# Prediction of Water Depth From Multispectral Satellite Imagery—The Regression Kriging Alternative

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***Abstract*—Bathymetric information is crucial to the study and management of coastal zones. Passive remote sensing provides a cost-effective alternative to acoustic surveys and bathymetric LiDAR techniques. Most previous studies estimated water depth from multispectral imagery in shallow coastal and inland waters by establishing the relationship between image pixel spectral values and known water depth measurements, in which the log-linear inversion model is most widely used. Given a set of known water depth sample points, a bathymetric grid/map can be created by using a spatial interpolation technique. However, when a limited number of water depth sample points are available, the interpolation result is often unsatisfactory for portraying benthic morphology. In this letter, we propose to use the regression kriging (RK) approach to combine the optimal spatial interpolation of kriging with the high-resolution auxiliary information of multispectral imagery for a detailed bathymetric mapping. A case study has been performed to demonstrate and evaluate the performance of the RK method in comparison with ordinary kriging and log-linear inversion methods. It shows that the RK method can produce more accurate water depth estimations than the log-linear inversion method due to the account of the spatial pattern of the modeling residuals. The bathymetric grid created from the RK contains much more spatial details about the ocean floor morphology than that from the ordinary kriging owing to the incorporation of auxiliary information from multispectral satellite imagery.**

***Index Terms*—Bathymetry, interpolation, multispectral, regression kriging (RK), remote sensing, water depth.**

## I. Introduction

Bathymetric information is of fundamental importance to the study and management of coastal zones. Traditional shipborne echo sounding technology may not be feasible for shallow waters that are less than one Secchi disk depth due to sound saturation, narrow survey swath, and inaccessibility of survey vessels [1], [2]. Whereas airborne bathymetric light detection and ranging (LiDAR) systems can provide rapid and accurate bathymetric measurements for shallow coastal waters, this technique is limited by its relatively high cost. As a cost-effective alternative to acoustic surveys and bathymetric LiDAR techniques, various passive remotely sensed multispectral images have been used to retrieve water depth estimates in shallow coastal and inland waters. The key to the use of remote sensing images for bathymetric mapping is to establish the numerical relationship between image pixel spectral values and known water depth measurements [1]–[6]. The log-linear inversion model proposed by Lyzenga [3], [7] has been widely adopted for this purpose. This model uses the linear logarithmic-transformed multispectral bands as the predictors to estimate water depth. It only requires multispectral imagery and a sparse set of water depth measurements. Because of the wide availability, high spatial resolution, and relatively low cost of multispectral imagery, the log-linear inversion model is very attractive in practice.

Given a set of known water depth points, a bathymetric grid (map) can be directly created using a spatial interpolation technique. While the spatial interpolation technique requires no data other than water depth sample points, the accuracy and the spatial details of the resulting bathymetric grid (map) depend strongly on the spacing of water depth samples, the geometry configuration of the sampled and interpolated points, and the spatial autocorrelation of the water depth [5]. When a limited number of water depth sample points are available, the interpolation result is often unsatisfactory for portraying the underwater geomorphology. Compared with Lyzenga's log-linear inversion model, the spatial interpolation methods only make use of the spatial autocorrelation between water depth points but ignore the correlation between image pixel spectral values and water depth measurements. In contrast, the log-linear inversion model exploits the correlation between image pixel spectral values and water depth, but the spatial autocorrelation between water depths is not utilized in the modeling. It is expected that the full use of both kinds of correlations can improve the accuracy and spatial resolution of the depth estimates.

In recognition of the limitations of the log-linear inversion model and spatial interpolation methods, we intend to find a method that can fully exploit the comparative advantage of the log-linear inversion model and spatial interpolation while overcoming their shortages for improved bathymetric mapping. Among various "hybrid" techniques developed in the past decade [8], [9], cokriging and regression kriging (RK) methods have been used in other fields to tackle the similar problem,

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particularly in soil mapping [8]–[15]. Some researchers have shown that the RK method is more attractive than the cokriging method because of fewer model parameters needed to be estimated [8], [16]. As its name implies, it contains two technical components: regression and kriging. Many previous studies have demonstrated that the RK is superior to the ordinary kriging technique since it gives more accurate and detailed results [9], [15], [16]. Although the RK method has been widely used in other fields, to our best knowledge, no application has been reported for its use in bathymetric mapping. In this letter, we propose to use the RK technique for better bathymetric mapping. This technique would utilize auxiliary information from multispectral imagery to enhance the spatial details through the regression component of the technique, and meanwhile, it fully utilizes the spatial autocorrelation of water depths through the optimal spatial interpolation of the kriging component. In the following sections, we will first introduce the kriging as a spatial interpolation method and the log-linear inversion method. Then, the mathematical formulation of the RK method will be presented. Next, the comparisons between the three methods will be performed through a case study. In the final section, we will discuss our application results and draw conclusions.

## II. Spatial Interpolation Method

Spatial interpolation is the procedure of estimating the value of a geographical variable at unsampled sites based on existing observations on the variable value at a set of sampling sites. Among various interpolation methods, kriging is often preferred because it allows one to quantify and exploit the spatial autocorrelation and joint dependence between neighboring observations to provide an optimal prediction for the variable values at unsampled locations, with the associated uncertainty estimate [17]. Kriging is based on the rate at which the variance between points changes over space, which is expressed in the form of a semivariogram, a diagram showing how the average difference between values at points changes with the distance between points. Ordinary kriging, which is the most commonly used kriging variant, is used as the benchmark method for comparison in this study. Given a set of water depth samples, the ordinary kriging estimator is written as

$$\hat{z}(s) = \sum_{j=1}^{n} w_j(s) z(s_j)$$

$$\sum_{j=1}^{n} w_j = 1$$

where $\hat{z}(s)$ is the estimated water depth at location $s$, $z(s_j)$ is the observed water depth at location $s_j$, $n$ is the number of water depth sample points used in the calculation, and $w_j$ is the weight assigned to the sample point at $s_j$. The weight $w_j$ is optimally determined such that the estimated water depth value is unbiased and that the estimation variance is less than that for any other linear combination of the observed water depth values. Mathematically, the weights are computed by inverting covariance matrix of observed water depth values that are used to estimate $\hat{z}(s)$.

## III. Log-Linear Regression Method

Assuming that the ratio of the bottom reflectance between two spectral bands is constant for all bottom types within a given scene, Lyzenga [3], [7] derived a log-linear inversion model for inverting multispectral imagery to water depth as follows:

$$z = \alpha_0 + \sum_{i=1}^{N} \alpha_i \ln\left[L(\lambda_i) - L_\infty(\lambda_i)\right]$$

where $L(\lambda_i)$ is the water-leaving radiance measured by a remote sensor for spectral band $\lambda_i$, $L_\infty(\lambda_i)$ is the deep water radiance for spectral band $\lambda_i$, $\alpha_i$ $(i = 0, 1, \ldots, N)$ are the model parameters to be determined, and $N$ is the number of spectral bands to be used. A set of points with known water depth values is required to calibrate these model parameters using the least squares regression approach.

## IV. RK Approach

RK jointly employs the spatial autocorrelation of the primary variable and its correlation with the secondary variable (auxiliary information) sampled at higher spatial resolution (density) than the primary variable [11], [18]. This technique is also known as "kriging with an external drift" [12]. In our study, the primary variable is water depth (bathymetry), and the secondary variable (auxiliary information) is the spectral values of multispectral imagery at pixels.

Conceptually, spatial variation in water depth can be decomposed into two components: large-scale variation and small-scale variation. The external drift represents the large-scale variation of the water depth. The residuals from the external drift represent the small-scale variation. Let the samples of water depth be denoted as $z(s_1), z(s_2), \ldots, z(s_n)$, where $s_j$ $(j = 1, 2, \ldots, n)$ is a sampled location and $n$ is the number of samples. In the case of RK, the water depth at a new unsampled location $(s)$ is predicted by summing the predicted drift and residual [11]

$$\hat{z}(s) = \hat{m}(s) + \hat{e}(s)$$

where the drift $\hat{m}(s)$ is estimated from the log-linear inversion model

$$\hat{m}(s) = a_0 + \sum_{i=1}^{N} \alpha_i \ln\left[L(\lambda_i)_s - L_\infty(\lambda_i)\right]$$

and the residuals $\hat{e}(s)$ are interpolated using the ordinary kriging method

$$\hat{e}(s) = \sum_{j=1}^{n} w_j(s) \cdot e(s_j)$$

$$\sum_{j=1}^{n} w_j(s) = 1$$

where $e(s_j)$ represents the regression residuals from the log-linear inversion model and $w_j(s)$ represents the weights

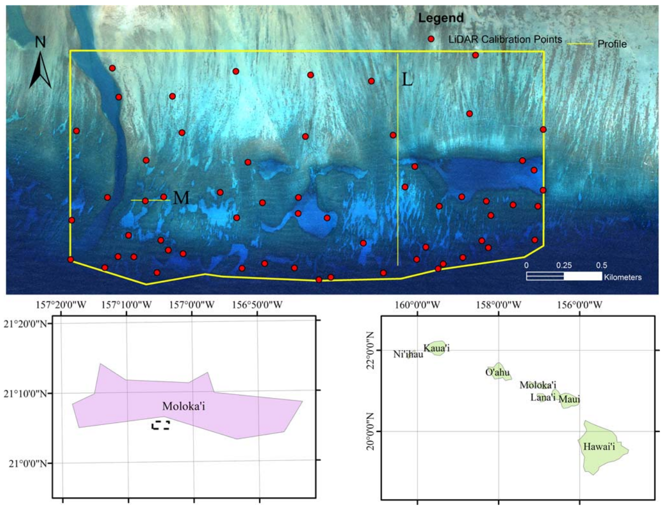



Fig. 1. Location of Molokai Island, color composition of IKONOS blue, green, and red bands and spatial distribution of LiDAR depth points used for model calibration.

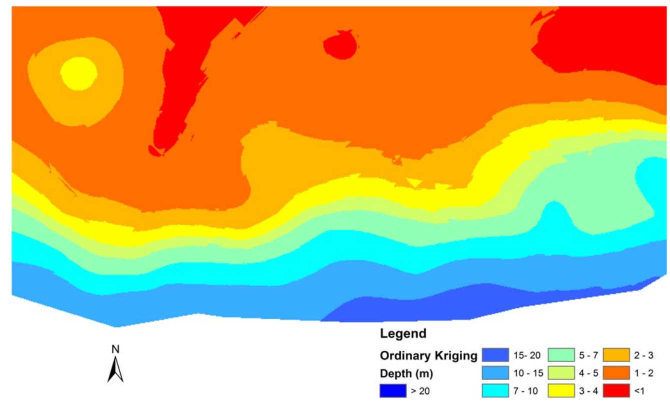



Fig. 2. Bathymetric grid estimated from LiDAR points using the ordinary kriging method.

determined by the covariance matrix of $e(s_j)$. Instead of using the ordinary least squares method, the drift model coefficients (log-linear inversion model parameters in this case) are preferably solved using the generalized least squares estimation to account for the correlation of residuals [8].

## V. Accuracy Comparisons

A case study has been performed to demonstrate and evaluate the performance of the RK method in comparison with the ordinary kriging and log-linear inversion methods alone.

### *A. Study Area and Data Sets*

The case study area is located in the south shore of Molokai Island, Hawaii (Fig. 1). We used high-resolution IKONOS satellite images for the remotely sensed imagery and airborne LiDAR measurements from the SHOALS system for model calibration and validation. Our analysis is conducted for a 3-km stretch of shallow waters along the south shore of Molokai. The substrates vary between sand, pavement, and live coral. The reef flat is characterized by a broad and shallow pavement platform, which extends nearly 1.5 km offshore. The fore reef is characterized by shore-normal spur-and-groove structures.

An IKONOS multispectral image acquired on February 21, 2005, was used for this case study. At the image acquisition time, the Sun had an elevation angle of 52.8° and an azimuth angle of 145.07° from true North. The image was orthorectified and georeferenced to UTM projection (zone 4 N) with reference to WGS84 ellipsoid. The horizontal positional accuracy of the orthorectified image was estimated to be 2.4 m. The IKONOS multispectral image contains four spectral bands (blue, green, red, and near infrared) at 4-m spatial resolution. The airborne LiDAR data were collected by the SHOALS system of the U.S. Army Corps of Engineers in 2000 with a horizontal accuracy of about 3 m and a vertical accuracy of 15 cm. There are 760, 919 LiDAR point measurements within our study area, ranging between 0 and 20 m in depth. The depth measurements are referenced to the tidal datum MLLW (the mean lower low water). The precise depth measurements from the SHOALS are used in this research as ground-truth to calibrate and compare the performance of different methods.

### *B. Model Calibration and Assessment*

In this research, we only randomly selected 60 water depth points from the whole airborne LiDAR data set as the sample points for the model calibration. To ensure evaluation reliability, we used the whole airborne LiDAR measurement data set for model validation, accuracy assessment, and comparisons between different methods, except for the 60 points that were used as known sample points for the model calibration (Fig. 1).

The 60 randomly selected bottom depth points were interpolated to bathymetric grid with a spacing of 4 m using the ordinary kriging method (Fig. 2). This represents the sea floor geomorphology derived from only 60 water depth samples, without utilizing the auxiliary information from the IKONOS multispectral imagery. The overall root-mean-square error (rmse) for the water depth estimates from the ordinary kriging method is 2.52 m, which is calculated by comparing the reserved LiDAR measurements as water depth truths. The correlation coefficient between the estimated depths and the water-truth depths is 0.873.

After the deep-water correction on IKONOS imagery [7], the log-linear inversion model was constructed based on the blue and green bands of the IKONOS image and the 60 randomly selected bottom depth points. With the calibrated log-linear inversion model, the water depth grid (Fig. 3) is created at 4-m spatial resolution with the input of the spectral values of the IKONOS blue and green bands. The overall rmse for the estimates from the log-linear inversion model is 1.85 m. The correlation coefficient between the estimated depths and the water-truth depths is 0.934.

A semivariogram is then constructed to analyze the spatial structure of the residuals of the water depth estimates from the log-linear inversion model (Fig. 4). The fitted semivariogram shows a range of 1152 m, a nugget value (the initial semivariance when the autocorrelation is highest) of 0.835,

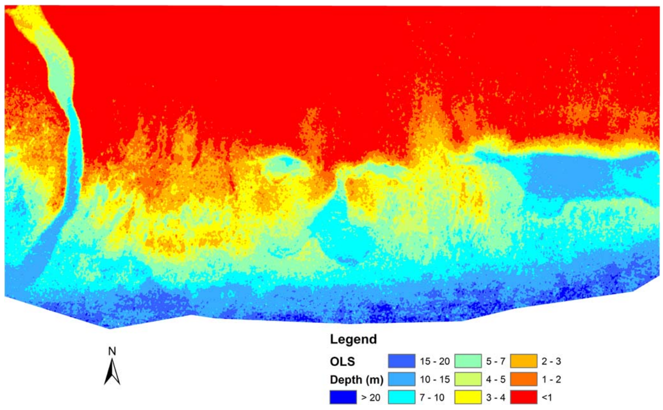



Fig. 3. Bathymetric grid derived from the IKONOS image using the log-linear regression method.

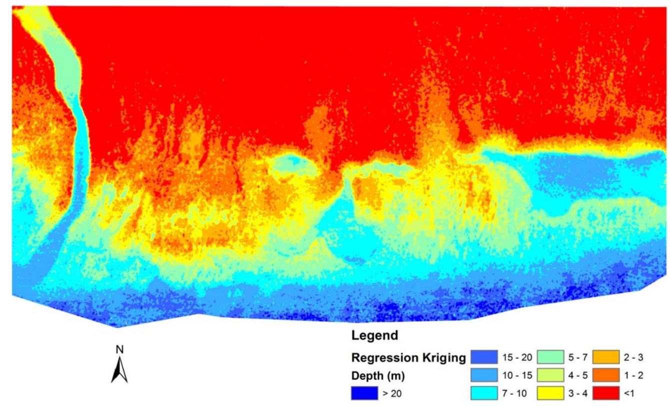



Fig. 6. Bathymetric grid derived from IKONOS image using RK method.

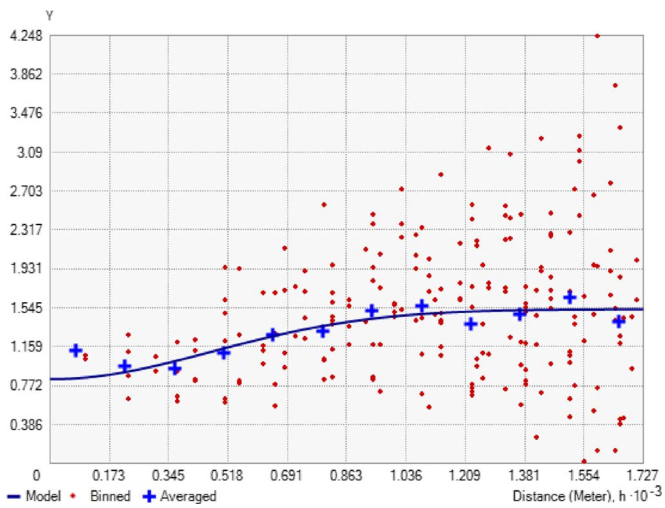



Fig. 4. Semivariogram for the residual from log-linear regression method.

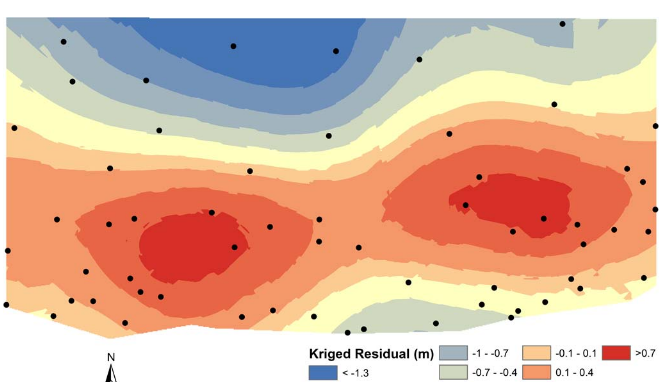
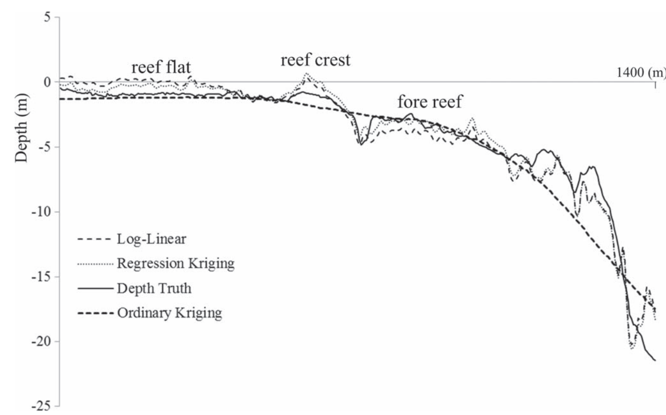
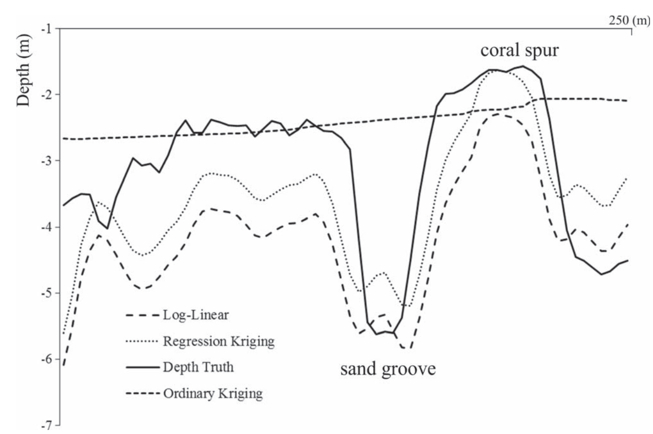



Fig. 5. Interpolated residual with the location of LiDAR depth points used for model calibration.




(a) Shore-normal profile along transect L




(b) Shore-parallel profile along transect M

Fig. 7. Geomorphological profiles. (a) Profile along transect L. (b) Profile along transect M. The locations of transects L and M are marked in Fig. 1.

and a sill value (the semivariance value where the empirical semivariogram appears to level off) of 1.531. Based on the fitted semivariogram, the residuals are then modeled and interpolated into a grid using the ordinary kriging method (Fig. 5). The water depth estimates by RK were then acquired by summation of the estimates from the log-linear regression model and the interpolated residuals (Fig. 6). The overall rmse for the estimates from RK is 1.63 m, which represents 12% decrease in comparison with the log-linear inversion method and 35% decrease in comparison with the ordinary kriging method. The correlation coefficient between the estimated depths of this method and the water-truth depths is 0.949, significantly higher than that of the ordinary kriging and log-linear methods.

To further evaluate the reliability and geomorphological content of the bathymetric data from different methods, we created geomorphological profiles along two transect lines (Fig. 7). The LiDAR data set has a high point density (about 0.16 point/m$^2$);

the interpolated profile can be treated as water depth truth to evaluate the depth estimates from RK. The shore-normal profiles from the RK method and log-linear method diverge from the actual sea floor profile mostly in the same way [Fig. 7(a)]. However, in many locations, the shore-normal profile from the RK method is closer to the actual sea floor profile compared to the log-linear method, most noticeably at the fore reef and the reef flat. In certain places, e.g., reef crest, the shore-normal profile from RK is worse compared to the log-linear method. The shore-parallel profile from RK [Fig. 7(b)] is more consistently closer to the actual sea floor profile compared to the profile from the log-linear method.

## VI. Discussion and Conclusion

This study has shown that RK can be used for more accurate estimation of water depth and better depiction of geomorphological features by using multispectral satellite imagery. Its performance is substantially better than the ordinary kriging and log-linear regression methods. The advantages of RK over the log-linear regression model are attributed to the fact that RK exploits the spatial autocorrelation of the residuals of the log-linear regression method. The advantage of the RK method over the log-linear inversion model decreases when the spatial autocorrelation between the regression residuals weakens (larger nugget effect for the residual semivariogram) [17]. Since the log-linear inversion model only compensates for a certain level of bottom-type variations and still suffers from the spatial heterogeneity in the reflectance of various bottom types [4], [6], the residuals from the inversion model are expected to have a strong spatial autocorrelation. This is evidenced in our case study: the sample points with a positive residual are mostly over coral cover, while the sample points with a large negative residual are mainly over macroalgae/sand (Fig. 1). The interpolated residual shows a horizontal band pattern linked to shore-parallel zones of different bottom types (Fig. 5). Therefore, RK will likely outperform the log-linear inversion model if there are various but still spatially autocorrelated bottom types in the study area.

The advantage of RK over ordinary kriging lies in the fact that it utilizes the detailed auxiliary information of multispectral imagery, which is ignored in all direct interpolation methods. The case study area is characterized by various microbenthic morphological features, which governs the small scale of topographical variations that cannot be captured by the spatial interpolation of a finite set of sample points. However, Kravchenko and Robertson [19] observed that RK performed not as good as ordinary kriging for data sets with strong spatial autocorrelation in the primary variable even when the correlation with a secondary variable is relatively strong. Thus, RK may be more suitable for bathymetric mapping of shallow waters with highly variable depth (low spatial autocorrelation) and may not be useful for areas without too much variation in water depth (high spatial autocorrelation).

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