agriculture is highly reliant on groundwater for irrigation while thousands of domestic wells underpin rural water security (Pauloo et al., 2020). Through the Sustainable Groundwater Management Act, there is a strong governance framework for groundwater in the state, which established local Groundwater Sustainability Agencies responsible for developing and implementing Groundwater Sustainability Plans (GSPs). Yet, through insufficient and uncoordinated stakeholder integration, the majority of GSPs currently fail to protect the majority of their agricultural wells, domestic wells, and ecosystems (Perrone et al., 2023).

In our mapping, the majority of the Central Valley is classified as Groundwaterscape 11 (industrial, large farms highly dependent on groundwater with effective national governance). Here, like in the Sahel example, groundwaterscapes broadly capture the dominant characteristics of these groundwater systems when evaluated in a global context. Yet, while the state-wide groundwater governance framework appears to be represented by the effective governance dimension of the groundwaterscape, this is a coincidental occurrence of state governance happening to correspond with the national governance indicator. Indeed, there exists a wide range of approaches to groundwater governance across U.S. states (for instance, 80% of land in neighboring Arizona has no groundwater regulation; Jacobs, 2009). While comparative reviews on groundwater governance have been conducted for specific regions or policy goals, such as the U.S. southwest (Nelson & Perrone, 2016) and in the context of managing GDEs (Rohde et al., 2017), there may be no good way to summarize and quantify sub-national levels of groundwater governance for use in quantitative global-scale studies.

These two examples point to the potential and limitations of these global groundwaterscapes. We show that the groundwaterscapes offer a capable tool to facilitate first-order differentiation of groundwater systems as social-ecological systems at the regional scale. Yet, simultaneously, we find that the methods we implement and our reliance on quantifiable processes and quantitative data simplify and “flatten” the place-based complexity of ecohydrological processes, governance, and on the interactions between water and food systems, which may be better expressed and represented at sub-global scales and/or in non-quantitative formats.

Characterizing groundwater systems as groundwaterscapes can facilitate science on the interlinkages between these diverse groundwater functions. While hypothesis testing is beyond the scope of this study, we pose hypothetical lines of inquiry to exemplify this potential. For instance, how might the expansion of irrigated agriculture across the Northwestern Sahara Aquifer System (UNECE, 2020) alter the dominant mode of groundwater-climate interactions and impact ecosystems in these landscapes? Alternatively, how might regional differences in storage capacity within the Guarani Aquifer contribute to different realities regarding climate resilience across groundwater irrigating regions in the north and south of the aquifer? This thinking can also be facilitated at groundwaterscape level. For instance, we find a point of interest in the co-occurrences of landscapes with extensive GDEs in nations with generally ineffective governance (i.e., GS14 and GS15). Might these groundwaterscapes simply be a product of an independent intersection of climate zones and national development trajectories? Else, might effective governance play a role in agricultural industrialization (cf. Thirtle & Piesse, 2007) that may in turn drive land use change and lead to degraded, fragmented, and more spare GDEs? These are the lines of inquiry and types of hypotheses that we envision the groundwaterscapes concept to facilitate.

Groundwaterscapes on their own cannot answer these questions. Yet, the groundwaterscapes provide a spatial template of comparable units to evaluate particular system behaviors across a variety of system conditions. Given that generalizing relationships in complex freshwater systems, such as biodiversity responses to environmental flow transgressions, has proven analytically challenging (Mohan et al., 2022), we suggest that integrating groundwaterscapes and their derivatives in similar investigations can provide an alternative zonal template for analysis of these complex, interlinked systems.

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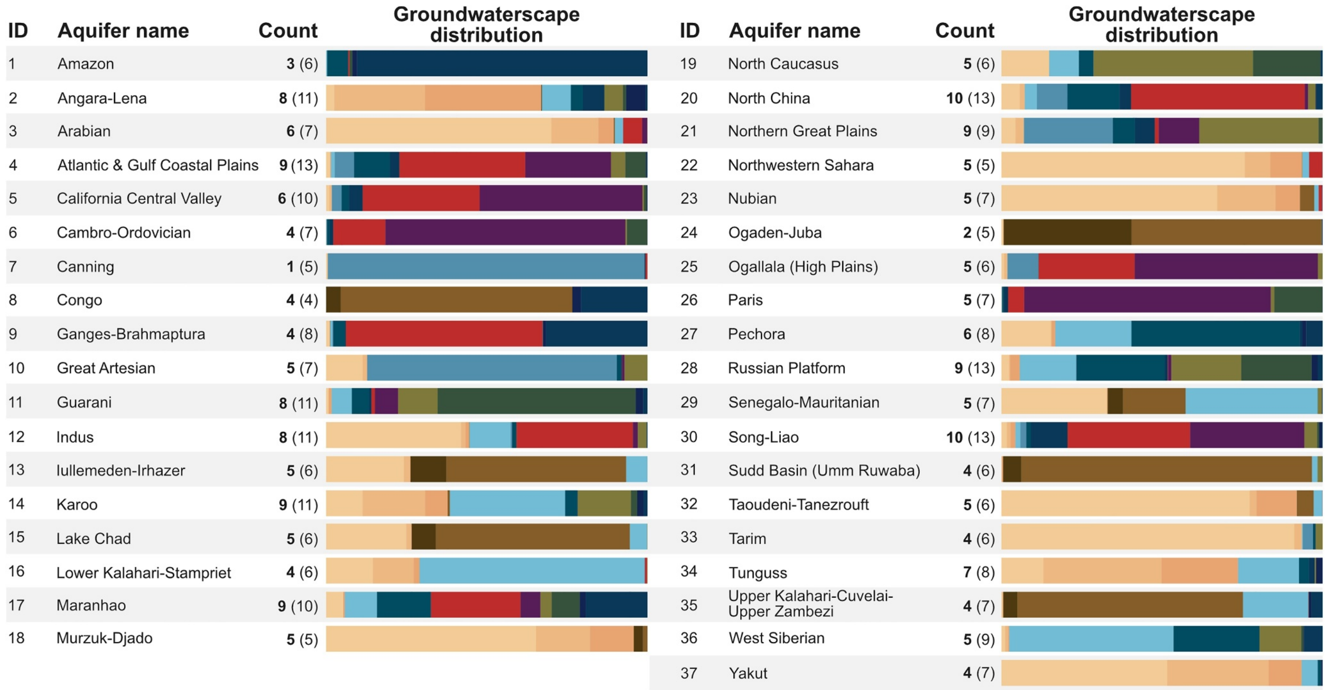

Figure 6. Groundwaterscape area distributions in the large aquifer systems of the world. Groundwaterscape counts are calculated based on those that cover a minimum of 1% (and 0.1%) of the aquifer's area.

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 2 and 1 groundwaterscapes, respectively, mapped across more than at least 1% of the aquifer's surface area (6 and 5 groundwaterscapes when using a 0.1% area threshold). For the remainder of this section, we will discuss groundwaterscape counts per aquifer in correspondence to the number of groundwaterscapes meeting a 1% area threshold.

In contrast to these relatively homogenous aquifers, the Karoo Basin (South Africa) and Maranhão Basin (Brazil) both contain nine groundwaterscapes. That 9 of the 15 groundwaterscapes (60%) are found within these aquifer's boundaries highlight their respective region's exceptional groundwater system heterogeneity. Groundwaterscape composition can also vary considerably over relatively short distances. For instance, the Maranhão Basin and Amazon Basin exist at opposite ends of this spectrum of groundwaterscape diversity yet are separated by less than 100 km at their nearest points.

We perceive the 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 contiguous

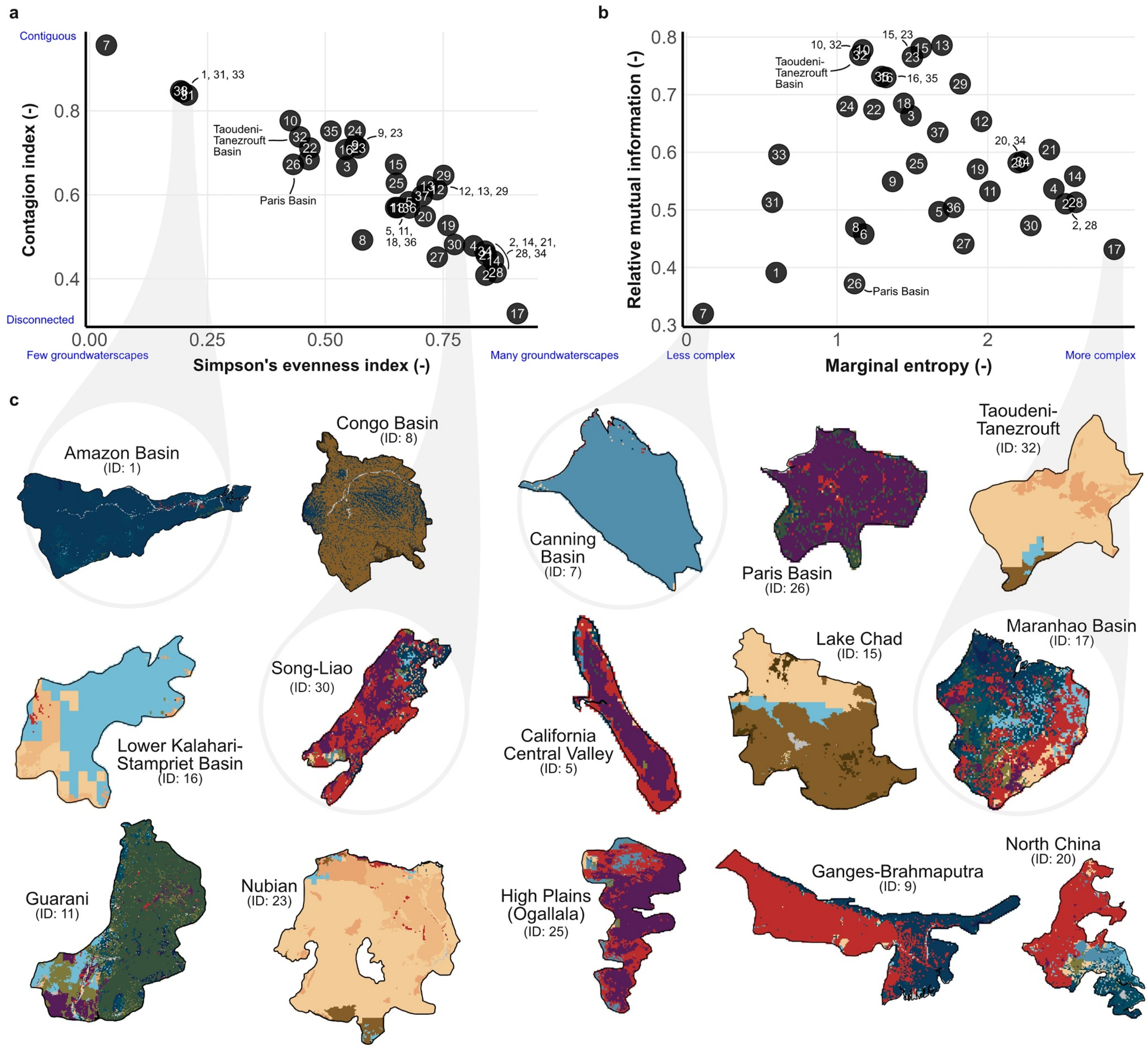

Figure 7. Landscape metrics of groundwaterscapes within the large aquifer systems of the world. (a) Plot of Simpson's evenness index (x-axis) and the contagion index (y-axis). (b) Plot of marginal entropy (x-axis) and relative mutual information (y-axis). (c) Groundwaterscape distributions within highlighted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

groundwaterscapes patches could support a more disaggregated specification of storage trends within aquifers while simultaneously facilitating contextualized thinking about the potential socioeconomic, ecological, and Earth system functions at risk due to hydrological change.

Simply counting the number of groundwaterscapes within an aquifer provides an introductory but incomplete description of the groundwaterscape distribution within aquifer systems. For instance, although the Guarani Aquifer System and Karoo Basin (South Africa) contain a similar number of groundwaterscapes within their boundaries (8 and 9, respectively), it can be observed that one groundwaterscape is relatively dominant and covers a considerable area fraction of the Guarani while the nine groundwaterscapes within the Karoo Basin are more evenly distributed by area (Figure 6). Thus, we supplemented this analysis by calculating several additional landscape metrics to further describe the spatial patterns of groundwaterscapes within aquifers (Figure 7). While

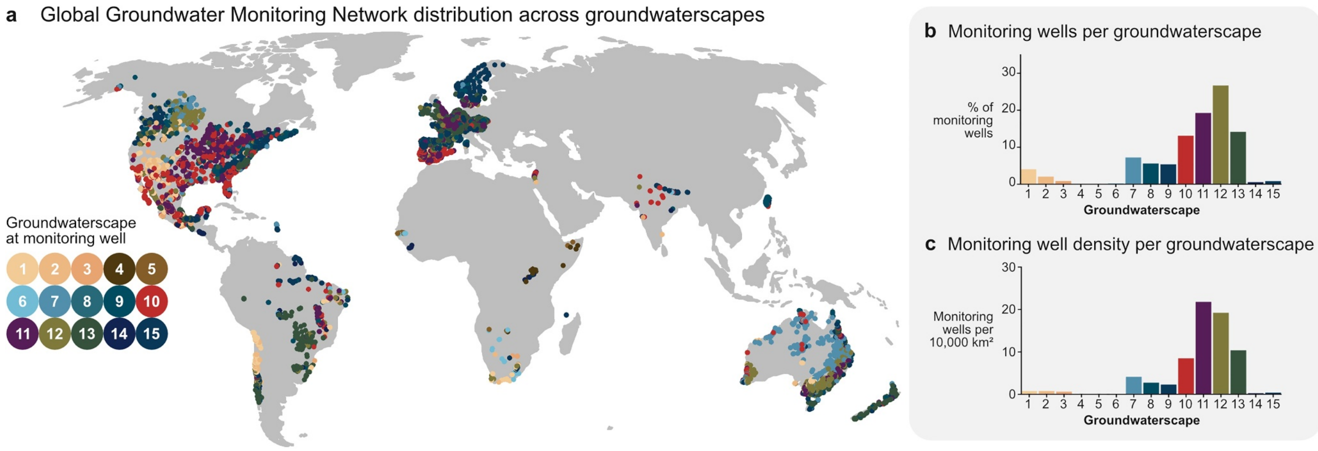

Figure 8. Distribution of Global Groundwater Monitoring Network (GGMN) wells (IGRAC, 2024) across groundwaterscapes. (a) Map of GGMN wells colored according to their groundwaterscape. (b) Proportion of GGMN wells found within each groundwaterscape. (c) GGMN well density per groundwaterscape.

similar analyses could be conducted across other zonal templates (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 and Canning Basin as among the least diverse and most contiguous in their groundwaterscape make-up, whereas the Song-Liao Basin (China) and Maranhão Basin 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 approach that has been used to differentiate and classify landscape patterns through indices with weaker correlation (Nowosad & Stepinski, 2019). When applying this approach (Figure 7), 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 future applications of the groundwaterscapes that would benefit from grouping aquifers based on similarity in their groundwaterscape composition and complexity.

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 behavior is a function of interacting Earth system, 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 GS11–GS13 (characterized by industrial agriculture) benefit from >60% of all monitoring wells despite covering a combined 13% of the land surface (Figure 8b). Conversely, some groundwaterscapes, such as GS4–GS6, have very little representation in the observation network. These groundwaterscapes cumulatively contain less than 1% of all monitoring wells yet cover over 18% of the land surface. These monitoring disparities widen when normalizing by surface area (Figure 8c). While GS12 contains the most monitoring wells, GS11 has a higher monitoring well density. As economic factors and governance capacity influence the ability of jurisdictions to monitor their groundwater resources, it is not surprising that groundwaterscapes characterizing industrial agriculture dominate the monitoring network distribution. Indeed,

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even within agricultural regions we see imbalances in monitoring. For instance, GS10 (groundwater-reliant smallholder agriculture) has about one-third of the monitoring well density of GS11.

The biases we observe in the well network may not be entirely independent from our derivation method as we may expect that groundwaterscapes characterized with more effective national governance would benefit from more 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 used as a tool to identify data collection priorities, and as a deliberation device to re-imagine what effective groundwater data collection entails in order to assemble more representative and capable sets of observations to understand change in groundwater- connected systems.

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 systems as social-ecological systems. Yet moreover, these groundwaterscapes represent a global mapping of the alternative conceptual model presented by the groundwater-connected systems framing (Huggins, Gleeson, Castilla-Rho, et al., 2023) and thus support an overarching ambition to characterize, understand, and manage groundwater systems on the basis of the resource's role in 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 rather is a general problem in 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 global data sets that correspond closely with our conceptual model, and in implementing a robust and reproducible derivation method. We bound our study by acknowledging that the groundwaterscapes only represent the groundwater functions included in our conceptual model, and omit important functions that occur in coastal environments, small islands, permafrost regions, and urban settings. We additionally do not consider non-agricultural economic uses of groundwater such as mining, manufacturing, and energy generation, nor do we consider groundwater quality or geochemical functions. We foresee the potential for adapted groundwaterscapes to address these conceptual limitations and readily welcome the pluralization 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, analysis ready, and open-access data to represent each function in our conceptual model, several data sets would benefit from further refinement. We used data layers for their most-recent year available, but some layers are now considerably dated such as groundwater irrigation areas which correspond to the year 2005. Additional challenges to individual data sets include a simple, inference-based approach used to map GDEs, the lack of a specific groundwater governance data set, and a reliance on a drinking water services data set that does not separate groundwater from other sources. Yet, we view these data limitations as opportunities for future groundwaterscape improvement. We note that our reproducible methods and script repository enable the update of our groundwaterscape map following the release of new data sets.

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 toward visions of "physically-based continental Earth system models" (Bierkens, 2015), could benefit from parameterization and conceptual model development facilitated through 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 modeling or field work studies.

Groundwaterscapes can more generally be used to test hypotheses on groundwater-connected system behavior. Thus, groundwaterscapes can support the application and development of middle range theories of change to groundwater science, which represent "contextual generalizations 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 the concept of groundwaterscapes, which are landscape units with common configurations of groundwater system functions. We classified and mapped groundwaterscapes globally based on eight large-scale groundwater functions across Earth systems, ecosystems, food systems, and water management systems using a two-stage, deeply iterative SOM method. The 15 groundwaterscapes characterize landscapes such as arid and desert regions with minimal functions, underserved populations with ineffective governance, Earth system functions in non-agricultural regions, moderate GDEs or Earth system functions with effective governance, agricultural regions with both high and low dependence on groundwater, and non-agricultural regions with extensive GDEs. 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 assessments. We found a striking imbalance in global monitoring wells across groundwaterscapes with only three groundwaterscapes benefiting from 60% 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 in social-ecological systems. Important steps are being taken in this direction by multiple research groups, mainly oriented around developing understanding of pairwise system interactions 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 toward developing a more holistic, system-of-systems understanding of groundwater at the global scale.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

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-organizing 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, 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, 2018), GDEs (Huggins et al., 2023a), groundwater irrigation (Siebert et al., 2013), farm field size (Lesiv et al., 2018), the Worldwide Governance Indicator of government effectiveness (Kaufmann & Kraay, 2023), safe 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 the results are deposited on Borealis, the Canadian Dataverse Repository (Huggins et al., 2024). The script repository is also accessible online at: https://github.com/XanderHuggins/groundwaterscapes.

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