Editor # Comment & Responses

Dear authors,

based on the comments received for your revised manuscript, it turns out that a few additional elements of information would be required. These relate essentially to methodological aspects - mainly related to the choice of a sinusoidal function in the SAS model (i.e., still justified or not after the removal of the YWF from the study), and the choices made for rainfall tracer data (one site vs. multiple sites). I consider these elements requiring a minor to moderate revision. I am looking forward to receive the revised version of your contribution.

Best regards,

Laurent Pfister

We thank the editor for approving the revision of our manuscript. In the revised version, we have explained the reasons for using sine interpolation for stable water isotopes in precipitation, while acknowledging its limitations. We have also tested the GAM approach as suggested by the reviewer and presented our findings; our major conclusions regarding the uncertainty of SAS-based modeling remain intact, regardless of the interpolation method used. We have provided a comprehensive explanation for using both raw (data from one station only) and kriged isotopes in precipitation and clarified the selection of raw isotopes at the catchment outlet. Finally, we have addressed the impact of different spatial representations of isotopes in precipitation on SAS-based results more effectively.

Please find below our point-to-point responses (text in blue) to the reviewer's comments (text in black) and implemented modifications (text in italic blue) in the original manuscript. The line number in this document refers to the track-changes document.

Reviewer #2 Comment & Responses

This revised manuscript shows improvements over the previous one. The authors have addressed some (but not all) of the issues in the previous manuscript by removing the use of the young water fraction and have instead focused on investigating the uncertainties associated with the SAS function modeling. This study reiterates a common concern about the uncertainty of SAS models when trace data sets are limited.

The authors considered the uncertainties arising from temporal interpolation and spatial interpolation of the rainfall tracer data, as well as the uncertainty arising from the predetermined formula describing the SAS function. Although investigating the model uncertainty arising from the temporal interpolation has been previously addressed, as acknowledged by the authors (e.g., Buzacott et al., 2020), it seems that the incorporation of spatial rainfall tracer data (in addition to the consideration of the predetermined shape of the SAS function) could offer a novel contribution.

The authors concluded that the temporal interpolation method affects the result significantly (L511-512), while the spatial interpolation method did not substantially affect the uncertainty (L516-519). (Note that the line number in this document is based on the track-change document.)

However, there are several study designs that I find unconvincing and thus I recommend a major revision. Please refer to my comments below. There may be something I'm missing, and if so, I think it would be relatively easy for the authors to respond to my comments.

We thank the reviewer for taking the time to review our manuscript, providing constructive comments and for raising relevant issues. We acknowledge them and have carefully addressed them in the revised manuscript. Please find our detailed responses to each comment below.

1. Temporal interpolation: On the use of the sinusoidal function

The purpose behind using the sinusoidal function in the SAS function model remains unclear. While I comprehend that the authors aimed to demonstrate the model's sensitivity to the choice of temporal interpolation method, it seems apparent that the sinusoidal function could not capture the observed input tracer signal well. Consequently, it is unclear why this particular method, which misses many features in data, was used with the SAS function model. Once this question arose, I found it challenging to follow the manuscript smoothly. In the previous manuscript, I speculated that, by using the sinusoidal function, the authors want to develop an argument related to the young water fraction (which utilizes the sinusoidal function), but this issue becomes apparent after the removal of the young water fraction from the manuscript.

Although the sinusoidal function has been utilized in TTD modeling, e.g., when estimating the young water fraction, its application there is to focus on capturing only dominant features like seasonality. Note that, for the estimation of young water fraction, the outflow tracer time series is also approximated using the sinusoidal function. I am unsure if capturing only seasonality is a valuable practice in the SAS function modeling. Also, I am not sure about the meaning of uncertainty when the input tracer data that only approximates the seasonality is used to model the outflow tracer data that contain more detailed features.

Thank you for bringing up these concerns on the use of the sine function interpolation.

We acknowledge the uncertainty in sine interpolation as it misses detailed temporal features of the tracer dataset, such as individual observed peak values, but rather captures basic characteristics of the temporal pattern, such as seasonality. However, the dominant trend in long-term δ^{18}Op is often the seasonal trend (Feng at al., 2009), which can be effectively captured using a sine-wave function (Kirchner, 2016).

In our study, we compared two relatively simple, rather opposing temporal interpolation approaches, one emphasizing seasonality (sine-wave function) and one individual measurements (step function). This distinction was highlighted in lines 171-173:

By employing step function and sine interpolation as techniques to reconstruct tracer data in precipitation, we aim to analyze the effects on SAS-based results from two relatively simple, rather opposing approaches: one focusing on individual measurements and the other on seasonality.

Our findings show that both step function and sine interpolation yielded satisfactory goodness-of-fit (Fig. 5 in the revised manuscript) and effectively captured the trend in simulated instream δ^{18}O (Fig. 4 in the revised manuscript). This highlights the appropriateness of capturing the dominant seasonal trend in instream δ^{18}O. However, using sine interpolation comes with limitations as individual observations are generally overestimated (Fig. 4g-l in the revised manuscript; consequently, it is important to acknowledge these uncertainties. Nonetheless, our results indicate that interpolation methods that precisely capture all observed data (e.g., step function) do not necessarily yield better SAS-based results as a whole. In fact, combining step function with raw δ^{18}Op resulted in larger uncertainty in simulated TT_{50} (Fig. 6d-f in the revised manuscript). This reflects the purpose of our study which is to showcase two relatively simple, opposing choices for temporal interpolation to highlight that both (and thus potentially also many other methods) give acceptable model results. Hence, we emphasize the need for a comprehensive exploration of the uncertainty range, rather than relying solely on a specific model setup which may be subjective.

It should also be noted that uncertainty associated with sine interpolation found in this study is specific to the isotopic dataset used. Under different circumstances, where the isotopic dataset has a more pronounced sinusoidal trend (for example, see Fig. 1 of Von Freyberg et al., 2018) and/or higher temporal resolution, where the sinusoidal pattern should be more evident, sine interpolation may be more suitable and yield better results. However, investigating these aspects goes beyond the scope of the study.

Overall, in the revised manuscript we have acknowledged the limitations of sine interpolation raised by the reviewer, and expressed them in lines 321-329:

The sine interpolation effectively captured the dominant features of the observed $\delta^{18}Op$, such as seasonality. Consequently, sine interpolation successfully reproduced the seasonal trend in instream $\delta^{18}O$, although simulations overestimated the measurements (Fig. 4g-l). On the other hand, sine interpolation poorly reproduced rainfall isotopes during short-term flashy events and missed detailed characteristics of the tracer dataset by smoothing the variability in the observed $\delta^{18}Op$ (Fig. 3). As a result, high values of tracer data in precipitation are underestimated, whereas low values are overestimated. It is critical to recognize these limitations when interpreting modeling results as uncertainty in the simulated $\delta^{18}Op$ may conceal a more pronounced hydrological response of the system (Dunn et al., 2008, Birkel et al., 2010, Hrachowitz et al., 2011).

Moreover, we acknowledge that sine-wave fitting of seasonal isotopic cycles is commonly used for estimating the young water fraction. However, the sine-wave function has been used in other studies to describe temporal variation in $\delta^{18}Op$ (McGuire & McDonnell, 2006; Allen et al., 2019) due to the sinusoidal pattern characterizing $\delta^{18}O$. We have clarified this point in lines 161-165:

… Second, we used a sine interpolation due to the fact that $\delta^{18}Op$ samples typically exhibit pronounced seasonal variations with more depleted values in winter than in summer (Fig. 2). The sine-wave function has been used in several studies to describe temporal variation in isotope in precipitation (McGuire & McDonnell, 2006; Feng et al., 2009; Allen et al., 2019).

Reference:

Allen, S. T., Jasechko, S., Berghuijs, W. R., Welker, J. M., Goldsmith, G. R., and Kirchner, J. W.: Global sinusoidal seasonality in precipitation isotopes, Hydrol. Earth Syst. Sci., 23, 3423–3436, https://doi.org/10.5194/hess-23-3423-2019, 2019.

Feng, X., Faiia, A. M., and Posmentier, E. S.: Seasonality of isotopes in precipitation: A global perspective, J. Geophys. Res, 114, D08 116, https://doi.org/10.1029/2008JD011279, 2009.

Kirchner, J. W.: Getting the right answers for the right reasons: Linking measurements, analyses, and models to advance the science of hydrology, Water Resour. Res., 42, W03S04, https://doi.org/10.1029/2005WR004362, 2006.

von Freyberg, J., Allen, S. T., Seeger, S., Weiler, M., and Kirchner, J. W.: Sensitivity of young water fractions to hydro-climatic forcing and655 landscape properties across 22 Swiss catchments, Hydrol. Earth Syst. Sci., 22, 3841–3861, https://doi.org/10.5194/hess-22-3841-2018, 2018.

Buzacott et al. (2020) employed a sophisticated temporal interpolation method in the SAS function modeling, namely the Generalised Additive Model (GAM), to perform gap-filling and estimate the uncertainty of the gap-filled data. They subsequently explored how this estimated input uncertainty propagated through the SAS model. I believe that this approach provided more informative insights compared to utilizing multiple methods that include the uncommon practice of fitting the sinusoidal function in the SAS function modeling.

Thank you for raising this interesting point. We tested the GAM for the reconstruction of both kriged and raw δ^{18}Op used in this study; our findings can be seen below.

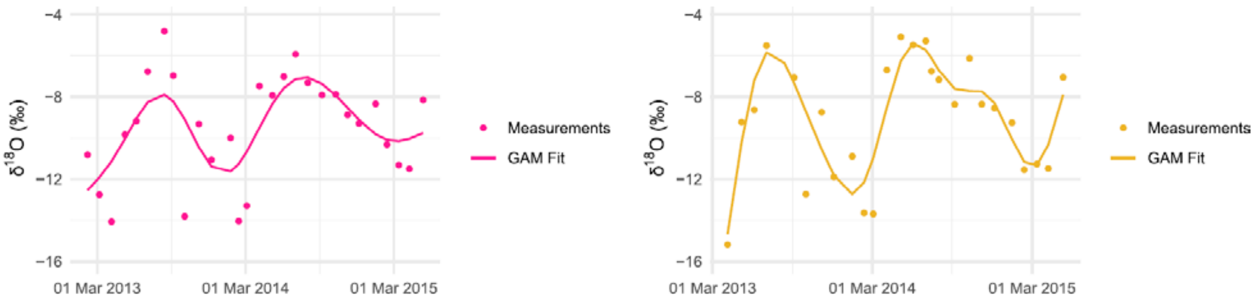

Fig 1: Predicted δ^{18}Op via GAM with kriged (left) and raw (right) data.

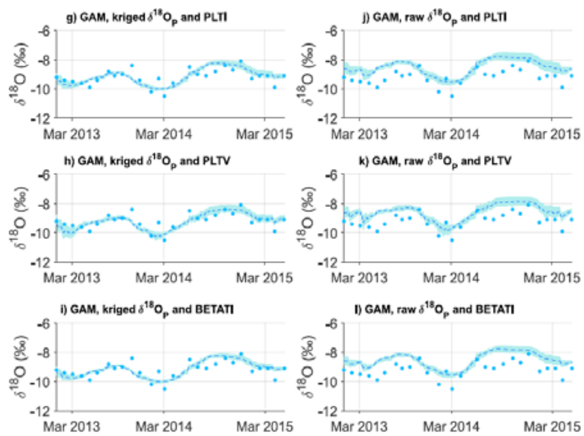

Fig. 2: Simulated instream δ^{18}O from GAM.

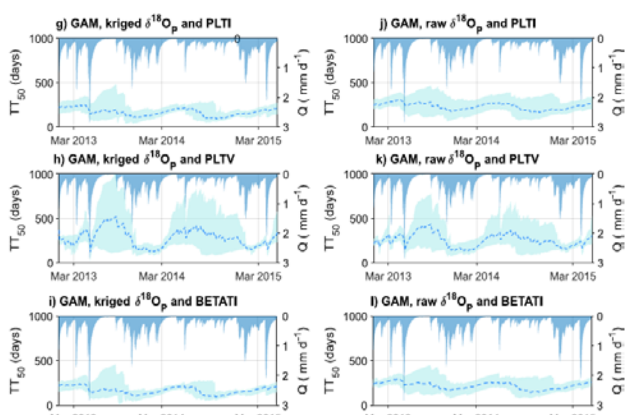

Fig. 3: Simulated TT_{50} from GAM.

Our results show that in our analysis GAM generally produced a closer fit to the input tracer data (Fig. 1 in this document) compared to sine interpolation (Fig. 3 in the revised manuscript). However, when analyzing the temporal evolution of simulated instream δ^{18}Op (Fig. 2 in this document) and TT_{50} (Fig. 3 in this document) using the same SAS function and spatial representation of δ^{18}Op, GAM did not lead to significantly different SAS model results in comparison to sine interpolation (Fig. 4g-l and 6g-l in the revised manuscript). Furthermore, the magnitudes of uncertainty in $\delta^{18}Op$ and TT_{50} are generally comparable, except in the case of TT_{50} when PLTV is utilized.

We conclude that the improved input reconstruction by GAM does not provide significantly improved SAS-model output (probably due to the conceptual simplifications inherent to the SAS-model) and, in turn, new insights or conclusions in our study. Indeed, similar to what found when using step function and sine interpolation, the time-variant SAS functions (PLTI and BETATI) show moderate fluctuations in the TT_{50} time series compared to the time-variant function (PLTV), whereas the uncertainty is generally higher during low flow conditions. Therefore, in this study we decided to maintain step function and sine interpolation as the two techniques for reconstructing tracer data in time, as they allowed us to explore the specific effects of general seasonality (sine function) and individual measurements (step function), while evaluating their influence on generating distinct results. However, we acknowledge the existence of other interpolation methods, such as the GAM suggested by the reviewer, and have included the results for GAM in the Supplement of the revised manuscript for comparison (lines 339-346):

It is important to note that alternative methods, such as Generalized Additive Models (GAM; Buzacott et al., 2020) offer other options for interpolating tracer data. We conducted further tests with the SAS model using GAM to reconstruct both kriged and raw $\delta^{18}Op$ using smoothing functions; this provides a more sophisticated approach than the intuitive methods used in this study. However, the results, available in the Supplement, show that while GAM provided more detailed reconstructed input tracer data (Fig. S1), it did not significantly alter the SAS-based results (Figs. S2 and S3) or yield any new insights or conclusions with respect to using step function and sine interpolation. Therefore, we conclude that while highly resolved input data may seem appealing, it does not lead to substantial benefits for the SAS-based output, supposedly due to the conceptual simplifications in the SAS model.

If the authors still intend to present the results using the sinusoidal function, it is essential for them to provide a compelling argument justifying the necessity of using the sinusoidal function over other methods that have been applied for the gap-filling, despite the concerns and points I have raised earlier. Without that, I worry that others could argue that the presented large uncertainty (or the significant differences in the median transit time, e.g., L511-512) is just because the temporal interpolation method utilizing the sinusoidal function was poorly performing.

Please see our answers above for further clarification. Here we would like to add that because of the uncertainties and potential errors in the observed data, determining the best temporal interpolation method is a challenge and is outside the scope of this study; our primary objective is to explore the uncertainties arising from different, commonly used choices in the model setup. Additionally, our main results regarding the uncertainty of the SAS modeling approach remain consistent, even when comparing our more simplistic reconstruction methods of $\delta^{18}Op$ with the use of GAM. Finally, despite the limitations, sine interpolation reasonably captures the essential characteristics of the tracer input signal for the SAS model at a hand.

2. Spatial Interpolation: Conclusion regarding the use of spatial rainfall tracer data

Despite having rainfall data from multiple locations, the authors have chosen to only present results for two cases: 1) the SAS model result using the data collected around the outlet, and 2) the result obtained by using spatially interpolating values based on data collected at 24 locations using kriging. The decision to focus solely on these two rainfall tracer time series is unfortunate and appears to underutilize the full potential of the dataset.

Thank you for raising these relevant concerns on the spatial distribution of isotopes in precipitation.

In our study, we investigated two contrasting spatial representations of $\delta^{18}O$ to compare their effects on model performance, results, and uncertainty. We examined a simple approach using single point $\delta^{18}O$ measurements taken at the catchment outlet and a more sophisticated method involving spatial interpolation of $\delta^{18}O$ with kriging based on multiple locations, including stations outside the catchment boundary to capture regional precipitation patterns. This analysis allowed us to evaluate the influence of spatial variability on SAS-based results. Exploring these two contrasting approaches in spatial representation of $\delta^{18}O$ aligns with the use of two contrasting temporal interpolation methods, one focusing on seasonality and the other on individual measurements. We have clarified this point in lines 150-152:

By considering these two options for spatial representation of $\delta^{18}Op$, we intend to assess the range of uncertainty in the simulated outputs between two opposing cases i.e., raw isotopes representing the simplest approach and kriged isotopes derived from a more sophisticated method.

While there are certainly other choices for tracer data or interpolation techniques that could be explored, we had to make a choice for our experimental design and selected these two cases to provide insights into the research question, i.e., are SAS models affected by whether $\delta^{18}Op$ is collected at a single location within the catchment or at multiple locations? We have emphasized this point in lines 152-155:

While there are other possibilities for spatial representation of $\delta^{18}Op$, our choice allows us to effectively address our research question regarding the effects on SAS models of tracer data in precipitation collected at a single location within the catchment or spatially interpolated from multiple locations.

It remains unclear whether the authors would reach the same conclusion when utilizing other rainfall time series collected at different locations (for their ‘raw’ case). Consequently, it is unclear what meaningful insights can be gleaned from the presented results.

What was the reasoning behind exploring the two cases (e.g., for the ‘raw’ case, why is the location close to the catchment outlet selected)?

Figure 4 in this document shows raw $\delta^{18}Op$ measured at various locations in the Upper Selke, revealing minimal spatial variability. In our study, we particularly focused on using raw data from the outlet. While we could have opted for another location, we chose the station close to the gauge at the outlet in the lowlands, assuming that at this location a precipitation collector would most likely be found in most catchments. Logistically, sampling instream $\delta^{18}O$ at the outlet is common practice as it is the location where all precipitation inputs across the catchment are integrated into streamflow. For convenience, also precipitation is often monitored at or near the gauging station at the outlet. We acknowledge that this approach may not be the best practice in catchments where several precipitation stations exist, as it has its own limitations, and we stated this at lines 353-356. However, it is important to note that our goal was not to determine the best approach for the spatial representation of $\delta^{18}Op$ (even the absence of interpolation) but rather we aimed to compare two contrasting methods to examine differences in SAS-based outcomes and uncertainties.

We have provided further clarification on this point in lines 139-142:

The selection of $\delta^{18}Op$ at the outlet assumes a precipitation collector close to the stream gauge at the outlet, which is a common occurrence in many catchments for logistical reasons. Indeed, the outlet, where instream $\delta^{18}O$ is sampled, serves as location where all precipitation inputs across the catchment are integrated. For convenience, precipitation monitoring is also often conducted at or near the gauging station at the outlet.

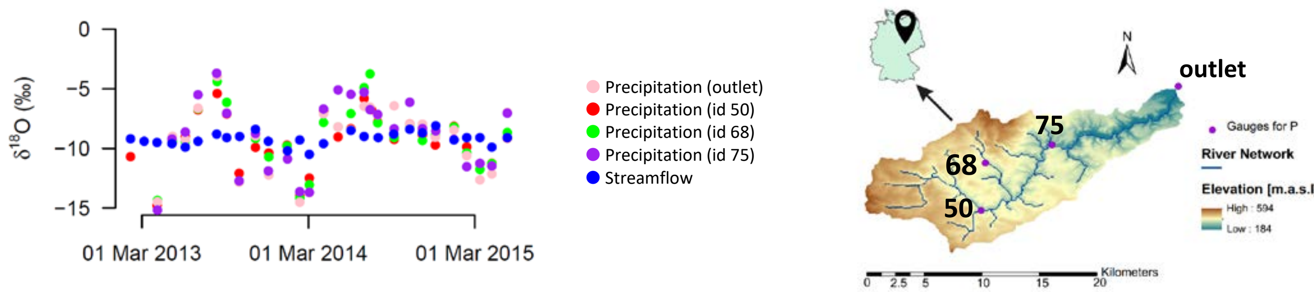

Fig. 4: Measured δ^{18}Op (left) from the four precipitation collectors in the Upper Selke (right).

Why do the two rainfall tracer time series presented in Figure S1 are similar?

In our study, we found that differences between the δ^{18}Op time series reconstructed using step function and sine interpolation methods were similar, except for a slightly more depleted signal in the kriged δ^{18}Op due to the inclusion of isotopes from higher-altitude locations within the kriging process. This could be different for other catchments and it is outside the scope of the study to test the accuracy/representativeness of specific interpolation methods.

While there were no significant differences in the evolution of the TT_{50} time series and instream δ^{18}O between the two methods for spatial representation of δ^{18}Op, higher uncertainty was observed when using raw δ^{18}Op. This highlights the potential advantages of spatial interpolation over the simplistic use of δ^{18}Op from a single location, particularly with step function. This finding shows how relying solely on model performance (Fig. 5 in the revised manuscript) may not reveal the increased uncertainty associated with the single-station method (or other chosen methods). By incorporating uncertainty analysis, it is possible to make informed decisions about the most suitable representation/interpolation method for a specific application.

Taking this into consideration, we have revised the text to emphasize the distinct implications of using raw and kriged δ^{18}Op in SAS models.

Lines 12-14:

The large 95% CI and the notable differences across the tested setups highlight the sensitivity and, in turn, uncertainty of predicted TT_{50} associated with the model parameterization, choice of temporal interpolation of input data, hydrologic conditions and non-spatially interpolated δ^{18}Op.

Lines 347-358:

The spatial representation of δ^{18}Op values had limited impact on the overall pattern of simulated TT_{50} as the TT_{50} time series were comparable with both kriged (Fig. 6a-c and g-i) or raw (Fig. 6d-f and j-l) δ^{18}Op. Nonetheless, the spatial interpolation of δ^{18}Op from different locations resulted in a reduction in the uncertainty of TT_{50}, which was particularly evident with step function. This difference may be attributed to the fact that the Upper Selke is a large (mesoscale) catchment with a substantial gradient in elevation, and, as a consequence, a single point measurement for δ^{18}Op may be generally overly simplistic.

This finding highlights the importance of considering not only the model performance in terms of goodness-of-fit (Fig. 5; raw values with a step function interpolation produced higher KGE values), but also the uncertainty range in predicted TT_{50}.

Lines 376-379:

Furthermore, our results highlight the importance of gaining tracer datasets of good quality (i.e., tracer data with a finer temporal resolution), considering the spatial variability of the isotopic composition in precipitation and, possibly, employing a model parameterization that best describes the catchment-specific storage and release dynamics.

When should we expect a spatially interpolated value to be similar to at-a-point measurement and when we shouldn't?

The spatially interpolated $\delta^{18}O$ used in this study were obtained by applying kriging with altitude as external drift (work done in Lutz et al., 2018) on a set of stations that also includes some stations outside the catchment boundaries, after which a catchment-average of the kriged values was obtained. This was done because the isotopic composition can vary with altitude due to factors such as temperature. The kriging process predicts isotopes at unknown locations by using isotopes which are known only at given locations of the study area. In our study, we found that the values for kriged and spatially averaged $\delta^{18}Op$ are slightly more negative than raw $\delta^{18}Op$, as the raw $\delta^{18}Op$ at the multiple locations (partially in the mountainous area) considered in the kriging process are more negative than the raw $\delta^{18}Op$ measured at the catchment outlet (in the lowland part) of the study area.

The above points have been incorporated at lines 144-149:

The spatial interpolation was conducted in Lutz et al., (2018) using $\delta^{18}Op$ from 24 precipitation collectors spread over the larger Bode region, and altitude as external drift. In a further step, the kriged $\delta^{18}Op$ were weighted with spatially distributed monthly precipitation to obtain representative estimates for the study catchment. In our study, the kriged (and spatially averaged) $\delta^{18}Op$ resulted in slightly more negative values than the raw $\delta^{18}Op$ from the catchment outlet (Fig. 2 and 3) because of the inclusion of more depleted $\delta^{18}Op$ values from locations with higher altitudes during the kriging process.

I personally like the arguments provided in L392-395 as they read like the additional information (the information used in the kriging) is valuable in the SAS function model (though unclear if the authors would get to the same conclusion if they chose another location for the 'raw' case). However, it is not clearly stated in the Conclusion section (e.g., in L516-519). That part of the Conclusion may be to be modified.

We revised the part about spatial interpolation in the Conclusions section on lines 4566-470:

Finally, there was a comparable pattern in the modeled results when using kriged versus raw isotopes, but the kriged values yielded an uncertainty reduction in TT_{50}. This highlights the potential advantage of spatially interpolated values over a single measurement representative of the entire catchment, particularly in mesoscale catchments varying in elevation.

3. Other comments

Figures S1 and S2: The figures illustrate one of the most important results, i.e., the interpolation results. It would greatly enhance the manuscript's comprehensibility if these figures were included in the main manuscript not in the supplement, as they are essential to understand the study.

Figures S1 and S2 have been moved from the Supplement to the main text and now represent Figures 2 and 3, respectively.

L224: The meaning of '2.5% and 97.5% CIs' is unclear.

We have clarified the meaning of '2.5% and 97.5% CIs' by writing in lines 202-206: *To assess the range of possible behavioral solutions and understand the level of uncertainty associated with the solutions, we computed the 95% Confidence Interval (CI), which was derived by calculating the values of the 2.5% and 97.5% percentile of the cumulative distribution in the time series of the output variables. These values represent the lower and upper limits of the CI, respectively.*

L227: The definition provided for 'backward' median transit time seems to align more with the definition of 'forward' median transit time.

The median transit time is the time it takes for half of the water particles to leave the system; the backward representation relates to the ages of water particles leaving the system at a given time, thus they are considered in terms of the distribution of entrance times. Therefore, at lines 208-209 we have revised the text on the backward median transit time as: *the time it takes for half of the water particles to leave the system as streamflow at the catchment outlet*.

L356-357: I would recommend removing such trivial and somewhat unrelated results and interpretations from the manuscript.

L505-507: The same argument repeated in the Conclusions section. It is unclear if this trivial statement is relevant to the uncertainty explored in this study.

L356-357, L505-507: I noticed that I have already provided the same comment for the previous manuscript. I still do not see the relevance of this argument in this study. If the authors think that the argument is necessary, please explain how you arrived at the argument based on the findings presented in this study.

In the revised manuscript we have removed results and interpretations referring to the suitability of a time-invariant or time-variant SAS function depending on the presence or absence of pronounced seasonality in hydrological conditions.

Figure 3: Please correct the legend.

We have corrected the legend.

L402: The term 'uniform' may not be appropriate here. It seems that the authors are referring to potential event-to-event variations in the flow pathway during low-flow conditions. (Maybe I am wrong here.)

The term 'uniform' in the phrase '...flows in the soil matrix are less uniform...' refers to the variability of flow pattern and direction under dry conditions. We have clarified this in lines 362-378:

… Conversely, under dry conditions, when usually only longer flowpaths carrying older water are active (Soulsby and Tetzlaff, 2008; Jasechko et al., 2017), water partially flows through a drier soil zone where flow is more erratic (i.e. flow directions and patterns can vary widely) as the conductivity is controlled by soil moisture. As a result, wet areas can be patchy and water flows preferentially at certain locations only, as opposed to spatially uniform flow through the soil matrix; this might make it more challenging to constrain older water ages.

'raw' vs. 'kriged': Just a suggestion, it may be better with something like 'at-a-point' vs. 'kriged'.

We chose to keep the term "raw" to emphasize that the isotopic observations were directly sampled without undergoing post-processing or adjustment. This distinguishes them from the kriged values, which involves additional processing. However, we also clarified in the manuscript that the term "raw" also refers to data from a single station only as opposed to an average value from multiple stations.

L162-164: The use of 'time steps' in these sentences is confusing. It might be better to replace the first instance with something like 'finer temporal resolution'.

We have replaced *time steps* with *a finer temporal resolution* at line 156.

L412: The meaning of "true" model parameterization is unclear.

By *true* model parameterization, we refer to the type of SAS function (e.g. PLTI, PLTV or BETATI in our case study) that is best suited to describe the catchment-specific storage and release dynamics. To avoid misunderstandings, we have written *best* instead of *true* at line 378.

L455-456: Not clear in what sense the median transit time has relevant implications for water 'quantity'.

The implications of median transit time for the water quantity we refer to are water storage, groundwater and hydrological processes, provided in Section 5.3 in the previous version of the manuscript. To make it clearer, we have rephrased this aspect in the revised version in lines 402-418:

The value of TT_{50} has relevant implications for both water quantity and quality, as does its uncertainty. The larger the 95% CI in the simulated TT_{50}, the greater the difference in the TT_{50} values, which, ultimately, implies distinct hydrological processes, water availability, groundwater recharge and solute export dynamics (McDonnel et al., 2010).

For example, knowing the TTD and its uncertainty may be crucial for characterizing the catchment's response to climatic change (Wilusz et al., 2017). Considering the increasing severity of droughts in the past decades (Dai, 2013), a catchment with a shorter TT_{50} and a dominant release of young water might be more affected by droughts than a catchment with a longer TT_{50} whose stream is fed by relatively old water sources. Therefore, a short TT_{50} reveals a low drought resilience of the catchment and limited water availability, which could limit streamflow generation processes and change the instream water quality status during drought periods (Winter et al., 2023). Likewise, TTD uncertainty may affect the understanding of the water infiltration rate, hydrological processes and aquifer recharge, as a shorter TT_{50} suggests that water is quickly routed to the catchment outlet rather than infiltrating deeply into the groundwater. Finally, TTD uncertainty can have an impact on the quantification of the modern groundwater age, i.e., groundwater younger than 50 years (Bethke and Johnson, 2008). According to (Jasechko, 2019) the correct identification of modern groundwater abundance and distribution can help determine its renewal (Le Gal La Salle et al., 2001; Huang et al., 2017), groundwater wells and depths most likely to contain contaminants (Visser et al., 2013; Opazo et al., 2016), and the part of the aquifer flushed more rapidly.

L489: What does 'data fitting' refer to here?

Data fitting refers to tracer data interpolation. To be consistent with the rest of the text, we have changed *data fitting* to *tracer data interpolation technique in time and space* at line 438.