An interpretation of the relationship between dominant rainfall-runoff processes and the shape of flow duration curve by using data-based modeling approach

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Abstract:

Seeking a process-based understanding for the shape of the flow duration curve (FDC) uniqueness to a catchment, this study applied a data-based rainfall-runoff modeling approach in perennial, intermittent and ephemeral catchments which would have different dominant rainfall-runoff processes. Using this approach, we identified (1) the number of dominant runoff processes in a catchment, (2) rainwater storage in all processes, (3) infiltrations and return flows between the processes. We then identified reasons for different FDC shapes in the catchments in terms of identified dominant processes. Our results showed a humid climate with lower aridity index (\(AI\)) would cause perennial flow created by the combination of four dominant processes of fast flow, faster and slower interflows and base flow components. On the contrary, an arid climate with higher \(AI\) would cause ephemeral flow created by the combination of two dominant processes of fast and faster interflow components. These indicate a FDC in arid catchments would become ephemeral because of less dominant runoff processes occurring only near ground surface, whereas a humid catchment would become perennial because of more dominant runoff processes occurring from near ground surface to deep underground. These findings contribute in estimating FDCs in ungauged catchments from climatic conditions.

KEYWORDS dominant processes; prediction in ungauged basins; data-based model; process-based model; rainfall-runoff model; flow duration curves

INTRODUCTION

A flow duration curve (FDC) is unique to a catchment, hence many studies have discussed the relationship between the shape of the FDC and its catchment attributes in order to understand the physical reasons for its shape and to enable its estimation in ungauged basins (Predictions in Ungauged Basins, PUB; Sivapalan, 2003). The FDC is often used to explain a catchment’s runoff response to potential impacts of climate and physical changes (Searcy, 1959) as in Ward and Robinson (1990), Burt and Swank (1992), and Sefton and Howarth (1998). However, the usefulness of these studies are limited to only understanding the physical reasons for the variable shape of FDCs among the targeted catchments.

Other significant approaches attempted to apply probabilistic functions to explain the shape of the FDC where runoff or both rainfall and runoff data are dealt with as the results of probabilistic processes from a process perspective. Castellarin et al. (2004) proposed a stochastic index flow representation of the FDC to derive annual and long-term FDC. Botter et al. (2007a) and the extension Botter et al. (2007b) approached the probabilistic modeling mathematically for base flow to explain the relationship between hydrologic processes and the FDC. Botter et al. (2009) worked on an extension and the application of the Yilmaz et al. (2008) probabilistic model in US catchments to explain observed runoff. Muneepeerakul et al. (2010) developed a framework to simulate runoff components of the FDC by extending the stochastic models from Botter (2007a; 2007b; 2009). These studies expanded our understanding of how the FDC is shaped from probabilistic viewpoints. However, less explanations were made from a rainfall-runoff processes perspective.

One notable study that sets a pathway for the process-based understandings on the relationship between the shape of FDCs and rainfall-runoff processes was done by Yokoo and Sivapalan (2011). The study developed a conceptual framework for predicting FDCs in ungauged catchments by investigating the FDC shapes under different combinations of climate and landscape properties. However, the study was done in hypothetical catchments and therefore needed conclusive testing with observed data (Yokoo and Sivapalan, 2011). Following this framework, a four-part study to analyze the physical controls on the shape of the FDC in continental US catchments by Cheng et al. (2012), Ye et al. (2012), Coopersmith et al. (2012) and Yaeger et al. (2012) revealed that the FDC’s uniqueness to catchments can be well explained by the FDC reconstruction approach by Yokoo and Sivapalan (2011). Among them, Cheng et al. (2012) empirically studied the physical controls in regional patterns of the FDC in order to perform regionalization for PUB. Ye et al. (2012) explored the regional patterns by using a mean monthly flow approach.
Although, the success of these studies were promising, they lack in intimately recognizing the critical details about climate and landscape properties that results in the various shapes of the FDC in continental US (Chouaib et al., 2018). The study by Chouaib et al. (2018) attempted to improve this by developing a framework to identify how the FDC is influenced by measuring the interaction of similarities and difference in landscape properties with precipitation and also clarifying the effects of FDC controls on the different runoff processes and components. These studies advanced our understanding on the relationship between hydrological processes in catchments and the shape of the FDC. Yet, they were forced to view catchments from a fixed model structure perspective for subsurface hydrological processes.

Recently, Yokoo et al. (2017) suggested a data-based modeling method based on dominant rainfall-runoff process identifications. This method uses only observed precipitation and runoff data to identify dominant rainfall-runoff processes and construct a unique rainfall-runoff model. If we apply this method to the observed data of a catchment and model them, we would be able to further advance our understanding on the relationship between rainfall-runoff processes and the shape of FDCs. Such would allow us to expand our ability to estimate the shapes of the FDCs in ungauged basins. Therefore, this study is aimed at applying the data-based modeling approach by Yokoo et al. (2017) to identify the dominant processes of different catchments for estimating the physical reasons for the different shapes of FDCs in perennial, intermittent, and ephemeral runoff catchments.

METHODS

Study area and data

The study uses three catchments in Hawaii as in Figure 1. The three catchments Hanalei, Kamananui and Makaha are examples of perennial, intermittent, and ephemeral catchments, respectively. The data used in the study was taken from US Geological Survey (USGS, 2012a) and the catchment boundaries were downloaded from USGS (2012b). Some catchment properties are in Table SI.

Hydrograph separation

The data-based modeling approach of Yokoo et al. (2017) starts with data-based hydrograph separation. The hydrograph for each catchment plotted on a semi-logarithmic axis was separated into several components by using the Hino and Hasebe (1984) filter separation method (FSM). Firstly, a recession time constant ($T_c$) from the slowest runoff was calculated using an exponential decay function applied to the lowest runoff section. The $T_c$ is the inverse of the absolute power value in the exponential decay function. This identified $T_c$ was then used to separate the hydrograph into slow and fast runoff components. The fast component was also considered as the residual component to be used as runoff in the next separation. The FSM governing equations can be viewed in Hino and Hasebe (1984) or a short description in Yokoo et al. (2017).

Data-based rainfall-runoff modeling

This study follows the framework developed by Yokoo et al. (2017) to identify dominant rainfall-runoff processes in a catchment and to construct a tank model (Sugawara, 1995) from it. Yokoo et al. (2017) developed process-based equations for a tank model similar to Sugawara (1995) in Figure S1. The method assumes the number of components identified from the FSM represents the number of dominant processes and hence the number of tanks in the model. At this stage, there is only the runoff from each tank identified from the FSM. By using a bottom up approach, Yokoo et al. (2017) identified storage in the lowest tanks by integrating the separated runoff components and a storage estimation method (SEM) developed by Chiba and Yokoo (2015, explained in Text S1) to identify all the parameters and build the storage-discharge equations as explained in detail in Text S2.

RESULTS

Identified dominant processes

The hydrograph separation for the catchments into different components is in Figure 2. In the figure, the difference in the dampness of the separated components are noticeable, from Hanalei to Makaha the dampness...
decreases. The $T_c$ used for separating different runoff components for the catchments is in Table I.

The number of tanks in the model represents the number of dominant processes within the catchment identified by the number of identical characteristic recession curves on the hydrograph. For a chosen recession, we identify its $T_c$ and by using the $\log_5 T_c$, the resulting magnitude rounded off to the nearest whole number can identify whether a particular recession belongs to the identified dominant process or not. The suitability of $\log_5 T_c$ used in this study is the applicability to classify different ranges of $T_c$ as a component or dominant process. For linear segments on the hydrograph plotted on a semi-logarithmic scale, there are different recessions and as a result different $T_c$. Minor differences in the gradients are acceptable but there must be a threshold to differentiate a set of identical recessions from the next. Such have been done subjectively but we can objectively detect the transition from one process to another by using $\log_5 T_c$. More details can be found in Kobayashi and Yokoo (2013) and Yokoo et al. (2017). For example, the first hydrograph separation for Hanalei catchment yields the slowest runoff recession time constant of around 167 days (Tank 3), although there were several other identical recessions with different $T_c$ values, when applied in $\log_5 T_c$, it registers a rounded off ’3’ meaning that all belong to the same ‘3rd’ dominant process. The same procedure applied to the second hydrograph separation for Hanalei catchment registers a rounded off ’2’ and so forth. This implies that Hanalei catchment has four tanks or four dominant processes, inclusive of a Tank 0 which is the surface runoff and does not have any separation applied to it. Kamananui and Makaha have three and two tanks or dominant processes respectively. Figure 3 shows the conceptual figure for each catchment with different number of Tanks (i.e. components).

The mean values for the processes and parameters for each tank is in Table I. Among the three catchments, Hanalei has more mean infiltration ($q_f$) to the lower tanks with Makaha having the least. In Figure 4, we assume the dominant processes for each Tank number are the same regardless of the catchments; that is Tank 0 for all catchments have the same dominant processes and so forth for the other tanks. For all three catchments mean runoff ($q_{i+}$)

![Figure 2. Hydrograph separation for the catchments.](image)

Table I. Tank model parameters and mean values of physical quantities

| Catchment | Tank No. ($\log_5 T_c$) | $T_c$ (d) | $\alpha$ (d$^{-1}$) | $\overline{q}$ (mm d$^{-1}$) | $\overline{b}$ (d$^{-1}$) | $\overline{\theta}$ (mm d$^{-1}$) | $\overline{z}$ (mm) | $\overline{\pi}$ (mm) | $\overline{P_{eff}}$ (mm d$^{-1}$) |
|-----------|------------------------|-----------|-------------------|------------------|----------------|-----------------|------|--------|-------------------|
| Hanalei   | 0                      | 4.59      | 0.105             | 6.97             | 0.201          | 7.76            | –14.7 | 66.4   | 14.7              |
|           | 1                      | 29.4      | 0.0127            | 4.09             | 0.231          | 3.69            | –13.0 | 36.6   |                   |
|           | 2                      | 167       | 0.00120           | 0.574            | 0.253          | 3.15            | –22.4 | 45.2   |                   |
|           | 3                      | 0         | 0.120             | 1.07             | 0.0141         | 0.0817          | –2.74 | 8.29   | 1.07              |
| Kamananui | 0                      | 3.07      | 0.119             | 0.0806           | 0.149          | 0.0317          | –0.228 | 0.421 |                   |
|           | 2                      | 24.4      | 0.0176            | 0.0306           |                |                 |       |        | 1.74              |
| Makaha    | 0                      | 4.67      | 0.0117            | 0.0785           | 0.0238         | 0.00817         | –1.12 | 0.676  | 0.0869             |
|           | 1                      | 0.846     | 0.00814           |                 |                |                 |       |        |                   |
decreases with mean storage ($s$) from Tank 0 to Tank 1. But from Tank 1 to Tank 2 as $s$ increases, the $q$ decreases for both Hanalei and Kamananui (Makaha has no Tank 2). For Hanalei catchment from Tank 2 to Tank 3 (Kamananui and Makaha do not have Tank 3) $s$ increases with $q$, hence Hanalei Tank 3 has more runoff than the preceding Tank 2 (baseflow > interflow).

From the above statistics, we can interpret dominant processes in the three catchments. Hanalei receives more effective rainfall ($p_{\text{eff}} = 14.7 \text{ mm d}^{-1}$) that causes relatively higher storage ($s$) for all four processes. The higher storages in Hanalei generate more runoff ($q$) and infiltration ($p$) to slower processes. In contrast, Makaha receives less effective rainfall ($p_{\text{eff}} = 0.0869 \text{ mm d}^{-1}$, which is about 0.6% of Hanalei) that causes relatively less storage ($s$) for all two processes. These processes have only shorter $T_c$, which indicate Makaha has only the two fast processes near the surface with less storage ($s$) under relatively arid climate ($AI = 4.0$). Because of such processes, Makaha generates relatively less runoff ($q$) and infiltration ($p$). Kamananui receives intermediate rainfall and hence its dominant processes and behavior are expected to have intermediate characteristics among Hanalei and Makaha. The $AI$ is the ratio of annual potential evapotranspiration ($pet$) estimated by the Thornthwaite (1948) method to precipitation ($p_a$) at annual scale.

**Effects of dominant processes to the shapes of FDCs**

The precipitation duration curves (PDC) in Figure 3 and mean effective precipitation ($p_{\text{eff}}$) in Table I show Hanalei has more rainfall than Kamananui and Makaha. In Figure 4, the aridity indices for Hanalei, Kamananui and Makaha are 0.15, 1.0 and 4.0 respectively. The combination of rainfall and $AI$ influences the number of dominant processes in the catchments which in turn influences the shape of the FDC. Hanalei has four dominant processes and is perennial, Kamananui has three and is intermittent and Makaha has two dominant processes and is ephemeral. When the catchment is wet or supplied with adequate rainfall, there is more cause for infiltration to lower layers and more processes involved, as in more baseflow to influence perennial runoff as in Hanalei catchment. When the catchments get drier as in Kamananui and Makaha, there is less infiltration to the lower layers resulting in less processes in the deeper layer, hence, the hydrologic activity moves near to the surface. The runoff in the last tanks for both catchments are less than the mid-tanks and not sufficient enough or nullified by the catchment’s dryness; therefore, cannot influence perennial runoff so Kamananui and Makaha become intermittent and ephemeral respectively. These results verify the proposed reasoning for the shape of the lower tail of the FDC by Yokoo and Sivapalan (2011) framework.
CONCLUDING DISCUSSION

Reasons for unique shape of FDCs

By using a data-based modeling approach, this study was able to identify the number of dominant processes in perennial, intermittent and ephemeral catchments. This number of dominant processes were then used to build a tank model unique to the catchment. Process-based equations were then applied to the tank model, hence a process-based tank model whose role is to realize the transfer of processes within each catchment to explain the FDC shape differences from a process-based perspective. The study found that there are slower processes occurring in wetter catchments than in drier ones thus influencing perennial and ephemeral shapes respectively.

The dip of the FDC shape at the low ends is what indicates whether a catchment is ephemeral or remains perennial. Therefore, we assume that when a rainfall event ceases, the runoff in the catchments will continue until there is no runoff at all $(runoff = 0 \text{ mm d}^{-1})$ to force a dip in the FDC shape. In our study, we find that the wet catchment has slower processes involved in it and because of this there is a time delay for the runoff to be zero and therefore the catchment remains perennial (no FDC dip). These processes delay the runoff approaching zero until the next rainfall event, having more baseflow supply (in case of no other rainfall event) preventing the catchment from becoming ephemeral thus remaining perennial under low $AI$ climate. Hanalei under low $AI$ climate has four processes, the

![Figure 4. Number of tanks corresponds with the number of dominant processes in the catchment. Hanalei is perennial and has four processes, Kamananui is intermittent with 3 processes and Makaha is ephemeral with two processes. $AI$ is aridity index.](image-url)
DOMINANT PROCESS AND FLOW DURATION CURVE

lowest component has a \( T_c \) of 167 days, more rainfall events, more infiltration to lower layers and baseflow is supplying runoff to keep the catchment perennial.

In drier catchments with higher AI, we find it is time-sensitive as there are less processes occurring to delay runoff becoming zero, and it is easier for the catchment and shape of the FDC to dip and turn ephemeral. The Makaha catchment has only the faster two processes, the lowest component has a \( T_c \) of 5 days, there is less infiltration to the lower layer, few rainfall events, and insufficient baseflow to influence runoff (possibly negated by high AI). These fast track the processes and the catchment becomes ephemeral. The time delay seems to be primarily controlled by climatic factors.

The main advantage of this study is the simplicity and reliance on process-based models and knowledge rather than fixed model structures with priori assumptions and heavy parameterizations. This study uses only observed rainfall and runoff data to identify the number of dominant runoff processes in the catchments. Fixed model structures with complex parametrization or priori assumptions lead to unreliability and instability of the used parameters and assumptions because of the underlying uncertainties caused by various components (Banasik, 2011; Yokoo et al., 2017) as no one knows the exactness of the processes occurring especially in the subsurface zone. The flexibility in our study allows models to be built according to the hydrologic nature of the catchments.

Similarities and differences with related literatures

According to Ponce et al. (2000) AI classification, Hanalei, Kamananui and Makaha are hyper-humid, subhumid and arid, respectively. This study found that the combination of rainfall and AI is influencing the number of dominant processes in the catchments thus affecting the FDC shape. Basically, the wetter the catchment the slower processes occurring resulting in perennial flow and the drier the catchment the lesser the slower processes occurring resulting in ephemeral flow. Partial results in this study are similar to Chouaib et al. (2018) who identified the controls of climate and landscape properties on the shape of the FDC to explain the knowledge from Cheng et al. (2012), Ye et al. (2012) and Yaeger et al. (2012). Our study is similar to the aforementioned studies using process-based models to relate the processes influencing the FDC shapes, the difference is that our study used a model identified from observed data unique to the catchment and not a fixed model structure. These studies including the current study are connected by the Yokoo and Sivapalan (2011) framework on FDC, showing precipitation and evapotranspiration having different roles at each end of the FDC. Botter et al. (2007a; 2007b) showed that when precipitation ceases evapotranspiration is dominant supported by literatures showing a catchment’s dryness has a direct effect on the hydrologic nature of the catchment (Budyko, 1974; Milly, 1994; Yokoo and Sivapalan, 2011; Petersen et al., 2012). Our study is consistent with precipitation and the dryness of the catchments having a primary role in influencing the shape of the FDC.

Toward estimating FDC in ungauged basins

This study attempted to provide process-based explanations to the uniqueness of FDCs’ shapes under different climatic conditions and found that the climate of a catchment can control the characteristics of rainfall-runoff processes that eventually shapes the FDC. Nowadays, we can obtain annual precipitation and mean monthly temperature data to calculate potential evapotranspiration which allow us to estimate AI anywhere on Earth. With AI, we can roughly estimate the number of dominant processes as found in this study. The question is “what would be the AI threshold values that decides the number of dominant processes?” By applying our approach to more catchments, we would be able to answer this question. We believe we can make an acceptable estimation of the FDC in ungauged catchments only from the estimated AI value, which would be one of our future works.

In the study, we also recognize the different catchment attributes such as catchment sizes possibly having an effect on the number of dominant processes within a catchment. However, given that the number of dominant runoff processes is dependent on the recession flow variability, our presumption is that the effect of catchment size is minimal. The recession variability on a hydrograph determines the number of dominant processes for a catchment. Therefore, a small humid catchment with more flow variability can have more processes in contrast to a large catchment with less flow variability having less processes. However, this is speculation and not part of this study, though it will be part of another study addressing the question “What are the controls of catchment attributes such as catchment size, topography, land-use, soil type, geology type, etc.?” To answer this question, we would apply statistical investigations on the relationship between the unique parameters of the data-based models and catchment attributes under similar AI values as done by Ward and Robinson (1990), Burt and Swank (1992), Sefton and Howarth (1998).

Based on our findings and the above idea, we have a prospect that we will gradually increase our ability to estimate the shape of FDCs even in ungauged basins in the near future.

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SUPPLEMENTS

Text S1. Storage estimation method
Text S2. Process-based equations
Figure S1. Process-based tank model
Figure S2. Method to obtain parameters
Table S1. Catchment properties

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