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Karst spring recession curve analysis: efficient, accurate methods for both fast and slow flow components

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Abstract.

Analysis of karst spring recession hydrographs is essential for determining hydraulic parameters, geometric characteristics and transfer mechanisms that describe the dynamic nature of karst aquifer systems. The extraction and separation of different fast and slow flow components constituting karst spring recession hydrograph typically involve manual and subjective procedures. This subjectivity introduces bias, while manual procedures can introduce errors to the derived parameters representing the system. To provide an alternative recession extraction procedure that is automated, fully objective and easy to apply, we modified traditional streamflow extraction methods to identify components relevant for karst spring recession analysis. Mangin's karst-specific recession analysis model was fitted to individual extracted recession segments to determine matrix and conduit recession parameters. We introduced different parameters optimisation approaches of the Mangin's model to increase degree of freedom thereby allowing for more parameters interaction. The modified recession extraction and parameters optimisation approaches were tested on 3 karst springs in different climate conditions. The results show that the modified extraction methods are capable of distinguishing different recession components and derived parameters reasonably represent the analysed karst systems. We recorded an average KGE >0.7 among all recession events simulated by recession parameters derived from all combinations of recession extraction methods and parameters optimisation approaches. While there are variability among parameters estimated by different combinations of extraction methods and optimisation approaches, we find even much higher variability among individual recession events. We provide suggestions to reduce the uncertainty among individual recession events and to create a more robust analysis by using multiple pairs of recession extraction method and parameters optimisation approach.

1 Introduction

Groundwater from karst aquifers are essential water sources globally (Stevanović 2018; Goldscheider et al. 2020). Karst aquifers are characterised by high degree of heterogeneity and complex flow dynamics resulting from the interplay of conduit and matrix drainage systems (Kiraly 2003; Goldscheider and Drew 2007). Groundwater flow is rapid in the highly-conductive conduit system whereas it is several order of magnitude slower in the less-conductive matrix system (Goldscheider 2015). While both systems have significant storage capacities, groundwater residence time is longer in the matrix than the conduit system (Kovács et al. 2005).

Several methods including detailed site-specific speleological investigation (Ford and Williams 2007), tracer tests (Goldscheider and Drew 2007; Goldscheider and Neukum 2010), hydrograph analysis (Kovács et al. 2005; Fiorillo 2014) and model ensembles (Fandel et al. 2020) are used to characterize groundwater flow dynamics in karst systems. Aside from hydrograph analysis which usually requires only spring discharge time series data, other methods are either expensive to apply, time consuming or require more input, thus making time series a commonly applied method for karst aquifer flow analyses and modelling (Ford and Williams 2007).

Quantitative time series analysis provides a lumped attributes of an entire karst aquifer system that are rather difficult to directly measure (Kovács et al. 2005). Karst spring recession analysis still remains a vital quantitative time series analysis tool for estimating aquifer parameters and geometric properties (Fiorillo 2011). Discharge from karst springs reflects the complex interplay of conduit and matrix systems, and provides insight about the characteristics of the aquifer which sustains the spring (Kovács et al. 2005; Fiorillo 2014). This also provide essential information for flow prediction as the shape of spring hydrograph reflects variable aquifer responses to different recharge pathways (Ford and Williams 2007). Since the shape of the spring hydrograph describe in an integrated manner how different aquifer storages and processes control the spring flow (Jeannin and Sauter 1998; WMO 2008a), analysing individual recession limbs of spring hydrograph therefore offers extensive understanding into the structural, storage and behavioral dynamics of the karst system's drainage (Bonacci 1993).

Numerous studies have employed recession analyses of karst spring hydrograph to characterise karst aquifers, evaluate aquifer properties, manage groundwater resources, predict low flow and estimate baseflow parameters (Padilla et al. 1994a; Dewandel et al. 2003; Kovács et al. 2005; Fiorillo 2014). Derived or estimated recession coefficients are also important parameters in karst models for simulating rainfall-discharge (Fleury et al. 2007; Mazzilli et al. 2019) and other process-based modelling (Hartmann et al. 2013, 2014).

Unlike porous media, karst systems cannot be represented by one single storage-discharge function (Ford and Williams 2007). They comprise of multiple subsystems of interconnected conduit and matrix reservoirs, each with their own storage-discharge characteristics (Jeannin and Sauter 1998). Recession analysis models specifically developed for karst spring analysis are thus comprised of two (Mangin 1975) or more (Fiorillo 2011; Xu et al. 2018) independent storage-discharge transfer functions to describe drainage characteristics of different reservoirs and simulate recession flows. Dewandel et al. (2003) provide general

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overview and main characteristics of commonly used recession models and those specifically applied to karst systems. Separating the conduit (quickflow) and matrix (slowflow) components of karst spring recession curve is key in correctly applying and fitting the recession models. Extracting these components is done through a semi-logarithmic plot that usually reveals two or more segments. At least one of these segments, which is typically the last, represents linear reservoir drainage and it is attributed to the matrix component (Bonacci 1993; Ford and Williams 2007). However, this extraction approach is manually and subjectively applied resulting to imprecise and inconsistent estimations. The amount of time required to manually fit a straight line and identify the matrix component also makes it impractical to apply this approach to large number of hydrographs or multiple recession curves.

While a handful of automated recession extraction routines have been developed for extracting streamflow recessions (Arciniega-Esparza et al. 2017), these approaches, based on different statistical indices to detect less variable flow conditions are explicitly used to extract the baseflow recession. During baseflow, streamflow is supported by groundwater and storage reservoirs which provide a less variable flow condition. Contributions from runoff and other unregulated sources that produce high variable flow during quickflow recession are discarded by the extraction routine (Vogel and Kroll 1996; Brutsaert 2008).

However, these recession extraction routines developed for streamflow could be adapted to extract conduit and matrix flow recession of karst springs. Since these routines are developed to identify baseflow (matrix) component of streamflow (karst spring flow) recessions and discard the quickflow (conduit) component, we can modify it to identify the quickflow as well rather than discarding them. But as these routines are based on different statistical indices for identifying the baseflow regime, they perform differently and could produce differing recession parameters (Stoelzle et al. 2013; Santos et al. 2019).

The objective of this study is to develop and test a robust and objective approach to extract karst spring recession components as well as derive parameters associated with the different components of karst drainage systems. Therefore, in this study we:

• Develop automated karst recession extraction methods that can identify conduit and matrix component of karst spring recession hydrograph by adapting and modifying different baseflow recession extraction routines for streamflow.

• Estimate conduit and matrix drainages recession parameters of sample springs using the combination of different modified extraction methods and parameters optimisation approaches of karst recession model.

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• Evaluate the performance of the different combinations of modified extraction procedures and karst recession model parameters optimisation approaches by comparing the ranges and distribution of recession parameters, efficiency measures and spring characterisations.

For this study, the recession parameters are estimated by fitting the karst recession model to individual recession segments extracted by the extraction methods. Unlike master recession curve, analysis of individual recession segments allows to explicitly account for variability in the individual recession events resulting from different input (precipitation) and other initial conditions (WMO 2008b).

2 Data and Methods

To develop an automatic karst-specific recession extraction and analysis procedure that is objective and applicable to large hydrograph samples, we first explore the applicability of generic recession extraction procedures originally developed for non-karst streamflow recessions (Vogel and Kroll 1992; Brutsaert 2008; Aksoy and Wittenberg 2011). Then we analyse karst recession parameters using two-parallel drainage recession model was used to simulate recession curves (Mangin 1975). In the following subsections, we described the recession extraction and analysis model, parameters optimisation approaches, as well as the various adaptations and modifications implemented. For consistency, we use the terms 'quick flow' for the turbulent flow from highly conductive karst drainage pathways (synonymous with conduit and storm flow) and 'slow flow' for the laminar flow contribution from less conductive fissures and pores (synonymous with matrix, diffuse and base flow) (Atkinson 1977; Larson and Mylroie 2018).

2.1 Adapting streamflow methods to extract matrix and conduit recession components

We adapt three different streamflow recession methods (Vogel and Kroll 1992; Brutsaert 2008; Aksoy and Wittenberg 2011) to extract matrix and conduit recession components (Table 1), herein called recession extraction methods (REMs). Vogel and Kroll (1992) developed an automated base flow recession extraction routine for streamflow. A 3-day moving average is firstly apply to smoothing the hydrograph, and the decreasing segments of the 3-day moving average are selected as the recession hydrograph. Only segments with 10 or more consecutive days are recognised as recession candidates. To exclude surface and storm runoff influence at the beginning of recession, the first 30% of each recession segment is deleted. Additionally, the difference between two consecutive streamflow values must be ≤ 30% for the pairs to be accepted. All recession segments that satisfy these conditions are then accepted as base flow (non-influenced) recessions segment.

In order to objectively determine streamflow recession that is derived purely from a dry or low flow period, Brutsaert (2008) introduced more strict recession extraction method. For streamflow Q, during time t, the Brutsaert method eliminates data

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point with increased or zero values of *dQ/dt*, as well as points with abrupt *dQ/dt* values. To exclude data points that might be influenced by storm runoff, three data points after a positive or zero *dQ/dt* are removed; in majors events, an additional fourth data point is removed. While Brutsaert (2008) did not provide a description for a majors event, Stoelzle et al. (2013) applied the Brutsaert method in their study and defined major event as streamflow values exceeding 30% streamflow frequency. Therefore, our study uses this definition of major event from Stoelzlz et al. (2013). Furthermore, the Brutsaert method also excludes last two data points before a positive or zero *dQ/dt* and spurious data points with larger *-dQ/dt* values.

Aksoy & Wittenberg (2011) extracted the baseflow component from daily streamflow hydrograph during recession by comparing the coefficient of variation (CV) of the recession segment. All days with decreasing or equal observed flowrate observations are considered as part of the recession curve. Subsequently, a non-linear reservoir model (Eq. 1) is iteratively fitted to the recession curve until the CV is ≤ 0.1. The CV is defined as the ratio of standard deviation between observed flowrates measurements (Qs) and calculated flowrate (Qcalc) to the mean of the observed flowrates as expressed by Eq. 2. Segment of the recession curve with the CV ≤ 0.1 is selected as the real baseflow recession, otherwise excluded. Only recession curves with 5-day periods or longer are considered. If the number of days becomes less than 5 during iterative curve fitting and CV ≤ 0.1 is not achieved, such recession event is discarded (Aksoy and Wittenberg 2011).

$$\mathbf{Q_t = Q_0\left[1 + \frac{(1-b)Q_0^{1-b}}{ab}\right]^{\frac{1}{b-1}}} \qquad (1)$$

$$\mathbf{CV = \sqrt{\frac{n^2}{n-1}\frac{\sum(Q-Q_{calc})^2}{\sum(Q)^2}}} \qquad (2)$$

The three recession extraction approaches (Vogel and Kroll 1992; Brutsaert 2008; Aksoy and Wittenberg 2011) were specifically developed to extract streamflow recessions that are mainly from baseflow contribution. Thus, rule based and exclusion criteria specified by each method ensure that quick flow influences were eliminated from extracted recession segments. In karst systems concentrated rapid flow through the conduit networks constitutes the quick flow, while the contribution from slow-velocity drains through the matrix pores constitutes the slow flow (baseflow). The quick and slow flow represents flows from two different drainage structures and both contribute to karst spring recession (Fiorillo, 2014; Ford & Williams, 2007; Padilla et al., 1994).

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Adapting streamflow methods for karst spring recession analysis requires both slow and fast flow components to model matrix and conduit spring discharges, so we (i) extract spring flow recession curve based on the specific method approach, (ii) attribute part of the recession curve that satisfies the specified method's exclusion criteria as slow flow (matrix) component, and (iii) assign the remaining part that is excluded as quick flow (conduit) component. Table 1 provides an overview of the rule-based baseflow recession extraction methods and changes made in adapting them to include quickflow component of recession.

Table 1: Criteria for recession extraction methods (REMs)

	Extraction method	General Criteria	Filter	Slow flow selection	Adaptation for Quick flow selection
Vogel	Vogel and Kroll (1992)	Decreasing 3-day moving day average	First 30% days	$\frac{Q_i - Q_{i+1}}{Q_{i+1}} \leq 30\%$	First 30% days, $\frac{Q_i - Q_{i+1}}{Q_{i+1}} \geq 30\%$
Brutsaert	Brutsaert (2008)	$\frac{dQ}{dt} < 0$	First 3 or 4, and last 2 days		First 3 or 4 days
Aksoy	Aksoy and Wittenberg (2011)	$\frac{dQ}{dt} \leq 0$	-	CV ≤ 0.10	CV ≥ 0.10

2.2 Karst recession analysis model

After extraction, we apply Mangin's (1975) recession analysis model which has been widely used for estimating drainage characteristics and aquifer dynamics in fractured non-homogeneous media (Fleury et al. 2007; Liu et al. 2010; Xu et al. 2018; Schuler et al. 2020; Sivelle 2020).To analyse the extracted recessions, we use this method which considers a two-component recession curve by distinguishing between quick flow (mostly through karstic conduits) and slow flow (mostly through the fissure matrix of the carbonate rock) recessions (Figure 1). Mangin presented two equations: Eq.3 describes the linear storage-discharge relationship from the saturated zone during slowflow condition represent by the Maillet (1905) equation.

$$\boldsymbol{\phi_t = Q_{r_0}\, e^{-\alpha t}} \qquad (3)$$

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where Q_{ro} is the baseflow contribution at the beginning of recession when $t = 0$, α is the recession coefficient with a unit of T^{-1} and t is the lapsed time between discharge at any time t, Q_t and initial discharge at $t = 0$, Q_0; and Eq. 4 describes the non-linear relationship during quickflow recession from the unsaturated zone.

$$\boldsymbol{\Psi_t = q_0 \frac{1-\eta t}{1+\varepsilon t}} \qquad (4)$$

where q_0 is the difference between Q_0 and Q_{ro}, parameter η describes the infiltration rate through the unsaturated zone. The parameter is defined as $1/t_i$ for the duration of quickflow recession between $t = 0$ and $t_i = 1/\eta$. ε in T^{-1} unit describes the regulating capacity of the unsaturated zone during infiltration and characterises importance of concavity of quickflow recession (Padilla et al. 1994). The algebraic sum of Eq. 3 and 4 gives Eq. 5, which defines the discharge at time t during the recession period.

$$\boldsymbol{Q_t = \phi_t + \Psi_t} \qquad (5)$$

Since t_i is the point of intersection of slowflow and quickflow component of the recession curve and infiltration stopped when $t > t_i$ ($t > 1/\eta$), so the quickflow component ψ_t in Eq. 5 is essentially assumed to be zero at that point ($\psi t = 0$) (Ford and Williams 2007; Civita and Civita 2008). Therefore, the application of the Mangin's model require, firstly fitting the slowflow component ϕ_t, to the slowflow segment of recession curve using Eq. 3 to determine the recession coefficient α. Afterwards, Eq. 5 is then fitted to determine the η and ε parameters of the quickflow segment. However, the accuracies of Q_{ro}, t_i and the linear representativeness of the slowflow component of the recession curve is critical for the reliable estimation of recession coefficients (Ford and Williams 2007). Also the dynamic volume, V_{dyn}, which is defined as the volume of water stored in the aquifer during depletion of spring discharge is estimated with Eq. 6.

$$\boldsymbol{V_{dyn} = \frac{Q_{ro}}{\alpha}} \qquad (6)$$

Additionally, Mangin introduced five classes of karst system based on two parameters that are calculated using the recession parameters: (1) the aquifer regulation capacity, K, defined as ratio between dynamic aquifer volume, V_{dyn}, and observed volume of discharge, V_{ann}, through the spring in one hydrological year (Eq. 7);

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$$\boldsymbol{K} = \frac{V_{dyn}}{V_{ann}} \qquad (7)$$

and (2) infiltration delay, *i*, given by Eq. 8 which is calculated as the value of the quickflow recession component after two days (t =2).

$$\boldsymbol{i} = \frac{1-\eta t}{1+\varepsilon t} \qquad (8)$$

Ford and Williams (2007) provided a detailed review of karst aquifer recession analysis and application of the Mangin model.

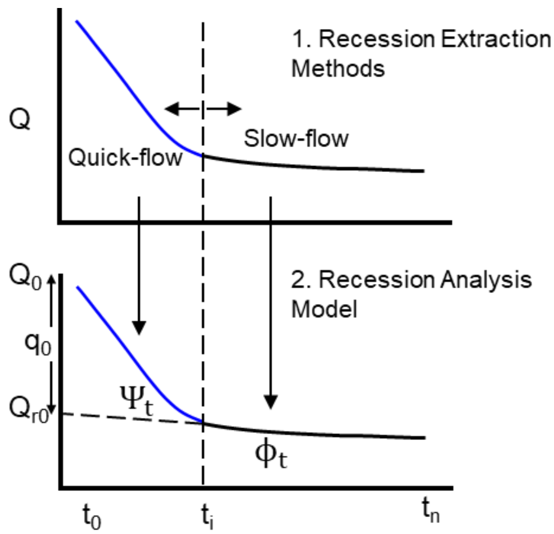

Figure 1. An illustration of karst spring recession curve showing separation into linear and non-linear components by recession extraction method and fitting appropriate components of recession analysis model.

2.3 Estimation of recession parameters

Recession parameters can be derived by: (i) considering accumulation of all extracted recession events, a so-called "master recession", and (ii) estimating multiple parameter combinations from individual recession event. In a recent study, Jachens et al., (2020) recommended avoiding the former approach as its estimated parameters do not represent average catchment responses nor their variability. For this study, the parameters are estimated for individual, automatically extracted recession events. That way, we capture variability of spring discharge across individual recharge events (Jachens et al. 2020). As mentioned in subsection 2.2, in the standard Mangin's approach, the slowflow component of the recession curve (Eq. 3) is fitted at first to determine *α*. Also, the *η* parameter of the quickflow component (Eq. 4) which is equivalent to $1/t_i$ is predetermined, meaning that quick flow abruptly ends at t_i days, which in reality is actually untrue. Hence, reliable

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determination of t_i through the extraction routines (REMs) is vital for estimation of recession parameters. These standard procedures involve with the application of Mangin's model result in less degree of freedom for parameter interaction and unrealistic abrupt ending of quick flow after t_i days. To increase the degree of freedom and assess the importance of t_i and the effect of a priori estimated η ($1/t_i$) on the Mangin's recession model, we introduced three optimization approaches which are referred to as three different parameters optimisation approaches (POAs) used in this study.

- **M1**: This follows the standard approach for applying the Mangin model as described by Padilla et al (1994) and Ford and Williams (2007). The slowflow component of the recession curve is fitted first with Eq. 3 for $t_i \leq t \leq t_n$ to determine α value while the quickflow component is asummed to be zero during this period. Afterwards, the second parameter ε is optimised by fitting the quickflow component with Eq. 5 using a predefined value of η parameter ($\eta = 1/t_i$) for the event duration between $t_0 \leq t < t_i$.

- **M2**: The conventional approach for fitting the Mangin model (M1) does not provide for independent or flexible estimation of η. The prior definition of η as $1/t_i$ rely on the accuracy of the extraction method to detect the point of inflexion t_i. This however does not give the flexibility to optimised η to a value that could provide better fit for the model. To provide for more flexible estimation of η, α parameter is determined as in M1, then Eq. 5 is fitted to the complete segment of recession curve for $t_0 \leq t \leq t_n$ to determine best values of ε and η parameters.

- **M3**: This is a very flexible approach that allows for α, ε, η and Q_{ro} values to be fitted numerically. The determination of t_i and Q_{ro} does not depend on the extraction method, rather the best fit for the parameters are obtained from optimisation process. The Mangin model (Eq. 5) is fitted to entire recession curve, which allows for absolute flexibility of t_i and robust parameters interaction during optimisation. With the model calibrated t_i ($1/\eta$), separating the quick- and slowflow segments now entirely rely on the optimisation exercise rather than extraction techniques.

For the optimisation exercise, a non-linear least squares procedure with spring discharge records was used. To avoid having negative value of conduit drainage contribution when the optimised t_i ($1/\eta$) is greater than the elapsing t value, the quick flow component, ψ_t (Eq. 4), is constrained to a minimum value of zero. Table 2 provides summary of the different optimisation approaches, parameters that were optimised as well as duration of the optimised corresponding flow component.

Table 2: Optimised recession parameters for the three different parameters optimisation approaches (POAs) of the Mangin recession analysis model.

Optim.	Optimized	Condition	Slowflow	Quickflow	Degree of

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approach	parameters		component	component	freedom
M1	α, ε	$\eta = 1/t_i$	$t_i \leq t \leq t_n$	$t_0 \leq t \leq t_i$	Less flexible
M2	α, ε, η	$\eta \neq 1/t_i$	$t_i \leq t \leq t_n$	$t_0 \leq t \leq t_n$	Intermediate
M3	α, ε, η, Q_{ro}	$\eta \neq 1/t_i$	$t_0 \leq t \leq t_n$	$t_0 \leq t \leq t_n$	Very flexible

2.4 Comparison and evaluation of REMs and POAs

The three REMs (Vogel, Brutsaert and Aksoy) are combined with the three POAs (M1, M2 and M3) of the recession model to derive slow and quick flow recession parameters of selected karst springs for a total of nine possible methods. The mean and interquartile ranges of the derived parameters are compared among different method pairs and individual recession events. Models performance is determined by calculating goodness of fit between observed spring recession discharges and ones simulated with the derived parameters using Kling Gupta Efficiency (KGE) measures (Gupta et al. 2009). The estimated recession parameters were used to identify the dynamic of the systems according to Mangin's karst system classification described in subsection 2.2. The Mangin classification scheme describes the aquifer drainage characteristics, conduit development and speleological network (Mangin 1975; El-Hakim and Bakalowicz 2007). Therefore, this is use to evaluate the representativeness of recession parameters estimated for the selected karst springs aquifer systems.

3 Test springs and data

The REMs and POAs were tested using three karst springs; Lehnbachquellen, Saivu and Qachquoch located in Austria, Switzerland and Lebanon respectively (Figure 2). The selection of these springs were based on geographical spread which covers different climate and hydrological settings, availability of discharge hydrograph in high resolution as well as literature reference on hydrological characterisation of aquifer systems drained by the spring. Daily and sub-daily spring discharge time series of the selected springs were obtained from WoKaS database (Olarinoye et al. 2020). Important characteristics of the spring hydrographs as well as the catchments in which they are sited are presented in (Table 3). The springs are sited in catchments distinguished by different climate conditions according to the Köppen-Gieger classification (Beck et al. 2018). Lehnbachquellen is sited in snow-dominated, Saivu in humid and Qachquoch is in the Mediterranean catchment. The spring discharge time series measured at a uniform time-step for each spring span between 3 and 13 years. All discharge time series were aggregated to daily temporal resolution and missing data values which were only found (<0.01%) in Lehnbachquellen spring discharge data were excluded.

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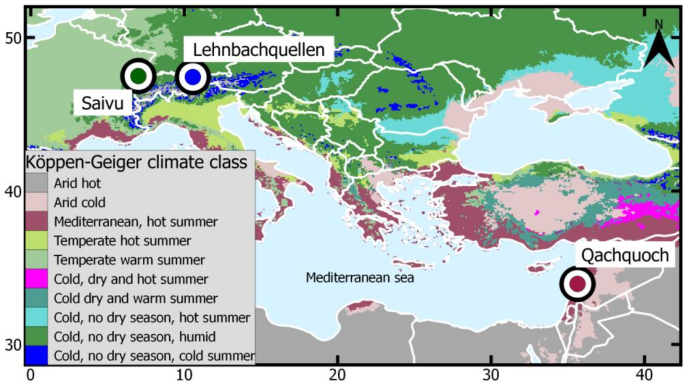

Figure 2. Map showing locations of the three test springs obtained from the WoKaS database and different Köppen-Geiger hydroclimatic classes.

Table 3. Summary of test springs site properties and characteristics of spring discharge hydrographs.

Properties	Lehnbachquellen	Saivu	Qachquoch
Climate description	Snow-dominated	Humid	Mediterranean
Spring elevation (masl)	1293	371	65
Köppen-Geiger	Cold and no dry season	Cold and humid	Mediterranean, hot summer
Temporal res.	Daily	Hourly	Sub-hourly
Length	1999-2012	1993-1995	2014-2018
Missing data	<0.01%	0	0
Mean discharge (m^3/s)	0.06	0.29	1.08
Mean precipitation (mm/y)	1396	1201	523

4 Results

4.1 Extracted recessions and performance of POAs

The adapted recession extraction methods adequately identify karst spring conduit and matrix flow components and the parameters obtained with the fitted Mangin's models produce a well satisfactory recession simulation. The combination of the three REMs (Vogel, Brutsaert and Aksoy) and three POAs (M1, M2 and M3) led to nine recession methods that were used for analysing the recession events of the three karst spring hydrographs. Only recession events >= 7 days period were considered for analysis. For each spring hydrograph, a different number of recession events are extracted by the REMs. As shown on Table 4, Vogel has the highest number of extracted recession events across all springs, followed by Brutsaert and Aksoy shows

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least ability to capture recession events of the observed spring discharges. With this, the REMs can be simply classified as permissive (Vogel), less permissive (Brutsaert) and restrictive (Aksoy).

Table 4: Recession events period extracted by the REMs for the three spring discharge hydrograph

			Number of extracted recession events		
Spring name	Location	Catchment description	Vogel	Brutsaert	Aksoy
Lehnbachquellen	Austria	Snow dominated	162	145	136
Saivu	Switzerland	Humid	30	28	13
Qachquoch	Lebanon	Mediterranean	67	63	49

Figure 3 shows how the different REMs and POAs combinations performed in simulating spring discharge during extracted recession events using KGE measures. With exclusion of the outliers, a high KGE values were achieved across all combinations, ranging between 0.72 and 1.00. More than half of all simulated events across the three springs produce a KGE >0.9 for all REM-POA pairs. However, the lowest performance in all three springs is related to POAs combined with Vogel extraction method. While there is no vivid observable pattern between the extraction methods (REMs) and recession model performance, the parameters optimisation approaches (POAs) show otherwise. A clear systematic order for the KGE median is found within the POAs: M1 < M2 < M3. This is more noticeable in the humid and Mediterranean springs, except for the Vogel-M2 combination in the humid spring that is not in the systematic order.

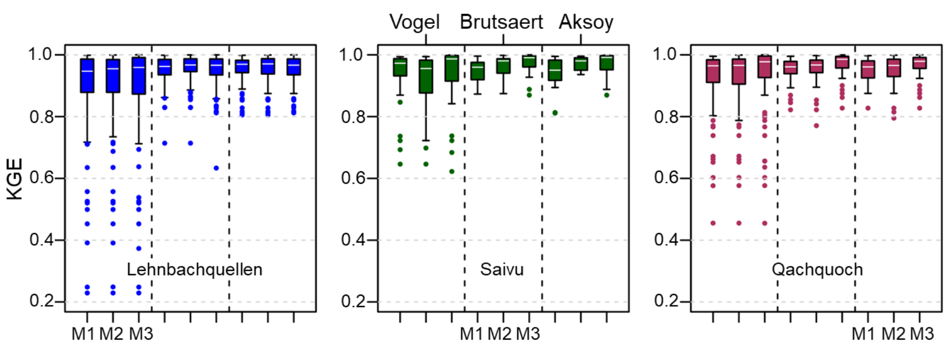

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Figure 3: Boxplot of KGE measures between observed and simulated recession events based on parameters derived from the different REMs and POAs. The boxplots represent the interquartile ranges of KGE with the median shown in white lines and outliers marked in coloured points.

4.2 Variability of recession parameters among different REM-POA combinations

Figure 4 shows the results of optimised recession parameters values with the different REM-POA pairs for each spring. These parameter sets are combinations of α, η and ε that produced the best simulation fit, that is highest KGE value for each recession event. Recession curve fitting based on the individual segment led to a large number of parameter combinations with the nine possible REM-POA pairs. Modification of REMs and POAs produce complex parameter interaction, to simplify the results, two categories of parameters were identified; (1) more consistent and less variable parameter (α); and (2) inconsistent parameter (η and ε) with higher variability. However, this does not imply that, a parameter always falls into defined category for all pairs of REM and POA.

The results in Figure 4 shows that POAs do not have a noticeable influence on the estimation of recession coefficients α. However, the REM has some impacts, which is only noticeable for Saivu and Qachquoch springs. For these springs, estimation associated with Aksoy extraction method shows less variability and gives a lower value of α. Results obtained from POAs paired Vogel and Brutsaert are within similar ranges but are slightly higher. Generally, there is relatively high consistency among REM-POA pairs in estimating α for each spring, as shown by the median and mean values. In fact, there is much higher variability in estimated α among recession events than the different REM-POA combinations. However, there is much higher consistency and lesser variability in α estimated for Lehnbachquellen compare to the other two spring locations. Also, when compare to other parameters, there is often lesser variability in estimated α among extracted events and parameters optimisation approaches.

Both REM and POA have significant influence on the estimated values of infiltration rate, η, and curve concavity, ε, parameters. Both parameters show relatively high inconsistency among the methods as well as instability within recession events. The most visible pattern from Figure 4 is that increasing degree of parameter freedom during optimisation usually result to higher estimates of η and vice-versa for parameter ε. The values of η parameter span one order of magnitude for REMs and POAs combinations across all spring locations. From the median and mean values, low estimates of η are related to pairing permissive extraction method (Vogel) with less-flexible optimisation approach (M1). Conversely, pairing the permissive extraction method with M2 and M3 which are more flexible optimisation approaches led to higher infiltration rates. Notably, a stationarity of η around $0.2d^{-1}$ is seen across all springs with Brutsaert-M1 pairs. Unexpectedly, estimation of η with the restrictive extraction method (Aksoy) generally led to higher variability especially when combined with the less-flexible optimisation approach.

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Estimation of curve concavity parameter, ε, with the different REM-POA combinations shows parameter behaviour opposite to that seen in the infiltration rate parameter. Pairing REMs with less-flexible optimisation procedure (M1) gives higher estimate of ε, yet the median and mean values derived from REM-POA pairs for each spring show some consistency. This consistency is higher for REMs paired with M2 and M3 optimisation approaches. While there are some coherency within REM-POA combinations, there is high variability in ε estimated for individual recession events. However, a significant reduction in the variability among recession events is seen with increasing restrictiveness of REM and more flexibility of POA. Overall, permissive REM and less-flexible POA result in slightly higher values and more variability in ε parameter estimates.

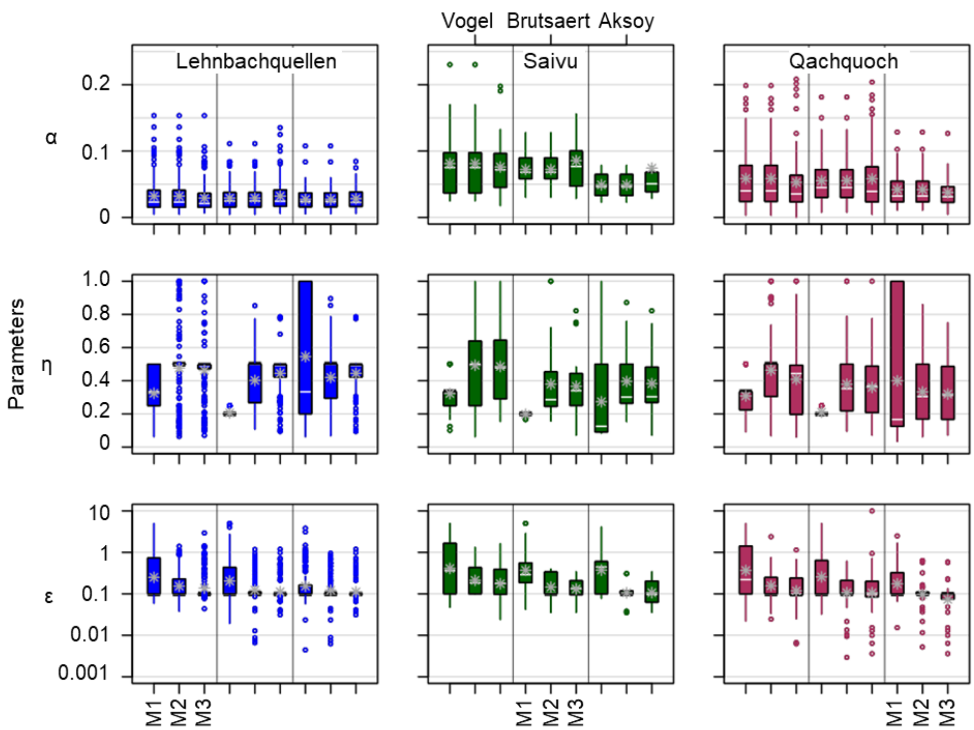

Figure 4. Distribution and variability of recession parameters α, η and ε (y-axis of ε in log scale, all units in day^{-1}) obtained by the combination of REM (Vogel, Brutsaert and Aksoy) and POA (M1, M2 and M3) for the three springs located in the different

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defined climate catchments. The boxplots represent the interquartile range, whisker lines correspond to the most extreme parameter values and outliers marked as circle with corresponding box colour.

4.3 Aquifer characterization

To evaluate the overall representativeness of estimated recession parameters based on the modified REMs and different POAs for the selected karst spring systems, we determined the drainage properties of the spring's aquifer using the parameters derived from the individual recession event. As described in subsection 2.2, retardation between infiltration and output defined by infiltration delay parameter, *i* and aquifer regulation power, *K*, were calculated for individual recession event. Figure 5 shows the grouped mean aquifer classifications as well as their standard deviations based on the per event *K* and *i* values, using the nine possible REM-POA combinations. Event-based estimated *K* and *i* values and their variability with respect to recession analysis methods are provided in the appendix (Figure A1). As shown by the standard deviation bounds of the drainage properties derived from individual recession segments in Figure 5, there is strong overlapping of calculated drainage properties and aquifer classes. However, with the calculated mean values of *K* and *i*, the three springs are identified as a distinct aquifer system. The aquifer systems are mostly distinguishable by their ability to store and regulate groundwater outflow through the springs.

With the exception of Qachquoch spring, there is high coherency for the mean *K* determined by the possible combinations of REM and POA for each springs. Conversely, methodological differences in selected REM and POA result in large variations in the estimated mean infiltration delay, *i*, among the springs. Lehnbachquellen spring located in snow-dominated catchment has a unanimous mean *K* of ca. 0.11 year and *i* values ranging from 0 to 0.4. The range covered by *i* is wide, yet most of the REM-POA combinations categorise the karst aquifer drained by Lehnbachquellen as speleologically well developed (class II) system. The only exception found was the Vogel-M1 paring, in which the system is ranked as fairly karstified (class III) (see Figure A1). Similarly, mean *K* value for the Saivu spring is also consistent across different extraction and parameter optimisation methods. The estimated mean *K* for the spring's karst system is 0.04 years while the mean infiltration delay, *i*, ranges between 0 and ca. 0.35. Unlike Lehnbachquellen, there is no predominant classification established by the different REM-POA combinations. The Saivu karst spring system is placed between very well developed (class I) and fairly karstified systems (class III). In contrast to the other two springs, there is no unanimous agreement between the combinations of REM and POA in the estimation of the mean regulation capacity, *K*, of the Qachquoch spring system. Extraction with Vogel and Brutsaert methods combined with M3 parameterisation procedure result in a significant departure from the mean *K* values calculated by other REM-POA pairs. The capacity of the Qachquoch karst spring's aquifer to withhold water within the system ranges between 0.06 and 0.11 years (range of mean *K* values). But in a similar trend to other springs, wide dispersion is also seen in the estimated mean infiltration delay, *i*, values which ranges from 0 to 0.4. Again, a decisive system class cannot be assigned, although most of the methods combination described the system as fairly karstified with retarded infiltration (class III). Classification of the aquifer system based on drainage characteristics (*K* and *i*) calculated by Brutsaert-M2 and Aksoy-M1 pairs categorized it as well-developed (class I) system (see Figure A1).

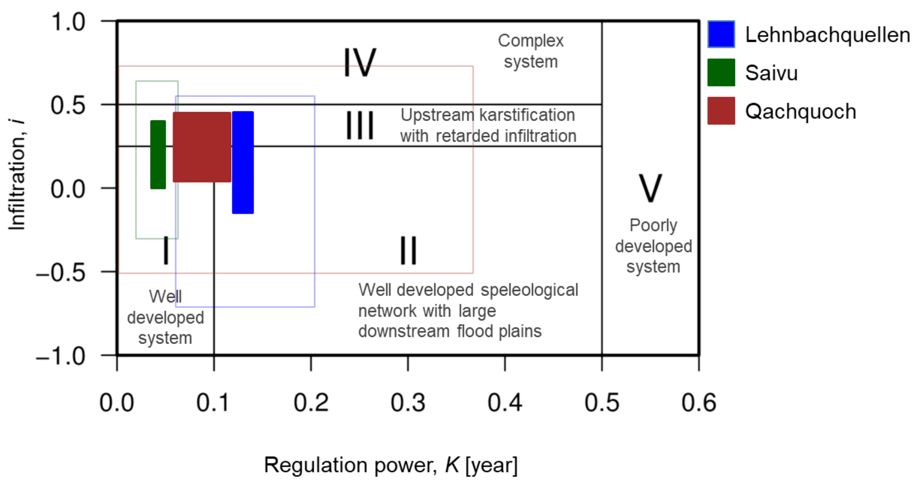

Figure 5. Karst aquifer type classification based on mean values of *K* and *i*, calculated with recession parameters estimated by the different combinations of REM and POA. Distributions of mean *K* and *i* derived from all method combinations for each spring are represented by coloured areas; areas covered by unfilled boxes are the standard deviations. Mean and standard deviations *K* and *i* from different pairs of REM and POA for each spring are plotted in Fig. A1 of the appendix.

5 Discussion

5.1 Quality of extracted recessions

With the modification of the traditional REMs, we are able to establish a completely objective approach to distinguish between slow and quick flow recession components. Furthermore, optimisation approaches (POAs) with more flexibility show better improvement over the conventional parametrisation procedure. The REMs tested uses different statistical indices to scrutinise genuine baseflow records, hence they have different level of tolerance. The ability of the extraction methods to identify recession periods from hydrograph time series depend on the level of their restrictiveness. Vogel extraction method defined by a 3-day moving average to smoothen the hydrograph and also allows for 30% increase in subsequent flowrates is more permissive than Brutsaert and Aksoy methods that strictly enforce $dQ/dt < 0$. Hence, more recession events are extracted by Vogel method. Study by Stoelzle et al. (2013) also showed the Vogel procedure to be more permissive, as it was able extract almost 50% more events than Brutsaert. Although main recession selection condition for Brutsaert and Aksoy method is

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determined by decreasing dQ/dt, constraining real baseflow recessions to discharge data points with less than 10% (CV ≤ 0.1) deviations makes the Aksoy more restrictive than Brutsaert method.

Generally, all combinations of REM-POA performed acceptably well, increasing restrictiveness of extraction method gave improved model performance. Even though restrictiveness led to better performance, this should not be a basis to out-rightly accept restrictive REM over less-restrictive one. For instance, standard removal of 3 or 4 days by Brutsaert method as stormflow-influenced period is speculative and consequently led to unrealistic stationarity in conduit flow duration, t_i, ($t_i = 1/\eta$), yet it performed better than permissive Vogel method. Although, problem of unrealistic t_i estimation inherent from Brutsaert was eliminated and general improvement in models performance was achieved by increasing parameters flexibility during optimisation. Overall, the adapted REMs and the introduced three POAs provide range of results that adequately represents the karst systems. This suggests that the modified REMs are well suited for application to karst spring recession analysis. While all REM-POA pairs are good from the model performance perspective, it will be misleading to define best pair of REM-POA base on this, without first evaluating if the estimated parameters are realistic. However, we strongly suggests avoiding the Brutsaert-M1 pair for karst recession analysis due to its stationarity problem.

5.2 Effects of different REM-POA combinations on extracted recession parameters

Methodological choices of REMs and POAs combinations have great impacts on the estimated recession parameters. The extent to which the parameters are influenced by the methods largely varies between the slow flow and quick flow recession parameters. There is relatively higher consistency and better stability among all REM-POA pairs in estimating slow flow recession parameter that describe the drainage characteristics of the matrix block within the phreatic zone. As observed by few other studies (Stoelzle et al. 2013; Santos et al. 2019) slow flow recession coefficient is more influenced by the extraction method used than the parameterisation approach, which only marginally impacts the estimated parameter. The heterogeneity of karst system results in different conduit processes being activated during recharge events, this is reflected in observed higher variability of quick flow parameters that represent the conduit drainage system. Unlike slow flow parameter, both REM and POA greatly impacted the estimation of parameters representing the conduit drainage systems.

More variability in estimated recession parameters is largely associated with analysis involving permissive extraction method, though increasing flexibility of model parameterisation often reduced the variability. Such large variability was also reported by Santos et al. (2019) who suggested avoiding combining the permissive extraction method with individual recession segment analysis to estimate recession parameters. Aside showing higher variability, permissive recession extraction tends to produce higher estimate of slow flow recession coefficients. However, as seen from Lehnbachquellen spring in snow-dominated catchment where outflow is generously sustained throughout the year without seasonality of baseflow regimes, all REMs produced very similar estimate of baseflow coefficients with narrow variability. The more variability and over-estimation of slow flow recession coefficients by permissive and less-permissive REMs (Vogel and Brutsaert) as early mentioned is specifically noticeable only for springs in the humid or mediterranean catchments. This observation suggests that the impact of methodological difference of various REMs associated with estimated baseflow parameters might only be pronounced in catchments with hydrological seasonality.

Although the combination of REM and POA affects the estimation of conduit drainage characteristics, the effect of the POA tends to be more pronounced. Increasing degree of parameter freedom during optimisation with the different POAs formulations often result to significant reduction in parameters variability. This is also accompanied by either over- or under-estimation of conduit drainage parameters. The more flexible parameterisation approaches (M2 and M3) generally lead to higher the infiltration rates through the unsaturated zone. Infiltration rate is predetermined ($\eta = 1/t_i$) in the original parameterisation procedure of Mangin's model (M1) which restricts fitting the quick flow recession curve only to the optimisation of the regulating capacity, ε. To compensate the inflexibility due to predetermined infiltration rate, the regulation capacities of the reservoir estimated with M1 parameterisation procedure are higher and more varied. By means of excluding a fixed number of days (3-4) as influenced stage of recession, Brutsaert paired with M1 also leads to stationarity in the estimated infiltration rates. This makes it an unsuitable combination, especially with long recession period. Santos et al. (2019) found analysis with Brutsaert method to be more robust and appropriate for short recession samples.

Despite the impacts of methodological choices on the uncertainty of estimated recession parameters, variability among events exceed the variability among methods. These high variabilities are attributed to different lengths of extracted recession events, differences in karstic processes such as recharge and infiltration that are activated within the unsaturated zone for each event. Even though karst systems are very heterogeneous and it is important to capture the impacts of the variable karstic processes through analysis of individual recession segment, the high uncertainty among events make it difficult to define set of representative recession parameters. This uncertainty found with per event analysis can be reduced by considering different categories of recession lengths that represent short and long recession periods; estimated parameters can be compared to assess the system's dynamics. Another way of coping with this problem is to consider master recession curve analysis which is often criticize for its inability to adequately represent storage variability (Kresic and Bonacci 2010; Gregor and Malík 2012; Kovacs 2021). However, since per event analysis is useful for better understanding of the system's dynamic, defining a systematic approach to quantify parameters uncertainty will help to increase the confidence of individual recession segment analysis.

5.3 How realistic are adapted REM-POA for karst system analysis?

Interestingly, there is a strong coherence among possible pairs of REM and POA in determining the average regulation capacity of the aquifers drained by the springs. The determination of the dynamic volume used in calculating the regulation capacity is based on baseflow recession coefficients (Eq. 6). However, the effect of the extraction methods on baseflow recession coefficient (see previous sub-section) was not reflected in the determination of dynamic volume and regulation power. This effect that could have been transmitted was cancelled by different initial baseflow component, Q_{ro},estimated by the methods. In one study (Grasso & Jeannin 1994), the authors found regulation power, K, to be more stable for various years and events. These findings do not agree with our analysis, the outcomes of which show a large variability among K for different events, most significantly in the snow-dominated catchment (Figure A1 in Appendix). Regulation power is analogous to memory effect, periodic water release from an external snow storage that is not captured within the saturated zone in real time makes K to fluctuate more in snow-dominated catchment.

Infiltration delay, i, is strongly dependent on recharge type contribution as well as catchment size (Jeannin and Sauter 1998). Pairing extraction method that does not explicitly separately the spring discharge slow and fast recharge path (Brutsaert) with less flexible parameterisation procedure (M1) result in overestimation of infiltration delay. Aside this obvious bias with Brutsaert-M1 pairs, regardless of what extraction method (permissive or restrictive) is paired with parametrisation procedure, the complex interplay of REM and POA result in a compensation phenomenon; whereby infiltration rate, η, is compensated by recession concavity parameter, ε, and vice versa. Since the infiltration delay, is defined by these parameters, it is difficult to explicitly infer specific effect of REM and POA on infiltration delay.

The northern Alps karst system where the Lehnbachquellen spring is located has been defined as well karstified highly permeable unit interlayered with less permeable Flysch formation (Goldscheider 2005; Chen et al. 2018). This is very consistent with the classification we achieved (class II and III). Perrin, Jeannin, & Zwahlen (2003) described Saivu spring system as a well-developed karstic network, majority of the methods pair used in this study place this spring in class 1, therefore coherently agreeing with the authors description. From our analysis, Qachquoch spring is classified as medium karstified system by most method combinations. However recent study by Dubois et al. (2020) categorise the system as poorly karstified with a very large regulation capacity. Meanwhile, if we also consider two standard deviation distances from the calculate mean K values, a regulation capacity >0.5 will be obtained and the system will be equally classified as poorly karstified by REM-POA pairs used.

Given that existing common karst spring recession extraction method involves manual procedure and subjectively determined duration of conduit infiltration, alternative faster, automated and objective approach is very useful. From our analysis, resulting parameters of extracted recession segments are within reasonable ranges and derived systems classification correspond to those found in literatures. The good performance recorded between simulated and observed flowrates during recession events attest to the potential transferability of traditional extraction methods to karst systems. However, this good performance does not

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necessarily translate to reliable parameter estimates. It is therefore important to choose REM methods that gives reasonable parameters especially when paired with a less flexible optimisation approach. Furthermore, with prior knowledge of the spring system, parameters ranges can be reasonably constrained during optimisation to achieve a more representative optimum parameters.

6 Conclusions

The application of karst spring hydrographs recession analysis is very broad, including estimation of storage capacity (Fleury et al. 2007), describing discharge of unsaturated zone (Amit et al. 2002; Mudarra and Andreo 2011) as well as systems classification (El-Hakim and Bakalowicz 2007). Most often manual recession extraction is used and the high subjectivity of the approach introduces bias to estimated parameters. For the first time in literatures, this study explores the applicability of automated traditional recession extraction methods (REMs) originally developed for slow flow (baseflow) recession by adapting them to also identify quick flow flow recessions. We fit individual extracted recession segments with Mangin's recession model to determine the conduit and matrix drainages recession characteristics. We introduce new parameters optimisation approaches (POAs) different from the conventional procedure to increase degree of freedom of parameter interaction.

The three traditional REMs adapted in this study performed differently, depending on how permissive or constraining the method was, more or less recession periods were identified. The interaction between REMs and POAs is complex and has various degree of impacts on the derived recession parameters. We found that higher variability is associated with permissive extraction method but this variability is largely reduced with an increased degree of freedom during optimisation. Unlike with baseflow conditions, where estimated recession parameters are a bit consistent among REMs and POAs, there is high variability for the estimated conduit recession parameter. However, parameters variability among individual recession events exceed the variability resulting from different combinations of REM and POA. The original REMs were developed based on specific catchment features that control recession (Stoelzle et al. 2013), so they quantify recession extraction differently. As suggested in several recession studies (Stoelzle et al. 2013; Santos et al. 2019) and also done in this study, we recommend trying different combinations of REMs-POAs for more robust recession analysis.

The adapted traditional REMs tested produced reasonable results with regard performance and derived parameters. Application of the methods is quick and fully objective, therefore they proved to be a good alternative to manual recession extraction. This will be useful for the comparative analysis of karst spring systems using large number of hydrographs which would otherwise be a difficult exercise to execute. Although analysis with individual recession events is highly uncertain, we provide alternative for reducing or quantifying the uncertainties to improve the robustness of the analysis.

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Appendix

Table A1. Spearman's ranked correlation coefficients, ρ, between the recession parameters and length of extracted recession events.

	vog_M1	vog_M2	vog_M3	brut_M1	brut_M2	brut_M3	akw_M1	akw_M2	akw_M3
?	-0.19673	-0.19673	-0.08805	-0.0918	-0.09191	-0.1215	-0.05995	-0.06002	0.045158
?	-0.9722	-0.55059	-0.31179	-0.14328	-0.47121	-0.29442	-0.62963	-0.63559	-0.35843
?	0.04843	0.05108	-0.0257	-0.16752	-0.0788	-0.03305	0.106504	-0.10938	-0.08331

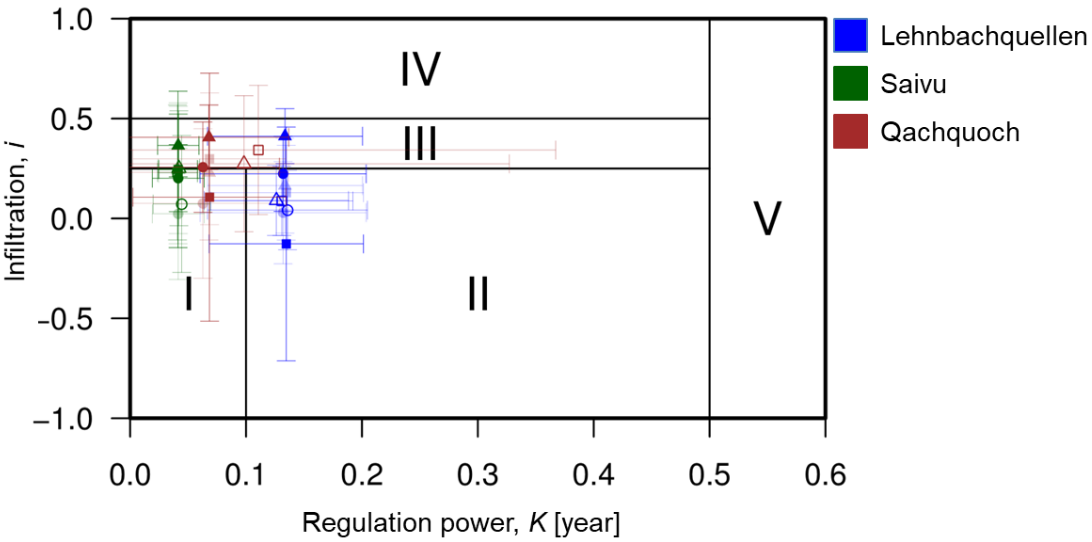

Figure A1. Karst aquifer classification according to the different combinations of REMs and POAs. The shapes circle, triangle and square represents (Vogel, Brutsaert and Aksoy) extraction methods. Different colour fills relate to parameterisation procedures; solid colour for M1, transparent for M2 and no-fill for M3.