Hidden flux partitioning in the global water cycle

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Abstract

The various water fluxes of the global terrestrial water cycle are integral to the Earth system and the well-being of societies. However, fluxes occurring below the land surface, such as groundwater recharge and discharge, are more poorly constrained observationally than surface fluxes like streamflow. Consequently, the broader relevance of these hidden fluxes is less well understood and their global estimates are more uncertain. Here we combine multiple observational datasets and theoretical considerations within a *Budyko*-type water balance framework, providing a starting point for enhanced understanding of subsurface water partitioning at large scales. Observations indicate that climatic aridity substantially influences subsurface flux partitioning, but that there is considerable variability in need of further explanation. We show how this framework can be used to integrate empirical data, theoretical constraints, and model-based insights to better understand subsurface flux partitioning and its controlling factors. Such a holistic approach is essential to better understand subsurface water cycling, especially in the face of increasing resource demands and climate change.

Main

Freshwater resources are essential for sustaining life on Earth and supporting human survival. However, human activities, including land-use changes, freshwater use and climate change, are substantially altering the global water cycle [1], making sustainable water management increasingly critical. Achieving this requires a thorough understanding of the complex partitioning of water fluxes within the terrestrial water cycle across both space and time.

The movement of water between the atmosphere and subsurface – including through vegetation (i.e., green water) and surface or groundwater (i.e., blue water) – has garnered considerable scientific attention [e.g., 2–4]. However, understanding how these fluxes partition within the water cycle, particularly in the subsurface, remains a major challenge [5]. This is largely due to the hidden nature of groundwater, which is difficult to observe across large areas because most data come from sparse, spatially biased point measurements such as boreholes [6]. In addition, limited knowledge of the spatial variability of hydrogeological properties further complicates assessments of subsurface fluxes [7].

To address some of these limitations, assembling quasi-global observational datasets from in-situ measurements has become an important approach for tracking water fluxes and storage across space and time [e.g., 8–12]. In addition, satellite-based and airborne remote sensing provide spatial and temporal information on precipitation, evaporation, surface water (liquid and frozen), soil moisture, and groundwater [e.g., 13]. For subsurface observations, the *Gravity Recovery and Climate Experiment* (GRACE) and follow up (GRACE-FO) missions have been offering a unique approach by measuring temporal variations in Earth's gravity field to infer changes in total terrestrial water storage over space and time [e.g., 14–16].

Despite advances in observational tools, major gaps remain in our ability to quantify and understand subsurface water partitioning. This is particularly concerning because groundwater – the largest usable freshwater reservoir – is deeply interconnected with surface processes [8]. It sustains billions of livelihoods [e.g., 17], supports ecosystems [e.g., 18], and provides vital services such as water purification, contaminant biodegradation, nutrient recycling, and flood and drought mitigation [e.g., 19]. A clear understanding of both surface and subsurface water fluxes is essential due to their central role in Earth system processes like biogeochemical cycling [20], ecosystem function [21], and human well-being [22], as well as their importance for achieving the UN Sustainable Development Goals [23]. In summary, groundwater plays a key role in the global water cycle [24] and is a vital resource [25], making it crucial to understand how, where, and why it is partitioned.

The proportion of precipitation that leaves the land surface as streamflow and (complementary to this) as evaporation is relatively well constrained through in-situ and remote observational methods, at least at climatological time scales. Early 20th-century researchers developed empirical formulas to estimate mean annual streamflow and evaporation using climatic data, with *Schreiber*'s [26] exponential equation being a notable early effort. Based on observations from 29 large (>10,000 km^2) basins, *Mikhail Ivanovich Budyko* [27] refined these early models and suggested that a catchment's long-term mean evaporation (E, evaporation which includes transpiration) and streamflow (Q) are largely governed by the balance between water availability (mean precipitation, P) and energy availability (originally quantified as net radiation divided by latent heat of vaporization, but now commonly as mean potential evaporation, PE). These factors are often combined into climatic aridity (A), defined as the fraction PE/P. Regions can be classified as water-limited, where E is constrained by available precipitation ($A > 1$), or energy-limited, where E is constrained by available energy ($A < 1$). Despite its simplicity, *Budyko*'s conceptual model works surprisingly well and thus provides a comprehensive baseline for constraining the main fluxes leaving the land surface, even if open questions and exceptions remain [28].

Infiltrated precipitation can follow multiple pathways: it may be stored in the soil and taken up by plants, run off as stormflow, or percolate deeper into the subsurface to recharge groundwater. This water adds to subsurface storage and travels along flow paths with residence times ranging from hours (e.g., surface water-groundwater interactions; [29]) to millions of years (e.g., deep groundwater; [30]). Along the way, it can end up as transpiration [31], interact with rivers and streams as baseflow or transmission loss [e.g., 32], resurface as spring flow [e.g., 33], discharge into the ocean as submarine groundwater [e.g., 34], or be extracted by humans [e.g., 35].

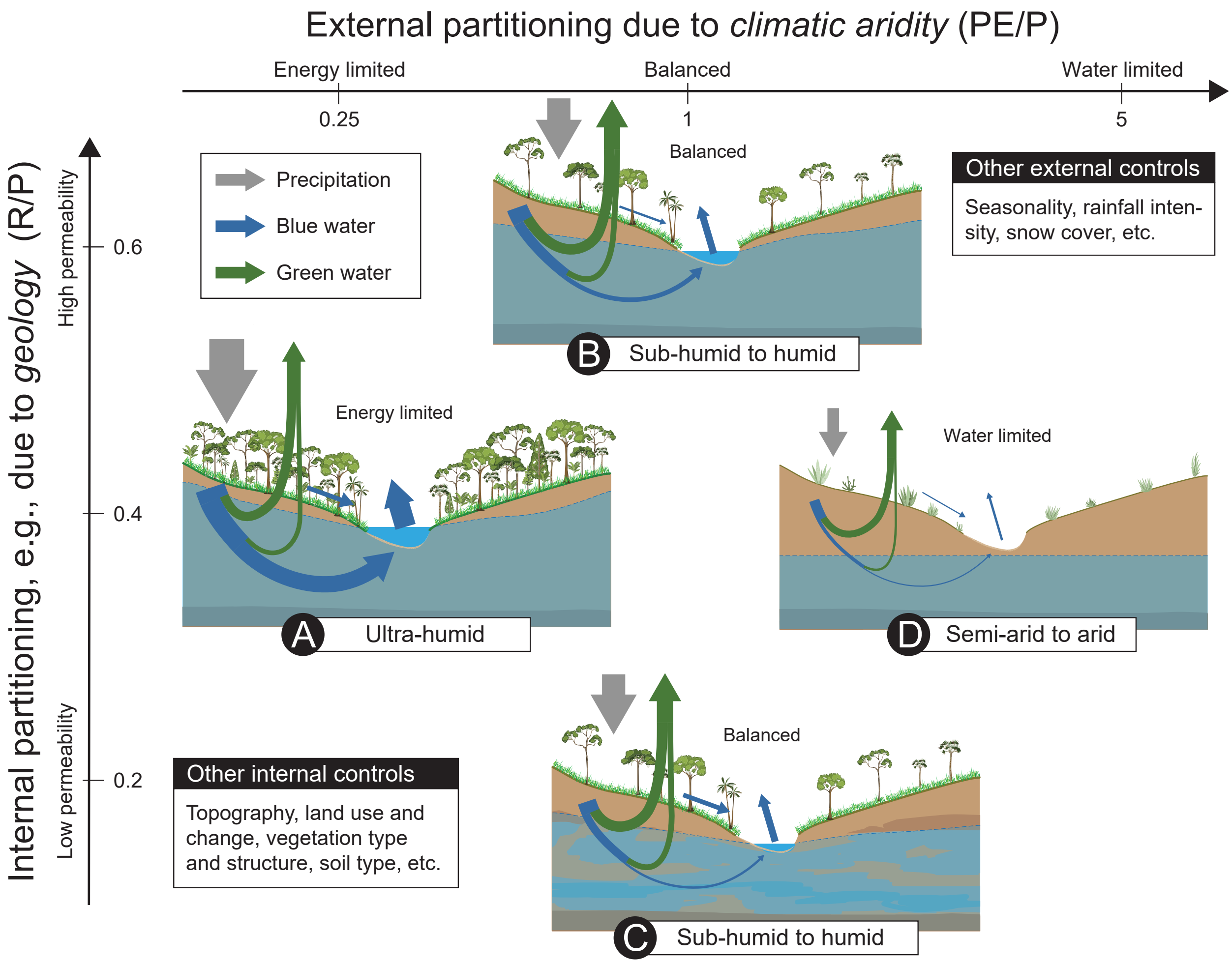


Fig. 1: **Illustrative overview of how climatic aridity and geology can influence water cycle flux partitioning.** Scenarios A to D demonstrate how flux partitioning may be affected by climatic aridity as an external driver and geology as an example of an internal control. Geology influences flux partitioning primarily through permeability and storage properties. Surface water and groundwater fluxes are shown in blue, while evaporation and transpiration are indicated by green arrows. Understanding the influence of different internal controls (e.g., topography, land-use and change, vegetation type and structure, etc.) on water flux partitioning remains challenging but is essential for advancing our knowledge of subsurface water cycling. Scenarios are illustrated at the catchment scale, typically reflecting headwater catchments, but the conceptual framework is intended to be applicable to larger domains. Human impacts and water use are acknowledged as additional factors affecting flux partitioning but are not explicitly represented in this overview.

While surface water fluxes such as evaporation and streamflow are often conceptualized as being primarily driven by climatic factors [e.g., 36], subsurface water fluxes are commonly perceived to be more strongly influenced by non-climatic controls [37]. These include topography [e.g., 38], vegetation and soil properties [e.g., 5, 39], as well as geological features [e.g., 40]. For example, vegetation regulates evaporation – the dominant component of many ecosystem water balances [41, 42] – and therefore influences soil moisture, and also modifies soil properties and facilitates deep drainage [e.g., 5, 43, 44]. Topography influences whether infiltrated water moves mainly vertically or laterally, and areas of topographic convergence can constitute hot-spots for localized recharge [38]. In addition, lateral redistribution of water along topographic gradients can partly decouple water availability from precipitation, both at hill slope [45] and at larger scales, for instance as mountain block recharge [46]. Geology, through its control on soil and hydrogeological properties, modulates groundwater flow and associated partitioning across spatial scales [e.g., 40, 47], but is inherently heterogeneous [48].

Controls influencing water flux partitioning may be broadly grouped as '*external*' (e.g., precipitation, energy availability) or '*internal*' (e.g., vegetation, soil, geology), depending on the spatial and conceptual boundaries of the system under study. In Figure 1, we illustrate this distinction at the catchment scale, with climatic aridity as a widely accepted external driver (following *Budyko*'s approach), and geology as an internal control. It should be noted that aridity and geology are just two examples of external and internal controls, and other external (e.g., seasonality) and internal (e.g., vegetation type, topography, geology) controls may influence partitioning in different (and sometimes interacting) ways.

The partitioning of infiltrated water – how much of it becomes recharge or other subsurface fluxes – is difficult to quantify and generally less well constrained than surface fluxes. *Abbott et al.* [49], for example, have shown particularly large uncertainties for global groundwater recharge (10,000–25,000 km^3/yr) and submarine groundwater discharge (100–6,500 km^3/yr). Hydrological models have advanced and are widely used to simulate water cycle fluxes from local to global scales [e.g., 50–54]. However, subsurface fluxes remain challenging to represent due to limited observability. GRACE data show that models often underestimate decadal water storage trends [55], and comparisons with recharge estimates reveal significant discrepancies in precipitation partitioning [56, 57]. These findings are echoed in recent efforts to "*close the water cycle from observations across scales*", where some of the largest relative uncertainties were reported for groundwater recharge (13%) and discharge (60%) [58].

The disconnect between observations and models contributes to persistent uncertainties in the quantification of global water cycling [e.g., 59], posing challenges for the understanding of groundwater's role in the Earth system [6], for the sustainable use of groundwater [60] and for understanding the effects of irrigation on subsurface water partitioning [61]. *Budyko*-type constraints have shown potential in reducing uncertainties in the simulation of streamflow and evaporation across catchments globally [62], and similar constraints might exist for subsurface variables such as groundwater recharge [56]. Here we propose a generalized *Budyko*-type framework leveraging existing datasets and theoretical considerations to constrain subsurface water flux partitioning, initially focusing on large temporal and spatial scales. This simple yet versatile framework provides a first step towards bridging observations and models, as well as surface and subsurface hydrology.

Insights from a synthesis of observations and theory

Similar to *Budyko*, we first consider long-term (i.e., climatologically driven) average water fluxes. This is partly because available quasi-global recharge datasets rarely provide temporal information, and partly because understanding the long-term water balance is a simple yet crucial starting point. We note that the term spatial scale is often used to refer to both the scale of the study domain (e.g., the globe) and that of the study unit (e.g., a catchment). Here, our focus is on large domains, as we want to compare many sites globally, while the individual units may still be classified as small-scale (e.g., headwater catchments or local recharge estimates). The extent to which observations at different spatial scales are comparable remains a largely unresolved question. However, we hypothesize that by comparing many sites, the scale of individual measurements becomes less important and, instead, relationships emerge that capture the dominant controls at larger scales.

Recent analyses of large groundwater recharge datasets show that long-term average recharge is primarily controlled by climate, particularly climatic aridity, and tends to follow a broadly predictable *Budyko*-type relationship [56, 63, 64] – though considerable scatter remains due to secondary influences. Building on these insights, we propose a generalized water balance framework that extends the classical *Budyko* curve to include not only evaporation and streamflow, but also groundwater recharge and other subsurface fluxes (Box 1), akin to earlier concepts by *L'vovich* [65]. This enables all major fluxes to be expressed as fractions of precipitation, which – under closed-system assumptions – should sum to the total input, offering a coherent basis for diagnosing water partitioning.

This extended *Budyko*-type framework offers two main advantages. First, it aligns water fluxes along the dominant global environmental gradient – climatic aridity – thus enabling systematic comparisons across climates and regions. Second, it provides physically based bounds based on water and energy availability, which, when combined with internal water balance constraints, enable joint evaluation of multiple fluxes. This helps to identify inconsistencies between observed, inferred, or modeled water fluxes across the surface–subsurface continuum.

In Figure 2, we illustrate how aridity-recharge relationships from three recent large-scale datasets [63, 64, 66] can be interpreted within this extended water balance framework, providing a first step toward integrating subsurface fluxes into broader hydrological partitioning frameworks. Although significant variability exists within and across datasets, calculating binned medians reveals a consistent pattern: recharge fractions (R/P) decrease as aridity increases, aligning with decreasing streamflow fractions (Q/P) as predicted by the *Budyko* curve, and with decreasing soil moisture observations (not shown here) [67].

We note that most available recharge data are concentrated in dry (water-limited) regions, leaving recharge behavior in humid (energy-limited) climates relatively poorly constrained. Also, while existing datasets reveal strong relationships between climatic aridity and subsurface fluxes such as groundwater recharge – supporting the view that aridity is a dominant global control [56] – they also exhibit substantial scatter (shown by shaded areas in Figure 2) and diverge between sources. These discrepancies arise from both data uncertainties and secondary influences such as topography, vegetation, and geology, which differ across datasets and affect the shape of the recharge–aridity relationships. For example, the dataset from *Moeck et al.* [63] suggests considerably higher recharge at $PE/P \approx 1$ than that of *MacDonald et al.* [64]. Much of the *Moeck et al.* dataset originates from Australia and includes some implausible values (e.g., $R/P > 1$) reported without uncertainty bounds – potentially contributing to deviations from theoretical expectations.

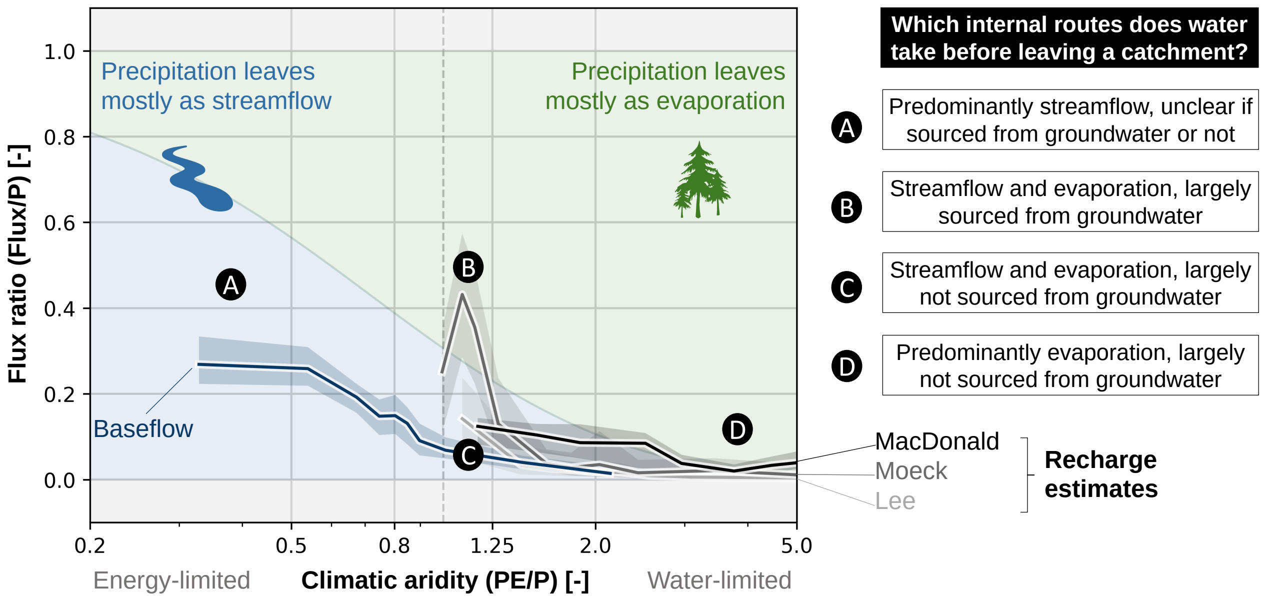


Fig. 2: **Subsurface partitioning of water fluxes plotted against climatic aridity.** Evaporation (green water) and streamflow (blue water) are based on the *Budyko* equation [36] and indicated by the green and blue areas, respectively. Long-term average groundwater recharge data are based on different observational datasets (*MacDonald et al.* [64]; *Moeck et al.* [63]; *Lee et al.* [66]), each paired with precipitation and potential evaporation data from *CHELSA* [68, 69]. Spearman rank correlations (ρ_s) between climatic aridity and recharge fractions are -0.54, -0.63, -0.51, respectively. Baseflow estimates and their corresponding aridity values are taken from *Gnann et al.* [70], with $\rho_s = -0.82$ between climatic aridity and baseflow fractions. The lines connect binned medians (10 equally sized bins) and the shaded areas show the 25^{th} and 75^{th} percentiles of the bins. Scenarios A to D correspond to those shown in Figure 1. The scenarios show different examples of external partitioning (streamflow vs. evaporation) and internal partitioning (i.e., if streamflow and evaporation are sourced from groundwater or not).

A notable advantage of the proposed framework (Figure 2 and Box 1) is its ability to explore hypotheses about flux combinations and their implications. For instance, if recharge fractions (R/P) are consistently high for a given level of aridity, this suggests substantial groundwater-fed streamflow, that is, baseflow (Q_b) [71, 72].

This hypothesis can be tested using independent estimates of baseflow, so we added baseflow fractions (Q_b/P) to Figure 2 [70]. Although these baseflow estimates are uncertain due to reliance on somewhat arbitrary baseflow separation methods, they indicate that baseflow fractions reach a plateau in humid regions (i.e., become less influenced by climate). Similar patterns have indeed been observed for recharge, which may point towards the important role of geology. In humid regions with sufficient rainfall, some fraction of potential recharge may be rejected due to a limited capacity of the subsurface to transmit or store infiltrated water, resulting in a non-climatic limit to the maximum amount of recharge and baseflow that can be generated [e.g., 70, 73, 74].

Beyond framing empirical observations, the water balance framework can also be used to examine theoretical implications of fitted curves for other fluxes. This can be illustrated by combining the water balance framework (Box 1) with fitted functions for recharge [56] and streamflow [36]. If we specify recharge and streamflow with these functions, the possible ranges of all other fluxes (e.g., baseflow) can be estimated by generating random flux combinations and only retaining those that respect the water balance constraints. For example, Figure 3a shows the theoretically possible ranges of baseflow fraction that can occur if we use the recharge curve from *Berghuijs et al.* [56]. We can now choose any functional relationship between aridity and recharge and explore the implications of this decision for other fluxes, assuming the assumptions made in Box 1 hold.

Figure 3a shows that the curve used in *Berghuijs et al.* [56] leads to high recharge fractions for humid climates for which there is little data constraint, and thus also to high baseflow fractions (approaching total streamflow, thus implying a baseflow index of close to 1 in humid regions). Based on the baseflow curve shown in Figure 2 and the presumption of a geology-related limit to recharge and baseflow in humid regions, we also fitted an alternative curve where recharge fractions decrease again for low aridities, shown in Figure 3b. This, by contrast, leads to a baseflow curve that decreases again for more humid regions and thus aligns more closely with the pattern shown in Figure 2. While this numerical experiment is simple and will need refinement, it demonstrates how the joint analysis of different flux fractions within the *Budyko*-type framework can lead to insights not possible from individual fluxes alone. Choosing a certain recharge curve has implications for the resulting baseflow pattern – as well as other fluxes – and thus reveals joint hypotheses that can be tested with observations and models. For instance, large differences between recharge and baseflow may indicate that a lot of recharge is subsequently taken up by vegetation. This may happen in regions where riparian vegetation transpires a lot of groundwater before it can discharge into the stream channel, thus reducing baseflow [33].

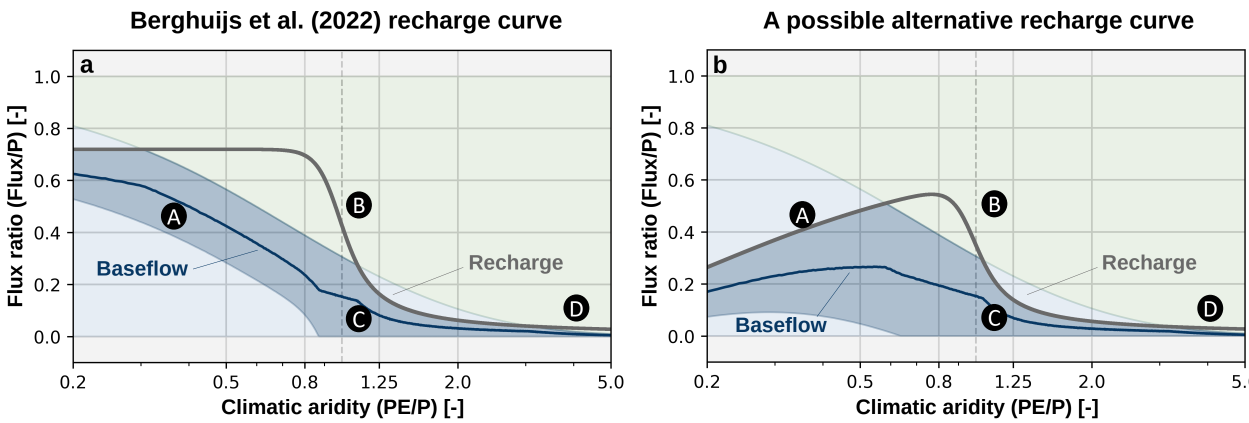
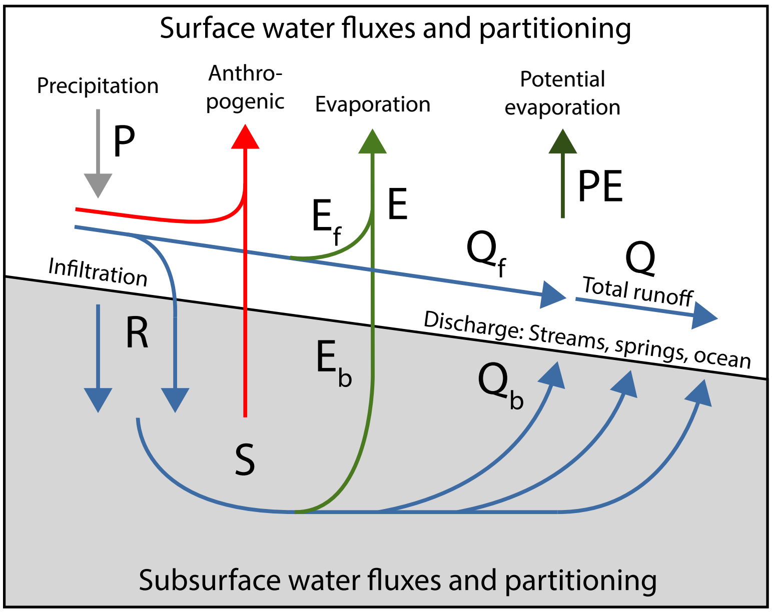


Fig. 3: **Possible groundwater recharge scenarios as a function of climatic aridity.** Combining *Budyko*'s curve and different groundwater recharge curves with the water balance equations (Box 1) reveals possible behaviors of internal flux partitioning. (a) Constrained range of baseflow values when using the recharge curve published in *Berghuijs et al.* [56]. (b) Recharge values and constrained range of baseflow for an alternative groundwater recharge curve, created by multiplying the Berghuijs et al. [56] values with an exponential decay factor that lowers the recharge fractions progressively towards lower aridities and thus mimics the baseflow pattern visible in Figure 2. To obtain possible ranges for the different internal fluxes (E_f, E_b, Q_f, Q_b), we randomly sampled values for all flux fractions not specified with any curve (i.e., for all but recharge, evaporation and streamflow) between 0 and 1 and only retained them if they did not violate any water balance assumptions (Box 1). The shaded areas represent the ranges of possible values, and the lines represent mean values. Scenarios A to D correspond to those shown in Figure 1.

In addition to uncertainties in individual flux measurements, baseflow estimation, climate data, and comparability issues (e.g., whether recharge was measured in a specific part of the catchment), the *Budyko*-type approach relies on three key assumptions. First, it assumes that the jointly considered flux datasets are representative of the same underlying relationships, for example the actual global flux distributions. This assumption may become problematic if the combined datasets are heavily biased towards certain regions (e.g., most recharge estimates are from Australia, while the baseflow estimates are from the US and the UK). Second, it assumes negligible changes in subsurface storage, implying steady-state conditions. Third, it presumes a closed water balance, which depends on the scale of consideration and may not hold true for as many catchments as commonly assumed [75].

Groundwater response times tend to be longer in arid regions [76] – for instance, some Saharan and Arabian aquifers are likely still responding to higher rates of recharge that increased hydraulic heads in the late Pleistocene [77] – , and arid catchments often exhibit more groundwater import or export [78]. This suggests that deviations from the idealized framework are more likely in arid regions. In contrast, such deviations are less significant in humid regions, where the relationship between recharge and baseflow should generally be more straightforward. It is generally possible to extend the framework to account for these issues. However, this is not our focus here and should stimulate follow-on research.

Box 1: Formulation of a simplified water balance framework.



To combine multiple water fluxes into a single water balance framework, we can use a set of water balance equations that establish quantitative links between various fluxes within a closed catchment system. The overall catchment water balance is given by:

$$\frac{dS}{dt} = P - Q - E, \tag{1}$$

where S is storage, t is time, P is precipitation (grey), Q is streamflow (blue), and E is evaporation (green, includes transpiration). Anthropogenic fluxes (red) are illustrated for completeness but not further considered. We also assume that there are no other inputs or outputs (e.g., groundwater flow) and that measurement errors are comparatively small.

Streamflow (Q) and evaporation (E) are assumed to consist of a part that originates from the land surface and unsaturated zone (subscript f) and from groundwater (subscript b). Together, groundwater-fed streamflow (i.e., baseflow) Q_b and evaporation E_b are assumed to equal groundwater recharge (R).

Internally to a system's boundary, we thus get more water balance equations:

$$Q = Q_f + Q_b, \tag{2}$$

$$E = E_f + E_b, \tag{3}$$

$$R = E_b + Q_b. \tag{4}$$

At long (i.e., climatological) timescales, storage changes are assumed to become negligible compared to water fluxes:

$$\frac{dS}{dt} \approx 0. \tag{5}$$

Overall, we can therefore write a water balance equation that integrates all water fluxes and respects the external water balance:

$$P = Q_f + Q_b + E_f + E_b = Q + E. \tag{6}$$

The assumptions made in this water balance framework may break down for individual sites or catchments, for instance due to cross-boundary fluxes such as inter-catchment groundwater flow or focused recharge from streams into the groundwater. Nevertheless, when looking across large domains with many individual sites, we expect these assumptions to hold on average and thus enable the identification of large-scale (e.g., global) relationships. Further, the simplicity of the framework enables exploration of how specific functional relationships (e.g., the recharge curve by *Berghuijs et al.* [56]; see Figures 2 and 3) influence other fluxes (e.g., baseflow), since all fluxes are interlinked through the above water balance equations.

Transient dynamics of water flux partitioning – challenges and implications

Applications such as global hydrological models and water resource assessments depend on accurate recharge estimates to constrain simulations of water availability [e.g., 79], assess groundwater sustainability, and inform policy decisions [e.g., 80]. However, these efforts are frequently hampered by large uncertainties or discrepancies with observed trends or patterns [53, 55–57]. Our proposed framework helps address this challenge by offering hydrologically informed constraints on multiple fluxes (Figure 3), yielding insights that complement individual observations. Like many current approaches, however, it focuses on long-term averages and assumes steady-state conditions. While these assumptions are essential for establishing baseline conditions and remain foundational to understanding Earth system processes, they limit our ability to capture dynamic system responses.

In reality, water cycle processes are highly dynamic and rarely operate in steady-state. Natural variability across time scales – seasonal to multi-decadal – as well as human activities and climate change, introduce transient and spatially heterogeneous forcings that alter internal flux partitioning. For instance, snow melt runoff in the western US has been shown to consist largely of older groundwater, revealing previously hidden subsurface dynamics [47]. Groundwater recharge responds to multiple factors, including seasonality [81], rainfall intensity [82, 83], and human water use [84], all of which may shift under climate change, which is projected to affect rainfall seasonality [85], flash flood and drought frequency [86, 87], and transient groundwater storage and recharge patterns [88]. In areas of depletion, streamflow can reverse from gaining to losing [89], and over-extraction may increase groundwater capture [90] or lead to land subsidence [91], whereas irrigation or managed aquifer recharge can enhance recharge under certain conditions [84]. These dynamics highlight the need for improved observational networks and models that explicitly account for non-stationarity [92].

Sustainable water management begins with quantifying renewable water use, as this provides the foundation for setting abstraction limits with value-based considerations [60]. Achieving this requires an understanding of how internal flux partitioning responds to both abstraction and system transients, such as climate or land-use changes. The '*water budget myth*' [e.g., 93], widely discussed in the hydrogeological literature, underscores that knowledge of long-term recharge alone is insufficient to predict hydrological responses to pumping. In reality, groundwater abstraction can affect partitioning across multiple components of the water balance. These impacts are highly context dependent and influenced by the spatial distribution and temporal dynamics of pumping itself. This principle extends beyond groundwater abstraction to encompass any temporally dynamic or spatially heterogeneous forcing, including climate change, land-use shifts, or engineered interventions.

Hydrological responses and water management strategies also vary regionally, particularly between humid and arid climates. In humid (i.e., energy-limited) regions, shallow water tables are more common [76, 94], leading to tighter coupling between the surface and subsurface, and more frequent bi-directional hydraulic interactions [95]. The generally faster hydraulic response times in such systems [76] are often evident on human timescales, enabling more adaptive water management approaches [96]. While knowledge of absolute flux magnitudes may be less critical in these regions, uncertainties in relative flux partitioning can still be significant.

In contrast, arid (i.e., water-limited) regions tend to exhibit slower response times and less continuous coupling between groundwater and surface water. These short-lived but intense exchanges underscore the importance of recognising transient climate–groundwater relationships in water-limited systems. Bi-directional interactions have historically been considered less significant than in humid regions, and the longer response times often limit the feasibility of adaptive management strategies in arid regions [e.g., 96]. In such settings, flux-based management supported by long-term monitoring [e.g., 97] is more appropriate. This approach focuses on managing flows between water cycle components rather than tracking absolute storage states alone. However, surface–groundwater interactions can still be highly dynamic where recharge is spatially and temporally focused, such as along mountain fronts, in river valleys, or during episodic events associated with spring run-off [e.g., 98].

While climatic aridity is a strong predictor of recharge rates, it does not fully determine them. The substantial scatter seen in aridity-recharge relationships (Figure 2) indicates that internal flux partitioning – and therefore responses to abstraction – can differ considerably even under similar climatic conditions. In more arid regions, pumped water is more likely to originate from long-term storage rather than from captured discharge (e.g., baseflow), making depletion more likely [99, 100]. However, this pattern is not universal, reinforcing the need to interpret changes in water fluxes and storage with caution, especially when robust partitioning frameworks are lacking. This is particularly important in irrigated regions, where irrigation return flows can constitute a major internal flux [25].

Finally, it remains unclear how transient or spatially heterogeneous changes in fluxes influence a system's position within the *Budyko* framework. Adjustments in internal water partitioning ultimately drive the external partitioning patterns we observe. For instance, if abstraction mainly captures streamflow, the impact would be a reduction in streamflow fractions – a scenario more likely in humid systems, yet dependent on abstraction rates and system dynamics. Understanding these internal processes is therefore critical for detecting and interpreting water cycle changes, improving predictive models, and managing water resources sustainably.

Constraining internal water fluxes for a resilient water future

As global environmental and socio-economic crises converge, the concept of a '*safe and just*' operating space for humanity is gaining traction [101]. This highlights the growing need for integrated, rather than isolated, solutions to manage interconnected systems [102]. Defining global boundaries for water sustainability, however, remains contested, with ongoing debates over appropriate methodologies and their feasibility [103–106]. A fundamental prerequisite for any meaningful boundary-setting is an accurate understanding of internal water flux partitioning, which governs how water moves between storage and flow components within the terrestrial system.

Our proposed *Budyko*-type framework offers a scalable approach to explore, integrate, and constrain internal water fluxes, addressing key challenges in global water sustainability as we have illustrated in Figure 4. The conceptual distinction between external and internal controls introduced in Figure 1 provides a practical lens: climatic aridity sets the external baseline, while factors such as geology, topography, and vegetation explain departures from this baseline. Within this framework, empirical patterns of recharge and baseflow (Figure 2) can be interpreted across spatial and temporal scales, linking the conceptual overview (Figure 1) to observational evidence (Figure 2) and to broader implications for internal controls and management strategies (Figure 4).

This is particularly valuable given ongoing uncertainty around the dominant controls on recharge [107] and its sensitivity to climate and land-use change [53, 108]. While geology is one important secondary control (Figure 1), others such as land cover or vegetation also influence partitioning (Figure 4b). For instance, karst systems tend to show higher recharge due to rapid infiltration [40], whereas reforestation can reduce recharge through increased transpiration [109]. Accurately representing the balance between focused and diffuse recharge also remains challenging, especially under shifting climatic and land-use regimes [73, 110, 111]. Nevertheless, the simplicity of the framework allows large-scale exploration of how certain functional relationships (e.g., the recharge curve by *Berghuijs et al.* [56]) influence other interdependent fluxes such as baseflow (Figure 3).

Existing large-scale datasets on groundwater recharge reveal significant gaps, particularly in humid regions. As a result, plausible aridity-recharge relationships vary widely in humid regions (see Figure 3), which poses a challenge for constraining internal flux partitioning over large areas of the land surface (Figure 4c). Furthermore, many recharge datasets – with the notable exception of *MacDonald et al.* [64] – do not provide uncertainty bounds, complicating efforts to identify outliers or assess confidence levels. In arid regions, observational constraints on recharge fractions are more stringent (Figure 2), yet relative uncertainties remain a pressing issue (Figure 4c), particularly for water security and ecosystem health. Dryland groundwater systems also tend to exhibit long response timescales [76], limiting the utility of short observational records. Addressing these limitations requires combining long-term records, process-based modeling, and palaeoclimate proxies to reconstruct hydrological responses across timescales [e.g., 112].

Improving the quantity, quality, and consistency of recharge observations across all climatic regions is thus a critical research priority [113]. This challenge is amplified when considering transient dynamics, for which no global databases currently exist. Consequently, researchers often resort to strong assumptions such as space-time symmetry [108], which may not hold under non-stationary stressors. Expanding observational networks and synthesizing existing data would support more robust predictions of water flux responses to controls such as climate variability, land-use change, and human abstraction.

While we have integrated several variables and data sources, the terrestrial water cycle includes many more variables that can provide additional insights. Collections of in-situ observations of groundwater levels [114], soil moisture [115] or latent heat fluxes [116], as well as remote observations of terrestrial water storage [14], near-surface soil moisture [67], or vegetation status [e.g., 117], can provide further constraints or process insights, but not without conceptual advances on how to integrate them.

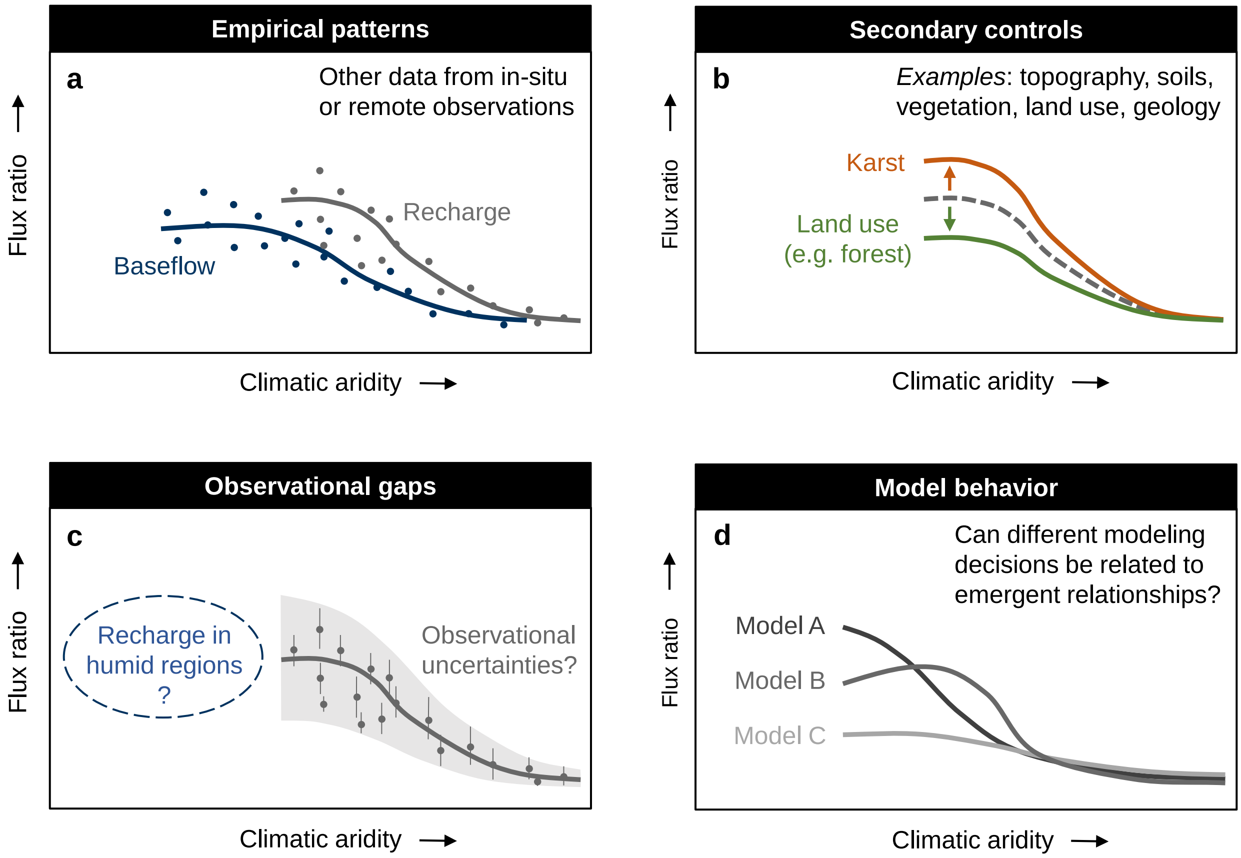


Fig. 4: **Challenges in internal water flux partitioning illustrated through our *Budyko*-type framework. a**: Empirical datasets reveal relationships between climatic aridity and different water fluxes (e.g., recharge, baseflow), but ideally these relationships should be explained through a unified process-based framework. **b**: Once baseline relationships are established, secondary controls such as geology (e.g., karst) or land-use (e.g., reforestation) can be explored through their influence on flux partitioning. **c**: Observational gaps, especially in humid regions, limit our ability to constrain internal partitioning; current datasets also often lack uncertainty estimates. **d**: Functional relationships derived from models can highlight differences in model behavior and structure, revealing the consequences of key assumptions (e.g., recharge parameterizations) and enabling comparison with empirical data.

Our framework can also serve as a valuable benchmark for evaluating model performance (Figure 4d). Hydrological models that accurately simulate external fluxes such as streamflow may still misrepresent internal fluxes like recharge, particularly under changing conditions [39, 40]. Structural uncertainties are compounded by limited information on aquifer architecture [7] and the spatial variability of subsurface hydraulic properties [118]. Since geological heterogeneity can influence partitioning (Figure 1), efforts should focus on synthesizing existing geological datasets [e.g., 119] and expanding data collection suitable for new methods [e.g., 120], including less visible processes such as groundwater transpiration and inter-catchment groundwater flows [121].

A promising pathway forward involves the use of functional relationships between different water stores and fluxes, which may be mediated by other controls such as geology. These relationships can capture emergent (spatial) patterns at regional or global scales and facilitate comparisons between observations and models. Here we focused on relationships between climatic aridity and different water fluxes (Figures 2 and 3), and discussed secondary controls which may influence these relationships (Figure 4b). However, other flux combinations can also be used. For instance, especially in regions where precipitation variability is much stronger than potential evaporation variability, or in case where absolute precipitation magnitudes matter (e.g., due to threshold-dependent processes), we might instead focus on functional relationships between precipitation and recharge [e.g., 64, 122]. The use of functional relationships has already proved valuable in hydrology and related disciplines [e.g., 123–125], and thus warrants a more widespread adoption in hydrology [57]. Without a better theoretical understanding and a broader observational base, we lack the tools to evaluate which model structures are most plausible.

Enhancing model reliability requires interdisciplinary collaboration. Closer dialogue among atmospheric scientists, hydrologists, hydrogeologists, and specialists in both modeling and measurement is essential to develop shared frameworks and common terminologies [126, 127]. Such collaboration fosters the synergistic advancement of theories and models across disciplines. Iterative exchanges between modelers and observational scientists are particularly valuable: models can help identify observation gaps, while empirical data and process knowledge should inform model structure and parameter estimation (Figure 4d). For example, recent advances have shown the benefits of incorporating preferential flow mechanisms into large-scale infiltration [128] and recharge models [40], thereby enhancing realism and predictive accuracy.

A better understanding of how water is partitioned in the global terrestrial water cycle is vital for sustaining ecosystems and societies facing growing anthropogenic pressures. Our perspective underscores the importance of hidden subsurface processes, particularly groundwater recharge and discharge, in shaping water availability and ecosystem resilience. Through our *Budyko*-type lens, we advocate for a more integrated approach to constraining water fluxes, bridging observations and models, and addressing persistent theoretical gaps. As the global community aspires to move toward a sustainable water future, improving knowledge of internal water partitioning will be essential to safeguard this critical resource for generations to come.

Declarations

Author contribution

MOC conceived the idea for this work. Each author wrote one section as a first draft. GCR coordinated the writing, crafted Figure 1 and the visual in Box 1. SG created Figures 2 and 3 from existing datasets as well as Figure 4 in discussion with GCR. All authors revised the text and provided feedback to improve the visuals.

Data and code availability

Groundwater recharge observations from *MacDonald et al.* [64] are available from https://www2.bgs.ac.uk/nationalgeosciencedatacentre/citedData/catalogue/45d2b71c-d413-44d4-8b4b-6190527912ff.html. Groundwater recharge data from *Moeck et al.* [63] are available from https://opendata.eawag.ch/dataset/globalscale_groundwater_moeck. Groundwater recharge data from *Lee et al.* [66] are available from https://www.hydroshare.org/resource/5e7b8bfcc1514680902f8ff43cc254b8/. CHELSA data are available from https://chelsa-climate.org/downloads/ [68, 69]. Baseflow data from *Gnann et al.* [70] and code to reproduce the figures can be found at https://github.com/SebastianGnann/Flux_partitioning and is permanently archived at https://doi.org/10.5281/zenodo.17280947.

Conflict of interest

The authors declare no existing conflict of interest related to this work.

References

[1] Porkka, M. *et al.* Notable shifts beyond pre-industrial streamflow and soil moisture conditions transgress the planetary boundary for freshwater change. *Nature Water* **2**, 262–273 (2024).

[2] Falkenmark, M. & Rockström, J. The new blue and green water paradigm: Breaking new ground for water resources planning and management. *Journal of Water Resources Planning and Management* **132**, 129–132 (2006).

[3] Orth, R. & Destouni, G. Drought reduces blue-water fluxes more strongly than green-water fluxes in europe. *Nature Communications* **9**, 3602 (2018).

[4] Wang-Erlandsson, L., Tobian, A., van der Ent, R. *et al.* A planetary boundary for green water. *Nature Reviews Earth & Environment* **3**, 380–392 (2022).

[5] Brooks, P. *et al.* Hydrological partitioning in the critical zone: Recent advances and opportunities for developing transferable understanding of water cycle dynamics: Critical zone hydrology. *Water Resources Research* **51**, 6973–6987 (2015).

[6] Condon, L. *et al.* Global groundwater modeling and monitoring: Opportunities and challenges. *Water Resources Research* **57** (2021).

[7] Bierkens, M. Global hydrology 2015: State, trends, and directions. *Water Resources Research* **51**, 4923–4947 (2015).

[8] Gleeson, T., Befus, K., Jasechko, S., Luijendijk, E. & Cardenas, M. The global volume and distribution of modern groundwater. *Nature Geoscience* **9**, 161–167 (2015).

[9] Evaristo, J., Jasechko, S. & McDonnell, J. Global separation of plant transpiration from groundwater and streamflow. *Nature* **525**, 91–94 (2015).

[10] Sun, Q. *et al.* A review of global precipitation data sets: Data sources, estimation, and intercomparisons. *Reviews of Geophysics* **56**, 79–107 (2018).

[11] Jasechko, S. & Perrone, D. Global groundwater wells at risk of running dry. *Science* **372**, 418–421 (2021).

[12] Chen, X., Jiang, L., Luo, Y. & Liu, J. A global streamflow indices time series dataset for large-sample hydrological analyses on streamflow regime (until 2022). *Earth System Science Data* **15**, 4463–4479 (2023).

[13] Cui, Y. *et al.* Global water cycle and remote sensing big data: overview, challenge, and opportunities. *Big Earth Data* **2**, 282–297 (2018).

[14] Tapley, B. D., Bettadpur, S., Ries, J. C., Thompson, P. F. & Watkins, M. M. Grace measurements of mass variability in the earth system. *Science* **305**, 503–505 (2004).

[15] Lo, M.-H. *et al.* Grace-based estimates of global groundwater depletion. *Geophysical Monograph Series* 135–146 (2016).

[16] Rodell, M. & Reager, J. T. Water cycle science enabled by the grace and grace-fo satellite missions. *Nature Water* **1**, 47–59 (2023).

[17] Gleeson, T., Wada, Y., Bierkens, M. *et al.* Water balance of global aquifers revealed by groundwater footprint. *Nature* **488**, 197–200 (2012).

[18] Saccò, M. *et al.* Groundwater is a hidden global keystone ecosystem. *Global Change Biology* **30** (2023).

[19] Griebler, C. & Avramov, M. Groundwater ecosystem services: a review. *Freshwater Science* **34**, 355–367 (2015).

[20] McDonough, L. K. *et al.* Changes in global groundwater organic carbon driven by climate change and urbanization. *Nature Communications* **11** (2020).

[21] At the interface between hydrology and ecology (2024).

[22] Huggins, X. *et al.* Groundwater connections and sustainability in social-ecological systems. *Groundwater* **61**, 463–478 (2023).

[23] Bhaduri, A. *et al.* Achieving sustainable development goals from a water perspective. *Frontiers in Environmental Science* **4** (2016).

[24] Kuang, X. *et al.* The changing nature of groundwater in the global water cycle. *Science* **383** (2024).

[25] Scanlon, B. R. *et al.* Global water resources and the role of groundwater in a resilient water future. *Nature Reviews Earth and Environment* **4**, 87–101 (2023).

[26] Schreiber, P. Über die beziehungen zwischen dem niederschlag und der wasserführung der flüsse in mitteleuropa. *Meteorologische Zeitschrift* **21**, 441–452 (1904).

[27] Budyko, M. I. On climatic factors of runoff (in russian). *Prob. Fiz. Geogr* **16**, 41–48 (1951).

[28] Berghuijs, W. R., Gnann, S. J. & Woods, R. A. Unanswered questions on the budyko framework. *Hydrological Processes* **34**, 5699–5703 (2020).

[29] Boano, F. *et al.* Hyporheic flow and transport processes: Mechanisms, models, and biogeochemical implications. *Reviews of Geophysics* **52**, 603–679 (2014).

[30] Warr, O. *et al.* 86kr excess and other noble gases identify a billion-year-old radiogenically-enriched groundwater system. *Nature Communications* **13** (2022).

[31] Miguez-Macho, G. & Fan, Y. Spatiotemporal origin of soil water taken up by vegetation. *Nature* **598**, 624–628 (2021).

[32] McMahon, T. & Nathan, R. Baseflow and transmission loss: A review. *WIREs Water* **8** (2021).

[33] Winter, T. C., Harvey, J. W., Franke, O. L. & Alley, W. M. *Ground water and surface water: A single resource* (1998).

[34] Moosdorf, N. & Oehler, T. Societal use of fresh submarine groundwater discharge: An overlooked water resource. *Earth-Science Reviews* **171**, 338–348 (2017).

[35] Bierkens, M. F. P. & Wada, Y. Non-renewable groundwater use and groundwater depletion: a review. *Environmental Research Letters* **14**, 063002 (2019). URL http://dx.doi.org/10.1088/1748-9326/ab1a5f.

[36] Budyko, M. I. *Climate and Life* No. 18 in International geophysics series (Academic Press, New York, 1974). Includes bibliographical references and index. - Description based on print version record.

[37] de Vries, J. J. & Simmers, I. Groundwater recharge: an overview of processes and challenges. *Hydrogeology Journal* **10**, 5–17 (2002).

[38] Delin, G. N., Healy, R. W., Landon, M. K. & Böhlke, J. K. Effects of topography and soil properties on recharge at two sites in an agricultural field. *JAWRA Journal of the American Water Resources Association* **36**, 1401–1416 (2000).

[39] Kim, J. & Jackson, R. A global analysis of groundwater recharge for vegetation, climate, and soils. *Vadose Zone Journal* **11** (2012).

[40] Hartmann, A., Gleeson, T., Wada, Y. & Wagener, T. Enhanced groundwater recharge rates and altered recharge sensitivity to climate variability through subsurface heterogeneity. *Proceedings of the National Academy of Sciences* **114**, 2842–2847 (2017).

[41] Zhang, L., Dawes, W. R. & Walker, G. R. Response of mean annual evapotranspiration to vegetation changes at catchment scale. *Water Resources Research* **37**, 701–708 (2001).

[42] Jasechko, S. *et al.* Terrestrial water fluxes dominated by transpiration. *Nature* **496**, 347–350 (2013).

[43] Troch, P. A. *et al.* Climate and vegetation water use efficiency at catchment scales. *Hydrological Processes* **23**, 2409–2414 (2009).

[44] Ellison, D. *et al.* Trees, forests and water: Cool insights for a hot world. *Global Environmental Change* **43**, 51–61 (2017).

[45] Fan, Y. *et al.* Hillslope hydrology in global change research and earth system modeling. *Water Resources Research* **55**, 1737–1772 (2019).

[46] Markovich, K. H., Manning, A. H., Condon, L. E. & McIntosh, J. Mountain-block recharge: A review of current understanding. *Water Resources Research* **55**, 8278–8304 (2019).

[47] Brooks, P. D. *et al.* Groundwater dominates snowmelt runoff and controls streamflow efficiency in the western united states. *Communications Earth and Environment* **6** (2025).

[48] Huscroft, J., Gleeson, T., Hartmann, J. & Börker, J. Compiling and mapping global permeability of the unconsolidated and consolidated earth: Global hydrogeology maps 2.0 (glhymps 2.0). *Geophysical Research Letters* **45**, 1897–1904 (2018).

[49] Abbott, B. W. *et al.* Human domination of the global water cycle absent from depictions and perceptions. *Nature Geoscience* **12**, 533–540 (2019).

[50] Quichimbo, E. *et al.* Dryp 1.0: a parsimonious hydrological model of dryland partitioning of the water balance. *Geoscientific Model Development* **14**, 6893–6917 (2021).

[51] Keller, A. A., Garner, K., Rao, N., Knipping, E. & Thomas, J. Hydrological models for climate-based assessments at the watershed scale: A critical review of existing hydrologic and water quality models. *Science of The Total Environment* **867**, 161209 (2023).

[52] Hanasaki, N. *et al.* An integrated model for the assessment of global water resources – part 1: Model description and input meteorological forcing. *Hydrology and Earth System Sciences* **12**, 1007–1025 (2008).

[53] Reinecke, R. *et al.* Uncertainty of simulated groundwater recharge at different global warming levels: a global-scale multi-model ensemble study. *Hydrology and Earth System Sciences* **25**, 787–810 (2021).

[54] Murray, A. M., Jørgensen, G. H., Godiksen, P. N., Anthonj, J. & Madsen, H. Dhi-ghm: Real-time and forecasted hydrology for the entire planet. *Journal of Hydrology* **620**, 129431 (2023).

[55] Scanlon, B. R. *et al.* Global models underestimate large decadal declining and rising water storage trends relative to grace satellite data. *Proceedings of the National Academy of Sciences* **115** (2018).

[56] Berghuijs, W., Luijendijk, E., Moeck, C., van der Velde, Y. & Allen, S. Global recharge data set indicates strengthened groundwater connection to surface fluxes. *Geophysical Research Letters* **49**, e2022GL099010 (2022).

[57] Gnann, S. *et al.* Functional relationships reveal differences in the water cycle representation of global water models. *Nature Water* 1–12 (2023).

[58] Dorigo, W. *et al.* Closing the water cycle from observations across scales: Where do we stand? *Bulletin of the American Meteorological Society* **102**, E1897–E1935 (2021).

[59] Reinecke, R. *et al.* Uncertainties as a guide for global water model advancement. *WIREs Water* **12** (2025).

[60] Cuthbert, M., Gleeson, T., Bierkens, M., Ferguson, G. & Taylor, R. Defining renewable groundwater use and its relevance to sustainable groundwater management. *Water Resources Research* **59**, e2022WR032831 (2023).

[61] Althoff, D. & Destouni, G. Global patterns in water flux partitioning: Irrigated and rainfed agriculture drives asymmetrical flux to vegetation over runoff. *One Earth* **6**, 1246–1257 (2023).

[62] Greve, P., Burek, P. & Wada, Y. Using the budyko framework for calibrating a global hydrological model. *Water Resources Research* **56** (2020).

[63] Moeck, C. *et al.* A global-scale dataset of direct natural groundwater recharge rates: A review of variables, processes and relationships. *Science of the Total Environment* **717**, 137042 (2020).

[64] MacDonald, A. *et al.* Mapping groundwater recharge in africa from ground observations and implications for water security. *Environmental Research Letters* **16**, 034012 (2021).

[65] L'vovich, M. I. *World Water Resources and Their Future* (American Geophysical Union, 1979).

[66] Lee, S., Irvine, D. J., Duvert, C., Rau, G. C. & Cartwright, I. A high-resolution map of diffuse groundwater recharge rates for australia. *Hydrology and Earth System Sciences* **28**, 1771–1790 (2024).

[67] McColl, K., Alemohammad, S., Akbar, R. *et al.* The global distribution and dynamics of surface soil moisture. *Nature Geoscience* **10**, 100–104 (2017).

[68] Brun, P., Zimmermann, N. E., Hari, C., Pellissier, L. & Karger, D. N. Global climate-related predictors at kilometer resolution for the past and future. *Earth System Science Data* **14**, 5573–5603 (2022).

[69] Karger, D. N. *et al.* Climatologies at high resolution for the earth's land surface areas. *Scientific Data* **4** (2017).

[70] Gnann, S. J., Woods, R. A. & Howden, N. J. K. Is there a baseflow budyko curve? *Water Resources Research* **55**, 2838–2855 (2019).

[71] Schilling, K. E., Langel, R. J., Wolter, C. F. & Arenas-Amado, A. Using baseflow to quantify diffuse groundwater recharge and drought at a regional scale. *Journal of Hydrology* **602**, 126765 (2021).

[72] Xie, J. *et al.* Majority of global river flow sustained by groundwater. *Nature Geoscience* **17**, 770–777 (2024).

[73] Cuthbert, M. O. *et al.* Observed controls on resilience of groundwater to climate variability in sub-saharan africa. *Nature* **572**, 230–234 (2019).

[74] Lapworth, D. J. *et al.* Residence times of shallow groundwater in west africa: implications for hydrogeology and resilience to future changes in climate. *Hydrogeology Journal* **21**, 673–686 (2012).

[75] Fan, Y. Are catchments leaky? *WIREs Water* **6** (2019).

[76] Cuthbert, M., Gleeson, T., Moosdorf, N. *et al.* Global patterns and dynamics of climate–groundwater interactions. *Nature Climate Change* **9**, 137–141 (2019).

[77] Lloyd, J. W. & Farag, M. H. Fossil ground-water gradients in arid regional sedimentary basins. *Groundwater* **16**, 388–392 (1978).

[78] Liu, Y., Wagener, T., Beck, H. E. & Hartmann, A. What is the hydrologically effective area of a catchment? *Environmental Research Letters* **15**, 104024 (2020).

[79] Schellekens, J. *et al.* A global water resources ensemble of hydrological models: the earth2observe tier-1 dataset. *Earth System Science Data* **9**, 389–413 (2017).

[80] Elshall, A. S. *et al.* Groundwater sustainability: a review of the interactions between science and policy. *Environmental Research Letters* **15**, 093004 (2020).

[81] Jasechko, S. *et al.* The pronounced seasonality of global groundwater recharge. *Water Resources Research* **50**, 8845–8867 (2014).

[82] Owor, M., Taylor, R. G., Tindimugaya, C. & Mwesigwa, D. Rainfall intensity and groundwater recharge: empirical evidence from the upper nile basin. *Environmental Research Letters* **4**, 035009 (2009).

[83] Jasechko, S. & Taylor, R. Intensive rainfall recharges tropical groundwaters. *Environmental Research Letters* **10**, 124015 (2015).

[84] Meixner, T. *et al.* Implications of projected climate change for groundwater recharge in the western united states. *Journal of Hydrology* **534**, 124–138 (2016).

[85] Konapala, G., Mishra, A. K., Wada, Y. & Mann, M. E. Climate change will affect global water availability through compounding changes in seasonal precipitation and evaporation. *Nature Communications* **11** (2020).

[86] Ayat, H., Evans, J. P., Sherwood, S. C. & Soderholm, J. Intensification of subhourly heavy rainfall. *Science* **378**, 655–659 (2022).

[87] Yuan, X. *et al.* A global transition to flash droughts under climate change. *Science* **380**, 187–191 (2023).

[88] Atawneh, D., Cartwright, N. & Bertone, E. Climate change and its impact on the projected values of groundwater recharge: A review. *Journal of Hydrology* **601**, 126602 (2021).

[89] Uhl, A. *et al.* Making waves: Pulling the plug—climate change effects will turn gaining into losing streams with detrimental effects on groundwater quality. *Water Research* **220**, 118649 (2022).

[90] de Graaf, I., Gleeson, T., van Beek, L. *et al.* Environmental flow limits to global groundwater pumping. *Nature* **574**, 90–94 (2019).

[91] Hasan, M., Smith, R., Vajedian, S. *et al.* Global land subsidence mapping reveals widespread loss of aquifer storage capacity. *Nature Communications* **14**, 6180 (2023).

[92] Milly, P. C. D. *et al.* Stationarity is dead: Whither water management? *Science* **319**, 573–574 (2008).

[93] Bredehoeft, J. D. The water budget myth revisited: Why hydrogeologists model. *Groundwater* **40**, 340–345 (2002).

[94] Reinecke, R. *et al.* Uncertainty in model estimates of global groundwater depth. *Environmental Research Letters* **19**, 114066 (2024).

[95] Quichimbo, E., Singer, M. & Cuthbert, M. Characterising groundwater–surface water interactions in idealised ephemeral stream systems. *Hydrological Processes* **34**, 3792–3806 (2020).

[96] Thomann, J. A., Werner, A. D., Irvine, D. J. & Currell, M. J. Adaptive management in groundwater planning and development: A review of theory and applications. *Journal of Hydrology* **586**, 124871 (2020).

[97] Werner, A. D. *et al.* Current practice and future challenges in coastal aquifer management: Flux-based and trigger-level approaches with application to an australian case study. *Water Resources Management* **25**, 1831–1853 (2011).

[98] Masbruch, M. D., Rumsey, C. A., Gangopadhyay, S., Susong, D. D. & Pruitt, T. Analyses of infrequent (quasi-decadal) large groundwater recharge events in the northern great basin: Their importance for groundwater availability, use, and management: Large groundwater recharge events. *Water Resources Research* **52**, 7819–7836 (2016). URL http://dx.doi.org/10.1002/2016WR019060.

[99] Konikow, L. & Leake, S. Depletion and capture: Revisiting "the source of water derived from wells". *Groundwater* **52**, 100–111 (2014).

[100] de Graaf, I. E. M., Marinelli, B. & Liu, S. Global analysis of groundwater pumping from increased river capture. *Environmental Research Letters* **19**, 044064 (2024).

[101] Rockström, J. *et al.* A safe operating space for humanity. *Nature* **461**, 472–475 (2009).

[102] Hickel, J. The contradiction of the sustainable development goals: Growth versus ecology on a finite planet. *Sustainable Development* **27**, 873–884 (2019).

[103] Ziegler, R., Gerten, D. & Döll, P. *Safe, just and sufficient space: The planetary boundary for human water use in a more-than-human world*. Earthscan studies in water resource management (Routledge, Taylor and Francis Group,, London, 2017).

[104] Gleeson, T. Global groundwater sustainability. *Groundwater* **58**, 484–485 (2020).

[105] Zipper, S. C. Water resources: Science and society. *Groundwater* **58**, 692–692 (2020).

[106] Cuthbert, M. O., Gleeson, T., Bierkens, M. F. P., Ferguson, G. & Taylor, R. G. Concerns regarding proposed groundwater earth system boundary. *Nature* **635**, E4–E5 (2024).

[107] Moeck, C., Collenteur, R. A., Berghuijs, W. R., Luijendijk, E. & Gurdak, J. J. A global assessment of groundwater recharge response to infiltration variability at monthly to decadal timescales. *Water Resources Research* **60** (2024).

[108] Berghuijs, W. R. *et al.* Groundwater recharge is sensitive to changing long-term aridity. *Nature Climate Change* **14**, 357–363 (2024).

[109] Huang, T., Pang, Z., Yang, S. & Yin, L. Impact of afforestation on atmospheric recharge to groundwater in a semiarid area. *Journal of Geophysical Research: Atmospheres* **125** (2020).

[110] Scanlon, B. R. *et al.* Global synthesis of groundwater recharge in semiarid and arid regions. *Hydrological Processes* **20**, 3335–3370 (2006).

[111] Zhu, R., Croke, B. F. & Jakeman, A. J. Diffuse groundwater recharge estimation confronting hydrological modelling uncertainty. *Journal of Hydrology* **584**, 124642 (2020).

[112] Markowska, M. *et al.* Modern speleothem oxygen isotope hydroclimate records in water-limited se australia. *Geochimica et Cosmochimica Acta* **270**, 431–448 (2020).

[113] Beven, K. How to make advances in hydrological modelling. *Hydrology Research* **50**, 1481–1494 (2019).

[114] Fan, Y., Li, H. & Miguez-Macho, G. Global patterns of groundwater table depth. *Science* **339**, 940–943 (2013).

[115] Dorigo, W. *et al.* The international soil moisture network: serving earth system science for over a decade. *Hydrology and Earth System Sciences* **25**, 5749–5804 (2021).

[116] Pastorello, G. *et al.* The fluxnet2015 dataset and the oneflux processing pipeline for eddy covariance data. *Scientific Data* **7** (2020).

[117] Zeng, Y. *et al.* Optical vegetation indices for monitoring terrestrial ecosystems globally. *Nature Reviews Earth and Environment* **3**, 477–493 (2022).

[118] Lin, H.-R., Wen, J.-C., Zhang, Z. & Wang, Y.-L. Characterizing basin-scale subsurface hydraulic heterogeneity with multiscale geological and hydrological measurements. *Journal of Hydrology* **625**, 130061 (2023).

[119] de Graaf, I., Condon, L. & Maxwell, R. Hyper-resolution continental-scale 3-d aquifer parameterization for groundwater modeling. *Water Resources Research* **56** (2020).

[120] Rau, G. C. *et al.* Future-proofing hydrogeology by revising groundwater monitoring practice. *Hydrogeology Journal* **28**, 2963–2969 (2020).

[121] Yang, C., Condon, L. E. & Maxwell, R. M. Unravelling groundwater–stream connections over the continental united states. *Nature Water* **3**, 70–79 (2025).

[122] West, C. *et al.* Ground truthing global-scale model estimates of groundwater recharge across africa. *Science of The Total Environment* **858**, 159765 (2023).

[123] Koster, R. & Milly, P. The interplay between transpiration and runoff formulations in land surface schemes used with atmospheric models. *Journal of Climate* **10**, 1578–1591 (1997).

[124] Randerson, J. *et al.* Systematic assessment of terrestrial biogeochemistry in coupled climate–carbon models. *Global Change Biology* **15**, 2462–2484 (2009).

[125] Koster, R. & Mahanama, S. Land surface controls on hydroclimatic means and variability. *Journal of Hydrometeorology* **13**, 1604–1620 (2012).

[126] Staudinger, M. *et al.* Your work is my boundary condition! *Journal of Hydrology* **571**, 235–243 (2019).

[127] Chen, L. & Wang, L. Recent advance in earth observation big data for hydrology. *Big Earth Data* **2**, 86–107 (2018).

[128] Bonetti, S., Wei, Z. & Or, D. A framework for quantifying hydrologic effects of soil structure across scales. *Communications Earth and Environment* **2** (2021).