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Key Points:
• Data-driven geospatial models are used to predict depth change between 2005 and 2017 over ~100 km² of the Mississippi River Delta Front.
• Training models on 1% of available data resulted in 1-2 cm average predicted error depth change estimates for three methods tested.
• The K-nearest neighbor machine learning algorithm is recommended for geologically realistic depth change models.

Supporting Information:
• Supporting Information SI

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Abstract The subaqueous Mississippi River Delta Front is prone to seabed instabilities >1 m of vertical bathymetric change per year, but the ability to predict the location and magnitude of instability-driven depth change is limited. Here we demonstrate that data-driven geospatial models can predict MRDF depth change from a small amount (1% of full coverage) of training data. We predict depth change at 100 m² resolution between 2005 and 2017 over a ~100 km² area. Models trained on ~1% of full-coverage depth change data produce comparable and relatively low average predicted depth change errors (1–2 cm). K-nearest neighbors best reproduce the spatial variability of depth change and can interpolate and extrapolate from training data. This approach has immediate applications for geohazard monitoring on the MRDF and other geologically similar settings and can be applied in other settings if the drivers of depth change variance are well known.

Plain Language Summary Many river deltas worldwide have unstable seabeds that move vertically and laterally on yearly intervals, threatening seafloor infrastructure such as communication cables and pipelines. A common method to measure seafloor movement is with repeat bathymetric surveys, which are expensive and require considerable expertise. Here we introduce a new method that greatly reduces the resurvey data required to assess seafloor instability: using geospatial models to estimate depth change where it is not measured. We test three different models trained on a small amount (1% of complete resurvey coverage) of Mississippi River Delta Front (MRDF) depth change data and find the predicted depth change is comparably accurate (1–2 cm error) for all methods. We recommend the K-nearest neighbors machine learning method of the three, as it produces the most geologically realistic estimates and can predict depth change from multiple types of resurvey data. This method is applicable to MRDF-like deltas and can be modified to predict depth change in different geologic environments as well.

1. Introduction

Proximal accumulation dominated river deltas are characterized by flocculation and rapid deposition of fine-grained sediments (Walsh & Nittrouer, 2009). Gravity-driven instability features such as mudflow gullies, collapse depressions, delta-lip failures, and turbidity currents are documented on such deltas, displacing and destroying seafloor infrastructure such as pipelines and cables (Chaytor et al., 2019; Clare et al., 2016). Preconditioning and triggering factors of seabed instability on proximal accumulation dominated deltas include, but are not limited to, underconsolidated sedimentation and associated oversteepening (Adams & Roberts, 1993), biogenic gas accumulation (Whelan et al., 1976), and cyclic sediment loading via storm wave passage (Bennett, 1977).

The subaqueous Mississippi River Delta Front (MRDF) is a large proximal accumulation dominated delta extending from Louisiana, USA, into the Gulf of Mexico (Figure 1a). The MRDF has been morphologically categorized into zones of mudflow gullies, mudflow lobes that coalesce downslope of the gullies, and undisturbed seafloor (Coleman & Prior, 1981). Morphology-based classification efforts provide broad guidelines for seafloor infrastructure geohazard risk, but recent studies show that instability-driven MRDF depth change is heterogenous in location and magnitude (Obelcz et al., 2017). Multibeam mapping efforts are resource-intensive and yield relatively small coverage areas (Hughes Clarke et al., 2014).

The paucity of marine geological data has spurred data-driven efforts to predict seafloor parameters at unsampled locations based on geologic similarity to sampled locations (Phrampus et al., 2020; Stephens &
Such techniques provide estimates of the parameter derived from observations and do not require parameterized, deterministic models. In this study, we use geospatial models trained on multibeam bathymetric survey-derived depth change data collected on the MRDF to predict depth change.

2. Study Site and Data

2.1. Depth Change Observations

Depth change on the MRDF is primarily controlled by three factors: (1) seabed movement within mudflow zones, (2) self-weight sediment compaction, and (3) accretion via river plume sediment deposition (Maloney et al., 2020). The latter two factors are relatively invariant over the ~100 km² prediction domain (Figure 1b).
and produce an order of magnitude less depth change (decimeters/year vs. meters/year) than instability-driven seabed movement over decadal timescales (Keller et al., 2017; Figure 2 in Obelcz et al., 2017; Tornqvist et al., 2008). This allows difference of depth (DoD) between bathymetric surveys to be used as a proxy for seabed instability.

The training and validation data set for DoD models is from two multibeam bathymetric surveys conducted at the MRDF Southwest Pass region (Figure 1). Previous repeat surveys of mudflow zones in 2005 and 2009 showed average depth change ~1 m/year (Obelcz et al., 2017). The first survey was conducted October, post-Hurricanes Katrina (August)/Rita (September) 2005 (Figure 1b, Walsh et al., 2006) and the second in 2017 (Figure 1c, Baldwin et al., 2017). Maximum depth change exceeded ±10 m (Figure 1d), with an average value of ~2.6 m deepening, a trend reflecting the overall deepening of the subaqueous MRDF since the 1970s (Maloney et al., 2018).

2.2. Predictors

Predictors are defined here as geologic or geomorphic parameters that collectively explain the geospatial DoD variance observed on the MRDF. Factors possibly contributing to MRDF DoD variance are included as predictors: sedimentation rate, biogenic gas depth, morphology, and sediment shear strength. These parameters are estimated using radiochemical tracers, depth to acoustic signal attenuation derived from subbottom profiles, bathymetry, and geotechnical measurements, respectively. Other core-derived predictors used (grain size, clay fraction) may be correlated with seabed instability but do not degrade predictive skill if not.

Predictors used come from four data sets: (1) the 2005 multibeam bathymetry survey (Figure 1b, Walsh et al., 2006), (2) a 2014 seabed sampling campaign (Keller et al., 2017), (3) a 2014 Chirp subbottom profiler survey (unpublished data), and (4) a 2017 geotechnical campaign (methods can be found in Moernaut et al., 2017). A description of the predictors derived from these data sets can be found in the supporting information.

All predictors were resampled and/or interpolated to the extents (Figure 1c) and resolution (100 m²) of the 2017 bathymetric survey. For measurements derived from seabed samples (cores, shear strength), inverse distance weighting was used to interpolate between points. The depth to signal loss was digitized from Chirp subbottom profiles and interpolated to produce a continuous surface in methods following Benites et al. (2015).

3. Difference of Depth Prediction Methods

Machine learning predictions were generated using the Naval Research Lab’s Global Predictive Seabed Model (GPSM) framework. GPSM is built on the Python SciKit-Learn library and produces machine learning geospatial predictions of seabed measurements. The k-nearest neighbor (KNN) algorithm provides minimal hyperparameters to tune and was therefore chosen over other machine learning methods encoded within GPSM, including random decision forests and support vector machine.

KNN uses proximity in normalized parameter space between observations and unmeasured locations as a proxy for similarity. The distance from each DoD observation (in parameter, not geographic space) is calculated for each predicted location, and the average of KNNs (weighted for distance in parameter space, k = 7 for this study) is assigned. This approach is nonparametric, makes no assumptions regarding the probability distribution of observed data, and does not assume spatial autocorrelation. A full description of the KNN method as implemented within GPSM can be found in Lee et al. (2019).

3.1. KNN Predictor Selection, Ranking, and Dimensionality Reduction

Statistics of predictor grids (mean, log mean, average absolution deviation, log deviation) were calculated from predictors described in section 2.2. The statistics were recursively calculated using a moving radial window of increasing size: 0.2, 0.4, 0.6, 0.8, 1, 1.5, 2.0, 2.5, and 5 km. This allows the KNN algorithm to detect predictor-observation correlation at various length scales.

All predictors (original grids and derived statistics) are standardized with a mean of 0 and a standard deviation of 1. Grids are ranked by correlation with observed values, and predictors with ≥99% correlation with other predictors are discarded. In addition, three random noise grids are added to the predictor list, and
any predictors with lower correlation to observations than a random noise grid are omitted. An $n$-dimensional prediction parameter space is then constructed, where $n$ is the final number of predictors.

### 3.2. Prediction Validation, Benchmarking, and Uncertainty

Prediction validation is conducted by comparing predictions to withheld test data. The metrics of prediction skill include mean and median prediction error, the coefficient of determination ($r^2$) of the predicted-observed validation, and a qualitative assessment of how geologically “realistic” the predicted DoD appears. As a benchmark for DoD prediction using KNN, DoD predictions were also made using the inverse distance weighting (IDW) and Kriging methods via ArcGIS’s Geostatistical Wizard toolbox.

Prediction uncertainty can be parsed into two main components: observation uncertainty and prediction uncertainty. A uniform observation uncertainty was assigned as values within the 95% confidence interval ($2\sigma$) of DoD in the “prodelta” region of the MRDF, where depth change is generally invariant over small (km-scale) length scales (Obelcz et al., 2017). The prediction uncertainty is assigned to each predicted location as the sum of the observation uncertainty and the standard deviation of the KNNs, which has been empirically shown to scale with prediction error (Lee et al., 2019).

### 4. Results

Continuous DoD data (Figure 1d) were subsampled into regular one-dimensional north-south transects at 1% of the original data density as model training data. This subsampling emulates an initial full-coverage multibeam bathymetric survey reoccupied by a single beam echosounder survey or widely spaced multibeam swaths. The withheld 99% of data were then used as test data for validation.

The KNN DoD prediction (Figure 2a) generalized DoD geospatial trends, predicting accelerated deepening around gully zones and below average deepening on mudflow lobes. The IDW prediction also generalized DoD trends, but the interpolation methodology produced linear artifacts (Figure 2b). Kriging predicted the smallest DoD range and had more gradual spatial variance in predicted DoD (Figure 2c).

DoD prediction methods can be quantitatively compared (Figure 3). Error metrics are generally comparable between the three methods, with mean and median predicted error clustered around 1 cm. Standard deviation of the errors, however, is on the order of 1 m, indicating that the predictions are on average accurate but with a wide scatter. This can be visualized by plotting the observed and predicted data against each other (Figure 4). KNN predicts depth change location correctly but generally underpredicts the magnitude, IDW produces bands of elevated error, and Kriging does not resolve mudflow gullies or lobes. These trends can be qualitatively visualized through a transect across the prediction domain; KNN trained on 10% of observed data converged with observed DoD (Figure 5). KNN also has the capability to extrapolate, in addition to...
interpolate from a continuous patch of data, provided that data adequately sample the geological parameter space (Figure 6).

5. Discussion

5.1. Depth Change and Spatiotemporal Survey Resolution

Discussion of repeat bathymetric surveys for geohazard monitoring must acknowledge that time series depth change observations alias events of higher frequency than the resurvey interval used. For example, daily bathymetric resurveys resolved rapid meter-scale sedimentation and subsequent delta-lip collapse on the Squamish River Delta that would have registered as little to no change with annual resurveys (Vendettuoli et al., 2019). Therefore, baseline knowledge regarding frequency and magnitude of instability events is critical to designing a hazard monitoring program, with or without machine learning augmentation—an MRDF knowledge gap that has yet to be resolved.

Figure 3. Observed-predicted residual maps for difference of depth predictions shown in Figure 2, with statistics inset. (a) K-nearest neighbor. (b) Inverse distance weighting. (c) Kriging. (d) Mudflow gullies (red polygons) and lobes (blue polygons) as digitized from 2005 bathymetric survey.
5.2. Generalizing Difference of Depth Trends From Sparse Observations

This study tests whether geospatial prediction models can reduce the volume of data required for marine geohazard assessment surveys. Using three geospatial prediction models trained on regularly spaced, sparse (1% of full coverage) DoD observations, we show that DoD can be approximated where it is not directly measured. Furthermore, we show that the KNN machine learning method can not only predict DoD with comparable accuracy as methods that rely on explicit spatial autocorrelation (here, IDW and Kriging, Figure 3), but it creates more geologically realistic predictions as well (Figures 2 and 5). Provided the level of DoD prediction accuracy and uncertainty demonstrated is acceptable (Figure 4) for a given application, resurvey data required for geohazard assessment could be reduced by 2 orders of magnitude.

There are limitations and caveats that must be heeded for any geospatial modeling technique. IDW and Kriging rely on spatial autocorrelation, but in dynamic areas such as the MRDF spatial proximity does not always imply similarity. This can result in severe misfit between observed and predicted values, particularly near the boundary between undisturbed seafloor and mudflow zones (Figure 5). Kriging also assumes (or fits the observed data to) a Gaussian probability distribution, while many geohazard-related phenomena instead follow power law distributions (Chaytor et al., 2009).

![Figure 4](image1.png)

Figure 4. (a) Observed-predicted validation of K-nearest neighbor difference of depth prediction trained on 1% of available data. Gray ellipses represent prediction uncertainty. (b) Validation heat map, showing same data in (a) as log-transformed binned count instead of individual points.

![Figure 5](image2.png)

Figure 5. Comparison of difference of depth predictions and observed data visualized as a one-dimensional West-East transect across the study area; transect location shown in Figure 1d.
The KNN machine learning method bypasses several of the limitations of IDW and Kriging—namely, that spatial autocorrelation is not explicitly assumed and no a priori data probability distribution is assumed. However, KNN still requires (1) predictions to be made in the appropriate parameter space and (2) training observations that sample the entire parameter space. Specific to this application, this requires all predictors that control depth change to be provided and a representative range of DoD values for the prediction domain.

5.3. Applying Machine Learning Difference of Depth Predictions to Other Settings

Predictors selection for this study was guided by previous studies identifying factors important in controlling MRDF seabed stability. Therefore, this approach should be applicable to other proximal accumulation dominated delta systems, such as the Po, Nile, and Yellow River deltas (Walsh & Nittrouer, 2009), provided predictors collectively explain depth change over the spatiotemporal prediction domain. Heavily sedimented river deltas also tend to be societally and economically important, and the ability to produce comprehensive DoD maps with a fraction of the field effort previously required represents a significant advancement.

For dissimilar geologic settings, depth change will be controlled by other processes, such as tectonics, oceanographic processes, or anthropogenic activity. Therefore, a relatively high knowledge baseline regarding the area where depth change is to be predicted is a prerequisite. Fortunately, data acquired during field efforts to acquire this baseline knowledge can frequently be repurposed post facto into predictors—this was the case for all predictors used in this study.

6. Conclusions

This study demonstrates that data-driven geospatial prediction models can reduce the volume of data required for marine geohazard assessment surveys in instability-prone regions by a factor of 3. Sparse sub-samples of a full-coverage multibeam bathymetric difference of depth (DoD) resurvey between 2005 and 2017 on a ~100 km² area of the MRDF were used to train the models, and residuals between the withheld and predicted values were used for model validation. IDW and Kriging rely on spatial autocorrelation to make predictions, while KNN searches a user-defined parameter space to find and assign average values of the KNNs.
The three geospatial models were found to all make comparably accurate DoD predictions (mean and median errors ~1–2 cm), with a higher prediction standard deviation (80–100 cm). The models produced characteristic error patterns: IDW predictions had East-West “bands” of high error, Kriging predictions did not deviate far from average depth change values, and KNN underpredicted and overpredicted DoD in mudflow zones. The KNN method performed best resolving locations of elevated depth change. Additionally, KNN is capable of extrapolating DoD variance from a “patch” of resurvey data, a capability not shared by IDW and KNN.

This approach to modeling depth change has immediate applicability to geohazard monitoring in settings geologically similar to the MRDF; instead of resurveying an entire previously surveyed location to assess instability-driven depth change, sparse resurvey transects or patches could be acquired and KNN could be used to interpolate between measurements. Similarly, this approach could be applied to geologically dissimilar settings provided the drivers of depth change are qualitatively known and can be included as predictor grids.

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