

BED FORCE DISTRIBUTIONS IN GRANULAR FLOWS

by

AMELIA H. WINNER

A DISSERTATION

Presented to the Department of Earth Sciences
and the Graduate School of the University of Oregon
in partial fulfillment of the requirements
for the degree of
Doctor of Philosophy

March 2021

DISSERTATION APPROVAL PAGE

Student: Amelia H. Winner

Title: Bed Force Distributions in Granular Flows

This dissertation has been accepted and approved in partial fulfillment of the requirements for the Doctor of Philosophy degree in the Department of Earth Sciences by:

Josef Dufek	Chairperson
Leif Karlstrom	Core Member
Ken Ferrier	Core Member
Josh Roering	Core Member
Eric Corwin	Institutional Representative

and

Kate Mondloch	Interim Vice Provost and Dean of the Graduate School
---------------	--

Original approval signatures are on file with the University of Oregon Graduate School.

Degree awarded March 2021

© 2021 Amelia H. Winner

DISSERTATION ABSTRACT

Amelia H. Winner

Doctor of Philosophy

Department of Earth Sciences

March 2021

Title: Bed Force Distributions in Granular Flows

Granular flows are particle-laden gravity currents that are ubiquitous in nature in a variety of different geologic settings. Their high mobility and potential for harm to human populations and infrastructure motivate workers to better understand their dynamics in hopes of predicting their behavior and runout. Forecasting the movement of these hazardous flows, however, requires understanding the mass and momentum transfer between the flow and its substrate. In this dissertation, I analyze the normalized frequency-magnitude distribution of bed force excursions generated by idealized granular flows through a combination of laboratory experiments and discrete element simulations. I explore a wide range of flow behaviors by varying mean grain size, shear rate, and standard deviation of grain size. In the discrete element simulations, I also explore the role of interstitial fluids in determining the shape of the bed force distributions by varying fluid density and viscosity. The flows explored in this dissertation span three flow regimes, encapsulating elastic-quasi-static, elastic-inertial, and inertial-collisional behaviors. Resulting distributions show a dependence of the best-fit functional form on flow regime with diffuse boundaries between regimes. Bed force distributions are sensitive to changes in shear rate and the standard deviation of grain size, weakly sensitive to changes in fluid properties, and robust to changes in mean grain size. Distribution tails generally become more elongated with increasing values of inertial and

Stokes numbers. The results of this work highlight the relative erosive potential for granular flows in different flow regimes, showing a higher erosive potential for flows exhibiting more inertial behaviors. In addition to my analysis of bed force distributions in granular flows, I explore the effects of sediment redistribution on sea level in the Bengal Basin and Ganges-Brahmaputra-Meghna river system which is responsible for transporting roughly 1 billion tons of sediment annually. Using a gravitationally self-consistent sea level model, I show that sediment redistribution in this region is likely responsible for ~ 30 m of sea-level change over the last glacial cycle, but the results of these simulations are sensitive to model input parameters such as the effective elastic lithospheric thickness and mantle viscosity profile.

CURRICULUM VITAE

NAME OF AUTHOR: Amelia H. Winner

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENDED:

University of Oregon, Eugene
The Pennsylvania State University, State College

DEGREES AWARDED:

Doctor of Philosophy, Earth Sciences, 2021, University of Oregon
Bachelor of Science, Physics, 2015, The Pennsylvania State University

AREAS OF SPECIAL INTEREST:

Granular Physics
Discrete Element Modeling
Mechanical Erosion

PROFESSIONAL EXPERIENCE:

Teaching Assistant, University of Oregon, 2020

Faculty Search Committee Member, Georgia Institute of Technology, 2018

Graduates in Earth and Atmospheric Sciences, President, Georgia Institute of Technology, 2016-2018

Teaching Assistant, Georgia Institute of Technology, 2016-2017

Teaching Assistant, The Pennsylvania State University, 2014

ACKNOWLEDGMENTS

I would like to acknowledge my father and stepmother for their unwavering love and support. The sense of humor and stubbornness that they instilled in me from a young age have gotten me to this point in my career. I love you very much.

I would like to acknowledge Pat Wittick for never losing faith in me and for putting up with the countless late nights in the lab, and difficult years apart. I certainly would not have made it this far without you.

I would like to acknowledge the many wonderful friends I have met in graduate school, both at Georgia Tech and the University of Oregon. You all have kept me remotely sane throughout this process and I will cherish these relationships for the rest of my life.

I would like to acknowledge my advisors, Ken Ferrier and Joe Dufek, for the support and guidance they provided during my graduate career. I am incredibly grateful for the opportunities you gave me. Thank you for always being patient with me and shaping me into the scientist I am today.

I would like to acknowledge my committee members, Leif Karlstrom, Josh Roering, and Eric Corwin for the thoughtful discussions and critical feedback on my projects. Your insights have improved the quality of this dissertation.

This dissertation is dedicated to Sage Kemmerlin and Kathleen Trafton without whom,
this would not have been possible.

TABLE OF CONTENTS

Chapter	Page
I. INTRODUCTION	1
II. INVESTIGATING BED FORCES IN EXPERIMENTAL GRANULAR FLOWS	5
2.1 Introduction.....	5
2.1.1 Importance of bed forces in granular flow dynamics	5
2.1.2 Probability distribution of bed forces	7
2.1.3 Observed dependences on PDFs on flow properties	10
2.2 Materials and Methods	15
2.2.1 Materials	15
2.2.2 Methods.....	17
2.3 Results.....	19
2.3.1 Visual analysis of the experimental flows.....	20
2.3.2 Bed force distributions	22
2.4 Discussion	25
2.4.1 Sensitivity of bed force distributions on flow properties	25
2.4.2 Relation of distribution fit parameters to non-dimensional numbers	29
2.4.3 Implications for granular flow dynamics	31
2.5 Bridge	33

III. QUANTIFYING THE ROLE OF FLUID AND SOLID FLOW

PROPERTIES ON BED FORCE DISTRIBUTIONS IN MUTLIPHASE

GRANULAR FLOWS	35
3.1 Introduction.....	35
3.1.1 Background	35
3.1.2 Bed forces in granular systems.....	37
3.1.3 Scaling of Granular Flow Regimes.....	38
3.1.4 Study Goals	41
3.2 Methods	42
3.2.1 MFIX Multiphase Model	42
3.2.1.1 Governing equations.....	43
3.2.1.2 Contact force model.....	45
3.2.1.3 Solid-fluid coupling.....	46
3.2.2 Model Implementation.....	48
3.2.2.1 Granular flows with interstitial fluid.....	49
3.2.2.2 Pure granular flows.....	50
3.2.3 Data analysis.....	50
3.3 Results.....	51
3.3.1 Flow property controls on bed force distributions.....	51
3.3.1.1 Fluid flow properties.....	51
3.3.1.2 Granular properties.....	52
3.3.2 Distribution shape as a function of non-dimensional numbers	55

Chapter	Page
3.4 Discussion	57
3.4.1 Relation of distribution fit parameters to flow properties and non-dimensional numbers	57
3.4.2 Effects of polydispersity on bed force distributions	59
3.4.3 Dry versus wet flows	61
3.4.4 Recommendations and implications for granular flows	64
3.5 Bridge	68
IV. SEA-LEVEL RESPONSES TO SEDIMENT REDISTRIBUTION IN THE BENGAL BASIN OVER THE LAST GLACIAL CYCLE	69
4.1 Introduction	69
4.2 Methods	71
4.2.1 Static sea-level theory and model	72
4.2.2 Model Implementation	75
4.3 Sediment redistribution history	75
4.4 Results	83
4.5 Discussion	85
4.5.1 Effects of sediment redistribution on sea level	85
4.5.2 Importance of erosion in sediment transfer history	88
4.5.3 Sensitivity of modeled sea-level changes to uncertainties in sediment transfer scenarios	91
4.5.3.1 Spatial variability	92

Chapter	Page
4.5.3.2 Earth model.....	93
4.5.3.3 Temporal variability.....	96
4.6 Conclusions.....	98
V. CONCLUSIONS.....	99
APPENDICES	
A. LABORATORY EXPERIMENTS SUPPLEMENTARY MATERIAL.....	105
A.1 Run conditions for BERTHA experiments	105
A.2 Example of sensor calibration results	106
A.3 Single-sided amplitude spectrum of the resampled (2 kHz) bed force signal measured in BERTHA.....	107
A.4 χ^2 statistics for GPD and power law fits to the tails of bed force probability distributions.....	108
B. DISCRETE ELEMENT SIMULATIONS SUPPLEMENTARY MATERIAL.....	109
B.1 Model parameters used in discrete element simulations.....	109
C. SEA LEVEL RESPONSE TO SEDIMENT REDISTRIBUTION SUPPLEMENTARY MATERIAL.....	110
C.1 Compiled erosion rate data used to construct sediment transfer scenarios.....	111
C.2 Compiled sedimentation rate data used to construct sediment transfer scenarios.....	112

Chapter	Page
REFERENCES CITED	113

LIST OF FIGURES

Figure	Page
1. Examples of granular flows.	6
2. Sensitivity of hypothesized probability distributions for normalized bed force excursions $P(F - F_{mean})/F_{mean}$ to distribution parameters.	9
3. Inertial number-Stokes number phase space	12
4. Experimental apparatus	16
5. Bed force time series	18
6. Snapshots of experimental flows.	21
7. Best-fit distributions	22
8. Contribution of wall effects on PDF of bed forces	24
9. Normalized versus non-normalized force excursions.	26
10. Best fit values for GPD shape parameter and scale parameter fit to normalized bed force distributions as a function of inertial and Stokes numbers for each experimental run.	29
11. Best-fit Generalized Pareto distributions for high, intermediate, and low values of the Inertial number and Stokes number in granular flow experiments in BERTHA.	31
12. Examples of natural granular flows.	36
13. Granular flow regimes can be delineated by visco-inertial number and Stokes number	40
14. Geometry of rotating cylindrical flume used in discrete element simulations	48
15. Sensitivity of normalized bed force distributions to mean grain size, shear rate, degree of polydispersity, fluid viscosity, and fluid density	53
16. χ^2 statistics for GPD and power law fits to the tails of bed force probability distributions	56

Figure	Page
17. Best fit values for power law and GPD parameters in fits to normalized bed force distributions as a function of visco-inertial and Stokes numbers.....	58
18. Variations in fit parameter trends with non-dimensional numbers	59
19. Influence of the standard deviation of grain size on distribution fit parameters...	60
20. Comparison of pure granular flows to flows containing a fluid phase	63
21. The functional form of the best-fit distribution for normalized bed force excursions in granular flows as a function of flow regime.....	65
22. Schematic of factors controlling sea-level change.....	73
23. Locations of basin-averaged erosion rate measurements and depositional areas.....	76
24. Rates of sediment erosion and deposition over the past glacial cycle in the sediment redistribution history	80
25. Cumulative changes in sediment thickness and sea level over the 122-kyr simulation.	84
26. Difference in RSL_{GR} at 122 ka between two simulations, one driven by global ice variations and regional sediment redistribution, and one driven only by global ice variations.....	84
27. Modeled sea-level histories at Dhaka and Kolkata	87
28. Mean rate of change of ΔSL_{GR} over the last century in the simulation driven by variations in ice and sediment.....	88
29. Difference in ΔSL_{GR} between the standard scenario and a scenario in which the model input only includes sediment deposition.....	89
30. Comparison of model results to field observations.....	90
31. Sensitivity of ΔSL_{GR} to spatial variability.....	93
32. Sensitivity of ΔSL_{GR} to effective elastic lithospheric thickness and mantle viscosity profile.....	95
33. Sensitivity of ΔSL_{GR} to temporal variability.....	97

Figure	Page
A.2 Example of sensor calibration results.....	106
A.3 Single-sided amplitude spectrum of the resampled bed force signal measured in BERTHA	107
A.4 χ^2 statistics for GPD and power law fits to the tails of bed force probability distributions.....	108

LIST OF TABLES

Table	Page
A.1 Run conditions for BERTHA experiments.	105
B.1 Model parameters used in discrete element simulations	109
C.1 Compiled erosion rate data used to construct sediment transfer scenarios	111
C.2 Compiled deposition rate data used to construct sediment transfer scenarios.....	112

CHAPTER I

INTRODUCTION

Granular flows are gravity currents comprised of a particle phase and an interstitial fluid. Gravity-driven granular flows encompass a wide range of geophysical flows from rock avalanches and pyroclastic density currents, to debris flows and turbidity currents. Because these flows are ubiquitous in nature, they vary greatly in formation process, physical properties, and behavior. As granular flows move over their substrates, they impose forces on the bed which span several orders of magnitude (McCoy et al., 2013), exchanging mass and momentum with the bed which may have significant implications for flow dynamics and related hazards (Iverson, 1997). Of particular importance are the large magnitude but infrequent forces that constitute the tails of this distributions as these can have implications mobilization of the substrate and can confound continuum descriptions of these flows. While the entire distribution of bed forces is likely important for threshold processes such as erosion and entrainment, there is thought to be an outsized influence from the tail of the distribution which is poorly constrained (Hsu et al., 2014). For this reason, constraining the functional form of the distribution of bed forces in granular flows and the flow property controls on the shape of this distribution is imperative for understanding their erosive potential. Several distinct functional forms have been proposed to describe the shape of the magnitude-frequency distribution of bed forces, signaling a discordance on the controlling parameters governing the form of the distribution. In this dissertation, I measure bed forces generated by granular flows

over a wide range of flow conditions, using a combination of laboratory experiments and discrete element simulations. Using these data, I am able to comment on the most appropriate functional form of the bed force distribution for each flow regime and quantify the sensitivity of distribution shape to changes in granular and fluid properties.

In Chapter II, I present the results of laboratory experiments of dry granular flows comprised of borosilicate glass beads conducted in a rotating cylindrical flume. Bed forces are measured at the base of the flow by a high-precision 3-by-3 rectangular force sensor array. The array geometry enables me to capture spatial variations in the distribution of bed forces within the experimental granular flows and quantify wall effects at the flow boundaries. In these experiments, I explore granular flows with inertial numbers ranging from 3×10^{-2} to 0.5 and Stokes number from 850 to 5×10^4 . Mean grain size, shear rate, and the standard deviation of grain size is varied from 2 – 10 mm, 17 – 51 Hz, and 0 – 3.55 mm, respectively. I collect highspeed videos of each experimental run in order to link grain-scale behavior to the shape of the bed force distributions. Through analysis of the resulting force distributions and highspeed videos, I show that small grain size flows at low to moderate shear rates are susceptible to significant wall effects and that the shape of the distribution in these flows may vary substantially depending on the distance from the flow boundary. The bed force distributions are sensitive to changes in shear rate and the width of the grain size distributions and robust to changes in mean grain size. Distribution tails become more elongated with inertial and Stokes numbers, although the domain over which the distribution is defined is likely to impact the interpretation of these results.

In Chapter III, I describe the results from discrete element simulations which employ a similar geometry to the flume used in the laboratory experiments. This technique enables the measurement of the force contributed by every particle in contact with the bed, generating a more complete spatial distribution of bed forces. The use of discrete element simulations, allows me to explore a wider parameter space than was possible in the laboratory, specifically in regards to the shear rate and interstitial fluid used to simulate granular flows. Using this method expands the parameter space explored to Stokes numbers of 1×10^{-5} to 1×10^5 and visco-inertial numbers of 2×10^{-5} to 2. I employ the visco-inertial number in place of the inertial number used in Chapter II due to the increased viscous interactions present in the simulated flows caused by the use of viscous interstitial fluids. These simulated flows span elastic-quasi-static to inertial-collisional flow regimes, which allows the analysis of bed force distributions near both flow regime transitions. The results of this work show a dependence of the best-fit distribution of bed forces on flow regime, with diffuse boundaries between regimes. Distribution shapes were sensitive to changes in shear rate and width of the grain size distribution and only sensitive to changes in mean grain size at the high fluid density and viscosity limit, likely due to increased drag. Distributions showed a low sensitivity to changes in fluid properties and showed no difference between simulations run in a vacuum and simulations using air as an interstitial fluid.

During my graduate studies, I explored a range of research interests including sea level response to large-scale sediment redistribution. In Chapter IV, I present the results from a gravitationally self-consistent sea level model in which I explore the

variations in sea level caused by sediment redistribution in the Bengal Basin over the last glacial cycle. The results of this work show ~ 30 m sea level perturbations in the Ganges-Brahmaputra delta caused by sediment redistribution over the 122 ka simulation and rates of sea-level change as large as 1.5 mm yr^{-1} in the delta over the past 100 years. These sedimentary effects on modeled sea level have a wide footprint, extending several hundred km from the location of fastest deposition in the delta. Comparison of these simulations to simulations driven only by global ice mass variations shows that sediment redistribution is large enough to affect the sign of modeled relative sea-level over the last 10 ka at sites near the delta. These simulations illustrate the importance of sediment redistribution as a driver of sea-level change in this region, and imply a strong feedback between sea-level change and sediment redistribution in the Ganges-Brahmaputra-Meghna Delta over glacial-interglacial time scales.

CHAPTER II

BED FORCES IN DRY EXPERIMENTAL GRANULAR FLOWS

2.1 Introduction

2.1.1 Importance of bed forces in RGF dynamics

Rapid granular flows (RGFs) are extremely mobile, high-energy gravity currents that include debris flows, pyroclastic density currents, and rock avalanches. RGFs play a critical role in many geologic processes and can impact their surroundings over a wide range of timescales. On geologic timescales, RGFs reshape Earth's topography through erosional and depositional processes, leaving information in their deposits about flow dynamics and ambient conditions during deposition (Valentine et al., 1989; Buesch, 1992; Calder et al., 2000; Stock and Dietrich, 2006; Schürch, 2011; Scarpati and Perrotta, 2012). On much shorter timescales, RGFs pose an enormous threat to human populations and infrastructure, and are responsible for over \$500 million USD in damage and the displacement of over 50,000 people annually (Hilker et al., 2009; Annen and Wagner, 2003). These RGF-associated hazards have motivated many workers to explore initiation conditions for these flows (Coe et al., 2007) as well as understand interactions within the flows themselves (Dufek, 2016).

A challenge in understanding RGF dynamics is their diversity of behavior, as they vary greatly in size, formation process, composition, fluid content, temperature, flow velocity, and runout distance. Grain size, for example, varies over six orders of magnitude from fine volcanic ash (~10 microns) to large boulders (~10 m), and flow velocity varies from meters per second in debris flows to hundreds of meters per second

in pyroclastic density currents (Wilson, 1985). A unifying factor of all RGFs, however, is that they impose forces upon the beds they flow over, which influences their dynamics in many ways. The bed controls flow behavior through frictional or inelastic interactions, dissipating the flow's energy and ultimately leading to flow arrest (e.g., Iverson, 1997). If bed forces are sufficiently high, they can fracture bedrock (e.g., Stock and Dietrich, 2006), abrade the bed (e.g., Sklar and Dietrich, 1998, 2004), and entrain particles from the bed (e.g., Iverson et al., 2011, 2012; McCoy et al., 2012; Brand et al., 2014), thereby directly affecting the flow's mass and momentum. Thus, the erosive potential of these flows is directly linked to the frequency-magnitude distribution of bed forces.

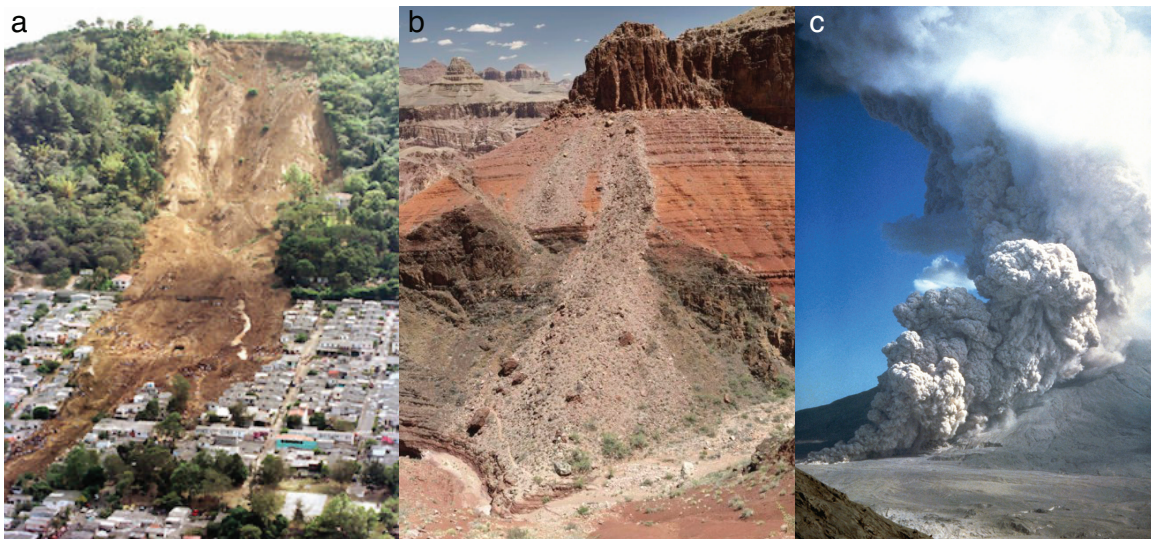


Figure 1. Examples of granular flows. (a) Landslide, Las Colinas, El Salvador (USGS, 2001). (b) Rock avalanche, Grand Canyon National Park, AZ (Miller, 2018). (c) Pyroclastic density current, Mount Saint Helens, WA (Lipman, 1980).

As a flow travels downslope, the RGF may interact with the underlying substrate through a number of complex processes including abrasion, single particle collisions, force chain formation, plowing, and pore-pressure gradients (Brand et al., 2014; Hsu et al., 2008; Estep and Dufek, 2013; Lu et al., 2016; Roche et al., 2013a). These interactions generate forces on the bed which loosen material allowing it to be more easily

incorporated by the overlying flow. The resulting forces drive bed entrainment and change the RGF's shear rate $\dot{\gamma}$, grain size d , and grain size distribution σ_g . Changes to the RGF's flow properties change the internal dynamics of the flow and, therefore, change the distribution of forces imposed on the bed by the RGF. The goal of this study is to address the first leg of this feedback, specifically, analyzing the distribution of bed forces generated by RGFs.

As entrainment is largely thought to be a supply-dependent process (Iverson, 2012), a key component of the bed entrainment feedback is the frequency-magnitude distribution of bed forces imposed by the granular flow. Regardless of dominant entrainment mechanism, several workers suggest that force excursions much larger than the mean force are responsible for dictating bed entrainment capabilities (Estep and Dufek, 2012; McCoy et al., 2012; Hsu et al., 2014). For this reason, the analysis will be restricted to the distribution of bed forces greater than the mean force imparted by the flow. The normalized frequency- magnitude distribution is often represented as $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$, the probability density of bed forces, F , that exceed the mean force, $\bar{F}$. Identifying the functional form of $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ for RGFs is essential to the understanding of mass and momentum transfer at the bed.

2.1.2 Probability distribution of bed forces

There are two leading hypotheses for the functional form of $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ in granular flows. Studies of large-scale experimental and natural debris flows indicate that $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ is best described by a generalized Pareto distribution (GPD, Figure 2; Equation 1; Hsu et al., 2010, 2014; McCoy et al., 2013).

$$P\left(\frac{F - \bar{F}}{\bar{F}}\right) = \left(\frac{1}{\sigma}\right) \left(1 + k \frac{F - \bar{F}}{\bar{F}\sigma}\right)^{-1 - \frac{1}{k}} \quad \text{Eq. 1}$$

In Equation 1, k and σ are constants known as the GPD shape parameter and scale parameter, respectively. The scale parameter, σ , sets the y-intercept for the distribution with larger values of σ leading to lower y-intercepts and thus longer distribution tails. The shape parameter, k , influences the curvature of the distribution in plots of $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$, with positive values producing more elongated tails and negative values generating distributions with more truncated tails (Figure 2). In the limit $k \rightarrow 0$, the GPD becomes the exponential distribution. Some laboratory studies of monodisperse and relatively low-velocity or static granular systems find that $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ follows an exponential distribution (Liu et al., 1995; Mueth et al., 1998; Longhi et al., 2002; Majmudar and Behringer, 2005; Gardel et al., 2009) a shape which can be captured by the GPD. These qualities highlight the usefulness of the GPD and suggest it might be a reasonable choice to unite both rapidly moving and static granular systems.

In another set of slowly sheared granular flow experiments, Corwin et al. (2005) show that the distribution of normal forces in a granular material under shear follows a power law distribution. A benefit of using this distribution is the potential to infer physical meaning from changes in the fit parameters (Corwin et al., 2005). The use of this functional form is supported by other experiments of slowly sheared granular systems (Denisov et al., 2016) as well as in granular packings undergoing quasi-static compression (Boberski et al., 2013) The general form of the power law distribution is given in Equation 2.

$$P\left(\frac{F - \bar{F}}{\bar{F}}\right) = \left(\frac{\alpha - 1}{x_{min}}\right) \left(\frac{F - \bar{F}}{\bar{F} x_{min}}\right)^{-\alpha} \quad \text{Eq. 2}$$

Here, the shape of the distribution is controlled by two fit parameters, α , which sets the slope of the distribution, and, x_{min} , which determines the minimum value of the normalized bed force excursions, $\frac{F - \bar{F}}{\bar{F}}$, over which the distribution is defined. The way in which these

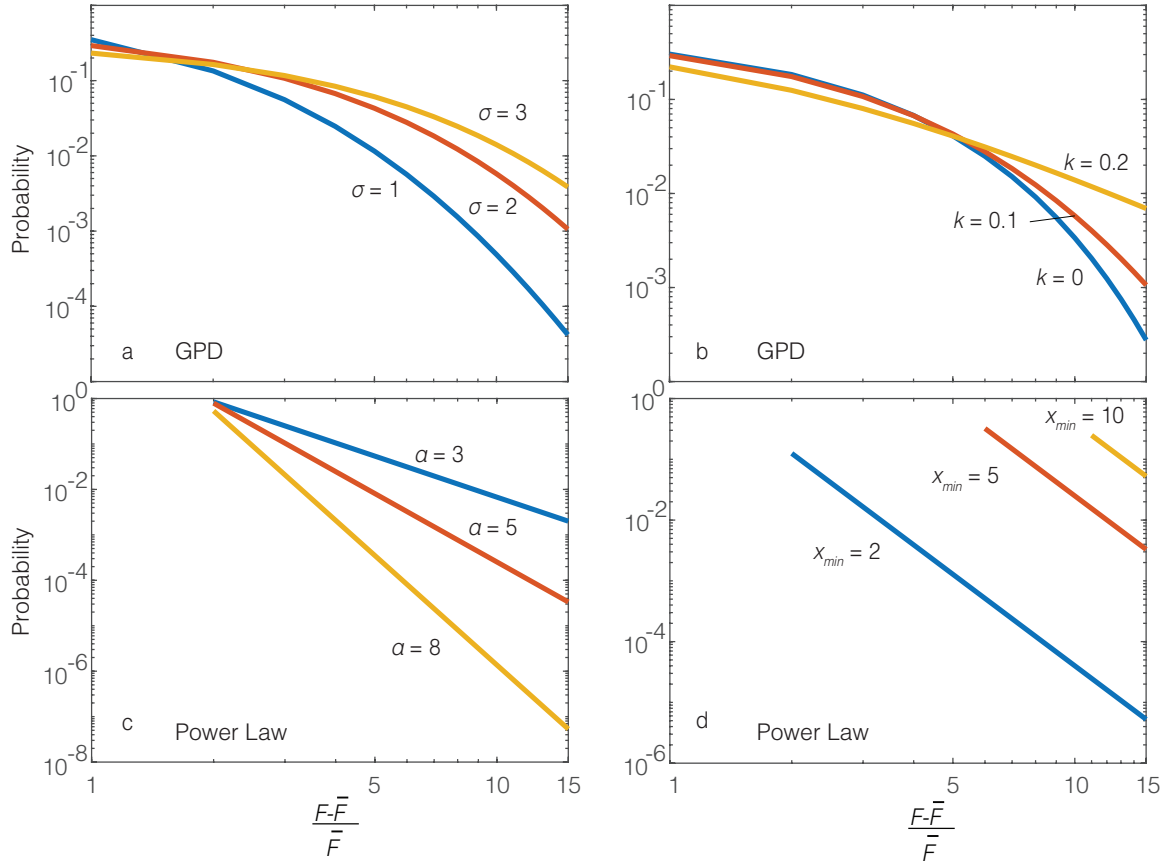


Figure 2. Sensitivity of hypothesized probability distributions for normalized bed force excursions $(F - \bar{F})/\bar{F}$ to distribution parameters. (a) Larger values of the Generalized Pareto distribution (GPD; Equation 2) scale parameter, σ , produce normalized bed force distributions with lower y-intercepts and longer tails. (b) Larger values of the GPD shape parameter, k , lead to longer tails and lower y-intercepts. (c) Larger values of the power law distribution (Equation 1) parameter α produce steeper slopes and shorter tails. (d) The power law distribution parameter x_{min} defines the lower limit of the normalized force excursions over which the power-law portion of the distribution is defined.

distribution fit parameters affect the shape of the PDF is shown in Figure 2c and 2d. As the magnitude of α increases, the tail of the distribution steepens which results in a

decrease in the frequency of high-magnitude force excursions. An increase in x_{min} does not affect the shape of the distribution but, instead, shifts the start of the distribution to the right, truncating the domain. The power law distribution forms a straight line in log-log space which allows for a clear graphical confirmation of its appropriateness to describe the data. This distribution was initially proposed and shown to agree well with experimental data for granular systems exhibiting slow shear rates ($\dot{\gamma} = 5 \times 10^{-6} - 1 \times 10^{-2}$ Hz), however, it remains untested whether or not this distribution is an appropriate choice for more rapid flows.

Defining the functional form of has important implications for bed entrainment, as only forces greater than some threshold value are capable of entraining bed material (Haas and Woerkom, 2016). Different distributions have been shown to differ from each other as much as 2-10 orders of magnitude for the highest magnitude forces in their tails (McCoy et al., 2013; Hsu et al., 2014). Because of this feature, distributions with elongated tails will be more likely to erode and entrain bed material than those with shorter tails. Thus, determining which distribution best fits RGFs as well as determining the how their respective fit parameters depend on flow properties, is necessary in constraining material entrainment at the base of RGFs.

2.1.3 Observed dependences of PDFs on flow properties

In a series of laboratory experiments in a rotating drum, Hsu et al. (2014) found that exponential distributions can overestimate or underestimate the frequency of high-magnitude bed forces, but that the GPD was able to capture these variations in the tail of the distribution. They found that the sign of the best-fit shape factor, k , varied systematically with σ_g with more positive values for wider distributions and negative

values for narrower distributions at a given rotation rate. In their experiments, best-fit values of σ increased with the width of the grain size distribution. They also found that at a given σ_g , the effective grain diameter had little influence on the mean bed force. They showed that the magnitude of the largest bed forces (i.e., the top 1% of the distribution) increased as a power law function of effective grain diameter to the power of 0.8-1.7.

In the same study, the best-fit σ increased linearly with flow velocity, while neither the mean bed force nor the shape parameter, k , varied systematically with flow velocity. The top 1% of bed forces scaled as a power-law function of flow velocity to the power of -0.3 to 1.1, generally with more scatter around the regression than in the regression with effective grain size. These observations, which were made under a relatively narrow range of flow properties, suggest that $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ covaries strongly with certain flow properties. It remains to be determined how this dependence varies over a wider range of flow properties.

Further evidence for GPD in granular flows comes from field observations of bed forces under natural debris flows in Chalk Cliffs, Colorado (McCoy et al., 2013; Figure 3). These flows showed force distributions that were well fit by GPD with k values of 0.21-0.41, implying a high frequency of large magnitude forces, and longer tails than those in exponential distributions (Figure 2). McCoy et al. (2013) interpreted the elongated tail to be a result of the large width of the grain size distribution observed in these flows. Interestingly, McCoy et al. (2013) observed no obvious differences in the force distributions generated by coarse-grained granular surges and intersurge flows, regardless of their differences in flow properties.

One proposed explanation for the observed differences in force distributions is that bed forces are governed by different granular behaviors in different flow regimes due to fundamental differences in grain-scale interactions (Campbell 2005; Forterre and Pouliquen, 2008). In some flows, like dilute pyroclastic density currents, bed forces are

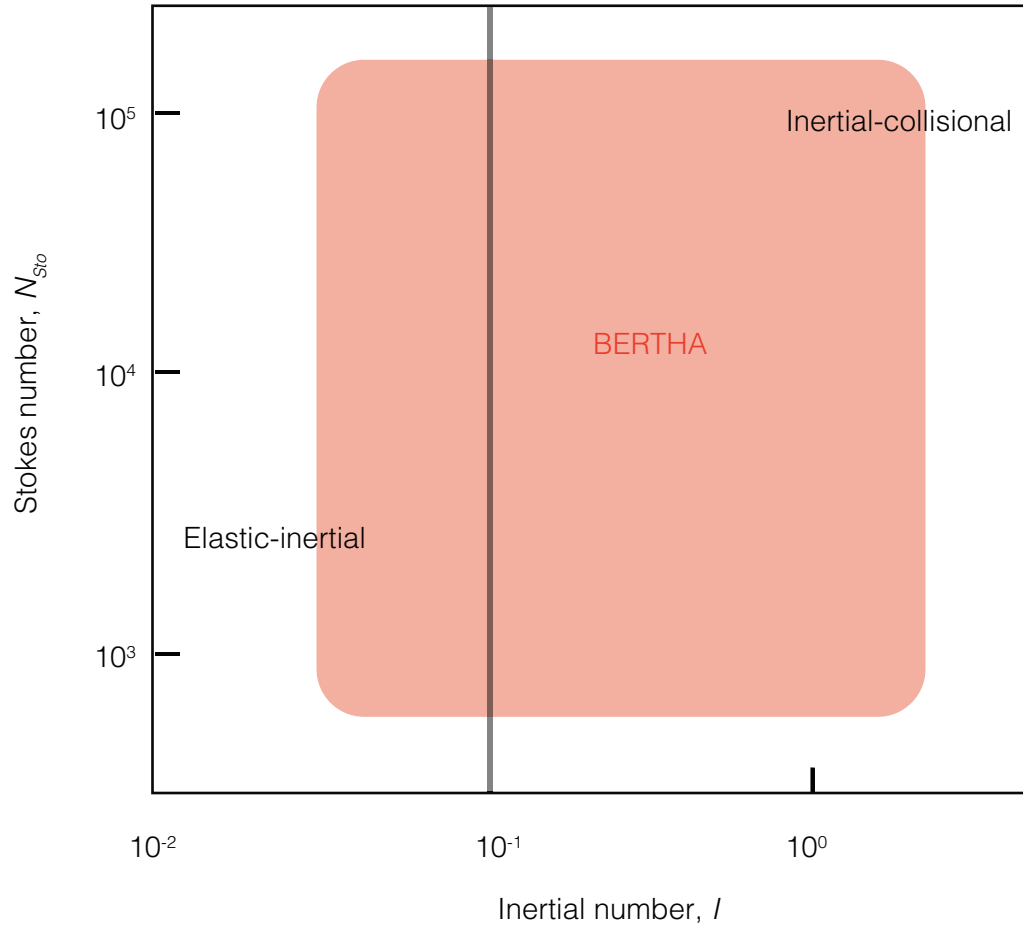


Figure 3. Inertial number-Stokes number phase space. Salmon box delineates the parameter space spanned by the experiments presented in this study.

dominated by the inertia of single-particle collisions with the bed. This is often referred to as the inertial-collisional regime (Campbell, 2005). In other flows like slow-moving landslides, particles are closely packed with long-lasting contacts and experience little relative motion. This regime is dominated by stresses transmitted through elastic

deformation of persistent contacts between particles and the bed, and is often referred to as the elastic-quasi-static regime (Campbell, 2005). The intermediate regime is known as the elastic-inertial regime, in which stresses due to particle inertia are comparable to those due to elastic deformation (e.g., Hsu et al., 2008, 2014; Campbell, 2005). These flow regimes are differentiated from one another by the dependence of the mean force $\bar{F}$ on the shear rate $\dot{\gamma}$. In the elastic-quasi-static regime $\bar{F}$ is independent of $\dot{\gamma}$. In the elastic-inertial regime $\bar{F}$ scales linearly with $\dot{\gamma}$, and in the inertial-collisional regime $\bar{F}$ scales quadratically with $\dot{\gamma}$ (Bagnold, 1954; Savage, 1984; Campbell, 2005; Forterre and Pouliquen, 2008; Da Cruz et al., 2005). In the experiments, I restrict the analysis to elastic-inertial and inertial-collisional regimes, as generating flow conditions to mimic quasi-static behavior is challenging in the setup.

In the analysis, I use an inertial number-Stokes number, $I-N_{Sto}$, phase spaces to enable comparison of the experimental results to those of field-based measurements (McCoy et al., 2013; Figure 3). For free surface flows, the inertial number can be written as:

$$I = \frac{\dot{\gamma}d}{\sqrt{\frac{(\rho_p - \rho_f)gh}{\rho_p}}} \quad \text{Eq. 3}$$

where ρ_p is the density of the solid phase, $\dot{\gamma}$ is the shear rate, d is the diameter of the particles, ρ_f is the density of the fluid phase, g is the gravitational acceleration, and h is the height of material above the plane of interest (Savage, 1984; Forterre and Pouliquen, 2008; Da Cruz et al., 2005). The $(\rho_p - \rho_f)$ factor accounts for hydrostatic pore-fluid pressure (Iverson, 1997). I is interpreted as a ratio of the timescales relevant for grain-

scale (microscopic) and bulk flow (macroscopic) behaviors. The microscopic timescale is the timescale associated with grain rearrangement, $\frac{d}{\sqrt{gh}}$, while the macroscopic timescale refers to the timescale set by the shearing of the bulk flow, $\frac{1}{\dot{\gamma}}$. As shown in Figure 3, the inertial-collisional regime lies at high I values and the elastic-inertial regime lies at lower values of I in the case of dry flows.

Next, I use N_{Sto} , which is a non-dimensional parameter commonly used to assess the role of viscous forces and the degree of particle-fluid coupling in grain-fluid mixtures (e.g., Tang et al., 1992; Raju and Meiburg, 1995). Here I write N_{Sto} for low particle Reynolds numbers using a characteristic velocity equal to $d\dot{\gamma}$,

$$N_{sto} = \frac{\rho_p \dot{\gamma} d^2}{18\mu_f} \quad \text{Eq. 4}$$

N_{Sto} can be interpreted as the ratio of the time to decelerate a grain by an amount equal to the characteristic velocity through application of a Stokes viscous drag force, to the time required for a grain to move a distance of one particle diameter, d , through the interstitial fluid at the characteristic velocity (Armanini et al., 2005). If N_{Sto} is large, motion of the grains and the fluid are largely decoupled, but if N_{Sto} is small, particle motion is modulated by the fluid due to viscous interactions.

While the dependence of the mean force on flow properties in different flow regimes is well understood, the dependence of $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ on flow properties in different flow regimes remains poorly constrained. This piece of information is imperative for understanding threshold-dependent processes, as the highest-magnitude forces are likely to drive these processes. Therefore, understanding the differences in the behavior of

$P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ in different flow regimes and the flow regimes spanned by RGFs is critical in the analysis of hazards posed by granular flows.

These considerations motivate the central goal of this study, which is to better understand the distribution of bed forces generated by RGFs. In this work, I focus on the following questions: (1) what is the functional form of $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ for RGFs; (2) how does $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ depend on solid-phase flow properties; and (3) how do these dependences vary between flow regimes? To answer these questions, I simulate small-scale granular flows in the laboratory, vary flow properties to capture flow behaviors spanning elastic-inertial to inertial-collisional regimes, and record the distribution of bed forces these flows impose on the bed. Measurements reveal that $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ generally follows a GPD, and the shape of the distribution is sensitive to changes in shear rate and the width of the grain size distribution in both flow regimes.

2.2 Materials and Methods

2.2.1 Materials

I constructed a rotating cylindrical flume, BERTHA (Bed Entrainment RoTating High-shear Apparatus) to measure bed forces generated by small-scale idealized granular flows in a laboratory setting. BERTHA is comprised of a 33 cm-wide cylindrical insert with an inner radius of 25 cm housed within a protective outer cylinder, both made of 8 mm thick carbon steel. Acrylic windows are attached to both sides of the drum to create spatially consistent boundary conditions and to facilitate the observation of the experimental flows (Figure 4A). The flume rests on two cylindrical aluminum rods, one

of which is attached to motor shaft to drive rotation. The flume is powered by an NMA-brand 7.5 horsepower motor capable of driving rotation at 0.25-5.54 rotations/s, which translate to linear velocities of 0.4 to 8.7 m/s at the bed. The electronics used for data collection (sensor circuit board, microcontroller, and its power source) are mounted on the back window. This configuration allows for all wired components to rotate with the drum.

To measure bed forces generated by the experimental flows, the bed of the inner cylinder is instrumented with a 3-by-3 array of SMD S100 high-precision thin film analog force sensors which have a maximum capacity of 0.5 N and a resolution of 500 μN . Each sensor measures forces striking the circular end of a cylindrical load plate, which is 12 mm in diameter, flush with the bed of the inner cylinder. The remainder of the cylindrical load plate passes through the inner cylinder, where it rests on the sensor, which is installed between the outer drum and the inner cylinder. The portion of the plate passing through the insert is encased in a steel sleeve to ensure the plate remains in place during rotation. I installed nine sensors in a rectangular array with

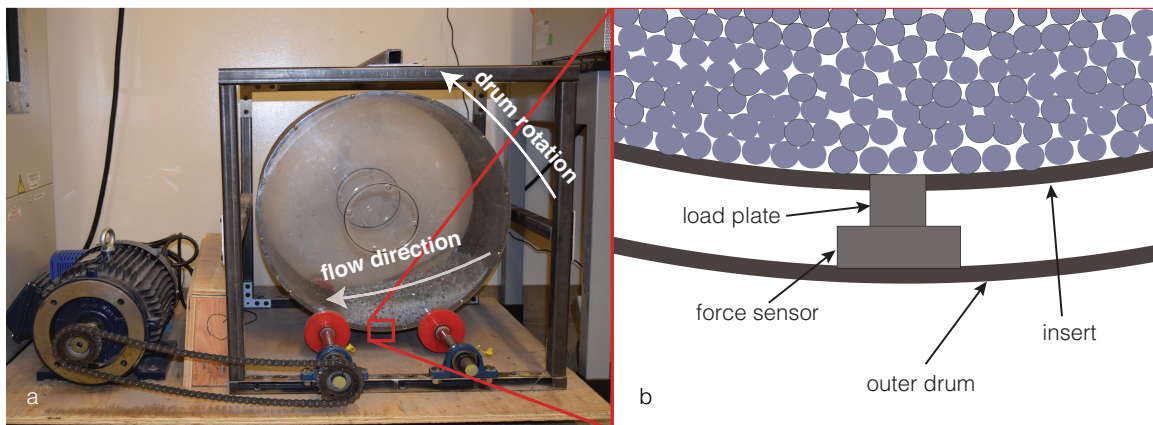


Figure 4. (A) Experimental apparatus, BERTHA. (B) Zoomed-in schematic of force sensor and load plate geometry.

13.5 cm spacing between sensors and 2.5 cm spacing between the wall and the nearest sensor, with the entire array spanning 17% of the drum's circumference. The analog signals are split between two analog-to-digital converters wired to a Raspberry Pi where the force data is sampled at a rate of 7 kHz.

I calibrated each sensor in its mounted position in the flume by dropping particles of known mass and velocity onto the sensor. I used a Phantom high-speed camera to measure the particle velocity and impact duration, capturing images at a rate of 1000 fps. I dropped particles with masses of 0.2 to 1.3 g from a height of 25 cm above the sensor, and computed the acceleration due to impact from the change in velocity before and after impact. From this, I calculated the impact force from the particle on the sensor.

Uncertainties in the calculated particle accelerations were on the order of $0.01 \frac{m}{s^2}$ which yields force uncertainties on the order of 10 μ N, below the resolvable forces in the system. An example of these force calibrations can be found in Figure A.2.

Experimental granular flows of borosilicate glass beads ($\rho = 2230 \text{ kg/m}^3$) of varying diameters (2-10 mm) are used to simulate natural granular material without added complications due to comminution. Particles have a young's modulus of 64 GPa, a restitution coefficient of ~ 0.9 , and sphericity of $\sim 1 \pm 0.1$. The experimental flows occupy 10 – 20% of the drum's total internal volume and have an approximate interparticle stiffness of $2.68 \times 10^4 - 1.34 \times 10^5 \text{ N/m}$ based of the estimation methods presented in Campbell (2005)..

2.2.2 Methods

I processed the raw voltages measured by the force sensors in several steps. First, I resample the data at 2 kHz to maintain a constant sampling rate and reduce noise. I then apply a bandpass filter to the data to remove noise > 900 Hz and $< 0.3N$ Hz which I determine as distinct from the signal based off a frequency spectrum analysis (Figure A.3). Here, N is a number defined by the ratio of the rotation rate versus the low endmember rotation rate used in the experiments (5 Hz). Because the low-frequency component corresponds to the portion of the signal associated with the rotation rate, the value of the dominant low-frequency signal varies with rotation rate. The sinusoidal signal of the weight of the load plate is subtracted from the signal to isolate only the contribution due to the granular flow. To focus on the forces that exceed

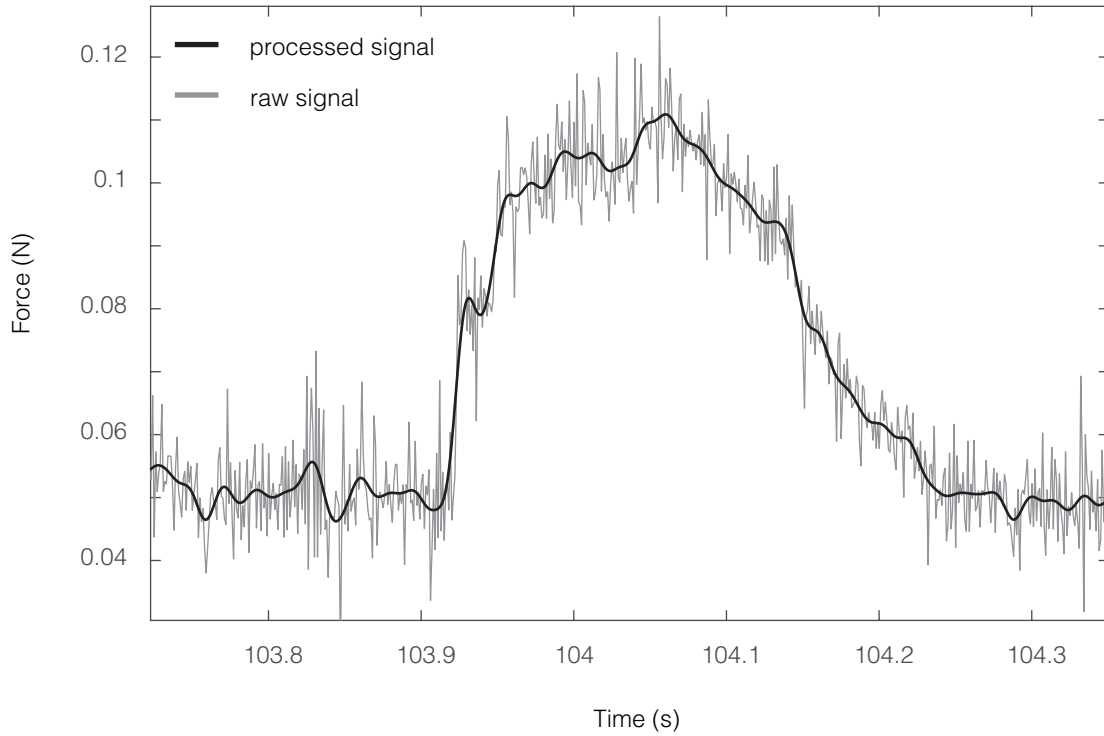


Figure 5. Raw and processed force time series for a monodisperse flow with grain size $d = 10$ mm and shear rate $\dot{\gamma} = 34$ Hz. The processed signal has been resampled at 2 kHz and passed through a bandpass filter with cutoff frequencies of 0.6 and 900 Hz. Time on the x-axis refers to the time, in seconds, since the start of the experiment.

the mean force, I subtract the mean force and discard all results equal to or less than zero and normalize these excursions by the mean force. Next, I create probability distributions by generating normalized histograms containing the remaining force data. Binning of the data is done in order to help generate a smooth distribution (Hsu et al., 2014). To avoid biasing data due to an arbitrary choice of bin width, I use bin widths calculated according to the Freedman-Diaconis method (Freedman and Diaconis, 1981) for each data set. This method calculates the ideal bin size as $bin\ width = 2 \frac{IQR(x)}{\sqrt[3]{n}}$, where $IQR(x)$ represents the interquartile range of the bed force data and n is the total number of measurements. From here, a GPD and power law distribution are fit to the data and the best-fit distribution parameters are calculated. I calculate the χ^2 statistic for both the best-fit power law and Generalized Pareto distributions to determine the goodness of fit (Figure A.4). Once the best-fit distribution is determined, I analyze how the distribution fit parameters vary with flow properties and non-dimensional numbers. The results of this analysis are presented in the next sections.

2.3 Results

I simulate 20 experimental granular flows in the cylindrical flume, varying mean grain size (2 to 10 mm), shear rate (17 to 51 Hz), and standard deviation of the grain size distribution (0 to 3.55 mm) to analyze the effects of these flow properties on the shape of the bed force distribution. This set of flow parameters equate to inertial number flows from 3×10^{-2} to 0.5 and Stokes number flows from 850 to 5×10^4 (Figure 3). The passage the flow is clear in the processed force data (Figure 5) which can be identified by a sudden increase in the force signal, followed by a decay due to the passage of the tail. The shape of this signal is consistent for all flows, showing a general uniformity in flow

shape regardless of flow properties. The resulting bed force distributions are best-fit by a GPD at all inertial and Stokes number as shown by a χ^2 analysis given in Figure A.4. I see in many cases, the GPD and power law perform similarly in fitting the experimental data but the GPD performs marginally better (Figure 7). Further discussion of the trends found in the best-fit distributions can be found in section 2.4.

2.3.1 Visual analysis of the experimental flows

In addition to the bed force data, I record highspeed videos (1000 fps) for all of the experimental runs to be able to capture any changes in grain scale behavior which might help explain trends seen in the force data. At low inertial numbers ($I < 10^{-1}$), flows are concentrated and particles show little relative motion in the bulk of the flow (Figure 6a,c). For polydisperse mixtures, flows remain well-mixed with little noticeable size-segregation. At high inertial numbers ($I > 10^{-1}$) monodisperse flows with low grain size (2mm and 5 mm) begin to show kinetic behavior, in which flows become disconnected and more dilute (Figure 6b). For monodisperse flows with large grain sizes (8 and 10 mm), flows slide along the bed and moves together as a cohesive unit, exhibiting very little energetic behavior in the body of the flow. Due to the geometry of the flume, however, particles in the tail of the flow become lofted and collapse back onto the body of flow which may lead to elevated forces at the bed due to these impacts (Figure 6d). For polydisperse mixtures, high inertial number flows show more obvious grain size segregation than in the low inertial number case. In this portion of the parameter space, larger particles separate out into the flow front, the center of the flow appears well-mixed, and the tail is dominated by smaller grain size.

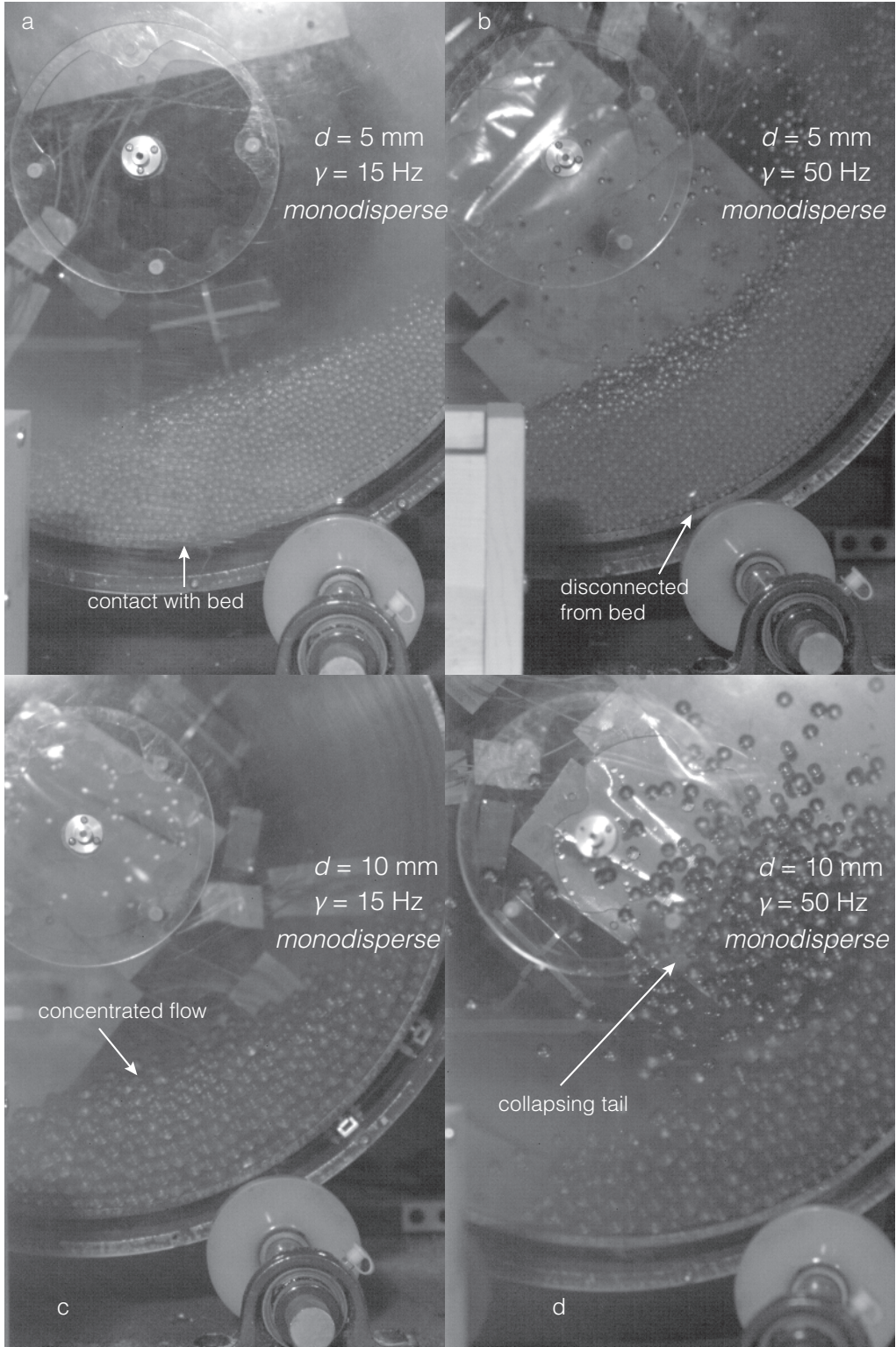


Figure 6. Snapshots of experimental flows. Monodisperse flows with (a) grain size $d = 5$ mm, and shear rate $\dot{\gamma} = 15$ Hz; (b) $d = 5$ mm, $\dot{\gamma} = 50$ Hz; (c) $d = 10$ mm, $\dot{\gamma} = 15$ Hz; and (d) $d = 10$ mm, $\dot{\gamma} = 50$ Hz.

2.3.2 Bed force distributions

For each of the experimental runs, I fit a GPD and power law distribution to the normalized bed force data. The goodness of fit for each of these distributions is quantified by a χ^2 test statistic (Figure A3). The bed force distributions in all of the experimental runs

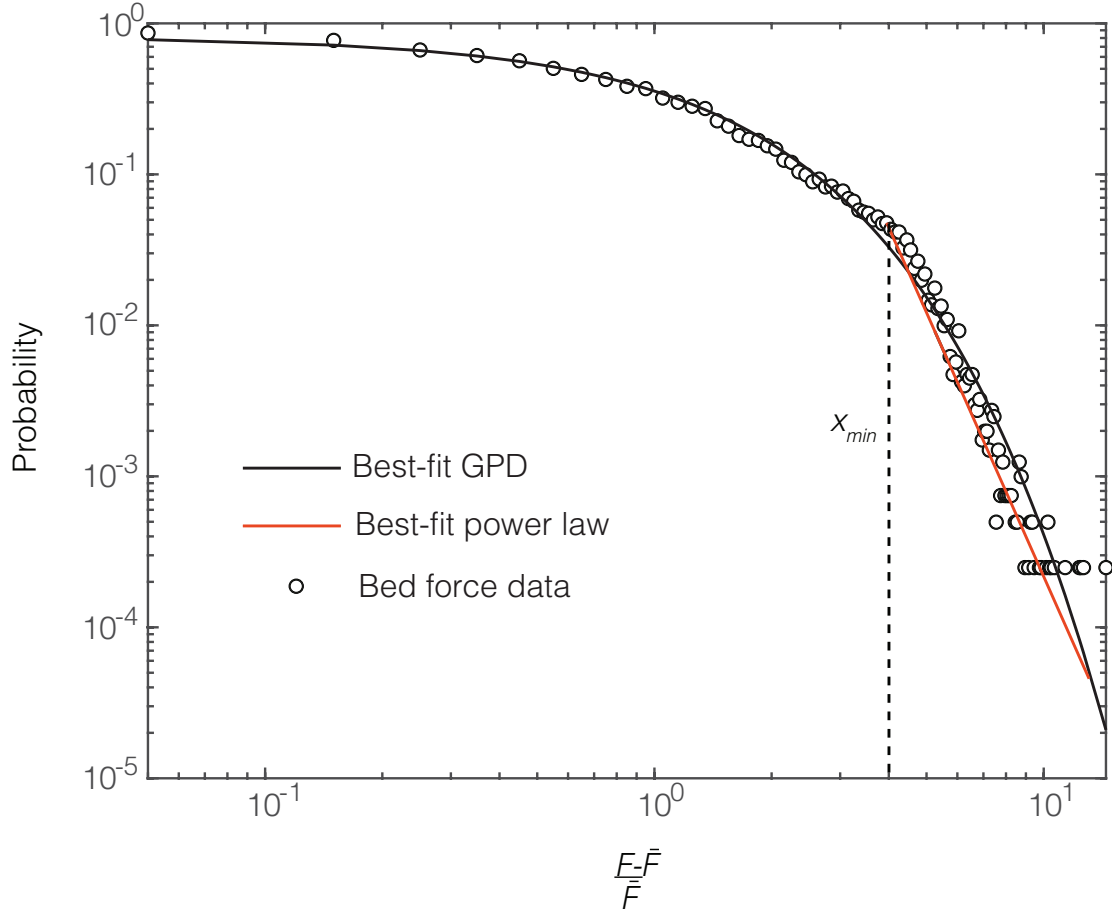


Figure 7. Best-fit distributions. Circles represent binned force measurements from a BERTHA experimental run with grain size $d = 5$ mm, shear rate $\dot{\gamma} = 15$ Hz, and grain size standard deviation $\sigma_g = 0$. The black line represents the best-fit GPD and the red line denotes the best-fit power law distribution. The power law fit parameter x_{min} , which describes the minimum value of the normalized force excursion over which the power law distribution is defined, is shown by the vertical dashed line. GPD and power law distributions fit the tail of the bed force distributions equally well in this laboratory experiment.

are best fit by a GPD but in many cases, the power law distribution also performs well (Figure 7). In all of these cases, I rely on the χ^2 analysis to determine the best fit

distribution. There is no clear trend in the performance of the power law distribution with changes in flow properties, and thus, no trend between power law performance and inertial and Stokes numbers. Similarly, I see no change in the best fit distribution between bed forces measured by sensors at the flow center compared to measurements collected near the walls, indicating the robustness of the best-fit distribution to changes in boundary conditions. While the functional form of the best-fit distribution is consistent across the width of the flow, the shape of the bed force distribution is often anisotropic. In the results, I see both a grain size and shear rate dependence on the relative distribution shapes between forces measured at the flow center and those measured near the walls. The results of this analysis are presented in Figure 8. Monodisperse flows with small grain sizes ($d \leq 5\text{mm}$) exhibit more truncated distribution tails near the walls at the low shear rate end member (15 Hz; Figure 8a), which is likely due to increased shear at the flow boundaries. As the shear rate increases, the trend reverses as particle advection increases along the flow boundaries, leading to an increased rate of grain reorganization in this region (34 Hz; Figure 8b). As shear rate continues to increase, the flow becomes highly energetic and frictional interactions between particles decrease due to a lower particle concentration. At this point, the trend once again begins to reverse, leading to distributions which largely overlap but show slightly dampened forces at the flow boundaries due to wall interactions (Figure 8c). At larger grain sizes ($d \geq 8\text{ mm}$), the distribution tails are insensitive to the location of the sensor as the tails of these distributions behave similarly (Figure 8d,e,f). I believe the difference in behavior between small and large grain sizes is likely due to the number of particles between the flow boundaries which varies as a function of particle size. For small grain size flows, a

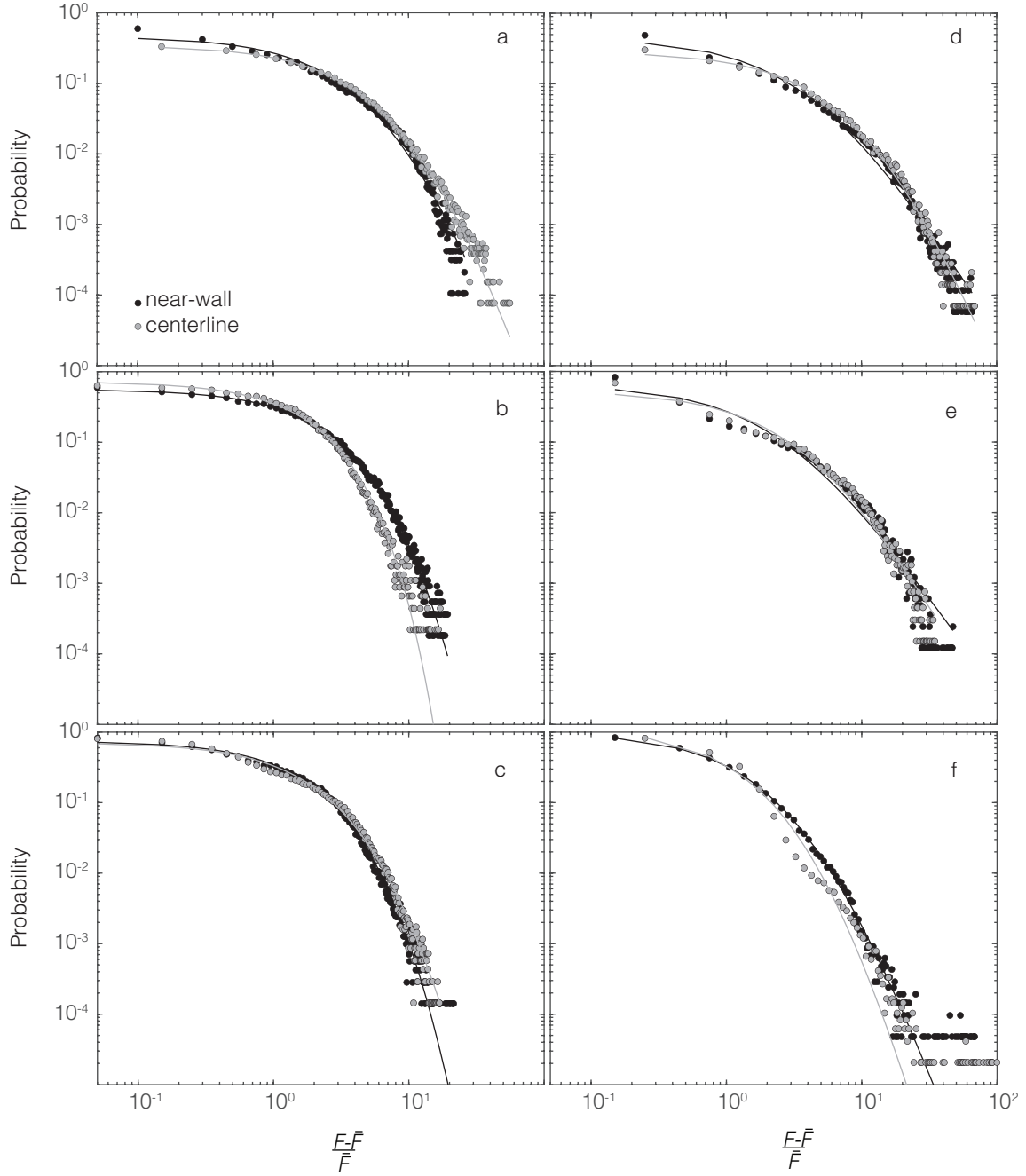


Figure 8. Contribution of wall effects on PDF of bed forces. Circles represent binned force data and solid lines represent the best-fit GPD. Gray denotes distributions associated with sensors located at the flow center and black denotes distributions associated with near-wall sensors. BERTHA runs with (a) grain size $d = 5$ mm, shear rate $\dot{\gamma} = 15$ Hz, and grain size standard deviation $\sigma_g = 0$; (b) $d = 5$ mm, $\dot{\gamma} = 34$ Hz, $\sigma_g = 0$; (c) $d = 5$ mm, $\dot{\gamma} = 50$ Hz, $\sigma_g = 0$; (d) $d = 8$ mm, $\dot{\gamma} = 15$ Hz, $\sigma_g = 0$; (e) $d = 8$ mm, $\dot{\gamma} = 34$ Hz, $\sigma_g = 0$; (f) $d = 8$ mm, $\dot{\gamma} = 50$ Hz, $\sigma_g = 0$. Concentrated small grain size flows ($d \leq 5$ mm) generate force distributions that show a dependence on the position of the sensor relative to the flow center. Large grain size flows ($d \geq 8$ mm) show little variation between near-wall and centerline sensors regardless of shear rate.

greater number of particles exist between the wall and flow center, yielding a smaller length scale over which boundary effects are important. Therefore, particles at the flow center are largely decoupled from the walls in concentrated small grain size flows. Conversely, particles along the centerline in large grain size flows are more strongly coupled to the flow boundary as there are a fewer number of grains between the flow center and the wall. Increased sensitivity of particles near the flow center to conditions along the flow boundaries results in little variation between flow behavior at the wall and flow behavior near the flow center.

2.4 Discussion

2.4.1 Sensitivity of bed force distribution on flow properties

Previous workers have shown that granular flow properties influence the shape of the probability distribution of bed forces (McCoy et al., 2013; Hsu et al., 2014), however, it remains unclear how the functional form is affected by these flow properties. Here, I present the results of varying the mean grain size, shear rate, and the degree of polydispersity in dry experimental granular flows within a rotating flume. I include both the mean and standard deviation of the grain size distribution to capture the major controls on grain size distribution, as there is significant debate about the most appropriate choice of grain size proxy (Stock and Dietrich, 2006). I note that the quasi-spherical particles used in the experiments are idealized compared to the variability present in natural granular flows, however, their use reduces effects due to particle shape on the bed force distributions which may be significant (Cleary, 2008; Njobuenwu and Fairweather, 2014; Höhner and Scherer, 2014). The results of the analysis of flow properties' effect on distribution shape is summarized in Figure 9. I vary mean grain size

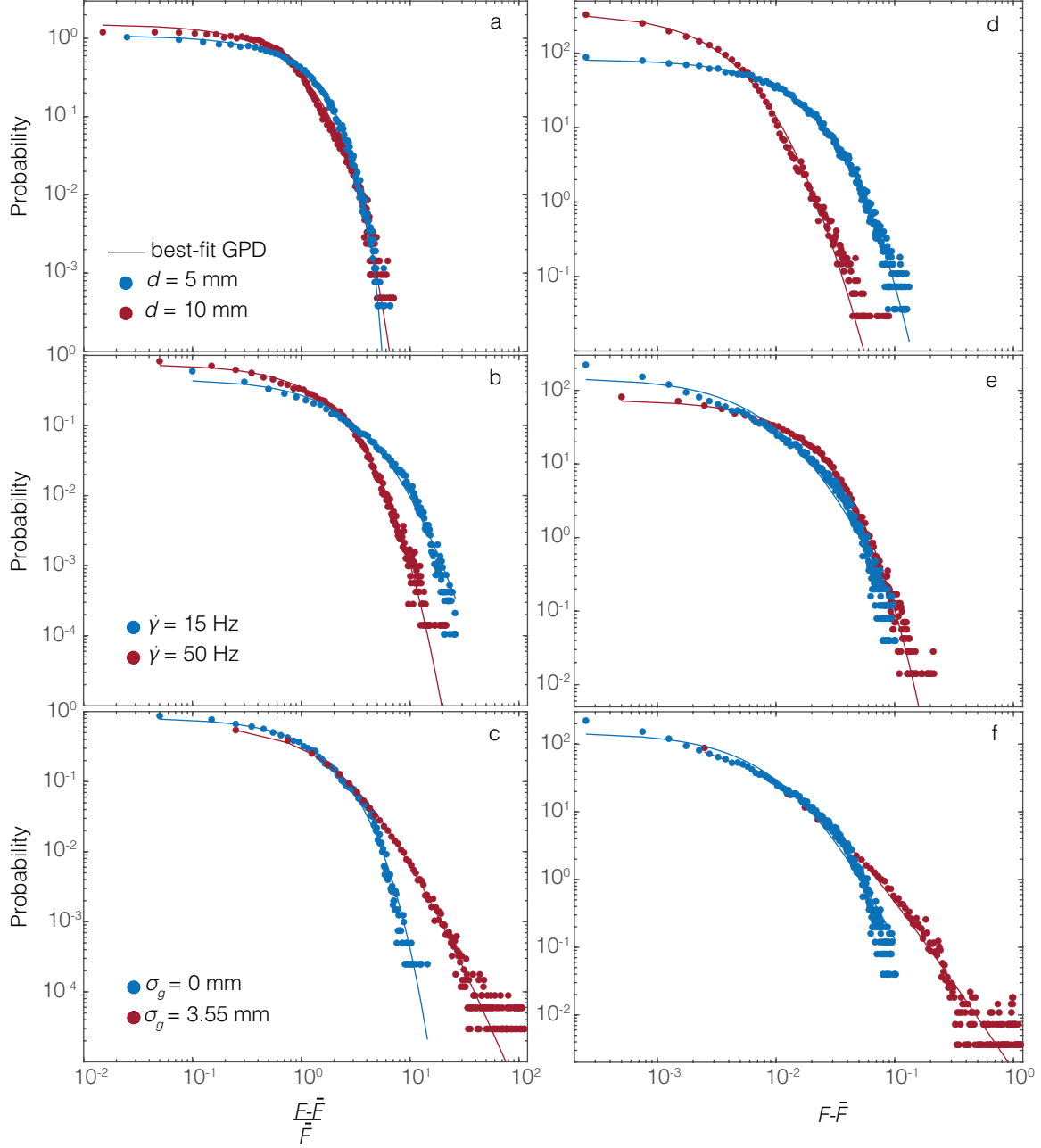


Figure 9. Sensitivity of normalized bed force distributions to (a) mean grain size (5 mm, 10 mm), (b) shear rate (15 Hz, 50Hz), (c) degree of polydispersity (monodisperse, 0 mm; 3.55 mm). Sensitivity of non-normalized bed force distributions to (d) mean grain size (5 mm, 10 mm), (e) shear rate (15 Hz, 50Hz), (f) degree of polydispersity (monodisperse, 0 mm; 3.55 mm). Blue and red circles correspond to binned forces for low and high values of each flow property, respectively. Solid lines denote the best-fit GPD. Variations in mean grain size show trends that can be explained by variations in grain size (a, e). The shortened tails present in the normalized bed force distributions are a consequence of the mean force's dependence on shear rate. Polydisperse flows generate larger bed force excursion than monodisperse flows and this trend is robust to normalization.

from 2 mm to 10 mm in the monodisperse flows. The results show no sensitivity of normalized bed force distributions to changes in mean grain size, a result which is consistent throughout the explored parameter space (Figure 9a). While nonnormalized bed force excursions, show a dependence on mean grain size, in which smaller particles show more elongated distribution tails relative to larger grain sizes, this trend can be entirely explained by variations in the mean force which is removed upon normalization (Figure 9d).

I vary shear rate from 15 to 50 Hz to capture elastic-inertial to inertial-collisional flow behavior. Unlike the case for grain size, the length of the bed force distribution decreases systematically with shear rate, suggesting a higher frequency of high magnitude bed force excursions for flows experiencing low shear rates relative to flows experiencing high shear rates with all other variables held constant (Figure 9b). By changing shear rate from 50 Hz to 15 Hz, the frequency of the high magnitude forces predicted by the best-fit distribution can vary by more than an order of magnitude. This result likely arises from the decrease in flow concentration as shear rate is increased as was observed in the experimental flows. Flows at high shear rates are generally less connected to their bed relative to slowly shearing flows (Figure 6b and 6a). Both of these trends in flow behavior may decrease the likelihood of generating high-magnitude bed forces due to force chains by reducing long lasting contacts between particles and may signal a transition in the dominant bed force generating mechanism. I see no significant change in the location of the high frequency component of the frequency distribution with changes in shear rate, regardless of the resampling frequency, which rules out the possibility of high frequency signals being accidentally removed from the signal due to resampling

techniques or signal filtering. When I analyze the nonnormalized distributions of bed forces, I see no trend between the length of the distribution tails and the shear rate (Figure 9e). In the flow regimes explored in this study, I expect the mean force to increase systematically with shear rate (Bagnold, 1954; Savage, 1984; Campbell, 2005; Forterre and Pouliquen, 2008; Da Cruz et al., 2005), a trend which is reflected in the normalized distributions presented here.

To explore the effects of the width of the grain size distribution on the shape of PDF of bed forces in granular systems, I simulate both monodisperse and polydisperse flows in the experiments. For the polydisperse case, I generate grain size distributions with standard deviations of 0.5 mm, 1.5 mm, 2.3 mm, and 3.5 mm, while keeping the mean grain size fixed at 5 mm. Maximum and minimum values of grain size are held constant at 10 mm and 2 mm, respectively, for all polydisperse runs to prevent extreme values of grain size influencing results. The results show that the length of the tail of the distribution increases with the standard deviation of grain size (Figure 9c), causing a higher frequency of large magnitude force excursions in polydisperse flows relative to monodisperse flows. I see roughly an order of magnitude increase in the predicted frequency of large magnitude forces for the best-fit distributions of flows with a standard deviation in grain size of 3.5 mm compared to a monodisperse flow. This trend is monotonic and consistent throughout the explored parameter space. This behavior seen in the tail of the bed force distributions is likely due to increased relative motion between particles, increasing velocity fluctuations within the flow. In the non-normalized distributions, the same trend is present which implies that this trend has no dependence to variations in the mean force (Figure 9f).

2.4.2 Relation of distribution fit parameters to non-dimensional numbers

In the previous section, I demonstrated how individual flow properties can have significantly different effects on the shape of the distribution of bed forces in granular flows. In this section I quantify the combined effects of varying flow properties using the inertial and Stokes number. These nondimensional numbers also allow us to compare the results of the small-scale granular flows to those large-scale natural flows to discuss how the results may carry over to natural systems. The combined effects of varying flow properties on the shape of the bed force distributions can be seen in Figure 10.

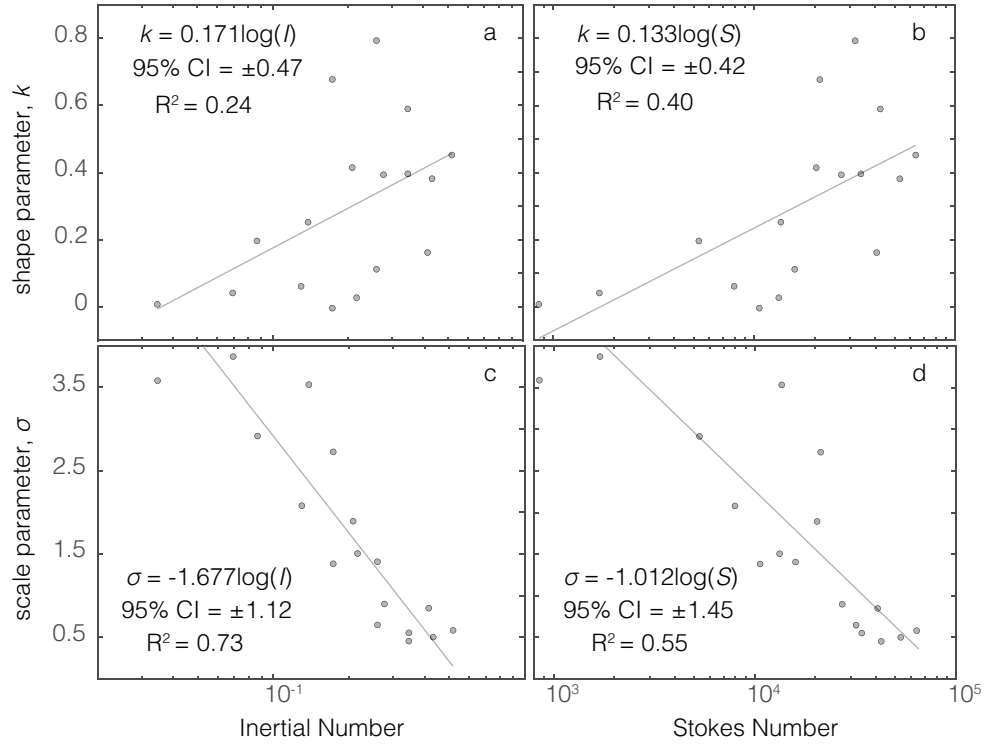


Figure 10. Best fit values for GPD shape parameter (k ; panels a-b) and scale parameter (σ ; panels c-d) fit to normalized bed force distributions as a function of inertial and Stokes numbers for each experimental run (Table A1). Solid lines denote a linear regression for each fit parameter versus $\log(I)$ or $\log(N_{Sto})$. The GPD fit parameters show opposite trends with I and N_{Sto} , as the shape parameter becomes more positive and the scale parameter becomes more negative with both nondimensional numbers. These trends have conflicting effects on the length of the tail of bed force distributions.

Here, I see that the GPD shape parameter increases with both inertial number and Stokes number, although there is significant scatter around the best-fit regression line for both nondimensional numbers (Figure 10a,b). More positive values of the shape parameter yield more elongated tails in the bed force distributions, however, the value of the scale parameter also impacts the length of the tail. In panels c and d, I see the opposite trend for the scale parameter in which σ decreases with inertial and Stokes number with a better fit to the linear regression. Decreasing the scale parameter leads to an increase in the y-intercept of the distribution which leads to a more truncated tail. Because these two parameters show opposite trends with the nondimensional numbers, I must analyze them for their combined effects in distribution form in order to understand how these trends impact the general shape of bed force distributions in granular flows. The results of this analysis are seen in Figure 11. Large values of I and N_{Sto} yield best-fit distributions that decay more slowly than best-fit distributions for flows with lower values of inertial and Stokes numbers. However, it is important to bring attention to the fact that the interpretation of these distributions is highly dependent on the domain over which the distribution is defined. For example, if I were to restrict the analysis to normalized bed force excursions $< 10^1$, I would conclude that high I and N_{Sto} flows produce distributions with more truncated tails than low I and N_{Sto} flows. However, if I were to expand the analysis to normalized bed force excursions $< 2 \times 10^2$ I would draw the opposite conclusion. For this reason, it is necessary that a minimum frequency or maximum magnitude of force excursion be defined when extrapolating these results to other applications. In the experiments, the results are constrained by the largest measured force

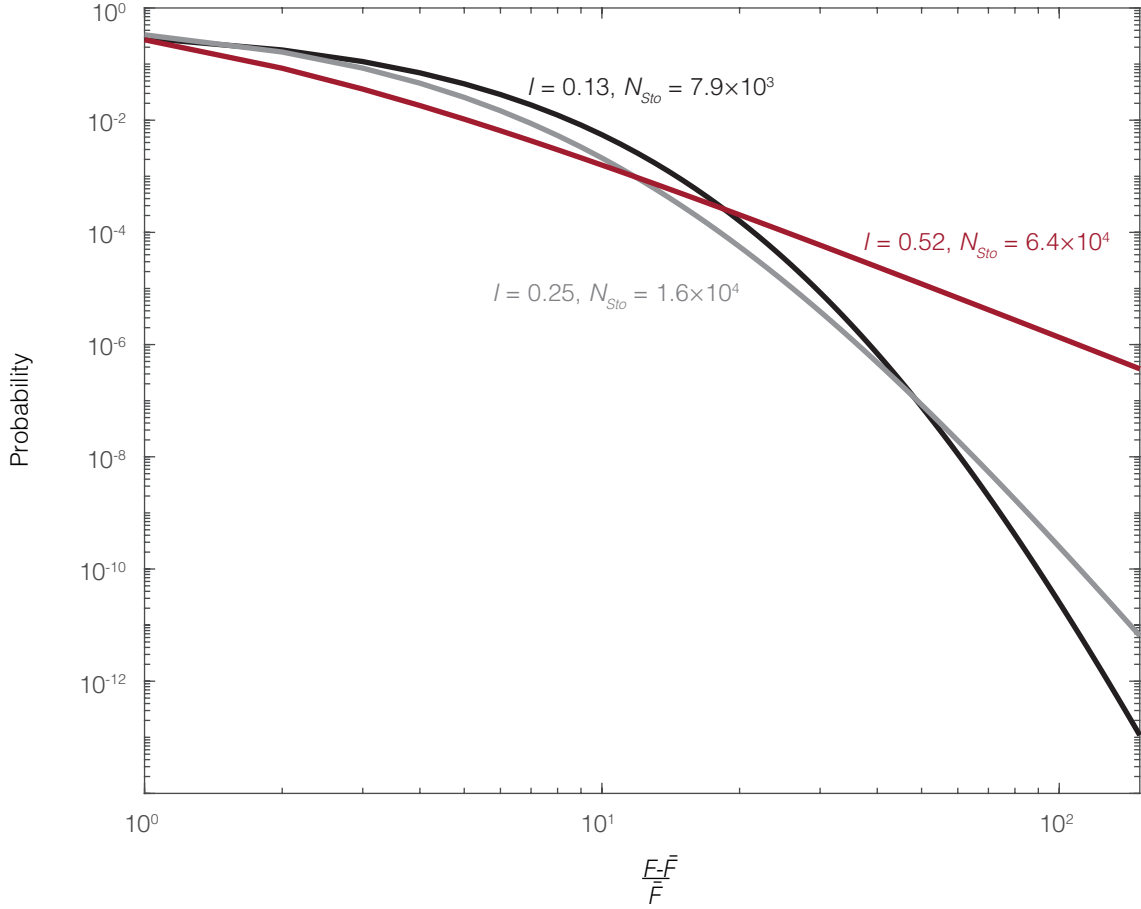


Figure 11. Best-fit Generalized Pareto distributions for high (red), intermediate (gray), and low (black) values of the Inertial number (I) and Stokes number (N_{Sto}) in granular flow experiments in BERTHA. The tails of the distribution tend to grow longer with I and N_{Sto} , implying a greater frequency of high bed forces in flows with high I and N_{Sto} . Note that the relative length of the tails is dependent on the domain over which the distribution is defined and therefore a maximum value of normalized force excursion or minimum frequency is likely needed to be defined in order to apply these results to other studies.

excursions present in the signal, which provides context for the interpretation of the distribution tails. In larger systems or in cases of long-duration flows, which may be most relevant in industry settings, it may be necessary to consider the limit of $\frac{F - \bar{F}}{\bar{F}} \rightarrow \infty$.

2.4.3 Implications for RGF Dynamics

The first observation is that the force distributions measured in the experimental granular flows are sensitive to changes in shear rate and the width of the grain size

distribution. While the nonnormalized force excursions showed systematic variation with mean grain size, this trend was explained by variations in the mean force between experimental runs. The experiments suggest that high magnitude force excursions are more likely to be generated by flows with larger values of I and N_{Sto} . This implies that flows exhibiting inertial-collisional behavior (i.e. dilute, highly energetic flows) and flows with weaker solid-fluid couplings may have an increased erosive potential due to the increased frequency of high magnitude forces they impose on their beds. However, as I only conducted experiments in air, the role of interstitial fluids needs to be further explored. These results may have significant implications for granular flow dynamics. For example, changes in flow properties (e.g., due to settling of large particles, generation of fines due to clast abrasion, bed material entrainment, loss of energy due to frictional interactions) impact flow dynamics by influencing energy transfer between the flow and the bed. This is part of a larger feedback in which flow properties control the bed forces that regulate mass and momentum transfer between the flow and the bed, which in turn affect the flow properties themselves. While individual couplings in this feedback have been explored in a number of studies (Hungr and Evans, 2004; Iverson et al., 2011; Kueppers et al., 2012; McCoy et al., 2013; Hsu et al., 2008; 2014, Fauria et al., 2016), the full feedback including all couplings remains relatively unexplored.

In the second observation, I notice that the functional form of the distribution of bed forces is best described by a Generalized Pareto distribution, however, in many cases the power law distribution performs similarly in fitting the tail end of the distributions. This suggests that the functional form of the distribution of bed forces may be approximated well by both distributions near the elastic-inertial-inertial-collisional flow

regime boundary, though, a larger parameter space should be explored to make recommendations on the most appropriate functional form for a given flow regime. Regardless, I can confidently say that bed force distributions in this regime are well-fit by the GPD, consistent with previous studies observing experimental and natural flows spanning a similar portion of the parameter space (Hsu et al., 2014; McCoy et al., 2013). This result supports the use of the GPD to capture the shape of the distribution of bed forces for granular flows in the explored parameter space.

2.5 Bridge

The experiments presented in Chapter II provide new insights into the behavior of the distribution of bed forces in dry granular flows, and how the shape of these distributions is sensitive to variations in flow properties. However, it remains unclear if these trends are restricted to the portion of the I - N_{Sto} phase space explored in this chapter or if they are more generally applicable to the entire phase space spanned by granular flows. In Chapter III, I employ discrete element simulations in a similar geometry to that used in the experiments described above to analyze the bed force distributions of granular flows under flow conditions which are unattainable in BERTHA. Chapter III extends the analysis of the previous chapter to include the role of fluid density and viscosity in determining the shape of the bed force distribution. These flows span elastic-quasi-static, elastic-inertial, and inertial collisional regimes in which N_{Sto} is varied from 1×10^{-5} to 1×10^5 and I_m is varied from 1×10^{-5} to 3, where I_m is the visco-inertial number which describes the ratio of the microscopic timescale to the macroscopic timescale in viscous flows. This phase space expansion enables investigation of the dependence of the force

distribution's functional form on flow regime and provides further context for the results from my experiments.

CHAPTER III

QUANTIFYING THE ROLE OF FLUID AND SOLID FLOW PROPERTIES ON BED FORCE DISTRIBUTIONS IN MULTIPHASE GRANULAR FLOWS

3.1 Introduction

3.1.1 Background

Granular flows are natural phenomena in which a collection of particles and an interstitial fluid flow under the force of gravity. They are capable of exhibiting both fluid and solid characteristics (Forterre and Pouliquen, 2008; Delannay et al., 2017). These flows vary greatly in initiation process, volume, shear rate, temperature, fluid content, and grain size, leading to a wide range of possible behaviors. Common examples of granular flows include debris flows (i.e. Iverson et al., 1997), pyroclastic density currents (i.e. Sulpizio et al., 2014; Lube et al., 2020), and rock avalanches (i.e. Hungr, 2006), depicted in Figure 12. These flows are hazardous to infrastructure, water supplies, and agriculture, and are estimated to cost \$1 to \$2 billion USD in economic losses every year in the United States alone (National Research Council, 1985) and claim a global average of 4000 lives annually from 2004 to 2016 (Froude & Petley, 2018). In addition to the threats they pose to life and infrastructure, granular flows also reshape landscapes by eroding and transporting material as they flow. The incorporation of bed material at the base of granular flows is a key component of granular flow behavior because it can increase their volume, momentum, and hence runout (e.g., Kolderup, 1955; Bernard et al., 2014), which amplifies their hazards (Iverson, 1997; Hungr & Evans; 2004; Druitt et al., 2007; Iverson et al., 2010).

The amount of material a granular flow is able to erode is, ultimately, controlled by the mass and momentum transfer between the flow and the underlying bed which is regulated by flow properties. These flow properties are likely responsible for influencing the primary force mechanisms within the flow, determining the frequency and magnitude of bed force excursions from the mean force. While significant progress has been made in recent years to understand granular flow behavior from depth-averaged models (i.e. Iverson and George, 2014; Delgado-Sánchez et al., 2020), modeling granular systems as discrete particles is necessary in order to capture the entire distribution of forces generated by these flows as opposed to only reporting mean forces. Because erosion is a threshold process, it is the bed forces greater than the mean that are responsible for generating material that can be removed by a granular flow through rapid changes in pressure or shear induced at the base of the flow. Therefore, understanding the shape of the probability density function (PDF) of bed forces greater than the mean force is necessary for understanding the potential for these flows to erode their underlying substrate. For this reason, this study focuses on describing the tail end of PDF of bed force excursions, neglecting sub-mean and near-mean forces in the primary analysis.



Figure 12. Examples of natural granular flows. A. Debris flow near Mount Saint Helens, WA (Martinson, 1980). B. Pyroclastic density current from Mount Sinabung, Indonesia (Bracken, 2014). C. Sand avalanche on dune crest in the Mojave Desert, CA (Wilson, 2010).

Over the last few decades, a significant amount of work has been done to better understand granular flows and the forces they generate through laboratory experiments (e.g. Howell et al., 1999; Longhi et al., 2002; Ferguson et al., 2004; Majmudar and Behringer, 2005; Gardel et al., 2009; Estep & Dufek, 2012), numerical simulations (e.g. Bardenhagen et al., 2000; O’Hern et al., 2001; Lois et al., 2007; Yohannes et al., 2012; Estep & Dufek, 2013; Breard et al., 2020), and observations of natural and large-scale experimental flows (McCoy et al., 2013; Lube et al., 2019; Allstadt et al., 2020). These efforts have had a substantial impact on understanding the behavior of these flows under specific flow conditions, revealing a wide range of bed force distributions. Because granular flows have the propensity to have their flow properties rapidly evolve during transport (e.g. Iverson, 2003), there is a great need to explore a large range of flow properties to unite conflicting hypotheses for the most appropriate choice for the functional form of bed force distributions in granular flows.

3.1.2 Bed forces in granular systems

At the base of granular flows, the flow can interact and exchange energy with its substrate in several ways. Loose substrates are mobilized by shear forces generated by the overlying flow over a wide range of spatial and temporal scales from clear incorporation into the body of the flow to creeping behaviors far beneath what would typically be considered the substrate’s surface (Houssais et al., 2015). Single particles impact the bed in the form of collisions which may be a dominant form of energy transfer in more dilute and poorly connected flows (Campbell, 2005; Fauria et al., 2016). In concentrated flows, long-lasting contacts between grains can form quasi-linear force networks called force chains. These force chains are capable of generating forces much larger than the depth

averaged weight of the flow (Majmudar and Behringer, 2005; Estep and Dufek, 2012; Estep and Dufek, 2013; Hsu et al., 2014; Zhang et al., 2017; Zadeh et al., 2019) and can impose these large forces on the bed should they terminate at the flow-substrate boundary. Low pressure regions behind the head of gravity currents have been shown to drive substrate entrainment (Roche et al., 2010). Fluidization can occur due to pore fluids in the substrate by reducing frictional interactions within the flow (Breard et al., 2017). The relative importance of each of these processes for mass and momentum transfer is dependent on flow behavior and substrate characteristics. In this study, I explore the supply-limited case in which I focus purely on the normal component bed forces which are necessary for generating erodible material, neglecting shear and pore pressure driven processes.

3.1.3 Scaling of Granular Flow Regimes

Natural granular flows encompass a wide range of interactions and the dominant mechanism for momentum exchange locally ultimately controls the PDF. One explanation for the observed disparities in the PDF described above is that different flows occupy distinctive flow regimes. This explanation is based on the reasoning that different flow regimes produce different grain-scale behaviors, and that these should yield different forms of $P\left(\frac{F-\bar{F}}{\bar{F}}\right)$ and different sensitivities of $P\left(\frac{F-\bar{F}}{\bar{F}}\right)$ to flow properties. In flows like dilute pyroclastic density currents (surges), binary collisions dominate momentum transfer, and bed forces are dominated by single-particle collisions analogous to molecular interactions in gases but modified by inelasticity of the grains (e.g., Dufek, 2016; Lube et al., 2020). This is referred to as the inertial-collisional regime (Campbell,

2005; Forterre & Pouliquen 2008). In other flows like slow-moving landslides, particles are closely packed with enduring contacts between particles, exhibiting little relative motion (e.g., Scheingross et al., 2013). In these flows, forces are transmitted through long-lasting frictional contacts between particles. This is referred to as the elastic-quasi-static regime which is analogous to solid behavior (Forterre & Pouliquen, 2008). Other flows occupy an intermediate regime more analogous to a fluid state in which stresses due to particle inertia are comparable to those due to confining loads (Campbell, 2005; Forterre & Pouliquen 2008; Brodu et al., 2015) which is referred to as the elastic-inertial regime. Many granular flows likely contain a range of these regimes in a single current, as flows likely have varying flow properties within different region of the flow (Lube et al., 2020).

I use a visco-inertial number-Stokes number, $I_m - N_{Sto}$, phase space (Figure 13) to enable comparison between the proposed discrete element simulations across each of the flow regimes described above. To account for different interstitial fluids in each experimental configuration I use N_{Sto} , which is commonly used to assess the role of viscous forces and the degree of particle-fluid coupling in grain-fluid mixtures (e.g., Tang et al., 1992; Raju and Meiburg, 1995) and is given in Equation 4. At low Stokes numbers ($N_{Sto} < 1$) flows are dominated by viscous interactions and, thus, a new inertial number, the visco-inertial number, is required to describe flow behavior (Iverson and George, 2014). Equation 5 gives this inertial number modulated by the Stokes number, where at $N_{Sto} > 1$, $I_m \sim I$.

$$I_m = I \sqrt{1 + \frac{\alpha_v}{N_{Sto}}} \quad \text{Eq. 5}$$

Here, α_v is a constant which I assign a value of 2 based off of previous studies of inertial granular flows sheared by a viscous fluid (Amarsid et al., 2017). The scaling of granular flow properties through a generalized inertial number, which assumes stress additivity, has been shown to successfully capture the rheology of granular flows immersed in fluid of high to low viscosity (Vo et al., 2020).

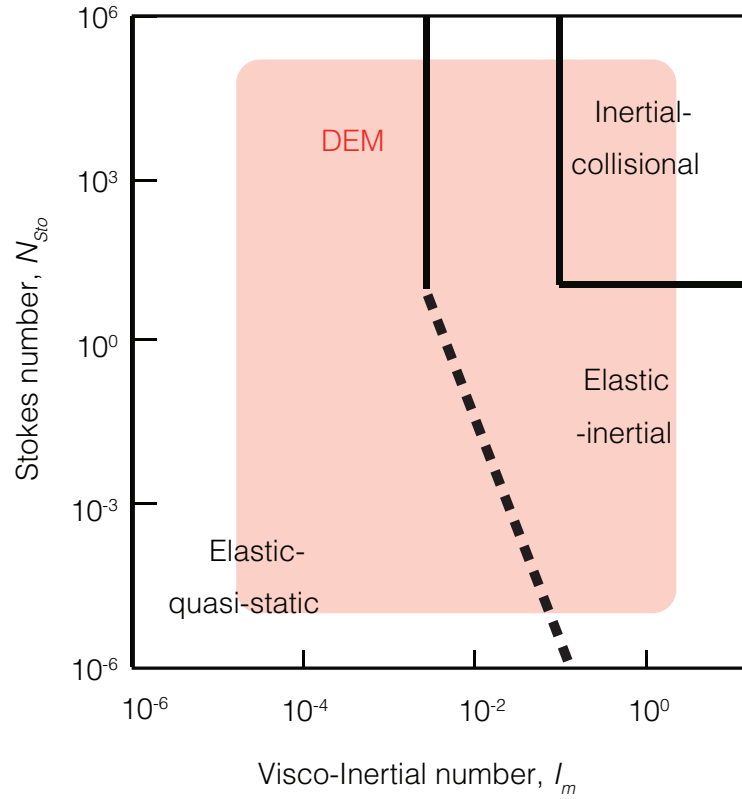


Figure 13. Granular flow regimes can be delineated by visco-inertial number (I_m , Equation 5) and Stokes number (N_{Sto} , Equation 4). Salmon box delineates the parameter space explored in the discrete element simulations in this study. Solid black lines indicate flow regime transitions that have been tightly constrained in previous studies (Savage, 1984; Armanini et al., 2005; Campbell, 2005; Forterre and Pouliquen, 2008; Da Cruz et al., 2005), and dashed lines indicate transitions that are uncertain.

These flow regimes may strongly affect bed force distributions and the sensitivity of these distributions to flow properties. The mean force scales quadratically with $\dot{\gamma}$ in the inertial-collisional regime, linearly with $\dot{\gamma}$ in the elastic-inertial regime, and is independent of $\dot{\gamma}$ in the elastic-quasi-static regime (Savage, 1984; Campbell,

2005; Forterre and Pouliquen, 2008; Da Cruz et al., 2005). This suggests that $P\left(\frac{F-\bar{F}}{\bar{F}}\right)$ should depend on flow regime as well, but this relationship is currently unknown. This is the critical knowledge gap I seek to fill, as it is the distribution of forces – not the mean force – that is most important for a number of threshold-sensitive processes in geomorphology (e.g., sediment entrainment, bedrock incision, flow runout).

3.1.4 Study Goals

This study aims to determine the optimal functional form of the probability distribution of bed force excursions for each of the previously described flow regimes. This will predict the magnitude and probability of high magnitude force excursions at the bed (i.e. the shape of the tail of the PDF) given granular flow conditions. I analyze the relationship between distribution fit parameters and flow properties to emphasize any existing systematic variations of distribution shape with mean grain size, shear rate, standard deviation of the grain size distribution, fluid density, and viscosity. This allows us to determine when flow properties may need to be better constrained to help inform hazard mitigation efforts.

I therefore carry out discrete element simulations of granular flows in a rotating cylinder to answer the research questions: (1) What is the functional form of the distribution of bed force excursions in granular systems in each flow regime? (2) By describing the underlying physics in each flow regime, can I confidently delineate the boundaries between flow regimes in the chosen parameter space (I_m - N_{Sto}) through changes in the shape of the PDF of bed forces? (3) Do the best-fit distribution fit parameters vary systematically with changes in mean grain size, shear rate, width of the

grain size distribution, fluid density, and viscosity? (4) How sensitive is the shape of the PDF to changes in Stokes number (i.e. When do fluids matter?)?

3.2 Methods

To answer these questions, I carried out 900 discrete element simulations to capture the bed forces generated by granular flows in a rotating cylindrical flume with interstitial fluids of varying viscosity and density. Employing the discrete element method allows us to resolve these force excursions from the mean by tracking the velocity and position of every particle within the system through time. I measure only the normal component of forces felt on the bed of the rotating flume sampled at 1 kHz. In the following section I describe the DEM used to collect these data.

3.2.1 MFiX Multiphase Model

I examine the implications of flow properties on bed force distributions using the open source MFiX (Multiphase Flow with Interphase eXchanges) discrete element model (Garg et al., 2012). The MFiX suite is a set of multiphase computational fluid dynamics models for describing the hydrodynamics, heat transfer, and chemical reaction in dilute and dense multiphase mixtures (Syamlal et al., 1993). MFiX development has been ongoing at National Energy Technology Laboratory, beginning with a multi-particle algorithm (Syamlal, 1985) based on the Eulerian-Eulerian approach. MFiX has undergone continuous model development and validation with a wide range of applications (Benyahia et al., 2007; Benyahia, 2008; Bergantz et al., 2015; Darteville, 2007; Darteville & Valentine, 2008; Dufek & Bergantz, 2005; Li et al., 2017; Srivastava & Sundaresan, 2003; Syamlal et al., 2017; Breard et al., 2019; Fullard et al., 2019). In the discrete element model, I use a DEM-CFD (Computational Fluid Dynamic) approach for

cases with an interstitial fluid or a Lagrangian approach for the pure granular case (no fluid).

3.2.1.1 Governing Equations

The mass and momentum conservation relationships for the fluid phase are defined in Equations 6 and 7, respectively. In these equations and those described below I use the notation of bold variables to indicate vector quantities, double bars to indicate tensor quantities, and italicized variables to indicate scalar quantities.

$$\frac{D}{Dt}(\varepsilon_f \rho_f) + \nabla \cdot (\varepsilon_f \rho_f \mathbf{v}_f) = 0 \quad \text{Eq. 6}$$

$$\frac{D}{Dt}(\varepsilon_f \rho_f \mathbf{v}_f) = \nabla \cdot \bar{\bar{S}}_f + \varepsilon_f \rho_f \mathbf{g} - \sum_{m=1}^M \mathbf{I}_{fm} \quad \text{Eq. 7}$$

I note that the formulation given in Equation 7 does not include terms which may be important in the limit where fluid and solid density is similar such as the Basset history and added mass terms found in the Basset-Boussinesq-Oseen equation. Here, $\frac{D}{Dt}$ represents the material derivative which is defined as the rate of change of a physical quantity of a material that is subjected to a spatially and temporally dependent velocity field. $\mathbf{g}$ is gravitational acceleration, ε_f is the fluid volume fraction, ρ_f is the thermodynamic density of the fluid phase, $\mathbf{v}_f$ is the volume-averaged fluid phase velocity, $\mathbf{I}_{fm}$ is the momentum transfer term between the fluid and the m^{th} solid phase (discussed in section 3.2.1.3), and $\bar{\bar{S}}_f$ is the fluid-phase stress tensor given by Equation 8.

$$\bar{\bar{S}}_f = -P_f \bar{\bar{I}} + \bar{\bar{\tau}}_f \quad \text{Eq. 8}$$

P_f is the fluid-phase pressure and $\bar{\bar{\tau}}_f$ is the fluid-phase shear stress tensor,

$$\bar{\bar{\tau}}_f = 2\mu_f \bar{\bar{D}}_f + \lambda_f \nabla \cdot \text{tr}(\bar{\bar{D}}_f) \bar{\bar{I}} \quad \text{Eq. 9}$$

where $\bar{\bar{D}}_f$ is the strain rate tensor, μ_f is the fluid-phase dynamic coefficient of viscosity, and λ_f is the second coefficient of viscosity. For the m^{th} solid phase, the position, linear, and angular velocity of the i^{th} particle evolves according to Newton's laws (Equations 10, 11, and 12).

$$\frac{d\mathbf{X}^{(i)}(t)}{dt} = \mathbf{V}^{(i)}(t) \quad \text{Eq. 10}$$

$$m^{(i)} \frac{d\mathbf{V}^{(i)}(t)}{dt} = \mathbf{F}_T^{(i)} = m^{(i)} \mathbf{g} + \mathbf{F}_d^{(i \in k, m)}(t) + \mathbf{F}_c^{(i)}(t) \quad \text{Eq. 11}$$

$$I^{(i)} \frac{d\omega^{(i)}(t)}{dt} = \mathbf{T}^{(i)} \quad \text{Eq. 12}$$

Here, $\mathbf{F}_d^{(i \in k, m)}$ is the total drag force, including both pressure and viscous components, on the i^{th} particle residing in k^{th} cell and belonging to the m^{th} solid-phase, $\mathbf{F}_c^{(i)}$ is the net contact force acting as a result of contact with other particles, $\mathbf{T}^{(i)}$ is the sum of all torques acting on the i^{th} particle, and $\mathbf{F}_T^{(i)}$ is the net sum of all forces acting on the i^{th} particle.

3.2.1.2 Contact Force Model

One advantage of using a DEM to model the solid phase of granular flows is the explicit treatment of particle-particle collisions. In the simulations, I use a soft-sphere model (Cundall and Strack, 1978) based on the spring-dashpot model. The soft-sphere approach makes it possible to have enduring multi-particle contacts, unlike the hard-sphere approach which requires all collisions to be binary and instantaneous. Consider two particles i and j with diameters $D^{(i)}$ and $D^{(j)}$, respectively, located at $X^{(i)}$ and $X^{(j)}$. Particles i and j are moving with linear velocities $V^{(i)}$ and $V^{(j)}$ and angular velocities $\omega^{(i)}$ and $\omega^{(j)}$, respectively. The normal overlap, δ_n , between particles is then calculated as,

$$\delta_n = 0.5(D^{(i)} + D^{(j)}) - |X^{(i)} - X^{(j)}| \quad \text{Eq. 13}$$

The unit vector along the line of contact pointing from particle i to particle j , η_{ij} , is

$$\eta_{ij} = \frac{X^{(j)} - X^{(i)}}{|X^{(j)} - X^{(i)}|} \quad \text{Eq. 14}$$

In the soft-sphere approach, the overlap between the two particles is represented as a system of springs and dashpots. The spring causes the rebound of the colliding particles and the dashpot mimics the dissipation of kinetic energy due to inelastic collisions. The spring stiffness coefficients in the tangential and normal directions are k_t and k_n , respectively. To ensure the simulations are in the hard collisional regime, I use a value of $k_n > P_s \cdot D \cdot 10^4$, where P_s is the solid pressure (Zhang and Kamrin, 2017). Similarly, the dashpot damping coefficients in the tangential and normal directions are η_t and η_n , respectively. The spring stiffness and dashpot damping coefficients are essentially a

function of the solid-phases the colliding particles belong to. The normal and tangential components of the contact force $\mathbf{F}_{ij}$, at time t , are decomposed into the spring (conservative) force $\mathbf{F}_{ij}^S$ and the dashpot (dissipative) force $\mathbf{F}_{ij}^D$ as

$$\mathbf{F}_{nij}(t) = \mathbf{F}_{nij}^S(t) + \mathbf{F}_{nij}^D(t), \quad \text{Eq. 15}$$

and

$$\mathbf{F}_{tij}(t) = \mathbf{F}_{tij}^S(t) + \mathbf{F}_{tij}^D(t). \quad \text{Eq. 16}$$

The normal spring force $\mathbf{F}_{nij}^S$ at any time during the contact is calculated based on the overlap δ_n between the particles and is given by

$$\mathbf{F}_{nij}^S = -k_n \delta_n \boldsymbol{\eta}_{ij}. \quad \text{Eq. 17}$$

Therefore, the total contact force $\mathbf{F}_c^{(i)}(t)$ at any time on the i^{th} particle is given as

$$\mathbf{F}_c^{(i)}(t) = \sum_{\substack{j=1 \\ j \neq i}}^N (\mathbf{F}_{ij}^S(t) + \mathbf{F}_{ij}^D(t)). \quad \text{Eq. 18}$$

3.2.1.3 Solid-fluid coupling

In this section, I discuss the details of calculating the momentum interaction term, $\mathbf{I}_{fm}$.

The drag force acting on a particle, existing in the k^{th} computation cell at time t is given by Equation 19.

$$\mathbf{F}_d^{(i \in k, m)} = -\nabla P_f(\mathbf{x}_k) v_m + \frac{\beta_m^{(k)} v_m}{\varepsilon_{sm}} (\mathbf{v}_f(\mathbf{x}_k) - \mathbf{v}_{sm}(\mathbf{x}_k)) \quad \text{Eq. 19}$$

Here $P_f(\mathbf{x}_k)$ and $\mathbf{v}_f(\mathbf{x}_k)$ are the fluid-phase pressure and velocity values calculated at the cell center $\mathbf{x}_k$. $\mathbf{v}_{sm}$ is the local cell-averaged velocity of the m^{th} solid phase, v_m is the particle volume, and $\beta_m^{(k)}$ is the local fluid-solid momentum transfer coefficient for all particles of the m^{th} solid phase and, using a Gidaspow drag correlation, has the form of,

$$\beta_m^{(k)} = \begin{cases} \frac{3}{4} C_D \frac{\rho_f \varepsilon_f \varepsilon_m |\mathbf{u}_f - \mathbf{u}_m|}{d_m} \varepsilon_f^{-2.65} & \varepsilon_g \geq 0.8 \\ \frac{150 \varepsilon_s (1 - \varepsilon_g) \mu_g}{\varepsilon_g d_m^2} + \frac{1.75 \rho_g \varepsilon_m |\mathbf{u}_f - \mathbf{u}_m|}{d_m} & \varepsilon_g < 0.8 \end{cases} \quad \text{Eq. 20}$$

In this drag correlation, the drag coefficient C_D is dependent on the particle Reynolds number where C_D is defined as

$$C_D = \begin{cases} \frac{24}{Re(1 + 0.15 Re^{0.687})} & Re < 1000 \\ 0.44 & Re \geq 1000 \end{cases}. \quad \text{Eq. 21}$$

The momentum transfer term is then estimated using this approximation of constant drag force on all particles in each computational cell as

$$I_{fm}^k = -\varepsilon_{sm} \nabla P_f(\mathbf{x}_k) + \beta_m^{(k)} (\mathbf{v}_f(\mathbf{x}_k) - \mathbf{v}_{sm}(\mathbf{x}_k)) \quad \text{Eq. 22}$$

This term is then used in Equation 7 to complete the conservation of momentum equation, relating momentum transfer between the fluid and solid phases.

3.2.2 Model Implementation

Using the above described discrete element model, I simulate glass beads in a rotating cylindrical flume to understand how the shape of probability distribution of bed forces varies with visco-inertial number, Stokes number, and degree of polydispersity. The simulated flume has a radius of 0.25 m and a depth of 0.33 m (Fig 14). Glass beads of density $2,300 \text{ kg/m}^3$ are initially dropped onto the bed of a static drum where they are allowed to settle before the drum begins to rotate. After the drum achieves a constant rotation rate, I allow the flow to reach a steady state

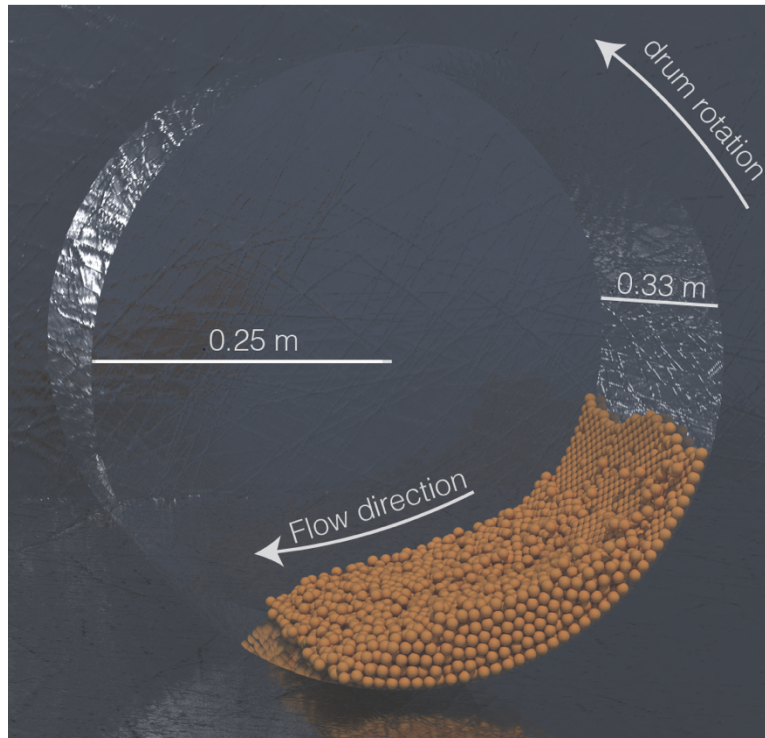


Figure 14. Geometry of rotating cylindrical flume used in this study's discrete element simulations. Brown spheres represent the grains in this simulation. Arrow in the upper righthand corner indicates direction of flume rotation.

before collecting bed forces. I define steady state in this system to mean the point in the simulation when the position of the flow front remains fixed within a tolerance of ± 0.05 m. I assume a no-slip boundary condition between the solid and the fluid phases. Particle-

particle and particle wall interactions are frictional with friction coefficients of 0.382 and 0.4, respectively. I explore flows with quasi-static to inertial behaviors by varying mean grain size, shear rate, fluid viscosity, and fluid density. I also analyze the effects of polydispersity in the flows has been suggested to have a sizeable effect on the length of the tail of bed forces distributions (Hsu, 2010). The complete list of model parameters used in the simulations can be found in the supplemental material in Table. B1.

3.2.2.1 Granular Flows with Interstitial Fluid

To explore the sensitivity of bed force distributions to changes in mean grain size, shear rate, width of the grain size distribution, fluid viscosity, and fluid density, I vary mean grain size from 8 mm to 16 mm and shear rates between 2.5×10^{-3} and 75 Hz to capture creeping to kinetic behavior in the simulated flows. I test the effects of the degree of polydispersity on the shape of the bed force distributions by modeling monodisperse flows (grain size standard deviation of 0 mm) to polydisperse flows with a maximum grain size standard deviation, σ_g , of 4 mm. Lastly, I explore the effects of fluid-particle coupling by varying fluid viscosity and the density contrast between the solid and fluid phase in the granular flows. I vary the fluid viscosity over 5 orders of magnitude (1×10^{-5} – 1 Pa·s) and fluid density over 3 orders of magnitude ($1 - 1000 \frac{\text{kg}}{\text{m}^3}$) to explore a wide range of fluid-particle couplings which may be present in natural systems. Grid cell size is kept at a factor of two larger than the maximum particle diameter to retain high resolution within the model while ensuring I am able to resolve bed forces from all particles. Note that in DEM-CFD, the Eulerian grid size Δx has to be larger than the maximum particle size and that $\Delta x \in (1.85d_{mean}, 2.5d_{mean})$ since bed statistics in that range are independent of Δx (Bernard et al., 2017).

3.2.2.2 *Pure Granular Flows*

Many studies which model granular flows as discrete particles often ignore fluid phases especially in the case of dry flows (air as an interstitial fluid). However, it has not been quantified at exactly what fluid viscosity that omission is appropriate. To provide an answer to this gap in knowledge, I run a suite of simulations in which I do not include a fluid phase. These flows, contained in a vacuum, provide a basis against which I can compare bed force distributions to determine the viscosity and density-contrast thresholds at which the fluid component can be considered to be of little importance in reconstructing bed forces due to granular interactions.

In this suite of pure granular flow simulations, I keep all model parameters the same as in the case of flows with an interstitial fluid except for the presence of a fluid phase. As in the case with a fluid component, I explore the sensitivity of the shape of bed force distributions to mean grain size, shear rate, and width of the grain size distribution. These simulations are not included in the phase space depicted in Figure 13 as the pure granular flow limit describes an infinite Stokes number flow due to an effective fluid viscosity of zero. I can, however, describe these flows with a finite inertial number which spans 10^{-2} - 10^0 for this suite of model runs.

3.2.3 Data Analysis

To analyze the data output from the simulations, I generate probability distributions of bed forces greater than the mean force felt on the bed. This is done by generating normalized histograms containing the force data. Binning of the data is done in order to help smooth the distribution which is susceptible to a significant

amount of noise when every sample is considered (Hsu et al., 2014). To avoid biasing data due to an arbitrary choice of bin width, I use bin widths calculated according to the Freedman-Diaconis method (Freedman and Diaconis, 1981) for each simulation. This method calculates the ideal bin size as $bin\ width = 2 \frac{IQR(x)}{\sqrt[3]{n}}$, where $IQR(x)$ represents the interquartile range of the bed force data and n is the total number of measurements. From here, a GPD and power law distribution are fit to the data and the best-fit distribution parameters are calculated. I calculate the χ^2 statistic for both the best-fit power law and Generalized Pareto distributions to determine the goodness of fit, the results of which are shown in Figure 16. Once the best-fit distribution is determined, I separate each distribution by its best-fit functional form and analyze how the distribution fit parameters vary with flow properties (Figures 18 and 19) and non-dimensional numbers (Figure 17). The results of this analysis are presented in the next sections.

3.3 Results

3.3.1 Flow property controls on bed force distributions

3.3.1.1 Fluid flow properties

I begin by analyzing the effects of fluid viscosity on the shape of bed force distributions. I vary fluid viscosity from 1×10^{-5} to 1 Pa·s to explore a conservative range of values encompassing the variation present in naturally occurring geophysical flows (Iverson, 1997). While holding all other flow properties constant, increasing fluid viscosity leads to a less elongated tail in the bed force distribution (Figure 15d). This is likely due to an increased coupling between the solid and fluid phases, leading to a dampening of particle impacts with the bed. It should be noted, however, that the

predicted frequency of high magnitude bed force excursions for the best-fit distributions only changes by a factor of 2 over 5 orders of magnitude variations in fluid viscosity, consistent with findings from previous studies (Hsu et al., 2014). So, while capturing the effects of fluid viscosity is important for accurately predicting the tail of the distribution of bed forces, the PDF is not particularly sensitive to changes in fluid viscosity.

Next, I analyze the effects of fluid density, specifically, the density contrast between the fluid and solid phase, on the shape of the bed force probability distributions. I vary fluid density by 3 orders of magnitude $\left(1 - 1000 \frac{\text{kg}}{\text{m}^3}\right)$ to capture how density impacts the distributions shape in both dry (air as an interstitial fluid) and wet (water as an interstitial fluid) flows and model all fluids as incompressible. Similar to the case for fluid viscosity, increasing fluid density leads to a less elongated tail for the bed force distributions (Figure 15e). By varying the fluid density 3 orders of magnitude, I see that the predicted frequency of high magnitude bed force excursions for the best-fit distributions only changes by a factor of 2. Again, this result implies that it is necessary to include a fluid phase for accurately capturing the frequency of large force excursions, but the shape of the PDF is robust to significant changes in fluid density. Overall, I see that fluid flow properties do alter the shape of the distribution of bed forces in granular flows, however, the magnitude of this change only becomes significant over large (orders of magnitude) variations in fluid flow properties.

3.3.1.2 Granular properties

Granular properties have been shown by previous workers to influence the shape of the probability distribution of bed forces (McCoy et al., 2013; Hsu et al., 2014), however,

the degree to which the functional form is affected by these flow properties has not been quantified. Here, I present the results of varying the mean grain size, shear rate, and the degree of polydispersity in simulated flows of granular material within a rotating flume. While there is significant debate about the most appropriate choice for grain size proxy, I choose to include both the mean and standard deviation of the grain size distribution to capture the major controls on grain size distribution. I also note that the shapes used here (spheres) are idealized compared to the variability present in natural granular materials. When analyzing the effects of the mean grain size, it is necessary to examine the effects of grain size at different end members of fluid viscosity and density. Only at high values of fluid density and viscosity do I see a monotonic decrease in tail length with increasing values of mean grain size (Figure 15a). At all other fluid property combinations, all distributions plot roughly on top of one another, showing no clear trend of distribution shape with increasing grain size.

I vary shear rate from 2.5×10^{-3} to 75 Hz to capture the full range of behaviors from quasi-static to inertial flows. Unlike the case for grain size, the length of the bed force distribution increases systematically with shear rate regardless of the value of fluid flow properties, suggesting a lower frequency of high magnitude bed force excursions for flows experiencing low shear rates relative to flows experiencing high shear rates with all other variables held constant (Figure 15b). By changing shear rate from 75 Hz to 2.5×10^{-3} Hz, the frequency of the high magnitude forces predicted by the best-fit distribution can vary as much as an order of magnitude. Another trend which appears when analyzing the effects of shear rate is the dependence of the functional form of the best-fit distribution.

At low shear rates ($\dot{\gamma} < 0.2$ Hz) the bed force distributions are best fit by a GPD with shape parameter values very close to zero, consistent with previously published

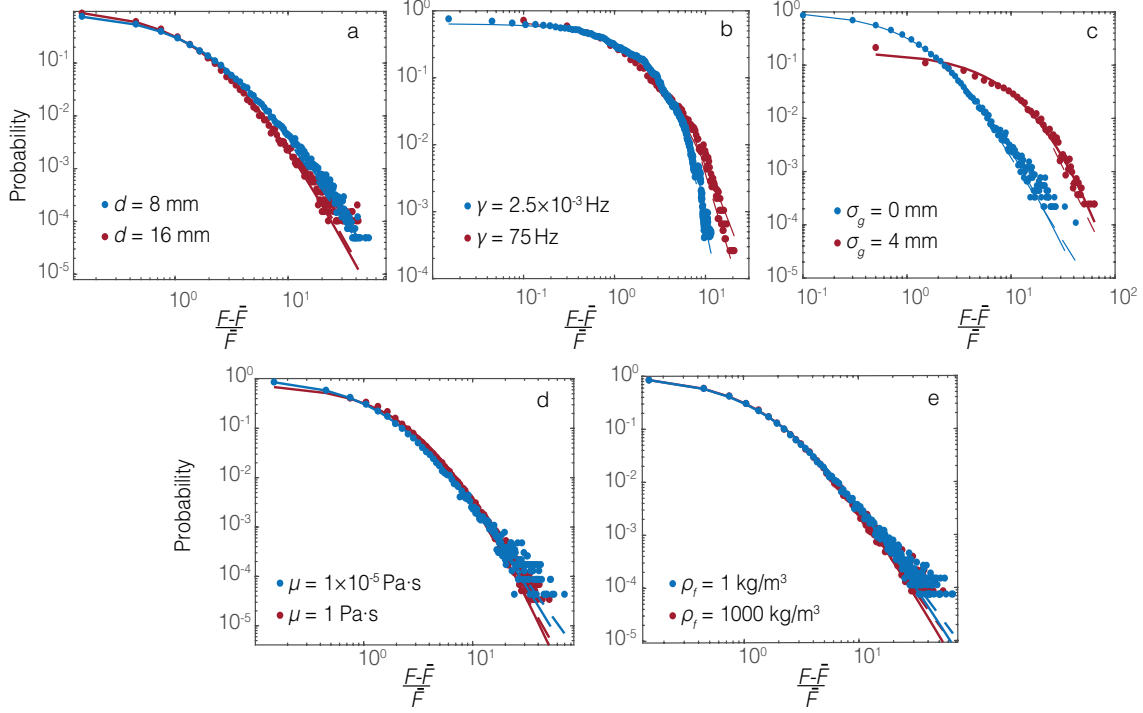


Figure 15. Sensitivity of normalized bed force distributions to (a) mean grain size (8 mm, 16 mm), (b) shear rate (2.5×10^{-3} Hz, 75 Hz), (c) degree of polydispersity (0 mm, 4 mm), (d) fluid viscosity (1×10^{-5} Pa s, 1 Pa s), (e) fluid density (1 kg m^{-3} , 1000 kg m^{-3}). Red indicates a maximum value of each respective flow property and blue indicates a minimum value.

studies showing exponentially distributed forces for slowly shearing and static granular systems. At intermediate shear rates ($0.2 < \dot{\gamma} < 10$ Hz) the PDF of bed force excursions is systematically better fit by the power law distribution than the GPD. In these cases, the GPD under predicts the frequency of high magnitude force excursions by over an order of magnitude. At high values of shear rate ($\dot{\gamma} > 10$ Hz), the GPD does a better job at describing the distribution of bed forces for most of flows except for those with low N_{St0} (~ 10) which are generally better described by a power law distribution.

To explore the effects of the width of the grain size distribution on the shape of PDF of bed forces in granular systems, I model both monodisperse and polydisperse flows. For the polydisperse case, I apply a normally distributed grain size distribution with standard deviation ranging from 1 mm to 4 mm and keep the mean grain size constant at 14 mm. Maximum and minimum values of grain size are held constant at 27 mm and 1 mm, respectively, for all polydisperse runs to prevent extreme values of grain size influencing results. The results show that the length of the tail of the distribution generally increases with the standard deviation of grain size (Figure 15c), causing a higher frequency of large magnitude force excursions in polydisperse flows relative to monodisperse flows. I see an order of magnitude or more increase in the predicted frequency of large magnitude forces for the best-fit distributions of flows with a standard deviation in grain size of 4 mm compared to a monodisperse flow. However, this trend is not consistent throughout the parameter space. At values of $Re_p < 1000$, flows with low viscosity fluids show the opposite trend, in which the distribution tail decreases with increasing values of the standard deviation in grain size. Under these flow conditions, grain size segregation does not occur, due to the lack of relative motion of the grains.

3.3.2 Distribution shape as a function of Non-dimensional Numbers

I next test the goodness of fit for both the power law and GPD for each of the simulations. To analyze whether or not there is a relationship between flow behavior and the functional form of the best-fit distribution, I plot the chi-squared statistic against visco-inertial number (Figure 16). At low values of visco-inertial number ($I_m < 10^{-3}$), the bed force distributions are best fit by a GPD with a shape parameter value close to zero,

consistent with an exponential distribution. I see significant misfit between the data and the best-fit GPD at intermediate visco-inertial numbers ($10^{-3} < I_m < 10^{-1}$). In this region of the parameter space, $P\left(\frac{F-\bar{F}}{\bar{F}}\right)$ is well fit by a power distribution in the tail of distributions. For large values of I_m ($I_m > 10^{-1}$), the GPD and power law have similar values of the chi-squared statistic, making the best-fit distribution more difficult to distinguish. The GPD is

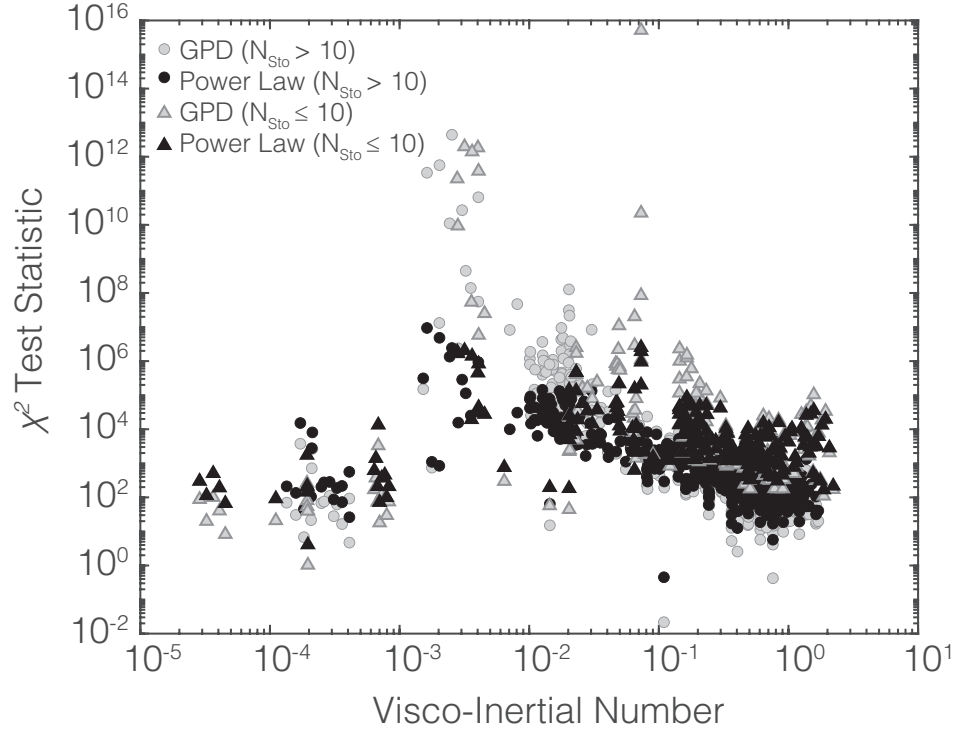


Figure 16. χ^2 statistics for GPD and power law fits to the tails of bed force probability distributions. At low visco-inertial numbers ($I_m < 10^{-3}$), χ^2 statistics for GPD fits tend to be lower than those for power law fits. This indicates that the tails of most bed force distributions in this regime are better fit by GPD than by power law fits. By contrast, at intermediate visco-inertial numbers ($10^{-3} < I_m < 10^{-1}$), χ^2 statistics for most GPD fits are higher than those for power law fits, indicating that bed force distributions in this regime are better fit by power law distributions. At high visco-inertial numbers ($I_m > 10^{-1}$), bed force distributions tend to be better fit by a GPD, except at high values of N_{Sto} (> 10), in which case distributions tend to be better fit by a power law distribution.

generally the more appropriate choice in this part of the parameter space, however, at low values of N_{Sto} , the power law fits the tail end of the distribution better than the best-fit GPD. In all cases, I rely on the chi-squared statistic to choose the more appropriate

choice for the best-fit distribution and confirm this choice through a visual inspection of the goodness-of-fit.

3.4 Discussion

3.4.1 Relation of distribution fit parameters to flow properties and non-dimensional numbers

In this section, I analyze the relationship between best-fit distribution parameters and the two non-dimensional numbers, I_m and N_{Sto} , which are both calculated using bulk flow properties. Figure 17 shows the results of this analysis. In each of the panels, the best-fit distribution parameters are only shown for distributions which are best fit by that particular distribution (i.e. α and x_{min} values are only shown for simulations that are best fit by the power law distribution), a determination which is made by comparison of the χ^2 statistic values. Upon first inspection, it is clear that there are some general trends in distribution fit parameters with both I_m and N_{Sto} , however, there is also a significant amount of scatter around some of these trends. For example, in Figure 17g, there is an overall positive trend between the GPD shape parameter, k , and the I_m , however, the data do not collapse to single line. This is due to the fact that I_m and N_{Sto} are dependent on several different flow properties that are varying in each one of the simulations. Thus, these trends represent the combined effects of varying grain size, shear rate, fluid density, and viscosity. The contribution of individual flow properties can be seen by color coding the panels of Figure 17 for each property, an example of which is displayed in Figure 18.

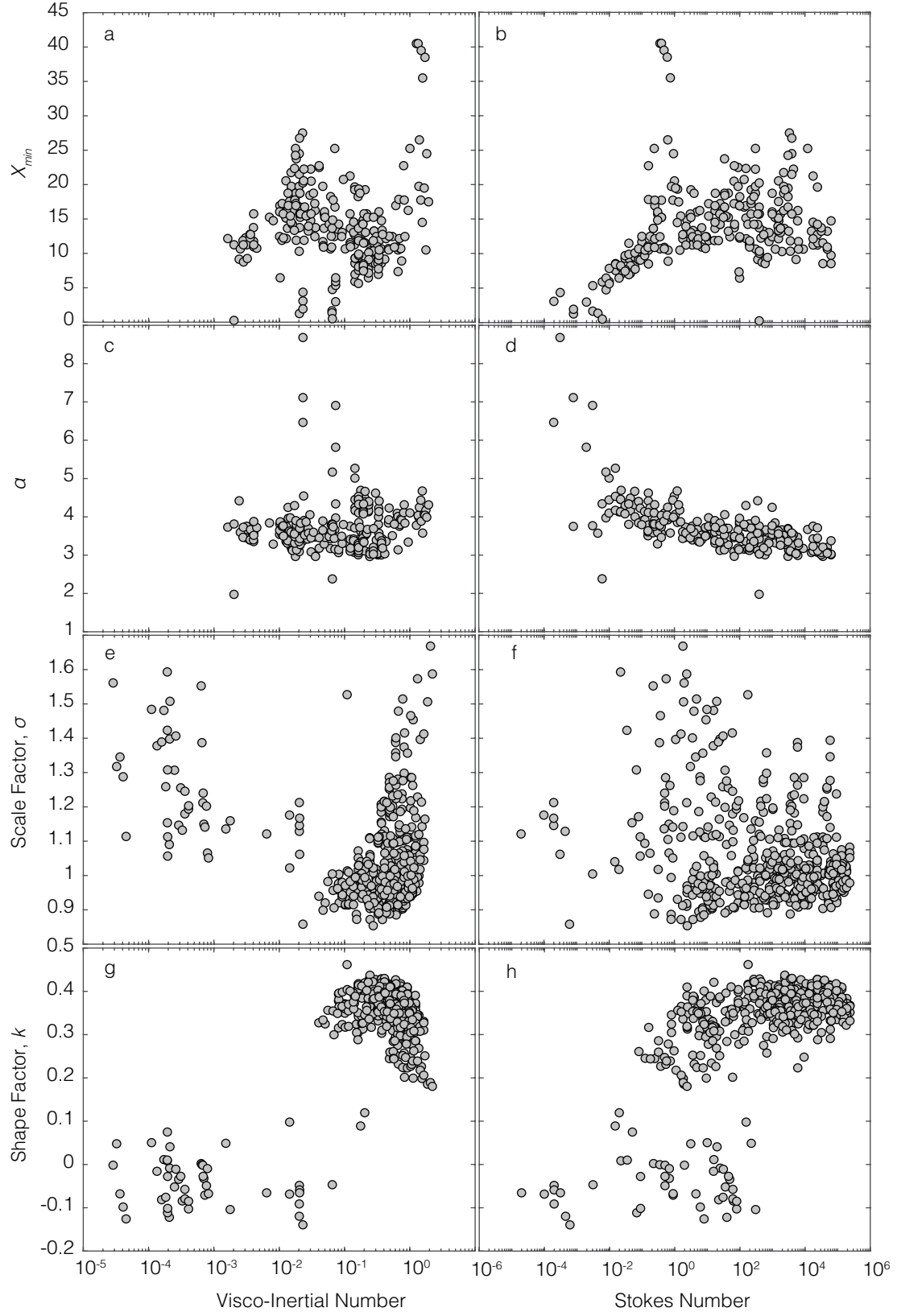


Figure 17. Best fit values for power law (x_{min} , α) and GPD (k , σ) parameters in fits to normalized bed force distributions as a function of visco-inertial and Stokes numbers.

Figure 17 shows that x_{min} and α respond differently to changes in I_m and N_{Sto} . The slope of the power law distribution decreases with N_{Sto} , but shows little change with I_m . The steeper slope of this trend for N_{Sto} than for I_m indicates a small sensitivity of the tail of distribution to changes in solid-fluid coupling. X_{min} shows a positive trend with N_{Sto} , and no clear trend is obvious with respect to I_m . When I analyze these trends between the power law fit parameters and non-dimensional numbers by isolating individual flow properties, there is no clear relationship between the observed trends and flow properties. Conversely, for the GPD fit parameters, I see no clear trend with N_{Sto} , but there is a strong relationship between the GPD fit parameters and I_m , with some scatter about these trends. This scatter can be explained by isolating the effects of grain size which is shown in Figure 8. These results highlight two very different responses of the best fit distributions to changes in flow properties and non-dimensional numbers.

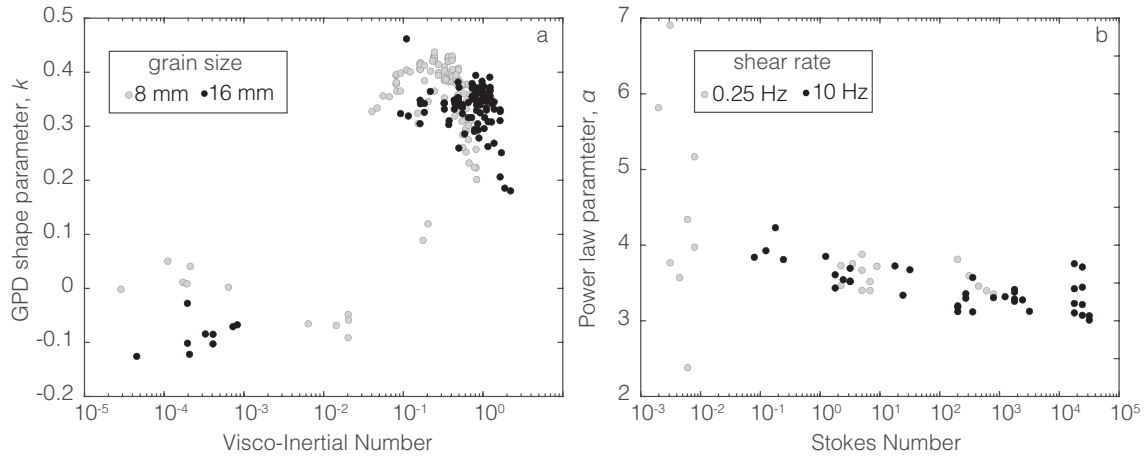


Figure 18. (a) Best fit values of the GPD shape parameter k as a function of visco-inertial number I_m . Colors show that best fit values of k tend to be higher at smaller grain size. (b) Best fit values of the power law slope parameter, α , as a function of N_{Sto} , color-coded by shear rate. Shear rate does not change the shape of the trend between the power law slope parameter, α , and N_{Sto} , as all values of shear rate follow a single trend.

3.4.2 Effects of polydispersity on bed force distributions

Because neither the visco-inertial number or stokes number is capable of capturing changes in the spread of the grain size distribution, it is necessary to perform a separate analysis of how distribution fit parameters respond to changes in the standard deviation of grain size. Polydisperse flows that generate bed force distributions best described by the power law distribution show a decrease in the median value of the slope parameter, α , with increasing values of σ_g (Figure 19B). To test whether these medians are statically different from one another, I carry out a Kruskal-Wallis H-test which yields a H-test statistic of 0.51, preventing the rejection of the null hypothesis that these median values are statistically equivalent. At the monodisperse limit there is also a decrease in the

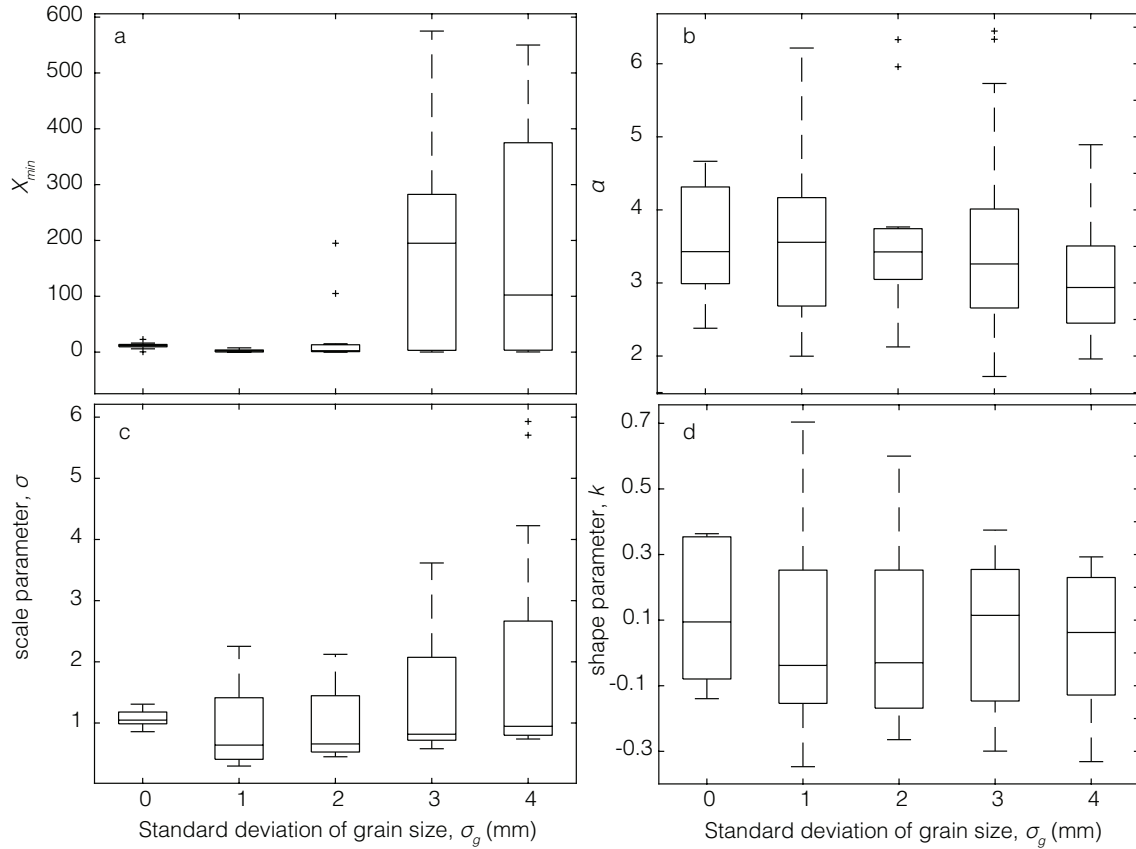


Figure 19. Influence of the standard deviation of grain size, σ_g , on power law distribution fit parameters x_{min} (panel a) and α (b) and GPD scale parameter σ (c) and shape parameter k (d). These show that, in polydisperse flows ($\sigma_g > 0$), the median k increases monotonically with σ_g and the median α decreases monotonically with σ_g .

median value of α , breaking from the trend seen in the polydisperse flows. Median values of x_{min} show no clear trends with σ_g , however, there is a systematic increase in the interquartile range of x_{min} with increasing values of σ_g (Figure 19A). For distributions best described by a GPD, σ_g most strongly affects the GPD scale parameter. Figure 19C shows a monotonic increase in the median value of the scale parameter with σ_g for polydisperse flows. Again, I carry out a Kruskal-Wallis H-test with p-value = 0.05 for testing the statistically significant difference between scale parameter median values. In this case, I calculate a H-test statistic value of 7.9×10^{-5} which allows us to reject the null hypothesis and confidently say that there is a statistically significant difference between median scale parameter values. The shape parameter (Figure 19D) shows no clear relationship with σ_g , suggesting the systematic change in distribution shape associated with changes in σ_g (Figure 15C) is largely due to the relationship between scale parameter and σ_g . As in the case of the power law fit parameter α , the GPD scale parameter also shows a non-monotonic relationship with σ_g once the monodisperse case is included in the analysis. While the cause of this change in behavior is not immediately clear, I believe this may be due to the phenomenon of granular crystallization which is known to occur in monodisperse granular assemblies.

3.4.3 Dry vs. Wet Flows

The importance of including a fluid phase in modeling granular flows is still poorly understood due to the complexity of understanding flow property controls on bed force distributions even in dry flows. Previous workers have suggested that the interstitial

fluid in pyroclastic density currents and debris flows (Iverson, 1997; Druitt et al., 2007; Lube et al., 2019) may strongly affect the runout distance, which may be due to increased pore pressure within the flow (Girolami et al., 2008; Roche et al., 2016; Breard et al., 2017). Hsu et al. (2014), however, found only a weak dependence of the PDF of bed forces on fluid viscosity with only small changes in the distribution over five orders of magnitude variation in viscosity. Similarly, McCoy et al. (2013) found no measurable difference in the bed force distributions with or without a viscous interstitial fluid. For this reason, I attempt to quantify the effects of including an interstitial fluid on the shape of the distribution of bed forces in a granular flow, specifically looking at the effects of fluid viscosity and decreased density contrast between the fluid and solid phase.

To do this, I compare distributions from a case in which no interstitial fluid was included, and two more distributions presenting the end member values of fluid viscosity used in the simulations, with all other flow parameters being held constant. The results show that wet flows with high ($1 \text{ Pa}\cdot\text{s}$) values of fluid viscosity differ in the expected frequency of high magnitude forces from the dry case by a factor of 2, however there is no detectable difference in the bed force distributions for the low viscosity case ($10^{-5} \text{ Pa}\cdot\text{s}$). This result is consistent with the results of Hsu et al. (2014) who showed a weak dependence of the PDF of bed forces on fluid viscosity. These results suggest that it is important to include a fluid phase when modeling granular flows with a fluid viscosity greater than that of air, as this will change the frequency of high magnitude bed forces, however, the sensitivity of the PDF to fluid viscosity is small when compared to the effects of other flow properties as discussed previously. Relating this back to the parameter space I present in Figure 13, this corresponds to flows with $N_{Sto} \sim < 1$. Natural

flows which may fall into this range include, debris flows, mudflows, and saturated landslides.

Next, I compare the bed force distributions from a simulation which, again, has no interstitial fluid and two distributions with the end member values of fluid density I explored in the simulations. The frequency of high magnitude bed forces does not vary significantly from the dry case for low fluid densities ($\sim 1 \text{ kg/m}^3$), but can differ by a factor of 2 for fluid densities of 1000 kg/m^3 . Large values of fluid density shorten the tails of the bed force distributions likely due to a decreased density contrast between the fluid and solid components. High viscosity fluids also truncate the tails of the bed force distributions due to an increase in coupling between the solid and fluid phases which

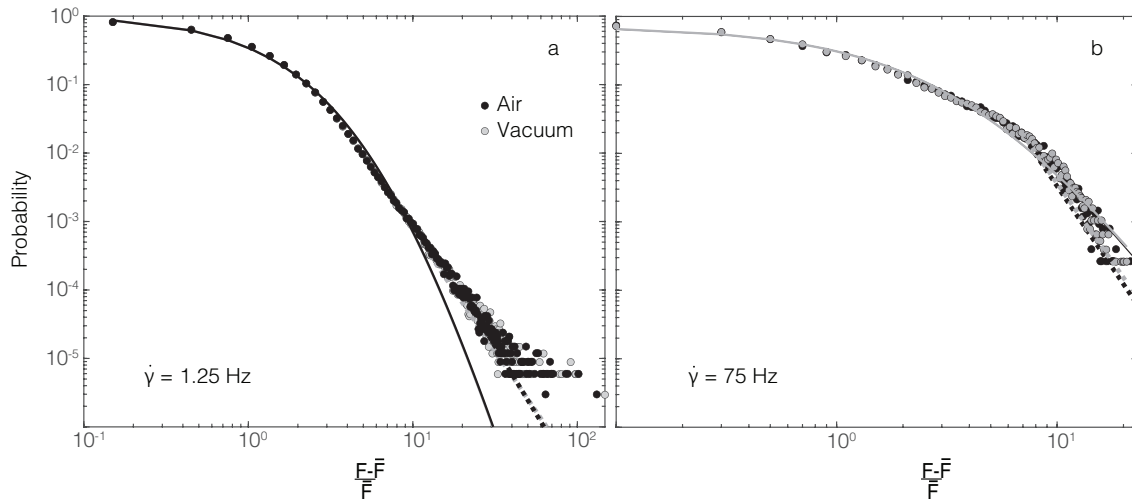


Figure 20. Comparison of bed force distributions between flows with air as the interstitial fluid (black) and flows simulated in a vacuum (gray) for (a) slowly shearing flows and (b) quickly shearing flows.

likely dampens particle impacts with the bed. These results suggest that granular flows which contain fluids with large values of fluid density or viscosity are expected to produce a lower frequency of high magnitude forces on their bed in comparison to similar flows with a low density or low viscosity interstitial fluid. These results also highlight the

low sensitivity of the shape of the PDF to changes in fluid flow properties which justifies the exclusion of a fluid phase in the case of dry flows to decrease computational expense.

In Figure 20, I show the bed force distributions generated by flows simulated with air as the interstitial fluid and pure granular flows simulated in a vacuum. Both the data and best-fit distributions for these flows are visually indistinguishable at low shear rates (Figure 20a). At high shear rates, the difference between the data and best-fit distributions for these flows is larger than in the low shear rate case but still negligible (Figure 20b). This confirms that in the case of dry flows, it is acceptable to neglect the fluid component when modeling granular flows, as this is unlikely to impact the behavior of the bed force distributions.

3.4.4 Recommendations and Implications for granular flows

In this section, I discuss the recommendations for the functional form of bed force distributions in monodisperse granular flows, the results of which are summarized in Figure 21. In this plot, I show that transitions in the best-fit distributions for the simulated flows align well with proposed estimates of flow regime boundaries (MiDi, 2004; Armanini et al., 2005; Da Cruz et al, 2005; Forterre and Pouliquen, 2008; Ness and Sun, 2015). I note that the transitions between best-fit distributions are not sharp which inhibits us from further refining flow regime transitions within the simulations by distribution form. It is likely that the exact location of these flow regime transitions depends on other system properties, such as friction, and for this reason, the recommendations for the functional form of the PDF of bed forces is based off of flow behavior instead of exact threshold values of I_m and N_{Sto} . For flows around the proposed flow regime transitions (within a factor of 5 of the estimated boundary), I integrate the

normalized bed force excursions above x_{min} for both the best-fit power law and Generalized Pareto distributions for comparison. Because $> 90\%$ the results of these integrations fall within a factor of 2 of one another, I recommend using a switching function based on local flow parameters when applying these results to continuum models.

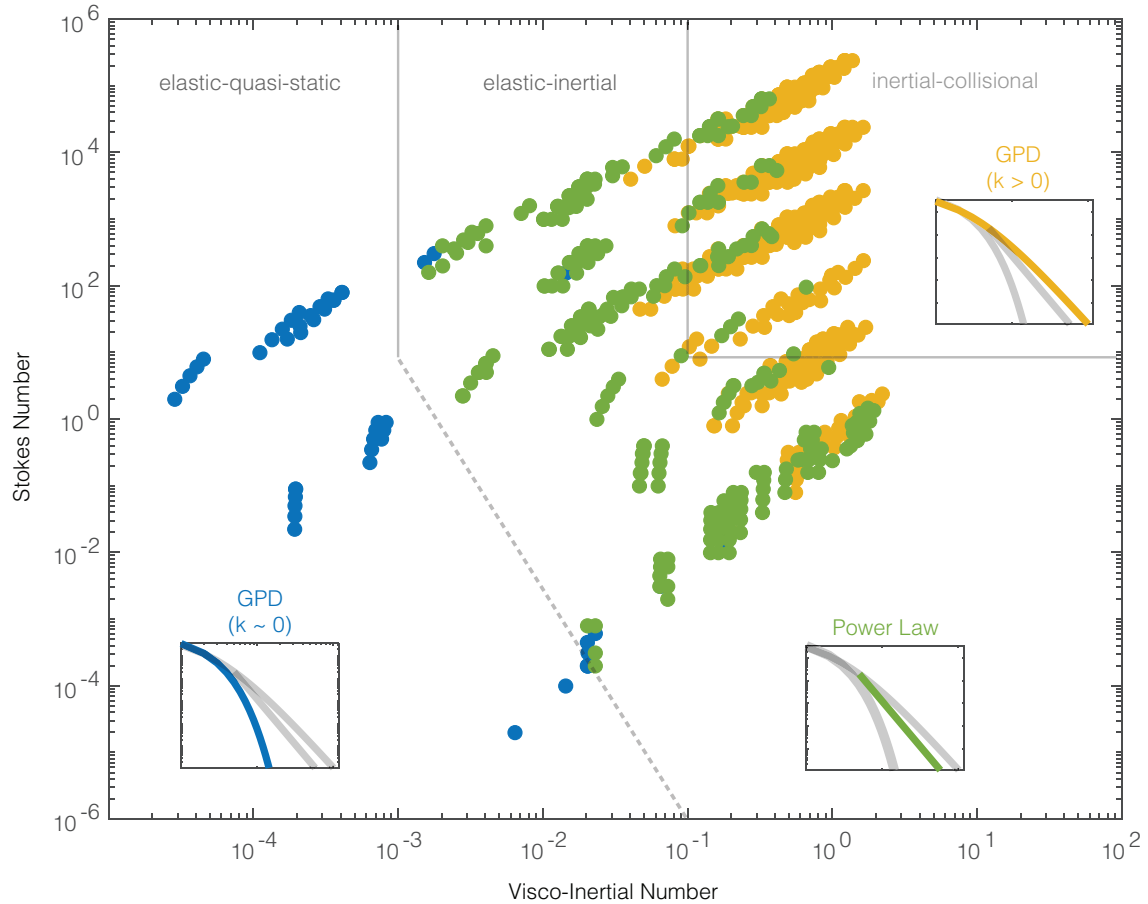


Figure 21. Lines indicate transitions between granular flow regimes as in Figure 13. Dots indicate visco-inertial and Stokes numbers of the DEM simulations in this study. Dot colors indicate the best-fit form (GPD or power law) of the distribution to the tail of simulated bed force distributions. These simulations show that the flow regime boundaries roughly correspond to the boundaries between types of best fits for the tails of bed force distributions. Overlap in the best-fit distribution highlights the gradual change in distribution form across flow regime transitions. In regions of significant overlap between distribution forms (e.g. transition between elastic-inertial and inertial collisional flows) the power law and GPD perform similarly, and the choice for the best-fit distribution is determined through comparison of the χ^2 fit statistic.

For quasi-static flows such as slowly-moving landslides, the shape of the bed force distribution follows a GPD (Figure 16) with $k \sim 0$ consistent with previously published results for static or near-static granular systems. These flows are best described as well-connected, near-jammed systems which typically rearrange by sliding, rolling, and slow shearing of the top layer of particles. In this region of the parameter space, the mean force is independent of shear rate and high-magnitude force excursions are likely caused by force chains, terminating at the flow-bed boundary, as these flows are not energetic enough to generate high-velocity impacts with the bed (Campbell, 2005). These short-tailed distributions suggest that these flows are not likely to generate a significant amount of material for entrainment and, for this reason, may be less likely to experience bulking when traversing supply-poor substrates. The shape of the tail of these distributions is sensitive to changes in mean grain size which highlights the importance of constraining this variable when reconstructing bed force distributions in this flow regime. Other flow properties have a much weaker impact on the shape of these distributions and for this reason are likely less important when trying to determine the potential for erosion in these flows. Elastic-inertial flows generate bed force distributions that are described well by a power law distribution, which can occur at high values of I_m for low values of N_{Sto} . The resulting distributions have more elongated tails than their quasi-static counterparts and thus, have the potential to be more erosive.

In the intermediate flow regime, flows now begin to display both quasi-static and kinetic flow behaviors in the elastic-inertial regime. Here, flows can still be described as well-connected although flows begin to display more energetic behavior, with binary collisions becoming more apparent particularly in the snout of the flows, and particles

becoming lofted in the tail end of the flow as the drum rotates. In this flow regime, the GPD begins to fail and the best fit distribution overwhelmingly becomes the power law distribution (Figure 16). Force chains are still predicted to exist in this regime due to the long-lasting frictional connections in the flow itself, while single particle impacts become another force producing mechanism due to increased flow energy. Elastic-inertial flows are sensitive to changes in fluid-solid coupling, quantified by N_{Sto} , displaying steeper slopes for more strongly coupled phases. Variations in this relationship can be explained by changes in shear rate, making shear rate an important variable to constrain when attempting to predict bed force distributions in this flow regime.

In the most energetic portion of the parameter space, I enter the inertial-collisional flow regime for moderate to high values of N_{Sto} in which the flow begins to exhibit collisional behavior much like that of a gas. Here the flows are poorly connected and are more analogous to dilute currents which primarily interact through binary collisions. Because of the absence of long-lasting particle connections, this regime is likely dominated by single particle impacts with the bed signaling a transition in dominant force mechanism (Campbell, 2005). For inertial-collisional flows such as dilute pyroclastic density currents, the shape of the bed force distributions is best described by a GPD with $k > 0.1$. Here, the exponential distribution greatly under predicts the frequency of high-magnitude bed forces as the tail becomes more elongated. This implies that these flows may be highly erosive, generating the highest frequency of large-magnitude forces on their beds out of all the flow regimes described here.

3.5 Bridge

In the previous two chapters, I explored bed force distributions in granular flows, and presented an analysis of flow property controls on the shape of the distribution. In Chapter IV, I describe a gravitationally self-consistent sea level model which I employ to study the effects of sediment redistribution in the Bengal Basin over the last glacial cycle. I construct a sedimentation history based off of published ^{10}Be , sediment flux, and sediment core data, where it is available, and use this as an input for the sea level model. I compare the results of these simulations to field observations and quantify the uncertainty in the results due to uncertainties in model inputs.

CHAPTER IV

SEA-LEVEL RESPONSES TO SEDIMENT REDISTRIBUTION IN THE BENGAL BASIN OVER THE LAST GLACIAL CYCLE

4.1 Introduction

As modern sea level continues to rise, low-lying coastal regions grow increasingly vulnerable to extreme flooding events. Monsoons and tropical storms can devastate these regions and are capable of causing over 100 billion dollars (US) worth of damages and thousands of deaths in a single event (Emanuel, 2017; Rappaport and Blanchard, 2016). Current estimates indicate approximately 10% of the world's population resides in regions with elevations below 10 m (McGranahan et al., 2007), highlighting the enormous hazard small changes in sea level pose to coastal inhabitants. This threat to coastal populations will likely increase as sea level is projected to rise up to 83 cm by the year 2100 relative to sea level during the time interval of 1985-2005 (Church et al., 2013).

Coastal hazards are modulated by minor changes in sea level, which provide the backdrop upon which storms are superimposed. An important component of modern sea-level changes is the ongoing asthenospheric response to past changes in the loading of mass at the Earth's surface. Previous studies have incorporated sediment redistribution into a gravitationally self-consistent framework for sea-level change (Dalca et al., 2013; Ferrier et al., 2017) and applied it in a variety of places (Wolstencroft et al., 2014; Ferrier et al., 2015; Pico et al., 2016; van der Wal and IJpelaar., 2017; Kuchar et al., 2018; Ruetenik et al., 2020). These studies have demonstrated the importance of accounting for

sediment redistribution when modeling sea-level change, as it is capable of producing significant spatial and temporal changes in sea level. Because the impact of sediment redistribution on sea-level change depends on a number of factors that vary regionally, including the rate of mass redistribution, sediment compaction, and Earth structure, the impact of sediment redistribution on sea-level change may vary greatly in space.

Therefore, to understand patterns of sea-level variation at any particular location, it is necessary to constrain the regional history of surface mass redistribution of ice, water, and sediment.

One site that is particularly susceptible to sedimentary effects on sea level is the Ganges-Brahmaputra-Meghna (GBM) delta, which is home to one of the highest fluvial sediment loads on Earth (~1 billions tons/year; Subramanian and Ramanathan, 1996), fed by rapid erosion in the Himalaya. Here, small changes in sea level can induce significant changes in flood hazard that affect the > 150 million inhabitants of this broad, low-gradient delta (UNFPA, 2018). Previous studies have explored the role of sediment deposition in the Ganges-Brahmaputra-Meghna (GBM) delta and Bay of Bengal regions. Grall et al. (2018) estimated the scale and pattern of Holocene subsidence in the GBM delta using an extensive database of stratigraphic, radiocarbon, and seismic reflection data, and reported subsidence rates of 2-5 mm/yr in the middle and lower portions of the delta. Karpytchev et al. (2018) employed previously published delta sediment storage data (Goodbred and Kuehl, 2000a) and a eustatic sea-level curve (Lambeck et al., 2014) to drive deformation of a Maxwell viscoelastic, spherically symmetric Earth model (Spada and Stocchi, 2003). In this study, Holocene sediment loading produced subsidence rates of 1.6 mm/yr, similar to global rates of sea-level rise in the twentieth

century. Krien et al. (2019) computed subsidence rates in the GBM delta induced by sediment loading over the past 11,000 years using a 3D Earth model to explore the effects of lateral variability in mantle and lithosphere structure. The results of this study suggested modern subsidence rates of 2-3 mm/yr, although authors note the high sensitivity of subsidence rate to mantle and lithosphere properties.

In this study, I build on this work by modeling gravitationally self-consistent sea-level responses to the complex history of sediment loading and unloading in the Ganges-Brahmaputra basin and Bay of Bengal over the last glacial cycle (122 ka to present). These simulations are the first of their kind to include the effects of sediment erosion on sea-level change in this region, the importance of which is discussed in detail in section 4.5.2. This study is also the first to analyze the importance of sediment redistribution over an entire glacial cycle, providing a more in-depth analysis of the effects of sediment redistribution on sea-level change over the timescales which are relevant for natural climate variability. In the following sections, I describe how I constructed a sediment redistribution history over the most recent glacial cycle that incorporates recent constraints on the sediment redistribution history throughout the region (Grall et al. 2018; Grimaud et al., 2020; Pickering et al., 2019; Sincavage et al., 2019). The simulations suggest that sediment fluxes from the GBM river system are large enough to produce relative sea-level perturbations of up to 30 m since the last interglacial, illustrating the importance of accounting for sediment redistribution in studies of sea-level change near large rivers.

4.2 Methods

4.2.1 Static sea-level theory and model

Unlike sea-level variations over decadal timescales, which are influenced by ocean and atmosphere dynamics (e.g., Cazenave and Llovel, 2010), sea-level changes over longer timescales (10^3 - 10^6 years) are dominantly driven by ice sheet growth/loss, tectonic activity, and variations in sediment distribution, which perturb Earth's crustal elevation, gravity field, and rotation axis (e.g., Farrell and Clark, 1976). These responses have been hypothesized to be the dominant driver of sea-level change near large river systems over long time scales, locally exceeding sea-level changes due to variations in ocean water volume.

The theory of post-glacial sea-level change is based on expressions for the gravitationally self-consistent redistribution of water in response to variations in ice and sediment loading (Farrell and Clark, 1976; Dalca et al., 2013). In this framework, sea level SL at a given point is the elevation difference between the sea surface equipotential G and the Earth's solid surface, which is defined as the sum of the crustal elevation R , sediment thickness H , and ice thickness I (Figure 22; Dalca et al., 2013). Because G , R , H , and I are all globally defined fields, the sea-level field SL is also globally defined, over oceans (where SL is positive) and over continents (where SL is negative). Using these definitions, the cumulative change in sea level ΔSL from one time to another is given by the changes in each of these terms in Equation 23 (Dalca et al., 2013). Here each term is implicitly a function of time, latitude, and longitude.

$$\Delta SL = \Delta G - \Delta R - \Delta H - \Delta I \quad \text{Eq. 23}$$

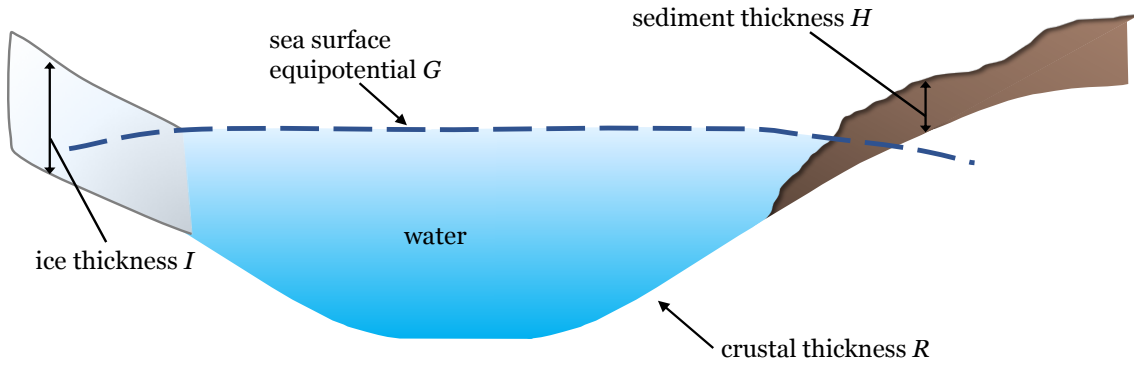


Figure 22. Schematic of factors controlling sea-level change in Equation 23.

For a given location, relative sea level, $RSL(t)$, is defined as sea level at a time in the past, t , relative to sea level at the present time, t_p . This can be written as (Ferrier et al., 2015):

$$RSL(t) = \Delta SL(t) - \Delta SL(t_p). \quad \text{Eq. 24}$$

Here, $RSL(t)$ represents the present elevation of a sea-level marker of age t .

It is convenient to consider related terms that describe sea-level changes at sites that avoided direct erosion or sedimentation (i.e., where $\Delta H = 0$ locally), but which nonetheless have been influenced by the effects of regional sediment redistribution on ΔG and ΔR . This is useful for interpreting the effects of regional sediment redistribution on sea-level histories inferred from preserved paleoshorelines. For sites like these that have also avoided direct changes in ice thickness (such as those considered in this study), the changes in SL and RSL can be written as ΔSL_{GR} and RSL_{GR} , modified versions of Equations 23 and 24 (Ferrier et al., 2015).

$$\Delta SL_{GR} = \Delta G - \Delta R \quad \text{Eq. 25}$$

$$RSL_{GR}(t) = \Delta SL_{GR}(t) - \Delta SL_{GR}(t_p) \quad \text{Eq. 26}$$

In large river deltas, changes in sea level are strongly influenced by deposition and compaction of fluvial and marine sediment. While deposition affects sea level by increasing the elevation of the seafloor, compaction affects sea level by lowering the bed elevation and by purging porewater out of sediments. Compaction can also produce sea-level changes in coastal regions by influencing shoreline migration and the location of seawater loading, which perturb crustal elevations. In my simulations, I account for sediment compaction following the methodology of Ferrier et al. (2017). This approach assumes that subaqueous sediment is fully saturated, and that sediment porosity ϕ changes at a rate that depends on the porosity ϕ itself and the difference between lithostatic pressure and hydrostatic pressure. Under the assumptions that ρ_s , ρ_w and g are constant with depth, I can write this as Equation (27).

$$d\phi / dt = -kgz(\rho_s - \rho_w C)(1 - \bar{\phi}_z)(\phi - \phi_{min}) \quad \text{Eq. 27}$$

Here k is a rate constant for changes in porosity [$\text{Pa}^{-1} \text{s}^{-1}$], ϕ_{min} is a minimum allowable porosity set by the densest possible grain packing (e.g., Bahr et al. 2001) and $\bar{\phi}_z$ is the mean porosity in the column from the top of the column to depth z , and C is the ocean function (1 over oceans and 0 elsewhere).

4.2.2. Model implementation

I compute sea-level responses by implementing the gravitationally self-consistent sea level model of Dalca et al. (2013), extended to account for the effects of sediment compaction and water conservation within sediment pore space following Ferrier et al. (2017, 2018). Sea-level responses are computed for a spherically symmetric viscoelastic Earth model characterized by a lithospheric effective elastic thickness of 90 km, a mantle viscosity profile given by the VM2 model (Peltier, 2004) and density profiles and elasticity parameters given by the Preliminary Reference Earth Model (PREM; Dziewonski and Anderson, 1981). I use the ETOPO2 topographic data set for the present-day global topography (United States Department of Commerce, 2001). Perturbations in ΔG and ΔR are computed following viscoelastic Love number theory and spherical harmonic degree and order 1024 (Peltier, 1974; Kendall et al., 2005; Dalca et al., 2013).

In these simulations, sea-level changes are driven by spatiotemporal variations in sediment thickness and grounded ice over the most recent glacial cycle from 122 ka to the present. For the ice load history, I adopt the ICE-5G model (Peltier, 2004), extended from the Last Glacial Maximum to 122 ka following Raymo et al. (2011). In Section 4.3, I describe how I constructed a sediment redistribution history for the study area.

4.3 Sediment redistribution history

Modeling sea-level responses to sediment redistribution requires a time series of global grids for three quantities: the cumulative change in sediment thickness ΔH since the start of the simulation, the sediment column's mean porosity $\bar{\phi}$, and the fraction of the sediment's pore space that is filled with water f_w . In this study, I refer to this

collection of global grids as a sediment transfer scenario. Here, I describe the sediment transfer scenario I constructed for the Bengal Basin and northern Bay of Bengal based on published erosion and deposition rates (Tables C1 and C2) and modeled changes in $\bar{\phi}$ computed with Equation 27. The rate of change in sediment thickness is given by the difference between the sediment deposition rate (positive for deposition, negative for erosion) and the sediment compaction rate ($H(1 - \bar{\phi})^{-1} d\bar{\phi}/dt$; Ferrier et al., 2017). For simplicity, I follow Ferrier et al. (2017) in assuming that submarine sediment is saturated

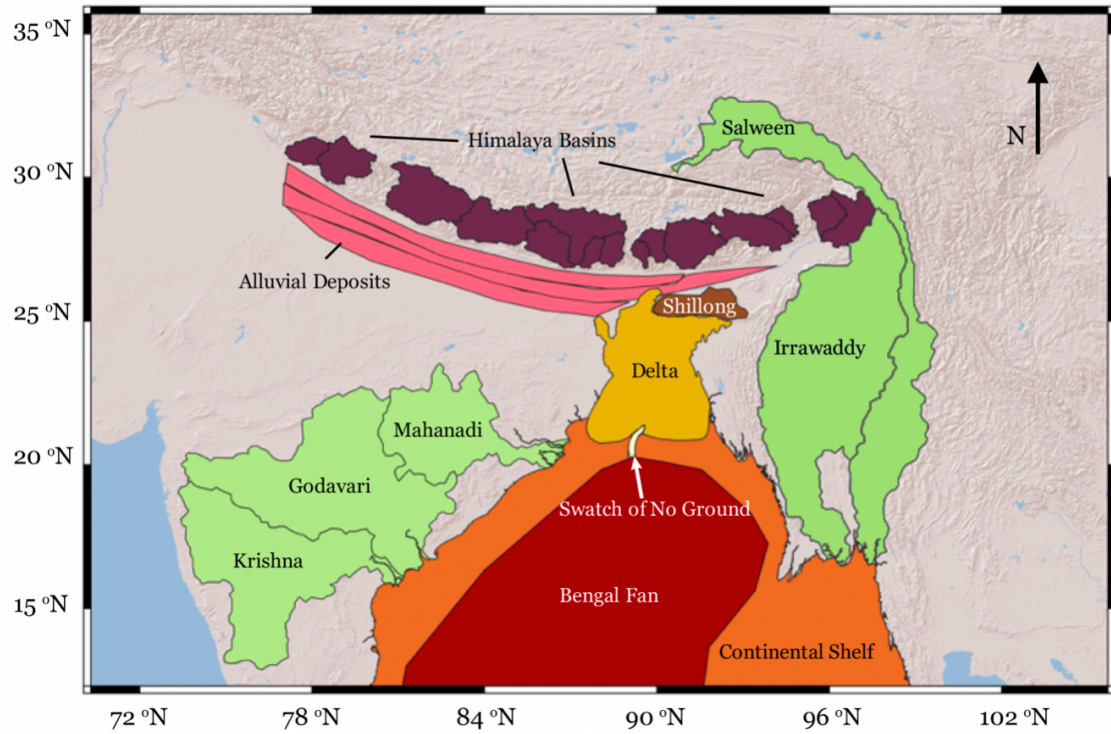


Figure 23. Locations of basin-averaged erosion rate measurements and depositional areas (Tables C1-C2) that were used to construct the sediment redistribution history in Figure 24. Erosion and deposition rates for regions lacking published measurements were interpolated from neighboring regions, as described in Section 4.3.

with water ($f_w = 1$) and subaerial sediment is dry ($f_w = 0$), and that eroding regions have $\bar{\phi} = 0$. The result is a best estimate for the study region's sediment loading history over the

last glacial cycle. Thus, in my simulations the sediment properties in the tidal and the fluvial domains of the delta are treated identically (Grall et al., 2018).

I began constructing the sediment transfer scenario by dividing the study region into the sub-regions in Figure 23. Erosional regions include the Himalayan basins, the Salween and Irrawaddy basins to the east, the Shillong Plateau just north of the GBM delta, and the Krishna, Godavari, and Mahanadi basins in eastern India. Depositional regions include the GBM delta, the alluvial deposits just south of the Himalayan basins, the continental shelf, and the Bengal fan. I do not include a depositional area for the Swatch of No Ground submarine canyon due to its small spatial extent relative to the model resolution (~ 1 grid cell), but include a hot spot of deposition in the Bengal Fan due to channelization of sediments through the canyon.

Within each of the sub-regions in Figure 23, I used published measurements (Tables C1 and C2) to create grids of erosion rates and deposition rates with a spatial resolution of 0.05° . While the Ganges-Brahmaputra Basin and Bengal Fan are well studied regions, constraints on the timing and spatial extent of deposition and erosion are limited over the time interval analyzed in this study, particularly during pre-Holocene periods (Table 1). Because of these significant gaps in data, I use a global eustatic sea-level trends (Peltier and Fairbanks, 2006) to inform estimates for sediment redistribution for periods in which I do not have published field measurements. Erosion measurements are taken from measurements of cosmogenic ^{10}Be concentrations or fluvial sediment flux in basins in which cosmogenic data is not available. Measurements of cosmogenic ^{10}Be concentrations in stream sediment yield basin-averaged mass loss rates in the upper few meters below the Earth's surface (Brown et al., 1995; Bierman et al., 1996; Granger et

al., 1996). These rates are averaged over the time period of cosmogenic nuclide accumulation, which scales inversely with erosion rate (e.g., Granger and Riebe, 2014), and which is typically $\sim 10^3$ - 10^4 years for most erosion rates in the study area. For basins without published cosmogenic nuclide-based erosion rates, I apply river sediment flux measurements. Rates derived from fluvial sediment fluxes are averaged over the basin's area and the duration of monitoring (4 - 40 years). Drainage basins were delineated using 30-m topographic data (NASA/METI/AIST/Japan Spacesystems, and U.S./Japan ASTER Science Team, 2009).

Modern deposition rates were taken from published sediment core data, which are most abundant in the GBM delta (Table C2). Deposition rates used in the sediment transfer history are averaged over $\sim 10^1$ - 10^4 years. In the Bengal Fan, which has few deposition rate measurements, I apply a pattern of sedimentation rates that decreases inversely with distance from the continental shelf. The resulting sediment redistribution rate maps are resampled onto a global grid with 512 rows and 1024 columns, the resolution required for the sea-level model input. To account for variations in erosion and deposition rates over time, I break down the last glacial cycle into the following six time intervals which capture the large-scale changes in the GBM-Bay of Bengal system over the past 122 ka (Figure 24). In each time period, I enforce conservation of sediment mass so that the cumulative eroded mass is balanced by the cumulative deposited mass, following the approach of Ferrier et al. (2015).

Table 1. Constraints on timing and spatial distribution of sediment erosion and deposition used for constructing sea level model input grids. Blank spaces indicate time intervals in which little or no data exists in the region of interest and blacked-out spaces are indicative of time intervals in which the region of interest is inactive.

Region Time interval (ka)	Fan	Shelf	Delta	Alluvial fans	Himalayas	Shillong Plateau	Eastern River Basins	Western River Basins
0-7		²¹⁰ Pb derived deposition rates from sediment cores	Radiocarbon dated borehole samples		¹⁰ Be and fluvial sediment fluxes	¹⁰ Be	Fluvial sediment fluxes	Fluvial sediment fluxes
7-12			Radiocarbon dated borehole samples		¹⁰ Be - increased monsoon strength	¹⁰ Be		
12-20			Coarse- grained paleovalley floor imaged by seismic survey		¹⁰ Be - increased monsoon strength			
20-30	Carbonate formation under low water and sediment discharge		Coarse- grained paleovalley floor imaged by seismic survey					
30-115				luminescence dated borehole samples				
115-122								

122-115 and 7-0 ka

During these periods, I apply modern erosion rates derived from basin-averaged ¹⁰Be-derived denudation rates and fluvial sediment fluxes to the Shillong Plateau and the Himalayan, Eastern Indian, Irrawaddy, and Salween basins (Table C2). I assume no deposition in the Alluvial Deposits region (Figure 23) during these time intervals to be consistent with luminescence dating of borehole samples collected from alluvial deposits

in the region (Roy et al., 2012). Delta deposition is assumed to occur at modern rates at both of these periods of sea-level highstand. For the GBM delta, I adopt the Holocene sedimentation rates and patterns in Goodbred and Kuehl (2000a) and several recent studies (Grall et al. 2018; Grimaud et al., 2020; Pickering et al., 2019; Sincavage et al., 2019), while the continental shelf and Bengal fan are assigned modern deposition rates (Goodbred, 2003). To maintain conservation of sediment mass during these periods, I increased deposition in the fan by a factor of 1.56.

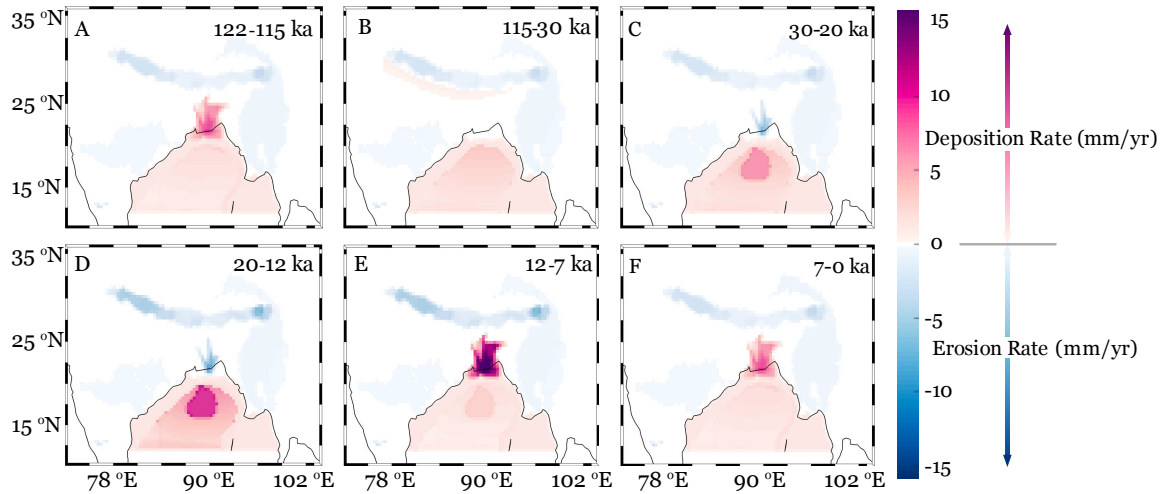


Figure 24. Rates of sediment erosion (blue) and deposition (red) over the past glacial cycle in the sediment redistribution history (Section 4.3). **A.** (122-115 ka) Modern erosion and deposition rates and patterns are applied in all regions, as in panel F. **B.** (115-30 ka) Deposition in the delta ceases and deposition begins in the Alluvial Deposits region. **C.** (30-20 ka) Deposition in the Alluvial Deposits region ceases and rapid deposition in the northern Bengal fan begins. **D.** (20-12 ka) Rapid erosion begins in the Himalayan basins in response to strengthening monsoon. **E.** (12-7 ka) Rapid deposition in the delta begins. **F.** (7-0 ka) Modern erosion and deposition rates and patterns.

115-30 ka

During this time period, the transition from a sea-level highstand to a long-lasting midstand was accompanied by the onset of sediment accumulation in the Alluvial Deposits region (Goodbred, 2003; Roy et al., 2012), which I simulate with a temporally steady deposition rate of 0.15, 0.32, and 0.5 mm/yr for the southern, middle, and northern

swaths, respectively. Deposition in the delta ceases while sedimentation on the shelf remains unchanged from the previous time period, reflecting large amounts of sediment stored in the region's alluvial valleys (Goodbred, 2003; Weber et al., 2003, 2018). I assign the Himalayan, Salween, Irrawaddy, and Eastern Indian basins and the Shillong Plateau erosion rates that match their modern rates as there is no evidence to suggest a significant change in sediment supply during this time interval. To maintain sediment mass conservation during this period, I scaled deposition rates in the Bengal fan region upward by a factor of 2.5204.

30-20 ka

During this period, I assigned a deposition rate of 0 mm/yr in the Alluvial Deposits region, reflecting the reduction in sediment supply from the Himalaya at this time (Singh, 1996). I assigned erosion rates of 2.5-7.5 mm/yr along the major river valleys in the subaerial and subaqueous delta to account for incision driven by Tibetan lake-burst floods (Goodbred, 2003; Pickering et al., 2019). The fastest deposition occurs in the Bengal fan as sediment bypasses the delta via incised valleys and the Swatch of No Ground canyon (Palamenghi et al., 2011; Pickering et al., 2019). All erosional basins remain unchanged from those during the previous time period. To maintain sediment mass conservation during this period I scaled deposition rates in the Bengal fan region upward by a factor of 1.9943.

20-12 ka

During this time period, the river valleys in the subaerial and subaqueous delta are assigned erosion rates 1.25 times higher than the erosion rates in the 30 – 20 ka period. This is done to maintain the same total mass removal as in the previous time period while accounting for the difference in the duration of the two periods (10 ka versus 8 ka). The location of fastest deposition in the Bengal fan persists (Goodbred, 2003; Weber et al., 2003). Erosion rates in the Himalayan basins are increased by a factor of two to simulate increased erosion under the strengthened monsoon, the magnitude of which is constrained by ^{10}Be -derived paleo-erosion rates (Pratt et al., 2002; Finkel et al., 2003; Scherler et al., 2015). All other erosional basins are assigned their modern erosion rates. To maintain mass conservation during this period I scaled deposition rates in the Bengal fan region upward by a factor of 1.6236.

12-7 ka

This period marks a rapid transition in depositional regime. I maintained the increased Himalayan erosion rates during the 20-12 ka period while setting erosion rates in the rest of the erosional basins to the values assigned in the earlier time periods (122-20 ka) (Goodbred, 2003). The subaerial and subaqueous delta begin to aggrade rapidly with deposition rates approximately twice that of the modern deposition rates (Goodbred and Kuehl, 2000b). I assume the same spatial pattern for the deposition in the Bengal fan and on the shelf. However, the rates of deposition in the Bengal fan region are decreased relative to the previous time period due to a shift of deposition to the delta following margin flooding around 12 ka (Weber et al., 2003). To maintain mass conservation

during this period I scaled deposition rates in the Bengal fan region upward by a factor of 1.3622.

4.4 Results

Using the sea-level model presented in Section 4.2, I simulated sea-level responses to the adopted ice history and the sediment redistribution history in Section 4.3. Figure 25A shows the cumulative changes in the input sediment thickness ΔH , and Figure 25B shows the sea-level response ΔSL_{GR} (Equation 3) at the end of the 122-kyr simulation. In the context of Equation 4, ΔSL_{GR} in Figure 25B corresponds to $\Delta SL_{GR}(t_p)$, the change in sea level from 122 ka to the present day. Because $\Delta SL_{GR}(t)$ at the onset of the simulation is 0 m, Equation 4 implies that ΔSL_{GR} in Figure 25B equals $-RSL_{GR}(122 \text{ ka})$. Thus, Figure 25B shows the negative of present-day elevations of hypothetical paleoshorelines formed at 122 ka.

In addition to the simulation driven by both ice and sediment variations, I also computed sea-level responses to the ICE-5G ice mass variations alone. Figure 26 displays the difference in RSL at 122 ka between scenarios with and without sediment redistribution in the Bengal basin. This isolates the net effect of sediment redistribution on modeled sea-level changes. These results indicate that sediment redistribution is responsible for up to ~15 m of variation in relative sea-level at the modern coast along the delta.

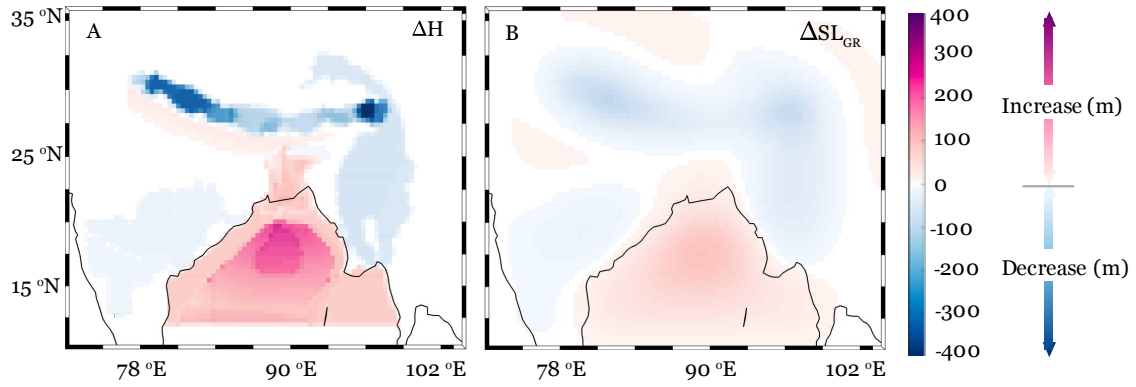


Figure 25. Cumulative changes in (A) sediment thickness (ΔH) and (B) sea level (ΔSL_{GR} ; Equation 25) over the 122-kyr simulation.

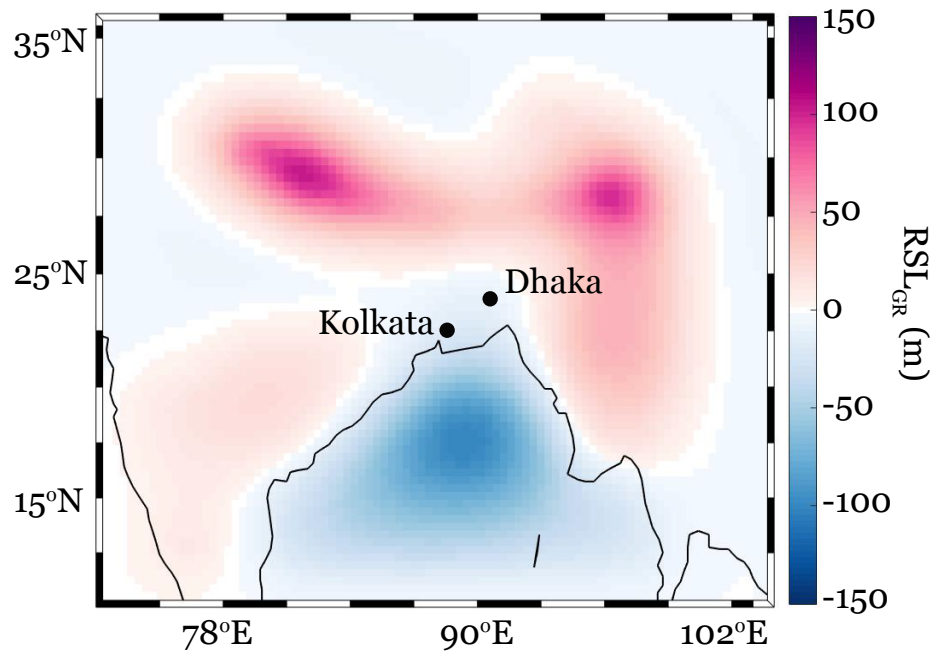


Figure 26. Difference in RSL_{GR} (Equation 26) at 122 ka between two simulations, one driven by global ice variations and regional sediment redistribution, and one driven only by global ice variations. This shows the net impact of sediment redistribution on RSL_{GR} at 122 ka. RSL_{GR} histories at Dhaka and Kolkata are shown in Figure 27.

4.5 Discussion

4.5.1 Effects of sediment redistribution on sea level

Figure 27 shows the history of RSL_{GR} over the 122-kyr simulation at two coastal mega-cities, Dhaka and Kolkata, on the eastern and western sides of the GBM delta, respectively. The solid line represents RSL_{GR} responses in a simulation driven by both sediment and ice variations, while the dashed line represents RSL_{GR} responses in a simulation driven only by ice variations. Figures 27C-D show the difference in RSL_{GR} between the simulation driven only by ice and that driven by both ice and sediment, which isolates the net effect of sediment on RSL_{GR} .

The effect of sediment redistribution on RSL_{GR} in these simulations is as high as ~19 m at Dhaka and ~17 m at Kolkata (Figures 27C-D). The shapes of the RSL_{GR} time series at these sites are broadly similar to one another, but differ in some respects. In Kolkata (Figure 27D), the magnitude of the difference in RSL_{GR} decreases linearly by ~5 m from 110 to 30 ka before steeply increasing by ~5 m between 30 and 12 ka. Meanwhile, the magnitude of the difference in RSL_{GR} at Dhaka (Figure 27C) shows almost no change between 110 and 30 ka, but increases by ~8 m from 30 to 12 ka. This difference is a result of the disparity in their proximity to depositional and erosional centers. Dhaka is located ~170 km north of the modern coastline, which is far enough from the shelf and bay to be minimally affected by deposition there. Dhaka also lies between depositional centers to the south (shelf and bay) and erosional centers to the north and east (Shillong, Salween, and Irrawaddy) resulting in only minor changes in sea level during periods of no deposition in the delta. Kolkata, by contrast, lies about 95 km from the modern coastline, and therefore is relatively more sensitive to the sedimentation along the shelf and bay. This leads to a steadily decreasing magnitude of sediment's

impact on RSL_{GR} from 110 to 30 ka and a smaller increase in RSL_{GR} from 30 to 12 ka than at Dhaka.

These simulations show that sediment redistribution can affect the sign of the modeled sea-level response in certain places and time periods. For example, in Figures 6A-B, modeled RSL_{GR} from 10 ka to the present is positive for the simulation driven only by ice and negative for the simulation driven by both ice and sediment. This illustrates how strongly sediment redistribution can influence sea-level change and highlights the importance of quantifying spatiotemporal variations in sediment redistribution, especially over the last few thousand years.

In addition to revealing the impact of sediment redistribution on modeled sea-level change in the past, these simulations also illustrate the impact of sediment redistribution on modeled sea-level changes today, which is a consequence of the long response time of the viscous mantle to past changes in surface loading (e.g., Cathles, 1975). Figure 28 shows the average rate of change in ΔSL_{GR} over the last timestep of the simulation (the most recent 100 years) excluding the contributions from changes in ice sheet volume. Along the modern coast, this indicates increases in ΔSL_{GR} at rates up to ~ 1.5 mm/yr in the GBM delta. This is the rate of change in sea level that would be experienced by an object that avoided direct changes in sediment erosion or deposition (i.e., for which $\Delta H = 0$), such as a preserved paleoshoreline or a tide gauge. This excludes changes in topography caused by direct sediment erosion or deposition. This ongoing sea-level response to past sediment redistribution is significant: it is ~ 1.1 - 1.5 times greater than the increase in global mean sea level from 1901 to 1990 that was dominantly driven by changes in ice sheet volume and thermosteric effects (Hay et al., 2015).

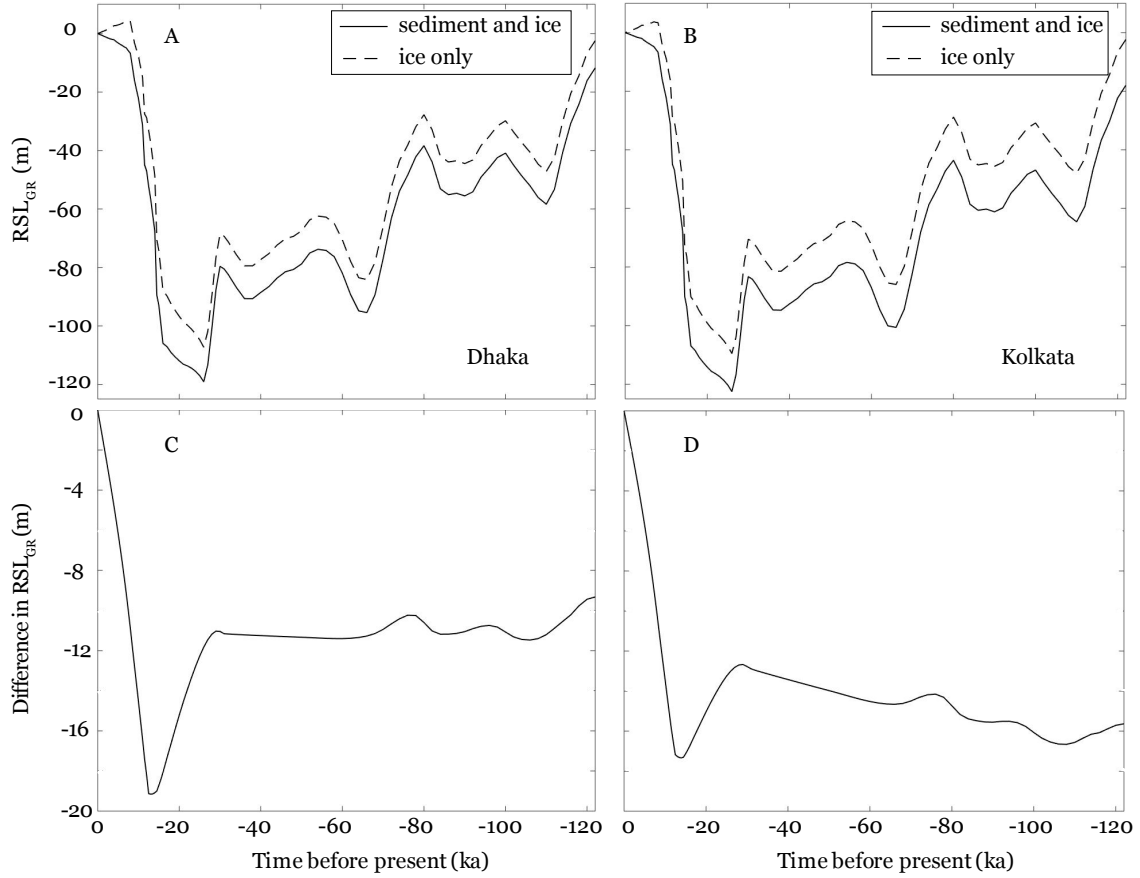


Figure 27A, B. Modeled sea-level histories at two coastal sites, one east of the GBM delta (Dhaka, panel A), and one west of the GBM delta (Kolkata, panel B; Figure 26). Solid lines show RSL_{GR} (Equation 26) in a simulation driven by global ice variations and regional sediment redistribution, while dashed lines show RSL_{GR} in a simulation driven only by global ice variations. **C, D.** Difference between simulations with and without sediment redistribution in panels A and B, respectively. This shows that the cumulative effect of sediment redistribution on RSL_{GR} at 122 ka at these sites is large (~19 and ~17 m), and that the impact of sediment on RSL_{GR} at a given site is sensitive to the site's location relative to the locations of sediment redistribution.

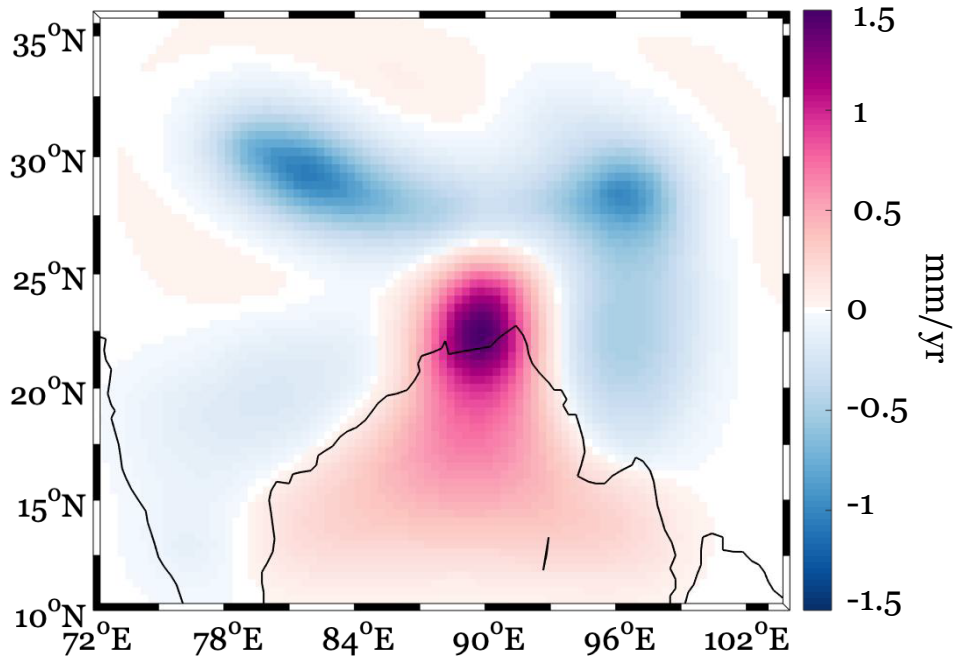


Figure 28. Mean rate of change of ΔSL_{GR} over the last century in the simulation driven by variations in ice and sediment (Figure 25B). This illustrates the effect of sediment redistribution on modeled modern sea-level markers.

4.5.2 Importance of erosion in sediment transfer history

In this section, I quantify the importance of including sediment erosion in the sediment transfer history. I do this by running a simulation in which I only include sediment deposition and compare these results to those obtained by the standard scenario. I then compare both of these cases to published field observations and discuss how the inclusion of erosion impacts the fit of model results to these data. Specifically, I compare these two scenarios to carbon-dated sediment cores in the lower delta reported by Grall et al. (2018) and paleoshoreline markers in the form of carbonate ooids located off of the modern shoreline of Bangladesh (Wiedicke et al., 1999). Previous studies which have focused on the effects of sediment redistribution on driving changes in sea level in GBM delta (Grall et al., 2018; Karpytchev et al., 2018; Krien et al., 2019) only include

sediment deposition in their model inputs due to the small spatial and temporal scales considered in these studies. In this chapter, however, I expand on previous work by analyzing a wider region of interest to include regions of large-scale erosion (i.e. Himalayan basins) which might affect regional responses to local changes in sediment redistribution. I also explore a longer sediment redistribution history than other studies in this area to ensure that I capture changes in sedimentation patterns over an entire glacial cycle, requiring a more comprehensive sediment transfer history to be able to confidently simulate sea level variations due to changes in sediment thickness.

Figure 29 illustrates the importance of including erosion in the sediment transfer history in the Bengal basin by quantifying the difference in ΔSL_{GR} at the end of the 122 kyr simulation between the standard scenario and a simulation in which I only include deposition in the model input grids. In panel A, the signal is dominated by the difference in erosion in the Himalayan basins. Zooming into the delta, as is depicted in panel B (note change in color bar bounds), the maximum difference between these simulations is on the order of 5 meters which changes sign from positive to negative about midway through the delta moving from west to east.

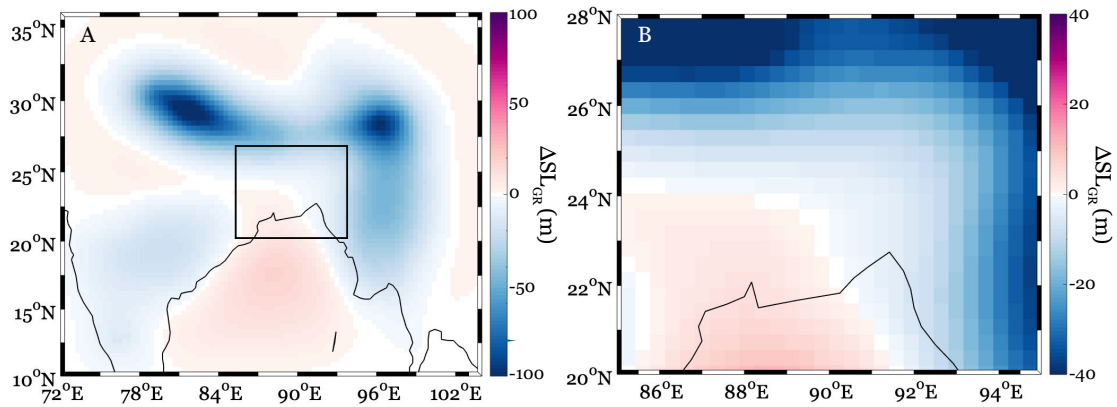


Figure 29A, B. Difference in ΔSL_{GR} between the standard scenario and a scenario in which the model input only includes sediment deposition. The central rectangle in panel A outlines the area depicted in panel B. Note change in color bar limits between panels.

Next, I compare the results from both the standard scenario and the deposition only scenario to previously published field observations. Because the GBM delta experiences significant flooding due to consistent monsoons, there are scarce records of previous shorelines, however there are two data sets of interest in this area which I am able to compare to the model results. The first of which are carbon dated sediment thickness measurements reported in Grall et al, 2018. Here, I focus on the data from the tidal region (lower subaerial delta) as this is likely the area least affected by tectonic forcing in this region which are not considered by the sea level model. When I look at sediment age and thickness measurements taken from carbon dated sediment cores compared to the model results (Figure 30A), I see good agreement with field measurements, the standard scenario case, and the deposition-only case, particularly during the early Holocene. During the last 10 ka, both models slightly over predict sediment thickness in this region with a maximum difference of ~ 8 m.

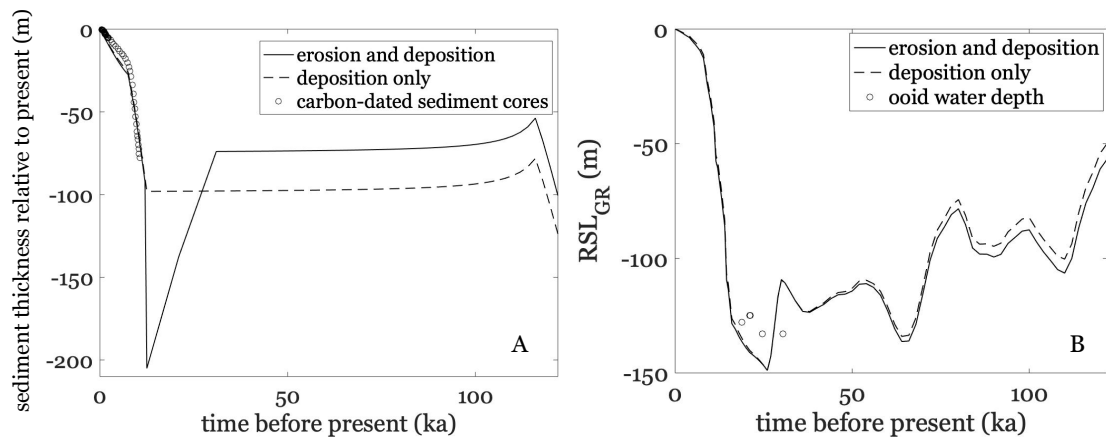


Figure 30. (A) Comparison of sediment thickness from the standard scenario (solid line), the deposition only scenario (dashed line) and carbon-dated sediment cores (open circles) collected in the lower subaerial delta taken from Grall et al., (2018). (B) Comparison of relative sea level from the standard scenario (solid line), the deposition only scenario (dashed line) and the water depth at which carbon-dated carbonate ooids (Wiedicke et al., 1999) were found off of the coast Bangladesh (open circles).

In Figure 30B, I show a similar analysis in which I compare relative sea level history over the 122 ka simulation for the standard scenario, deposition only scenario, and the water depth at which carbonate ooids and oolites were found off of the modern shoreline of Bangladesh (Wiedicke et al., 1999). In this case, there is no significant difference between the relative sea level histories for the standard and deposition-only scenarios after 30 ka, however, both scenarios fail to match the water depth predicted by the carbonate ooids. This disagreement likely stems from the poor spatial resolution of available sedimentation rate data and the large variability in reported sedimentation rates in the shelf region. While, the deposition rate used in this region is an appropriate choice for describing average shelf sedimentation rates, the high spatial variability in these rates may lead to more localized changes in sea level which are not captured in the model. Additionally, the results of our model are subject to uncertainties in input parameters including the magnitude and timing of sedimentation events, lithospheric thickness, and mantle viscosity profile. In the following sections, I quantify the sensitivity of the model results to variation in the input parameters to potentially explain discrepancies between the model output and field observations.

4.5.3 Sensitivity of modeled sea-level changes to uncertainties in sediment transfer scenarios

Modeled sea-level changes are sensitive to uncertainties in the sediment loading history, the ice loading history, and the Earth model. Given that this study's focus is the effects of sediment redistribution, and that the sensitivity of sea-level responses to Earth model parameters and ice histories have been explored elsewhere (e.g., Milne and

Mitrovica, 2008; Wickert et al., 2013), and in the GBM (Krien et al., 2019) here I focus on the sensitivity of modeled sea-level responses to uncertainties in the temporal and spatial distributions of sediment within the Ganges-Brahmaputra basin over the last glacial cycle. The results of each of these analyses are summarized in the following sections.

4.5.3.1 Spatial variability

To illustrate the sensitivity of modeled sea-level responses to uncertainties in the location of sediment redistribution in the GBM delta, I conducted two additional simulations in which the deposition and erosion rates in the delta were shifted one grid cell (~40 km) to the east or west, and I compared the resulting sea-level responses to those in the standard simulation in Figure 25B. In these two additional simulations, rates and patterns of sediment redistribution were identical to those in the standard scenario in all regions aside from the delta, and sediment mass balance was enforced at all time steps, as in the standard scenario.

For the simulation in which delta sedimentation redistribution was shifted to the east by one grid cell, patterns in ΔSL_{GR} in the delta were translated eastward by approximately one grid cell as well. Figure 31 shows the difference between ΔSL_{GR} in the standard simulation (Figure 25B) and in this simulation. This reveals a bipolar pattern around an approximately north-south line that is coincident with the delta's highest values of ΔSL_{GR} in Figure 25B. East of this line, the standard simulation exhibits lower values of ΔSL_{GR} than in the alternative simulation, while west of this line it exhibits higher values (Figure 31). The positive and negative signals both have a maximum

amplitude of approximately 1.5 m which decays to zero over a wavelength of ~ 650 km in the east-west direction. Similarly, I simulate the scenario in which delta sediment redistribution was translated one grid cell to the west. As in Figure 31, this results in a bipolar pattern in the difference in ΔSL_{GR} , but with the sign reversed: the standard simulation has values of ΔSL_{GR} that are higher to the east and lower to the west. These differences in ΔSL_{GR} highlight the importance of uncertainties in rates and patterns of sedimentation and erosion in modeling sea-level responses to sediment redistribution.

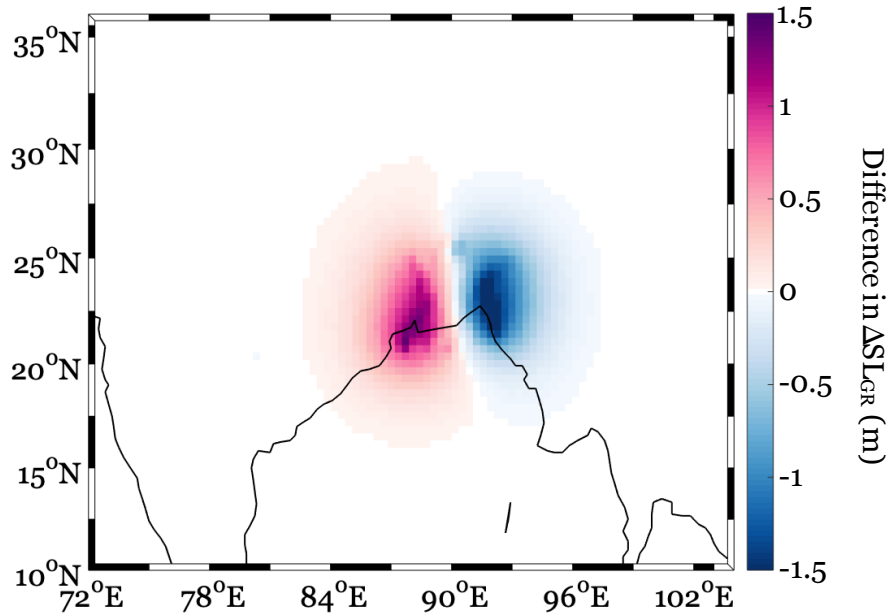


Figure 31. Difference in ΔSL_{GR} between the standard simulation (Figure 25B) and a simulation in which delta deposition was shifted one grid cell (~ 40 km) eastward relative to its position in the standard simulation. The maximum differences in ΔSL_{GR} have an amplitude of approximately 1.5 m, illustrating the significance of uncertainties in rates and patterns of deposition.

4.5.3.2 Earth model

To illustrate the sensitivity of modeled sea-level responses to the adopted Earth model, I conducted an additional simulation under an Earth model with identical parameters except with a 50-km lithospheric effective elastic thickness, rather than 90

km. I adopt a 50 km thick lithosphere because it represents a lower bound in published estimates of regional lithospheric effective elastic thickness (Tesauro et al., 2012, 2013). Estimates of the lithospheric effective elastic thickness under the Ganges basin and the northern part of the Bay of Bengal suggest values of 90-100 km (Watts et al., 2013; Steinberger and Becker 2018). Figure 32A shows that modeled values of ΔSL_{GR} in this simulation differ by as much as ~ 7 m from those in the standard simulation (Figure 25B) at the end of the 122 kyr simulations. This maximum variation in the value of ΔSL_{GR} in the delta decays to zero over a length scale of 240 km to the north and east.

In all the simulations, I use a spherically symmetric Earth, a feature common to nearly all gravitationally self-consistent sea-level simulations due to the computational expense of modeling gravitationally self-consistent sea-level change on a laterally varying Earth model (e.g., Powell et al., 2020). It is important to note that the cities of Dhaka and Kolkata, used in the RSL_{GR} analysis, are in a different context regarding the regional tectonic setting (Steckler et al., 2016). Dhaka may be right at the contact between the two tectonic plates, located at the westward prolongation at the surface of the Indo-Burman detachment fault. Kolkata is located ~ 200 km further east of this plate boundary. The eastern side of this tectonic boarder is thought to experience amplified subsidence rates under sediment loading due to the weakened Indo-Burman margin which is not captured in the spherically symmetric Earth model. While I have not explored the importance of capturing these variations in the simulations, Krien et al. (2019) computed subsidence rates in the GBM delta induced by sediment loading over the Holocene using a 3D Earth model with laterally variable mantle and lithosphere structure. The results of this study suggest that the incorporation of a laterally variable

lithospheric structure, specifically the addition of including the effects of a thickened lithosphere from the Indian craton, result in a slower vertical motion in the region of thickened lithosphere away from the delta.

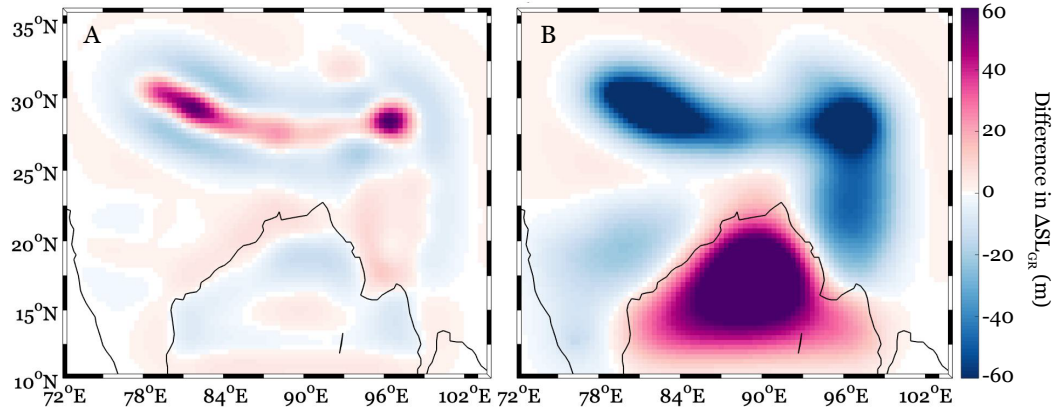


Figure 32. (A) Difference in ΔSL_{GR} between the standard simulation (Figure 25B), which was conducted on an Earth model with an effective elastic lithosphere thickness of 90 km, and a simulation conducted on an Earth model with an effective elastic lithosphere thickness of 50 km. Near the GBM delta, the maximum difference in ΔSL_{GR} between these simulations is approximately 7 m. **(B)** Difference in ΔSL_{GR} between the standard simulation using VM2 mantle viscosity model and a simulation which uses a 2-layer mantle viscosity profile ($\mu_{\text{upper mantle}} = 5 \times 10^{19}$ Pas, $\mu_{\text{lower mantle}} = 2 \times 10^{21}$ Pas).

To quantify the sensitivity of the model to changes in the mantle viscosity profile, I use a two-layer viscosity profile ($\mu_{\text{upper mantle}} = 5 \times 10^{19}$ Pas, $\mu_{\text{lower mantle}} = 2 \times 10^{21}$ Pas) while keeping an effective elastic lithospheric thickness of 90 km. Figure 32B shows the difference between the standard scenario with the VM2 mantle viscosity profile and the two-layer viscosity profile. The resulting signal has a maximum amplitude in the GBM delta is about 30 m along the modern coastline of Bangladesh. Maximum amplitudes over the entire region of interest are on the order of 60 m in the Himalayan basins and Bengal Fan although the

signals have opposite signs consistent with the dominant sign of sediment redistribution in each region.

4.5.3.3 Temporal variability

Lastly, I assess the sensitivity of modeled ΔSL_{GR} to uncertainties in the timing of sediment redistribution. Because variations in sea level are linearly proportional to the total sediment flux (Ferrier et al., 2017), I expect that variations in the timing of transitional periods, on the order of a few thousand years, should yield results consistent with the best estimate scenario for a given mass of redistributed sediment. Previous work has shown that changes in sea level are most sensitive to variations in sediment redistribution near the present, which is also when sediment redistribution rates are best constrained. The rates used in the model for earlier parts of the simulations match well (within a factor of 2) with long-term (10^6 years) rates from exhumation rates in this part of the world (Herman et al., 2013), further increasing confidence in the accuracy of the model results.

To illustrate the sensitivity of ΔSL_{GR} to uncertainties in the timing of sediment redistribution, I conducted an additional simulation in which I moved the transition to rapid delta aggradation from 12 ka to 15 ka. The resulting values of ΔSL_{GR} at the end of the simulation differ by as much as 40 cm in the GBM delta, which is ~2% of the total ΔSL_{GR} at this site (Figure 33).

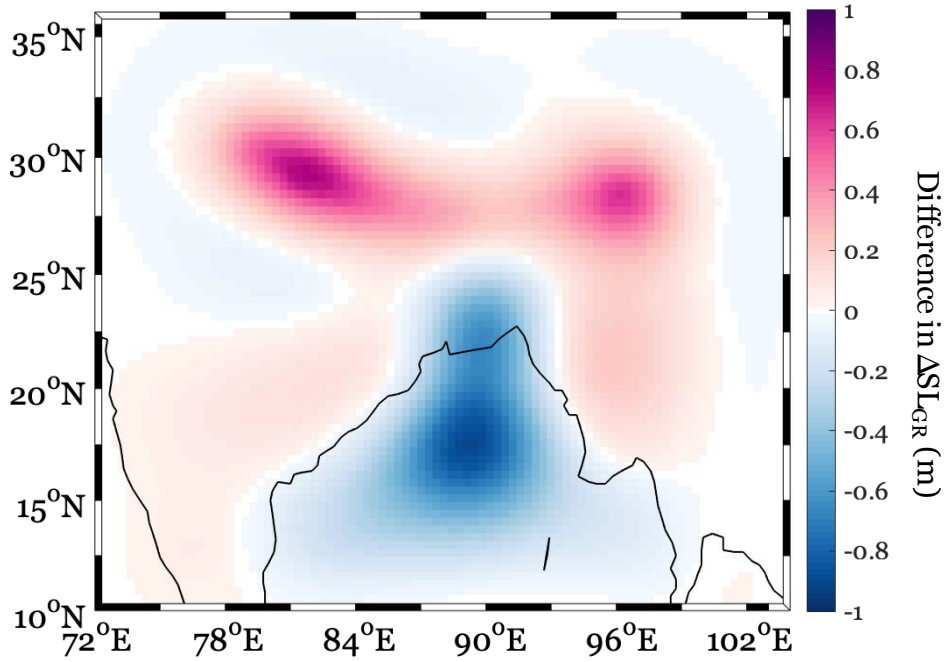


Figure 33. Difference in ΔSL_{GR} between the standard simulation (Figure 25B) and a simulation driven by sediment redistribution history in which the transition to rapid aggradation in the delta begins at 15 ka instead of 12 ka. In the delta region, the maximum difference in ΔSL_{GR} is approximately 40 cm.

In summary, my sensitivity analysis suggests that modeled ΔSL_{GR} is subject to meter-scale errors due to uncertainties in the spatial distribution of sediment redistribution in the Ganges Basin over the last glacial cycle. This highlights that, in the delta, relatively small variations in the spatial distribution of sediment (on the order of tens of kilometers) can cause variations in ΔSL_{GR} of up to 10% of the total signal. Similarly, the simulations show that effective elastic lithospheric thickness can significantly influence modeled ΔSL_{GR} , with a ~ 7 m difference in ΔSL_{GR} near the GBM delta between simulations on Earth models with an lithospheric effective elastic thickness of 90 and 50 km. Temporal variations in sediment redistribution near the present have the smallest effect on ΔSL_{GR} , with a 3-ka shift in the onset of rapid aggradation in the delta

generating a perturbation in ΔSL_{GR} with a maximum amplitude of 40 cm near the modern coastline of Bangladesh.

4.6 Conclusions

I modelled gravitationally self-consistent sea-level responses to sediment redistribution in the Ganges-Brahmaputra-Meghna river system and Bengal Basin over the last glacial cycle. My results indicate that sediment redistribution perturbed modeled sea-level changes by as much as ~ 30 m since the last interglacial. The amplitude of these perturbations decay to 0 m over an average wavelength of 445 km. These results have implications for understanding the drivers of sea-level change along the GBM delta coast, as the modeled modern rates of sea-level rise due to sediment redistribution are on par with the rate of increase in global mean sea level over the 20th century. The effects of this lithospheric deformation due to past sediment loading could therefore be responsible for increasing changes in sea level by a factor of two or more within the GBM delta.

CHAPTER V

CONCLUSIONS

This dissertation explored the effects of flow properties on the distribution of bed forces in granular flows using laboratory experiments and discrete element simulations. By varying shear rate, mean grain size, width of the grain size distribution, fluid density, and viscosity, I was able to generate flows exhibiting elastic-quasi-static, elastic-inertial, and inertial-collisional behaviors using idealized particles in a rotating cylindrical flume. The relative importance of dominant grain-scale interactions is quantified using the Stokes number to describe the degree of coupling between solid and fluid phases and the inertial or visco-inertial number to describe the ratio of the timescale for grain rearrangement to the timescale for mean deformation.

In Chapter II, I presented a new experimental apparatus, BERTHA, capable of measuring bed forces generated by experimental granular flows exhibiting elastic-inertial to inertial-collisional flow behaviors. The apparatus is made novel by its high spatial and temporal resolution, capable of measuring bed forces at a frequency of 7 kHz with a spacing of 13.5 cm between sensors. With the use of this apparatus, I was successfully able to construct the distribution of bed forces generated by experimental flows in order to analyze the dependence of distribution shape on flow properties. Wall effects were determined to be most significant for concentrated, low grain size flows. $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ measured by near-wall sensors showed a significantly different shape than $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ measured at the flow center. At low shear rates, near-wall force

distributions had more truncated tails relative to the centerline distributions, indicating increased shear at the flow boundary. At intermediate values of shear rate, this trend reverses due to increased particle advection at the walls. At high shear rates, the flow is no longer concentrated which yields fewer frictional interactions between particles and a poorer connection to the apparatus walls. The near-wall and centerline distributions no longer show substantial differences in shape once the flow becomes dilute. At large grain sizes, there is no difference between the shape of the distributions across the flow due to a decreased number of grains between the windows and the flow center. This lower grain count leads to particles at the center of the flow being more susceptible to flow conditions, yielding similar behavior between the flow boundaries and flow center.

The results of these experiments indicated that $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ is best-fit by the Generalized Pareto distribution while in many cases, the power law distribution also fits the tail of the distribution well. The best-fit GPD shape parameter increased with inertial number and Stokes number, while the scale parameter showed a negative trend with both nondimensional numbers. The combined effects of the trends seen in the GPS fit parameters resulted in longer-tailed distributions with increasing values of I and N_{Sto} . The observed PDFs were sensitive to the width of grain size distribution and shear rate but are robust to changes in mean grain size. The trends seen in the normalized distributions for mean grain size and shear rate can be explained by variations in the mean force, while the elongated distribution tails in polydisperse flows are present in both the normalized and non-normalized force excursion distributions.

In Chapter III, I carried out 900 discrete element simulations of granular flows of spherical particles in a rotating cylindrical flume. The simulated granular flows spanned Stokes numbers from 1×10^{-5} to 1×10^5 and visco-inertial numbers from 1×10^{-5} to 3. I varied mean grain size, shear rate, standard deviation of the grain size distribution, fluid density, and viscosity to simulate flows exhibiting quasi-static to inertial behaviors. In the elastic-quasi static regime, $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ is best described by a GPD with shape parameter values close to zero, consistent with the exponential distribution proposed by previous authors studying static or very slowly shearing granular systems. In the elastic-inertial regime, the best-fit functional form of $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ took the form of a power law distribution. The shape of these distributions was sensitive to changes in Stokes number, showing distributions with shorter tails for more strongly coupled fluid and solid phases. Inertial-collisional flows generated bed force PDFs that were well fit by the GPD with shape parameter > 0.1 . These distributions had the most elongated tails of all flow regimes, highlighting the potential erosive capabilities of these high-energy flows.

Solid flow properties have significant impacts on the shape of distribution of bed forces. Increases in shear rate from 2.5×10^{-3} to 75 Hz led to a tenfold increase in the predicted frequency of high-magnitude bed forces. Mean grain size had a more complicated effect on the shape of the distribution which was heavily dependent on the values of fluid flow properties. At high values of fluid density and viscosity, a change in mean grain size from 8 mm to 16 mm leads to a factor 3 decrease in the predicted frequency of high magnitude forces, while at all other values of fluid flow properties, no clear trend between distribution shape and mean grain size emerged.

Polydisperse flows produced longer-tailed distributions compared to monodisperse flows. Fluid flow properties had a much weaker direct influence on the shape of bed force distributions overall. Both fluid viscosity and fluid density only showed small changes (factor of 2) in the predicted frequency of high-magnitude forces with variations in fluid properties on the order of 10^4 and 10^3 , respectively. These results suggest that the PDF of bed forces is not sensitive to changes in fluid flow properties, assuming all other flow properties are held constant, but may have more of an indirect influence on the shape of the PDF when other flow properties are allowed to vary like in the case in natural flows.

The results of the experiments in Chapter II compare well with results presented in Chapter III. The DEM simulations predict distributions best-fit by the GPD for the inertial-collisional regime but show diffuse boundaries suggesting that elastic-inertial flows near the regime boundary may also be best-fit by the GPD as seen in the experimental flows. The experimental flows which were well fit by the GPD and the power law, resided near the flow regime boundary which demonstrated a gradual change in the functional form of the best-fit distribution in the simulations. Results from both chapters indicate that the tail of $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ becomes more elongated with (visco-)inertial number and Stokes number. $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$ was robust to variations in mean grain size in both the experiments and DEM, however this trend breaks down at low values of N_{Sto} , likely to increased drag on the particles which is dependent on grain size. The effect of polydispersity on the shape of the distribution is consistent between experiments and simulations, as flows with a wider grain size distribution generate longer-tailed distributions. At fluid properties consistent with air, the DEM

simulations show the same trend in shear rate as is seen in the experimental results when shear rate is varied over similar values. These results suggest that the DEM simulations are likely capturing the behaviors seen in the experiments and that these experiments serve as a sample of the wide parameter space explored in the DEM.

The results presented in Chapters II and III of this dissertation indicate that solid flow properties need to be well-constrained in order to accurately predict bed force distributions in viscous granular flows, while fluid flow properties do not have a significant direct impact on the shape of bed force distributions, suggesting order of magnitude estimates are likely sufficient for predicting the appropriate form of $P\left(\frac{F - \bar{F}}{\bar{F}}\right)$. Bed force distributions in dry granular flows are most strongly controlled by variations in the width of the grain size distribution and robust to variations in other flow properties. This work highlights the need for future studies to analyze the dominant force mechanisms in each flow regime to connect bed force distribution shapes to the processes responsible for generating high-magnitude forces. Future work will focus on experimentally determining the shape of bed force distributions in more viscous fluids. The relationship between the shape of the bed force distribution and bed erosion rates should be explored as well as the effects of bed entrainment on flow properties to fully understand the feedback between bed forces, erosion, entrainment, and flow properties.

In Chapter IV, I presented the results of a gravitationally self-consistent sea level model in which I study the effects of sediment redistribution on local sea level in the Bengal Basin over the last 122 ka. I concluded that sediment redistribution perturbed modeled sea-level changes by as much as ~30 m since the last interglacial. The

results of these sea level simulations showed significant sensitivity to the choice of lithospheric thickness and mantle viscosity profile used in the model inputs, suggesting that the ~ 10 m discrepancies seen in the model results in comparison to field data may be explained by uncertainties in model inputs.

APPENDIX A

LABORATORY EXPERIMENTS SUPPLEMENTARY MATERIAL

Table A1. Run conditions for BERTHA experiments.

Run Number	Mean Grain Size (mm)	STD Grain Size (mm)	Shear Rate (Hz)	Shape Parameter	Scale Parameter	Inertial Number	Stokes Number
1	10	0	17	0.677	2.725	1.73×10^{-1}	2.12×10^4
2	10	0	26	0.793	0.647	2.60×10^{-1}	3.19×10^4
3	10	0	34	0.590	0.453	3.46×10^{-1}	4.25×10^4
4	10	0	43	0.382	0.502	4.33×10^{-1}	5.31×10^4
5	10	0	51	0.452	0.583	5.20×10^{-1}	6.37×10^4
6	8	0	17	0.252	3.532	1.39×10^{-1}	1.36×10^4
7	8	0	26	0.415	1.893	2.08×10^{-1}	2.04×10^4
8	8	0	34	0.394	0.899	2.77×10^{-1}	2.72×10^4
9	8	0	43	0.396	0.553	3.46×10^{-1}	3.40×10^4
10	8	0	51	0.162	0.849	4.16×10^{-1}	4.08×10^4
11	5	0	17	0.196	2.914	8.66×10^{-2}	5.31×10^3
12	5	0	26	0.061	2.079	1.30×10^{-1}	7.96×10^3
13	5	0	34	-0.004	1.382	1.73×10^{-1}	1.06×10^4
14	5	0	43	0.027	1.505	2.17×10^{-1}	1.33×10^4
15	5	0	51	0.112	1.407	2.60×10^{-1}	1.59×10^4
16	2	0	17	0.008	3.647	3.46×10^{-2}	8.50×10^2
17	2	0	26	0.041	3.761	6.93×10^{-2}	1.70×10^3
18	5	1.4	17	0.233	2.541	8.66×10^{-2}	5.31×10^3
19	5	2.28	17	0.467	1.893	8.66×10^{-2}	5.31×10^3
20	5	3.55	17	0.621	0.008	8.66×10^{-2}	5.31×10^3

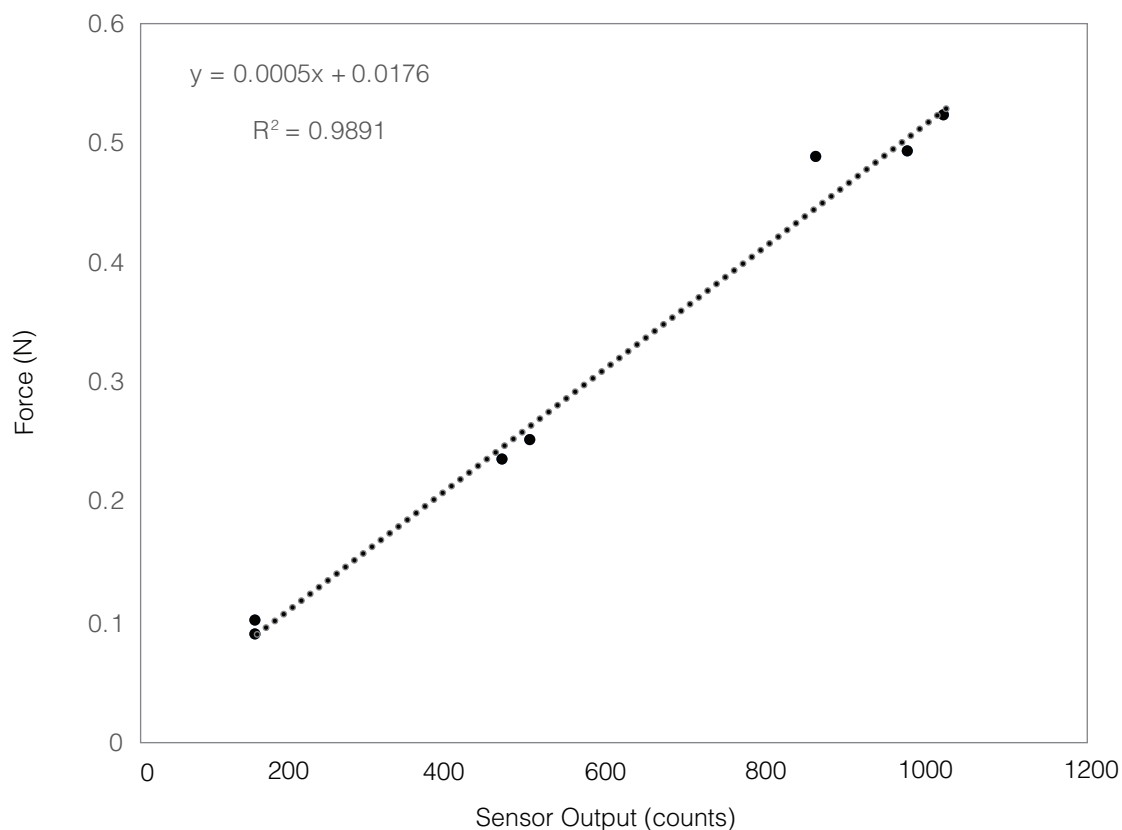


Figure A2. Example of sensor calibration results. Calibrations were performed while sensors were in their mounted positions in the drum. Particles with a known mass (0.2 g, 0.5 g, 1.2 g) were dropped from a height of 25 cm above the load plate and the impact was recorded with a highspeed camera at a rate of 1000fps.

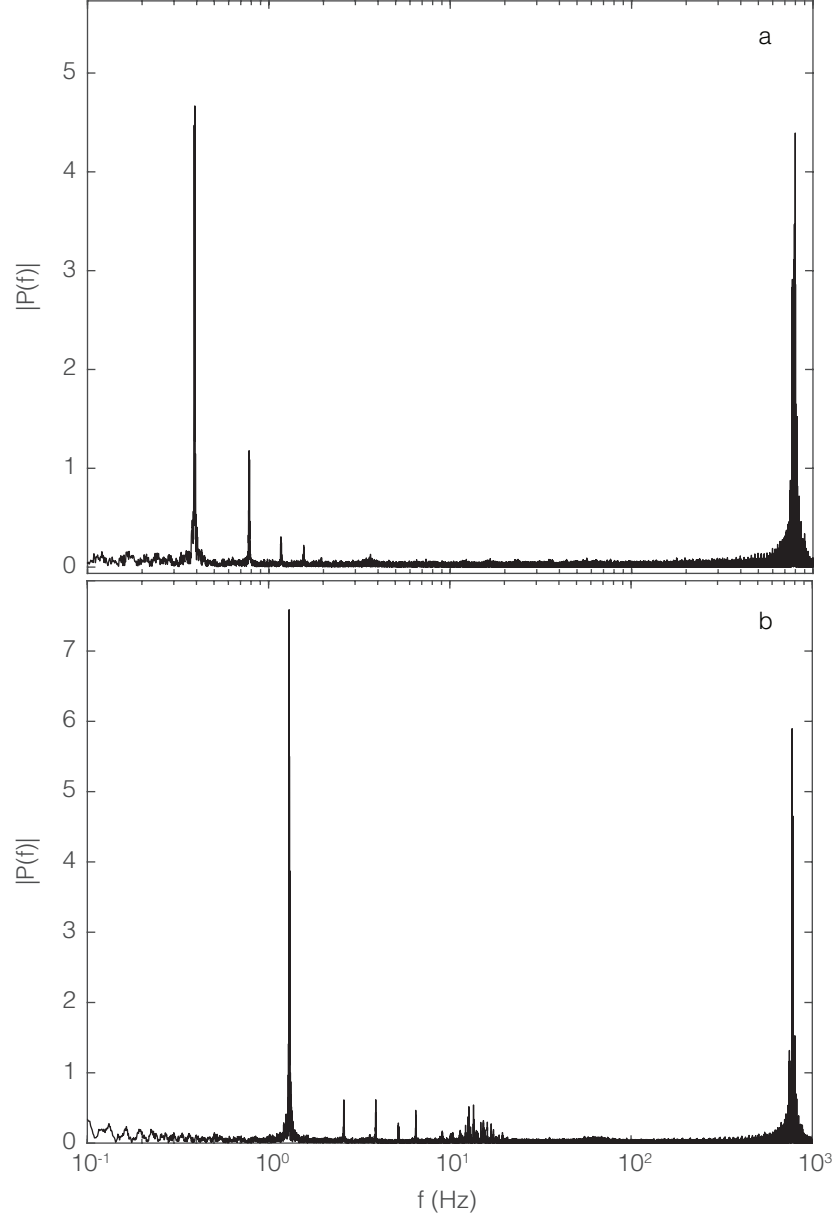


Figure A3. Single-sided amplitude spectrum of the resampled (2 kHz) bed force signal measured in BERTHA. (a) Grain size $d = 5$ mm and shear rate $\dot{\gamma} = 17$ Hz; and (b) $d = 5$ mm and $\dot{\gamma} = 51$ Hz. The low-frequency peak corresponds to the portion of the signal associated with the rotation of the drum as the location of the peak varies proportionally with the rotation rate. The small peaks with decreasing amplitude that follow the dominant low-frequency component correspond to harmonic frequencies of the rotation frequency. The high-frequency peak is likely associated with grain-scale fluctuations as it is on the same order of magnitude as the reciprocal of the microscopic timescale for these flows and the location of this peak is robust to changes in shear rate.

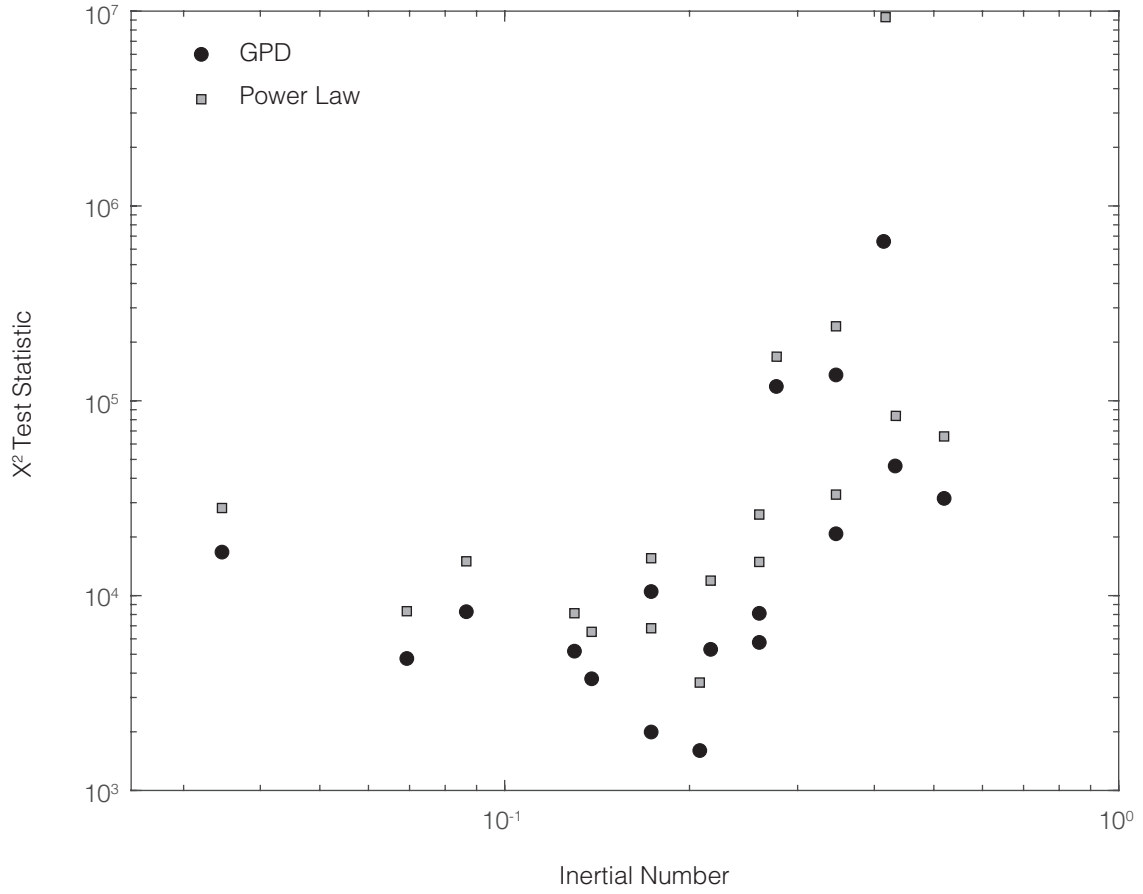


Figure A4. χ^2 statistics for GPD and power law fits to the tails of bed force probability distributions. All bed force distributions generated by these experiments are best fit by a GPD regardless of inertial number. While some distributions are also well fit by the power distribution, there is no clear trend in the goodness of fit of the power law relative to the GPD with inertial number.

APPENDIX B

DISCRETE ELEMENT SIMULATIONS SUPPLEMENTARY MATERIAL

Table B1. Model parameters used in discrete element simulations

Model Parameter	Min Value	Max Value	Comments
Mean Grain Size (mm)	8	16	
Grain Size (mm)	1	27	Limits in polydisperse runs
Shear Rate (Hz)	2.5×10^{-3}	75	
STD Grain Size (mm)	0	4	
Fluid Density (kg/m ³)	1	1000	
Fluid Viscosity (Pas)	1×10^{-5}	1	
Particle Stiffness	2×10^4	5.4×10^5	
Grid Size (mm)	16	54	(Bernard et al., 2017)
Particle Friction	0.382	0.382	
Wall Friction	0.4	0.4	
Particle Restitution Coefficient	0.9	0.9	

APPENDIX C

SEA LEVEL CHANGE SUPPLEMENTARY MATERIAL

Construction of sediment redistribution scenarios

To reconstruct rates and patterns of sediment redistribution in the study area, I compiled published erosion and deposition rates (Tables C1 and C2). Erosion rate estimates are derived from cosmogenic ^{10}Be measurements or from fluvial sediment yield measurements (Table C1). For both data types, I applied a spatially uniform erosion rate across the contributing drainage basin, which I delineated using ~75-m ASTER GDEM 2 digital elevation data in QGIS version 2.18. Deposition rate maps were constructed from published rates (Table C2) for depositional regions delineated in Figure 23 in the main text (alluvial deposits, delta, continental shelf, and Bay of Bengal). Erosion and deposition rate maps were mapped on 0.05° grids and resampled onto global 512×1024 grids (grid spacing $\sim 0.35^\circ$), the required format for model inputs.

Table C1. Compiled erosion rate data used to construct sediment transfer scenarios. Erosion rate estimates are taken from ^{10}Be measurements unless otherwise noted.

Site name	Sample name	Lat (°N)	Long (°E)	Basin area (km ²)	Mass yield (t/km ² /yr)	Mass flux (Mt/yr)	Mass flux uncertainty (Mt/yr)	Erosion rate (μm/yr)	Timescale (yr)	Ref
Arun	ARU-11-26	26.92332	87.15508	33513	-	-	-	750 ± 60	779	a
Karnali	PB80	28.639	81.283	45430	6494	295	77	2400 ± 600	250	b
Yamuna	YAM Q3	30.443	77.674	7620	1,706	13	5	700 ± 300	910	b
Ganga	BR924	30.127	78.33	21690	6,408	139	37	2400 ± 600	250	b
Narayani	CA10-10	27.703	84.427	31770	4564	145	49	1700 ± 600	400	b
Sun Kosi	ARU-11-27	26.926	87.146	18100	-	-	-	820 ± 60	746	a
Tamor	ARU-11-25	26.929	87.317	5886.36	-	-	-	1390 ± 110	445	a
Tista	TST-22	26.8887	88.4762	8033	-	-	-	1310 ± 290	409	c
West Bhutan	591_	26.8311	89.5878	4583	-	-	-	330 ± 54	1830	d
Puna Tsang Chhu	99-09-xf	27.033	90.0738	7912	-	-	-	746 ± 83	-	e
Manas*	-	26.814	90.937	34690	1581	55	-	689	-	f
Subansiri*	-	27.459	94.27	29674	2696	80	-	1172	-	g
Kameng	BRM 1425	26.80959	92.87534	9700	3093	30	30	1000 ± 1100	600	h
Siyom	BR 1226	28.21881	94.86374	5600	1786	10	-	600 ± 500	1000	h
Dibang	BRM 1404	27.89446	95.61633	12200	9016	110	-	3400 ± 2500	200	h
Lohit	BR 1208	27.79972	95.64930	24300	5350	130	80	2000 ± 1100	300	h
Godavari*	-	16.30944°	81.71528°	320776.2	180.645	56	-	116.4	-	i
Krishna*	-	15.70972°	80.93167°	252468.66	1.538	0.4	-	1.1	-	i
Mahanadi*	-	20.2925°	86.72278°	149529.4	114.286	16	-	71.3	-	i
Salween*	-	16.17222	97.59056	270000	666.667	180	-	444.4	-	i
Irrawaddy*	-	15.70139	94.94389	430000	755.814	325	-	503.9	-	i
Shillong Plateau	-	-	-	29750	-	-	-	81.6 ± 8.2	4.15 ± 0.34 (Myr)	j

*Erosion rates are estimated from sediment yield data and basin geometry; coordinates indicate approximate outlet

^aOlen et al., 2015

^bLupker et al., 2012

^cAbrahami et al., 2016

^dLe Roux-Mallouf et al., 2015

^ePortenga et al., 2015

^fBora, 2004

^gHazarika, 2017

^hLupker et al., 2017

ⁱMilliman and Farnsworth, 2011

^jRosenkranz et al., 2018

Table C2. Compiled sedimentation rate data used to construct sediment transfer scenarios. Deposition rates from each region are presented as the mean sedimentation rate with the range of rates displayed in parentheses. Deposition rate estimates are taken from a combination of previously published sediment core and seismic reflection data.

Region	Mean Deposition Rate (Range) (mm/yr)	Ref
Delta	4.89 (0.87-9.15)	a
Alluvial Deposits	0.32 (0.15-0.5)	b
Shelf	1.07 (1.07-1.07)	c, d, e
Bengal Fan	0.77 (0.17-1.8)	f, g

^aGoodbred and Kuehl., 2000

^bRoy et al., 2012

^cVaithyanathan et al., 1988

^dChakrapani and Subramanian, 1993

^eMichels et al., 1998

^fSobotovich, 1984

^gKrishna et al., 2016

REFERENCES CITED

- Abrahami, R., Beek, P., Huyghe, P., Hardwick, E., & Carcaillet, J. (2016). Decoupling of long-term exhumation and short-term erosion rates in the Sikkim Himalaya. *Earth and Planetary Science Letters*, 433, 76–88. <https://doi.org/10.1016/j.epsl.2015.10.039>
- Allstadt, K. E., Farin, M., Iverson, R. M., Obryk, M. K., Kean, J. W., Tsai, V. C., Rapstine, T. D., & Logan, M. (2020). Measuring Basal Force Fluctuations of Debris Flows Using Seismic Recordings and Empirical Green's Functions. *Journal of Geophysical Research: Earth Surface*, 125(9), e2020JF005590. <https://doi.org/10.1029/2020JF005590>
- Annen, C., & Wagner, J.-J. (2003). The Impact of Volcanic Eruptions During the 1990s. *Natural Hazards Review*, 4(4), 169–175. [https://doi.org/10.1061/\(ASCE\)1527-6988\(2003\)4:4\(169\)](https://doi.org/10.1061/(ASCE)1527-6988(2003)4:4(169))
- Antony, S. (2001). Evolution of force distribution in three-dimensional granular media. *Physical Review. E, Statistical, Nonlinear, and Soft Matter Physics*, 63, 011302. <https://doi.org/10.1103/PhysRevE.63.011302>
- Armanini, A., Fraccarollo, L., & Larcher, M. (2005). Rheological stratification in experimental free-surface flows of granular–liquid mixtures. *Journal of Fluid Mechanics*, 532, 269–319. <https://doi.org/10.1017/S0022112005004283>
- Bagnold, R. A. (1954). Experiments on a gravity-free dispersion of large solid spheres in a Newtonian fluid under shear. *Proceedings of the Royal Society of London. Series A. Mathematical and Physical Sciences*, 225(1160), 49–63. <https://doi.org/10.1098/rspa.1954.0186>
- Bahr, D. B., Hutton, E. W. H., Syvitski, J. P. M., & Pratson, L. F. (2001). Exponential approximations to compacted sediment porosity profiles. *Computers & Geosciences*, 27(6), 691–700. [https://doi.org/10.1016/S0098-3004\(00\)00140-0](https://doi.org/10.1016/S0098-3004(00)00140-0)
- Bardenhagen, S. G., Brackbill, J. U., & Sulsky, D. (2000). Numerical study of stress distribution in sheared granular material in two dimensions. *Physical Review E*, 62(3), 3882–3890. <https://doi.org/10.1103/PhysRevE.62.3882>
- Benyahia, S. (2008). Validation Study of Two Continuum Granular Frictional Flow Theories. *Industrial & Engineering Chemistry Research*, 47(22), 8926–8932. <https://doi.org/10.1021/ie8003557>
- Benyahia, S., Syamlal, M., & O'Brien, T. J. (2007). Study of the ability of multiphase continuum models to predict core-annulus flow. *AIChE Journal*, 53(10), 2549–2568. <https://doi.org/10.1002/aic.11276>

- Bergantz, G. W., Schleicher, J. M., & Burgisser, A. (2015). Open-system dynamics and mixing in magma mushes. *Nature Geoscience*, 8(10), 793–796.
<https://doi.org/10.1038/ngeo2534>
- Bernard, J., K. Kelfoun, J.-L. Le Pennec, and S. Vallejo Vargas (2014), Pyroclastic flow erosion and bulking processes; comparing field-based vs. modeling results at Tungurahua Volcano, Ecuador, *Bull. Volcanol.*, 76(9), 1-16,
[doi:http://dx.doi.org/10.1007/s00445-014-0858-y](http://dx.doi.org/10.1007/s00445-014-0858-y).
- Bierman, P., & Steig, E. J. (1996). Estimating rates of denudation using cosmogenic isotope abundances in sediment. *Earth Surface Processes and Landforms*, 21(2), 125-139.
- Boberski, J., Shaebani, M. R., & Wolf, D. E. (2013). Evolution of the force distributions in jammed packings of soft particles. *Physical Review E*, 88(6), 064201.
<https://doi.org/10.1103/PhysRevE.88.064201>
- Bora, A.K. (2004) Fluvial geomorphology. In: Singh, V.P., Sharma, N. and Ojha, C.S.P. (Eds.), *The Brahmaputra Basin Water Resources*. Kluwer Academic Publishers, Dordrecht, pp.88–112.
- Bracken. (2014). *3901sin04f.jpg (640×449)*.
<https://volcano.si.edu/images/bulletin/261080/3901sin04f.jpg>
- Brand, B. D., Mackaman-Lofland, C., Pollock, N. M., Bendaña, S., Dawson, B., & Wichgers, P. (2014). Dynamics of pyroclastic density currents: Conditions that promote substrate erosion and self-channelization — Mount St Helens, Washington (USA). *Journal of Volcanology and Geothermal Research*, 276, 189–214.
- Breard, E. C. P., J. Dufek, and G. Lube (2017), Enhanced Mobility in Concentrated Pyroclastic Density Currents: An Examination of a Self-Fluidization Mechanism, *Geophys. R. Lett.*, 45, 654–664, doi:10.1002/2017GL075759.
- Breard, E. C. P., J. Dufek, and O. Roche (2019), Continuum Modeling of Pressure-Balanced and Fluidized Granular Flows in 2-D: Comparison With Glass Bead Experiments and Implications for Concentrated Pyroclastic Density Currents, *J. Geophys. Res. Solid Earth*, 124(6), 5557-5583, doi:10.1029/2018JB016874.
- Breard, E. C. P., J. Dufek, L. Fullard, and A. Carrara (2020), The Basal Friction Coefficient of Granular Flows With and Without Excess Pore Pressure: Implications for Pyroclastic Density Currents, Water-Rich Debris Flows, and Rock and Submarine Avalanches, *J. Geophys. Res. Solid Earth*, 125(12), e2020JB020203, doi:<https://doi.org/10.1029/2020JB020203>.
- Brodu, N., R. Delannay, A. Valance, and P. Richard (2015), New patterns in high-speed granular flows, *J. Fluid. Mech.*, 769, 218-228, doi:10.1017/jfm.2015.109.

- Brown, E. T., Stallard, R. F., Larsen, M. C., Raisbeck, G. M., & Yiou, F. (1995). Denudation rates determined from the accumulation of in situ-produced ^{10}Be in the luquillo experimental forest, Puerto Rico. *Earth and Planetary Science Letters*, 129(1), 193–202. [https://doi.org/10.1016/0012-821X\(94\)00249-X](https://doi.org/10.1016/0012-821X(94)00249-X)
- Buesch, D. C. (1992). Incorporation and redistribution of locally derived lithic fragments within a pyroclastic flow. *Geological Society of America Bulletin*, 104(9), 1193–1207. USGS Publications Warehouse. [https://doi.org/10.1130/0016-7606\(1992\)104<1193:IAROLD>2.3.CO;2](https://doi.org/10.1130/0016-7606(1992)104<1193:IAROLD>2.3.CO;2)
- Calder, E. S., Sparks, R. S. J., & Gardeweg, M. C. (2000). Erosion, transport and segregation of pumice and lithic clasts in pyroclastic flows inferred from ignimbrite at Lascar Volcano, Chile. *Journal of Volcanology and Geothermal Research*, 104(1), 201–235. [https://doi.org/10.1016/S0377-0273\(00\)00207-9](https://doi.org/10.1016/S0377-0273(00)00207-9)
- Campbell, C. (2005). Stress-controlled elastic granular shear flows. *Journal of Fluid Mechanics*, 539, 273–297. <https://doi.org/10.1017/S0022112005005616>
- Cathles, L. M. (1975). The viscosity of the earth's mantle. Princeton (N.J.) : Princeton university press. <http://lib.ugent.be/catalog/rug01:001350016>
- Cazenave, Anny, and William Llovel. 2010. "Contemporary Sea Level Rise." *Annual Review of Marine Science* 2 (1): 145–73. <https://doi.org/10.1146/annurev-marine-120308-081105>.
- Chakrapani, G. J., & Subramanian, V. (1993). Rates of erosion and sedimentation in the Mahanadi river basin, India. *Journal of Hydrology*, 149(1), 39–48. [https://doi.org/10.1016/0022-1694\(93\)90098-T](https://doi.org/10.1016/0022-1694(93)90098-T)
- Church, J. A., Clark, P. U., Cazenave, A., Gregory, J. M., Jevrejeva, S., Levermann, A., Merrifield, M. A., Milne, G. A., Nerem, R. S., Nunn, P. D., Payne, A. J., Pfeffer, W. T., Stammer, D., & Unnikrishnan, A. S. (2013). *Sea level change* [Technical Report]. P.M. Cambridge University Press. <http://drs.nio.org/drs/handle/2264/4605>
- Cleary, P. W. (2008). The effect of particle shape on simple shear flows. *Powder Technology*, 179(3), 144–163. <https://doi.org/10.1016/j.powtec.2007.06.018>
- Coe, J.A., Godt, J.W., Wait, T.C., and Kean, J.W., 2007, Field Reconnaissance of Debris Flows Triggered by a July 21, 2007, Thunderstorm in Alpine, Colorado, and Vicinity: U.S. Geological Survey Open-File Report 2007-1237, 25 p.
- Corwin, E. I., Jaeger, H. M., & Nagel, S. R. (2005). Structural signature of jamming in granular media. *Nature*, 435(7045), 1075–1078. <https://doi.org/10.1038/nature03698>
- da Cruz, F., Emam, S., Prochnow, M., Roux, J.-N., & Chevoir, F. (2005). Rheophysics of dense granular materials: Discrete simulation of plane shear flows. *Physical Review E*, 72(2), 021309. <https://doi.org/10.1103/PhysRevE.72.021309>

- Dalca, A. V., Ferrier, K. L., Mitrovica, J. X., Perron, J. T., Milne, G. A., & Creveling, J. R. (2013). On postglacial sea level—III. Incorporating sediment redistribution. *Geophysical Journal International*, 194(1), 45–60. <https://doi.org/10.1093/gji/ggt089>
- Delannay, R., A. Valance, A. Mangeney, O. Roche, and P. Richard (2017), Granular and particle-laden flows: from laboratory experiments to field observations, *J. Phys. D: App. Phys.*, 50(5).
- Delgado-Sánchez, J. M., F. Bouchut, E. D. Fernández-Nieto, A. Mangeney, and G. Narbona-Reina (2020), A two-layer shallow flow model with two axes of integration, well-balanced discretization and application to submarine avalanches, *Journal of Computational Physics*, 406, 109186, [doi:https://doi.org/10.1016/j.jcp.2019.109186](https://doi.org/10.1016/j.jcp.2019.109186).
- Denisov, D. V., Lörincz, K. A., Uhl, J. T., Dahmen, K. A., & Schall, P. (2016). Universality of slip avalanches in flowing granular matter. *Nature Communications*, 7(1), 10641. <https://doi.org/10.1038/ncomms10641>
- Darteville, S., & Valentine, G. A. (2008). Multiphase magmatic flows at Yucca Mountain, Nevada. *Journal of Geophysical Research: Solid Earth*, 113(B12). <https://doi.org/10.1029/2007JB005367>
- Darteville, Sebastian. (2007). *From model conception to verification and validation, a global approach to multiphase Navier-Stoke models with an emphasis on volcanic explosive phenomenology* (LA-14346). Los Alamos National Laboratory (LANL), Los Alamos, NM. <https://doi.org/10.2172/948564>
- Druitt, T. H., Avard, G., Bruni, G., Lettieri, P., & Maez, F. (2007). Gas retention in fine-grained pyroclastic flow materials at high temperatures. *Bulletin of Volcanology*, 69(8), 881–901. <https://doi.org/10.1007/s00445-007-0116-7>
- Dufek, J. (2016). The Fluid Mechanics of Pyroclastic Density Currents. *Annual Review of Fluid Mechanics*, 48(1), 459–485. <https://doi.org/10.1146/annurev-fluid-122414-034252>
- Dufek, J., & Bergantz, G. W. (2005). Lower Crustal Magma Genesis and Preservation: A Stochastic Framework for the Evaluation of Basalt–Crust Interaction. *Journal of Petrology*, 46(11), 2167–2195. <https://doi.org/10.1093/petrology/egi049>
- Dziewonski, A. M., & Anderson, D. L. (1981). Preliminary reference Earth model. *Physics of the Earth and Planetary Interiors*, 25(4), 297–356. [https://doi.org/10.1016/0031-9201\(81\)90046-7](https://doi.org/10.1016/0031-9201(81)90046-7)
- Emanuel, K. (2017). Assessing the present and future probability of Hurricane Harvey’s rainfall. *Proceedings of the National Academy of Sciences*, 114(48), 12681–12684. <https://doi.org/10.1073/pnas.1716222114>

- Estep, J., & Dufek, J. (2012). Substrate effects from force chain dynamics in dense granular flows. *Journal of Geophysical Research: Earth Surface*, 117(F1). <https://doi.org/10.1029/2011JF002125>
- Estep, J., & Dufek, J. (2013). Discrete element simulations of bed force anomalies due to force chains in dense granular flows. *Journal of Volcanology and Geothermal Research*, 254, 108–117. <https://doi.org/10.1016/j.jvolgeores.2012.12.023>
- Fauria, K. E., M. Manga, and M. Chamberlain (2016), Effect of particle entrainment on the runout of pyroclastic density currents, *J. Geophys. Res. Solid Earth*, 121(9), 6445–6461, doi:10.1002/2016JB013263.
- Farrell, W. E., & Clark, J. A. (1976). On Postglacial Sea Level. *Geophysical Journal of the Royal Astronomical Society*, 46(3), 647–667. <https://doi.org/10.1111/j.1365-246X.1976.tb01252.x>
- Ferguson, A., Fisher, B., & Chakraborty, B. (2004). Impulse distributions in dense granular flows: Signatures of large-scale spatial structures. *EPL (Europhysics Letters)*, 66(2), 277. <https://doi.org/10.1209/epl/i2003-10190-3>
- Ferrier, K., Mitrovica, J., Giosan, L., & Clift, P. (2015). Sea-level responses to erosion and deposition of sediment in the Indus River basin and the Arabian Sea. *Earth and Planetary Sciences Letters*, 416, 12–20. <https://doi.org/10.1016/j.epsl.2015.01.026>
- Ferrier, K. L., Austermann, J., Mitrovica, J. X., & Pico, T. (2017). Incorporating sediment compaction into a gravitationally self-consistent model for ice age sea-level change. *Geophysical Journal International*, 211(1), 663–672. <https://doi.org/10.1093/gji/ggx293>
- Ferrier, K. L., Li, Q., Pico, T., & Austermann, J. (2018). The Influence of Water Storage in Marine Sediment on Sea-Level Change. *Geophysical Research Letters*, 45(5), 2444–2454. <https://doi.org/10.1002/2017GL076592>
- Finkel, R. C., Owen, L. A., Barnard, P. L., & Caffee, M. W. (2003). Beryllium-10 dating of Mount Everest moraines indicates a strong monsoon influence and glacial synchronicity throughout the Himalaya. *Geology*, 31(6), 561–564. [https://doi.org/10.1130/0091-7613\(2003\)031<0561:BDOMEM>2.0.CO;2](https://doi.org/10.1130/0091-7613(2003)031<0561:BDOMEM>2.0.CO;2)
- Forterre, Y., & Pouliquen, O. (2008). Flows of Dense Granular Media. *Annual Review of Fluid Mechanics*, 40(1), 1–24. <https://doi.org/10.1146/annurev.fluid.40.111406.102142>
- Freedman, D., & Diaconis, P. (1981). On the histogram as a density estimator:L2 theory. *Zeitschrift Für Wahrscheinlichkeitstheorie Und Verwandte Gebiete*, 57(4), 453–476. <https://doi.org/10.1007/BF01025868>

- Froude, M. J., & Petley, D. N. (2018). Global fatal landslide occurrence from 2004 to 2016. *Natural Hazards and Earth System Sciences*, 18(8), 2161–2181. <https://doi.org/10.5194/nhess-18-2161-2018>
- Fullard, L. A., E. C. P. Breard, C. E. Davies, A. J. R. Godfrey, M. Fukuoka, A. Wade, J. Dufek, and G. Lube (2019), The dynamics of granular flow from a silo with two symmetric openings, *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 475(2221), 20180462, doi:10.1098/rspa.2018.0462.
- Gardel, E., Sitaridou, E., Facto, K., Keene, E., Hattam, K., Easwar, N., & Menon, N. (2009). Dynamical fluctuations in dense granular flows. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 367(1909), 5109–5121. <https://doi.org/10.1098/rsta.2009.0189>
- Girolami, L., T. H. Druitt, O. Roche, and Z. Khrabrykh (2008), Propagation and hindered settling of laboratory ash flows, *J. Geophys. Res.*, 113(B2), doi:10.1029/2007JB005074.
- GDR MiDi. (2004). On dense granular flows. *The European Physical Journal E*, 14(4), 341–365. <https://doi.org/10.1140/epje/i2003-10153-0>
- Goodbred, S. L., & Kuehl, S. A. (2000a). The significance of large sediment supply, active tectonism, and eustasy on margin sequence development: Late Quaternary stratigraphy and evolution of the Ganges–Brahmaputra delta. *Sedimentary Geology*, 133(3), 227–248. [https://doi.org/10.1016/S0037-0738\(00\)00041-5](https://doi.org/10.1016/S0037-0738(00)00041-5)
- Goodbred, S. L., & Kuehl, S. A. (2000b). Enormous Ganges-Brahmaputra sediment discharge during strengthened early Holocene monsoon. *Geology*, 28(12), 1083–1086. [https://doi.org/10.1130/0091-7613\(2000\)28<1083:EGSDDS>2.0.CO;2](https://doi.org/10.1130/0091-7613(2000)28<1083:EGSDDS>2.0.CO;2)
- Goodbred, S. (2003). Response of the Ganges dispersal system to climate change: A source-to-sink view since the last interstade. *Sedimentary Geology - SEDIMENT GEOL*, 162, 83–104. [https://doi.org/10.1016/S0037-0738\(03\)00217-3](https://doi.org/10.1016/S0037-0738(03)00217-3)
- Goodbred, S., Paola, P., Ullah, M., Pate, R., Khan, S., Kuehl, S., Singh, S., & Rahaman, W. (2014). Piecing together the Ganges-Brahmaputra-Meghna River delta: Use of sediment provenance to reconstruct the history and interaction of multiple fluvial systems during Holocene delta evolution. *Geological Society of America Bulletin*, 126, 1495–1510. <https://doi.org/10.1130/B30965.1>
- Grall, C., Steckler, M. S., Pickering, J. L., Goodbred, S., Sincavage, R., Paola, C., Akhter, S. H., & Spiess, V. (2018). A base-level stratigraphic approach to determining Holocene subsidence of the Ganges–Meghna–Brahmaputra Delta plain. *Earth and Planetary Science Letters*, 499, 23–36. <https://doi.org/10.1016/j.epsl.2018.07.008>

- Granger, D. E., Kirchner, J. W., & Finkel, R. (1996). Spatially Averaged Long-Term Erosion Rates Measured from in Situ-Produced Cosmogenic Nuclides in Alluvial Sediment. *The Journal of Geology*, 104(3), 249–257. JSTOR.
- Granger, D. E., & Riebe, C. S. (2014). Cosmogenic Nuclides in Weathering and Erosion. In *Treatise on Geochemistry* (pp. 401–436). Elsevier. <https://doi.org/10.1016/B978-0-08-095975-7.00514-3>
- Grimaud, J., Grall, C., Goodbred, S., Steckler, M. S., Sincavage, R., Pickering, J. L., Paola, C., Seeber, L., and Hossain, S. (2020). Flexural deformation controls on Late Quaternary sediment dispersal in the Garo-Rajmahal Gap, NW Bengal Basin. *Basin Research*, <https://doi.org/10.1111/bre.12425>
- Haas, T. de, & Woerkom, T. van. (2016). Bed scathe by debris flows: Experimental investigation of effects of debris-flow composition. *Earth Surface Processes and Landforms*, 41(13), 1951–1966. <https://doi.org/10.1002/esp.3963>
- Hay, C. C., Morrow, E., Kopp, R. E., & Mitrovica, J. X. (2015). Probabilistic reanalysis of twentieth-century sea-level rise. *Nature*, 517(7535), 481–484. <https://doi.org/10.1038/nature14093>
- Hazarika, L. P. (2017, September 25). Changes In River Morphology Through Siltation And Erosion With Special Reference To River Subansiri. Paper presented at the Brahmaputra River Symposium 2017: Knowledge Beyond Boundaries, New Delhi, India.
- Herman, F., Seward, D., Valla, P. G., Carter, A., Kohn, B., Willett, S. D., & Ehlers, T. A. (2013). Worldwide acceleration of mountain erosion under a cooling climate. *Nature*, 504(7480), 423–426. <https://doi.org/10.1038/nature12877>
- Hilker, N., Badoux, A., & Hegg, C. (2009). The Swiss flood and landslide damage database 1972–2007. *Natural Hazards and Earth System Sciences*, 9(3), 913–925. <https://doi.org/10.5194/nhess-9-913-2009>
- Höhner, D., Wirtz, S., & Scherer, V. (2014). A study on the influence of particle shape and shape approximation on particle mechanics in a rotating drum using the discrete element method. *Powder Technology*, 253, 256–265. <https://doi.org/10.1016/j.powtec.2013.11.023>
- Houssais, M., Ortiz, C. P., Durian, D. J., & Jerolmack, D. J. (2015). Onset of sediment transport is a continuous transition driven by fluid shear and granular creep. *Nature Communications*, 6(1), 6527. <https://doi.org/10.1038/ncomms7527>
- Howell, D. W., Behringer, R. P., & Veje, C. T. (1999). Fluctuations in granular media. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 9(3), 559–572. <https://doi.org/10.1063/1.166430>

- Hsu, L., Dietrich, W. E., & Sklar, L. S. (2014). Mean and fluctuating basal forces generated by granular flows: Laboratory observations in a large vertically rotating drum. *Journal of Geophysical Research: Earth Surface*, 119(6), 1283–1309. <https://doi.org/10.1002/2013JF003078>
- Hsu, Leslie. (2010). *Bedrock Erosion by Granular Flow* [UC Berkeley]. <https://escholarship.org/uc/item/55v19271>
- Hungr, O., & Evans, S. G. (2004). Entrainment of debris in rock avalanches: An analysis of a long run-out mechanism. *GSA Bulletin*, 116(9–10), 1240–1252. <https://doi.org/10.1130/B25362.1>
- Hungr, O. (2006). Rock avalanche occurrence, process and modelling, in *Landslides from massive rock slope failure*, edited, pp. 243–266, Springer.
- Iverson, R. M. (1997). The physics of debris flows. *Reviews of Geophysics*, 35(3), 245–296. <https://doi.org/10.1029/97RG00426>
- Iverson, R. M. (2012). Elementary theory of bed-sediment entrainment by debris flows and avalanches. *Journal of Geophysical Research: Earth Surface*, 117(F3). <https://doi.org/10.1029/2011JF002189>
- Iverson, R. M., M. E. Reid, M. Logan, R. G. LaHusen, J. W. Godt, and J. P. Griswold (2010). Positive feedback and momentum growth during debris-flow entrainment of wet bed sediment, *Nat. Geosci.*, 4, 116, doi:10.1038/ngeo1040
- Iverson, R. M., Reid, M. E., Logan, M., LaHusen, R. G., Godt, J. W., & Griswold, J. P. (2011). Positive feedback and momentum growth during debris-flow entrainment of wet bed sediment. *Nature Geoscience*, 4(2), 116–121. <https://doi.org/10.1038/ngeo1040>
- Jalali, P., Ritvanen, J., & Sarkomaa, P. (2006). Stress fluctuations in monodisperse and bidisperse rapid granular shear flows. *Physica A: Statistical Mechanics and Its Applications*, 369(2), 535–544. <https://doi.org/10.1016/j.physa.2005.12.008>
- Karpytchev, M., Ballu, V., Krien, Y., Becker, M., Goodbred, S., Spada, G., Calmant, S., Shum, C. K., & Khan, Z. (2018). Contributions of a Strengthened Early Holocene Monsoon and Sediment Loading to Present-Day Subsidence of the Ganges-Brahmaputra Delta. *Geophysical Research Letters*, 45(3), 1433–1442. <https://doi.org/10.1002/2017GL076388>
- Kendall, R. A., Mitrovica, J. X., & Milne, G. A. (2005). On post-glacial sea level – II. Numerical formulation and comparative results on spherically symmetric models. *Geophysical Journal International*, 161(3), 679–706. <https://doi.org/10.1111/j.1365-246X.2005.02553.x>

- Kolderup, N.-H., 1955, Raset I Modalen, 14 August 1953: Norsk Geologisk Tidsskrift , v. 34p. 211–217.
- Krien, Y., Karpytchev, M., Ballu, V., Becker, M., Grall, C., Goodbred, S., Calmant, S., Shum, C. K., & Khan, Z. (2019). Present-day subsidence in the Ganges-Brahmaputra-Meghna Delta: Eastern amplification of the Holocene sediment loading contribution. *Geophysical Research Letters*, 0(ja). <https://doi.org/10.1029/2019GL083601>
- Krishna, K. S., Ismaiel, M., Srinivas, K., Rao, D., & Mishra, J. (2016). Sediment pathways and emergence of Himalayan source material in the Bay of Bengal. *Current Science*, 110. <https://doi.org/10.18520/cs/v110/i3/363-372>.
- Kueppers, U., Putz, C., Spieler, O., & Dingwell, D. B. (2012). Abrasion in pyroclastic density currents: Insights from tumbling experiments. *Physics and Chemistry of the Earth, Parts A/B/C*, 45–46, 33–39. <https://doi.org/10.1016/j.pce.2011.09.002>
- Kuchar, J., Milne, G., Wolstencroft, M., Love, R., Tarasov, L., & Hijma, M. (2018). The influence of sediment isostatic adjustment on sea level change and land motion along the U.S. Gulf Coast. *Journal of Geophysical Research: Solid Earth*, 123, 780–796. <https://doi.org/10.1002/2017JB014695>
- Lambeck, K., Rouby, H., Purcell, A., Sun, Y., & Sambridge, M. (2014). Sea level and global ice volumes from the Last Glacial Maximum to the Holocene. *Proceedings of the National Academy of Sciences*, 111(43), 15296–15303. <https://doi.org/10.1073/pnas.1411762111>
- Langroudi, M. K., Turek, S., Ouazzi, A., & Tardos, G. I. (2010). An investigation of frictional and collisional powder flows using a unified constitutive equation. *Powder Technology*, 197(1), 91–101. <https://doi.org/10.1016/j.powtec.2009.09.001>
- Le Roux-Mallouf, R., Godard, V., Cattin, R., Ferry, M., Gyeltshen, J., Ritz, J.-F., Drupka, D., Guillou, V., Arnold, M., Aumaître, G., Bourlès, D. L., & Keddadouche, K. (2015). Evidence for a wide and gently dipping Main Himalayan Thrust in western Bhutan. *Geophysical Research Letters*, 42(9), 3257–3265. <https://doi.org/10.1002/2015GL063767>
- Li, T., Rabha, S., Verma, V., Dietiker, J.-F., Xu, Y., Lu, L., Rogers, W., Gopalan, B., Breault, G., Tucker, J., & Panday, R. (2017). Experimental study and discrete element method simulation of Geldart Group A particles in a small-scale fluidized bed. *Advanced Powder Technology*, 28(11), 2961–2973. <https://doi.org/10.1016/j.apr.2017.09.003>
- Lipman, P. (1980). *Vhp_img531.jpg (1951×2873)*. https://prd-wret.s3.us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/vhp_img531.jpg

- Liu, C. -h, Nagel, S. R., Schecter, D. A., Coppersmith, S. N., Majumdar, S., Narayan, O., & Witten, T. A. (1995). Force Fluctuations in Bead Packs. *Science*, 269(5223), 513–515. <https://doi.org/10.1126/science.269.5223.513>
- Lois, G., & Carlson, J. M. (2007). Force networks and the dynamic approach to jamming in sheared granular media. *Europhysics Letters (EPL)*, 80(5), 58001. <https://doi.org/10.1209/0295-5075/80/58001>
- Longhi, E., Easwar, N., & Menon, N. (2002). Large Force Fluctuations in a Flowing Granular Medium. *Physical Review Letters*, 89(4), 045501. <https://doi.org/10.1103/PhysRevLett.89.045501>
- Lu, P., Yang, X., Xu, F., Hou, T., & Zhou, J. (2016). An analysis of the entrainment effect of dry debris avalanches on loose bed materials. *SpringerPlus*, 5(1), 1621. <https://doi.org/10.1186/s40064-016-3272-4>
- Lube, G., E. C. P. Breard, J. Jones, L. Fullard, J. Dufek, S. J. Cronin, and T. Wang (2019), Generation of air lubrication within pyroclastic density currents, *Nat. Geosci.*, 12(5), 381–386, doi:10.1038/s41561-019-0338-2.
- Lube, G., E. C. P. Breard, T. Esposti-Ongaro, J. Dufek, and B. Brand (2020), Multiphase flow behavior and hazard prediction of pyroclastic density currents, *Nature Reviews Earth & Environment*, 1(7), 348–365, doi:10.1038/s43017-020-0064-8.
- Lupker, M., Blard, P. H., Lavé, J., France-Lanord, C., Leanni, L., Puchol, N., Charreau, J., & Bourlès, D. (2012). ¹⁰Be-Derived Himalayan denudation rates and sediment budgets in the Ganga Basin. *Earth and Planetary Science Letters*, 333–334, 146–156. <https://doi.org/10.1016/j.epsl.2012.04.020>
- Lupker, M., Lavé, J., France-Lanord, C., Christl, M., Bourlès, D., Carcaillet, J., Maden, C., Wieler, R., Rahman, M., Bezbaruah, D., & Xiaohan, L. (2017). 10Be systematics in the Tsangpo-Brahmaputra catchment: The cosmogenic nuclide legacy of the eastern Himalayan syntaxis. *Earth Surface Dynamics*, 5(3), 429–449. <https://doi.org/10.5194/esurf-5-429-2017>
- Majmudar, T. S., & Behringer, R. P. (2005). Contact force measurements and stress-induced anisotropy in granular materials. *Nature*, 435(7045), 1079–1082. <https://doi.org/10.1038/nature03805>
- Martinson, H. (1980). *Mount Saint Helens Debris Flow*. <https://www.facebook.com/USGSVolcanoes/photos/a.984262971602264.1073741827.984239038271324/1821398727888680/?type=3&theater>
- McCoy, S. W., Kean, J. W., Coe, J. A., Tucker, G. E., Staley, D. M., & Wasklewicz, T. A. (2012). Sediment entrainment by debris flows: In situ measurements from the headwaters of a steep catchment. *Journal of Geophysical Research: Earth Surface*, 117(F3). <https://doi.org/10.1029/2011JF002278>

- McCoy, S. W., Tucker, G. E., Kean, J. W., & Coe, J. A. (2013). Field measurement of basal forces generated by erosive debris flows. *Journal of Geophysical Research: Earth Surface*, 118(2), 589–602. <https://doi.org/10.1002/jgrf.20041>
- McGranahan, G., Balk, D., & Anderson, B. (2007). The rising tide: Assessing the risks of climate change and human settlements in low elevation coastal zones. *Environment and Urbanization*, 19(1), 17–37. <https://doi.org/10.1177/0956247807076960>
- Michels, K. H., Kudrass, H. R., Hübscher, C., Suckow, A., & Wiedicke, M. (1998). The submarine delta of the Ganges–Brahmaputra: Cyclone-dominated sedimentation patterns. *Marine Geology*, 149(1), 133–154. [https://doi.org/10.1016/S0025-3227\(98\)00021-8](https://doi.org/10.1016/S0025-3227(98)00021-8)
- Miller, M. (2018). *Rock Avalanche deposit (vertical)*. <https://geologypics.com/rock-avalanche-deposit-vertical-2/>
- Milliman, J., & Farnsworth, K. (2011). River Discharge to the Coastal Ocean – A Global Synthesis. <https://doi.org/10.1017/CBO9780511781247>
- Milne, G. A., & Mitrovica, J. X. (2008). Searching for eustasy in deglacial sea-level histories. *Quaternary Science Reviews*, 27, 2292–2302. <https://doi.org/10.1016/j.quascirev.2008.08.018>
- Mitrovica, J. X., & Milne, G. A. (2002). On the origin of late Holocene sea-level highstands within equatorial ocean basins. *Quaternary Science Reviews*, 21(20), 2179–2190. [https://doi.org/10.1016/S0277-3791\(02\)00080-X](https://doi.org/10.1016/S0277-3791(02)00080-X)
- Mitrovica, J. X., Tamisiea, M. E., Davis, J. L., & Milne, G. A. (2001). Recent mass balance of polar ice sheets inferred from patterns of global sea-level change. *Nature*, 409(6823), 1026–1029. <https://doi.org/10.1038/35059054>
- Mueth, D. M., Jaeger, H. M., & Nagel, S. R. (1998). Force distribution in a granular medium. *Physical Review E*, 57(3), 3164–3169. <https://doi.org/10.1103/PhysRevE.57.3164>
- NASA/METI/AIST/Japan Spacesystems, and U.S./Japan ASTER Science Team (2009). ASTER Global Digital Elevation Model [Data set]. NASA EOSDIS Land Processes DAAC. Accessed 2020-05-28 from <https://doi.org/10.5067/ASTER/ASTGTM.002>
- National Geophysical Data Center, (2006). 2-minute Gridded Global Relief Data (ETOPO2) v2. National Geophysical Data Center, NOAA. doi:10.7289/V5J1012Q

- Ness, C., and J. Sun (2015), Flow regime transitions in dense non-Brownian suspensions: Rheology, microstructural characterization, and constitutive modeling, *Phys. Rev. E*, *91*(1), 012201, doi:10.1103/PhysRevE.91.012201.
- Njobuenwu, D. O., & Fairweather, M. (2014). Effect of shape on inertial particle dynamics in a channel flow. *Flow, Turbulence and Combustion*, *92*(1–2), 83–101.
- O’Hern, C. S., Langer, S. A., Liu, A. J., & Nagel, S. R. (2001). Force Distributions near Jamming and Glass Transitions. *Physical Review Letters*, *86*(1), 111–114. <https://doi.org/10.1103/PhysRevLett.86.111>
- Olen, S. M., Bookhagen, B., Hoffmann, B., Sachse, D., Adhikari, D. P., & Strecker, M. R. (2015). Understanding erosion rates in the Himalayan orogen: A case study from the Arun Valley. *Journal of Geophysical Research: Earth Surface*, *120*(10), 2080–2102. <https://doi.org/10.1002/2014JF003410>
- Palamenghi, L., Schwenk, T., Spiess, V., & Kudrass, H. R. (2011). Seismostratigraphic analysis with centennial to decadal time resolution of the sediment sink in the Ganges–Brahmaputra subaqueous delta. *Continental Shelf Research*, *31*(6), 712–730. <https://doi.org/10.1016/j.csr.2011.01.008>
- Peltier, W. R. (1974). The impulse response of a Maxwell Earth. *Reviews of Geophysics*, *12*(4), 649–669. <https://doi.org/10.1029/RG012i004p00649>
- Peltier, W. R. (2004). Global Glacial Isostasy and the Surface of the Ice-age Earth: The ICE-5G (VM2) Model and GRACE. *Annual Review of Earth and Planetary Sciences*, *32*(1), 111–149. <https://doi.org/10.1146/annurev.earth.32.082503.144359>
- Pickering, J. L., Diamond, M. S., Goodbred, S. L., Grall, C., Martin, J. M., Palamenghi, L., Paola, C., Schwenk, T., Sincavage, R., and Spiess, V. (2019). Impact of glacial-lake paleofloods on valley development since glacial termination II: A conundrum of hydrology and scale for the lowstand Brahmaputra-Jamuna paleovalley system. *Geological Society of America Bulletin*, *131*(1–2), 58–70. <https://doi.org/10.1130/B31941.1>
- Pico, T., Mitrovica, J. X., Ferrier, K. L., & Braun, J. (2016). Global ice volume during MIS 3 inferred from a sea-level analysis of sedimentary core records in the Yellow River Delta. *Quaternary Science Reviews*, *152*, 72–79. <https://doi.org/10.1016/j.quascirev.2016.09.012>
- Pollock, N. M., B. D. Brand, P. J. Rowley, D. Sarocchi, and R. Sulpizio (2019), Inferring pyroclastic density current flow conditions using syn-depositional sedimentary structures, *Bull. Volcanol.*, *81*(8), 46, doi:10.1007/s00445-019-1303-z.
- Powell, E., Gomez, N., Hay, C., Latychev, K., & Mitrovica, J. X. (2020). Viscous Effects in the Solid Earth Response to Modern Antarctic Ice Mass Flux: Implications for Geodetic Studies of WAIS Stability in a Warming World. *Journal of Climate*, *33*(2), 443–459.

- Portenga, E. W., Bierman, P. R., Duncan, C., Corbett, L. B., Kehrwald, N. M., & Rood, D. H. (2015). Erosion rates of the Bhutanese Himalaya determined using in situ-produced ^{10}Be . *Geomorphology*, 233, 112–126. <https://doi.org/10.1016/j.geomorph.2014.09.027>
- Pratt, B., Burbank, D. W., Heimsath, A., & Ojha, T. (2002). Impulsive alluviation during early Holocene strengthened monsoons, central Nepal Himalaya. *Geology*, 30(10), 911–914. [https://doi.org/10.1130/0091-7613\(2002\)030<0911:IADEHS>2.0.CO;2](https://doi.org/10.1130/0091-7613(2002)030<0911:IADEHS>2.0.CO;2)
- Radjai, F., Roux, S., & Moreau, J. J. (1999). Contact forces in a granular packing. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 9(3), 544–550. <https://doi.org/10.1063/1.166428>
- Raju, N., & Meiburg, E. (1995). The accumulation and dispersion of heavy particles in forced two-dimensional mixing layers. Part 2: The effect of gravity. *Physics of Fluids*, 7(6), 1241–1264. <https://doi.org/10.1063/1.868581>
- Rappaport, E. N., & Blanchard, B. W. (2015). Fatalities in the United States Indirectly Associated with Atlantic Tropical Cyclones. *Bulletin of the American Meteorological Society*, 97(7), 1139–1148. <https://doi.org/10.1175/BAMS-D-15-00042.1>
- Raymo, M. E., Mitrovica, J. X., O’Leary, M. J., Deconto, R. M., & Hearty, P. J. (2011). Departures from eustasy in Pliocene sea-level records. *Nature Geoscience*, 4(5), 328–332. <https://doi.org/10.1038/ngeo1118>
- Roche, O., D. C. Buesch, and G. A. Valentine (2016), Slow-moving and far-travelled dense pyroclastic flows during the Peach Spring super-eruption, *Nat Commun*, 7, [doi:10.1038/ncomms10890](https://doi.org/10.1038/ncomms10890).
- Roche, O., Y. Nino, A. Mangeney, B. Brand, N. Pollock, and G. A. Valentine (2013), Dynamic pore-pressure variations induce substrate erosion by pyroclastic flows, *Geology*, 41(10), 1107-1110.
- Rosenkranz, R., Schildgen, T., Wittmann, H., & Spiegel, C. (2018). Coupling erosion and topographic development in the rainiest place on Earth: Reconstructing the Shillong Plateau uplift history with in-situ cosmogenic ^{10}Be . *Earth and Planetary Science Letters*, 483, 39–51. <https://doi.org/10.1016/j.epsl.2017.11.047>
- Roy, N. G., Sinha, R., & Gibling, M. R. (2012). Aggradation, incision and interfluvial flooding in the Ganga Valley over the past 100,000 years: Testing the influence of monsoonal precipitation. *Palaeogeography, Palaeoclimatology, Palaeoecology*, 356–357, 38–53. <https://doi.org/10.1016/j.palaeo.2011.08.012>
- Ruetenik, G., Ferrier, K., Creveling, J., & Fox, M. (2020). Sea-level responses to rapid sediment erosion and deposition in Taiwan. *Earth and Planetary Science Letters*, 538, 116198. <https://doi.org/10.1016/j.epsl.2020.116198>

- Savage, S. B. (1984). The Mechanics of Rapid Granular Flows. In J. W. Hutchinson & T. Y. Wu (Eds.), *Advances in Applied Mechanics* (Vol. 24, pp. 289–366). Elsevier. [https://doi.org/10.1016/S0065-2156\(08\)70047-4](https://doi.org/10.1016/S0065-2156(08)70047-4)
- Scarpato, C., & Perrotta, A. (2012). Erosional characteristics and behavior of large pyroclastic density currents. *Geology*, 40(11), 1035–1038. <https://doi.org/10.1130/G33380.1>
- Scheingross, J. S., Minchew, B. M., Mackey, B. H., Simons, M., Lamb, M. P., & Hensley, S. (2013). Fault-zone controls on the spatial distribution of slow-moving landslides. *GSA Bulletin*, 125(3–4), 473–489. <https://doi.org/10.1130/B30719.1>
- Scherler, D., Bookhagen, B., Wulf, H., Preusser, F., & Strecker, M. R. (2015). Increased late Pleistocene erosion rates during fluvial aggradation in the Garhwal Himalaya, northern India. *Earth and Planetary Science Letters*, 428, 255–266. <https://doi.org/10.1016/j.epsl.2015.06.034>
- Sincavage, R. S., Paola, C., and Goodbred, S. L. (2019). Coupling mass extraction and downstream fining with fluvial facies changes across the Sylhet Basin of the Ganges-Brahmaputra-Meghna Delta. *Journal of Geophysical Research: Earth Surface*, 124(2), 1–14. <https://doi.org/10.1029/2018JF004840>
- Sklar, L., & Dietrich, W. (1998). River Longitudinal Profiles and Bedrock Incision Models: Stream Power and the Influence of Sediment Supply. *Washington DC American Geophysical Union Geophysical Monograph Series*, 107. <https://doi.org/10.1029/GM107p0237>
- Sklar, L. S., & Dietrich, W. E. (2004). A mechanistic model for river incision into bedrock by saltating bed load. *Water Resources Research*, 40(6).
- Sobotovitch, E. V. (1984). (Table 8) Sedimentation rates in the Bay of Bengal [Data set]. In supplement to: Shnyukov, Evgeny F; Starostenko, V I; Belevtsev, R Ya; Gozhik, P F; Kalyaev, G I; Koptiyukh, Yu M; Overchuk, V O; Slipchenko, V V; Sobotovitch, Emlen V; Sobolevsky, Yu V; Chugunny, Yu G; Shcherbakov, I B (1984): Geology and Metallogeny of the Northern and Equatorial Indian Ocean. Kiev, Naukova Dumka (E.F. Shnyukov, Ed.), 168 pp. <https://doi.org/10.1594/PANGAEA.737089>
- Spada, G., & Stocchi, P. (2007). SELEN: A Fortran 90 program for solving the “sea-level equation.” *Computers & Geosciences*, 33(4), 538–562. <https://doi.org/10.1016/j.cageo.2006.08.006>

- Srivastava, A., & Sundaresan, S. (2003). Analysis of a frictional-kinetic model for gas-particle flow. *Powder Technology*, 129(1–3), 72–85. [https://doi.org/10.1016/S0032-5910\(02\)00132-8](https://doi.org/10.1016/S0032-5910(02)00132-8)
- Steinberger, B., & Becker, T. W. (2018). A comparison of lithospheric thickness models. *Understanding Geological Processes through Modelling - A Memorial Volume Honouring Evgenii Burov*, 746, 325–338. <https://doi.org/10.1016/j.tecto.2016.08.001>
- Steckler, M. S., Mondal, D. R., Akhter, S. H., Seeber, L., Feng, L., Gale, J., Hill, E. M., & Howe, M. (2016). Locked and loading megathrust linked to active subduction beneath the Indo-Burman Ranges. *Nature Geoscience*, 9(8), 615–618. <https://doi.org/10.1038/ngeo2760>
- Strack, O. D. L., & Cundall, P. A. (1978). *The distinct element method as a tool for research in granular media*. Department of Civil and Mineral Engineering, University of Minnesota.
- Stock, J. D., & Dietrich, W. E. (2006). Erosion of steepland valleys by debris flows. *Geological Society of America Bulletin*, 118(9–10), 1125–1148. <https://doi.org/10.1130/B25902.1>
- Subramanian, V., & Ramanathan, A. L. (1996). Nature of Sediment Load in the Ganges-Brahmaputra River Systems in India. In J. D. Milliman & B. U. Haq (Eds.), *Sea-Level Rise and Coastal Subsidence: Causes, Consequences, and Strategies* (pp. 151–168). Springer Netherlands. https://doi.org/10.1007/978-94-015-8719-8_8
- Sulpizio, R., P. Dellino, D. M. Doronzo, and D. Sarocchi (2014), Pyroclastic density currents; state of the art and perspectives, *J. Volcanol. Geotherm. Res.*, 283, 36-65.
- Syamlal, M. (1985). *Multiphase hydrodynamics of gas-solids flow* [PhD Thesis]. Illinois Institute of Technology.
- Syamlal, M., Rogers, W., O'Brien, T. J., & Documentation, M. (1993). Theory guide. *US Department of Energy (DOE), Morgantown Energy Technology Center, Morgantown, West Virginia*.
- Syamlal, Madhava, Celik, I. B., & Benyahia, S. (2017). Quantifying the uncertainty introduced by discretization and time-averaging in two-fluid model predictions. *AIChE Journal*, 63(12), 5343–5360. <https://doi.org/10.1002/aic.15868>
- Tang, L., Wen, F., Yang, Y., Crowe, C. T., Chung, J. N., & Troutt, T. R. (1992). Self-organizing particle dispersion mechanism in a plane wake. *Physics of Fluids A: Fluid Dynamics*, 4(10), 2244–2251. <https://doi.org/10.1063/1.858465>

- Tesauro, M., Kaban, M. K., & Cloetingh, S. A. P. L. (2012). Global strength and elastic thickness of the lithosphere. *Coupled Deep Earth and Surface Processes in System Earth: Monitoring, Reconstruction and Process Modeling*, 90–91, 51–57. <https://doi.org/10.1016/j.gloplacha.2011.12.003>
- Tesauro, M., Kaban, M. K., & Cloetingh, S. A. P. L. (2013). Global model for the lithospheric strength and effective elastic thickness. *TOPO-EUROPE III*, 602, 78–86. <https://doi.org/10.1016/j.tecto.2013.01.006>
- USGS. (2001). *ElSalvadorslide.jpg (1474×1992)*. <https://upload.wikimedia.org/wikipedia/commons/7/73/ElSalvadorslide.jpg>
- Vaithiyanathan, P., Ramanathan, A. L., & Subramanian, V. (1988). Erosion, transport and deposition of sediments by the tropical rivers of India. In M. P. Bordas & Walling, D. E. (Eds.), *Sediment budgets: Proceedings of the symposium held at Porto Alegre, Brazil, 11-15 December 1988*. Wallingford, England: IAHS.
- Valentine, G. A., Buesch, D. C., & Fisher, R. V. (1989). Basal layered deposits of the Peach Springs Tuff, northwestern Arizona, USA. *Bulletin of Volcanology*, 51(6), 395–414. <https://doi.org/10.1007/BF01078808>
- Van Der Wal, W., & Ijpelaar, T. (2017). The effect of sediment loading in Fennoscandia and the Barents Sea during the last glacial cycle on glacial isostatic adjustment observations. *Solid Earth*, 8(5), 955–968. <https://doi.org/10.5194/se-8-955-2017>
- Wang, D., & Zhou, Y. (2010). Particle dynamics in dense shear granular flow. *Acta Mechanica Sinica*, 26, 91–100. <https://doi.org/10.1007/s10409-009-0322-y>
- Watts, A. B., Zhong, S. J., & Hunter, J. (2013). The Behavior of the Lithosphere on Seismic to Geologic Timescales. *Annual Review of Earth and Planetary Sciences*, 41(1), 443–468. <https://doi.org/10.1146/annurev-earth-042711-105457>
- Weber, M. E., Wiedicke-Hombach, M., Kudrass, H. R., & Erlenkeuser, H. (2003). Bengal Fan sediment transport activity and response to climate forcing inferred from sediment physical properties. *Sedimentary Geology of the Bengal Basin, Bangladesh, in Relation to the Asia-Greater India Collision and the Evolution of the Eastern Bay of Bengal*, 155(3), 361–381. [https://doi.org/10.1016/S0037-0738\(02\)00187-2](https://doi.org/10.1016/S0037-0738(02)00187-2)
- Weber, M. E., Lantzsich, H., Dekens, P., Das, S. K., Reilly, B. T., Martos, Y. M., Meyer-Jacob, C., Agrahari, S., Ekblad, A., Titschack, J., Holmes, B., & Wolfgramm, P. (2018). 200,000 years of monsoonal history recorded on the lower Bengal Fan—Strong response to insolation forcing. *Global and Planetary Change*, 166, 107–119. <https://doi.org/10.1016/j.gloplacha.2018.04.003>

- Wickert, A. D., Mitrovica, J. X., Williams, C., & Anderson, R. S. (2013). Gradual demise of a thin southern Laurentide ice sheet recorded by Mississippi drainage. *Nature*, 502(7473), 668–671. <https://doi.org/10.1038/nature12609>
- Wilson, M. (2010). *Kelso Dunes Avalanche Deposits*.
<https://commons.wikimedia.org/wiki/User:Wilson44691#/media/File:KelsoDunesAvalancheDeposits.JPG>
- Wilson, C. J. N., & Walker, G. P. L. (1985). The Taupo eruption, New Zealand. II. The Taupo Ignimbrite. *Philosophical Transactions of the Royal Society of London. Series A, Mathematical and Physical Sciences*, 314(1529), 229–310.
<https://doi.org/10.1098/rsta.1985.0020>
- Wolstencroft, M., Shen, Z., Törnqvist, T. E., Milne, G. A., & Kulp, M. (2014). Understanding subsidence in the Mississippi Delta region due to sediment, ice, and ocean loading: Insights from geophysical modeling: Modeling load-induced subsidence. *Journal of Geophysical Research: Solid Earth*, 119(4), 3838–3856.
<https://doi.org/10.1002/2013JB010928>
- Yohannes, B., Hsu, L., Dietrich, W. E., & Hill, K. M. (2012). Boundary stresses due to impacts from dry granular flows. *Journal of Geophysical Research: Earth Surface*, 117(F2). <https://doi.org/10.1029/2011JF002150>
- Zadeh, A.A., Barés, J., Brzinski, T.A. *et al.* Enlightening force chains: a review of photoelasticimetry in granular matter. *Granular Matter* **21**, 83 (2019).
<https://doi.org/10.1007/s10035-019-0942-2>
- Zhang, L., N. G. H. Nguyen, S. Lambert, F. Nicot, F. Prunier, and I. Djeran-Maigre (2017), The role of force chains in granular materials: from statics to dynamics, *European Journal of Environmental and Civil Engineering*, 21(7-8), 874-895, doi:10.1080/19648189.2016.1194332.
- Zhang, Q., and K. Kamrin (2017), Microscopic Description of the Granular Fluidity Field in Nonlocal Flow Modeling, *Phys. Rev. Lett.*, 118(5), 058001.