



# Technical note: An evaluation of error propagation in MixSIAR for root water uptake

Han Fu<sup>1</sup>, Ruiqi Ren<sup>2</sup>, Huijie Li<sup>2</sup>, Jeffrey McDonnell<sup>3,4,5</sup>, Adrià Barbeta<sup>6</sup>, Wenxiu Zou<sup>1</sup>, Bingcheng Si<sup>2,7</sup>

<sup>1</sup>State Key Laboratory of Black Soils Conservation and Utilization, Northeast Institute of Geography and Agroecology, Chinese Academy of Sciences, Harbin, China

<sup>2</sup>College of Hydraulic and Civil Engineering, Ludong University, Yantai, China

<sup>3</sup>Global Institute for Water Security, School of Environment and Sustainability, University of Saskatchewan, Saskatoon, Saskatchewan, Canada

<sup>4</sup>North China University of Water Resources and Electric Power, Zhengzhou 450046, China

<sup>5</sup>School of Geography, Earth & Environmental Sciences, University of Birmingham, Birmingham, UK.

<sup>6</sup>IRTA, Fruit Production, Torre Marimon, 08140 Caldes de Montbui, Catalonia, Spain

<sup>7</sup>Department of Soil Science, University of Saskatchewan, Saskatoon, SK, Canada

*Correspondence to:* Wenxiu Zou (zouwenxiu@iga.ac.cn) and Bingcheng Si (bing.si@usask.ca)

**Abstract.** Quantifying root water uptake (RWU) using hydrogen and oxygen stable isotopes and Bayesian mixing models is widely applied in ecohydrology. But its reliability remains unclear due to multiple uncertainties and the underdetermined nature of the problem. Here we systematically evaluate error propagation in MixSIAR-based RWU estimation using synthetic datasets with known RWU profiles. Through 2,916 controlled simulations, we assess the contributions of eight factors, including observed soil and plant water isotopic compositions, RWU patterns, and model configuration (source grouping, prior information, and error structure) to the variance in accuracy and uncertainty of estimated root water uptake proportions using MixSIAR. Results show that prior information and source grouping dominate RWU inference, explaining over 40% of the total variance. By contrast, when evaluated using posterior-predicted plant water isotopic compositions, their contribution falls below 10%, while soil and plant isotopic compositions and error structure together explain over 40%. This shift results in two things: (1) it masks the influence of prior information and source grouping for inferring RWU proportions using MixSIAR, and (2) it reveals a critical limitation in the approach: accurate isotope fits of observed plant water do not guarantee correct RWU inference, since multiple RWU solutions can produce identical isotopic compositions. These findings demonstrate that prior information and source grouping should be explicitly specified and carefully justified in future applications of MixSIAR in studies of quantifying RWU using Bayesian mixing models. Also, the multi-criteria evaluation frameworks beyond posterior predicted plant water isotopic composition are needed to assess the performance of MixSIAR in isotope-based RWU estimation.



## 1. Introduction

Root water uptake (RWU) is a key process linking soil, vegetation, and atmosphere across hydrological, ecological, and climatic systems (Brantley et al., 2017; Dawson et al., 2002). It plays a central role in the terrestrial water cycle, accounting for approximately 60% of global evapotranspiration (Good et al., 2015; Wei et al., 2017). Accurate quantification of RWU is therefore essential for understanding plant water use strategies and for improving water resource management under changing environmental conditions. The isotopic composition in hydrogen and oxygen ( $\delta^2\text{H}$  and  $\delta^{18}\text{O}$ ), combined with Bayesian mixing models, have become one of the most widely used approaches for quantifying RWU (Fu et al., 2026). This method is based on isotope mass balance and typically relies on the assumptions of negligible isotopic fractionation during root water uptake and instantaneous mixing under steady-state conditions (Dawson, 1993). Among the available tools, MixSIAR (Stock and Semmens, 2016) has emerged as one of the most widely adopted frameworks due to its flexibility in incorporating multiple sources of uncertainty and prior information (see recent review by Fu et al., 2026). It has been applied extensively in studies of plant responses to environmental stress, agricultural and forest water management, and hydrological processes to infer RWU patterns and water use strategies (Granda et al., 2022; Huang et al., 2023; Shi et al., 2021).

However, MixSIAR was widely applied for dietary source partitioning in ecological studies (Guerrero and Rogers, 2020; Phillips et al., 2014). Applying it to RWU studies introduces several fundamental assumptions and challenges. First, unlike discrete sources in dietary studies, soil water sources are inherently continuous along the soil profile (Neil et al., 2024). This means that MixSIAR requires discretization into a limited number of sources (Fu et al., 2024). Second, the number of tracers (typically two) is often insufficient relative to the number of sources, leading to an underdetermined inference problem (Neil et al., 2024). Third, both soil and plant water isotope measurements are subject to substantial uncertainties, including sampling, extraction, and analytical errors (von Freyberg et al., 2020; Penna et al., 2018). Finally, the error structure governing uncertainty propagation from soil to plant water isotopic compositions is often insufficiently justified in practical MixSIAR applications (Fu et al., 2026). Collectively, these challenges result in the inferred RWU profiles from MixSIAR being highly uncertain and potentially biased. Critically, because the RWU profiles are rarely observable under field conditions, such uncertainties and biases often remain undetected and thus, unreported.

Several studies have evaluated the performance of MixSIAR and related isotope mixing models (Gai et al., 2023; Liu et al., 2023a; Stock and Semmens, 2016; Wang et al., 2019). However, instead of direct assessment of RWU estimates, these performance evaluations have typically been based on comparisons between posterior predicted and observed plant water isotopic compositions. This is inherently limited because a good fit to plant water isotopes does not guarantee the accuracy of RWU proportions in an underdetermined system (Fu et al., 2024, 2026). Additionally, existing studies often examine individual sources of uncertainty in isolation, without systematically quantifying their relative contributions or interactions.

For example, prior information (a critical component of Bayesian inference) is often overlooked, despite its strong influence on RWU estimates (Fu et al., 2026).

To address these gaps and building upon our recent review (Fu et al., 2026) of the key sources of error and uncertainty in isotope-based RWU estimation, here we provide the first systematic quantitative evaluation error propagation in MixSIAR. We use a synthetic dataset with known RWU profiles to directly evaluate the estimation accuracy and in so doing, disentangle the effects of multiple uncertainty sources, including soil and plant water isotopic variabilities, RWU patterns, and model structural assumptions. Through controlled numerical experiments, we quantify both the individual and interactive effects of these factors on RWU inference. Our results provide new insights into the reliability and limitations of isotope-based RWU estimation using MixSIAR that we discuss in the following sections.

## 2. Methods

Our recent review on the application of Bayesian mixing models for root water uptake (Fu et al., 2026), identified several key factors influencing the performance of MixSIAR can be identified, including prior information, source grouping, and error structure. To quantify the effects of these factors on the accuracy and uncertainty of RWU estimates, we consider a set of variables is considered (Figure 1), including (1) *soil water isotopic contrasts*, (2) *soil water isotopic measurement errors*, (3) *root water uptake patterns*, (4) *plant water isotopic variance*, (5) *source grouping numbers*, (6) *source grouping schemes*, (7) *prior information*, and (8) *error structure*.

For clarity, these variables are grouped into four categories. (1) ***Soil water isotopic compositions*** category, which includes *Soil water isotopic contrasts* and *measurement errors*; (2) ***Model configuration category***, which contains *Source grouping number*, *grouping scheme*, *prior information*, and *error structure*; The remaining variables represent (3) ***“Root water uptake pattern”*** and (4) ***“Plant water isotopic compositions”*** categories, respectively (Figure 1).

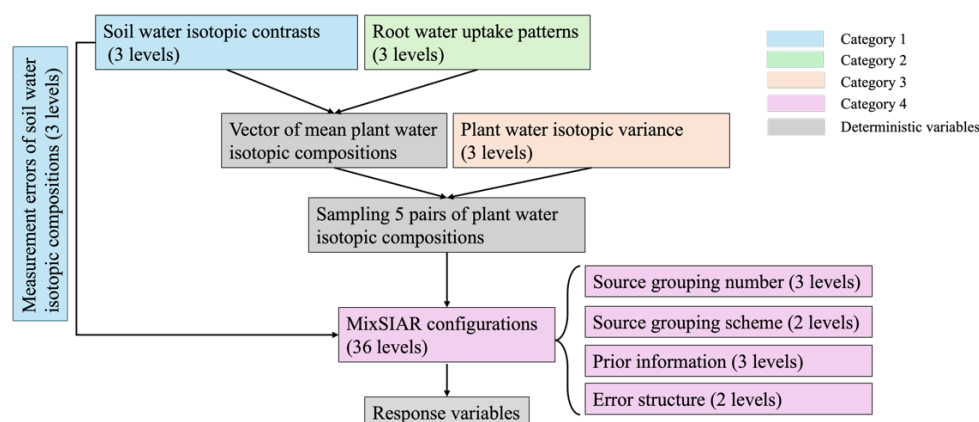


**Figure 1. Illustration of variables and the numerical simulation flow.**



## 2.1 Variable categories

### Category 1. Soil water isotopic compositions

90 This category includes two variables: (1) soil water isotopic contrasts and (2) measurement errors of soil water isotopic compositions.

#### (1) Soil water isotopic contrasts

This variable refers to the vertical variation of soil isotopic compositions within the rooting zone. It includes three levels: large contrast, medium contrast, and small contrast, with corresponding coefficients of variation (CV) values are 0.3, 0.2, and 0.1, respectively (Figure 2).

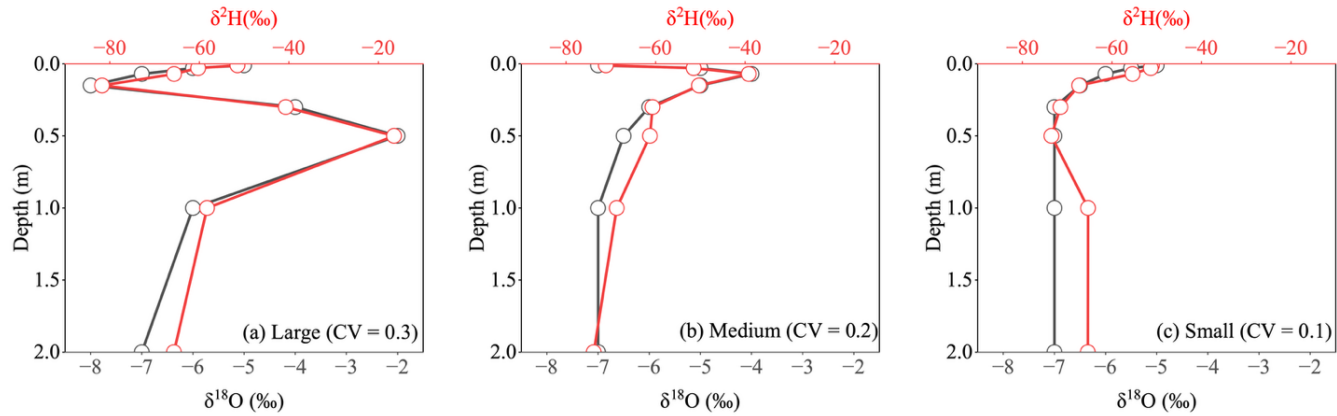


**Figure 2. Soil water isotopic profiles at varying levels of isotopic contrast. The data is based on Rothfuss and Javaux (2017), with modifications made to suit the simulations in this study (Replotted from Fu et al., 2026). Slight differences between the red and black profiles are retained to represent realistic covariance between the two tracers rather than assuming perfect correlation.**

#### 100 (2) Measurement errors of soil water isotopic compositions

This variable is the measurement error of soil water isotopic compositions refers to the potential errors that may occur during soil water extraction and machine errors. A z-score is typically used to quantify this error (Orlowski et al., 2016):

$$z = \frac{E-R}{SD} \quad (1)$$

where  $E$  is the extracted  $\delta^2\text{H}$  ( $\delta^{18}\text{O}$ ) value,  $R$  is the  $\delta^2\text{H}$  ( $\delta^{18}\text{O}$ ) value of the reference water, and  $SD$  is the target standard deviation, which is assumed to be 2‰ for  $\delta^2\text{H}$  and 0.2‰ for  $\delta^{18}\text{O}$  (He et al., 2023). When the z-score is greater than 5, the measurement error of soil water isotopes is considered unacceptable (He et al., 2023; Orlowski et al., 2016). Therefore, we set three levels (ranges) of z-scores, [0, 1], [1, 3], and [3, 5], to describe different degrees of acceptable errors. For each soil isotopic measurement, z-score is a random value from the respective level range. For example, when considering the z-score level [0, 1] and there are 8 soil water isotopic measurements (Figure 2), the z-score for each measurement is randomly sampled from [0, 1] and the soil water isotopic compositions are modified using Eq. (1).

## Category 2: Root water uptake patterns

Three levels are considered in this category and used as the benchmark root water uptake patterns: shallow-dominated, deep-dominated, and bimodal (Figure 3). These three patterns cover the most spatial and temporal root water uptake patterns of trees during their growing season (Bachofen et al., 2024). In our simulation, these benchmark RWU profiles are calculated based on the given fine root distribution and soil water potential distribution (Figure 3) using the Couvreur model (Couvreur et al., 2012; Rothfuss and Javaux, 2017).

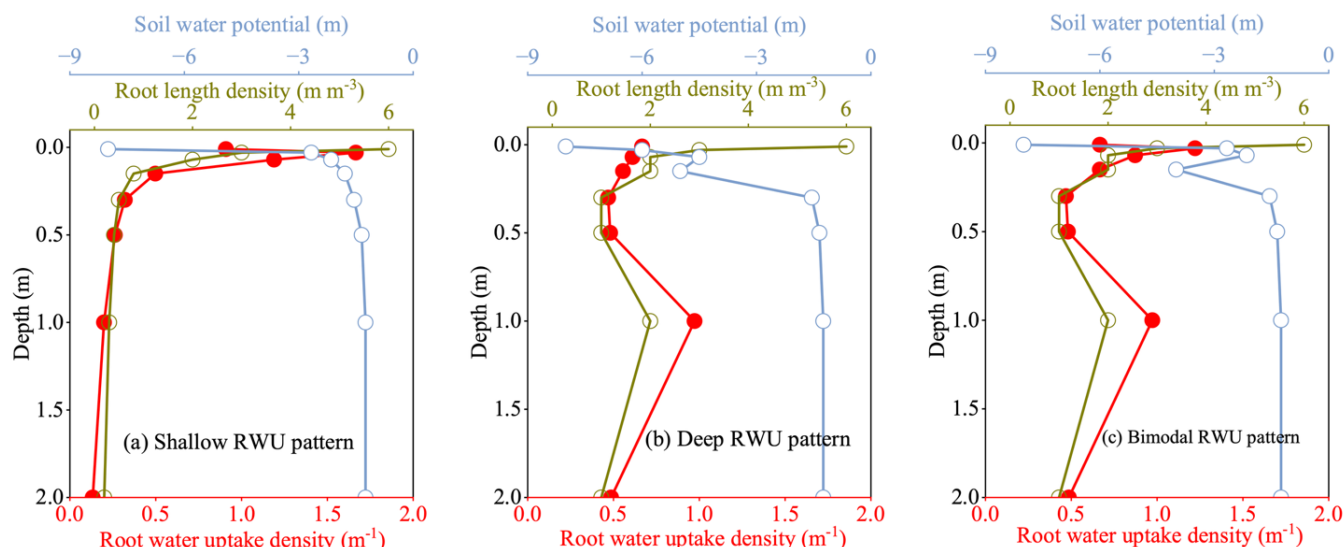


**Figure 3.** Fine root length density (dark yellow) and soil water potential (blue) profiles that used to generate benchmark root water uptake profiles (red) of shallow-dominated (a), deep-dominated (b) and bimodal (c) patterns, using Couvreur model. Data are from Rothfuss and Javaux (2017), with modifications to suit the simulations in this study (Replotted from Fu et al., 2026).

## Category 3: Plant water isotopic variance

Mean plant water isotopic compositions are obtained by multiplying the given soil isotope profile (Figure 2, without introducing measurement errors) and the benchmark root water uptake proportions (red curves in Figure 3). The variance of plant water isotopic compositions has three levels: small, medium, and large, with respective values for  $\delta^2\text{H}$  being 2.1‰, 3.3‰, and 4.4‰, and for  $\delta^{18}\text{O}$  being 0.8‰, 1.2‰, and 1.6‰ (von Freyberg et al., 2020). These prescribed plant water isotopic variances are intended to represent the combined uncertainty associated with observed plant water isotopic compositions, including natural variability, sampling effects, extraction-related biases, and analytical errors reported in previous studies (Li et al., 2026).

Additionally, due to the strong correlation between  $\delta^2\text{H}$  and  $\delta^{18}\text{O}$  (Finkenbiner et al., 2021), we assumed a correlation coefficient of 0.9. Based on this, the covariance matrix for observed plant water  $\delta^2\text{H}$  and  $\delta^{18}\text{O}$  can be calculated for each observed plant water isotopic variance level. Using the calculated covariance matrix and the mean vector of observed plant



water isotopic compositions, a bivariate normal distribution is generated, from which five pairs of  $\delta^2\text{H}$  and  $\delta^{18}\text{O}$  values are randomly sampled to serve as the mixture data (Figure 1).

#### 135 **Category 4: MixSIAR configurations**

Based on the previous review (Fu et al., 2026), four variables are identified within the model configuration category: source grouping numbers, source grouping schemes, prior information, and error structure. Other factors, such as random and fixed effects, are not considered here, as this study focuses on the dominant sources of uncertainty directly influencing RWU partitioning. While these additional components may be relevant in specific applications, they primarily affect hierarchical variability rather than the core identifiability and uncertainty structure of RWU estimates examined in this study.

##### **(1) Source grouping number and schemes**

The source grouping number includes three levels: 3, 5, and 8. While the source grouping scheme has two levels: one based on isotope information and another based on fine root and soil water content distributions. Both grouping schemes are conducted using the K-means clustering (Liu et al., 2023b; Wang et al., 2025; Zhao and Wang, 2023).

##### 145 **(2) Prior Information**

The prior information has three levels: uniform density, uniform proportion, and combined fine root and soil water content distributions (Fu et al., 2026). Uniform proportion means that, given the number of sources, each source starts with the same initial uptake proportion. This is the default flat prior in MixSIAR (also called the non-informative prior):

$$P \sim \text{Dirichlet}(\alpha_1, \dots, \alpha_n)$$

$$150 \quad \alpha_1 = \dots = \alpha_n = 1 \quad (2)$$

Uniform density implies that, for a given number of sources, each source is assigned the same initial root water uptake density, and the corresponding uptake proportion is calculated as the product of this density and the layer thickness. In other words, thicker soil layers receive greater weight in the Dirichlet distribution, because their associated uptake proportions are larger under a uniform density assumption.

$$155 \quad P \sim \text{Dirichlet}(\alpha_1, \dots, \alpha_n)$$

$$\alpha_i = \frac{\Delta z_i}{z_r} n \quad (3)$$

where  $z_r$  is the rooting depth;  $\Delta z_i$  is the layer thickness of source  $i$ ;  $n$  is the number of sources (unknowns).

Prior information based on combined fine roots and soil water content distributions assumes that the root water uptake profile is proportional to the product of fine root distribution and soil water distribution, with layers containing more fine roots and soil water being weighed more heavily. Shape parameters of the Dirichlet distribution in this prior setting are



estimated from the normalized profile of the product of fine root length density (RLD) and soil water content (SWC) distributions (Mahindawansha et al., 2018):

$$P \sim \text{Dirichlet}(\alpha_1, \dots, \alpha_n)$$

$$\alpha_i = RLD_i \frac{SWC_i}{\sum_{i=1}^n RLD_i SWC_i} n \quad (4)$$

### (3) Error structure

Finally, two error structures are considered in this study: residual-only and residual  $\times$  process. Although MixSIAR provides three options (residual-only, process-only, and residual  $\times$  process), the process-only structure is excluded for two reasons: First, process variability is already incorporated within the residual  $\times$  process structure. Second, the process-only structure requires the mixture to contain a single datapoint (Stock and Semmens, 2016), which is not the case in our simulations.

## 2.2 Numerical simulations procedures

Altogether, there are 2,916 combinations from all variable levels (2,916 simulations). The simulation process involves the following steps:

Step 1: Virtual soil water isotope profiles with different soil water isotope contrasts and measurement errors are constructed and used as the source data (blue cells in Figure 1).

Step 2: By applying the Couvreur model using the given soil water potential and fine root distributions, the root water uptake profiles can be approximated and treated as the benchmark root water uptake profiles (orange cells in Figure 1).

Step 3: The benchmark root water uptake profiles and soil water isotope profiles (without measurement errors) are used to calculate the average of observed plant water isotopic compositions. Then, by incorporating the covariance matrix based on varying levels of observed plant water isotopic variance, a two-dimensional normal distribution is constructed, from which five pairs of observed plant water isotope values are randomly sampled as the mixture data (grey and green cells in Figure 1).

Step 4: Constructed source and mixture data serve as inputs for MixSIAR (pink cells in Figure 1). After simulating the posterior distributions of root water uptake proportions using Markov chain Monte Carlo (MCMC) and verifying convergence by the Geweke criterion, the mean and 95% credible intervals (CI) are used to represent the root water uptake proportion and associated uncertainty for each source. Then, response variables, including root mean squared error (RMSE) and the average width of 95% CI of estimated root water uptake proportions as well as the mean absolute errors of the mean and standard deviation of the posterior predicted plant water isotopic compositions, are calculated (grey cells in Figure 1).

Step 5: The generalized linear model (GLM) and analysis of variance (ANOVA) are performed to estimate the contribution of each variable and their interactions to the response variable. This allowed us to identify the dominant variable(s).



The selected variables and simulation workflow encompass the key components involved in applying MixSIAR for RWU estimation. This design allows us to systematically evaluate how uncertainties arising from different stages of the modelling process influence RWU estimates. In addition, the large number of simulated combinations ensures that the variance decomposition based on ANOVA is statistically robust, enabling reliable quantification of the relative contributions of individual factors and their interactions.

### 2.3 Evaluation metrics

For each simulation, MixSIAR is employed to solve the posterior distributions of root water uptake proportions, which are further used to calculate the following four response variables:

(1) Root mean squared error of root water uptake proportions ( $RWU_{err}$ , root water uptake accuracy):

$$RWU_{err} = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_{E,i} - P_{T,i})^2} \quad (5)$$

where  $P_{E,i}$  and  $P_{T,i}$  are estimated and true root water uptake proportion of soil layer  $i$ ;  $n$  is the number of soil layers.

(2) Average widths of 95% credible intervals of estimated root water uptake proportions ( $RWU_{CI}$ , root water uptake uncertainty):

$$RWU_{CI} = \frac{\sum_{i=1}^n \Delta z_i CI_i}{z_r} \quad (6)$$

where  $\Delta z_i$  and  $CI_i$  are thickness of layer  $i$  and width of 95% credible interval of estimated root water uptake proportion from layer  $i$ ;  $z_r$  is the rooting depth.

(3) Mean absolute error of estimated mean of posterior predicted plant water isotopic compositions ( $Plant_{ave, err}$ ):

$$Plant_{ave, err} = \frac{abs(\delta^2 H_{e,ave} - \delta^2 H_{B,ave}) + abs(\delta^{18} O_{e,ave} - \delta^{18} O_{B,ave})}{2} \quad (7)$$

(4) Mean absolute error of estimated standard deviation of posterior predicted plant water isotopic compositions ( $Plant_{std, err}$ ):

$$Plant_{std, err} = \frac{abs(\delta^2 H_{e,std} - \delta^2 H_{B,std}) + abs(\delta^{18} O_{e,std} - \delta^{18} O_{B,std})}{2} \quad (8)$$

where subscript  $e$  and  $B$  are estimated and benchmark values, respectively;  $ave$  and  $std$  represent the mean and standard deviation, respectively. Note that the estimated mean and standard deviation of posterior predicted plant water isotopic compositions are obtained using posterior predictive checks (detailed procedures can be referred to Fu et al., 2024).



## 2.4 Root water uptake error and uncertainty partitioning

Contributions of all variables and their interactions to each response variable are determined through Generalized Linear Model (GLM) fitting and analysed by analysis of variance (ANOVA):

$$Y \sim V_1 + V_2 + V_3 + V_4 + V_5 + V_6 + V_7 + V_8 + I_r \quad (9)$$

where  $Y$  is the response variable,  $V_1$  to  $V_8$  are eight variables that defined in Figure 1 (Soil water isotopic contrasts, measurement errors of soil water isotopic compositions, root water uptake patterns, plant water isotopic variance, source grouping number, source grouping scheme, prior information, and error structure);  $I_r$  is the interactions among variables (248 types of interaction in total). The fitted linear model is analysed by ANOVA. Then, the Sum of Squares (SS) values from all components are normalized and used to represent the contribution of components to the response variable. All simulations and analysis are completed using R programming language.

## 3. Results

### 3.1 Accuracy and uncertainty assessment based on estimated root water uptake proportions

When RWU accuracy ( $RWU_{err}$ , Eq. 5) was used as the response variable, model configuration dominated the total contribution of RWU accuracy (62.76%, Figure 4a), followed by interactions among categories (34.96%), of which a substantial fraction (33.24%) was associated with model configuration (Table S1 in the supplementary material). By contrast, the contributions from soil water isotopic compositions (2.19%), RWU patterns (0.06%), and observed plant water isotopic compositions (0.03%) to RWU accuracy were negligible (Figure 4a). These results indicated that errors in RWU accuracy were governed overwhelmingly by model configuration, both directly and through its interactions with other categories.

Within the model configuration category, prior information contributed the largest amount of RWU accuracy (35.58%), followed by source grouping number (20.13%, Figure 4a). The interaction between these two variables accounted for an additional 4.02% of RWU accuracy (Table S1 in the supplementary material), while the total contribution of all interactions within this category was relatively limited (6.64%). Contributions from error structure and source grouping scheme were marginal (Figure 4a). These values highlight prior information is the single most influential factor controlling RWU accuracy in MixSIAR, with grouping number playing a secondary, but substantial role.

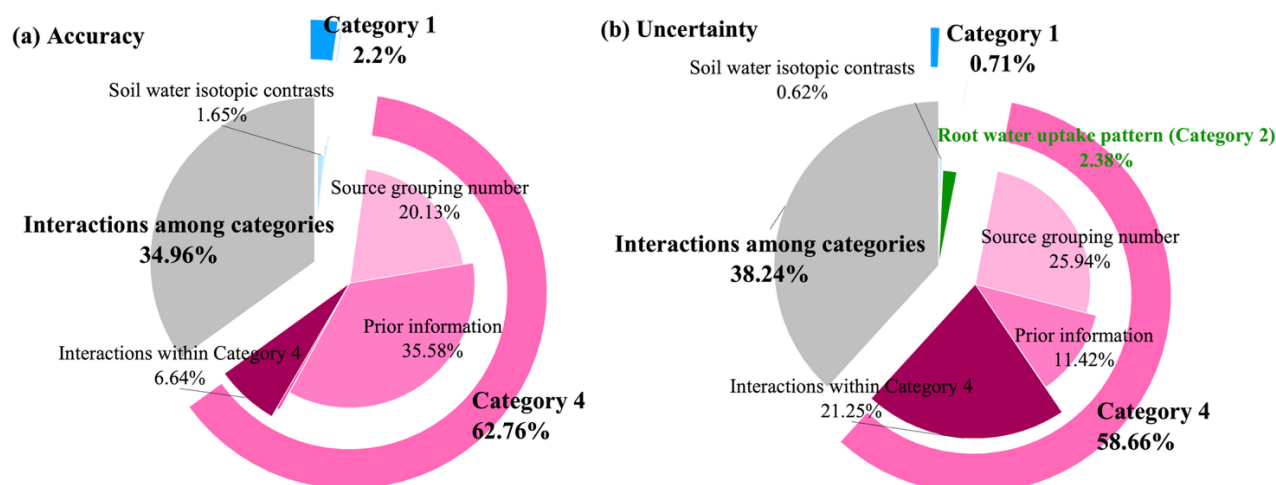


**Figure 4. Contributions of different variables to the accuracy (a) and uncertainty (b) of estimated root water uptake proportions using MixSIAR. Categories 1-4 are shown in blue, green, orange, and pink, respectively, while the grey colour represent interactions among categories. Individual variables within each category (also see Figure 1) are represented by different shades of the corresponding colour. Note that variables with contributions less than 0.01% (e.g., source grouping scheme) are omitted for clarity. Please note that for clarity, variables with contributions smaller than 0.5% are not shown.**

For the uncertainty of estimated RWU proportions ( $RWU_{CI}$ , Eq. 6), model configuration dominated the total contribution (58.66%, Figure 4b), followed by interactions among categories (38.24%), of which a substantial proportion (37.54%) was attributable to model configuration (Figure 4b). By contrast, root water uptake pattern (2.38%), soil water isotopic compositions (0.71%), and observed plant water isotopic compositions (0.01%) contributed minimally to RWU uncertainty (Figure 4b). These indicate that  $RWU_{CI}$  was controlled overwhelmingly by model configuration, both directly and via its interactions with other factors. Within the model configuration category, source grouping number (25.94%) and prior information (11.42%) were the two dominant contributors (Figure 4b). Their interaction accounted for 19.0% of the total 21.25% contribution from interactions within this category, indicating a strong coupling effect between these two variables.

Although prior information exerted a stronger influence on  $RWU_{err}$  (35.58%) than source grouping number (20.13%) on RWU uncertainty (Figure 4a), the source grouping number played a more important role in driving  $RWU_{CI}$  (Figure 4b). This difference arises because increasing the source grouping number effectively increases the dimensionality of the mixing space, leading to a more underdetermined system with a larger number of unknown proportions relative to constraints. As a result, the posterior solution space expands, and  $RWU_{CI}$  increases substantially.

### 3.2 Accuracy and uncertainty assessment based on posterior predicted plant water isotopic composition

When the mean absolute error of the posterior predicted plant water isotopic composition ( $Plant_{ave, err}$ , Eq. 7) was used as the response variable, the dominant contribution to the accuracy of predicted plant water isotopic compositions arose from interactions among categories (56.38%), followed by soil water isotopic compositions (20.83%), model configuration

(10.52%), observed plant water isotopic compositions (8.86%), and root water uptake pattern (3.42%) (Figure 5a). This pattern indicates that  $Plant_{ave, err}$  was dominated by interactions among categories rather than by any single dominant driver.

At the variable level, soil water isotopic composition contributed the most to the accuracy of predicted plant water isotopic compositions (12.06%), followed by observed plant water isotopic composition (8.86%) and source grouping number (7.33%) (Figure 5a). Notably, prior information contributed only marginally to  $Plant_{ave, err}$ , despite being the dominant factor of  $RWU_{err}$  (Figure 5a). This discrepancy can be attributed to the inferred RWU proportions may deviate significantly from the benchmark RWU proportions yet remain mathematically consistent with the observed plant water isotopic compositions. Therefore, accurate reproduction of observed plant water isotopic compositions does not guarantee correct inference of RWU patterns, highlighting a fundamental limitation of using posterior predicted plant water isotopic compositions as the sole evaluation criterion.

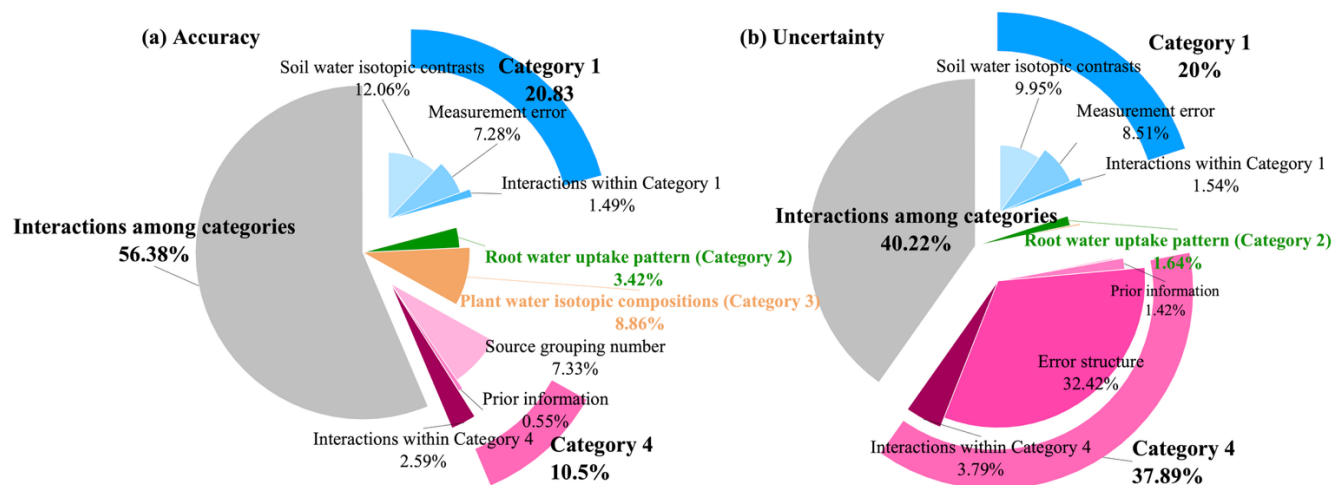


**Figure 5. Relative contributions of different variables to the accuracy (a) and uncertainty (b) of posterior predicted plant water isotopic compositions. Categories 1-4 are represented by blue, green, orange, and pink, respectively, while the grey colour represent interactions among categories. Individual variables within each category (also see Figure 1) are represented by different shades of the corresponding colour. Note that variables with contributions less than 0.01% (e.g., source grouping scheme) are omitted for clarity. Please note that for clarity, variables with contributions smaller than 0.5% are not shown.**

Like  $Plant_{ave, err}$ , the uncertainty of posterior predicted plant water isotopic compositions ( $Plant_{std, err}$ , Eq. 8) was dominated by interactions among categories (40.22%), followed by model configuration (37.89%) and soil water isotopic compositions (20.00%). By contrast, contributions from root water uptake pattern (1.64%) and observed plant water isotopic compositions (0.24%) were negligible (Figure 5b).

Notably, within the contribution of model configuration, error structure alone accounted for 32.42% out of 37.89% of the uncertainty of predicted plant water isotopic compositions (Figure 5b). In addition, of the 40.22% attributed to interactions among categories, approximately 18% involved error structure (SI). Taken together, the total contribution of error structure



to  $Plant_{std, err}$  exceeded 50%, indicating that it was the primary driver of  $Plant_{std, err}$ . This dominance arose because under the  
 295 residual  $\times$  process error structure, source variability was explicitly propagated explicitly into the mixture (plant water),  
 whereas this was excluded in the residual-only structure. Moreover, the scaling parameter  $\epsilon$  (uniform prior 0-20) in the  
 residual  $\times$  process error structure allows expansion ( $\epsilon > 1$ ) or contraction ( $\epsilon < 1$ ) of the propagated variance. Variable  $\epsilon$  can  
 exceed one and thereby inflate posterior predictive plant water variance and amplify uncertainty. This is especially the case  
 in a weakly identifiable system where the number of unknown source contributions exceeds the information provided by  
 300 isotopic tracers, resulting in multiple plausible RWU solutions.

## 4. Discussion

### 4.1 The importance of prior information and source grouping

Our numerical experiments show that model configuration is the dominant factor controlling both accuracy and uncertainty  
 for MixSIAR calculation of RWU proportions. Within the model configuration category, prior information and source  
 305 grouping are identified as the two most influential factors. Although their importance has been recognized in previous  
 studies (Banner et al., 2020; Popp et al., 2025), to our knowledge, this study provides the first quantitative assessment of  
 their contributions (Figure 4).

The dominance of prior information in determining RWU accuracy arises from prior sensitivity, whereby the dominance of  
 310 prior information in determining RWU accuracy arises from the strong influence of the specified prior distributions on the  
 posterior estimates of RWU (Fu et al., 2024). This sensitivity stems from the limited information content of data, particularly  
 when multiple intersections exist between plant water isotopic compositions and the soil water isotopic profile (e.g., Figure  
 2a). In such cases, multiple combinations of source contributions can reproduce the observed plant water isotopic  
 composition, resulting in a non-unique solution space. Consequently, the data provide only weak constraints on RWU  
 315 approximation across soil layers, and posterior distributions become increasingly dependent on prior assumptions (van de  
 Schoot et al., 2021). Importantly, this dependence persisted even when using width-balanced flat priors (uniform density),  
 suggesting that prior sensitivity cannot be attributed solely to inappropriate prior specification. Rather, it appears to be an  
 intrinsic feature of weakly identifiable RWU mixing problems (multiple combinations of source contributions can reproduce  
 the observed plant water isotopic composition, resulting in a non-unique solution space). This explains why prior  
 320 information contributed more to RWU accuracy than any other variable considered in this study.

The sensitivity of RWU accuracy to prior information becomes pronounced as the number of sources increases, since the  
 dimensionality of the solution space expands while the number of independent tracers remains fixed. Source grouping  
 directly alters the number of sources and thus the degree of underdetermination (Fu et al., 2024). As the number of sources  
 325 increases, the prior distribution assigns progressively smaller proportions to each individual source. Consequently, posterior



RWU estimates become more strongly influenced by prior assumptions (Fu et al., 2026). Combined with prior sensitivity, this leads to posterior distributions that are strongly shaped by prior assumptions determined by source number. This explains why source grouping contributes more to RWU uncertainty than prior information alone. Although source grouping does not directly constrain RWU estimates, it alters the dimensionality of the mixing problem and the effective influence of prior distributions, thereby amplifying prior sensitivity.

Source grouping is often introduced to improve model solvability, and soil profiles are commonly simplified into three to four layers in practice (Fu et al., 2026). However, even under a simplified three-layer configuration, which is often considered the most favourable case for systems with two tracers (Kirchner, 2023), MixSIAR can still produce biased RWU estimates: a systematic tendency to overestimate shallow water uptake (by 10.7% on average, Figure 6) while underestimating deep water contributions (by 18.8% on average, Figure 6). This systematic bias reflects the weak identifiability of RWU inference: shallow sources generally exhibit stronger isotopic contrasts and are therefore better constrained by isotope observations, whereas deeper sources remain less distinguishable. Consequently, multiple RWU solutions are consistent with the observed plant water isotopic composition, leading to a preferential redistribution of uptake toward shallow layers. This suggests that considering source number alone is insufficient, as its interactions with other factors (e.g., prior information) can exert a comparably strong influence on RWU estimates using MixSAIR (Figure 3). This raises an important question regarding the interpretation of RWU patterns in the literature: some studies suggest that a small fraction of deep roots can contribute disproportionately to total water uptake (Thomas et al., 2020; Tzohar et al., 2021), whereas others report limited deep-water contributions (Gai et al., 2023; He et al., 2023; Markewitz et al., 2010; Nardini et al., 2021; Ripullone et al., 2020). Our results suggest that this discrepancy may partially stem from methodological limitations, rather than reflecting true ecological differences.

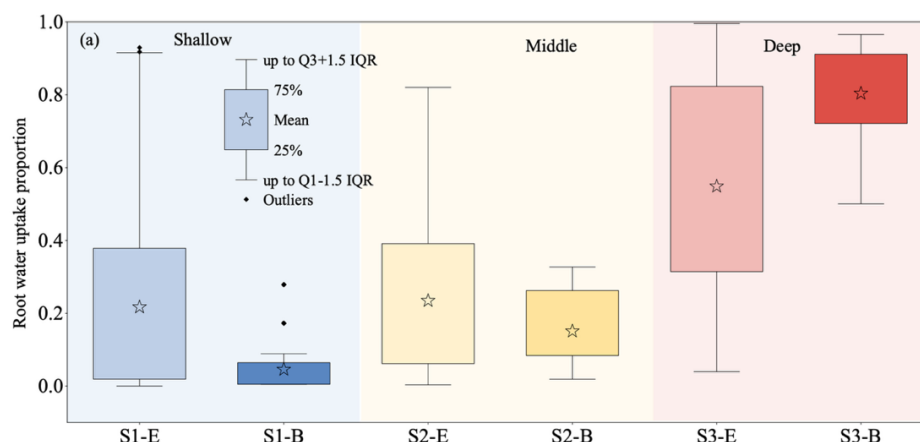


**Figure 6. Comparison between estimated and benchmark root water uptake proportions with 3 sources. The prior type is “non-informative”. Note that S1-E and S1-B represent the estimated and benchmark root water uptake proportion from Source #1 and so on.**



Additionally, Fu et al. (2026) suggested that grouping schemes can implicitly define layer thickness and discretization, thereby altering the effective weighting imposed by prior distributions across soil layers. In practice, multiple plausible grouping strategies exist, such as grouping based on empirical rules (Liu et al., 2026; Tan et al., 2026), soil water content (Dong et al., 2024; Wang et al., 2023), or isotopic similarity (Cai et al., 2024; Li et al., 2025). But no universally accepted criterion is available. Our quantitative analysis shows that the standalone effect of grouping scheme on RWU estimation error and uncertainty is relatively minor (Figures 4 and 5). Rather, RWU estimation error and uncertainty are manifested primarily through interactions with other variables, particularly prior information and source grouping number, which together exert a much stronger control on MixSIAR-derived RWU estimates. This means that modelling decisions should not be evaluated independently, as their combined effects dominate RWU inference in weakly identifiable mixing systems.

Overall, prior information, source grouping, and their interactions jointly control RWU estimation by shaping both the dimensionality of the solution space and the strength of prior constraints. This highlights that isotope-based RWU estimation is fundamentally a structure- and prior-driven inverse problem, rather than a purely data-driven one. These findings have several important implications for future applications of MixSIAR. First, reduce the number of sources whenever appropriate (Fu et al., 2026). Second, explicitly justify and routinely test prior assumptions because source grouping is often unavoidable and prior information is intrinsic to Bayesian inference (Allcott et al., 2014). Finally, move beyond purely statistical inversion by incorporating physically informed priors and process-based constraints, thereby improving the robustness and mechanistic realism of isotope-based RWU estimates (Beria et al., 2020). Consequently, future developments should move beyond purely statistical inversion toward process-informed and physically constrained approaches, which are expected to provide more robust and mechanistically consistent RWU estimates.

#### 4.2 Posterior predicted plant water isotopic composition may not be a reliable “gold standard” indicator

When the response variable is switched from RWU proportions to posterior predicted plant water isotopic compositions, soil water isotopic compositions (including isotopic contrast and measurement errors) and error structure emerge as the dominant drivers of MixSIAR performance, instead of prior settings and source grouping (Figure 5). This is because the isotopic composition of the mixture is directly controlled by the mixing of source isotopic signals, making it inherently more sensitive to data characteristics (e.g., isotopic contrasts and measurement noise) than to model configuration.

For example, Phillips and Gregg (2001) showed that the analytical solution of mixture variance in a two-source system can be written as:

$$\sigma_{\delta_M}^2 = \sigma_{f_A}^2 (\bar{\delta}_A - \bar{\delta}_B)^2 - \left( f_A^2 \sigma_{\delta_A}^2 + (1-f_A)^2 \sigma_{\delta_B}^2 \right) \quad (10)$$

where  $\sigma_{\delta_M}^2$ ,  $\sigma_{\delta_A}^2$ , and  $\sigma_{\delta_B}^2$  represent variances of the mean isotopic signatures for the mixture  $M$ , and sources  $A$  and  $B$ , respectively.  $\bar{\delta}_A$  and  $\bar{\delta}_B$  are average isotopic signals of sources  $A$  and  $B$ , respectively.  $f_A$  is the contribution of source  $A$ ,  $\sigma_{f_A}^2$  is



the variance of  $f_A$ . Equation (10) describes the linear relationship between squared source difference  $(\bar{\delta}_A - \bar{\delta}_B)^2$  and the  
 385 variance of mixture with an intercept of the error structure  $(f_A^2 \sigma_{\delta_A}^2 + (1 - f_A)^2 \sigma_{\delta_B}^2)$  and a slope of  $\sigma_{f_A}^2$ . Therefore, isotopic contrasts  
 among sources and error structure are key factors influencing mixture uncertainty in a determined system. Although an  
 explicit analytical solution cannot be derived for underdetermined systems, our numerical experiments reveal consistent  
 patterns that support this interpretation: Although an explicit analytical solution is unavailable for underdetermined systems,  
 our numerical experiments demonstrate that the same fundamental relationship persists isotopic contrasts and error structure  
 390 remain the primary determinants of uncertainty in mixture isotopic compositions.

Our findings are consistent with previous studies emphasizing the role of soil water isotopic contrast in controlling mixing  
 model performance (Allen et al., 2022; von Freyberg et al., 2020). However, our work exposes an important limitation:  
 model performance is typically evaluated based on the posterior predicted plant water isotopic composition, rather than the  
 395 accuracy of RWU estimates themselves. While this approach is practical (given that RWU profiles are generally  
 unobservable), it should not be treated as a gold standard. In an underdetermined system, multiple RWU solutions can  
 reproduce the observed plant water isotopic composition, meaning that a good agreement reflects mathematical consistency  
 rather than biophysical correctness of the inferred RWU profile (Fu et al., 2024, 2026). Our study further demonstrates that  
 the choice of response variable fundamentally alters conclusions regarding error and uncertainty partitioning in Bayesian  
 400 mixing models. Consequently, using posterior predicted plant water isotopic compositions as the primary evaluation metric  
 may obscure the influence of model configuration, particularly the roles of prior specification and source grouping, which is  
 defined in this study. This finding highlights the need for a more comprehensive evaluation framework. Future studies  
 should complement isotope-based metrics with additional constraints or independent observations (e.g., soil water potential,  
 root distribution, or process-based modelling) to better assess the reliability of inferred RWU profiles.

## 405 5. Conclusion

Using 2,916 synthetic experiments with known benchmark RWU profiles, this study provides the first quantitative  
 assessment of how different sources of uncertainty contribute to MixSIAR-derived RWU estimation. The results  
 demonstrate that RWU inference is governed primarily by model configuration, particularly prior information and source  
 grouping, whereas uncertainty associated with soil and plant isotopic data plays a comparatively minor role. Moreover, we  
 410 show that conclusions regarding dominant uncertainty sources depend strongly on the chosen evaluation metric. While  
 posterior-predicted plant water isotopic compositions are widely used to assess model performance, agreement between  
 observed and predicted isotopic compositions does not necessarily indicate accurate RWU estimates in weakly identifiable  
 systems. These findings highlight that isotope-based RWU estimation should be regarded as a structure- and prior-driven  
 inverse problem rather than a purely data-driven one. Future applications should therefore explicitly justify model



415 configuration choices, routinely evaluate prior sensitivity, and, whenever possible, integrate independent physical or physiological constraints to improve the robustness and interpretability of RWU inference.

### Code and data availability

Codes of MixSIAR and data used in this study are publicly available from Stock and Semmens (2016) (<https://brianstock.github.io/MixSIAR/>) and Rothfuss and Javaux (2012) (10.5194/bg-14-2199-2017).

### 420 Author contributions

Conceptualization: HF, BS, and WZ; Method development: HF, RR, HL; Data collection, simulation, analysis, and visualization: HF, RR, HL, JM, AB; Writing and revision: HF, RR, HL, JM, AB, WZ, and BS.

### Competing interests

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

### 425 Acknowledgements

This research has been supported by the National Natural Science Foundation of China (grant no. 42507413), the Natural Science Foundation of Heilongjiang Province (grant no. JQ2024D002), and the Agriculture Research System of China (grant no. CARS04). AB acknowledges the Grant RYC2022-037566-I G funded by MICIU/ AEI/10.13039/501100011033 and by the ESF+.

### 430 References

- Allcoot, H., Braghieri, L., Eichmeyer, S., and Gentzkow, M.: Model averaging in ecology: a review of Bayesian, information-theoretic, and tactical approaches for predictive inference, *Ecological Monographs*, 2014.
- Allen, S. T., Sprenger, M., Bowen, G. J., and Brooks, J. R.: Spatial and temporal variations in plant source water: O and H isotope ratios from precipitation to xylem water, in: *In Stable Isotopes in Tree Rings: Inferring Physiological, Climatic and Environmental Responses*, edited by: Siegwolf, R. T. W., Brooks, J. R., Roden, J. S., and Saurer, M., Springer Nature, Cham, 501–535, [https://doi.org/10.1007/978-3-030-92698-4\\_18](https://doi.org/10.1007/978-3-030-92698-4_18), 2022.
- 435 Bachofen, C., Tumber-Davila, S. J., Mackay, D. S., McDowell, N. G., Carminati, A., Klein, T., Stocker, B. D., Mencuccini, M., and Charlotte, G.: Tree water uptake patterns across the globe, *New Phytologist*, 242, 1891–1910, <https://doi.org/10.1111/nph.19762>, 2024.



- 440 Banner, K. M., Irvine, K. M., and Rodhouse, T. J.: The use of Bayesian priors in Ecology: The good, the bad and the not great, *Methods in Ecology and Evolution*, 11, 882–889, <https://doi.org/10.1111/2041-210X.13407>, 2020.
- Beria, H., Larsen, J. R., Michelon, A., Ceperley, N. C., and Schaeffli, B.: HydroMix v1.0: A new Bayesian mixing framework for attributing uncertain hydrological sources, *Geoscientific Model Development*, 13, 2433–2450, <https://doi.org/10.5194/gmd-13-2433-2020>, 2020.
- 445 Brantley, S. L., Eissenstat, D. M., Marshall, J. A., Godsey, S. E., Balogh-Brunstad, Z., Karwan, D. L., Papuga, S. A., Roering, J., Dawson, T. E., Evaristo, J., Chadwick, O., McDonnell, J. J., and Weathers, K. C.: Reviews and syntheses: On the roles trees play in building and plumbing the critical zone, *Biogeosciences*, 14, 5115–5142, <https://doi.org/10.5194/bg-14-5115-2017>, 2017.
- Cai, Y., Luo, L., Gao, X., Zhou, Y., Tian, L., An, J., Wen, M., and Zhao, X.: Effect of hydrogen isotopic offset and input data on the isotope-based estimation of plant water sources, *Journal of Hydrology*, 637, 131422, <https://doi.org/10.1016/j.jhydrol.2024.131422>, 2024.
- 450 Dawson, T. E.: Hydraulic lift and water use by plants: implications for water balance, performance and plant-plant interactions, *Oecologia*, 95, 565–574, <https://doi.org/10.1007/BF00317442>, 1993.
- Dawson, T. E., Mambelli, S., Plamboeck, A. H., Templer, P. H., and Tu, K. P.: Stable isotopes in plant ecology, *Annual Review of Ecology and Systematics*, 33, 507–559, <https://doi.org/10.1146/annurev.ecolsys.33.020602.095451>, 2002.
- 455 Dong, W., Wang, G., Sun, J., Guo, L., Chang, R., Wang, W., Wang, Y., and Sun, X.: Plant water source effects on plant-soil feedback for primary succession of terrestrial ecosystems in a glacier region in China, *Science of the Total Environment*, 927, 172269, <https://doi.org/10.1016/j.scitotenv.2024.172269>, 2024.
- Finkenbiner, C. E., Good, S. P., Allen, S. T., Fiorella, R. P., and Bowen, G. J.: A statistical method for generating temporally downscaled geochemical tracers in precipitation, *Journal of Hydrometeorology*, 22, 1473–1486, <https://doi.org/10.1175/JHM-D-20-0142.1>, 2021.
- 460 von Freyberg, J., Allen, S. T., Grossiord, C., and Dawson, T. E.: Plant and root-zone water isotopes are difficult to measure, explain, and predict: Some practical recommendations for determining plant water sources, *Methods in Ecology and Evolution*, 11, 1352–1367, <https://doi.org/10.1111/2041-210X.13461>, 2020.
- 465 Fu, H., Neil, E. J., Liu, J., and Si, B.: A Continuous Root Water Uptake Isotope Mixing Model, *Water Resources Research*, 60, <https://doi.org/10.1029/2023WR036852>, 2024.
- Fu, H., Ren, R., Li, H., McDonnell, J., Barbeta, A., Zou, W., and Si, B.: The Use of Bayesian Mixing Models for Root Water Uptake: A Critical Review, *WIREs Water*, 13, e70069, <https://doi.org/10.1002/wat2.70069>, 2026.
- Gai, H., Shi, P., and Li, Z.: Untangling the Uncertainties in Plant Water Source Partitioning With Isotopes, *Water Resources Research*, 59, <https://doi.org/10.1029/2022WR033849>, 2023.
- 470 Good, S. P., Noone, D., and Bowen, G.: Hydrologic connectivity constrains partitioning of global terrestrial water fluxes, *Science*, 349, 175–177, <https://doi.org/10.1126/science.aaa5931>, 2015.
- Granda, E., Antunes, C., Máguas, C., and Castro-Díez, P.: Water use partitioning of native and non-native tree species in riparian ecosystems under contrasting climatic conditions, *Functional Ecology*, 36, 2480–2492, <https://doi.org/10.1111/1365-2435.14149>, 2022.



- Guerrero, A. I. and Rogers, T. L.: Evaluating the performance of the Bayesian mixing tool MixSIAR with fatty acid data for quantitative estimation of diet, *Scientific Reports*, 10, 1–14, <https://doi.org/10.1038/s41598-020-77396-1>, 2020.
- He, D., Wen, M., Wang, Y., Du, G., Zhang, C., He, H., Jin, J., Li, M., and Si, B.: Xylem water cryogenic vacuum extraction : Testing correction methods with CaviTron-based apple twig sampling, *Journal of Hydrology*, 621, 129572, <https://doi.org/10.1016/j.jhydrol.2023.129572>, 2023.
- Huang, Z., Zhang, X., Ashton, R. W., Hawkesford, M. J., and Richard Whalley, W.: Root phenotyping and root water uptake calculation using soil water contents measured in a winter wheat field, *Agricultural Water Management*, 290, 108607, <https://doi.org/10.1016/j.agwat.2023.108607>, 2023.
- Kirchner, J. W.: Mixing Models With Multiple, Overlapping, or Incomplete End-Members, Quantified Using Time Series of a Single Tracer, *Geophysical Research Letters*, 50, <https://doi.org/10.1029/2023GL104147>, 2023.
- Li, L., Ren, W., and Tian, L.: Temporal patterns in root water uptake and intrinsic water-use efficiency of overstory and understory tree species in a subtropical humid pine forest, *Agricultural and Forest Meteorology*, 371, <https://doi.org/10.1016/j.agrformet.2025.110626>, 2025.
- Li, Y., Good, S. P., and Wang, L.: Demystifying stable hydrogen isotope offsets between plants and source waters, *Commun Earth Environ*, <https://doi.org/10.1038/s43247-026-03230-7>, 2026.
- Liu, J., Si, Z., Li, S., Abubakar, S. A., Zhang, Y., Wu, L., Gao, Y., and Duan, A.: Three Bayesian tracer models : Which is better for determining sources of root water uptake based on stable isotopes under various soil water conditions ?, *Agronomy*, 13, 843, <https://doi.org/10.3390/agronomy13030843>, 2023a.
- Liu, J., Si, Z., Li, S., Kader Mounkaila Hamani, A., Zhang, Y., Wu, L., Gao, Y., and Duan, A.: Variations in water sources used by winter wheat across distinct rainfall years in the North China Plain, *Journal of Hydrology*, 618, 129186, <https://doi.org/10.1016/j.jhydrol.2023.129186>, 2023b.
- Liu, L., Yin, L., Yang, Z., Cui, L., Han, B., Bian, J., and Lu, Y.: Stable isotope insights into water use sources and adaptation strategies of *Tamarix Chinensis* in desert ecotone of arid regions, *Sci Rep*, 16, 7218, <https://doi.org/10.1038/s41598-026-38933-6>, 2026.
- Mahindawansha, A., Orlowski, N., Kraft, P., Rothfuss, Y., Racela, H., and Breuer, L.: Quantification of plant water uptake by water stable isotopes in rice paddy systems, *Plant and Soil*, 429, 281–302, <https://doi.org/10.1007/s11104-018-3693-7>, 2018.
- Markewitz, D., Devine, S., Davidson, E. A., Brando, P., and Nepstad, D. C.: Soil moisture depletion under simulated drought in the Amazon: Impacts on deep root uptake, *New Phytologist*, 187, 592–607, <https://doi.org/10.1111/j.1469-8137.2010.03391.x>, 2010.
- Nardini, A., Petruzzellis, F., Marusig, D., Tomasella, M., Natale, S., Altobelli, A., Calligaris, C., Floriddia, G., Cucchi, F., Forte, E., and Zini, L.: Water ‘on the rocks’: a summer drink for thirsty trees?, *New Phytologist*, 229, 199–212, <https://doi.org/10.1111/nph.16859>, 2021.
- Neil, E. J., Fu, H., and Si, B.: A process-based water stable isotope mixing model for plant water sourcing, *Ecohydrology*, 17, 1–24, <https://doi.org/10.1002/eco.2611>, 2024.
- Orlowski, N., Pratt, D. L., and McDonnell, J. J.: Intercomparison of soil pore water extraction methods for stable isotope analysis, *Hydrological Processes*, 30, 3434–3449, <https://doi.org/10.1002/hyp.10870>, 2016.



- Penna, D., Hopp, L., Scandellari, F., Allen, S. T., Benettin, P., Beyer, M., Geris, J., Klaus, J., Marshall, J. D., Schwendenmann, L., Volkmann, T. H. M., Von Freyberg, J., Amin, A., Ceperley, N., Engel, M., Frentress, J., Giambastiani, Y., McDonnell, J. J., Zuecco, G., Llorens, P., Siegwolf, R. T. W., Dawson, T. E., and Kirchner, J. W.: Ideas and perspectives: Tracing terrestrial ecosystem water fluxes using hydrogen and oxygen stable isotopes - Challenges and opportunities from an interdisciplinary perspective, *Biogeosciences*, 15, 6399–6415, <https://doi.org/10.5194/bg-15-6399-2018>, 2018.
- Phillips, D. L. and Gregg, J. W.: Uncertainty in source partitioning using stable isotopes, *Oecologia*, 127, 171–179, <https://doi.org/10.1007/s004420000578>, 2001.
- Phillips, D. L., Inger, R., Bearhop, S., Jackson, A. L., Moore, J. W., Parnell, A. C., Semmens, B. X., and Ward, E. J.: Best practices for use of stable isotope mixing models in food-web studies, *Canadian Journal of Zoology*, 92, 823–835, <https://doi.org/10.1139/cjz-2014-0127>, 2014.
- Popp, A. L., Beria, H., Sprenger, M., Ala-Aho, P., Coenders-Gerrits, M., Groh, J., Klaus, J., Knapp, J. L. A., Koren, G., Bakiri, I., Xu Fei, E., Gillon, M., Harman, C., Hissler, C., Holmes, T., Jeelani, G., Kalvans, A., Montemagno, A., Zeraý Öztürk, E., Žvab Rožič, P., Stadnyk, T., Stumpp, C., Valiente, N., von Freyberg, J., Vreča, P., Zuecco, G., van Meerveld, I., Penna, D., and Kirchner, J. W.: Recent Advances in Tracer-Aided Mixing Modeling of Water in the Critical Zone, *Reviews of Geophysics*, 63, <https://doi.org/10.1029/2024RG000866>, 2025.
- Ripullone, F., Camarero, J. J., Colangelo, M., and Voltas, J.: Variation in the access to deep soil water pools explains tree-to-tree differences in drought-triggered dieback of mediterranean oaks, *Tree Physiology*, 40, 591–604, <https://doi.org/10.1093/treephys/tpaa026>, 2020.
- van de Schoot, R., Depaoli, S., King, R., Kramer, B., Märtens, K., Tadesse, M. G., Vannucci, M., Gelman, A., Veen, D., Willemsen, J., and Yau, C.: Bayesian statistics and modelling, *Nature Reviews Methods Primers*, 1, <https://doi.org/10.1038/s43586-020-00001-2>, 2021.
- Shi, Y., Jia, W., Zhu, G., Ding, D., Yuan, R., Xu, X., Zhang, Z., Yang, L., and Xiong, H.: Hydrogen and oxygen isotope characteristics of water and the recharge sources in subalpine of qilian mountains, china, *Polish Journal of Environmental Studies*, 30, 2325–2339, <https://doi.org/10.15244/pjoes/127870>, 2021.
- Stock, B. C. and Semmens, B. X.: Unifying error structures in commonly used biotracer mixing models, *Ecology*, 97, 2562–2569, <https://doi.org/10.1002/ecy.1517>, 2016.
- Tan, Z., Li, M., Hu, Y., Zhu, J., Peng, Y., Deng, S., and Jia, Z.: Irrigation Depth Modulates Root Water Uptake in Subtropical Citrus Orchards: Insights from Stable Isotopes and MixSIAR Modelling, *Plants*, 15, 537, <https://doi.org/10.3390/plants15040537>, 2026.
- Thomas, A., Yadav, B. K., and Šimůnek, J.: Root water uptake under heterogeneous soil moisture conditions: an experimental study for unraveling compensatory root water uptake and hydraulic redistribution, *Plant and Soil*, 457, 421–435, <https://doi.org/10.1007/s11104-020-04738-3>, 2020.
- Tzohar, D., Moshelion, M., and Ben-Gal, A.: Compensatory hydraulic uptake of water by tomato due to variable root-zone salinity, *Vadose Zone Journal*, 20, 1–14, <https://doi.org/10.1002/vzj2.20161>, 2021.
- Wang, J., Lu, N., and Fu, B.: Inter-comparison of stable isotope mixing models for determining plant water source partitioning, *Science of the Total Environment*, 666, 685–693, <https://doi.org/10.1016/j.scitotenv.2019.02.262>, 2019.



- 550 Wang, J., Wang, C., Li, H., Liu, Y., Li, H., Ren, R., and Si, B.: Rock water use by apple trees affected by physical properties of the underlying weathered rock, *Agricultural Water Management*, 287, 108413, <https://doi.org/10.1016/j.agwat.2023.108413>, 2023.
- Wang, Y., Li, Y., and Wang, L.: Applying stable isotopes to illuminate the mechanism of water use in wheat fields under ridge-furrow planting with plastic film, *Soil and Tillage Research*, 253, <https://doi.org/10.1016/j.still.2025.106652>, 2025.
- 555 Wei, Z., Yoshimura, K., Wang, L., Miralles, D. G., Jasechko, S., and Lee, X.: Revisiting the contribution of transpiration to global terrestrial evapotranspiration, *Geophysical Research Letters*, 44, 2792–2801, <https://doi.org/10.1002/2016GL072235>, 2017.
- Zhao, Y. and Wang, L.: Coordination of available soil water content and root distribution modifies water source apportionment of the shrub plant *Caragana korshinskii*, *Science of the Total Environment*, 900, 165893, <https://doi.org/10.1016/j.scitotenv.2023.165893>, 2023.
- 560