HOW LANDSCAPE DYNAMICS CAN ALTER THE PRESERVATION AND

INTERPRETATION OF PALEOENVIRONMENTAL SIGNALS

IN FLUVIODELTAIC ENVIRONMENTS

A Dissertation in

Geosciences

by

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ABSTRACT

Fluviodeltaic environments are some of the most dynamic sedimentary systems on Earth. They are highly sensitive to changes in external boundary conditions, such as sea level, sediment supply, and climate. In addition, they have a wide range of internally generated (autogenic) sediment transport processes that control where sediment is deposited or eroded over short to intermediate timescales (up to ~10^5 years). Example of these autogenic processes include channel avulsion or bifurcation. Because of the highly dynamic nature of fluviodeltaic environments, it is hard to predict how they will respond to future changes in sea level and climate. However, they are critical environments for society, and so efforts have focused on better understanding how they have responded to perturbations in the stratigraphic record in order to better predict the future.

The challenge of directly applying analyses of the stratigraphic record is that the very landscape dynamics that make it hard to predict delta behavior in the future, complicate the preservation and interpretation of past paleoenvironmental signals of all sorts. The autogenic processes in particular cause sediment to be unevenly deposited in both time and space. This means that the stratigraphic record of paleoenvironmental signals is likely to have large amounts of missing time at any given study location within a fluviodeltaic system. Previous work has demonstrated that autogenic processes, and the gaps in the record caused by autogenic processes, can expand, condense, or remove entire portions of paleoenvironmental signals if they occur at timescales less than the longest timescale autogenic processes. In this dissertation, I use a combination of numerical models and field datasets to explore how landscape dynamics control signal preservation and how we can use landscape dynamics to improve the uncertainties related to reconstructing paleoenvironmental signals in dynamic landscapes.
In the first project of this dissertation, I investigate how to measure the scale of landscape dynamics using depositional patterns preserved in outcrops that are limited in spatial extent or resolution. To accomplish this I used synthetic stratigraphy from a physical delta experiment to test the sensitivity of a proposed tool to identify the maximum autogenic scale, called the compensation statistic. I also applied this analysis to four field fluviodeltaic datasets. In the second project, I demonstrate the effect of stochastic sedimentation from landscape dynamics on the probability of preservation and the accuracy of reconstructions of paleoenvironmental signals from geochemical paleoenvironmental proxies. To this end, I compiled sedimentation event magnitudes and frequencies from published data from modern and ancient river, delta, and shallow shelf environments. Based on this compilation, I wrote a stochastic sedimentation model that tracked the preservation of an input proxy signal. In the third project, I investigate how autogenic landscape dynamics control the spatiotemporal distribution of erosion and deposition across a fluviodeltaic system using a numerical delta evolution model. I then used multiple models to predict how these landscape dynamics control how many samples are needed to reconstruct complete and accurate reconstructions of paleoenvironmental signals of different durations. Finally, I applied the concepts developed in the first three projects to a case of the preservation of the Paleocene-Eocene Thermal Maximum, a rapid global warming event ~56 Ma, within deltaic and shelf deposits from the Mid-Atlantic.

Overall, this dissertation demonstrates that rapid paleoenvironmental signals can be reconstructed even in highly dynamic sedimentary system when the system is sampled sufficiently to overcome the combined effects of landscape dynamics. Additionally, my analyses demonstrate that under-sampled fluviodeltaic systems are highly likely to significantly bias reconstructions of the original signal.
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Chapter 1

Introduction to landscape dynamics and the stratigraphic record

Fluviodeltaic landscapes are inherently dynamic landscapes: sediment is supplied by the growth and erosion of upland sources, redistributed by river channels, and ultimately fed into the ocean by deltas. Along the path between the sediment source and ultimate sink, sediment can be stored within the system wherever there is enough space (accommodation) or eroded or bypassed if there is not. Sediment can be stored or eroded from both the channel, floodplain, or within the delta. These feedbacks between the supply of sediment, accommodation for the storage of sediment, and between the spatial and temporal distribution of deposition and erosion create a wide range of deterministic and stochastic controls on how sediment is moved within the landscape.

At the largest temporal and spatial scales, sediment behaves deterministically: tectonics and climate control how much sediment is available to be transported in a given landscape, while tectonics and sea level control how much sediment can be stored in a given region [Paola et al., 1992; Strong et al., 2005; Paola and Martin, 2012; Straub and Wang, 2013]. These external forces (called allogenic forces) comprise the boundary conditions of a sediment transport system, (e.g., a single river drainage basin). Within a given sediment-transport system feedbacks between sediment deposition and erosion arise spontaneously as material is transported from the sediment source to the final sediment sink; these types of processes are called autogenic, or self-formed, processes. For example, a river which selectively deposits near the channel will elevate its bed, which will eventually cause the channel to avulse (or abandon the old, elevated channel) and move to a lower portion of the floodplain [Mohrig et al., 2000; Slingerland and Smith, 2004;]
Other examples of autogenic sedimentation include high-frequency processes, like the migration of dunes on a river bed (which occur over minutes to days) [Jerolmack and Mohrig, 2005], intermediate frequency processes like channel migration and avulsion (which occurs over years to hundreds of years) [Jerolmack and Mohrig, 2007], or low frequency processes, like fluctuation in depositional slope (which occurs of hundreds to thousands of years) [Kim and Jerolmack, 2008]. Additionally variability in sedimentation across landscapes arises from external, high-frequency environmental perturbations from floods, storms, or earthquakes, which are external to the sediment transport system, but distinct from the tectonic and climatic boundary conditions that dictate large scale patterns of sediment erosion and deposition. Examples of this “environmental variability” include waves and tides acting to redistribute sand in a delta [Nardin and Fagherazzi, 2012; Leonardi et al., 2013; Hajek and Straub, 2017] or earthquakes that episodically deliver pulses of sediment to river networks [Goodbred et al., 2003].

Stratigraphy can be described as the sum of all three types of processes; any given deposit likely contains information on large-scale trends in climate, tectonics and sea level (allogenic boundary conditions), autogenic processes within the sediment transport system, and environmental variability in a given region. Since all of these processes occur at much different time scales, in general, the largest scale stratigraphy (i.e. packages of sediment that took longer than $1 \times 10^6$ years to deposit) can be safely attributed to boundary conditions while stratigraphy at the smallest scales (i.e. sediments deposited over the course of seconds to days) is attributable to random transport processes [Schumer and Jerolmack, 2009; Straub et al., 2009; Schumer et al., 2011; Wang et al., 2011]. However, between these scales, it becomes difficult to uniquely separate stratigraphy resulting from internal sediment-transport dynamics from that controlled by high frequency (~$10^4$ to $10^6$ years ) changes in climate or sea level [Straub et al., 2009; Wang et al., 2011; Li et al., 2016]. When autogenic sediment-transport processes span the same
frequencies as an allogenic change, there is the possibility that stratigraphic evidence of that allogenic change may be altered or completely destroyed [Jerolmack and Paola, 2010; Schumer et al., 2011; Li et al., 2016].

Despite the potential for signals of ancient climate or tectonic changes to be lost in dynamic landscapes over some timescales, the stratigraphic record contains the most complete record of how rivers, deltas, and shallow marine environments can respond to climate change, so it is important to develop approaches to maximizing our ability to recover and interpret paleoenvironmental signals from the sedimentary archive of dynamic landscapes. These environments are critical for the health of modern society (both economically and ecologically) and they are among the hardest environments to predict how they will respond to a warming Earth and a rising sea level [Syvitski and Saito, 2007; Parker et al., 2008; Blum and Hattier-Womack, 2009; Syvitski et al., 2009, 2012]. The historical and long-timescale perspectives provided by ancient fluvial, deltaic, and shallow marine deposits provide important constraints on modeling and predicting changes to modern environments. However, before we can use the stratigraphic record to improve predictions of the response of fluviodeltaic landscapes, we need to be able to distinguish the record of climate change from the effects of autogenic processes and environmental variability.

### 1.1 Distinguishing Climate Change from Landscape Dynamics

There has been a long history of interest in how to best reconstruct past conditions despite the ubiquitous presence of missing time and stochastic sedimentation. Early efforts to understand the distributions of bed thicknesses and controls on sedimentation rates focused on the presence of hiatuses, or gaps, in sedimentation [Barrell, 1917; Kolmogorov, 1951; Ager, 1973; Sadler, 1981; Tipper, 1983; Plotnick, 1986; Strauss and Sadler, 1989; Sadler and Strauss, 1990].
While more recent work has continued to advance our understanding on the theoretical causes for random variations in sedimentation, especially how random variations in sedimentation affects long-term sedimentation rate [Jerolmack and Sadler, 2007; Schumer and Jerolmack, 2009; Schumer et al., 2011; Sadler and Jerolmack, 2015; Tipper, 2016], there is still considerable uncertainty in how these processes impact paleoclimate interpretations and how we can distinguish a climate record that is complete from one that is heavily altered.

Previous efforts to identify the impact of autogenic processes have focused on identifying a signature of the longest-timescale autogenic processes in the geometry and grain size of clastic basin fills. Paola et al. [1992] defined an equilibrium time scale that above which allogenic signals ought to be recorded directly by the distribution of sediment within an alluvial basin; this equilibrium time scale depended on a characteristic length scale of the system and a diffusivity term which described how well the system could distribute sediment across the basin, where a long system would have a long response time and a high diffusivity system, which easily distributed sediment across a basin, would have a short response time. This is a useful idea for understanding large-scale basin-filling patterns, and conceptually, the generic diffusivity term encodes the sense that some sediment-transport networks move material efficiently and others take longer to traverse across and sculpt a landscape. In practice, measuring equilibrium timescales of ancient systems is difficult because system length is not often fully preserved and “diffusivity” is impossible to measure directly and difficult to estimate from sedimentary deposits [Heller and Paola, 1992; Paola et al., 1992]. Mohrig et al. [2000] reasoned that in fluvial systems, the largest autogenic process that could influence stratigraphic architecture is channel avulsion. In their study of fluvial systems in northern Spain and Colorado, they found that channels rarely were able to deposit more than a channel depth above the floodplain before they were forced to avulse [Mohrig et al., 2000]. If that observation is true in most channelized systems, it would be difficult to differentiate a paleoenvironmental signal of change in
sedimentation from autogenic avulsion processes at scales similar to a channel depth. Subsequent work has emphasized that signals of change near the channel depth scale are difficult to distinguish autogenic variations from true paleoenvironmental signals [Sheets et al., 2002; Jones and Hajek, 2007; Straub et al., 2009; Hajek et al., 2010; Wang et al., 2011; Hajek and Heller, 2012; Hajek and Wolinsky, 2012].

Because autogenic processes are difficult to separate from environmental signals, various metrics have been proposed to measure the maximum time (and length) scale over which autogenic processes operate [Straub et al., 2009; Hajek et al., 2010; Jerolmack and Paola, 2010; Wang et al., 2011]. While measuring equilibrium time usually requires time series of elevation change or sediment flux, both the compensation scale, which uses chronostratigraphic (i.e. a surface that was made at roughly one time, instead of being built over multiple times) surfaces to measure the evenness of basin filling, and k-statistic, a point process statistic that can detect clustering or evenness of channel centroids, require only outcrop geometry. In particular, Wang et al. [2011] proposed the compensation scale as a tool to identify the timescale and length scale between stratigraphy that is influenced by autogenic processes and stratigraphy where allogenic processes could be identified. Additionally, they found that in one fluvial system the maximum autogenic length scale may be much larger than a channel depth. There are significant uncertainties about the extent to which these tools can be used to accurately identify the largest autogenic scale, especially when the dataset is limited in extent or resolution. It is currently not well understood how the compensation scale or scale of clustering can be uniquely tied to a process, although they are both theorized to be tied to the maximum relief a system can either deposit or erode.
1.2 Dissertation Goals and Approach

The prior work on identifying the signature of autogenic processes has left a number of questions relating to predicting where a signal may be preserved. First, while the compensation scale in theory is a very powerful tool to predict whether the inherent variability of an environment has the potential to influence the preservation of the signal of interest, it is much less clear how sensitive it is to the data limitations common in most field studies. This is further complicated in the imperfect understanding of what controls the compensation in different environments. Second, if the signal of interest is below the compensation scale, it is not clear how variable sedimentation that characterizes sub-compensation time scales affects geochemical proxy records. Third, it is not clear how compensation and signal preservation varies spatially across a landscape. Without answers to these issues, we are limited in our ability to confidently and accurately reconstruct climate signals from deposits from highly variable sedimentary environments.

The goal of this dissertation is to predict how the preservation and interpretation of climate signals varies in accordance to the relative strength of the landscape dynamics across fluviodeltaic landscapes. To this end, I worked to 1) correctly identify and scale landscape dynamics in fluviodeltaic stratigraphy, 2) assess how landscape variability affects the ability to reconstruct paleoenvironmental signals from geochemical proxies, 3) understand how 3D landscape dynamics convolve with basin aggradation to control signal preservation in different settings, and 4) demonstrate that these tools and concepts can be directly applied to real datasets to improve estimates of the uncertainty in paleoclimate reconstructions.

To answer the questions listed above, I analyzed the sensitivity of existing tools, like the compensation scale, with field data and physical experiments, created numerical models of stochastic sedimentation to understand how proxy systems may be preserved, and used a reduced
complexity landscape model to predict how preservation varies by location in the landscape and the relative strength of the autogenic processes. Finally, I demonstrated the applicability of these tools and concepts to a case study of the rapid period of global warming called the Paleocene-Eocene Thermal Maximum as it is preserved in pro-deltaic and shelf deposits in Maryland and New Jersey.

1.3 Summary of Dissertation Chapters

This dissertation has been organized in four main chapters (2-5) that are written as research articles that have either been published, are in press, or will soon be submitted to a journal for publication. In the following section, I will describe the main contributions of each chapter and describe the contributions of co-authors and where each has been or will be published.

Chapter 2: Identifying autogenic sedimentation in fluvial-deltaic stratigraphy: evaluating the effect of outcrop-quality data on the compensation statistic

In order to determine if we can accurately and precisely identify the maximum autogenic scale in natural systems, Chapter 2 applies the compensation statistic to stratigraphy generated by a physical delta experiment, which was then down-sampled to simulate the data extent and resolution typical of outcrop data. I then applied the compensation statistic to four field datasets, two previously published fluvial datasets and two deltaic datasets collected for this manuscript. The results of this study demonstrate that the compensation scale is relatively insensitive to data limitations, if the outcrop meets or exceeds a minimum size. Further, this study demonstrated that the compensation length scale (the thickness over which topographic landscape relief is evenly smoothed out by sediment deposition) in many field datasets may be much larger than a channel
depth, and that a compensation length scale larger than a channel depth is not likely to be an artifact of limited data extent or resolution. This chapter has been published in the Journal of Geophysical Research, with my coauthors Drs. Elizabeth Hajek, Ellen Chamberlin, and Kyle Straub [Trampush et al., 2017].

Chapter 3: Preserving proxy records in dynamic landscapes: Modeling and examples from the Paleocene-Eocene Thermal Maximum

Chapter 3 demonstrates the potential effect of landscape dynamics on the preservation and interpretation of geochemical proxy records. For this project, I created a stochastic sedimentation model which builds stratigraphy from random draws from a heavy-tailed probability distribution; the model then assigns a proxy value for every preserved year. The study tested four models that combined high and low long-term sedimentation rates and high and low sedimentation variability, based on a compilation of event frequencies in modern rivers, deltas, and shelves. The results of this study are that all environments can produce records which distort or remove the input proxy signal, but models with low variability relative to their long-term sedimentation rate were less likely to produce heavily distorted records. Additionally, this study shows that the input signal can be recovered with ensembles of even low-quality records. This chapter is in press at Geology, with Dr. Hajek as a coauthor [Trampus and Hajek, 2017].

Chapter 4: Exploring how landscape dynamics influence the sampling of paleoenvironmental signals

The results of Chapter 3 suggested that we can reliably reconstruct even high-frequency paleoenvironmental proxies using ensemble records, if enough individual records are included to average out the effect of landscape variability relative to the long-term sedimentation rate. In
Chapter 4, I test how many individual records need to be used to create an accurate reconstruction of high frequency paleoenvironmental signals. I used a reduced-complexity numerical delta evolution model to create synthetic stratigraphy with different scales of variability relative to the sedimentation rate. Deposits were randomly sampled to predict the minimum number of 1D records that would be necessary to accurately reconstruct signals with different periods relative to the scale of landscape variability and long-term accumulation rate. This study demonstrates that the number of cores needed for accurate signal reconstructions scales directly with the scale of landscape variability relative to the long-term sedimentation rate and the duration of the signal. Additionally, this study shows that the preservation of signals in individual records also depends on location within the transport system, as the probability of erosion and reworking is highest in proximal localities and non-deposition punctuated by rapid deposition is most common in distal localities. This chapter is being prepared for submission to the *Journal of Geophysical Research – Earth Surface*.

Chapter 5: Characterizing landscape dynamics and variability in sedimentation on the Mid-Atlantic shelf during the Paleocene-Eocene Thermal Maximum

Chapter 5 is a case study of the practical application of measures of stratigraphic completeness to records of climate change. The Paleocene-Eocene Thermal Maximum (PETM) was a period of rapid global warming ~56 Ma; in the Mid-Atlantic, the PETM is preserved in shelf and pro-deltaic deposits. This chapter presents a compilation of lithology and carbon isotope records for a number of cores through the PETM interval in the Mid-Atlantic. I use a compilation of core lithology, carbon isotope records, and the results from chapters 3 and 4 to demonstrate how stochastic sedimentation can explain differences in the presence and appearance of the PETM interval across the Salisbury Embayment in the Mid-Atlantic shelf.
1.4 References


Chapter 2

Identifying autogenic sedimentation in fluvial-deltaic stratigraphy: evaluating the effect of outcrop-quality data on the compensation statistic

Key Points

- The compensation statistic can determine the handoff between autogenic and allogenic sedimentation even from low quality datasets.
- Topographic relief can be inferred from ancient fluvial and deltaic deposits using the compensation statistic.
- The compensation statistic can be successfully applied to natural data from a broad range of extents and resolutions.

Abstract

Stratigraphy preserves an extensive record of Earth-surface dynamics acting over a range of scales in a variety of environments. To take advantage of this record, we first must distinguish depositional patterns that arise due to intrinsic (i.e. autogenic) landscape dynamics from sedimentation that results from changes in climate, tectonic, or eustatic boundary conditions. The compensation statistic is a quantitative tool that has been used to estimate scales and patterns of autogenic sedimentation in experimental deposits; it has been applied to a few outcrop studies, but its sensitivity to data limitations common in natural deposits remains unconstrained. To explore how the compensation statistic may be applied to outcrop data, we evaluate the sensitivity of the tool to stratigraphic datasets limited in extent and resolution by subsampling an autogenic
experimental deposit to create pseudo-outcrop-scale datasets. Results show that for datasets more than three-times thicker than a characteristic depositional element (e.g., channel or lobe), the compensation statistic can be used reliably constrain the maximum scale of autogenic sedimentation even for low-resolution datasets. Additionally, we show that autogenic sedimentation patterns may be characterized as persistent, random, or compensational using the compensation statistic when datasets are high-resolution. We demonstrate how these measurements can be applied to natural datasets with comparative case studies of two fluvial and two deltaic outcrops. These case studies show how the compensation statistic can provide insight into what controls the maximum scale of autogenic sedimentation in different systems and how landscape dynamics can produce organized sedimentation patterns over long timescales.

2.1 Introduction

Our ability to use stratigraphy to understand Earth history is limited by how well we can distinguish intrinsic (autogenic) behavior from external (allogenic) environmental forcing in sedimentary deposits. Autogenic processes, such as channel avulsion or delta-lobes switching, have the potential to remove all evidence of low-magnitude or high-frequency climate or tectonic changes from the sedimentary archive, a phenomenon that Jerolmack and Paola [2010] call “signal shredding.” The maximum scale of autogenic sedimentation in a landscape may set the upper limit of this signal-shredding regime [Jerolmack and Paola, 2010; Wang et al., 2011; Ganti et al., 2014; Li et al., 2016]. This means that over small spatial and temporal scales, stratigraphic patterns may reflect dominantly autogenic landscape variations and signals of allogenic processes (such as climate or sea-level changes altering the balance of sediment supply and accommodation
creation) will dominate sedimentation patterns at larger scales, but what sets the scale 
between these two behaviors is heavily dependent on the particulars of the system under 
consideration [Jerolmack and Paola, 2010; Wang et al., 2011; Ganti et al., 2014]. 
Consequently, to know whether a given deposit reflects predominantly landscape 
dynamics or significant changes in climate, for example, we need tools for identifying the 
scale (thickness and width) at which this handoff from autogenic to allogenic 
sedimentation occurs. A key outstanding question is: how can autogenic and allogenic 
scales be identified in natural stratigraphy? In channelized fluvial and deltaic systems, 
there is evidence that the maximum scale of autogenic sedimentation is the maximum 
channel depth [Straub et al., 2009; Wang et al., 2011] or greater [Hajek et al., 2010; 
Wang et al., 2011; Chamberlin et al., 2016]. It is unclear why the autogenic limit in some 
systems scales with a characteristic channel depth but is significantly greater in others. To 
answer this question maximum autogenic scale needs to be measured in more deposits 
from a diverse range of settings and the uncertainty of these measurements needs to be 
estimated to facilitate robust comparison.

Physical and numerical experimental studies have established methods to evaluate 
scales of autogenic organization in fluvial and deltaic systems; a key challenge, however, 
is applying these approaches and insights to natural systems where data availability is, at 
best, sparser by several orders of magnitude compared to experimental datasets. The 
compensation statistic is one tool that has been successfully applied to physical 
experiments and numerical models in order to evaluate autogenic sedimentation patterns 
and scales [Straub et al., 2009; Wang et al., 2011; Straub and Wang, 2013]. It has also
been applied to some ancient natural systems, including fluvial [Wang et al., 2011; Chamberlin et al., 2016], debris flows [Pederson et al., 2015], and deep water systems [Straub and Pyles, 2012]. Despite its promise as a tool, the degree to which sparse sampling affects the accuracy and interpretability of the compensation statistic has not previously been evaluated; consequently, the degree to which the results from one study may be compared to other studies is unknown. Similarly, there remain outstanding questions about the precision with which allogenic scales and autogenic organization can be measured using the compensation statistic.

In order to appropriately use the compensation statistic in natural deposits, it is necessary to determine how the maximum autogenic scale may be determined and the degree to which measures of autogenic organization may be compared among different systems. Here we address these issues by evaluating high-resolution data from a physical experiment and demonstrate how autogenic scale and organization can be measured in outcrop datasets. First, we show how topographic relief in an experimental fluvial-deltaic system is expressed in compensation plots and how we can use these plots to identify scales of autogenic sedimentation. We then explore how subsampling experimental data to typical outcrop resolution affects our ability to measure maximum autogenic scale and autogenic sedimentation patterns. Finally, we apply this insight to a pair of case-study comparisons where we evaluate outcrop data of ancient fluvial and deltaic successions.
2.2 Background

Compensation describes the tendency of depositional events to preferentially fill topographic lows, smoothing out topographic relief by “compensating” for the localization of sedimentation in discrete landform elements. The term “compensational stacking” has been used to qualitatively describe the large-scale architecture of deepwater, fluvial, and delta deposits [e.g. Van Wagoner and Mitchum, 1990; Olariu and Bhattacharya, 2006], wherein the sediment-transport network episodically reorganizes along regional topographic lows during channel or lobe avulsions. Straub et al. [2009] and others [Sheets et al., 2002; Lyons, 2004; Wang et al., 2011; Straub and Pyles, 2012] have established a quantitative way of characterizing the tendency for a given depositional system to organize compensationally; we call this metric the compensation statistic.

The compensation statistic compares observed sedimentation patterns to what would be expected from uncorrelated random deposition by evaluating the standard deviation of sedimentation across a basin over a range of chronostratigraphic windows (e.g. Figure 2-1). For experiments, the compensation statistic can be measured with respect to absolute time, since the entire depositional history of an experimental deposit is known. In ancient deposits, where high-resolution age control is often unobtainable, the compensation statistic can be evaluated over a range of characteristic sediment-package thicknesses defined by pseudo-chronostratigraphic surfaces identifiable in outcrop, well, or seismic data (e.g. Figure 2-1b). These surfaces could include stratal termination (e.g.,
truncation, downlap, or onlap) surfaces, marker beds, facies boundaries, bed-set boundaries or other relative timelines that can be mapped within a given deposit.

Over a range of chronostratigraphic intervals, the compensation statistic \((CV)\) is the standard deviation of the thickness of a given sediment package across a basin of width \(L\) relative to the expected average sediment-package thickness across the basin \((\Delta \eta_{A,B})\) [Wang et al., 2011; Straub and Pyles, 2012].

\[
CV = \left\{ \int_{L} \left[ \frac{\Delta \eta_{A,B}(x)}{\Delta \eta_{A,B}} - 1 \right] dL \right\}^{1/2}
\]

where \(\Delta \eta_{A,B} = \frac{T}{n} i\)

In the case of chronostratigraphic packages lacking absolute time constraints, the expected average sediment-package thickness \((\Delta \eta_{A,B})\) is derived from the average thickness of the entire deposit \((T)\), the total number of chronostratigraphic surfaces \((n)\), and the number of chronostratigraphic surfaces that separate surface \(A\) from surface \(B\) \((i)\). For all chronostratigraphic pairs with similar measured mean thickness \((\Delta \eta_{m})\), \(CV\) will be high when the thickness across a chronostratigraphic package is variable or low when the surfaces that define a chronostratigraphic package have similar shape (e.g. Figure 2-1B). The population of \(CV\) values over a range of chronostratigraphic windows reflects the morphodynamic history of the landscape. For example, a variable (high \(CV\)) chronostratigraphic package could result from a highly channelized phase in a delta, and a low \(CV\) package could result from sheet-flow dominated deposition (Figure 2-1a and b). When observed over a range of thickness windows, \(CV\) shows power-law decay:
\[ CV = a \Delta \bar{\eta}_m^{-\kappa} \]  

For uncorrelated random sedimentation – i.e. depositional events occur randomly across a basin in space and time – \( CV \) decays as a power law with exponent \( \kappa = 0.5 \). In cases where aggradation occurs evenly across a basin, sedimentation patterns are compensational (i.e. deposition events commonly fill topographic lows), and local sedimentation at any given time largely matches the long-term background sedimentation pattern fairly well. This results in \( CV \) decaying according to Equation 2 with exponent \( \kappa > 0.5 \), where a value equal to 1.0 would represent perfect compensation. In contrast, situations where sedimentation patterns are clustered such that there is a tendency for depositional events of similar scale to persist in one area of a basin, \( CV \) decays with \( \kappa < 0.5 \). We call \( \kappa \) the compensation index [Straub et al., 2009; Straub and Pyles, 2012; Straub and Wang, 2013].

Because the compensation index is calculated over a range of chronostratigraphic windows, changes in sedimentation patterns at different scales can be detected and compared. Multiple studies have demonstrated that the compensation index is scale dependent, and in experiments there is significant change in stratigraphic organization at the scale equivalent to a maximum channel depth [Wang et al., 2011; Straub and Pyles, 2012; Straub and Wang, 2013]. In these systems, the compensation index for scales less than a channel depth show “sub-compensation” depositional patterns (i.e. \( \kappa < 1.0 \)) and at scales much larger than a channel depth, deposition is organized compensationally (i.e. \( \kappa \sim 1.0 \)). We call this transition between sub-compensational and perfectly compensational sedimentation the compensation scale; it is hypothesized to mark the transition between
deposits which reflect autogenic patterns at small scales and stratigraphy controlled by the allogenic balance of sediment supply and accommodation creation at large scales [Wang et al., 2011; Straub and Wang, 2013].

The compensation statistic therefore provides a powerful hypothesis-testing tool to investigate landscape dynamics and allogenic signal preservation in stratigraphy provided we can 1) reliably identify the compensation scale in a given system and, 2) estimate sub-compensation (autogenic) organization accurately. At present, it is untested whether these measures can be accurately quantified and compared in natural systems, particularly given the constraints imposed by the limited extent and resolution of stratigraphic datasets.

2.2.1 Identifying autogenic scales and organization using the compensation statistic

To explore how the compensation statistic can be used to identify autogenic scales and organization in natural deposits, we leverage stratigraphy generated in a well-constrained, autogenic experiment. The Tulane Delta Basin 10-1 (TDB-10-1) experiment was designed to observe autogenic behavior in a physical experimental delta built in 4.2 m long, 2.8 m wide, and 0.65 m deep experimental basin [Wang et al., 2011; Straub and Esposito, 2013; Straub and Wang, 2013]. Sedimentation rate, water discharge, and base-level rise were kept constant throughout the run (Table 1). Laser topography scans were acquired every two minutes for the duration of the experiment (78.2 hours) with 1 mm-horizontal and 0.5 mm-vertical resolution. Here we use a flow-perpendicular laser-topography transect 2.1 m from the sediment infeed point (TDB-10-1M or medial
transect in Wang et al., [2011] and Straub & Wang, [2013]; Figure 2-1A). The compensation statistic (CV) was calculated for every possible pair of preserved chronostratigraphic surfaces according to Equation 1 (Figure 2-1b).

Chronostratigraphic-thickness and compensation-statistic data pairs are binned before fitting Equation 2. Following best practices for widely scattered data [Newman, 2005; Clauset et al., 2009] we use logarithmic bins to group the CV values by thickness and use the median CV value for each bin to estimate power law relations for the data (Equation 2). In practice, we choose the maximum number of bins that maintains both a relatively smooth 95% envelope and stable bin medians across the thickness ranges of interest (Figure 2-1c; Supplement). For fitting Equation 2, we exclude the first and last bins because they are only partially characterized. In the case of limited instrument or mapping resolution, we also exclude all bins that fall below a minimum cutoff that accounts for incompletely characterized bins at small thickness intervals (Supplement). In the TDB 10-1 dataset we chose a cutoff of 1.0 mm because of the resolution limits of the laser-topography measurements.

Identifying the compensation scale can be difficult in a widely scattered CV data. Previous compensation analyses of the TDB-10-1 experiment have used chronostratigraphic surfaces based on absolute time [Wang et al., 2011; Straub and Wang, 2013] and chronostratigraphic thickness [Wang et al., 2011] have shown that sedimentation patterns shift from random (\(\kappa \sim 0.5\)) to compensational (\(\kappa = 1\)) at scales ranging from 9-14 mm. This scale range coincides with the characteristic channel scale observed in the experiment, specifically the 50\(^{th}\)-90\(^{th}\) percentile topographic relief
measured in this study (Figure 2-2, Table 1). Similarly, in our analysis of preserved stratigraphic surfaces it is difficult to identify one specific scale at which the data become perfectly compensational; rather there is a range of scales over which sedimentary packages transition from being randomly distributed or clustered to evenly (compensationally) distributed (e.g., at small scales (< 5 mm) median CV values yield a $\kappa \ll 1.0$ and at very large scales (> 30 mm) $\kappa = 1.0$).

To constrain the minimum extent of this “compensation zone” we identify the smallest scale for which $\kappa = 1.0$ (using a five-point moving window to calculate Equation 2; Supplement). This scale – $H_{\text{min}}$ – is 7.4 mm for TDB-10-1 stratigraphy. $H_{\text{min}}$ is a conservative estimate of the smallest possible window at which the boundary conditions of the basin (i.e. the mass balance of sediment supply and accommodation) may be influencing how sedimentary packages are deposited. Because this estimate is affected by the number of CV points in a dataset and data binning (Supplement), it should be considered a heuristic guide for identifying scales that are unequivocally not influenced by mass-balance sedimentation, not a definitive scale at which allogenic sedimentation takes over. Consequently, with sufficient data Equation 2 fit to scales smaller than $H_{\text{min}}$ characterizes autogenic sedimentation patterns in TDB-10-1 ($\kappa = 0.4$ reflecting random or slightly persistent sedimentation patterns; Figure 2-1).

Another notable characteristic of the compensation statistic analysis of TDB-10-1 is that the range of CV values decreases abruptly around 17 mm; CV values for packages thinner than 17 mm span four orders of magnitude, but the range of CV values collapses significantly and remains fairly constant for packages thicker than 17 mm. This scale
corresponds closely to the maximum relief observed in experimental topography (17 mm = 97th percentile relief; Figure 2-2). This indicates that the maximum autogenic relief on the autogenic landscape sets the upper limit of variability in sediment-package thickness within the deposit. Packages thicker than this are generally flatter and are filling the basin evenly. Consequently, the scale at which CV scatter collapses (shown by the “funneling” of the 95% envelope; Figure 2-1; Supplemental) can be used to estimate the maximum possible scale of autogenic stratigraphy – H_{max}. Although estimating H_{max} is subjective, other more robust ways to estimate it are impractical (for example, a maximum-likelihood based approach), given that the amount that the CV scatter reduces is highly variable and may depend on the resolution of the dataset.

Together, H_{min} and H_{max} can be used to bracket the zone over which the handoff between autogenic and allogenic sedimentation occurs. Observations from this TDB-10-1 analysis are consistent with the hypothesis that the maximum relief across a landscape sets the compensation scale – below which sedimentation patterns are highly variable and reflect intrinsic dynamics in the sedimentary system and above which sedimentation patterns are even reflecting the long-term balance of sediment-supply and accommodation creation in a basin. Compensation-statistic analysis of TDB-10-1 stratigraphy yields a compensation scale range that is within 20% of the modal and maximum channels observed in the experiment.
2.3 Effects of dataset resolution on autogenic scales and organization estimates

Even the best-characterized datasets from natural deposits are significantly lower resolution and smaller in extent than what is available for experiments. In order to compare across multiple systems, and between experimental and field datasets, it is useful to scale the extent of stratigraphic exposures to the characteristic scale of formative elements of the depositional system (e.g., channel-element width and thickness in fluvial-deltaic systems (e.g., Wang et al., 2011), or lobe dimensions for deepwater fans (e.g. Straub and Pyles, 2012). Some of the best-exposed fluvial-deltaic outcrop belts show continuous exposure that reaches up to five-times the width and 10-times the thickness of a typical channel deposit (e.g. Mohrig et al., 2000; Olariu and Bhattacharya, 2006; Pranter et al., 2009; Enge et al., 2010; Fielding, 2010; Schomacker et al., 2010; Olariu et al., 2012; Bhattacharya et al., 2015); however, many field exposures of ancient fluvial-deltaic deposits are much more limited and subsurface (seismic or well) datasets typically have low vertical (thickness) resolution, limited spatial extent, or both.

To explore how dataset extent and resolution may influence the degree to which compensation scale and sub-compensation organization can be characterized, we subsampled TDB-10-1 experimental data and re-calculated compensation scale and compensation index values for a series of restricted-extent and –resolution datasets. The entire TDB-10-1 experiment is approximately ten-times wider and 27-times thicker that the dimensions of the 90th percentile channel (Figure 2-1 and Table 1); we restricted our analysis to the portions of the experiment that are at least one channel-width away from the edge of the experiment to limit potential edge effects. We randomly selected portions
of the dataset that range from 2-12 times the channel depth and 1-10 times the channel width (locations in Figure 2-3, results in Figure 2-4, 2-5, and 2-6). Additionally, we extracted every 2<sup>nd</sup> and 5<sup>th</sup> surface from one subsampled dataset to represent high-and low-resolution outcrop mapping (Figure 7). Using the approach for data aggregation outlined in the section 2.1 we estimated $H_{\text{min}}$ from each subsampled dataset by locating the minimum chronostratigraphic bin that maintained a compensation index of $\kappa = 1$ and estimated the sub-compensation index by fitting Equation 2 to the remaining (smaller) bin medians (Figures 2-4, 2-5 and 2-6). In cases where no range of chronostratigraphic thicknesses yielded a compensation index of $\kappa = 1.0$, we considered $H_{\text{min}}$ undetectable. $H_{\text{max}}$ was estimated as the bin center that coincided with the end of the CV scatter-reduction zone (often highlighted by the transition from a wide, funnel-shaped to a parallel 95% envelope; Figures 2-4, 2-5 and 2-6). As a reference we use results from analysis of the full dataset (Figure 2-4A) which yielded $H_{\text{min}} = 7.4$ mm, $H_{\text{max}} = 17.0$ mm, and a sub-compensation index of $\kappa = 0.4$.

### 2.3.1 Dataset extent

All sub-samples of the full TDB-10-1 dataset yield $H_{\text{max}}$ values of 17-20 mm. Regardless of whether datasets were reduced in width or thickness, the abrupt decrease in $CV$ variability consistently reflects the highest range of topographic relief observed on the experimental delta, between the 95<sup>th</sup> and 99<sup>th</sup> percentiles. This range is fairly precise, given that each dataset has different numbers of surfaces, different thickness-ranges, and slightly different data-binning divisions (Supplement). This demonstrates that the
maximum autogenic scale may be observable as an abrupt reduction in CV even in stratigraphic datasets that are relatively thin or narrow.

Some datasets, failed to produce $\kappa = 1.0$ over any stratigraphic thickness ranges (Figure 2-4 n, s, x, j, and y). These datasets tend to be thin ($\leq 3$ channel depths), but other datasets similar in thickness did yield $\kappa = 1.0$ (e.g., Figure 2-4t). Similarly, $H_{\text{min}}$ values are less consistent than $H_{\text{max}}$ estimates, ranging from 3-10 mm. (The 50$^{\text{th}}$ percentile channel depth in the experiment was 9 mm.) Furthermore, sub-compensation index values for the reduced-scale datasets varied widely from $\kappa = 0.1$-0.8. This uncertainty is only in part due to the numerical sensitivity of identifying $H_{\text{min}}$ and $\kappa$ over small scales (Supplement); it may also reflect different dominant autogenic sedimentation patterns present locally within the sub-sections of the experiment.

Replicate subsamples of the same width and thickness show similar consistency among $H_{\text{max}}$ estimates, variability in $H_{\text{min}}$ estimates, and widely ranging $\kappa$ values (Figures 2-5 and 2-6). For stratigraphic samples the size of relatively large outcrops (12 channel-depths thick by three channel-widths wide; comparable to the fluvial outcrops presented below; Figure 2-5), $H_{\text{max}}$ estimates range from 15-20 mm, $H_{\text{min}}$ estimates range from 3-7 mm, and $\kappa$ values range from 0.3-0.7. These datasets are all the same size, so they have the same number of surfaces and rely on the same binning scheme. However, qualitatively each subsample has different characteristic architectures, particularly with respect to the abundance and distribution of channel or sheet-like deposits (Figure 2-5A). For example, panel g has stratigraphic intervals extending across the panel width that are dominated by channels (low in the section) and sheets (middle of the panel), panel d
appears to have clusters of channels interspersed vertically and laterally with patches of sheet-like deposition, and panel c has a more random-looking mix of channels and sheets. These local differences in architecture may be reflected in the sub-compensation index $\kappa$ values (e.g., where $\kappa = 0.6$ for panel g may be indicating fairly even autogenic sedimentation, $\kappa = 0.3$ for panel d may indicate persistent or clustered autogenic sedimentation). Similar variability is seen in datasets that approximate smaller outcrops (three channel-depths thick and only one channel-width wide; similar to the delta outcrops presented below; Figure 2-6). Here again, $H_{\text{max}}$ (12-18 mm) is consistent with other estimates for TDB-10-1, and panels that produce vastly different sub-compensation index $\kappa$ values appear to have different architectures. Collectively, the ensemble average of $\kappa$ measured in the sub-samples approximates the estimate obtained from the full dataset. This underscores the possibility that small outcrops may reflect primarily the local manifestation of autogenic sedimentation, but that by making the same measurements in a number of outcrops spread across a basin, it may be possible to reconstruct the basin-wide average autogenic sedimentation patterns.

### 2.3.2 Dataset resolution

The resolution of a subsampled region does not appreciably change the estimate of the compensation scale until the smallest resolved thicknesses are larger than the compensation scale (Figure 2-7). The primary consequence of reduced dataset resolution is that there are simply fewer chronostratigraphic packages resolvable at small mean thicknesses, so the density of CV values increases with chronostratigraphic thickness.
(Figure 2-7, in contrast to the large number of CV pairs at small mean thicknesses in Figure 2-7a). In general, reducing the number of resolvable surfaces in an outcrop can lead to misestimating the sub-compensation index, as it may be poorly constrained because of a lack of data at small scales, but does not significantly change the compensation scale until there are too few surfaces mapped below the compensation scale to fit any sub-compensation index. Because the compensation statistic robustly reconstructs compensation scale, even in relatively low-resolution datasets, it can successfully be applied to many different types of stratigraphic data (e.g. well logs, GPR, or seismic surveys) provided the minimum resolution of chronostratigraphic packages is smaller than the expected compensation scale.

2.3.3 Implications

Data quality can be partially inferred from compensation plots. Datasets that are sufficiently wide and thick will have enough bins to resolve two power law regions on the plot: one sub-compensation $\kappa < 1.0$ relationship and one, where $\kappa = 1.0$, that defines the thickness scales over which chronostratigraphic packages are evenly (i.e., compensationally) deposited. If a dataset is not thick enough, the compensation index will be below $\kappa = 1.0$ (e.g., Figure 2-4 j, n, s, x, and y). If a dataset is too narrow, the sub-compensation bins may not fit a power-law relationship well (e.g. the relation will look curved or nonlinear on the loglog CV plot). An outcrop that has full resolution will have an even, dense pattern of CV pairs across all chronostratigraphic windows (e.g., Figure 2-
1 & 2-7a) and an outcrop that is partially resolved will show limited point density for small chronostratigraphic windows (e.g. Figure 2-7b and c).

Overall, these results suggest that compensation scale estimates are quite robust for most stratigraphic datasets. $H_{\text{max}}$ consistently corresponds to the large tail of the distribution of relief on the delta surface and is insensitive to dataset precision as long as the minimum usable bin is smaller than the compensation scale. These results also show that limitations on dataset extent or resolution are unlikely to show compensation scales that are artificially large; when a compensation scale is detected in a given dataset (i.e. there is a range of chronostratigraphic thicknesses for which $\kappa = 1$), that scale is likely to be within a factor of two, if not within 50% of the actual maximum autogenic scale of a given system.

Interpreting autogenic sedimentation patterns using the sub-compensation index can be complicated because for small datasets, system behavior may only be partially sampled and an individual dataset is likely to show local organization, not the average autogenic behavior of the system. It may be possible to ascertain the characteristic autogenic behavior of a system using a large number of limited-extent or limited-resolution observations from a given system (e.g., multiple discontinuous outcrop belts or multiple well-log or core cross-sections), although currently it is not clear how sampling variability and dataset resolution interact and define uncertainties associated with sub-compensation-index estimates.

These results underscore the importance of estimating dataset size relative to the size of characteristic depositional elements within a given system. This can be
challenging because we may not know what type of landforms are driving compensational sedimentation patterns – and thus setting the scale of autogenic stratigraphy – in different landscapes or seascapes. Wang et al. [2011] propose that the compensation scale should approximate the maximum topographic relief that can develop in a particular environment. In channelized landscapes (e.g., fluvial, deltaic, and deepwater systems), it is reasonable and useful to use the channel scale as a null estimate of the compensation scale for designing mapping campaigns and for evaluating and comparing compensation-statistic results.

2.4 Identifying autogenic scales and organization in ancient fluvial and deltaic deposits

The compensation statistic is a useful tool for identifying the upper limit of autogenically driven sedimentation patterns in a depositional system and can provide insight into the nature of self-organized depositional patterns in different environments. This information is necessary for stratigraphers to answer key outstanding questions about landscape dynamics in sedimentary systems including 1) what controls the maximum autogenic scale in a given setting, and 2) the degree to which autogenic sedimentation patterns are random or organized over long timescales.

Using insight from analyzing TDB-10-1 subsampled datasets of limited extent and resolution, we demonstrate how the compensation statistic may be applied to outcrop data of ancient fluvial and deltaic deposits. We evaluate four datasets – two fluvial and two deltaic – that exemplify outcrops with extensive and high-quality exposures and span a range of scales and resolutions relative to their formative depositional systems (Table
2). This set of four case studies shows how outcrop extent, mapping, and data quality may influence the detectability of the compensation scale and sub-compensation organization and highlights how this approach may be used to understand controls on autogenic dynamics in ancient systems.

2.4.1 Fluvial case studies

Recent work has highlighted the possibility that some fluvial systems may be self-organized on relatively long temporal and spatial scales. Studies in several fluvial systems using a variety of statistical approaches have shown that intrinsic avulsion dynamics may produce random or organized basin-filling sedimentation patterns [Hajek et al., 2010; Jerolmack and Paola, 2010; Hofmann et al., 2011; Wang et al., 2011; Flood and Hampson, 2015; Chamberlin et al., 2016]. In light of these results and remaining outstanding questions about fluvial avulsion dynamics, it is important be able to detect and estimate both the nature of and scale over which autogenic sedimentation patterns occur with methods that allow meaningful comparisons among natural systems and between outcrop and experimental results. To demonstrate how the compensation statistic may be used practically in pursuit of answers to these questions, we present outcrop-based analyses of ancient sedimentation patterns in the Ferris Formation (Cretaceous/Paleocene, Hanna Basin, Wyoming) and the Williams Fork Formation (Upper Cretaceous, Piceance Basin, Colorado).
2.4.1.1 Ferris Formation

The Ferris Formation was deposited as a rapidly aggrading upland fluvial system draining Laramide uplifts in the Late Cretaceous and Early Paleogene, filling the Hanna Basin, Wyoming [Weimer, 1984; Lillegraven et al., 2004; Hajek et al., 2012]. The Ferris Formation exposure in the northern Hanna Basin is steeply dipping, exposing a stratigraphic cross section (orthogonal to mean paleoflow direction) across the present-day land surface (Figure 2-8a). Ferris rivers were 0.3-0.9 m (mean = 0.59 m) deep, as measured by bar clinoforms (Figure 2-8b), and deposited single- and multi-story sand bodies ranging from 1-10 m thick (mean = 4.4 m) and 10-900 m (mean = 162 m) wide [Hajek et al., 2012]. Individual channel-belt deposits were mapped with differential GPS across a 1700-m wide by 250-m thick study area [Hajek et al., 2010]. Chronostratigraphic surfaces (n = 119) were constructed by projecting pseudo-horizons laterally away from channel body rectangles that represent the maximum thickness and width of each channel-belt sand body (Figure 2-8c) [Wang et al., 2011]. This strategy for mapping chronostratigraphic surfaces captured paleo-topography larger than 2 m. The full dataset represents a stratigraphic package that is more than 50-times thicker and 10-times wider than the average Ferris channel-belt sand body.

Compensation statistic (CV) values for the Ferris Formation were calculated over a range of 2-200 m. CV points were aggregated into 17 logarithmic bins; the largest bin and the bins smaller than 3m were excluded (Figure 2-8d). The density of CV points increases after the compensation scale. \( H_{\text{min}} \) and \( H_{\text{max}} \) both appear to be at the bin centered at 30.7 m. The “funneling” or scatter-reduction in CV values also appears
complete at the bin centered at 30.7 m. The sub-compensation index is 0.8, estimated over chronostratigraphic thicknesses between 2.5 – 21.2 m.

All evidence suggests that the compensation scale for the Ferris Formation is much larger than the channel depth. Both the numerically defined $H_{\text{min}}$ and the qualitative $H_{\text{max}}$ indicate that the compensation scale is around 30.7 m. Although it is extensive, the Ferris Formation dataset is fairly low resolution. Our results from down-sampling TDB-10-1 data show that the low resolution of the Ferris Formation dataset is not likely to artificially increase the compensation scale. The compensation scale is at least 30 times the maximum flow depth observed in Hajek et al. (2012) and more than three times the average sand-body thickness. The Ferris Formation data are likely too poorly resolved to accurately determine the sub-compensation index. Sparse $CV$ points below ~10m indicate low resolution (e.g. Figure 2-7c and d). Similarly, the muted funneling of the $CV$ ranges in sub-compensation bins also indicates that sedimentation patterns over small chronostratigraphic thickness windows are not well characterized.

Wang et al. [2011] estimate sub-compensation organization using a slightly different data-handling and binning approach and obtain $\kappa = 0.5$. Hajek et al. [2010] use spatial point process statistics to show that channel belt deposits are statistically clustered in the same stratigraphic panel (this would correspond to $\kappa < 0.5$). Given the lack of resolution over this critical sub-compensation window, the sub-compensation index of this dataset is unreliable.
2.4.1.2 Williams Fork Formation

The Williams Fork Formation was deposited in a lowland river system draining the Sevier highlands and filling the Piceance Basin in the Late Cretaceous, and comprises a mud-dominated lower member (the subject of this study) and a sand-dominated upper member [e.g. Cole and Cumella, 2005; Pranter et al., 2009]. An extensive and well-studied outcrop belt of the lower member is exposed in Coal Canyon near Palisade, Colorado. Coal Canyon exposes a cross section 1500 m wide and 200 m thick of the lower Williams Fork Formation oriented orthogonal to mean paleoflow direction in Pranter et al. [2009] (Figure 2-9a). Paleoflow depths measured from bar clinoforms are 1.0-3.7 m (mean = 2.5 m) and sand body dimensions range from 1.9 – 11.9 m (mean = 4.7 m) thick and 20-380 m (mean = 93 m) wide in the study area (Figure 2-9b) [Cole and Cumella, 2005; Pranter et al., 2009; Chamberlin et al., 2016]. Using terrestrial lidar scans, chronostratigraphic surfaces (n = 67) were mapped at the bases of channel belts, with flat pseudo-horizons projected across floodplain deposits (Figure 2-9c) [Chamberlin et al., 2016]. These surfaces were projected onto a 2D plain orthogonal to mean paleoflow direction and corrected for a gentle regional tectonic dip (Figure 2-9c). Channel belts thicker than 1m are resolved within this dataset. The entire dataset is 15 times wider and 50 times thicker than the average channel-belt sand body.

Compensation statistic (CV) values for the lower Williams Fork Formation were calculated over a range of 4-150 m. All CV points were aggregated into 15 logarithmic bins; the largest bin and bins smaller than 4 m were excluded (Figure 2-9d). The density of CV points increases near the compensation scale. $H_{\text{min}}$ is at the bin centered at 12.1 m;
$H_{\text{max}}$ at the bin centered at 17.3 m. The sub-compensation index is 0.7, estimated over chronostratigraphic thicknesses between 2.1 – 12.1 m.

Like the Ferris Formation, the compensation scale of the lower Williams Fork is much larger than the range of channel depths. The compensation scale is over three times the largest paleoflow depth reported but less than two times the largest sand body scale. The sparse points at stratigraphic thicknesses <12 m on the compensation plot and the muted funneling of the 95% envelope both indicate low resolution (e.g. Figure 2-7c and d). This means that the lower Williams Fork Formation outcrop is likely too poorly resolved to confidently determine sub-compensation behavior using the compensation statistic.

### 2.4.1.3 Comparison of fluvial case studies

Both fluvial case studies use datasets of large extent but low resolution. From our down-sampling experiments, both systems are large enough to enable system wide characterization. However, the resolution at which they were mapped does not enable us to characterize their sub-compensational organization using the compensation statistic. Chamberlin et al. [2016], conducted a compensation statistic analysis using slightly different binning strategy; they estimated the sub-compensation index as 0.5 but this value was heavily dependent on the minimum bin that was included in the analysis [e.g. fig. 8 Chamberlin et al., 2016]. Our analysis of low resolution datasets in section 3.2 determined that the sub-compensation bins become unreliable with low-resolution datasets, such as the lower Williams Fork and Ferris Formation datasets (Supplemental).
In these cases, autogenic sedimentation patterns are better characterized by other statistical approaches. One such approach is the k-function, which has demonstrated that channel bodies within the Ferris are indeed clustered [Hajek et al., 2010]. Similarly, independent analyses of the channel centroids and the probability of multistoried sand bodies both indicate that the lower Williams Fork has spatially un-correlated (random) sedimentation [Chamberlin and Hajek, 2015; Chamberlin et al., 2016]. While the low resolution of the datsets limits the utility of the sub-compensation indices, from our down-sampling experiments, the compensation scales should still represent the regional compensation scale within a factor of two.

The compensation scales of the Ferris Formation and the lower Williams Fork Formation indicate that there was topographic relief larger than a channel depth present in both systems. The Ferris Formation compensation scale was at least 30 times as large as the maximum reported channel depth. The lower Williams Fork compensation scale was at least five times as large as the maximum reported channel depth. It is unlikely that the reported channel depths are incorrect since channel depth in both systems is well constrained by multiple lines of evidence, including the bar clinoform height, thickness of the abandonment facies (the “mud plug”), and the height of dunes and cross bedding. Additionally, the Ferris Formation compensation scale is over three times larger than the largest sand body thickness but the lower Williams Fork compensation scale is less than two times as large. Sand body thickness is likely heavily influenced by channel reoccupation events, levee aggradation and alluvial ridge development [e.g. Mohrig et al., 2000; Farrell, 2001; Tornqvist and Bridge, 2002; Chamberlin and Hajek, 2015; Edmonds
et al., 2016]. Larger sources of relief in aggradational fluvial systems include the development of megafans [Jones et al., 2002; Leier et al., 2005; Hartley et al., 2010; Weissmann et al., 2010].

The development of features like alluvial ridges and megafans all dependent on sediment cohesion, which is a variable that is frequently omitted from experimental deltas, including the experiment we use here [Hoyal and Sheets, 2009]. Since both the Ferris and Williams Fork Formation have significant proportions of fine-grained deposits, they likely had enough cohesion to build relief larger than the depth of a channel scour. The differences in compensation scale relative to sand body thickness suggests that where the Ferris Formation may be controlled by some larger source of relief (such as the development of a megafan), the Williams Fork Formation can be explained by normal alluvial ridge development. This also has implication for the lateral scales of both systems: outcrops within the Williams Fork Formation should be scaled to the width of the alluvial ridge, but the width of outcrops within the Ferris Formation might be scaled to the width of a much larger depositional element, potentially to the width of a megafan.

2.4.2 Deltaic case studies

The degree to which deltaic deposits reflect landscape processes, sediment supply from the hinterland, or basinal forces is an important question in sedimentary geology. For example, it is unclear whether sea-level or basin depth is the primary control on scales of deltaic packages (e.g., parasequences) or if autogenic organization can play a role [Sheets et al., 2002; Hoyal and Sheets, 2009; Martin et al., 2009; Edmonds et al.,
Additionally, if landscape dynamics are a prominent control on sedimentation patterns in deltaic deposits, the role of waves, tides, and fluvial processes should result in different styles of autogenic organization [Bhattacharya and Giosan, 2003; Dalrymple and Choi, 2007; Jerolmack and Swenson, 2007; Ashton and Giosan, 2011; Leonardi et al., 2013; Nienhuis et al., 2013]. Here we use the compensation statistic in two well-constrained deltaic deposits from the Cretaceous Western Interior Seaway (U.S.A.) – one interpreted as tide-dominated and the other interpreted as being river-dominated – to evaluate how compensation scale and autogenic organization differs between the systems.

2.4.2.1 Sego Sandstone

The Sego Sandstone (Campanian) is a member of the Mancos Shale and was an eastward prograding, tide-dominated delta building into the Western Interior Seaway [e.g. Willis, 2000; Willis and Gabel, 2001, 2003]. The studied outcrop of lower Sego Sandstone (“Sandstone 2” of Willis and Gabel 2001) is located in San Arroyo Canyon near the Utah-Colorado border and is oriented slightly oblique to paleoflow (Figure 2-10a). The outcrop contains primarily tidal bar and distributary channel deposits; as much as was possible, we chose this outcrop to avoid areas which may have been scoured by genetically unrelated, incised valleys [Willis and Gabel, 2003]. We collected terrestrial lidar scans of the outcrop and mapped chronostratigraphic surfaces from digital outcrop models generated from the lidar scans. Additionally, we estimated channel dimensions of 150 m wide and 2 m deep from channel clinoform thicknesses measured with a laser
rangepfinder in the field and measured on the digital outcrop model (Figure 2-10b).

Chronostratigraphic surfaces (n = 271) were mapped at bed-set boundary scale, with bed sets larger than 20 cm resolved with confidence. Surfaces were projected onto a 2D plane parallel to the outcrop exposure, which is within 10° perpendicular to regional paleoflow direction (Figure 2-10c). Surfaces are discontinuous. The outcrop is over 10 times thicker and 2 times wider than individual channel elements.

Compensation statistic values for the lower Sego Sandstone were calculated over a range of 0.2-15 m. All CV points were aggregated into 17 logarithmic bins; the largest bin and bins smaller than 0.2 m were excluded (Figure 2-10d). The density of CV points increases slightly near the compensation scale, but in general, the field of CV values is quite dense over the entire stratigraphic-thickness range. Fitting Equation 2 reveals that the $H_{\text{min}}$ is at the bin centered at 1.9 m; $H_{\text{max}}$ is at the bin centered at 6.4 m. The sub-compensation index is 0.3, estimated over chronostratigraphic thicknesses between 0.2 – 1.2 m.

The lower Sego Sandstone outcrop shows compensation at a scale consistent with observed channel paleoflow depths. The sub-compensation index of the lower Sego Sandstone is well characterized by the high resolution mapping of chronostratigraphic packages much smaller than the compensation scale. The sub-compensation index demonstrates strongly persistent autogenic behavior. While the sub-compensation index value artificially due to poorly characterized sub-compensation bins, the strong power law fit is inconsistent with the weak power law fits observed in the experiments with an artificially reduced sub-compensation index value.
2.4.2.2 Ferron Sandstone

The Ferron Sandstone (Turonian) is a member of the Mancos Shale and is interpreted as a river-dominated delta prograding northeastward into the Western Interior Seaway [Cotter, 1971; Corbeanu et al., 2001; Garrison and van den Bergh, 2004; Bhattacharya and MacEachern, 2009; Enge et al., 2010]. The studied outcrop of the upper Ferron Sandstone is located near Emery, Utah in the “Last Chance Delta” portion of the Ferron Sandstone, specifically in parasequence set 2C of Garrison and van den Bergh [2004]. The outcrop consists primarily of mouth bar and distributary channel deposits; the outcrop was chosen to avoid major unconformities within the outcrop extent (Figure 2-11a). Channels from the Last Chance Delta are typically 3.9 - 5.2 m deep by 150 - 220 m wide [Corbeanu et al., 2004]. We collected terrestrial lidar scans of the outcrop and mapped chronostratigraphic surfaces from digital-outcrop models generated from the lidar scans. Additionally, we estimated channel depths and widths from clinoform geometries on the digital outcrop model; channel dimensions in the outcrop area are ~5 m deep and ~150 m wide (Figure 2-11b). Chronostratigraphic surfaces (n = 82) were mapped at bed-set boundary scale, with bed sets ≥ 40 cm resolved with confidence. Surfaces were projected onto a 2D plane parallel to the outcrop exposure, which is within 10° perpendicular to regional paleoflow direction (Figure 2-11c). Surfaces are discontinuous across the outcrop area. The outcrop is 9 times thicker than an individual channel element, although it is also only as wide as a single channel.

Compensation statistic values for the Ferron Sandstone were calculated over a range of 0.4-30 m. All CV points were aggregated into 11 logarithmic bins; the largest
bin and smallest bins were excluded (Figure 2-11d). The density of $CV$ points increases slightly over the entire range, but is moderately low overall. We could not determine $H_{\text{min}}$; there are no scales that would result in a compensation index equal to 1.0. Additionally, scatter continues to decrease across the entire range, although the rate of reduction decreases near the bin centered at 11.1m. The sub-compensation index is 0.7, measured over the entire range of $CV$ values.

The compensation scale of the Ferron Sandstone outcrop cannot be determined with confidence, but it is likely larger than the channel depth. The height of the Ferron Sandstone outcrop is about 7 times the local channel depth. Even with a very narrow outcrop the width of a single channel, a $H_{\text{min}}$ smaller than 6m should be detectable (e.g. Figure 2-4w). It is possible that a $H_{\text{min}}$ between 6-15 m might be missed by the fitting procedure within some narrow outcrops (e.g. Figure 2-6b). There is a possible $H_{\text{max}}$ at 11.1 m, but the reduction in scatter is not as clearly marked as in the experiment sub-samples of a similar sized extent (Figure 2-6). We consider it likely that the compensation scale is larger than 12 m.

2.4.2.3 Comparison of deltaic case studies

Unlike the fluvial case studies, both of the deltaic case studies were very small but relatively high resolution. The lower Sego Sandstone dataset in particular is very high resolution but the extent is very narrow. The autogenic sedimentation could reflect strong persistence due to the influence of tides within the Sego system or it could simply be a local aberration; to determine which of these interpretations is more likely, we would
need data from more outcrops of similar size and quality from around the basin. The upper Ferron Sandstone shows signs of being extremely thin and narrow. Unlike the Sego dataset, the Ferron Sandstone has a lower density of CV points, despite being mapped at a similar scale (i.e. bed-set resolution). This is likely because of how small the dataset is both in width and thickness; the overall low density of CV values is most similar to the experiment sub-samples that are less than three depositional elements thick and one depositional element wide. This would be consistent with a compensation scale that is much larger (i.e. over 10 m) than the observed channel depths. While the sub-compensation index suggests that the Ferron dataset demonstrates random sedimentation, it is impossible to determine what the autogenic sedimentation was without being able to determine $H_{\text{min}}$ and without more data from around the basin.

Although both datasets are too small to be definitive, they suggest that there may be multiple scales of relief possible in deltaic deposits, similar to fluvial deposits. The compensation scale for the Sego Sandstone is consistent with the null hypothesis that channel depth is the main source of relief within deltaic systems [Wang et al., 2011; Straub and Wang, 2013]. If the compensation scale of the Ferron Sandstone is indeed larger than 10m, this may indicate that basin depth, not channel depth, dominates compensation in some deltas. This is suggestive of the idea of foreset-dominated deltas and topset-dominated that has been proposed, where some deltas have thick foresets and thin topsets (foreset-dominated or “Gilbert-type” deltas), but others have thick topsets and thin foresets (topset-dominated deltas) [Edmonds et al., 2011b]. Edmonds et al [2011b] predicts that in shallow, low slope environments, the channel depth is able to
incise deeper than the height of the foreset; in deep, high slope environments, the foreset is much larger than the channel depth. It is possible that the Sego Sandstone developed in shallower water and is more consistent with a topset-dominated delta, whereas the Ferron Sandstone is more consistent with a deeper basin and is a foreset-dominated delta. However, the extents of both of our datasets are insufficient to fully investigate whether deltaic systems developed within deep and shallow basins have different compensation scales.

Both case studies provide an opportunity to explore the degree to which tides can alter the autogenic sedimentation patterns within deltaic deposits. The Sego Sandstone sub-compensation index indicates strong persistence. Persistent behavior is consistent with the observed behavior of modern tide-dominated deltas, where tides have been observed to limit the mobility of distributary channels and also produce more regular bed set thicknesses during the growth of tidal bars [e.g. Dalrymple and Choi, 2007; Fagherazzi, 2008; Geleynse et al., 2011; Leonardi et al., 2013]. Similarly, the Ferron Sandstone sub-compensation index does suggest random to weakly compensational sedimentation. Random sedimentation is largely consistent with observations of a river-dominated delta, with presumably limited cohesion [Edmonds and Slingerland, 2007, 2010; Nardin and Fagherazzi, 2012; Straub and Wang, 2013; Burpee et al., 2015]. However, we would need more datasets from both systems to determine whether these results truly reflect differences in the morphodynamics of each system, rather than being the result of local aberrations. Specifically, it would be necessary to have an extent wide enough to represent variability across the delta lobe, especially in the Ferron Sandstone
which may be controlled by the lobe width and depth instead of the channel width and depth.

2.5 Discussion

Dataset extent and resolution surprisingly do not seem to be major limitations of the compensation statistic, especially when using the compensation statistic to detect the compensation scale. As long as there are usable CV values below the zone of compensation, $H_{\text{min}}$ and $H_{\text{max}}$ can be reliably detected. Indeed, the most significant effect of resolution is on the low density of CV values below the zone of compensation which limits the use of the sub-compensation index to describe autogenic sedimentation. For example, both fluvial case studies have very low density of CV values in their hypothesized compensation range, the density does not increase until after $H_{\text{max}}$. This is different than the overall low density of CV values that is common in very small datasets such as the Ferron dataset, which has low density of points to either side of the hypothesized (channel depth) compensation range. Similarly, the extent needs to be at least six-times the compensation scale to be sure to capture the compensation scale, but is less sensitive to the lateral extent of the dataset. Indeed, the primary effect of narrow extents is that the sub-compensation index tends to reflect local autogenic behaviors instead of the system-wide average, which may be an advantage in some situations.

While we focused on cross-sections that are perpendicular to paleoflow for our analyses, the compensation statistic can still be applied to cross-sections of different orientations. When the compensation statistic is applied to oblique cross-sections, the
extent should be scaled to the apparent thickness and width of the depositional unit (e.g. channel, lobe, or sand body scale). Unless there is a systematic change in the paleoflow direction across the dataset, the compensation statistic should be comparable between cross-sections with different orientations. However, oblique sections in heavily channelized deposits are likely to underestimate the compensation scale and the sub-compensation index (i.e. the sub-compensation index will look more persistent), since the probability of seeing the maximum amount of variability is reduced in oblique cuts (e.g. channel scour or levee deposition are more likely to be measurable in a section that is approximately perpendicular to the paleoflow direction). A system where the depositional element is more lobe-like would likely be less sensitive to the orientation of the cross-section.

The maximum autogenic scale is a consequence of the distribution of depositional and erosional scales possible within a depositional environment. The maximum relief that a system can produce depends heavily on the specific morphodynamics of the individual depositional system. The simplest source of relief that all fluvial and deltaic systems share is channel scour, but larger sources of relief (e.g. alluvial ridge, megafan, delta foreset) may or may not exist in any given system. If the compensation statistic is to be useful for hypothesis testing, it must be able to distinguish between these different scales of relief.

Both the fluvial and deltaic case studies demonstrate the utility of the compensation scale to test hypotheses about the largest scale of relief that can be developed within a system. Within fluvial environments, there has been a question
whether the largest autogenic landform equates primarily to a channel scour, an entire channel-belt-scale alluvial ridge, or some larger megafan feature [Mohrig et al., 2000; Hartley et al., 2010; Hajek and Heller, 2012; Hajek and Wolinsky, 2012; Edmonds et al., 2016]. Both the Ferris Formation and lower Williams Fork Formation datasets have compensation scales much larger than the size of their channel scours, although rivers in the Ferris Formation may have been able to produce much more relief relative to their channel depth than the lower Williams Fork Formation. This underscores the potential importance of long-term sediment storage-and-release episodes in some fluvial landscapes (e.g. Dalman and Weltje, 2008; Kim and Jerolmack, 2008).

Similarly, there is a question about if and when the autogenic dynamics of deltaic systems should be controlled by the delta’s fluvial topset ($H_{\text{max}} \sim$ channel depth) or the relief of the delta foreset ($H_{\text{max}} \sim$ basin depth) (e.g. Muto and Steel, 2004; Muto et al., 2007; Kim and Jerolmack, 2008). Basin depth and subsidence patterns influence how sediment is partitioned between the fluvial topset and the subaqueous foreset during delta growth [Cederberg, 2014; Hajek et al., 2014; Leva Lopez et al., 2014]. When delta mass is sequestered in the fluvial topset, fluvial-system scale may be the dominant influence on autogenic dynamics; however, in systems where the balance of sediment is in the delta foreset, basin depth and growth may set autogenic sedimentation patterns. In our deltaic case studies, the lower Sego Sandstone has a compensation scale consistent with channel depth, but the upper Ferron Sandstone has a compensation depth that is at least two or three times larger. It is possible that Ferron compensation scale is more reflective of basin
depth (where the delta front clinoform would be the largest source of “relief” in the system) rather than morphodynamic organization of the delta topset.

The sub-compensation index can also be a valuable hypothesis-testing tool to describe characteristic autogenic sedimentation patterns, especially when used in conjunction with other statistical analyses. With extensive, well-resolved datasets, sub-compensation index values are describing average autogenic sedimentation patterns and can be used to readily distinguish persistent (or clustered) sedimentation from compensational sedimentation. However, a random value (e.g., \( \sim 0.4 < \kappa < \sim 0.6 \)) may indicate either truly random sedimentation or a mixture of persistent and compensational sedimentation.

Another consideration is the degree to which an individual sub-compensation index value reflects local sediment dynamics versus system-wide autogenic behavior. In general, the smaller datasets should reflect more local conditions. However, assemblages of small datasets can give insight into the larger-scale, system-wide landscape dynamics. For example, Figures 2-5 and 2-6 demonstrate that while the entire experiment has a sub-compensation index that indicates random sedimentation, the sub-compensation indices of small subsamples span the range of random, persistent, and compensational sedimentation. This suggests that the experiment TDB 10-1 may be (weakly) clustered instead of purely randomly organized. We suggest that in systems where large dataset extents are not possible, the assemblages of small datasets may be used to infer system-wide autogenic organization.
2.6 Conclusions

1) We can reliably estimate the maximum autogenic scale using the compensation statistic. The compensation statistic is relatively insensitive to the extent and resolution typical in outcrop data. We have shown that in some fluvial and deltaic systems, such as the Ferris Formation and the lower Williams Fork Formation, have a maximum autogenic scale much larger than what would be predicted based on the channel geometry.

2) We can use the compensation statistic to gain valuable insight into autogenic (sub-compensation) sedimentation within ancient fluvial and deltaic systems, especially when it is used in combination with other metrics and observations. The sub-compensation index reflects system morphodynamics, although it is much more sensitive to data-handling choices than the compensation scale.

   We have shown that there is persistent sedimentation in the tide-dominated Sego Sandstone but random to weakly compensational organization within the river-dominated Ferron Sandstone.

3) We recommend that the compensation statistic is best applied to datasets that are thicker than 6-times the anticipated compensation scale and with a resolution sufficiently smaller than the anticipated compensation scale to ensure that the compensation scale can be identified. Narrow lateral extents demonstrate variable, local autogenic behavior whereas wider extents can be used to determine system-wide, average autogenic behavior.
4) Our analyses provide guidelines for constraining the scale of effective morphodynamics in ancient systems. Both compensation scale (i.e. maximum autogenic scale) and sub-compensation organization (i.e. patterns of autogenic sedimentation) can be investigated in datasets with a wide range of data extents and resolutions. The robustness of the compensation statistic opens up a rich range of questions about allogenic and autogenic processes that operate at long timescales within many fluvial and deltaic deposits.

**Acknowledgments and Data**

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Data for the experiment TD-1-1 can be found at [https://sen.ncsa.illinois.edu/acr/#collection?uri=tag:ncsa.ncsa.edu,2008:/bean/Collection/5A2390DB-5C8E-4393-BEE1-C7C3D2DEF644](https://sen.ncsa.illinois.edu/acr/#collection?uri=tag:ncsa.ncsa.edu,2008:/bean/Collection/5A2390DB-5C8E-4393-BEE1-C7C3D2DEF644). Stratigraphic and terrestrial lidar data for the case studies can be found at [https://scholarsphere.psu.edu/collections/5999n353w](https://scholarsphere.psu.edu/collections/5999n353w) for the Ferris Formation, [https://scholarsphere.psu.edu/collections/7s75dc52b](https://scholarsphere.psu.edu/collections/7s75dc52b) for the lower
Williams Fork Formation, https://scholarsphere.psu.edu/collections/xk81jk48h for the lower Sego Sandstone, and https://scholarsphere.psu.edu/collections/x346d576t for the upper Ferron Sandstone. Details of our analyses can be found in the supplementary materials. Code we used to calculate CV and bin CV values can be found at https://scholarsphere.psu.edu/collections/bn999687g.

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2.7 Figures and Tables

TDB-10-01 is a physical experimental delta that was constructed by self-formed channels under constant sediment- and water-supply conditions and constant base-level rise [Wang et al., 2011; Straub and Esposito, 2013; Straub and Wang, 2013]. a) Overhead photos of the experiment show channels in blue and the intensity of blue dye approximates local flow depth. The active channel network on the delta is sometimes highly localized (e.g., green) or broadly distributed into sheetflows (e.g., magenta). Data used in this study come from laser-topography scans collected 2.13 m downstream from the sediment-water infeed (dashed black line). b) Stratigraphic cross-section of the TDB-10-01 experiment generated using topography scans collected every two minutes throughout the duration of the run. The topographic scans were clipped so that only chronostratigraphic surfaces that were not later eroded remain in the dataset. These preserved chronostratigraphic surfaces are used to calculate the compensation statistic in c. Yellow rectangle shows a characteristic channel dimension corresponding to the 90th percentile depth and a typical width of a single channel. Colored sand bodies represent high CV surface pairs that result from highly channelized deposits (green) and low CV surfaces pairs that result from sheetflow deposits (magenta). c) Compensation statistic (CV) values (gray dots) for stratigraphic thicknesses ranging from 0.5-1400 mm for the TDB-10-01 experiment. The 95% envelope for all CV data is shown with cyan lines. Median values for CV bins are shown as red squares are sub-compensational bins (bins below Hmin), blue circles are compensational bins (bins Hmin and above), and hollow circles are bins that have been excluded from the fit. Dashed line indicates Hmax. The grey box corresponds to the 50th-90th percentiles of relief present within the experiment. Topographic data from within one channel width of the edge of the experiment have been excluded from the analysis to eliminate potential edge effects.

Figure 1 Introduction to TDB-10-2.
Figure 2: Histogram of the maximum relief measured from every preserved chronostratigraphic surface. Gray box indicates the 50th to 90th percentiles of the maximum relief. Relief was measured from the maximum relief of the preserved topographic surfaces in Figure 2-1b, excluding the regions within one channel width of the edge of the experiment. Most of the relief on an individual chronostratigraphic surface is from the channel depth, although some relief is due to the larger, convex up trend of the experimental delta surface.
Figure 3: Location of the datasets used in Figure 2-4. Note the boundaries have been shifted slightly to indicate that the datasets are nested. The characteristic channel is 14 mm deep (the 90th percentile relief) and 220 mm wide.
Figure 4: Compensation statistic (CV) plots of the sub-sampled TDB-10-01 stratigraphic datasets scaled by the experimental channel scale (e.g., Figure 2-1b) arranged in rows of decreasing thickness from top to bottom and columns of decreasing width from left to right, with the full TDB-10-01 dataset from Figure 2-1 shown in A. Annotations and colors are the same as in Figure 2-1. Subsampled datasets that are shown again in Figure 2-5, 2-6, 2-7, and 2-8 are indicated. Background shading on the Figure indicates the degree to which the sample of the dataset reflects the system-wide scale and organization: green demonstrate system-wide behavior, red demonstrate local behavior, yellow are systems that could be heavily influenced by local effects.
Figure 5: Replicates of samples with the same dimensions as Figure 2-4l. Replicates estimate $H_{\text{min}}$ between 3.0–6.7 mm and a $H_{\text{max}}$ between 15.2–19.9 mm, compared to the 7.4 and 17.0 mm measured in the largest sample (Figure 2-1c). The extent of these samples is roughly equivalent to the extent of the lower Williams Fork Formation dataset.
Figure 6: Replicate samples of the Figure 2-4x sample. Estimates of $H_{\text{min}}$ are 2.4–6.3 mm, the $H_{\text{max}}$ are 10.3 – 16.7 mm, compared to the 7.4 and 17.0 mm of the largest sample (Figure 2-1c). For a minority of sample, a compensation scale cannot be determined (e.g. b). The extent of these samples is likely similar to that of the lower Ferron Sandstone dataset.
Figure 7: Compensation statistic (CV) plots of down-sampled TDB-10-1 sub-samples (Figure 2-4g). Annotations and symbols are the same as in Figure 2-1b has half the number of chronostratigraphic surfaces as the original sub-sample a, c has 1/5 the number of chronostratigraphic surfaces as the original. Samples a and b have similar compensation scales, but the sub-compensation indices differ. Sample c does not have enough surfaces below the compensation scale to determine the compensation scale or the sub-compensation index. The extent of these samples is similar to the Ferris Formation dataset.
Figure 8: a) Airphoto of the Ferris Formation outcrop in the Hanna Basin, Wyoming (Supplement). White areas are sand bodies. Outcrop is 1700 m wide and 350 m thick. Flow is into the ground; stratigraphic up is to the top of the photo. b) Field photograph of a representative channel sandstone in the Ferris Formation. The photo has been rotated so that stratigraphic up is to the top of the photo; paleoflow direction is to the left, into the ground. Bar clinoforms can be seen at the top of the sand body dipping down to the left. The height of these clinoforms (dashed white line) indicates a paleoflow depth around 1 m. Dune cross-stratification in the upper left of the sand body is 15-30 cm high, which is also consistent with flow depths ~1 m. c) Chronostratigraphic surfaces (119) for the Ferris Formation outcrop were constructed with horizontal pseudo-horizons projected through the floodplain and rectangles representing the maximum width of a channel and the mean sand body thickness. Pseudo-horizons were clipped to represent only preserved surfaces. d) Compensation statistic (CV) plot of the Ferris Formation. The density of CV points increases significantly across the sub-compensation bins and the reduction in scatter evident in the 95% envelope is not pronounced. We had to exclude bins smaller than 3 m due to the scarcity of data within those bins. Annotations and colors are the same as in Figure 2-1.
Figure 9: a) Field photo of the lower Williams Fork Formation outcrop exposed in Coal Canyon, Colorado (Supplement). Channel sand bodies are the resistant units in the hillside. b) Field photograph of a representative channel sandstone in the lower Williams Fork Formation. The height of the bar clinoforms dip down to the right (dashed white line) indicates a paleoflow depth less than 3 m deep. The depth of the scour at the base of the sand body also indicates a relatively shallow flow. c) Chronostratigraphic surfaces (67) for the Williams Fork Formation. Base of channels were mapped on a digital outcrop model and pseudo-horizons were projected through floodplain deposits. Pseudo-horizons were clipped to represent only preserved surfaces. d) Compensation statistic (CV) plot of the Williams Fork Formation. Note the overall low density in CV points that increases at larger stratigraphic thicknesses. We had to use a large minimum cutoff value of 4m because of the scarcity of CV values in smaller bins. Annotations and colors are the same as in Figure 2-1.
Figure 10: a) Field photo of the Sego Sandstone outcrop in San Arroyo Canyon, Utah (Supplement). Mouth bar and channel sandstones are the cliff-forming layers. Paleoflow direction is into the cliff. b) Field photograph of a representative channel sandstone in the Sego Sandstone. The height of the bar clinoforms dip down to the right (dashed white line) indicates a depth around 2 m. c) Chronostratigraphic surfaces (271) for the Sego Sandstone. d) Compensation statistic (CV) plot of the Sego Sandstone. The density of CV points is high over all and increases slightly at larger thicknesses. Bins below the mapping resolution (0.2 m) were excluded. Annotations are the same as in Figure 2-1.
Figure 11: a) The upper Ferron Sandstone outcrop near Emery, Utah (Supplement). Mouth bar and channel sandstones are the cliff-forming layers. Flow is out of the cliff. b) Field photograph of a representative channel sandstone in the Ferron Sandstone. The height of the bar clinoforms dip down to the right (dashed white line) indicates a paleoflow depth around 5 m. c) Chronostratigraphic surfaces (82) for the Ferron Sandstone. Surfaces were mapped. d) Compensation statistic (CV) plot of the Ferron Sandstone. $H_{\text{min}}$ could not be determined. CV point density is low over all and does not greatly increase at larger thicknesses. There is a slight reduction of scatter at the bin centered at 11.1 m, but it is not pronounced. Annotations are the same as in Figure 2-1.
### Table 2-1 Experiment TDB-10-1 Parameters

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<tr>
<th>Parameter</th>
<th>Value</th>
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<tr>
<td>Duration (h)</td>
<td>78.2</td>
</tr>
<tr>
<td>Water discharge Q&lt;sub&gt;w&lt;/sub&gt; (L/s)</td>
<td>0.4511</td>
</tr>
<tr>
<td>Sediment discharge, Q&lt;sub&gt;s&lt;/sub&gt; (L/s)</td>
<td>0.011</td>
</tr>
<tr>
<td>Q&lt;sub&gt;w&lt;/sub&gt;:Q&lt;sub&gt;s&lt;/sub&gt; (-)</td>
<td>41</td>
</tr>
<tr>
<td>Base level rise (mm/h)</td>
<td>5</td>
</tr>
<tr>
<td>Cross section location (m from sediment infeed)</td>
<td>2.13</td>
</tr>
<tr>
<td>Cross section thickness (mm)</td>
<td>65</td>
</tr>
<tr>
<td>Cross section width (mm)</td>
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</tr>
<tr>
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<td>9-14</td>
</tr>
<tr>
<td>Channel width (mm)</td>
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<tr>
<td>Unit</td>
<td>Depositional Environment</td>
</tr>
<tr>
<td>--------------</td>
<td>--------------------------</td>
</tr>
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<td>Ferris</td>
<td>Fluvial</td>
</tr>
<tr>
<td>Williams Fork Formation</td>
<td>Fluvial</td>
</tr>
<tr>
<td>Sego Sandstone</td>
<td>Deltaic</td>
</tr>
<tr>
<td>Ferron Sandstone</td>
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</table>
Chapter 3

Preserving proxy records in dynamic landscapes: Modeling and examples from the Paleocene-Eocene Thermal Maximum

Abstract

The stratigraphic record is an important archive of how Earth systems have responded to different rates and magnitudes of climate change. Much of what we know about past climate comes from paleoenvironmental proxies preserved within sedimentary deposits, but proxy records of the same event often show significant differences, leading to uncertainty in climate reconstructions. Recent work has underscored the concept that intrinsic variability in sedimentation extends over large spatiotemporal scales in many sedimentary environments. Here we use a stochastic sedimentation model with a known input signal to evaluate whether variable sedimentation may contribute to discrepancies between proxy records. We find that even small variability in sedimentation results in uneven preservation of time, leading to significant differences between proxy records. Some records fail to preserve any evidence of the input signal and others preserve signals with different apparent magnitudes, durations, and shapes. Our results suggest that averaging across multiple, low-resolution records may be a robust approach to accurately reconstructing paleoclimate and paleoenvironmental conditions, particularly in depositional settings where variability in sedimentation is large relative to long-term sedimentation rates.
3.1 Introduction

Sedimentary rocks host important archives of past climate conditions recorded by geochemical proxies such as carbon and oxygen isotopes, biomarkers, and trace metals. Proxy records are critical for reconstructing the causes, rates, and magnitudes of past climate changes and for understanding how Earth’s landscapes and oceans respond to change. Despite their utility, individual proxy records of the same event sometimes show significant differences which complicate paleoclimate and paleoenvironmental reconstructions. For example, the Paleocene-Eocene Thermal Maximum (PETM), a global warming event that occurred ~56 Ma, has been intensively studied in order to reconstruct the magnitude, rate, and cause of carbon release that triggered the event and to understand how the Earth-system recovered (McInerney and Wing, 2011). However, carbon isotope records of the PETM show a wide range of overall magnitude (−3 to −7 ‰), apparent duration of onset (5–20 k.y.), and apparent duration of the event (120–220 k.y.) (McInerney and Wing, 2011) (Figure 3-1). Furthermore, the overall shape of the carbon isotope excursion (CIE) varies among records, with some records showing a rapid onset and a slow recovery (e.g., Figure 3-1A and 3-1I) and other records showing a protracted peak excursion followed by a rapid recovery (e.g., Figure 3-1B and 3-1I). Presently it is unclear which records most faithfully reflect global and regional paleoclimate conditions through the PETM.

Some differences between proxy records arise because proxy systems themselves can be variable and sensitive to issues like source-material mixing or time averaging. For example, differences in bulk organic carbon records can reflect different mixtures of contemporary carbon sources (e.g., algal versus bacterial producers; (e.g., Farquhar et al., 1989), different proportions of terrestrial and marine carbon input (e.g., Sluijs and Dickens, 2012), or mixtures of contemporary and reworked (fossil) carbon (e.g., Bataille et al., 2013; Baczynski et al., 2016)). Even when the source material is identifiable, individual samples may average different amounts
time. For example, organism-specific nannofossil assemblages accumulate over multiple seasons or generations and in situ pedogenic carbonate forms over 1–10 k.y. (e.g., Gocke et al., 2010). Furthermore, bioturbation and diagenesis can mix, smear, or overprint environmental signals recorded by proxies. These challenges might be overcome through careful sampling or detailed comparisons of, for example, compound-specific or multi-proxy systems. However, proxy-data sampling is fundamentally limited by sediment preservation.

Because sedimentation is inherently variable in any environment, time is not evenly represented in preserved deposits. The uneven representation of time in a given stratigraphic section is the direct result of autogenic landscape dynamics (e.g., channel avulsion) and environmental variability (e.g., floods and storms) (e.g., Straub and Esposito, 2013; Hajek and Straub, 2017). These processes focus erosion and deposition in geographically limited swaths of a basin. Areas experiencing significant sedimentation or erosion shift through time, meaning that two stratigraphic sections that are relatively close in space may have different local sediment-accumulation histories (Ganti et al., 2011; Straub et al., 2012). This type of variability cannot often be resolved chronostratigraphically and may not be obvious sedimentologically; consequently, it is not always possible to identify intervals of expanded, condensed, or missing time in an individual record.

Efforts to maximize the temporal resolution of proxy records have focused on high-sedimentation-rate sections or low energy depositional environments where sedimentation is presumably relatively constant. However, it is unclear how sedimentation rate and environmental variability influence how climate signals are recorded in proxy records or whether observed differences in existing collections of proxy records, such as those of the PETM, could be the result of variability in sedimentation. This becomes particularly important as we seek to understand how terrestrial and shallow marine siliciclastic environments responded to past climate changes, because the intrinsic range of variability in sedimentation in these landscapes
may exceed the magnitude of orbitally forced climate changes (Li et al., 2016; Hajek and Straub, 2017). Here we use a stochastic sedimentation model to evaluate how faithfully proxy records preserve a known input signal in settings with different long-term aggradation rates and different ranges of environmental variability in sedimentation.

3.2 Stochastic Sedimentation Model

To a first order, variable sedimentation can be approximated by estimating the magnitude and frequency of erosion and deposition events in different landscapes. Most parts of terrestrial and marine environments do not experience significant erosion or deposition on an annual basis (Sadler and Strauss, 1990; Jerolmack and Sadler, 2007). Instead, erosion and deposition primarily occur during infrequent events like large floods and storms influencing marine environments, or floods, levee breaches, and channel avulsions in fluvial environments (e.g., Wiberg, 2000; Aalto et al., 2008). Such events are generally spatially restricted and influence only limited portions of a basin. Studies have shown that deposition and erosion in sediment-transport systems can be described using a heavy-tailed probability distribution (e.g., Ganti et al., 2011; Schumer et al., 2011; Straub et al., 2012).

We leveraged this concept to build stratigraphic proxy records of a generalized climate history using stochastic sedimentation models (Figure 3-2). We defined distributions of annual sedimentation-event probabilities using a truncated double Pareto distribution centered at an expected long-term sedimentation rate and specified shape parameter values that approximate recurrence intervals of large deposition and erosion events documented in fluvial and shelf environments (Figure 3-2A; Data Repository). To generate an individual synthetic record, we drew from this probability distribution 350,000 times to simulate 350 k.y. of local sedimentation history (Figure 3-2B). We then assigned a proxy value to the record for each year sediment was
preserved (Figure 3-2C and D). The input proxy signal included a large and a small event (loosely based on the PETM and Eocene Thermal Maximum-2 CIEs) and contained a small amount of variability representative of what has been documented in replicate analyses of some proxy systems (Foreman et al., 2012; Baczynski et al., 2013).

We simulated four end-member scenarios representing environments with high (30 cm/kyr) and low (10 cm/kyr) long-term sedimentation rates and relatively high and low variability in sedimentation. For each model we generated 500 synthetic records and manually interpreted the onset, peak, and end of the recovery for the large and small climate events (Figure 3-2D).

3.3 Results

Evidence of the large event had a high probability of being recorded in all models (Table 3-1). The large event was preserved in all records from the high-sedimentation-rate, low-sedimentation-variability scenario (Model 1), 88% (Model 2) and 87% (Model 3) of records from models with relatively strong variability compared to their sedimentation rate, and in 69% of the records from the low-sedimentation-rate, high-sedimentation-variability scenario (Model 4). A similar pattern emerged for preservation of the small event, with Model 1 recording it most often (89%) and Model 4 least often (44%). Across all models there was a weak tendency for thicker records to be more likely to preserve either the large or small event.

The magnitude, duration, and shape of the large event were commonly modified in all models (Table 3-1, Figure 3-3). Across 1,716 synthetic proxy records that preserved the large event, only 20% record the event magnitude, duration, and onset duration within 50% error. Forty-one percent of Model 1 records and only 8% of Model 4 records reflect input attributes within 50% error. The duration of the onset was often underestimated – sometimes significantly –
in all model scenarios, and the magnitude of the excursion was likely to be underestimated. The shape of the large event in any individual record often includes pre-onset excursions, secondary peaks, or protracted excursions (e.g., Figure 3-3).

Although individual records can deviate significantly from the input signal, the aggregate of all records accurately reflects the imposed signal (median values Table 3-1). Additionally, ensemble records are at least twice as likely to be within 50% of the input signal as any individual record (Table 3-1; Figure 3-4A and B).

3.4 Discussion

This analysis demonstrates that individual sedimentary records are likely to distort the shape or duration of an input climate signal solely as a consequence of variability in sedimentation inherent in depositional landscapes. Many records from these models show an apparent body or sustained excursion even though none existed in the input signal, and most records underestimate the duration of the excursion onset – many significantly. It is common for records to show secondary peaks or a complicated recovery structure even though the input signal was very simple. These effects are a consequence of time being unevenly represented in each section because of the unique sequence of deposition, erosion, and hiatus in each record. This suggests that any single record might not accurately reflect the timing and amplitude of a global climate event no matter how well it can be sampled or analyzed.

Sedimentation varies both in space and time in most marine and terrestrial environments; consequently two records from the same basin may show very different proxy signals. This means that attempts to interpret the veracity or relative accuracy of records from two localities may be futile. In contrast, ensemble records average across environmental variability and therefore are more likely to give accurate estimates of the duration, magnitude, and shape of our
synthetic climate signal than any individual record. Model ensemble averages are relatively insensitive to age models suggesting that even low-resolution or poorly dated records may be useful for accurately reconstructing past climate changes. To explore this concept we created an ensemble record of the PETM from 15 bulk organic carbon isotope records from terrestrial and marine settings worldwide (Figure 3-4C). While the population of individual records shows a wide range of onset and recovery durations, the aggregate record shows a -2.5‰ excursion occurring over 5–10 k.y. and a ~180 k.y. total event duration with no pronounced body, which is consistent with PETM CIE reconstructions from deep-sea records (e.g., Zachos et al., 2008).

Our models show that signal preservation is dependent on the scale of variability relative to the long-term sedimentation rate. While Model 1 was most likely to yield records that accurately captured the input climate signal and Model 4 was clearly the least likely, Models 2 and 3 were equally likely to recover the input signal. This underscores that preservation is a tradeoff between expanded potential to record time in high-sedimentation records and the higher possibility of eroding large intervals in high-variability settings. For warming events like the PETM this could mean no net change in how well an input signal can be preserved if, for example, increases in overall sedimentation rates (e.g., John et al., 2008; Self-Trail et al., 2012) are coupled with increases in precipitation extremes or storminess that would increase variability in sedimentation (e.g., Sluijs et al., 2011; Foreman et al., 2012).

### 3.5 Conclusions

This analysis shows that spatiotemporal variability in sedimentation can significantly influence the apparent timing and magnitudes of climate and paleoenvironmental changes recorded by proxy data. Improved understanding of characteristic sedimentation variability in different environments, including biogeochemical controls on sedimentation in marine settings,
will help constrain uncertainties associated with proxy reconstructions and determine whether
differences between records from the same system are significant or whether they reflect
background variability inherent in a particular setting.

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Figure 12: Example Paleocene-Eocene Thermal Maximum (PETM) carbon isotope records from the bulk organic carbon in the Bighorn Basin (Wyoming, USA; A-E) and bulk carbonate from in mid-Atlantic shelf (Maryland and New Jersey, USA; F-J). In both regions the magnitude, shape, and duration of the CIE varies among records. A-E) Colors indicate mammalian biozones: Clarkforkian-3 (brown), Wasatchian-0 (red), and Wasatchian-1 (yellow), and samples with ambiguous biostratigraphy in gray. Localities are A) Pocat Bench (Magioncalda et al., 2004), B) Highway 16, C) CAB10, D) Big Red Split, and E) North Butte (Baczynski et al., 2013). F-J) Colors indicate nannoplankton biozones: NP 9a (dark green), NP 9b (light green), undifferentiated NP 10 (medium blue), NP 10a (light blue), NP 10b-d (dark blue), NP 11 (purple), and samples with ambiguous biostratigraphy in gray. Localities are F) South Dover Bridge (Self-Trail et al., 2012), G) Clayton (Stassen et al., 2012), H) Wilson Lake (Zachos et al., 2006), I) Ancora (Kent et al., 2003), and J) Bass River (Kent et al., 2003).
Figure 13: Example stochastic sedimentation model output. A) Semi-log plot showing truncated double-Pareto distributions of annual event sizes for the high sedimentation rate, low variability model (Model 1, solid black line), and the low sedimentation rate, high variability model (Model 4, dashed gray line). Solid arrows show the 1 k.y. event size and dashed arrows show the 10 k.y. event size for each distribution (low-variability models in black and high-variability models in gray). Gray histogram shows the actual distribution of event sizes for the record in B and D. Data used to calibrate distributions are included in the Data Repository. B) Sediment-accumulation history (gray line) of a Model 1 record constructed from 350,000 independent draws from the prescribed distribution (A) Preserved years (colored points) are those which have an event size > 0.5 mm and are not removed by subsequent erosion events. Dotted line shows the long-term sedimentation rate (30 cm/k.y.). C) Imposed generic proxy curve with a large (-5‰ excursion and recovery spanning 200 k.y.) and a small (-1‰ excursion and recovery spanning 40 k.y.) event. Proxy values for each year preserved are drawn from a normal distribution with standard deviation of 0.3‰ (dark gray; light gray range shows two std. dev.). D) The final synthetic record only includes preserved years colored by age. The onset, peak, and end of the recovery were interpreted using a 10-point moving average of the preserved years (black line). The appearance of the input signal gets stretched during extended runs of deposition (interval i in B and D) or extremely large annual events (ii), and erosion can truncate large portions of the input signal (iii) leaving abrupt steps in the preserved record.
Figure 14: Example synthetic records from model runs (colored as in Figure 3-2D). Black line is a moving average of preserved beds. Across 500 iterations of each model, some models closely reflected the input signal records (A, E, I, and M) and many were moderately (B, C, F, J, and N) or heavily (D, G, K, and O) modified. Models 2, 3, and 4 all produced records which failed to preserve any evidence of the large event (H, L, and P).
Figure 15: Ensemble medians (bold line) of 15 individual records (light lines) from A) Model 1 and B) Model 4 synthetic records and C) PETM bulk organic δ13C records from 15 fluvial and marine sections worldwide (Magioncalda et al., 2004; John et al., 2008; Sluijs et al., 2011; Foreman et al., 2012; Baczynski et al., 2013; Manners et al., 2013). Details of ensemble construction are included in the Data Repository.
<table>
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<tr>
<th>Measurement (input parameter)</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Preserved record of large event</td>
<td>100%</td>
<td>88%</td>
<td>87%</td>
<td>69%</td>
</tr>
<tr>
<td>Preserved record of small event</td>
<td>89%</td>
<td>53%</td>
<td>58%</td>
<td>44%</td>
</tr>
<tr>
<td>Apparent Total Duration [kyr] (200 k.y.)</td>
<td>193</td>
<td>165</td>
<td>176</td>
<td>154</td>
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<tr>
<td>Apparent Magnitude [%] (−5 ± 0.3 %)</td>
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<td>−4.6</td>
<td>−4.7</td>
<td>−4.1</td>
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<tr>
<td>Apparent Onset Duration [kyr] (20 k.y.)</td>
<td>19</td>
<td>15</td>
<td>16</td>
<td>10</td>
</tr>
<tr>
<td>Apparent Recovery Duration [kyr] (180 k.y.)</td>
<td>171</td>
<td>131</td>
<td>138</td>
<td>117</td>
</tr>
<tr>
<td>Records within 50% error of input</td>
<td>41%</td>
<td>13%</td>
<td>15%</td>
<td>8%</td>
</tr>
</tbody>
</table>

Note: All entries reflect the median of 500 iterations, the parentheses contain the 10th to 90th percentile range. Durations are calculated with the measured sedimentation rate for each synthetic record.
Chapter 4

Exploring how landscape dynamics influence the sampling of paleoenvironmental signals

Key Points:

- Ensemble records are needed to accurately reconstruct paleoenvironmental signals that occur over a timescale near the scale of landscape dynamics.
- The number of records that need to be included in ensemble records scales directly with the scale of landscape variability relative to the net sedimentation rate.
- Twice as many records may be needed to accurately reconstruct a signal from a high variability and low sedimentation rate environment than an environment that has half the variability or twice the sedimentation rate.
Abstract

Fluviodeltaic environments are some of the most dynamic landscapes on Earth and are particularly sensitive to sediment supply, land-cover, and sea-level change. Fluviodeltaic sedimentary deposits are a critical archive for reconstructing terrestrial and oceanographic conditions throughout Earth history and for understanding how these vulnerable regions responded to past changes in climate and sea level. Fluviodeltaic sediment-transport networks show a range of internally generated (autogenic) dynamics, such as channel avulsion, which gives rise to significant spatial and temporal variability in sedimentation rates and can limit how well signals of climate change can be preserved in these deposits. Previous work has demonstrated that high-fidelity paleoenvironmental proxy records are likely to be preserved only in settings where the characteristic autogenic dynamics are small relative to the long-term sediment accumulation rate, and that the accuracy of paleoclimate proxy records can be improved by combining multiple partially preserved individual records into an ensemble. While it seems obvious that more records are needed to fully characterize a highly variable system, it is not clear just how many individual records are necessary to generate an accurate ensemble paleoenvironmental proxy record. Additionally, the best spatial sampling strategies for maximizing the recovery of paleoenvironmental signals from individual cores is unconstrained. Here, we addressed this need using numerical models of delta deposition and evaluating how many 1D observations are needed to fully characterize paleoenvironmental proxies from delta deposits with different scales of variability and long-term accumulation rates. We used DeltaRCM, a reduced complexity delta evolution model, to generate synthetic stratigraphy. We varied the scale of autogenic dynamics in each delta by changing the ratio of coarse and fine sediment supplied to each system, and we built deltas under different rates of sea-level rise. We analyzed how many randomly located 1D cores are needed to ensure an ensemble record is complete (i.e. all intervals of time are represented) and
accurate (i.e. all intervals of time are represented evenly) ensemble record. This analysis shows that the number of randomly located 1D cores needed to generate a complete and accurate ensemble proxy record scales directly with the autogenic timescale relative to accumulation rate. Our results are important not only to better plan sampling strategies in deltas, but offer new ways to assess the likely completeness of existing records within dynamic landscapes.

4.1 Introduction

Fluviodeltaic landscapes are among the most sensitive landscapes to changes in climate and sea level, but it is hard to predict how they will respond to anthropogenic climate change and sea level rise. It is useful to reconstruct how these landscapes responded to past periods of rapid, large-magnitude global climate change, such as the Paleocene-Eocene Thermal Maximum or Pleistocene glacial-interglacial cycles. However, because of internally generated (autogenic) processes in fluviodeltaic landscapes, such as channel bifurcations or avulsions, it can be particularly hard to uniquely attribute changes in stratigraphic architecture, apparent sedimentation rate, or an environmental proxy to a response to changes in climate or sea level [e.g., Heller et al., 2001; Muto and Steel, 2002; Nijhuis et al., 2015; Li et al., 2016; Trampush and Hajek, 2017; Trampush et al., 2017]. Relatively rapid events are especially likely to be altered or removed entirely [Jerolmack and Paola, 2010; Schumer et al., 2011; Li et al., 2016; Trampush and Hajek, 2017].

One of the primary issues in reconstructing accurate, high-precision paleoenvironmental signals is sedimentation is not constant in time and space; random fluctuations in erosion, deposition, and non-deposition caused by autogenic processes and other stochastic events (e.g., storms or floods) result in a stratigraphic record composed of large gaps in time (hiatuses) [Sadler, 1981; Plotnick, 1986; Schumer and Jerolmack, 2009; Ganti et al., 2011; Straub and
Esposito, 2013]. The problem of variable preservation of time has long been a subject of research in sedimentary geology [e.g., Barrell, 1917; Kolmogorov, 1951; Ager, 1973; Sadler, 1981; Tipper, 1983; Sadler and Strauss, 1990; Kemp, 2012; Straub and Esposito, 2013; Sadler and Jerolmack, 2015]. Sadler [1981] used the concept of incomplete preservation of time to explain why sedimentation rates continue to decrease when measured over increasingly larger periods of time, regardless of depositional environment. This behavior (termed the Sadler effect) is likely the result of incorporating more hiatuses (from either erosion or periods of non-deposition) when sedimentation rate is measured over longer intervals [Sadler, 1981; Strauss and Sadler, 1989; Sadler and Strauss, 1990; Schumer and Jerolmack, 2009; Schumer et al., 2011]. Subsequent work has shown that the probability of hiatuses present in a 1D section are best explained by heavy-tailed distributions [Jerolmack and Sadler, 2007; Sadler and Jerolmack, 2015]. Collectively, this work has aimed to understand the degree to which time is completely represented in the stratigraphic record – a concept called “stratigraphic completeness” [c.f., Ager, 1973].

Another challenge to reconstructing complete records of paleoenvironmental signals is that the resolution of age dating is rarely high enough to recognize where in a sedimentary section the representation of time has been expanded, compressed, or removed entirely. In younger sediments, high-resolution age control can help reveal gaps in time or expanded sections. For example, in Pleistocene records of climate change, the resolution of age dating can get down to 100 years or less and advanced statistical approaches can be used to correlate records and identify small temporal and spatial variability in sedimentation [e.g., Parnell et al., 2008, 2011]. However, in older records that lack high-resolution age control, it remains difficult to identify and account for spatially and temporally variable sedimentation when correlating records [Kemp and Sexton, 2014].
Using physical experiments, numerical models, and a limited number of natural examples, there has been considerable advancement in the last 10 years to estimate the time scale at which sediment transport systems transition from being dominated by episodic, local, stochastic sedimentation events to relatively constant, deterministic sedimentation predictable from long-term basin boundary conditions [e.g., Hajek et al., 2010; Wang et al., 2011; Straub and Wang, 2013; Chamberlin et al., 2016; Trampush et al., 2017]. In particular, the compensation scale, which measures the amount of variability in sedimentation relative to the long term sedimentation rate, has been shown to be a robust tool for detecting the handoff between “short” (i.e. variable or stochastic) and “long” (i.e. deterministic) timescales, and thus is a useful tool for estimating at what scales stratigraphic successions can be considered complete [Wang et al., 2011; Pyles et al., 2013; Straub and Esposito, 2013; Trampush et al., 2017]. This statistic also has been hypothesized to be able to detect the maximum amount of relief that can be built in a given system, in both experimental and field studies [Wang et al., 2011; Trampush et al., 2017].

In terms of the spatial control on completeness, Straub and Esposito [2013] have shown that completeness does vary with distance from the sediment source. However, the lateral variability of systems, especially deltaic ones, has been much harder to address. It has been proposed that the spatial variability (and compensation scale) of fluvial and deltaic systems can vary dramatically between systems with different initial grain size distributions because the cohesion imparted by fine sediment (silt and clay) reduces the lateral mobility of channel networks resulting in more spatially variable sedimentation patterns [Edmonds and Slingerland, 2010; Straub et al., 2015].

Two strategies have been suggested to reconstruct paleoenvironmental signals: 1) focus on environments where the scale of autogenic processes is much lower than the magnitude and frequency of a given signal, or 2) try to combine multiple records to “fill in” the gaps. Examples of the first strategy include the extensive sampling of deep marine sediments or lacustrine sediments for paleoclimate reconstructions [e.g., Nicolo et al., 2007; Zachos et al., 2008].
Examples of the second strategy include obtaining multiple samples of a single depositional region in order to reconstruct a single geochemical signal [e.g., John et al., 2008; Kopp et al., 2009; Stassen et al., 2012]. Trampush and Hajek [in press] suggest that the variability between geochemical record imparted by variability in sedimentation can be overcome by averaging across sufficient records that have independent sedimentation histories. However, the number of cores needed to accurately reconstruct an environmental signal and the spatial distribution of those cores, remains unknown and largely unexplored.

Here we present a way to predict preservation of environmental signals (both physical and chemical) based on the amount of autogenic variability in a system relative to the long-term aggradation rate. We use a series of reduced-complexity landscape models to build a range of deltaic stratigraphic datasets and evaluate how stratigraphic completeness and signal preservation vary spatially among systems with different autogenic character in basins with different long-term aggradation rates. In order to establish the minimum number of cores that are needed to create a complete ensemble record for signals that are slightly smaller and larger than the expected scale of autogenic variability, we randomly sampled synthetic stratigraphy built from each model. Additionally, to understand how stratigraphic completeness varies spatially within each delta deposit, we created a series of cross sections and maps of deposit age and the magnitude and location erosion and deposition events. At each cross section, we also calculated the compensation scale. We demonstrate that the inherent variability of sedimentary systems can be overcome with sufficient sampling across the landscape, although this may be prohibitive in large systems or in deposits that have been heavily reworked and eroded by subsequent geodynamics and tectonic events.
4.2 Modeling Approach

In order to explore how landscape dynamics and long-term accumulation rates control how paleoenvironmental signals are preserved in the stratigraphic record, we used a reduced-complexity delta evolution model called DeltaRCM created by Liang et al. [2015] and shared via the repository at CSDMS. By specifying a limited number of sediment and water transport rules, the model is able to spontaneously generate autogenic processes such as channel avulsion, channel bifurcation, and channel migration [Liang et al., 2014, 2015]. This model mimics the effects of cohesion induced by fine sediment by setting different critical shear values for fine and coarse-grained sediment as well as different rules for when a fine or coarse parcel of sediment will be deposited, eroded, or transported. Furthermore, the package keeps track of stratigraphy generated throughout each model run, including the time of deposition and the fraction of sand and mud in each location.

Using DeltaRCM we generated nine synthetic deposits spanning three rates of accommodation and three initial grain-size distributions (Table 4-1). We chose aggradation rates to produce a deposit that was roughly 7, 5, and 3 times as thick as the compensation scale predicted from the input channel depth (5 m). The three initial grain-size distributions where chosen to produce a range of autogenic variability in the deltas, where the highest variability resulted from deltas with the lowest fraction of coarse sediment (10% coarse and 90% fine sediment) and the lowest variability occurred in models with the highest fraction of coarse sediment (50% coarse and 50% fine sediment). For all model runs the input channel dimensions and sediment and water flux were kept identical, as were the grid spacing and number of time steps. Accommodation was achieved by setting steady sea-level rise in the receiving basin (Table 4-1 for rates). The initial basin depth for all runs was set at twice the input channel depth (5 m).
All models were run for 6000 time steps. Full description of the model and parameters used to generate the nine models is available in the supplement.

4.2.1 Analysis of spatial and temporal variability of sedimentation

To compare across delta deposits with different degrees of progradation vs. aggradation we scaled the distance from the sediment source using the $\chi$ mass balance scaling proposed by Strong et al. [2005]:

$$\chi(d) = \frac{\int_0^x r_{\Delta T}(d) dx}{\int_0^L r_{\Delta T}(d) dx}$$

(1)

where $r_{\Delta T}(d)$ is the rate of deposition (units LT$^{-1}$) measured at $d$ distance downstream (units L) and over time interval $\Delta T$ (units T$^{-1}$), here chosen as the duration of the entire model run, and L is total length of depositional system (units L). Proximal, medial, and distal radial cross sections were extracted from the stratigraphy of each model at $\chi$ of 0.25, 0.50, and 0.75 (Figure 4-1a).

Chronostratigraphic surfaces were constructed for every 50 time steps. The compensation statistic ($\sigma_{ss}$) as defined in Straub et al. [2009] was measured for every cross section using the chronostratigraphic surfaces and the equation:

$$\sigma_{ss} = \left\{ \int_{W} \left[ \frac{r(\Delta T; x)}{\hat{r}(x)} - 1 \right]^2 dW \right\}^{\frac{1}{2}}$$

(2)

where $r(\Delta T; x)$ is the sedimentation rate (units LT$^{-1}$) measured over interval $\Delta T$ (units T$^{-1}$) at cross-basin distance of $x$ (units L), $\hat{r}(x)$ is the long-term sedimentation rate (units LT$^{-1}$), and $W$ is cross-basin length (units L). The compensation scale was determined by fitting the power function below to either side of the scale break visible on the compensation statistic plot in Figure 1g:

$$\sigma_{ss} = a \Delta T^{-\kappa}$$

(3)

where $a$ is a fitting parameter and $\kappa$ is the slope of the function on a loglog plot (Figure 4-1g) and it describes the relationship between different chronostratigraphic surfaces. A fully
compensational organization of chronostratigraphic surfaces has a slope (κ) of 1; a κ near 0.5 indicates random organization, and a κ less than 0.5 indicates persistent or clustered organization. While eqs. 1, 2, and 3 can be measured strictly in space when age control is absent or too low-resolution, we chose to use the temporal definitions to more accurately characterize the dynamics of the modeled delta.

We also used the techniques outlined in Trampush et al. [2017] (Chapter 3) to determine the scale break, namely by identifying the location where the 95% envelope of the compensation statistic for individual surfaces abruptly narrows and finding the minimum bin which can be used to fit a κ=1. Full methodologies and code used to calculate the compensation scale is available in the supplement. In order to verify whether larger compensation scales are associated with higher spatiotemporal heterogeneity of sedimentation, and to understand the spatial distribution of similarly aged sediments in different deltas, we analyzed the preserved sediments and the evolution of the chronostratigraphic surfaces over the duration of the model run. We again used the proximal, medial, and distal cross sections explained in section 2.1 to show the relief on chronostratigraphic surfaces, the amount of deposition and erosion through time (Figure 4-1d), the fraction of sand (Figure 4-1e), and variations in the age of deposition, across each cross section (Figure 4-1f). Histograms of the amount of change between the chronostratigraphic surfaces was constructed for each cross section as well as for every cell within the delta deposit (Figure 4-1h). Additionally, we also constructed maps which show the distribution of time and grain size across a constant depth (here, always at half the medial thickness of the total deposit) (Figure 4-1b and c). Finally, we show the location and magnitude of sedimentation events (defined as the difference between successive chronostratigraphic surfaces) at each cross section through the entire length of the model run.
4.2.2 Random sampling of model deposits

To determine how many 1D cores or sections would be needed to reconstruct a paleoenvironmental signal, we create a number of 1D records randomly from the synthetic deposit where sediment accumulation is greater than zero (Figure 4-2a). Packages of sediment within each 1D pseudo-cores are then grouped into intervals of time, simulating biostratigraphic zones that divide the synthetic stratigraphy into either four coarse-resolution intervals or eight finer-resolution intervals (Figure 4-2b). The duration of the coarse-resolution age control was chosen to be slightly larger than the measured compensation scale in most of the models, while the finer-resolution age control was chosen to be as low as or slightly lower than the measured compensation scale in all the models. Ensembles of increasing number of randomly sampled cores were constructed, and the median, minimum, and maximum thickness of sediment within each interval across the ensemble is then normalized by the expected thickness of each interval if time was evenly represented within the ensemble record (Figure 4-2b-c). We then measured the minimum number of cores needed to have a record which preserves all time intervals and the minimum number of cores needed to preserve an ensemble where all intervals are preserved evenly (Figure 4-2d). Finally, the average sedimentation rate was calculated for each interval using the average thickness of the interval across the ensemble and the duration of the interval.

4.3 Results

3.1 Spatial and temporal variability in sedimentation within the deltas

The proximal cross sections all have compensation scales within a (factor of 2) of their theoretical values predicted from their accumulation rate and maximum relief observed on the cross section (Table 4-1). The maximum amount of relief in the proximal cross sections increased
with increased fractions of fine grained material (Table 4-1). The resulting compensation scales also increased with increasing mud content. While the low-sedimentation-rate models also tended to have slightly larger compensation scales, this difference was small and not consistent across all models (e.g. Models B, E, and H). Similarly, compensation scales increase for the medial cross section. None of the most distal cross sections are fully compensational; only models A, B, and C show any signs of being close to compensating (Table 4-1, supplement). While the sub-compensational κ values indicate a weak tendency for the muddiest models to be clustered and the sandiest models to be more even, the sub-compensational κ values did not vary greatly between models.

Models that are either high sand content or high sedimentation rates have the most even and predictable distributions of time and lithology, although all models were less even and predictable in their most distal deposits (Table 4-2). Proximal, medial, and distal cross sections show age ranges are relatively well represented on the proximal and medial cross sections of models B, C, E, and F (Figure 4-2, 4-3, and 4-4). It is only in the cohesive models (A, D, and G) and the progradational models (G, H, and I) where large intervals of time are either overrepresented, in either channel fills (sandy deposits) or lobe deposits (muddy deposits), or missing entirely, either due to erosion or nondeposition (Figures 4-3, 4-4, 4-5). In maps of deposit age at a constant depth (Figure 4-6), again the more aggradation models (especially B and C, and to a lesser extent A) show relatively even distribution of time, with channel deposits generally a bit younger (due to channel incision) and floodplain deposits mostly the same age range. It is only towards the outer edges of the deltas where ages much younger than the average are found in the slowly prograding delta foreset. The sandy, intermediate and low sedimentation rate models (E, F, H, and I) show a pronounced zonation in ages in the muddy deposits, representing the progradation of the delta, punctuated by younger, sandier channel fills. The muddiest deltas, especially the intermediate and low sedimentation rate models (D and G) show very little
coherence in ages, except that single ages tend to be deposited in relatively large lobes or narrow channel fills. However, the progression from older, proximal sediment to younger, distal sediment seen in the fine-grained deposits of the other models is not obvious in models A, D, or G.

The probability of large depositional events is highest in channel fills or near the distal edge of the delta, especially in the less cohesive models (Figure 4-7). Sandier models and higher sedimentation rate models tend to be much more likely to have large depositional events at any given cell within the model domain (Figure 4-8). Similarly, cells in the more distal cross sections are also much more likely to have large depositional events than more proximal cells (Figure 4-8). Maximum deposition amounts tend to be concentrated in wide lobes across a wide area of the basin (Figure 4-7). By contrast, maximum erosion is most common in more proximal cells, especially in the muddier models and tends to be concentrated to narrow (channel-wide) swaths of the delta, especially near the apex of the delta (Figures 4-7; Table 4-2). The consequence of the spatial distribution of sedimentation and erosion events is apparent in the Wheeler diagrams of selected cross sections in Figure 4-9: in more cohesive or less aggradational models that hiatuses are longer and affect larger portions of the cross section at any given time.

4.3.2 Minimum sampling

Models with high compensation scales or low sedimentation rates needed the most cores to evenly preserve all time intervals (Figure 4-10 and 4-11). For the most variable models (Models A, D, and G) ~20-30 cores are needed before all four time intervals are represented evenly on average. In the least variable models (Models C, E, and I) only ~10-20 cores are needed before all intervals are evenly represented. Models with the highest sedimentation rate (Models A, B, and C) needed 5-10 cores to evenly represent all four intervals, while the lowest
sedimentation rate models (models G, H, and I) needed over 10 cores to represent all four time intervals.

When the length of the time intervals is larger than the compensation scale, fewer cores are needed to evenly preserve all time intervals. All models needed less than 40 cores to fully and evenly preserve all four time intervals, but all need more than 50 cores to fully and evenly preserve all eight time intervals (Figure 4-11). Additionally, the difference between the most underestimated time interval and the most overestimated time interval is much less for four time intervals than eight time intervals for all models (Figure 4-10 and 4-11).

The difference in the minimum cores needed to preserve some sediment of each time interval and the minimum cores need to evenly preserve all time interval can be large, especially in highly variable or low sedimentation rate models. In the most variable model relative to sedimentation rate (Model G), 30 cores are needed to ensure all 8 intervals are present and well over 50 are needed to evenly represent all 8 intervals. In contrast, the least variable model relative to sedimentation rate (Model C) needs ~10 cores to represent all 8 intervals and ~50 to represent all 8 intervals evenly.

The number of cores needed to accurately reconstruct the average sedimentation rate of the interval follows similar patterns to the number of cores needed to evenly reconstruct the preservation of time: more cores are needed to estimate the average sedimentation rate for short intervals, highly variable models, or low-aggradation models (Figures 4-12 and 4-13). For all models, it takes more than 20 cores to estimate the average sedimentation rate within a factor of 2 when the interval length is 1500 time steps (Figure 4-12). In contrast, it takes well over 40 cores to estimate the average sedimentation rate within a factor of 4 when the interval length is 750 time steps (Figure 4-13). In all models for both interval lengths, the average sedimentation rate is likely to be larger than the rate of accommodation creation, especially for the low aggradation rate models.
4.4 Discussion

In order to predict whether a given paleoenvironmental signal can be reconstructed from a suite of cores or stratigraphic sections from the same depositional system, there are four considerations in siliciclastic systems: the length of time over which the signal of interest varies, how variable the sedimentation is due to landscape dynamics, and the accumulation rate of the system, and whether all portions of the record need to simply be present or whether all portions of the signal need to be evenly represented. Paleoenvironmental signals which are shorter than the compensational scale may need an order of magnitude more cores to accurately reconstruct the signal than a change which over a timescale longer than the compensation scale. A system that has twice as large a compensation scale will need twice as many cores to reconstruct the same signal. Conversely, a system with twice as high accumulation rate may need half as many cores to accurately reconstruct the same signal. In all models and for both signal lengths we tested, an ensemble that has all portions of the record present is likely even with less than 10 records, and in the best cases, may only need fewer than five records. However, for each case, more than twice as many cores are needed to build an ensemble record in which each time interval is represented evenly, which would be necessary to reconstruct rates of change in paleoenvironmental conditions, for example.

The duration of the paleoenvironmental signal and the desired accuracy of the reconstruction will be dictated by the requirements of specific studies, but the scale of landscape variability and the accumulation rate of individual study locations can be estimated, even with sparse data. The compensation scale can be applied to both 2D and 1D data types, and in the 2D case at least, can be robustly applied to datasets with limited vertical resolution and narrow spatial extent. Even when specific metrics of variability cannot be directly measured, it is reasonable to estimate potential scales of landscape variability from known characteristics, including grain size,
channel or basin depths, or distance from the sediment source, for example, using the observations in section 3.1. Similarly, the results from Trampush and Hajek [in press] (Chapter 3) suggest that estimates of sedimentation rate do not need to be highly precise; the coarse estimates of sedimentation rate that are available in most situations can be used to create accurate ensemble records. Additionally, stretched, condensed, or missing intervals of time may be recognizable when chronostratigraphic packages have highly variable thicknesses or if those packages are not correlatable, even across short distances. Our analyses of average sedimentation rate suggest that we can estimate the accuracy of a sedimentation rate that is averaged across an ensemble. In ensembles with more than 10 cores will likely be able to estimate the long-term sedimentation rate within a factor of 2, as long as the measurement interval is longer than the compensation scale of the delta.

Our analyses focused on variations in sedimentation caused by autogenic processes. Equally important for accurately reconstructing paleoenvironmental signals is variations in sedimentation due to high-frequency events like floods, storms, or even earthquakes. Additional processes that can compound the problems associated with variable sedimentation, like bioturbation which can completely mix sediment, effectively homogenizing the ages of different sediment events, and bioturbation intensity is frequently correlated to sedimentation rate [Meysman et al., 2003, 2006; Bentley et al., 2006]. Similarly, early diagenesis, including the degradation of organic matter or the growth of minerals such as glauconite or carbonate nodules are also likely to be impacted by sedimentation rate, especially when diagenesis depends on staying shallow in the sediment column for extended amounts of time, which may alternately enhance or degrade the possibility to reconstruct complete, accurate paleoenvironmental reconstructions [El Albani et al., 2005; Payne et al., 2010; Gocke et al., 2012; Bataille et al., 2013]. Future studies should explore how these additional complications may interact with the autogenic processes to better design sampling strategies to reconstruct Earth’s history.
4.5 Conclusions

Here, we demonstrate how we can use landscape dynamics to predict how many 1D records are needed to accurately reconstruct paleoenvironmental signals. We demonstrate that there are two landscape controls on the sampling density needed to reconstruct rapid paleoenvironmental signals: the scale of landscape variability, which can be estimated using the compensation scale, and the long-term accumulation rate. Producing complete ensemble records from systems that are highly variable, such as muddy deltas, or systems that have low accumulation rates, such as deltas building on slowly subsiding passive margins, requires more than twice as many records as a delta with half the cohesion or twice the long-term sediment-accumulation rate. This difference in the sampling density is the result of the magnitude and spatiotemporal distribution of erosional and depositional event across the delta network. Our results demonstrate how an understanding of landscape dynamics can be used to improve the accuracy and constrain uncertainties of paleoenvironmental reconstructions. Future work should help integrate other processes that control the preservation of signals, such as non-autogenic sedimentation variability (e.g., sedimentation caused by floods and storms), bioturbation, and diagenesis.

Acknowledgments

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References


Figure 16: Example model output from an intermediate sedimentation rate and intermediate variability model. a. Map of final delta elevation, with the location of the proximal medial ($\chi=0.5$) cross section shown in red. b. Maps of the fraction sand and c. age of deposition of sediment found at a constant depth of half the deposit thickness. d. Erosion (blue) and deposition (red) that occurred through the model run at the medial cross section shown in a. e. Grain size fraction at the medial cross section. Black lines are chronostratigraphic surfaces extracted from the surface elevations every 50 time steps. f. Age of sediment packages deposited at the medial cross section. g. Compensation plot of the surfaces shown in b, black points are the median $\sigma ss$, black lines show the 2.5 and 97.5 percentiles of the $\sigma ss$. Dashed line shows the compensation scale. Blue line and text show the fit of eq. 2 to bins larger than the compensation scale while red lines and text show the fit of eq. 1 to bins smaller than the compensation scale. h. Histogram of the amount of change between the surface elevations calculated every 50 time steps for every cell within the model domain.
Figure 17: Example of random sampled cores. **a.** location of 5 random cores (red points). **b.** Plot of core stratigraphy colored by the finer resolution age control (each interval is 750 time steps long). **c.** Thickness of each time interval normalized by the expected thickness if time were evenly represented (black points and line), red line is the median time interval fraction of the ensemble of the ensemble, and dashed lines are the minimum and maximum time fraction. A median value closer to 1 indicate more even preservation. **d.** Median (red line), minimum and maximum (dashed lines) of ensembles created 1 to 50 randomly chosen cores. The first dashed line marks where ensembles are likely to preserve all time intervals, the second dashed line marks the minimum number of cores that are likely to have relatively even preservation of all time intervals (defined by the median representation near 1 and a narrowing of the minimum and maximum envelope). Medium, minimum, and maximum values are calculated using 1,000 Monte Carlo simulations of each ensemble.
Figure 18: Grain size fraction (above) and age of deposition (below) of the proximal ($\chi = 0.25$) cross section of all nine models. Color scale is the same as in Figure 4-1, letters indicate model name. Letters correspond to the model name listed in Table 1; variability decreases towards the right (i.e. the input grain size fraction is coarser) and sedimentation rate decreases towards the bottom (i.e. the rate of accommodation creation is slower). Note that while the high sedimentation rate (Models A-C) or low variability models (Models C, F, and I) show relatively even intervals of similar age sediment, more variable models and lower sedimentation rate models have much more patchy preservation.
Figure 19: Grain size fraction (above) and age of deposition (below) of the medial ($\chi = 0.50$) cross section of all nine models. Color scale is the same as in Figure 4-1. Letters correspond to the model name listed in Table 1; variability decreases towards the right (i.e. the input grain size fraction is coarser) and sedimentation rate decreases towards the bottom (i.e. the rate of accommodation creation is slower). While the highest sedimentation rate and lower variability models still have relatively even preservation, high variability and lower sedimentation rate models have very patchy preservation.
Figure 20: Grain size fraction (above) and age of deposition (below) of the proximal ($\chi = 0.25$) cross section of all nine models. Color scale is the same as in Figure 4-1. Letters correspond to the model name listed in Table 1; variability decreases towards the right (i.e. the input grain size fraction is coarser) and sedimentation rate decreases towards the bottom (i.e. the rate of accommodation creation is slower). Note that even the highest sedimentation rate and lowest variability models are more patchy than the proximal cross section. The highest variability and lowest sedimentation rate models have very obvious gaps and spatial heterogeneity even over small lateral distances.
Figure 21: Distribution of ages and lithology found at a constant depth equivalent to half the median thickness of each deposit. Color ranges are the same from Figure 4-1. Letters correspond to the model name listed in Table 1: variability decreases towards the right (i.e. the input grain size fraction is coarser) and sedimentation rate decreases towards the bottom (i.e. the rate of accommodation creation is slower). High sedimentation rate models have similar age materials at ~the same depth for most of the delta area, with only the distal edge of the deltas showing any significant deviations. Low sedimentation rate but low variability models show a clearly defined and predictable progression of old sediment near the river mouth and younger sediment prograding out into the basin. High variability models, however have large differences in sediment age over relatively small regions.
Figure 22: Plots of erosion and deposition over time at the proximal, medial, and distal cross sections for the highest variability models (top 3 rows) and the lowest variability models (bottom three rows). Color scale is the same as in Figure 4-1. In all models deposition is more broadly distributed than erosion. Erosional events increase in frequency and magnitude for the higher cohesion model and for the lower sedimentation rate models. Erosion is also more common in the proximal cross section. The low cohesion models seem to have more small events that are spread evenly over the cross section, whereas the high cohesion models have distinct focuses of sedimentation and erosion that persist over longer periods before moving to another location on the cross section. The initial sediment flux to the basin is marked by a short period of high deposition in all models.
Figure 23: Histograms for the amount of change observed at every cell on the delta between the elevations of every 50th time step (the same surfaces shown in Figures 4-1e,f). High sedimentation rate models are dominated by depositional events while low sedimentation models have increasingly more contribution of erosion. Higher cohesion models are associated with higher magnitude, low frequency erosional events.
Figure 24: Wheeler diagrams of the preserved sediment shown in Figure 4-7; bottom axis is cross stream distance in km, the vertical axis is time (increasing to the top), and the colored pixels represent sediment that was preserved at the end of the model simulation. Colors are the same as Figure 4-1f. The high variability models (A, D, and G) have longer hiatuses with a larger spatial correlation than the lowest variability models (C, F, and I). The length and spatial distribution of hiatuses increases for the more distal cross sections. The models that have the high rates of accommodation creation (models A and C) have fewer hiatuses than models with the lowest rate of accommodation creation (models G and I).
Figure 25: Number of cores needed to evenly represent all 4 intervals in an ensemble, when the interval length is 1500 time steps. Symbols are the same as in Figure 4-2d. Both the minimum number of cores to preserve all time intervals and the minimum number of cores to evenly preserve all time intervals is highest for low sedimentation rate, high variability environments.
Figure 26: Number of cores needed to evenly represent all 8 intervals in an ensemble when the interval length is 750 time steps. Symbols are the same as in Figure 4-2d. Both the minimum number of cores to preserve all time intervals and the minimum number of cores to preserve all time intervals is highest for low sedimentation rate, high variability environments. None of these models are likely to preserve all 8 intervals evenly within a factor of 2.
Figure 27: Average sedimentation rate for any of the four intervals measured in Figure 4-10. Red line is the median estimate of the average sedimentation rate for the ensemble record for any of the four time intervals, black lines are the minimum and maximum estimates of the average sedimentation rate for the ensemble record of any of the four time intervals. Blue line is the rate of accommodation creation for each model. Medium, minimum, and maximum average sedimentation rate lines are calculated using 1,000 Monte Carlo simulations of each ensemble. All models can reconstruct the average sedimentation rate within a factor of 2 when the ensemble is larger than 10 cores. However, estimates are highly likely to slightly over-estimate the average sedimentation rate.
Figure 28: Average sedimentation rate for any of the eight intervals measured in Figure 4-11. Red line is the median estimate of the average sedimentation rate for the ensemble record for any of the four time intervals, black lines are the minimum and maximum estimates of the average sedimentation rate for the ensemble record of any of the four time intervals. Blue line is the rate of accommodation creation for each model. Medium, minimum, and maximum average sedimentation rate lines are calculated using 1,000 Monte Carlo simulations of each ensemble. All models can reconstruct the average sedimentation rate within a factor of 2 when the ensemble is larger than 40 cores. However, estimates are highly likely to slightly over-estimate the average sedimentation rate.
<table>
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<th>Model Name</th>
<th>Sand content (%)</th>
<th>Sea level rise (m/time step)</th>
<th>Basin length (km)</th>
<th>Basin width (km)</th>
<th>Initial channel depth (m)</th>
<th>Initial basin depth</th>
<th>Total time steps</th>
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<td>10.00</td>
<td>5</td>
<td>10</td>
<td>6000</td>
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<td>5.00</td>
<td>10.00</td>
<td>5</td>
<td>10</td>
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<td>5.00</td>
<td>10.00</td>
<td>5</td>
<td>10</td>
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### Table 4-2 Cross section measurements

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<th>Median depth (m)</th>
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Chapter 5

Landscape dynamics and stratigraphic completeness across the Paleocene-Eocene Thermal Maximum on the Mid-Atlantic shelf

Abstract

Understanding how the Mid-Atlantic shelf responded to the Paleocene-Eocene Thermal Maximum (PETM) is important for evaluating how sedimentary and biological systems on continental shelves respond to periods of abrupt warming. While specific biological and geochemical responses have been extensively studied in this region, a comprehensive picture of sedimentary environments and depositional processes throughout the PETM remains elusive. Constraining these changes in sedimentary dynamics is necessary to understand how the North American shelf environments responded to the PETM and to evaluate the completeness and fidelity of the PETM record in general. In order to improve paleoenvironmental and sedimentary-process interpretations of the PETM mid-Atlantic shelf, we analyzed 16 cores drilled in New Jersey, Maryland, and Virginia. We find that during the PETM the environment transitioned from a low accumulation rate, storm-dominated shelf to a rapidly aggrading river-dominated shelf. While only the most proximal cores show sedimentary features associated with hyperpycnal deposits derived from river discharges with high concentrations of suspended sediment, all cores locations show signs of a progradation of fine grained, likely terrestrial sourced sediment. After the PETM recovery, the entire shelf transitions back to a low aggradation storm-dominated shelf remarkably similar to the pre-PETM environment. We use insight from modeling studies to evaluate the degree to which variability in sedimentation inherent in prodelta settings may influence geochemical proxy records of the PETM. We find that, particularly in the Maryland and
Virginia sections, PETM records are likely to be highly variable. Even nearby records with similar-looking lithological characteristics are likely to record very different intervals of time and likely contain significant temporal gaps. As a consequence of this variability, it may be difficult to correlate chronostratigraphic packages accurately among the cores, ultimately causing the apparent timing of onset, rate of onset, duration, and recovery of the PETM to differ between cores.

5.1. Introduction

Anthropogenic climate change is predicted to severely impact landscapes around the world, but there remains significant uncertainty about the rate and the magnitude of response expected in different environments, especially along our coasts and shallow shelves [e.g., Syvitski et al., 2009, 2012; Bentley et al., 2016]. Marine biogeochemical systems are sensitive to ocean temperature, salinity, pH, dissolved oxygen content, and nutrient availability – conditions which are influenced by the flux of water, sediment, and nutrients from land. Studying how shallow-marine systems in Earth’s past have responded to abrupt climate warming provides an opportunity to improve our understanding of the sensitivity and resilience of Earth systems and to better understand the coupling between terrestrial landscapes and marine environments. The stratigraphic record of shelf environments is an important resource for studying the complex interactions and responses of physical, chemical, and biological systems along continental margins.

One of the best natural analogs for the landscape response to anthropogenic climate change may come from the Paleocene-Eocene Thermal Maximum (PETM), a rapid global warming event ~56 Ma that resulted from a rapid injection of carbon into the atmosphere [McInerney and Wing, 2011; Tipple et al., 2011; Sluijs et al., 2014; Kirtland Turner and
Globally, records from different settings show a wide range of landscape responses to the PETM. For example, some fluvial systems, like the Wasatch Formation in western Colorado, show a dramatic change in the width and depth of channel sand bodies, and likely flow velocity (as evidenced by an increase in bed form associated with supercritical flow) [Foreman et al., 2012]. Other fluvial systems, even nearby fluvial systems like in the Willwood Formation of northern Wyoming, show a much more subdued response [E. Greenberg, unpublished M.S. thesis]. Similarly, some shelf systems show a radical change in sedimentology of PETM deposits (e.g. the mid-Atlantic shelf) whereas other shelf deposits do not (e.g. shelf deposits in California) [John et al., 2008]. This has led to many outstanding questions about how resilient or sensitive different physical landscapes were to changes during the PETM [e.g., Gibson et al., 2000; Handley et al., 2011, 2012; Foreman et al., 2012; Stassen et al., 2012; Foreman, 2014].

In addition to the range of paleoenvironmental changes documented across the PETM in different settings, there are significant differences in the apparent rate and duration of forcing driving the global carbon cycle and the amount of time it took for the Earth system to recover from the PETM event [Bowen and Zachos, 2010; McInerney and Wing, 2011; Wright and Schaller, 2013; Penman et al., 2014]. We have shown that some of these apparent differences may be related to differences in sediment-accumulation rates – particularly in clastic, sediment-transport dominated settings like fluvial landscapes, deltaic coastlines, and clastic storm shelves [Trampush and Hajek, in press; Trampush and Hajek, in prep] (Chapter 3 & Chapter 4). This is because in these settings, sediment-transport dynamics are highly nonlinear resulting in patchy and uneven representation of time in a given locality. Furthermore, sediment transport in fluviodeltaic and clastic shelves is inherently dynamic with variability that can extend up to many 10s of kyr meaning that changes in environmental conditions caused by the PETM may not be differentiable from the background environmental “noise” in some systems [Jerolmack and
Sadler, 2007; Jerolmack and Paola, 2010; Ganti et al., 2011; Schumer et al., 2011; Trampush and Hajek, 2017; Trampush et al., 2017]. This is especially true for environments with highly variable internal (autogenic) dynamics and relatively low net sedimentation rate, poorly exposed or sparsely sampled environments, or small magnitude or particularly rapid climate changes [Trampush et al., 2017, Trampush and Hajek, in press, Trampush and Hajek, in prep] (Chapters 2, 3, and 4).

Shelf deposits from the Mid-Atlantic Paleocene-Eocene section show significant biological, chemical, and physical sedimentological changes during the PETM [Kopp et al., 2009; Stassen et al., 2012a; Self-Trail et al., 2017]. This region has been intensely studied for the biological, ecological, and ocean chemistry response to the PETM [e.g., John et al., 2008; Kopp et al., 2009; Self-Trail et al., 2012, 2017, Stassen et al., 2012a, 2015; Babila et al., 2016; Bralower and Self-Trail, 2016]. In the Mid-Atlantic shelf deposits, the PETM carbon isotope excursion (CIE) is synchronous with the change in deposition from a glauconitic sand or mud to a kaolinite-rich clay across the broad region from Maryland through New Jersey (Figure 5-1) [Gibson et al., 2000; Kopp et al., 2009; Stassen et al., 2012a, 2014]. After the CIE recovers to pre-PETM values, lithologies very similar to pre-CIE sediments reappear [Kopp et al., 2009; Stassen et al., 2012a]. While the high levels of kaolinite may or may not be related to a change in weathering in the sediment source region [Gibson et al., 2000; Stassen et al., 2014], it is apparent that the processes active on the shelf must have changed significantly [John et al., 2008; Stassen et al., 2012a; Self-Trail et al., 2017]. On the basis of microfossil assemblages, Kopp et al. [2009] suggested that there may have been a dramatic change in riverine input over the PETM. Similarly, Self-Trail et al. [2017] use changes in nannofossil assemblages, early diagenic minerologies, and the presence of pro-delta sediments to suggest a high terrestrial input of water and sediment during the peak of the PETM.
The shift to more terrestrially influenced sedimentation on the mid-Atlantic shelf suggests that the dominant sediment-transport processes acting on the shelf changed during the PETM. This change, and the likelihood that both fluviodeltaic sediment supply and storm events contributed significantly to episodicity of sedimentation on the shelf during the peak of the PETM, raise the possibility that paleoenvironmental proxy records from the PETM may be significantly influenced by variability in sedimentation, which may contribute to uncertainties in correlation and apparent differences in the rate of onset, duration, and recovery reconstructed from Atlantic shelf cores. Here, we use 16 cores that have been collected in Maryland, Virginia, and New Jersey to assess the sedimentologic evidence for a change in the supply and transport of sediment across the Mid-Atlantic shelf. Additionally, we assess how stratigraphically complete the record of landscape change is using evidence from the sedimentology, published biostratigraphy, and published bulk carbonate carbon isotope from a selection of the cores.

5.2. Geologic Setting

The Paleocene-Eocene Thermal Maximum (PETM) is preserved in the sediment in the coastal plain of the Mid-Atlantic (mainly in Maryland, Virginia, and New Jersey, USA). These sediments were deposited in a coastal shelf environment, called the Salisbury Embayment, which is a basement structure bound by the Norfolk arch and James River structural zone to the south, the fall line to the west and the South New Jersey High to the north [Kopp et al., 2009; Self-Trail et al., 2017]. The PETM carbon isotope excursion (CIE) is found in the kaolinite-rich formation called the Marlboro Clay and the lowest member of the Nanjemoy Formation in Maryland and Virginia and the equivalent clay found in the lowest member of the Manasquan Formation in New Jersey (Figure 5-1). The Marlboro Clay and equivalents are immediately above the Aquia Formation of Maryland and New Jersey and the Vincentown Formation of New Jersey. This
lower contact has been described as depositional and gradational by some authors and unconformable by others [Kopp et al., 2009; Stassen et al., 2012a; Self-Trail et al., 2017]. The upper contact has been described as erosional to varying degrees [John et al., 2008; Stassen et al., 2012a; Self-Trail et al., 2017].

Subsidence rates in the Salisbury Embayment are generally controlled by the thermal cooling of the basement and loading by sediment [Poag and Sevon, 1989; Kopp et al., 2009]. Sediment was supplied to the margin mostly by the paleo-Susquehanna and paleo-Potomac in roughly their modern locations [Poag and Sevon, 1989]. Sedimentation rates have been described as ~30 cm/kyr on the high end [Kopp et al., 2009] and ~10 cm/kyr on the low end [Self-Trail et al., 2012]. Much of the disagreement may be related to geographic differences. However, the higher sedimentation rates use empirical relationships between depth and porosity to decompact the sediment and estimate a sedimentation rate for the interval, while the estimates on the low end correlate the carbon isotope excursion to an astronomically calibrated deep marine record [John et al., 2002; Kopp et al., 2009; Self-Trail et al., 2012]. Similarly, water depth has been interpreted as ~100 m at the deepest area measured and <50 m at the shallowest area measured by some research groups, while others have the range closer to 200 m at deepest section and 50 m at the shallowest [Kopp et al., 2009; Harris et al., 2010; Stassen et al., 2015; Self-Trail et al., 2017].

Sea level rise across the PETM has been described as ~25m based on downdip associations of facies and depth control from foraminifera [Harris et al., 2010; Stassen et al., 2015], but this has also been contested [McInerney and Wing, 2011]. One problem with both water depth and sea level rise is that shoreline sediments are not preserved, and the best constraint on the location of the shoreline is somewhere near the Fall Line [Kopp et al., 2009; Self-Trail et al., 2017].
5.3. Methods and data

To reconstruct the depositional processes across the Salisbury Embayment, data were collected from 16 cores in Maryland, Virginia, and New Jersey (Figure 5-2). Observations on the lithology and sedimentary structures in selected cores from Maryland and Virginia were collected using both the original drilling lithology descriptions, published studies, and descriptions collected from the cores stored at the U.S. Geological Survey core repository in Reston, Virginia [Kopp et al., 2009; Self-Trail et al., 2017]. Data from the New Jersey cores was collected using the original drilling logs and published data [Stassen et al., 2012a; Wright and Schaller, 2013]. Cores were then correlated based on the bottom and top of the Marlboro or equivalent and placed in proximal to distal transects (Figure 5-3 and 5-4).

Basic facies analysis was created using the grain size, mineralogy, and sedimentary structures of each core. Isopach maps were created of the Marlboro Clay using the isopach published in Kopp et al. [2009], updated with more recent cores at Merkel, MCBR, Knapp’s Narrows, and Howards Track. Published biostratigraphy and carbon isotope analyses from bulk carbonate records were compiled for all available cores [Self-Trail et al., 2012; Stassen et al., 2012a; Wright and Schaller, 2013]. To get event types (i.e. hyperpycnal flow, storm or wave deposits, etc.) and event frequencies, the bed thickness, grain size, and sedimentary bed structures were collected from the most proximal core using a combination of detailed measurements of both the core and radiographs from the Marlboro Clay in the MCBR site.

Finally, we use environmental interpretations to apply the modeling results from Trampush and Hajek [in press] (Chapter 3) and Trampush and Hajek [in prep] (Chapter 4) to determine the probability that individual records have been altered by landscape dynamics and whether there are enough cores to be able to reconstruct the environmental response to the PETM with certainty.
5.4. Depositional Environments before, during, and after the PETM

5.4.1 Facies description

The Aquia Formation facies are dominated by glauconitic sands that have been heavily bioturbated such that few primary structures are preserved. In intervals that are less bioturbated and with a higher percent of a muddy matrix, burrows are clearly subhorizontal and mud lined, with diameters up to 2 cm. Sand grains are either sub- to well-rounded quartz grains or sub- to well-rounded glauconite grains, indicating some amount of transport has occurred. Matrix contains varying percentages of clay and silt, many with visible flakes of muscovite and fine flakes of black material which may be organic material or crushed glauconite. There are common shell beds throughout the Aquia Formation (Figure 5-5), shell beds are generally dominated by a few genera of gastropods and bivalves. The Vincentown Formation facies are generally described as very similar to the Aquia Formation, but the overall grain size is much finer and shell beds may be less numerous.

The Marlboro Clay is dominated by finely laminated clay and silt with rare sub-horizontal burrows. Color of the laminated clay ranges from light pink in the proximal cores to light gray in the distal cores. Burrows tend to be slightly siltier than the surrounding material and are sometimes filled with pyrite. In the Maryland and Virginia cores, the grain size increases from almost pure clay at the base to a much siltier clay (verging on a clayey silt) at the top of the Marlboro. However, the core descriptions and published lithology of the New Jersey cores are not sufficient to resolve this subtle difference in grain size. The bottom contact of all the cores occurs over 2-10 cm and it is more bioturbated than the overlying formation. The upper contact is sharp
and is irregular in some of the few outcrop exposures of the formation, although there is some bioturbation that obscures the contact in some cores (Figure 5-3 and 5-4).

The Marlboro Clay in the most proximal cores (MCBR and MWS) has an additional facies that is characterized by sharp-based, very thin beds of laminated to massive coarse silt to very fine lower sand. In the most proximal core (MCBR), these silt beds where very common and thicker beds have low angle cross lamination consistent with current ripples (Figure 5-6). The beds at MCBR are between 0.5 cm and 10 cm thick, with an average thickness ~5 cm. Other cores have wispy lamina of silt, but they rarely are thicker than 0.5 cm.

The Nanjemoy Formation has facies very similar to the Aquia. It consists of glauconitic sands with varying levels of muddy matrix (20 - 40%). The quartz sand grains are subrounded and slightly coarser than in the Aquia Formation. Glauconite grains are rounded and sand sized. Shell beds are common and are more diverse than the Aquia Formation’s shell beds, with many different bivalves and gastropods. Some isolated phosphate layers were identified throughout the Nanjemoy. The formation is highly bioturbated throughout and burrows, where visible in less well bioturbated intervals, are subhorizontal and mud lined, with diameters up to 2 cm. The portions of the Manasquan Formation that are equivalent to the Nanjemoy is notably finer; in more distal cores it rarely has grains coarser than fine silt. It still has a high proportion of glauconite, but the morphology of the grains is not described in the core logs or published descriptions [Harris et al., 2010; Stassen et al., 2012a].

5.4.2 Map distribution of facies and isopach

The larger quartz grains fine away from the modern day location of the mouths of the Susquehanna and Potomac Rivers in both the Aquia/Vincentown Formations (Figure 5-7) and the Nanjemoy/Manasquan Facies (Figure 5-8). Similarly, the amount and thickness of the silt event
beds decreases away from the modern location of the Susquehanna and Potomac Rivers (Figure 5-9).

The isopach of the Marlboro clay shows the thickest accumulations of clay are located in a band that runs northeast-southwest starting near the Cam-Dor/South Dover Bridge cores and ending near the Millville core (Figure 5-10 and 5-11). The upper contact shows the unit thins and disappears toward the modern day location of the Chesapeake Bay and the Knapps Narrows core and again near the Double Trouble core in New Jersey. One explanation of this isopach pattern is small windows in the deposition of the unit or isolated regions of erosion (Figure 5-10). Another explanation is that these are larger erosional features that may be related to channels or active faults centered near Double Trouble in New Jersey and Knapps Narrows in Maryland (Figure 5-11). We argue the second model is a better explanation, for the following reasons: the upper contact of the Marlboro Clay is erosional in all locations and the erosion appears to increase for cores near both Double Trouble and Knapps Narrows, the underlying Aquia Formation is coarser and has much less cohesive material and so would be easily eroded, and small thrust faults in the Mid-Atlantic Coastal Plain have a similar trend (D. Powars pers. comm.). Regardless, the isopach pattern indicates a minimum incision of around 15 m near the location of the coarsest grain sizes in the Aquia and Nanjemoy formations.

5.4.3 Correlation of biostratigraphy and bulk carbonate isotope records

A updip to downdip transect of the bulk carbonate carbon isotope curves in Maryland and New Jersey (Figure 5-12) shows that the onset is apparently most expanded (i.e. is thickest) in the most proximal cores, especially in the Maryland cores. The apparent rapidity of the onset increases with the more distal cores, with the Bass River onset appearing as almost instantaneous (Figure 5-12d). The maximum magnitude of the negative excursion varies between -7‰ and -
The shape of the CIE also varies between a more box-like excursion in Clayton and a more triangular excursion in Bass River. The biostratigraphy of the interval shows considerable variability between the thicknesses of biozones as they appear in multiple cores. There are multiple unconformities identifiable from the biostratigraphy, most notably one at the top of the Marlboro Clay, typically after NP 10a. However, the magnitude of this unconformity appears to be larger in more proximal locations or locations near the where the coarsest grain sizes are found in the underlying and overlaying formations (Figure 5-7 to 5-9). In two cores, Double Trouble and Knapps Narrows, the entire PETM interval has been removed along with some amount of the Late Paleocene deposits (Figure 5-10 and 5-11). The biostratigraphy of the lower contact of the Marlboro does not demonstrate any significant unconformity in the proximal cores (Figure 5-12). However, because of barren zones near the contact, biostratigraphy cannot be precisely established near the lower boundary [Bralower and Self-Trail, 2016]. Notably, the sharpest apparent CIE onset (Bass River) has little to no sediment from the lowest PETM-associated biozone (NP 9b).

5.4.4 Interpretation of depositional environments

The pre-PETM and post-PETM facies are consistent with a storm dominated shelf that has a significant supply of riverine sediment, similar to the modern Eel River and Brazos river shelves in northern California and Texas, respectively [Wiberg, 2000; Bentley and Nittrouer, 2003; Carlin and Dellapenna, 2014]. Sediment is coarse near the river mouth(s) and heavily bioturbated and wave-reworked enough to remove evidence of primary sedimentary structures, which is very consistent with shelf sediments in storm dominated shelves [Bentley and Nittrouer, 2003; Hale et al., 2014]. While glauconite does indicate a very low sedimentation rate when it is formed in situ, the rounding of the glauconite in the Maryland cores indicate some degree of
transportation [El Albani et al., 2005; Sluijs et al., 2014]. It is possible that the glauconite was not
developed in the local sediment column, but perhaps in sediment at shallower depths on the shelf,
indicating that the local sedimentation may be higher than the glauconite suggests [El Albani et
al., 2005]. Alternatively, the glauconite rounding may be the result of wave reworking the
sediment column but may not indicate down-shelf transportation. Resuspension and cross shelf
transportation are common occurrences on modern shelves [Bentley and Nittouer, 2003; Carlin
and DellaPenna, 2014]. Shell beds in both the pre-PETM and post-PETM also show evidence of
wave reworking, as all the bivalves are disarticulated, turritellid gastropods occasionally show a
preferential orientation, and shell beds are commonly graded.

The Marlboro Clay, by contrast, shows signs of being a river dominated shelf. The event
beds in the proximal Maryland cores are most consistent with facies models of deposits from
hyperpycnal flows (a type of density flow originating from high-density, sediment-rich river
discharge entering lower density, still water) [Bhattacharya and MacEachern, 2009; Lamb and
Mohrig, 2009; Olariu et al., 2010]. Moreover, the limited variety and abundance of trace fossils
are indications of an environment that is stressful for most organisms, most commonly related to
high levels of freshwater input and/or high concentrations of sediment (and the corresponding
high levels of turbidity) [Dalrymple and Choi, 2007; Bhattacharya and MacEachern, 2009]. The
presence of larval mollusks and the absence of adult mollusks suggest that there may have been
seasonally low oxygen concentrations in the Maryland cores [Self-Trail et al. 2017]. Additionally,
the coarsening up nature of the Marlboro Clay indicates progradation of fine grained sediment, an
interpretation which is also supported by the large hiatuses common in the most proximal
locations.
Based on comparisons to models of signal preservation in variable landscapes, the individual records of the PETM from the Salisbury Embayment are highly likely to be incomplete. Based on Trampush and Hajek [in press] (Chapter 3), the probability of signal preservation depends on net sedimentation rate and the variability of the environment. The distribution of hyperpycnal event beds suggest that the flood frequency during the PETM was similar to rivers like the modern day Eel River or Brazos River, both of which are highly variable [Wiberg, 2000; Bentley and Nittouer, 2003; Carlin and Dellapenna, 2014]. Similarly, other paleontological indicators suggest that the Salisbury Embayment may have experienced increased seasonality, potentially including large storms that can move sediment even across deeper portions of the shelf [Sluijs et al., 2011; Self-Trail et al., 2012, 2017; Stassen et al., 2015]. Sedimentation rate did increase over the PETM, but they were likely still relatively low [John et al., 2008; Self-Trail et al., 2012]. Although estimates of much higher sedimentation rates exist [e.g. Kopp et al. 2009], biostratigraphic control suggests low sedimentation [Self-Trail et al., 2012]. High variability and low sedimentation rate were the models most likely to produce heavily altered (i.e. incomplete) proxy records in Trampush and Hajek [in press] (Chapter 3).

Indeed, the bulk carbon CIE records in Figure 5-12 show broad differences between the magnitude and shape of the CIE that are consistent in results from the “Model 4” scenario; even the number of cores missing the CIE is similar to the model predictions: 1 out of 8 records in the model (see Chapter 3 supplement in Appendix B) compared to 2 in 16 cores that lack the PETM interval. However, there are indications that the erosion in at least the Knapps Narrows site may be associated with a thrust fault active during the deposition [D. Powars pers. comm.].

Comparisons of the Salisbury Embayment PETM records to the results of Trampush and Hajek [in prep] (Chapter 4) further indicates that the ensemble of all 16 records within the system
are still likely to be incomplete. As the Maryland and Virginia cores seem to be from a prodeltaic environment, they are likely impacted by autogenic variability in addition to variability imparted by storms and floods described above. The overall extremely fine nature of the Marlboro Clay, even the flood deposits, indicates that the delta which supplied sediment was likely also fine grained. In the models with high cohesion and low sedimentation rate in Trampush and Hajek [in prep] (e.g. “Model G”), distal deposits were highly incomplete due to the spatiotemporal distribution of depositional events. Additionally, high cohesion and low sedimentation rate environments all needed more than 15 records to accurately record paleoenvironmental signals under the best circumstances (e.g., no storms or floods, unambiguous age control, no bioturbation, or diagenesis). The Salisbury Embayment may have over 16 cores, but age control is frequently ambiguous, bioturbation and diagenesis are both present, and there is evidence of storms and floods impacting the sediment with some regularity. This suggests that while the Salisbury Embayment PETM deposits are among the most sampled single-depositional systems within global PETM records, they should not be viewed as complete or unbiased.

5.6. Discussion and Conclusions

The Salisbury Embayment on the Mid-Atlantic shelf did experience a large change in landscape dynamics coincident with the PETM as the shelf switched from a storm-dominated shelf with extremely low sedimentation rates to a river-dominated shelf with relatively higher sedimentation rate. This is demonstrated by a progradation of fine grained sediment likely associated with an increase in fluvial supply to the shelf near the probable location of the Paleo-Susquehanna and Potomac rivers. We argue that while this change is likely due to the response of the shelf to the PETM, individual records of the event are highly likely to be incomplete. Additionally, even an ensemble across all known cores within the Salisbury Embayment, one of
the most studied individual basin with global PETM records, are still likely to be incomplete.

Future work to improve the resolution and uncertainties of the reconstruction of the PETM may need to incorporate additional core localities and better estimate the frequency and magnitude of the active landscape dynamics.

References


Foreman, B. Z. (2014), Climate-driven generation of a fluvial sheet sand body at the


Stassen, P., R. P. Speijer, and E. Thomas (2014), Unsettled puzzle of the Marlboro clays,


Figure 29: Generalized chronology, lithology, and carbon isotope expression of the Paleocene-Eocene Thermal Maximum (PETM) in the Salisbury Embayment in Maryland, Virginia, and New Jersey. The PETM Carbon Isotope Excursion (CIE) occurs predominately in the kaolinite-rich Marlboro Clay. The final recovery of the CIE can be in the lowest members of the Nanjemoy or Manasquan Formation, but this portion of the event is not always preserved. Biostratigraphy is from Self-Trail et al. [2012] and Stassen et al. [2012].
Figure 30: Location of cores within the Salisbury Embayment. MCBR = Mattawoman Creek, JL = Jackson Landing, MWS = Merkle Wildlife Sanctuary, Lo = Loretto, KN = Knapps Narrows, SDB = South Dover Bridge, CD “Cam-Dor” or Cambridge-Dorchester Airport, SH = Surprise Hill, WL = Wilson Lake, An = Ancora, SG = Sea Girt, DT = Double Trouble, and BR = Bass River. Solid lines show the New Jersey and Maryland down dip transects.
Figure 31: Maryland core lithologic log and correlations. Measurements are in depth (feet), symbology is the same as in Figure 5-1. Horizontal spacing is not to scale.
**Figure 32:** New Jersey core lithologic log and correlations. Measurements are in depth (feet), symbology is the same as in Figure 5-1. Horizontal spacing is not to scale.
Figure 33: Glauconite sands and shell beds in the a) Nanjemoy Formation near Eagle’s landing on the bank of the Potomac River in the hanging wall of a small thrust fault (to the left of the picture location), and b) Aquia Formation across from Aquia Creek on the Potomac River. Black bars are a meter.
Figure 34: a. X-radiograph of a portion of MCBR hole 1. Coarser grains appear lighter. Core is 3.25 in wide. b. Interpreted bedding and lamination showing silt beds with erosive bases, graded bedding, and low angle cross laminations. c. Core photograph of a similar interval of silt beds in MCBR hole 3. Red sediments are finer grained, grey sediments contain higher levels of silt, ripple cross lamination near the 0.1 mark on the measuring tape is coarse silt to very fine lower sand. d. Interpreted bedding and laminations of core photograph showing a sharp-based silt bed with low-angle cross lamination.
Figure 35: Map of the coarsest quartz grain size immediately below the Marlboro Clay contact with the Aquia Formation in Maryland or the Vincentown Formation in New Jersey.
Figure 36: Map of the coarsest quartz grain size immediately above the Marlboro Clay contact with the Nanjemoy Formation in Maryland or the Manasquan Formation in New Jersey.
Figure 37: Map of facies interpretations of the Marlboro Clay based on grain size and the presence or absence of the silt event beds shown in Figure 5.
Figure 38: Isopach map of the preserved thickness of the Marlboro Clay. Gray “X” and contours are data and interpretations from Kopp et al. [2009]. This isopach map assumes that erosion of the Marlboro Clay occurred in highly localized, circular regions.
Figure 39: Isopach map of the preserved thickness of the Marlboro Clay. Gray “X” and contours are data and interpretations from Kopp et al. [2009]. This isopach map assumes that erosion of the Marlboro Clay occurred along a linear trend and increased towards the shoreline.
Figure 40: Bulk carbon isotope excursions from New Jersey colored by nannofossil biostratigraphic zone (dark green = NP 9a, light green = NP 9b, light blue = NP 10a, dark blue = NP b-d, purple = NP 11, grey are regions where a biostratigraphic zone cannot be assigned) and arranged from proximal to distal. a. is Clayton, an outcrop to the northwest of Wilson Lake, b. is Wilson Lake, c. is Ancora, and d. is Bass River. Bass River, the most distal core, shows evidence of truncation of the onset and peak of the excursion: NP 9b aged sediment is either missing entirely or occurs exclusively in the thin barren zone near the excursion, the excursion appears nearly instantaneous, and the magnitude of the excursion is the least out of all four CIE’s. By contrast the more proximal localities show relatively large excursion, a more gradual excursion, and they have relatively thick NP 9b packages of sediment.
Chapter 6

Conclusions

6.1 Summary

The stratigraphic record is a critical archive for understanding how sensitive landscapes, ecosystems, and other geosystems are to climatic forcing. While landscape dynamics remain a challenge to reconstructing paleoenvironmental signals, they are not an insurmountable challenge. Through the four projects described in this dissertation, I have demonstrated how we can measure the scale of landscape variability, assess the likely influence of that variability on the preservation and interpretation of geochemical paleoenvironmental proxies, and demonstrated how the original paleoenvironmental signals—even relatively rapid signals—can be successfully reconstructed with ensemble records made of a sufficient number of individual records for the landscape variability relative to the sedimentation rate of the study environment. Additionally, I demonstrated that signal preservation can be assessed and predicted in field systems, even with the presence of sparse data. Future research opportunities that stem from all four projects include analyses of different types of signals, including Milankovitch cycles, the incorporation of different processes that limit signal preservation, such as bioturbation or biologically mediated changes in sedimentation rate, and new ways to measure landscape variability in sparsely sampled deposits.
6.2 Key Contributions

Chapter 2: Identifying autogenic sedimentation in fluvial-deltaic stratigraphy: evaluating the effect of outcrop-quality data on the compensation statistic

The first project used a physical experiment and four example field datasets in order to test the sensitivity of the compensation statistic to identify landscape dynamics when data has limited vertical resolution or spatial extent. This project demonstrated that the compensation statistic does not need extremely high-resolution or large spatial extent data in order to successfully identify landscape dynamics in field studies. The compensation scale can be identified from deposits which are only three times as thick as the compensation scale and at least as wide as individual depositional elements (which can be channel belts or lobes in most fluviodeltaic environments). Additionally this project demonstrated that the compensation scale does seem to be sensitive to the relief a depositional system is capable of creating. It also confirmed that many, but not all, systems can create relief well in excess of the channel depth.

Chapter 3: Preserving proxy records in dynamic landscapes: Modeling and examples from the Paleocene-Eocene Thermal Maximum

The second project created a stochastic sedimentation model to test how heavy-tailed sedimentation events can alternately shrink, stretch, or remove portions of geochemical paleoenvironmental proxy records and what impact those alterations have on the ability to correctly reconstruct the original paleoenvironmental signal. This project predicts that the probability of individual records to accurately preserve the duration, magnitude, and shape of geochemical proxy records depends on the variability of the depositional environment scaled to the net sedimentation rate. Additionally, it predicts that while individual records in all environments are highly likely to be incompletely preserved, accurate reconstructions of the
original signal if a sufficient number of independent records are averaged to create an ensemble record, even in highly variable environments, rapid signals, or poor age control. It suggests that the number of individual records needed to reconstruct accurate paleoenvironmental signals likely depends on the scale of landscape variability relative to the long-term sedimentation rate. This project also demonstrates that differences in signal reconstructions from individual records induced by variable sedimentation is equivalent to other sources of differences observed in existing PETM carbon isotope records, including diagenesis and mixing of carbon sources.

Chapter 4: Exploring how landscape dynamics influence the sampling of paleoenvironmental signals

The third project used a 3D landscape evolution model to test how landscape dynamics alter the preservation of paleoenvironmental signals in order to predict how many 1D cores are necessary to completely and accurately reconstruct paleoenvironmental signals of different durations. This project demonstrates that the spatial distribution of deposition and erosion events naturally creates the temporal sediment event distributions assumed in the third chapter. Additionally, it uses the scale of landscape variability relative to the sedimentation rate to understand the minimum number of 1D records (“cores”) that are needed to reconstruct paleoenvironmental signals that are slightly faster or slower than the scale of landscape variability. Additionally, it explores how cohesion and the rate of accommodation creation control the relative landscape variability, as measured by the compensation scale, and alter the spatiotemporal distribution of depositional and erosional events across environments. By doing so, this project helps to explain many of the results and limitation of the previous two projects.
Chapter 5: Landscape dynamics across the PETM on the Mid-Atlantic shelf

The final project is a case study of how the Paleocene-Eocene Thermal Maximum is preserved in records from the Salisbury Embayment of the Mid-Atlantic shelf. This project nicely demonstrates the core challenges to reconstructing paleoenvironmental signals outlined in the first three projects: data from the Salisbury Embayment are sparse, the depositional environment is highly variable relative to the sedimentation rate, the age control in the basin is limited and ambiguous in critical portions of the records, and the environmental signal was rapid. This project also nicely demonstrates how these challenges can be recognized and mitigated using the results from the previous three projects. For example, this project demonstrates that landscape dynamics can be estimated in field systems, even with sparse 1D records and limited age control. Additionally, it demonstrates that although the Salisbury Embayment is one of the most heavily sampled single depositional system among global PETM records, it is still likely to be under sampled in order to accurately and completely reconstruct the carbon isotope excursion or the landscape and ecological response to the PETM.

6.3 Future Research Directions

All four projects have provided new opportunities for future investigations. The first project focused on the compensation statistic applied to 2D datasets to estimate the scale of landscape dynamics, however, the compensation statistic can be applied to 1D datasets [Straub et al., 2009], as can other 1D spatial statistics [e.g., Loosemore and Ford, 2006; Burgess, 2016]. Future investigations can and should test the sensitivity of these statistics to determine how reliably to determine landscape dynamics from relatively few stratigraphic sections or cores.
Project two focused on PETM-like signals that are rapid but not repeated, there are other signals, such as Milankovitch cycles, which are also critical signals to reconstruct for astrochronology [e.g., Hinnov and Hilgen, 2012; Kemp and Sexton, 2014; Meyers, 2015; Waltham, 2015] or climate forcing of landscapes [e.g., Abdul Aziz et al., 2008; Zhu et al., 2012]. More focused modeling of how landscape dynamics of varying intensities may limit the abilities to recognize and reconstruct Milankovitch cycles may help clarify what environments can be accurately dated using astrochronology and where sedimentologic responses to Milankovitch cycles may or may not be detected.

Project three focused on variability from autogenic processes, but there are many other processes that are likely to have a spatiotemporal distribution across a depositional environment that can degrade the potential for signal preservation, including non-autogenic sediment transport events, such as those associated with storms, floods, or earthquakes [e.g., Lamb and Mohrig, 2009; Goldfinger, 2011; Hale et al., 2014], bioturbation [e.g., Bentley et al., 2006; Rose and Kuehl, 2010], and early diagenesis or degradation of geochemical proxies [McKee et al., 2004; Baczynski et al., 2016]. These processes can be integrated into the existing models from project two and three in order to better predict signal preservation and sampling requirements.

The project four case study underlines the need for better analysis of signal preservation that incorporates autogenic and non-autogenic sedimentation variability, bioturbation, diagenesis, limited age resolution, and limited sampling. Future and on-going collaborations will continue to refine our understanding on how all of these processes interacted and how we can improve our reconstructions of how the sedimentology, chemistry, and ecology of the mid-Atlantic shelf responded to the PETM and the subsequent Eocene hyperthermals [e.g., Bralower and Self-Trail, 2016; Janssen et al., 2016; Self-Trail et al., 2017].
References


Appendix A

Chapter 2 Supplementary Material

Introduction

To successfully use the compensation statistic in natural deposits, there are many choices a user has to make in terms of how to handle the data and details of the analysis. This supplemental is meant to guide users in how we applied the compensation statistic to the experimental and natural data in our paper.

I. Data Handling

A. Mapping surfaces

Interpreting chronostratigraphic surfaces in natural deposits is one of the most important and time consuming steps in the analysis. Chronostratigraphic surfaces were interpreted in the lower Williams Fork Formation, lower Sego Sandstone, and upper Ferron Sandstone from terrestrial lidar scans of the outcrop. Terrestrial lidar is useful for interpreting accurate and precise 3D geometry of chronostratigraphic surfaces. However, the resolution of the scan determines how much detail can be mapped from the deposit. The lidar scans of the Ferron and Sego Sandstones deposits have sufficient resolution to map bed sets as small as 20cm thick. In contrast, the resolution of the scan of the lower Williams Fork was only sufficient to map the basal channel scours of the channel sandstones in the panel. Outcrop weathering also limits the potential mapping resolution of the lidar scan. The Ferron Sandstone outcrop was weathered strongly along joint planes (which were nearly perpendicular to bedding) and bedding planes, so it was relatively straightforward to map directly on the true-color pointcloud and a mesh derived from the pointcloud (Figure S1). The weathering of the Sego Sandstone outcrop did not emphasize bedding, but the reflectance of the lidar returns (which is partially controlled by grain size and mineralogy) did tend to emphasize bedsets, so the Sego Sandstone dataset was mapped primarily on the pointcloud colored by reflectance (Figure S2). In the Williams Fork outcrop, weathering prevented us from mapping any chronostratigraphic surfaces through the floodplain deposits (Figure S3). We used RiScan Pro and ISite Studio to map the chronostratigraphic surfaces on the lidar datasets.

The chronostratigraphic surfaces for the Ferris Formation outcrop were mapped based on GPS surveys of the channel sandstones. Because of the steep dip of the deposit, GPS points were useful for distinguishing the location of channel scours. The geometry of the channel scours was not as easy to map with GPS, so the measured maximum width and thickness of the sandbody were used to create rectangular channels centered on the measured channel
centroids. More details on how the Ferris Formation data was collected is available in [Hajek et al., 2010, 2012; Wang et al., 2011].

Both fluvial case studies needed to have pseudo-horizons mapped in order for there to be enough overlapping surfaces to run the compensation statistic. Assuming a perfectly flat floodplain likely introduces a small amount of error, but it is not an unreasonable approximation for fluvial systems with limited relief on the floodplain. We have not tested the effect of flattening floodplain relief would have on the compensation statistic. More justification for the pseudo-horizons is available in [Wang et al., 2011; Chamberlin et al., 2016].

To calculate the compensation statistic, surfaces are placed in chronostratigraphic order. Ideally, this sequence would be deduced exactly based on superposition and cross cutting relations, but this can be impossible when the lateral relationship of sandbodies is obscured by erosion or weathering. The order of surfaces in each field case study was based on the strict vertical position of the centroids.

Figure S41: Ferron Sandstone terrestrial lidar pointcloud colored by true color.
Figure S42: Sego Sandstone terrestrial lidar pointcloud colored by reflectance. Interpreted chronostratigraphic surfaces are in blue.

Figure S43: Williams Fork terrestrial lidar colored by true color.
B. Calculate the CV

Here we calculate the compensation statistic in 2D; in order to minimize error associated with the 3-dimensionality of the outcrop surface, we projected each mapped dataset onto a 2D plane before calculating CV values. The Williams Fork dataset has paleoflow measurements throughout the panel, allowing us to project the surfaces onto a plane perpendicular to the mean paleoflow direction. The paleoflow direction of the Sego and Ferron datasets is not locally constrained, so both were projected onto a plane roughly parallel to the outcrop exposure. In both cases, the outcrop exposure was within 10° perpendicular to regional mean paleoflow direction. However, the compensation statistic does not appear to be strongly sensitive to the orientation of the outcrop. All datasets were rotated to horizontal, because any residual dip can artificially increase the variability of the CV values.

The CV values of all surface pairs in the 2D datasets was calculated using the Matlab code cited at the end of this document.

C. Binning schemes

To establish $H_{\text{min}}$ and the sub-compensation index, we fit curves to the CV data. Because of the highly variable data, especially in the sub-compensation thicknesses, we binned the data. This is also consistent with how the compensation statistic has been treated by previous studies [Straub et al., 2009; Wang et al., 2011; Straub and Wang, 2013]. However, unlike those previous studies, we use logarithmic bin spacing instead of linear bin spacing. Fitting a power law relation to linear bins introduces a large amount of bias [Newman, 2005; Clauset et al., 2009]. All fits done in this paper use the geometric mean of the logarithmic bins.

In binning the CV data, we specify the number of bins. If we use too few bins, we have very limited ability to precisely determine the compensation scale. The zone where compensation occurs is less pronounced because each bin averages over too wide a stratigraphic thickness (Figure S4A). If we choose too many bins, the bins become numerically unstable—each bin averages over too few pairs, so they start to oscillate (Figure S4B). We choose the number of bins to maximize the possible precision while minimizing the numeric instability (Figure S4C). This numeric instability affects the bin means as well as the 95% envelope. In practice, we found it easiest to pick a large number of bins then progressively reduce the bin number until the 95% envelope appears smooth. The importance of picking the correct binning strategy is most important in smaller datasets. For example, if we chose too many bins for the Ferron Sandstone, there appears to be a rollover after 25m. However, this “rollover” would have a compensation index of 3.1, which is a meaningless value. This apparent rollover is likely an artifact of a very few low CV values at the thickest extent of the data (Figure S5).
Figure S44: Three binning strategies of Figure4W which has a dataset 6 times the 90th percentile channel depth, and 1 times the channel width. A) 7 bins are too few to determine the zone of compensation with precision. B) 37 bins are too many, note the oscillations in both bin means and the 95% envelope. C) 11 bins is a good compromise between well characterized bins that can also determine $H_{\text{min}}$ and $H_{\text{max}}$ with greater precision than A).

Figure S45: The upper Ferron Sandstone dataset when too many bins have been specified. There is an apparent rollover at 25 m, but the slope of that rollover is -3.1 (a slope of -1 is the highest that the compensation statistic should reasonably produce), which has no meaning. This appears to be an artifact of the numerical instability of bins that have been incompletely characterized.

D. Quality of data

Qualitative indicators of the quality of the dataset are present on the compensation plots. A highly resolved and well characterized dataset has a very dense cloud of CV values. The
95% envelope shows a clear reduction in scatter. You can also see the bottom edge of the 95% envelope rolls over from a relatively flat line to one that is parallel to the bin mean and the upper edge of the 95% envelope. The sub-compensation thicknesses have bin means that are relatively stable and fit well to a power law. The Sego Sandstone dataset indicates that it is a high quality dataset, despite the size (Figure S6A). However, the resolution of the data is independent of how well the dataset reflects the system-wide behavior. In the case of the Sego dataset, it is a high resolution dataset that has a limited ability to be extrapolated to the entire Sego system. In contrast, the lower Williams Fork Formation dataset is a low resolution dataset (note the low density of CV points that increase at larger thicknesses) that should represent the behavior of the lower Williams Fork fluvial system (Figure S6B).

![Figure S46](image)

**Figure S46:** A) the Sego Sandstone dataset has all the signs of being a high-quality dataset: density of CV points is high overall with very slight increase after compensation, sub-compensational bins are very steady and are well described by a power law, and the minimum bin cutoff does not have a large effect on the sub-compensation index. B) The lower Williams Fork Formation dataset is much lower quality: density of CV values is low overall and increases strongly after compensation, there are few sub-compensation bins, and the minimum bin cutoff has a large effect on the sub-compensation index.

II. **Analysis**

A. **Identify $H_{\text{max}}$**

To find $H_{\text{max}}$, we use the 95% envelope of the CV values in each bin, defined by the 2.5 and 97.5 percentiles of the CV values in each bin. We look for three things to define the $H_{\text{max}}$: 1) the range of the 95% envelope to reduce dramatically, 2) after the range reduces, we look for the first bin in which the 95% envelope is constant for the remaining bins, and 3) for the number of points outside the 95% envelope to significantly decrease. Picking $H_{\text{max}}$ is subjective, but once criteria are chosen and applied consistently we found that $H_{\text{max}}$ was remarkably consistent across different sub-samples and different binning schemes. When choosing between two bins that seem identical based on our criteria, we chose the larger bin. Since $H_{\text{max}}$ should be the scale
at which there is entirely compensational sedimentation, we felt the conservative choice should be the larger bin.

**Figure S47**: Subsample dataset from Figure 4U. \( H_{\text{max}} \) is determined based on the funneling of the 95% envelope, which appears complete at the bin centered at 17.0 mm. After that, the edges of the 95% envelope are smooth and parallel to each other.

**B. Identify \( H_{\text{min}} \)**

To find \( H_{\text{min}} \), we test bins smaller than \( H_{\text{max}} \) to find the smallest bin that will maintain a compensation index of 1.0. We fit power laws to either side of the chosen scale; we use a graphics based curve fitting tool in matlab called ezfit 2.42 (available at [http://www.fast.up-psud.fr/ezyfit/](http://www.fast.up-psud.fr/ezyfit/) and [https://www.mathworks.com/matlabcentral/fileexchange/10176-ezyfit-2-44](https://www.mathworks.com/matlabcentral/fileexchange/10176-ezyfit-2-44)). In the subsamples from the experiment where there are a large number of bins we decided to use a 5 bin moving average to find \( H_{\text{min}} \). We always omit the largest bin from the fit, because the largest bin is incompletely characterized. When tried to find \( H_{\text{min}} \) using the entire set of compensation bins, there was not a bin that would produce a compensation index less than 1 due to the large number of compensational bins (Figure S8). When we use only the 5 bins to the left of the compensation scale, we found \( H_{\text{min}} \) that was reasonable given the distribution of relief in the subsample (Figure S7). It is, however, a conservative estimate. Larger \( H_{\text{min}} \) would be estimated using a 3 bin moving window; we found a three bin moving window to be too sensitive to minor irregularities in the bin means. Also, since \( H_{\text{min}} \) is meant to describe the upper
edge of purely autogenic sedimentation, we felt it was more conservative to underestimate $H_{\text{min}}$ than overestimate it.

![Figure S48](image)

**Figure S48:** Screenshots of the ezfit curves fit to bins larger than 2.6mm (one bin smaller than $H_{\text{min}}$) in the subsample from Figure 4U and S7. A) Although this fit includes bins that should be much smaller than $H_{\text{min}}$, the overall fit is still $\kappa = 1.0$ ($n^2$ in the dialog box in the lower left corner) because of the number of compensational bins that are included. B) When we use a moving window of 5 bins, we see that $H_{\text{min}}$ must be larger than 2.6 mm, since $\kappa = 0.7$.

C. **Calculate sub-compensation index (if possible)**

Before we can fit a power law to the sub-compensational bins, we excluded bins which are not completely characterized. Bins which have too few CV values bias the power law fits. At small thicknesses, these incomplete bins have means that are generally much lower than they ought to be. For example, in Figure S9 the hollow circles on the left indicate values that increase with increasing thickness—because the number of CV points within the bins increases. We choose a cutoff value for each dataset based on how sensitive the bin mean is to outliers. If the bin mean will shift based on the inclusion or exclusion of a handful of outliers, the bin is excluded. In the fluvial case studies, the cutoff is rather large because of the coarse mapping resolution—there are very few channel scours that are within 3-4m of each other. The deltaic case studies have cutoffs that are very close to the mean bedset thickness, which was also the mapping resolution. For a similar reason, we always exclude the largest bin. In poorly resolved datasets, such as the fluvial case studies, the sub-compensation fits are unreliable because small differences in the cutoff value can cause dramatically different indices. To return to the Williams Fork dataset (Figure S9A-C), with a cutoff of 4m, the index is 0.7 based on three sub-compensation bins. If the cutoff was moved one bin down to 3m, the index is 0.8 based on four sub-compensation bins. If the cutoff is moved by 2 bins (2m), the index is 0.6 based on 5 sub-compensation bins. By contrast, the high-resolution Sego dataset is not nearly as sensitive to the cutoff until the cutoff is below 15 cm.
Figure S49: Lower Williams Fork Formation dataset. A) A cutoff of 4 m produces a κ of 0.7 to three sub-compensation bins. B) A cutoff of 3 m produces a κ of 0.8 to four bins, C) a cutoff of 2 m produces a κ of 0.6. None of these fits are consistent with the independent evidence of random autogenic sedimentation [Hajek et al., 2010; Chamberlin et al., in press].

III. Interpretation

A. Precision of sub-compensation index

In our experience, the sub-compensation index is best used to define broad trends in behavior—it is not a precise measure. In general, we would consider compensation indices that are within 0.2 of each other to be indistinguishable. This means that the compensation statistic is not well suited to judge small differences in organization. Rather, it is best used to distinguish broadly persistent, random, or compensational sedimentation. Also, the compensation index is an average of the behavior of the system. Perfectly random sedimentation can produce the same compensation index as a system that alternates between pure compensation and pure persistence. Other spatial statistics (e.g. the k-function) can complement the compensation statistic in these cases.

B. Precision of compensation scale

The zone of compensation has a precision less than a factor of two. The $H_{\text{max}}$ varied little in our tests of extent and resolution of the dataset. At the most, it varied by 60%. The $H_{\text{min}}$ was less stable, but it also was usually within a factor of two. While we report the zone based on the location of the bin center, the ultimate precision of the zone is limited by the bin spacing.

C. Local v. regional

The degree to which any natural deposit represents the system-wide behavior depends on both the extent of the dataset as well as the organization of the system. In general, the larger the dataset the more it can be extrapolated to the entire system. However, there are two complications: 1) the size of the depositional element, and 2) the scale of organization of the system. The importance of the size of the depositional element is made clear by the deltaic case.
studies: the Ferron Sandstone dataset should be thick enough to see the compensation scale if the depositional element was the size of the channel, not the delta lobe. The second complication is a bit more subtle. If a system is persistent (clustered) on a large scale, even relatively large extents may not show this organization directly. In these cases, the best bet to determine the system-wide organization may be to average the scale and indices from many different small datasets. The number of datasets you need before you can measure a stable average may be useful to determine the strength of the clustering.

IV. Location of field datasets

![Figure S50 Location of the fluvial (red) and deltaic (light blue) case study datasets.](image)

V. Link to Data and Code

Data from the experiment TDB-1-1 is hosted by the SEAD network at

Lidar, mapped surfaces, and code used to calculate and bin CV values is hosted by the Pennsylvania State University Library’s service ScholarSphere at the following URL’s:

Ferris Formation: https://scholarsphere.psu.edu/collections/5999n353w
Williams Fork Formation: https://scholarsphere.psu.edu/collections/7s75dc52b
Sego Sandstone: https://scholarsphere.psu.edu/collections/xk81jk48h
Ferron Sandstone: https://scholarsphere.psu.edu/collections/x346d576t
Matlab code: https://scholarsphere.psu.edu/collections/bn999687g
Appendix B

Chapter 3 Supplementary Material

1. Introduction

This document is a selection of tables and Figures that support the main conclusions and discussion points in our article “Climate signals from proxy records are influenced by variability in sedimentation”. We also provide links and DOI’s for the data and model we created and used in the manuscript. Material is arranged topically in the order presented in the manuscript.

2. PETM Bulk Organic Records

We compiled 15 bulk organic carbon isotope curves from the Bighorn basin in Wyoming, the Piceance basin in Colorado, the Californian margin, the tremp-Gaus and Basque-Cantabrian basins from northern Spain, and from the Southern Ocean (John et al., 2008; Sluijs et al., 2011; Foreman et al., 2012; Baczynski et al., 2013; Manners et al., 2013). A text file of the compilation is available at [https://scholarsphere.psu.edu/files/wm117p117](https://scholarsphere.psu.edu/files/wm117p117).

3. Sedimentation Rates and Variability from Modern Systems

We calibrated the input parameters for our stochastic sedimentation model using observations from extant and ancient systems. Sedimentation rates from a variety of tectonic settings inform our “high sedimentation” and “low sedimentation” scenarios (Table S1). We used measurements and models of event deposition in shelf and fluvial environments to scale the “high-sedimentation-variability” and “low-sedimentation-variability” model scenarios (Table S2).

<table>
<thead>
<tr>
<th>Environment</th>
<th>Location</th>
<th>Sedimentation rate (mm/yr)</th>
<th>How sedimentation rate was measured</th>
<th>Citation</th>
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<td>1-4</td>
<td>$^{210}$Pb</td>
<td>(Lewis et al., 2002)</td>
</tr>
<tr>
<td>Pro-delta</td>
<td>Brazos River pro-delta, U.S.A.</td>
<td>1-5</td>
<td>$^{210}$Pb</td>
<td>(Carlin and Dellapenna, 2014)</td>
</tr>
<tr>
<td>Shelf</td>
<td>Eel River shelf, U.S.A.</td>
<td>2-14 mean = 4</td>
<td>$^{210}$Pb</td>
<td>(Sommerfield and Nittrouer, 1999)</td>
</tr>
<tr>
<td>Shelf</td>
<td>Waipaoa River margin, New Zealand</td>
<td>2-20</td>
<td>$^{210}$Pb</td>
<td>(Rose and Kuehl, 2010; Hale et al., 2014; Walsh et al., 2014)</td>
</tr>
<tr>
<td>Shelf</td>
<td>Palos Verde Shelf, U.S.A.</td>
<td>5</td>
<td>Sediment transport model</td>
<td>(Ferré et al., 2010)</td>
</tr>
<tr>
<td>---------------------------</td>
<td>---------------------------------</td>
<td>---</td>
<td>--------------------------</td>
<td>----------------------</td>
</tr>
<tr>
<td>Shelf</td>
<td>Eocene Marlboro Clay, North Atlantic Margin, Maryland, U.S.A.</td>
<td>0.1-0.3</td>
<td>Biostratigraphy</td>
<td>(Kopp et al., 2009; Self-Trail et al., 2012)</td>
</tr>
<tr>
<td>Shelf</td>
<td>Eocene Marlboro Clay, North Atlantic Margin, New Jersey, U.S.A.</td>
<td>0.1</td>
<td>Biostratigraphy</td>
<td>(Sluijs and Brinkhuis, 2009)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Rio Grande River delta</td>
<td>0.71</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Niger River delta</td>
<td>0.71</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Orinoco River delta</td>
<td>2.7</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Po River delta</td>
<td>1.0</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Rhine River delta</td>
<td>0.15</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Baram River delta</td>
<td>0.43</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Nile River delta</td>
<td>0.39</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Yellow River delta</td>
<td>0.6</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Mackenzie River delta</td>
<td>0.12</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Ganges River delta</td>
<td>0.31</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Mississippi River delta</td>
<td>0.25</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Indus River delta</td>
<td>0.12</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Deltaic</td>
<td>Yangtze River delta</td>
<td>0.09</td>
<td>NA</td>
<td>Cited in: (Straub and Wang, 2013)</td>
</tr>
<tr>
<td>Fluvial</td>
<td>Eocene Willwood Formation, Bighorn basin, Wyoming, U.S.A.</td>
<td>0.275-0.35</td>
<td>Biostratigraphy</td>
<td>(Foreman, 2014)</td>
</tr>
<tr>
<td>Fluvial</td>
<td>Lower Mississippi River</td>
<td>34-58</td>
<td>OSL</td>
<td>(Rowland et al., 2005)</td>
</tr>
<tr>
<td>Environment</td>
<td>Location</td>
<td>Event size (deposition is positive, erosion negative)</td>
<td>Approximate return interval</td>
<td>Citation</td>
</tr>
<tr>
<td>-------------</td>
<td>----------</td>
<td>--------------------------------------------------------</td>
<td>----------------------------</td>
<td>----------</td>
</tr>
<tr>
<td>Shelf</td>
<td>Eel river shelf</td>
<td>10 cm</td>
<td>~100 yr</td>
<td>(Sommerfield and Nittrouer, 1999)</td>
</tr>
<tr>
<td>Shelf</td>
<td>Eel river shelf</td>
<td>&lt;5cm</td>
<td>~10-20 yr</td>
<td>(Wiberg, 2000)</td>
</tr>
<tr>
<td>Shelf</td>
<td>Gulf coast</td>
<td>-0.3 cm</td>
<td>&lt;50 yr</td>
<td>(Teague et al., 2006)</td>
</tr>
<tr>
<td>Shelf</td>
<td>Gulf coast</td>
<td>0.5-2m</td>
<td>50-100 yr</td>
<td>(Bentley et al., 2002; Keen et al., 2004)</td>
</tr>
<tr>
<td>Shelf</td>
<td>Waipaoa River margin, New Zealand</td>
<td>+/- 5cm</td>
<td>~2 yr</td>
<td>(Hale et al., 2014; Walsh et al., 2014)</td>
</tr>
</tbody>
</table>

- Fluvial—over bank deposition
- Fluvial—over bank erosion

All sedimentation rates are for Quaternary accumulation unless otherwise indicated.

Table S4 Event bed or scour depth size and return interval from shelf and river depositional environments
Fluvial—floodplain channels

<table>
<thead>
<tr>
<th>Channels</th>
<th>Location</th>
<th>Width (m)</th>
<th>Age (kyr)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bighorn Basin</td>
<td>+/- 3m - 1 kyr</td>
<td></td>
<td></td>
<td>(Kraus and Davies-Vollum, 2004)</td>
</tr>
</tbody>
</table>

Fluvial—channel

<table>
<thead>
<tr>
<th>Channels</th>
<th>Location</th>
<th>Width (m)</th>
<th>Age (yr)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nahal Me’arot, NW Israel</td>
<td>+/- 1m - 50</td>
<td></td>
<td></td>
<td>(Greenbaum and Bergman, 2006)</td>
</tr>
<tr>
<td>Redwood Creek, California U.S.A.</td>
<td>+/- 1m &lt; 5</td>
<td></td>
<td></td>
<td>(Madej and Ozaki, 1996)</td>
</tr>
</tbody>
</table>

Fluvial—channel

<table>
<thead>
<tr>
<th>Channels</th>
<th>Location</th>
<th>Width (m)</th>
<th>Age (yr)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Howgill Fells, northwest England</td>
<td>+/- 2m ~100</td>
<td></td>
<td></td>
<td>(Harvey, 2007)</td>
</tr>
</tbody>
</table>

Fluvial—avulsion

<table>
<thead>
<tr>
<th>Channels</th>
<th>Location</th>
<th>Width (m)</th>
<th>Age (yr)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Columbia River, British Columbia, Canada</td>
<td>+/- 2m 800-3,000</td>
<td></td>
<td></td>
<td>(Makaske et al., 2002)</td>
</tr>
<tr>
<td>Saskatchewan River, Canada</td>
<td>+/- 2-3 m ~600</td>
<td></td>
<td></td>
<td>(Morozova and Smith, 2000)</td>
</tr>
</tbody>
</table>

Fluvial—splays

<table>
<thead>
<tr>
<th>Channels</th>
<th>Location</th>
<th>Width (m)</th>
<th>Age (yr)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sandover River, Australia</td>
<td>+/- 2 m ~ 50</td>
<td></td>
<td></td>
<td>(Tooth, 2005)</td>
</tr>
</tbody>
</table>

4. Stochastic Sedimentation Model

We wrote a model that creates synthetic proxy records with stochastic sedimentation in the R statistical computing language, using the packages TTR and VGAM in addition to the base R library (R Core Team, 2015; Yee, 2015; Ulrich, 2016). We verified that stratigraphy built with the model reproduces the “Sadler Effect” where there is a power law relationship between sedimentation rate and the amount of time over which the sedimentation rate is calculated, with a power ~0.5 (Sadler, 1981; Sadler and Strauss, 1990; Jerolmack and Sadler, 2007).

The complete model source code and the 2,000 synthetic records we produced for this manuscript are available at [https://scholarsphere.psu.edu/collections/02870v99r](https://scholarsphere.psu.edu/collections/02870v99r).

Interpretation of the synthetic records was done manually by S. Trampush. The interpretations we used for this manuscript are available at [https://scholarsphere.psu.edu/collections/02870v99r](https://scholarsphere.psu.edu/collections/02870v99r).

Table S5 Model Parameters

<table>
<thead>
<tr>
<th>Model Parameter</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of iterations</td>
<td>500</td>
<td>500</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>Duration (kyr)</td>
<td>350</td>
<td>350</td>
<td>350</td>
<td>350</td>
</tr>
<tr>
<td>Scaling parameter (α)</td>
<td>1</td>
<td>0.75</td>
<td>1</td>
<td>0.75</td>
</tr>
<tr>
<td>Maximum allowed event size (</td>
<td>(</td>
<td>x_{max}</td>
<td>)</td>
<td>(cm))</td>
</tr>
<tr>
<td>Median sediment rate (\langle x \rangle cm/kyr)</td>
<td>30</td>
<td>30</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>100 yr event (cm)</td>
<td>5</td>
<td>16</td>
<td>5</td>
<td>16</td>
</tr>
<tr>
<td>1,000 yr event (cm)</td>
<td>40</td>
<td>170</td>
<td>40</td>
<td>170</td>
</tr>
</tbody>
</table>
Table 2 in the main text provides the median, 10th, and 90th percentiles of all the model (thickness, sedimentation rate, gap size, etc.) and interpreted parameters (event magnitude, duration, shape, etc). Here we show full distributions for every parameter (Figure S1).

Additionally, we used these distributions to evaluate whether climate signal characteristics estimated from individual records (e.g., total duration and duration of onset) were significantly different if a specific local age model was used instead of a generalized age model. For each record the measured local sedimentation rate was obtained by dividing the thickness of the record by the time span between the age of the lowermost and uppermost beds preserved. This is
analogous to using biozones at the base and top of a section to estimate local sedimentation rates. In contrast, the generalized age model is simply the total record thickness divided by 350 kyr. This difference had little influence on the estimated duration, magnitude, or shape of the large or small event (Figure S2). The only exception to this apparent insensitivity to sedimentation rate was the small number of records which only preserved the small event: because these records only preserved the last ~100 kyr, the generalized sedimentation rate was much smaller than the measured rate, which made the duration of the small event appear excessively long. Table 2 event statistics were made with the measured local sedimentation rate, not the general sedimentation rate.

Figure S52: Kernel density estimates of the distributions of the parameters in Table 2. Colors are the same as in Figure 3: green is Model 1 (high sedimentation, low sediment variability), blue is Model 2 (high sedimentation, high sedimentation variability), grey is Model 3 (low sedimentation, low sedimentation variability), and pink is Model 4 (low sedimentation, high sedimentation variability). The black box shows the parameters that were measured using the
measured sedimentation rate (thick lines) and the interval sedimentation rate (thin lines). The estimates are essentially identical for both sedimentation rates, with the exception of the records which only preserved the small event.

Figure S53: Detail of the 6 event parameters kernel density estimate (black box Figure S1) calculated by the measured sedimentation rate (thick lines) and interval sedimentation rate (thin lines).

5.1 Appearance of a Body in the Large Event

In addition to the parameters reported in Table 2, we also measured the duration of any apparent body in synthetic proxy records (Table S3). A body was defined as an extended excursion, i.e. a thick or protracted period of proxy values within 1‰ of the peak excursion (e.g., second Model 2 record of Figure 3).
Table S6: Duration of large climate events in records with excursion bodies.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Apparent Body Duration (kyr) (input = 1 yr)</td>
<td>36 (12-82)</td>
<td>39 (8-103)</td>
<td>43 (8-112)</td>
<td>48 (7-131)</td>
</tr>
<tr>
<td>Apparent Recovery Duration (kyr) (input = 180 kyr)</td>
<td>132 (70-183)</td>
<td>81 (5-167)</td>
<td>84 (3-163)</td>
<td>64 (6-160)</td>
</tr>
<tr>
<td>Apparent Recovery + Body Duration (kyr) (input = 180 kyr)</td>
<td>171 (116-215)</td>
<td>131 (51-215)</td>
<td>138 (51-224)</td>
<td>117 (40-210)</td>
</tr>
</tbody>
</table>

5.2 Small Event Preservation

The small event was more likely to be preserved than might be expected given its short duration. This is because the small event occurs at the top of the section (late in the model succession) there is less opportunity for it to be removed by large erosion events. It is very difficult to preserve the small event if it is placed earlier in the model succession. Additionally, because the 1‰ excursion is small relative to the noise of the proxy system (st. dev. 0.3‰), when the small event was identifiable it was likely to be slightly overestimated in magnitude and duration, and its shape tended to be well represented since preservation only occurred if there was a run of thick beds deposited in succession.

5.3 Thickness of Deposit and Event Preservation Probability

We assessed whether thicker sections had a higher probability of preservation (Figure S3, Table S5). We found that records that preserved either the large or small event were slightly thicker than the distribution of the entire population of synthetic records. However, many thin records (e.g. second Model 3 record in Figure 3) preserved one or both events, and many thick records failed to preserve either events (e.g. fourth Model 4 record in Figure 3).
Figure S54: Kernel density estimates of the thickness of all records (thick lines) and records which preserved one or both of the events (thin lines) from Models 1 (green), 2 (blue), 3 (grey), and 4 (pink).

Table S7: Thickness of records which preserved one, both, or neither events

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>thickness (m)</td>
<td>110</td>
<td>130</td>
<td>44</td>
<td>82</td>
</tr>
<tr>
<td></td>
<td>(78-141)</td>
<td>(49-213)</td>
<td>(16-75)</td>
<td>(20-174)</td>
</tr>
<tr>
<td>Thickness if large event preserved</td>
<td>110</td>
<td>139</td>
<td>49</td>
<td>104</td>
</tr>
<tr>
<td>thickness (m)</td>
<td>(78-141)</td>
<td>(64-217)</td>
<td>(23-77)</td>
<td>(47-184)</td>
</tr>
<tr>
<td>Thickness if small event preserved</td>
<td>112</td>
<td>148</td>
<td>52</td>
<td>110</td>
</tr>
<tr>
<td>thickness (m)</td>
<td>(80-143)</td>
<td>(71-235)</td>
<td>(24-82)</td>
<td>(51-191)</td>
</tr>
<tr>
<td>Thickness if both events preserved</td>
<td>112</td>
<td>158</td>
<td>54</td>
<td>129</td>
</tr>
<tr>
<td>thickness (m)</td>
<td>(80-143)</td>
<td>(89-241)</td>
<td>(29-83)</td>
<td>(74-198)</td>
</tr>
<tr>
<td>Thickness if neither event preserved</td>
<td>NA</td>
<td>32</td>
<td>9</td>
<td>22</td>
</tr>
<tr>
<td>thickness (m)</td>
<td></td>
<td>(13-62)</td>
<td>(2-19)</td>
<td>(5-53)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(n=35)</td>
<td>(n=37)</td>
<td>(n=100)</td>
</tr>
</tbody>
</table>

Parentheses contain the 10th to 90th percentiles.

6. Probability of Accurately Reconstructing the Input Signal
To gauge and compare how accurately records from different models reconstructed the input climate signal, we used the age model created with the measured local sedimentation rate and counted the number of interpreted records that were within 50, 20, and 10% of the magnitude, duration, onset duration, and recovery duration of the input signal (Table S5). The recovery duration includes the duration of the body if one appeared in a record.

**Table S8:** Number of records that estimate the magnitude, duration, duration of onset, and duration of recovery within 50, 20, and 10% of the input large climate event. Input large-event values shown in parentheses.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Model 1 (n=500)</th>
<th>Model 2 (n=438)</th>
<th>Model 3 (n=434)</th>
<th>Model 4 (n=344)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Magnitude (input = -5‰)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error (-7.7 to -2.5‰):</td>
<td>499 (100%)</td>
<td>380 (87%)</td>
<td>395 (91%)</td>
<td>267 (78%)</td>
</tr>
<tr>
<td>20% error (-6 to -4‰):</td>
<td>484 (97%)</td>
<td>281 (64%)</td>
<td>303 (70%)</td>
<td>180 (52%)</td>
</tr>
<tr>
<td>10% error (-5.5 to -4.5‰):</td>
<td>449 (90%)</td>
<td>238 (54%)</td>
<td>246 (57%)</td>
<td>130 (38%)</td>
</tr>
<tr>
<td><strong>Duration (input = 200 kyr)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error (100 to 300 kyr):</td>
<td>469 (94%)</td>
<td>228 (52%)</td>
<td>241 (56%)</td>
<td>125 (36%)</td>
</tr>
<tr>
<td>20% error (160 to 240 kyr):</td>
<td>348 (70%)</td>
<td>127 (29%)</td>
<td>120 (28%)</td>
<td>65 (19%)</td>
</tr>
<tr>
<td>10% error (180 to 220 kyr):</td>
<td>203 (41%)</td>
<td>52 (12%)</td>
<td>71 (16%)</td>
<td>36 (10%)</td>
</tr>
<tr>
<td><strong>Onset duration (input = 20 kyr)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error (10 to 30 kyr):</td>
<td>211 (42%)</td>
<td>77 (18%)</td>
<td>84 (19%)</td>
<td>30 (9%)</td>
</tr>
<tr>
<td>20% error (16 to 24 kyr):</td>
<td>85 (17%)</td>
<td>26 (6%)</td>
<td>36 (8%)</td>
<td>24 (7%)</td>
</tr>
<tr>
<td>10% error (18 to 22 kyr):</td>
<td>58 (12%)</td>
<td>15 (3%)</td>
<td>17 (4%)</td>
<td>14 (4%)</td>
</tr>
<tr>
<td>Could not be determined:</td>
<td>21 (4%)</td>
<td>163 (37%)</td>
<td>141 (32%)</td>
<td>175 (51%)</td>
</tr>
<tr>
<td><strong>Recovery (input = 180 kyr)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error (85 to 255 kyr):</td>
<td>482 (96%)</td>
<td>326 (74%)</td>
<td>327 (75%)</td>
<td>226 (66%)</td>
</tr>
<tr>
<td>20% error (136 to 204 kyr):</td>
<td>307 (61%)</td>
<td>142 (32%)</td>
<td>145 (33%)</td>
<td>104 (30%)</td>
</tr>
<tr>
<td>10% error (153 to 187 kyr):</td>
<td>175 (35%)</td>
<td>69 (16%)</td>
<td>81 (19%)</td>
<td>52 (15%)</td>
</tr>
<tr>
<td><strong>Total within error for magnitude, total duration, and onset duration</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error:</td>
<td>207 (41%)</td>
<td>55 (13%)</td>
<td>65 (15%)</td>
<td>27 (8%)</td>
</tr>
<tr>
<td>20% error:</td>
<td>59 (12%)</td>
<td>15 (3%)</td>
<td>15 (3%)</td>
<td>6 (2%)</td>
</tr>
<tr>
<td>10% error:</td>
<td>25 (5%)</td>
<td>3 (0.7%)</td>
<td>3 (0.7%)</td>
<td>1 (0.3%)</td>
</tr>
</tbody>
</table>

7. Ensemble Records of Models (Figure 4A & B)

Multiple ensemble records were constructed to evaluate how accurately aggregate records reconstruct the input climate signal. We generated ensemble records for the best preserved (Model 1) and worst preserved (Model 4) models using the median of 15 randomly selected individual records that preserve the large event and where the onset and recovery of the large event can be measured. Individual records in the ensembles were datumed on the onset of the excursion and used the measured local sedimentation rate for an age model. Example ensemble records are shown in Figure 4 A & B. For each scenario we generated 500 unique ensemble
records. Age models for the records were made using the measured sedimentation rate. The ensemble record was made by taking the median of all 15 records of the magnitude, duration, onset duration, and recovery duration. We then counted how many ensembles were within 50, 20, and 10% of the input signal (Table S6).

**Table S9: Error of ensembles of 15 random records**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Model 1 (Count of 500 ensembles of 15 records)</th>
<th>Model 4 (Count of 500 ensembles of 15 records)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Magnitude</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error:</td>
<td>500 (100%)</td>
<td>500 (100%)</td>
</tr>
<tr>
<td>20% error:</td>
<td>500 (100%)</td>
<td>464 (93%)</td>
</tr>
<tr>
<td>10% error:</td>
<td>500 (100%)</td>
<td>305 (61%)</td>
</tr>
<tr>
<td><strong>Duration</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error:</td>
<td>500 (100%)</td>
<td>493 (99%)</td>
</tr>
<tr>
<td>20% error:</td>
<td>499 (100%)</td>
<td>224 (45%)</td>
</tr>
<tr>
<td>10% error:</td>
<td>422 (84%)</td>
<td>63 (13%)</td>
</tr>
<tr>
<td><strong>Onset</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error:</td>
<td>473 (95%)</td>
<td>226 (45%)</td>
</tr>
<tr>
<td>20% error:</td>
<td>266 (53%)</td>
<td>134 (27%)</td>
</tr>
<tr>
<td>10% error:</td>
<td>185 (37%)</td>
<td>68 (13%)</td>
</tr>
<tr>
<td><strong>Recovery</strong></td>
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<td></td>
</tr>
<tr>
<td>50% error:</td>
<td>500 (100%)</td>
<td>477 (95%)</td>
</tr>
<tr>
<td>20% error:</td>
<td>493 (99%)</td>
<td>230 (46%)</td>
</tr>
<tr>
<td>10% error:</td>
<td>425 (85%)</td>
<td>107 (21%)</td>
</tr>
<tr>
<td><strong>Total within error for magnitude, total duration, and onset duration:</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% error:</td>
<td>473 (95%)</td>
<td>225 (45%)</td>
</tr>
<tr>
<td>20% error:</td>
<td>265 (53%)</td>
<td>72 (14%)</td>
</tr>
<tr>
<td>10% error:</td>
<td>163 (33%)</td>
<td>9 (2%)</td>
</tr>
</tbody>
</table>

**Table S10: Medians and range in parentheses of ensemble curves used in Figure 4C.**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Ensemble in Fig4A</th>
<th>Ensemble in Fig4B</th>
<th>Ensemble in Fig4C</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Magnitude</strong></td>
<td>-5.1‰ (-4.6 to -5.3‰)</td>
<td>-4.0‰ (-3.1 to -5.2‰)</td>
<td>-2.5‰ (-1 to -5‰)</td>
</tr>
<tr>
<td><strong>Total duration</strong></td>
<td>198 kyr (119 to 271 kyr)</td>
<td>195 kyr (43 to 290 kyr)</td>
<td>185 kyr (35 to 600 kyr)</td>
</tr>
<tr>
<td><strong>Onset duration</strong></td>
<td>18 kyr (1.4 to 57 kyr)</td>
<td>22 kyr (0.4 to 118 kyr)</td>
<td>10 kyr (5 to 50 kyr)</td>
</tr>
</tbody>
</table>

Parentheses contain the min/max values for each parameter.
8. PETM Ensemble (Figure 4C)

The ensemble of PETM curves in Figure 4C was made using the same 15 records in the compilation above (also Figure 1). We used the elevation of the onset (as defined by the original authors), a long term sedimentation rate calculated using the author-reported sedimentation rate, biostratigraphy, or subsidence rates. We also subtracted the individual record’s pre-CIE $\delta^{13}C_{org}$ value to compare a relative $\delta^{13}C_{org}$ offset (Table S7). We then compared the amount of variability in estimates of the magnitude, duration, and onset duration of the PETM individual records to the values estimated from the ensemble record (Table S8). Finally, we assessed the sensitivity of the PETM ensemble to the age models derived from the linear sedimentation rates by randomly changing 1/3 of the sedimentation rates by a factor of 2 (Figure S4 A-J, Table S9). We also assess what would happen if the sedimentation rate for the northern Spain records were all too low, or if the Wyoming records were all too high (Figure S4J & L, Table S9). We find that the magnitude, duration, onset duration, and overall shape are relatively insensitive to sedimentation rate errors within a factor of two.

While it has been proposed that sedimentation rate increased dramatically across the PETM, the amount of increase and the timing of the increase is not clear (Schmitz et al., 2001; Schmitz and Pujalte, 2007; Kopp et al., 2009; McInerney and Wing, 2011; Foreman et al., 2012; Garel et al., 2013). Additionally several studies have suggested that variability in sedimentation would also have increased during this time; our model results show that if sedimentation rates increase commensurately with variability in sedimentation, the net effect is no change on signal preservation. Since we are using the PETM as a heuristic example, and not trying to precisely define the true PETM signal, we ignore this complexity. More complicated sedimentation rate age models would be more appropriate if a more precise ensemble of the PETM is desired.

**Table S11**: Bulk organic carbon isotope records used in ensemble Figure 4C.

<table>
<thead>
<tr>
<th>Name</th>
<th>Location</th>
<th>Depositional Environment</th>
<th>Sedimentation Rate* (cm/kyr)</th>
<th>Pre-CIE $\delta^{13}C_{org}$ value (%)</th>
<th>Citations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highway 16</td>
<td>Bighorn Basin, Wyoming, USA Fluvial 20 -24.5</td>
<td>Data: (Baczynski et al., 2013) Sedimentation rate: (Secord et al., 2010)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CAB10</td>
<td>Bighorn Basin, Wyoming, USA Fluvial 20 -24.0</td>
<td>Data: (Baczynski et al., 2013) Sedimentation rate: (Secord et al., 2010)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Big Red Spit</td>
<td>Bighorn Basin, Wyoming, USA Fluvial 20 -25.0</td>
<td>Data: (Baczynski et al., 2013) Sedimentation rate: (Secord et al., 2010)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>North Butte</td>
<td>Bighorn Basin, Wyoming, USA Fluvial 20 -25.0</td>
<td>Data: (Baczynski et al., 2013) Sedimentation rate: (Secord et al., 2010)</td>
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<td></td>
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</tr>
<tr>
<td>Polecat Bench</td>
<td>Bighorn Basin, Wyoming, USA Fluvial 40 -24.5</td>
<td>Data: (Magioncalda et al., 2004) Sedimentation rate:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Location</td>
<td>Type</td>
<td>Marine Environment</td>
<td>Water Depth</td>
<td>Sedimentation Rate</td>
<td>Source(s)</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------------------------------------</td>
<td>--------------------</td>
<td>-------------</td>
<td>--------------------</td>
<td>----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>De Beque, Piceance</td>
<td>Fluvial</td>
<td>Log</td>
<td>27.5</td>
<td>-23.5</td>
<td>(Clyde, 1997)</td>
</tr>
<tr>
<td>Lodo Gulch, Californian margin</td>
<td>Marginal marine</td>
<td>Log</td>
<td>20</td>
<td>-23.5</td>
<td>(Foreman et al., 2012)</td>
</tr>
<tr>
<td>Tumey Gulch, Californian margin</td>
<td>Marginal marine</td>
<td>Log</td>
<td>5</td>
<td>-24.0</td>
<td>(John et al., 2008)</td>
</tr>
<tr>
<td>Claret, Tremp–Graus basin,</td>
<td>Fluvial</td>
<td>Log</td>
<td>20</td>
<td>-23.5</td>
<td>(Manners et al., 2013)</td>
</tr>
<tr>
<td>Tendrui, Tremp–Graus basin,</td>
<td>Fluvial</td>
<td>Log</td>
<td>20</td>
<td>-25.0</td>
<td>(Manners et al., 2013)</td>
</tr>
<tr>
<td>Campo, Tremp–Graus basin,</td>
<td>Transitional mixed shallow marine and</td>
<td>Log</td>
<td>2</td>
<td>-26.5</td>
<td>(Molina et al., 2000)</td>
</tr>
<tr>
<td>Esplugafreda, Tremp–Graus basin</td>
<td>Fluvial</td>
<td>Log</td>
<td>20</td>
<td>-23.0</td>
<td>(Manners et al., 2013)</td>
</tr>
<tr>
<td>Ermua, Basque–Cantabrian basin</td>
<td>Marine; “base-of-slope-apron”</td>
<td>Log</td>
<td>15</td>
<td>-24.0</td>
<td>(Gomez et al., 2002)</td>
</tr>
<tr>
<td>Zumaia, Basque–Cantabrian basin</td>
<td>Bathyal marine/Marine turbidites</td>
<td>Log</td>
<td>5</td>
<td>-25.0</td>
<td>(Gomez et al., 2002)</td>
</tr>
<tr>
<td>IODP 1172, Southern Ocean</td>
<td>Marginal marine/deltaic</td>
<td>Log</td>
<td>0.57</td>
<td>-26.5</td>
<td>(Sluijs et al., 2011)</td>
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</tbody>
</table>

*Sedimentation rate refers to the median value measured across the PETM
**Inferred from the subsidence rate in the Basque–Cantabrian basin and from the relative thickness of the correlations between Ermua and Zumaia (i.e. Ermua is ~3 times as thick as Zumaia, therefore sedimentation rate should be ~3 times as rapid)
***Inferred from subsidence rate in the Basque–Cantabrian basin
**Table S12:** Sensitivity of Ensembles to Sedimentation Rate

<table>
<thead>
<tr>
<th>Name</th>
<th>A (Figure 4C)</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
<th>G</th>
<th>H</th>
<th>I</th>
<th>J</th>
<th>K</th>
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<td>0.57</td>
<td>0.57</td>
<td>0.57</td>
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</tr>
</tbody>
</table>

**Ensemble values**

| Magnitude (%)         | 2.5 | 2.8 | 2.7 | 2.5 | 2.4 | 2.7 | 3.0 | 2.5 | 2.6 | 2.8 | 2.7 | 2.7 |
|-----------------------|     |     |     |     |     |     |     |     |     |     |     |     |
| Total Duration (kyr)  | 190 | 180 | 220 | 190 | 220 | 210 | 210 | 190 | 220 | 190 | 170 | 220 |
| Onset duration (kyr)  | 10  | 10  | 10  | 6   | 6   | 10  | 8   | 6   | 7   | 10  | 5   | 15  |

Red boxes: sedimentation rate decreased by factor of 2, blue boxes: sedimentation rate increased by a factor of 2
Figure S55: Sensitivity of PETM ensemble to factor of 2 errors in sedimentation rate. Sedimentation rates used for each ensemble in Table S9.

10. References

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Appendix C

Chapter 4 Supplementary Material

1. Location of Model Code and Analysis Code

The code of the modified DeltaRCM model is available at
https://scholarsphere.psu.edu/collections/q8336h3788.

2. Location of Model data and analysis

The complete dataset is available at
https://scholarsphere.psu.edu/collections/q8336h3788. Dataset includes figures produced
during analysis.

3. Model Parameters

Table S1: Input parameters for all model runs

<table>
<thead>
<tr>
<th>Model Name</th>
<th>L0</th>
<th>W0</th>
<th>Qw0</th>
<th>Qs0</th>
<th>h0</th>
<th>hB</th>
<th>C0</th>
<th>f_bed</th>
<th>SLR</th>
<th>SLR (per time step)</th>
<th>dt</th>
<th>dx</th>
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<tbody>
<tr>
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<td>200</td>
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<td>10</td>
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<td>0.1</td>
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<td>5.00E-03</td>
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</tr>
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<td>5</td>
<td>10</td>
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<td>0.25</td>
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<td>5.00E-03</td>
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<td>2500</td>
<td>2.5</td>
<td>5</td>
<td>10</td>
<td>0.001</td>
<td>0.5</td>
<td>1.00E-07</td>
<td>5.00E-03</td>
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<td>100</td>
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<td>2500</td>
<td>2.5</td>
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<td>10</td>
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<td>2.50E-03</td>
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<td>2.50E-08</td>
<td>1.25E-03</td>
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</tr>
</tbody>
</table>

Abbreviations in the column headings of Table S1 are the variable names used in the
DeltaRCM code; L0 is basin length in cells, W0 is basin width in cells, Qw0 is initial
water discharge in cms, Qs0 is initial sediment discharge in volume per second, C0 is
initial concentration of sediment, f_bed is the fraction of sediment which is the coarse
parcel type (“sand”), SLR is sea level rise in m/s, dt is the length of time in seconds
between model time steps, dx is the width of the model cells. Although much of this
model has been scaled to a natural system, we do not use the time scaling in our analyses
because the scaling is unrealistic (e.g. it assumes constant sediment and water flux for the
entire length of the model run), and because this scaling is highly dependent on the
individual delta but we are trying to produce more general sampling guidelines.
4. Additional Analysis data and figures
In addition to the analyses outlined in the main manuscript, we also conducted additional analyses.

a. Description of deposit geometry and composition

In order to determine if the model was building stratigraphy correctly, we constructed isopach maps of the final deposit thickness (Figure S1).

![Isopach maps of the total deposit thickness for all 9 models.](image)

**Figure S1** Isopach maps of the total deposit thickness for all 9 models.

**Table S2**: Basic statistics of the deposit geometry and composition

<table>
<thead>
<tr>
<th>Model Name</th>
<th>System length (km)</th>
<th>Deposit thickness (m) (50th percentile)</th>
<th>Deposit thickness (m) (10th percentile)</th>
<th>Deposit thickness (m) (90th percentile)</th>
<th>Net: Gross</th>
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<tr>
<td>B</td>
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<td>37.4</td>
<td>34.45</td>
<td>39.65</td>
<td>0.29</td>
</tr>
<tr>
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<td>39.25</td>
<td>37.6</td>
<td>39.95</td>
<td>0.51</td>
</tr>
<tr>
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<td>4.7</td>
<td>20.7</td>
<td>12.5</td>
<td>24.15</td>
<td>0.14</td>
</tr>
<tr>
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<td>4.6</td>
<td>24.35</td>
<td>22.1</td>
<td>25.05</td>
<td>0.31</td>
</tr>
<tr>
<td>F</td>
<td>4.55</td>
<td>24.45</td>
<td>22.95</td>
<td>25.15</td>
<td>0.54</td>
</tr>
<tr>
<td>G</td>
<td>6.25</td>
<td>16.15</td>
<td>10.65</td>
<td>17.5</td>
<td>0.13</td>
</tr>
<tr>
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<td>6.05</td>
<td>17.05</td>
<td>14.8</td>
<td>17.65</td>
<td>0.29</td>
</tr>
<tr>
<td>I</td>
<td>6</td>
<td>17.05</td>
<td>15.25</td>
<td>17.75</td>
<td>13.6</td>
</tr>
</tbody>
</table>
b. Elevation change

In addition to the histograms of elevation change at every cell in the model between the chronostratigraphic surfaces produced every 50th time step that is in the main manuscript (Figure 4-8), we produced histograms of the elevation change experienced at all three cross sections (Figures S2-4). More sandy models or more distal cross sections have a reduced probability of erosion and an increased probability of large amounts of deposition, likely related to the formation of mouth bars.

Figure S2: Histograms for elevation change for every cell along the proximal cross section. Notice that the depositional tail has much larger events for the sandy models and the erosional tail is more symmetric for the muddier models.
Figure S3: Histogram of elevation change between chronostratigraphic surfaces for every cell on the medial cross section. All models have a larger probability of depositional events than seen on the proximal cross section. Similarly, all models have a reduced probability of erosional events compared to the proximal cross section.
Figure S4: Histogram of elevation change between chronostratigraphic surfaces for every cell on the distal cross section. All models have a larger probability of depositional events than seen on the proximal or medial cross sections. Similarly, all models have a greatly reduced probability of erosional events compared to the proximal and medial cross sections, almost certainly related to the larger proportion of the stratigraphy built from the mouth bar facies.

Table S3: Elevation change statistics

<table>
<thead>
<tr>
<th>Model Name</th>
<th>Elevation change (50th prctile)*</th>
<th>Elevation change (10th prctile)*</th>
<th>Elevation change (90th prctile)*</th>
<th>Mean elevation change</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
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<td>0</td>
<td>0.223</td>
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<tr>
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<td>0.0771</td>
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<tr>
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<td>0.125</td>
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<td>0.0595</td>
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<tr>
<td>I</td>
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</tbody>
</table>

* Elevation change is measured at every cell in the model domain between chronostratigraphic surfaces produced every 50th time step.

c. Compensation statistic
Figures S5-7 are the plots of measurement window vs. compensation statistic and the fits of equation 4-3, the results of which are reported in Table 4-2.

Figure S5: Compensation fit for proximal cross section of all 9 models. Red line is the sub-compensation fit of equation 4-3, blue line is the post-compensation fit, and the vertical line is the compensation scale.
Figure S6: Compensation plots of all 9 models for the medial cross section. Red line is the sub-compensation fit of equation 4-3, blue line is the post-compensation fit, and the vertical line is the compensation scale.
Figure S7: Compensation plots of all 9 models for the distal cross section. None of the models fully compensate on the distal cross section, although models A and B are likely close.
Appendix D

Chapter 5 Supplementary Material

Location of core logs and other data used:

The lithologic core logs I used to build the facies descriptions and facies maps can be located at https://scholarsphere.psu.edu/collections/sxk81jm066. The logs for Wilson Lake, Merkle Wildlife Sanctuary, Cam-Dor, Surprise Hill, Knapps Narrows, and South Dover Bridge are the original core logs that were produced during coring, supplemented with my own notes on observations of the (now dry) cores. Loretto and Mattawoman core logs are my descriptions made on the cores stored at Reston (the Loretto core and core from one of the holes from Mattawoman, both now dry) and at Penn State (cores from two of the holes from Mattawoman, both still wrapped and refrigerated). The remaining core descriptions I used (Bass River, Sea Girt, and Double Trouble) are from the published IODP drilling reports. Additional photographs of the cores and outcrops are available at https://scholarsphere.psu.edu/collections/sxk81jm066.
VITA

Sheila M. Trampush

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A.S. Earth Science, with honors, Columbia College, 2009

Publications


