

What Can We Learn from a Reduced-Dimensional Groundwater Representation for Diagnosing Groundwater– Land Interactions? Insights from the Water Table Ratio

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Abstract

Groundwater exerts an important control on land–atmosphere interactions, yet its explicit representation in Earth system models remains computationally prohibitive. Reduced-dimensional metrics, such as the Water Table Ratio (WTR), have been proposed to represent groundwater influences on land–atmosphere interactions. However, their uncertainty, classification stability, and correspondence with process-based representations remain largely unexplored. Here, because groundwater influences on the atmosphere are mediated through land surface processes, we compare WTR-based diagnoses of groundwater–land interactions with those derived from ParFlow–CLM simulations over a 34,000 km² catchment. Groundwater-sensitive regions are first identified by comparing paired ParFlow–CLM simulations with and without groundwater feedback and then used as a physically explicit reference for comparison with WTR. A total of 63 WTR configurations were examined, with Monte Carlo analyses performed for each to quantify uncertainty and classification stability.

Hydraulic conductivity (K) is the dominant source of uncertainty in WTR and exerts the strongest destabilizing effect on its threshold-based classification. Although the domain-wide proportions of correctly classified sensitive and insensitive areas remain nearly unchanged across alternative configurations and Monte Carlo realizations, substantial switching occurs among individual grid cells. Across the 63 WTR configurations, the mean correctly classified fraction was 0.40. In comparison, the critical-water-table-depth (WTD) approach yielded fractions of 0.59, 0.70, and 0.64 using WTD estimates from ParFlow–CLM, PCR-GLOBWB, and Fan et al., respectively. WTR errors are dominated by overestimation rather than underestimation, indicating a conservative screening tendency. Combining observed parameter contrasts with analytical WTR elasticities further identifies K as the dominant contributor to classification discrepancies, with characteristic length (L) providing a secondary contribution. The dominant role of K reveals a key consequence of reducing a heterogeneous three-dimensional groundwater system to a one-dimensional metric governed by a few effective parameters: the resulting classification becomes disproportionately dependent on a single effective hydraulic conductivity field. WTR can therefore support precautionary regional screening, but its local classifications should be interpreted cautiously, particularly where K is poorly constrained or subsurface heterogeneity is strong.

1. Introduction

Groundwater is an integral component of the Earth system and plays a fundamental role in regulating terrestrial water cycling, ecosystem functioning, and land–atmosphere interactions (Yang et al., 2026). Consequently, representing groundwater processes has become an increasingly important objective in land surface and Earth system models (Fan, 2015). However, explicitly resolving three-dimensional variably saturated groundwater flow at regional to continental scales remains computationally prohibitive (Kollet et al., 2026), particularly for long-term Earth system simulations. This challenge has stimulated growing interest in simplified yet physically meaningful representations that capture the essential impacts of groundwater while maintaining computational efficiency (Fan and Miguez-Macho, 2024).

Among the simplified approaches proposed over the past two decades, the Water Table Ratio (WTR) is a physically based metric linking water-table configuration to landscape characteristics. Originally introduced by Haitjema and Mitchell-Bruker (2005), WTR was developed to distinguish whether the water table is primarily controlled by topography or groundwater recharge. Gleeson and Manning (2008); Gleeson et al. (2011a) subsequently extended WTR to continental scales and related it to the spatial scale of groundwater flow systems and to water table depth. These relationships were important because regional groundwater flow redistributes water laterally across landscapes (Yang et al., 2025a), whereas water-table depth controls the hydraulic connection between groundwater and the land surface (Fan et al., 2017). By linking WTR to these two fundamental controls on groundwater influence, these studies implicitly suggested that WTR may contain information not only about water-table morphology, but also about the potential for groundwater to affect land-surface water and energy exchanges. Building on this interpretation, Cuthbert et al. (2019) explicitly proposed WTR as a diagnostic indicator of groundwater–climate interactions, suggesting that $WTR > 1$ is generally associated with stronger bidirectional coupling, whereas $WTR < 1$ represents a predominantly recharge-driven regime in which groundwater exerts comparatively weak feedbacks on land-surface and atmospheric processes.

Because of its simple formulation and intuitive physical interpretation, WTR has since been increasingly applied to analyze groundwater-flow organization (Gleeson and Manning, 2008), groundwater-depth patterns (Gleeson et al., 2011a), groundwater landscapes (Huggins et al., 2024), and spatial variations in groundwater–land and groundwater–climate interactions (Gleeson et al., 2020). Its growing use reflects a broader interest in whether the essential influence of groundwater on Earth system processes can be captured through a physics-based reduced-dimensional representation. In this sense, WTR collapses complex three-dimensional groundwater flow and subsurface heterogeneity into an idealized one-dimensional interstream aquifer characterized by a small number of effective landscape and hydrogeological parameters. This reduced-dimensional structure makes large-domain mapping and extensive uncertainty analysis computationally tractable. If its diagnostic interpretation proves reliable, WTR could provide a physically informed basis for simplifying groundwater representation in land surface and Earth system models. It may also offer a useful criterion for adaptive modeling strategies, in which computationally intensive groundwater simulations are preferentially applied in strongly coupled regions while simpler representations are used elsewhere.

Despite these promising developments, the interpretation of WTR at regional scales remains subject to several theoretical and practical uncertainties. The theoretical derivation of WTR relies on several simplifying assumptions (Haitjema and Mitchell-Bruker, 2005), including the Dupuit–Forchheimer approximation, a horizontal aquifer base, and constant aquifer thickness. These assumptions are generally consistent with gently sloping aquifer systems but may be less applicable in regions characterized by complex topography, strong vertical groundwater exchange, or pronounced subsurface heterogeneity. Furthermore, estimating groundwater recharge, hydraulic conductivity, and characteristic flow length at regional scales is often associated with considerable uncertainty. These theoretical assumptions and parameter uncertainties may jointly influence WTR values and consequently affect the inferred groundwater interaction regimes. Moreover, previous global-scale studies have shown that a substantial proportion of landscapes exhibit WTR values close to the threshold separating different interaction regimes (Cuthbert et al., 2019), raising further questions about the stability of WTR-based classifications near this transition. Collectively, these issues motivate examining how uncertainty propagates into WTR values and classifications and how the resulting spatial patterns compare with a process-based representation of groundwater–land interactions.

Integrated surface–subsurface models offer one way to address these questions because they explicitly represent groundwater flow together with surface-water and land-surface processes within a unified physical framework. Although these models do not constitute error-free ground truth, they provide a physically explicit reference for comparison. The purpose of this comparison is not to accept or reject WTR, but to examine the correspondence between the reduced-dimensional and process-based representations and to investigate the sources of their discrepancies. In this study, we employ an integrated ParFlow–CLM modeling framework (Kollet and Maxwell, 2008) to examine WTR as a reduced-dimensional diagnostic of groundwater–land interactions. Specifically, we quantify how alternative parameter estimates and parameter uncertainty affect WTR values and classification stability, compare WTR-based classifications with groundwater-sensitive regions identified from paired ParFlow–CLM simulations, and identify the parameters most strongly associated with classification discrepancies. More broadly, we use WTR as an entry point to explore what can be learned from reduced-dimensional groundwater representations and how such diagnostics may support adaptive groundwater representation in Earth system models.

2. Study area and ParFlow–CLM simulations

The Upper Beijiang River basin was selected as the study domain (**Figure 1**), and the corresponding regional model was extracted from CONCN, a previously developed continental-scale ParFlow model for mainland China (Yang et al., 2025b). ParFlow provides an integrated representation of overland flow and three-dimensional variably saturated subsurface flow. The regional model retained the model structure and parameterization of CONCN. It contained 252 and 146 grid cells in the x and y directions, respectively, with a horizontal resolution of approximately 1 km. The subsurface was discretized into 10 vertical layers with a total thickness of 492 m.

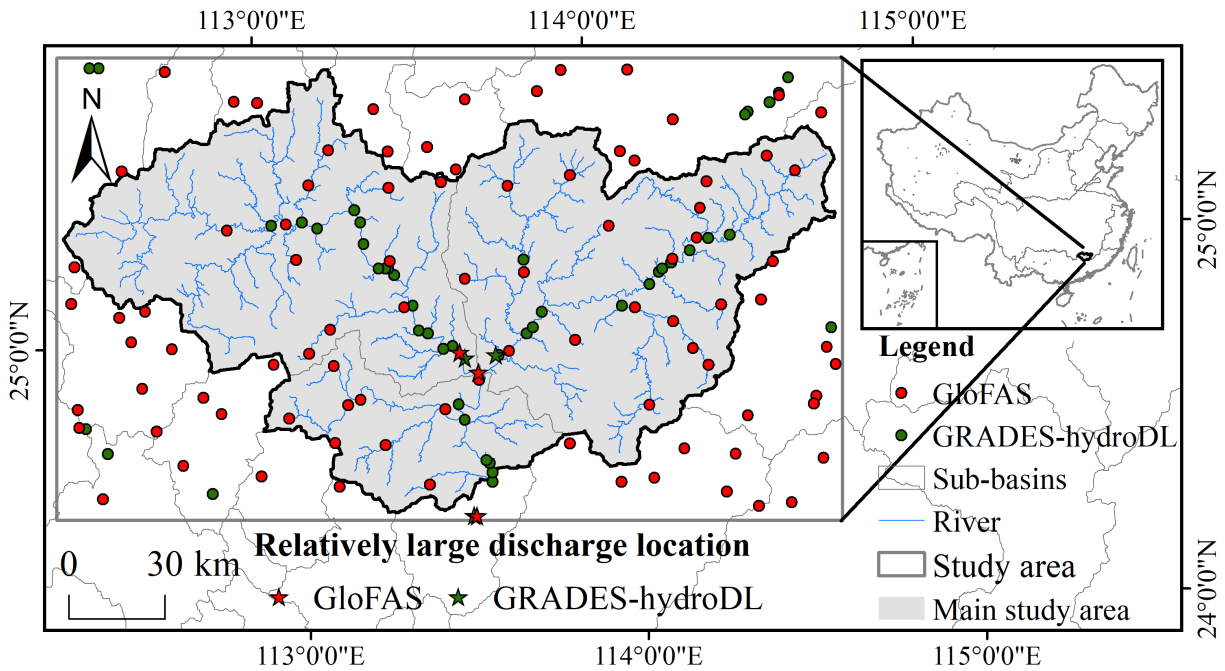


Figure 1. Upper Beijiang River basin study domain, including the river network, sub-basin boundaries, and discharge-data locations. The inset shows the location of the study domain within mainland China. Circles denote discharge-data locations from GloFAS and GRADES-hydroDL, and stars indicate the locations selected for the hydrograph comparisons in Figure S2.

The regional ParFlow model included spatially distributed parameter fields for surface routing, shallow soil, and the deeper aquifer, together with the forcing used for steady-state spin-up. The surface-routing parameters included spatially distributed Manning’s roughness coefficients and terrain slopes. Elevation data from MERIT Hydro IHU (Eilander et al., 2021) were processed to establish hydrologically consistent drainage connectivity across the model grid, after which terrain slope was calculated from the processed elevation field. For the subsurface, spatially distributed soil types and their associated hydraulic parameters were derived from GSDE (Shangguan et al., 2014), while deeper-aquifer units and their associated permeability values were obtained from GLHYMPS 1.0 (Gleeson et al., 2011b). A long-term mean precipitation-minus-evapotranspiration ($P - ET$) field was assembled and applied as the upper-boundary water flux during steady-state

spin-up. Further details of the CONCN input datasets, model parameterization, and steady-state spin-up are provided in Yang et al. (2025b).

For the transient simulations conducted in this study, ParFlow and CLM were coupled through the upper four subsurface layers. During the coupling, ParFlow supplied soil-moisture and pressure-head states to CLM, while CLM calculated the land-surface water and energy balances and returned the resulting net water fluxes to ParFlow as source–sink terms. The coupled ParFlow–CLM model was driven by ERA5-Land meteorological forcing (Muñoz-Sabater et al., 2021). Starting from the steady-state CONCN solution, the model first underwent an additional steady-state spin-up. CLM was then activated, and the WY2019 ERA5-Land forcing was repeatedly applied until the coupled system reached dynamic equilibrium. The resulting model state was subsequently used to simulate WY2020 and WY2021. Each water year spans from 1 October of the preceding calendar year to 30 September of the named year.

The CONCN solution used to initialize the regional model had been spun up to a quasi-steady state and previously evaluated at the continental scale against global data products and observations of streamflow and water-table depth (Yang et al., 2025b). Building on this continental-scale evaluation, the performance of the transient ParFlow–CLM simulation for WY2019 was further evaluated within the study domain using multiple datasets representing streamflow, groundwater conditions, and land-surface variables. Simulated streamflow was compared with estimates from GloFAS (Alfieri et al., 2013) and GRADES-hydroDL (Yang et al., 2025c) at 92 and 48 locations, respectively (**Figures S1–S2**). Simulated groundwater levels were compared with estimates from two global groundwater models, PCR-GLOBWB (Verkaik et al., 2022) and the model of Fan et al. (2013) (**Figure S3**). Finally, simulated latent heat flux, sensible heat flux, transpiration, and land-surface temperature were compared with the corresponding ERA5-Land products (**Figure S4**). Although direct observations sufficient for a comprehensive local evaluation are scarce in this headwater basin, these widely used products provide complementary benchmarks for assessing model behavior relative to current community datasets. Whereas each reference dataset characterizes a particular component of the hydrological system, the coupled ParFlow–CLM model simultaneously represents surface-water dynamics, groundwater conditions, and land-surface water and energy exchanges. Together, these comparisons provide a multi-component evaluation of the integrated processes that underpin the subsequent diagnosis of groundwater–land interactions.

3. Physical-model-based characterization of groundwater–land interactions

3.1 Identification of groundwater-sensitive areas

Groundwater-sensitive areas were identified by comparing simulations with and without groundwater feedback to the land surface. The reference simulation used the original model configuration, including a terrain-following grid and a no-flow boundary at the base of the 492-m-thick model domain. This configuration allowed topography-driven groundwater flow systems to develop and interact naturally with land-surface processes. In the groundwater-suppressed simulation, the terrain-following grid was disabled for subsurface flow and a free-drainage lower boundary condition was applied, thereby approximating the soil-water representation commonly used in conventional land surface models and effectively removing groundwater feedback to the land surface. Both configurations were simulated for WY2019–WY2021. Their differences were

evaluated using latent heat flux (LE) and evaporative fraction, defined as $EF = LE/(LE + H)$, where H is sensible heat flux (**Figure S5**). The threshold for each variable was determined separately from its own spatial distribution of absolute differences. For both variables, the domain-wide mean and median were nearly coincident. Rounded values slightly above these central tendencies were therefore adopted as operational thresholds: 25 W/m² for $|\Delta LE|$ and 0.30 (30 percentage points) for $|\Delta EF|$ (**Figure S6**). Groundwater-sensitive areas were delineated separately using the two thresholds, and the resulting spatial masks were found to be broadly consistent (**Figure S7**).

3.2 Identification of critical-water-table-depth range

Following Kollet and Maxwell (2008), the critical water-table-depth (WTD) range was identified from the relationship between land-surface variables and WTD. For a given averaging period, the mean value of each land-surface variable at each grid cell was plotted against the corresponding mean WTD. This relationship can be divided conceptually into three regimes. When the water table is shallow, land-surface processes are primarily energy limited and respond weakly to changes in WTD. When the water table is deep, the land surface becomes water limited and is largely decoupled from groundwater. The intermediate transition range, within which land-surface variables change strongly with WTD, defines the critical WTD range. Because this range may vary with climatic conditions, season, and study region, it must be identified for the specific simulation being analyzed.

Using outputs from the reference simulation, hourly model outputs for each year from WY2019 to WY2021 were aggregated to daily, monthly, and annual means. At each temporal scale, four land-surface variables were plotted against WTD: latent heat flux (LE), sensible heat flux (H), ground heat flux (G), and land-surface temperature (T_s). Three sets of plots were produced, corresponding to the daily, monthly, and annual scales. Within each set, the relationships for WY2019, WY2020, and WY2021 were shown as three separate curves for each variable. A single critical WTD range was then determined qualitatively by jointly inspecting all three sets of plots and identifying the WTD interval over which the four variables collectively exhibited pronounced changes across the temporal scales (**Figure S8**). The resulting critical WTD range was approximately 0.2–10 m, consistent with ranges reported in previous studies (Vogelbacher et al., 2025; Ferguson and Maxwell, 2011; Yang et al., 2020; Yang et al., 2023; Kollet and Maxwell, 2008). Grid cells whose mean WTD during WY2019 fell within this range were classified as groundwater sensitive. For comparison, the same range was also applied to the steady-state WTD estimates from PCR-GLOBWB (Verkaik et al., 2022) and Fan et al. (2013) to delineate groundwater-sensitive areas.

4. WTR calculation and uncertainty quantification

4.1 WTR formulation

Following Cuthbert et al. (2019), WTR was calculated from a nonlinear steady-state solution for one-dimensional groundwater flow. The solution assumes an idealized, homogeneous, horizontal, unconfined aquifer receiving spatially uniform recharge (**Figure S9**). The aquifer extends from a no-flow groundwater divide to a perennial stream acting as a fixed-head discharge boundary, with $L/2$ representing the characteristic distance between the divide and the stream. Under the Dupuit–Forchheimer approximation, WTR is expressed as

$$\text{WTR} = \frac{\sqrt{b^2 + \frac{RL^2}{4K}} - b}{d}$$

where R is groundwater recharge, K is hydraulic conductivity, L is the characteristic length between the two perennial-stream boundaries, b is the minimum saturated aquifer thickness at the fixed-head boundary, and d is the maximum terrain rise above that boundary. The numerator represents the potential water table rise from the fixed-head boundary to the divide, and WTR therefore measures this rise relative to the corresponding terrain rise. WTR is dimensionless, and a threshold of 1 was used throughout the analysis.

Following its original interpretation in terms of groundwater–atmosphere coupling, which is mediated through land-surface processes, $\text{WTR} > 1$ was treated here as indicating groundwater-sensitive land-surface conditions, whereas $\text{WTR} < 1$ was treated as indicating groundwater-insensitive conditions. Comparing this WTR-based classification with the physical-model benchmark yielded four groups: correctly classified as sensitive (CS; sensitive in the physical model and $\text{WTR} > 1$), correctly classified as insensitive (CI; insensitive in the physical model and $\text{WTR} < 1$), underestimation error (UE; sensitive in the physical model but $\text{WTR} < 1$), and overestimation error (OE; insensitive in the physical model but $\text{WTR} > 1$).

4.2 Analytical sensitivity analysis of WTR

To characterize the response of WTR to each input, we first define

$$A = b^2 + \frac{RL^2}{4K}$$

$$\text{WTR} = \frac{\sqrt{A} - b}{d}$$

The partial derivatives of WTR with respect to the five inputs are

$$\frac{\partial \text{WTR}}{\partial K} = -\frac{RL^2}{8K^2 d \sqrt{A}}$$

$$\frac{\partial \text{WTR}}{\partial R} = \frac{L^2}{8K d \sqrt{A}}$$

$$\frac{\partial \text{WTR}}{\partial L} = \frac{RL}{4K d \sqrt{A}}$$

$$\frac{\partial \text{WTR}}{\partial b} = \frac{1}{d} \left(\frac{b}{\sqrt{A}} - 1 \right)$$

$$\frac{\partial \text{WTR}}{\partial d} = -\frac{\text{WTR}}{d}$$

Because the inputs differ in their units and magnitudes, their effects were compared using the dimensionless local elasticity

$$E_x = \frac{\partial \text{WTR}}{\partial x} \frac{x}{\text{WTR}}$$

The resulting elasticities are

$$E_K = -\frac{1}{2} \left(1 + \frac{b}{\sqrt{A}} \right)$$

$$E_R = \frac{1}{2} \left(1 + \frac{b}{\sqrt{A}} \right)$$

$$E_L = 1 + \frac{b}{\sqrt{A}}$$

$$E_d = -1$$

$$E_b = -\frac{b}{\sqrt{A}}$$

These expressions show that WTR increases with R and L but decreases with K , d , and b . The elasticity for K is the negative of that for R , the elasticity for L is twice that for R , and the elasticity for d equals -1; the elasticity for b is also negative but varies with the local parameter state.

We next applied these elasticities to the UE and OE groups defined in **Section 4.1**. The logarithmic change in WTR associated with an adjustment to parameter x was represented using the following first-order approximation:

$$\Delta \ln(\text{WTR}) \approx E_x \Delta \ln x$$

For each parameter x , where x denotes R , K , L , d , or b , its mean was calculated within each of the four groups. Let M denote the group mean, with the parameter and group identified by its subscripts. Because UE and OE correspond to different physical-model states, each error group was paired with the correctly classified group sharing the same physical-model classification: UE with CS and OE with CI. The parameter adjustments required to move each error group toward its corresponding reference group were defined as

$$\Delta \ln x_{\text{UE} \rightarrow \text{CS}} = \ln\left(\frac{M_{x,\text{CS}}}{M_{x,\text{UE}}}\right), \quad \Delta \ln x_{\text{OE} \rightarrow \text{CI}} = \ln\left(\frac{M_{x,\text{CI}}}{M_{x,\text{OE}}}\right)$$

Applying the first-order approximation to these groupwise parameter adjustments gives

$$C_{x,g \rightarrow \text{ref}} \approx E_{x,g} \Delta \ln x_{g \rightarrow \text{ref}}, \quad g = \text{UE or OE}$$

where the elasticity was evaluated at the mean parameter state of the relevant error group (UE or OE). Thus, C estimates the first-order contribution of parameter x to the logarithmic change in WTR, $\Delta \ln(\text{WTR})$, when that parameter is adjusted from its mean value in an error group to its mean value in the corresponding correctly classified reference group (CS or CI), while the other parameters are held fixed. Its sign indicates whether the adjustment increases or decreases WTR, whereas its absolute magnitude measures the importance of that parameter to the first-order change in $\ln(\text{WTR})$. A parameter with a substantially larger $|C|$ therefore makes a larger contribution to the estimated log-scale WTR adjustment. This first-order analysis varies one parameter at a time and is based on group means. It can be used to compare the relative contributions of individual parameters, but it does not show that the full nonlinear WTR difference or the mismatch with the physical benchmark is caused by any single parameter.

4.3 Input datasets and parameter estimation methods

To account for alternative representations of the five inputs to WTR, we assembled multiple datasets and estimation methods for K , R , L , d , and b . Hydraulic conductivity (K) was derived from the intrinsic permeability provided by GLHYMPS 1.0 (Gleeson et al., 2011b) using the standard conversion under reference temperature and pressure conditions (**Figure 2f**). The same GLHYMPS 1.0 permeability dataset was used to parameterize the deeper aquifer in ParFlow-CLM, providing a consistent hydraulic-conductivity data source for the two approaches. Groundwater recharge (R) was obtained using three approaches (**Figure S10**). R_1 was obtained from the long-term mean groundwater-recharge input dataset used by the Superwell model (Niazi et al., 2025), which integrates recharge estimates from Döll and Fiedler (2008) and Gleeson et al. (2016). Following Condon and Maxwell (2015), R_2 was approximated as precipitation minus evapotranspiration ($P - ET$), using independently sourced precipitation and evapotranspiration datasets assembled for CONCN. R_3 was obtained from PCR-GLOBWB (Verkaik et al., 2022), in which recharge calculated by its surface-water component is used as an input to the groundwater module.

Several estimates of L , d , and b were derived from the datasets produced during the construction and simulation of CONCN, as described in **Section 2**. In particular, the sub-basin delineation, river network, and flow-routing products provided a consistent representation of surface drainage connectivity for deriving these WTR inputs. Characteristic length (L) was estimated using three approaches (**Figure S10**). L_1 was obtained from the published characteristic-length dataset of Cuthbert et al. (2019). L_2 was calculated as the square root of the area of each sub-basin (Gleeson et al., 2011a). For L_3 , flow paths were traced from each drainage divide to the corresponding river cells on its two sides, and the two path lengths were summed to represent the distance between the river boundaries. All grid cells along the paired flow paths were assigned the same L_3 .

In the WTR framework, L represents the characteristic length of an interstream aquifer bounded by two perennial streams. Its spatial estimation should therefore capture a representative hydraulic and geomorphic dimension of the interstream area, which can be conceptualized as two hillslope

segments extending from a drainage divide toward the bounding streams. However, this characteristic dimension cannot be identified uniquely from regional-scale data. Cuthbert et al. (2019) estimated L_1 using the shortest combined Euclidean distance between perennial river locations on opposing sides of each grid cell. In comparison, L_2 represents the characteristic spatial scale of a sub-basin, while L_3 follows the drainage organization from a divide to the river cells on its two sides. These approaches provide different but plausible approximations of the characteristic interstream length, and none can be assumed a priori to provide a universally superior representation. To examine whether terrain relief substantially affected the path-based estimate, L_3 was additionally corrected using d_3 to approximate its horizontal component. This correction produced only minor differences because L_3 was generally much larger than the associated terrain rise (**Figure S11**).

Maximum terrain rise above the fixed-head boundary (d) was calculated using three approaches (**Figure S10**). d_1 was obtained from the elevation range of each basin in HydroSHEDS (Danielson and Gesch, 2011; Lehner et al., 2008). d_2 was defined as the difference between the maximum and minimum elevations within each sub-basin (Gleeson et al., 2011a). For d_3 , the elevation difference between the drainage divide and the river cell reached by the flow path was calculated separately for each side of the divide and assigned to grid cells on the corresponding side. Three estimates were considered for the minimum saturated aquifer thickness (b) (**Figure S10**). b_1 was prescribed as a spatially uniform value of 100 m, following Cuthbert et al. (2019). Following Condon and Maxwell (2015), b_2 was calculated locally for each grid cell using the CONCN-simulated water-table depth as $b_2 = 492 \text{ m} - \text{WTD}$, where 492 m is the total modeled subsurface thickness. Finally, b_3 was defined as the CONCN-derived saturated thickness at the river cell reached by each flow path and assigned to grid cells on the corresponding side of the divide.

4.4 WTR configurations and uncertainty experiments

Combining the three estimates of R , three estimates of L , three estimates of d , and three estimates of b with the single K dataset yielded 81 possible WTR calculation configurations (**Table S1**). Each configuration was evaluated against the geometric requirement underlying the Dupuit–Forchheimer approximation, namely $(L/2)/b > 5$ (Cuthbert et al., 2019), where $L/2$ approximates the horizontal aquifer extent and b represents its minimum saturated thickness. Configurations combining L_1 with either b_2 or b_3 failed this criterion across approximately 90% of the grid cells. The corresponding 18 configurations were therefore excluded, leaving 63 configurations for subsequent analysis (**Figure S12**).

To evaluate the effects of alternative input estimation methods around each retained configuration, we constructed configuration-centered comparison ensembles. For each of the 63 retained configurations, a parameter-specific ensemble was generated by holding the estimation methods for the other inputs fixed and replacing only the target input with each of its available estimates (R_1 – R_3 , L_1 – L_3 , d_1 – d_3 , or b_1 – b_3). An all-method ensemble for the focal configuration was then formed as the union of its four parameter-specific ensembles. The all-method ensembles associated with different focal configurations were not mutually exclusive, because the same retained configuration could appear in the all-method ensembles of multiple focal configurations. Moreover, the all-method ensemble associated with a given focal configuration did not necessarily include

all 63 retained configurations. No estimation-method comparison was conducted for K , because only one estimate of K was available.

For each of the 63 retained WTR calculation configurations, parameter uncertainty was quantified through a full-perturbation experiment and five single-parameter experiments, each comprising 10,000 Monte Carlo realizations. For each WTR configuration, the grid-cell-specific estimates were used to define the centers of the sampling distributions for all inputs except hydraulic conductivity. Monte Carlo realizations were then generated by randomly perturbing the five input fields according to the distributions described below (Cuthbert et al., 2019). Groundwater recharge (R) and maximum terrain rise (d) were sampled from normal distributions with standard deviations of $0.22R$ and $0.10d$, respectively. To prevent physically unrealistic values, R was constrained to a minimum of 1×10^{-5} m/yr, and d to a minimum of 1 m. Minimum saturated aquifer thickness (b) and characteristic length (L) were sampled from lognormal distributions by using the base-10 logarithms of their grid-cell-specific estimates as the means in base-10 logarithmic space, with standard deviations of 0.3 in that space. Hydraulic conductivity (K) was sampled from a lognormal distribution, with both its mean and standard deviation in base-10 logarithmic space assigned according to the corresponding hydrolithological class (**Table S2**). In the full-perturbation experiment, all five input fields were sampled simultaneously. In each single-parameter experiment, only R , K , L , d , or b was perturbed, while the other four inputs were held fixed at their configuration-specific estimates. WTR was recalculated across the entire study domain for every realization.

4.5 Uncertainty and stability metrics

Uncertainty metric. Using the same ensemble structure, uncertainty in the magnitude of WTR was quantified at each grid cell using the standard deviation of the base-10 logarithm of WTR, $\sigma_{\log_{10}(\text{WTR})}$. For the across-configuration analysis, this metric represents uncertainty arising from alternative input estimation methods, whereas for the within-configuration analysis, it represents uncertainty arising from random parameter perturbations within a given WTR configuration. The spatial distributions of the grid-cell-level standard deviations were compared to assess the relative magnitudes of these two sources of uncertainty and the contribution of each individual input. Because only one estimate of K was available, its contribution could be evaluated only through the Monte Carlo experiments.

Stability metric. The stability of the WTR-based regime classification was evaluated at each grid cell using the fraction of ensemble members satisfying $\text{WTR} > 1$, denoted $Pr(\text{WTR} > 1)$. For the across-configuration analysis, this fraction was calculated for each focal configuration using either its all-method ensemble or one of its parameter-specific ensembles. For the within-configuration analysis, it was calculated across the 10,000 Monte Carlo realizations from either the full-perturbation experiment or each single-parameter experiment. Values of $Pr(\text{WTR} > 1)$ close to 1 indicate a stable classification as $\text{WTR} > 1$, whereas values close to 0 indicate a stable classification as $\text{WTR} < 1$. Values close to 0.5 indicate maximum classification instability because the grid cell frequently switches across the threshold of 1.

To further evaluate the persistence of the benchmark-relative classifications, we calculated, for each grid cell, the fraction of ensemble members assigned to each applicable classification

outcome. For grid cells identified as sensitive by the physical benchmark, the possible outcomes were CS and UE, with $Pr(CS) + Pr(UE) = 1$. For physically insensitive grid cells, the possible outcomes were CI and OE, with $Pr(CI) + Pr(OE) = 1$. Class frequencies close to 0 or 1 indicate persistent classification into one of the paired outcomes, whereas intermediate frequencies indicate frequent switching between them.

5. Results

5.1 WTR variability, uncertainty, and classification stability

Among the 63 retained configurations, S1, S16, S41, and S81 were selected to represent contrasting input-estimation strategies. S1 (R_1 , L_1 , d_1 , and b_1) was designed to reproduce the WTR calculation of Cuthbert et al. (2019) as closely as possible, using the original inputs where available and reconstructing the unavailable inputs from the methods described in that study. It therefore represents an approximate reconstruction rather than an exact replication. S41 combined the sub-basin-based estimates L_2 and d_2 with R_2 and b_2 , which were calculated from CONCN data using the approaches adopted by Condon and Maxwell (2015). S81 represents a new parameter-estimation strategy developed in this study. It combines R_3 from PCR-GLOBWB with L_3 , d_3 , and b_3 , which were derived by tracing flow paths from each drainage divide to river cells on its two sides. S16 was included as a mixed configuration, combining R_1 and b_1 from S1, L_2 from S41, and d_3 from S81. The published WTR dataset of Cuthbert et al. (2019) was additionally included as the original reference.

The estimated WTR exhibited substantial spatial heterogeneity across the study domain (**Figure 2**). WTR values were generally lower in the western part of the domain and higher toward the east. S16, S41, and S81 also tended to produce higher WTR values than S1 and the published Cuthbert et al. (2019) dataset. These systematic shifts were primarily associated with the larger characteristic lengths and smaller terrain-rise estimates used in the newer configurations (**Figure S10**). In particular, S16 retained the same R_1 , b_1 , and K as S1 but replaced L_1 and d_1 with the larger L_2 and smaller d_3 , respectively, demonstrating that these two changes alone were sufficient to produce a marked increase in WTR. The larger L and smaller d values in S41 and S81 similarly increased WTR, while their higher recharge estimates further reinforced this increase. By contrast, the substantially larger b_2 and b_3 values acted in the opposite direction and partly offset these effects. Despite the differences in magnitude, all WTR estimates exhibited broadly similar spatial patterns that closely, but inversely, resembled the distribution of hydraulic conductivity. Regions with higher K generally exhibited lower WTR, whereas regions with lower K tended to exhibit higher WTR. This spatial correspondence is consistent with the analytical dependence of WTR on K .

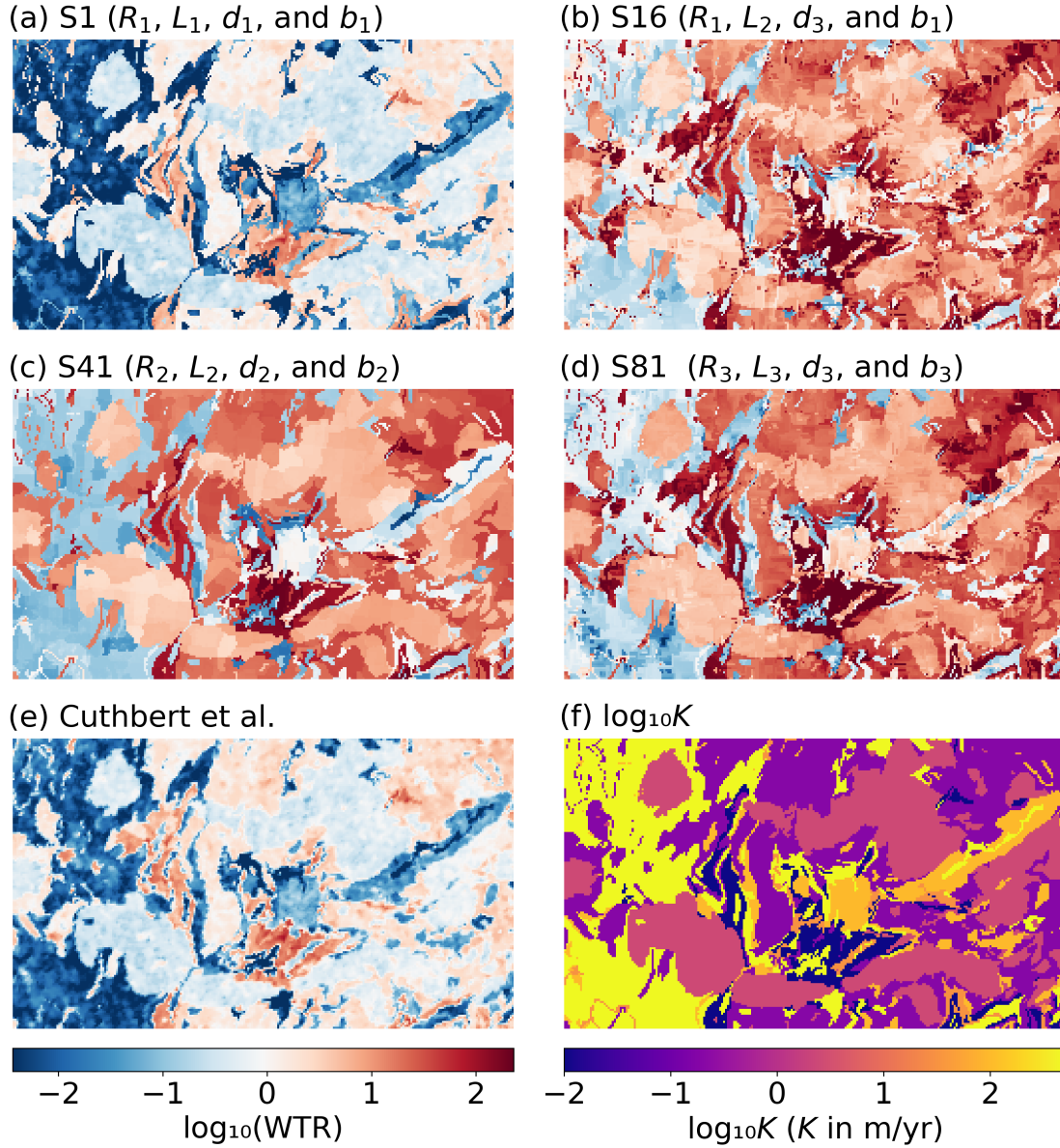


Figure 2. Spatial distributions of $\log_{10}(\text{WTR})$ for four representative WTR configurations and the published dataset of Cuthbert et al. (2019), together with $\log_{10}K$. (a) S1, an approximate reconstruction of the WTR calculation of Cuthbert et al. (2019); (b) S16, a mixed configuration combining different input-estimation strategies; (c) S41, a configuration based primarily on sub-basin-scale estimates; (d) S81, a configuration based primarily on drainage-divide-to-river flow-path estimates; (e) the published WTR dataset of Cuthbert et al. (2019); and (f) hydraulic conductivity, expressed as $\log_{10}K$, where K is in m/yr.

Uncertainty in WTR arising from alternative parameter-estimation methods was compared with that produced by within-configuration Monte Carlo perturbations for the four representative configurations (**Figure 3**). For R , L , and d , variation among the available estimation methods generally produced greater uncertainty than the corresponding Monte Carlo perturbations, indicating that methodological choices can be more consequential than the prescribed random

variability within an individual configuration. The results for b were less consistent, with the relative magnitudes varying among the four representative configurations. In contrast, Monte Carlo perturbation of K produced substantially greater uncertainty than perturbation of any other individual input. Because only one K dataset was available, uncertainty associated with alternative estimates of K could not be evaluated in the across-method analysis. When all five inputs were perturbed simultaneously, the resulting Monte Carlo uncertainty exceeded that obtained from the all-method ensembles, whose members did not include alternative estimates of K . The similarity in magnitude between the K -only and full-perturbation results therefore indicates that uncertainty in K was the principal contributor to the total within-configuration WTR uncertainty under the assumed perturbation distributions. These overall patterns were also evident across all 63 retained configurations (Figures S13–S15).

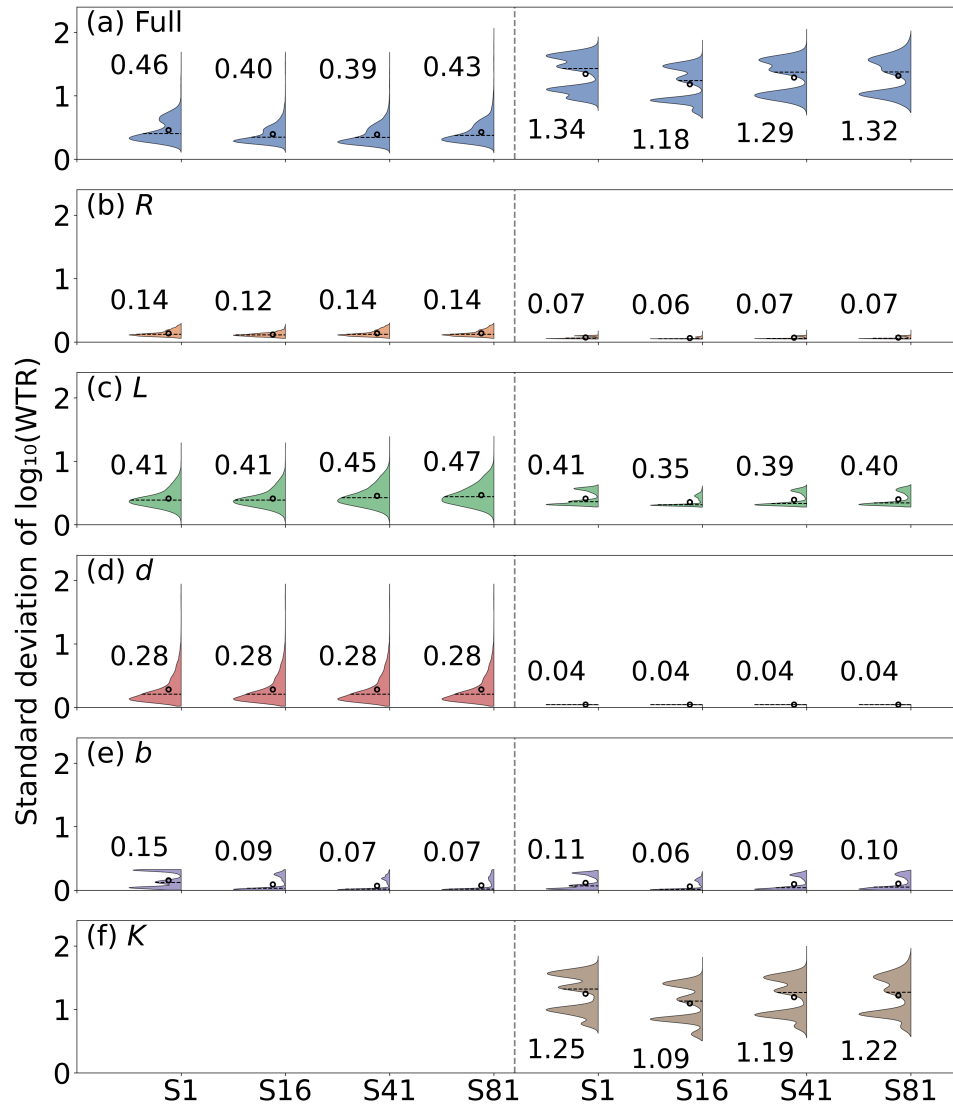


Figure 3. Comparison of grid-cell-level WTR uncertainty arising from alternative parameter-estimation methods and within-configuration Monte Carlo perturbations for four representative WTR configurations. WTR uncertainty was quantified as the standard deviation of $\log_{10}(\text{WTR})$. The half-violin plots to the left of the vertical dashed line show uncertainty from the all-method

ensembles (a) and the parameter-specific ensembles for R , L , d , and b (b–e), whereas those to the right show uncertainty from the full-perturbation experiment (a) and the single-parameter Monte Carlo experiments for R , L , d , b , and K (b–f). No across-method result is shown for K because only one K estimate was available. Open circles and the accompanying values indicate spatial means, and horizontal dashed lines indicate medians.

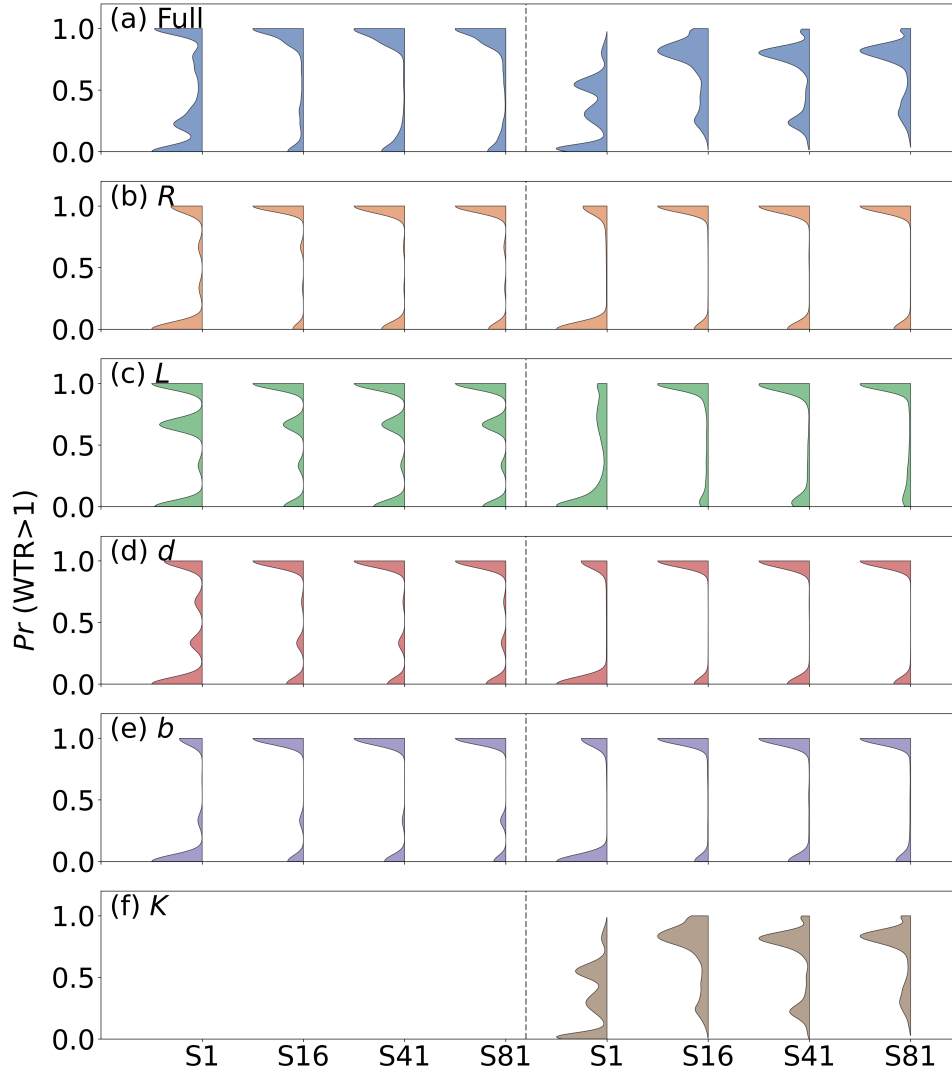


Figure 4. Comparison of grid-cell-level WTR classification stability across alternative parameter-estimation methods and within-configuration Monte Carlo perturbations for four representative WTR configurations. Classification stability was quantified as $Pr(WTR > 1)$, the fraction of ensemble members for which WTR exceeded 1. The half-violin plots to the left of the vertical dashed line show results from the all-method ensembles (a) and the parameter-specific ensembles for R , L , d , and b (b–e), whereas those to the right show results from the full-perturbation experiment (a) and the single-parameter Monte Carlo experiments for R , L , d , b , and K (b–f). Values close to 0 or 1 indicate stable classifications, whereas values close to 0.5 indicate frequent switching across the WTR threshold. No across-method result is shown for K because only one K estimate was available.

The stability of the WTR-based classification was evaluated using $Pr(WTR>1)$ for the four representative configurations (**Figure 4**). In the across-method analysis, both the all-method ensembles (**Figure 4a, left**) and most parameter-specific ensembles (**Figures 4b–e, left**) produced distributions concentrated near 0 and 1, indicating that the WTR classification was generally consistent among the available input-estimation methods. However, additional peaks at intermediate values of $Pr(WTR>1)$ indicate that the classification of some grid cells depended on the estimation method used. This effect was most pronounced for L , followed by d , R , and b . In the within-configuration Monte Carlo experiments, perturbations of R , d , and b generally retained pronounced peaks near 0 and 1, whereas perturbation of L substantially reduced classification stability for S1. Perturbation of K produced the strongest destabilizing effect: the distributions broadened and shifted away from 0 and 1 toward 0.5, particularly for S1. The full-perturbation distributions closely resembled the K -only results, indicating that K dominated the instability when all five inputs were perturbed simultaneously. Thus, WTR classifications were relatively stable across the available estimation methods and under perturbations of most individual inputs, but became substantially less stable when uncertainty in K was included. The same overall patterns were evident across all 63 retained configurations (**Figures S16–S17**). Moreover, relative log-scale WTR uncertainty was generally greatest where $Pr(WTR>1)$ approached 0.5 and decreased toward the two stable endpoints of 0 and 1 (**Figure S18**). This relationship supports the interpretation that classification instability arises when WTR uncertainty is large relative to the distance of its mean from the threshold of 1.

5.2 WTR classification outcomes relative to the physical-model benchmark

Groundwater-sensitive areas identified by the physical benchmark were compared with those obtained using the critical-WTD approach and four representative WTR configurations (**Figure 5**). According to the physical benchmark (**Figure 5a**), groundwater-sensitive areas are primarily distributed in the eastern part of the catchment, with a smaller number of sensitive patches occurring in the western region. Overall, the sensitive areas identified by all four WTR configurations were concentrated primarily in the eastern part of the catchment, with comparatively few sensitive areas identified in the west. In contrast, the critical-WTD approach captures a relatively larger fraction of the western sensitive areas. The resulting classifications exhibited distinct spatial error patterns (**Figures 5b–5f**). The critical-WTD and S1 classifications show relatively large correctly identified insensitive (CI) areas, indicating better agreement with the physical benchmark in regions with weak groundwater–land interactions. However, the remaining representative WTR configurations (S16, S41, and S81) exhibit substantially larger overestimated (OE) areas, suggesting that insensitive regions are more frequently classified as sensitive. By comparison, S1 is characterized by a larger fraction of underestimated (UE) areas, indicating that a considerable proportion of physically sensitive regions are instead classified as insensitive. For the critical-WTD approach, classification discrepancies are also dominated by OE rather than UE regions, although the overall spatial agreement with the physical benchmark remains higher than that of all four representative WTR configurations.

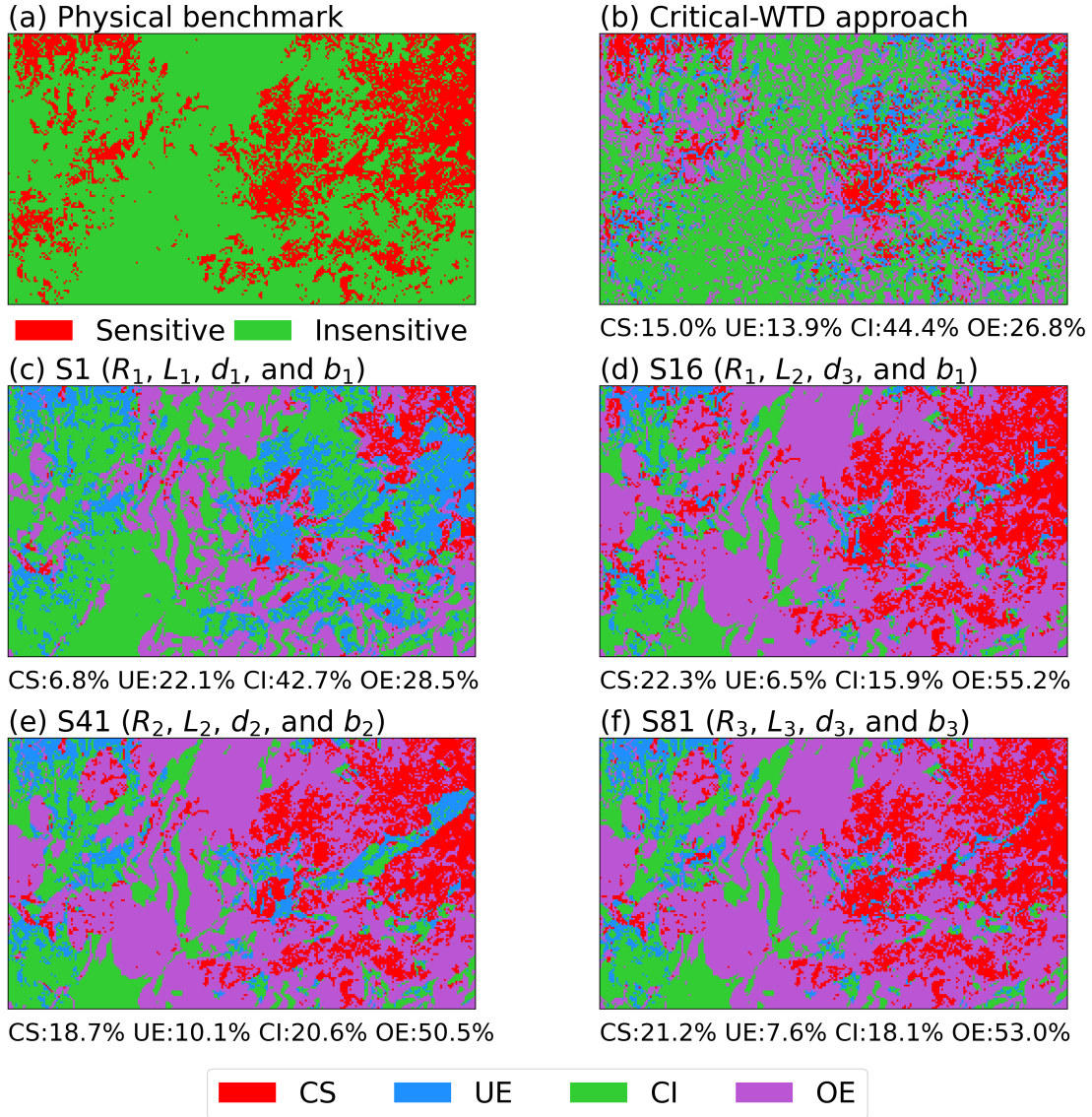


Figure 5. Spatial comparison of groundwater-sensitive-area classifications obtained from the physical benchmark, the critical-WTD approach, and four representative WTR configurations. (a) Physical benchmark defined using $|\Delta EF| > 0.30$; (b) critical-WTD classification based on WY2019 mean WTD from the ParFlow-CLM reference simulation; and WTR classifications from (c) S1, (d) S16, (e) S41, and (f) S81. Panel (a) shows physically sensitive areas in red and physically insensitive areas in green. In panels (b–f), red denotes correctly classified sensitive areas (CS), blue underestimated sensitive areas (UE), green correctly classified insensitive areas (CI), and purple overestimated sensitive areas (OE). Percentages below each map indicate the areal fractions of the four classification outcomes.

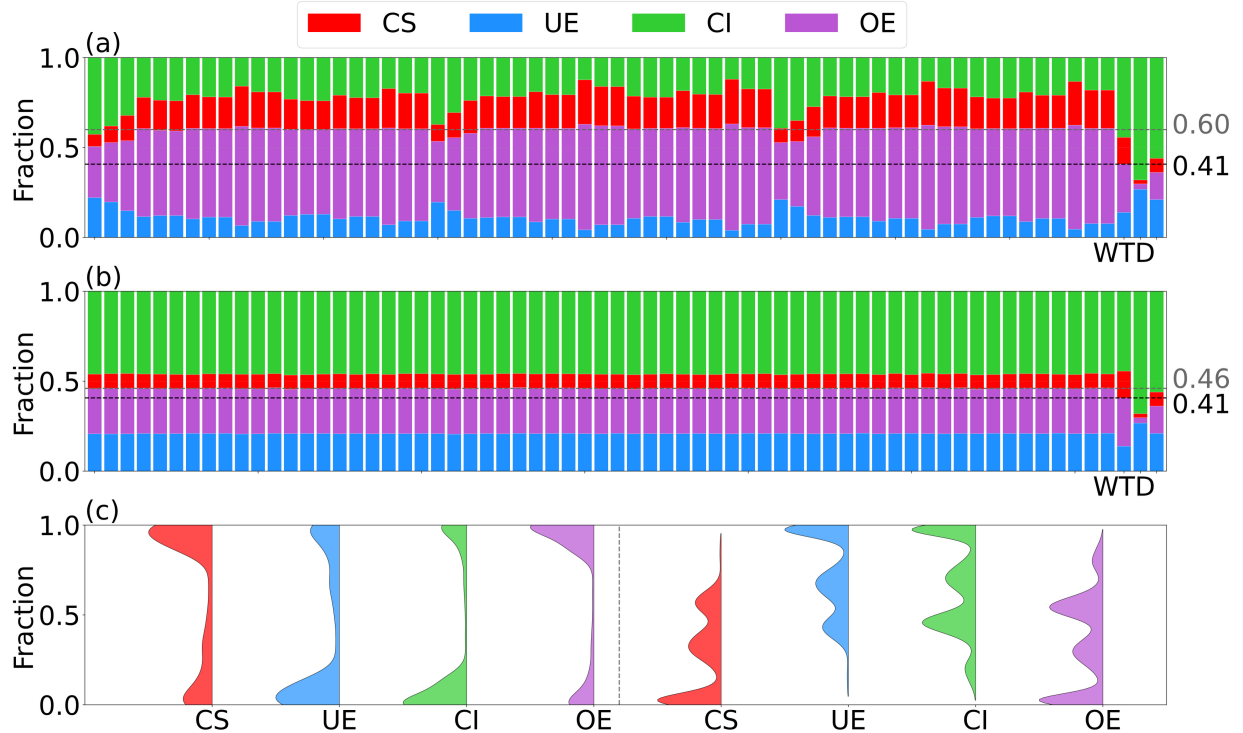


Figure 6. Domain-wide composition and grid-cell persistence of classification outcomes relative to the physical benchmark. (a) Areal fractions of correctly classified sensitive (CS), underestimated sensitive (UE), correctly classified insensitive (CI), and overestimated sensitive (OE) areas for the 63 retained WTR configurations. The three bars at the far right show the critical-WTD classifications based on WY2019 mean WTD from the ParFlow-CLM reference simulation and steady-state WTD estimates from PCR-GLOBWB and Fan et al. (2013), respectively. (b) Corresponding areal fractions for 63 randomly selected realizations from the 10,000-member full-perturbation Monte Carlo experiment for S1, together with the same three critical-WTD classifications at the far right. Horizontal dashed lines in (a) and (b) indicate the mean total misclassified fraction, UE + OE, for the WTR configurations or Monte Carlo realizations. The line labeled 0.41 indicates the corresponding fraction for the ParFlow-CLM-based critical-WTD classification and therefore refers to the first of the three critical-WTD bars. (c) Distributions across grid cells of the fraction of ensemble members assigned to each classification outcome, calculated across the 63 WTR configurations (left) and the 10,000 full-perturbation Monte Carlo realizations for S1 (right); the vertical dashed line separates the two analyses. Colors are consistent across all panels: red for CS, blue for UE, green for CI, and purple for OE.

Figure 6a further quantifies the areal fractions of the four classification outcomes for the critical-WTD approach and the 63 retained WTR configurations. Compared with the critical-WTD approach, the 63 WTR configurations produced a lower mean fraction of correctly classified area (CS + CI; 0.40 versus 0.59), corresponding to a higher total misclassified fraction [$1 - (CS + CI)$; 0.60 versus 0.41]. The critical-WTD classifications based on PCR-GLOBWB (Verkaik et al., 2022) and Fan et al. (2013) showed even greater agreement with the physical benchmark, with correctly classified fractions (CS + CI) of 0.70 and 0.64, respectively. Across the WTR configurations, OE accounted on average for a substantially larger area than UE (0.49 versus 0.11), quantitatively confirming the error pattern observed in **Figure 5**. WTR therefore exhibited a relatively

conservative screening tendency: it reduced the omission of physically sensitive areas, but at the expense of classifying additional physically insensitive areas as sensitive.

Despite differences among the 63 WTR configurations, their aggregate CS, UE, CI, and OE fractions varied only slightly, with small standard deviations of 0.0360, 0.0360, 0.0604, and 0.0604, respectively. A similarly stable classification composition was obtained from 63 randomly selected realizations of the 10,000-member full-perturbation Monte Carlo experiment for S1 (**Figure 6b**), for which the class fractions were nearly unchanged among realizations. Thus, the domain-wide proportions of the four classification outcomes were stable under both alternative parameter-estimation methods and within-configuration parameter perturbations. However, this aggregate stability does not necessarily mean that individual grid cells retained the same classification, which is examined in **Figure 6c**.

Figure 6c therefore examines classification persistence at the grid-cell scale. Because the physical benchmark was held fixed, CS and UE were complementary outcomes within physically sensitive areas, whereas CI and OE were complementary within physically insensitive areas. Across the 63 WTR configurations, physically sensitive grid cells were generally more likely to be classified as CS than UE, indicating predominantly correct and relatively persistent classifications, although a subset of cells remained dependent on the parameter configuration. In physically insensitive areas, the classification frequencies were even more strongly concentrated near the endpoints, but the dominant outcome was OE rather than CI. Many of these grid cells were therefore classified consistently across the configurations, but consistently incorrectly.

A different pattern emerged from the 10,000 full-perturbation Monte Carlo realizations. Within physically sensitive areas, pronounced modes near intermediate classification frequencies indicated substantial switching between CS and UE, while the endpoint modes near CS = 0 and UE = 1 identified grid cells that were persistently underestimated. Within physically insensitive areas, the strongest endpoint modes occurred near CI = 1 and OE = 0, indicating a subset of persistently correct classifications, but substantial intermediate modes revealed continued switching between CI and OE elsewhere. Consequently, Monte Carlo perturbations produced considerable grid-cell-level classification turnover even though the domain-wide class fractions remained nearly unchanged. The apparent stability of the aggregate proportions therefore resulted from compensating transitions between paired classes rather than from spatially stable classifications.

5.3 Parameter controls on classification discrepancies

The distributions of the five WTR parameters within correctly and incorrectly classified regions were compared for the four representative WTR configurations (**Figure 7**). Distinct and consistent patterns emerge for hydraulic conductivity (K) and characteristic length (L). Across all representative configurations, regions classified as insensitive (UE and CI) generally exhibit higher K but lower L than regions classified as sensitive (CS and OE), indicating that both parameters consistently separate the two classification groups. In contrast, terrain rise (d) primarily reflects differences between the underlying physically sensitive and insensitive regions rather than the classification outcomes, showing no clear separation between correctly and incorrectly classified areas. Recharge (R) exhibits no systematic pattern across the four representative

configurations, while minimum saturated aquifer thickness (b) varies only marginally among the four classification outcomes. Overall, only K and L exhibit consistent differences across the four representative configurations, whereas d , R and b show substantially weaker or less consistent patterns. To move beyond these descriptive patterns and quantify the relative contribution of each parameter to the classification discrepancies, we next combined the observed groupwise parameter differences with the analytical elasticities of WTR (**Figure 8**).

Figure 8 shows the estimated first-order contribution of each WTR parameter to $\Delta \ln(\text{WTR})$. The calculation combines each parameter's analytical elasticity with the difference between its group means. Across all four representative configurations, hydraulic conductivity (K) consistently has the largest absolute contribution for both the UE $\rightarrow$ CS and OE $\rightarrow$ CI transitions. Under this one-parameter, first-order approximation, K therefore makes the largest estimated contribution to $\Delta \ln(\text{WTR})$. Characteristic length (L) has the second-largest contribution, although it is substantially smaller than that of K . In contrast, recharge (R), terrain rise (d), and minimum saturated aquifer thickness (b) have smaller or less consistent contributions.

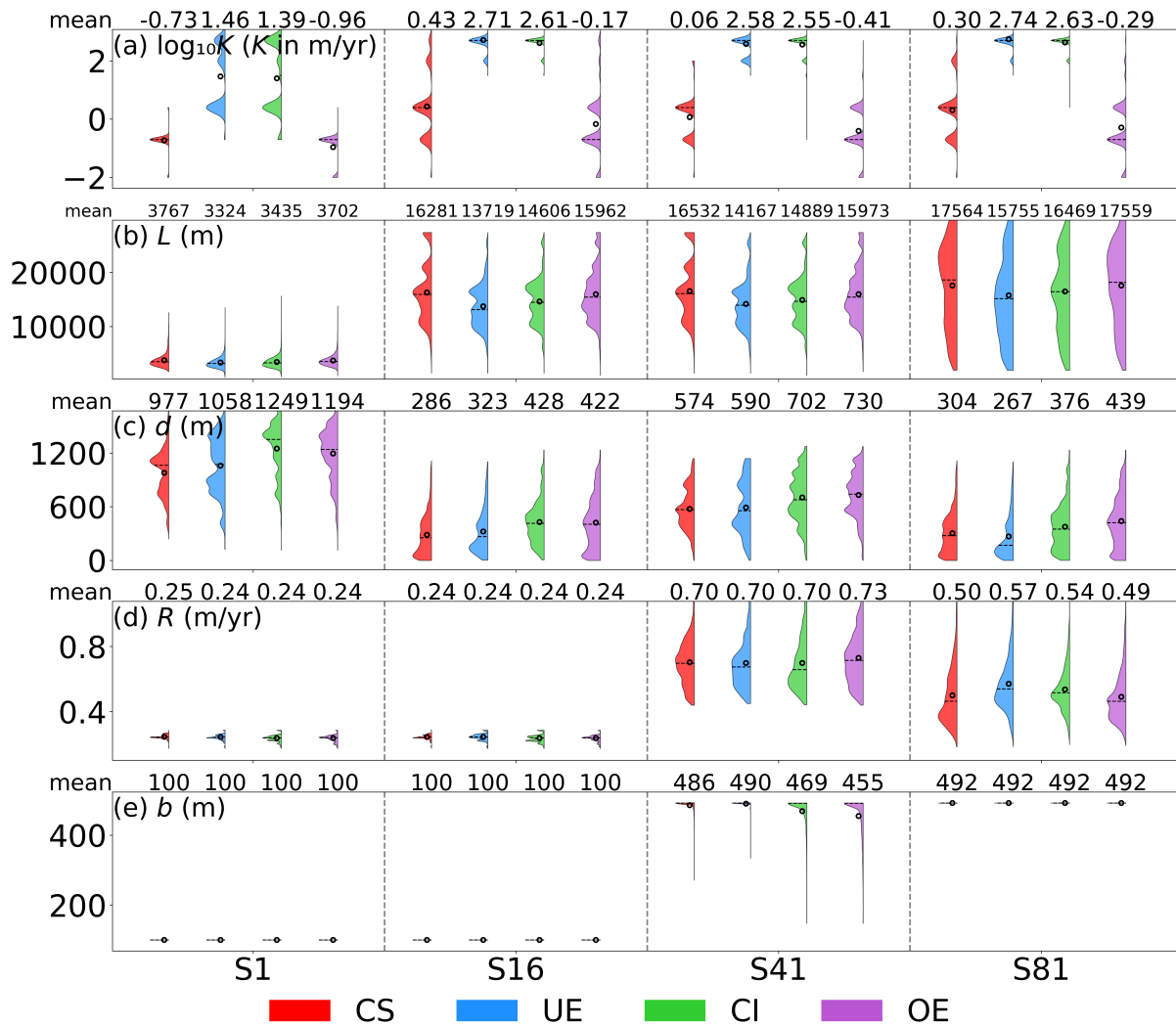


Figure 7. Distributions of the five WTR input parameters among the four benchmark-relative classification outcomes for four representative WTR configurations. Panels show (a) $\log_{10}K$, where

K is hydraulic conductivity in m/yr; (b) characteristic length L (m); (c) maximum terrain rise d (m); (d) groundwater recharge R (m/yr); and (e) minimum saturated aquifer thickness b (m). Within each configuration, red denotes correctly classified sensitive areas (CS), blue underestimated sensitive areas (UE), green correctly classified insensitive areas (CI), and purple overestimated sensitive areas (OE). Vertical dashed lines separate the four WTR configurations. Open circles and the values above the distributions indicate group means; horizontal dashed lines indicate medians.

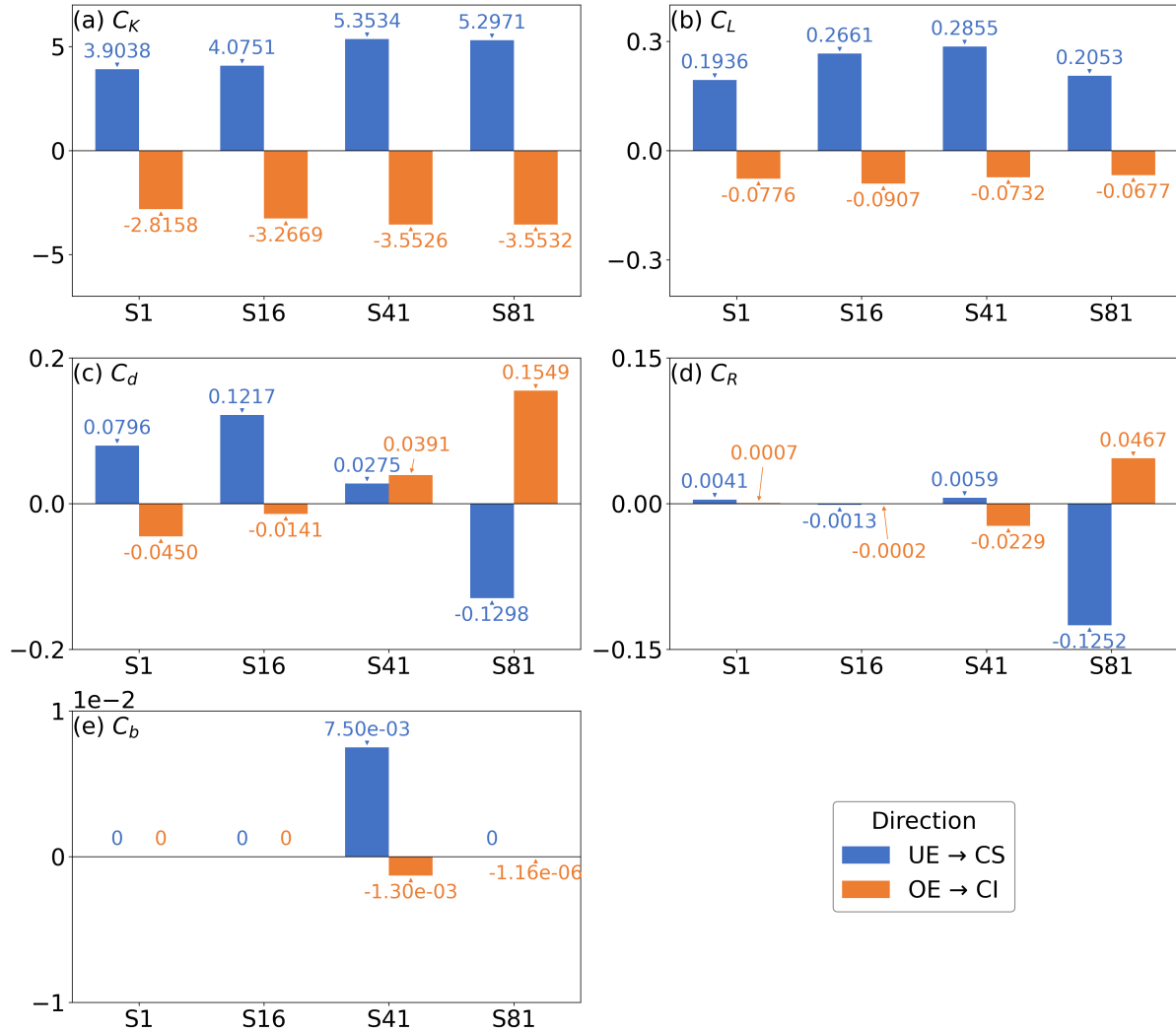


Figure 8. First-order contributions of individual WTR parameters to the estimated changes in $\ln(\text{WTR})$ between incorrectly and correctly classified groups for four representative WTR configurations. Panels show contributions from (a) hydraulic conductivity, C_K ; (b) characteristic length, C_L ; (c) maximum terrain rise, C_d ; (d) groundwater recharge, C_R ; and (e) minimum saturated aquifer thickness, C_b . Contributions were calculated as $C_x \approx E_x \Delta \ln x$, combining the analytical elasticity of WTR with the difference in group-mean parameter values. Blue bars represent the estimated change in $\ln(\text{WTR})$ when one parameter is adjusted from its mean in UE to its corresponding mean in CS, whereas orange bars represent the adjustment from OE to CI; all other parameters are held fixed. Positive and negative values indicate increases and decreases in WTR,

respectively, while larger absolute values indicate stronger first-order contributions to the estimated change in $\ln(\text{WTR})$.

6. Discussion and conclusions

By combining 63 alternative WTR configurations with within-configuration Monte Carlo perturbations, this study examined how WTR estimates and classifications vary with parameterization and uncertainty. The resulting WTR classifications were then compared with groundwater-sensitive areas identified by a physically based model to explore the correspondence between the reduced-dimensional diagnostic and a process-based representation of groundwater–land interactions. The process-based classification is used here as a physically explicit reference rather than as an error-free ground truth. Its plausibility is supported by comparisons with multiple datasets representing streamflow, groundwater conditions, and land-surface variables. In addition, both ParFlow–CLM and WTR derive hydraulic conductivity from GLHYMPS 1.0, providing a consistent hydrogeological basis for comparison. The remaining discrepancies should therefore be interpreted as differences between a reduced-dimensional diagnostic and a process-based representation, rather than as definitive evidence that either approach is universally correct or incorrect.

Hydraulic conductivity (K) was the dominant source of uncertainty in WTR. Perturbing K produced substantially greater variation than perturbing any other individual input, and the full-perturbation results closely resembled those obtained from K alone. For R , L , and d , differences among alternative estimation methods were generally greater than the uncertainty generated by random perturbations around a fixed estimate, whereas the result for b was less consistent. These findings show that WTR uncertainty arises from both parameter-estimation choices and uncertainty within a selected estimate, but that its overall magnitude is primarily controlled by K . The uncertainty in K also reduced the stability of the threshold-based WTR classification. This was particularly evident in the Monte Carlo experiments, in which many grid cells switched between $\text{WTR} > 1$ and $\text{WTR} < 1$. Such instability is particularly relevant where WTR values lie close to the threshold of 1, as in the global distribution presented by Cuthbert et al. (2019), because even moderate parameter perturbations can reverse the classification. Nevertheless, the domain-wide proportions of CS, UE, CI, and OE remained nearly unchanged across both the 63 configurations and the Monte Carlo realizations. This apparent consistency concealed substantial spatial turnover, because transitions between CS and UE and between CI and OE compensated for one another when aggregated over the domain. Aggregate area fractions therefore provide little information about whether individual locations are classified consistently.

The comparison with the physically based benchmark further distinguished classification stability from classification accuracy. WTR produced considerably more OE than UE, indicating a conservative screening tendency: it omitted relatively few physically sensitive areas but classified many physically insensitive areas as sensitive. Its overall agreement with the benchmark was also lower than that obtained using the critical-WTD approach. The parameter distributions within CS, UE, CI, and OE areas, together with the elasticity-based contribution analysis, provided a further explanation for these classification discrepancies. Differences in K made the largest contribution to shifts between the correctly and incorrectly classified groups, with L providing a secondary contribution, whereas the effects of R , d , and b were generally smaller or less consistent. Thus, K

not only controls WTR uncertainty and classification instability, but is also the parameter most strongly associated with where WTR agrees or disagrees with the physical benchmark.

The central role of K exposes a limitation of the dimensional reduction underlying WTR. WTR reduces a heterogeneous three-dimensional groundwater system to a one-dimensional conceptual model described by a small number of effective parameters. Although this reduction makes regional application straightforward, it cannot explicitly represent vertical layering, lateral heterogeneity, preferential pathways, or complex groundwater–surface-water connections. A disproportionate share of this unresolved subsurface information must consequently be represented through an effective hydraulic conductivity, making K both highly influential and difficult to constrain. The dominance of K should therefore be interpreted not only as a data-uncertainty problem, but also as evidence of the limited capacity of a single effective parameter to represent complex groundwater systems.

Overall, WTR remains useful as a simple and conservative indicator for regional screening, but its local classifications should not be regarded as definitive. Particular caution is required where hydraulic conductivity is poorly constrained, subsurface heterogeneity is strong, or WTR values lie close to one. In these settings, WTR should be interpreted together with groundwater-depth indicators, physically based simulations, or other independent evidence. More generally, the results demonstrate that the convenience gained by reducing complex groundwater processes to a low-dimensional index must be weighed against the uncertainty and loss of spatial information introduced by that reduction.

703 **Code and data availability**

704 The model outputs and other data underlying the analyses, together with the scripts used to
705 generate all figures, are available at <https://doi.org/10.57760/sciencedb.46348>

706 **Author contribution**

707 Conceptualization: CY. Methodology: CY and AS. Investigation: CY, AS, and ZT. Resources:
708 CY. Writing (original draft): CY, AS, and ZT. Writing (review and editing): CY, AS, ZT, CZ, and
709 WS.

710 **Competing interests**

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

712

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Supplementary Information

Table S1. The 81 WTR configurations generated by combining alternative estimates of groundwater recharge (R), characteristic length (L), maximum terrain rise (d), and minimum saturated aquifer thickness (b). Configurations highlighted in red failed the Dupuit–Forchheimer applicability criterion, $(L/2)/b > 5$, and were excluded, leaving 63 configurations for subsequent analysis.

Schemes	Parameters				Schemes	Parameters				Schemes	Parameters			
1	R_1	L_1	d_1	b_1	28	R_2	L_1	d_1	b_1	55	R_3	L_1	d_1	b_1
2	R_1	L_1	d_1	b_2	29	R_2	L_1	d_1	b_2	56	R_3	L_1	d_1	b_2
3	R_1	L_1	d_1	b_3	30	R_2	L_1	d_1	b_3	57	R_3	L_1	d_1	b_3
4	R_1	L_1	d_2	b_1	31	R_2	L_1	d_2	b_1	58	R_3	L_1	d_2	b_1
5	R_1	L_1	d_2	b_2	32	R_2	L_1	d_2	b_2	59	R_3	L_1	d_2	b_2
6	R_1	L_1	d_2	b_3	33	R_2	L_1	d_2	b_3	60	R_3	L_1	d_2	b_3
7	R_1	L_1	d_3	b_1	34	R_2	L_1	d_3	b_1	61	R_3	L_1	d_3	b_1
8	R_1	L_1	d_3	b_2	35	R_2	L_1	d_3	b_2	62	R_3	L_1	d_3	b_2
9	R_1	L_1	d_3	b_3	36	R_2	L_1	d_3	b_3	63	R_3	L_1	d_3	b_3
10	R_1	L_2	d_1	b_1	37	R_2	L_2	d_1	b_1	64	R_3	L_2	d_1	b_1
11	R_1	L_2	d_1	b_2	38	R_2	L_2	d_1	b_2	65	R_3	L_2	d_1	b_2
12	R_1	L_2	d_1	b_3	39	R_2	L_2	d_1	b_3	66	R_3	L_2	d_1	b_3
13	R_1	L_2	d_2	b_1	40	R_2	L_2	d_2	b_1	67	R_3	L_2	d_2	b_1
14	R_1	L_2	d_2	b_2	41	R_2	L_2	d_2	b_2	68	R_3	L_2	d_2	b_2
15	R_1	L_2	d_2	b_3	42	R_2	L_2	d_2	b_3	69	R_3	L_2	d_2	b_3
16	R_1	L_2	d_3	b_1	43	R_2	L_2	d_3	b_1	70	R_3	L_2	d_3	b_1
17	R_1	L_2	d_3	b_2	44	R_2	L_2	d_3	b_2	71	R_3	L_2	d_3	b_2
18	R_1	L_2	d_3	b_3	45	R_2	L_2	d_3	b_3	72	R_3	L_2	d_3	b_3
19	R_1	L_3	d_1	b_1	46	R_2	L_3	d_1	b_1	73	R_3	L_3	d_1	b_1
20	R_1	L_3	d_1	b_2	47	R_2	L_3	d_1	b_2	74	R_3	L_3	d_1	b_2
21	R_1	L_3	d_1	b_3	48	R_2	L_3	d_1	b_3	75	R_3	L_3	d_1	b_3
22	R_1	L_3	d_2	b_1	49	R_2	L_3	d_2	b_1	76	R_3	L_3	d_2	b_1
23	R_1	L_3	d_2	b_2	50	R_2	L_3	d_2	b_2	77	R_3	L_3	d_2	b_2
24	R_1	L_3	d_2	b_3	51	R_2	L_3	d_2	b_3	78	R_3	L_3	d_2	b_3
25	R_1	L_3	d_3	b_1	52	R_2	L_3	d_3	b_1	79	R_3	L_3	d_3	b_1
26	R_1	L_3	d_3	b_2	53	R_2	L_3	d_3	b_2	80	R_3	L_3	d_3	b_2
27	R_1	L_3	d_3	b_3	54	R_2	L_3	d_3	b_3	81	R_3	L_3	d_3	b_3

Table S2. Parameter perturbation settings in Monte Carlo realizations

(a) General parameter settings

Parameter	Distribution type	Standard deviation/ Log-standard deviation	Physical truncation
R	Normal	$0.22 \times R$	$R \geq 0.00001$
d	Normal	$0.1 \times d$	$d \geq 1$
b	Log-normal	0.3	None
L	Log-normal	0.3	None
K	Log-normal	Hydrolithology- dependent; see (b)	None

(b) Lithology-dependent settings for K

Hydrolithology	$\log_{10}k$	Standard deviation	Number of grid cells
f.g. sil. sedimentary	-16.5	1.7	2295
sil. sedimentary	-15.2	2.5	11863
crystalline	-14.1	1.5	10389
f.g. unconsolidated	-14.0	1.8	21
unconsolidated	-13.0	2.0	710
c.g. sil. sedimentary	-12.5	0.9	2963
carbonate	-11.8	1.5	7969
c.g. unconsolidated	-10.9	1.2	582

$\log_{10}K = \log_{10}k + 7 + \log_{10}(3600 \times 8760)$, where k is permeability in m^2

c.g. = coarse-grained, f.g. = fine-grained, sil. = siliciclastic

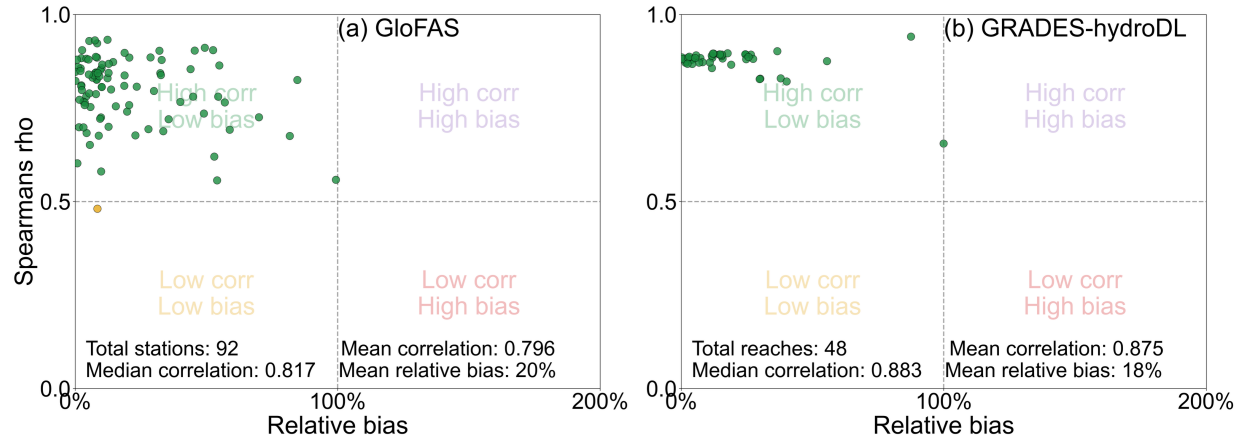


Figure S1. Comparison of daily streamflow simulated by ParFlow-CLM with (a) GloFAS estimates at 92 locations and (b) GRADES-hydroDL estimates at 48 locations during WY2019. Each point represents one location, positioned according to the Spearman rank correlation coefficient and relative bias between the simulated and reference daily time series; the locations are shown in Figure 1. Dashed lines indicate correlation and relative-bias thresholds of 0.5 and 100%, respectively. Summary statistics across all locations are reported in the lower-left corner of each panel.

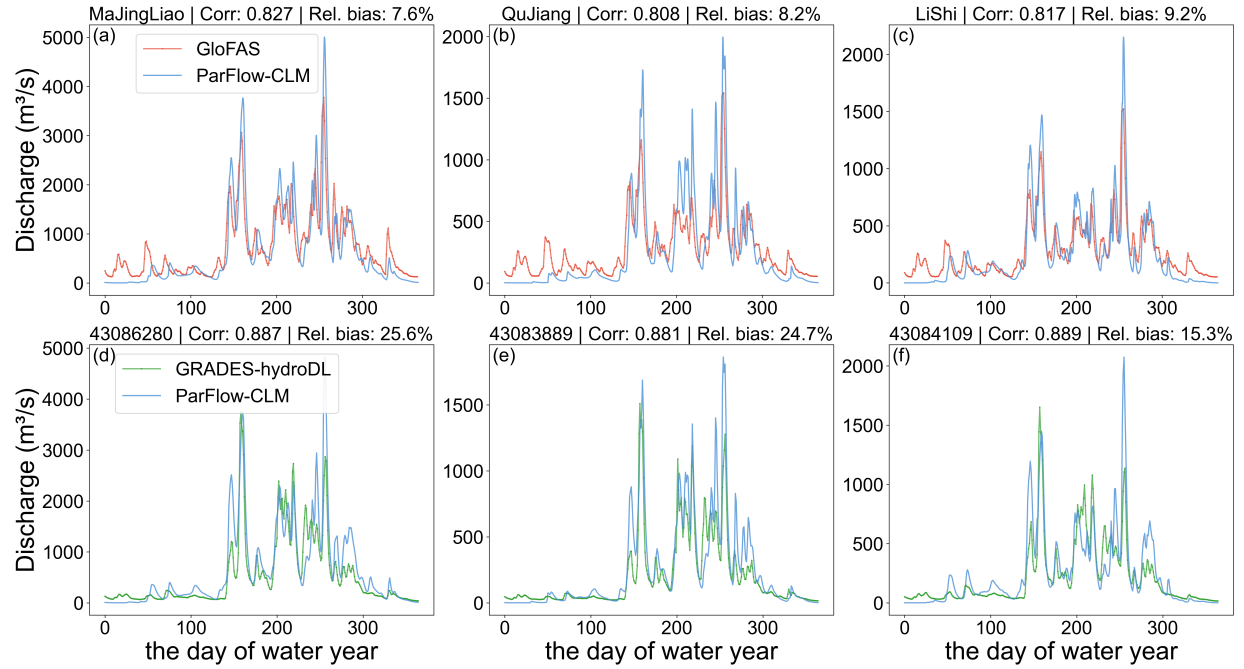


Figure S2. Daily streamflow time series from ParFlow-CLM and the reference products at six relatively high-discharge locations during WY2019: GloFAS at (a) MaJingLiao, (b) QuJiang, and (c) ShaoGuan, and GRADES-hydroDL at (d) LiShi, (e) ZhangBa, and (f) YangXi. Three locations were selected from each product, and their locations are indicated by stars in Figure 1. Panel titles report the Spearman rank correlation coefficient and relative bias.

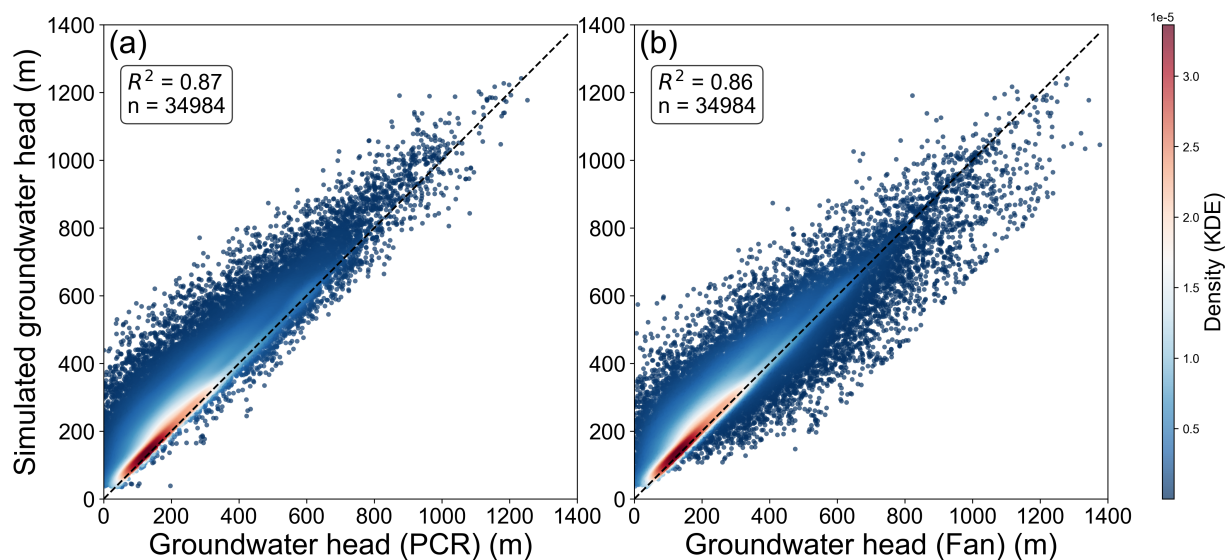


Figure S3. Comparison of WY2019 mean groundwater head simulated by ParFlow-CLM with steady-state groundwater-head estimates from (a) PCR-GLOBWB and (b) Fan et al. (2013). Each point represents one model grid cell, and colors indicate point density estimated using kernel density estimation.

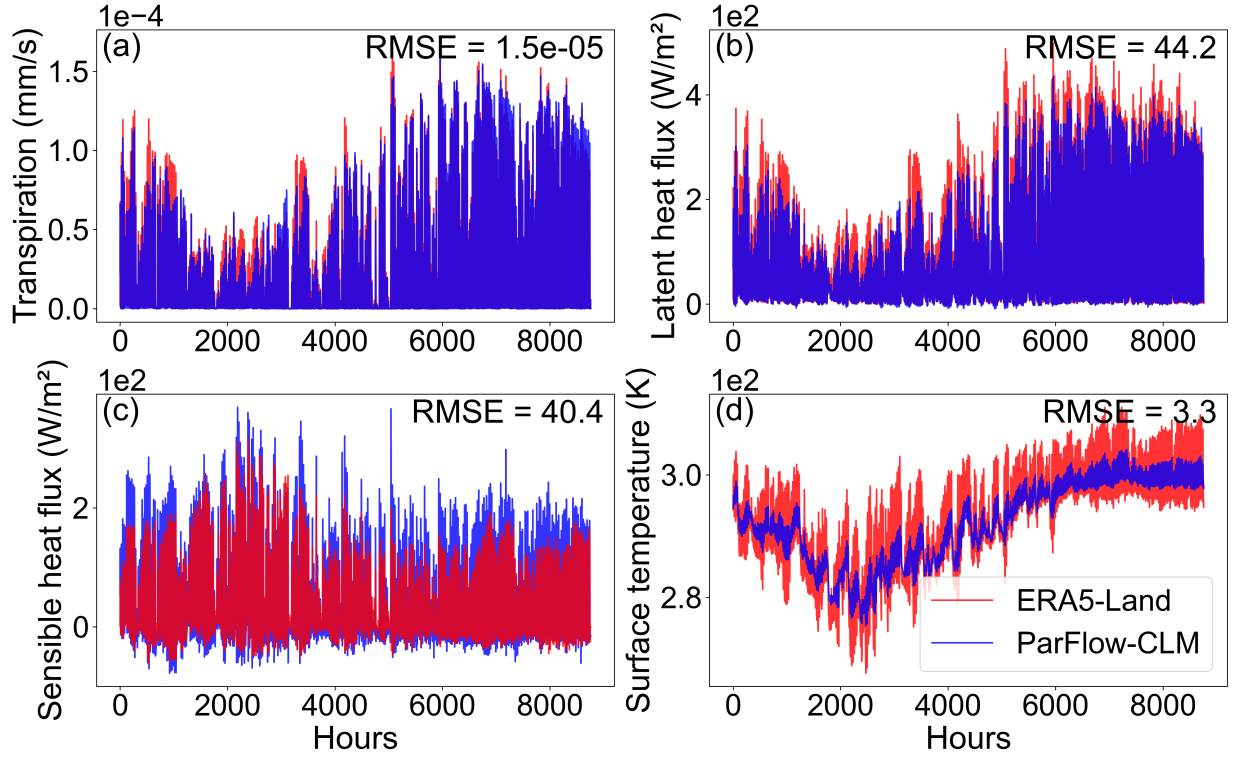


Figure S4. Comparison of domain-mean hourly land-surface variables simulated by ParFlow-CLM with ERA5-Land during WY2019: (a) transpiration, (b) latent heat flux, (c) sensible heat flux, and (d) land-surface temperature. Red and blue lines represent ERA5-Land and ParFlow-CLM, respectively. Root-mean-square errors are reported in each panel.

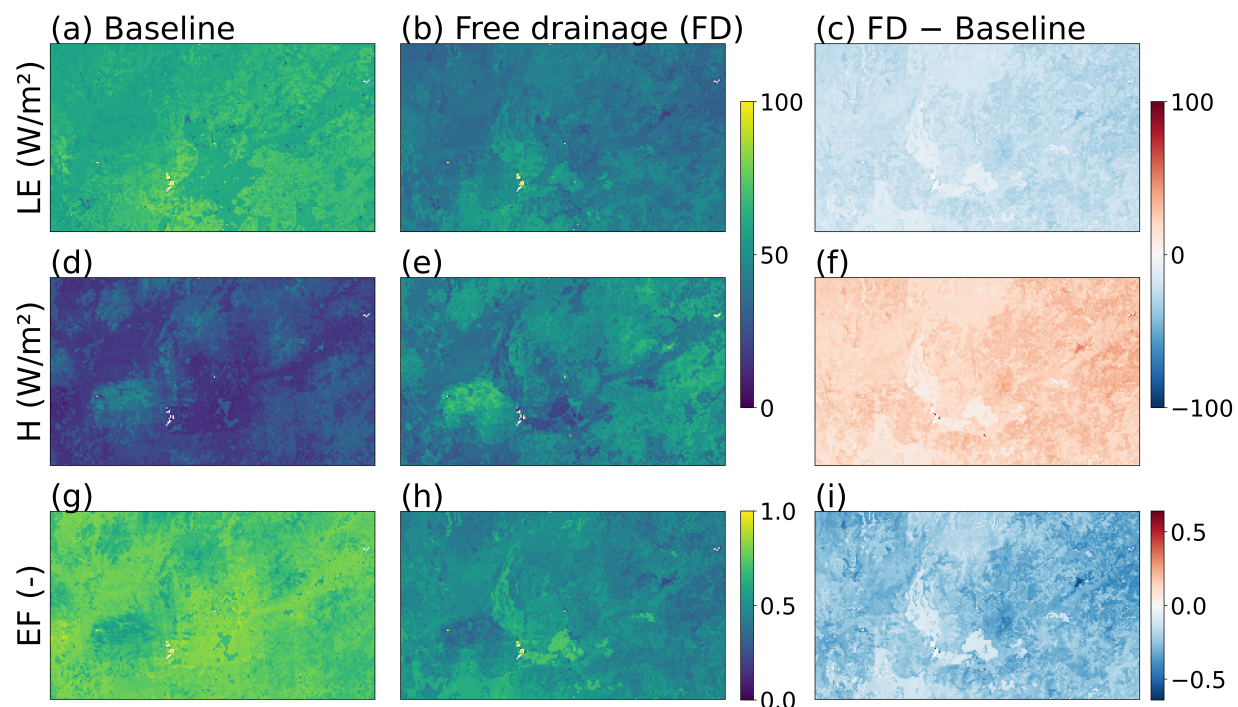


Figure S5. Spatial distributions of mean land-surface variables during WY2019 from the baseline (reference) and free-drainage (groundwater-suppressed) simulations. The first column shows the baseline simulation, the second column the free-drainage simulation, and the third column their difference, calculated as free drainage minus baseline. Rows show (a–c) latent heat flux (LE), (d–f) sensible heat flux (H), and (g–i) evaporative fraction (EF).

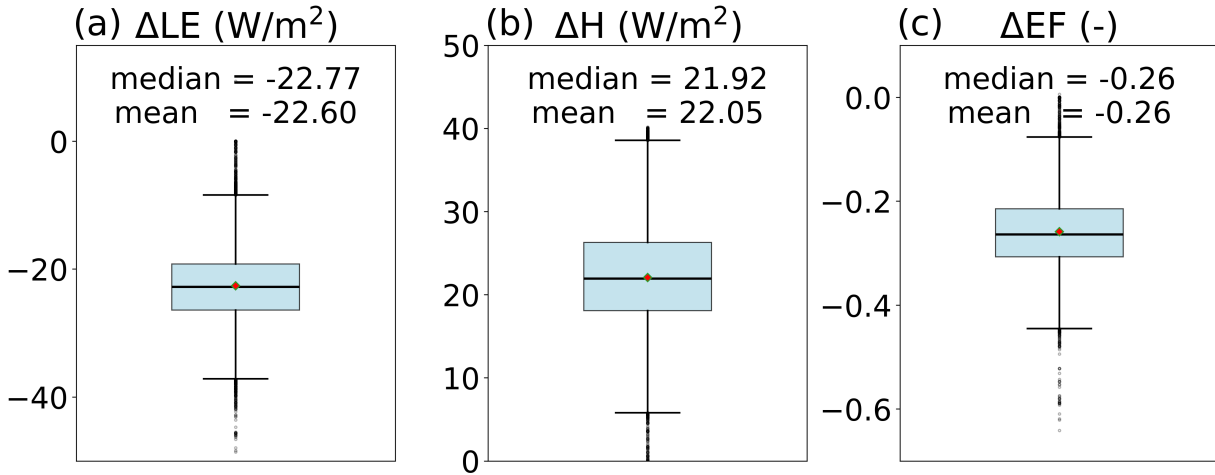


Figure S6. Distributions of grid-cell differences in WY2019 mean land-surface variables between the free-drainage (groundwater-suppressed) and baseline (reference) simulations: (a) latent heat flux (ΔLE), (b) sensible heat flux (ΔH), and (c) evaporative fraction (ΔEF). Differences are calculated as free drainage minus baseline. Boxplots summarize values across the study domain; annotated values report the spatial median and mean.

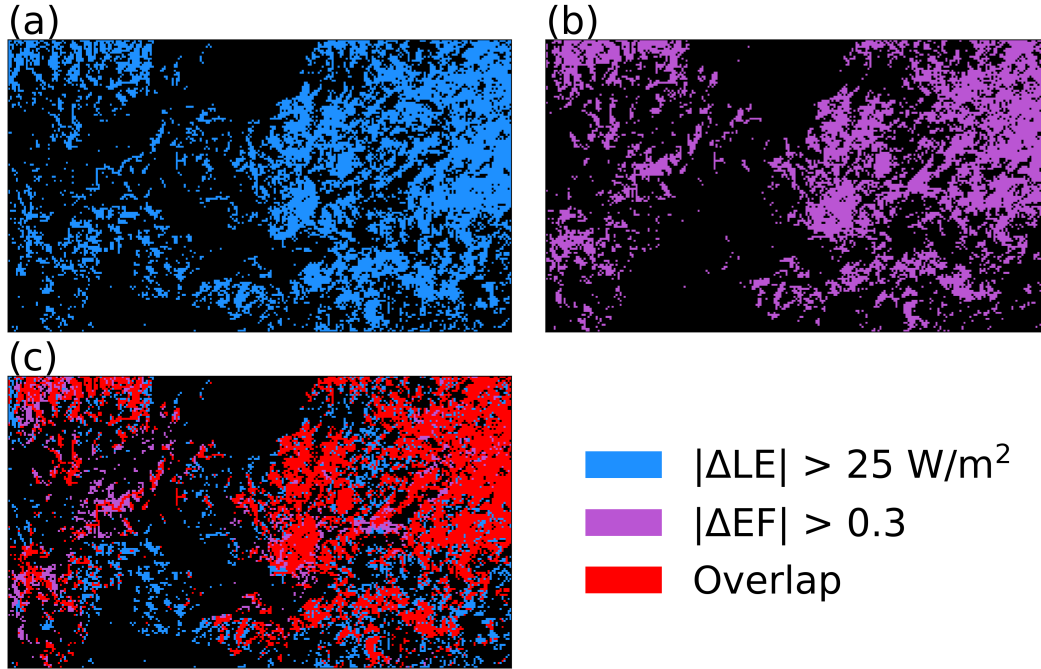


Figure S7. Groundwater-sensitive areas identified from differences in WY2019 mean latent heat flux (ΔLE) and evaporative fraction (ΔEF) between the free-drainage (groundwater-suppressed) and baseline (reference) simulations. (a) Grid cells satisfying $|\Delta LE| > 25 \text{ W/m}^2$; (b) grid cells satisfying $|\Delta EF| > 0.30$; and (c) spatial comparison of the two masks. Blue and purple indicate areas identified only by the ΔLE and ΔEF criteria, respectively, while red indicates their overlap.

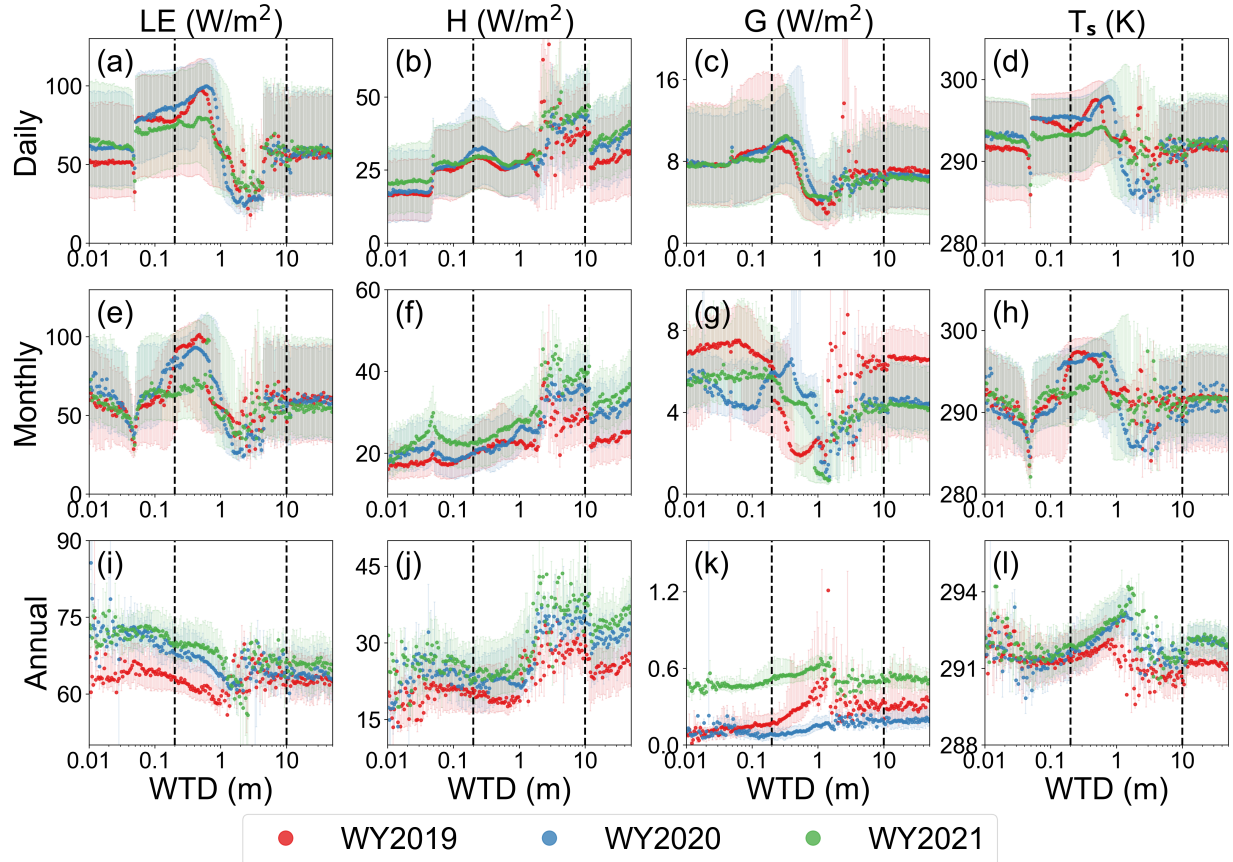


Figure S8. Relationships between water table depth (WTD) and four land-surface variables at daily, monthly, and annual averaging scales. Columns show latent heat flux (LE), sensible heat flux (H), ground heat flux (G), and land-surface temperature (T_s); rows show daily (a–d), monthly (e–h), and annual (i–l) averages. Red, blue, and green represent WY2019, WY2020, and WY2021, respectively. Vertical dashed lines delimit the critical WTD range identified by jointly examining the relationships across variables, years, and temporal scales.

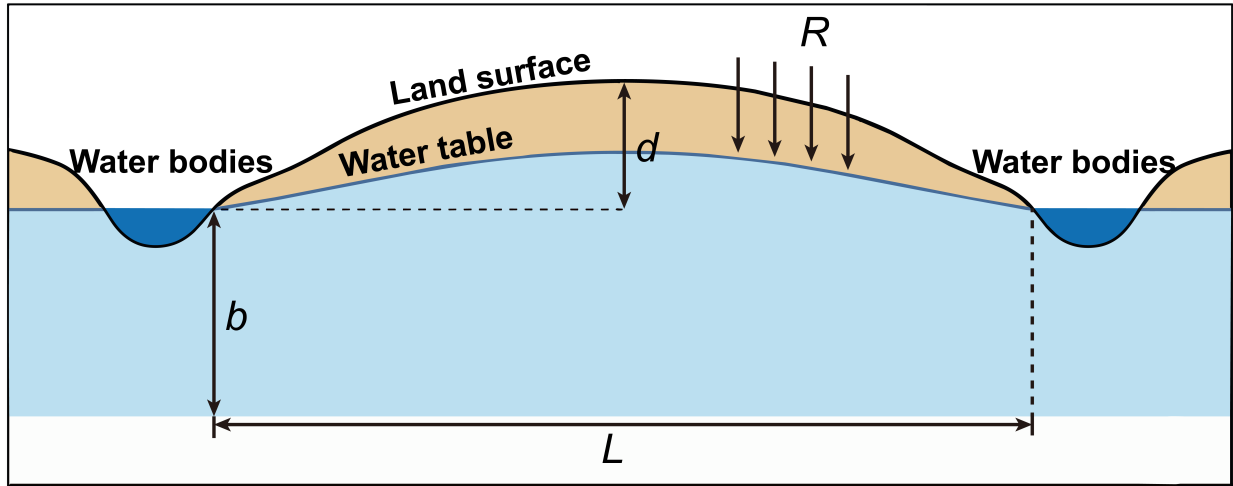


Figure S9. Conceptual representation of the idealized interstream aquifer underlying the WTR formulation. R is groundwater recharge, L is the characteristic distance between the two fixed-head stream boundaries, b is the minimum saturated aquifer thickness at the fixed-head boundary, and d is the maximum terrain rise above that boundary. The water table rises from the bounding streams toward the groundwater divide.

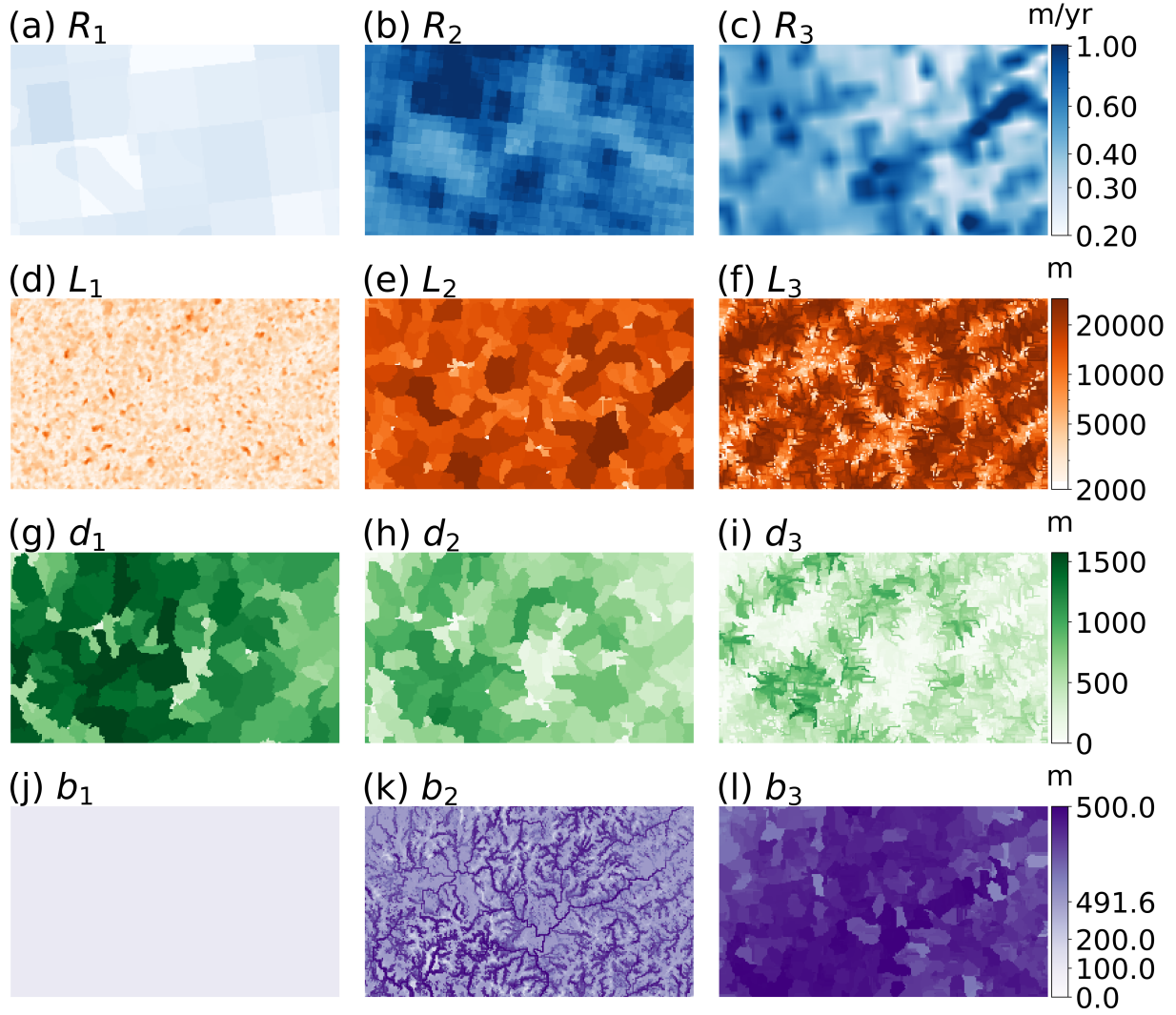


Figure S10. Spatial distributions of the alternative input estimates used to calculate WTR. Panels show groundwater recharge (a) R_1 , (b) R_2 , and (c) R_3 in m/yr; characteristic length (d) L_1 , (e) L_2 , and (f) L_3 in m; maximum terrain rise (g) d_1 , (h) d_2 , and (i) d_3 in m; and minimum saturated aquifer thickness (j) b_1 , (k) b_2 , and (l) b_3 in m.

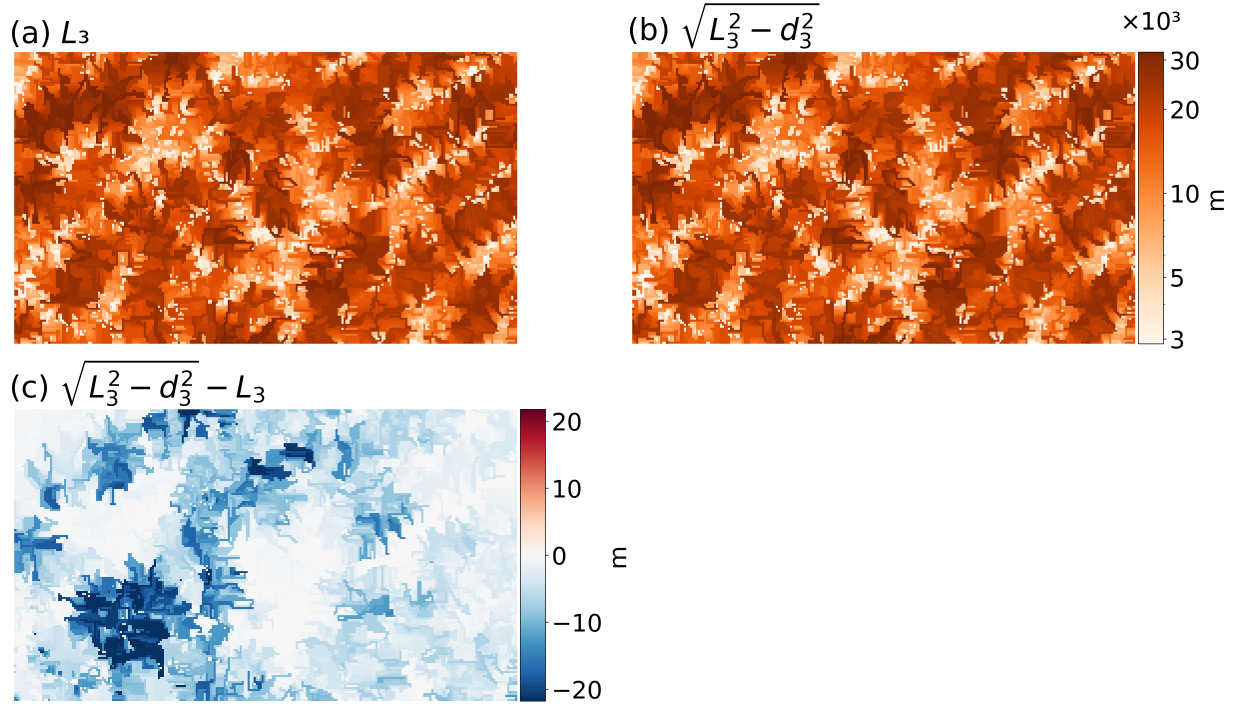


Figure S11. Effect of correcting the path-based characteristic length for terrain rise. (a) Original path-based estimate L_3 ; (b) its approximate horizontal component, calculated as $\sqrt{L_3^2 - d_3^2}$; and (c) the difference $\sqrt{L_3^2 - d_3^2} - L_3$. All values are in metres.

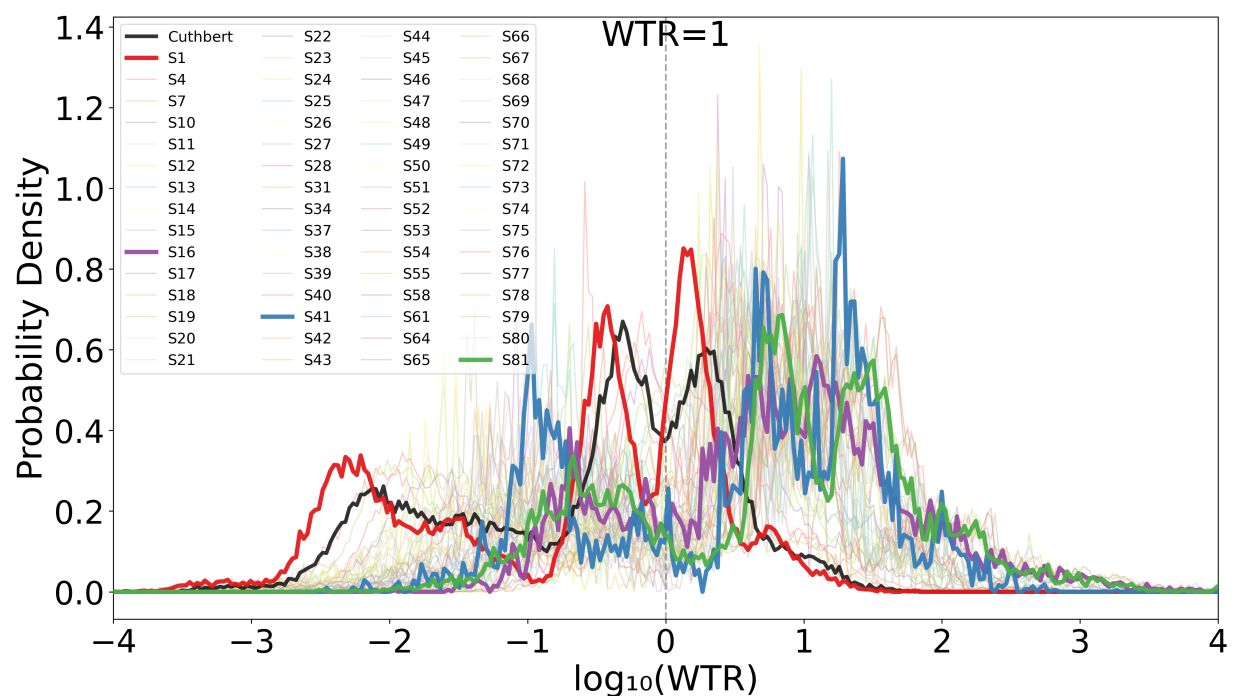


Figure S12. Probability-density distributions of $\log_{10}(\text{WTR})$ for the 63 retained WTR configurations and the published WTR dataset of Cuthbert et al. (2019). The four representative configurations S1, S16, S41, and S81 are highlighted. The vertical dashed line at $\log_{10}(\text{WTR})=0$ corresponds to the classification threshold $\text{WTR}=1$.

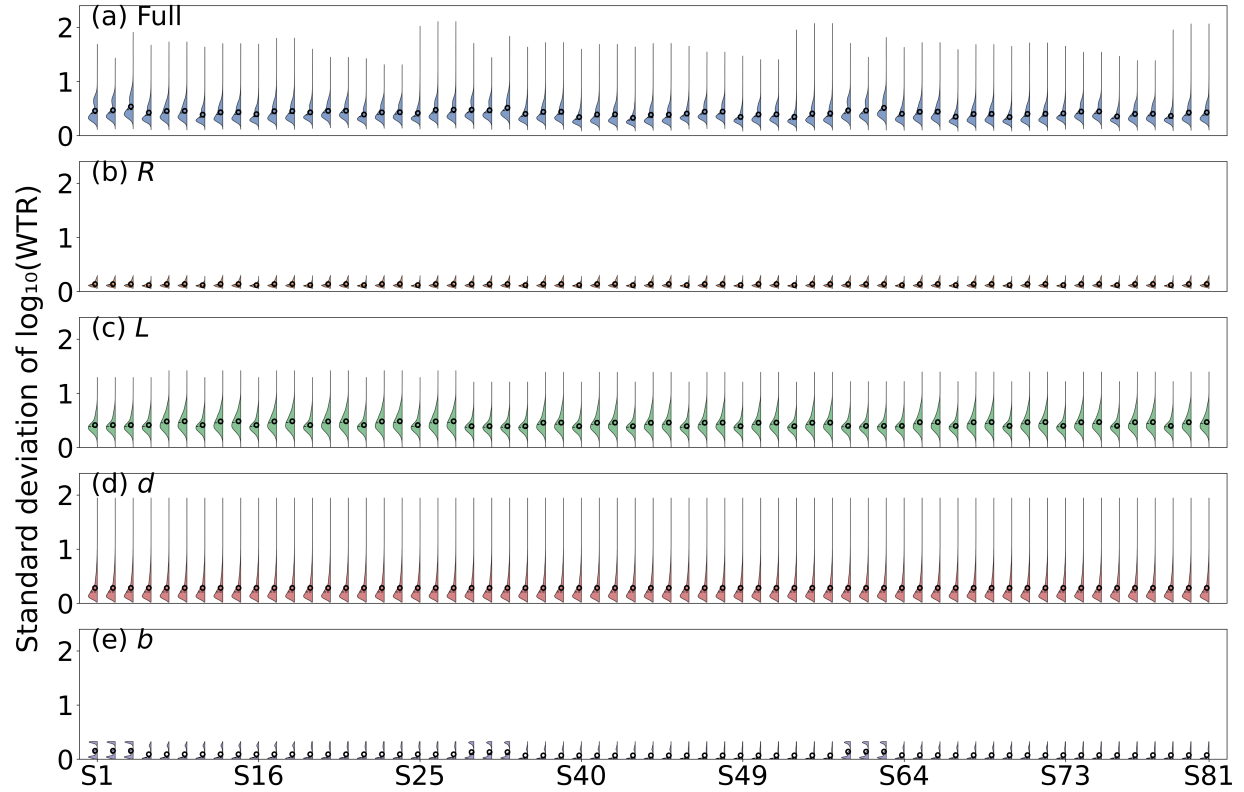


Figure S13. Distributions of grid-cell-level WTR uncertainty arising from alternative parameter-estimation methods for all 63 retained focal configurations. Uncertainty was quantified as the standard deviation of $\log_{10}(\text{WTR})$. Rows show results from (a) the all-method ensembles and the parameter-specific ensembles for (b) R , (c) L , (d) d , and (e) b . Horizontal dashed lines and open circles indicate spatial medians and means, respectively. No across-method result is shown for K because only one K estimate was available.

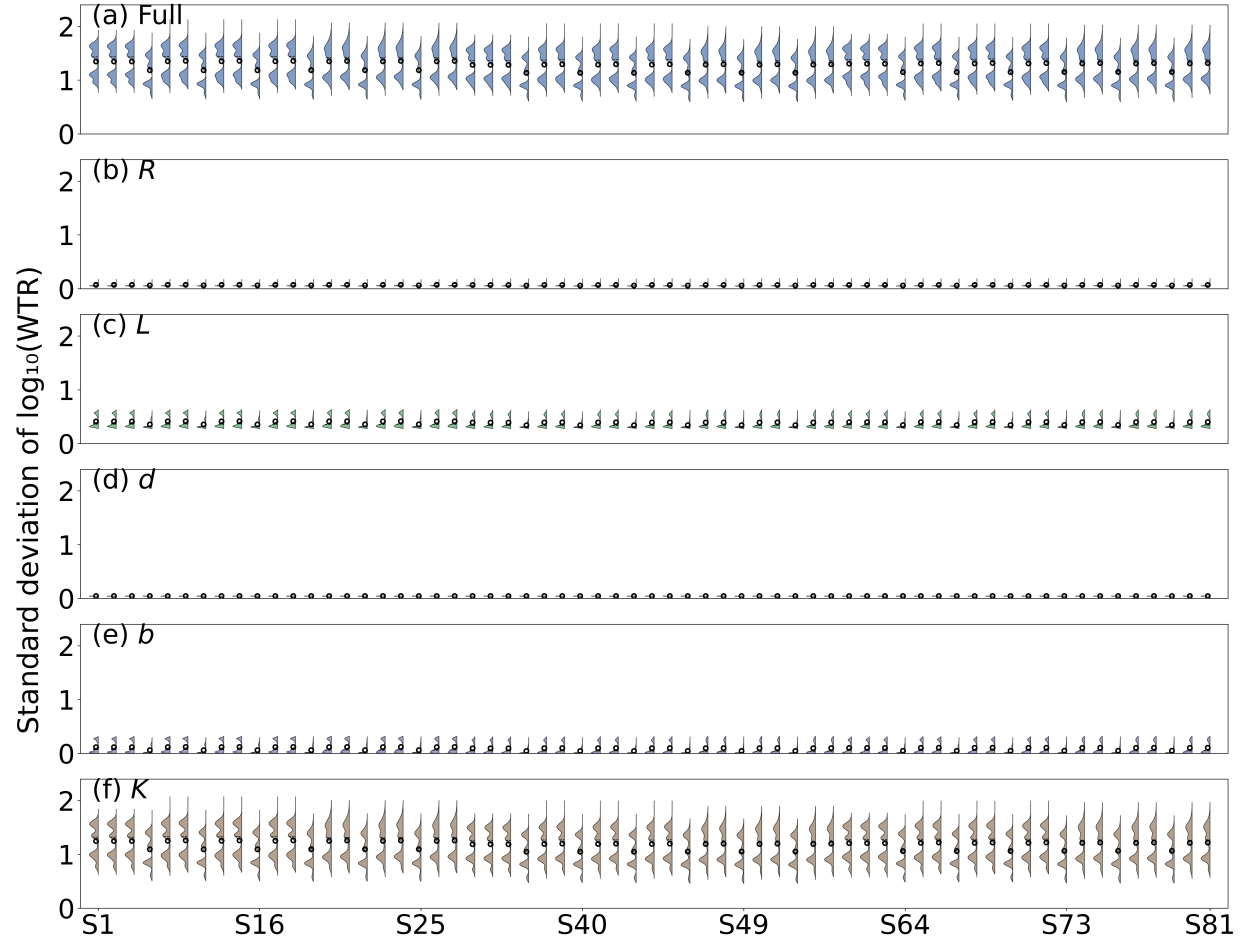


Figure S14. Distributions of grid-cell-level WTR uncertainty from within-configuration Monte Carlo perturbations for all 63 retained WTR configurations. Uncertainty was quantified as the standard deviation of $\log_{10}(\text{WTR})$ across 10,000 realizations. Rows show (a) the full-perturbation experiment and the single-parameter experiments for (b) R , (c) L , (d) d , (e) b , and (f) K . Horizontal dashed lines and open circles indicate spatial medians and means, respectively.

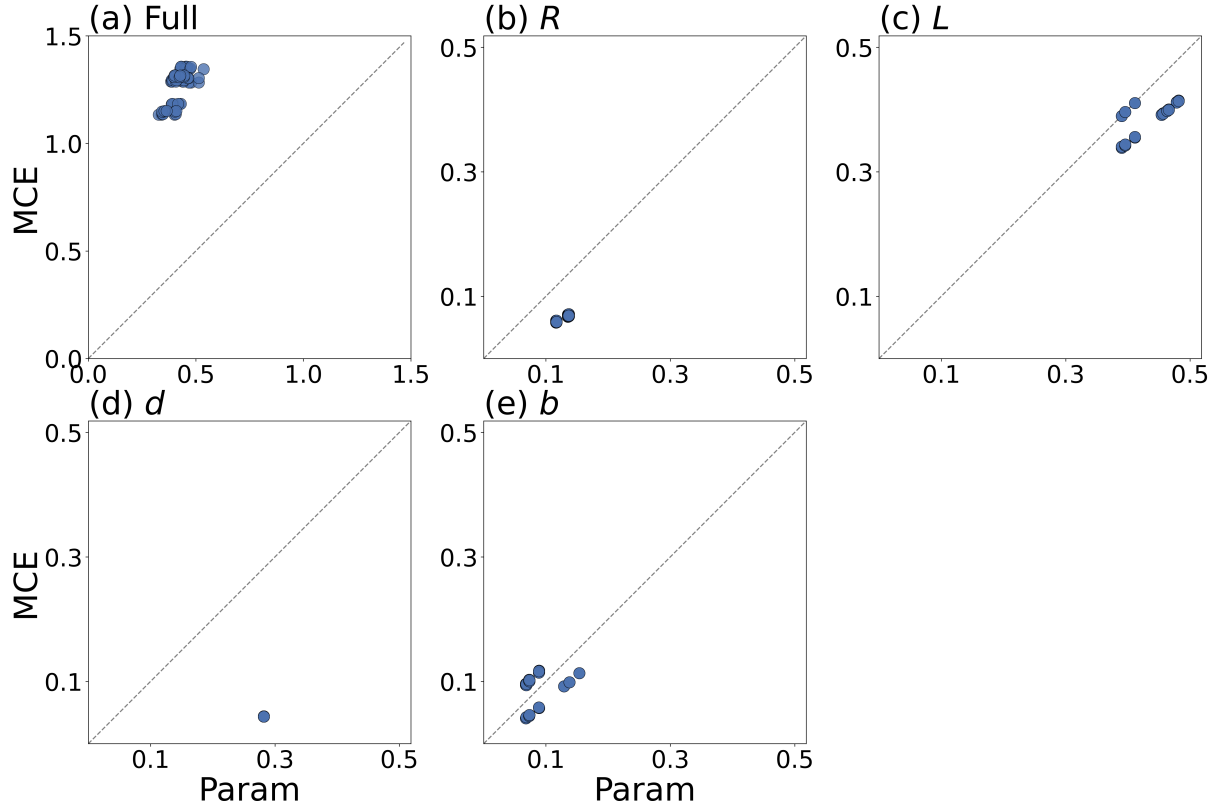


Figure S15. Comparison of spatially averaged WTR uncertainty arising from alternative parameter-estimation methods and within-configuration Monte Carlo perturbations across the retained configurations. Panels show (a) all inputs and the individual contributions of (b) R , (c) L , (d) d , and (e) b . The horizontal axis represents uncertainty from the parameter-estimation-method ensembles (Param), and the vertical axis represents uncertainty from the corresponding Monte Carlo experiments (MCE). Dashed diagonal lines indicate the 1:1 relationship.

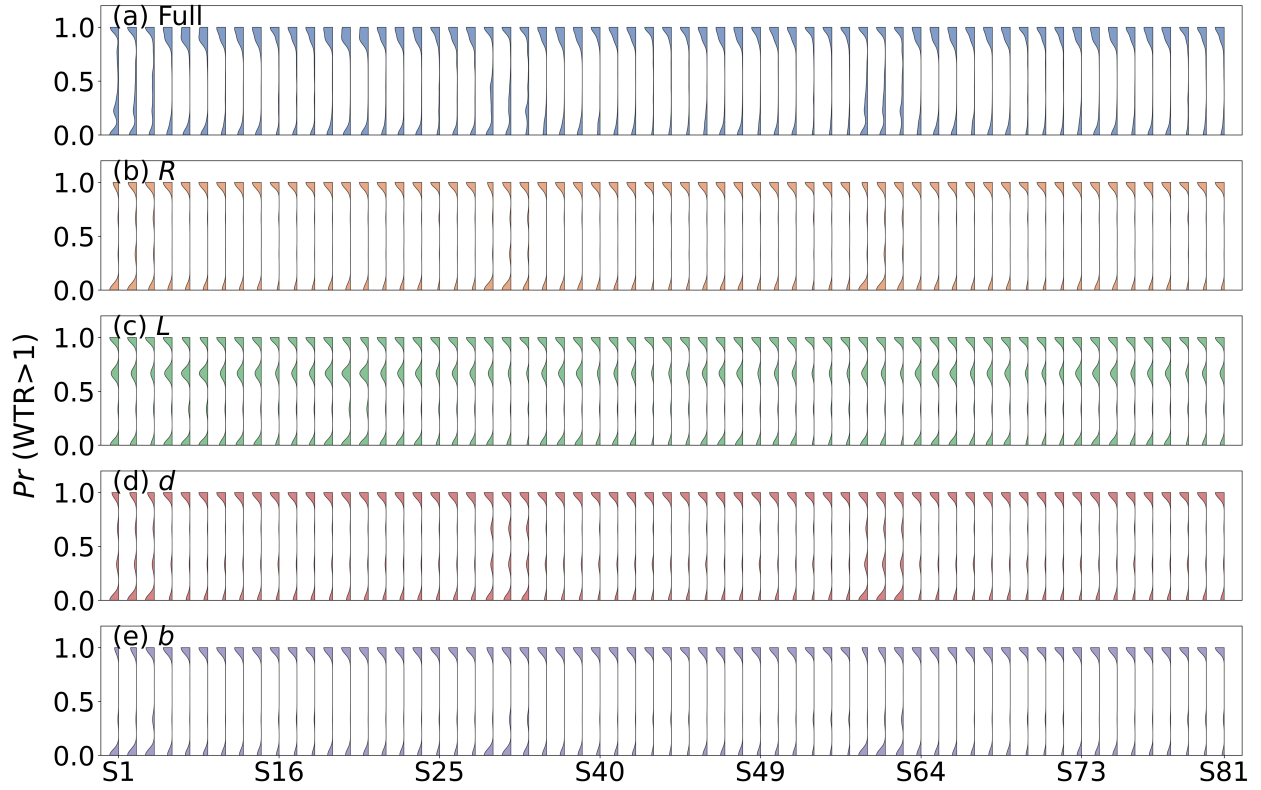


Figure S16. Distributions of grid-cell-level WTR classification stability across alternative parameter-estimation methods for all 63 retained focal configurations. Stability was represented by $Pr(WTR>1)$, calculated from (a) the all-method ensembles and the parameter-specific ensembles for (b) R , (c) L , (d) d , and (e) b . Values close to 0 or 1 indicate persistent classifications, whereas values close to 0.5 indicate frequent switching across the WTR threshold.

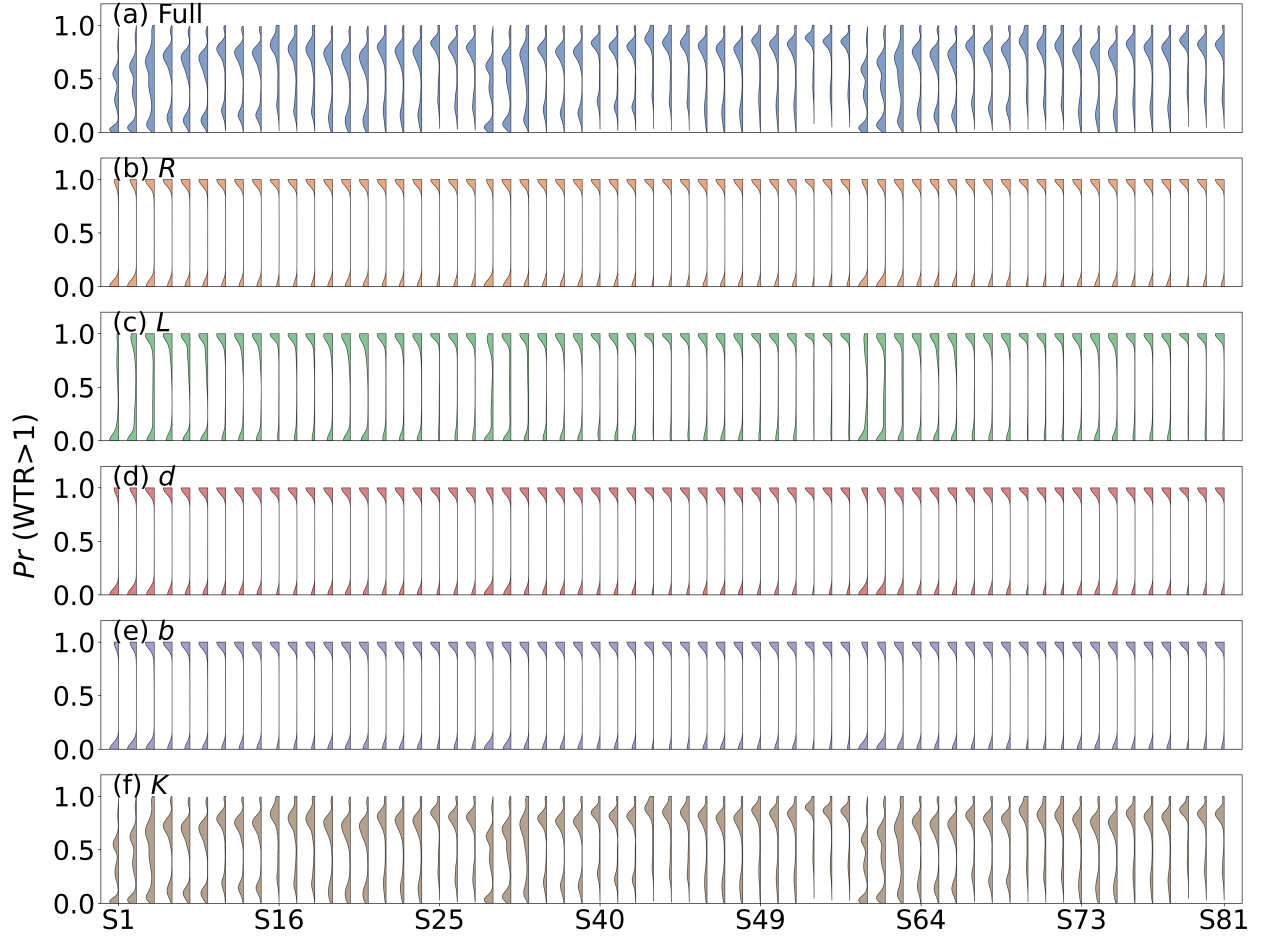


Figure S17. Distributions of grid-cell-level WTR classification stability under within-configuration Monte Carlo perturbations for all 63 retained WTR configurations. $Pr(WTR > 1)$ was calculated across 10,000 realizations from (a) the full-perturbation experiment and the single-parameter experiments for (b) R , (c) L , (d) d , (e) b , and (f) K . Values close to 0 or 1 indicate persistent classifications, whereas values close to 0.5 indicate frequent switching across the threshold.

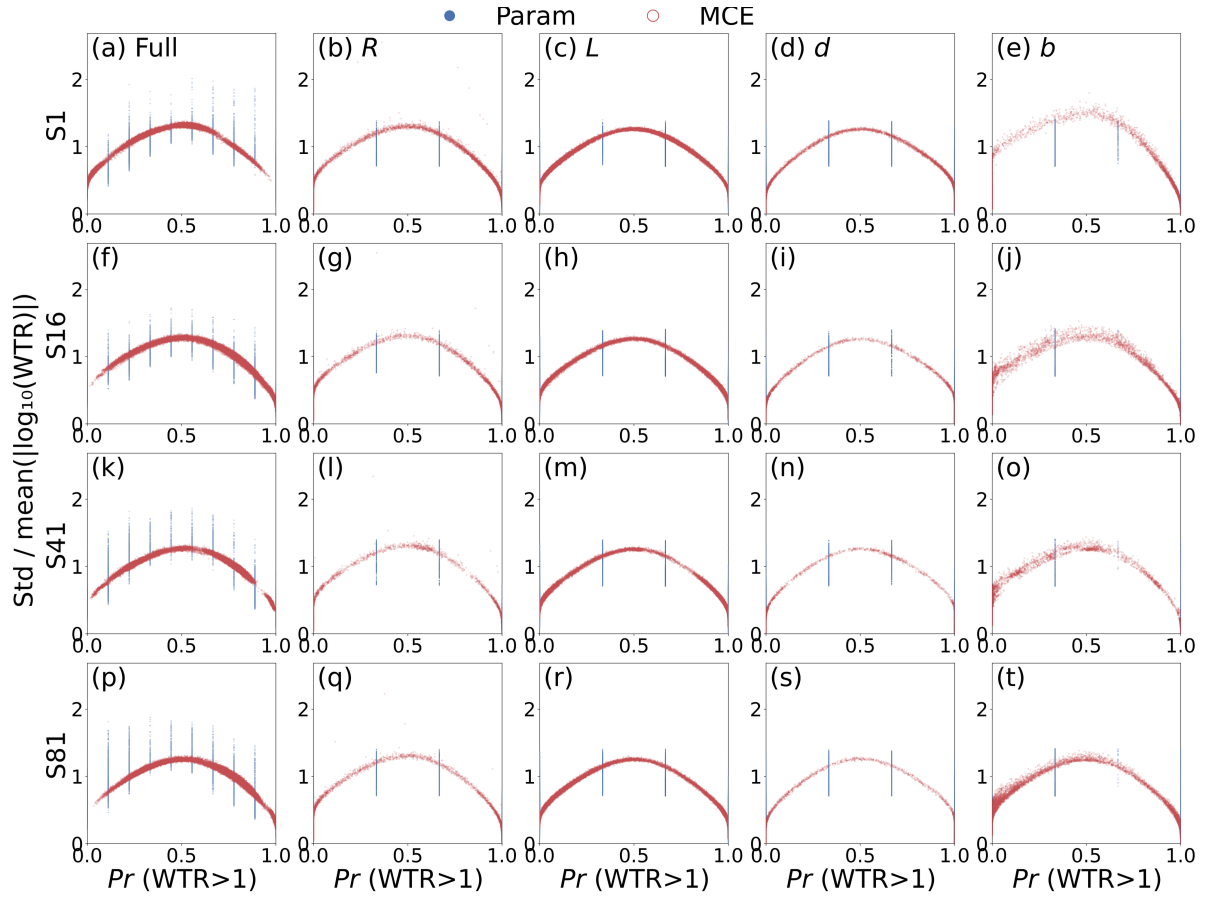


Figure S18. Relationship between WTR classification stability and relative log-scale WTR dispersion for four representative configurations. Rows correspond to S1 (a–e), S16 (f–j), S41 (k–o), and S81 (p–t); columns show results for all inputs and for R , L , d , and b , respectively. The horizontal axis is $Pr(WTR > 1)$, and the vertical axis is the standard deviation of $\log_{10}(WTR)$ divided by the mean absolute value of $\log_{10}(WTR)$. Blue and red points show results from the parameter-estimation-method ensembles (Param) and Monte Carlo experiments (MCE), respectively.