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Extrapolating near-shore depth using geographically weighted regression of multi-spectral satellite images with consideration of bottom class types

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1. Introduction

Estimation of near-shore depth from satellite imageries have been discussed in the last two decades. Optical remote sensing imagery offers a cost-effective alternative to echo sounding and LiDAR surveys to derive high density bottom depth estimates for coastal water. Multi-spectral band linear regression algorithms are most common practiced to estimate depth from satellite imagery. The performance of conventional global model is limited when the bottom type and water quality vary spatially within the scene. Recently to address the heterogeneity of the bottom type and water quality, a Geographical Linear Regression model (GWR) model was introduced (Haibin *et al.*, 2013). Further, this study made aims to extrapolate near-shore depth using coefficients derived by GWR model with due consideration to bottom class types.

2. Materials and Methods

Two satellite imageries (Landsat 8 and RapidEye) and with different spatial and radiometric resolutions are used to estimate depth from near-shore area at Puerto Rico. The *in-situ* depth collected from NOAA is used to calibrate the depth estimates by GWR model.

2.1 Correction and log transformation

In comparison to existing methods, we utilize infrared band to correct the atmospheric and water surface components from the image and assume that the corrected bands are linearly related to the water depth. For Landsat 8 available Short Wave Infrared band (1.57 – 1.65 μm) and for RapidEye Near-infrared band (0.76 – 0.85 μm) were used. The equation for correction is following below (Vinayaraj *et al*, 2014)

$$X(\lambda)_i = \log\left(L\lambda_i - \alpha_0 - \alpha_1 (L\lambda_i I)\right) / L\lambda_i$$

Where, $X(\lambda)_i$ log transformed radiance after correction, $L\lambda_i$ is the radiance of the band to be corrected, α_0 is intercept, α_1 is slope of regression and $L\lambda_i I$ is the radiance of the band used for correction.

2.2 Classification of the study area

The study area is classified in to different classes according to the variation of the reflectance from bottom types and water quality. The log-transformed bands are used to classify by maximum likelihood classification method.

2.3 Estimating coefficients for each class from GWR model.

For improving depth retrieval in complex and heterogeneous marine environments, the spatial non-stationarity in the image scene was addressed by this method. Similar to the kernel regression method, the GWR model uses a window to define the local neighborhood, the equation is written as follows,

$$h_j = \beta_{0j} + \beta_{1j} X(\lambda)_{1j} + \beta_{2j} X(\lambda)_{2j} + \ldots\ldots. + \beta_{nj} X(\lambda)_{nj}$$

Where, j is the respective pixel, therefore coefficients for each pixel (j) was derived by assigning a fixed bandwidth. The bandwidth represents the size of the kernel used for regression. The points close to the centroid point were weighted more heavily in the regression process than those points far away from the centroid point. Implementation GWR model carried out by GRASS GIS open source software (http://grass.osgeo.org/) to estimate coefficients (intercept and slope of multiple linear regression) for each pixels. Further, the coefficients are estimated for each class by averaging the coefficients in a particular class. These coefficients applied to extrapolate depth for other region where *in-situ* dept is not available

3. Results and discussion

The evaluation of the results derived from the proposed method carried out by correlation coefficients (R), coefficient of determination (R^2) and RMSE shows that the estimation accuracy is good. The depth results derived by the proposed method is compared with the depth results derived by conventional global multiple linear regression also show that the results are reliable and better (Table 1).

Fig 1 and Fig 2 show that both global model and proposed model are good. Fig 3 and Fig 4 show that the histogram of the proposed model is closer to zero, meaning that the difference is less compared to global model.

Table 1. Comparing the results between proposed method and global model.

Data	Global model			Proposed method		
	R	R^2	RMSE	R	R^2	RMSE
Landsat 8	0.85	0.72	4.02	0.87	0.76	4.47
RapidEye	0.82	0.68	4.36	0.85	0.72	4.27

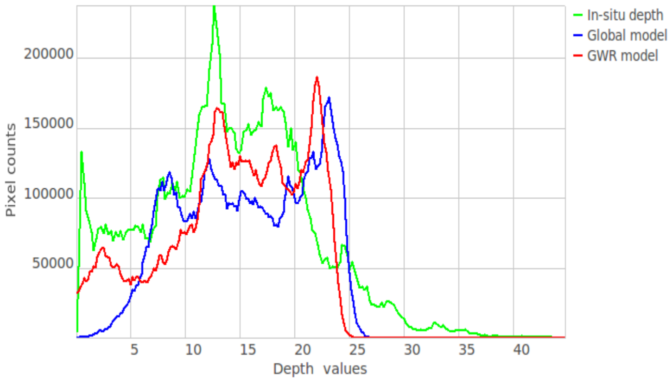

Figure 1. Histogram of *in-situ* depth, depth map derived from proposed method (GWR model) and global model from Landsat 8 data.

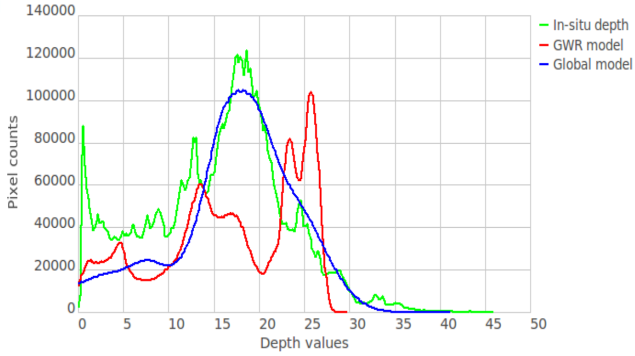

Figure 2. Histogram of *in-situ* depth, depth map derived from proposed method (GWR model) and global model from RapidEye.

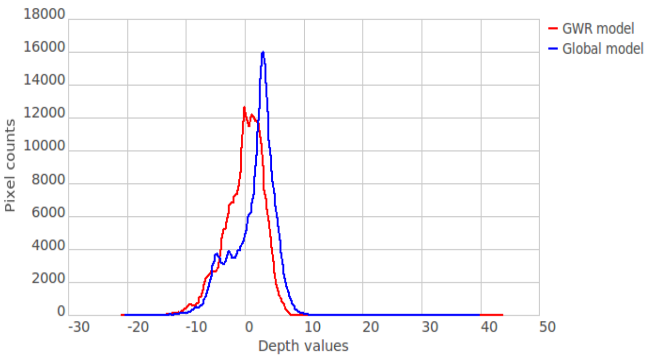

Figure 3. Histogram of the difference map. Difference calculated between *in-situ* depth and estimated depth respectively from Landsat 8 data.

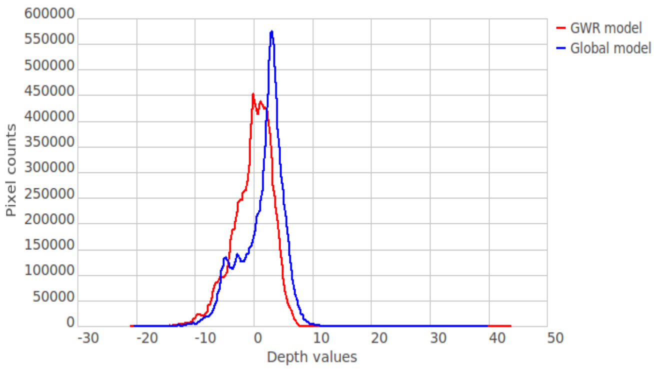

Figure 4. Histogram of the difference map. Difference calculated between *in-situ* depth and estimated depth respectively from RapidEye data.

4. Conclusion

GWR model is very efficient to estimate near-shore depth from the optical remote sensing images. But the density of the in-situ depth data is potential to impact the accuracy of the results. Therefore, this study demonstrated a new depth extrapolation method from class based coefficients. *In-situ* depth for a small region was used to estimate coefficients considering bottom types and further these coefficients used to estimate depth from where no *in-situ* depth available.

References

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