Benford's law as mass movement detector in seismic signals

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Key Points:

- The first-digit distribution of seismic signals generated by high-energy mass movements and fluvial processes follows Benford's law
- When Benford's law appears, raw seismic signals tend to increase exponentially and converge to a power law distribution with exponent one
- A computationally cheap and novel detector based on Benford's law is developed for debris-flow events

Abstract

Seismic instruments placed outside of spatially extensive hazard zones can be used to rapidly sense a range of mass movements. However, it remains challenging to automatically detect specific events of interest. Benford's law, which states that first non-zero-digit of given datasets follow a specific probability distribution, can provide a computationally cheap approach to identifying anomalies in large datasets and potentially be used for event detection. Here, we select raw seismic signals to derive the first-digit distribution. The seismic signals generated by debris flows, landslides, lahars, and glacier-lake-outburst floods follow Benford's law, while those generated by ambient noise, rockfalls, and bedload transports do not. Focusing on debris flows, our Benford's-law-based detector is comparable to an existing random forest method for the Illgraben, Switzerland, but requires only single station data and three non-dimensional parameters. We suggest this computationally cheap, novel technique offers an alternative for event recognition and potentially for real-time warnings.

Plain Language Summary

Natural hazards, such as debris flows and landslides, pose a significant threat to the exposed communities. Seismic instruments as seen as effective tools for detecting these hazardous processes and may be used in early warning systems. However, the difficulty lies in identifying the events of interest concisely and objectively. Our study explores Benford's law, a probability distribution of the first-non-zero digit. We collected seismic data generated by various hazard events and compared the observed first-digit distribution with their agreement with Benford's law. We found seismic signals of high-energy mass movements follow Benford's law during the running phase, while ambient noise and other small mass movements do not. In order to explain why Benford's law is followed, we argue that raw signals increase exponentially and fit a power law distribution with exponent as one. Our detector, based on Benford's law and designed for debris flow, which is a computationally cheap and novel model, performs similar to a machine learning algorithm previously used in the study site. Our work illustrates a new approach to detecting events and designing warning systems, which can be used in different regions.

Keywords Environmental seismology, mass movement, Benford's law, event detector, debris flow, early warning system.

1 Introduction

Mass movements (e.g., landslide and debris flow) and extreme fluvial processes (e.g., flash floods and glacier-lake-outburst flood) are of significant concerns in populated areas, as they can cause huge loss of life and damage to civil infrastructure each year (Holub & Hübl, 2008; Merz et al., 2021; Regmi et al., 2015). Classification criteria for mass movements may vary depending on the focus of interest (Coussot & Meunier, 1996; Nemčok et al., 1972). Yet, the most widespread and destructive mass movements are generally considered to be debris flows, landslides, and rockslides (Dowling & Santi, 2014; Froude & Petley, 2018). Despite extensive efforts to mitigate their hazard through risk assessment and structural measures (Dai et al., 2002; Fuchs et al., 2007; Huebl & Fiebiger, 2015), the intricate geological conditions and dynamic processes of mass movements frequently pose challenges in preventing property damage and fatalities (Fan et al., 2019; Kean et al., 2019; Tiwari et al., 2022).

Early warning systems are an established approach to mitigating the impact of mass movements (Badoux et al., 2009; Guzzetti et al., 2020; Hürlimann et al., 2019). For example, systems based on measured rainfall intensity and predefined thresholds for triggering alarms (Baum & Godt, 2010; Marra et al., 2016) are among the most popular warning approaches. However, maintaining rain gauges and obtaining accurate rainfall intensity data in real-time is challenging for the operation of a warning system, especially for catchments with large elevation differences. Inaccurate measurements and uncertainty in data interpolation lead to significant errors in rainfall thresholds (Nikolopoulos et al., 2015). In addition, due to the variability in geological and hydrological conditions, empirical thresholds for triggering debris flows and landslides are not transferable between catchments (Gregoretti et al., 2016; Wilson & Wieczorek, 1995). Detecting specific events of interest from time-series signals is essential for releasing a warning. Force plates, radar, laser, and video cameras are the most common sensors used for monitoring in early warning systems (Comiti et al., 2014; McArdell et al., 2007). However, some of these devices require a high-power supply and regular maintenance, and can be easily destroyed by the hazard processes itself.

Continuous seismic and acoustic signals offer a new way to monitor mass movements with high temporal resolution (Le Breton et al., 2021; Burtin et al., 2016; Cook & Dietze, 2022; Farin et al., 2019; Schimmel et al., 2013). The instruments can be installed outside the zones affected by the hazard and are thus in lesser danger of being destroyed. An array of seismic stations can help to detect and locate extreme, high-energy events on a regional scale (Cook et al., 2021; Ekström & Stark, 2013; Hammer et al., 2012). However, a seismic station records all ground vibration signals within its bandwidth, blending events of interest and those considered as noise. Current seismology-based detectors of mass movements and fluvial processes, such as seismic attributes-based methods (Dietze et al., 2022; Govi et al., 1993; Schimmel & Hübl, 2016; Wei & Liu, 2020), short-term average to long-term average ratio (Coviello et al., 2019), random forests (Hibert et al., 2019; Provost et al., 2017), and hidden Markov models (Dammeier et al., 2016; Hammer et al., 2012) require numerous waveform, spectral, network features or parameters to be fed into the model to identify events. In addition, collecting and labeling the data to parameterize or train such a model is time-consuming and requires experience. Applying these existing approaches to other sites requires re-training the model or calibrating the parameters; worse, often no historical data are available for most new sites to do this. Before warning systems can be constructed, implemented, and promoted, a convenient and portable approach to event detection must be found. Compared to ambient noise and signals not associated with extreme events in a natural environment, the temporal occurrence probability of mass movements is relatively low. Therefore, detecting debris flows and other mass movements in seismic time-series signals can be treated as an anomaly detection.

The Newcomb–Benford law (BL) or the first-digit law, which is widely used in fraud and data quality detection, is a probability distribution of the first digit of a dataset (Castañeda, 2011; Cho & Gaines, 2007; Ley, 1996). Newcomb (1881) stated that the probability of occurrence of the first digits is such that the mantissae of their logarithms are equally probable:

$$P(d) = \log_{10}(1+d^{-1}) \tag{1}$$

where $P(d)$ is the theoretical probability of the first none zero digits, d={1, 2, …, 9}. For example, -0.01 and 100 share one as the same first digit with a likelihood of 0.301. Frank Benford rediscovered this relationship, tested it with twenty different datasets. It was later named after him as Benford's law (Benford, 1938). BL has been used to several fields of the geosciences, such as in studying the homogeneity of natural hazard datasets and anomalies

(Geyer & Martí, 2012; Joannes-Boyau et al., 2015). Earthquakes and Mars quakes were detected in seismic signals with BL (Díaz et al., 2015; Sambridge et al., 2010; Sun & Tkalčić, 2022). Due to the dimensionless and low computational cost of BL, it has the potential to be used to identify mass movements in seismic data at different catchments, perhaps even as detector in data loggers.

In this study, we compiled seismic data generated by various mass movements and fluvial processes, calculated the first-digit distribution of seismic signals, and investigated which processes or periods follow the BL. We explain why BL appears in seismic signals generated by some of the processes and not by others. Finally, we present a BL-based event detector for debris flows and compare its performance with a previously developed random forest model (Chmiel et al., 2021) for the same seismic network. This work shows a novel approach for detecting high-energy mass movements and the potential for establishing a real-time warning system using BL.

2 Data Source and Event Catalog

2.1 Study Site and Data Source

The Illgraben catchment near the village of Leuk, southwest Switzerland (Figure 1a) is one of the most active debris flow catchments in the Alps. It covers an area of about 9.5 km^2 and extends from the Rhône River at 610 m to the Illhorn Mountain, peaking at 2716 m (Badoux et al., 2009). The annual rainfall is concentrated from May to October, and the Illgraben catchment roughly experiences three to five debris flows and several floods each year, mainly triggered by short-duration convective storms (McArdell et al., 2007). To mitigate the risk of debris flows and floods, a warning system has been implemented at the Illgraben that triggers an alarm when the impulse of in-torrent ground vibration sensors exceeds empirically determined thresholds (Badoux et al., 2009).

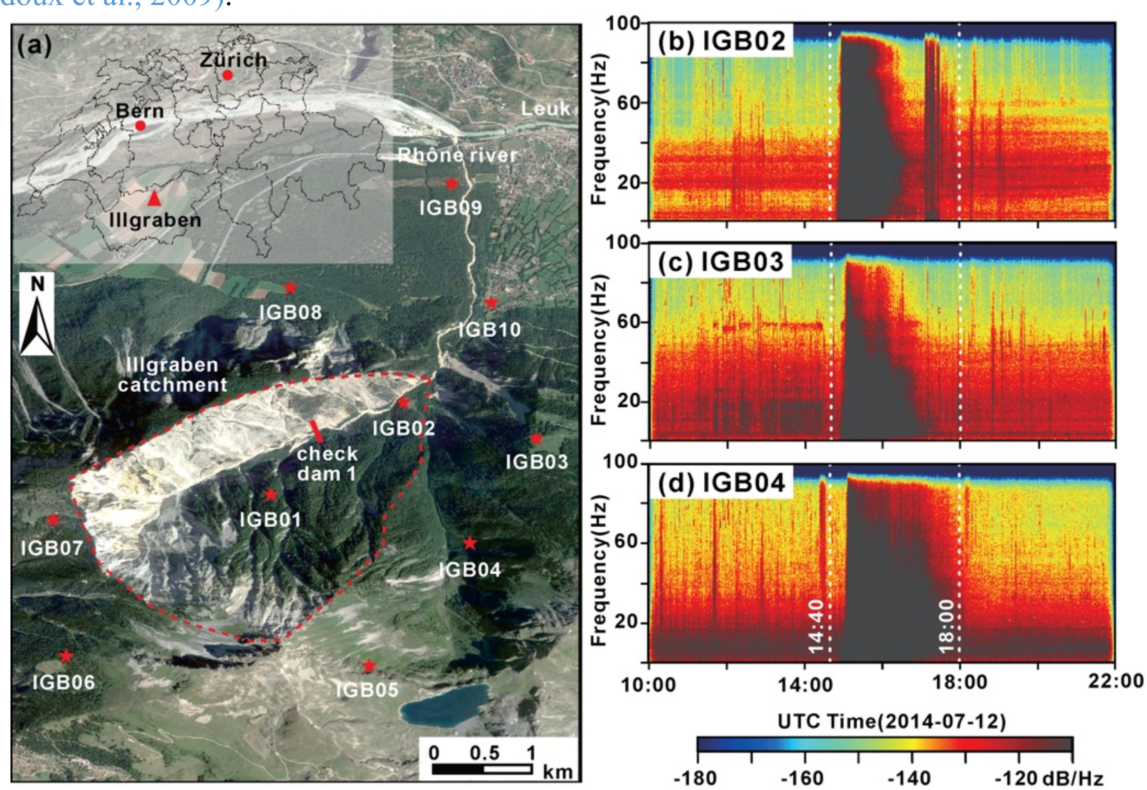

Figure 1 Study area and debris flow at Illgraben catchment. (a) Location and distribution of seismic stations (red stars, Table S1 for details). (b) to (d) are the spectrograms of the vertical component for a debris flow event between 14:40 and 18:00, 12th July 2014.

Considering that seismic data are not available for all stations for the whole year and the complexity of signals from stations far from the spatially propagating event, we mainly selected the IGB02 station for this study (same location as ILL02/ILL2 deployed by Swiss Federal Institute for Forest, Snow and Landscape Research WSL), which is closest to the channel and far from the nearby residential area of Leuk.

2.2 Event Catalog

To calculate the first-digit distribution of seismic signals and quantify which processes or periods follow BL, we examined 24 debris flows (one of which may be a flood event) that occurred 2013-2014 and 21 debris flows that occurred 2017-2019 (Tables S2-S3) in the Illgraben catchment. For the 2013-2014 debris flows, ten of the 24 events were recorded by local warning systems (WSL events), and we manually labeled an additional 14 debris flows based on the event duration of waveforms and the 1-50 Hz features of the spectrogram (GFZ events, Text S1). One example of the debris flow that occurred on 12th July 2014, with the WSL label and high signal-to-noise ratio SNR (about 20 based on IGB02), is shown in Figures 1b-1d.

To complement the data with events from other locations and instruments for calculating the first-digit distribution, we added seismic signals from other mass movements and fluvial processes (Table S4), such as a 2013 rockfall event in Illgraben, Switzerland (Burtin et al., 2016), a 2015 rockfall event in Lauterbrunnen, Switzerland (Dietze et al., 2017), a 2014 landslide in Askja, Iceland (Schöpa et al., 2018), a 2015 hurricane-induced lahar in Volcán de Colima, Mexico (Capra et al., 2018), a 2016 glacial-lake-outburst flood GLOF in Bhotekoshi, Nepal (Cook et al., 2018), and a 2019 bedload transport event in Liwu catchment, Hualien.

3 Methods

3.1 Data Preparation

Processing seismic signals using demeaning, detrending, filtering, or deconvolution may alter the first-digit distribution and obscure the difference between BL in ambient noise and the event phase (Figure S1). Therefore, we use the raw vertical-component seismograms (units are counts) to calculate the first-digit distribution and check whether the observed distribution adheres to BL. We choose a one-minute moving window (no overlap) to calculate the probability distribution of digits one to nine to avoid statistical errors associated with a small dataset. The number of data points (n) for each window is equal to the moving window length (W_L, units are seconds) multiplied by the sampling frequency (f_S, units are Hertz, Table S1 for details):

$$n = W_L * f_S \tag{2}$$

For each window, data points with a raw amplitude equal to zero are discarded.

3.2 First-digit Distribution and Benford's Law

We used two established statistical methods, the Chi-squared test (Geyer & Martí, 2012; Patefield, 1981) and the Kolmogorov-Smirnov test (Kaiser, 2019; Feller, 1948), to validate whether the observed first-digit distribution follows BL. The hypothesis is that the frequency of the observed first digits is not distinct from the theoretical BL values, or both represent the same distribution. We define that a p-value greater than 0.95 for any test means acceptance of the hypothesis. The observed first-digit distribution is considered consistent with BL if the hypotheses of two tests are accepted. In addition, the goodness of fit φ introduced by Sambridge et al. (2010) is used to evaluate the difference between the observed distribution and BL:

$$\varphi = \left(1 - \left(\sum_{D=1}^{9} \frac{(f_{obs_d} - f_{BL_d})^2}{f_{BL_d}}\right)^{1/2}\right) \times 100\% \quad (3)$$

where f_{obs} and f_{BL} are the observed digit frequency and theoretical probability of BL, d={1, 2, …, 9}. A value of φ closer to one means that the distribution is closer to the theoretical BL value.

To investigate the occurrence of BL in seismic signals, we examine the relationship between the time series of seismic signals and their corresponding first-digit distribution. This analysis allows us to understand the underlying factors contributing to the emergence of BL during specific processes or periods.

For the processes or periods that follow BL, we examine the relationship between the time series of seismic signals and their first-digit distribution to investigate why BL appears. In the time domain, the raw seismic signal $S(t)$ is a function of time (t) and can be described with an interquartile range iq as magnitude changes of the measurements. Here, the seismic signals before the optimal goodness of fit $\varphi_{optimal}$ were selected to fit an exponential curve for the increased parts (Text S3 for details):

$$S(t) = a * e^{b*t} + c \quad (4)$$

$$iq = Q_{75} - Q_{25} \quad (5)$$

where S is the seismic signals (units are counts), t is time (units are second), and a, b, and c are the coefficients of the exponential function. Q_{75} and Q_{25} are the upper and lower quartile of the data for each window.

Previous studies have demonstrated that datasets with a power law relationship (exponent one) in data pairs satisfy BL, such as the data on many hydrological phenomena (Nigrini & Miller, 2007). In this study, we assume that the seismic data in all one-minute moving windows have this power law distribution, then the data of each window were selected and sorted from smallest to largest (rank order) to calculate α by Equation (6-7) based on its magnitude (Newman, 2005). We subsequently examine whether the seismic data follow the power law with exponent one when BL appears:

$$p(x) = C * x^{-\alpha} \quad (6)$$

$$\alpha = 1 + n\left(\sum_{i=1}^{n} \ln \frac{x_i}{x_{\min}}\right)^{-1} \quad (7)$$

where $p(x)$ is the seismic data in any one-minute moving windows. C and α are the coefficients of the power law function. x_i, and $x_{\min}$ are the i-th data and minimum data in the dataset of length n.

3.3 Data Preparation Debris Flow Detector Implementation

To demonstrate the application of BL, we developed a two-fold debris flow classification detector using seismic data from Illgraben. There are three non-dimensional parameters in our classification model to reduce uncertainty (Figure S2): the ratio between the interquartile range iq at time i and its average value of the previous 20 minutes (R_{iq}), the power exponent at time i (α_i, Equation 6), and the averaged power exponent for d minutes after time i (α_d). We define the debris flow (positive events) by manual interpretation of the seismic data (Text S1 and S4). With a one-minute moving window, all events with all three non-dimensional variables are scanned, and the detector returns either a positive (debris flow) or negative (not debris flow) labels. Finally, in order to test the sensitivity of moving window size or the number of data points for each window, a varying window length from 1s to 600s in a one-second interval was chosen to test the variation of the power law exponent.

Our dataset includes 14 manually marked debris flow events out of a total of debris flow 24 events, we divided the available dataset into a training dataset (24 events, 2013-2014) and a validation dataset (21 events, 2017-2019). The details to define positive and negative cases for training and validation are described in Text S4. We used a confusion matrix to evaluate our detector performance (Beguería, 2006; Staley et al., 2013). The definition of true positive (TP), true negative (TN), false positive (FP), false negative (FN), F1 score (F1), and Threat Score (TS) are given in Text S4. The detector model is considered the best when F1 is one or closest to one. We compare the validation results with an existing random forest model trained with data from 2017 to 2019 recorded by the same seismic network using more than 70 seismic features (Chmiel et al., 2021).

4 Results

4.1 Benford's Law and Seismic Signals

BL was observed in 38 out of the 45 debris flows events, while it was absent for two events from the 2013-2014 GFZ dataset and five events from the 2017-2019 WSL dataset (Figures 2f-2g, S3-S5 and Tables S2-S3). In the debris flow events that follow BL, we observed that both Chi-squared and Kolmogorov-Smirnov tests only accept the hypothesis during the running phase. For example, the debris flow event on 12th July 2014 (Figures 1b and 2a-2d) exhibits $\varphi_{optimal}$ of 87.97% and suggests that the first-digit distribution of seismic signals follows BL. Moreover, the first-digit distributions of station IGB03 and IGB04 are similar to what was observed for this event (Figure 2e). In addition, for other mass movements, the first-digit distribution of the seismic signal generated by the landslide (Figure S8) and the lahar (Figure S9) also exhibit BL. However, our two rockfall cases failed to follow BL (Figures S6-S7).

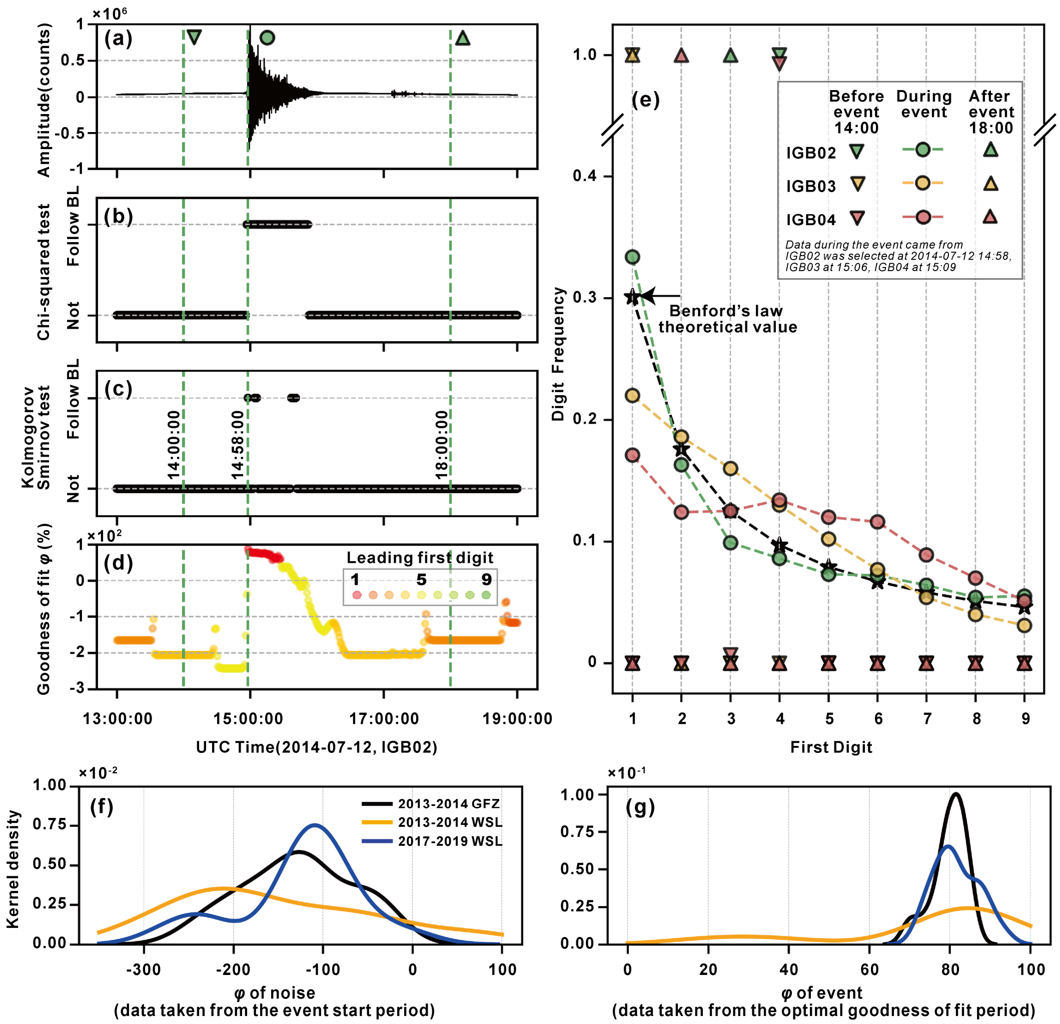

Figure 2 First-digit distribution of seismic signal generated by debris flow. (a) Raw waveform. (b) to (d) are results from the Chi-squared test, Kolmogorov-Smirnov test, goodness of fit. (e) First-digit distribution of different stations during this debris flow. (f) and (g) are kernel density of goodness of fit of the 38 BL-followed events.

For fluvial processes, the 2014 flood case in Illgraben only exhibits a one-minute window obeying BL (Figure S3), but the GLOF obeys BL for a much longer period of 8 minutes (Figure S10). In contrast, the bedload transport cannot be distinguished by BL (Figure S11). Interestingly, the first-digit distribution of seismic waveform generated by long-period seismic signals and when amplitude is close to zero counts fluctuation (named LP0), also follows BL (Figure S12).

4.2 Empirical Analysis for BL

As the debris flow front approaches, both the *iq* and φ rapidly increase in the time series domain (Figure 3a). We observed a good fit between seismic signals S and time t using the exponential function. The kernel density and coefficient of determination R^2 were used to show the exponential fitting difference between the event ($\varphi_{optimal}$ period) and noise (manually labeled event start time period). The averaged R^2 of 2013-2014 WSL and 2017-2019 WSL label events are 0.853 and 0.840, respectively, and the averaged R^2 of 2013-2014 GFZ label events is 0.649, however, the raw amplitude data of the noise period could not be fitted with an averaged R^2 of 0.434 (Figure S13a-b). For instance, event 2014-07-12 has a R^2 of 0.944 (Figure 3a). The same fitting method did not yield an exponential curve for the noise period data of event 2014-07-12 (Figure S14).

In addition, we found that the α for the debris flow, lahar, landslide, and GLOF is 1.10-1.13 (Figure 3b). However, the exponent of two rockfall cases, bedload transport case, and most ambient noise is much higher than one. Values of α close to one could also be observed for ambient noise generated by LP0. The kernel density of α of all 38 BL-obeying debris flow events is much closer to one than the noise period (Figure S13c-d).

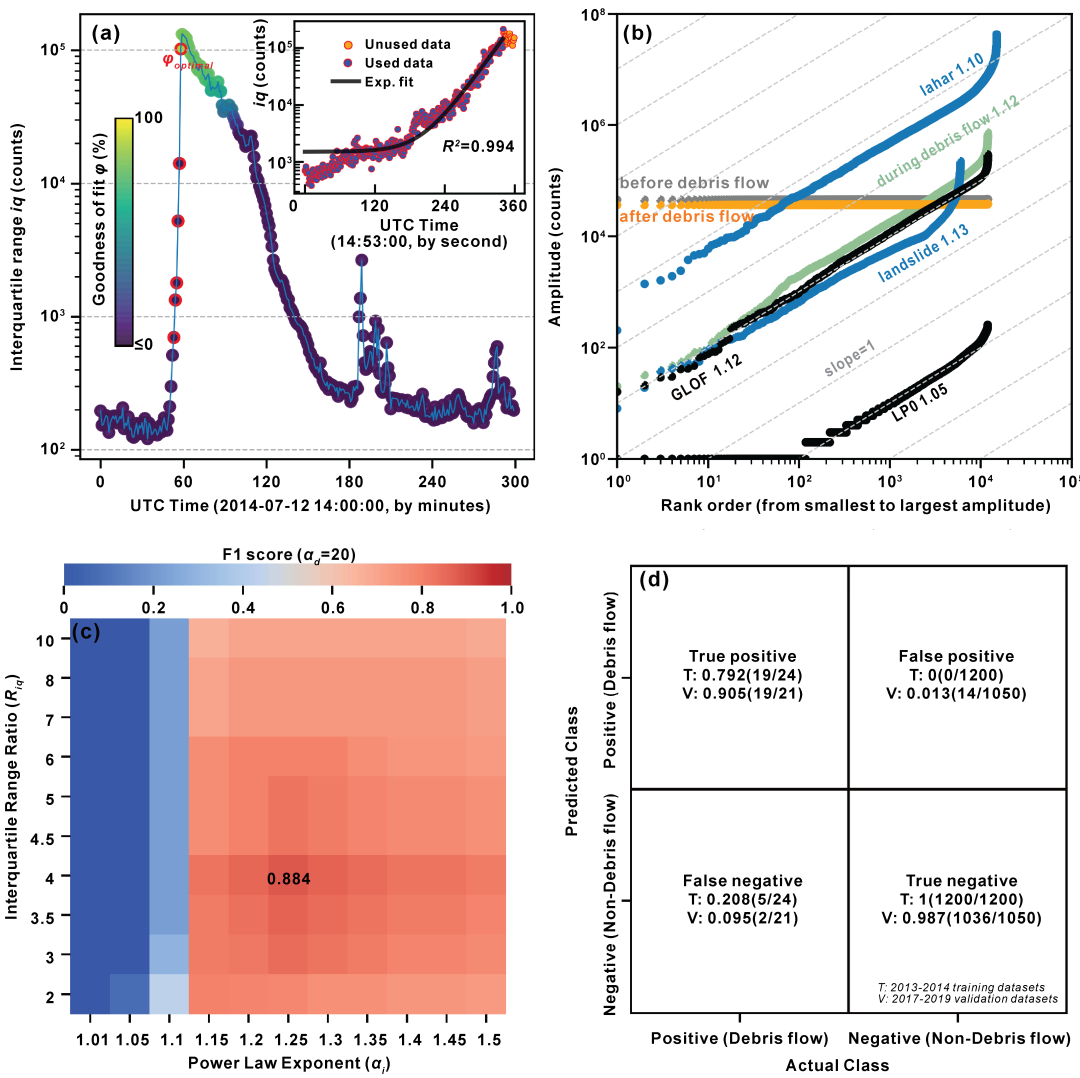

Figure 3 Correlation between seismic signals and BL, and BL-based debris-flow detector performance. (a) *iq* changes in the seismic signals for a debris flow event and exponential fitting (Exp. fitting). (b) Power law relationship in raw amplitude for different events. (c) F1 score for debris-flow event detectors (Figure S15 for details). (d) Confusion matrix of the best detector for training and output of validation dataset under the same parameters.

4.3 Debris-flow Detector Based on BL

The power exponent, which is calculated from the ten-minute average value when the debris flows front approaches station IGB02, converges with an increasing moving window (Figure S16a). During the training procedure, the performance of the detector was examined by the 2013-2014 dataset (Figures 3c and S15-S16). Results show that the power law exponent (α_i=1.25), interquartile range ratio (R_{iq}=4), and event duration (α_d=20 minutes) produce the best detector, yielding an F1 score of 0.884 (TS=0.792, Figure 3c). Under this set of parameters, there are five false-negative events in the training dataset (two events do not follow BL, Figure S17-S21). These three optimal parameters (α_i=1.25, R_{iq}=4, α_d=20) obtained from the training procedure were tested with the validation dataset. We found that the detector produced a higher TPR=0.905 (F1=0.704, TS=0.543) than the training procedure (Figure 3d). However, two false-negative cases for the validation dataset were observed, 14 cases were mislabeled as positive events (false positive) in the validation catalog (Figure 3d).

5 Discussion

5.1 Why Do Some Seismic Datasets Follow BL

The results show that BL is an efficient approach for detecting high-energy mass movements and some fluvial processes with seismic signals. The processes that do follow BL (debris flow, landslide, lahar, and GLOF) usually contain more kinetic energy during the running process than cases that do not follow BL (ambient noise, rockfall, and bedload transport). Interestingly, when the raw waveform is close to zero fluctuation (e.g., one-minute amplitude data between -227 and 342 counts, Figure S12), the observed first-digit distribution could also follow BL. For rockfall and other events that do not follow BL, we argue that the highly attenuated signals or low SNR make it difficult to distinguish between an event and ambient noise in the raw waveform domain. Generally, the low SNR is due to geometric spreading and anelastic attenuation, the energy and amplitude of the signals dissipate during propagation, especially for high-frequency waves (Battaglia, 2003; Tsai & Atiganyanun, 2014).

For seismic datasets, Sambridge et al. (2010) first stated that a sufficient dynamic range may lead the first-digit distribution (e.g., seismic signals generated by an earthquake) to follow BL. However, the claim that regularity and large spread imply BL is not always correct (Berger & Hill, 2011). In theory, datasets crossing several orders of magnitude do not necessarily follow BL (Figure S22a); in practice, we found that the seismic signals that cross two orders of magnitude within one minute follow BL (*iq* 119 counts, Figure S12). For teleseismic events and local seismicity, Díaz et al. (2015) observed using both natural and artificial data that compliance to BL does not depend primarily on the dynamic amplitude range, but rather relates to changes in frequency content. Yet, it is nearly impossible to obtain seismic data in the field that feature only frequency changes without changes in the dynamic range. For seismic signals generated by high-energy mass movements or fluvial processes, signals usually have significant changes in both magnitude (> two orders) and frequency (>1 Hz change in central frequency) when compared to an earthquake (Figures 2a and 3a). In theory, the sole change in the frequency domain does not necessarily cause compliance to BL (Figure S22b). We propose two possible mathematical explanations for the appearance of BL in seismic signals. Firstly, when data adheres to BL, it follows Zipf's law (Newman, 2005). BL appears exactly when the scaling exponent α=1 (Pietronero et al., 2001), so empirical values of the exponent close to one in seismic data will yield compliance to BL. Secondly, BL appears exactly for processes that rise or fall exponentially in time, which mathematically corresponds to a mapping from a linear to a logarithmic space (Cong et al., 2019; Engel & Leuenberger, 2003). Thus, processes that develop with exponential dynamics in time can be expected to follow BL (Figure 3a). This implies that the data from exponentially evolving processes will also follow Zipf's law with a scaling exponent of one.

We suggest that events with an exponentially rising signal can follow BL is primarily caused by their spatial mobility. The amplitude of an approaching seismic source is controlled by the ground quality factor (as an exponential term) and source-receiver distance (as 1 over the square root of the distance) (Burtin et al., 2016). As long as the distance at which a process emits sufficient energy to be detected by a seismometer is much larger than the channel-sensor distance (Figure 1a), a fast-moving mass will produce a signal sufficiently close to exponential increase (Dietze et al., 2022) to be in agreement with BL. In other words, BL is an efficient detector of fast approaching seismic sources at the landscape scale.

5.2 Application of BL as early warning tool

BL is a computationally cheap and novel approach to detect debris flow and establish real-time warning systems. Since only the raw data need to be counted, the computation time for parameter preparation and model evolution is strongly reduced, e.g., our validation process could be completed in 113 seconds (Figure S2). We expect that BL can be applied to different sites without a change in parameter values, because of the predefined non-dimensional variables and their general applicability. Therefore, we suggest that the dimensionless detector input parameters are independent of catchment geometry and seismic station characteristics. Furthermore, our approach could be a simplified version of an early warning system for triggering or turning on high-power supply and data transmission devices to catch events, such as radar and laser, for full-scale warning. In practice, a BL-based early warning system can be implemented using data from two or three seismic stations along the main flow path to detect and cross-validate events.

Our purpose in this paper is to explore the potential of BL as a prerequisite to developing an operational event detector or warning system for debris flows, which can be adapted to other processes as well. An efficient real-time warning system requires the rapid detection of the event of interest, and signal processing plays a critical role in validating seismology-driven warning systems (Arattano et al., 2014, 2016; Coviello et al., 2015). By using BL, high-energy processes lasting longer than a few minutes can be reliably distinguished from background noise. Without changing input parameters, our detector achieves a detection accuracy of 0.905 and 0.982 for both debris flows and non-debris-flow events in the validation catalog (Figure 3d). This is similar to the detection accuracy from a random forest model calibrated in the same catchment (Chmiel et al., 2021), which gives 0.83 and 0.94 for debris flows before or after check dam 1 (marked in Figure 1a) and 0.92 for non-debris-flow events, respectively. Any supervised machine-learning-based model, including those based on random forests, requires a large training dataset from multiple seismic stations and many seismic features. The efficacy of our debris-flow detector is at least comparable to the random forest model, but does not require recalibration of parameters. Furthermore, the false-positive example of our model in the validation catalog can be filtered out using data from multiple seismic stations (Figure S23), and a full seismic network can improve true positive detection accuracy (Figures S24-S25).

More mass movements are needed to help understanding the scope of application of BL and the detector proposed in this paper needs to be further explored. This study suggests that a single seismic station could efficiently detect events such as debris flow that move continuously in the channel. However, the BL approach neglects frequency domain information, which could be used to improve the identification of other high-energy mass movements or fluvial processes type.

6 Conclusion

Detecting events of interest from seismic signals to establish early warning systems is critical for hazard mitigation. In this study, we demonstrated that the first-digit distribution of seismic signals generated by some high-energy mass movements and fluvial processes follows Benford's law. Our detector model offers a less computationally intensive and novel approach for extracting anomalous energetic events, such as debris flows and landslides, from massive seismic signals. Moreover, the high-energy mass movement detector provides a promising strategy for building warning systems using seismic signals to mitigate hazards. In the future, we will collect more mass movements to calculate their first-digit distribution and develop a seismic network-based detector system and implement our method for real-time detection.

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The seismic data between 2013 and 2014 is available at https://doi.org/10.14470/4W615776. Please refer to *Chmiel, M., Walter, F., Wenner, M., Zhang, Z., McArdell, B. W., & Hibert, C. (2021). Machine learning improves debris flow warning. Geophysical Research Letters, 48, e2020GL090874. https://doi.org/10.1029/2020GL090874* for 2017 to 2019 seismic data. Our figures were generated using R ESEIS, Obspy, Matplotlib and Seaborn. All seismic data processing codes are available in *https://github.com/Nedasd/Benfords-law-in-environmental-seismology.git*

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