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GRASS GIS Pythonスクリプトと Rを用いた衛星画像推定水深のためのアルゴリズムの実装

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Implementation of Algorithm for Satellite Derived Bathymetry using GRASS GIS Python Scripting and R

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1. Introduction

Near-shore bathymetry is likely to be the coastal variable that most limits the investigation of coastal processes and the accuracy of numerical models in coastal areas, as acquiring medium spatial resolution data in the near-shore is highly demanding and costly. As such, the ability to derive bathymetry using remote sensing techniques is a topic of increasing interest in coastal monitoring and research. Many authors (Lyzenga *et al.*, 2006; Stumpf *et al.*, 2003) have been proposed different methods to estimate bathymetry. However, this contribution focuses on the implementation of the linear transform algorithm to obtain satellite-derived bathymetry as GRASS GIS module using python scripting and R. Proposed GRASS GIS module (i.image.bathymetry) automates the bathymetry estimation directly from multi-spectral bands.

2. Materials and Methods

Python scripting in GRASS and PyGRASS is powerful interface to call python functionality in to GRASS. i.image.bathymetry module is also using existing GRASS scripts and R packages. Main functionalities of the module are delineating water region, atmospheric and water column correction, Geographical Weighted Regression (GWR). R package called 'GWmodel' has been used to estimate GWR between corrected spectral bands as independent variables and calibration depth points as dependent variable.

2.1 Delineating water region

Delineating water region without visual interpretation is potential to produce error. To prevail over this problem rule based combination of NDVI and band ratio between green band and infrared band was used. NDVI has used to delineate water from land. Band ratio has used to separate the delineated water from clouds, ice etc (Vinayaraj *et al.*, 2015). GRASS module 'r.mapcalc' has been used to delineate the water region.

2.2 Atmospheric and water column correction

The radiance observed by a satellite sensor on shallow water basically consists of four components, namely, atmospheric scattering component, surface reflection component, in-water volume scattering component, and bottom reflection component. This study adopted more refined way of retrieving bottom reflectance originally proposed by Lyzenga *et al.* (2006). Assumes that algorithm can effectively eliminate components except bottom reflectance. The following definition of Lyzenga *et al.*'s algorithm is used for correction.

$$X(\lambda)_i = \log\ (L\lambda_i - \alpha_0 - \ \alpha_1\ (L\lambda NIR/L\lambda_i) \qquad (1)$$

Where, $X(\lambda)_i$ is the transformed radiance, $L\lambda_i$ spectral radiance of shallow water pixel (area of interest), α_0 and α_1 are coefficients estimated by least squares using the $L_\infty(\lambda)$ and $L\lambda NIR$ values of the deep-water pixels. Using the estimated values of α_0 and α_1 for the shallow-water pixels, we evaluate $X(\lambda)_i$ of the shallow-water pixels for each band by using the equation (1). GRASS module r.mapcalc has used to compute the equation (1).

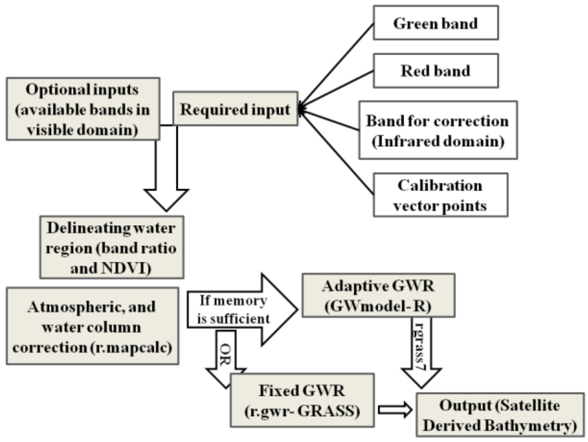

Figure 1. Flowchart of workflow of i.image.bathymetry.

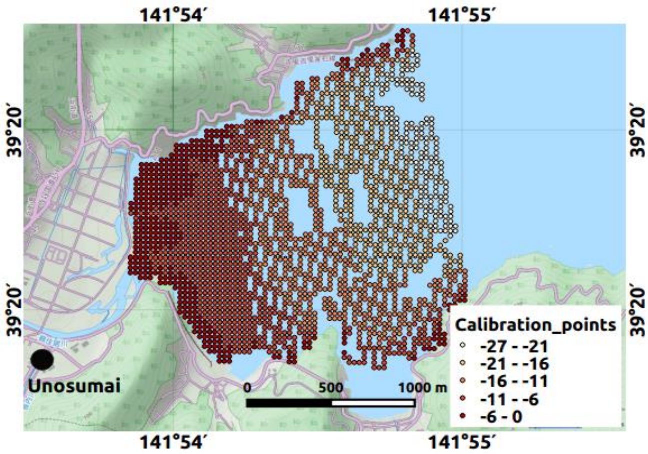

Figure 2. Study area used to test the module.

2.3 Geographical Weighted Regression

The transformed radiance ($X(\lambda)_i$) has been generated from all the visible bands (equation 1), and is assumed that the transformed radiance is linearly related to the depth and water attenuation coefficient. Thus we will apply a linear least square regression between LiDAR depth and transformed radiance to estimate coefficients. Further, these coefficients have been used to estimate the depth. R package ('GWmodel') has been used to compute GWR with adaptive bandwidth functionality. Since 'GWmodel' is memory consuming, big data cannot process in low memory computers. Computer memory specification also should be increased to use the adaptive GWR. Therefore, in the computers that cannot process 'GWmodel' due to low memory will use 'r.gwr' module in GRASS to compute GWR with fixed bandwidth functionality. Workflow of the i.image.bathymetry has shown in Figure 1.

3. Results and Discussion

The module has been tested and evaluated with many study areas with different satellite images irrespective spatial, radiometric resolution and size of the data. In this study we demonstrate bathymetry estimation in coastal area of Iwate prefecture, Tohoku, Japan (Figure 2).

Freely available Landsat8 data has been used estimate bathymetry using 500 depth points surveyed by echo sounder. SWIR band (1.57-1.65μm) has been used as 'band for correction'. All the available multispectral bands in the visible domain have been used for estimation. Figure 3 is a screenshot of i.image.bathymetry showing details of required input data, optional input data of i.image.bathymetry and the resulted bathymetry. The domain extent of the bathymetry estimation is set from the input calibration points. Therefore, the limited calibration points given by the user should cover the entire region need to be estimated. Evaluation of the result has been carried out by comparing the estimated bathymetry and echo sounder depth data which is not used for estimation. Result illustrate that the module produces good accuracy bathymetry in terms of correlation coefficient (R=0.96), coefficient of determination (R^2=0.92) and Root Mean Square Error (RMSE =1.17m).

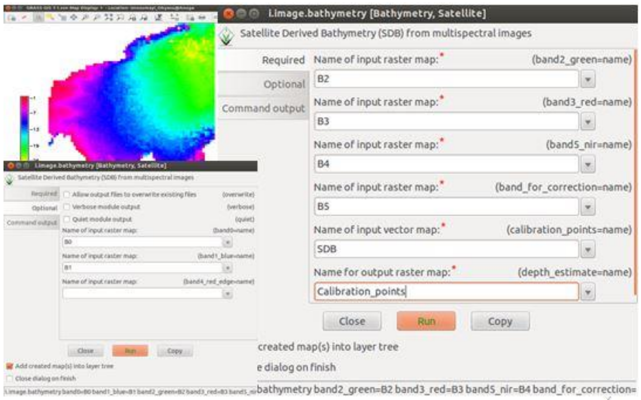

Figure 3. Screenshot of i.image.bathymetry

4. Conclusion

There are several methods to estimate near-shore bathymetry from satellite images, but there is not much software to automate the estimation procedure. Therefor this study implements a module in open source GIS software (GRASS GIS) using python scripting and R. Study demonstrates good performance of the module using a case study. Results of this case study is suggesting that the developed module reliable to automate near-shore bathymetry estimation over any other study area, where the assumptions of bathymetry estimation algorithm satisfies.

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