

Introduction

Observed vertical sediment accumulation rates ($n = 1031$) were gathered from ~55 years of peer reviewed literature. Original methods of rate calculation include long-term isotope geochronology (^{14}C , ^{210}Pb , and ^{137}Cs), pollen analysis, horizon markers, and box coring. These observations are used to create a database of global, contemporary vertical sediment accumulation rates. Rates were converted to cm yr^{-1} , paired with the observation's longitude and latitude, and placed into a machine-learning based Geospatial Predictive Seafloor Model (GPSM). GPSM finds correlations between the data and established global "predictors" (quantities known or estimable everywhere; e.g. distance from coast line, river mouths, etc.). The result, using a k-nearest neighbor (k-NN) algorithm, is a 5-arc-minute global map of predicted vertical sediment accumulation rates. The map generated provides a global reference for vertical sedimentation from coastal to abyssal depths. Areas of highest sedimentation, $\sim 3\text{--}8 \text{ cm yr}^{-1}$, are generally river mouth proximal coastal zones and continental shelves on passive tectonic margins (e.g. the Gulf of Mexico, eastern United States, eastern continental Asia, the islands of Southeast Asia north of Australia), with rates falling exponentially towards the deepest parts of the oceans. Coastal zones on active tectonic margins display vertical sedimentation of $\sim 1 \text{ cm yr}^{-1}$, which is limited to near shore when compared to passive margins. Abyssal depth rates are functionally zero at the time scale examined ($\sim 10^{-4} \text{ cm yr}^{-1}$) and increase one order of magnitude near the Mid-Atlantic ridge and at the Galapagos Triple Junction.

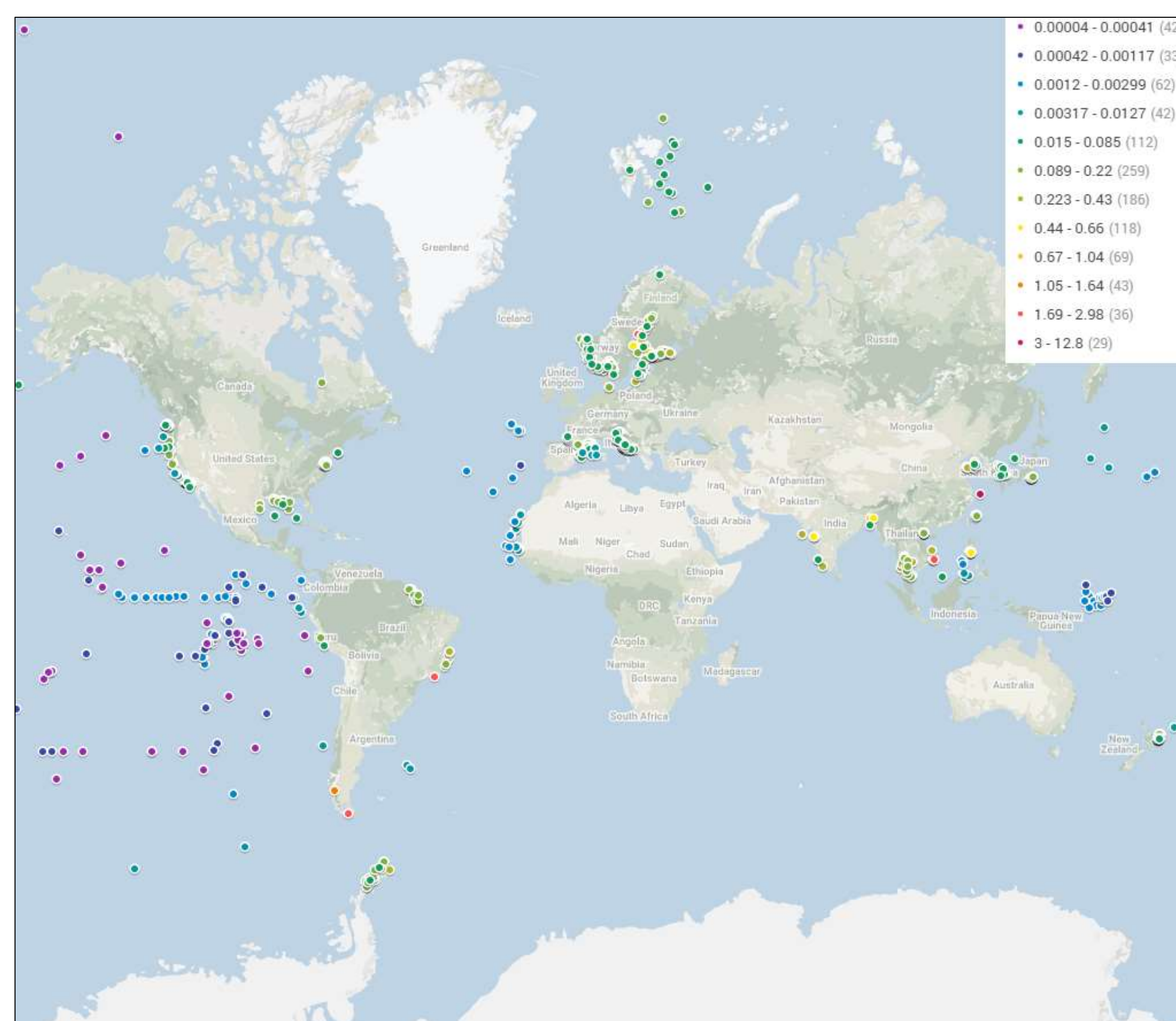


Fig. 1 Location and magnitude of all observations used in prediction.

Methodology

The k-nearest neighbor (k-NN) algorithm used in this study has been detailed in great technical depth in Lee et al. (2019). To briefly summarize, k-NN uses parametrically, not geospatially, nearest observed data points to calculate probable values in an area with no data. The parametric distance is calculated using predictor grids which are known or estimated properties about the water column and seafloor (i.e. water depth, distance from a river mouth, etc.) that are known globally. Predictor grids are generated from previously published research and open databases, for instance the 1/12 degree global HYCOM+NCODA Ocean Reanalysis and NASA's MODIS Aqua mission. In order to select the most relevant predictors, ten-fold validation is used. Ten-fold validation withholds a random 10% of all observations, with the remaining 90% used to predict. This is repeated until all points have been withheld and used in prediction. During feature selection, the prediction uses each grid individually and then cross validates to define the predictive skill of each individual grid. This is then compared to uniform random noise grids. Only the best predictors are used to define the final prediction and error; grids ranked below random noise grids are discarded.

Results

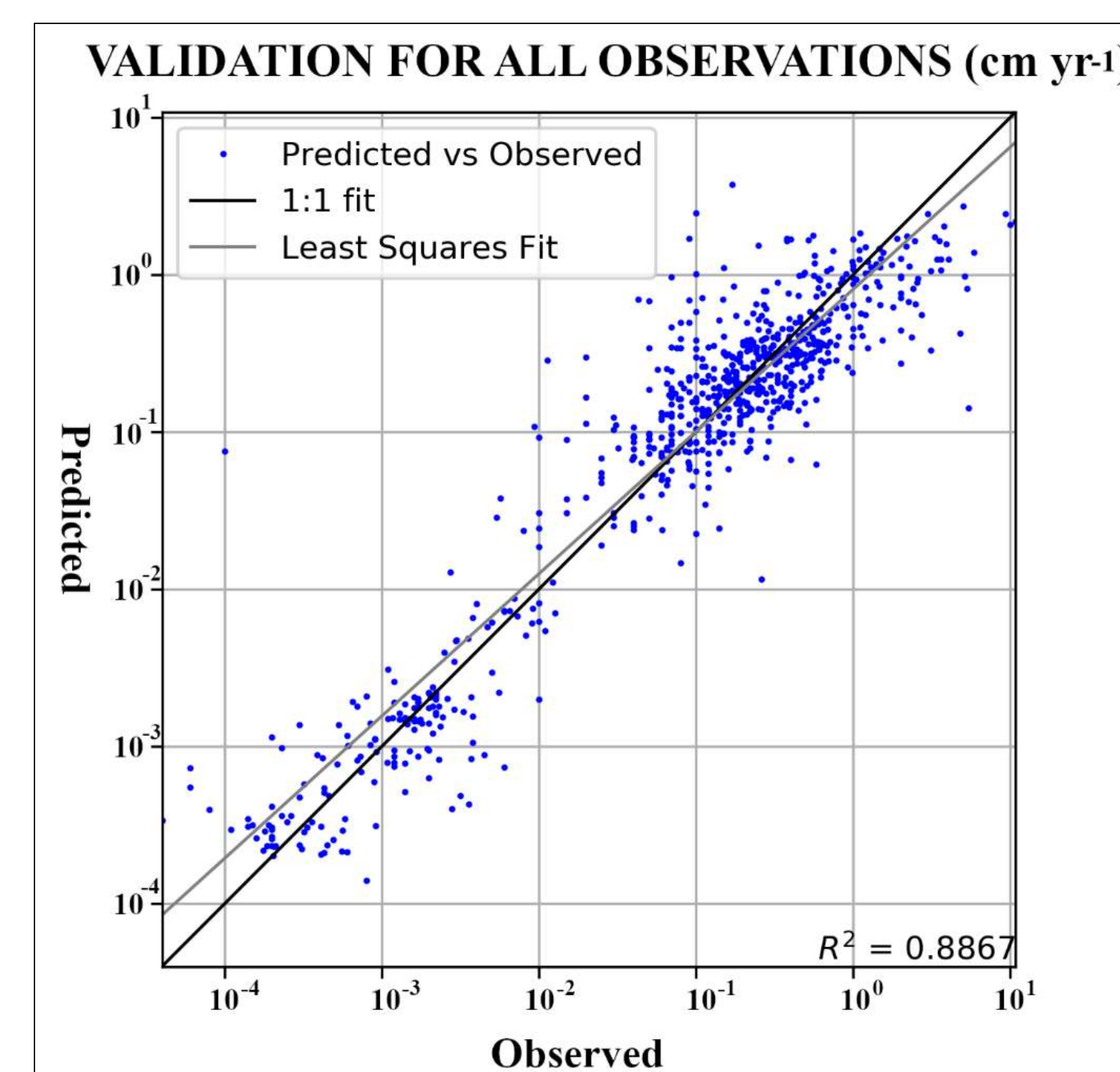
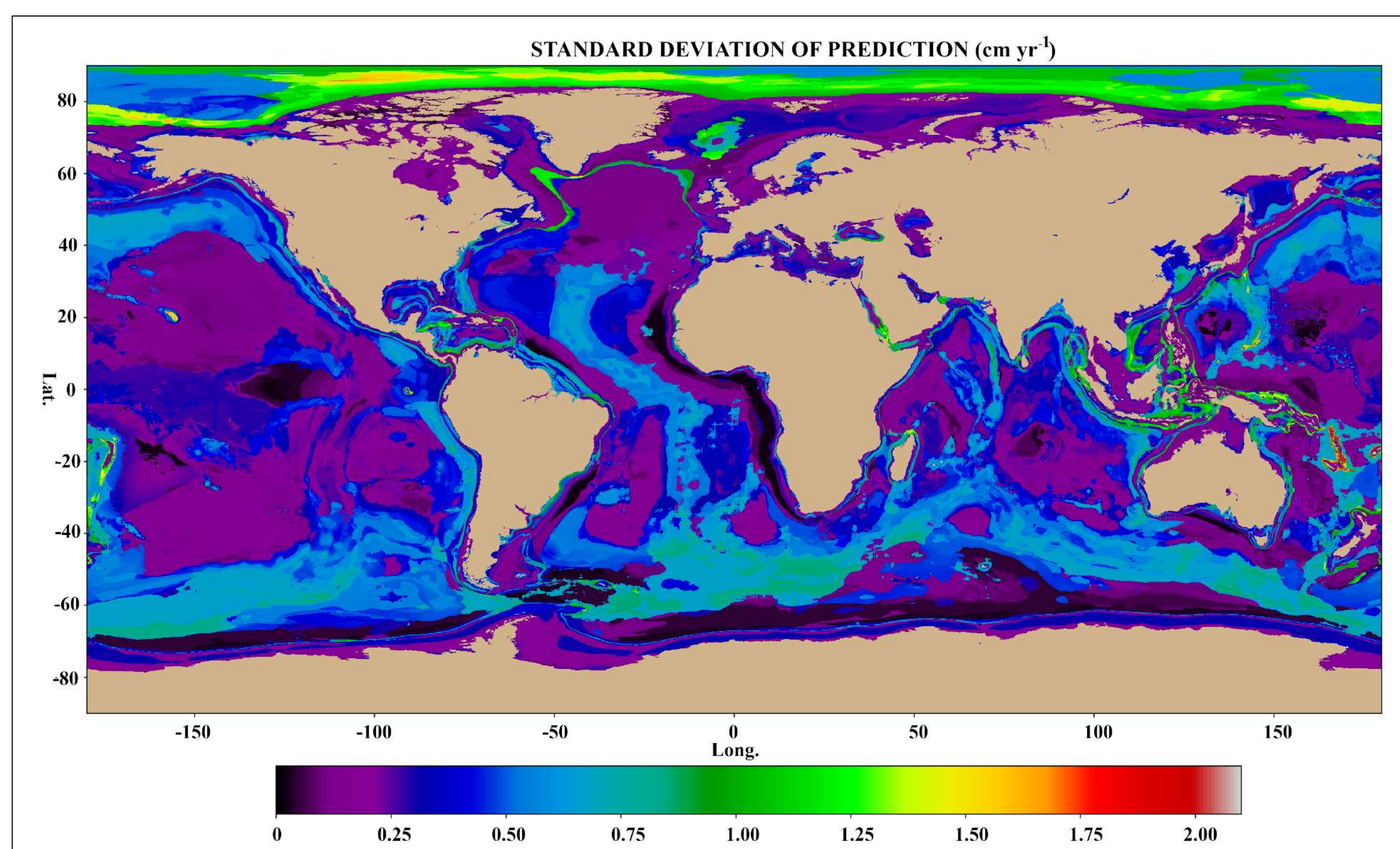
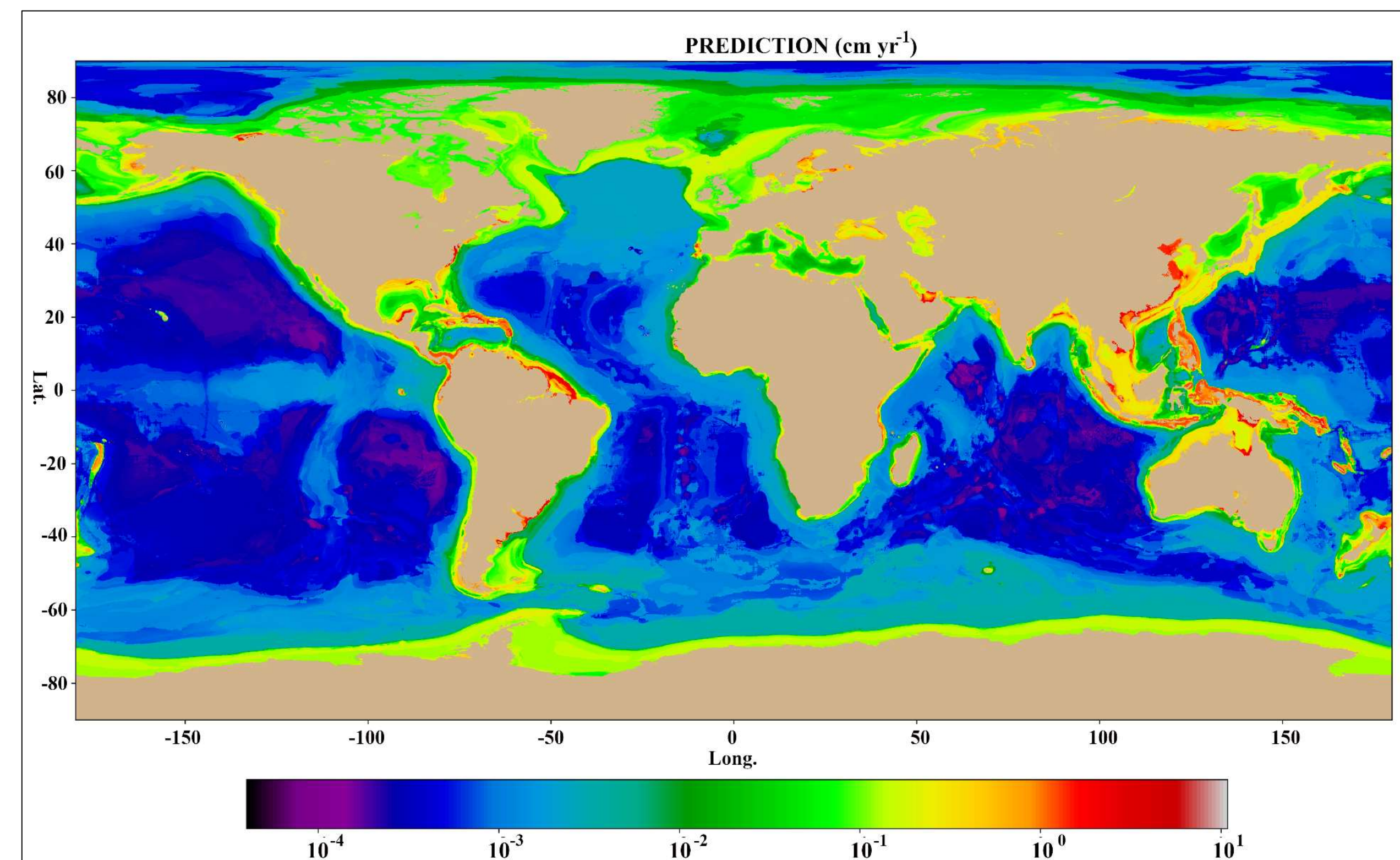


Fig. 2a-2c (top to bottom). Figure 2a is predicted vertical sedimentation rate across the globe. Note increase around major river outlets; 2b is standard deviation of the prediction; 2c is validation for the prediction.

Results

- The highest sedimentation rates ($\sim 1 - 8 \text{ cm yr}^{-1}$) occur proximal to river outlets on passive tectonic margins.
- Generally, shelf zones around all continents and islands display vertical sedimentation between $\sim 0.1\text{--}1 \text{ cm yr}^{-1}$.
- Rates in the deep ocean steadily decline by orders of magnitude towards deeper basins and away from subaerial land masses. The Pacific and Indian oceans contain the lowest values, functionally zero at the yearly time scale ($\sim 10^{-5} \text{ cm yr}^{-1}$). Rates increase slightly along the Mid-Atlantic Ridge and at the conjunction of the Cocos, Nazca, and Pacific tectonic plates, but remain functionally zero ($\sim 10^{-4} \text{ cm yr}^{-1}$).
- Coefficient of determination for the validation portion of the model is high ($R^2 = 0.89$). Standard deviation of the prediction is low to moderate in the deep oceans and along most coastlines; deviation increases along portions of the islands of Southeast Asia, a section of the northernmost Atlantic Ocean, and across the Arctic Ocean.
- The highest correlated predictor grids include river mouth TSS and dissolved organic carbon, wave direction, mean decadal sea salinity, and megafauna biomass, of which river mouth TSS was ranked highest.

Conclusions

- Presented herein is the first map of global sedimentation rates that provides a well-founded view of global, benthic sedimentation patterns with quantitative uncertainties. However, this is not a final prediction; the model is ever-evolving as new data on sedimentation rates is generated or discovered and added to the dataset.
- Austral-Asia is associated with the highest quantity of vertical sedimentation over the largest region, followed by the Amazon region and the Gulf of Mexico. These results are in line with the fluvial TSS flux to the oceans in Milliman and Farnsworth (2011).
- The deeps oceans aggrade vertically at a rate that is functionally zero at the yearly time scale, increasing one order of magnitude at the mid-Atlantic ridge and at the conjunction of the Pacific, Cocos, and Nazca tectonic plates.
- The extent of vertical sedimentation appears dependent on both fluvial flux and bathymetric gradient and depth. While fluvial sediment flux is required for significant vertical sedimentation, the gradient at which bathymetry deepens, as well as the depth itself, appear to be the primary controls on vertical sedimentation. Generally, the shallower the gradient the more extensive the vertical accumulation.
- Identification of areas with substantial vertical sedimentation allows for the recognition of unstable, slope failure prone regions, as the two are linked. This is of special importance in areas with sensitive infrastructure on or buried in the sea floor such as offshore oil platforms and pipelines.

References

- Lee TR, Wood WT, Phrampus BJ (2019) A machine learning (kNN) approach to predicting global seafloor total organic carbon. *Global Biogeochemical Cycles* (33):37–46.
- Milliman JD and Farnsworth KL (2011) *River Discharge to the Coastal Ocean: A Global Synthesis*. Cambridge University Press.

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