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Recession analysis 42 years later - work yet to be done

Elizabeth R. Jachens[1], David E. Rupp[2], Clément Roques[3], John S. Selker[1]

[1]Department of Biological and Ecologic Engineering, Oregon State University, Corvallis, OR, 97330, USA
[2]Oregon Climate Change Research Institute, College of Earth, Oceanic and Atmospheric Sciences, Oregon State University, Corvallis, OR, 97330, USA
[3]Department of Earth Sciences, ETH Zurich, 8092 Zürich, Switzerland

Correspondence to: Elizabeth R. Jachens (jachense@oregonstate.edu)

Abstract. Recession analysis is a classical method employed in hydrology to assess watersheds' hydrological properties by means of the receding limb of a hydrograph, frequently expressed as the rate of change in discharge (*dQ/dt*) against discharge (*Q*). This relationship is often assumed to take the form of a power law $-dQ/dt=aQ^b$ where *a* and *b* are recession parameters. Recent studies have highlighted major differences in the estimation of the recession parameters depending on the method, casting doubt on our ability to properly evaluate and compare hydrological properties across watersheds based on recession analysis. This study shows that estimation based on collective recessions as an average watershed response is strongly affected by the distributions of event inter-arrival time, magnitudes, and antecedent conditions, implying that the resulting recession parameters do not represent watershed properties as much as they represent the climate. The clear conclusion is that proper evaluation of watershed properties using recession analysis requires considering individual recession events.

1 Introduction

Accurate estimations of watershed-scale hydrological processes involved in the critical zone is urgent in a global change perspective. Streamflow recession analysis has been routinely used for about half a century to assess a watershed properties and their vulnerability to climatic and anthropogenic factors (Brooks et al., 2015; Buttle, 2018; Fan et al., 2019). Recession analysis is commonly presented by plotting the time rate of change in discharge *-dQ/dt* as a function of discharge *Q* in a bilogarithmic plot. Theory predicts a power law relationship with parameters that can be expressed by the slope *b* and intercept log(*a*) in log-transformed space: i.e. $log(-dQ/dt) = b \cdot log(Q) + log(a)$. However, it has been recognized for more than 15 years that the accuracy in the estimation of those parameters is highly sensitive to the methods used (Chen et al., 2018; Dralle et al., 2017; Roques et al., 2017; Rupp & Selker, 2006; Santos et al., 2019; Stoelzle et al., 2013).

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The two primary categories of parameter estimation methods are: 1) the collection of all *-dQ/dt vs Q* points, hereafter referred to as the "point cloud", to describe as the average watershed behavior over time; and 2) using individual recessions to look at the variability of a watershed's response (Roques et al., 2017). In recent literature, there has been a shift away from using collective recessions to evaluate recession parameters in favor of using individual recessions (Karlsen et al., 2018; Roques et al., 2017; Santos et al., 2019). These studies have not discredited the use of the point cloud, but rather suggest the individual recessions as a more accurate alternative. However, the use of collective recessions remains common (Brutsaert, 2008; Ploum et al., 2019; Sánchez-Murillo et al., 2015; Stewart, 2015; Stoelzle et al., 2013).

When recession analysis was first proposed in 1977, recession behavior was identified by fitting the lower envelope of the point cloud by assuming small values represent drought flow and anything larger has quick flow contributions (Brutsaert & Lopez, 1998; Brutsaert & Nieber, 1977). The lower envelope method was shown to be subject to artifacts arising from instrument precision (Rupp and Selker, 2006; Troch et al., 1993). An alternative fitting method wherein *b* was estimated as the best linear fit to the point cloud was introduced by Vogel and Kroll (1992) as the central tendency (Vogel and Kroll, 1992). The central tendency method was adapted by Kirchner (2009) to address the undue weight of highly uncertain extreme points. Kirchner (2009) instead suggested fitting a polynomial function to average bins of the cloud data (Kirchner, 2009). All of these point cloud fitting approaches fundamentally treat each computation of *dQ/dt* and *Q* as reflecting a single average underlying curve, effectively ignoring the variability of individual events. The variability between events may include but not limited to, event recharge magnitude, duration of the recession event, spatial distribution of the event within the watershed, and the flow superposition from previous events.

The variability in watershed response to individual events can be depicted by looking specifically at individual recession events. Authors have observed that individual recessions had greater *b* than did the point cloud (Biswal and Marani, 2010; McMillan et al., 2011; Mutzner et al., 2013; Shaw and Riha, 2012). Consistent with previous literature, we have also observed individual recessions that have a larger *b* than the point cloud fit across watersheds in the Oregon Cascades. To serve as example we present a recession analysis plot in Figure 1 for the Lookout Creek discharge data (station USGS# 14161500) (USGS, 2019). It is striking to see that values of *b* for individual recession events tend to be significantly larger than *b* for the point cloud particularly for those at lower discharges. In this example, individual event selection criteria include recessions lasting longer than 5 days, starting 1 day after the peak to exclude the influence of overland flow, and ending at the following precipitation event. The *b* parameter estimated using point cloud analysis (binning average method) is smaller $b = 1.5$ compared to median individual $b = 2.8$, with 50% of individual recessions taking values from 2.0 to 4.7 (standard deviation = 4.2). The variability of individual recessions seems to suggest that hydrology of the individual events influence the individual recession curves.

For a given discharge range, there appear to be multiple individual recessions that are horizontally offset but appear to conserve the parameter *b*, whereas *a* is not conserved. The offset of individual recession events suggests that antecedent conditions may

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influence recession analysis coefficients and thus the point cloud may only represent the variability of individual recessions and not represent an average behavior (e.g. Rupp et al., 2009). If the point cloud is a result of individual recessions being offset by conditions, the point cloud should be considered an artifact instead of the average behavior representations. If true, recession parameters should be evaluated using the median parameters from individual recession analysis along with their variability to describe watershed. Being able to accurately describe watershed hydrologic properties is crucial for climate vulnerability studies (Berghuijs et al., 2016; Yeh and Huang, 2019).

[Insert Fig. 1]

This paper explores the source of the offset on individual recessions. Using a time-series of synthetic hydrographs with superimposed recessions of a known shape, we compare different methods for estimating the recession analysis parameters and the sensitivity to the method on the frequency and magnitude of events that make up the hydrograph. We are particularly concerned with how individual recessions collectively create the point cloud. We illustrate why the point cloud in recession analysis plots is an artifact and thus any parameter estimated from it is misleading.

2 Methods

The section presents methods for: 1) the comparison between four fitting methods for parameter estimation applied to a discharge time series for Lookout Creek, and 2) the definition of three synthetic hydrographs.

2.1 Parameter Estimation Fitting Methods

To compare parameter estimation methods and the dependency on the fitting method, first the definition of the transition from early to late-time was defined. In an attempt to reduce the subjectivity of distinguishing late-time from early-time, the breakpoint in discharge separating early from late-time behavior was optimized to best represent the analytical solutions. By separating the data into two subgroups, either smaller or larger than a defined breakpoint discharge, the best fit line was determined for each subgroup. The location of the breakpoint is defined so the error between the observed ratio of b for the two subgroups and the theatrical ratio (b=3 for early and 1.5 for late give a ratio of 2) is minimized, theoretically defining the subgroup above the breakpoint as early-time and the subgroup below the breakpoint at late-time.

In order to compare recession analysis parameters between methods, four fitting methods were evaluated: lower envelope (LE), central tendency method (CT), binning average (BA), and the median of individual recessions (MI). Recession parameters for all methods were determined by linear fitting in bi-logarithmic space for consistency across methods. For the LE method, a defined b of 3 and 1.5 for early and late-time respectively where a is fit such that 5% of points are left below the lower envelope (Troch et al., 1993). For the CT method, the fit included all $-dQ/dt$ vs Q points unweighted. For the BA method,

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bins spanned at least 1% of the logarithmic range, and a linear fit was applied to the bins based on the inverse-variance weighting. For the MI method, parameter estimation for individual recessions was performed and the median for *a* and *b* value were determined independently from all individual recessions. In all cases, the time derivative *-dQ/dt* was computed using the Exponential Time Step method (ETS) proposed by Roques et al. (2017).

2.2 Synthetic Hydrograph Methods

This paper makes use of synthetic hydrographs to explore factors that change *b* for individual recession events as well as the inter-arrival times of individual events that create the point cloud. The specifications of the synthetic hydrograph were chosen to explore the effects of the magnitudes and frequency of recharge events on the recession analysis parameters from collective vs individual recessions.

The falling limb of the hydrograph is assumed to follow a power law following Eq. (1) (Dewandel et al., 2003; Drogue, 1972; Rupp and Woods, 2008):

$$Q(t) = Q_o \cdot \left(\frac{t}{t_o} + 1\right)^{-w}, \quad (1)$$

where Q is the discharge, Q_o the initial discharge prior recession at t=0, t is the time in days since the recession started, t_o is the characteristic timescale, and w is the dimensionless power law decay exponent. The characteristic timescale is assumed to be 45 days and constant between individual recessions (Brutsaert, 2008). By maintaining a constant characteristic timescale the result is a hysteretic dQ/dt vs. Q relationship, in contrast to constant a value which produces a single non-hysteric relationship. Consequentially, a is variable and equal to $-w/(t_o Q_o^{1/w})$.

We compared three hypothetical cases with different hydrologic controls (Table 1). This design allowed us to specifically examine hydrologic controls in order to assess their influences on individual recessions. We can also determine the influence of parameter estimation for individual recessions and the point cloud. The hydrologic controls we looked at were the inter-arrival time and magnitude of recharge events and antecedent conditions controlled by the falling limb *w* control the distribution of individual recession analysis events and thus the point cloud. The inter-arrival times of events are distributed log-normally (Cases 1 & 3) or uniformly (Case 2). Event magnitudes are either distributed log-normally (Cases 1 & 3) or all of the same magnitude (Case 2). Events are either independent of antecedent conditions (Case 1), or events are superimposed on antecedent conditions (Cases 2 & 3) (Table 1 and Fig. 2). As a result, Case 1 looks specifically at a time series events where the falling limb of each event maintains the same decay constant, and the effects of having no antecedent baseflow influence on streamflow. By including baseflow to Case 2 but maintaining equal inter-arrival times and event magnitudes, we look specifically at the effect of antecedent conditions on individual recessions and the point cloud. Case 3 combines the distribution of event inter-arrival times and magnitudes of Case 1 with the baseflow conditions of Case 2, best representing the variability

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and inter-arrival times of individual recession events seen in Fig. 1 for data from Lookout Creek. Each case will address how the controls on the hydrograph affect the recession analysis plot, estimated by *a* and *b*.

[Insert Fig. 2]

[Insert Table 1]

After defining the hydrograph, recession extraction and parameter estimation were performed. Because events are based on a synthetic hydrograph, recession extraction was based on the individually defined events that make up the hydrograph. The beginning of the recession was defined as the peak in discharge because no potential influence of overland flows exist. Events of any length were included with the end of the recession defined as the time step before the next chronological peak. The exponential time step method was used for derivative calculation.

3 Methods

3.1 Parameter Estimation Fitting Results

LE, CT, and BA all fit the point cloud and all result in different estimations of *a* and *b* evident when applied to the observed streamflow for Lookout Creek with early-time values for *a* and *b* resulting in estimates that are 50% larger for LE than BA (Fig.3 and Table 2). Furthermore, parameter estimation is sensitive to the fitting method using the point cloud or individual recessions, notably for the late-time b value which is used for climate sensitivity analysis where *b* for MI is 6x greater for the estimation compared to CT (Table 2). The CT and BA methods are fairly consistent with each other for both early and late-time, with BA resulting in smaller *a* values than CT. The pre-defined theoretical b values for the LE appear to provide poor fits for the point cloud. Using the MI method, the *b* value is larger than any other method for both early and late-time. Hereafter and for the synthetic hydrographs, we use the binning average method (BA) and the median individual recessions (MI) to compare between the point cloud and individual recessions, respectively, for parameter estimation for the synthetic hydrographs presented.

[Insert Fig. 3]

[Insert Table 2]

3.2 Synthetic Hydrograph Results

The falling limb recession for all three cases is defined using $w=0.7$ as the dimensionless decay constant related to *b* by $w=1/(b-1)$. The expected value of *b* is 2.4 given this decay constant, which falls within the range of the median individual *b* values of

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2.0 by Biswal and Marani (2010), 2.1 by both Shaw and Riha (2012) and Roques et al. (2017), and the median individual *b* of 2.8 for Lookout Creek in Figure 1.

The *b* values and the offset of individual recessions resulting from Eq. 1 are highly sensitive to the magnitude of the decay constant chosen, *w*. Decreasing *w* would result in larger values of *b* while also increasing the offset between individual recessions, resulting in a larger range of *a* values and a more scattered point cloud. In contrast, as *w* approaches infinity, the offset is minimized and *b* goes to 1, representing in an exponential falling limb recession (Rupp and Woods, 2008). In this special case, the recession analysis plot of the individual recessions all plot on the same $b=1$ with constant *a* (i.e., there is no offset among individual recessions lines). While b=1 is interpreted as a linear reservoir according to traditional theory and is a convenience often assumed, yet this result suggests that a condition where b=1 would not be consistent with a point cloud, except to the degree at which observation error introduce noise into the recession hydrograph. In summary, the more linear the response is (the closer *b* is to 1), the smaller the offset, whereas the more non-linear the response (the larger the *b*), the greater the offset will be and thus the worse the parameter estimation from the point cloud will be.

The 3 subsequent cases using synthetic hydrographs are intended to highlight the offset of the individual recession curves, using an underlying decay constant of w=0.7 that is sensitive enough to showcase the offset of individual recessions but still providing a reasonable recession analysis plot. Case 1 uses events with a constant *w* across the hydrograph, while Case 2 & 3 to include superposition of an underlying event with a constant *w* and the antecedent flows which results in a less negative effective decay constant resulting in an increased *b*.

Due to the nature of the synthetic hydrograph, the omission of noise in the data results in discrete individual recessions. Bins from BA often contained just a few points with very low variance and thus an infinite weight. This would rarely be the case using real data. Consequentially, we do not use inverse-variance weighting for the synthetic cases to avoid outlier bins with low variance. Instead, a direct linear fit on the log bins without weights was performed, which is not suggested to be applied to real datasets.

3.2.1 Case 1

Recession analysis of a hydrograph with log-normally distributed event inter-arrival times and peak discharge with a constant falling limb decay constant (no baseflow represented) results in individual recession events with the same *b*, horizontally shifted based on the initial discharge (Figure 4). For this case, the peak flow of the event is the only cause variability in the recession parameter *a*. The variable event magnitudes result in individual events located over a range of ln(Q) values. Of interest, if the same flow magnitude was preserved for each event, each individual recession would plot on top of one another creating a single line without a point cloud. The variable event inter-arrival times change the duration of an event, with longer events occurring over a greater range on the y-axis. Even in this simple hydrograph representation, parallel individual

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recessions are present and b of the point cloud is significantly less than the median individual b. Furthermore, the median individual b is equal to the expected b (2.4) because each recession t has the same shape. By only considering an event without antecedent conditions, individual recessions maintain a value of b while a is variable.

[Insert Fig. 4]

3.2.1 Case 2

The addition of superposition accounts for the effects of antecedent baseflow. The superposition of the events changes the effective w of the falling limb of the hydrograph as the event recession is added to the antecedent events, resulting in variable b in the recession analysis plot (Figure 5). Superposition results in a larger b than what would arise from non-superposition. Steeper recessions (higher b) are associated with events with higher baseflow contribution given the same addition of flow. By including antecedent flow conditions, neither a nor b is preserved between individual recessions.

[Insert Fig. 5]

3.2.1 Case 3

A hydrograph more representative of real-world conditions includes variable inter-arrival times and event magnitudes from Case 1 and baseflow antecedent conditions from Case 2. These complexities result in a recession plot where the individual recessions represent the variability in watershed response represented by the hydrograph (Figure 6), where a and b are different between individual recessions. As with Case 1 and 2, the median individual b is greater than the point cloud b.

[Insert Fig. 6]

4 Discussion and Conclusions

In the 42 years since Brutsaert and Nieber (1977) proposed their recession analysis, it has provided a seemingly simple analytical method for estimating basin-scale hydrologic properties. However, recent studies have highlighted the sensitivity of parameter estimation to the fitting method used and the influence on the interpretation for average watershed behavior. This paper explores the effect of the distribution of individual recessions on parameter estimation and compares that to the parameter estimation for collective recessions. We hypothesize that the underlying hydrology controls the distribution of individual recessions. Using three case studies of synthetic hydrographs, we compare the effects of event inter-arrival time, magnitude, and antecedent conditions on the distribution of individual recession events that together comprise the collective recessions.

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We conclude that recession analysis performed on collective recessions does not capture average watershed behavior, regardless of the fitting method used with the collective recessions. The frequency between events creates different event lengths that span different ranges of Q. The point cloud is an artifact of the variability of the individual recessions, including the event inter-arrival times and distribution of magnitudes. Individual recessions with the same b can be produced by the same falling limb of the hydrograph at different ranges of initial discharges (Case 1), variability of b for individual recessions can be produced by superimposing events on antecedent flow conditions (Case 2), and different recession event lengths with different b's can be produced by including variable event inter-arrival times and magnitudes (Case 3). In all three hydrograph representations, the median individual recession b is significantly greater than b from the point cloud. The point cloud does not represent the average watershed behavior that it has been claimed to represent. In contrast, individual recession analysis provides insights into the average and variability of watershed responses which is highly dependent on the memory effect of the watershed. The variability in individual responses gives insight into watershed heterogeneity. However, the hydrologic controls need to be further investigated as accurate predictions baseflow predictions require both the average and variability in watershed behavior.

While the mean individual recessions in Case 1 are representative of the underlying events, that is not true when the underlying recession are superimposed on the antecedent flows in Case 2 & 3. This superposition of events results in a range of individual recession b's often observed in the literature, thus it appears that the superposition of events represents the watershed behavior. A first approximation could be using linear superposition of individual events on the antecedent baseflow to back out an underlying recession curve. This underlying recession curve would be a master recession that describes the watershed's underlying hydrology controlling the falling limb of the hydrograph in order to predict watershed recession behavior based on streamflow. However, as many watersheds have unconfined aquifers, the superposition may be nonlinear and instead follow the sum of the squares. The methods employed for recession analysis certainly require more attention: Correct methods are critical to understanding the underlying hydrology and thus the interpretation of a watershed's vulnerability to climate change.

While the underlying hydrology that controls individual recessions remains widely uncertain, being able to deconvolve these controls is important to assess the vulnerability of a river system to climate change. The parameter estimation for recession analysis may be vastly different based on the method employed, and thus having indirect impacts of misinterpretation of hydrological properties and predictions within the critical zone. When using the point cloud, the smaller recession analysis b at late-time is interpreted as a more vulnerable watershed to drought and the accompanying larger a indicates a flow that will continue to decline. However, the median of the individual recessions at late-time better represents the watershed's response with a larger b and smaller a indicating less drought vulnerability compared to the point cloud. Previously, the interpretation of groundwater systems to conductivity and flow length based on the point cloud may be a product of event organization, which could explain why these trends have been difficult to synthesize into larger predictive behaviors. With the point cloud b being smaller than the median individual b and a is larger, which for climate assessment and watershed vulnerability

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evaluation the point cloud will produce more dire conclusions while the individual recessions suggest a more stable flow regime for the watershed. Consequently, the parameter estimation method has a huge impact in the estimation of baseflow and has consequences for the prediction of critical zone processes.

A strength of the critical zone community is the ability to create a global analysis by comparing across studies (Brooks et al., 2015; Fan et al., 2019). However, a lack of consensus for a standard method for recession analysis procedures exists and thus inhibits recession analysis studies from being widely compared. If streamflow analysis is to be included in a global analysis, results need to be comparable across scales and observatories. There is a need for a common method employed to compare the average and variability in watershed responses. We suggest that the use of collective recession analysis should be avoided in favor of individual recession analysis as the standard to describe the average and variability in watershed response.

Code and Data Availability

Streamflow record for Lookout Creek is freely available from the USGS website. Source code for the exponential time-step method is available by request (Roques et al., 2017). Randomly generated log-normal event magnitudes and inter-arrival times presented in this paper for Cases 1 & 3 are available at: http://www.hydroshare.org/resource/e3c159631acd470cbeef5fa1abe0142e. Respective codes can be obtained from the corresponding author.

Author Contribution

Elizabeth R. Jachens, David. E. Rupp, and John S. Selker were involved in conceptualization. Elizabeth R. Jachens and Clément Roques developed the methodology and performed the analysis. Elizabeth R. Jachens prepared the manuscript with contributions from all co-authors.

Competing Interests

The authors declare that they have no conflict of interest.

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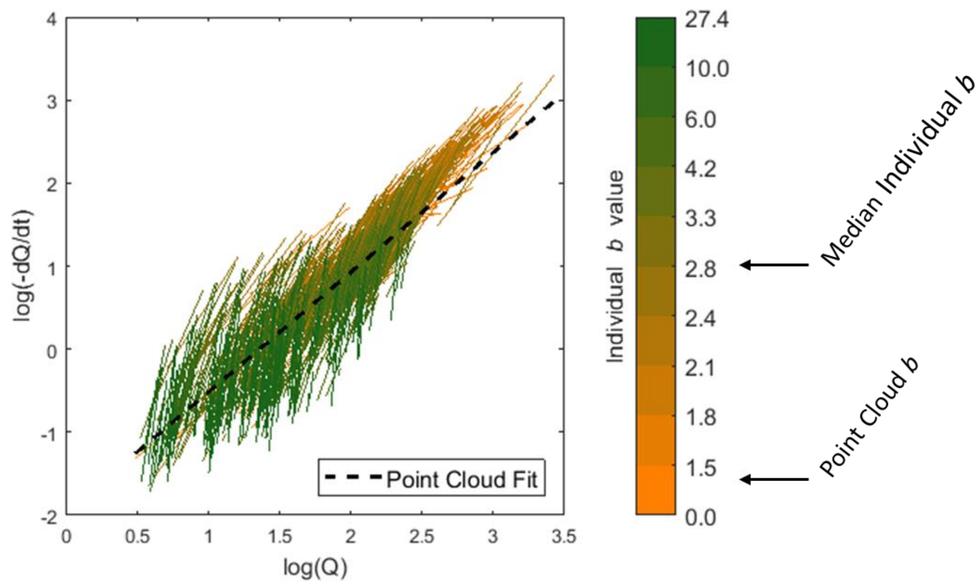

Figure 1. Recession analysis plot in log-log space for Lookout Creek (USGS# 14161500). Individual recession fits are displayed with color scale differencing by values following a discretization according to decile groups. This discretization allows the description of the organization of individual recessions where recessions with similar *b*'s that appear to be horizontally offset. The point cloud has b = 1.4 (binning average shown as black dotted line) compared to b = 2.8 for the median individual recession.

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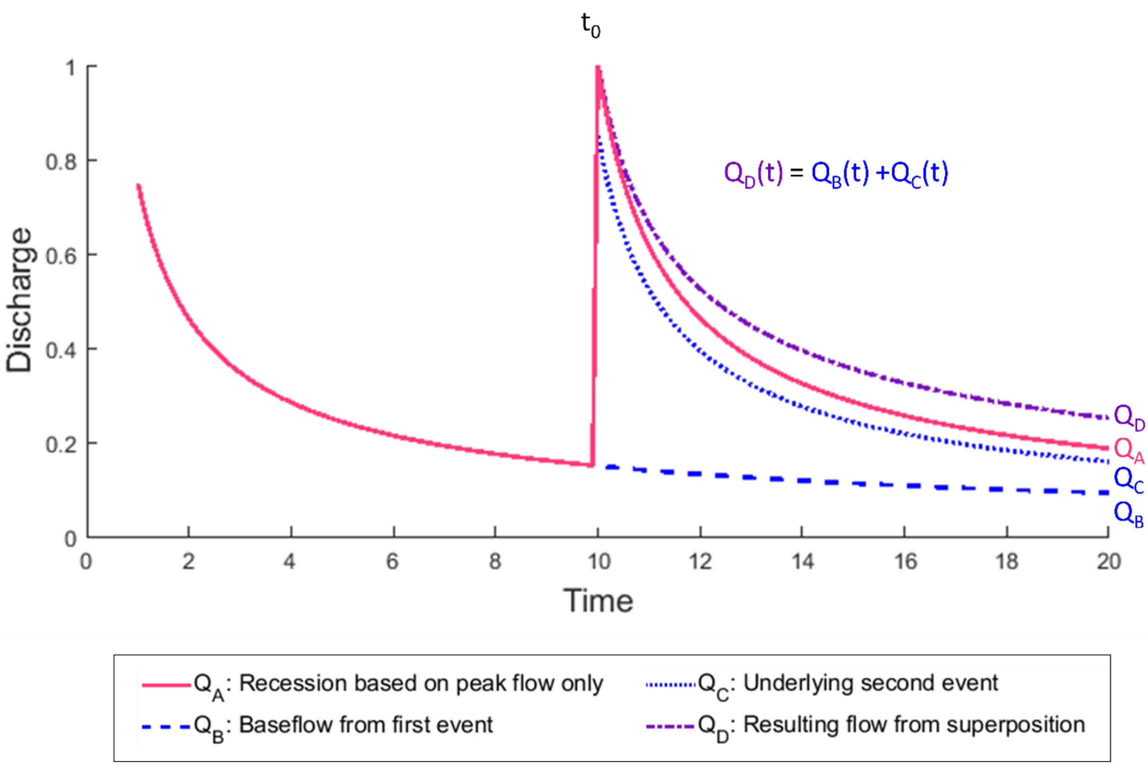

Figure 2. Conceptual model of identical recession events only dependent on the initial flow (Q_A representing Case 1) and superposition of events to include antecedent conditions (summation of the blue dotted (Q_C) and dashed line (Q_B) resulting in the superposition of the flow in the purple dash-dot line (Q_D representing Case 2&3)). By superimposing the antecedent flows (Q_B) on the underlying event (Q_C), the effective falling limb (Q_D) is less steep than the non-superimposed falling limb (Q_A).

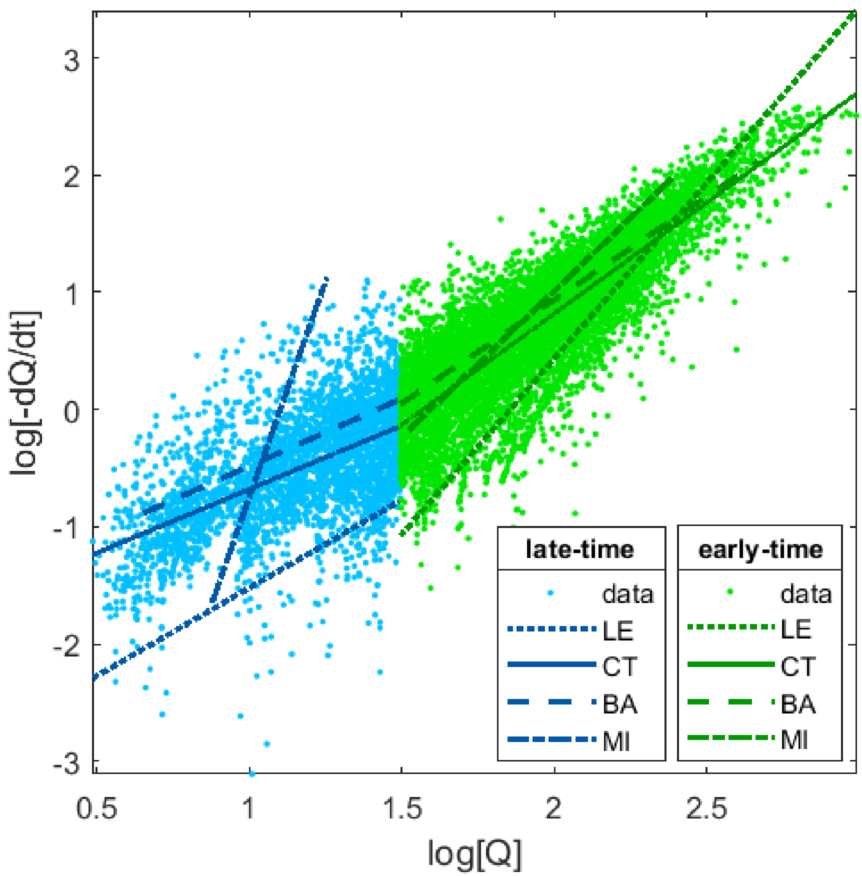

Figure 3. Recession analysis for Lookout Creek to aid in the comparison of four different fitting methods and the dependency on parameter estimation shown visually (lower envelope (LE), central tendency (CT), binning average (BA)) and individual recessions parameters (median individual recession (MI)). Depending on the fitting method, the parameter estimation for *a* and *b* will be different.

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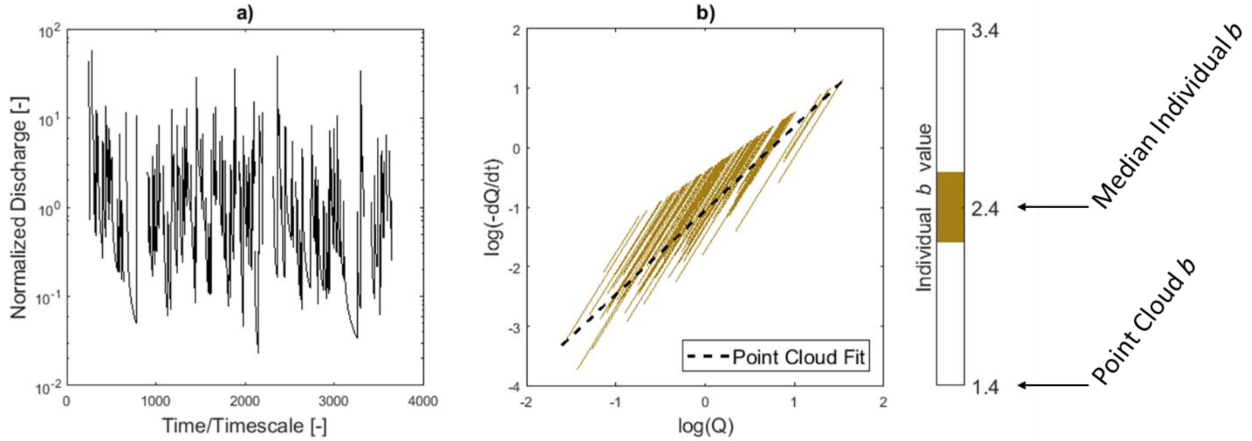

Figure 4. a) Hydrograph with log-normally distributed event inter-arrival times and peak magnitudes with each event maintaining a constant falling limb decay constant, and b) recession analysis with resulting parallel individual recessions having a constant *b* value (MI *b* = 2.4) compared to the point cloud fit (black dotted line) which results in *b* = 1.4). The individual recessions are offset which when viewed collectively, results in the point cloud.

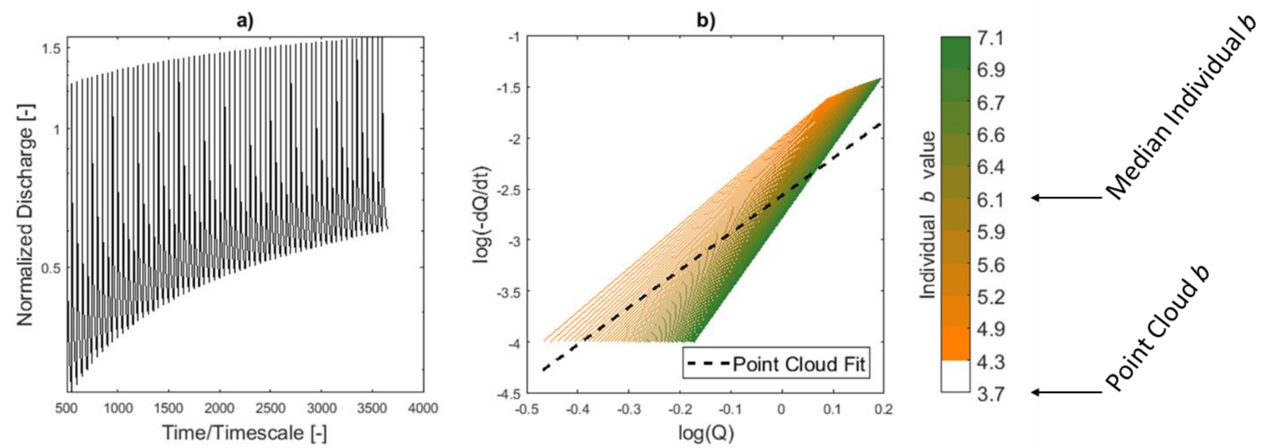

Figure 5. a) Hydrograph of equally spaced recharge events with each underlying equal magnitude recession event superimposed on previous ones resulting in varying falling limb decay constant, and b) recession analysis plot showing a range of *b*'s of individual recessions (MI *b* = 6.1), with steeper recessions associated with events with higher baseflow contribution, compared to the point cloud fit (black dotted line- BA *b* = 3.7). The color bar is divided into 10 ranges based on the individual *b* value, each range contains 10% of individual recessions, and the lowest range in white for comparison to the point cloud range.

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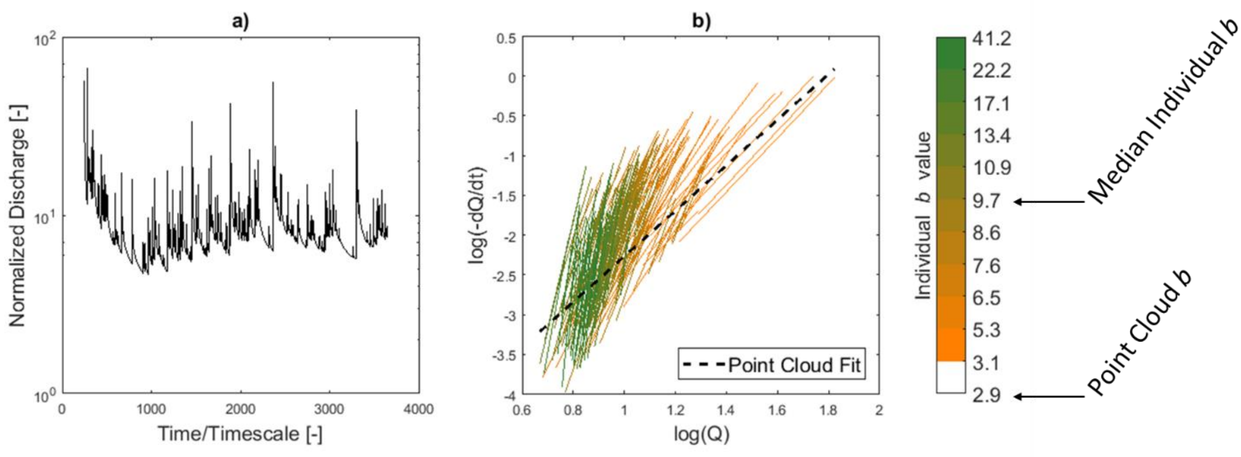

Figure 6. a) Hydrograph with lognormal distribution in recharge event inter-arrival times and magnitudes, and b) recession analysis plot showing a large range of *b* values (with the median of *b* = 9.7), compared to the point cloud fit (black dotted line- BA *b* = 2.9). The color bar is divided into deciles in the distribution of b values compared to the point cloud range.

Table 1. Controls for synthetic hydrograph creation

	Event Magnitudes	**Event Inter-Arrival Time**	**Superposition of antecedent flow?**
Case 1	Log-normal	Log-normal	No
Case 2	Constant	Constant	Yes
Case 3	Log-normal	Log-normal	Yes

Table 2. Comparison of recession analysis parameters *a* and *b* for Lookout Creek between different methods: lower envelope (LE), central tendency (CT), binning average (BA), and the median individual recession (MI). Each value is represented as a ratio of parameter estimation for early to late time. Depending on the derivative method and the fitting method, the parameter estimation for *a* and *b* will be different.

	log(a) **[$m^{1-b}\cdot d^{b-2}$]**		***b*** **[-]**	
	early	**late**	**early**	**late**
LE	-5.6	-3.0	3.0	1.5
CT	-3.0	-1.8	1.9	1.0
BA	-2.6	-1.6	1.8	1.2
MI	-3.9	-8.1	2.7	6.4