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Temporal variation of intermittent surges of debris flow

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SUMMARY

Debris flows (especially those of high-density or high viscosity) usually appear in the form of surge sequence. Each debris flow event consists of tens or hundreds of surges. A debris flow is thus equal to a surge series which is expected to feature the intrinsic properties. Statistics of observation data indicates that different events have the similar distributions in parameters such as velocity, flow depth, discharge, runoff, and time interval, which can be considered as the signs of an underlying dynamics. But there are currently difficulties in extracting the dynamics from the surge series. This paper is concerned with the temporal variations of surge series based on observation data in the last forty years in Jiangjia Gully (JJG). The temporal process of a surge series is characterized by the accumulative curve of the interval time. A surge series is found to be dominated by the peak discharge in that the peak discharge determines the exponent of the distribution. Moreover, the average discharge evolves with surge progress and finally decays in a power-law form. It follows that a surge series behaves as a whole which requires a unified dynamical framework to encompass all the appearances.

Introduction

Debris flow differs much from the relevant phenomena such as landslides, rockfalls, and fluvial sediment transport in that it moves in the form of surge. A surge is a wave-like locomotion of high-density liquid which is restricted to a certain volume and spatial shape. Surges appear commonly in gravity currents (Simpson, 1997) of which debris flow has been identified as a special case (Takahashi, 1981). Debris flow surge has been long known since its first recognition over a hundred years ago (Conway, 1893; Pack, 1923; Sharp, 1942) and ubiquitous all over the world (Sharp and Nobles, 1953; Pierson, 1980, 1986; Takahashi, 1991; Major, 1997; Saucedo et al., 2005). As observed in Jiagjia Gully (JJG), a famous debris flow valley in the southwest of China, debris flow comes about in successive surges. Each debris flow event consists of tens or hundreds of surges. The surge is practically the elementary unit of debris flow (Wu and Kang, 1993; Li et al., 2004; Ni and Lu, 2005). Many mechanisms may operate in producing surge waves, such as instability of fluid, structure of debris flow, kinetic wave or roll wave (Weir, 1982; Chiu-On Ng and Chiang, 1993; Wan and Wang, 1994; Hungr, 2000). "However, observations indicate that successive surges are usually in different densities and materials, so they are unlikely to emerge from a single source. More importantly, there is no mechanism that has ever been proposed to account for the properties of the surge sequence as a whole.

It is nature to treat the surge sequence as a time series. Then here arises the question as to whether the series is deterministic or stochastic. If it is stochastic, a debris flow is simply a group of random surges; if it is deterministic, however, there must be a dynamics underlying the observed phenomena and the debris flow can be treated as a nonlinear system. The most conspicuous sign of nonlinear dynamics is the attractor reconstructed from the time series (Abarbanel et al., 1993; Broomhead and King, 1986; Eckmann and Ruelle, 1992; Takens, 1981). The fractal dimension of the attractor is calculated by the Grassberg–Procaccia algorithm (Grassberg and Procaccia, 1983). But this usually requires a long, noiseless, and stationary data set (Maurer et al., 1997). And the surge series, at most several hundreds in length, is usually not long enough to feed the algorithm (Smith, 1988; Eckmann and Ruelle, 1992), let alone the uncertain noises due to environment. To our knowledge, there seems no practical method to tackle this situation.

Although it is hard to extract the dynamics directly from the surge series, there are evidences mounting to support a dynamical perspective. First, debris flow may inherit the dynamic features in its origin from the soil failures on slopes and its extension in the network of tributary channels (Li et al., 2008) because the failure is generally believed having the nature of self-organized criticality (SOC) (Turcotte, 1997, 1999; Malamud et al., 2004) and the channel network forming a self-similar structure (Rodriguz-Iturbe and Rinaldo, 1997). Secondly, there are many results derived from

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observation data hinting at a possible underlying system, such as the long-term dependence, the frequency–magnitude relationship, and the parameter distributions which can be generally fitted by the Weibull distribution or even more general distributional function involving power and exponential components (Li et al., 2002, 2004, 2007). Such distribution is supposed to be universally applicable to interevent time statistics in the same way that power-law distributions are applicable to frequency–magnitude statistics (Yakovlev et al., 2006; Turcotte et al., 2007). Alternatively, the underlying dynamics may constitute both deterministic and stochastic components, for which will develop different prediction strategies (Hallerberg et al., 2007). The present study is contributed to build the integrity feature of the surge series in terms of the temporal variations of the discharges within an event. An average analysis is introduced to reveal the decaying of the discharge during the course and the integrity of the series.

Distribution properties of surges

Living debris flow is rarely seen in field. But it is fortunate that the Jiangjia Gully (JJG) in the southwest of China has provided an ideal spot for real-time monitoring of debris flow (e.g., Li et al., 1983, 2003, 2004; Davies, 1986, 1990; Davies et al., 1991, 1992; Chen et al., 2005; Cui et al., 2005). Every year witnesses a dozen of events on average and each event consists of tens or hundreds of surges. Since its establishment in 1960s, the Dongchuan Station of Debris Flow Observation and Research, Chinese Academy of Science, has achieved a relatively complete database which includes more than 400 debris flows (e.g., Li et al., 2004; Cui et al., 2005; Liu et al., 2008; Kang et al., 2006).

JJG is 48.1 km^2 in area, a rather large valley regarding debris flow. In such a gully, debris flow is by no means a full-valley process; rather, every surge originates in some special tributaries and finally converges into the downstream channel. Surges are measured at the fixed sections in the mainstream channel in the lower part, as indicated by the black triangle in Fig. 1 (Li et al., 2004). The discharge of a surge is estimated by the product of the flow velocity between the fixed sections and the average section area (e.g., Kang et al., 2006). The temporal interval between successive surges ranges from tens to hundreds of seconds. Corresponding to the time $t_1, t_2, \ldots, t_n$, at which the surge front passes the section, a debris flow is constituted by the time series: $X_1, X_2, \ldots, X_n$, where X denotes one of the measured parameters, such as discharge Q, velocity V, and interval τ, and so on (Fig. 2).

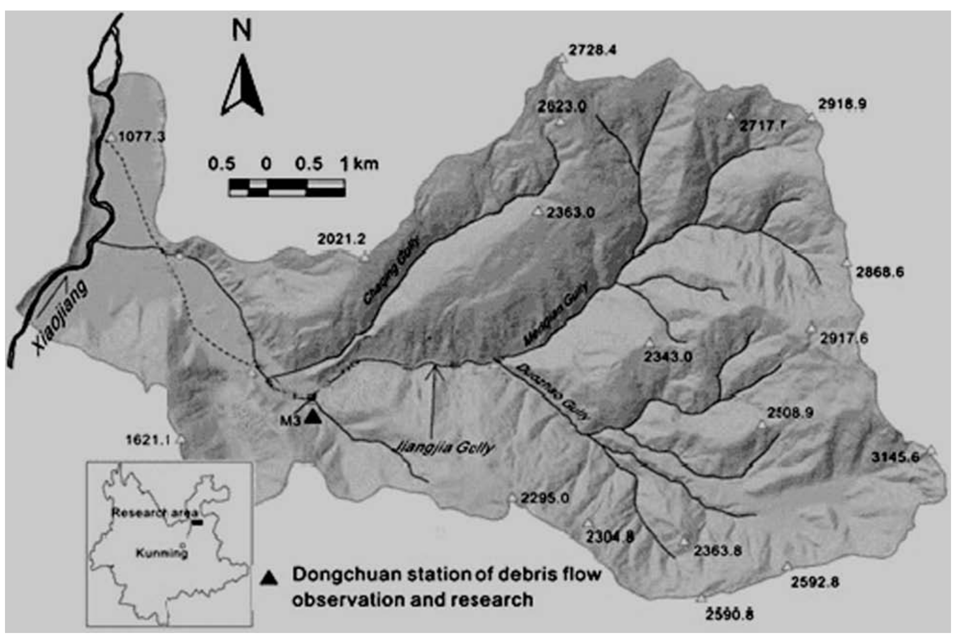

Fig. 1. Debris flow in JJG, observed at the delta point of the Dongchuan Station.

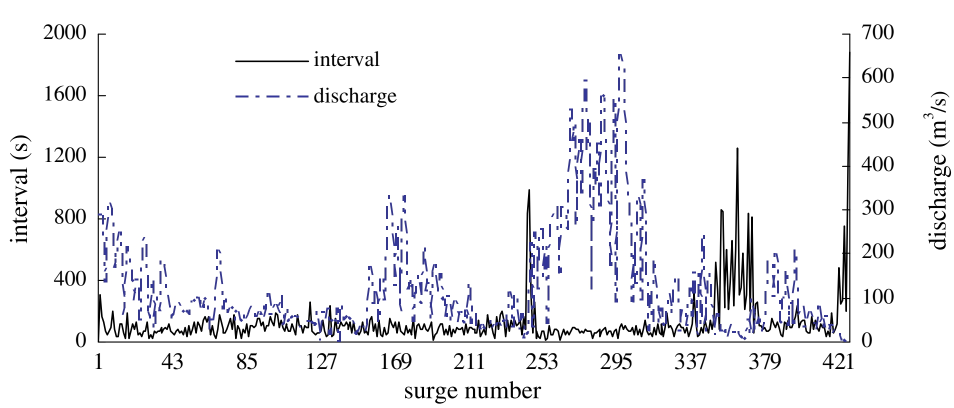

Fig. 2. A surge series of debris flow in JJG (event 910709).

It is notable that the series for different parameters are subject to an exponential family of distributions, special cases of which are Gamma and Weibull distributions (Kalbfleisch and Prentice, 1980). Such distributions share the scaling invariance in that if two parameters are related by a power-law, they would have the same distribution. One example is the similarity between distributions of flow depth and velocity. It has been also found that the planimetric factors of the valley (e.g., drainage area, relief, slope, and mainstream length) satisfy the same distribution (Li et al., 2002). Exploring the implications of the similarity in distributions of parameters and valley factors should provide an insight into the probabilistic perspective of debris flow and it might be as well an interesting topic for the future. Particularly, it is expected that the power-law relations may play the same role in a physical model of debris flow as in the models of flood.

Apart from these numerical results, qualitative properties have been found in the series which differ in many ways from the stochastic events and share the features that have been recognized as nonlinear dynamics (e.g., rainfall series, earthquake series, volcanic eruption series, and so forth) (Li et al., 2004). However, there remain major difficulties in applying the existing nonlinear dynamical methods to the measured time series (e.g., Maurer et al., 1997; Schreiber, 1999). In the following, instead of direct extracting the dynamics, discussion is focused on the tangible properties of the surge series in terms of the intermittence and the discharge variation, which are the most representative of the tempo-spatial properties of debris flow.

Temporal intermittence of the surge series

The most conspicuous of surge series is the intermittence. Intervals between surges rang from tens to hundreds of seconds. And the high fluctuation of discharge shown by Fig. 2 can be ascribed to the fact that the surges are coming from different tributaries and undergoing different processes. It is of special interest to note the intermediate flows of small discharges. They are usually of low density (e.g., between 1.3 and 1.6 g/cm^3) and actually not typical debris flow in nature. However, from the viewpoint of time series, they are indispensable for constituting a complete data set. In other words, an event of debris flow should be identified as a series of flows in various properties, instead of only a group of high-density surges.

The emergence of the temporally separated flow implies that a debris flow surge has its own origin independent on the flood flow; otherwise the flood surges should have picked up the sediment and turned into typical debris flow surges. Therefore, debris flow is a mass flow in its own way (e.g., as mentioned above, from the slope failure to the channel flow), which would come about only when the mass is ready to move. At this point, rainstorm is perhaps overestimated as to make up a debris flow; here one sees that it is more stimulative than decisive. The intermittence of surge is in many ways similar to a variety of intermittent phenomena in nonlinear dynamics (Li, 2004). Although the dynamics is unknown, the intermittence might have shed a light on the origin of the surge.

A possible way to explore the mechanism of the surge is to look at the distribution of the intervals. For example, the exponential distribution is often the sign for the Poisson process, which means that the events occur continuously and independently of one another. For the case of surge series, statistics shows that the probability distribution is not exponential, but rather has a peak at the small interval (100 s or so). In other words, the successive surges are far away from the origin of Poisson process. Several probability distributions are possible to fit the observation data, such as the Weibull, Lognormal, and the generalized extreme value distribution (GED). Calculation shows that the GED fits the best (Fig. 3).

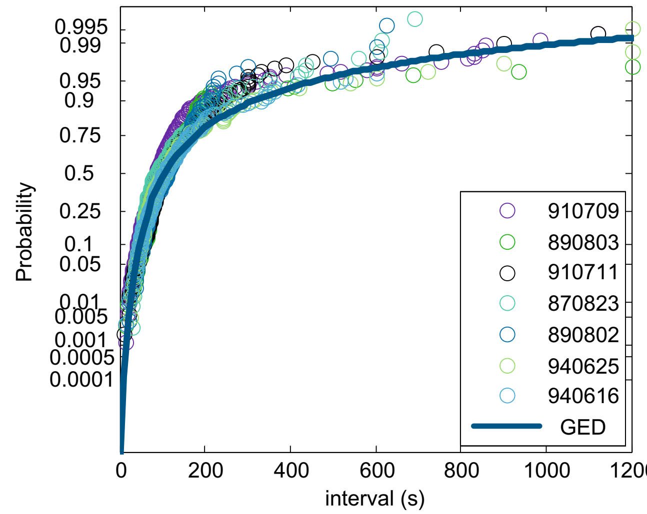

Fig. 3. Probability distribution of intervals.

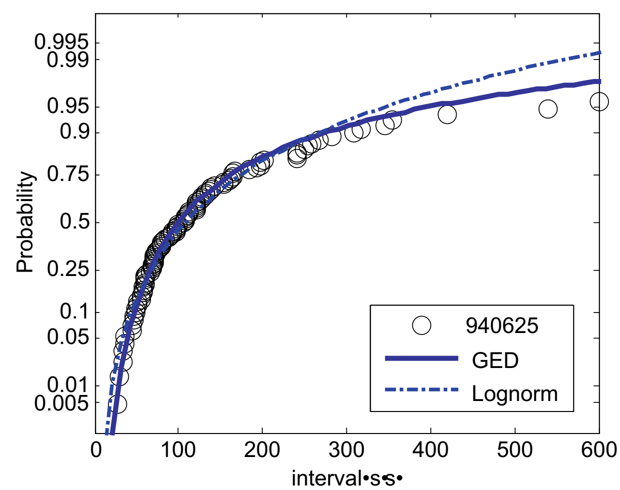

Fig. 4. Comparison of the distributions.

Fig. 4 displays the comparison between GED and Lognormal distribution. In terms of Log likelihood, GED is generally several orders of magnitude higher than the Lognormal distribution.

The importance of GED relies in the fact that it is the limit distribution of the maxima of a sequence of independent and identically distributed random variables. Then there is a natural interpretation for GED: the interval is the waiting time for the next surge to come from the processes such as soil failures and landslides on slopes; and each interval can be regarded as the maximal time duration for these pregnant processes.

On the other hand, the accumulative of the intervals, i.e. the series of occurring time (as observed a the fixed section), $t_1, t_2, \ldots, t_N$, exhibits another aspect of the temporal feature. These discrete time points can be considered as the measured values of a continuous function (curve). Four types of processes are identified, as represented in Fig. 5, where the unit of time is formalized by the last time t_N (i.e. let $t_N = 1$ for each sequence, with N being the total number of surges).

Types C and D are so simple that they can be fit by exponential and linear function, respectively. When considering types C and D as the elementary processes, the types A and B should be combinative ones. In general, slope of the curve describes the rate of the surge production. Since the surges originate from different slopes

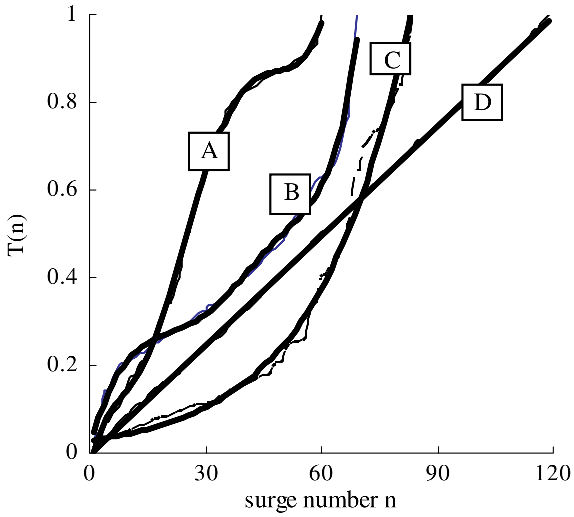

Fig. 5. Time curves describing the temporal processes of the surge series.

and tributaries and involve different processes, it is interesting to link the time curves with the possible routes of the surges. This requires a complete scenario of a surge from origination to the reach of observation.

Temporal variation of discharge

Discharge distribution

Discussions above suggest there should be a dynamics to describe all the presented phenomena. Although the dynamics underlying the surges is unknown yet, there are tangible properties that specify the integrity of surge series. It has been found that the discharges, although fluctuate strongly, share the same accumulative distribution (Liu et al., 2008). That is, the percentage of surges with discharge bigger than a given value Q is well featured by the exponential function

$$P(Q) \sim \exp(-kQ) \tag{1}$$

where k is the exponent, and the coefficient of the exponent function is omitted which matters little for our discussion. Statistics of thirty events are listed in Table 1, in which the maximal and average discharge of each event is also listed. Fig. 6 displays three of the fitted curves.

Actually, Eq. (1) provides a magnitude-frequency relationship, which can be further considered as playing the same role as the Gutenberg–Richter law in earthquake (Turcotte, 1997) that has been recognized as SOC (Bak and Tang, 1989; Bhattacharya and Manna, 2007).

In Table 1 the biggest exponent appears notably at the lowest peak discharge (i.e. event 8908021) and the smallest exponent at the highest one (event 980709). In deed, statistics on the data does yield a power-law relationship between the exponent k and the peak discharge Q_{max}

$$k \sim Q_{max}^{-\beta} \tag{2}$$

with $\beta = 0.9821$ (Fig. 7).

Then, normalizing the discharge for each surge sequence by Q_{max}, i.e. let $Q^* = Q/Q_{max}$, Eq. (1) can be rewritten as

$$P(Q^*) \sim \exp(-k^*Q^*) \tag{3}$$

with exponent

$$k^* \sim Q_{max}^{1-\beta} \tag{4}$$

Table 1
The exponents and related parameters for the distribution of surge discharges.

Event	k	Q_{max} (m^3/s)	$\langle Q \rangle$ (m^3/s)	R^2
660627	2.3866	2391	351.5	0.9940
660628	11.991	399.3	133.7	0.9617
670731	2.7761	1558.9	618.8	0.9443
750810	13.394	413.6	106.5	0.9454
820611	2.5394	1673	664.3	0.9399
870823	9.6102	728.9	88	0.9840
880703	4.694	818.1	263.5	0.9516
890627	3.7053	1050	205	0.9783
890727	5.3131	740.9	128.6	0.9817
890802	19.994	238.2	67.2	0.9832
900620	14.748	467.8	92	0.9852
907018	8.4334	626.3	149.4	0.9908
900729	9.4948	397.4	135.25	0.9535
910708	6.4405	754	166.4	0.9350
910717	4.1897	1319.4	175.2	0.9677
910813	7.7798	801.4	158.5	0.9842
920617	5.2599	826.5	227.2	0.9718
920717	3.127	1053	240.6	0.9718
930826	7.3478	571.9	146.5	0.9837
940616	4.1613	1382.5	459.8	0.986
940625	2.4048	2027.8	459.8	0.9840
940702	6.3812	929.2	223.65	0.9783
980709	1.3577	2913.9	960.6	0.9202
990810	7.1263	756.8	221.6	0.906
990818	5.9418	1060	224.46	0.9948
990825	3.5604	1350	355.4	0.9679
00809	4.284	1133.1	269.3	0.9896
010704	8.5645	497.7	221.6	0.9060
010805	6.3497	747	201	0.9606
010822	3.8273	1278.9	350.2	0.9372
020718	4.3628	856.8	191.2	0.9242
020820	4.9119	863.2	338.1	0.8801
030611	3.0968	1425.1	489.1	0.9700
030726	4.1418	1240.6	325	0.8586
040731	13.577	279.8	73	0.9679

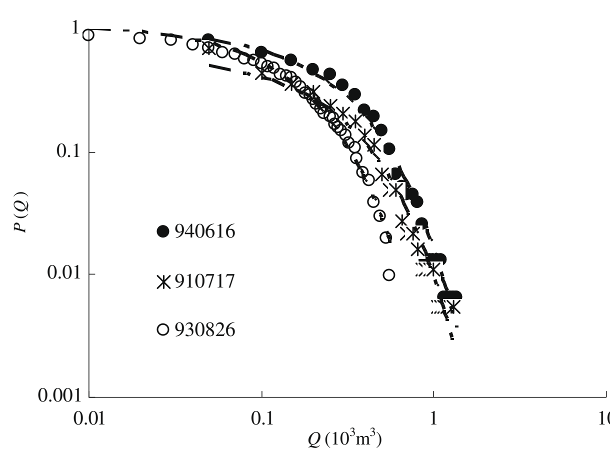

Fig. 6. Distribution of surge discharges.

Substituting the value of exponent β, $k^* = Q_{max}^{0.0179}$. The small exponent here makes the k^* value much less variable. For instance, there is a wide gap in exponent value between events 890802 and 940625 (see Table 1), but their k^* values are nearly the same: 4.69 and 4.82, respectively. The little variation of the exponent for the rescaled discharge implies the universal significance of peak discharge in debris flow event.

Decaying of the surge series

The peak discharge is also found to dominate the surge progress. Define a time-dependent average of discharge (for

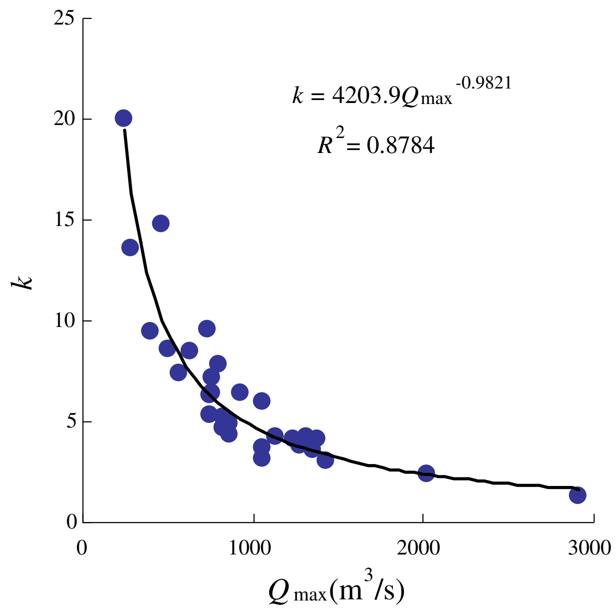

Fig. 7. Relation between the distribution exponent and the maximal discharge.

convenience, the normalized discharge Q^* is used hereinafter, with the asterisk omitted)

$$\langle Q \rangle_n = (Q1 + Q2 + \cdots + Q_n)/n \quad (5)$$

It is found that $\langle Q \rangle_n$ is exclusively inclined to decrease after some surge number (Fig. 8). Despite the abrupt rising in the early episode, $\langle Q \rangle_n$ finally decays in a power-law form

$$\langle Q \rangle_n \sim n^{-a} \quad (6)$$

where the exponent a ranges between 0.20 and 0.80 or so (Table 2). This differs much from the random data in which the averaging curve sways around the average value of the total set of data.

To see the domination of $Q_{\max}$ in this situation, note that the maximal decaying exponents emerge at the events with the highest peak discharges. Specifically, consider three series 890802 (A) and 940625 (B), which have the similar appearance of discharge fluctuation (Fig. 9) but distinctive peak discharge, and series

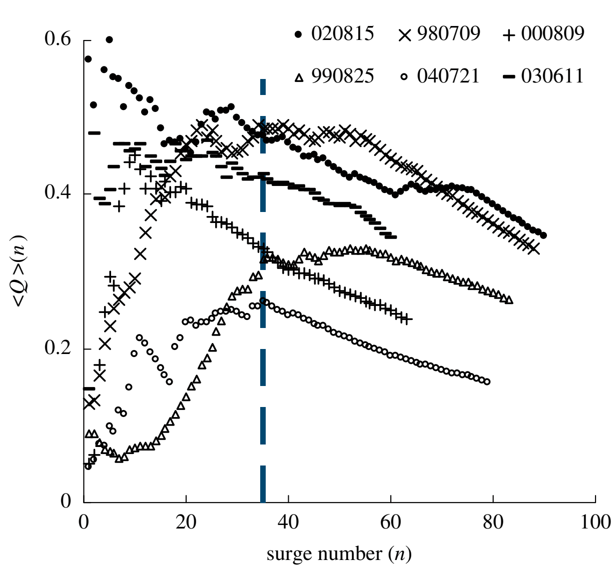

Fig. 8. Averaged discharge decaying with surge number.

Table 2
Exponents of averaged discharge decaying.

Event	Surge number	$Q_{\max}$ (m^3/s)	Decaying exponent
890802	127	238.2	0.5584
940625	107	2027.8	0.7481
870823	180	728.9	0.2056
020815	90	629.8	0.2773
980709	88	2913.9	0.7558
000809	63	1133.1	0.4544
010822	161	1278.9	0.4959
990825	83	1350	0.5413
040721	79	684	0.6445
030611	60	1425.1	0.2827
990810	68	756.8	0.4343
990818	78	1060	0.4213
980716	74	945	0.6217
010704	73	497.7	0.5081
020718	61	856.8	0.6633
020816	77	863.2	0.5917
030726	53	1240.6	0.7840
880703	105	818.1	0.4037

870823 (C), which is relatively long (180 surges involved) and has a moderate peak discharge (Table 1). Fig. 10 presents the decaying curves. One sees that A and B are similar in averaged discharge curve, but B, with the higher $Q_{\max}$, falls more steeply. Generally speaking, for series of the similar length, the lower the peak discharge, the more steady the process. As for the longer series 870823, it has a long decaying tail, which rightly responds to the persistence of the series. However, it is not clear whether there is a specific relation between the peak discharge and the surge number. A unified theoretic framework is wanted to account for the persisting and decaying of the surge series.

Dynamical implications

Two facts here are especially remarkable that concern with the systematic properties underlying the series. First, $\langle Q \rangle_n$ <0.5 is satisfied for almost all the series. This means most surges are in small discharges, thus the peak discharge $Q_{\max}$ appear more significantly conspicuous in a series. A series turns out to be a group of dwarf surges dominated by several giant surges. Taking $Q_{\max}$ as the representative magnitude of the series, it is found that the magnitude-frequency relation at event scale is the power-law (Liu et al., 2008). Moreover, the intervals between "giant" surges (e.g., surges with discharge beyond half the average) turn out to have a power-law distribution. The emergence of power-law out of the "filtered" series reveals the SOC nature, which might be disturbed by noise of those small surges. Then the domination effect of the peak discharge has its origin from the SOC background signed by the power-laws.

Secondly, no series has ever been observed to have a rising averaged discharge similar to the early part of the surge series. This means that any event that occurs, no matter how short it might be, is a complete series that always present the same decaying trend. In other words, a series appears as a whole; there is no debris flow in nature that is "uncompleted" or "suspended". The integrity of the series may enforce the assertion that, although there has been not so far a dynamics extracted from the surge series, it is compelling to consider these phenomena under a framework of system dynamics.

Conclusions and discussion

Temporal variations of debris flow are discussed in terms of surge series based on observation data. Firstly, the discharges in a surge series are found to have an accumulative distribution in

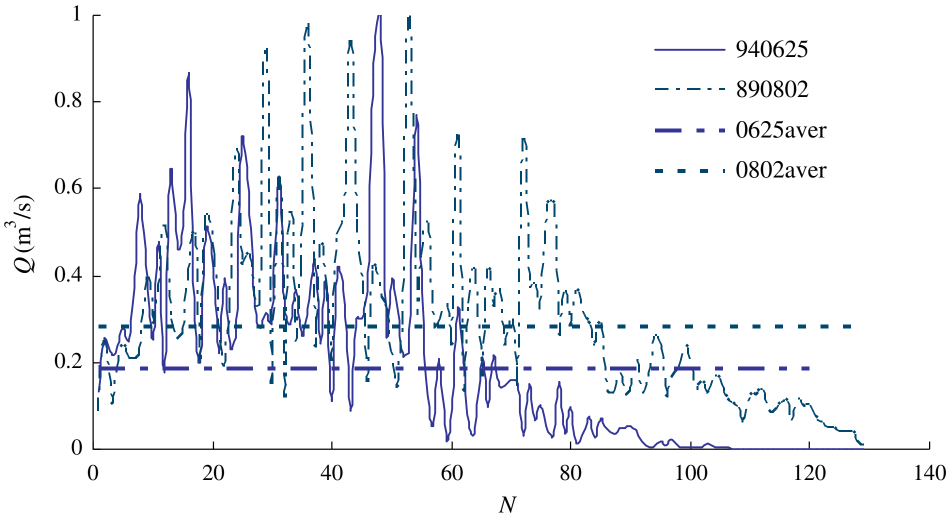

Fig. 9. Hydrographs of debris flow events with extreme maximal and minimal discharge.

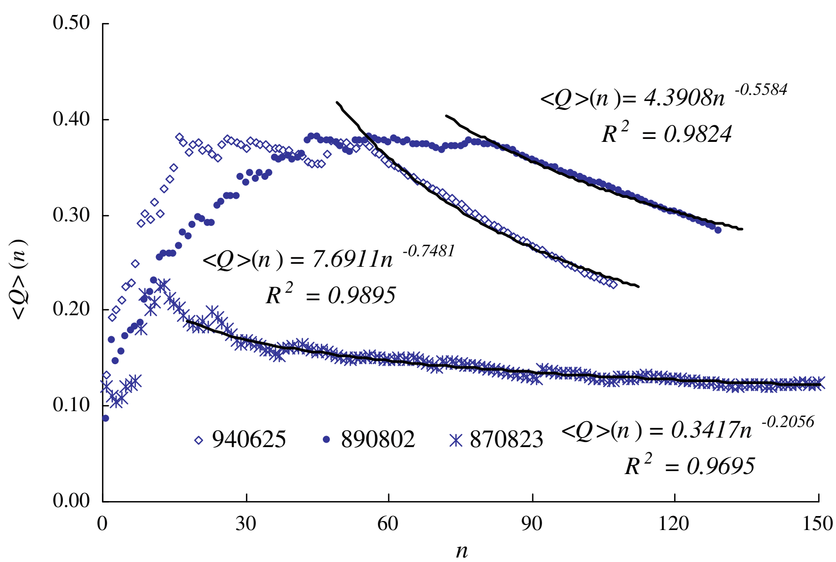

Fig. 10. Comparison of averaged discharges for different surge series.

thr form of exponential function, with exponents varying with the peak discharge in a power-law form. This suggests the dominant role of the peak discharge in the surge progress. Secondly, the averaged discharge varies with the progress of the series and finally decays in a power-law form. It follows that a debris flow as a whole is a sequence of various surges dominated by the peak discharge. These findings represent the intrinsic feature of debris flow. Because the data come from the same valley and the surges in a sequence are under the same circumstances, the variations involved should be dynamically determined but not dependent on the external influences. Therefore, the characteristics presented here might be of universal importance for debris flows in whatever environmental conditions.

Furthermore, it is suggested that the domination effect of the peak discharge has the origin from the SOC background associated with landslides and slope failures; and these prosseses in turn are precisely the origins of a debris flow surge. Therefore, debris flow through the surge series finds an access to the system dynamics. Although there has not been so far any dynamics extracted from the surge series, evidences reported here are supporting a dynamical perspective.

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