

1 **Sampling frequency trade-offs in the assessment of mean transit times of**
2 **tropical montane catchment waters under semi-steady-state conditions.**

3 **E. Timbe^{1,2}, D. Windhorst², R. Celleri^{1,3}, L. Timbe^{1,4}, P. Crespo^{1,3}, H.-G. Frede², J. Feyen¹,**
4 **L. Breuer²**

5 [1]{Departamento de Recursos Hídricos y Ciencias Ambientales, Universidad de Cuenca,
6 Cuenca, Ecuador}

7 [2]{Institute for Landscape Ecology and Resources Management (ILR), Research Centre for Bio
8 Systems, Land Use and Nutrition (IFZ), Justus-Liebig-Universität Gießen, Germany}

9 [3]{Facultad de Ciencias Agropecuarias, Universidad de Cuenca, Cuenca, Ecuador}

10 [4]{Facultad de Ciencias Químicas, Universidad de Cuenca, Cuenca, Ecuador}

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12 Correspondence to: Edison Timbe (edison_timbe@yahoo.com)

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14 **Abstract**

15 Precipitation event samples and weekly-based water samples from streams and soils, were
16 collected in a tropical montane cloud forest catchment for two years and analyzed for stable water
17 isotopes in order to understand the effect of sampling frequency in the performance of three
18 lumped-parameter distribution functions: Exponential-Piston flow, Linear-Piston flow and
19 Gamma; which were used to estimate mean transit times of waters. Precipitation data, used as input
20 function for the models, were aggregated to daily, weekly, bi-weekly, monthly and bi-monthly
21 sampling resolutions; while analyzed frequencies for outflows went from weekly to bi-monthly.
22 By using different scenarios involving diverse sampling frequencies, this study reveals that the
23 effect of lowering the sampling frequency depends on the water type. For soil waters, with transit
24 times in the order of few weeks, there was a clear trend of over predictions. In contrast, the trend
25 for stream waters, which have a more damped isotopic signal and mean transit times in the order
26 of 2 to 4 years, was less clear and showed a dependence on the type of model used. The trade-off
27 to coarse data resolutions could potentially lead to misleading conclusions on how water actually
28 moves through the catchment, notwithstanding that these predictions could reach better fitting
29 efficiencies, lesser uncertainties, errors and biases. For both water types an optimal sampling
30 frequency seems to be one or at most two weeks. The results of our analyses provide information
31 for the planning of future fieldwork in similar Andean or other catchments.

32 **1. Introduction**

1 In catchment hydrology, the application of environmental isotopes as tracers, and particularly
2 stable water isotopes, was enhanced by the contributions of Maloszewski and Zuber (1982, 1993),
3 who described and applied the methodology of tracer dating in detail. In their approach the routing
4 of water in a catchment was mathematically expressed by a lumped-parameter transit time
5 distribution function (TTD). In this method, fundamental conditions are the homogeneity of the
6 system and steady-state conditions. Although presently more complex models are being tested
7 (e.g., models dealing with time-variable conditions: Rinaldo et al., 2011; Botter et al., 2010, 2011),
8 the lumped model approaches are still widely used since they provide basic inferences of the water
9 paths and the transit times of water (e.g., Muñoz-Villers and McDonnell, 2012; Hrachowitz et al.,
10 2009; Kabeya et al., 2006; Maloszewski et al., 2006; McGuire and McDonnell, 2006; Rodgers et
11 al., 2005; McGuire et al., 2002; Soulsby et al., 2000; Dewalle et al., 1997; Timbe et al., 2014).

12 The insights on TTDs and mean transit times (MTTs) of streams, springs, groundwater or even
13 soil waters to be gained by the jointly application of lumped-parameter models and tracers also
14 can serve as a starting point towards employing an improved sampling campaign which integrates
15 more sources of data or other types of tracers (e.g., Kirchner et al., 2010; Stewart et al., 2010), not
16 to mention a more accurate sampling length and frequency. Along with the increase of their
17 applicability, the handling and processing of tracer data, and even the estimation of uncertainties
18 of the inferred results, is becoming a routine process in hydrologic research (e.g., McGuire and
19 McDonnell, 2006). Solutions, formerly based only on the best fit to a particular model, now
20 frequently include a range of behavioral or possible solutions (Weiler et al., 2003; Vaché and
21 McDonnell, 2006; McGuire et al., 2007; Hrachowitz et al., 2009, 2010, 2013; Birkel et al., 2011;
22 Capell et al., 2012; Muñoz-Villers and McDonnell, 2012; Timbe et al., 2014). However, an
23 appropriate sensitivity analysis of the model parameters to factors such as the degree of temporal
24 resolution of the input data used to calibrate tracer-based lumped models is still uncommon as it
25 is in traditional rainfall-runoff modelling (McGuire and McDonnell, 2006).

26 Such an analysis is necessary; the predictions provided by steady-state approaches are simple
27 approximations of the real functioning of a catchment system, although only valid in waters in
28 which time-invariant conditions are applicable (e.g., groundwater systems). Besides, most steady-
29 state analyses of published studies are based on relatively poor information in terms of temporal
30 and spatial variability of environmental tracers (Rinaldo et al., 2011). For instance, by using a
31 conceptual-lumped model, Birkel et al. (2010) found that isotope data of high temporal resolution
32 were beneficial for model conceptualization and calibration. That assertion was corroborated by
33 Hrachowitz et al. (2011) who, using a lumped-parameter model, found evidence of potential
34 misleading insights when low sampling resolution data were used. The sampling frequency should

1 be in accordance to the expected time scale of the transit or residence time of the analyzed waters
2 (McGuire and McDonnell, 2006). However, in practice, this factor is constrained by logistical
3 reasons, especially in remote catchments.

4 Most tracer studies looking for the TTD or MTT of a catchment are based on weekly, bi-weekly,
5 and less common on monthly data. Rare are samplings at higher time scales than weekly (e.g.,
6 Kirchner et al., 2000; Birkel et al., 2010). Sometimes high temporal resolution measurements are
7 used for the analysis of rainfall-runoff events at smaller spatial scales, e.g., hillslope, in which the
8 transit time of fast flows of the order of hours to few days is being searched for. But for those
9 cases, time-variant instead of steady-state approaches are necessary (e.g., Heidbüchel et al., 2012;
10 Rinaldo et al., 2011; Botter et al., 2011; Weiler et al., 2003; Barnes and Bonell, 1996). In general,
11 the temporal resolution of the data employed to infer hydrological process understanding from
12 lumped-parameter models can influence the results, thereby making it difficult to compare
13 predictions from different studies (Hrachowitz et al., 2011).

14 To gain insights from the effect of the sampling frequency on the results of lumped-parameter
15 models, we collected time-series of stable water isotopes in a baseflow-dominated Ecuadorian
16 tropical montane cloud forest catchment. Data were aggregated into diverse levels of temporal
17 resolution in order to analyze their effect on the predictions from three widely known lumped
18 models, whose applicability was identified in a previous research (Timbe et al. 2014). The
19 temporal resolution of this study consists of: around two years of high-resolution samples of
20 rainfall events, weekly grab samples of stream waters from the main river and its seven tributaries,
21 and bulk water samples from six representative soils sites. For the analyzed waters, only baseflow
22 or steady-state conditions were considered.

23 The hypotheses on which this study is based are: 1) for the analyzed waters, some temporal
24 resolutions of input data could substantially influence the results of lumped parameter models; in
25 this regard 2) a sensitivity analysis of the sampling resolution is essential as part of analyzing the
26 suitability of a lumped-parameter model, similarities or divergences of results from diverse
27 sampling trade-offs could provide insights on the degree of reliability of a particular sampling
28 frequency.

29 **2. Materials and Methods**

30 **2.1 Study Area**

31 The study area of the Rio San Francisco catchment (76.9 km², Fig. 1) is located in the eastern
32 escarpments of the Andean mountains in south Ecuador. The local tropical climate is mainly

1 influenced by easterly trade winds and thus by the Atlantic circulation patterns (Beck et al., 2008).
2 The mean annual temperature ranges from 15°C in the lower part of the catchment to 10°C on the
3 ridges. Annual precipitation ranges from 2,500 to 4,000 mm in wet years. Rainfall intensities are
4 low (less than 10 mm h⁻¹) and the relative humidity is high, up to 96% at the ridges. The topography
5 of the area has an altitudinal range of 1,725 to 3,150 m a.s.l. and is characterized by steep valleys
6 with an average slope of 63%. Seven main tributaries feed the San Francisco River, their catchment
7 areas vary in size from 0.7 to 34.9 km² and in their land cover, constituted mainly by pristine forest
8 and pastures (Goettlicher et al., 2009). According Timbe et al. (2014), who used weekly resolution
9 data, MTT of water in the surficial horizons is of the order of few weeks to months. The stream
10 waters of the river and its tributaries are perennial and baseflow-dominated. Previous research
11 accounted the groundwater contribution in 85% of the total runoff, characterized by MTTs of the
12 order of 2 to 4 years (Timbe et al., 2014; Crespo et al., 2012). A detailed description of the physical,
13 hydrological and land cover characteristics of the catchment and main tributaries are given in
14 Timbe et al. (2014), whereas additional information on the climate and ecosystem gradients of the
15 research area can be found in Bendix et al. (2008), Fiedler and Beck (2008) and Wilcke et al.
16 (2008).

17 **2.2 Sampling site selection and methodology**

18 For the present study, the same field data used in Timbe et al. (2014) was employed. In brief, for
19 around two years and starting in mid-August 2010, samples for isotopic analyses ($\delta^{18}\text{O}$ and $\delta^2\text{H}$)
20 were collected in the study catchment. Weekly-based dip samples were taken for stream waters at
21 every sub-catchment and main catchment outlets while volume-weighted samples for soil waters
22 were collected using wick-samplers located in soil sites covered with pastures and forest (Fig. 1).
23 As stream water samples represent an instantaneous condition in time, in order to account for the
24 baseflow conditions of the catchment, samples taken during extreme rainfall-runoff events were
25 discarded. Rainfall samples for isotopic analyses were taken after every rainfall event, in the lower
26 part of the catchment at 1,900 m a.s.l. The end of every event of rainfall was marked by a time
27 span of at least 30 min without rainfall. The isotopic variation of rainfall through the catchment
28 was inferred from the sampled point by using the altitudinal isotopic gradient of -0.22‰ $\delta^{18}\text{O}$,
29 -1.12‰ $\delta^2\text{H}$ and 0.6‰ deuterium excess per 100 m elevation gain, as estimated by Windhorst et
30 al. (2013) for the same investigated area. In this study only $\delta^{18}\text{O}$ was selected for further analysis
31 since $\delta^{18}\text{O}$ and $\delta^2\text{H}$ showed a high linear correlation. The stable isotope signatures are reported in
32 per-mil value relative to the Vienna Standard Mean Ocean Water (VSMOW) (Craig, 1961). The
33 water isotopic composition was analyzed by wavelength-scanned cavity ring down spectroscopy
34 (WS-CRDS) with a precision of 0.1 ‰ for $\delta^{18}\text{O}$ and 0.5 ‰ for $\delta^2\text{H}$ (PicarroL1102-i, CA, US).

1 It should be noticed that while the aim of Timbe et al. (2014) was to identify the most reliable
2 TTDs and to characterize the MTTs for all the sampled sites (i.e. a total of 32 sites covering waters
3 from streams, soils and springs) based on the intercomparison of fitting efficiencies and ranges of
4 uncertainties provided by predictions of seven lumped-parameter models, for the present research
5 we focused on accounting the average trends of predictions as a results of using diverse sampling
6 frequencies. In Timbe et al. (2014) a fixed weekly sampling frequency was used. To avoid over-
7 representation of a specific isotopic signal in the depiction of general predictive trends, the number
8 of analyzed stream waters was limited to the seven main nested sub-catchments: Navidades (QN),
9 Pastos (QP), Cruces (QC), Milagro (QM), Ramon (QR), Francisco Head (FH), Zurita (QZ) and
10 the main catchment outlet Planta (PL) (Fig. 1). Accordingly, only lumped models were considered.
11 Since differences between soil water sampling sites were bigger than on-site differences (Timbe
12 et al., 2014) we limited in this study the number of soil depths from three to one specific soil depth,
13 more precisely at 0.25 m, resulting in a total of 6 sampling locations (A, B, C, D, E, F) instead of
14 18 as performed in Timbe et al. (2014). In the latter research water samples were collected at three
15 depths, respective at 0.10, 0.25 and 0.40 m below surface.

16 Besides selecting only representative sampling locations, also a slight variance in the length of the
17 data set characterizes both studies. In the present study rainfall and stream waters were analyzed
18 for the period of the 1st of October 2010 till mid August 2012, while in Timbe et al. (2014) the
19 used data set stretched from mid-August 2010 till mid August 2012. The decision to shorten the
20 time series by shifting the beginning of the study period to the last quarter of 2010 was taken in
21 order to homogenize the different time series for the aggregation into different sampling
22 frequencies (up to 3 months during tryouts) and to assure that divergences among predictions are
23 only due to the applied temporal resolutions. An additional reason for shortening the time series is
24 that the wick-samplers for the collection of soil water samples were installed after October 2010
25 (Timbe et al., 2014).

26 **2.3 Lumped-parameter equation and distribution functions to infer transit times of water**

27 For the calculation of the MTT, the lumped-parameter approach was utilized. This method
28 considers the aquifer system as an integral unit, while the flow pattern is assumed to be constant.
29 Particular for conservative tracers, the transport of a tracer through a catchment can be
30 mathematically expressed by the convolution integral equation for stable tracers (Eq. 1), in which
31 the tracer's outflow composition C_{out} at a time t (time of exit) consists of the tracer's input
32 composition C_{in} that falls uniformly on the catchment in a previous time step t' (time of entry).
33 C_{out} is lagged according to a TTD that rules the tracer's transit time (τ). This TTD is represented

1 by the normalized distribution function of the tracer $g(\tau)$ injected instantaneously over an entire
2 area.

$$3 \quad C_{out}(t) = \int_0^{\infty} C_{in}(t - \tau) g(\tau) d\tau \quad (1)$$

4 Based on findings from a previous research (Timbe et al., 2014), for the stream waters of San
5 Francisco, Exponential-Piston (EPM) and Gamma (GM) models were identified as reliable TTDs
6 in terms of providing predictions with high fitting efficiencies and low uncertainty ranges; while
7 Linear-Piston (LPM) and GM models were found most appropriate for soil water data (a detailed
8 description of the TTD models is shown in Timbe et al., 2014). These models are widely known
9 among the two-parameter TTD models (Kirchner et al., 2000, 2001; Maloszewski and Zuber,
10 1982; McGuire and McDonnell, 2006; Amin and Campana, 1996). EPM and LPM are defined by
11 τ and η (η explains the portion of contribution of each type of flow), while the GM model is defined
12 by the shape α and scale β parameters.

13 **2.4 Model performance**

14 The convolution method for the calibration of every model, describing each sampled water and
15 sampling frequency, was used. Input data for models consisted of isotopic time-series of rainfall,
16 while the observed variation of each analyzed effluent (e.g., stream or soil waters) were used for
17 calibration. The used approach follows nearly the same methodology applied in Timbe et al.
18 (2014), with some slight modifications to allow the analysis of diverse sampling resolutions.
19 Briefly, the goodness of fit of every simulation, as defined by the Nash-Sutcliffe Efficiency
20 coefficient NSE (Nash and Sutcliffe, 1970), was calculated. To automate and standardize the
21 equation's resolution, we repeated 10,000 simulations by randomly sampling using the Monte
22 Carlo based Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Freer, 2001)
23 method. Behavioral solutions, for which weighted quantiles between 0.05 and 0.95 (90% of the
24 behavioral limits) were calculated, were selected for every prediction based on a lower limit (5%)
25 which were dependent on the best NSE reached for every case. From these values, in order to ease
26 inter-comparisons, the magnitude of uncertainty for each predicted parameter was calculated by
27 subtracting the lower behavioral limit from the maximum one ($\Delta\tau$, $\Delta\alpha$, $\Delta\eta$). For the best
28 predictions, the Root Mean Square Error (RMSE) and the bias with respect to the mean (BIAS)
29 were calculated to account for errors and deviations of predictions. In both cases they were reported
30 in per mil (‰) units.

31 In most simulations, the convergence of solutions towards one solution peak was clearly defined
32 within a predefined fixed range dependent on the type of model: τ [0-10 yr], α [0.01-10], η [1-10].

1 For cases with more than one solution peak, in order to improve the convergence of τ , we restricted
2 the behavioral solutions to the largest peak for the second model parameter (assumption made by
3 the authors). It should also be noticed that for the particular case of LPM, in order to easy the
4 interpretation of results and at the same time improve the convergence of τ , the lower limit value
5 for η was set to 1 instead of 0.5 as it was in Timbe et al. (2014). The latter consideration was
6 performed after accounting the results from the referred study in which for most of the analyzed
7 soil water sites the best solutions provided by an LPM model were characterized by a η slightly
8 larger than 1.

9 Similarly to Timbe et al. (2014) and other related studies (Hrachowitz et al., 2011; Muñoz-Villers
10 and McDonnell, 2012) an artificial warm-up period was generated by repeating measured isotopic
11 rainfall time series in a loop. For our case, to guarantee stable results, the warming-up period was
12 set to 20 times the length of the observed time series.

13 **2.5 Temporal resolution of data**

14 Solving the convolution method requires a fixed time step for the input function C_{in} , which in turn
15 will be the same time step resolution of the predicted output data C_{out} . In order to check the effect
16 of the temporal resolution of sampling on the predictions, the simulations were performed by
17 aggregating high-resolution samples of rainfall (i.e., per event) into five levels of temporal
18 resolution: daily, weekly, bi-weekly, monthly and bi-monthly. For each data set, the isotopic
19 composition for every event was weighted according to the collected volume for the considered
20 time span. For time spans corresponding to zero rainfall, the isotope signal of the antecedent time
21 step was used. By using a predefined TTD function $g(\tau)$, Eq. (1) could be solved and it became
22 possible to derive the best possible fit to the observed data for every outflow by varying the model
23 parameters. Depending on how we aggregated the data, two distinct scenarios were considered.

24 Scenario 1: For every sampled site, observed isotopic data series of rainfall and outflows were
25 aggregated into coarser levels of data resolution. Since the finest resolution of outflow waters was
26 weekly, we used this data resolution to calibrate models having daily rainfall data sets as input.
27 For weekly, bi-weekly, monthly and bi-monthly data sets, we used the corresponding time step
28 resolution. For stream water, due to the smooth variation between two successive isotopic data, no
29 volumetric weighting was applied, but a simple averaging of weekly isotopic values. For soil
30 water, volumetric weighting was applied.

31 Scenario 2: Diminishing the sampling resolution in both types of observed data at the same time
32 (rainfall and outflows), as performed in Scenarios 1, could lead to incomplete insights if we

1 consider that coarse data resolutions, such as monthly or bi-monthly, could provide lesser
2 uncertainties or better simulation statistics than finer data resolutions (by the simple fact that less
3 data is involved in the analyses). In this regard, a second scenario was set up, in which only the
4 highest temporal resolution data of observed outflows (i.e. weekly) was considered for calibration;
5 while the rainfall data were considered the same as in Scenario 1. Results from this second scenario
6 facilitate to discern the adequacy of a particular time resolution over another.

7 It should be noted that, given these considerations, the predictive results for daily and weekly time
8 resolutions are the same for both scenarios. For data resolutions larger than weekly, the
9 combination of two different levels of information in the same lumped predictive model (e.g.,
10 monthly data for the input function of rainfall and weekly for the observed outflows) was handled
11 through considering weekly time steps, although previously those rainfall values were derived as
12 volumetrically weighted rainfall data from bi-weekly, monthly or bi-monthly sampling
13 resolutions.

14 Analysis of these two scenarios provides a quantifiable effect of data resolution on parameter
15 estimation of the applied models. For comparative purposes among sampling trade-offs, the finest
16 analyzed temporal resolution (i.e., daily rainfall and weekly outflow data) was considered as the
17 main reference in order to define a particular result as lower or higher estimate. In order to look
18 for similarities, divergences and trends between predictions, results were visually compared using
19 Box-Whisker plots and the respective median (expressed in this text with a tilde on the top of a
20 parameter symbol, e.g., $\tilde{\tau}$) for the grouped six soil water sites and the eight stream water sites.
21 Interpretation of the physical meaning of results considers that the MTT of water can be adequately
22 characterized by τ .

23 **3. Results**

24 For this study, as a result of the use of a slightly shorter time-series than those used in Timbe et al.
25 (2014), slight differences for model parameter predictions can be found when weekly-based
26 predictions are compared to the former published results.

27 **3.1 Soil water (Table 1, Fig. 2)**

28 **3.1.1 Type 1 scenarios – varying resolution of rain and soil water isotope data**

29 Median values of NSE for GM and LPM were rather similar, ranging between 0.76 to 0.86.
30 Likewise, for both models the RMSE and BIAS were comparable between time resolutions.
31 Furthermore, best predictions of τ , as defined by the NSE, showed a clear increasing trend of this

1 parameter versus a decreasing temporal sampling resolution. For GM the median value of τ
2 between sampled sites (i.e., $\bar{\tau}$) for the daily sampling resolution was 4.66 weeks, while for weekly
3 and bi-weekly resolutions data this value slightly rose to 5.15 and 5.89 weeks. Considering coarser
4 data resolutions, as monthly or bi-monthly, τ even went up to 6.62 and 8.99 weeks. The values and
5 the corresponding trend for LPM were similar to the one obtained using GM. For LPM $\bar{\tau}$ varied
6 from 4.59 to 8.87 weeks using the finest and the coarsest time resolutions, respectively. In general,
7 GLUE-based uncertainties for τ estimations, as defined by median values ($\widetilde{\Delta\tau}$), were lower using
8 daily rather than coarser sampling resolutions. In this regard, larger differences were found for
9 LPM ranging from 1.44 weeks using daily data to 3.47 weeks using bi-monthly data; while for
10 GM the range of uncertainty varied from 1.83 to 2.06 weeks.

11 Estimations for GM's α parameter showed a similar median value for daily, weekly or bi-weekly
12 sampling frequencies ($\bar{\alpha}$ varied from 1.88 to 1.95), while it was larger for coarser time resolutions;
13 as for example the α value was 3.73 for monthly and 4.55 for bi-monthly data. Using LPM, the
14 variation of the median value of η slightly changed among time resolutions (e.g., $\bar{\eta}$ varied from
15 1.02 for daily up to 1.14 for bi-monthly data). However, results for particular sites for coarser data,
16 such as monthly or bi-monthly, showed larger values (e.g., for the A soil site η varied from 1.02
17 for daily data to 1.40 for bi-monthly data). Median values of GLUE-based uncertainties for these
18 parameters did not show a clear trend or significant variation as a function of the time resolution.
19 In all cases $\widetilde{\Delta\alpha}$ varied between 2.13 and 3.09 weeks, while $\widetilde{\Delta\eta}$ varied from 0.17 to 0.45 weeks.

20 As a typical case among soil water sites, results for every sampling resolution using the GM are
21 depicted in Fig. 3 showing respectively the convergence of model parameters, the simulated versus
22 observed $\delta^{18}\text{O}$, and the TTD.

23 **3.1.2 Type 2 scenarios – varying resolution of rain data and fixed resolution of soil water** 24 **isotope data**

25 For both models, the NSE, RMSE and BIAS of the best predictions followed similar trends as for
26 type 1 scenarios. When compared to results from the reference sampling resolution, NSE values
27 were higher for weekly and bi-weekly input data. For instance, using GM the median value of the
28 best NSE was 0.81 for daily and 0.84 for both weekly and bi-weekly data. Monthly data sets
29 provided predictions with similar efficiencies than daily, while for bi-monthly data the median
30 value of NSE was 0.78, the lowest among all sampling resolutions of type 2 scenarios.

31 Compared to type 1 scenarios, predictions of parameter results and uncertainties among time
32 resolutions were more stable. Using GM, $\bar{\tau}$ for the finest and coarsest time resolutions varied

1 between 4.66 and 5.00 weeks, while $\widetilde{\Delta\tau}$ showed extreme values between 1.83 and 2.06 weeks. The
2 variation of α between sampling frequencies was also smaller: $\tilde{\alpha}$ was between 1.73 and 2.23, while
3 $\widetilde{\Delta\alpha}$ was similar to results from type 1 scenarios (e.g., smaller uncertainties for finer than coarser
4 resolution data sets: 2.99 for daily and 4.25 for bi-monthly data). However, there were larger
5 uncertainties for particular sites when low resolution data sets were used (e.g., the most extreme
6 case was found for the A site where there was a $\Delta\alpha$ increase from 2.83 using daily data to 18.82
7 using bi-monthly data). Using LPM the trends and values were similar to the ones obtained with
8 GM. Comparing the daily and bi-monthly time resolutions $\tilde{\tau}$ varied from 4.59 to 4.68 weeks, and
9 their respective $\widetilde{\Delta\tau}$ ranged from 1.44 to 1.66 weeks. The median value for η was around 1 for all
10 sampling frequencies. Although small for all cases, $\widetilde{\Delta\eta}$ was larger for coarser than for finer time
11 resolution data: 0.36 for daily up to 0.56 for bi-monthly data.

12 **3.2 Stream water (Table 2, Fig. 4)**

13 **3.2.1 Type 1 scenarios – varying resolution of rain and stream water isotope data**

14 Regardless of the used model, the best solutions showed an increasing trend from finer to coarser
15 data resolutions. For GM, median NSE values of 0.74 and 0.79 were reached using monthly and
16 bi-monthly data while for daily data it was 0.60. Analogously, RMSE values were smaller for
17 coarse data resolutions. Median RMSE declined from 0.31‰ for daily to 0.17‰ for bi-monthly
18 data. BIAS remained small for all cases, with an average value of 0.04%. For EPM we obtained
19 similar trends and values.

20 Using GM, parameter results revealed lower values of τ for coarser time resolutions data when
21 compared to daily data resolution, e.g., $\tilde{\tau}$ went from 2.10 yr for daily data to 1.23 yr for bi-monthly
22 data. Furthermore, a clear decreasing trend of uncertainty lengths was detected. In general $\Delta\tau$ was
23 smaller for coarser than for finer time resolution data, e.g., 1.74 yr for daily and 0.58 yr for bi-
24 monthly data. For the GM's α showed a trend to higher values proportional to the decrease of
25 sampling resolution: $\tilde{\alpha}$ was 0.63 for the reference while it reached a value of 0.93 for bi-monthly
26 data. The median values of uncertainty lengths for this parameter ($\widetilde{\Delta\alpha}$) only slightly increased from
27 daily (0.14) to the coarsest data resolution (0.18). On the other hand, for the same conditions but
28 using EPM, τ values only slightly increased with coarser time resolutions ($\tilde{\tau}$ varied little from 2.71
29 to 3.03 yr between daily and bi-monthly data resolutions). The variation of $\Delta\tau$ was also small
30 between sampling frequencies. Extreme $\widetilde{\Delta\tau}$ values were accounted for daily and bi-monthly data:
31 0.28 and 0.37 yr, respectively. The parameter η , as a median value among sites, depicted subtle
32 smaller values for lower sampling frequencies. It decreased from 3.01 for daily data to 2.60 for bi-

1 monthly ones. In general, $\Delta\eta$ slightly decreased for coarser time resolutions: $\widetilde{\Delta\eta}$ dropped from 0.59
2 using daily to 0.46 using bi-monthly data.

3 Results for particular sites follow nearly the trends described by the median values for all analyzed
4 sites. Similarly to results depicted in Fig. 3 for the soil site C, Fig. 5 depicts the variation in results
5 for different data resolutions applied to the stream water of the main outlet of the catchment (PL).

6 **3.2.2 Type 2 scenarios – varying resolution of rain data and fixed resolution of stream water** 7 **isotope data**

8 Contrary to type 1 scenarios, the median NSE decreased for coarser temporal resolution data; e.g.
9 NSE for GM dropped from 0.60 using daily data to 0.44 using bi-monthly ones. The value of
10 RMSE and BIAS remained low amidst the temporal resolutions. Median RMSE was around
11 0.33% while the largest BIAS was 0.05%. The trend of NSE values for EPM was similar to GM,
12 although less sensitive to temporal resolution data. It declined from a median of 0.60 for daily data
13 to 0.54 for bi-monthly. RMSE and BIAS yielded for GM and EPM were comparable.

14 Similar to soil waters, for both models the variation of parameter results among diverse sampling
15 frequencies was smaller than for the corresponding type 1 scenarios. When GM was used, $\bar{\tau}$
16 predictions varied from 2.10 yr for daily data to 1.70 yr for bi-monthly. The largest estimated $\tilde{\alpha}$
17 was 0.71 (using bi-monthly data) which was not far from the predicted value using daily data:
18 0.63, considering that the range of behavioral solutions for this parameter was around 0.14 for
19 every case. Uncertainty ranges for both parameters between diverse temporal resolution data
20 yielded similar average estimations: $\widetilde{\Delta\tau} \approx 1.6$ yr and $\widetilde{\Delta\alpha} \approx 0.14$. Also for the EPM model did the
21 best solution parameters slightly vary amongst data resolutions. For example, considering daily
22 and bi-monthly sampling frequencies $\bar{\tau}$ predictions varied from 2.71 to 2.81 yr and $\bar{\eta}$ from 3.01 to
23 2.81. Uncertainties for both parameters were small and similar between time resolutions: $\widetilde{\Delta\tau}$
24 ranged from 0.28 to 0.30 yr and $\widetilde{\Delta\eta}$ from 0.59 to 0.51.

25 **4. Discussion**

26 Results indicate that in some cases, like the present one, it is not sufficient to assess the supremacy
27 of one model over another based only on their performance; instead, additional knowledge on the
28 conceptual functioning of the studied system is necessary. For instance in Timbe et al. (2014),
29 where a weekly time step was considered, EPM and LPM predictions showed lesser uncertainty
30 ranges (for stream and soil waters respectively) when compared to predictions provided by a GM
31 model, which in counterpart provided better fitting efficiencies for most of the cases. The current

1 results corroborate those previous findings. Further research is needed to identify not only the best
2 TTD in terms of statistical performance; meanwhile, the use of any of the analyzed models cannot
3 be discarded.

4 For studies dealing with coarse stable isotope data sets (e.g., monthly or bi-monthly), considering
5 the differences of the performances between data sets of diverse sampling resolutions, the
6 uncertainties associated to the predictions should be acknowledged and considered at the moment
7 of the evaluation of hypotheses associated to these results. Monthly sampling resolution and
8 monthly data is still frequently used in stable water isotope studies when either the effort or the
9 costs are too high to realize a higher sampling frequency (e.g., Goller et al., 2005; Rodgers et al.,
10 2005; Viville et al., 2006; Liu et al., 2007; Rock and Mayer 2007; Chen et al., 2012), which goes
11 in line with a large share of observation points of the Global Network of Isotopes in Precipitation
12 and Rivers (GNIP) of the I.A.E.A.-W.M.O.

13 **4.1 Sensitivity of model-parameter results to sampling frequency**

14 In general, for soil and stream waters, model parameters for type 1 scenarios (Tables 1 and 2, Figs.
15 2-5): τ , α and η , showed distinct values between results from finer and lower data resolutions.
16 Keeping this finding in mind, whenever a high resolution isotope sampling is feasible, a sensitivity
17 analysis considering the effect of sampling frequency should be a common part of the workflow
18 while applying lumped-parameter models. This practice would help to build a broader data base
19 on the sensitivity of lumped convolution modelling to sampling frequencies, which might be useful
20 to correct effects caused by coarse sampling frequencies. In recent literature only two studies
21 dealing with the sampling frequency effect issue could be found: Hrachowitz et al. (2010) using
22 the gamma distribution model and Birkel et al. (2010) through adding information from tracers to
23 a lumped-conceptual hydrological model.

24 For soil waters, an increasing trend of τ predictions related to a decrease of sampling data
25 frequency was clear for GM and LPM. Using GM, best predictions for α were similar for time
26 resolutions up to bi-weekly sampling ($\alpha \approx 1.9$), but they were significantly higher for coarser data
27 resolutions.

28 Using GM for stream waters, parameter predictions depicted a different trend than found for soil
29 waters: τ yielded lower values for decreasing input resolution data. This descending trend matched
30 the increasing trend of α predictions. The trend depicted by our results differs from the one
31 obtained by Hrachowitz et al. (2011) who applied the same distribution function and convolution
32 method to chloride data in a headwater catchment in Scotland. In their case, a decreasing sampling

1 frequency went hand in hand with a decreasing trend of α , which consequently affected the
2 estimations for τ , resulting in systematically larger values. Even though any further comparison of
3 the two studies is difficult, as they represent two different hydrological systems and therefore favor
4 different distribution functions and shape parameters to describe the transport processes at hand,
5 it can be seen that the MTTs greatly differ in accordance with the chosen sampling frequency.

6 Considering the GLUE-based uncertainties derived from type 1 scenarios, results between soil and
7 stream waters were contrasting. For soil waters the uncertainty magnitudes $\Delta\tau$ remained similar
8 with decreasing time resolution while for stream waters they were systematically shorter. By using
9 type 2 scenarios (Tables 1 and 2, Figs. 2 and 4), where the same weekly temporal resolution of
10 observed data at outflows was kept for the calibration of models, additional insights on the degree
11 of the mismatch of coarse data resolutions compared to finer ones were provided. For these cases,
12 the NSE, RMSE and BIAS of the predictions were in general poorer for low temporal resolutions,
13 hinting towards a higher reliability of finer resolution data sets. Besides the fact that parameter
14 results derived from finer resolution data sets were more similar between each other, they did not
15 show marked trends of either over- or underestimations as compared to using type 1 scenarios.

16 For our analyses, given the subtle divergence of results when using daily, weekly or even bi-
17 weekly sampling resolutions, we consider them as adequate for the estimation of MTTs and TTDs.
18 It should be noted that this finding is valid for semi-steady-state conditions of waters. In this
19 regard, the utility of the highest sampling resolution, as daily or even sub-daily, could be noticeable
20 when temporal dynamics are to be considered. In this regard Birkel et al. (2010) provided insights
21 when dealing with the sampling frequency as part of the evaluation of the performance of a
22 lumped-conceptual flow-tracer model. They found that the use of daily isotope data from rainfall
23 and stream water, when compared to weekly or bi-weekly, besides providing higher fitting
24 efficiencies, was beneficial for the conceptualization and calibration of that model.

25 **4.2 Comparison of distribution functions**

26 Considering all the analyzed sampled frequencies, according to NSE values, GM performed
27 slightly better than the other two models (Tables 1 and 2). However, GLUE-based uncertainties
28 were also larger for this model (Figs. 2 and 4), hindering the clear preference of one model over
29 another. This finding goes in line with previous insights in the same research area (Timbe et al.,
30 2014) in which a fixed weekly-based sampling frequency was used to infer MTTs and TTDs.

31 For soil waters LPM yielded similar τ predictions to those of GM, thereby, justifying the use of
32 linear functions such as LPM as a first approximation, despite of presenting a simplification of the

1 water movement of real systems. On the other hand, GM was characterized by a delayed
2 occurrence of the tracer's peak signal ($\alpha \approx 2$).

3 For the case of stream waters, the comparison of predicted TTD shows that EPM traces a peak
4 signal delayed over time. We estimated η values between 2.15 and 3.23, the largest values we
5 found in related studies that used the same distribution function. Reported values are normally
6 lower than 2 (e.g., Hrachowitz et al., 2009; Katsuyama et al., 2009; McGuire and McDonnell,
7 2006; Viville et al., 2006; Kabeya et al., 2006), indicating that a large portion of 'old' water is
8 released first to the river as depicted by the isotopic composition of the stream. At the contrary,
9 when analyzing the behavior of water flow as derived from GM, the tracer signal's peak at the
10 outflow occurs instantaneously, meaning that a considerable portion of the event rainfall water
11 rapidly contributes to discharge, as for instance via lateral flow from near-surface deposits. Over
12 time, the tracer signal decreases (for either EPM or GM), but once again the implications are
13 different for both models comparing their flow recessions. As shown in Timbe et al. (2014) for
14 weekly data, the tracer signal decreases more rapidly for EPM than for GM. Thus, depending on
15 which distribution function is used, the interpretation is different. For example, in water
16 management using the EPM predictions one could argue that the effects of contamination of water
17 sources will not be immediately reflected in the river water and further that its effect will be rather
18 quickly disappearing. Contrary, inferences provided by a gamma distribution would tell that
19 pollutants in the catchment would have an instantaneous impact on the river water and that the
20 effect will sustain longer over time.

21 Considering a gamma distribution for the analyzed streams, τ varied between 1.62 and 4.16 years
22 and α between 0.54 and 0.68, using finer sampling resolutions. This range of α values is similar to
23 findings from other tracer studies on stream water using spectral analyses and high resolution
24 samples of chloride. Kirchner et al. (2000) demonstrated that an α value of approximately 0.5
25 provides a more proper representation of several stream waters in Wales. As stated by Soulsby et
26 al. (2010) gamma distributions with $\alpha < 1$ are most suitable to represent non-linear processes.
27 Similarly several other studies found α values significantly smaller than 1 (McGuire et al., 2005;
28 Hrachowitz et al., 2009, 2010; Godsey et al., 2010; Kirchner et al., 2010; Speed et al., 2010; Birkel
29 et al., 2012; Heidbüchel et al., 2012; Muñoz-Villers and McDonnell, 2012). On the other hand,
30 our results reported that when coarse temporal resolutions were used (monthly or bi-monthly), the
31 value of α approached to 1, which could lead to erroneous deductions.

32 Bearing in mind that each TTD describes different flow characteristics although they could yield
33 similar performances in terms of fitting efficiencies or uncertainties (e.g., LPM versus GM), for

1 our study catchment additional insights (e.g. tracer data associated with different flow paths) are
2 required in order to correctly unveil the prevailing TTD, as solely relying on model performances
3 could lead to misleading results. In this regard, studies at smaller spatial scales using high sampling
4 frequencies and time-variant conditions should be performed in order to cover a wider spectral
5 range of the different water sources.

6 **5. Conclusion**

7 Environmental tracer data of rainfall, stream and soil water were collected in the San Francisco
8 catchment with the objective to delineate the reliability of transit time predictions as a function of
9 the input data resolution. The collected information was used to test the prediction accuracy of
10 commonly used lumped models with respect to sampling frequency. Compared to results from
11 coarse data sets, finer temporal resolutions provided more similar outputs. Overall, discrepancies
12 between predictions of diverse sampling frequencies point out that the assessment of the
13 convergence and sensitivity of model parameters is essential for defining TTD through model
14 calibration. Especially for waters with dampened isotopic signals (i.e., stream waters), model
15 parameters seem to be highly sensitive to sampling frequencies, considerably increasing the risk
16 of misinterpretation of the underlying processes.

17 The study clearly demonstrates that estimations of the TTD for catchments with similar
18 characteristics or located in the same region using different frequencies of data sampling provides
19 an additional source of uncertainty, which might hinder a correct model comparison and
20 misrepresentation of the water routing system. The present research also provides a better
21 framework for future related research in the San Francisco basin and similar basins in the Andean
22 mountain region. Based on the new insights presented in this manuscript more elaborated sampling
23 campaigns could be undertaken, which would contribute to a more efficient management of the
24 water resources of Andean and similar mountain basins.

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1 **References**

- 2 Amin, I. E. and Campana, M. E.: A general lumped parameter model for the interpretation of
3 tracer data and transit time calculation in hydrologic systems, *J. Hydrol.*, 179, 1–21,
4 doi:10.1016/0022-1694(95)02880-3, 1996.
- 5 Barnes, C. J. and Bonell, M.: Application of unit hydrograph techniques to solute transport in
6 catchments, *Hydrol. Process.*, 10, 793–802, doi:10.1002/(SICI)1099-
7 1085(199606)10:6<793::AID-HYP372>3.3.CO;2-B, 1996.
- 8 Beck, E., Kottke, I., Bendix, J., Makeschin, F. and Mosandl, R.: Gradients in a tropical mountain
9 ecosystem — a synthesis, in: *Gradients in a Tropical Mountain Ecosystem of Ecuador*, vol. 198,
10 edited by Beck E., Bendix J., Kottke I., Makeschin F., and Mosandl R., Springer, Berlin, 451-
11 463, 2008.
- 12 Bendix, J., Rollenbeck, R., Fabian, P., Emck, P., Richter, M. and Beck, E.: Climate variability,
13 in: *Gradients in a Tropical Mountain Ecosystem of Ecuador*, edited by Beck E., Bendix J.,
14 Kottke I., Makeschin F., and Mosandl R., Springer, Berlin, 281-290, 2008.
- 15 Beven, K. and Freer, J.: Equifinality, data assimilation, and uncertainty estimation in mechanistic
16 modelling of complex environmental systems using the GLUE methodology, *J. Hydrol.*, 249,
17 11–29, doi:10.1016/S0022-1694(01)00421-8, 2001.
- 18 Birkel, C., Dunn, S. M., Tetzlaff, D. and Soulsby, C.: Assessing the value of high-resolution
19 isotope tracer data in the stepwise development of a lumped conceptual rainfall-runoff model,
20 *Hydrol. Process.*, 24, 2335–2348, doi:10.1002/hyp.7763, 2010.
- 21 Birkel, C., Soulsby, C., Tetzlaff, D., Dunn, S. and Spezia, L.: High-frequency storm event
22 isotope sampling reveals time-variant transit time distributions and influence of diurnal cycles,
23 *Hydrol. Process.*, 26, 308–316, doi:10.1002/hyp.8210, 2012.
- 24 Birkel, C., Tetzlaff, D., Dunn, S. M. and Soulsby, C.: Using lumped conceptual rainfall-runoff
25 models to simulate daily isotope variability with fractionation in a nested mesoscale catchment,
26 *Adv. Water Resour.*, 34, 383–394, doi:10.1016/j.advwatres.2010.12.006, 2011.
- 27 Botter, G., Bertuzzo, E. and Rinaldo, A.: Transport in the hydrologic response: Travel time
28 distributions, soil moisture dynamics, and the old water paradox, *Water Resour. Res.*, 46,
29 W03514, doi:10.1029/2009WR008371, 2010.
- 30 Botter, G., Bertuzzo, E. and Rinaldo, A.: Catchment residence and travel time distributions: The
31 master equation, *Geophys. Res. Lett.*, 38, L11403, doi:10.1029/2011GL047666, 2011.
- 32 Capell, R., Tetzlaff, D., Hartley, A. J. and Soulsby, C.: Linking metrics of hydrological function
33 and transit times to landscape controls in a heterogeneous mesoscale catchment, *Hydrol.*
34 *Process.*, 26, 405–420, doi:10.1002/hyp.8139, 2012.
- 35 Chen, J., Liu, X., Wang, C., Rao, W., Tan, H., Dong, H., Sun, X., Wang, Y. and Su, Z.: Isotopic
36 constraints on the origin of groundwater in the Ordos Basin of northern China, *Environ. Earth*
37 *Sci.*, 66, 505–517, doi:10.1007/s12665-011-1259-6, 2012.

38

- 1 Craig, H.: Standard for reporting concentrations of deuterium and oxygen-18 in natural waters,
2 Science, 133, 1833, doi:10.1126/science.133.3467.1833, 1961.
- 3 Crespo, P., Bücker, A., Feyen, J., Vaché, K. B., Frede, H.-G. and Breuer, L.: Preliminary
4 evaluation of the runoff processes in a remote montane cloud forest basin using mixing model
5 analysis and mean transit time, Hydrol. Process., 26, 3896–3910, doi:10.1002/hyp.8382, 2012.
- 6 Dewalle, D. R., Edwards, P. J., Swistock, B. R., Aravena, R. and Drimmie, R. J.: Seasonal
7 isotope hydrology of three Appalachian forest catchments, Hydrol. Process., 11, 1895–1906,
8 doi:10.1002/(SICI)1099-1085(199712)11:15<1895::AID-HYP538>3.3.CO;2-R, 1997.
- 9 Fiedler, K. and Beck, E.: Investigating gradients in ecosystem analysis, in: Gradients in a
10 Tropical Mountain Ecosystem of Ecuador, edited by Beck E., Bendix J., Kottke I., Makeschin F.,
11 and Mosandl R., Springer, Berlin, 49-54, 2008.
- 12 Godsey, S. E., Aas, W., Clair, T. A., de Wit, H. A., Fernandez, I. J., Kahl, J. S., Malcolm, I. A.,
13 Neal, C., Neal, M., Nelson, S. J., Norton, S. A., Palucis, M. C., Skjelkvale, B. L., Soulsby, C.,
14 Tetzlaff, D. and Kirchner, J. W.: Generality of fractal 1/f scaling in catchment tracer time series,
15 and its implications for catchment travel time distributions, Hydrol. Process., 24, 1660–1671,
16 doi:10.1002/hyp.7677, 2010.
- 17 Goettlicher, D., Obregon, A., Homeier, J., Rollenbeck, R., Naus, T. and Bendix, J.: Land-cover
18 classification in the Andes of southern Ecuador using Landsat ETM plus data as a basis for
19 SVAT modelling, Int. J. Remote Sens., 30, 1867–1886, doi:10.1080/01431160802541531, 2009.
- 20 Goller, R., Wilcke, W., Leng, M. J., Tobschall, H. J., Wagner, K., Valarezo, C. and Zech, W.:
21 Tracing water paths through small catchments under a tropical montane rain forest in south
22 Ecuador by an oxygen isotope approach, J. Hydrol., 308, 67–80,
23 doi:10.1016/j.jhydrol.2004.10.022, 2005.
- 24 Heidbüchel, I., Troch, P. A., Lyon, S. W. and Weiler, M.: The master transit time distribution of
25 variable flow systems, Water Resour. Res., 48, W06520, doi:10.1029/2011WR011293, 2012.
- 26 Hrachowitz, M., Savenije, H., Bogaard, T. A., Tetzlaff, D. and Soulsby, C.: What can flux
27 tracking teach us about water age distribution patterns and their temporal dynamics?, Hydrol.
28 Earth Syst. Sci., 17, 533–564, doi:10.5194/hess-17-533-2013, 2013.
- 29 Hrachowitz, M., Soulsby, C., Tetzlaff, D., Dawson, J. J. C., Dunn, S. M. and Malcolm, I. A.:
30 Using long-term data sets to understand transit times in contrasting headwater catchments, J.
31 Hydrol., 367, 237–248, doi:10.1016/j.jhydrol.2009.01.001, 2009.
- 32 Hrachowitz, M., Soulsby, C., Tetzlaff, D. and Malcolm, I. A.: Sensitivity of mean transit time
33 estimates to model conditioning and data availability, Hydrol. Process., 25, 980–990,
34 doi:10.1002/hyp.7922, 2011.
- 35 Hrachowitz, M., Soulsby, C., Tetzlaff, D., Malcolm, I. A. and Schoups, G.: Gamma distribution
36 models for transit time estimation in catchments: Physical interpretation of parameters and
37 implications for time-variant transit time assessment, Water Resour. Res., 46, W10536,
38 doi:10.1029/2010WR009148, 2010.
- 39 Kabeya, N., Katsuyama, M., Kawasaki, M., Ohte, N. and Sugimoto, A.: Estimation of mean
40 residence times of subsurface waters using seasonal variation in deuterium excess in a small
41 headwater catchment in Japan, Hydrol. Process., 21, 308–322, doi:10.1002/hyp.6231, 2006.

- 1 Katsuyama, M., Kabeya, N. and Ohte, N.: Elucidation of the relationship between geographic
2 and time sources of stream water using a tracer approach in a headwater catchment, *Water*
3 *Resour. Res.*, 45, W06414, doi:10.1029/2008WR007458, 2009.
- 4 Kirchner, J. W., Feng, X. H. and Neal, C.: Fractal stream chemistry and its implications for
5 contaminant transport in catchments, *Nature*, 403, 524–527, doi:10.1038/35000537, 2000.
- 6 Kirchner, J. W., Feng, X. H. and Neal, C.: Catchment-scale advection and dispersion as a
7 mechanism for fractal scaling in stream tracer concentrations, *J. Hydrol.*, 254, 82–101,
8 doi:10.1016/S0022-1694(01)00487-5, 2001.
- 9 Kirchner, J. W., Tetzlaff, D. and Soulsby, C.: Comparing chloride and water isotopes as
10 hydrological tracers in two Scottish catchments, *Hydrol. Process.*, 24, 1631–1645,
11 doi:10.1002/hyp.7676, 2010.
- 12 Liu, W. J., Liu, W. Y., Li, P. J., Gao, L., Shen, Y. X., Wang, P. Y., Zhang, Y. P. and Li, H. M.:
13 Using stable isotopes to determine sources of fog drip in a tropical seasonal rain forest of
14 Xishuangbanna, SW China, *Agric. For. Meteorol.*, 143, 80–91,
15 doi:10.1016/j.agrformet.2006.11.009, 2007.
- 16 Maloszewski, P., Maciejewski, S., Stumpp, C., Stichler, W., Trimborn, P. and Klotz, D.:
17 Modelling of water flow through typical Bavarian soils: 2. Environmental deuterium transport,
18 *Hydrol. Sci. J.-J. Sci. Hydrol.*, 51, 298–313, doi:10.1623/hysj.51.2.298, 2006.
- 19 Maloszewski, P. and Zuber, A.: Determining the turnover time of groundwater systems with the
20 aid of environmental tracers. 1. Models and their applicability, *J. Hydrol.*, 57, 207–231, 1982.
- 21 Maloszewski, P. and Zuber, A.: Principles and practice of calibration and validation of
22 mathematical-models for the interpretation of environmental tracer data, *Adv. Water Resour.*, 16,
23 173–190, doi:10.1016/0309-1708(93)90036-F, 1993.
- 24 McGuire, K. J., DeWalle, D. R. and Gburek, W. J.: Evaluation of mean residence time in
25 subsurface waters using oxygen-18 fluctuations during drought conditions in the mid-
26 Appalachians, *J. Hydrol.*, 261, 132–149, doi:10.1016/S0022-1694(02)00006-9, 2002.
- 27 McGuire, K. J. and McDonnell, J. J.: A review and evaluation of catchment transit time
28 modeling, *J. Hydrol.*, 330, 543–563, doi:10.1016/j.jhydrol.2006.04.020, 2006.
- 29 McGuire, K. J., McDonnell, J. J., Weiler, M., Kendall, C., McGlynn, B. L., Welker, J. M. and
30 Seibert, J.: The role of topography on catchment-scale water residence time, *Water Resour. Res.*,
31 41, W05002, doi:10.1029/2004WR003657, 2005.
- 32 McGuire, K. J., Weiler, M. and McDonnell, J. J.: Integrating tracer experiments with modeling
33 to assess runoff processes and water transit times, *Adv. Water Resour.*, 30, 824–837,
34 doi:10.1016/j.advwatres.2006.07.004, 2007.
- 35 Muñoz-Villers, L. E. and McDonnell, J. J.: Runoff generation in a steep, tropical montane cloud
36 forest catchment on permeable volcanic substrate, *Water Resour. Res.*, 48, W09528,
37 doi:10.1029/2011WR011316, 2012.
- 38 Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models part I — A
39 discussion of principles, *J. Hydrol.*, 10, 282–290, doi:10.1016/0022-1694(70)90255-6, 1970.

- 1 Rinaldo, A., Beven, K. J., Bertuzzo, E., Nicotina, L., Davies, J., Fiori, A., Russo, D. and Botter,
2 G.: Catchment travel time distributions and water flow in soils, *Water Resour. Res.*, 47, W07537,
3 doi:10.1029/2011WR010478, 2011.
- 4 Rock, L. and Mayer, B.: Isotope hydrology of the Oldman River basin, southern Alberta,
5 Canada, *Hydrol. Process.*, 21, 3301–3315, doi:10.1002/hyp.6545, 2007.
- 6 Rodgers, P., Soulsby, C., Waldron, S. and Tetzlaff, D.: Using stable isotope tracers to assess
7 hydrological flow paths, residence times and landscape influences in a nested mesoscale
8 catchment, *Hydrol. Earth Syst. Sci.*, 9, 139–155, doi:10.5194/hess-9-139-2005, 2005.
- 9 Soulsby, C., Malcolm, R., Helliwell, R., Ferrier, R. C. and Jenkins, A.: Isotope hydrology of the
10 Allt a' Mharcaidh catchment, Cairngorms, Scotland: implications for hydrological pathways and
11 residence times, *Hydrol. Process.*, 14, 747–762, doi:10.1002/(SICI)1099-
12 1085(200003)14:4<747::AID-HYP970>3.0.CO;2-0, 2000.
- 13 Soulsby, C., Tetzlaff, D. and Hrachowitz, M.: Are transit times useful process-based tools for
14 flow prediction and classification in ungauged basins in montane regions?, *Hydrol. Process.*, 24,
15 1685–1696, doi:10.1002/hyp.7578, 2010.
- 16 Speed, M., Tetzlaff, D., Soulsby, C., Hrachowitz, M. and Waldron, S.: Isotopic and geochemical
17 tracers reveal similarities in transit times in contrasting mesoscale catchments, *Hydrol. Process.*,
18 24, 1211–1224, doi:10.1002/hyp.7593, 2010.
- 19 Stewart, M. K., Morgenstern, U. and McDonnell, J. J.: Truncation of stream residence time: how
20 the use of stable isotopes has skewed our concept of streamwater age and origin, *Hydrol.*
21 *Process.*, 24, 1646–1659, doi:10.1002/hyp.7576, 2010.
- 22 Timbe, E., Windhorst, D., Crespo, P., Frede, H.-G., Feyen, J. and Breuer, L.: Understanding
23 uncertainties when inferring mean transit times of water trough tracer-based lumped-parameter
24 models in Andean tropical montane cloud forest catchments, *Hydrol Earth Syst Sci*, 18, 1503–
25 1523, doi:10.5194/hess-18-1503-2014, 2014.
- 26 Vaché, K. B. and McDonnell, J. J.: A process-based rejectionist framework for evaluating
27 catchment runoff model structure, *Water Resour. Res.*, 42, W02409,
28 doi:10.1029/2005WR004247, 2006.
- 29 Viville, D., Ladouche, B. and Bariac, T.: Isotope hydrological study of mean transit time in the
30 granitic Strengbach catchment (Vosges massif, France): application of the FlowPC model with
31 modified input function, *Hydrol. Process.*, 20, 1737–1751, doi:10.1002/hyp.5950, 2006.
- 32 Weiler, M., McGlynn, B. L., McGuire, K. J. and McDonnell, J. J.: How does rainfall become
33 runoff? A combined tracer and runoff transfer function approach, *Water Resour. Res.*, 39, 1315,
34 doi:10.1029/2003WR002331, 2003.
- 35 Wilcke, W., Yasin, S., Schmitt, A., Valarezo, C. and Zech, W.: Soils along the altitudinal
36 transect and in catchments, in: *Gradients in a Tropical Mountain Ecosystem of Ecuador*, edited
37 by Beck E., Bendix J., Kottke I., Makeschin F., and Mosandl R., Springer, Berlin, 75-85, 2008.
- 38 Windhorst, D., Waltz, T., Timbe, E., Frede, H.-G. and Breuer, L.: Impact of elevation and
39 weather patterns on the isotopic composition of precipitation in a tropical montane rainforest,
40 *Hydrol. Earth Syst. Sci.*, 17, 409–419, doi:10.5194/hess-17-409-2013, 2013.

1 Table 1. Soil water simulation results using GM and LPM models considering scenarios 1 & 2

	P	Sc	Sf _R	Sf _S	A _{GM}	B _{GM}	C _{GM}	D _{GM}	E _{GM}	F _{GM}	\bar{X}_{GM}	ALPM	BLPM	CLPM	DLPM	ELPM	FLPM	\bar{X}_{LPM}
τ [weeks]	1 & 2	D	W	4.82	4.50	3.42	6.93	6.74	4.44	4.66	4.58	4.61	3.23	5.99	6.14	4.36	4.59	
	1 & 2	W	W	5.33	4.97	3.75	7.48	7.02	4.67	5.15	5.69	4.53	3.79	6.29	6.11	4.49	5.11	
	1	Bw	Bw	6.01	5.41	4.56	8.43	8.26	5.77	5.89	5.96	5.18	4.27	7.71	7.34	5.92	5.94	
	2	Bw	W	5.50	4.99	3.88	7.67	7.21	4.81	5.25	5.80	4.88	3.64	6.88	6.89	4.81	5.34	
	1	M	M	7.27	5.79	4.98	9.30	9.75	5.97	6.62	7.17	7.69	4.19	8.31	9.17	6.18	7.43	
	2	M	W	5.57	5.01	3.95	7.75	7.24	4.49	5.29	5.77	4.72	3.86	6.73	6.88	4.46	5.25	
	1	Bm	Bm	9.68	8.22	7.55	9.74	10.58	8.29	8.99	11.02	8.87	8.87	8.75	8.17	11.60	8.87	
	2	Bm	W	5.38	4.16	2.69	6.46	6.37	4.63	5.00	4.99	3.92	2.83	5.62	6.17	4.37	4.68	
Δτ [weeks]	1 & 2	D	W	2.05	1.62	1.68	2.03	1.58	1.98	1.83	1.64	1.43	1.67	1.12	1.25	1.44	1.44	
	1 & 2	W	W	2.08	1.92	1.69	2.17	1.95	1.89	1.93	1.75	1.27	1.52	1.43	1.52	1.75	1.52	
	1	Bw	Bw	1.84	2.16	1.75	2.39	2.27	2.06	2.11	1.55	2.22	2.00	1.04	0.93	1.77	1.66	
	2	Bw	W	2.11	2.04	1.79	2.07	2.07	1.97	2.06	1.45	1.35	1.61	1.00	1.31	1.73	1.40	
	1	M	M	1.62	1.93	1.49	2.40	2.55	1.82	1.87	1.60	1.48	3.07	1.59	1.65	1.43	1.60	
	2	M	W	1.87	1.91	1.77	2.52	2.05	1.81	1.89	1.53	1.66	1.81	0.89	1.41	1.74	1.60	
	1	Bm	Bm	1.87	2.41	1.95	2.17	2.44	1.67	2.06	3.49	3.73	3.53	3.31	3.45	3.34	3.47	
	2	Bm	W	1.74	2.30	1.93	2.20	1.84	1.80	1.89	1.35	1.72	2.04	1.60	1.79	1.28	1.66	
α or η [-]	1 & 2	D	W	1.51	1.76	1.59	2.11	3.64	2.66	1.94	1.02	1.01	1.02	1.00	1.07	1.17	1.02	
	1 & 2	W	W	1.64	1.72	1.71	2.04	2.76	2.21	1.88	1.07	1.01	1.07	1.03	1.00	1.03	1.03	
	1	Bw	Bw	1.85	1.97	3.11	1.93	2.37	1.78	1.95	1.01	1.03	1.02	1.08	1.02	1.19	1.03	
	2	Bw	W	1.70	1.61	1.53	1.76	2.32	1.83	1.73	1.08	1.08	1.02	1.05	1.06	1.08	1.07	
	1	M	M	3.91	4.75	5.06	2.73	2.32	3.55	3.73	1.16	1.22	1.00	1.01	1.12	1.02	1.07	
	2	M	W	1.85	2.38	2.26	1.87	2.31	2.19	2.23	1.06	1.04	1.08	1.00	1.06	1.02	1.05	
	1	Bm	Bm	4.50	4.86	6.19	4.58	3.94	4.52	4.55	1.40	1.15	1.12	1.08	1.03	1.51	1.14	
	2	Bm	W	2.31	1.42	1.37	1.91	3.71	1.65	1.78	1.07	1.03	1.17	1.03	1.26	1.04	1.06	
Δα or Δη [-]	1 & 2	D	W	2.83	3.02	2.95	2.70	5.64	6.72	2.99	0.17	0.36	0.37	0.27	0.39	0.59	0.36	
	1 & 2	W	W	1.69	2.65	3.69	1.76	3.53	3.56	3.09	0.09	0.34	0.51	0.23	0.45	0.39	0.37	
	1	Bw	Bw	1.98	2.96	4.89	1.51	2.11	2.14	2.13	0.16	0.18	1.16	0.12	0.14	0.17	0.17	
	2	Bw	W	1.90	2.41	4.05	1.40	2.59	3.47	2.50	0.24	0.34	0.54	0.18	0.25	0.39	0.29	
	1	M	M	2.86	4.07	3.26	1.92	1.23	3.51	3.06	0.30	0.26	0.39	0.21	0.21	0.27	0.27	
	2	M	W	2.42	5.39	6.35	1.69	2.80	5.95	4.10	0.29	0.73	1.16	0.17	0.25	0.92	0.51	
	1	Bm	Bm	1.92	4.01	6.28	2.11	1.94	3.38	2.75	0.46	0.48	0.45	0.44	0.44	0.44	0.45	
	2	Bm	W	18.82	2.41	2.45	3.31	9.09	5.19	4.25	0.64	0.42	1.18	0.47	0.92	0.41	0.56	
NSE [-]	1 & 2	D	W	0.69	0.76	0.86	0.83	0.78	0.88	0.81	0.70	0.76	0.85	0.82	0.78	0.88	0.80	
	1 & 2	W	W	0.74	0.81	0.89	0.87	0.82	0.94	0.84	0.74	0.80	0.88	0.84	0.81	0.92	0.83	
	1	Bw	Bw	0.81	0.84	0.90	0.88	0.79	0.91	0.86	0.81	0.81	0.90	0.83	0.78	0.87	0.82	
	2	Bw	W	0.73	0.82	0.89	0.86	0.82	0.93	0.84	0.73	0.80	0.88	0.82	0.82	0.90	0.82	
	1	M	M	0.78	0.88	0.87	0.80	0.64	0.92	0.84	0.77	0.87	0.84	0.72	0.58	0.89	0.81	
	2	M	W	0.68	0.82	0.88	0.79	0.76	0.91	0.81	0.68	0.82	0.87	0.77	0.75	0.89	0.80	
	1	Bm	Bm	0.66	0.83	0.83	0.87	0.76	0.82	0.83	0.67	0.78	0.73	0.85	0.70	0.79	0.76	
	2	Bm	W	0.64	0.71	0.77	0.84	0.79	0.81	0.78	0.69	0.70	0.75	0.82	0.79	0.83	0.77	
RMSE [%]	1 & 2	D	W	1.85	1.65	1.28	1.06	1.36	1.10	1.32	1.81	1.65	1.35	1.10	1.35	1.10	1.35	
	1 & 2	W	W	1.67	1.46	1.14	0.93	1.24	0.79	1.19	1.67	1.50	1.21	1.03	1.26	0.87	1.23	
	1	Bw	Bw	1.36	1.41	1.05	0.89	1.31	0.86	1.18	1.36	1.51	1.08	1.02	1.33	1.05	1.20	
	2	Bw	W	1.71	1.43	1.12	0.96	1.22	0.85	1.17	1.71	1.52	1.22	1.09	1.25	1.00	1.24	
	1	M	M	1.29	1.04	1.13	1.07	1.59	0.78	1.10	1.32	1.09	1.28	1.26	1.72	0.94	1.27	
	2	M	W	1.88	1.42	1.21	1.19	1.44	0.96	1.31	1.88	1.42	1.25	1.24	1.46	1.03	1.33	
	1	Bm	Bm	1.42	1.11	1.28	0.80	1.20	1.05	1.16	1.42	1.25	1.60	0.86	1.35	1.13	1.30	
	2	Bm	W	2.00	1.84	1.67	1.04	1.34	1.37	1.52	1.85	1.87	1.75	1.09	1.34	1.30	1.54	
BIAS [%]	1 & 2	D	W	0.34	0.03	-0.06	0.10	-0.09	0.23	0.07	0.22	0.00	-0.15	0.03	-0.06	0.11	0.02	
	1 & 2	W	W	0.21	-0.06	-0.28	-0.02	-0.14	0.14	-0.04	-0.04	-0.03	-0.10	0.11	-0.03	-0.02	-0.03	
	1	Bw	Bw	-0.01	-0.20	-0.39	-0.11	-0.20	-0.07	-0.16	-0.07	-0.01	0.03	0.07	0.00	0.08	0.02	
	2	Bw	W	0.16	-0.14	-0.20	0.00	0.01	0.10	0.01	-0.03	-0.03	0.03	0.04	-0.02	0.09	0.00	
	1	M	M	-0.17	-0.30	-0.07	-0.24	-0.13	-0.16	-0.16	0.05	-0.07	0.07	0.08	0.12	-0.05	0.06	
	2	M	W	0.07	-0.28	-0.32	-0.22	0.03	0.13	-0.10	-0.04	-0.14	-0.09	0.00	-0.01	-0.05	-0.05	
	1	Bm	Bm	0.11	-0.09	-0.13	-0.07	-0.05	-0.08	-0.08	0.03	-0.07	-0.17	-0.01	0.03	-0.05	-0.03	
	2	Bm	W	0.43	0.23	0.10	0.00	0.07	0.36	0.17	-0.04	-0.04	0.07	0.00	-0.07	-0.04	-0.04	

2 P = Parameter; Sc = Scenario; Sf_R & Sf_S = Sampling frequency of rainfall and soil water data; D = Daily, W = Weekly, Bw = Bi-weekly, M =
3 Monthly, Bm = Bi-monthly; A, B and C = pasture soil water sites located at 2025, 1975 and 1925 m a.s.l.; D, E and F = soil water sites located at
4 2000, 1900 and 1825 m a.s.l. The subscript of the names of the soil site are related to the lumped model used: GM = Gamma, LPM = Linear Piston
5 Flow; \bar{X} = median of results of soil sites per sampling frequency; τ and Δτ = tracer's mean transit time (best match) and its corresponding uncertainty
6 range length; α and Δα for GM (or η and Δη for LPM) = best matching result for the second lumped parameter and corresponding uncertainty range
7 length; NSE = Nash-Sutcliffe Efficiency of best match; RMSE = Root Mean Square Error; BIAS = Bias with respect to the mean.
8

1 Table 2. Stream water simulation results using GM and EPM models considering scenarios 1 & 2

P	Sc	Sf _r	Sf _s	PL _{GM}	FH _{GM}	QC _{GM}	QM _{GM}	QN _{GM}	QP _{GM}	QR _{GM}	QZ _{GM}	\bar{X}_{GM}	PL _{EPM}	FH _{EPM}	QC _{EPM}	QM _{EPM}	QN _{EPM}	QP _{EPM}	QR _{EPM}	QZ _{EPM}	\bar{X}_{EPM}
τ [weeks]	1 & 2	D	W	1.98	1.62	4.16	1.99	1.56	3.91	3.13	2.22	2.10	2.61	2.68	3.33	2.59	2.67	3.24	2.76	2.74	2.71
	1 & 2	W	W	1.86	1.58	4.20	1.88	1.65	3.68	3.13	2.05	1.97	2.72	2.81	3.52	2.74	2.82	3.41	2.89	2.94	2.86
	1	Bw	Bw	1.55	1.34	4.07	1.40	1.43	3.12	2.36	1.61	1.58	2.78	2.87	3.68	2.70	2.86	3.53	2.95	2.89	2.88
	2	Bw	W	1.94	1.69	4.26	1.96	1.71	3.75	3.13	2.22	2.09	2.78	2.89	3.79	2.77	2.88	3.55	3.00	2.96	2.93
	1	M	M	1.52	1.60	3.59	1.57	1.39	2.40	2.38	1.61	1.61	3.03	3.23	4.89	3.00	3.05	3.82	3.28	3.21	3.22
	2	M	W	2.50	2.45	5.58	2.55	2.12	5.43	3.81	2.75	2.65	2.85	2.04	2.75	2.79	2.87	3.56	3.06	2.96	2.86
	1	Bm	Bm	1.16	1.23	2.22	1.08	1.24	1.95	1.63	1.23	1.23	2.90	2.94	5.56	2.82	3.01	3.68	3.19	3.06	3.03
	2	Bm	W	1.58	1.41	3.53	1.63	1.44	2.91	2.71	1.77	1.70	2.70	2.67	3.41	2.63	2.77	3.35	2.86	2.90	2.81
$\Delta\tau$ [weeks]	1 & 2	D	W	1.62	1.44	1.69	2.12	1.36	1.96	1.80	1.89	1.74	0.25	0.26	0.36	0.25	0.26	0.43	0.31	0.31	0.28
	1 & 2	W	W	1.43	1.25	1.59	1.52	1.30	1.94	1.84	1.66	1.56	0.27	0.31	0.52	0.29	0.30	0.50	0.32	0.33	0.32
	1	Bw	Bw	1.13	0.92	1.48	1.18	0.92	1.81	1.62	1.12	1.16	0.29	0.31	0.58	0.28	0.32	0.51	0.31	0.31	0.31
	2	Bw	W	1.58	1.37	1.58	1.61	1.44	1.86	1.63	1.71	1.59	0.29	0.33	0.49	0.28	0.33	0.50	0.36	0.37	0.35
	1	M	M	0.99	0.96	1.95	1.05	0.77	1.63	1.61	1.01	1.03	0.35	0.38	0.64	0.34	0.32	0.55	0.48	0.36	0.37
	2	M	W	2.08	2.36	1.41	2.13	2.02	1.71	1.98	2.47	2.05	0.28	0.37	0.56	0.26	0.25	0.33	0.28	0.28	0.28
	1	Bm	Bm	0.51	0.62	1.14	0.53	0.52	0.93	0.88	0.55	0.58	0.30	0.36	0.62	0.30	0.34	0.62	0.45	0.38	0.37
	2	Bm	W	1.05	0.77	1.18	1.17	0.93	1.39	1.47	1.09	1.13	0.27	0.30	0.48	0.23	0.26	0.46	0.31	0.30	0.30
α or η [-]	1 & 2	D	W	0.57	0.68	0.63	0.55	0.67	0.63	0.54	0.62	0.63	3.14	3.10	2.15	3.23	3.09	2.23	2.79	2.93	3.01
	1 & 2	W	W	0.63	0.73	0.65	0.60	0.70	0.67	0.60	0.68	0.66	2.97	2.89	2.05	2.92	2.89	2.14	2.66	2.63	2.77
	1	Bw	Bw	0.70	0.79	0.68	0.68	0.76	0.74	0.67	0.74	0.72	2.96	2.91	1.96	3.14	2.81	2.09	2.59	2.75	2.78
	2	Bw	W	0.62	0.71	0.66	0.60	0.69	0.68	0.60	0.67	0.66	2.85	2.76	1.91	2.86	2.77	2.06	2.47	2.60	2.68
	1	M	M	0.79	0.87	0.78	0.77	0.88	0.88	0.74	0.87	0.83	2.73	2.46	2.37	2.77	2.69	2.00	2.26	2.48	2.47
	2	M	W	0.56	0.62	0.60	0.53	0.63	0.60	0.54	0.59	0.60	2.75	1.78	1.46	2.85	2.77	2.03	2.42	2.62	2.52
	1	Bm	Bm	0.93	0.93	0.93	0.92	0.98	0.98	0.88	0.99	0.93	2.73	2.65	2.94	2.87	2.56	1.99	2.35	2.50	2.60
	2	Bm	W	0.65	0.73	0.70	0.64	0.73	0.75	0.64	0.72	0.71	3.05	3.17	2.11	3.20	2.95	2.18	2.67	2.67	2.81
$\Delta\alpha$ or $\Delta\eta$ [-]	1 & 2	D	W	0.16	0.20	0.09	0.14	0.19	0.11	0.10	0.15	0.14	0.68	0.60	0.27	0.69	0.59	0.35	0.45	0.60	0.59
	1 & 2	W	W	0.15	0.19	0.10	0.15	0.17	0.13	0.11	0.17	0.15	0.57	0.55	0.30	0.64	0.55	0.36	0.48	0.53	0.54
	1	Bw	Bw	0.16	0.21	0.09	0.16	0.19	0.16	0.13	0.18	0.16	0.58	0.58	0.28	0.64	0.54	0.32	0.45	0.48	0.51
	2	Bw	W	0.14	0.19	0.09	0.15	0.17	0.13	0.11	0.16	0.15	0.54	0.51	0.29	0.56	0.55	0.29	0.43	0.52	0.51
	1	M	M	0.19	0.21	0.14	0.18	0.20	0.22	0.16	0.22	0.19	0.50	0.43	0.41	0.48	0.43	0.27	0.40	0.41	0.42
	2	M	W	0.13	0.17	0.07	0.13	0.17	0.07	0.08	0.16	0.13	0.52	0.24	0.13	0.52	0.43	0.24	0.35	0.39	0.37
	1	Bm	Bm	0.18	0.16	0.18	0.18	0.19	0.20	0.15	0.19	0.18	0.48	0.54	0.60	0.53	0.45	0.32	0.42	0.44	0.46
	2	Bm	W	0.13	0.15	0.09	0.14	0.15	0.12	0.11	0.15	0.14	0.69	0.62	0.32	0.62	0.52	0.37	0.50	0.50	0.51
NSE [-]	1 & 2	D	W	0.63	0.56	0.59	0.60	0.70	0.57	0.50	0.63	0.60	0.59	0.55	0.62	0.54	0.66	0.61	0.49	0.63	0.60
	1 & 2	W	W	0.60	0.58	0.58	0.57	0.66	0.56	0.46	0.60	0.58	0.59	0.56	0.62	0.54	0.64	0.61	0.54	0.62	0.60
	1	Bw	Bw	0.68	0.62	0.66	0.67	0.72	0.63	0.54	0.71	0.66	0.62	0.57	0.67	0.60	0.69	0.64	0.62	0.70	0.63
	2	Bw	W	0.59	0.56	0.56	0.56	0.65	0.53	0.45	0.60	0.56	0.55	0.52	0.58	0.51	0.61	0.56	0.51	0.59	0.56
	1	M	M	0.71	0.60	0.73	0.75	0.79	0.76	0.72	0.79	0.74	0.65	0.58	0.83	0.66	0.77	0.74	0.70	0.77	0.72
	2	M	W	0.58	0.49	0.54	0.56	0.62	0.53	0.51	0.58	0.55	0.49	0.50	0.53	0.46	0.57	0.53	0.47	0.55	0.51
	1	Bm	Bm	0.76	0.73	0.78	0.80	0.78	0.80	0.81	0.85	0.79	0.75	0.72	0.77	0.78	0.78	0.80	0.78	0.85	0.78
	2	Bm	W	0.47	0.47	0.36	0.43	0.52	0.36	0.34	0.45	0.44	0.56	0.53	0.56	0.52	0.57	0.51	0.49	0.54	0.54

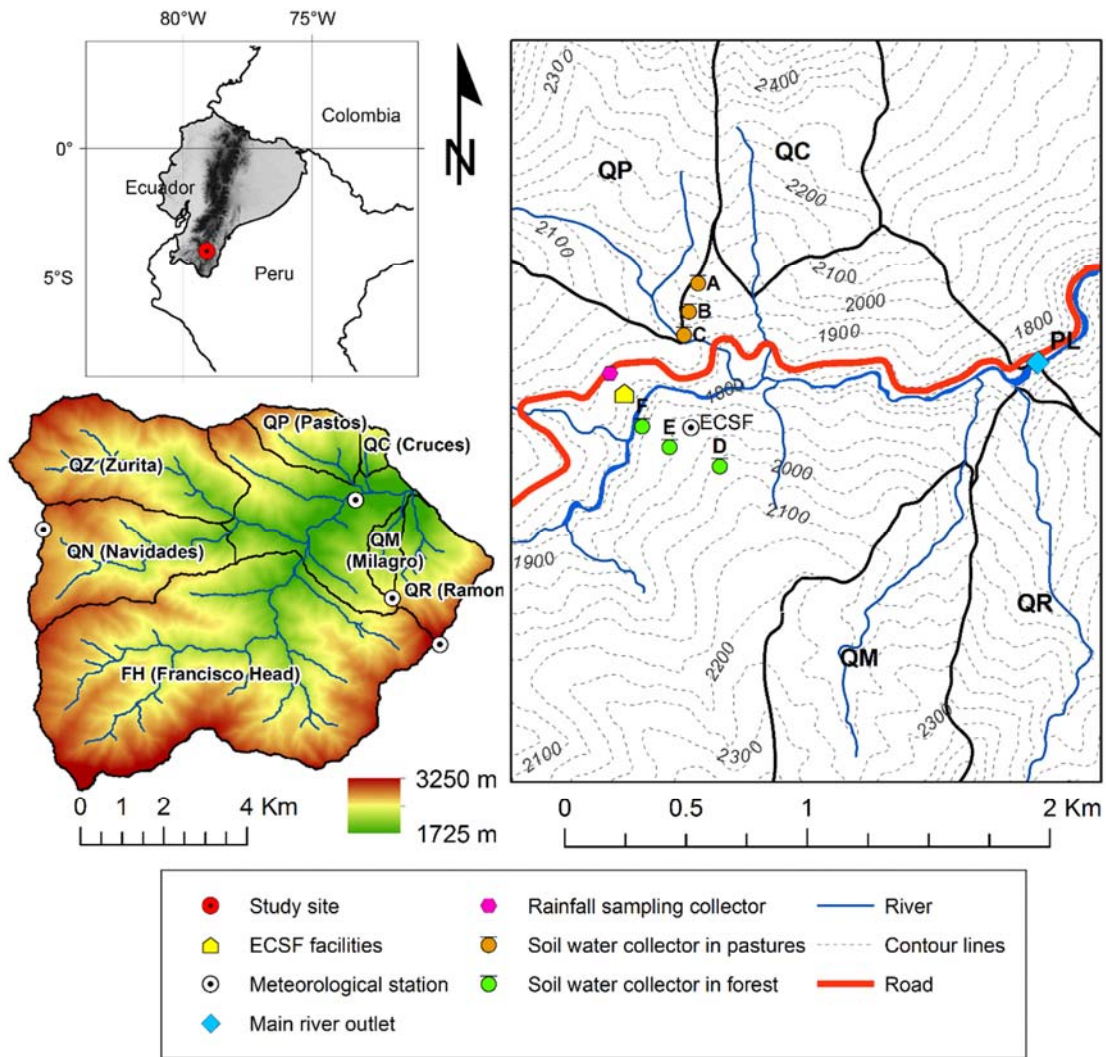
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3

1 Table 2 (Continued)

P	Sc	Sf _R	Sf _S	PL _{GM}	FH _{GM}	QC _{GM}	QM _{GM}	QN _{GM}	QP _{GM}	QR _{GM}	QZ _{GM}	\bar{X} _{GM}	PL _{EPM}	FH _{EPM}	QC _{EPM}	QM _{EPM}	QN _{EPM}	QP _{EPM}	QR _{EPM}	QZ _{EPM}	\bar{X} _{EPM}
RMSE [%]	1 & 2	D	W	0.33	0.35	0.19	0.38	0.27	0.22	0.34	0.28	0.31	0.35	0.35	0.19	0.40	0.29	0.21	0.34	0.28	0.32
	1 & 2	W	W	0.35	0.34	0.20	0.39	0.29	0.22	0.36	0.30	0.32	0.35	0.35	0.19	0.40	0.30	0.21	0.33	0.29	0.31
	1	Bw	Bw	0.31	0.34	0.16	0.35	0.27	0.19	0.33	0.26	0.29	0.34	0.36	0.16	0.38	0.28	0.19	0.30	0.26	0.29
	2	Bw	W	0.35	0.35	0.20	0.39	0.30	0.23	0.36	0.30	0.32	0.37	0.37	0.20	0.41	0.31	0.22	0.34	0.30	0.33
	1	M	M	0.26	0.29	0.13	0.25	0.21	0.14	0.20	0.18	0.20	0.29	0.30	0.11	0.28	0.22	0.14	0.21	0.19	0.21
	2	M	W	0.36	0.38	0.21	0.39	0.31	0.23	0.34	0.30	0.32	0.39	0.37	0.21	0.44	0.33	0.23	0.36	0.31	0.34
	1	Bm	Bm	0.22	0.23	0.12	0.21	0.19	0.11	0.15	0.14	0.17	0.22	0.23	0.12	0.21	0.19	0.11	0.16	0.14	0.17
	2	Bm	W	0.40	0.38	0.24	0.45	0.35	0.27	0.40	0.35	0.36	0.37	0.36	0.20	0.41	0.33	0.23	0.35	0.32	0.34
BIAS [%]	1 & 2	D	W	0.05	0.02	0.03	0.06	0.02	0.02	0.06	0.03	0.03	0.02	0.01	0.00	0.01	0.00	0.01	0.02	0.00	0.01
	1 & 2	W	W	0.09	0.04	0.05	0.10	0.05	0.04	0.08	0.06	0.05	0.01	0.00	0.00	0.02	0.00	0.01	0.00	0.01	0.00
	1	Bw	Bw	0.09	0.06	0.04	0.10	0.07	0.04	0.09	0.07	0.07	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00
	2	Bw	W	0.09	0.04	0.04	0.10	0.05	0.03	0.08	0.05	0.05	0.00	0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00
	1	M	M	0.07	0.03	0.04	0.08	0.03	0.02	0.07	0.03	0.03	0.00	-0.01	0.00	0.00	-0.01	0.00	0.00	0.00	0.00
	2	M	W	0.04	-0.02	0.01	0.04	-0.02	0.00	0.03	0.00	0.00	-0.01	-0.02	-0.06	-0.01	-0.02	-0.05	-0.02	-0.02	-0.02
	1	Bm	Bm	0.05	0.02	0.03	0.06	0.02	0.01	0.05	0.01	0.03	-0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
	2	Bm	W	0.15	0.11	0.10	0.15	0.11	0.09	0.13	0.11	0.11	0.01	-0.01	0.02	0.00	0.00	0.02	0.02	0.00	0.00

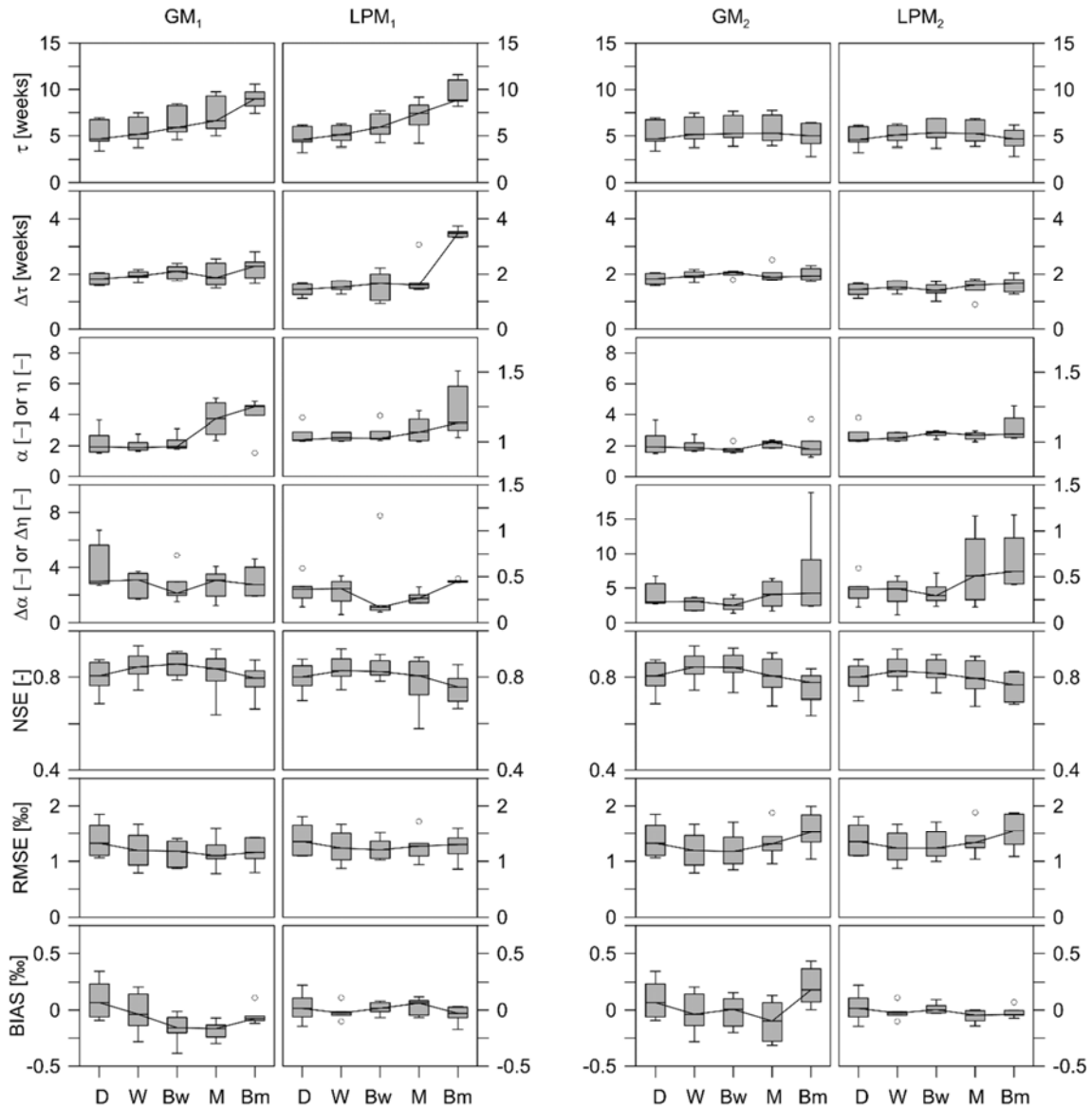
2 P = Parameter; Sc = Scenario; Sf_R and Sf_S = Sampling frequency of rainfall and stream water data: D = Daily, W = Weekly, BW = Bi-weekly, M = Monthly, BM = Bi-monthly. Acronyms for stream water are
3 defined in Figure 1 and the subscripts for stream water sites stands for the lumped model used: GM = Gamma, EPM = Exponential Piston Flow. \bar{X} = median of the results of stream water sites per sampling
4 frequency; τ and $\Delta\tau$ = tracer's mean transit time (best match) and its corresponding uncertainty range length; α and $\Delta\alpha$ for GM (or η and $\Delta\eta$ for EPM) = the best matching result for the second lumped parameter
5 and corresponding uncertainty range length; NSE = Nash-Sutcliffe Efficiency of best match; RMSE = Root Mean Square Error; BIAS = Bias with respect to the mean.



1

2 Fig. 1. San Francisco catchment with sampling locations and delineation of corresponding
 3 drainage area. Names and acronyms are showed in bold. Framed image shows the zoomed
 4 area of the lower part of the catchment.

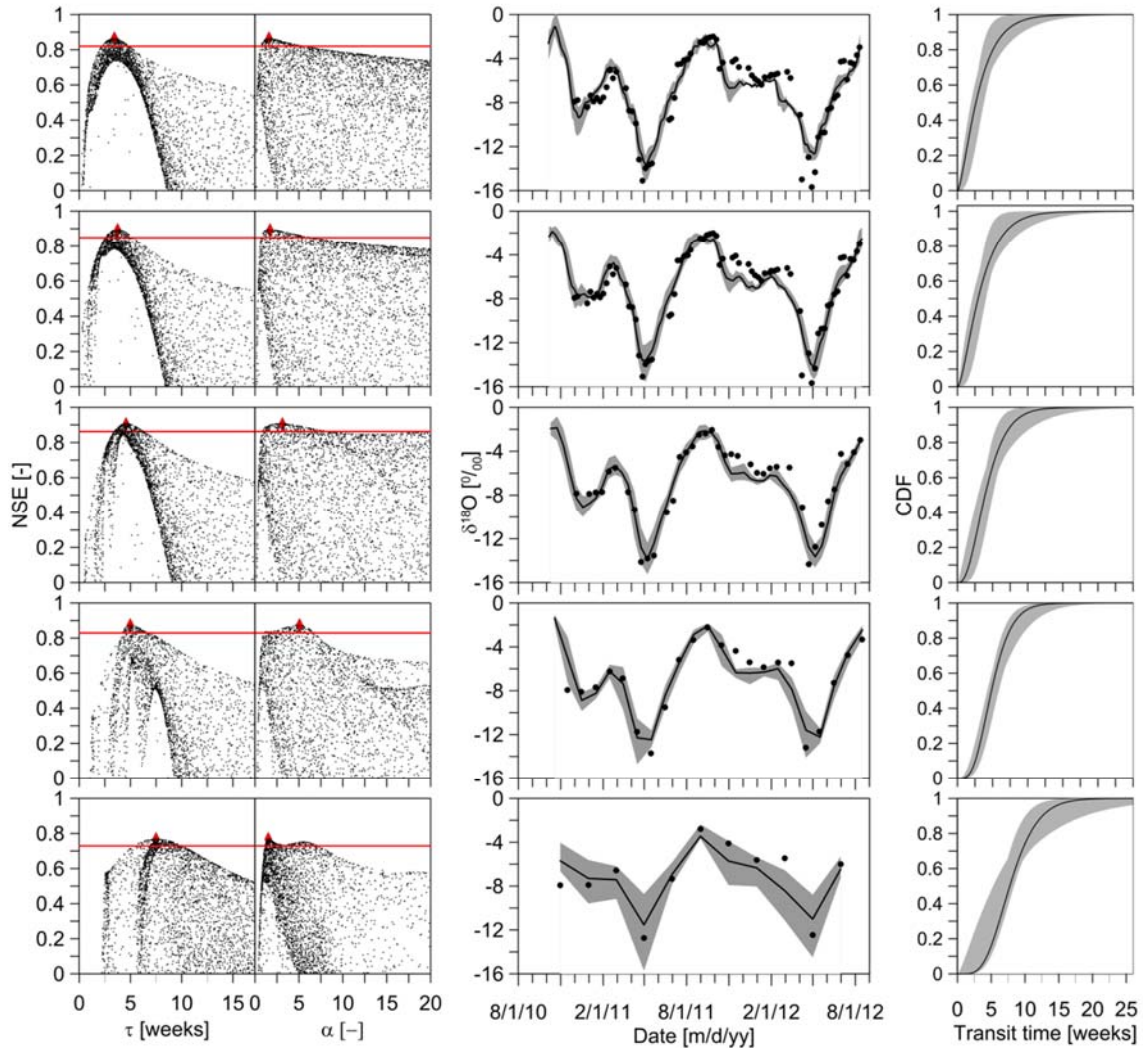
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1

2 Fig. 2. Comparison of predictions for soil water sites using GM and LPM lumped models.
 3 Subscript in the model name stands for the type of scenario: Sc1 = Aggregation of sampling
 4 frequency in the rainfall and also in the effluent, Sc2 = Aggregation of sampling frequency
 5 only in rainfall data. Acronyms in the X axis of all plots stands for five types of data
 6 resolution: D = Daily, W = Weekly; Bw = Bi-weekly, M = Monthly and Bm = Bi-monthly.
 7 Box-plots markers correspond to quartiles and median values (-). The length of Whiskers is
 8 limited to 1.5 times the width of the box and values located further away below the first
 9 quartile or above the third quartile are considered extreme ones (○).

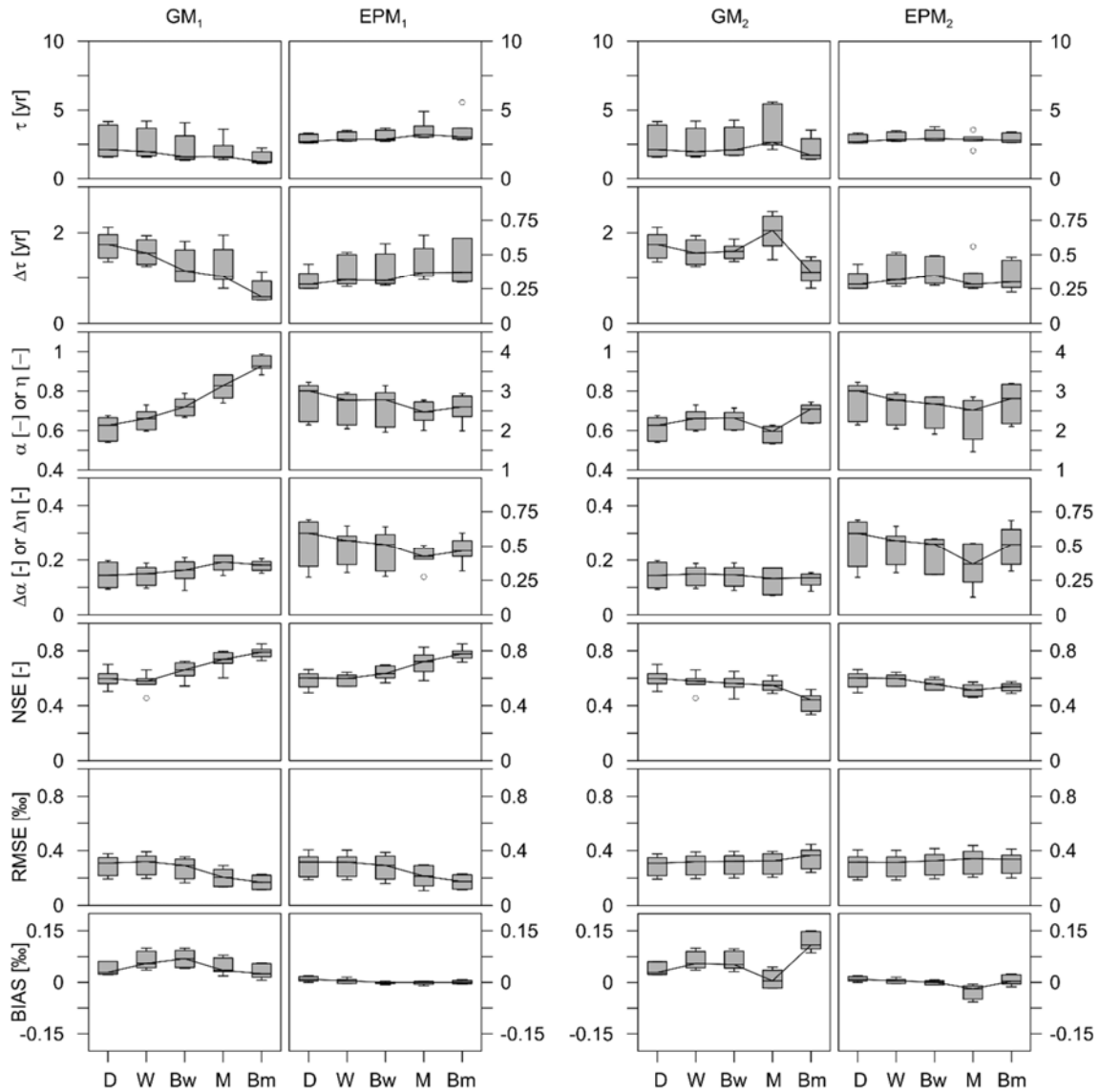
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1

2 Fig. 3. Predicted results for the soil water site C using the GM lumped model. Results are
 3 ranged from top to bottom according to the data resolution: daily (top), weekly,
 4 bi-weekly, monthly and bi-monthly (bottom). **Left column** shows dotty plots for the model parameters (τ
 5 and α) according to NSE using Monte Carlo random simulations (GLUE approach). Red line
 6 shows the feasible range of behavioral solutions of model parameters as a 5 % of the top best
 7 prediction (red diamond). **Center column** shows the measured (black filled circles) and
 8 simulated $\delta^{18}\text{O}$ (the black line and the shaded area represent the best possible solution and its
 9 range of variation according to the 5-95% of weighted quantiles derived from the confidence
 10 limits of behavioral solutions shown in the left column). **Right column:** soil water residence
 11 time distribution function corresponding to the best NSE; gray shaded area in each plot
 12 corresponds to the range of possible shapes of the distribution function.

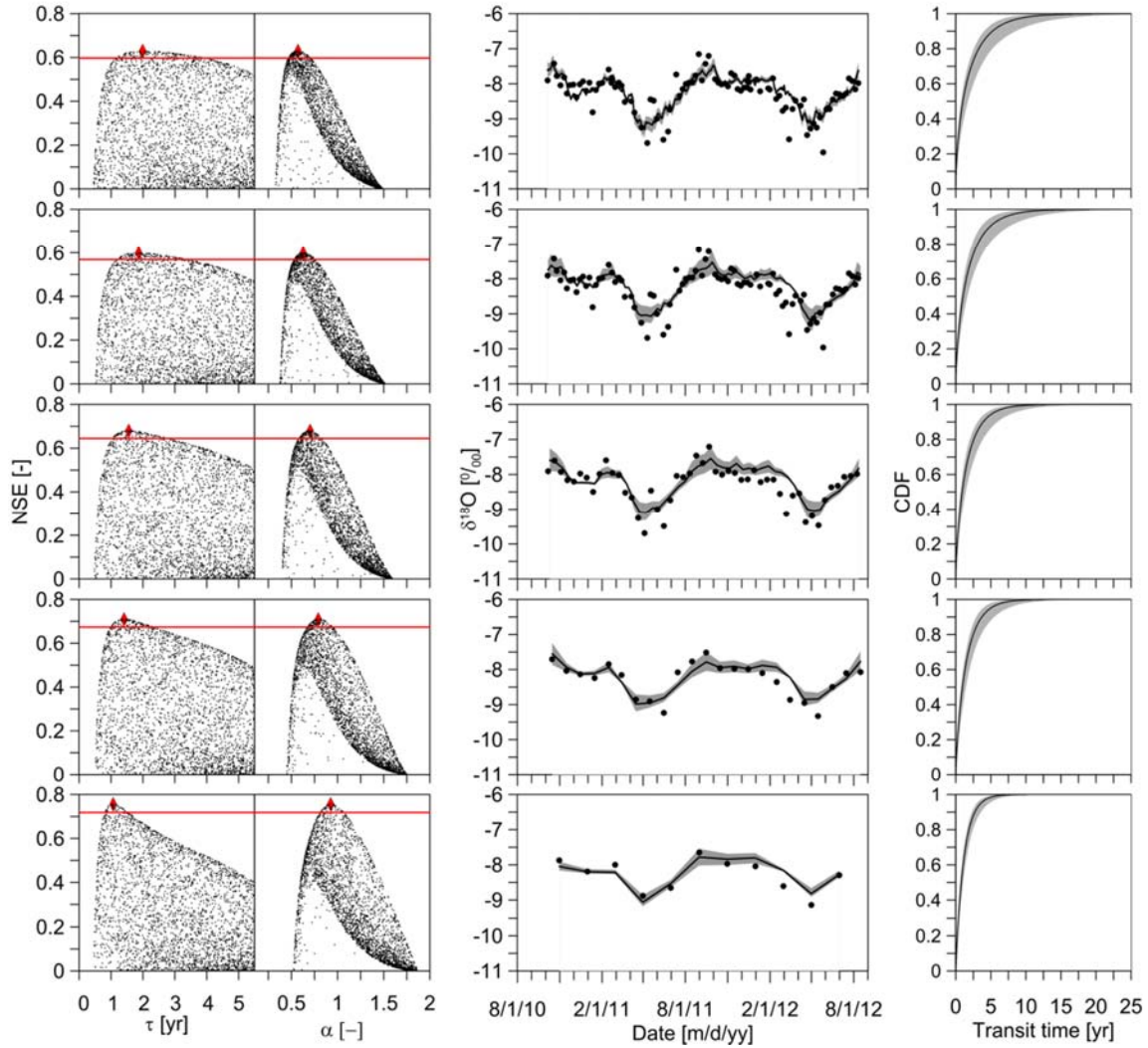
13



1

2 Fig. 4. Comparison of predictions for stream water sites using the GM and EPM lumped
 3 models. The subscript in the model name stands for the type of scenario: Sc1 = Aggregation
 4 of sampling frequency in the rainfall and also in the effluent, Sc2 = Aggregation of sampling
 5 frequency only in rainfall data. Acronyms in the X axis of all plots stands for five types of
 6 data resolution: D = Daily, W = Weekly; Bw = Bi-weekly, M = Monthly and Bm = Bi-
 7 monthly. Box-plots markers correspond to quartiles and median values are shown (-). The
 8 length of Whiskers is limited to 1.5 times the width of the box and values located further
 9 away below the first quartile or above the third quartile are considered extreme ones (○).

10



1

2 Fig. 5. Predicted results for the stream water site PL using the GM lumped model. Results are
 3 ranged from top to bottom according to the data resolution: daily (top), weekly, bi-weekly,
 4 monthly and bi-monthly (bottom). **Left column** shows dotted plots for the model parameters (τ
 5 and α) according to NSE using Monte Carlo random simulations (GLUE approach). Red line
 6 shows the feasible range of behavioral solutions of model parameters as a 5 % of the top best
 7 prediction (red diamond). **Center column** shows the measured (black filled circles) and
 8 simulated $\delta^{18}\text{O}$ (the black line and the shaded area represent the best possible solution and its
 9 range of variation according to the 5-95% of weighted quantiles derived from the confidence
 10 limits of behavioral solutions shown in the left column). **Right column:** soil water residence
 11 time distribution function corresponding to the best NSE; gray shaded area in each plot
 12 corresponds to the range of possible shapes of the distribution function.

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