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Discussions

Does discharge time source correspond to its geographic source in hydrograph separations? Toward identification of dominant runoff processes in a 300 square kilometer watershed

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Abstract

This study compared a time source hydrograph separation method to a geographic source separation method, to assess if the two methods produced similar results. The time source separation of a hydrograph was performed using a numerical filter method and the geographic source separation was performed using an end-member mixing analysis employing hourly discharge, electric conductivity, and turbidity data. These data were collected in 2006 at the Kuroiwa monitoring station on the Abukuma River, Japan. The results of the methods corresponded well in terms of both surface flow components and inter-flow components. In terms of the baseflow component, the result of the time source separation method corresponded with the moving average of the baseflow calculated by the geographic source separation method. These results suggest that the time source separation method is not only able to estimate numerical values for the discharge components, but that the estimates are also reasonable from a geographical viewpoint in the 3000 km^2 watershed discussed in this study. The consistent results obtained using the time source and geographic source separation methods demonstrate that it is possible to characterize dominant runoff processes using hourly discharge data, thereby enhancing our capability to interpret the dominant runoff processes of a watershed using observed discharge data alone.

1 Introduction

How much information can be discerned about the runoff processes in a watershed from observed discharge data alone? Literature reveals that it is difficult to identify the dominant runoff processes from such data (e.g. Grayson and Blöschl, 2000; Woods, 2002; Sivapalan et al., 2003; Sivakumar, 2004). Runoff modeling by spatially lumped hydrologic models (e.g. HBV, Bergström and Forsman, 1973; Tank, Sugawara, 1995; Yokoo et al., 2001) and distributed hydrologic models (e.g. TOPMODEL, Beven et al., 1984; the physically distributed model by Yokoo and Kazama, 2012) simulate dominant runoff processes; however, their structures are derived from a priori assumptions, and thus they are not well suited to identifying the dominant runoff processes in a watershed.

In possibly the only study of its kind, Barnes (1940) identified runoff processes in a watershed based on a recession analysis of the hydrograph and found that the recession curve reflects surface flow, interflow, and baseflow components, where these correspond to steep, intermediate, and flat sloped sections of the recession curve, respectively, plotted as logarithmic discharge vs. time.

Following Barnes (1940), Hino and Hasebe (1984) developed a numerical filtering method to separate a hydrograph into several discharge components, using the recession coefficients of Barnes (1940) as the parameter of the filter. The numerical filtering approach developed by Hino and Hasebe (1984) could potentially be a powerful tool in identifying the dominant runoff components within a watershed. Its potential for identifying runoff processes using only discharge data has recently been investigated by Kobayashi and Yokoo (2013) and Yokoo et al. (2014).

According to Furey and Gupta (2001), hydrograph separation without the need for geochemical data can be achieved using (1) a graphical approach (e.g. Fröhlich et al., 1994; Rutledge, 1998; Szilagyi and Parlange, 1998; Wittenberg, 1999; Wittenberg and Sivapalan, 1999), (2) a filtering approach (e.g. Lyne and Hollick, 1979; Hino and Hasebe, 1981, 1984; Nathan and McMahon, 1990; Chapman, 1991, 1999; Spongberg, 2000), or (3) an analytical approach (e.g. Birtles, 1978; Furey and Gupta, 2000). Ideally, the results of these mathematical hydrograph separation approaches should be comparable with those of geochemical approaches to ensure reliable separations that are useful for the identification of the dominant runoff processes. However, in most studies where these approaches have been applied, the results have not been compared with those of geochemical approaches to verify their reliability. Exceptions to this include the studies of Hino and Hasebe (1986), McNamura et al. (1997), Haga and Yokoo (2011), and Cartwright et al. (2014)

Hino and Hasebe (1986) demonstrated that the sum of baseflow and interflow obtained from an event-scale hydrograph separation was similar to an estimate based on a geochemical tracer (δ^{18}O); however, they did not verify estimates of the fractions of baseflow and interflow made using the mathematical approaches.

McNamura et al. (1997) illustrated that old water contribution calculated by recession analysis is well supported by that by mixing model based on event-scale investigations. They revealed that contribution of old water can change seasonally because of the possible input difference between rainwater and snowmelt.

Following Hino and Hasebe (1986), Haga and Yokoo (2011) compared estimates of discharge components (surface flows and interflows) made by numerical filtering (Hino and Hasebe, 1984) with estimates made by end-member mixing analysis (Christophersen et al., 1990; Hooper et al., 1990) for the watershed of the Akutsu discharge monitoring station on the Abukuma River, Japan. Filter separation of a hydrograph represents a time source separation method whereas end-member mixing analysis (EMMA) represents a geographic source separation method. The research by Haga and Yokoo (2011) may have been the first attempt to compare time source and geographic source separations of a hydrograph; however, problems were experienced with parameterization for both numerical filtering and EMMA. In the numerical filtering, the time constant used to characterize the discharge components was determined as the moving average of the somewhat noisy coherence of the cross-spectrum between precipitation data and discharge data, which made the results of separation questionable. In the EMMA, end-member water quality conditions were subjectively defined by the authors and lacked justification. These parameterization problems remain unresolved. Furthermore, baseflow separation by EMMA was not successful, and the results thereof were not presented or discussed by Haga and Yokoo (2011).

Cartwright et al. (2014) compared two-component hydrograph separation results based on chemical mass balance for Chloride with those of two different digital filters by Nathan and McMahon (1990) and Eckhardt (2005) as well as local minimum (Sloto and Crouse, 1996). They discussed that the difference between the four methods would not be an error in any of the techniques, but rather it would contain important information for runoff processes. Their discussion would be interpreted as the differences in the results would be useful for hydrograph separations into more than two components, which is consistent with the result of Haga and Yokoo (2011).

Based on the above, the present study again compares time source separations by numerical filtering (Hino and Hasebe, 1984) to geographic source separations by EMMA (Christophersen et al., 1990; Hooper et al., 1990). However, these comparisons are made after (1) solving the parameterization problems discussed above and (2) improving baseflow separation by EMMA. After assessing the level of agreement between the time source and geographic source separation methods, the potential of numerical filtering (Hino and Hasebe, 1984) as a fundamental tool for identifying dominant runoff processes at a watershed scale is discussed.

2 Method

2.1 Study area

The study area is the watershed of the Kuroiwa monitoring station on the Abukuma River, Japan (Fig. 1). The Abukuma River originates from Mt. Asahi at the southern end of Fukushima Prefecture, and runs for 239 km through Fukushima and Miyagi prefectures, draining an area of 5400 km^2. The Kuroiwa monitoring station is located in the city of Fukushima and has a watershed area of 2886 km^2. This station is a primary monitoring station of the Abukuma River, and covers about 53 % of the entire watershed. The station was established in 1963 and provides continuous recording of water level and flow magnitude. In 1972, the station was also equipped for the measurement of water quality. Digital records of water level and flow magnitude are currently accessible on the internet for data collected since 1988, whereas records of water quality are accessible for data collected since 1989.

2.2 Data

Flow magnitude and water quality data were downloaded from the Water Information System of the Ministry of Land, Infrastructure and Transport, Japan (accessible at http://www1.river.go.jp/). Five water quality variables were considered in the study: water temperature (T_w in °C), pH, dissolved oxygen (DO in $\mathrm{mg\,L^{-1}}$), electric conductivity (EC in $\mathrm{mS\,m^{-1}}$), and turbidity (Turb in deg). Water quality data were recorded at hourly monitoring intervals. Perusal of the downloaded data revealed no calendar years with a continuous record, and the years with the most available data are 2005 and 2006. The units of the flow magnitude data were converted from $\mathrm{m^3\,s^{-1}}$ to $\mathrm{mm\,h^{-1}}$ by dividing by the watershed area.

2.3 Time source separation of hydrographs

The filter-separation autoregressive (AR) method (Hino and Hasebe, 1984) was applied to the hourly hydrologic data. This method applies a low-pass filter to river flow data to calculate the delayed flow component of total flow using the following convolution integral:

$$Q^{(1)}(t) = f_\mathrm{w} \sum_{k=0}^{k_\mathrm{max}} w(k) Q(t-k) \tag{1}$$

where f_w is a weighting factor adjusted manually to fit the recession curve of the hydrograph, $w(k)$ is the numerical filter, $Q(t)$ is observed river flow, k is the elapsed time from the beginning of the numerical filter, and k_max is the maximum elapsed time from the beginning of the numerical filter, empirically set to five times the recession time constant T_c. This time constant is estimated directly as the inverse of the recession coefficient α, obtained by fitting the following exponential function to the recession curve of the hydrograph (Fig. 2):

$$Q = Q_0 \exp(-\alpha t) = Q_0 \exp(-t/T_\mathrm{c}) \tag{2}$$

The numerical filter and its components are defined as follows:

$$w(k) = \begin{cases} \left(c_0/\sqrt{c_1^2/4 - c_0}\right) \exp(-c_1 k/2) \sinh\left(k\sqrt{c_1^2/4 - c_0}\right) & (k \geq 0) \\ 0 & (k < 0) \end{cases} \tag{3}$$

$$c_0 = (\delta/T_c)^2 \tag{4}$$

$$c_1 = \delta^2/T_c \tag{5}$$

where δ is an attenuation coefficient that was kept constant at 2.1 h owing to its minimal influence on filter separation.

In general, a semi-logarithmic plot of a hydrograph has several linear segments. The changes in the gradients of the segments indicate changes in the rainfall–runoff processes in the watershed (Barnes, 1940). Therefore, we can assume a model as shown in the following equation for the case of three discharge components:

$$Q = Q_0^{(1)} \exp(-t/T_{c1}) + Q_0^{(2)} \exp(-t/T_{c2}) + Q_0^{(3)} \exp(-t/T_{c3}) \quad (T_{c1} > T_{c2} > T_{c3}) \tag{6}$$

where 1, 2, and 3 indicate different discharge components. Hino and Hasebe (1984) recommended ordering the determination of T_{c1}, T_{c2}, and T_{c3} so that the time constant of the slowest discharge component is first determined, and then sequentially thereafter the time constants of the more rapid discharge components. Hence, in the current study, the filter was first applied to a hydrograph to separate the discharge component with the highest time constant (T_{c1}) from the remaining discharge. The filter was then applied again to the remaining discharge to separate the component with time constant T_{c2}. This procedure was applied until no more inflection points were apparent on the hydrograph.

Apart from the ease of parameter adjustments, the filter-separation AR method would lead to questions regarding how many times we should separate a hydrograph by filtering. Here, the maximum number of filter passes was set to five, which corresponds to deriving at most six discharge components from the recession limb of the hydrograph (i.e. indicated by six changes in gradient).

2.4 Geographic source separation of hydrographs

The EMMA was first introduced by Christophersen et al. (1990) and Hooper et al. (1990) to identify geographic sources of discharge. The EMMA allows for a hydrograph to be separated into several discharge components, where these components differ with respect to their geographic sources and associated water quality characteristics.

If n end-members are employed for partitioning total discharge into n components, then $n-1$ continuous water quality datasets are necessary for conducting the EMMA. Hence, to partition the total discharge into three components using three end-members, two continuous water quality datasets are required, where the two variables concerned are chemically and physically independent of each other. For this case, three mass balance equations can be written, incorporating flow quantity and quality:

$$Q_\mathrm{t} = Q_\mathrm{a} + Q_\mathrm{b} + Q_\mathrm{c} \tag{7}$$

$$C_{1\mathrm{t}}Q_\mathrm{t} = C_{1\mathrm{a}}Q_\mathrm{a} + C_{1\mathrm{b}}Q_\mathrm{b} + C_{1\mathrm{c}}Q_\mathrm{c} \tag{8}$$

$$C_{2\mathrm{t}}Q_\mathrm{t} = C_{2\mathrm{a}}Q_\mathrm{a} + C_{2\mathrm{b}}Q_\mathrm{b} + C_{2\mathrm{c}}Q_\mathrm{c} \tag{9}$$

where Q_t, $C_{1\mathrm{t}}$, and $C_{2\mathrm{t}}$ are the total flow and associated values of the two water quality variables (1 and 2), respectively; Q_a is the flow component from source location "a" (i.e. surface water), and $C_{1\mathrm{a}}$ and $C_{2\mathrm{a}}$ are associated end-member values of the two water quality variables; Q_b is the flow component from source location "b" (i.e. soil water), and $C_{1\mathrm{b}}$ and $C_{2\mathrm{b}}$ are associated end-member values of the two water quality variables; and Q_c is the flow component from source location "c" (i.e. ground water), and $C_{1\mathrm{c}}$ and $C_{2\mathrm{c}}$ are associated end-member values of the two water quality variables. If it is assumed that the three end-member values of the two water quality variables may be determined from measurements of potential end-member waters (e.g. surface water, soil water, and groundwater), the three unknowns (Q_a, Q_b, and Q_c) may be estimated by solving Eqs. (7) to (9) simultaneously.

One thing to note is that continuous water quality data for a sufficiently long period are generally difficult to obtain for EMMA, and hence it is difficult to provide strong justification for the selected tracer type and values of the end-members, given the limited availability of water quality data. The difficulties for selecting the end-members in EMMA is also apparent in Laudon and Slaymaker (1997), Rice and Hornberger (1998), Hangen et al. (2001), and Iwagami et al. (2010), and recently such is well reviewed by Klause and McDonnell (2013).

Considering the above problem of data availability, the present study attempts to evaluate end-members based on the spatial distribution of long-term water quality data in a space consisting of multiple water quality data fields. In the case of three end-members, for example, the end-members constitute the vertices of a triangle on a mixing diagram, where the horizontal axis represents one water quality variable and the vertical axis the other (Fig. 3). This method for exploring the end-members is different from the original field-survey-based procedure of the EMMA, and could thus produce different results. These potential differences were not assessed in this study because the objective here was to investigate the methodological potential for partitioning total discharge using an hourly water quality record of up to a year. The potential differences between methods used to explore end-members will be investigated in a future study.

3 Results

3.1 Time source separation

Figure 4a shows the result of time source separations of the 2006 hydrograph by the method of Hino and Hasebe (1984), showing five discharge components ranging from Q_1 (quickest) to Q_5 (slowest). The figure shows that this method satisfactorily separated the hydrograph into discharge components having responses of varying swiftness to precipitation. The parameters used in the separations are summarized in Table 1.

Figure 4b also shows the result of time source separations of the 2006 hydrograph; however, the five discharge components are summarized into three components representing the quickest, intermediate, and slowest flows for comparison with the results of geographic source separations outlined in Sect. 3.2 below.

3.2 Geographic source separation

Figure 3 shows a mixing diagram for electric conductivity (EC) and turbidity (Turb) for 2005–2006, as used in the EMMA. The diagram shows a characteristic relationship between EC and Turb in the watershed of the Kuroiwa monitoring station. The relationship incorporates three types of end-member water quality conditions: (1) high EC and low Turb indicating settling of suspended solids (SS) and leaching of ions owing to longer contact time with soil and bedrock in the watershed, (2) low EC and high Turb indicating larger amounts of SS and shorter contact times with soil and bedrock in the watershed, and (3) low EC and low Turb indicating characteristics that are intermediate to the conditions in (1) and (2). These characteristic water quality conditions suggest that (1), (2), and (3) could potentially correspond to the water quality of groundwater flow, surface flow, and subsurface flow, respectively. Assuming that the characteristic conditions are indicative of these flow types, a triangle having minimum area was drawn around the observed data for Turb and EC (Fig. 3). The resulting vertex coordinates and equations for the sides of the triangle are summarized in Table 2.

Figure 5 shows the result of geographic source separation of the 2006 hydrograph by EMMA. The figure reveals the following: (1) the fraction of surface flow (Q_a) is very small, (2) the fraction of subsurface flow (Q_b) forms a large part of the hydrograph; and (3) the fraction of groundwater flow (Q_c) is relatively small and is very responsive to precipitation events. The responsiveness of groundwater flow to precipitation (Fig. 5) is contrary to the general perception that groundwater flow is relatively steady and is insensitive to individual precipitation events, in contrast to surface flow (i.e. Fig. 6.2.6 or 6.2.7 in Todd and Mays, 2005).

The groundwater flow response to precipitation in Fig. 5 would be a typical result of EMMA in a larger watershed. Consideration was given to modifying the EMMA methodology to obtain a smoother groundwater flow curve; however, such modifications might challenge the theoretical integrity of the method, and thus the curve was left unchanged at this stage.

3.3 Relationship between time source separation and geographic source separation

To explore the relationship between the time source hydrograph separations and the geographic source hydrograph separations, a comparison was made between the discharge components obtained by filter separation and the discharge components obtained by EMMA. The comparison revealed that (1) Q_a was best correlated with Q_5, (2) Q_b was best correlated with the sum of Q_2,Q_3, and Q_4 (i.e. $Q_2 + Q_3 + Q_4$); and (3) Q_c was best correlated with Q_1. The correlations between the time source and geographic source separations are explained through reference to Figs. 6–8.

Figure 6a compares surface flow (Q_a) obtained by EMMA against the fastest flow (Q_5) obtained by filter separation. Figure 6b compares the hourly time series of Q_5 and Q_a for the year 2006. It is apparent that Q_5 and Q_a show similar temporal patterns, although the magnitude of Q_a is about half that of Q_5 (Fig. 6a and b).

Figure 7a compares Q_b obtained by EMMA against $Q_2 + Q_3 + Q_4$ obtained by filter separation. Figure 7b compares the hourly time series of $Q_2 + Q_3 + Q_4$ and Q_b for the year of 2006. This figure reveals that $Q_2 + Q_3 + Q_4$ and Q_b are very similar in magnitude and display similar variations.

Figure 8a compares Q_c obtained by EMMA against Q_1 obtained by filter separation. Moving averages of Q_c, where the window size of 1585 h equals the recession time constant of Q_1, are also shown in the figure. Figure 8b compares the hourly time series of Q_1 and Q_c for the year 2006, and also shows the moving average of Q_c (window of 1585 h). This figure reveals that Q_1 and Q_c show considerably different temporal patterns. However, when looking at the moving average of Q_c, there is a much stronger relationship between Q_1 and Q_c, with the Q_c curve being only slightly higher than Q_1 in Fig. 8b.

These results suggest that Q_a is a surface flow component, originating from the water quality end-member having high Turb and low EC, as assumed in EMMA. Similarly, Q_b corresponds to the interflow component originating from the water quality end-member having low Turb and low EC, as assumed in EMMA. In contrast, Q_c initially seemed dissimilar to the slowest discharge component (Q_1) obtained by filter separations. However, its moving average (using a window size of 1585 h) is comparable to Q_1. This result suggests that it is difficult to estimate baseflow-type discharge using the standard EMMA approach in a watershed of this size (3000 km^2); hence, an additional simple averaging model or filter is necessary to quantify the baseflow component using EMMA.

4 Discussion

This study compared components of discharge calculated by filter separations (a time source separation scheme) with those calculated by EMMA (a geographic source separation scheme), with the aim of exploring the relationship between the approaches and to deduce the dominant runoff processes in the watershed considered. The ultimate aim of the work is to develop a discharge-data-based rainfall–runoff modeling approach. The results showed that time source separations and geographic source separations corresponded well in terms of surface flow and interflow estimates, but not in terms of baseflow estimates. However, the moving average of baseflow calculated by EMMA showed similar patterns to the slowest discharge component calculated by filter separation. The main implications of this research and the potential for further improvements are discussed in the following sections.

4.1 What are the main implications of this research?

One of the implications of the present results lies in the agreement found between certain estimates of discharge made by the time source separation and geographic source separation methods for the 3000 km^2 scale watershed considered. The degree of correspondence between the results of the two separation schemes could be higher, but they are nevertheless useful for understanding the dominant runoff processes (e.g. Grayson and Blöschl, 2000; Woods, 2002; Sivapalan et al., 2003; Sivakumar, 2004) at a watershed scale, within a framework of the "data-based modeling approach" (Sivakumar and Berndtsson, 2010) for characterizing systems in a watershed (Sharma and Mehrotra, 2014; Gupta and Nearing, 2014). For example, it would be possible to estimate discharge components by filter separation, whereby the discharge component with the lowest recession time constant would be regarded as a surface flow component, and components with intermediate and high recession time constants would be regarded as interflow and baseflow, respectively. All of these process identifications, which are summarized in Fig. 9, can now be achieved based solely on discharge data and the filter separation technique of Hino and Hasebe (1984). This was not previously possible because the results of filter separations were used only to explain the existence of different discharge sub-components with different sensitivities to precipitation without strong recognition of the geographic sources of the sub-components.

Another implication of the present results relates to the extended application of EMMA (Christophersen et al., 1990; Hooper et al., 1990) in the present study. Applications of EMMA have been conducted with the assumption of several end-member water quality conditions that correspond to sampled water from different geographic locations, such as rainwater, soil water, and groundwater in wells. Setting these water quality conditions as end-members, continuous event-scale water quality data are plotted between the end-members on a mixing diagram, as shown in Fig. 3. This data availability problem characterized by tracer type and data length was the source of methodological difficulty in applying EMMA (Laudon and Slaymaker, 1997; Rice and

Hornberger, 1998; Hangen et al., 2001; Iwagami et al., 2010; Klause and McDonnell, 2013). In contrast to the original EMMA procedure, the present study estimated the end-member water quality condition by fitting a triangle around the water quality monitoring data. This approach is possible because of the availability of continuous hourly water quality data for multiple years in the study area. The relative abundance of data allowed for the end-members to be selected based on the pattern of the data, rather than by a priori selection.

A third implication stems from the application of EMMA in a relatively large watershed. A regular EMMA requires accessible end-member waters and continuous water quality data covering several rainfall events to enable the delineation of an "event" hydrograph. This is normally possible in relatively small watersheds where experimentalists can investigate the watershed in detail. Instead of using end-member water sampling and continuous, but relatively "short", water quality datasets, the present study used hourly water quality data for two successive years to estimate the end-member water quality parameters. This was done by fitting a triangle of minimum area to a scatter diagram containing two different water quality variables, with the vertices of the triangle then representing the end-members. This unconventional application of EMMA was possible in the relatively large watershed considered, as continuous water quality data were available over a sufficiently long period and also the result of EMMA might be "stable" because of spatial aggregation of runoff processes as demonstrated by Laudon and Slaymaker (1997). If this approach gains acceptance, the application of EMMA could potentially aid efforts to understand runoff processes in watersheds, although it might not be possible to directly estimate the baseflow component in larger watersheds. In such cases a simple smoothing model might be necessary, as was found in this study (Fig. 8).

4.2 Further improvements to the EMMA approach

Why was EMMA unsuccessful in estimating the baseflow component? It is possible that EMMA is not applicable in larger watersheds where baseflow can dominate, such as the watershed of the Kuroiwa monitoring station considered in the present study. EMMA employs mass balance equations incorporating water flow and selected water quality constituents, as shown in Eqs. (7) to (9). Total discharge is included in these mass balances; hence, the estimated discharge components necessarily become functions of total discharge, which is highly sensitive to precipitation patterns. Such can be confirmed in Ogunkoya and Jenkins (1993), Laudon and Slyaymaker (1997), Hangen et al. (2001), Ladouche et al. (2001), Uhlenbrook et al. (2002), Uhlenbrook and Hoeg (2003), Pellerin et al. (2008), and Cartwright et al. (2014). The baseflow component, however, is generally regarded by hydrologists to display a smooth temporal pattern, and is quite different from that of total discharge (i.e. Fig. 6.2.6 or 6.2.7 in Todd and Mays, 2005). Therefore, the baseflow component estimated by EMMA is quite different from that estimated by filter separation, with the latter displaying a smooth pattern that is insensitive to precipitation. This problem has not been well highlighted previously in the literature, presumably because EMMA has been applied mostly for event-scale data in small watersheds. Thus, EMMA may be suited to application in smaller watersheds, and some modifications are necessary when estimating baseflow component in larger watersheds (e.g. Fig. 8), where time delays exist between the source of end-member water and the appearance of water in the river. This possible "scale effect" in hydrograph separation could be consistent with the discussion that "*the constrasting results reflect how the different methods characterise the water souces to rivers*" by Cartwright et al. (2014).

What can be done to resolve this problem? One solution is to explore other tracers that can successfully separate the baseflow component from the total flow. However, I believe this is not feasible, as EMMA uses mass balance equations that result in baseflow being dependent on total flow, which is highly sensitive to precipitation variations. Another solution would be to introduce a lag factor in the mass balance equations to make baseflows less sensitive to precipitation. However, in the mass balance equations of EMMA, there seems to be theoretically little justification for introducing a lag factor. The most effective alternative, therefore, is likely to be the introduction of a model to smooth the peak-like baseflow estimated by EMMA. This was done in Fig. 8 of the present study, but it is neither an elegant nor process-based approach.

How can the approach that was adopted in this study to estimate baseflow by EMMA be improved? I believe that combining the EMMA and filter separation approaches would be an alternative way forward as a data-based modeling approach. As the discharge components estimated by EMMA and filter separation were similar in most cases, discharge components estimated by EMMA could be replaced by those estimated by filter separation, and vice versa. If the results of filter separations are similar to those of EMMA, the discharge components can be assumed to be representative of the dominant runoff processes in a watershed, as they are coherent in terms of time source separation and geographic source separation.

A final consideration in this study is that suitable tracers need to be sought for interflows estimated by filter separation. There were three discharge components estimated by EMMA and five components estimated by filter separation. Hence, the additional two discharge components require that the water quality of two more end-members be known. The present study employed Turb and EC to characterize three end-member waters. Therefore, measurements of additional water quality variables would be needed to characterize the remaining two end-members. These data are unlikely to be available in Japan at present, although continuous in situ measurements of stable isotopes in luquid water is getting to be possible (i.e. Weiler et al., 2003; Berman et al., 2009; Koehler and Wassenaar, 2011; Herbstritt et al., 2012)

5 Conclusions

This study investigated the relationship between discharge components estimated by filter separation and those estimated by end-member mixing analysis, to explore how the results of time source hydrograph separation (filter separation) compare to those of geographic source separation (EMMA). The results showed a good correspondence between the methods for the components of surface flow and interflow. These findings suggest that discharge components estimated by filter separation are not just the result of mathematical equations, but are also reasonable from a physical viewpoint and from our current understanding of runoff generation processes. Thus, time sources and geographic sources correspond well, which should be helpful in estimating dominant runoff generation processes and in justifying or invalidating existing lumped-parameter runoff models by way of "soft data" approaches (Seibert and McDonnell, 2002; Vaché and McDonnell, 2006).

The conclusions obtained for baseflow were different to those for surface flow and interflow. The degree of agreement between baseflows estimated by filter separation and EMMA was less than that for the other flow components; however, a moving average of baseflow estimated by EMMA with a moving window of 1585 h (which is equal to the recession time constant used for baseflow estimation in filter separation), was comparable with the baseflow estimated by filter separation. This result indicates that a simple delay model was necessary for estimating baseflow from the hydrograph separation based on EMMA in the watershed considered. This need arises because the original EMMA does not account for the travel time of water from its geographic source to its appearance as discharge in the river.

In addition, it would be necessary to find another two end-member waters in EMMA, because the filter separation scheme separated the hydrograph into five discharge components, whereas EMMA separated the hydrograph into three components. Such end-member waters could not be found from the available water quality data in the study area; however, this may be possible in a different watershed, depending on data availability.

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Table 1. Parameters used in filter-separations. Letters in parentheses indicate the unit of the parameter, where "–" indicates a non-dimensional parameter.

Parameter	1st separation	2nd separation	3rd separation	4th separation
f_w (–)	0.22	0.15	0.25	0.30
Δ (h)	2.1	2.1	2.1	2.1
T_c (h)	1585	230.9	65.09	12.97
$\log_6 T_c$ (–)	4.11	3.04	2.33	1.43
Round ($\log_6 T_c$) (–)	4	3	2	1

Table 2. Parameters used in the EMMA.

Parameter type	End-member	Coordinates/equations
Coordinate of vertex (EC, Turb)	"a"	$\mathrm{EC} = 8.38\,\mathrm{mS\,m^{-1}}$, Turb = 308 deg.
	"b"	$\mathrm{EC} = 7.06\,\mathrm{mS\,m^{-1}}$. Turb = 0 deg.
	"c"	$\mathrm{EC} = 33.8\,\mathrm{mS\,m^{-1}}$, Turb = 0 deg.
Equation of line segments	"ab"	$\mathrm{Turb} = -12.1\mathrm{EC} + 409$
	"bc"	$\mathrm{Turb} = 233\,\mathrm{EC} - 1650$
	"ca"	$\mathrm{Turb} = 0$

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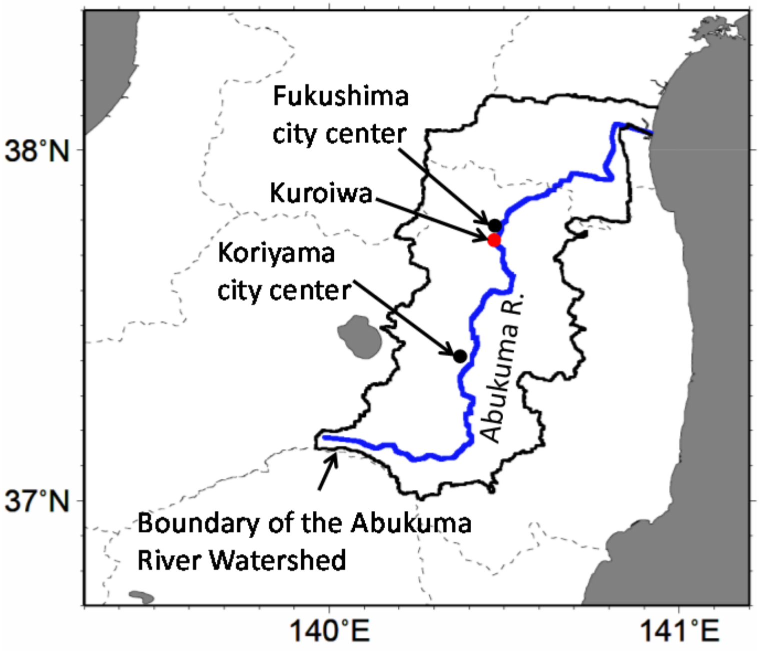

Figure 1. Map of the Abukuma River Watershed. The Kuroiwa monitoring station is marked by the red dot. Dashed lines indicate prefectural boundaries.

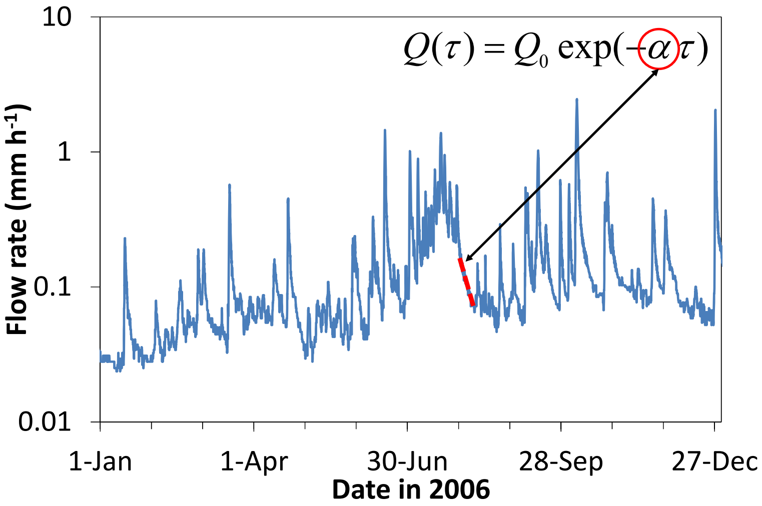

Figure 2. Schematic of the determination of the recession time constant $T_c = 1/\alpha$.

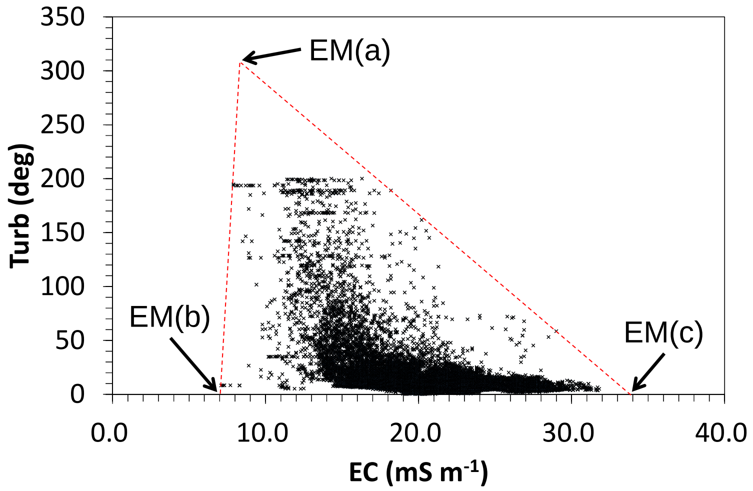

Figure 3. Mixing diagram of the EMMA containing data for 2005–2006 for the Kuroiwa monitoring station on the Abukuma River. EM(a), EM(b), EM(c) indicate end-member water quality for geographic sources “a”, “b”, and “c”, respectively.

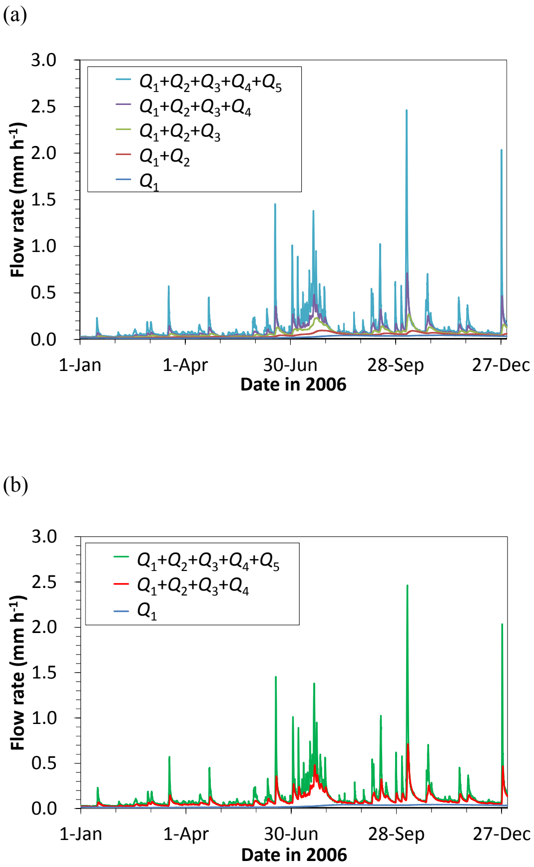

Figure 4. (a) Result of time source separation of the 2006 hydrograph by the filter-separation AR method at the Kuroiwa monitoring station on the Abukuma River. **(b)** Result of time source separation of the 2006 hydrograph by filtering where the five discharge components in **(a)** are summarized into three components for comparison with the three components in Fig. 5.

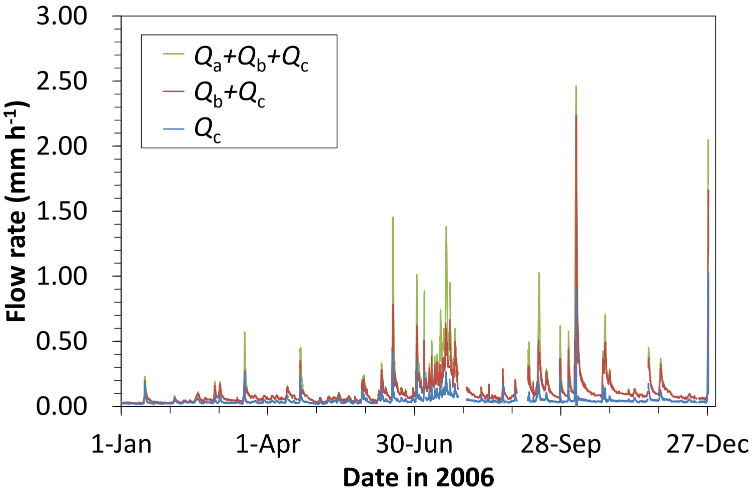

Figure 5. Result of geographic source separation of the 2006 hydrograph by EMMA at the Kuroiwa monitoring station on the Abukuma River.

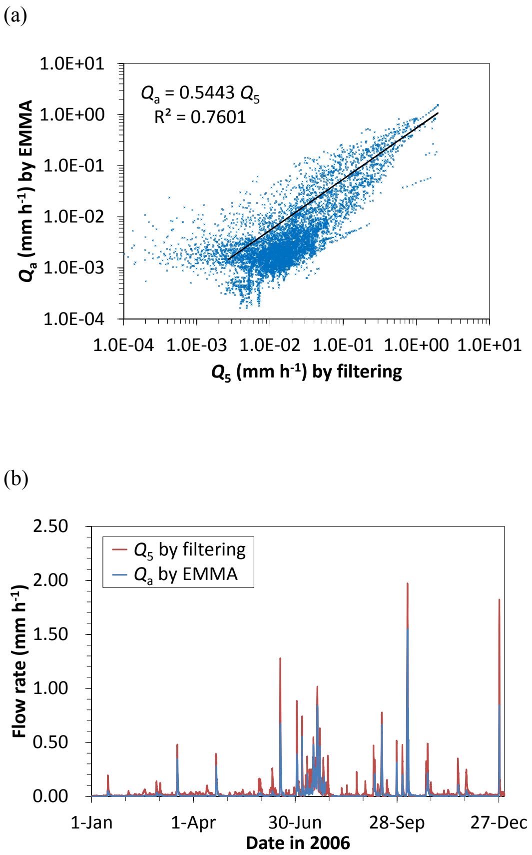

Figure 6. Comparison of surface flows estimated by the filter-separation AR method and EMMA. **(a)** Scatter plot of the surface flows. **(b)** Temporal comparison of the surface flows. "R2" is determination coefficient of regression equation.

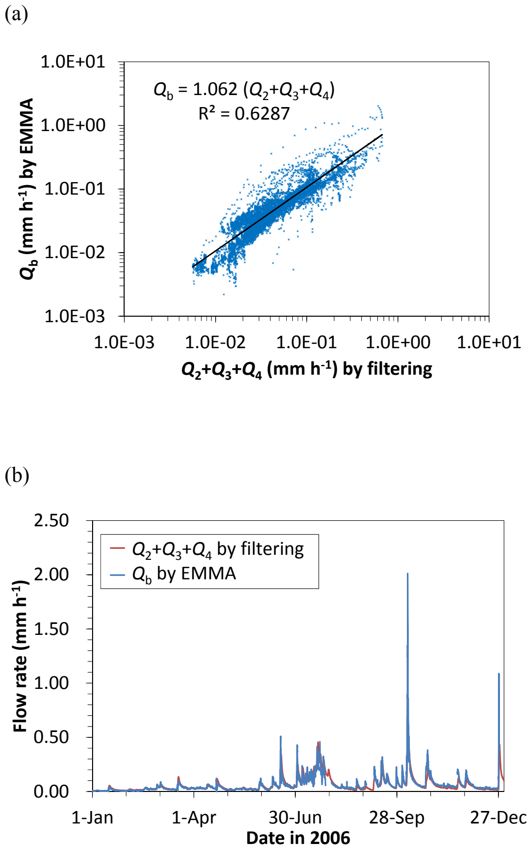

Figure 7. Comparison of interflows estimated by the filter-separation AR method and EMMA. **(a)** Scatter plot of the interflows. **(b)** Temporal comparison of the interflows. “R2” is coefficient of determination. “R2” is determination coefficient of regression equation.

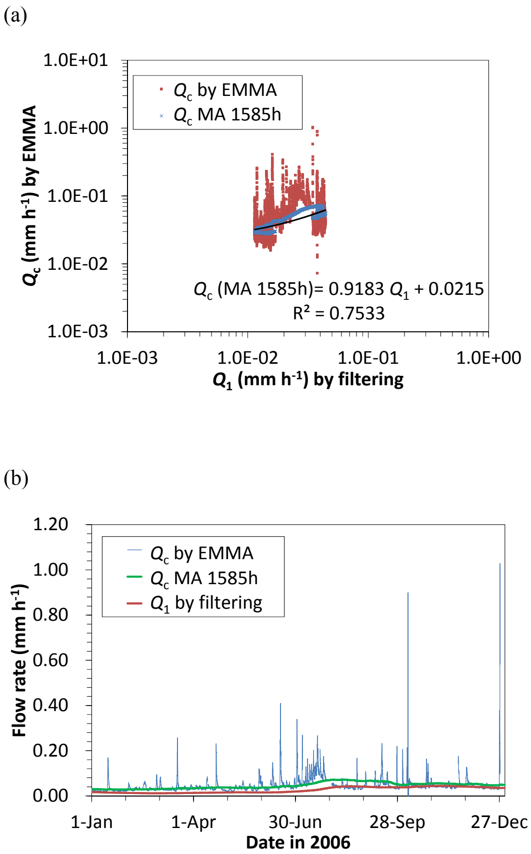

Figure 8. Comparison of baseflows estimated by the filter-separation AR method and EMMA. **(a)** Scatter plot of the baseflows. **(b)** Temporal comparison of the baseflows. In both panels, "Q_c MA 1585h" indicates the moving average obtained using a window size of 1585 h for Q_c estimated by EMMA. "R2" is determination coefficient of regression equation.

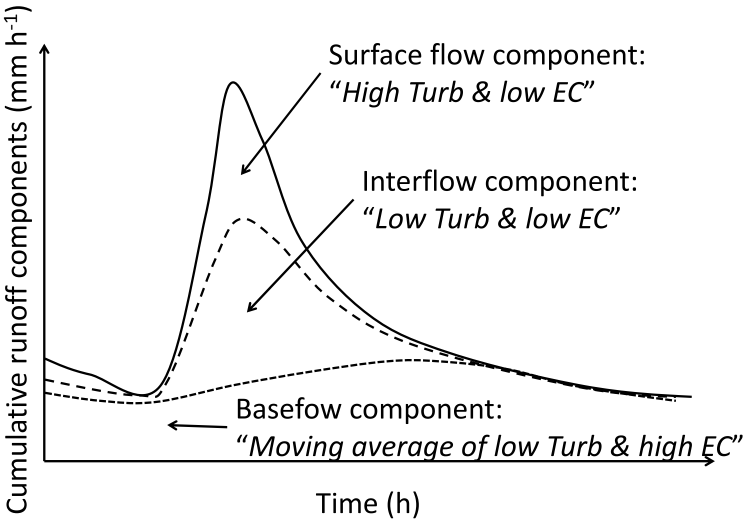

Figure 9. Concept of river water source estimation based on instantaneous water quality measurement of river water.