Using GIS to Explore the Tradeoffs in Hydrographic Survey Planning: An Investigation of Sampling, Interpolation, and Local Geomorphology

by

Sarah Rosenthal

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To Christopher Kelley.

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List of Abbreviations

ASV/AUV	Autonomous surface vehicle/autonomous underwater vehicle
CART	Classification and regression trees
DEM	Digital elevation model
EBK	Empirical Bayesian kriging
ENC	Electronic navigation chart
GEBCO	Global Bathymetric Chart of the Oceans
GIS	Geographic information science/system
GPS	Global positioning system
IDW	Inverse distance weighted
IoT	Internet of Things
LIDAR	Light detecting and ranging
LLN	Law of large numbers
MBARI	Monterey Bay Aquarium Research Institute
MBES	Multibeam echosounder
MLA	Machine learning algorithm
RF	Random forest
RTK	Real time kinematic
SDB	Satellite derived bathymetry
SDG	Sustainable Development Goal
SONAR	Sound navigation and ranging

Abstract

The lack of seafloor information is often a result of the challenging logistics and expenses involved with acquiring data in this unique environment. Yet, despite the sparsely sampled environment, many significant efforts exist to create global bathymetry models. However, there exists a public misunderstanding of the true sampling density in the ocean that can be largely attributed to contemporary interpolation and enhanced cartography. The seafloor is more sparsely sampled than most people realize. Thus, it is important to understand the influence of the underlying source data and the interpolation technique used when creating an accurate digital bathymetry model. The accuracy of a surfaces can depend on sampling density, interpolation method, and local geomorphology. However, if a bathymetry surface can be accurately created using sparse measurements, mission planning can be directed to sample the seafloor at a certain resolution. The results of this thesis research encourage future exploration of a computationally efficient method to assess the best method of interpolation method in different regions under different conditions.

Chapter 1 Introduction

This introductory chapter discusses the history of seafloor mapping, why bathymetry measurements remain so sparse, and why there are limited accurate measurements of shallow bathymetry. To conclude this section, the research goals and significance of this thesis are outlined.

1.1 History of ocean mapping

The term bathymetry refers to the measurement of various depths and shapes formed by underwater rock or sediment features on the seabed (NOAA 2019). Bathymetric data is an essential component within the field of hydrography that can be used to characterize baseline information. Bathymetry is critical to many multidisciplinary oceanographic operations including biological, geophysical, atmospheric, and even meteorological processes.

Endeavors to obtain bathymetry have presented a challenging task throughout history. The first historical accounts of recording measurements of underwater depth dates back to ancient Egypt in 1800 B.C. (Theberge 1989). Early measuring techniques involved a weighted lead rope deployed from the side of a ship and lowered into the water until it reached the bottom. While believed to be a practical preliminary tool at the time, this method did not consider more than one specific point on the seafloor at a time, and nor did it include precise position measurements.

Bathymetric surveys have since evolved from simple, extremely time-consuming techniques, to innovative methods involving sound waves. Largely inspired by submarine warfare in World War I (1920), sensors were developed that used sound waves to listen and detect objects underwater (University of Rhode Island 2019). This efficient two-way sound travel prompted the significant development of single beam echosounders (SBES) (Mayer 2006).

This improved technique involved an acoustic signal from a ship that is sent down towards the seafloor and back. This permits depth to be calculated based on the speed of the signals return. This method was expanded upon with the multibeam echosounder (MBES) which provided extended swath coverage and increased efficiency in terms of the ship resources.

While sound navigation and ranging (SONAR) are considered the most effective high-resolution acquisition technique, limitations do exist. These systems are typically mounted on the hull of ships which restrict their use to only mapping deep waters. Ships operating hydrographic missions require slower transit speeds in order to accurately acquire seafloor coverage and avoid gaps. The fuel required to operate large ships constrains their use to regions whose hydrographic offices have designated budgets to support these costly missions. The tradeoff between resolution, propagation, and coverage has been recognized as the limiting factor in collecting MBES data (Mayer 2016).

Often in shallow regions various physical and morphological features make these areas the most challenging to survey by ship. Modern remote sensing technology such as satellite-derived bathymetry (SDB) and light detecting and ranging (LIDAR) can also provide information on the seafloor. SDB is derived from multispectral imagery and uses remote platforms to collect data spanning multiple spectral bands. Bathymetric LIDAR uses a green wavelength to penetrate the water column through airborne acquisition technology. Both acquisition sources, however, come at a high cost in terms of the technical production and operation. These optical solutions to monitoring bathymetry also are limited by water clarity and depth. In coastal regions, collection of adequate shallow bathymetric measurements with optical techniques only work as well as the water clarity permits.

Currently, there is a shift in the hydrographic community towards applications of autonomous survey technology and processing techniques. Two common forms are autonomous surface vehicles (ASV) and autonomous underwater vehicles (AUV). This transition towards autonomy reduces time and human efforts, that are otherwise very costly in ship-based surveys. Autonomous systems offer an advantage of operating in hazardous sites and areas where ships cannot navigate, such as shallower waters or underwater caves. Nevertheless, high quality data of the shape and depth of the seafloor remain a foundational requirement for operation planning before a vehicle can be deployed.

1.2 Bathymetry compilation efforts

Technological advances in the past few decades have seen a substantial increase in the ability to compute and digitally visualize the globe. The international General Bathymetric Chart of the Oceans (GEBCO) has spent the past 100 years collecting and sharing global bathymetry data. This dataset compiles high resolution MBES data fused with a background of coarse resolution satellite altimetry. Figure 1 reveals the GEBCO 2014 model, an enhanced view of the quality of the surface, and the underlying data used to create the model. A recent evaluation by Mayer (2018) showed that 82% of the GEBCO data product contains no data values. This means that only 18% of gridded cells across the globe contain actual data values. The results of this gap analysis also revealed that of those gridded cells that contain data, only 9% contained data collected by modern sonar technology capable of producing reliable measurements.

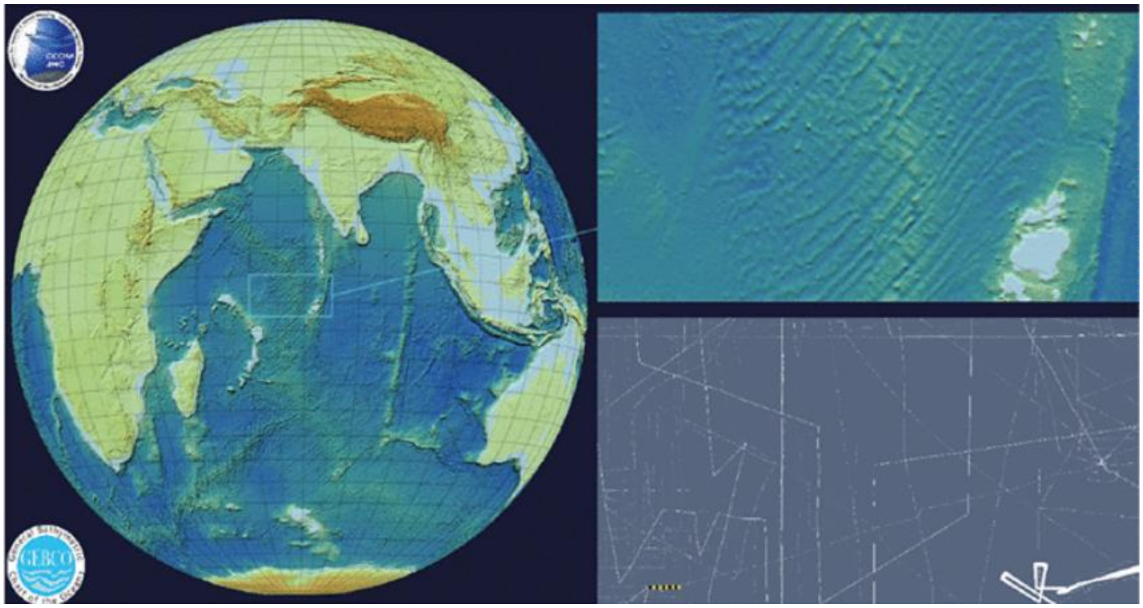

Figure 1: GEBCO 2014 model (left), the sparsity of underlying high-quality data (upper right), and the actual multibeam sonar tracks (lower right) traveled to collect the swath data. (Mayer 2018).

The coastal regions represent an unusually challenging area for hydrographers. Due to the lack of data in this highly transitional zone, the coastal zone is often referred to as the "white ribbon" (Leon et al. 2013). Much of the known data in coastal regions comes from electronic navigation chart (ENC) soundings. Hydrographic standards allow for contours or sounding points to be extracted from ENC to be used in the production of gridded models. There is often a strong bias in the spatial presence of these soundings in favor of societal needs (Zoraster and Bayer 1992, Haigang et al. 2005). The horizontal spacing of soundings are primarily concentrated around shoals, shipping lanes, and ports.

Many coastal regions also hold restrictions to data access making published ENC charts the only viable option for estimating the seafloor. Coastal regions are also notorious for continuous change due to many natural and anthropogenic influences. These frequent changes demand updated survey coverage in order to maintain accurate data. At a local scale, incomplete or missing coastal elevation data can prevent communities from understanding their own region and lead to misrepresented needs for management and protection (Hogrefe, Wright, and Hochberg 2008). Legacy depths displayed on ENCs are often less than ideal and do not accurately reflect the current depth.

1.4 Significance and goals of research

The ocean covers 71% of the Earth's surface and is a critical component to sustaining life, controlling climate, facilitating commerce and managing marine resources. A complete digital representation of the seafloor is necessary for an understanding of ocean science. Additionally, the physical, chemical, and biological characteristics of many marine systems are influenced by benthic depth and features. Yet despite its importance, most of the marine environment remains unmapped and unexplored.

A challenge in creating an accurate bathymetry model is filling the gaps where data acquisition is consistently difficult, expensive, or not accessible. Enabled by advances in computer science and geospatial technology, interpolation allows for continuous surfaces to be generated from remotely sensed data without the need to measure each individual location. Yet the elevation models obtained from interpolation analysis are often blindly accepted as the absolute truth. It is important to consider the underlying spatial configuration and choices made in the process of creating a surface.

This thesis works towards understanding the influence of source data density and interpolation methods on bathymetry accuracy. Specifically, this thesis research addresses the question, which interpolation method will provide superior results when measurements are collected with half the spatial frequency as the original sampling density. The second objective presses on to consider if fewer measurements can be taken while generating relatively similar results. In order to accomplish this objective, two geomorphic regions within Monterey Bay will be explored using three different interpolants and four different densities of input data.

The significance of this research will be an increased understanding about the trade-offs made when constructing a bathymetric model of a region with regard to sampling density, interpolation methods, and local geomorphology. The main takeaway from the results derived in this study is an improved understanding of how interpolants preform, with varying levels of sparsity in sampling, in different types of coastal geomorphology. The implications of these results can assist with decision making in planning future coastal surveys, as well as help understand the results and accuracy of existing surveys.

1.5 Thesis organization

The organization of the remainder of this thesis begins with a review of the published literature on the process of creating surfaces, and several interpolation techniques. The third chapter discusses the methodology used in this study, including an overview of the study area and its properties, GIS data preparation, and interpolation analysis. The fourth chapter provides the results of the analysis. The final chapter concludes with a detailed discussion of results, study limitations, and future work.

Chapter 2 Background

This section begins with an evaluation of literature studies that evaluate the process of generating surfaces from point measurements, and then considers different techniques of doing so along with their benefits and shortcomings.

2.1 Creating a surface

Models of elevation have been a subject of interest since the sixteenth century. Techniques that create these models have seen substantial changes over the last few decades as technology advances (Eakins and Grothe, 2014). In an ideal world, consumers of spatial data would be able to completely rely on digitized surfaces that are composed of tightly grouped measurements. Yet the ubiquitous nature of sparse remotely sensed data demands the existence of many different methods, techniques and models that create a surface from different types of data. Ultimately sources of error in a digital surface can be the result of input data or decisions made by an analyst. It is important to understand these sources of model uncertainty to understand the accuracy of elevation models created using these methods.

Digitizing elevation is a well-trodden area of research. This subject is unique because it is purely enabled by Geographic Information System (GIS) and computer technology, rather than direct measurements (Deng, Wilson, Gallant 2016). Many studies have evaluated the role of a GIS as a means of storage and management for elevation models. A study by Jordan (2007) suggested that the functionality provided by a GIS adds additional components of data management, analysis, and generation of various outputs to what would otherwise be limited to data collection and storage. Another major claim by the author was that problems inherent in remotely sensed image analysis can be overcome by using a GIS to tease out the bare earth surface in order to assess the field properly.

Reviews like Hogrefe, Wright, and Hochberg (2008) suggest the deficiency of reliable near coastal bathymetry is due to the turbidity, shallow features, and surf conditions that inhibit optimal sampling efforts. Plant et al. (2002) evaluated the magnitude and scale of errors that are related to sampling and use of nearshore bathymetry data. The results of the study supported the idea that environmental conditions and the type of sensor directly influence the arrangement and size of gridded pixels. Additionally, the authors stated that an analysis of the interpolation error can allow for future design of optimal sampling strategies. While many modern hybrid techniques have emerged to address this problem, it is well accepted that management of the dynamic coastal regions demand accurate and repetitive DEM techniques (Bernstein 2002, Mitasova et al. 2003, 2004, Bernstein et al. 2011)

While analyzing sparse data can be problematic, geographic solutions exist that enable continuous scalar fields to be created from sets of discrete measurements. O'Sullivan and Unwin (2010) outline a general workflow for creating a continuous surface from remotely sensed data. The authors suggest that this two-part process involves sampling the physical surface and choosing a form of interpolation. Sampling produces an output from electronic sensing equipment which is provided to an analyst as a series of numeric values that represent a mapped variable across a surface. Using these known points, values for unmeasured locations can be predicted using algorithms that summarize the spatial relationship between known points (Michell and Minami 1999). The underlying theory was originally demonstrated in a study by Tobler (1970). The author animated cartographic simulations of urban growth to show correlated patterns between neighbors. A major claim made by the author is that distance is the most important variable that determines the interaction between phenomena or objects in space. This concept is now widely known as spatial autocorrelation and is an assumed precondition for interpolation analysis.

2.2 Related Works

Interpolation analysis works to find the function that passes through known points while providing an accurate representation of all unmeasured values (Burrough 1986, McCullagh 1988, Robinson 1994). In the context of spatial data, interpolation is used to build continuous datasets from a limited amount of discretely measured points. Throughout the literature, a broad range of interpolation models, algorithms, and techniques are discussed. Additionally, over the past few decades, further developments in technology and computer science have broadened opportunities for control over different aspects within the interpolation process (Achiellos 2008).

The choice of an interpolation method is ultimately very subjective and should be chosen to best fit its application (McCullagh 1988, Achiellos 2008). The review by Schut (1976) demonstrated that the accuracy of a DEM is highly dependent on the complexity of terrain characteristics, sampling rates, and the interpolant used. Additionally, the study by Achiellos (2008) is a good example of the different results that can be produced when using different methods, techniques, and models. The study also claimed that the selection of parameters plays a significant role in the outcome of a DEM. The use of an interpolator or parameters that are not well suited for an application can lead to incorrect decision making. By contrast, given ideal conditions of spatial distribution and point density, even the most basic of interpolators can provide exceptional results (Schut 1976).

Accordingly, an in-depth knowledge of various methods and applications can assist in the selection of an appropriate interpolant. There is the basic assumption when creating a DEM that the raw data presents spatial dependence and the technique chosen will meet the needs of the desired product (Robinson 1994). While no comprehensive study has concluded that any method is more suitable than another, the wide range of published literature instead focuses on using various methods along with different data.

The following section describes the three methods used in this thesis research based on previous literature, along with contemporary applications and uses.

2.2.1 Inverse distance weighting

One of the most basic interpolation techniques available is the inverse distance weighted (IDW) interpolation method (Burrough 1968, Schut 1976, Achiellos 2008). Since this deterministic method is included in most systems that create and manage DEMs, its use in spatial research is very common. This interpolator considers a local neighborhood and predicts values that generate a surface that passes through every data point. IDW assumes that each measured location has local influence on the surrounding points that lessens as a function of distance. A review by de Mesnard (2012) supported this claim by demonstrating the use of IDW by modeling pollution. The author considered measured pollution data as “reference points” and used this to create a model. One flaw the study revealed was that different types of pollution data warrant different considerations instead of considering all types of data with the same arbitrary exponent. The author suggested future studies consider a more advanced method of interpolation, such as kriging, for this use case.

Another study by Lu and Wong (2008) used IDW interpolation analysis to evaluate the sensitivity of the parameters used for prediction. The authors reveal that the output surface produced by IDW can also vary depending on the user’s level of a priori knowledge of the subject and necessary parameters. One important parameter that is applied in the IDW method is the variable or search radius. A variable search radius controls the number of points considered at once while allowing for a varied distance depending on the spatial configuration of the data set. A fixed search radius holds a constant neighborhood size and uses a minimum number of points to determine what is considered for interpolation. A study by Chen and Liu (2011) used IDW to consider 46 rainfall stations along with rainfall data. The authors found that if the radius distance examined too many or too few stations, problems could arise within the analysis. The issues noted included increasing computational runtime (when too many stations are considered) and an inaccurate representation of the surface (if too few or no stations were considered).

The power function is considered the most important parameter used to compute predictions using IDW. A study by Fotheringham and O'Kelley (1989) served to exemplify this importance. The authors reveal that a decrease in the spatial relationship between two points is not simply proportional to distance alone. The IDW method corrects for this by using a power function, or distance decay parameter, to modify the weight of the spatial interaction. Several studies have identified that this power function is the most important factor in the IDW method (Burrough and McDonnel 1998, Priyakant et al. 2003). Another finding from this study was that an increased distance between prediction locations resulted in a decreased weight of measured points. This means that a higher power value will provide less influence on distant points.

Despite its popularity, the exact and deterministic IDW method has limitations. One restriction in this method is that it does not consider the spatial variability of the phenomena. Instead, IDW acts as an exact interpolator and the output surface created is identical to the measured points. One example of this is described in the study by Erodgan (2009). The author used IDW in a comparative analysis of interpolation methods while considering accuracy and uncertainty. The results of the study showed that the resulting surface produced higher uncertainty than other methods. The uncertainty can be attributed to the nature of the IDW method creating flattened peaks and valleys. This is often the case when interpolating a sparse density of point measurements and can create misleading representations of terrain. IDW is the most basic interpolant considered in this study and as a result can be considered a baseline to compare the more sophisticated methods to.

2.2.2 Empirical Bayesian kriging

While deterministic methods apply mathematical functions in order to describe a field, probabilistic techniques consider the points within a field to be statistical in nature (Krivoruchko 2012, Wilson 2018). Borgman et al. (1994) recognized that the simplified assumptions and exact predictions introduced by deterministic methods do not necessarily recognize environmental variability nor address the spatial behavior between sample points. Often for this reason, geographers favor describing fields with methods that are rooted in statistics because it leads to more realistic views of scalar data.

Within the class of probabilistic interpolators is a method called kriging. Kriging is also referred to as the optimal spatial predictor or best linear unbiased predictor (Cressie 1990). This method originally evolved to meet the demand for a quantitative way of characterizing spatial autocorrelation and building continuous datasets (Oliver and Webster 1990). Since the 1960s, many applications of kriging have been published within meteorology, agriculture, mining, epidemiology, hydrology and many other environmental sciences (e.g. Oliver and Webster 1990, Moore and Carpenter 1999, Skøien, Merz & Blöschl 2005, Krivoruchko 2012).

Kriging was explained in a study by Lev Gandin (1959) on optimum interpolation. The author suggested that optimal prediction and prediction uncertainty depends on covariance. The covariance can be quantified by estimating a semivariogram as a function of the distance and direction between pairs of coordinates (Krivoruchko 2012). Matherson (1963) expanded upon this concept through his Regionalized Variables Theory. A regionalized variable is a continuously varied numerical function where the spatial variation cannot be accurately described by simple mathematics across space (Dias et al. 2018).

Kriging is desirable because it offers the advantage of generating statistical estimations with minimum error in addition to a quantified measurement of that estimation (Cressie 1990). Other reviews have suggested that kriging predictors filter measurement error creating a highly a reduced prediction uncertainty when compared to other models of measurement errors (Krivoruchko 2012). Zimmerman et al. (1999) showed that kriging generated more accurate results that did IDW regardless of the landform type or sampling scheme. The author’s results demonstrate the flexibility of kriging along with its ability to analyze correlation and covariance across varying spatial structures (Arun 2013).

Among the many different flavors of kriging is an approach called Empirical Bayesian Kriging (EBK). This method requires minimal interaction from the analyst as it automatically calculates parameters through many subsets of local models and simulations (Krivoruchko and Butler 2013). EBK differs from other kriging methods because it accounts for the introduced error in other kriging methods. This is accomplished through a sophisticated kriging approach that calculates multiple semivariogram models throughout the study region, as opposed to a single semivariogram apparent in other methods (Krivoruchko 2012). The algorithm considers a subset of the data and through iterative simulations it averages many semivariograms across space. By using many local models, the algorithm can adapt to small scale changes in the data leading to accurate predictions. Although EBK does include attractive qualities, it comes at the cost of processing speed and only allows for a limited amount of customization (Esri 2018). This form of minimally interactive modeling also has the advantage of opening many doors for automating interpolation analysis across large scale data. One study suggested that Bayesian kriging not only obtained more precise results than other kriging methods, but the process leads to reduced costs without sacrificing quality of information (Cui, Stein, Myers 1995).

Across the literature regarding coastal studies, the generation of bathymetric models from interpolation analysis is a well-studied technique (e.g. Righton and Mills 2006, Ryan et al. 2007). The use of EBK was applied by the U.S. Geological Survey (USGS) to successfully interpolate topo bathymetric DEMs (Danielson et al. 2016). The authors found that this method performed well when mosaicking together both sparse bathymetry with dense topography. Another success of using EBK in this application was that the methods automated the large volumes of data. Since coastal models demand frequent updates because of the dynamic nature of the surf, automating interpolation with EBK provided a consistent and reliable technique to use repeatedly with these models.

2.2.3 Machine learning and random forests

An explosive amount of data is now available due to the rise of computers, the Internet of Things (IoT), and advanced acquisition technology. Yet in this world where nearly everything can be measured and monitored, a review by the New York Times (2009) expressed that "data is merely the raw material of knowledge". The use of machines to solve advanced problems offers an advantage because it allows for the discovery of relations that could not otherwise be detected by humans alone. Today, machine learning is pervasive among many different domains of real world-applications and its use is growing exponentially. The term machine learning encompasses many types of work such as data mining, pattern recognition, multivariate statistics, and predictive analytics.

A model refers to a generalized representation used for predictions that can be extrapolated to instances where data is not available (Esri 2019). In machine learning algorithms (MLA), relationships are learned by training a model to detect correlations between dependent and explanatory variables. Respectively, these variables refer to the phenomena to be predicted, and the variable that caused or explains the dependent variable. When no data is present, the model looks to collect information from explanatory variables in order to connect data that can provide information about predicting a value. Guisan and Zimmerman (2000) refer to this model formulation as a data driven prediction for a specific outcome based on an observed spatial pattern. A major claim by the authors stated that by combining machines with optimal statistics, the data speaks for itself with exceptional predictive abilities.

MLA iteratively explore datasets while connecting variables that infer accurate predictions through a series of questions. The model recursively goes through a series of questions and makes decisions which infer patterns. The use of MLA to classify remotely sensed data of Australian forests serves as an exceptional example of a large sample size that can be analyzed to form predictions (Brown de Colstoun et al. 2003). The results of the study showed that the land cover map produced an overall accuracy of 82% when tested against a validation dataset and 99.5% accuracy under conditions of forest classes. The successful results show that the results from the case study can be scaled up to applications of the entire national park system.

One strategy employed by MLA is classification and regression trees (CART). This technique was first introduced in a study by Breiman (2001). The author demonstrated that an efficient way to train predictive algorithms is through a series of decision trees where explanatory variables are split into different branches. Since this type of supervised learning algorithm can predict both categorical (classification) or continuous (regression) data, it has become one of the most used methods of MLAs. As the study stated, the objective of the model is to associate a desired output with a specific value of a specific variable at each stage. The study also demonstrated that features are recursively considered within a hypothesis class while searching for a function that fits the data. Depending on the training data and hypothesis space, MLA are commonly known to observe the data too well. Dietterich (1995) explained this central problem inherent in learning algorithms by describing the tendency of a model to fit an objective function too closely to the training dataset. This is known as overfitting a model and can create issues when noise is precisely mimicked from a dataset.

Breiman (2001) used random forests (RF) to directly tackle the issue of overfitting. As a more robust way to learn generalized patterns, a forest is built through an ensemble of random trees. When individual trees work together as a forest, a model has better predictive performance than otherwise with constituent learning algorithms (Esri 2019). Probability theory and the law of large numbers (LLN) states that the iterative result will be a more reliable approximation of the truth than would a single, independent realization (Judd 1985, Durrett 1995). Other studies also support this claim by investigating the impact of randomness on tree classifiers and model accuracy (Amit and Geman 1997).

While successful in many applications, RF are not specifically designed for spatial applications. Many published attempts have described the process of creating spatially specific implementations of the method. These modifications better allow for spatial applications. Sinha et al. (2019) explored the application of RF to model population density when predicting parcel aggregations that are downscaled from input training features. The results of the study strongly suggested that including spatial autocorrelation of the training data played an important role in minimizing the residual variance of predicted values. The authors concluded that more research and specialized variants of the RF algorithm may lead to better predictions to be used with spatially correlated and heterogeneous data.

Georganos et al. (2019) extended the RF algorithm and demonstrated its use with remote sensing data along with population modeling. This method was adapted to deal with the challenges of highly spatially heterogeneous data. The authors showed that their specialized implementation of a geographical RF algorithm offered encouraging support for its use as a spatially predictive and exploratory tool. This claim was validated by the study's results that showed a lower residual value of geographic RF when compared to non-spatial implementations of the same method.

Studies have demonstrated the construction of water depth models using machine learning. Manessa et al. (2016) suggested that the depth variable and surface reflectance have a complex influence on data collected in shallow coral reef waters. The authors advocate incorporating Worldview-2 satellite images and single beam echosounder measurements in order to create a robust non-linear regression of the RF algorithm. Additionally, the authors incorporated six variable bands and their logarithms in the regression equation as robust explanatory variables. Sagawa et al. (2019) also used satellite derived bathymetry and RF to predict bathymetric values under conditions of very sparse data. The authors were able to predict a depth estimation model with minimal error by incorporating satellite image analysis based on cloud computing.

2.3 Summary

Virtually all DEMs we interact with on a daily basis are created using some form of interpolation. The interpolation technique plays an important role in achieving a high accuracy elevation model from discretely collected points. However, there are many different approaches and techniques to consider when creating a surface. The published literature rarely supports the use of one method over another, but instead provides comparative case studies to support the superior use of an interpolant for a given application.

For the purpose of this project, the exact deterministic method of IDW was used as a benchmark to compare the results of the other methods. As supported by the literature above, the IDW method is distance based and provides an interpolant that includes every point in the output. Regardless of the underlying spatial process or location, IDW creates one model based on known points. To predict unmeasured values, this method connects measured values so that the minimum and maximum values occur at sampled points. This often creates surfaces with sharp features and can misrepresent areas with steep unmeasured peaks and valleys. In the context of this study, this method serves as a baseline to verify the hypothesized superior performance of for sophisticated geostatistical methods.

EBK is an advanced semi-automated method that integrates the data and creates predictions using multiple semivariogram models. This is accomplished by dividing the data into many subsets and selecting the best combination of parameters within that subset. EBK has been successfully demonstrated to capture multiple underlying spatial processes that drive geomorphology. Furthermore, the use of local models allows this method to accurately predict values in nonstationary data.

Lastly, given the presence of secondary variables, RF can provide a method to improve interpolation predictions. RF and other MLA are frequently used to generate spatial predictions. However, these methods often ignore the geography of measurements in the process (Hengl 2018). While this method is technically a non-spatial model, the use of spatial covariates are expected to increase a model’s effectiveness with spatial data. Previous research has used satellite images and regression models to predict bathymetry values in areas that are unreachable by boat or plane. Given more time and resources, this research would take a similar approach to explore this method. However, this thesis uses only the sampled data points and therefore excludes the use of secondary datasets to drive the regression equation.

Chapter 3 Methods

This chapter describes the study area and discusses the sample data used to explore multiple interpolation algorithms.

3.1 Research objectives

The purpose of this thesis is twofold. The first goal of this research addresses which interpolation method will provide superior results when creating a continuous bathymetric DEM using discrete measurements collected at half the frequency of the original survey. In order to accomplish this objective, two geomorphic regions within Monterey Bay will be explored using three different interpolants. As supported by the literature reviewed in the previous chapter, EBK and forest-based regression were hypothesized to produce predictions superior to those obtained by IDW. In order to validate this claim, IDW has been included to serve as a deterministic baseline for comparison. The second objective of this research examines if fewer measurements can be taken while generating relatively similar results. This can be addressed by creating a series of uniformly thinned measurements and interpolating each using different methods. It was hypothesized that different geomorphic regions will have varying thresholds of sampling density required to create a reasonably accurate surface. The methods for addressing these two research questions are outlined and discussed in this chapter.

3.2 Study area

For the purpose of this study, the well sampled region of Monterey Bay will be considered the bathymetric ground truth to which the interpolated models will be compared. Located off the central coast of California, the region's unique benthic environment makes it an attractive area to study. The Monterey Canyon is one of the largest underwater canyons in the world and can be characterized by a rocky nearshore environment and dense kelp forests. The region is also home to many species of marine life including sea otters, bottlenose dolphins, elephant seals, humpback whales, sharks, and turtles.

Research in Monterey Bay is prioritized by many different scientific and conservation initiatives with the goal of protecting this special area. The Monterey Bay Aquarium Research Institute has prioritized the need to map the seafloor in and around the bay. These DEMs provide researchers with a versatile source of information that can be leveraged for many research and operational purposes.

Figure 2 shows the swath bathymetry provided by the USGS formed the primary spatial data component used in this study. Bathymetry is traditionally considered fuzzy data, yet the high spatial resolution of this dataset validated its application in this thesis research. The survey tracks covered the area inside the bay and collected elevation data on the medium and high-profile shelf regions. The metadata provided with this bathymetry assessed the data's fitness of use. The information revealed cooperative weather conditions during hydrographic surveys which permitted marine survey equipment to operate in ideal sea states and collect quality data. The weather during data collection is important to note since high surface winds and bubbles under the transducer are the primary cause of poor-quality bathymetry acquisition.

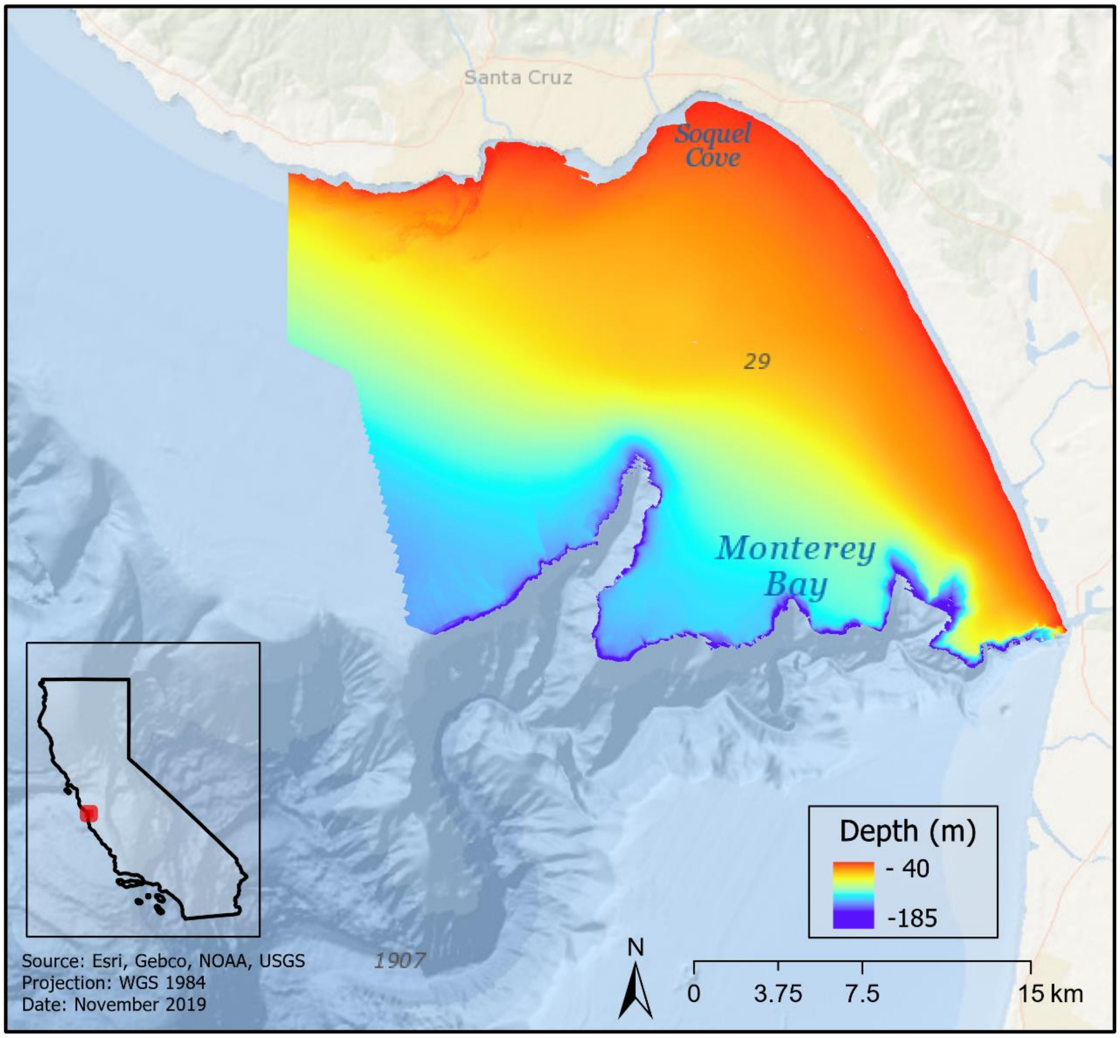

Figure 2: Bathymetry collected in Monterey Bay, California.

Bathymetry was acquired using a 234.5 kHz SEA (AP) Ltd. SWATHplus-M phase-differencing side-scan sonar mounted to a hull brace aboard the R/V *Parke Snavely* (Table 1). A common reference frame with a Geodimeter 640 Total Station was achieved throughout the survey with the use of sonar heads, GPS antennae, and a CodaOctupus F180 inertial measurement unit. Post processing of erroneous soundings was completed in a networked workstation aboard the R/V *Parke Snavely*. Information on the error inherently introduced by the sensor and survey equipment was not identified in the metadata. Consequently, the derived results are specific to this dataset and subject to additional inherent sources of error.

Table 1: SWATHplus-m sonar specifications used in bathymetric data collection in Monterey Bay (USGS 2009).

Specification	Value
Sonar frequency	234 kHz
Maximum swath width	300 m (typically 7-12 times water depth)
Resolution across track	5 cm
Transmit pulse length	34 µs to 500 µs
Ping pulse rater	
150 m swath width	10 pings per second
300 m swath width	5 pings per second
Vertical accuracy (range dependent)	
57 m	0.1 m
114 m	0.2 m
171 m	0.3 m

3.3 Spatial data preparation

To prepare the data for this thesis research, bathymetry surveyed in Monterey Bay was acquired and downloaded from the USGS repository. The downloaded raster was transformed to a point feature class in ArcMap10.7.1. The preparation for this analysis necessitated use of two versions of Esri’s ArcGIS software because the legacy Maritime Bathymetry extension is limited to use only in ArcMap. The bathymetric soundings were then thinned using a shallow-biased selection with a nominal thinning radius of 100 m. An advantage of using the Reduce Point Density tool enabled through the Maritime Bathymetry extension is that the output feature class is thinned for the purpose of increasing processing speed, while retaining the integrity of the original collected data. In this case, the total number of point measurements was reduced from 81,975,729 soundings to 47,293 soundings in the feature class. This step simplified the analysis by reducing the time spent running geoprocessing operations while ensuring that the program did not crash.

The geodatabase was then connected to ArcGIS Pro 2.4 to continue preparing the necessary datasets. The next step was to create multiple datasets composed of uniformly distributed random selections of points each representing different levels of sampling coverage and density. To accomplish this, an additional attribute was added to the original point feature class containing all the measured point values. This new field was populated for each point feature with a generated random number using a Python script. The feature class was then iteratively selected to include 50, 25, 10, and 5 percent of the original points. Each selection was individually exported to create a new point feature class. Introducing randomness in the process of selecting points to be included in each layer allowed for an unbiased analysis.

Different regions of the ocean can be characterized by different seabed geomorphology and benthic habitat. Including a constraint on the bathymetry data allowed for depths within different zones to be properly assessed according to specific semantics. For the purpose of this study, a geomorphologic classification scheme was adopted from Harris et al. (2014). The authors detailed analysis generated the first digital global seafloor geomorphic features and zones map. Applying this study to the methods in this thesis research provides the benefit of an easy mechanism for differentiating statistically validated types of benthic terrain. The study classified each region using quantitative differences analyzed in 30-arc second shuttle radar topography mission (STRM) data.

A folder of polygons was downloaded from the Blue Habits portal and visualized in ArcGIS Pro. Each of the polygons represented a different seafloor geomorphic zone or classified region. Visual interpretation showed that two polygons representing two geomorphic classifications of shelf profile (medium profile and high profile) intersected the study area. According to Harris et al. (2014), the distinction between high and medium profile classifications is recognized by analyzing the vertical relief of the continental shelf over a five-cell radius. The authors' study suggests that a medium shelf is classified by 10-50 m vertical relief while high profile shelfs exhibit a vertical relief greater than 50 m.

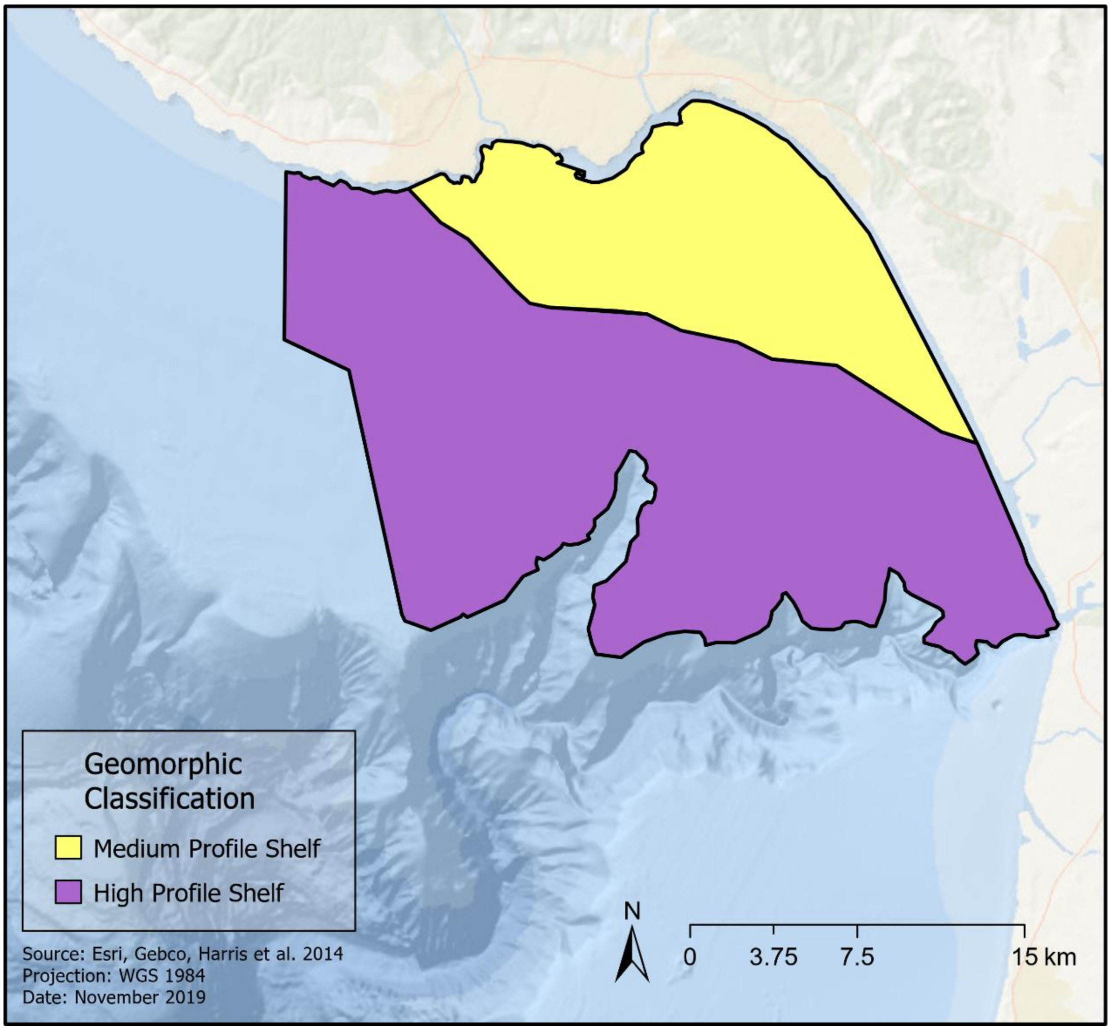

Figure 3. Study area classified by benthic region.

Each of the polygons acted as bounding units for the classified regions. Within each polygon, point features were selected using an intersect operation. This process was repeated with each of the down sampled feature classes. The number of features in the resulting eight different datasets are reported in Table 2.

Table 2: Number of points retained in each of the generated datasets.

Selection of original points (%)	Total point features retained	Medium profile shelf features	High profile shelf features
100	47,239	Not classified	Not classified
50	23,551	6,746	16,819
25	4,736	3,358	8,554
10	2,324	1,370	3,367
5	2,234	671	1,653

3.4 Procedure

This section discusses how the prepared set of reference points were interpolated to create a continuous surface and how the different surfaces obtained were assessed for accuracy.

3.4.1 Interpolating surfaces

The first method applied to the data was IDW. As discussed earlier this method is an exact, deterministic interpolator that places weight on each data point by averaging the value of points within each processing cell. This method assumes that the value associated with each point decreases its influence on neighbors as the distance between points increase. ArcGIS Pro's Spatial Analyst provided access to the geoprocessing tool necessary to complete this operation. The tool was used with a default power value of 2 and a variable search radius. This step was applied to each set of quadruplicate point datasets to produce a total of eight different surfaces.

Next, the geostatistical technique of EBK was applied to each of the point datasets. Kriging calculates averages by predicting error values that minimize the linear sum. The weights for each point represent a measure of covariance and location determined by the semivariogram. Unlike other kriging methods, this process models many semivariances for each subset of data and plots them together in an empirical semivariogram. Figure 4 provides the empirical semivariograms for all eight datasets.

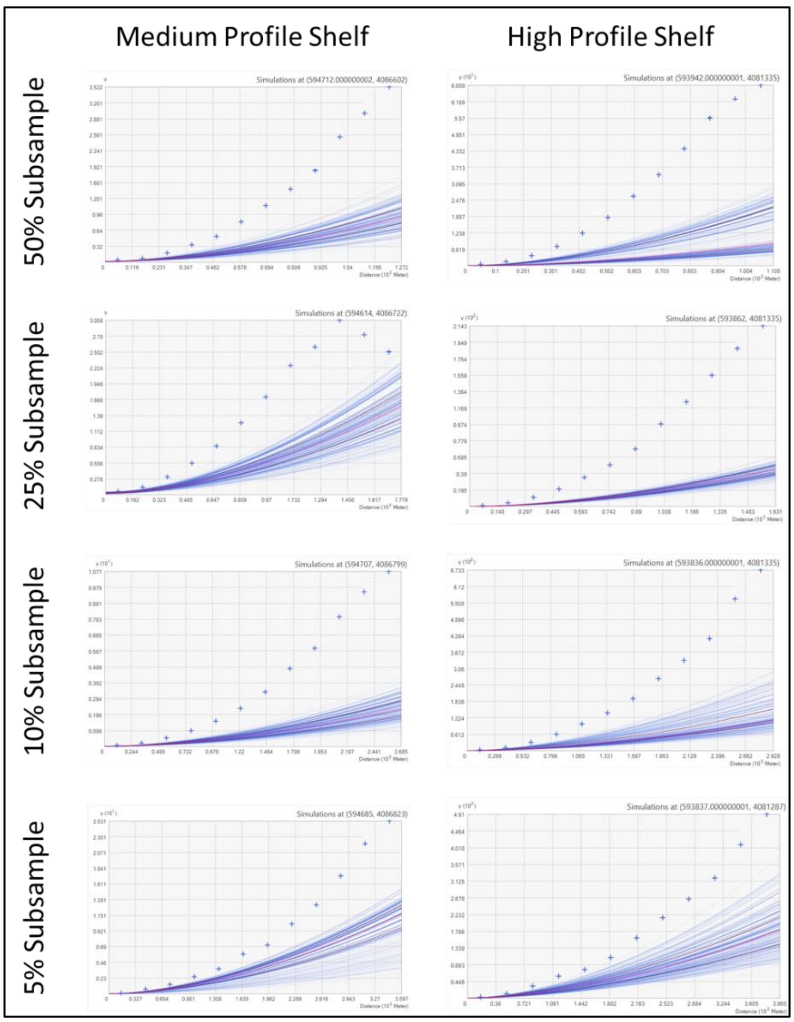

Figure 4. Empirical semivariograms for observed data values.

While EBK is known among the methods of kriging to automate the most difficult aspects of building a valid model, user knowledge and input is still required. For each dataset, EBK was executed through the Geostatistical Analyst tool in ArcGIS Pro. The nearly normal distribution of values did not warrant a data transformation. The default power semivariogram was used to calculate the output for each of the eight replicates. Additionally, a parameter was set to include the default number of 100 simulations per subset. Given a larger, dispersed dataset, increasing the value of allotted simulations can aid in the success of determining a valid kriging model.

Lastly, forest-based regression was used to generate an additional set of eight surfaces. Conceptually, a model needs to be trained in order to learn to predict values. In this study, distance to shore, slope, aspect, curvature, and a hot spot Getis-Gi* statistic was explored as predictor variables to train the model. All of the explanatory rasters were generated as derivatives from the downsampled data replicates. It was determined through exploratory spatial data analysis that distance to shore and Getis-Ord Gi* values explained most predicted values. The Forest Based Classification and Regression tool in ArcGIS Pro generates this claim through a Variable Importance Table output from the Train Only setting. These explanatory variables were then used to construct the model and predict values to a raster.

The Forest Based Classification and Regression tool in ArcGIS Pro creates a series of decision trees that are intelligently fused together into a forest. An ensemble, or forest, can produce a substantially more robust model than if the model is constructed from individual trees alone. From each input dataset, 30 percent of the original data was considered a test dataset and withheld from building the model. The remainder of the dataset comprised the measurements used to randomly construct the regression model. In accordance with the methods above, the result of this interpolation method produced a total of eight surfaces.

3.4.2 Comparing models

Three interpolants were used in this study and applied to eight different sets of bathymetry data to obtain a total of 24 surfaces. Quality assessment of each dataset is a critical part of DEM production. In this research the accuracy of a surface is considered the absence of measured differences between two DEMs. The 24 DEMs were symbolized in an identical manner. This was accomplished by applying a classified rendered spectral color ramp on a quantile interval scale from 0 to -180 m. This classification method allowed for each class to contain values spread across the entire distribution of the data range. Symbolizing the surfaces with identical colors and scale allowed for visual assessment by highlighting differences in depth.

With the goal of quantitatively determining the accuracy of each interpolated surface compared to the bathymetric truth, the root mean square error (RMSE) was used as a metric. The root mean square error is reported as the difference of residual values between rasters. To generate this metric, the raster calculator in ArcGIS was used to calculate in finding the squared difference of the surfaces. The mean of this calculated surface was determined using zonal statistics. Then, the square root of the mean was recorded. Calculations were repeated for each of the 24 rasters to obtain a RMSE between the “known” surface and the interpolated surfaces.

Chapter 4 Results

This section presents the findings of the study and graphically shows the comparison between different interpolation algorithms in different coastal geomorphologic regions with varying levels of sample sparsity.

4.1 Interpolation accuracy

Results of this research can be interpreted in several ways. To address the first objective of this thesis research, the surfaces generated from three different interpolation methods were analyzed to the most accurate surface when the seafloor measurements are collected half as frequently as the original sampling density. RMSE provided a quantitative means of determining the most accurate representation between the generated surface and the "known" surface. This error metric was calculated using the equation described by Li and Heap (2008). These values are first provided as a graph in Figure 5. This formula provides a way to establish how well a model agrees with the actual data. A higher RMSE value indicates that the predictions produced greater residual values further away from the mean or regression line. Thus, by this measure, a lower RMSE values represents a better interpolated model.

For both the medium and high shelf profile, the RF method provide substantially superior results. The RMSE for medium and high profile shelfs are 0.0846 m and 0.1422 m respectively. In the medium profile shelf, EBK functioned as a secondary accurate alternate interpolator with a RMSE of 0.7669 meters, while the high profile shelf EBK trial exhibited a more substantial jump in model differences with a RMSE of 2.9038 meters. As hypothesized in both geomorphic regions, IDW generated a surface model with the greatest variation from the true surface.

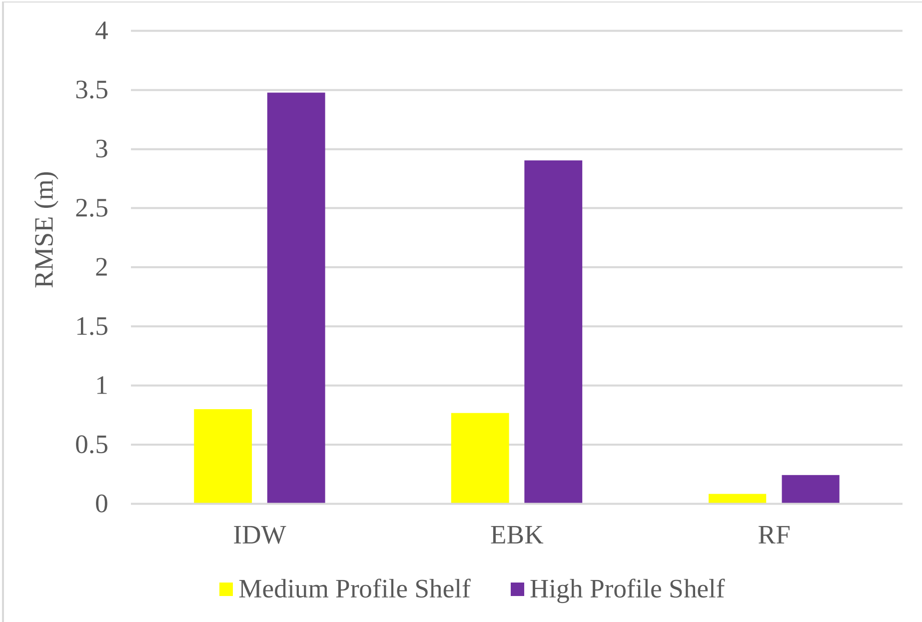

Figure 5. RMSE between ground truth and interpolated surfaces using half as frequently as the original measurements.

The morphological differences between shelf classifications can be demonstrated through these results. Overall, the interpolated surfaces classified as medium profile shelves revealed a lower RMSE for all interpolation methods. All reported surfaces within this zone contain residual values of less than one meter. On the contrary, the RMSEs of the high-profile shelf region revealed residual values between 0.1142 m and 3.4773 m. These values are a reflection of the ability of interpolation to capture the variation inherent in the surface it represents. Additionally, this quantitatively illustrates that relatively constant sloping morphology can be digitally captured better than that of rugged terrain across all methods.

Visual analysis provides an alternate method of assessing results. Mapped visuals is one of the benefits of using a GIS to generate surface models. In the case of this thesis, the generated interpolated surfaces show variation by depth across the bathymetry surface near the shores of Monterey Bay, California. While it does provide an attractive report, visual interpretation of outcomes can only capture a subjective idea of general trends obtained with different methods. As the precise differences between surfaces are challenging to visualize and results obtained in this manner can vary, it is important to consider the qualitative results below along with the quantitative results discussed above.

Figure 6 shows the medium profile shelf surfaces when considering half the sampling density of the original measured bathymetry values. Overall, the variation in depth displayed is relatively similar horizontally across the surface. In each of the three surfaces, the width of each classified depth range is about the same. However, the boundaries between each of the classified regions is more jagged in the IDW while the RF surface displays the smoothest transitions between classes. The differences are apparent when looking at the complex benthic terrain in the left corner of each surface. This northwest region of Monterey Bay reveals a portion of the shelf that only comes into focus with the RF interpolation. In the IDW interpolated surface, the same corner appears to not contain values of light orange region (-52 to -56 m) as the other depths sink more south across the terrain. In the EBK surface, the clarity of this region appears to lie in between that of the IDW and RF interpolation.

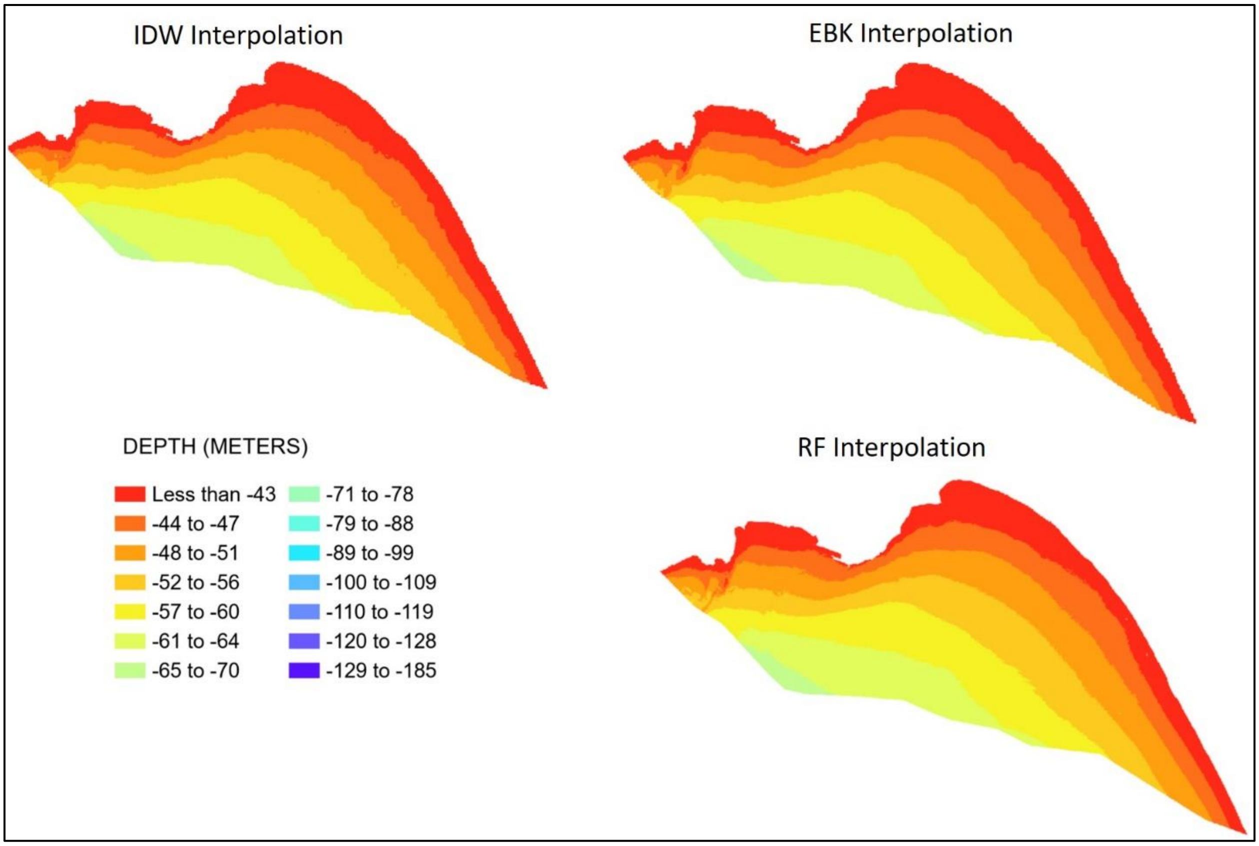

Figure 6: Side by side comparison of medium profile shelf interpolations using 50% of the sampled measurements.

The high profile shelf region is further from shore and exhibits a greater variation of depth than the medium shelf surfaces. Figure 7 shows the side by side comparison of high profile shelves when interpolating bathymetry composed of measurements with half the sampling density. The dark purple region indicating the greatest depths around the mouth of the submarine canyon shows a good example of the differences captured by the different interpolants. The RF interpolation captured two curved areas in the lower left corner that are not shown in the other two surfaces. The medium purple (-120 to -128 m) region in both the IDW and the EBK surface appear to have smoothed over the variation between this curved region. This entire classified area appears to drop lower through the benthic terrain than does in the RF surface.

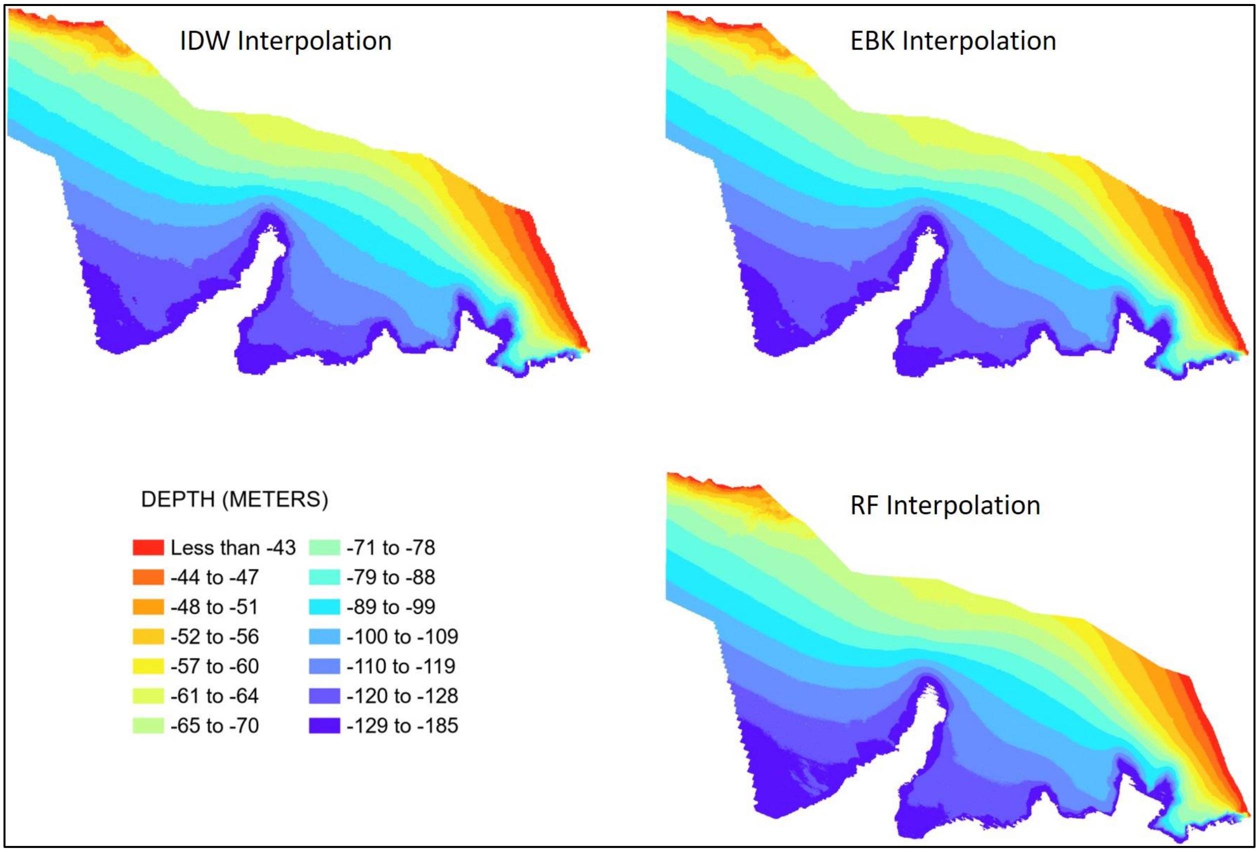

Figure 7: Side by side comparison of high profile shelf interpolations using 50% of the sampled measurements.

4.2 Subsample accuracy

To address the second objective of this thesis research, artificially created subsamples were interpolated to investigate the tradeoff between sampling efforts and the resulting accuracy of an interpolated surface. The RMSE for all interpolation replicates produced in this study are summarized in Table 3. In all but one trial (medium shelf 5% EBK), using less of the sampled data provided the least accurate results. One possible cause for the unlikely high value reported is bias due to the only one random subsampling of points that was included in the analysis. Across all the replicates, using more data generally tended to provide more accurate results. The transitions between accuracy of the trials were greater between the 25 and 10% subsamples than the transitions between the 50 and 25% subsamples. This nonlinear relationship between sampling density and an interpolated surface can be seen across all methods.

Table 3: Residual values (m) between random subsamples (predicted) compared to ground truth (observed) shallow bathymetry in Monterey Bay, California.

	50%	***25%***	***10%***	***5%***
Medium profile shelf geomorphology				
IDW	0.8005	0.8079	0.7844	0.9302
EBK	0.7669	0.6791	0.6311	0.7302
RF	0.0846	0.1224	0.3734	0.5412
High profile shelf geomorphology				
IDW	3.4773	4.2080	5.0856	5.9769
EBK	2.9038	3.2485	3.6754	4.4830
RF	0.1422	0.3546	1.0752	3.1566

The variation in RMSE between the trials with the greatest amount of points and the least amount of points can also provide insight into the capability of different interpolation methods to provide accurate predictions with varying levels of sampling density. In both geomorphic classes and across all levels of sampling density, EBK provided the least variation in RMSE values, while RF produced the greatest variation in model accuracy. Across both classes, the variation in RMSE produced by IDW interpolation showed intermediate variation. This provides results in accordance with how the interpolation methods assess a dataset as either as a global or local model.

Chapter 5 Conclusions

This study created a total of 24 bathymetry surfaces in order to address two research objectives. The first part of this project was to assess which interpolation method provided the most accurate results when using half of the “known” measurements. This was determined by the lowest RMSE value. In both classes, using RF produced the most accurate surface when sampling half as frequently as the source data. EBK was demonstrated to be a close alternative for accuracy, while IDW ranked third. The overall RMSE for a medium shelf surface was substantially lower than the error in the high-profile shelf. This can be attributed to the steady sloping terrain of nearshore environments that make it easier to fit a surface to a set of points. In other words, a surface that varies more dramatically can be more difficult to model. As demonstrated by the results, the high-profile shelf contains complex benthic features which may complicate the interpolation process.

The second objective of this research sought to determine if fewer samples can be taken while providing similar results. The rate of ocean mapping has historically been very slow and the goal of providing data in every grid of a global bathymetry model seems far from reachable given current sampling practices. However, as demonstrated by this thesis, smoother transitioning regions such as the medium profile shelf, can require less input data to obtain accurate results. In contrast, complex terrain such as high profile shelfs demand more input data for quality results. This represents potential for creating models to fill gaps in data in smooth, near coastal regions, where data acquisition is consistently difficult, expensive, or not accessible.

Across all replicates, using more data generally tended to provide more accurate results. However, as expected, local interpolants such as EBK were able to use less data to create more accurate results. While this was demonstrated clearly in the EBK medium profile shelf, the output of EBK trials in the high-profile shelf generated relatively similar results at all sampling levels. This indicates that the relationship between accuracy of the resulting interpolated surface and the sampling density is not linear, and not uniform for all interpolation algorithms. The real-world implications of this observation can provide important insight into designing sampling schemes and choices of interpolants given varying sampling densities when creating DEMs in the future.

The most important aspects of this thesis center around the tradeoffs between sampling density, interpolation methods, and local geomorphology. The results obtained demonstrate that all three criteria play a significant and interconnected role in the accuracy of a digital surface product. Assessing the accuracy of varying sampling densities demonstrated that while generally denser datasets resulted in more accurate products, this claim did not always hold true. When a global interpolator (IDW and RF) was applied to the points, the entire dataset was considered as a single model. Both methods resulted in an increase of error as sampling density was decreased. However, application of a local interpolator (EBK) was able to capture the fine scale details of a model by splitting the region into small subsets and modeling many semivariograms. In situations of less data, this method proved very successful. The promising results seen in the EBK and RF interpolated surfaces warrant the future exploration of EBK regression prediction as way to combine a local geostatistical interpolator along with regression analysis. Given appropriate explanatory variables, the potential to achieve more accurate results than either method can individually achieve could present a powerful interpolator for sparsely sampled regions.

5.2 Limitations

While this thesis research successfully demonstrated the main objectives, there are limitations in the claims made. The identification and future correction of spatial biases are essential for quality decision making. One such limitation is that the results discussed are subject to random bias. The point measurements included in each replicate were selected through a single random trial. By adding multiple random trials to each level of sampling density, statistically relevant results can be obtained by averaging the RMSE within each category.

The results generated from applying the RF algorithm shows promising potential for interpolation as it was able to more accurately produce results than IDW. However, the validity of the regression equation cannot be overlooked. The process of deriving the covariates proved difficult and no published literature exists on using only a single dataset to correct for a paucity of measurements. In many cases, additional SDB or other higher resolution products showed great potential for increasing confidence in spatial accuracy. However, more time and resources will be required outside the scope of this thesis in order to accurately determine spatial or nonspatial covariates that solely depend on the source data.

Additionally, a limitation of the RF algorithm is that is only performs well on data it has been trained on. This means that it is likely to derive poor results when extrapolating to other datasets. One possible way to overcome this challenge is to increase the sample size of the study region. This study used one set of geomorphologic classifications to assess the differences between seabed relief, geology, and formative processes, to provide a means of categorizing different complexities of benthic terrain. By including other study areas with the same benthic classification, the statistical validity can be increased as well as the possibility for a stronger covariate to be used in the regression equation.

Another option for deriving statistically distinct categories is exploring the use of indicator kriging (IK) methods. IK is commonly used in geologic and subsurface studies. Both applications are analogous to the interpolation of shallow bathymetry where different categories of geologic composition can overlap and become mixed within each other. While there are many different classification schemas for benthic environments, a coarse proxy will help to statistically infer parameters by controlling the spatial continuity within different environmental categories or thresholds.

5.3 Future work

With the ocean covering the majority of our planet, there is a great need to increase our knowledge of the accuracy of products representing the sparsely sampled seafloor. The accuracy of a product can impact its usefulness in future studies. It is important for applications of DEMs to identify both fine and large-scale details within benthic geomorphology. Misrepresentation of these features are likely to have a ripple effect on our overall understanding of ocean science as well as other environments across the entire blue planet.

While the obtained results successfully addressed the two research questions set forth by this thesis research, there is encouraging potential for its scalability and development of future work. Modifications of the methodology demonstrated in this research can increase the application of these results in the real world. Optimizing sampling density provides a means to understand the accuracy and results of existing surveys. It also provides a foundation for planning future coastal surveys to be optimally executed given that extensive time and resources are required to survey the seafloor. However, the ocean is sampled differently than a random configuration of points. To properly represent different patterns of coastal paucity of data, coastlines should be further studied to assess generalized sampling patterns. It is predicted that there will be three levels of sampling sparsity; low resolution based on satellite gravimeters, low resolution with well sampled transect lines throughout, and clustered datasets surrounding fixed observation stations. It is likely that different spatial configuration composed of different sampling densities will add an additional variable to be considered.

While this study specifically assessed only four tiers of sampling density, a more accurate threshold level can be assessed by exploring all possible levels of point density within particular geomorphic regions. In order to accomplish this, future studies can take advantage of many different types of data collected by many different sensors. By using a computationally efficient way to assess bathymetry data across the globe, such as machine learning, a model can be optimized within each geomorphic categorical group indicating the minimum required sampling density. Given a statistically relevant sample size, the possibility of using trained models to create optimized interpolants for various geomorphologic and sampling schemes or densities can assist in the most accurate representation of the seafloor.

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