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Seismic Advances in Process Geomorphology

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Abstract

One of the pillars of geomorphology is the study of geomorphic processes and their drivers, dynamics, and impacts. Like all activity that transfers energy to Earth's surface, a wide range of geomorphic process types create seismic waves that can be measured with standard seismic instruments. Seismic signals provide continuous high-resolution coverage with a spatial footprint that can vary from local to global, and in recent years, efforts to exploit these signals for information about surface processes have increased dramatically, coalescing into the emerging field of environmental seismology. The application of seismic methods has the potential to drive advances in our understanding of the occurrence, timing, and triggering of geomorphic events, the dynamics of geomorphic processes, fluvial bedload transport, and integrative geomorphic system monitoring. As new seismic applications move from development to proof of concept to routine application, integration between geomorphologists and seismologists is key for continued progress.

- Geomorphic activity on Earth's surface produces seismic signals that can be measured with standard seismic instruments.
- Seismic methods are driving advances in our understanding of the occurrence, triggering, and internal dynamics of a range of geomorphic processes.
- Dedicated seismic-based observatories offer the potential to comprehensively characterize geomorphic activity and its impacts across a landscape.
- Collaboration between seismologists and geomorphologists is fostering the development of new applications, models, and analysis techniques for geomorphic seismology.

INTRODUCTION

Throughout the past decades, the discipline of process geomorphology has gained significant momentum through the combination of quantitative empirical studies of geomorphic processes, the development of theoretical process laws, and numerical modeling of these processes and their interplay. This development of the discipline has occurred alongside significant advances in our ability to observe and measure geomorphic processes and their impacts through the development of a range of different techniques. One of these emerging observation methods is actually the adoption, adaptation, and continued development of old and established methods—taking continuous seismic monitoring from the realm of earthquakes into the study of geomorphology.

From the earliest days of instrumental seismology, scientists have recognized that processes acting at and near Earth's surface produce seismic waves (Ewing 1884, von Rebeur-Paschwitz 1892, Benndorf 1910). Following this early recognition, the first systematic application of seismic data to monitor surface processes involved the tracking of large storms over the ocean in the 1940s (Gilmore 1947), including installations established by the US Navy in the Caribbean and Pacific specifically for this purpose (Gutenberg 1947, Gilmore & Hubert 1948). Since this time, isolated studies linked seismic signals to geomorphic activity such as fluvial processes (Iyer & Hitchcock 1974, Kværna 1990, Govi et al. 1993), landslides (Kanamori & Given 1982, Kawakatsu 1989, Brodsky et al. 2003, Suriñach et al. 2005), glacial processes (Ekström et al. 2003), debris flows (Arattano & Moia 1999, Marchi et al. 2002), and snow avalanches (Lawrence & Williams 1976, Kishimura & Izumi 1997). However, signals from surface processes were more often considered to be unwanted noise by seismologists, and attention was largely focused on evaluating the background noise levels at seismic installations (e.g., Frantti 1963, Withers et al. 1996).

It is only in recent years that seismic data have been more broadly recognized as a valuable source of information about geomorphic processes, and efforts to exploit these data have intensified and grown dramatically over the past 10 years. Often called environmental seismology, the use of seismic data and techniques to study surface and near-surface processes has opened a new window into a wide range of geomorphic processes and process interactions. In this review we focus on four areas in which seismic techniques have the potential to enable significant advances in our understanding of geomorphic processes: (*a*) the occurrence, timing, and triggering of geomorphic events; (*b*) the dynamics of geomorphic processes; (*c*) fluvial bedload transport; and (*d*) integrative geomorphic system monitoring. In each of these areas, seismology allows the observation of processes in a new and unique way, with the potential to generate insights that are not possible with traditional techniques. In some areas seismic techniques are well established and are already being applied to geomorphic questions, while in others the use of seismic techniques is still largely in the proof-of-concept phase. Following a brief introduction to the basics of seismic signal generation, propagation, and measurement, we focus on each of the areas listed above and discuss the past development, state of the art, and potential for seismology to drive advances in our understanding of geomorphic processes. In this way, we aim to introduce geomorphologists to the potential of seismic techniques for their questions and to introduce seismologists to the potential geomorphological applications for their methods.

While we focus on the four themes delineated above, we emphasize this is not an exhaustive summary of the use of seismology to study Earth surface processes. In particular, fields such as glacial physics and processes (for a review of cryoseismology, see Podolskiy & Walter 2016), hydrology (Sens-Schönfelder & Wegler 2006, Clements & Denolle 2018, Illien et al. 2021), and monitoring of subsurface material properties (for a review, see Larose et al. 2015) are also making significant advances through the use of seismic techniques.

THE BASICS OF ENVIRONMENTAL SEISMOLOGY

Processes that act at or near Earth's surface generate elastic waves that may be detected by seismic instruments (see **Figure 1** for exemplary processes). This includes such varied sources as elephant communication (O'Connell-Rodwell 2007), aircraft movement (Meng & Ben-Zion 2018), ground-based travel (Riahi & Gerstoft 2015) and other anthropogenic activity (Díaz et al. 2017), and a wide range of hydrological, meteorological, and geomorphological processes (e.g., Larose et al. 2015, Burtin et al. 2016), the latter being the focus of this review. To turn recorded seismic signals into process understanding, one needs to consider three problems: (*a*) signal generation by the process at its source location, (*b*) modification of the signal during its propagation from the source location to the seismic sensor, and (*c*) how the signal is registered by the seismic station.

Seismic waves are generated by energy transfer from an object impacting the ground, such as a boulder falling off a rock slope, a hopping pebble in a river, or a raindrop hitting the ground. Likewise, energy transfer happens due to the rapid displacement of a mass, such as a detached landslide, turbulent flowing water, or wind dragging a forest canopy. For some of these energy transfer mechanisms, or in our case geomorphic processes, researchers have developed dedicated physical models that predict the emitted seismic energy for specific processes (Tsai et al. 2012, Ekström & Stark 2013, Gimbert et al. 2014, Farin et al. 2019).

Upon emission at the source location, the seismic energy is radiated and dissipated by waves. There are in principal two different classes of seismic waves: those that propagate in three dimensions from the source (body waves) and those that propagate along the free surface of Earth (surface waves). In most environmental seismological problems, especially when large ($>10^6$ m³) and remote mass wasting is not involved, the seismic signals are dominated by surface waves. Nevertheless, usually all wave types occur with no clear temporal separation, meaning that, in contrast to earthquake-generated signals, temporally discrete arrival times of different phases are not discernible (e.g., Helmstetter & Garambois 2010, Burtin et al. 2016, Lai et al. 2018). Hence, in most cases, the problem can be approached by describing the emission, propagation and registration of surface waves because they contribute most to the measured ground motion.

During dissipation of seismic energy by the different wave types, the amplitude of the source signal declines due to two major effects: geometric spreading and anelastic attenuation. Geometric spreading implies that as the wave propagates radially from the source, its amplitude declines by 1 over the square root of distance for surface waves (and 1 over distance for body waves). Anelastic attenuation draws wave energy by shearing at grain boundaries within the medium through which the seismic wave travels. The ground quality factor Q (ratio of initial energy to dispersed energy) describes this dampening effect with values for shear waves typically between 20 (unconsolidated sandy deposits) and 200 (intact granitic rock). In most cases, the quality factor is also frequency dependent. Hence, by combining these two effects one can consider the decay of the surface wave seismic amplitude A with distance d as

$$A(d, f) \sim (A_0/d^{1/2})e^{\left(\frac{-\pi f d}{Q(f) v}\right)},$$

where A_0 is the amplitude at the source location, f is the frequency of interest, and v is the seismic wave velocity. In addition to these two first-order effects, the ground through which seismic waves travel further modifies the signal. It is scattered at rock fractures, amplified locally due to topographic and rock structural effects, and modulated by anisotropic or stratified ground conditions. These compound effects along with geometric spreading and anelastic attenuation are collectively referred to as the Green's function or ground response (for a discussion of surface wave Green's functions, see Tsai & Atiganyanun 2014).

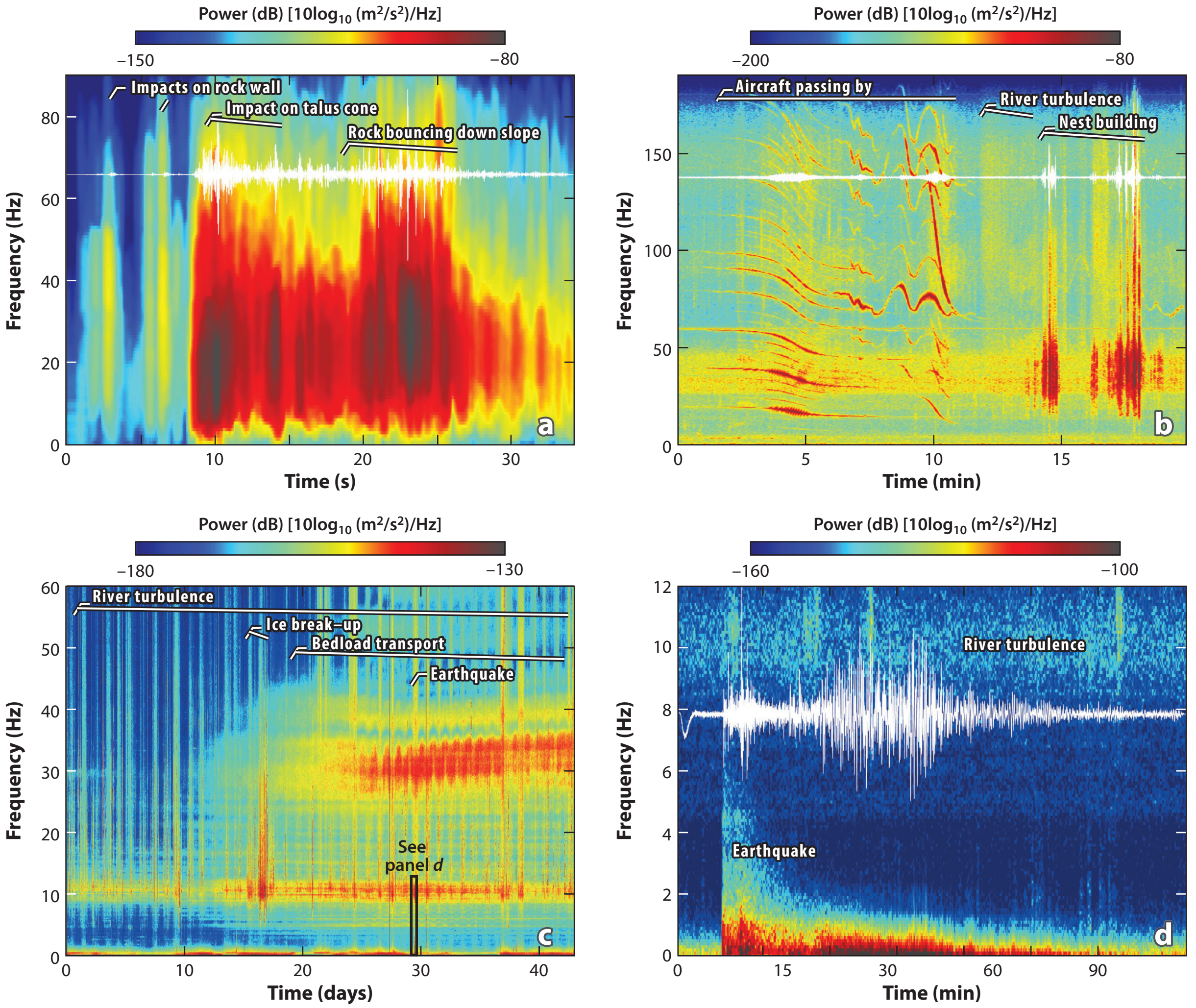

Figure 1

Spectrograms and overlaid seismograms (*white lines*) of different geomorphic processes. (*a*) Rockfall, Lauterbrunnen Valley, Switzerland. Panel data are from Dietze et al. (2017). A detached rock falls off the cliff and hits the wall twice before impacting the talus slope some 30 m away from the seismometer, creating a rock avalanche out of which eventually a single bouncing rock emerges. Note the strong differences in amplitude due to the different distances of the falling rock to the sensor and the discrete pulses in the seismogram caused by impacts of the bouncing rock. (*b*) Superposition of fluvial and anthropogenic signals, Mashel River, Washington, USA. Panel data are from Dietze et al. (2020b). The Mashel River's turbulent flow causes a constant frequency band peaking around 30–50 Hz, which is distorted by short broadband pulses (minutes 13–19) due to salmonid specimen preparing nests for spawning. Note also the sharp frequency bands between minutes 2 and 11 due to air traffic passing by. The sigmoidal shape depicts the Doppler effect with higher frequencies from approaching and lower frequencies from fading vessels, with the highest energy during passing time. The stacked frequency bands are harmonics of the lowest frequency, which is set by the rotation frequency of the engine. (*c*) Spring flood evolution in a Scandinavian river (Sävaron). Before surface ice cover breakup on April 15–26 (6–50 Hz peaks), only turbulent river flow causes a 9–12-Hz signal. With the onset of free flow, a higher-frequency band emerges (25–35 Hz) due to bedload sediment transport, with a clear diurnal pattern caused by meltwater availability. Note also the change in seismic power of the 9–12-Hz band related to river discharge as the spring flood evolves. (*d*) A 6.2-magnitude earthquake (see *black rectangle* in *panel c*) that originated in Afghanistan and was coregistered by the river sensing station. Note the emergence of P, S, and surface waves as low-frequency (<1 Hz) pulses and the spectral difference to the river turbulence signature (9–12 Hz). Data sets in panels *c* and *d* are from Polvi et al. (2020).

Very large geomorphic events, such as large landslides, can produce quakes on par with tectonic earthquakes, exhibiting low-frequency, 10^{-1}–10^{-3}-Hz seismic signals that may be recorded globally (Ekström & Stark 2013). In contrast, very small geomorphic events, such as a falling pebble, rain drops, or spawning salmon, can be detected only by very close stations because they emit rapidly attenuating high-frequency (10^{1}–10^{2} Hz) signals (**Figure 1**), which can nevertheless be recorded with large amplitudes locally. All these processes, along with further anthropogenic, meteorological, and fluvial signal sources, can in principle act at the same time and at different locations within their specific detection ranges and hence contribute to one superimposed seismic record. This effect imposes a trade-off when setting up a seismic network.

Seismic signals are registered as voltage fluctuations and, once digitized by the data logger, as counts. They need to be converted back to ground velocity (SI units m/s) using the characteristics of the seismometer and data logger. The resulting signals can be inspected in their most primitive form: as seismograms, also called waveforms or time series of ground velocity (**Figure 1**). Likewise, one can inspect the frequency content of this time series by calculating its Fourier transform to yield the spectrum or power spectral density estimate. In addition, one can also bridge these two views with spectrograms, time-resolved spectra (**Figure 1**) in which spectra are calculated for short consecutive time windows. Spectrograms provide an overview of a seismic record in terms of power at a given time and in a given frequency. This way, multiple superimposed seismic sources can be distinguished if they manifest in different frequency ranges. **Figure 1*b*** illustrates this by depicting a spectrogram of a turbulent flowing river, interspersed by brief pulses of activity at the riverbed due to salmonids shuffling around sediment to build their nest and by an aircraft passing by the station. Note that spectra and spectrograms are often shown in units of decibels (dB), which is logarithmic unit, with $1\ \text{dB} = 10\log_{10}\ (\text{m}^2/\text{s}^2/\text{Hz})$.

OCCURRENCE, TIMING, AND TRIGGERING OF GEOMORPHIC EVENTS

Stochastic events such as landslides, rockfalls, debris flows, and avalanches typically occur suddenly in response to a change in internal material properties (such as temperature, water content, rock strength, or fracture density) or to external forcing (such as earthquake shaking, loading, volcanic activity, or human activities). Understanding the relationships between events and their proximate causes requires precise and high-resolution information about the location and especially the timing of events in relation to the possible triggering processes. While the possible triggers can usually be monitored with sufficient resolution, it is more challenging to constrain the time of occurrence for geomorphic events with the range of classic methods available.

For large areas, remote sensing is the most commonly used monitoring technique. Recent advances in satellite imagery resolution and frequency have greatly increased the capability of this technique for event detection, and in some cases even daily resolution imagery is now possible. However, optical imagery can be hindered by visibility, and in some climates, cloud cover can interfere with event detection for weeks or months. Spatial resolution of remote sensing products is improving but also imposes limitations. Small events, or events that do not cause sufficient change in surface appearance, such as landslide reactivation or repeated channel activity events, may not be detected (e.g., Burtin et al. 2013). Monitoring techniques such as video or time-lapse cameras (D'Amato et al. 2016, Le Roy et al. 2019) or permanent terrestrial lidar (Williams et al. 2018) can provide higher time resolution and spatial sensitivity but are restricted in their coverage area, may also be hampered by weather and lighting conditions, and impose a significant amount of manual editing and analysis of the collected data.

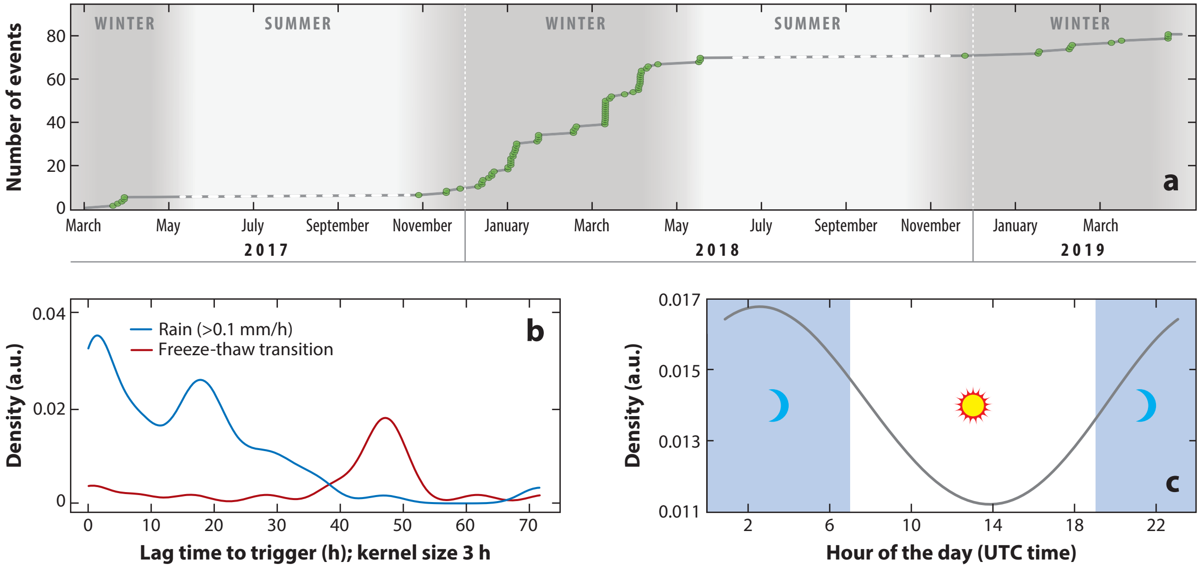

Figure 2

Triggering of coastal cliff collapses on the island of Rügen, Germany (Dietze et al. 2020a). (*a*) Cumulative number of seismically detected cliff failures. Panel adapted from Dietze et al. (2020a), figure 1b. (*b*) Lag times between events and possible forcings. Panel adapted from Dietze et al. (2020a), figure 6a. The 50-h lag time between freeze-thaw transitions and failures indicates that freeze-thaw is not a viable trigger. The two peaks in precipitation lag time are related to two modes of precipitation forcing: Rain directly impacts the cliff and rapidly triggers failures, and rainwater falling inland travels through the subsurface toward the cliff face, triggering failures after a delay of 16–20 h. (*c*) The diurnal pattern of failure times. Panel adapted from Dietze et al. (2020a), figure 6a. Most cliff failures took place during the night, when optical methods would not be able to detect them.

When the occurrence of an event can only be constrained to a given time window, say a week, then the potential triggers of the event must be scaled to this entire time window. This generally leads to a loss in explanatory strength for the nonlinear relationship between events and triggers, as only associations between average, peak, or cumulative magnitude of a potential trigger and event occurrence can be constructed. In addition, this makes it difficult to clearly distinguish between multiple potential triggers, as statistical unmixing approaches need to be employed (e.g., Vann Jones et al. 2015). Further, without sufficiently high temporal resolution, one can only identify the final stage of an event, missing any information on the occurrence of potential subevents.

Seismic monitoring techniques offer extremely high temporal resolution, enabling the precise timing of events. Combined with high-resolution records of potential triggers, this timing information can be used to more precisely investigate relationships between events and their potential triggers (**Figure 2**). Triggers may have an immediate effect or may require a characteristic lag time to initiate a mass wasting event (e.g., Stock et al. 2013, Dietze et al. 2017, Durand et al. 2018, Kuo et al. 2018). Access to precise time lag information can thus provide constraints on the relative importance of different triggers and even different operational modes of the same trigger, such as rain destabilizing a cliff directly or through seepage by water flow from the hinterland (Dietze et al. 2020a) (**Figure 2*b***), or 10-min rainfall rates better predicting slope failures than more integrated precipitation statistics (Burtin et al. 2013).

Before working with geomorphic events, one needs to detect them in the seismic record, a task that has both retrospective and near real-time applications. The retrospective scope involves the challenge of finding brief event signatures in existing seismic time series up to decades long (e.g., Hibert et al. 2019), while the near real-time scope involves the ability to rapidly and robustly detect events as they occur and is a foundation of any early warning or rapid response system for geomorphic hazard mitigation.

Seismologists have developed numerous approaches to this job of event picking (Bormann 2012). These approaches can be more or less directly applied to energetic and impulsive processes such as rockfalls or rock cracks (Senfaute et al. 2009, Hibert et al. 2011, Manconi et al. 2016). Detection of such discrete events is the most established application of environmental seismology and well beyond the proof-of-concept phase. In contrast to these events with a clear signature, many other geomorphic processes can have an emergent onset, meaning that the signal arises gradually from background noise and shows changing characteristics across a network of stations. In addition, geomorphic events of the same general type can vary significantly from event to event in their waveform properties. This makes the application of established techniques challenging. Research in environmental seismology has led to the development and application of other approaches, such as stacked spectral power thresholds (Helmstetter & Garambois 2010), correlation or template matching pickers (Poli 2017), short-term average/long-term average picking combined with rule-based winnowing of events to remove false detections (Burtin et al. 2016, Dietze et al. 2020a), and machine learning techniques such as random forest (Hibert et al. 2017a, Wenner et al. 2021) and hidden Markov models (Hammer et al. 2015, Dammeier et al. 2016, Heck et al. 2018).

Future research on geomorphic event detection should continue to yield improvements in the accuracy, efficiency, and flexibility of event identification and classification. As the number of available seismic data sets will grow progressively and, similarly, the sampling frequency of stations with a dedicated environmental seismological scope will increase, it will become crucial to develop efficient workflows to handle large data sets. Currently, many methods were developed for local-scale case studies, particularly the machine learning approaches to mass wasting event detection. A next step will be to find ways to generalize such approaches to overcome or at least mitigate the demanding task of collecting an extensive training data set for each case study, as well as to explore unsupervised machine learning techniques. Generalization also needs to be considered regarding the types of events that can be detected with existing seismic infrastructure (Provost et al. 2018). The current ability of seismic networks to detect events is mostly tailored to specific processes, such as debris flows (Coviello et al. 2015, Schimmel et al. 2021), rockfall (Helmstetter & Garambois 2010, Hibert et al. 2017a), or large-scale slope failures (Ekström & Stark 2013, Dammeier et al. 2016, Hibert et al. 2019). Broadening the detection algorithms for other processes too, especially in a process cascade scope (Burtin et al. 2014, Cook et al. 2021), would advance our ability to understand the triggers of such stochastic hazards, mitigate their impacts, and also gain a more realistic picture of the role of these processes in landscape dynamics. Finally, the development of implementation-ready real-time workflows of event detection, quantification, and reporting (e.g., Chao et al. 2017) will be crucial for the broader application of seismic techniques to event early warning and rapid response.

DYNAMICS OF GEOMORPHIC PROCESSES

One of the key aims of modern geomorphology is the understanding of the physics and internal dynamics of geomorphic processes. For high-energy processes such as landslides, debris flows, avalanches, and floods, it can be extremely difficult to make quantitative field observations while these processes are ongoing, as events occur unpredictably, often occur in remote areas, and may be destructive, making in situ observations dangerous for both instruments and researchers. Because of the difficulty in capturing such events in the field, study of their dynamics is often done using

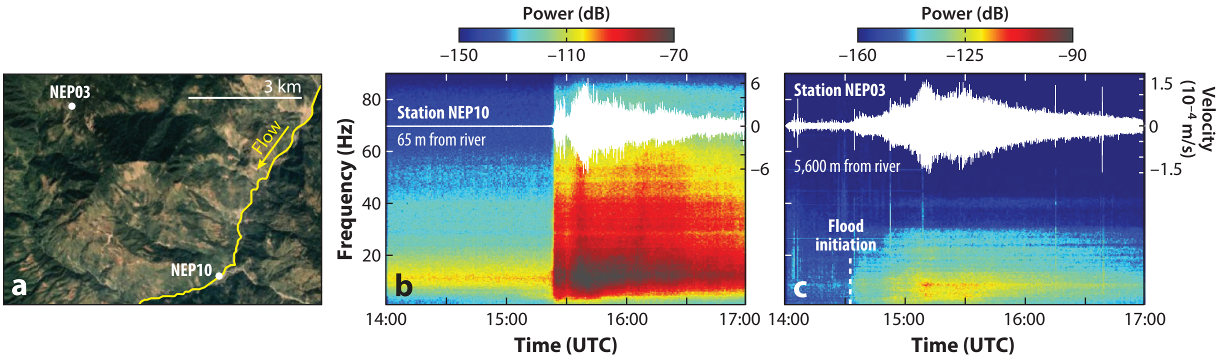

Figure 3

The effect of station distance on seismic observations of moving events. (*a*) Google Earth™ image showing two seismic stations and the flow path of a glacial lake outburst flood that occurred in July 2016. Panel data are from Cook et al. (2018). (*b*) The record of the outburst flood at a near-river station. The data show the arrival of the flood front at the station, as well as two distinct pulses that are interpreted as the flow front and a trailing pulse of bedload (Cook et al. 2018). (*c*) The record of the flood at a station 5.6 km from the river. The data show the initiation of the flood (∼25 km away) at ∼14:30. The two pulses seen in the near-channel station cannot be distinguished, and the signal is likely dominated by the bedload wave, recording its downstream propagation. Note the differences in power and amplitude scales between panels *b* and *c*.

flume or other analog experiments (e.g., Iverson et al. 2010, Carrivick et al. 2011), with controlled field experiments (e.g., Sovilla et al. 2008, Bourrier et al. 2012), or with dedicated infrastructure in places where events frequently occur (e.g., McArdell et al. 2007). In the absence of intraevent observations, pre- and postevent observations are typically used to constrain various aspects of an event and are often combined with numerical models (e.g., Lin & Lin 2015, Turzewski et al. 2019, Mergili et al. 2020). Such models can provide insights into the behavior of an event, but they cannot be a substitute for empirical observations, and additional observations of event dynamics across a range of settings will be valuable for improving model formulation and calibration (Schneider et al. 2010, Moretti et al. 2020).

Seismic methods are ideally suited for studies of event dynamics. The high temporal resolution allows for detailed observation of event progression, and the remote nature of seismic observation allows instruments to be installed in safe locations and to simultaneously monitor multiple potential event sources. Seismic observation of geomorphic events can range in type and complexity, from an individual station installed next to a river, landslide, or debris flow channel (Kean et al. 2015, Coviello et al. 2018) to a remote small-scale array (Eibl et al. 2020) to catchment-scale, regional, or global networks of seismic stations (Schneider et al. 2010, Ekström & Stark 2013, Burtin et al. 2014, Cook et al. 2021).

A key property of many geomorphic processes is that they involve material moving through the landscape. The combination of moving sources of seismic waves and the frequency-dependent attenuation of seismic energy with distance means that when seismic data are used to investigate the dynamics of moving events such as mass flows, avalanches, or flash floods, it is important to consider the distance between the seismic station and the path of the flow (**Figure 3**). Because stations are most sensitive to the closest sources, a near-event station (i.e., installed next to a river or debris flow channel) will primarily record the activity in the local part of the flow path, and the measured signal will be strongly influenced by the movement of the flow relative to the station. Near-event stations can provide detailed information about the passage of an event through the local section of the flow path, such as changes in properties from the front to tail of a debris flow (Kean et al. 2015, Farin et al. 2019, Zhang et al. 2021), debris flow surges (Arattano et al.

2012, Coviello et al. 2019), or water versus bedload pulses in an outburst flood (Cook et al. 2018) (**Figure 3*b***). In contrast, a station farther from the event path can give an overview of the entire event, particularly if the distance between the station and the source has relatively little change over the flow path. In this case, the station will be most sensitive to the most energetic part of the event [e.g., the snout of a debris flow (Coviello et al. 2019)]. This allows changes in properties to be tracked in space and time as an event moves and evolves through its flow path (e.g., Burtin et al. 2014, Maurer et al. 2020, Walter et al. 2020a, Cook et al. 2021) but prevents different phases of the event at a given time from being resolved (**Figure 3*c***).

Similarly, near-event versus far-event seismic installations allow different techniques to be used to locate and track a moving event through time. Multiple stations installed along a channel or flow path allow the downstream propagation of an event to be observed as the event front or distinct event pulses progressively arrive at different stations (e.g., Arattano & Moia 1999, Cook et al. 2018, Coviello et al. 2019). With a network of farther stations, event locations can be tracked through time by using cross-correlation functions to locate coherent seismic sources (Burtin et al. 2010, 2014; Lacroix et al. 2012; Maurer et al. 2020; Cook et al. 2021), by modeling seismic amplitude decay with distance across the network to estimate the source location (Walter et al. 2017, Pérez-Guillén et al. 2019, Cook et al. 2021), or with a combination of methods (Chang et al. 2021).

One of the most well-established applications of seismology to probe the dynamics of a geomorphic process is the reconstruction of landslide forces (Kanamori & Given 1982, Kawakatsu 1989, Brodsky et al. 2003, Ekström & Stark 2013). The acceleration of large masses during major rapid landslides generates low-frequency (i.e., <0.1 Hz) seismic signals that can be detected at far distances, in some cases globally, as shown by Ekström & Stark (2013). In a similar procedure to earthquake seismology, these signals can be modeled by assuming that the landslide exerts a single force on Earth's surface, and the characteristics of this landslide force can be estimated by inverting the seismic signals to yield a force-time history (e.g., Ekström & Stark 2013, Allstadt 2013, Yamada et al. 2013, Hibert et al. 2014, Schöpa et al. 2018). If the path of the landslide is independently known, the landslide mass and acceleration time series can be estimated by fitting the calculated and observed trajectories (e.g., Hibert et al. 2014, 2015). The low-frequency signals alone can be used to constrain landslide characteristics such as basal friction (Brodsky et al. 2003, Yamada et al. 2016), velocity (Allstadt 2013, Hibert et al. 2014), rheology (Moretti et al. 2020), and the occurrence of multiple failures (Allstadt 2013, Hibert et al. 2014). Combining force inversion with the high-frequency seismic signals generated by a landslide can yield additional insights into the dynamics of fragmentation (Hibert et al. 2014), interaction between the landslide material and the underlying topography (Allstadt 2013, Hibert et al. 2014, Walter et al. 2020a), and precursory signals of failure (Yamada et al. 2016, Schöpa et al. 2018).

Seismic techniques have also been used for decades to observe debris flows (Arattano & Moia 1999, Marchi et al. 2002, Huang et al. 2007). While much of this effort has focused on the detection and characterization of debris flows for the development of early warning systems (Marchi et al. 2002; Coviello et al. 2015, 2019; Walter et al. 2017; Chmiel et al. 2021), seismic observations are also increasingly used to constrain debris flow properties and behavior. Typically through the use of near-channel seismic installations in combination with traditional monitoring techniques, seismic data have been used to constrain debris flow entrainment (Kean et al. 2015), substrate properties (Kean et al. 2015), changes in sediment concentration (Coviello et al. 2018), basal forces (Allstadt et al. 2020), kinetic energy (Coviello et al. 2019), and how these characteristics vary throughout a flow. In recent years, several mechanistic models for the generation of seismic noise by debris flows have been proposed (Kean et al. 2015, Lai et al. 2018, Farin et al. 2019, Zhang et al. 2021); these generally aim to provide a framework for using measured seismic signals to obtain quantitative estimates of debris flow parameters.

Much of the effort on the seismic characterization of debris flows has been focused on technique development and proof of concept, with seismic instruments installed in existing debris flow observatories such as the Illgraben (Zhang et al. 2021) or the Chalk Cliffs of Colorado (Kean et al. 2015), and many of the efforts on landslide characterization have utilized permanent seismic networks. However, one of the advantages of seismic monitoring is the flexibility and relative ease of deployment. Temporary seismic stations can be quickly installed to observe potential events related to a disturbance such as a wildfire (e.g., Porter et al. 2021), earthquake (Andermann et al. 2016), volcanic eruption (Walsh et al. 2016), or approaching typhoon (Yamada et al. 2012, Ogiso & Yomogida 2015). As our understanding of the seismic signals generated by geomorphic events improves, seismology offers the potential to study the event dynamics across a wide range of settings and conditions.

While we have concentrated here on the application to landslides and debris flows, and we focus on bedload transport in the next section, seismic methods can be used to study the dynamics of a wide range of other processes, including avalanches (Schneider et al. 2010, Lacroix et al. 2012), rockfalls (Hibert et al. 2017b), dam-burst floods (Agurto-Detzel et al. 2016, Cook et al. 2018, Maurer et al. 2020), glacial dynamics (Podolskiy & Walter 2016), and biogeomorphic activity (e.g., Dietze et al. 2020b). For many these processes, a theoretical framework for the generation of seismic signals is still in development.

FLUVIAL BEDLOAD TRANSPORT

Constraining the rates and patterns of bedload transport remains a major challenge in fluvial geomorphology. Bedload, the portion of the sediment load that travels by rolling, sliding, or hopping along a riverbed, plays a fundamental role in fluvial dynamics. In bedrock rivers, bedload is key for partitioning erosion; it can drive erosion through the impacts of bedload clasts on the channel bed, but it can also inhibit erosion by covering the bed with sediment and protecting it from impacts (Gilbert 1877). Bedload also controls characteristics of the channel bed such as roughness, bedform development, sediment erosion and deposition, and the suitability of habitat for riverine species (e.g., Snyder et al. 2009). Finally, bedload flux may represent an important portion of the total sediment flux of a river.

In contrast with other fluvial properties such as discharge, suspended sediment concentration, and water chemistry, which are routinely measured in a wide range of river types and settings, measurement of bedload transport is challenging, and continuous or routine bedload monitoring is extremely rare. Measurement of bedload transport is traditionally done directly—using a sampler to collect and measure the amount of material transported into the sampler over a given interval (Bunte et al. 2004). This requires access to the channel bed, either through the installation of sampling devices or through deployment during periods of bedload transport, and sampling duration is limited by the volume of bedload each sampler can hold. This severely limits the range of rivers and discharges in which bedload transport can be measured. Seismology offers an alternative method—as bedload clasts slide, roll, or hop along the bed, each impact transfers energy to the bed, creating seismic waves (Tsai et al. 2012). This raises the possibility that, with sufficient understanding of the relationships between bedload characteristics and transport rate and the signals generated, seismic data can be used to constrain patterns and quantify rates of bedload transport.

The longest-running applied use of seismic instruments to monitor bedload transport is the use of impact plate sensors in mountain streams in Switzerland, which have been operating in some catchments since the 1990s (Rickenmann 1997). In these systems, geophone plates installed in the riverbed record the signals generated as passing bedload particles impact the plates and are able to reliably quantify bedload transport (Rickenmann et al. 2012). However, the broader applicability of the impact plate system is limited by the need to install sensors directly in the channel bed. This is very costly, requiring significant engineering work, and is generally limited to small rivers; also in-stream instruments are highly vulnerable to destructive flows. Other in-stream monitoring methods, such as underwater hydrophones (e.g., Geay et al. 2017) or pipe geophones (Mizuyama et al. 2010), may require less infrastructure but are still susceptible to damage during high flows.

The seismic signals created by moving bedload can also be observed with seismic stations located outside the river channel (e.g., **Figure 1*c***), reducing the cost of installation and the possibility of damage to instruments and increasing the range of potential monitoring locations (Burtin et al. 2016). Early work on the ambient seismic signals generated by rivers focused on establishing which fluvial processes could be identified in seismic data by comparing the seismic signals to independent records of river discharge or water level (Govi et al. 1993; Burtin et al. 2008, 2011; Hsu et al. 2011; Roth et al. 2014); if seismic noise was produced only by water flow, then seismic energy and discharge should correlate throughout a flow event. In contrast, many studies observed a hysteresis in this relationship, with different relationships between seismic energy and discharge on the rising versus falling limb of floods, which could be attributed to the seismic noise generated by moving bedload (Govi et al. 1993; Burtin et al. 2008, 2011; Hsu et al. 2011; Schmandt et al. 2013; Roth et al. 2014; Barrière et al. 2015; Chao et al. 2015). Comparing discharge to seismic data in different frequency ranges provided additional information about the frequencies most influenced by bedload, as lower-frequency signals (<10 Hz) often showed less hysteresis than higher-frequency signals (>10–15 Hz) (e.g., Schmandt et al. 2013, Gimbert et al. 2014), suggesting that discharge and bedload transport create seismic signals in different frequency ranges.

A significant step forward in fluvial seismology was made with the development of physical models for the seismic signals generated by bedload transport (Tsai et al. 2012) and turbulent flow (Gimbert et al. 2014) (**Figure 4**), with a later refinement to the bedload transport model by Gimbert et al. (2019). Each of these models incorporates both seismic signal generation and propagation, and each can be used to relate measured power spectra to fluvial processes. The models predict that turbulent flow generates seismic noise with a peak frequency lower than bedload transport-generated noise (Gimbert et al. 2014), but the frequency ranges of the two processes overlap (**Figure 4**). Critically, the models account for the frequency-dependent decay of seismic amplitude with distance, which means that both the dominant frequencies of each process and the relative amplitudes of turbulence- and bedload-generated seismic signals will be affected by river-station distance, leading to lower dominant frequencies and increased dominance of turbulence-generated signals as river-station distance increases (**Figure 4**). The general predictions of these models are consistent with field observations from a range of rivers (Schmandt et al. 2013, 2017; Cook et al. 2018; Bakker et al. 2020). In particular, Bakker et al. (2020) observe the seismic power at 10 Hz scales with discharge as predicted by the turbulence model of Gimbert et al. (2014), while the seismic power at 50 Hz scales linearly with measured bedload flux, as predicted by the bedload model (Tsai et al. 2012, Gimbert et al. 2019).

By combining the turbulence and bedload models, it is then possible to predict the full seismic signature of a river and to potentially invert observed seismic data for both bedload flux and water depth (Chao et al. 2015, Dietze et al. 2019, Lagarde et al. 2021). To date, these inversions generally reproduce the temporal patterns of bedload transport but have tended to systematically underestimate (Schmandt et al. 2017, Bakker et al. 2020) or overestimate (Lagarde et al. 2021) independent measures of bedload flux. Lagarde et al. (2021) point to the importance of properly characterizing the local Green's function (**Figure 4**), which can be done by stone drop experiments in braided or ephemeral rivers (Bakker et al. 2020, Lagarde et al. 2021) but may be more

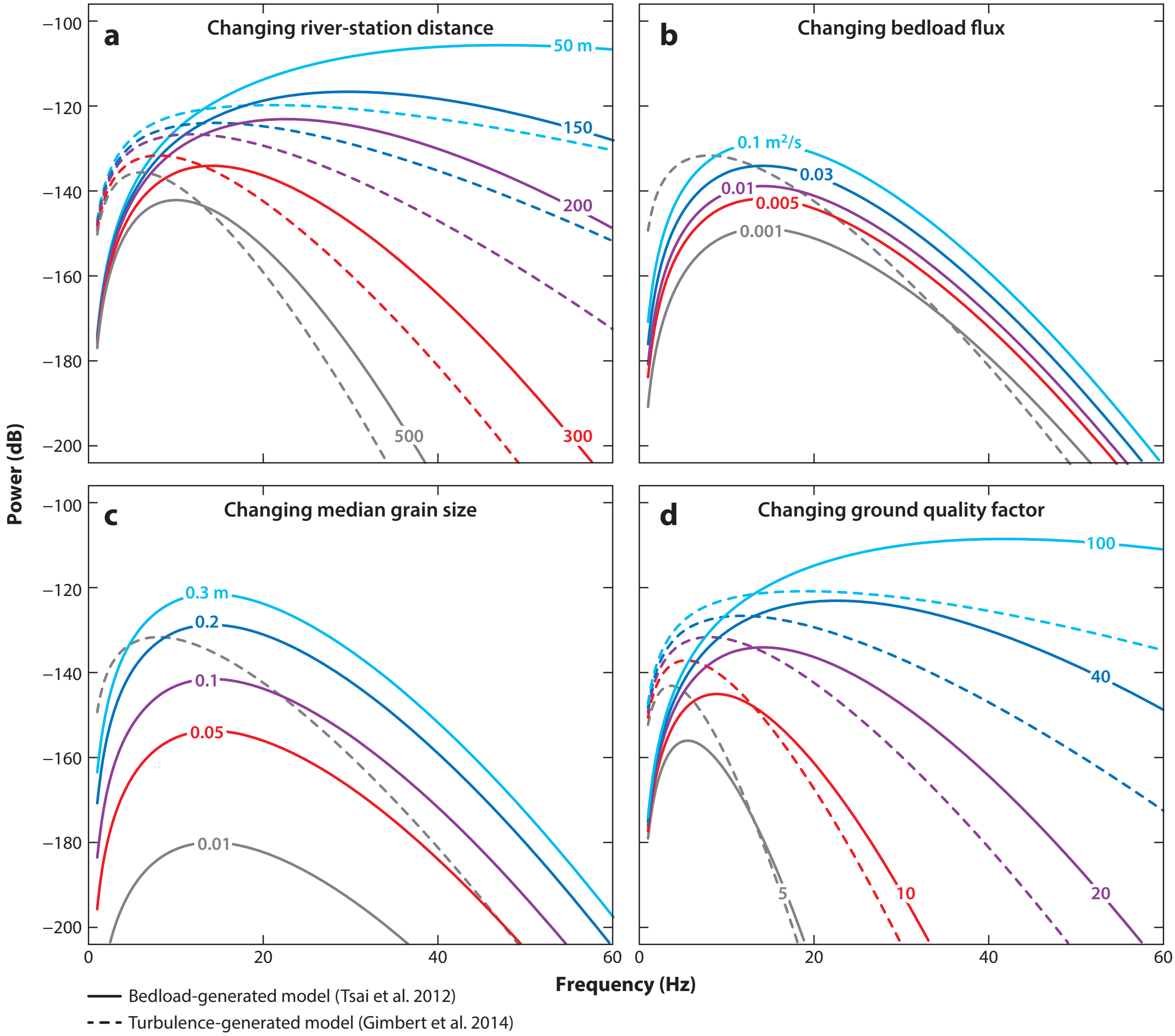

Figure 4

Modeled spectra for bedload- (*solid lines*) and turbulence-generated (*dashed lines*) seismic power using the models of Tsai et al. (2012) and Gimbert et al. (2014), respectively. All models use the Trisuli River, Nepal, parameters given by Gimbert et al. (2014) unless otherwise noted. (*a*) Models with varying river-station distance, with bedload flux of 0.03 m^2/s. (*b*) Models with varying bedload flux, with river-station distance of 300 m. (*c*) Models with varying median grain size, with river-station distance of 300 m and bedload flux of 0.03 m^2/s. Note that in panels *b* and *c*, the turbulence-generated signal does not change. (*d*) Models with varying ground quality factor *Q*, with river-station distance of 300 m and bedload flux of 0.03 m^2/s.

challenging in large rivers. An accurate grain size distribution is also important for performing model inversions, as the Tsai et al. (2012) model predicts that seismic power scales with grain size to the third power (**Figure 4**), so that the largest grains tend to dominate the signal. This adds a further complication because, as Bakker et al. (2020) point out, the grain size distribution of moving bedload likely changes throughout the course of a bedload transport event, particularly in rivers with a wide range of grain sizes. Changes in riverbed configuration or roughness as large clasts are mobilized can also influence the seismic signal, as demonstrated by Roth et al. (2017).

Seismic measurement of bedload transport is still largely in the proof-of-concept stage, with relatively few studies to date focused primarily on application of the technique. These include Misset et al. (2020), who combined seismic data with discharge and turbidity monitoring to investigate controls on partitioning between bedload and suspended load; Cook et al. (2018), who noted an increase in bedload transport following a glacial lake outburst flood; and Polvi et al. (2020), who investigated seasonal controls on bedload flux in an arctic river. While quantitative estimates of bedload flux from seismic data may require extensive local calibration (Misset et al. 2020), constraints on relative bedload flux are more tractable, and the initiation and temporal patterns of bedload transport can be identified using the scalings predicted by the Tsai et al. (2012) and Gimbert et al. (2014) models and demonstrated by Bakker et al. (2020) (e.g., Cook et al. 2018).

With an established framework for interpreting the seismic signals of bedload transport, more routine application should take place alongside further method development. Areas of potential interest include the spatial pattern of bedload transport and channel bed dynamics. Piantini et al. (2021) demonstrate that with a dense network of stations arranged into subarrays, bedload transport pulses in a braided river reach can be located in 2D, illustrating the potential to resolve bedload flux at high resolution in both space and time. While factors such as grain size, changes in bed roughness, and deposition or erosion of bed material present complications for the interpretation of bedload seismic signals, their influence on the generation of these signals may also present an opportunity. In most rivers, information about river behavior during a flood is generally limited to measurement of the water level (and perhaps velocity) and before/after observations of the channel, while everything happening underwater remains inaccessible (e.g., Cook et al. 2020). In addition to constraining bedload flux, seismic data have the potential to provide information about things such as the variable mobilization of different grain sizes, intraflood changes to sediment cover and thickness, or changes in channel geometry.

INTEGRATIVE GEOMORPHIC SYSTEM MONITORING

While the study of geomorphic processes often focuses on understanding the drivers, triggers, and dynamics of a particular process or process domain (i.e., hillslope versus channel), it is clear that processes interact with each other and that links across process domains are important for understanding landscape dynamics. However, with traditional before/after observations of geomorphic events and their impacts, the relationships between different geomorphic domains is not always clear. For example, during a large storm event, both hillslopes and channels may be activated, with landslides, debris flows, and bedload transport all taking place within a catchment at some point during the storm, but it is difficult to directly observe the potential interactions and feedbacks between them. In addition, geomorphic activity is often linked with external forcing, as discussed earlier in the section titled Occurrence, Timing, and Triggering of Geomorphic Events, but it is also strongly influenced by internal conditions, or by the material properties of the soil, rockmass, or riverbed. The links between changes in these properties and geomorphic activity are important for understanding the drivers of events.

One of the most challenging aspects of environmental seismology is that seismic instruments record all processes with sufficient magnitude in the sampling frequency range, and much of the work described in the previous sections relies on robustly distinguishing the seismic signals of a particular process from all of the other potential seismic sources. However, this indiscriminate recording of different types of activity is also one of the most powerful aspects of environmental seismology. It raises the possibility that with a single installation, one can monitor a wide range of geomorphic (and anthropogenic, volcanic, or tectonic) activity across a study region.

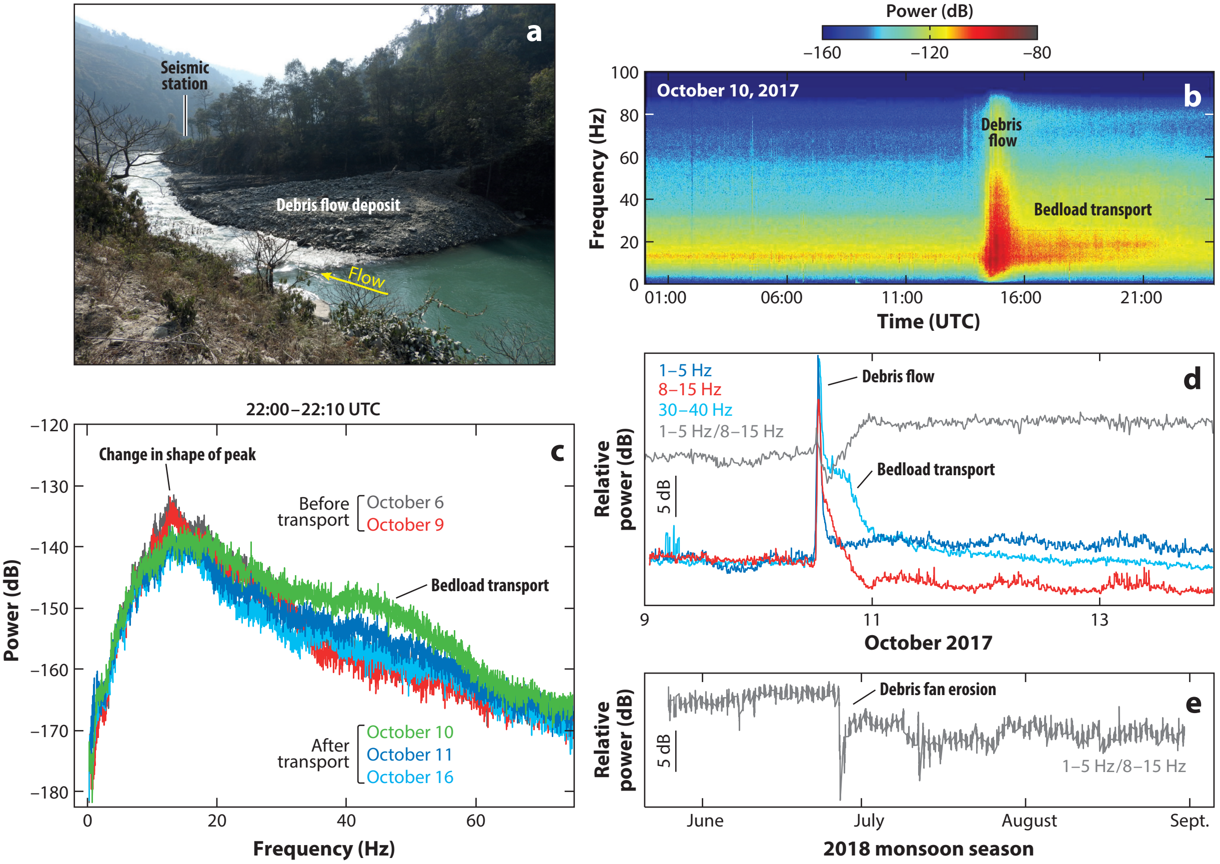

Figure 5

Seismic record of a sediment cascade from the Bhote Koshi River, central Nepal. (*a*) Photograph from January 2018 illustrating the debris flow deposit, partial channel blockage, and location of the seismic station. (*b*) Spectrogram from October 10, 2017. (*c*) Spectra from before and after the debris flow event, showing an increase and subsequent decline in power at 30–50 Hz indicative of bedload transport and a flattening of the peak at 8–15 Hz that appears related to the channel geometry change. (*d*) Time series of seismic power in different frequency ranges. The gray line shows the ratio of power at 1–5 Hz and 8–15 Hz, highlighting the step change in these frequency bands following the event. The diurnal variations in the 1–5-Hz and 8–15-Hz bands are due to anthropogenic noise. (*e*) Ratio of power at 1–5 Hz and 8–15 Hz during the 2018 monsoon season. The erosion of the deposit can be identified by the step change at the end of June (Planet Labs 3-m imagery constrains the disappearance of the deposit to between June 24 and July 6, 2018).

For example, **Figure 5** shows observations from a seismic station installed near the junction between a small tributary and the Bhote Koshi River in central Nepal. On October 10, 2017, a debris flow traveled down the tributary and deposited a fan in the main channel, partially blocking it. The seismic data record not only the occurrence of this event but also its short- and long-term impacts on the river, including increased bedload transport for several days after the event, the change in channel geometry caused by the partial blockage, and the eventual erosion of the fan and restoration of the channel geometry in June 2018. This is a simple example, but it demonstrates the power of even a single seismic station to observe interactions across process domains. At the catchment scale, Burtin et al. (2014) used a seismic network in Illgraben, Switzerland, to observe hillslope-channel interactions during a convective storm event. By combining near- and far-channel stations, they were able to detect a range of event types and observe their interactions, including the triggering of debris flows by rockfall events, the triggering of a slope failure by a passing debris flow, and changes in sediment load as debris flow pulses entrained or deposited material as they propagated downstream (Burtin et al. 2014).

In addition to the types of process analysis we have described in previous sections, seismic techniques can also be used to monitor variations in subsurface properties. Cross-correlation of ambient seismic noise can be used to monitor small variations in seismic wave velocity between a pair of stations (Snieder 2004, Larose et al. 2015) or within the vicinity of a single station (Sens-Schönfelder & Wegler 2006). These subtle changes (fractions of a percent) in seismic velocity (commonly termed *dv*/*v*) can be linked to changes in the mechanical properties of the shallow subsurface, which may be driven by hydrological processes and changing groundwater content (Sens-Schönfelder & Wegler 2006, Clements & Denolle 2018, Illien et al. 2021), temperature changes (Richter et al. 2014), internal deformation of landforms such as rock glaciers (Guillemot et al. 2020), or processes such as damage induced by ground shaking (Marc et al. 2021). In some cases these changes can be directly linked to a geomorphic response, as in some clay landslides, where *dv*/*v* values dropped hours to days before landslides became active (Le Breton et al. 2021). Landforms such as rock towers (Bottelin et al. 2013), arches (Moore et al. 2018), and mountain peaks (Weber et al. 2018) also have a seismic resonant frequency that is influenced by the rock mechanical properties and water or ice content of the material. A distinct advantage of monitoring *dv*/*v* and changes in the resonance frequency is that these data provide a metric that is characteristic for the wider landform rather than just a point measurement.

By simultaneously monitoring both processes and conditions with the same data, one can more robustly link changing subsurface characteristics to geomorphic processes (e.g., Dietze et al. 2020a). In addition, many of the external processes that force geomorphic events can also be observed with seismic data, such as heavy rainfall (Roth et al. 2016), wind (Withers et al. 1996), earthquakes, and anthropogenic activity (Guerriero et al. 2021). Thus, well-designed seismic networks have the potential to simultaneously address each of the three areas described above—the triggering of discrete geomorphic events, their internal dynamics, and their impact in terms of sediment flux out of a catchment—while at the same time monitoring subsurface properties and some types of external forcing. Integrating seismic instrumentation with traditional time-resolved monitoring of weather, discharge, suspended sediment, chemical fluxes, and remote sensing observations (e.g., Andermann et al. 2016) has the further potential to comprehensively characterize geomorphic activity and its impacts across a landscape. As the application of seismic data to detect and characterize geomorphic processes continues to grow and develop, seismic instruments should become a standard component of geomorphic observatories.

FUTURE DEVELOPMENT

In addition to the methodological developments outlined above, the instrument side of seismology is also undergoing a period of evolution, with two particular developments that move in opposite directions in terms of complexity, but each offers new opportunities for surface process seismology. First, the development of simple, low-cost telemetric geophones and data loggers, such as the Raspberry Shakes (Manconi et al. 2018), which are sold as both do-it-yourself kits and full packages, has democratized seismology and brought it into the realm of citizen science. Raspberry Shake data are generally public and uploaded in real time, and the increasing popularity of such instruments has the potential to expand the reach of seismic monitoring. While such crowd-sourced data cannot replace purpose-installed stations or networks aimed at a particular research question, they do greatly increase the chances that unexpected geomorphic events will be recorded seismically. For example, an initiative in Nepal to install Raspberry Shake geophones in local schools (Subedi et al. 2020) has significantly increased the amount of publicly available seismic data in Nepal, which has already contributed to the study of a destructive flood event (e.g., Bell et al. 2021).

At the opposite end of the spectrum, distributed acoustic sensing (DAS) is a rapidly growing technique that uses fiber-optic cables to measure ground strain at meter-scale resolution with kilometer-scale-long cables (Walter et al. 2020b, Lindsey & Martin 2021). While the applications of DAS to date have largely focused on earthquake detection (Fernández-Ruiz et al. 2020), traffic and other urban processes (Lindsey et al. 2020), and subsurface imaging (Jousset et al. 2018), its value for geomorphic process research is tempting, considering the high spatial resolution and the flexibility to lay out the linear device in relation to the research object: along a river, around a small catchment, across active sites, or across a glacier (Walter et al. 2020b).

These developments highlight a multi-lane path for moving the field of environmental seismology forward. Pushing the boundaries of techniques and instrumentation is key for broadening the scope of seismic observation of surface processes. However, for seismology to reach its full potential for advancing geomorphology, it needs to be more widely and routinely applied, and therefore it needs to become more accessible to the geomorphic community. One of the barriers to the wider adoption of seismological techniques in geomorphology is the height of the threshold for entry into the field. Seismology is a rich and complex discipline, one in which some geomorphologists may have little training. However, seismologists may need added geomorphological expertise to fully exploit their observations and to identify additional interesting and pressing applications. Collaborative efforts can bridge this gap and are key for pushing the boundaries of the field, but as applications leave the proof-of-concept phase and become ready for routine use, the development and sharing of dedicated environmental seismology code, source libraries, and packages should be promoted. Packages such as lsforce, a python package for landslide force inversion (Toney & Allstadt 2021), and eseis, an R package for environmental seismology (Dietze 2018), can make it substantially easier for newcomers to the field to begin working with seismic data. In this review, we have discussed four broad areas of geomorphic inquiry in which seismology is enabling unique and meaningful advances. We expect that the exposure of a broader range of geomorphologists to the power of seismic observation will yield a new array of geomorphic questions that can be addressed with seismic methods, spurring further technique development and continuing to broaden the discipline.

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