Mapping the Probability of Earthquake-Induced Submarine Slope Failure Along the U.S. Atlantic Margin: A First-Order, Second-Moment Approach

Eugene C. Morgan

Abstract

Submarine landslides pose a direct threat to offshore infrastructure, and an indirect threat to coastal communities via tsunami generation. Recent studies have investigated the potential role that submarine landslides play in causing tsunamis on the U.S. East Coast. This paper quantitatively assesses submarine landslide hazard offshore the eastern U.S., but the method herein can be applied to any area with sufficient data. Using publicly available bathymetry, surficial sediment data, shear strength values, and earthquake ground motion predictions, we map the conditional probability of slope failure over our entire study area. We calculate this probability using a first-order, second-moment estimate of the variance of critical acceleration needed to overcome the resisting forces in the infinite slope stability analysis. We show that this first-order, second-moment approximation serves as a convenient and computationally efficient way of assessing submarine landslide hazard over a broad region, while also accounting for the significant uncertainties in the slope stability parameters. Furthermore, we illustrate the importance of correcting for bias in the FOSM-derived estimates of critical acceleration, and show how the FOSM results can be used to direct future data collection towards the reduction of hazard uncertainty.

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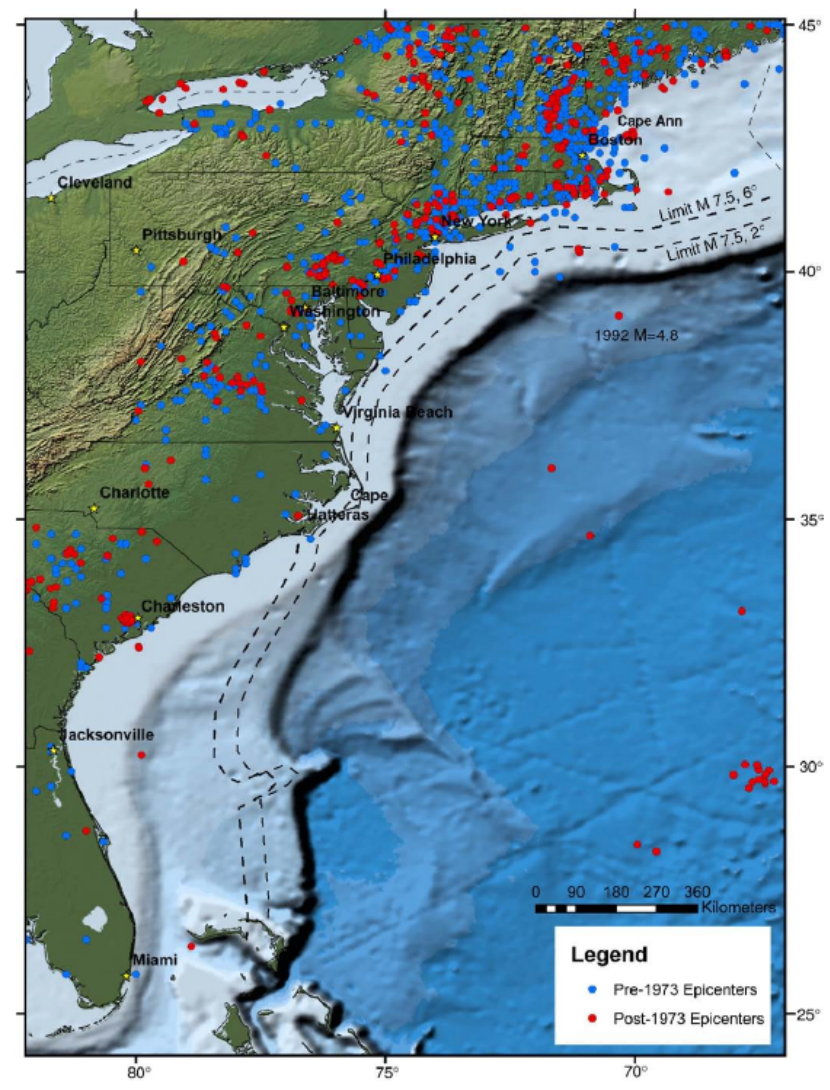
For U.S. East Coast, submarine landslides are the main source of tsunami genesis (ten Brink et al., 2009):



- Earthquakes as landslide triggers, not tsunami triggers (no large thrust faults)
- How does spatial variation of soil properties affect the distribution of landslide hazard?
- What about spatial distribution of seismic sources?
- Can we include uncertainties of these parameters in a probabilistic analysis with full spatial coverage?

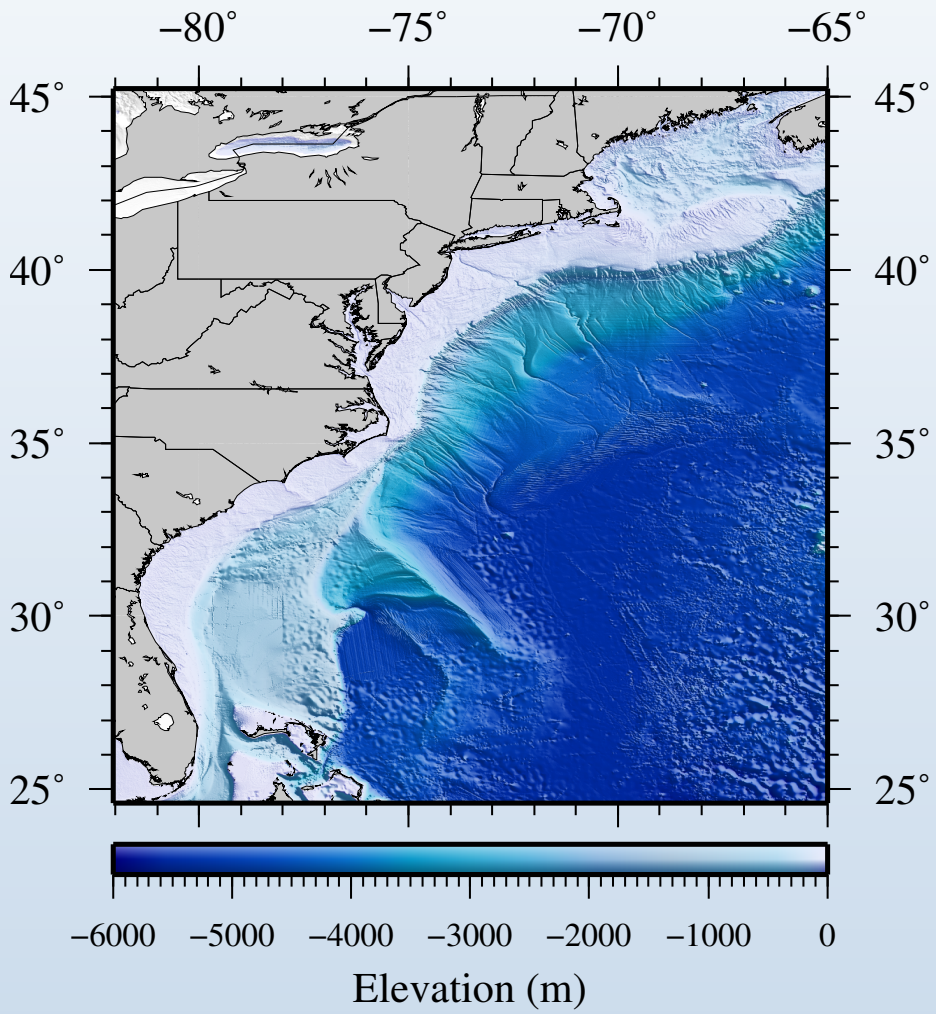
Objective

The goal of this work is to map submarine landslide hazard over the U.S. Atlantic margin.

- Sufficient data exist offshore the U.S. to get meaningful and detailed measurements of landslide hazard
- However, these data introduce significant uncertainty
  - Undrained shear strength data are sparse → use kriging to improve coverage and characterize uncertainty
  - Unit weight values are applied categorically → use range of literature values to assess uncertainty
- We demonstrate how the first-order, second-moment method can be applied in a GIS framework to handle this uncertainty and map *probability* of failure

These methods are not new! Consider this work as a case study that seeks to improve upon previous characterizations of offshore landslide hazard in this area (e.g. ten Brink et al., 2009; Grilli et al., 2009).

Study Area



The U.S. Atlantic margin:

- wide geographic distribution of landslide scarps and deposits (Chaytor et al., 2009; Twichell et al., 2009)
- geologic processes affecting hazard include:
  - Jurassic salt flows south of Cape Hatteras
  - [illegible] glacial deposits from Laurentide ice sheet in the north
- largest and most frequent landslides noted in these areas!

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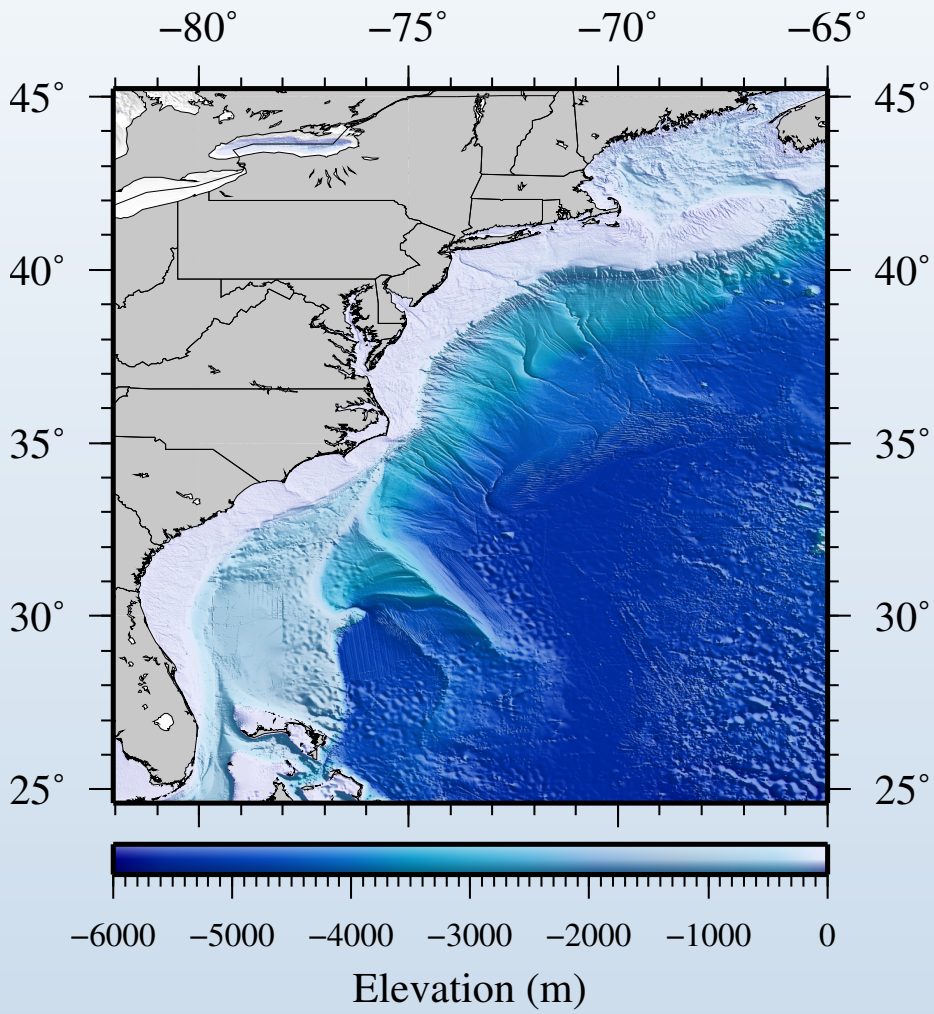

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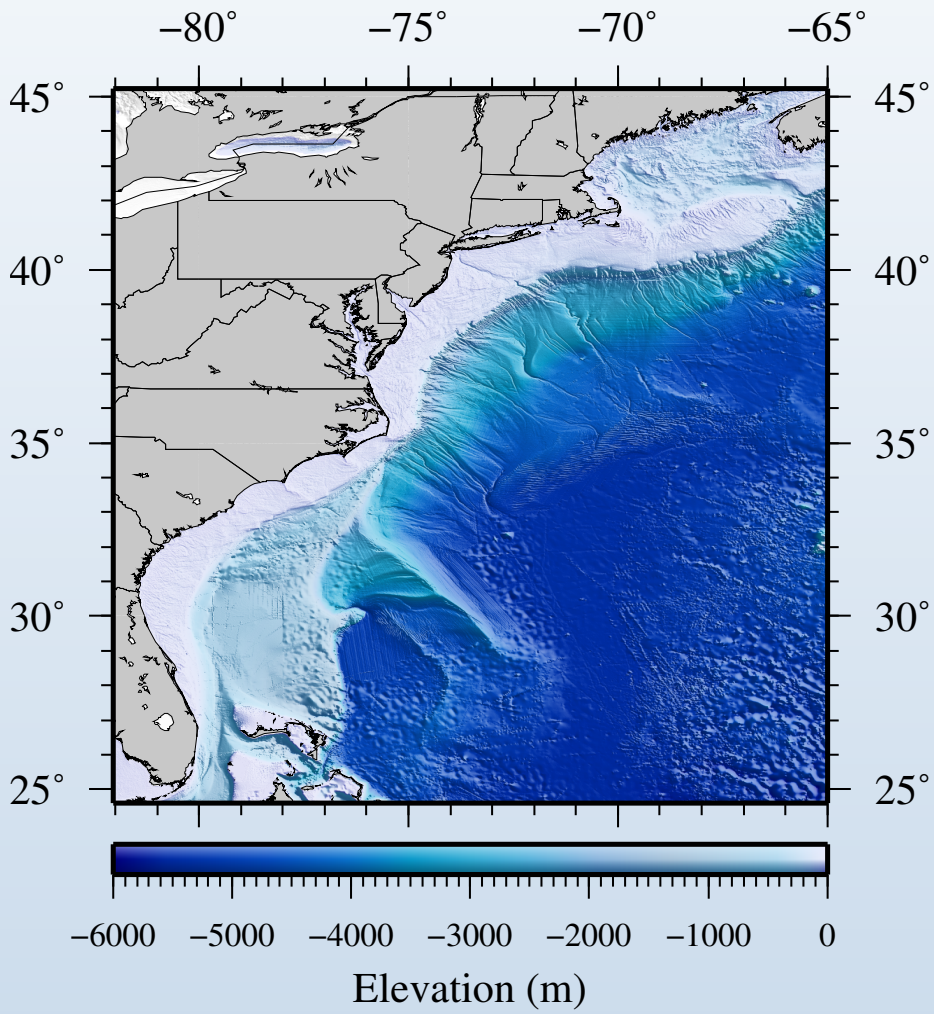

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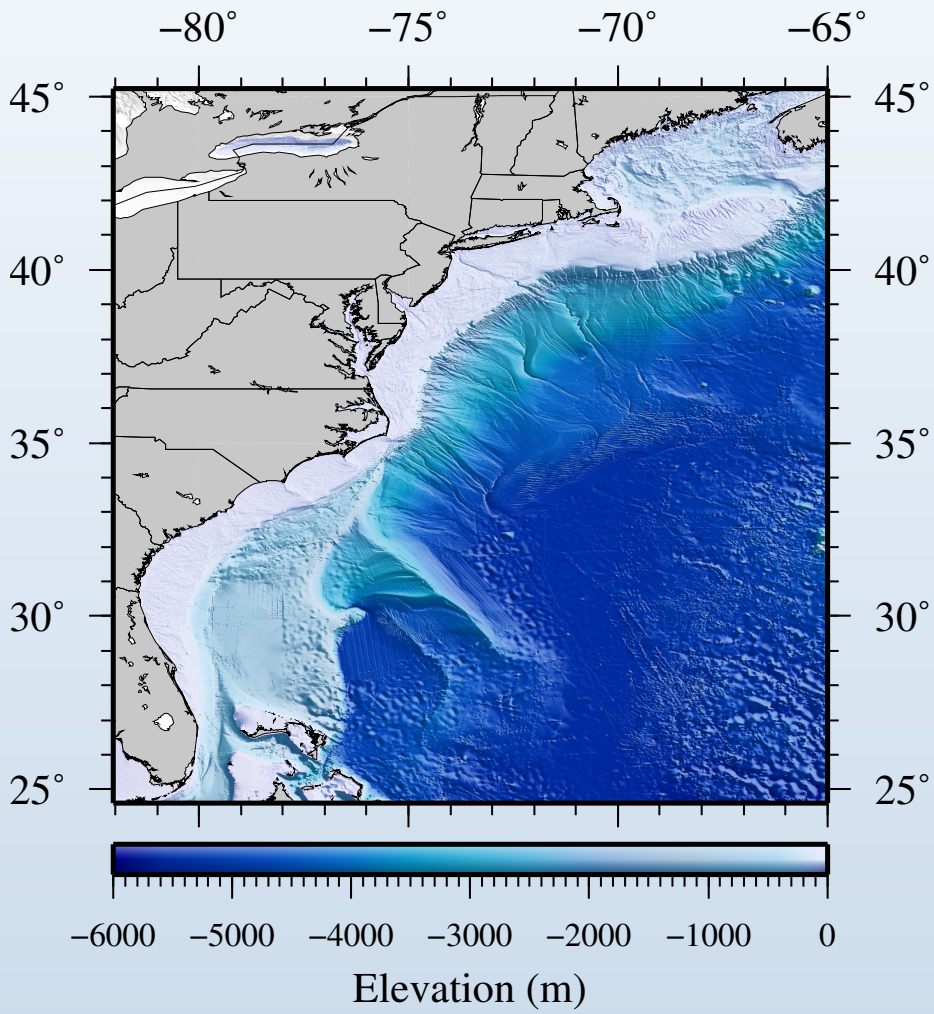

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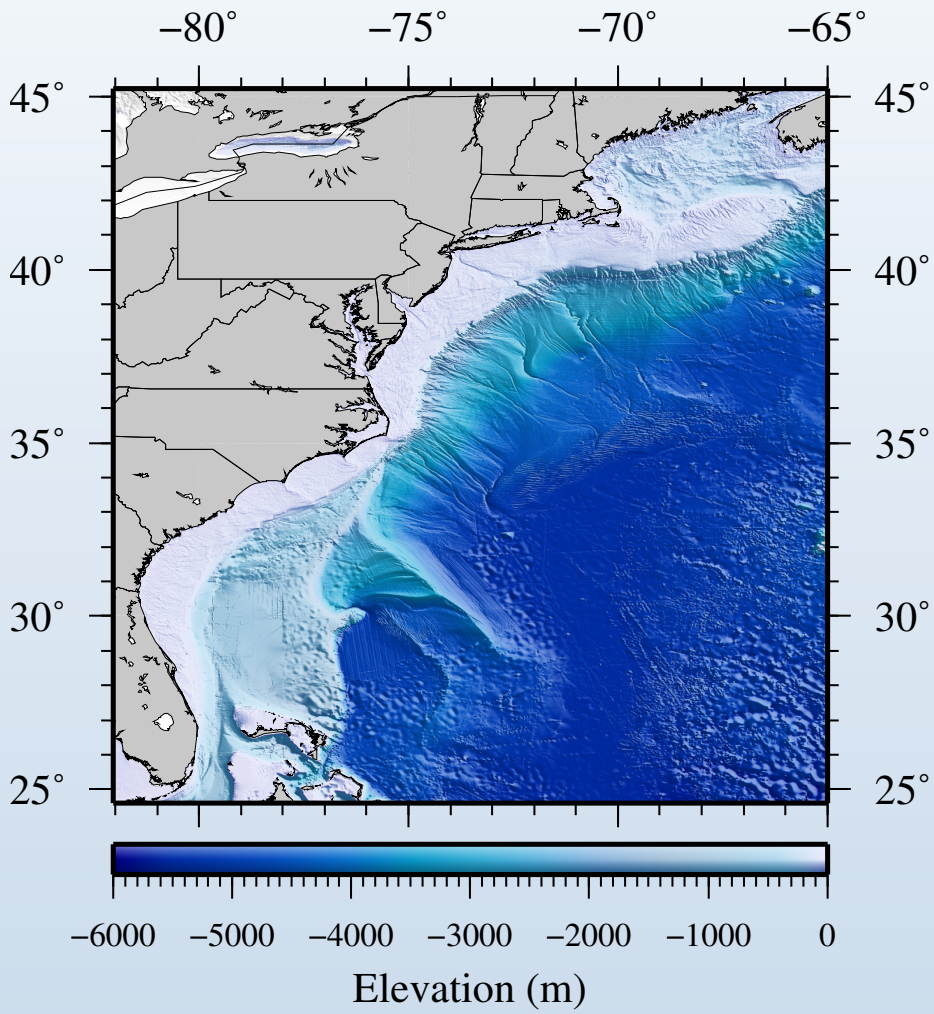

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Critical Acceleration

The critical acceleration (a_c) of a sliding block of soil is the base acceleration required to overcome shear resistance and initiate sliding.

$$a_c = (FS - 1)g \sin \alpha,$$

where g is gravity, α is slope angle, and FS is the static factor of safety:

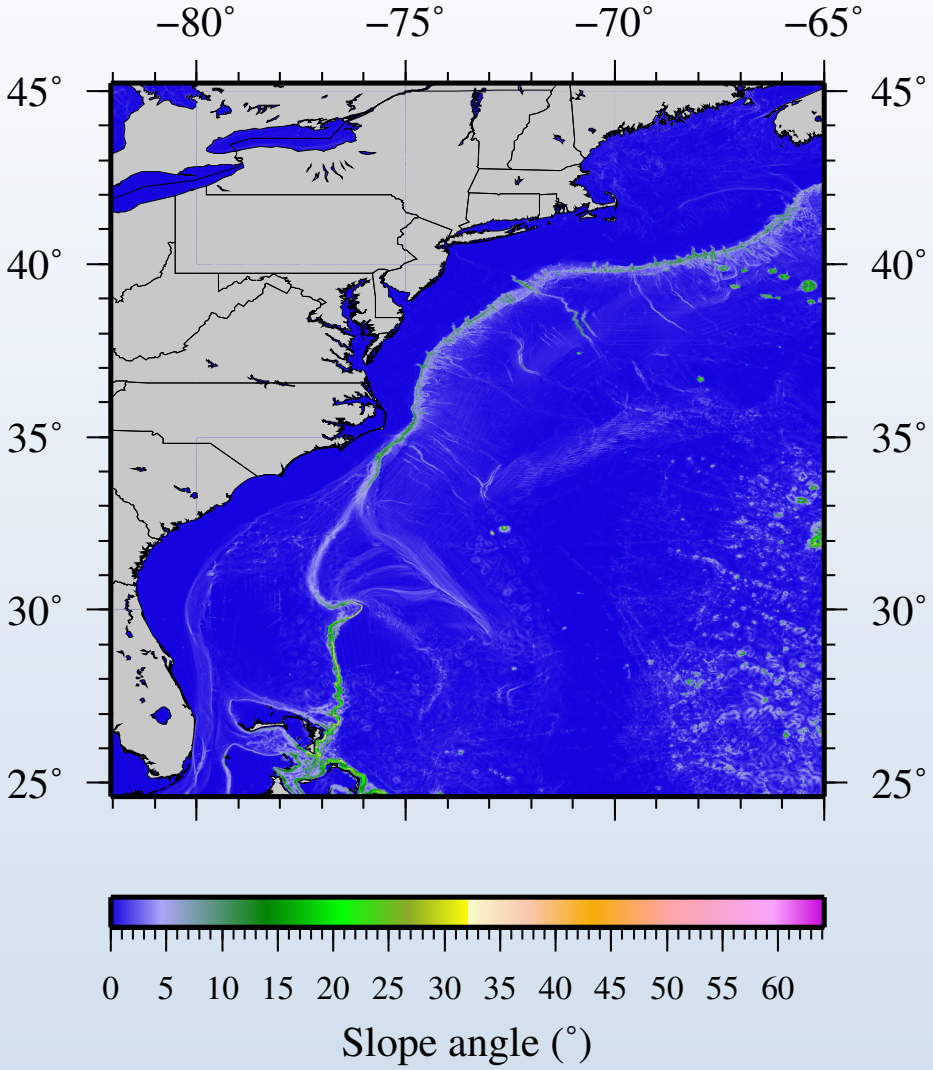
$$FS = \frac{s_u}{\gamma' z \sin \alpha \cos \alpha}.$$

Combining these, we get:

$$a_c = \frac{s_u g}{\gamma' z \cos \alpha} - g \sin \alpha.$$

Data:

- SRTM30: 30-arc sec. global topo
  - slope angle α
- East Coast Sediment Analysis: surficial sediment classification
  - bouyant unit weight γ'
- USGS's 2008 National Seismic Hazard Map: gridded, predicted ground motions
  - Peak Ground Acceleration (PGA) for 2% and 5% in 50 years earthquakes
- usSEABED: online compilation of offshore sample data
  - undrained shear strength s_u



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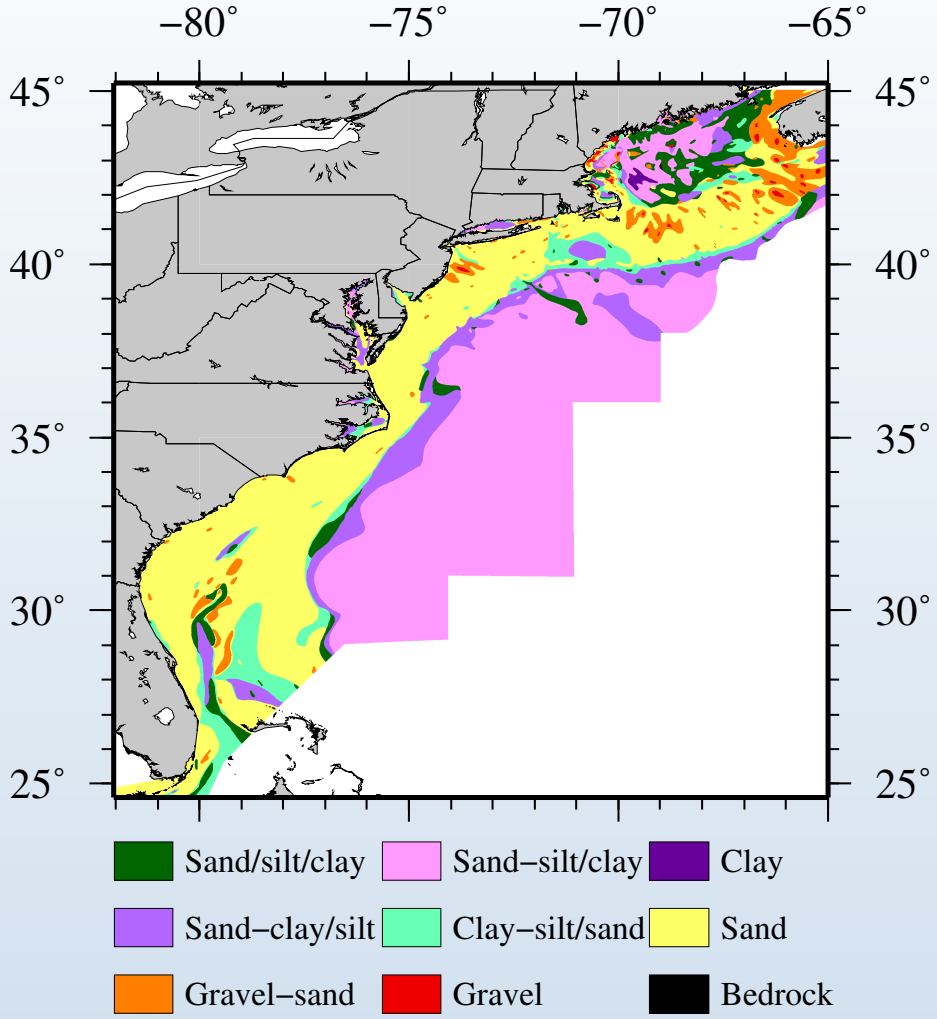

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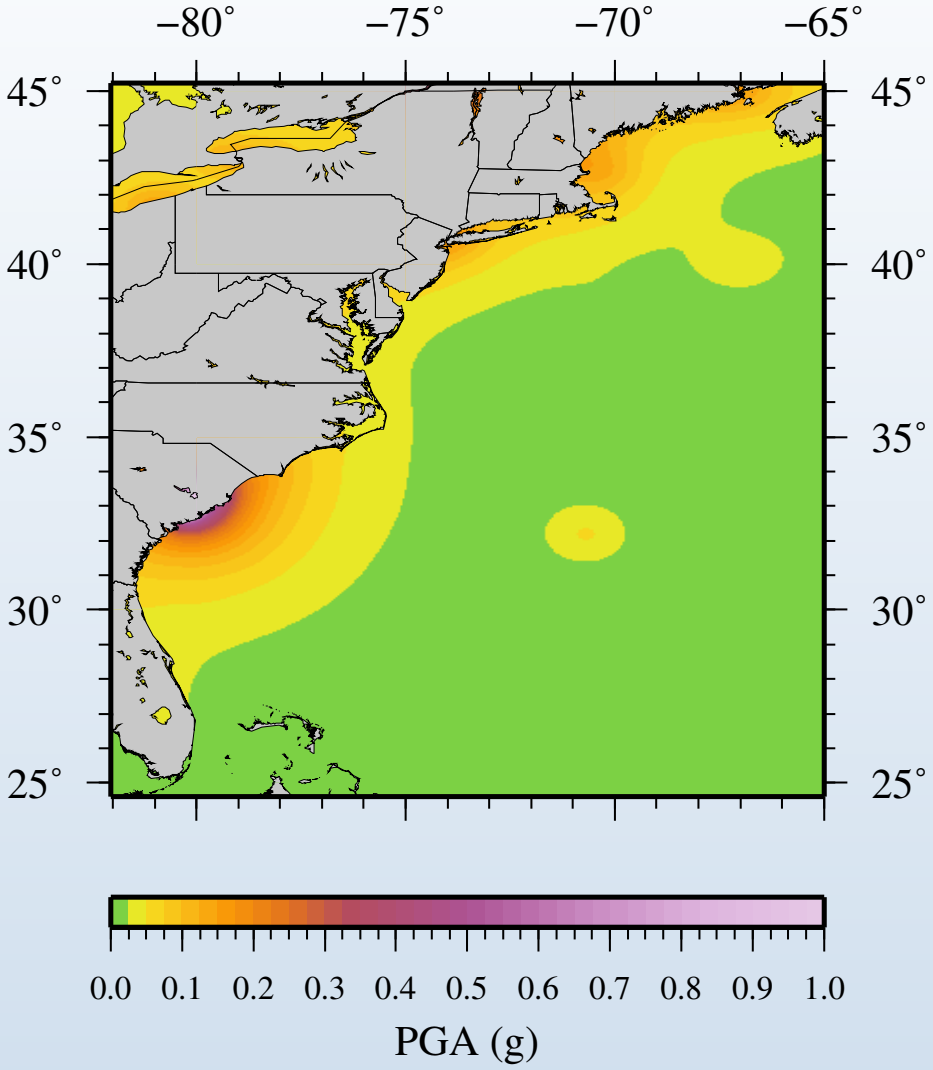

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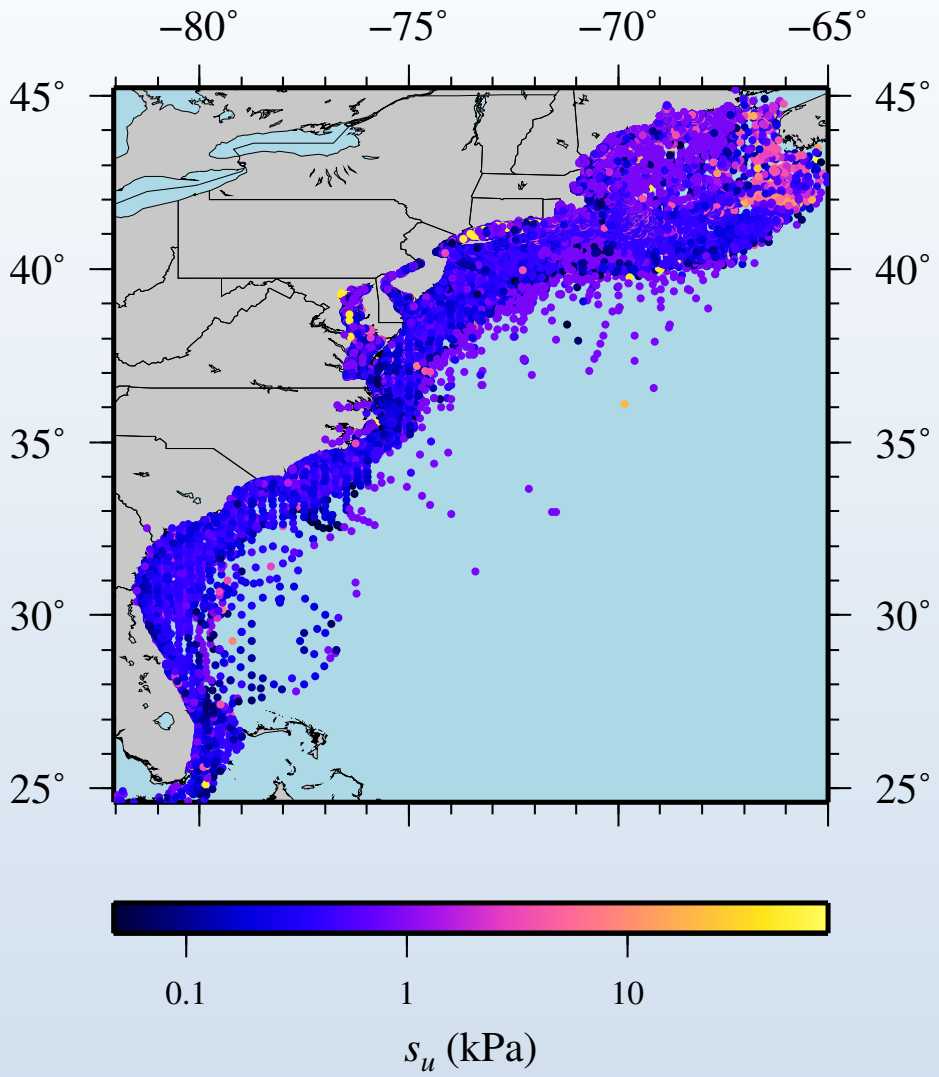
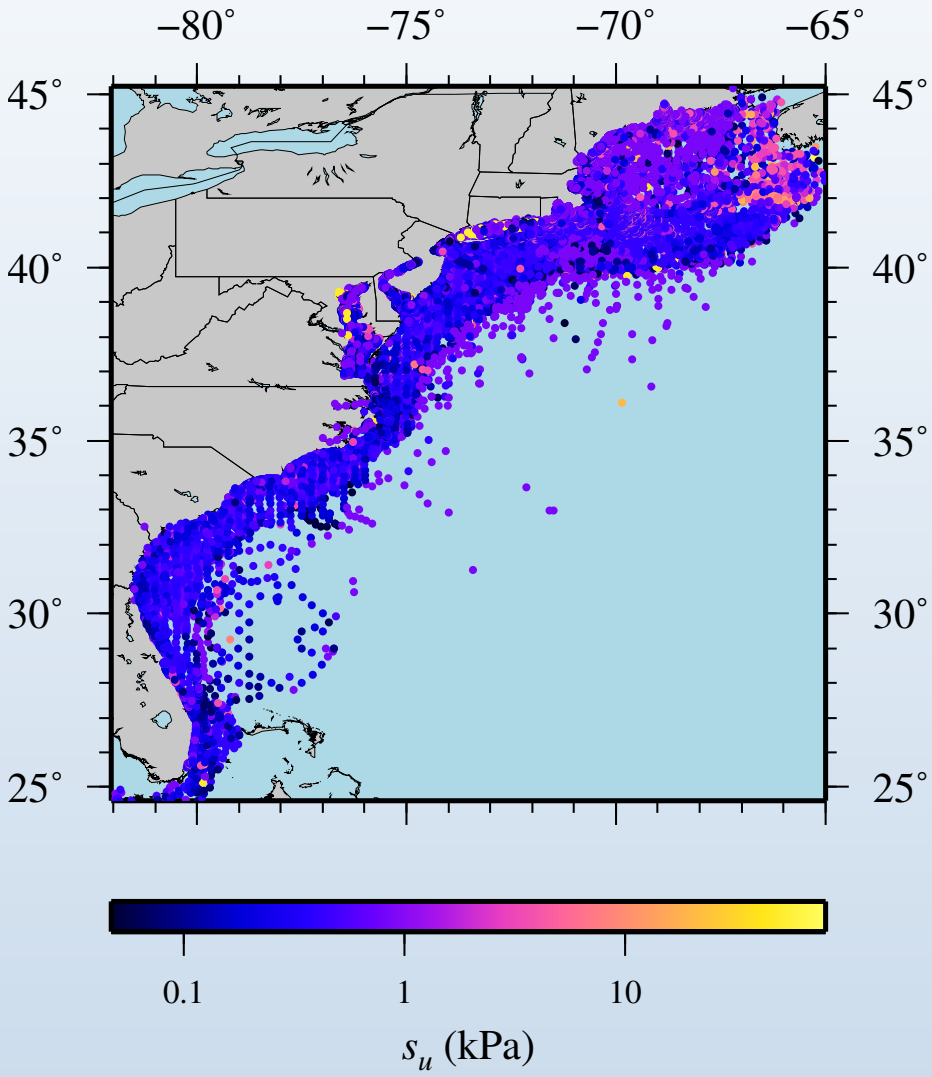
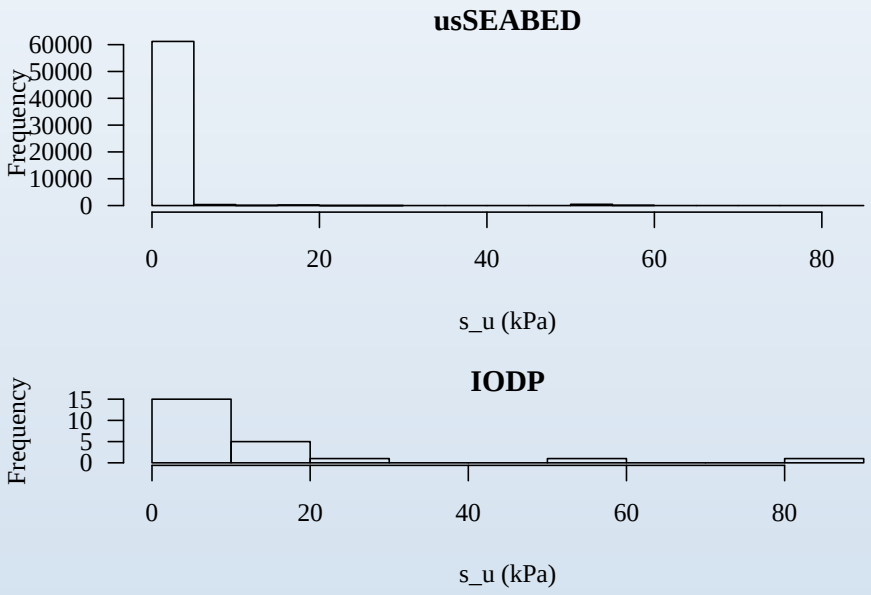


A bit more on s_u dataset





Why first-order, second-moment (FOSM)?

The basic first-order, second-moment method estimates the statistical distribution of some performance metric (e.g. critical acceleration a_c) via a Taylor series expansion of the function of that metric about some point (usually an estimate of the mean).

- FOSM can be applied within GIS (Haneberg, 2004) → predict hazard with complete spatial coverage
- FOSM takes into account predictive uncertainty arising from interpolation of sparse data (i.e., kriging s_u)
- Computationally inexpensive (compared to Monte Carlo analysis, e.g., Grilli et al., 2009)

While FOSM continues to be applied to landslides in the literature (Suchomel and Mašín, 2010; Chen et al., 2007; Haneberg, 2004; Luzi et al., 2000), no specific cases assess submarine landslides with this method.

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Applying FOSM to a_c

We start by taking partial derivatives of a_c:

$$\frac{\partial a_c}{\partial s_u} = \frac{g \sec \alpha}{\gamma' z}$$
$$\frac{\partial a_c}{\partial \gamma'} = \frac{-s_u g \sec \alpha}{\gamma'^2 z}.$$

These are the only parameters with significant uncertainty: α is measured from bathy, g is constant, and z we will arbitrarily assume. Using sample variances $\sigma^2_{x_i}$ of $x = \{s_u, \gamma'\}$, and calculating the above two terms at the sample means $\bar{x}_i$:

$$\sigma^2_{a_c} = \sum_i \left(\frac{\partial a_c}{\partial x_i}\right)^2_{\bar{x}_i} \sigma^2_{x_i} = \left(\frac{-s_u g \sec \alpha}{\gamma'^2 z}\right)^2 \sigma^2_{\gamma'} + \left(\frac{g \sec \alpha}{\gamma' z}\right)^2 \sigma^2_{s_u}.$$

Note: we assume independence between γ' and s_u to simplify the above expression (Mays, 1996).

Applying FOSM to a_c

Furthermore, our estimate of critical acceleration has bias:

$$\hat{a}_c = E[a_c(\hat{\gamma}', \hat{s}_u)] = a_c(\gamma', s_u) + \Delta_{a_c}.$$

We can estimate the bias via the second-order partial derivatives (Phatarfod, 1977):

$$\Delta_{a_c} = \frac{1}{2}\left[\frac{\partial^2 a_c}{\partial \gamma'^2}\sigma^2_{\gamma'} + \frac{\partial^2 a_c}{\partial s_u^2}\sigma^2_{s_u} + 2\frac{\partial^2 a_c}{\partial \gamma' \partial s_u}\sigma^2_{\gamma', s_u}\right].$$

Again, our assumption of independence and the derivatives

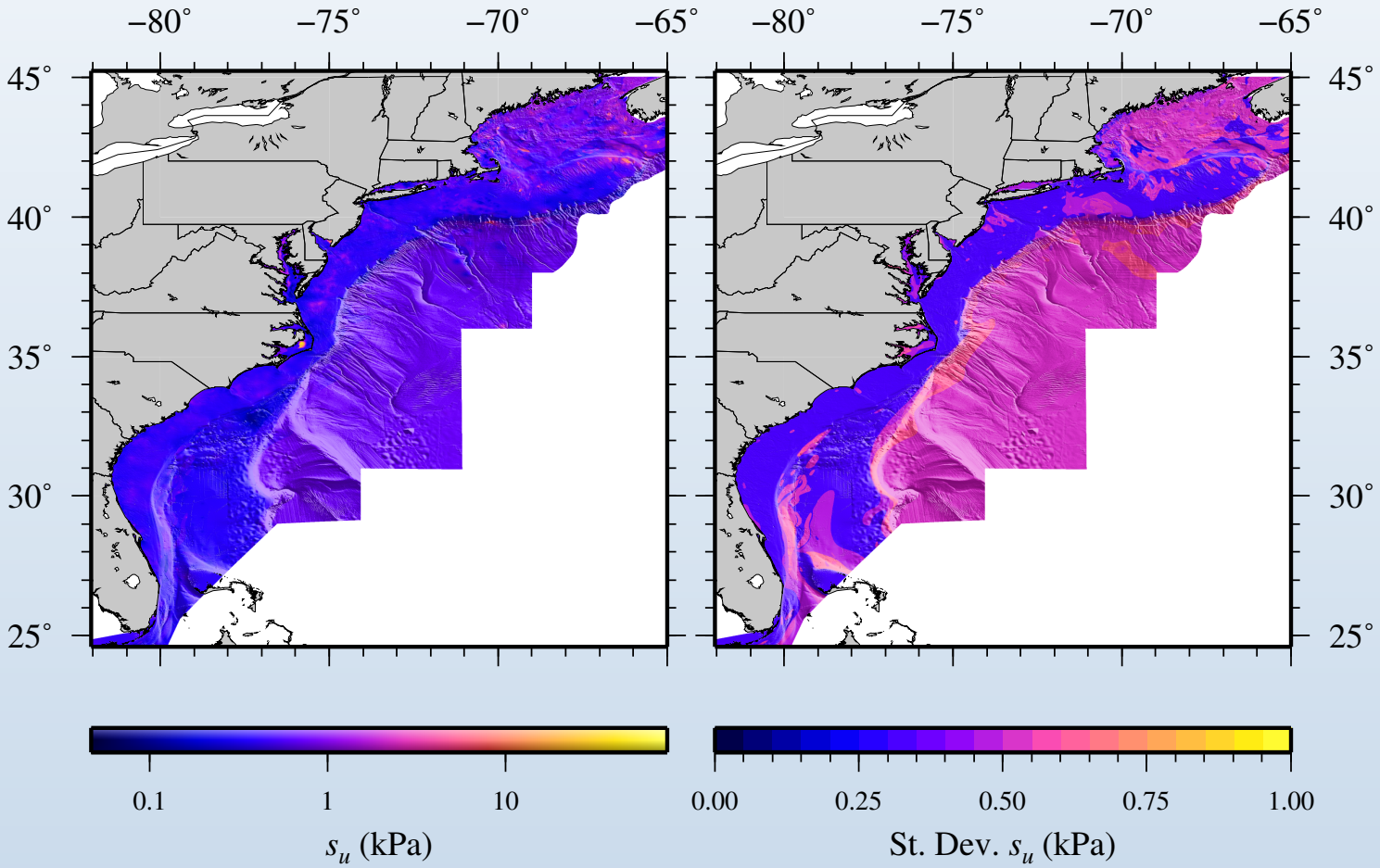
$$\frac{\partial^2 a_c}{\partial \gamma^2} = \frac{s_u g^2 \sec\alpha}{\gamma'^3 z}, \qquad \frac{\partial^2 a_c}{\partial s_u^2} = 0$$

simplify our formulation of bias to

$$\Delta_{a_c} = \frac{1}{2}\left[\frac{s_u g^2 \sec\alpha}{\gamma'^3 z}\sigma^2_{\gamma'}\right].$$

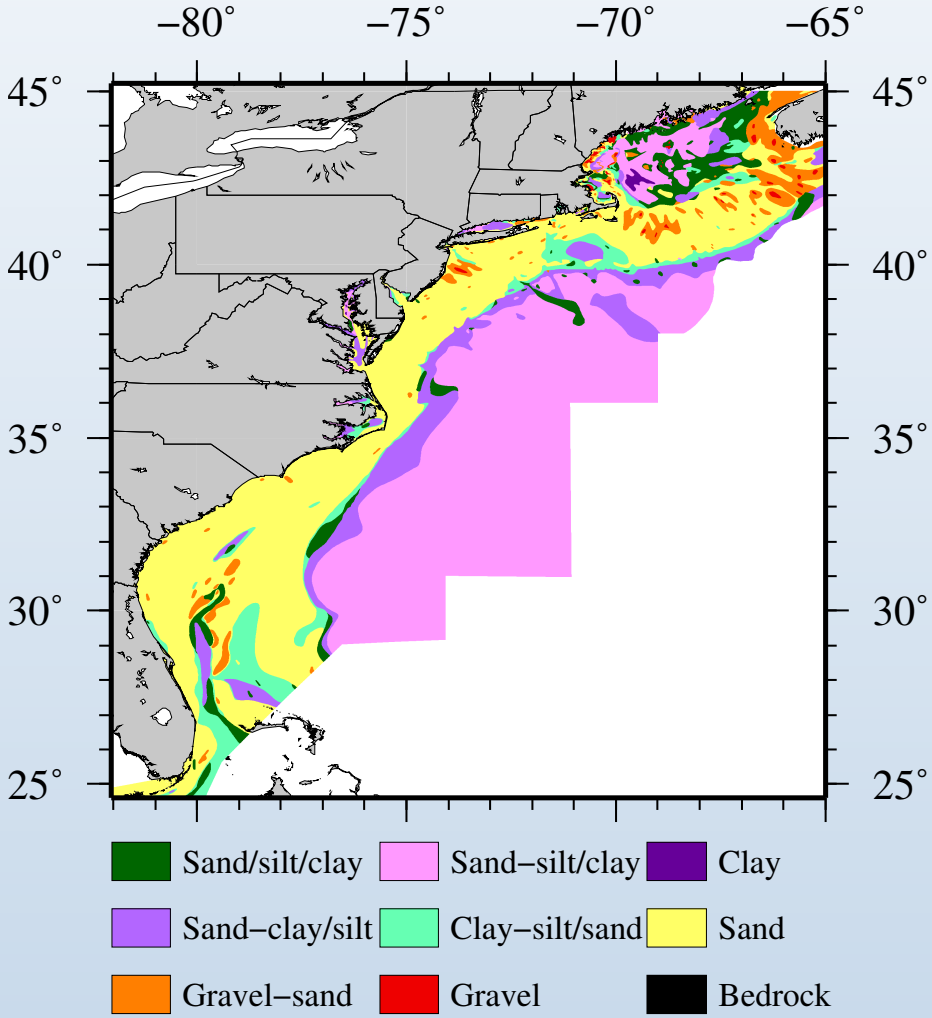
Kriging s_u

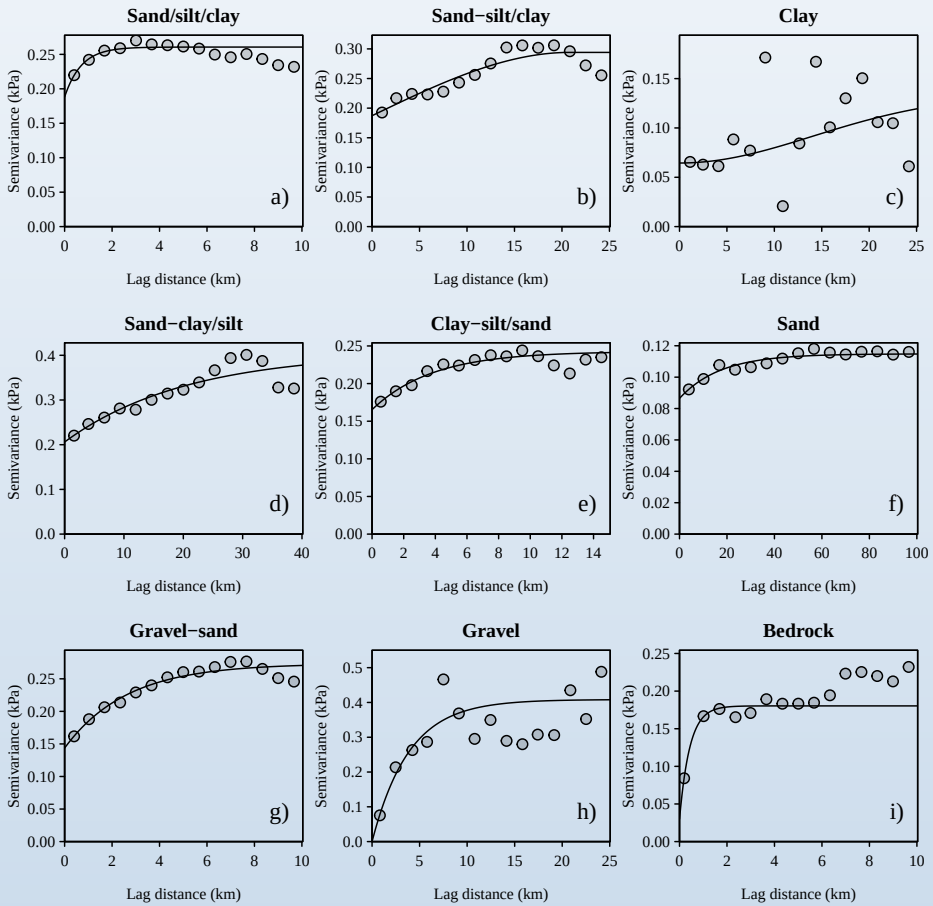
Kriging interpolates the usSEABED s_u points data, giving us $\bar{s}_u$ and σ_{s_u} at all locations:



Details on kriging s_u

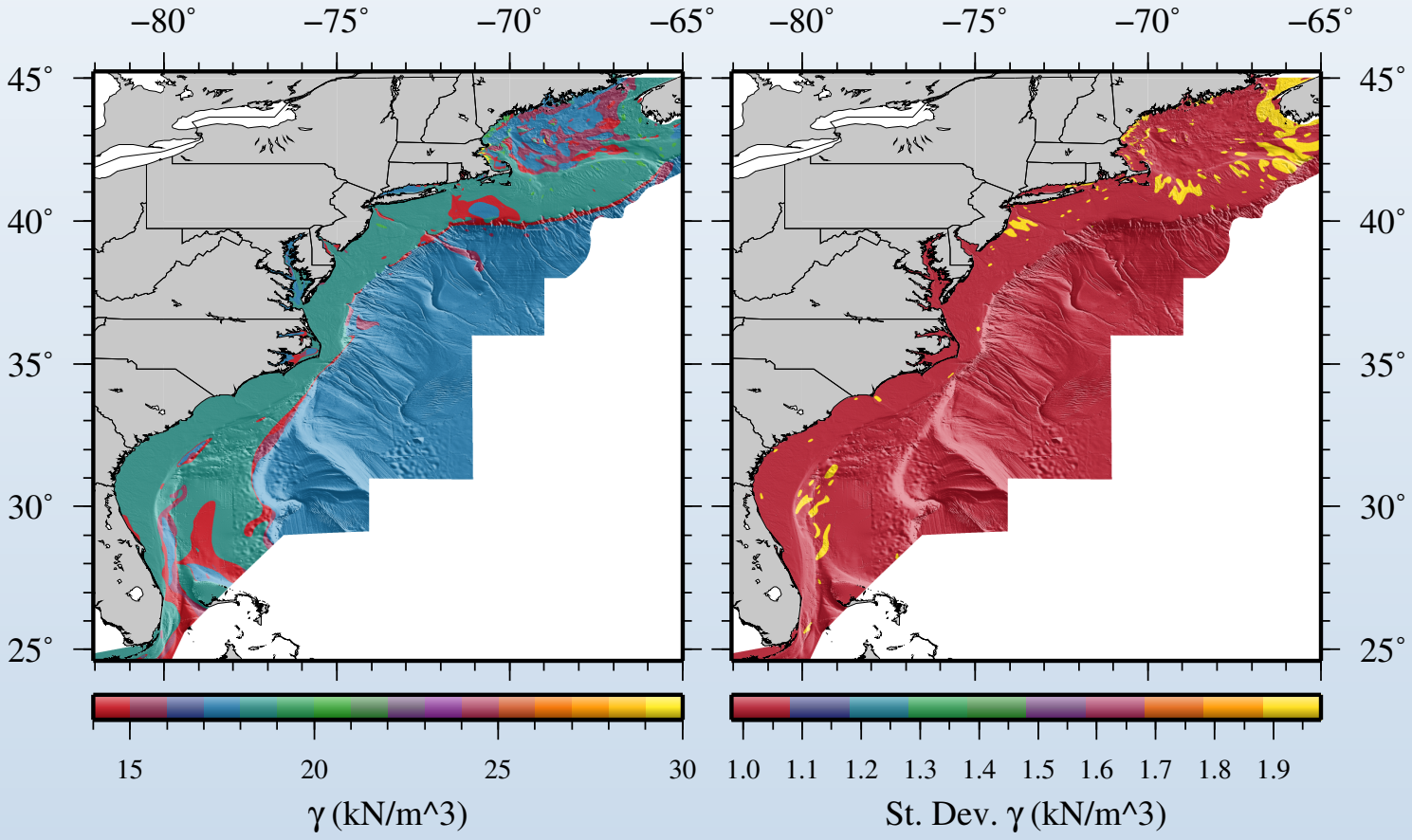
Here I use "stratified kriging", which is Ordinary Kriging applied to each sedimentary unit in turn.



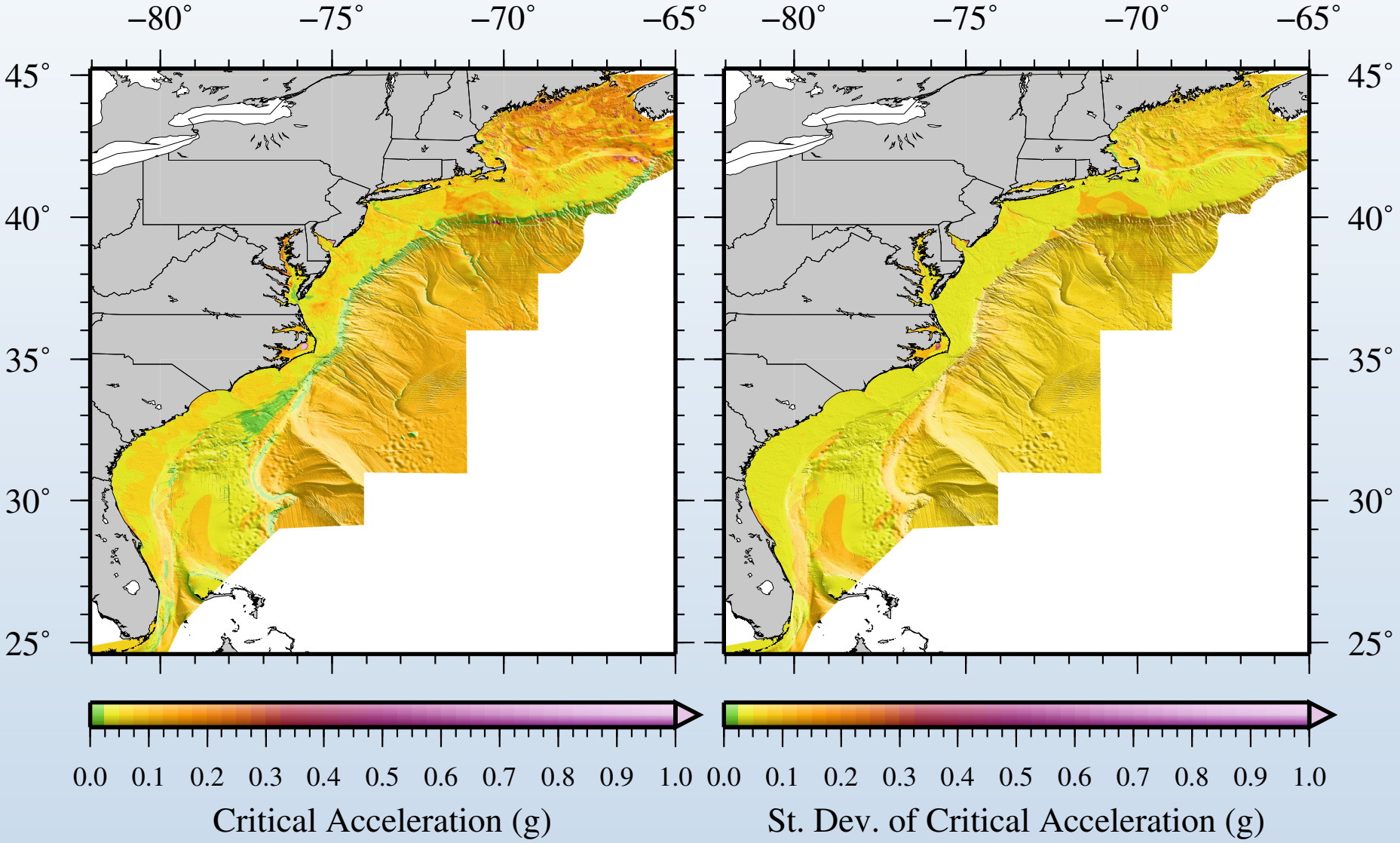


Unit weight γ

No direct measurements of γ exist, so interpolation is not possible. From ranges of literature values, I assess $\bar{\gamma}$ and σ_γ for the sediment classifications:



Results: critical acceleration (a_c)



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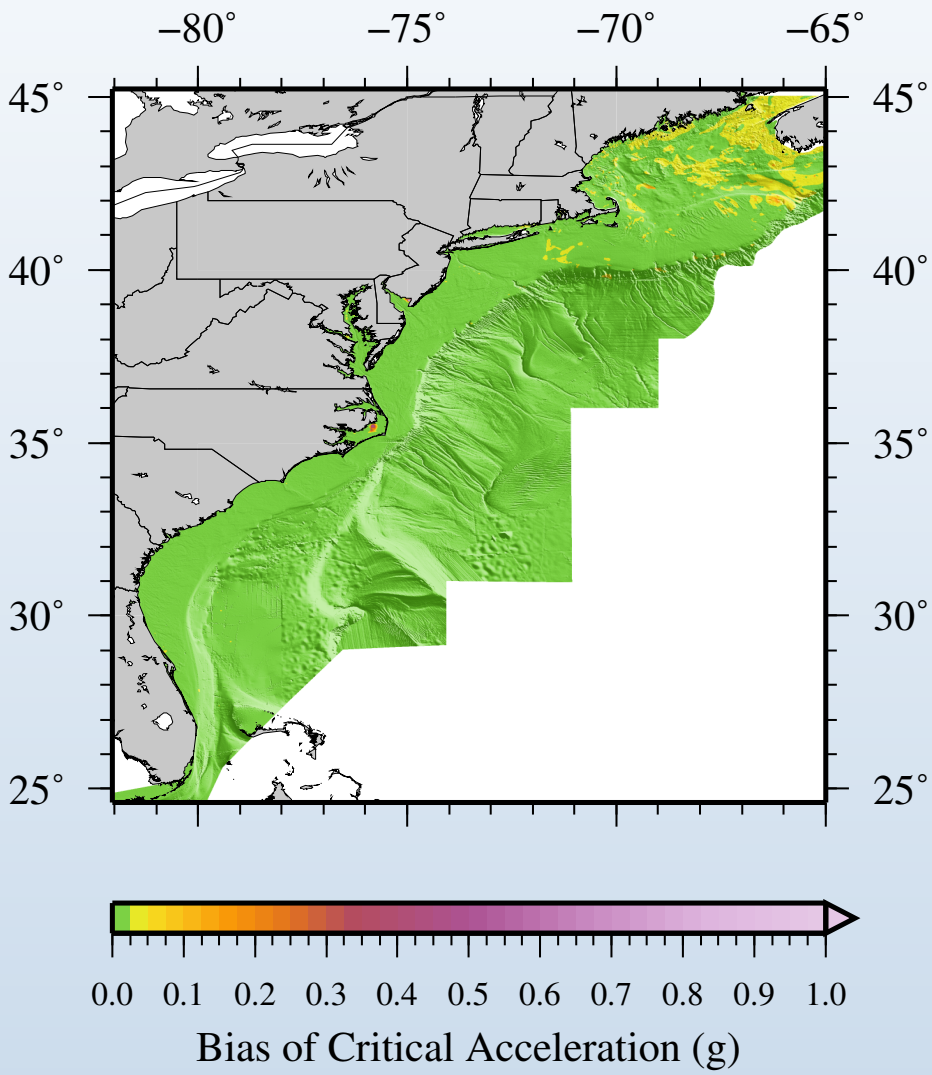
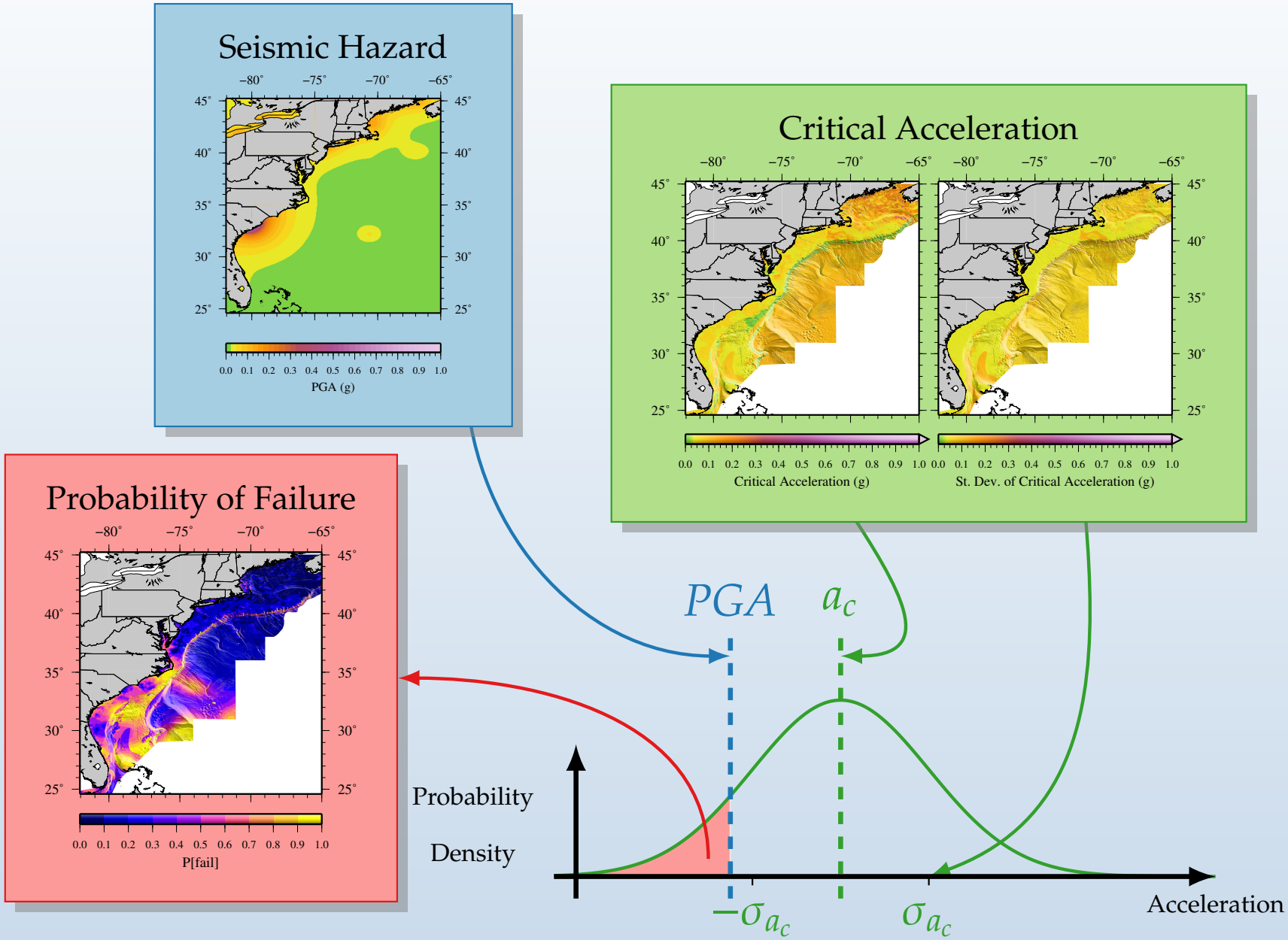
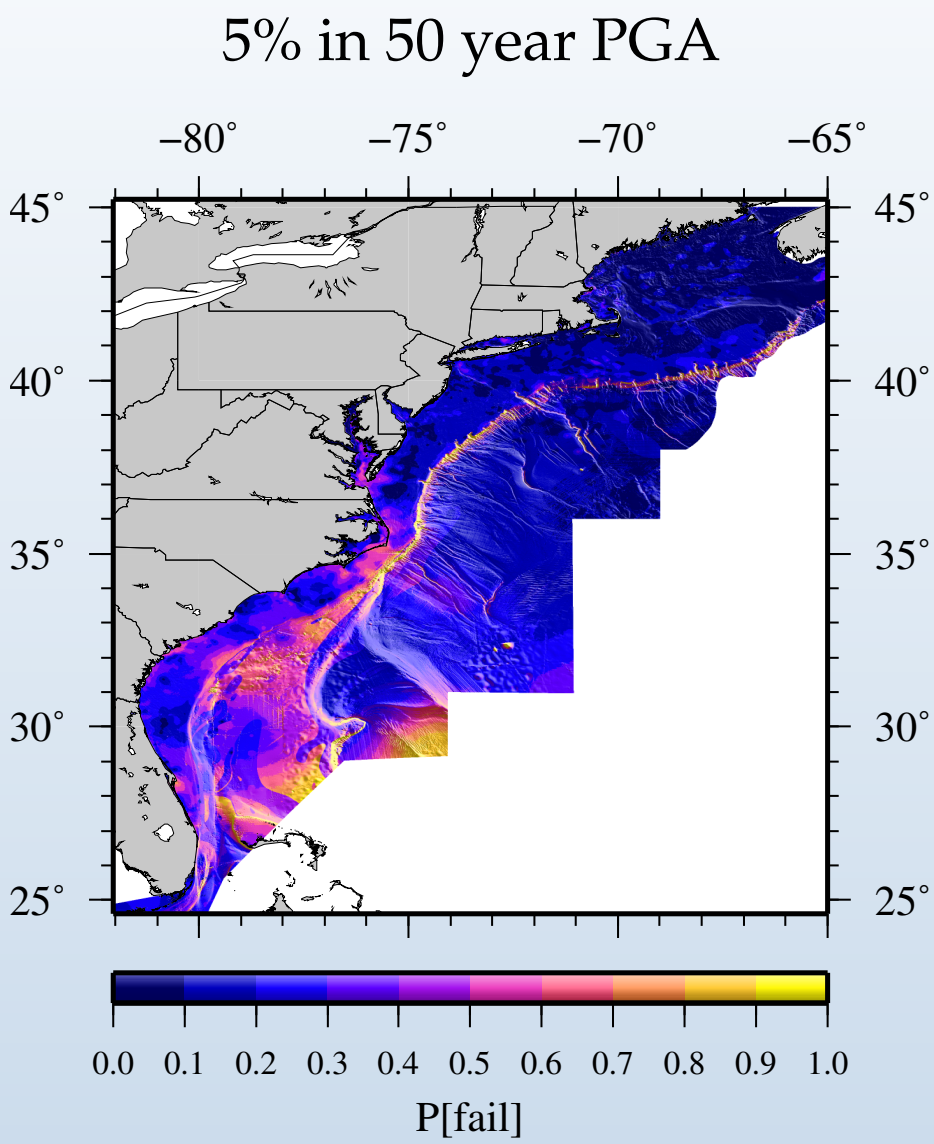
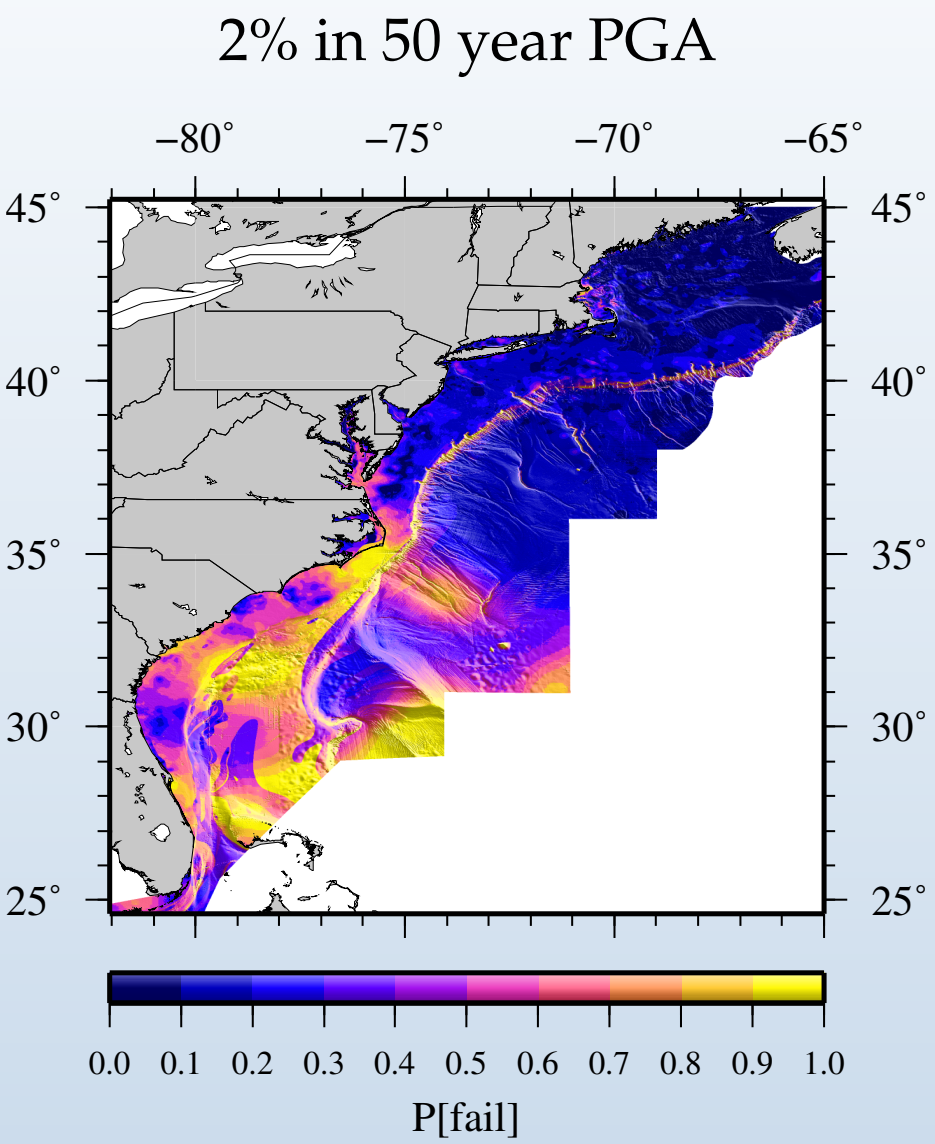


Those previous estimates of a_c were corrected by these biases.

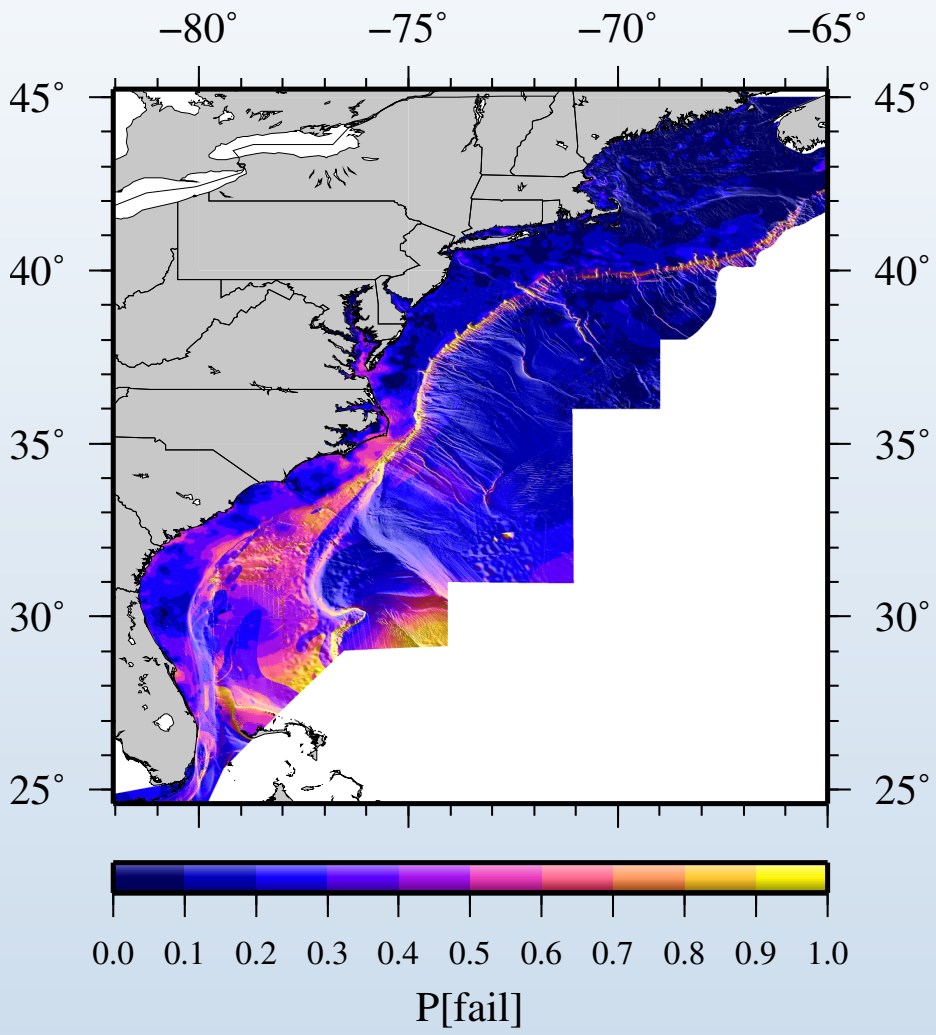
- Biases up to +15% of $a_c(\hat{\gamma}', \hat{s}_u)$
- Bias larger in north (southeast of Maine)
- Generally < 2% everywhere else


Seismic Hazard
−80° −75° −70° −65°
45° 40° 35° 30° 25°
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
PGA (g)
Critical Acceleration
Critical Acceleration (g)
St. Dev. of Critical Acceleration (g)
Probability of Failure
P[fail]
PGA
a_c
Probability
Density
$-\sigma_{a_c}$
σ_{a_c}
Acceleration


5% in 50 year PGA
−80°
−75°
−70°
−65°
45°
40°
35°
30°
25°
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
P[fail]


2% in 50 year PGA
−80°
−75°
−70°
−65°
45°
40°
35°
30°
25°
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0
P[fail]

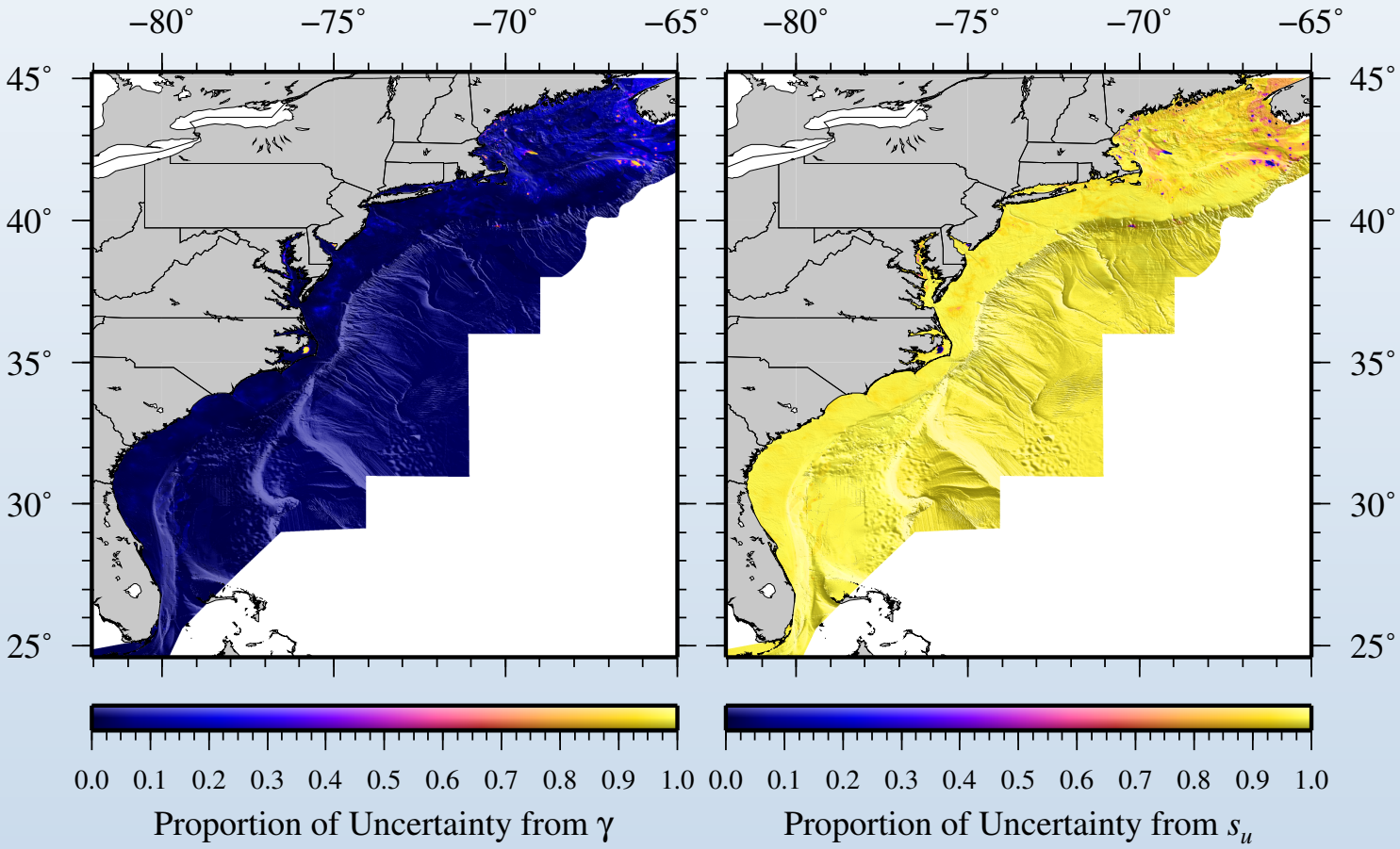
Probability of slope failure



- Continental slope ($2° < \alpha < 53°$) consistently has high P[fail] > 50%
- High hazard on open-slope and canyons
- But also high P[fail] in patches on shelf and abyssal plains
- Higher P[fail] in south partially due to higher PGA values (influence of $M = 7.3$ 1886 Charleston earthquake)

Proportion of $\hat{\sigma}_{a_c}$ from $\sigma_{\gamma'}$ and σ_{s_u} given by

$$\left(\frac{\partial a_c}{\partial \gamma'}\right)^2 \frac{\sigma^2_{\gamma'}}{\hat{\sigma}^2_{a_c}}, \quad \text{and} \quad \left(\frac{\partial a_c}{\partial s_u}\right)^2 \frac{\sigma^2_{s_u}}{\hat{\sigma}^2_{a_c}}.$$



Summary

- Combining FOSM, kriging, and basic slope stability model provides a detailed, rational, and well-informed map of P[fail]
  - Lateral variability of hazard along margin
- Continental slope:
  - generally P[fail] > 50%, both on open-slope and in canyons
  - slope angles > 2°
  - sand-clay/silt, sand-silt/clay, and sand/silt/clay, generally
- Sensitivity analysis tells us relative importance of parameter uncertainty: informs future data collection!
- Future work:
  - Extend to characterize tsunami hazard
  - This would involve knowing dimensions of probable slides; can use this FOSM analysis to find or simulate probable slides

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