Table of Contents

Abstract

Introduction ........................................................................................................................................1
The generation of stratigraphy and signal interpretation 1
Sediment transport and nonlinear behavior 7
Hypothesis 8

Experimental setup and methods ...............................................................................................9
The rice pile model 9
Methods 11

Time series data collection 11

Time series analysis 11

Results .........................................................................................................................................16
Rice efflux data tables 17

Discussion ...................................................................................................................................21
Implications for stratigraphic interpretations 21
Future work and applications 23

Sponsorships .............................................................................................................................28

Acknowledgements ...................................................................................................................28

References Cited ........................................................................................................................29
A primary method of stratigraphic analysis is the extraction and analysis of time series records that document changes in bedding thickness or lithology. These analyses can reveal evidence of cyclic allogenic processes that are imposed upon depositional systems. There is reason to doubt that cyclic processes of all frequencies are being clearly recorded in stratigraphic successions, however, as higher frequency cycles overlap the temporal range of autogenic fluctuations that arise from nonlinear sediment transport dynamics. Here we examine the record of imposed cycles in an avalanching pile of brown rice, which exhibits self-organizing behavior and can thus be used to model nonlinear sediment dynamics. The second-to-second measurement of rice avalanches produces a time series that can be analyzed with a Fourier analysis to show the finite temporal range of autogenic fluctuations that arise for a system with a steady input. The record of allogenic processes is then tested by imposing sinusoidal cycles on the input. Results show that signals of cycles that overlap the frequency domain of autogenic fluctuations are not recorded in the rice efflux, while signals of cycles that operate on timescales longer than the upper extent of autogenic variability are preserved. This means that we can place a hard lower limit on the extent to which we can accurately interpret the record of allogenic processes in stratigraphic sections, as higher frequency cycles that overlap the range of autogenic variability are obliterated by the system.

**Keywords:** Stratigraphy, time series analysis, sediment transport, self-organization, cyclic processes, climate forcing
INTRODUCTION

The generation of stratigraphy and signal interpretation

A primary method of stratigraphic analysis is the extraction of signals from the sedimentary rock record. Analysis of time series records of bed thickness or lithological change in stratigraphic sections can reveal evidence of cyclic environmental or climatic processes that are imposed on depositional systems (Schwarzacher, 2000). Interpretation of these signals can help in our understanding of various aspects of paleoclimate, including the influence of orbital forcing or eustatic sea level changes on climate cycles and environmental change (e.g., Nederbragt et al., 2007; Cecil et al., 1997). However, the formation of stratigraphic sections is an inherently variable process, with alternating periods of deposition and erosion or depositional hiatus pervading stratigraphy at all scales of observation (Plotnick, 1986; Sadler, 1999). This not only renders the process of assuming average sedimentation rates highly problematic, but it also gives reason to doubt that periodic cycles of all frequencies are being expressed in stratigraphic successions.

Previous studies highlight this problem through empirical and experimental examinations of the generation of stratigraphy. Jerolmack and Sadler (2007) compile thousands of empirical measurements of sediment aggradation along continental shelves, coastal plains and deltas to show two distinct scaling relations that arise about a calculated transitional crossover time of \(~10^4\) years for bed thickness preservation over time (Fig. 1). These scaling relations coincide with the different depositional processes that dominate at different timescales, with transport-dominant behavior and associated transient topographic forms such as ripples, bars, and leveed channels dominating over
Figure 1: Scaling relations from empirical data for mean sediment aggradation on channeled coastal plains (solid line) and deltas (thin dashed line), with thick dashed lines fit to their general trends. Vertical dashed line shows break between scaling relations, representing a crossover time of $\sim 10^4$ years between transient and persistent behavior. From Jerolmack and Sadler (2007).
shorter timescales (<10⁴ years) and accommodation-dominant behavior and associated persistent topographic forms such as fans, deltas, and shelves dominating over longer timescales (>10⁴ years). Small-scale fluctuations that result from alternating periods of deposition and erosion or non-deposition dominate at shorter timescales and render bed thickness preservation stochastic and unpredictable. On the other hand, steady sediment accumulation begins to dominate over timescales longer than the crossover time, where aggradation has a 1:1 linear relationship with time due to long-term sediment accommodation mechanisms like tectonic subsidence or eustatic sea level change. To solidify their empirical results, the authors produce identical scaling relations with a numerical “stochastic diffusion” model for basin filling based on Pelletier and Turcotte (1997), which produces synthetic stratigraphy using the assumptions that deposition and erosion events occur independently and that sediment transport is a noisy, diffusive process. Using the model to show the fluctuations that control excursions in vertical thickness over shorter timescales, the authors explain that, in order for sedimentation at a point to balance subsidence on average (resulting in net sediment accumulation), the accumulated sedimentary thickness must be significantly greater than the range of vertical excursions the surface undergoes resulting from small-scale noisiness (Fig. 2). This is to say that sediment will be constantly aggrading and eroding on the surface as a result of sediment transport dynamics, but over longer spans of time there will be net deposition.

Such conclusions have considerable implications. First, they show that the “steady state” assumption in which stratigraphy can be equated to periodic forcing is only applicable for timescales greater than the crossover time, where small-scale fluctuations
Figure 2: (A) Results of noisy diffusion numerical model showing the small-scale vertical excursions that arise in the generation of stratigraphy due to fluctuations in deposition and erosion, with thickness (y-axis) plotted against time (x-axis). (B) Resulting stratigraphic section from vertical excursions shown in (A) with vertical lines representing net accumulation and horizontal lines representing intervals of depositional hiatus. Figure demonstrates the concept that there will be net deposition only when sediment thickness at a given location is larger than the range of vertical excursions that occur on the surface. From Pelletier and Turcotte (1997).
average out and aggradation and time span have a 1:1 linear relationship. Second, they raise doubts about our ability to interpret signals whose cycle frequencies fall under the crossover time. Accurate signal interpretation depends on our ability to distinguish periodic cycles from noisy processes like sediment transport that cause fluctuations in sediment accumulation at shorter timescales. Unfortunately, this problem of differentiation cannot be pursued with the stochastic diffusion model because it models transport fluctuations as a random and internally uncorrelated process, which in turn produces synthetic bed-thickness sequences that show no evidence of persistence (Pelletier and Turcotte, 1997). In fact, bed-thickness sequences in the model do not exhibit persistence unless there is a periodicity imposed on the system, which is passed through a linear filter and reflected in the distribution of depositional and erosional events (Fig. 3). As will be discussed below, any periodic forcing should pass through a noisy, nonlinear filter because sediment transport fluctuations exhibit correlated, nonlinear behavior and occur according to a given probability—not randomly. In order to examine the response of sediment transport systems to climate cycles that fall within the interval dominated by noisy dynamics, a model in which autogenic variability is better understood through nonlinear dynamics, or treated stochastically through the measured distribution of fluctuations, will enhance the resolution within which we can confidently interpret the record of Earth-surface dynamics preserved in sedimentary rock (Jerolmack and Sadler, 2007).
Figure 3. Results of noisy diffusion model with imposed periodicity for bed thickness distribution (y-axis) over time (x-axis) showing recorded periodic component. Periodic component represents external forcing that is required for bed thickness persistence in the model because it is passed through a linear filter and influences the distribution of erosion and deposition events. Graph however shows a wide distribution of bed thicknesses arises because of fluctuations in deposition and erosion that occur at higher frequencies than the periodic forcing. From Pelletier and Turcotte (1997).
Sediment transport and nonlinear behavior

Sediment transport systems ranging from migrating surficial bedforms to avulsing channels exhibit nonlinear behavior, manifest in the storage and release of sediment through threshold processes that occur over many spatial and temporal scales (Leeder, 1999). Scale-invariant chaotic systems are proposed to evolve according to the concept of self-organizing criticality (SOC), a general mechanism that is used to explain the generation of fractals in a complex system by defining its natural oscillation between thresholds and a state of minimum stability (Turcotte, 1997). To demonstrate the concept of SOC, Bak et al. (1987; 1988) use a numerical sand pile model in which grains of sand are dropped on top of a pile at a controlled rate. Sand grains accumulate along the slope until a certain critical point is reached, at which point avalanches of magnitudes up to the size of the system are triggered and the system returns to a state of minimal stability. Avalanche magnitudes are distributed according to a given probability density that avalanches of size \( f \) will occur \( 1/f \) times, resulting in a fractal frequency-magnitude distribution of avalanche events. The idea of SOC has been applied to explain such disparate things as forest fires, landslides, earthquakes and stock market crashes (e.g., Kardar, 1996; Malamud and Turcotte, 1999; Turcotte and Malamud, 2004). Somewhat ironically though, attempts to physically produce SOC behavior using the classic sand pile model have produced ambiguous results, as the behavior of real sand is much more complex than what is accounted for in the numerical model (Kardar, 1996). But, after testing several types of granular media, Frette et al. (1996) are able to produce self-organizing critical behavior in an avalanching pile of brown rice. They attribute the success to the rice’s elongate form which allows it to interlock with other grains and
accumulate locally along the slope. This satisfies an exhibited shortcoming of sand grains, which are round and have a tendency to bypass the storage and release process and simply roll off the slope upon introduction to the pile (Frette et al., 1996).

Hypothesis

Here we adapt Frette et al.’s (1996) rice pile model as a simple, controlled proxy for sediment transport systems in order to observe the response of the autogenic system to hypothetical climate cycles of various frequencies. Storage and release threshold processes occurring at a range of spatial and temporal scales are modeled by rice-releasing avalanche events along the slope. With a steady input of rice, we can observe the fractal distribution of avalanche magnitudes by measuring the weight output of release events over time and analyzing the time series using a Fast Fourier Transform (FFT). This analysis yields a power spectrum that shows the timescales over which the autogenic system operates. Autogenic variability in the rice pile saturates at a distinct frequency, making it analogous to the interval of fluctuations that dominate over shorter timescales and equilibrate at a determined crossover time, as demonstrated in Figure 1. With these timescales in mind, we can observe the record of signals for periodic fluctuations above and below the crossover time by imposing a sinusoidal cycle on the input. If a cycle is imposed on the system with a period longer than the temporal range of the autogenic signal, we expect its signal to be recorded in the white noise, i.e., those timescales longer than the domain of the autogenic signal. Otherwise, we expect signals that overlap the autogenic signal to be obliterated by the inherent noisiness of the system.
This result would place a lower limit on the extent to which we can evoke periodic allogenic controls in our interpretation of the depositional record.

**EXPERIMENTAL SETUP AND METHODS**

**The rice pile model**

We base our rice pile model off of that used by Frette et al. (1996) (Fig. 4a). The rice used is brown, long grain rice that has an average length of ~8 mm, a width of ~1.5 mm and a weight of ~.02-.04 g per grain. Two vertical parallel plexiglass panels spaced 20 mm apart make a long, thin box with an opening in the front (and styrofoam blocks in the back). Rice is emptied from a hopper into the box via a software-controlled toothed wheel, which enables us to impose different rates and cycles on the input. Input rates are measured in teeth/second, and while rice grains/tooth is variable from tooth to tooth we expect that average grains/tooth is consistent. Rice builds up in the box and ultimately creates a long slope, along which rice is stored in a variety of packing configurations that allow avalanches of varying magnitudes to be triggered as rice is continually added to the pile (Fig. 4b). Avalanches are initiated by flowing grains that topple local areas of instability, or by grains that slide out and cause an upward-propagating chain reaction. The rice gradually builds the slope up to a maximum angle of steepness until a large, global avalanche occurs and the slope returns to a minimum angle of repose. Rice released by avalanche events empty out the end of the box onto a scale, which sits in a large bin and records weight measurements on a computer at 1 Hz. As the scale has a 400 g capacity, a blower is set up and connected to a timer to periodically blow rice off
Figure 4. (A) Close-up profile of rice pile. Rice slope builds up between two parallel plexiglass plates spaced ~20 mm apart. (B) Close-up of slope displaying pronounced step and variety of packing configurations obtained by rice in minimally stable state, from Frette et al. (1996). (C) Rice pile model setup showing experimental setup, with computer, wooden hopper, plexiglass box, mechanical wheel, scale and blower.
of the scale and into the bin (Fig. 4c). This allows the model to run for extended periods of time without supervision.

**Methods**

**Time series data collection**

Runs were conducted at a variety of steady input rates in order to obtain time series data that we can use to examine the effects of various rates on the autogenic signal. Rice efflux data produced by runs consist of cumulative weight measurements taken at 1-second intervals with periodic negative excursions as a result of the blower events. We ran the data through a MATLAB script that searches for these negative excursions and erases them, along with a specified number of data points on either side of the excursions, from the data set. Accumulated weight erased from the script or not recorded because of the blower events is assumed to be negligible: the data will produce the same statistical averages if the system achieves saturation, which will be discussed below. The script then produces a plot of the instantaneous sediment transport rate in g/s, which is simply the difference in cumulative weight from one second to the next. This time series plot shows the wide distribution of avalanches magnitudes that occur in a system with a steady input of sediment and is here termed the autogenic signal (Fig. 5).

**Time series analysis**

We ran the data through another MATLAB script that performs basic analyses on the time series to examine the output flux for any exhibited periodicity. Principal analyses consist of autocorrelation and a Fourier analysis (in the form of an FFT).
Figure 5. Example of instantaneous efflux plot showing scale invariance of avalanche magnitudes, recorded at 1 Hz.

Figure 6. Example of autocorrelation plot from numerical rice pile model showing perfect recorded periodicity in efflux as judged by the cyclic occurrence of the correlation coefficient (Y-axis), from Jerolmack (personal correspondence).
Autocorrelation analyzes the strength of the relationship between two consecutive readings in a time series of a stochastic process as a function of the time between them (Cliff and Ord, 1981). The autocorrelation plot computes the correlation coefficient for the lag time between values $t_1$ and $t_2$, $t_2$ and $t_3$, up through $t_n$ and $t_{n+1}$, which will show a cyclic fluctuation if there is a recorded periodicity in the efflux (Fig. 6). The FFT produces a power spectrum—a logarithmic plot that shows the frequency-magnitude distribution of time series values (Fig. 7) (Stade, 2005). Power spectra are generated by assigning best-fit sinusoids to equivalent values on a time series, multiplying the frequency components of the sinusoids by the entire time series, and arranging the array of products according to the frequency components by which they were multiplied. For instance, periodically distributed values will show a high spectral power at the frequency at which they occur, because the values are being squared. Spectral densities of aperiodic values will thus be arranged according to the frequency of the sinusoid they best match. Power spectra are ensemble-averaged, meaning that the time series data are split at random into a series of $n$ subsets and analyzed through an FFT, which computes the power spectrum for each data subset and averages them together. This is done in order to reduce the effects of noise on the spectral analyses and to produce more robust scaling relations. Here we use $n=10$ as the standard by which we generate and compare spectral analyses. Increasing the $n$ value reduces the magnitude of the spectral density and shortens the temporal range of the system, but it will be helpful in determining the extent of the record, if any, of signals from cycled runs.

In simple terms, for our purposes, the power spectrum shows the frequency distribution of avalanche magnitudes across the time series data. Avalanches magnitudes
Figure 7. (A) Example of power spectrum for a system that achieved saturation, with best-fit lines fitted to trends of power law and white noise showing distinct intersection and separation at rollover frequency. (B) Power spectrum of a system that failed to achieve saturation, showing no distinct separation between the power law and white noise.
are distributed along a power law—a negative sloping trend with a distinct scaling exponent that demonstrates a system’s scale invariance by crossing spatial and temporal orders of magnitude on a logarithmic power spectrum (Turcotte, 1997). As per SOC and the stipulation that avalanches of magnitude $f$ occur $1/f$ times (Bak et al., 1987; 1988), the power law shows that spectral density increases at lower magnitudes as frequency increases (Fig. 7a). The power law reveals the timescales over which the autogenic signal operates and abuts a white noise spectrum, which shows the frequencies over which the system does not operate. The system must run at a given input rate for an amount of time sufficient for the system to achieve “saturation”—i.e., a required amount of time for the system to attain equilibrium, whereby averaged time series data produce the same scaling relationships and distinct “rollover” between the power law and white noise (Fig. 7). We experimentally determined a satisfactory saturation time for the system at 1 t/s of ~2 days and distribute this time proportionally for other steady input rates. The rollover frequency represents the frequency of the largest avalanche event a system can produce at a given input rate. With this frequency in mind, we can test our hypothesis by imposing a sinusoidal cycle on the input with frequencies above and below the rollover time. Amplitudes of imposed sinusoids average about the steady input rate for which spectral data were initially collected, which we can confirm by placing a plexiglass slide between the wheel and the scale and comparing the average weight input in grains/tooth for steady and cycled inputs.
RESULTS

Compiled data statistics from runs at steady input rates are provided in Table 1. Mean efflux (g/s) shows average weight output per unit time. The rollover frequency \( (1/t_x) \) is determined by the intersection of best-fit lines to the trends of the power law and the white noise. Frequencies are translated to time (s) by multiplying the frequency by \( 2\pi \) to account for the sinusoid used in the algorithm to produce the power spectrum.

Room temperature for runs ranged from 13-20° C with a mean of ~17° C, and humidity ranged from 44-51% with a mean of ~46%, indicating that temperature and humidity had a negligible effect on the packing configurations of rice along the slope.

Rice efflux statistics reflect intuitive expectations on how the system would respond to variations in input rate. Mean efflux increases approximately proportional to increases in input rate. The rollover frequency increases over orders of magnitude with increasing input rate, meaning that the associated rollover time decreases over orders of magnitude with increasing input rate. These results show that more rice passes through the system at higher input rates, which in turn decreases the amount of time necessary to build the pile up to its maximum angle of steepness.

Compiled data statistics for runs with cycled inputs are provided in Table 2. We used the data obtained from the steady 1 t/s run (Fig. 8a) as a general standard to test our hypothesis: that cycles overlapping the temporal range of autogenic fluctuations will be obliterated and will not show up in the output flux. Spectral analysis of the time series for 1 t/s reveals a rollover frequency of ~10^{-2}, translating to a time of ~630 s. First, we cycled the input from 0 to 2 t/s, an average of 1 t/s, over a period of 1800 s, thus expecting the signal to break through the white noise at ~3^{-3} on the power spectrum.
Table 1. Compiled data for steady input runs.

<table>
<thead>
<tr>
<th>Run ID</th>
<th>Input Rate (t/s)</th>
<th>Determined saturation time (hours)</th>
<th>Mean efflux (g/s)</th>
<th>Rollover frequency (1/tₚ)</th>
<th>Rollover time (s) ((1/tₚ)*(2π))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run6V0point33_050307</td>
<td>0.33</td>
<td>~144</td>
<td>.0103</td>
<td>~3⁻³</td>
<td>~2000</td>
</tr>
<tr>
<td>Run20V1_120407</td>
<td>1</td>
<td>~48</td>
<td>.0622</td>
<td>~10⁻²</td>
<td>~630</td>
</tr>
<tr>
<td>Run14V2_062507</td>
<td>2</td>
<td>~24</td>
<td>.1281</td>
<td>~3⁻²</td>
<td>~200</td>
</tr>
<tr>
<td>Run13V3_062207</td>
<td>3</td>
<td>~16</td>
<td>.1939</td>
<td>~3⁻²</td>
<td>~200</td>
</tr>
<tr>
<td>Run8V5_051507</td>
<td>5</td>
<td>~10</td>
<td>.2869</td>
<td>~6⁻²</td>
<td>~100</td>
</tr>
</tbody>
</table>

Table 2. Compiled data for sinusoidal input runs.

<table>
<thead>
<tr>
<th>Run ID</th>
<th>Average rate (t/s)</th>
<th>Mean efflux (g/s)</th>
<th>Rollover frequency (1/tₚ)</th>
<th>Sinusoid properties</th>
<th>Signal expected (1/t)</th>
<th>Signal recorded?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run24_30minper0to2</td>
<td>1</td>
<td>.0704</td>
<td>~10⁻²</td>
<td>Amplitude: 0 to 2 t/s Period: 1800 s</td>
<td>~3⁻³</td>
<td>Yes</td>
</tr>
<tr>
<td>Run22_2minper0to2</td>
<td>1</td>
<td>.0734</td>
<td>~10⁻²</td>
<td>Amplitude: 0 to 2 t/s Period: 120 s</td>
<td>~5⁻²</td>
<td>No</td>
</tr>
<tr>
<td>Run23_30secper0to10</td>
<td>5</td>
<td>.3109</td>
<td>~6⁻²</td>
<td>Amplitude: 0 to 10 t/s Period: 30 s</td>
<td>~2⁻¹</td>
<td>No</td>
</tr>
</tbody>
</table>
Figure 8. (A) Instantaneous efflux plot and power spectrum for steady 1 t/s run. Estimated rollover frequency from power spectrum $\sim 10^{-2}$. (B) Power spectrum and autocorrelation plot for cycled input from 0 to 2 t/s over a 1800s period. Power spectrum is ensemble-averaged for $n=25$ to better show signal (circled) breaching white noise at a frequency of $\sim 3^{-3}$. However, autocorrelation plot shows no strong periodicity. (C) Ensemble averaged power spectra for cycled input from 0 to 2 t/s over a 120 second period. Spectrum on left for $n=10$ shows signal does not show up at expected frequency of $\sim 5^{-2}$, indicated by arrow. Spectrum on right with $n=50$ shows semblance of signal (circled), but it cannot be considered recorded because it shows the same strength as surrounding fluctuations.
Results show the signal breaking through the white noise at the predicted frequency (Fig. 8b), with a mean efflux of .0704 g/s matching up very well with .0622 g/s obtained from the 1 t/s steady input run. The autocorrelation plot however does not show a strong periodicity in the repetition of the correlation coefficient. Next, we cycled the input from 0 to 2 t/s, still averaging out to 1 t/s, over a period of 120 s which thus overlaps the autogenic system at a frequency of ~5^2. The signal does not show up in the spectral analysis (Fig. 8c), and the mean efflux of .0734 g/s is in good agreement with .0622 g/s obtained from the steady 1 t/s run. Ensemble-averaged spectral analysis for n=50 shows a slight semblance of the signal, but because it is not stronger than the surrounding fluctuations it cannot be considered to be recorded in the efflux. The signal has thus been obliterated by the system, meaning that the imposed low-amplitude cycle failed to exert a periodicity on the occurrence of avalanche events. Using the range of .02-.04 grams/grain, we calculated the average grains/tooth to be 1.7-3.3 for steady 1 t/s and 1.4-2.8 for cycled 0 to 2 t/s runs, validating the assumption that cycled input runs average out to steady input rates.

We then performed the same test for a faster steady input rate to see if the system could be breached by a high-amplitude cycle. The fastest steady input rate for which we have obtained a signal is 5 t/s. Spectral analysis of the time series reveals a rollover frequency of ~6^2, translating to a rollover time of ~100 s (Fig. 9a). We cycle the input from 0 to 10 t/s over a period of 30 s, thus overlapping the system at a frequency of ~2^1. The signal does not show up in the spectral analysis of the time series data, and the system produces a mean efflux of .3109 g/s which shows good correlation with .2869 g/s produced by the steady 5 t/s run. Ensemble-averaged spectral analysis for n=50 shows
Figure 9. (A) Instantaneous efflux plot and power spectrum for steady 5 t/s run. Estimated rollover frequency from power spectrum is \(\sim 6^{-2}\). (B) Ensemble-averaged power spectra for cycled input from 0 to 10 t/s over a period of 30 seconds. Power spectrum for \(n=10\) (left) shows rollover frequency of \(\sim 6^{-2}\). Signal of imposed cycle does not show up at the predicted frequency of \(\sim 2^{-1}\), indicated by arrow. Power spectrum for \(n=50\) (right) shows no semblance of signal.

no record of the signal (Fig. 9b). This shows the autogenic system responds consistently to smooth, overlapping sinusoidal cycles, regardless of amplitude.
DISCUSSION

Implications for stratigraphic interpretations

Here we use Frette et al.’s (1996) rice pile to simulate self-organized autogenic dynamics along passive continental margins and alluvial coastal plains in order to observe the record of long and short period hypothetical climate cycles that are imposed upon the system. The rice pile model exhibits nonlinear behavior through storage and release threshold processes, making it an effective analogue for sediment transport at scales of observation from migrating bedforms such as ripple and dune trains to channel and delta avulsions (Leeder, 1999). Through the 1 Hz measurement and analysis of intrinsic dynamics, we observe the timescales over which the autogenic system operates and can check for the signature of imposed cycles. Results show that signals of cycles with periods longer than the upper extent of autogenic variability are recorded in the output flux, while signals of cycles whose periods overlap the temporal range of the autogenic signal are obliterated.

Like other chaotic systems that behave according to self-organizing criticality, the rice pile naturally evolves to its critical state: as the pile builds up, the characteristic size of the largest avalanches grows, until at the critical state there are avalanches of all sizes up to the utmost size of the system (Bak et al., 1988). Periodic pulses in sediment influx that overlap the temporal range of autogenic variability are obliterated because they fail to dictate the system’s attainment of the critical state—i.e., they do not affect the distribution of storage and release fluctuations leading up to the generation of the largest avalanche the system can produce. This demonstrates the robust and correlated nature of inherent autogenic variability. On the other hand, longer period cycles are recorded in
the output flux because they operate over timescales beyond the reach of autogenic fluctuations. Longer period cycles effectively slow the process of storage and release along the slope, which in turn delays the attainment of the critical state and the lengthens the amount of time necessary for the slope to achieve maximum steepness. While the record of signals is different for high and low frequency cycles, the cycled runs produce the same scaling relations and rollover frequency as the steady input run they model because their amplitudes average out to the same steady input rate. Mean efflux data confirm this assumption, as mean efflux for cycled runs matches up well with mean efflux for the steady input rate they oscillate about.

The finite temporal range of autogenic variability in the rice pile saturates at a distinct rollover frequency, making it analogous to the empirical scaling relations derived for bed thickness persistence along continental margins and coastal plains (Fig. 1). Small-scale fluctuations resulting from alternating periods of deposition and erosion give way to steady sediment accumulation at a given equilibrium time. If the equilibration of small scale fluctuations along continental margins or coastal plains is represented by the saturation of autogenic variability in the rice, then nonlinear alternations between deposition and erosion are modeled by the nonlinear alternations between the storage and release of rice along the slope. Given this, our results show that a hard lower limit can be placed on the extent to which we can accurately interpret signals of allogenic processes that are imposed on depositional systems, since signals below this limit are obliterated by the inherent noisiness of the system. If depositional environments and average sediment accumulation rates can be accurately inferred from the stratigraphic record, we should only be concerned with the interpretation of climate cycles that we believe to operate on
timescales outside of the range of noisy sediment transport dynamics. The preservation of long period signals (Fig. 8b) shows that sediment transport systems respond to allogenic processes that operate on these timescales. Examples of such periodic forcings are Milankovich orbital cycles (e.g., Nederbragt et al., 2007), eustatic sea level changes (e.g., Mountain et al., 2007) or other longer period (>\(10^4\) years) cycles that dictate pulses in sediment influx in fluvial or deltaic systems or along passive continental margins (e.g., Cecil et al., 1997). It is this preserved periodicity component that allows us to infer paleoenvironments and climate patterns from the stratigraphic record. However, it must be stated that our results have no bearing on “closed” depositional systems that record cyclicity at a very high resolution, such as lacustrine varves that can record seasonal climate variations (e.g., Schettler et al., 2007) or estuarial tidal bundles that record neap and spring tide cycles (e.g., Tape et al., 2003), as sediment influx in these systems are controlled by the cycles they record.

**Future work and applications**

While our hypothesis was confirmed there are further tests that can be done to solidify our results. Of primary concern is the long (1800 s) period sinusoidal run from 0 to 2 t/s that resulted in the successful signal preservation in the output flux (Fig. 8b). The data was obtained from a two-day experimental run in accordance with the previously determined saturation time for 1 t/s. However, the power spectrum used to show the signal is for \(n=25\) instead of \(n=10\) because the signal for \(n=10\) is more of a concentrated area of strength than a well-defined spectral peak (Fig. 10). Results from a numerical rice pile model with an imposed long period cycle show a very strong preserved spectral
Figure 10. Ensemble-averaged power spectrum for \( n=10 \) for sinusoidal run over 1800 s period from 0 to 2 t/s. Circle denotes the general area of the preserved signal’s strength that arises instead of a distinct spectral peak. Poorly defined rollover time suggests system did not fully saturate, prompting further testing.

Figure 11. Example of power spectrum from numerical rice pile model for a sinusoidal run over a period longer than the rollover time, showing preserved signal (circled). Recorded peak shows a strong spectral density not observed for long period run in the physical model. From Jerolmack (personal correspondence).
peak (Fig. 11; Jerolmack, personal correspondence). Reasons for the disagreement between the physical and numerical models must lie either in the length of the physical rice pile run, or, more simply, in the response of the rice to the long period pulse. Given that the power law scaling does not show a sharp rollover, however, the system most likely did not run to saturation and we suspect that a longer run (five days to a week) under the same conditions will produce better scaling relations and a stronger record of the signal. A longer run should also produce a more periodic fluctuation in the correlation coefficient on the autocorrelation plot, which shows inconclusive evidence for recorded periodicity (Fig. 8b).

Another area that invites further exploration is the effect of changing the structure of the imposed periodicity component on the record of the signal in the rice efflux data. For this study we used smooth, perfectly proportional sinusoids in order to simulate cyclic variations in climate that cause gradual changes in sediment flux. Modifying this sinusoid to include large spikes in influx at the peaks of the wave, while still averaging about a steady input rate, would simulate climate cycles that trigger or culminate in large storm events. For example, wave amplitude conditions would be 0 to 2 t/s, averaging 1 t/s, but as the cycle nears its 2 t/s peak the wheel speed would shoot up to 10 t/s. Such conditions would be ideal to see if the autogenic signal in fact can be breached. Interesting comparisons could also be potentially made between preserved signals for long period runs under these conditions and smooth sinusoidal cycles.

Like numerical models of self-organizing systems, the physical rice pile can be applied universally to examine the response of a chaotic system to different perturbations. Not surprisingly, the rice pile can be used to examine different problems
surrounding the generation of stratigraphy. As mentioned above, inferences of sediment accumulation rates should be made cautiously because it is shown that determined rates are inexorably tied to the resolution being considered. Sediment accumulation rates have a negative power law correlation to the temporal range over which the rate is being inferred, because hiatuses in sedimentation pervade the stratigraphic record at all scales of observation and longer intervals of hiatus are included over longer periods of measured time (Plotnick, 1986; Sadler, 1999). In the rice pile model, increases in input rate result in increases in mean efflux rates (Table 1), meaning that hiatus intervals (the time between the introduction of grains or when the slope is in a state of minimum stability between critical states) must be relatively shorter for faster input rates than at slower input rates. The rice pile can thus serve as an experimental proxy for inferring sediment accumulation rates at different scales of observation. Faster input rates lead to shorter hiatuses and higher sediment efflux rates, making them synonymous with accumulation rates and hiatus intervals at smaller scales such as grain boundaries. On the other hand, slower input rates lead to longer hiatus intervals and slower accumulation rates that arise at a higher scale of observation. This relationship is illustrated in Figure 12, which shows agreement in the negative correlation between sediment accumulation rate and relative resolution for empirical and experimental data.

The rice pile could also be modified to model the generation of stratigraphy based on the scaling relationships presented in Figure 1. While storage and release (deposition and erosion) fluctuations occur along the slope, steady sediment accumulation could be modeled by a rising gate added to the open end of the box above the scale, which would rise at a very slow rate proportional to the input rate and the size of the box. This would
Figure 12. Log-log plots showing negative power law correlation of mean sediment accumulation rates with increasing time span, based on (A) empirical data for terrigenous sediments on passive continental margins from Sadler (1999) and (B) experimental mean efflux data from rice pile model. Mean efflux data for steady input rate runs from Table 1 are arranged according to relative scale of observation, with larger smaller efflux rates representing larger scales of observation due to the longer hiatus intervals that occur at slower input rates. Bottom plot shows effective application of rice efflux data to model determined sediment accumulation rates for different scales of observation.
result in net rice accumulation while fluctuations continue along the slope and empty out onto the scale. With a box constructed with large plexiglass plates and a mechanism emplaced to make the box subside at proportional rates, stratigraphic sections can be experimentally generated up to the size of the box.

**SPONSORSHIPS**

This research was funded by the National Science Foundation as part of an undergraduate research internship program administered by the Department of Geology and Geophysics at the University of Minnesota, Twin Cities. The research was performed at the University’s St. Anthony’s Falls Laboratory.

**ACKNOWLEDGEMENTS**

First and foremost, I would like to thank Chris Paola and Doug Jerolmack for allowing me to participate in their research. This has involved the introduction and explanation of a slew of topics and concepts that were previously unbeknownst to me, and I am grateful for their patience and enthusiasm as they have helped me get up to speed. I would also like to thank everybody at the St. Anthony’s Falls Laboratory for their interest and support, especially Chris Ellis, who played a large role in the technical setup of the experiment. Also in need of recognition are Clint Cowan for support and feedback during the writing process, Sharon Kressler of the U of M’s Geology Department for good humor and accommodation in spite of my irregular appearances
throughout the year, and my good friend Cody Killion for letting me stay in his apartment for two weeks in December so that I could finish the research.

REFERENCES CITED


