



Stable water isotopes as critical constraints for ecohydrological flux partitioning in a West African basin

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Abstract. This study investigates the added value of stable water isotopes in constraining ecohydrological flux partitioning within the Bétérou basin, a 10,000 km² tropical savanna watershed in northern Benin. It leverages a unique five-year record of high-frequency isotope measurements in river water at the outlet and in precipitation. Using the tracer-enabled, distributed model EcH₂O-iso, we evaluated how different calibration datasets influence the representation of internal flux partitioning, in particular runoff generation from surface and subsurface pathways, in a region where evapotranspiration (ET) dominates the water budget. A multi-objective calibration was performed across four scenarios, ranging from a baseline using only outlet discharge to a comprehensive setup incorporating intra-basin discharge and isotopic tracers. Our results demonstrate that isotopic tracers are essential for realistically reproducing internal flow partitioning. The inclusion of isotopes drove the model to mobilise older groundwater reservoirs, leading to increased simulated water ages and the dampening of stream isotopic signals. Scenarios calibrated solely on outlet discharge showed high fit for the hydrograph but simulated minimal subsurface contribution, contrary to field evidence from instrumented catchments. Isotopes provided only indirect constraints on ET, whose influence on water partitioning was governed primarily by root water uptake as modulated by land cover. These findings suggest that monitoring strategies in tropical environments where data are often scarce and monitoring priorities must be carefully weighed, should consider the inclusion of isotopic tracers alongside traditional hydrometric observations, as these constrain models to reproduce hydrological functioning for the right reasons and thus provide a more reliable basis for assessing water resources and climate change vulnerability.



1 Introduction

30 The intensification of the global water cycle since the mid-20th century is now well established as being linked to human activity, driving hydroclimatic extremes worldwide (IPCC, 2021). Yet these changes are not geographically uniform (Cai et al., 2026). In the tropics in particular, human-induced warming is weakening large-scale atmospheric circulations and reshaping regional precipitation patterns (Chemke & Yuval, 2023; Joseph et al., 2026). West Africa is especially vulnerable to these changes, as the West African Monsoon (WAM), embedded within these large-scale tropical circulations, constitutes the main source of precipitation (Gbode et al., 2021; Jackson et al., 2022). Rain-fed agriculture and herding sustain the regional economy, such that any disruption to monsoon dynamics carries severe socioeconomic repercussions, as the prolonged Sahelian droughts of the 1970s and 1980s demonstrated (McCrary et al., 2014; Ojo et al., 2004; Wongnaa et al., 2024). Monitoring and characterising these changes over the long term is therefore essential (Chagnaud, 2022). The AMMA-CATCH critical-zone observatory (CZO) was established to address this need, providing long-term monitoring across the sharp latitudinal eco-climatic gradient of West Africa (Galle et al., 2018).

Representative of the Sudanian sub-humid regime, the Bétérou basin (~10 000 km², upper Ouémé, Benin) is part of this CZO, lying between the humid Guinean coast and the semi-arid Sahel. The basin is drained by the intermittent Ouémé river, whose discharge responds to the rainfall variability in a markedly nonlinear manner (Descroix et al., 2009; Le Lay et al., 2007). Although this area is relatively wet (1200 mm of annual rainfall on average), this intermittent behaviour reflects the limited contribution of deep groundwater to streamflow, constrained by low-permeability crystalline bedrock, weathering profiles, and vegetation uptake. Instead, discharge is sustained mainly by shallow perched aquifers that respond rapidly to rainfall (Kamagaté et al., 2007; Richard et al., 2013; Fovet et al., 2021). This sensitivity is likely exacerbated by rapid land-use transitions driven by intense demographic pressure, with basin-scale modelling indicating increasing surface runoff and soil erosion (Giertz et al., 2006; Speth et al., 2010; Galle et al., 2018). As populations rely on groundwater due to seasonal surface water scarcity, the long-term reliability of this resource is constrained by low storage capacity and high aquifer heterogeneity (Alle et al., 2018; Vouillamoz et al., 2015), while contamination (El-Fahem, 2008) and climate change (Cuthbert et al., 2019; Dickson et al., 2019) further threaten its availability for ecosystem functioning and human use.

55 A comprehensive understanding of the hydrological processes governing water partitioning is thus essential to address these intertwined pressures (Speth et al., 2010). Decades of hydrological research in the upper Ouémé basin have documented a preferential partitioning toward the evapotranspirative flux, with 75 to 90 % of annual precipitation returned to the atmosphere, primarily through transpiration, while the remainder sustains streamflow and groundwater recharge (Galle et al., 2018; Hector et al., 2015; Mamadou et al., 2016). Upscaling process knowledge from instrumented hillslopes and experimental catchments to the larger basin scale remains, however, a major challenge (Boone et al., 2009a; Cappelaere et al., 2009). Spatially-distributed process-based modelling has traditionally been the approach of choice for addressing this



gap, owing to its explicit representation of flow path articulation across scales (Boone et al., 2009). Nonetheless, these modelling frameworks remain constrained by systematic partitioning biases that may misallocate water among the pathways of the regional water budget (Cornelissen et al., 2013; Peugeot et al., 2011). For instance, Getirana et al. (2014, 2017) showed that simulations performed with several land surface models misrepresented outlet discharge partitioning, consistently overestimating surface runoff at the expense of the dominant baseflow component. In their analysis, structural limitations in evapotranspiration simulation resulted in excess water being retained in the soil column, which required the introduction of a deep percolation term diverting excess water to an unconstrained sink to match the observed discharge. Such an approach has also been used in other studies to capture observed outgoing water fluxes (e.g. Le Lay et al., 2008).

These limitations point to the need for better constraints on internal water pathways within the critical zone. A coherent representation of subsurface flows and their interaction with vegetation remains challenging, since the internal structure of this hidden and heterogeneous compartment is difficult to characterise, introducing uncertainty in simulated water pathways (Cornelissen et al., 2013; Rashid et al., 2019; Herzog et al., 2021). Stable isotopes (^2H and ^{18}O) offer a means to disentangling signals of water storage, flow paths, and transit times that lie beyond the reach of flux- or storage-based hydrometric monitoring (Brooks et al., 2015; Sprenger et al., 2016; Stadnyk & Holmes, 2020).

Tracer-aided ecohydrological models leverage the diagnostic potential of stable water isotopes to track the water movement through the critical zone, operating at scales ranging from local plots to entire catchments (IAEA, 2023; Stadnyk & Holmes, 2023; Popp et al., 2025). By constraining the underlying storage and flux dynamics through isotopic signals, these models yield a more robust partitioning of water fluxes (Birkel & Soulsby, 2015; Kirchner & Allen, 2020; Refsgaard et al., 2022). Whether incorporating isotopic observations improves model behaviour therefore requires explicit testing, particularly in remote basins or at regional scales, where monitoring priorities must be carefully chosen (Kirchner, 2006a; Fenicia et al., 2008; Holmes et al., 2023; Stadnyk & Holmes, 2023).

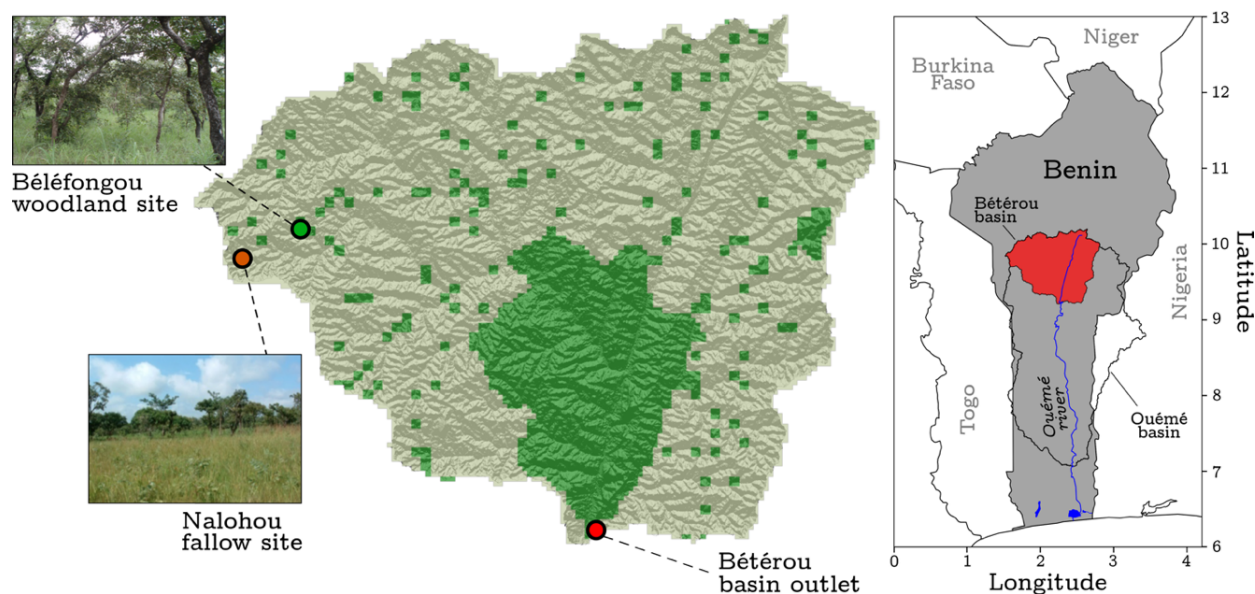
To this end, we designed and conducted several model-data calibration experiments carried out in the Bétérrou basin using the state-of-the-art tracer-enabled ecohydrological model Ech2O-iso (Kuppel et al., 2018). Our objective is to evaluate the information content of stable water isotopes within this multi-criteria calibration framework, in order to improve basin-scale process understanding. More specifically, we aim to (a) better constrain basin-scale water partitioning, complementing traditional hydrometric observations, and (b) resolve storage-flux-mixing dynamics to elucidate the subsurface pathways sustaining stream baseflow. This study advances tracer-enabled ecohydrological modelling, demonstrating how isotopic measurements inform model behaviour and contribute to a better-constrained water budget, while offering guidance for their integration within broader hydrometric monitoring efforts.



95 2 Data and Methods

2.1 Study site

The Bétérrou basin is located in central Benin (Figure 1) and coincides with the Upper Ouémé, a well-instrumented basin monitored by the AMMA-CATCH critical zone observatory (www.amma-catch.org). Covering an area of approximately 10,000 km², it extends from 1°30' to 2°49' E and 9°10' to 10°12' N, with elevations between 250 and 617 m. It overlies a
 100 crystalline basement, where successive pedimentation cycles have shaped the landscape into a gently southeastward-sloping peneplain of about 2.5 %, locally interrupted by isolated intrusive igneous rock bodies known as inselbergs. Tropical ferruginous soils cover the basin, supporting vegetation composed of a mosaic of woodlands, savannah, and croplands (Bormann & Dieckrüger, 2003; Galle et al., 2018). A tropical wet savannah climate characterizes the region according to the Köppen classification (Köppen, 1936; Peel et al., 2007), with a mean annual temperature of 25 °C and potential
 105 evapotranspiration on the order of 1500 mm/yr. Over the 2000-2022 period, annual precipitation amounts to around 1200 mm, mostly concentrated in a single wet season from April to October, produced mainly by mesoscale convective systems organized under the West African Monsoon (WAM) circulation (Nicholson, 2013). The Ouémé river flows from mid-July to mid-October, beginning one to three months after the first rains and peaking between mid-August and late September, with annual discharge amounting to around 160 mm, or about 13 % of annual precipitation.



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Figure 1. (Left) Simplified land cover map, reclassified into woodland and fallow categories, derived from the 2 km resolution West Africa Land Use Land Cover map (Tappan et al., 2016). Field photographs show the AMMA-CATCH experimental sites at Béléfongou and Nalohou. (Right) Location of the Bétérrou basin within the Ouémé basin.



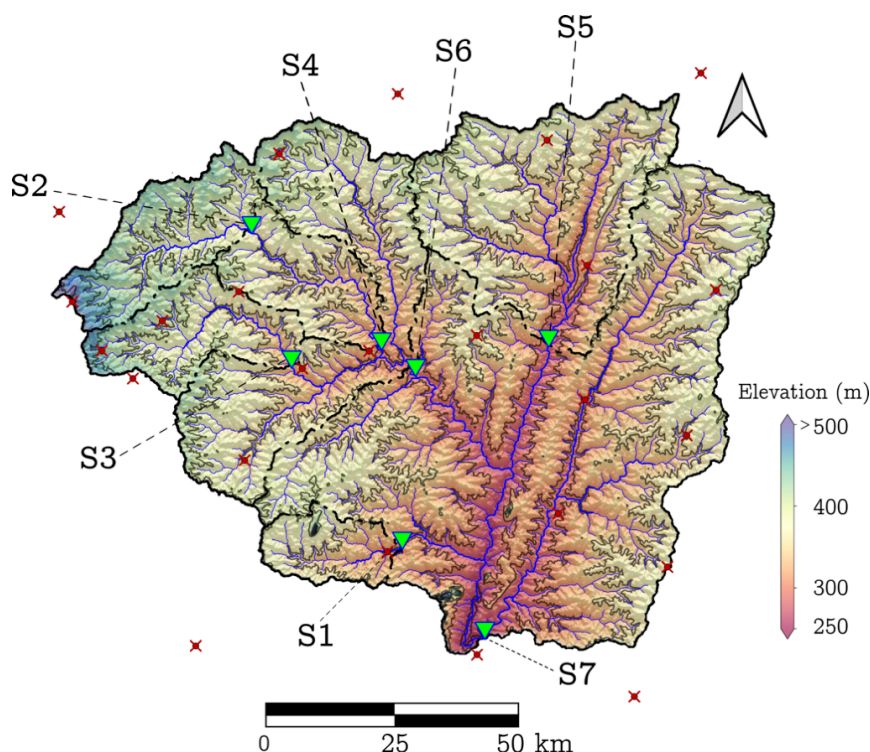
2.2 Datasets

2.2.1 Hydrometric and vegetation data

Hourly river discharge data from 7 stations, and precipitation data from 24 stations at 5-minute intervals, were obtained from the AMMA-CATCH monitoring network (Figure 2). The Table 1 lists the river gauging stations used in this study, along with their locations and characteristics, while Table S1 provides similar information for the rain gauge stations.

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Vegetation dynamics were represented by Leaf Area Index (LAI) time series (Figure 4i), derived from remote sensing and hemispherical photography at the Nalohou and Béléfongou experimental sites (Lohou et al., 2014). The two locations correspond respectively to the two broad vegetation categories present in the basin, herbaceous fallow and open-canopy woodland (Figure 1), whose spatial distribution followed a simplified classification of the West Africa Land Use and Land
 125 Cover map (Tappan et al., 2016). Given the low inter-annual variability of the dominant woodland cover, together with gaps in satellite-derived LAI caused by persistent cloud cover and limited site observations during the rainy season, the available 2005–2008 data were averaged into a single daily time series for each land cover type.



130 **Figure 2. Topographic map of the Bétérrou basin showing the main river network and the AMMA-CATCH monitoring network comprising seven discharge gauging stations (green triangles) with their contributing areas (dotted lines) and rain gauge stations (red crosses)**



Table 1. Hydrometric stations of the Bétérou basin, ordered by increasing contributing area. Multi-year mean discharge and sub-basin averaged precipitation, estimated by Thiessen polygon weighting, are shown for 2018–2022.

ID	Name	Location		Elevation (m)	Area (km ²)	Mean discharge (m ³ /s)	Specific discharge (mm/year)	Mean precipitation (mm/year)	Runoff coefficient
		E	N						
S1	Wewe	2°07'	9°23'	323	293	2	211	1411	0.15
S2	Tebou	1°52'	9°57'	375	515	5.8	353	1336	0.26
S3	Donga	1°57'	9°43'	349	586	5.3	285	1357	0.21
S4	Affon	2°06'	9°45'	328	1165	10	279	1326	0.21
S5	Bori	2°24'	9°45'	306	1607	6.9	135	1245	0.11
S6	Aval-Sani	2°10'	9°43'	322	3283	29.9	287	1356	0.21
S7	Bétérou	2°17'	9°14'	272	10400	66.3	201	1304	0.15

2.2.2 Climatic data

Grid-based climatic data (Figure 4d-h) were obtained from the ERA5-Land hourly reanalysis dataset (Muñoz Sabater, 2019), produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) at a spatial resolution of 0.1° x 0.1° (~9 x 9 km²). Air temperature and longwave and shortwave radiation were obtained directly from this dataset. Relative humidity was derived from air and dewpoint temperature (Lawrence, 2005), while wind speed was adjusted from a 10 m to a 2 m reference height assuming a logarithmic wind profile (Allen et al., 1998).

2.2.3 Isotopic observational data

Isotopic monitoring has been conducted continuously since 2018, with precipitation sampled at the Nalohou experimental site and river water at the Bétérou basin outlet (Figure 1). Precipitation samples were collected using an evaporation-free cumulative sampler (Gröning et al., 2012), and river water was sampled directly from the channel, both at irregular intervals ranging from 2 to 4 days. Samples were stored in glass vials sealed with parafilm to prevent evaporative enrichment during storage and transport, then shipped to France. A total of 478 samples (222 precipitation and 256 river water) were collected over the period from 2018 to 2022 and analysed at the CEREGE laboratory.

The analytical protocol followed the framework established by Vallet-Coulomb et al. (2021). In preparation for analysis, all samples were filtered at 0.45 µm to remove particulate matter during laser measurements. Filtered samples were then transferred into 2 mL glass vials and loaded onto the autosampler of a Picarro L2140-i wavelength-scanned cavity ring-down spectrometer (CRDS) (Picarro Inc., California, USA), coupled with an A0211 vaporizer and an A0325 autosampler. Each analytical run included three internal working standards, designated as ICE (δ-depleted), SEA (δ-enriched), and TAP (intermediate), used for normalization to the VSMOW-SLAP scale, instrument calibration, and drift monitoring. An additional working standard was included in every run for long-term quality assurance and quality control (QA/QC). Each vial was injected eight times (samples and QA/QC) or fifteen times (working standards for normalization). The run sequence



was designed to minimize the memory effects, defined as the carry-over of water vapour from preceding samples, and to compensate for potential instrumental drift. In addition, a memory correction was applied during post-processing. Finally, the two first injections of each vial were discarded, and the mean of the six last injections was retained. Overall, the long-term analytical precision was estimated from the standard deviation of the QA/QC was $\pm 0.03\text{‰}$ for $\delta^{18}\text{O}$ and $\pm 0.3\text{‰}$ for $\delta^2\text{H}$.

The isotopic measurements revealed distinct temporal dynamics in both precipitation and river water. The precipitation $\delta^{18}\text{O}$ time series (Figure 3a) showed large-amplitude, high-frequency fluctuations, with higher values prior to monsoon onset tending towards more depleted values as the monsoon season progressed. In the Ouémé river, highly enriched $\delta^{18}\text{O}$ values at flood onset became progressively depleted as the rainy season unfolded. During the high-flow period, the signal was generally dampened relative to precipitation, with transient shifts toward depleted values during peak river episodes. Values then gradually enriched as discharge declined towards the recession period. This variability was also reflected in the $\delta^{18}\text{O}$ – $\delta^2\text{H}$ relationship (Figure 3c). River samples were distributed between the Local Meteoric Water Line (LMWL), defined by precipitation, and a Local Evaporation Line (LEL). Along the LEL, increasing evaporative enrichment was associated with progressively lower d-excess (Figure 3d). This distinction allowed classification of river samples as evaporated or non-evaporated, corresponding to contrasting hydrological conditions, with non-evaporated samples occurring predominantly during high-flow periods.

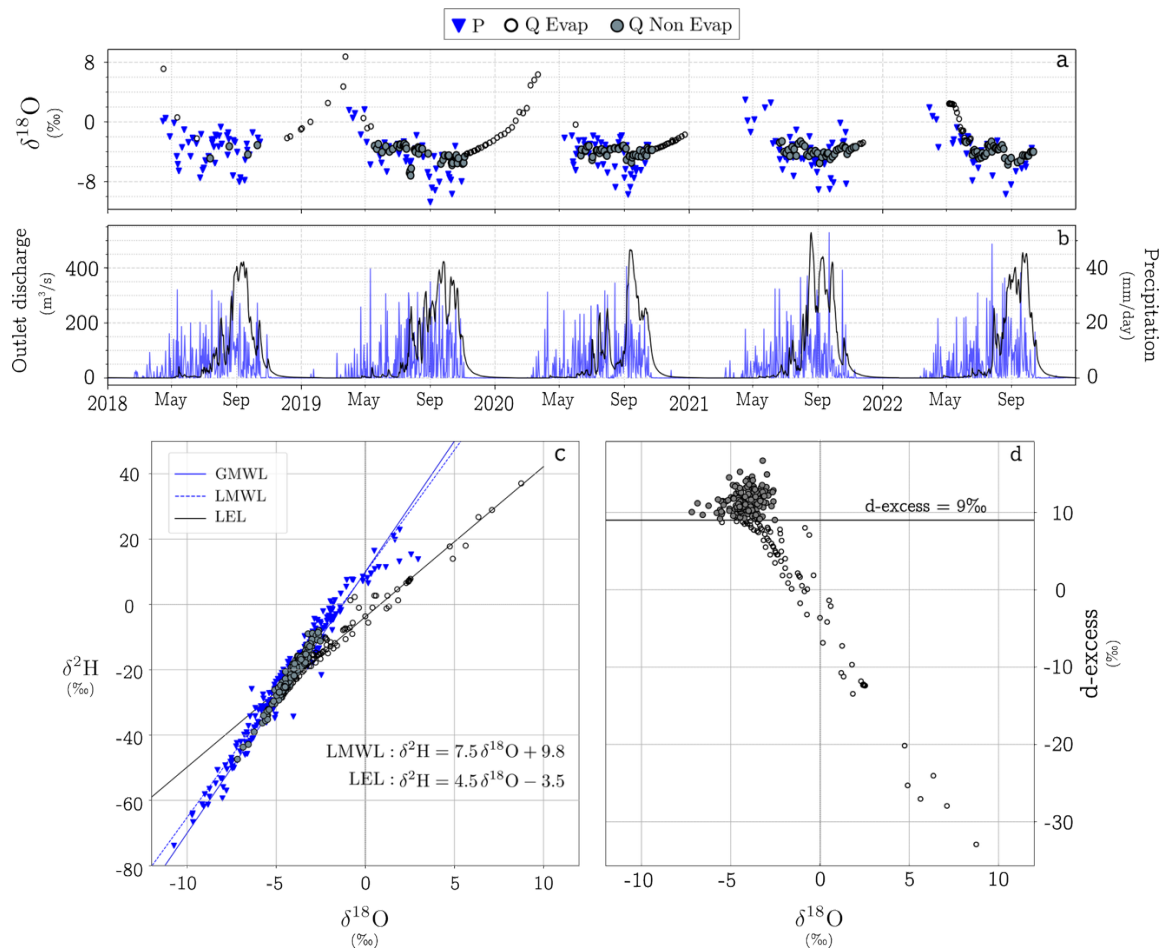


Figure 3. (a) Time series of precipitation $\delta^{18}\text{O}$ at the Nalohou experimental site (blue triangles, 222 samples), and river water at the Bétérou basin outlet (solid and hollow black points, 256 samples) for 2018 to 2022. (b) Daily discharge at the Bétérou gauging station and basin-averaged precipitation. (c) Bivariate $\delta^{18}\text{O} - \delta^{2}\text{H}$ plot of precipitation and evaporated and non-evaporated river samples relative to the Local Meteoric Water Line (LMWL), Local Evaporation Line (LEL) and Global Meteoric Water Line (GMWL). (d) $\delta^{18}\text{O} - \text{d-excess}$ plot for river samples

2.2.4 Isotopic reanalysis data

Spatially distributed isotopic composition ($\delta^{18}\text{O}$ and $\delta^{2}\text{H}$) of precipitation and atmospheric water vapour at a daily resolution was obtained from the Isotope-incorporated Global Spectral Model version 4 (IsoGSM4, Bong & Yoshimura, 2025). These time series gap fill and extend the available point-scale in situ observations. For precipitation, we first verified the good agreement between IsoGSM4 and observations (Figure 4a). For water vapour, a necessary input for simulating evaporative fractionation (see Sect. 2.3), we used the IsoGSM4 estimates despite the absence of local measurements (Figure 4b), given their physically based representation of vapour isotopic composition compared with estimates derived directly from precipitation signature, as is often done (see Chávez-Espinoza et al., 2025).



IsoGSM4 is an updated version of IsoGSM1 (Yoshimura et al., 2008) and a higher-spatial-resolution version of IsoGSM3 (Bong et al., 2024). It is nudged by 6-hourly atmospheric fields (winds and temperature) and ocean surface conditions (sea surface temperature and sea ice concentration) from ERA5 (Hersbach et al., 2020). The model employs a T248 spectral resolution, corresponding to a Gaussian grid spacing of approximately 0.47° (768×348 grid points), or about 52 km at the Equator. Compared with observations from the Global Network of Isotopes in Precipitation (GNIP) (e.g., IAEA/WMO, 2006), IsoGSM4 shows improved performance, with a global mean temporal correlation coefficient for precipitation $\delta^{18}\text{O}$ of $r = 0.644$, compared to $r = 0.621$ for IsoGSM3 and $r = 0.570$ for IsoGSM2.

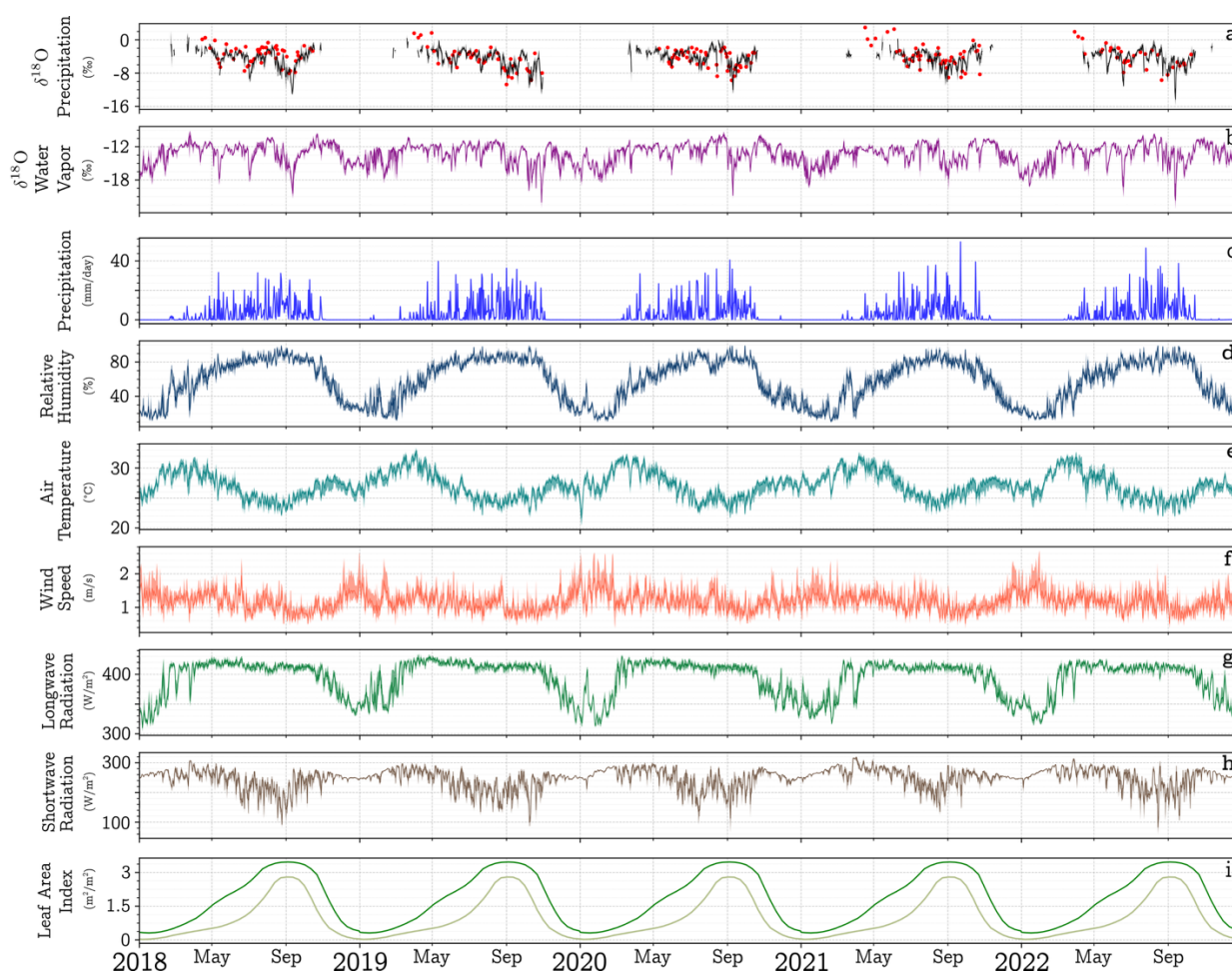


Figure 4. Daily time series of isotopic, climatic and vegetation forcings for 2018-2022. Shaded envelopes represent the full range of values of the ERA5-Land reanalysis and IsoGSM datasets across the Bétérou basin. Solid lines trace the median value at each time step. Panels show: (a) precipitation $\delta^{18}\text{O}$ from IsoGSM alongside observations at the Nalohou experimental site (red dots); (b) atmospheric water vapour $\delta^{18}\text{O}$ from IsoGSM; (c) basin-averaged precipitation; (d) to (h) climatic variables from ERA5-Land; and (i) LAI for woodland and fallow vegetation, shown in dark and light green, respectively.



2.3 Model description

EcH₂O-iso is a state-of-the-art, physically based, spatially distributed ecohydrological model that simulates coupled energy fluxes in the canopy and at the soil surface, and water fluxes across the surface and subsurface, while tracking conservative tracers ($\delta^2\text{H}$, $\delta^{18}\text{O}$, and Cl^-) and water ages throughout the critical zone (Douinot et al., 2019; Kuppel et al., 2018; Maneta & Silverman, 2013).

To represent its modelling domain, the model employs a digital elevation model (DEM) from which it derives its drainage network. Within each grid cell, energy and water balances are computed using a top-down approach, with separate calculations performed for each land cover type present and aggregated according to their fractional area.

Building on this spatial discretization, the energy balance is computed first for the canopy and then for the soil surface. At the canopy, available net radiation is partitioned into latent heat from intercepted water evaporation and transpiration, and sensible heat flux. At the soil surface, available energy is distributed among soil heat flux, sensible heat, and latent heat of evaporation and, when relevant, snowmelt. The resulting latent heat fluxes determine the evapotranspiration components, namely interception, soil evaporation, and transpiration, with the corresponding water mass losses imposed on the respective storage compartments. Soil moisture content in turn feeds back into the energy balance by constraining canopy conductance and limiting transpiration.

Coupled to the energy balance, the water balance module simulates water movement and storage using a multi-layer approach, representing water storage in compartments comprising the canopy, surface, and subsurface, the latter subdivided into three hydraulic layers. Vertical fluxes include infiltration, represented by the Green–Ampt model; percolation and drainage governed by soil moisture capacity; evaporation losses from the canopy and soil; transpiration driven by a potential-based root water uptake formulation (Fan et al., 2017; Míguez-Macho & Fan, 2021); and deep drainage leaving the model domain through the deepest soil layer. Horizontal fluxes include overland flow, which may infiltrate as it runs off towards river cells along the drainage network; lateral subsurface flow of gravitational water contributing to baseflow upon reaching the stream channel; and streamflow routed through the channel using a kinematic wave approach.

The tracking module operates in parallel (i.e. without feedback on water fluxes and stores calculations), quantifying stable isotope compositions and water ages as water moves through interconnected model compartments, using a conservative flux-storage approach that assumes complete and instantaneous mixing within each pool. Incoming fluxes update compartment tracer (isotopes or age) signatures via a volume-weighted mass balance, while outgoing fluxes carry the fully mixed signature of the source pool. Soil evaporation, the key process driving isotopic fractionation, is explicitly represented in the topsoil using a Craig–Gordon framework, whereas transpiration is treated as non-fractionating. Further details on the tracking



module formulation are given in Kuppel et al., (2018) and Smith et al., (2020), with recent updates given in Chávez-
 235 Espinoza et al., (2025).

A new development introduced virtual tagging of simulated seepage fluxes, enabling quantification of baseflow, hereafter
 defined as river water (in fraction of storage or in partial discharge) originating from subsurface layer(s) contribution(s). This
 terminology follows Hector et al., (2018), while other studies refer to it as “subsurface flow” (Kamagaté et al., 2007;
 240 Getirana et al., 2014; Rashid et al., 2019).

2.4 Simulation set-up

A DEM from the Shuttle Radar Topography Mission (1x1 km² resolution; NASA JPL, 2013) was used to delineate the
 Bétérou basin model domain and its drainage network. Climatic data were aggregated to daily averages, and both climatic
 and isotopic forcings (Figure 4a-h) were applied across the basin. Precipitation data from rain gauges (Figure 2) were
 245 spatially distributed using Thiessen polygons. Soil physical parameters were assumed uniform within each subsurface layer,
 while vegetation parameters and dynamic forcings (LAI time series, Figure 4i) were assigned by land cover type, fallow and
 woodland (Figure 1). The model was configured with an open deep vertical flow condition, using a saturated conductivity
 specific to each sub-basin, taken as a fraction of the saturated conductivity of the deepest model layer (“leakance” parameter
 in Table 2), with one parameter for S6 (Aval-Sani), a second for S5 (Bori), and a third for the remainder of the basin,
 250 reflecting distinct runoff coefficients across these areas (**Table 1**). Although regional deep drainage (i.e. groundwater flow
 through deep fractures in basement rocks that does not contribute to river discharge) has previously been considered
 negligible given the geological context (Séguis et al., 2011; Vouillamoz et al., 2015), this configuration was retained to allow
 more flexible exploration of model behaviour during calibration, providing an independent check on this assumption.

255 Simulations were conducted at a daily time step over five years, with a calibration period from 2018-2020 and an evaluation
 period from 2021-2022, preceded by a ten-year warm-up (2008-2017) excluded from subsequent analysis. The warm-up
 allowed the model to reach stable conditions by dissipating transient dynamics in hydrological states and tracer signatures
 across all reservoirs. In particular, stabilisation was sought for soil water and its isotopic signature, as this reservoir was the
 slowest to adjust during this period. To this end, initial soil isotopic composition was set to $\delta^2\text{H} = -20.5 \text{ ‰}$ and $\delta^{18}\text{O} = -3.5$
 260 ‰. Additionally, the initial baseflow fraction was set to zero in all stream cells.

All simulations employed the isotopic fractionation framework of Kuppel et al., (2018), with two departures from the default
 configuration following recent developments proposed by Chávez-Espinoza et al. (2025). First, the isotopic composition of
 atmospheric water vapour, used for quantifying kinetic fractionation from direct soil evaporation, was prescribed directly
 265 from IsoGSM4 rather than derived from isotopic equilibrium assumptions. Second, diffusivity ratios for heavy isotopologues
 were taken from Merlivat (1978).

2.4.1 Sensitivity analysis

Prior to calibration, the parameters to which model outputs were most sensitive were identified through a Morris sensitivity analysis (Morris, 1991; Sohler et al., 2014). This parsimonious and computationally efficient method quantifies the elementary effects (EE) of each parameter on a given output, by measuring how model output changes when the value of that parameter is varied while all others are held constant (e.g. RMSE between two time series of output Y, one generated *before* and one *after* changing parameter X). The parameter space is sampled using several starting points (i.e. sets of parameter values) within prescribed intervals. From each starting point, all parameters are varied, one after the other. This multiple initial sampling yields overall EEs for each parameter with respect to each output of interest and rank these EEs accordingly. Here, the method is applied to our modelling framework, as described in detail in Chávez-Espinoza et al. (2025). The outputs of interest were streamflow at the outlets of the Bétérrou basin and its sub-basins, stream water isotopic composition at the basin outlet, and basin-scale hydrological fluxes. To further reduce the dimensionality, selected soil physical parameters were set equal across the first two subsurface layers, and the second hydrological layer was fixed at a 2 m thickness, as it primarily serves as a transition zone between the evaporation-affected topsoil and the deeper, largest soil reservoir. As a result, 35 parameters were retained for calibration (21 surface and subsurface parameters and 7 parameters for each of the 2 vegetation types; Table 2), with bounds set to allow a broad exploration of the parameter space.

2.4.2 Calibration

Model calibration was conducted using a multi-criteria Monte Carlo sampling approach, evaluating performance across multiple model outputs using goodness-of-fit (GOF) metrics. Rather than relying on absolute GOF values, best performing runs were selected using GOF rankings, following Ala-aho et al., (2017) (see below). An ensemble of 50,000 simulations was run using parameters generated via Latin Hypercube Sampling (LHS) within the prescribed calibration ranges (Table 2). Model performance was evaluated using the Kling-Gupta Efficiency (KGE; Eq.(2)), a composite metric that integrates three elements, namely the Pearson correlation coefficient (r), the ratio of simulated to observed standard deviation (variability ratio, α), and the ratio of simulated to observed mean (bias ratio, β) (Gupta et al., 2009). KGE quantifies model performance by minimizing the Euclidean distance (ED; Eq. (1)) between the performance point and the ideal point $(r, \alpha, \beta) = (1, 1, 1)$, with value ranging from $-\infty$ to 1, and values approaching 1 indicating closer agreement between simulations and observations. Knoben et al. (2019) showed that KGE values no lower than -0.41 indicate performance better than simply using the mean of observed values.

$$ED = \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \dots (1)$$

$$KGE = 1 - ED \dots (2)$$

For each calibration target (streamflow and $\delta^{18}\text{O}$, see Sect. 2.5.1), the GOF values (i.e. KGE) were used to construct empirical cumulative distribution functions (eCDFs), ranking the 50,000 model realisations from lowest to highest KGE for each target. Rather than applying a fixed GOF threshold as in GLUE (Beven & Binley, 1992), a subset of “best” behavioural runs was identified by prescribing a fixed group size (here, 30) and selecting the quantile threshold above which 30 common runs were found among all eCDFs. As in GLUE, a quantile threshold shared across criteria (e.g. the GOF of a given output) implicitly rejects runs that perform poorly for any single output, even if they perform well for others, since a run is considered behavioural only if its performance is acceptable across all targets. This approach consequently reduces the risk of non-behavioural outputs arising from compensatory effects across GOF metrics, which can occur with arithmetic-based multi-objective functions.

Table 2. Range of soil and vegetation parameters used for model calibration. Soil physical parameters are specified for three subsurface layers, denoted L1 (topsoil), L2 (middle), and L3 (deep), and assumed uniform within each layer. Parameters labelled L1–L2 share a common value across the topsoil and middle layers. Vegetation parameter ranges are provided separately for fallow and forest cover types.

Parameter	Description	Units	Min	Max
Soil parameters				
D_{L1}	Thickness of the 1 st hydrological layer	m	0.05	0.3
D_{soil}	Total soil depth	m	5	30
θ_{L1}	Porosity of the 1 st hydrological layer	m^3m^{-3}	0.1	0.5
θ_{L2}	Porosity of the 2 nd hydrological layer	m^3m^{-3}	0.1	0.5
θ_{L3}	Porosity of the 3 rd hydrological layer	m^3m^{-3}	0.1	0.5
K_{L1}	Saturated horizontal hydraulic conductivity of the 1 st hydrol. layer	m^1s^{-1}	1E-06	1E-02
K_{L2}	Saturated horizontal hydraulic conductivity of the 2 nd hydrol. layer	m^1s^{-1}	1E-06	1E-02
K_{L3}	Saturated horizontal hydraulic conductivity of the 3 rd hydrol. layer	m^1s^{-1}	1E-08	1E-03
$\text{Leakance}_{\text{Bori}}$	Leakance parameter (Bori sub-basin)	-	1E-07	1E-02
$\text{Leakance}_{\text{Aval-Sani}}$	Leakance parameter (Aval-Sani sub-basin)	-	1E-07	1E-02
$\text{Leakance}_{\text{Bétérou}}$	Leakance parameter (rest of the basin)	-	1E-07	1E-02
$\lambda_{\text{BC-L1-L2}}$	Brook-Corey lambda of the 1 st and 2nd hydrological layer	-	2	12
$\lambda_{\text{BC-L3}}$	Brook-Corey lambda of the 3 rd hydrological layer	-	2	12
$\psi_{\text{aeL1-L2}}$	Air-entry pressure head of the 1 st and 2nd hydrological layer	m	0.1	0.8
ψ_{aeL3}	Air-entry pressure head of the 3 rd hydrological layer	m	0.1	0.8
$\theta_{\text{rL1-L2}}$	Residual soil moisture of the 1 st and 2nd hydrological layer	m^3m^{-3}	0.03	0.15
θ_{rL3}	Residual soil moisture of the 3 rd hydrological layer	m^3m^{-3}	0.03	0.15
gwseep_{L1}	Groundwater seepage from the 1 st hydrological layer	m^{-1}	2E-02	1
gwseep_{L2}	Groundwater seepage from the 2 nd hydrological layer	m^{-1}	2E-02	1
gwseep_{L3}	Groundwater seepage from the 3 rd hydrological layer	m^{-1}	2E-02	1
n	Manning's roughness coefficient	$\text{s}^1\text{m}^{-1/3}$	1	30
Vegetation Parameters				
g_{Smax}	Maximal stomatal conductance	m^1s^{-1}	0.001	0.015
g_{Slight}	Stomatal sensitivity to light	W.m^{-2}	0	300
g_{Svpd}	Stomatal sensitivity to vapor pressure deficit	Pa^{-1}	1E-05	2E-03
T_{opt}	Optimal photosynthesis temperature	°C	21	33
CWS_{max}	Maximum interception storage per unit LAI	m	1E-04	1E-02
K_{Beer}	Beer's light extinction coefficient	-	0.3	0.8
α_c	Effective canopy albedo	-	0.1	0.3

2.5 Multi-objective calibration scenarios and model evaluation

2.5.1 Calibration scenarios

Four calibration scenarios (Figure 5) were defined to assess how different combinations of observational data constrained model simulations, each following the general setup described in Sect. 2.4. The calibration strategy focused on the wet season, during which river water at the basin outlet showed no clear isotopic evidence of evaporative enrichment ($d\text{-excess} > 9\%$, see Sect. 2.2.3). During this period, the isotopic composition of streamflow was expected to be primarily controlled by the mixing of water from different hydrological compartments rather than by isotopic fractionation associated with evaporation. This provides a robust framework for evaluating how the model represents hydrological flow paths and storage dynamics. Furthermore, the wet season accounts, on average, for approximately 90 % of the total annual discharge over the 2018–2022 simulation period, making it the most relevant period for evaluating basin-scale water fluxes.

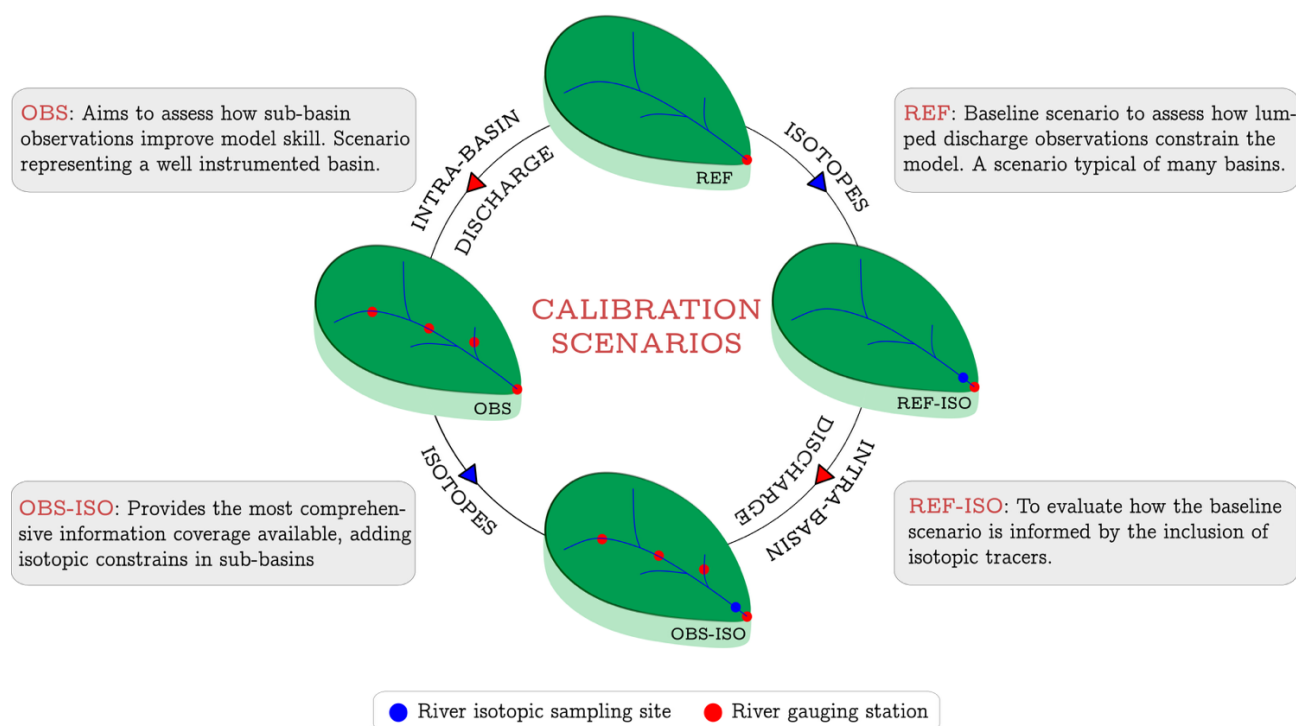


Figure 5. Overview of the calibration scenarios considered in this study. Each scenario represents a different combination of observations used for calibration, ranging from discharge measurements at the basin outlet alone (REF) to the full dataset comprising all discharge gauge stations and isotopic tracers (OBS-ISO). Arrows indicate the information added when moving from one scenario to another, blue for added outlet isotopic observations and red for added sub-basin discharge information.



330 2.5.2 Model evaluation

For each calibration scenario, model-data fit was evaluated for each target (i.e. measured quantity) using the daily-scale KGE, retaining the median value calculated across the 30 behavioral runs. Overall performance was obtained by first averaging KGE across all targets for each behavioural run, then taking the median of these averages.

335 The basin-scale annual water budget was computed for each calibration scenario to evaluate the overall representation of the hydrological cycle. As defined in Eq. (3), the budget comprises precipitation (P), evapotranspiration (ET), outlet discharge (Q), annual storage variation encompassing all model compartments (ΔS), and deep drainage (D), all expressed as water depth per unit time (mm/year). Deep drainage represents water leaving the deepest subsurface layer without contributing to streamflow at the basin outlet.

$$P = ET + Q + \Delta S + D \dots (3)$$

340 Baseflow contribution, quantified through water tracking (see Sect. 2.3), was evaluated across the simulation ensembles. ET at the local (pixel) scale was compared with literature-based benchmarks (see Table S2). These two components received particular attention because baseflow represents the dominant contribution to Q, whereas ET accounts for the largest share of the basin water budget (Galle et al., 2018).

The differences in the distributions of annual simulated fluxes among ensembles were evaluated using pairwise Wilcoxon–Mann–Whitney (WMW) tests ($\alpha = 0.05$) (Mann & Whitney, 1947). Significant results ($p_{WMW} < 0.05$) were interpreted as statistical evidence of distributional differences between the compared ensembles. In addition, point benchmark values for ET were compared with each ensemble using the Wilcoxon signed-rank test ($\alpha = 0.05$) (Wilcoxon, 1945) to assess whether the ensemble median differed from the benchmark value. Significant differences ($p_W < 0.05$) were considered as statistical evidence of a departure from the benchmark. These statistical tests were implemented using the SciPy Python package
 350 (Virtanen et al., 2020).

3 Results

3.1 Overall model performance

The overall performance (Figure 6), reported for the calibration (C: 2018–2020) and evaluation (E: 2021–2022) periods, was highest for OBS (C: 0.52, E: 0.23), followed by OBS-ISO (C: 0.42, E: 0.27), while REF (C: 0.13, E: –0.05) and REF-ISO
 355 (C: 0.11, E: 0.13) remained substantially lower, with REF-ISO marginally outperforming REF during evaluation. For most outputs considered in the calibration, the median model performance decreased during the evaluation period relative to calibration, except at stations S1 and S5, where KGE increased. Clear contrasts emerged among scenarios. At the basin

outlet (S7), REF achieved the best discharge performance (C: 0.9, E: 0.77), whereas REF-ISO and OBS performed similarly (C: 0.71, E: 0.63), and OBS-ISO performed slightly worse (C: 0.56, E: 0.53). For the isotopic target, the scenario ranking shifted, with REF-ISO producing the highest KGE values (C: 0.44, E: 0.25), followed by REF (C: 0.3, E: -0.04), OBS (C: 0.27, E: -0.06), and OBS-ISO (C: 0.2, E: -0.06). For sub-basins (S1 to S6), OBS and OBS-ISO generally outperformed REF and REF-ISO within both periods, as reflected by consistently higher KGE values. Across periods, all KGE values for OBS and OBS-ISO remained above -0.41, the benchmark proposed by Knoben et al. (2019), whereas REF-ISO fell below this threshold at S1 and S5 during calibration and at S1 and S3 during evaluation.

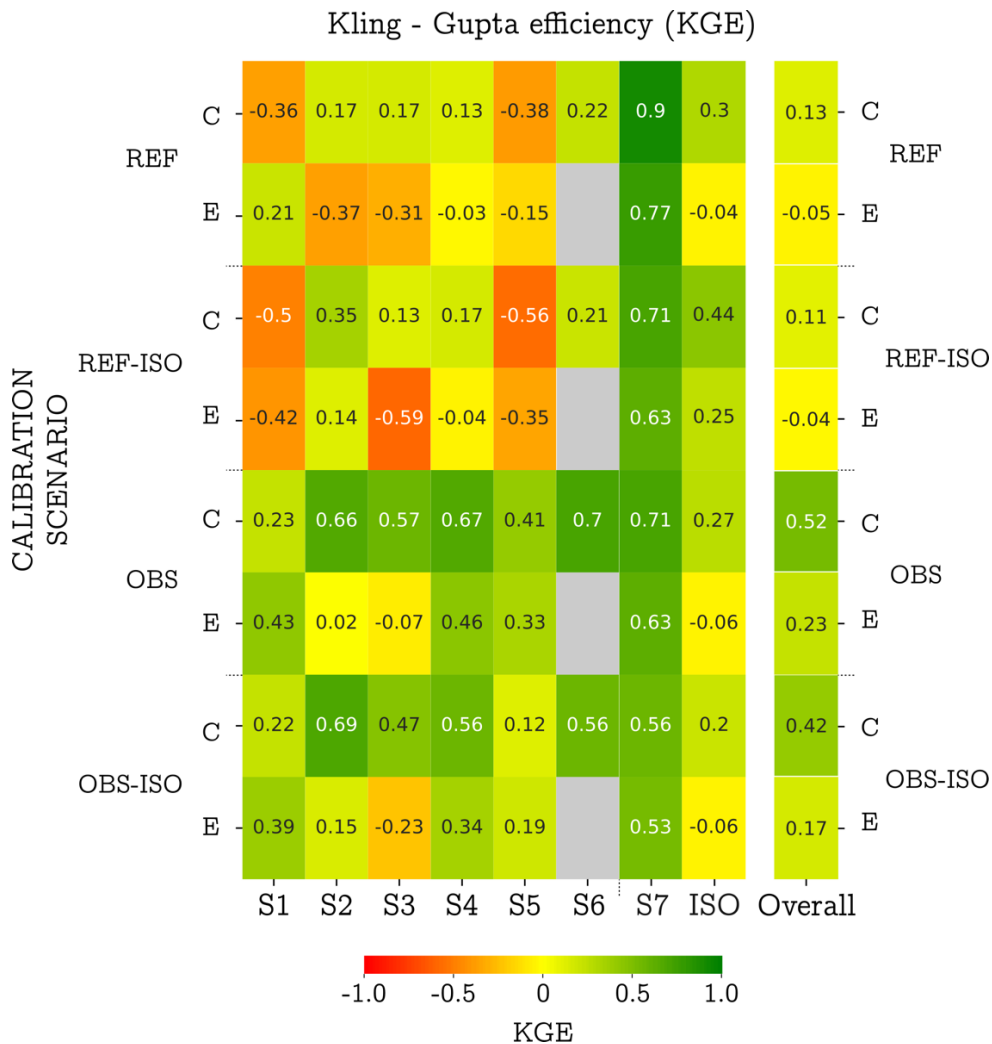


Figure 6. Median KGE for each scenario during the calibration (C, 2018-2020) and evaluation (E, 2021-2022) periods, across sub-basin discharge (S1 to S6) and discharge and isotopic targets at the basin outlet (S7 and ISO). Grey cells indicate missing discharge data at station S6 during the evaluation period. In the rightmost column KGE was first averaged across all targets (S1 to ISO) for each of the 30 behavioural runs, and the overall performance was estimated by the median of this ensemble



370 3.2 Outlet discharge and isotopic dynamics

The simulated $\delta^{18}\text{O}$ time series (Figure 7a-b) followed patterns closely linked to the seasonal dynamics of the Ouémé river. Fluctuations were particularly pronounced during the high-flow period from August to October, with simulation envelopes remaining narrow. During this period, the REF-ISO simulations achieved the closest agreement with observed $\delta^{18}\text{O}$ values, followed by OBS-ISO, whereas the OBS and REF shifted toward more depleted values. During the dry season, spanning the
 375 end-of-year recession around October-November to flood onset of the following year around May-June, there was an increased dispersion among calibrated runs (wider envelopes), although individual runs generally tended to become nearly constant, as shown by the flat median values, particularly for OBS-ISO and REF-ISO. At the flood onset, the observed $\delta^{18}\text{O}$ fluctuations were not fully captured by any scenario. Although evaporated data were excluded from calibration to prioritize the wet season (see Sect. 2.5.1), simulation envelopes partially captured the progressive $\delta^{18}\text{O}$ enrichment observed during the
 380 recession period. The simulated d-excess values, meanwhile, were generally shifted toward lower values relative to observations during the high-flow period, while being partially captured during the recession (Figure S1).

The simulated outlet discharges (Figure 7d-e) showed narrow, overlapping envelopes that broadly followed the seasonal dynamics of the river. The scenarios calibrated with isotopes (REF-ISO and OBS-ISO) showed slower recession periods, sustaining overestimated flows well into the dry season, long after the river had dried out. REF and REF-ISO captured small
 385 flood-onset flows well, with observed peak discharges encompassed by the simulation envelopes, although median peaks remained slightly below observed values between 2020 and 2022. The REF scenario, in particular, captured the recession period with high accuracy (Figure 7e). By contrast, small flood-onset flows in OBS and OBS-ISO were not always well reproduced, particularly in 2018 and 2021, while these scenarios showed pronounced discharge peaks in 2018 and 2019 that exceeded the observations (Figure 7d).

390 In terms of KGE, outlet discharge showed a narrower spread than $\delta^{18}\text{O}$ simulations, regardless of the calibration scenario (Figure 7c-f). At the sub-basin level, the outlet-based scenarios (REF and REF-ISO) displayed a wider spread of simulated discharge, reflected in both KGE values and their associated envelopes, than scenarios incorporating intra-basin information (OBS and OBS-ISO) (Figures S2 and S3).

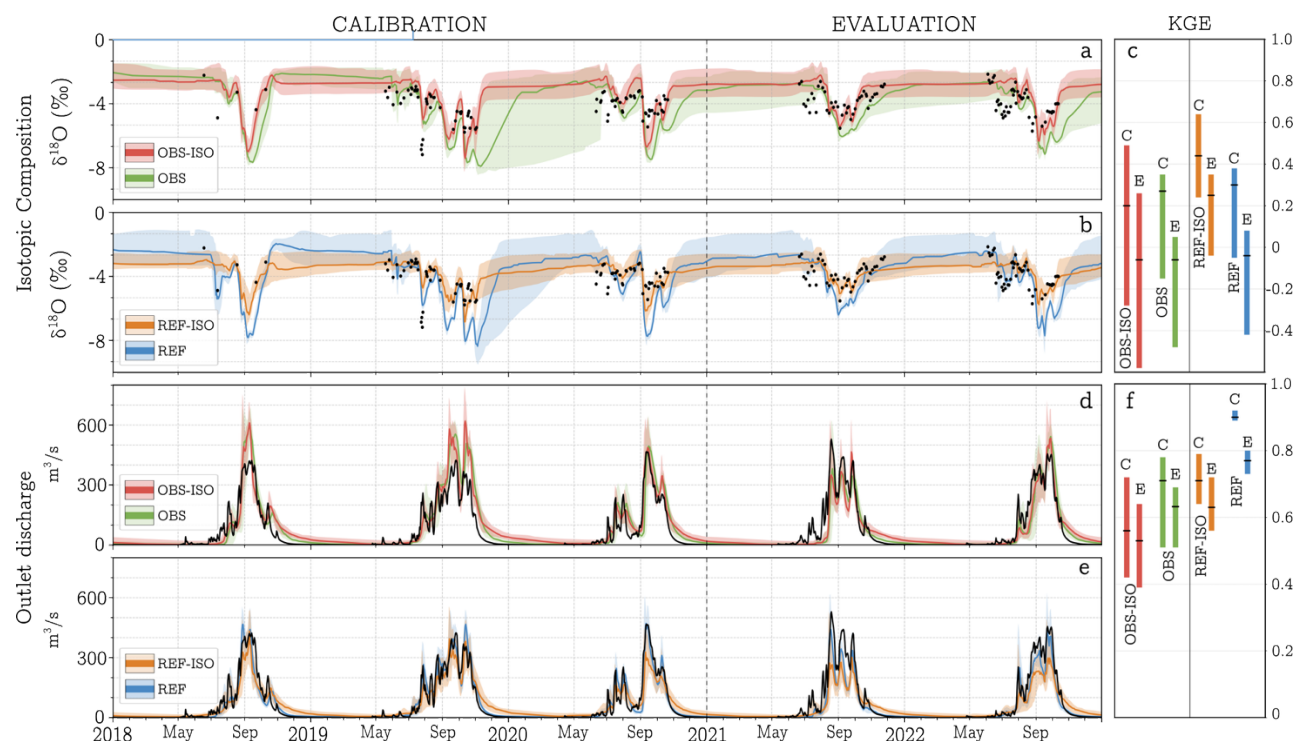


Figure 7. Left panels: simulated $\delta^{18}\text{O}$ (a–b) and discharge (d–e) time series at the basin outlet (S7) for each calibration scenario. Shaded envelopes indicate the 10th–90th percentile range of simulations, with solid lines representing the median. Observations are shown as black dots for $\delta^{18}\text{O}$ and black lines for discharge. Right panels: coloured bars represent the 10th–90th percentile range of KGE values across scenarios, for the calibration (C) and evaluation (E) period, with thin black horizontal bars indicating the median, for $\delta^{18}\text{O}$ (c) and discharge (f).

3.3 Baseflow dynamics assessment

At the basin outlet, the simulations calibrated with isotopes (REF-ISO and OBS-ISO) showed considerably higher baseflow (i.e. the fraction of stream discharge originating from subsurface seepage into the riverbed, see Sect. 2.3) than non-isotope scenarios. During the rainy season, the isotope-calibrated scenarios reached median values of around $100 \text{ m}^3/\text{s}$, representing a quarter to most of peak streamflow, while non-isotope scenarios remained below $10 \text{ m}^3/\text{s}$, with the lower envelope boundary approaching zero (Figure 8a-b). Simulated baseflow generally followed the observed discharge dynamics, responding to peak flows and increasing during the high-flow period. During the recession period, however, baseflow in isotope-calibrated scenarios clearly exceeded total observed discharge, persisting even after the observed discharge had ceased. Most of this baseflow originated from the middle subsurface layer (L2, extending to approximately 2 m depth), with the deep layer (L3) contributing a smaller but persistent fraction, and a negligible contribution from the topsoil layer (L1) (Figure S4).



Water ages in outlet discharge (Figure 8c-d) varied over three orders of magnitude across the hydrological year. They ranged from a few weeks during high-flow periods, reflecting the input of younger water at peak discharges, to several years during the recession. Isotope-calibrated scenarios (REF-ISO and OBS-ISO) showed median ages shifting toward higher values during the wet season, generally exceeding 100 days. This was consistent with the more persistent baseflow during recession described above, here reflected in a smoother increase in water ages compared to REF and OBS.

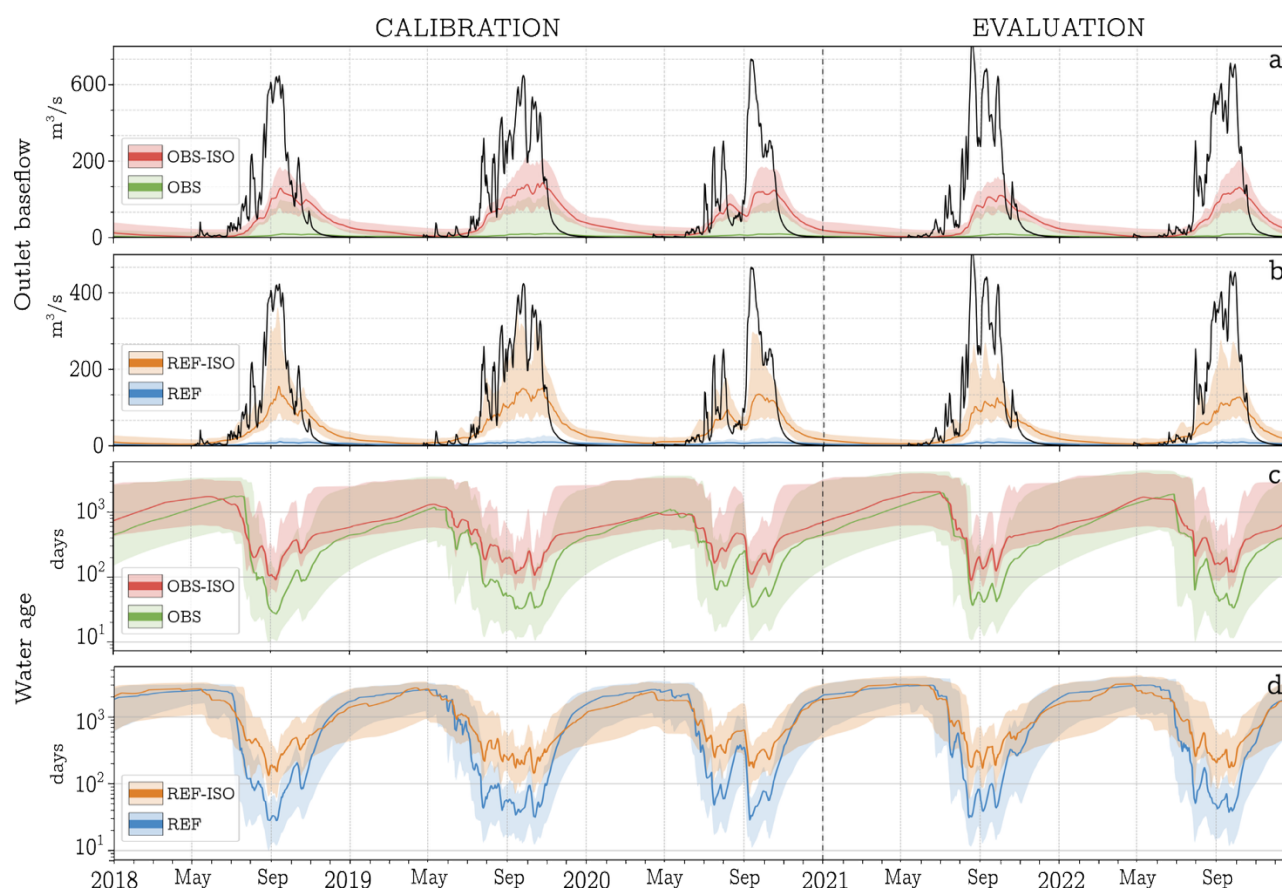


Figure 8. Simulated baseflow (a–b), and water age (c–d) time series at the basin outlet (S7) across calibration scenarios. The observed discharge is shown as a black line. Shaded envelopes indicate the 10th–90th percentile range of simulations, with solid lines representing the median.

The differences in distributions of simulated annual specific baseflow among scenarios at the sub-basin (S1 to S6) and basin (S7) levels (Figure 9) were formally assessed using pairwise Wilcoxon-Mann-Whitney (WMW) tests, with the corresponding p-values presented in the Figure S5.



Among all ensembles, REF-ISO showed the greatest dispersion across subbasins, with its upper distribution exceeding the observed specific discharge. From S2 to S7, baseflow distributions differed significantly ($p_{\text{WMW}} < 0.05$) between isotope-calibrated scenarios and their corresponding non-isotope configurations (OBS-ISO vs. OBS and REF-ISO vs. REF), with isotope-calibrated scenarios showing higher median values in each case. At S1, this was observed for OBS-ISO vs. OBS, whereas the non-significant test result for REF-ISO vs. REF was considered statistically unreliable, given the test sensitivity to the unequal dispersion (Fay & Proschan, 2010).

At the basin outlet (S7), no significant difference in distributions was detected between the isotope-calibrated scenarios. The dispersion differences observed upstream were absent here, with both ensembles showing comparable spreads and similar central tendencies (OBS-ISO median ≈ 120 mm/year; REF-ISO median ≈ 121 mm/year).

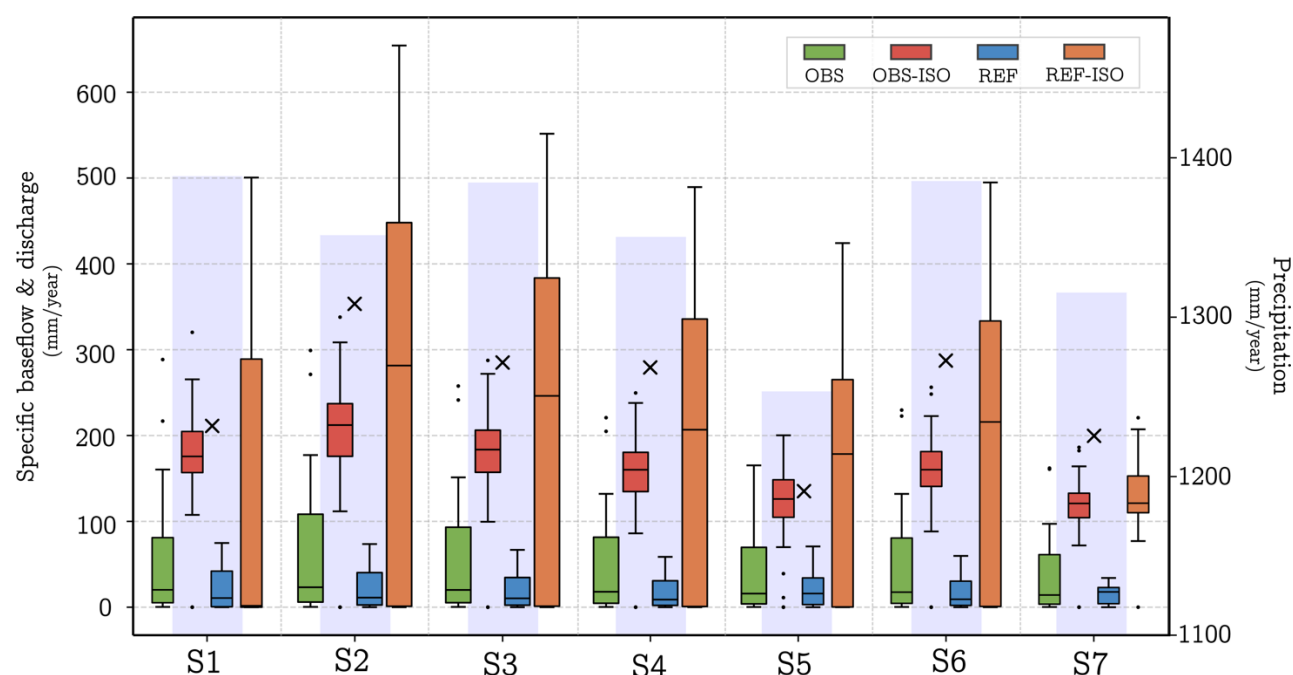


Figure 9. Mean annual simulated specific baseflow (2018–2022) across calibration scenarios at sub-basin stations (S1–S6) and the basin outlet (S7). Black crosses indicate mean observed specific discharge; the horizontal bar within each boxplot represents the median and black points represent outliers from the simulation ensembles. Light blue bars show mean annual precipitation for each sub-basin (right axis).

The median simulated baseflow generally followed the variations in annual precipitation across the sub-basins (Figure 9), although the relationship was not strictly proportional, indicating that spatial variability in simulated baseflow was influenced by factors beyond precipitation alone. At the interannual scale, median simulated baseflow at both sub-basin and

basin scales also followed variations in annual precipitation (Figure S8), with the isotope-calibrated scenarios consistently yielding higher median baseflows than their corresponding non-isotope scenarios in every simulation year.

445 3.4 Local-scale evapotranspiration assessment

The simulated evapotranspiration (ET) was compared with average eddy covariance measurements from Mamadou et al., (2016) at seasonal and annual scales (Figure 10). This comparison covered the two experimental sites with contrasting land cover, woodland and fallow (Figure 1). These measurements provided suitable benchmarks for model comparison, as they showed distinct signatures for each land cover type and low interannual variability. The corresponding benchmark values are reported in Table S2. Statistical significance of differences among ensembles and between benchmarks and simulations was tested, with p-values reported in Figures S6 and S9, respectively.

Seasonal ET ensembles (Figure 10, upper panel) differing only in isotope inclusion (OBS vs. OBS-ISO and REF vs. REF-ISO) generally showed no significant differences in distribution for either land cover (Figure S6). This was observed across all seasonal periods for woodland, and across all but the Wet-2 period for fallow, where OBS and OBS-ISO differed significantly ($p_{\text{WMW}} < 0.001$). For both land covers, the differences between the benchmarks and median simulated ET values were generally significant ($p_{\text{W}} < 0.05$), characterised by early-season underestimation transitioning to overestimation thereafter (Figures S9). During the Dry period, ET was underestimated by up to 0.3 mm.d⁻¹ across both land covers. The switch to overestimation occurred earlier for fallow, during the Moistening period (+0.6 to +0.9 mm.d⁻¹), than for woodland, where it occurred during Wet-1 (+0.1 to +0.2 mm.d⁻¹). Overestimation peaked for both land covers during Wet-2 (woodland: +1.6 to +1.7 mm.d⁻¹; fallow: +0.5 to +1.4 mm.d⁻¹), before easing into the Drying period, when fallow biases became smaller and mixed (+0.1 to +0.2 mm.d⁻¹; -0.1 mm.d⁻¹ for REF-ISO) while woodland overestimation remained large (+1.2 to +1.6 mm.d⁻¹).

At the annual scale, under woodland cover, three of the calibration ensembles (OBS-ISO, REF, and REF-ISO) showed no significant distributional differences from one another (Figure S6). OBS, in contrast, differed significantly from all other groups ($p_{\text{WMW}} < 0.001$). Under fallow cover, annual ET differed significantly across every pairwise ensemble comparison ($p_{\text{WMW}} < 0.001$). Overestimation of the annual ET benchmark was large across ensembles (Figure S9). Under woodland cover, it was consistent, ranging from +322.5 to +333.3 mm yr⁻¹ ($p_{\text{W}} < 0.001$). Under fallow cover, it varied by calibration scenario, highest for the distributed configurations (OBS: +269.0 mm.yr⁻¹; OBS-ISO: +211.4 mm.yr⁻¹; $p_{\text{W}} < 0.001$), lower for REF (+84.6 mm.yr⁻¹, $p_{\text{W}} < 0.001$), and smallest for REF-ISO (+33.9 mm.yr⁻¹, $p_{\text{W}} < 0.05$).

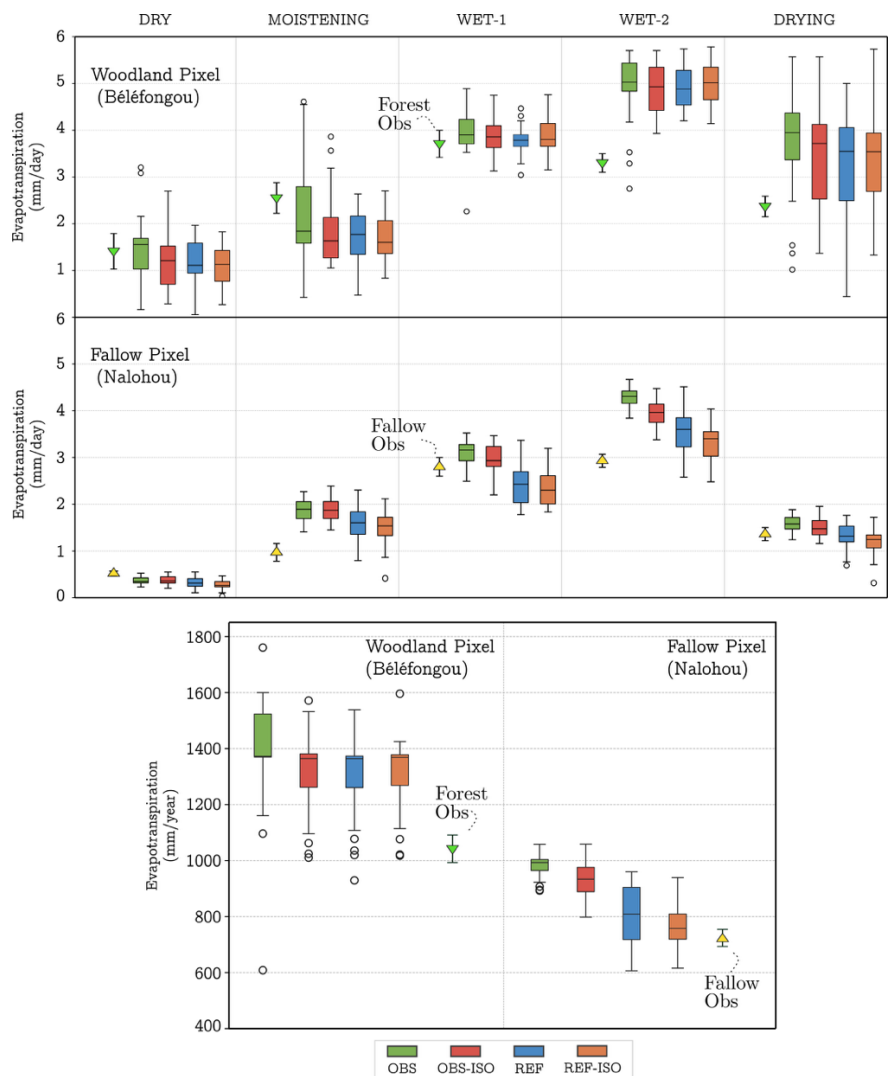


Figure 10. Mean seasonal (upper panel) and mean annual (lower panel) evapotranspiration for simulation ensembles (2018–2022) at the Woodland (Béléfongou) and Fallow (Nalohou) model pixels. Green and yellow triangles show reference woodland (Forest Obs) and fallow (Fallow Obs) values, with error bars, from Mamadou et al. (2016). Boxplot horizontal bars represent medians, and open circles represent outliers from the simulation ensembles. Details on the seasonal periods are provided in the Table S2.

3.5 Basin-scale water budget

The basin-scale mean annual water budget components for all simulation scenarios are shown in Figure 11a (see Eq. (3)), with the sub-components of evapotranspiration (ET) and outlet discharge (Q) shown in Figure 11b and Figure 11c, respectively. Their 10th, 50th and 90th percentiles, characterising central tendency and spread, are given in Tables S3 to S5. The statistical significance of differences among ensembles and between benchmarks and simulations was tested, with p-values reported in Figures S7 and S10, respectively.

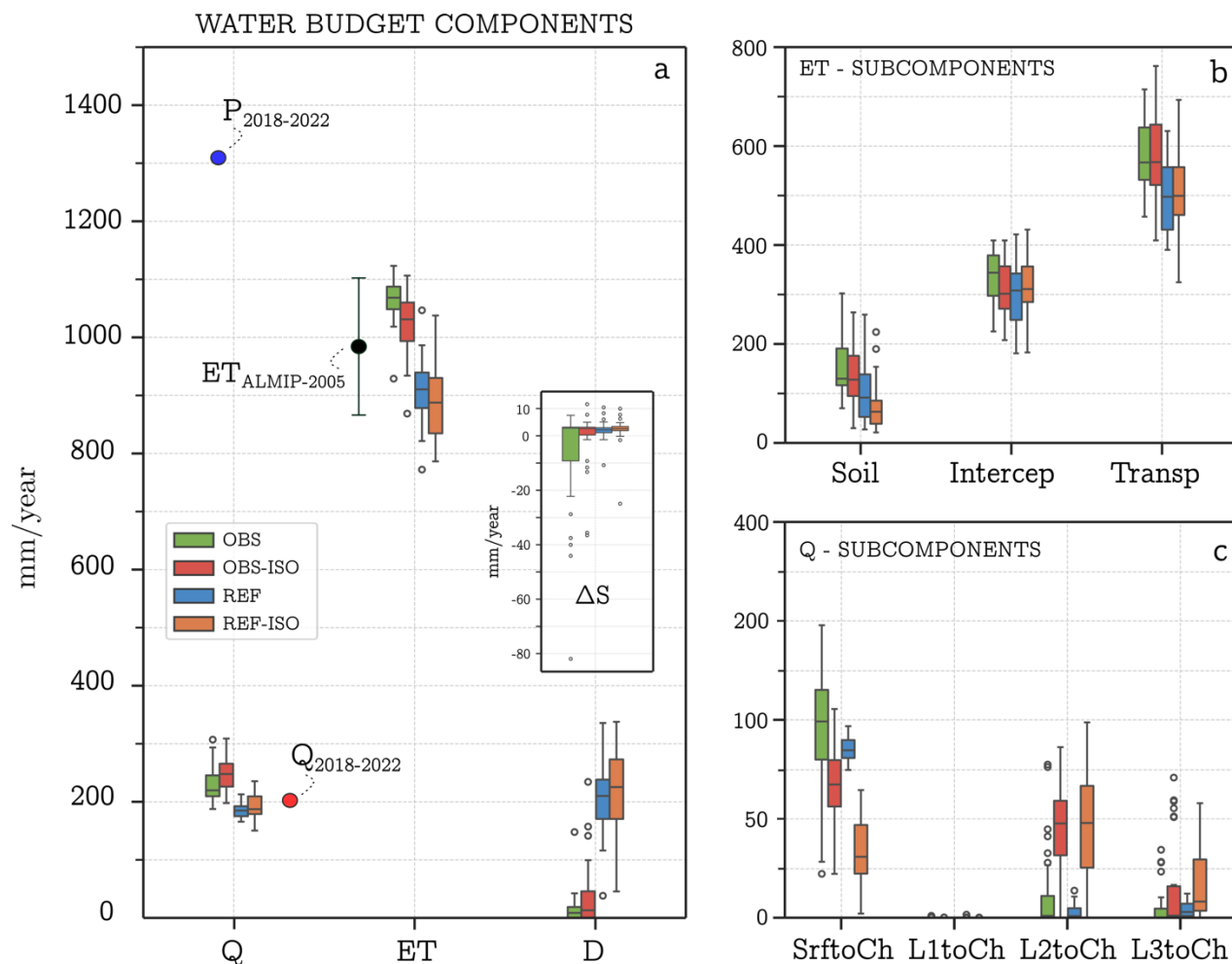


Figure 11. (a) Basin-scale mean annual water budget components for 2018-2022 for each calibration scenario. Black point with error bars shows the ALMIP1 evapotranspiration (ET) estimate (Peugeot et al., 2011), while the red point shows mean annual observed discharge. (b) Mean annual ET subcomponents, including soil evaporation (Soil), interception (Intercep) and transpiration (Transp). (c) Mean annual discharge (Q) subcomponents, including surface runoff (SrftoCh) and subsurface flow contribution from the topsoil (L1toCh), middle (L2toCh), and deep (L3toCh) layers.

3.5.1 Evapotranspiration

Evapotranspiration (ET) was the dominant water flux across all scenarios, with median values representing 68 to 81% of mean annual precipitation. Although these values fell within the ALMIP benchmark uncertainty range, all scenarios differed significantly from this benchmark ($p_w < 0.001$). OBS deviated by $+101.3 \text{ mm.yr}^{-1}$, reduced to $+64.1 \text{ mm.yr}^{-1}$ under OBS-ISO, while REF and REF-ISO deviated by -56.6 and -79.4 mm.yr^{-1} , respectively. Isotope inclusion resulted in a significant difference in the simulated annual ET distribution within the OBS scenario (OBS vs. OBS-ISO, $p_{\text{WMW}} < 0.001$) but had no significant effect within the REF scenario (REF vs. REF-ISO). All other comparisons differed significantly ($p_{\text{WMW}} < 0.001$).



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Among ET sub-components, transpiration dominated across all scenarios, followed by canopy interception and soil evaporation (Figure 11b), with median values representing 38 to 44 %, 23 to 26 %, and 5 to 10 % of precipitation, respectively. Vegetation transpiration (Transp) distributions were unaffected by the addition of isotopes within either baseline calibration scenario (OBS vs. OBS-ISO and REF vs. REF-ISO) but differed significantly in all other comparisons ($p_{WMW} < 0.01$). Canopy interception (Intercep) showed no significant differences in distribution across almost all pairings, with the only significant difference occurring between the baseline scenarios (OBS vs. REF, $p_{WMW} < 0.05$). Soil evaporation (Soil) distributions were not significantly affected by isotope inclusion under the OBS baseline scenario but differed significantly under the REF scenario (REF vs. REF-ISO, $p_{WMW} < 0.05$) and differed significantly across most other cross-scenario comparisons ($p_{WMW} < 0.01$).

505 3.5.2 Outlet discharge

Outlet discharge (Q) median values represented 14 to 19 % of mean annual precipitation across all scenarios. These values differed significantly from the benchmark ($p_w < 0.05$), with deviations of +18.7 mm.yr⁻¹ for OBS, +46.8 mm.yr⁻¹ for OBS-ISO, -16.1 mm yr⁻¹ for REF and -13.7 mm.yr⁻¹ for REF-ISO. Isotope inclusion had contrasting effects depending on the calibration strategy. It significantly affected the discharge distribution when distributed datasets were used for calibration (OBS vs. OBS-ISO, $p_{WMW} < 0.05$) but not when calibration relied on outlet-only data (REF vs. REF-ISO). All other cross-scenario comparisons differed significantly ($p_{WMW} < 0.001$).

Among the Q sub-components (Figure 11c), surface flow and lateral flow from the topsoil, middle, and deep layers represented median values of around 5 to 15 %, <1 %, 7 %, and 1 % of mean annual precipitation, respectively. Surface runoff (SrftoCh) distributions differed significantly with isotope inclusion under both baseline scenarios (OBS vs. OBS-ISO and REF vs. REF-ISO, $p_{WMW} < 0.001$), and across all other cross-scenario comparisons. Topsoil lateral subsurface flow (L1toCh) remained negligible (<1 mm yr⁻¹), with no significant distributional differences across scenarios. Middle soil layer lateral flux (L2toCh) distributions differed significantly with isotope inclusion under both baseline scenarios (OBS vs. OBS-ISO and REF vs. REF-ISO, $p_{WMW} < 0.001$) but did not differ between OBS-ISO and REF-ISO. For the deepest soil horizon (L3toCh), distributions differed significantly with isotope inclusion under REF ($p_{WMW} < 0.01$) but not OBS, while a significant difference remained between OBS-ISO and REF-ISO ($p_{WMW} < 0.05$).

3.5.3 Deep drainage and storage variation

Deep drainage (D) median values represented up to 16 % of mean annual precipitation in the outlet-calibrated scenarios (REF and REF-ISO) but remained near zero in the others. Isotope inclusion did not significantly alter drainage distributions within either baseline scenario (REF vs. REF-ISO; OBS vs. OBS-ISO), whereas all other pairwise comparisons differed



525 significantly ($p_{\text{WMW}} < 0.001$). Storage variation (ΔS) represented less than 0.5 % of mean annual precipitation across all scenarios, with no significant differences among any of the six pairwise comparisons.

At the interannual scale, differences in water budget partitioning among scenarios persisted despite the non-proportional responses of individual components to precipitation variability (Figure S11).

4 Discussion

530 4.1 Calibration data shape what the model can tell us about the basin

The degradation of performance under multi-output calibration is a fundamental trade-off and a well-recognized consequence of conflicting prediction errors, where reducing residuals for one target increases errors for another (Beven, 2006; Kuppel et al., 2018a; Holmes et al., 2020), even though the overall performance (i.e. averaged across outputs) is expected to improve. This is obvious in our results, where the scenarios incorporating distributed intra-basin information
 535 (OBS and OBS-ISO) tend to reduce performance for the main outlet (S7) discharge and isotopes during both calibration and evaluation periods, relative to scenarios focused exclusively on the outlet (REF and REF-ISO), reflecting differences in how each scenario balances competing observational constraints (Figure 6).

The high discharge performance of the REF scenario stems from fitting exclusively to the outlet hydrograph, albeit at the
 540 cost of low intra-basin discharge performance. In REF-ISO, adding isotopes as a calibration target further degrades outlet performance, as the model must now simultaneously reproduce the hydrograph and the $\delta^{18}\text{O}$ composition. The OBS scenario achieves the highest overall ensemble performance by leveraging more detailed internal information, although it still lacks the additional insights offered by isotopes in OBS-ISO (see Sect. 4.2). Across both baseline scenarios (REF and OBS), however, the inclusion of isotopes provided additional constraints on the representation of storage dynamics and runoff
 545 generation. Thus, the slightly overall performance "degradation" may be accompanied by a more realistic representation of internal flux partitioning by isotopic tracers (Holmes et al., 2023; Stadnyk & Holmes, 2020), particularly through an increased contribution of subsurface water (Figure 8). This highlights the value of comprehensive data coverage, particularly stable isotopes, for constraining internal basin functioning. It also points to the limitations of relying solely on performance metrics for model evaluation, since seemingly satisfactory calibration scores may mask deficiencies in process representation
 550 (Fenicia et al., 2008; Refsgaard et al., 2022; Ahmed et al., 2023).

These contrasting performances across calibration scenarios ultimately reflect how each ensemble resolved the interplay between evapotranspiration and deep drainage (Figure 11). Under the outlet-based scenarios (REF and REF-ISO), the basin behaved as a leaky bucket, with deep drainage providing an efficient way to divert excess water out of the domain, thereby
 555 reducing the performance at the sub-basin scale. Conversely, the scenarios incorporating distributed information (OBS and



OBS-ISO) reduced the need for deep drainage, increasing performance at the internal discharge stations. Similar compensatory roles for analogous terms have been documented in prior regional modelling across the Ouémé basin, where they adjusted the water balance (Getirana et al., 2014; Le Lay et al., 2008). Notably, including stable isotopes in either baseline scenario (REF and OBS) had no statistically discernible effect on deep drainage distributions.

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4.2 Unlocking baseflow dynamics through isotopic information content

Our results suggest that stable water isotopes leverage useful information for better constraining the simulation of the subsurface water component. At the basin outlet, isotopic constraints favoured greater contributions from subsurface flow paths over rapid, unmixed surface runoff. For REF-ISO and OBS-ISO, this resulted in a greater fraction of older water sustaining streamflow, substantially increasing simulated water ages (Figure 8) and dampening the streamflow $\delta^{18}\text{O}$ isotopic signal (Figure 7), an effect also reported in previous studies (Ala-aho et al., 2017; Holmes et al., 2020; Sprenger et al., 2019; Yang et al., 2021). This isotope-driven shift in internal water partitioning was associated with comparable baseflow responses for both above-mentioned scenarios, with no significant differences detected in annual distribution (Figure 9 and S5). Such convergence between isotope-driven scenarios suggests that isotopic constraints can steer distinct calibration strategies toward a comparable representation of baseflow, regardless of the differences (e.g. total streamflow and local drainage) imposed by the two baseline calibration frameworks (REF and OBS).

In isotope-informed scenarios, baseflow originated mainly from the near-surface middle layer (L2), with a smaller but persistent contribution from the deepest layer (L3). The predominance of L2 contributions reflects the tendency of these scenarios to select parameter sets with higher hydraulic conductivity in this layer (Figure S12). This intermediate reservoir (down to ~2 m) thus exerts strong control on streamflow generation, and corresponds well with the perched groundwater in the upper weathering zone that feeds the inland valley (bas-fonds) system, identified as the main contributor to river discharge, in a series of studies in the Upper Ouémé basin (Giertz et al., 2006; Le Lay et al., 2008; Séguis et al., 2011; Getirana et al., 2014, 2017; Hector et al., 2018; Herzog et al., 2021). By contrast, contributions from the deepest reservoir may be broadly associated with the unconfined, underlying, composite saprolite-fissured perennial aquifer system (Lachassagne et al., 2021). Although assumed to be disconnected from the river in some studies (Richard et al., 2013), this aquifer may nonetheless contribute to streamflow in this basin during high flows (Hector et al., 2018). Evidence from regions with similar geology further suggests that saprolite aquifer contributions can reach around 50 mm/year (Kouassi et al., 2024), and our study supports this deeper contribution, together with shallower subsurface flow, as seen in the multiyear estimates presented here (Figure 11c). Yet the simulated persistence of baseflow after observed river discharge ceases suggests parametrization or even structural issues in reproducing seasonal dynamics in our model, as it fails to curtail baseflow sharply. During this period, the simulated continued flow is driven by enhanced soil water transfer in the middle layer and the nearly constant contribution from the deepest reservoir.

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At the sub-basin scale, spatial variability in simulated specific baseflow (Figure 9) indicated controls beyond precipitation. Given the limited precipitation gradients across the basin (Figure S13), this variability likely reflects the influence of local land-surface properties on water partitioning processes, as suggested by other studies (Getirana et al., 2014; Giertz & Dieckkrüger, 2003; Herzog et al., 2021). In the model, these properties were represented mainly via sub-basin-specific drainage parameters (Table 2), which regulated water volume available for baseflow, given that soil parameterization, baseflow-contributing cell proportions, and vegetation types were uniform across sub-basins (Table S6). Differences in variance between isotope-informed scenarios highlighted the contrasting role of deep drainage as a compensatory mechanism (see Sect. 4.1).

4.3 Closing the water budget for the right reasons

Evapotranspiration (ET) is the dominant component of the water budget, accounting for two-thirds or more of annual precipitation. Yet, ET remains particularly difficult to constrain at the regional and subregional scales considered here because of the multiple interacting processes controlling its magnitude and variability (Mamadou et al., 2014). Our results showed that including stable isotopes in the calibration framework produced a statistically significant decrease of basin-scale annual ET (Figure 11a and S7), although only under internally constrained scenarios (OBS and OBS-ISO). This was associated with greater routing of water in the stream from subsurface flow paths under isotope-informed calibration (see Sect. 4.2).

Because fallow covers approximately three-quarters of the basin, the isotope-driven shift in bulk ET was largely influenced by this land cover (Figure 10). Isotopes did not induce statistically significant differences in woodland ET distributions in any season, whereas including these tracers significantly reduced Fallow ET for the OBS and OBS-ISO scenarios (Figure S6) during the Wet-2 period, from July to October, when simulated ET and baseflow both reach their seasonal maximum (Figure 10 and Figure 8, respectively). This contrast emerged from the effect of the potential-driven root uptake scheme of the model (see Sect. 2.3), which governed seasonal change in the vertical distribution of root water uptake for transpiration across subsurface layers (Figure S15). Woodland ET distributions remained statistically invariant across scenarios, as seasonal shifts in uptake depth prevented transpiration from becoming water-limited. During the dry and transitional phases (Dry, Moistening, Drying), woodland shifted uptake from shallow reservoirs (L1, L2) to the deeper L3 layer for sustaining its elevated transpiration demand. As moisture availability increased during the wet phases (Wet-1, Wet-2), uptake reverted to the shallow layers. Fallow, in contrast, drew predominantly from the two uppermost layers (i.e. above 2 m) throughout the year, while retaining limited access to deeper storage (<20 %, Figure S15). Because isotope-calibrated scenarios routed baseflow primarily through L2, this shallow-layer dependence placed fallow transpiration in direct competition with baseflow generation, accounting for the significant reduction in fallow ET.



ET showed a consistent seasonal bias across scenarios, transitioning from slight underestimation early in the season to overestimation later on (Figure 10, Figure S14). This bias may be linked to the flexible root uptake scheme, which does not impose a fixed maximum rooting depth, allowing vegetation to access the full subsurface storage. Such flexibility can prevent the ET underestimation that may arise when water uptake is confined to shallow soil reservoirs (Boone et al., 2009; Galle et al., 2018), which can in turn alter water partitioning and lead to an inadequate representation of baseflow generation (Getirana et al., 2014). Such flexible access to subsurface water is consistent with increasing evidence that trees can dynamically adjust their water uptake profile in response to water availability, at seasonal but also shorter time scales (e.g. Alexandre et al., 2025; Sprenger et al., 2025), including in the Sudanian region, where roots may occasionally reach substantially greater depths to access the permanent water table (Fan et al., 2017). However, under wet-season conditions, unrestricted access to subsurface water may contribute to ET overestimation. High transpiration during this period reflects the combination of non-limiting soil water availability and low canopy resistance.

At the subcomponent level (Figure 11b), adding stable isotopes to the baseline scenarios (REF and OBS) produced no statistically significant differences in ET subcomponent distributions in almost all cases (Figure S7). This limited isotope effect may be related to the distinct controls influencing each ET subcomponent. Transpiration was affected by deep drainage and associated subsurface water availability (Sect. 4.1). Canopy evaporation showed limited variation across scenarios, with median contributions within the range reported for tropical savanna zones (Magliano et al., 2019; Skhosana et al., 2023). Soil evaporation showed little sensitivity to isotopic information, as topsoil-water fractionation during evaporation barely propagated to the outlet isotopic signal (see also Chávez-Espinoza et al., 2025), which is consistent with the absence of a fractionated $\delta^{18}\text{O}$ signature during the high-flow period in both observations and simulations (Figure 3).

Determining why this topsoil isotopic signal is absent from the river, whether due to complete evaporation of topsoil water during the rainy season or limited hydrological connectivity of the topsoil, would require additional isotopic datasets beyond the scope of this study. The sustained $\delta^{18}\text{O}$ enrichment during recession is, however, partially reproduced by the declining contribution of younger water and the increasing dominance of older water from deeper layers, rather than by continued evaporation of channel water, which is not simulated by the model. At the same time, the overestimation of recession baseflow complicates the quantification of old-water isotopic contributions to total discharge and therefore limits our ability to disentangle competing mixing effects within this relatively small component of the annual water budget. Simulated d-excess partially captures the observed signal, but a negative bias persists during the high-flow period, inherited from IsoGSM4 precipitation (Figure S1), a limitation also reported in other studies (Tanoue et al., 2017; Wei et al., 2016).

Overall, our results demonstrated the utility of isotopic constraints in reducing equifinality in the basin-scale water balance (Eq. (3)). Recent studies in the region indicate that streamflow may convey a highly informative signal that can impose some level of constraint on other fluxes (Yonaba et al., 2026). We argue that, except in semi-arid areas where streamflow mainly



650 originates from surface runoff, discharge observations alone may overlook important subsurface flow dynamics in basins where this component is significant, which could compromise system representation.

Despite the strong coupling among ET, outlet discharge (Q), and deep drainage (D), that challenge the water budget partitioning, isotope-informed models yielded measurable improvements. Notably, the OBS-ISO scenario imposed an additional constraint on bulk ET fluxes, enhanced the internal consistency of simulated Q dynamics, and substantially
655 constrained D to near-negligible magnitudes, consistent with prior hypotheses suggesting minimal deep percolation in this basin.

Nevertheless, uncertainty persist in constraining ET, particularly at the basin scale, where further observations remain necessary. Data-fusion approaches combining remote sensing and reanalysis (Allies et al., 2020, 2022) could provide continuous, spatially resolved ET estimates for model evaluation, while improved dynamic land cover representations could
660 capture heterogeneous landscape changes, necessary for closing the gap toward more realistic simulations.

5 Conclusion

Several calibration experiments were conducted to evaluate contrasting basin representations arising from different calibration strategies, in order to identify which best reproduced the hydrological functioning of the Bétérou basin (Upper Ouémé). Particular attention was given to the additional information provided by stable isotopic observations at the basin
665 outlet and their effectiveness in resolving internal water partitioning.

Our findings may carry important implications for hydrological modelling practice and for our understanding of basin-scale processes. For modelling practice, reliance on discharge alone for model calibration risks misrepresentation of subsurface flow contribution, yielding inconsistent water partitioning in the hydrological system. Yet this limitation remains concealed until isotopic observations are introduced as complementary constraints. Indeed, integrating isotopes into model calibration
670 shifted the simulated streamflow partitioning away from a runoff-dominated regime toward greater subsurface flow contributions, reshaping the simulated water balance. From a process perspective, while the predominance of baseflow in river discharge have been documented at local scales in this region, the present work suggest this behaviour may extend across the entire basin. Notably, while field observations in headwater catchments have demonstrated that deeper saprolite zones are hydrologically disconnected from stream networks, our model results suggest that, at the scale of the entire 10,000
675 km² basin and under the modelling conditions considered here, these deeper zones may contribute to baseflow generation in addition to the shallow subsurface.

The partitioning between other hydrological pathways, such as evapotranspiration and deep drainage, benefited indirectly from isotope constraints, although uncertainty remains regarding their respective weight across the basin and seasons. This



partial resolution is nonetheless noteworthy, as it demonstrates that isotope data can effectively reduce the space of plausible system behaviours even where full process separation remains challenging. Such outcomes reflect the limitations inherent in calibration approaches relying on a single data type (e.g. stream discharge), highlighting the need for complementary observations to further constrain these processes.

Integrating isotopic tracers with conventional observational datasets provides a pathway to progressively narrow uncertainties in process representation and supports their incorporation into future monitoring frameworks. This holds relevance for tropical remote regions where existing process knowledge can be strengthened through the constraints delivered by isotope measurements. While distributed sampling offers the potential for greater information gain, spatially targeted monitoring with several types of observables may still represent a valuable advance over purely hydrometric approaches, providing useful insights for fit-for-purpose applications when full deployment proves logistically prohibitive.

690 **Code and data availability**

The code of the model EcH₂O-iso used in this study is available in the open repository <http://bitbucket.org/scicirc/ech2o-iso>, master branch (commit d598f06). All model outputs generated in this study are archived and are publicly accessible at <https://doi.org/10.5281/zenodo.22047584>. The rainfall and discharge datasets used in this study are available from the AMMA-CATCH database (<http://bd.amma-catch.org>), through the following DOIs: 10.17178/AMMA-CATCH.CL.Rain_O, 10.17178/AMMA-CATCH.CL.Rain_Od (rainfall), and 10.17178/AMMA-CATCH.CL.Run_O, 10.17178/AMMA-CATCH.CL.Run_Od (streamflow).

Author contributions

DCE, CVC, SK and CP conceptualized the study and performed the formal analysis; DCE curated the data, prepared visualisations and wrote the original draft; CVC initiated the isotopic modelling project, led the isotopic sampling and analytical work and secured funding; SK developed EcH₂O-iso and its associated algorithms; HB and KY curated the isotopic reanalysis data and developed IsoGSM4. All authors reviewed and edited the manuscript.

Competing interests

The authors declare that they have no conflict of interest.



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