A Comparative Analysis to Model Bathymetry using Multi-sensor Satellite Imageries

Prayudha Hartanto, Yustisi Lumban-Gaol, and Ratna Sari Dewi
Geospatial Information Agency (Badan Informasi Geospasial), Jl. Raya Jakarta-Bogor Km. 46, Cibinong, Bogor, 16911 – Indonesia
hartantoprayudha@gmail.com

Abstract. Accurate and high-resolution water depth information are important for wide range of coastal research and monitoring. In this case, providing an accurate bathymetric map is a major challenge for remote sensing. This study developed and evaluated a semi-parametric regression to extract depth information using various image datasets (Landsat 8, Sentinel 2A and Worldview 2). We compared the ability of these imageries to map depth information using generalized additive model (GAM). GAM is a semi-parametric generalized linear model which allow for nonlinear relationships between covariates and the target variable. We used the Morotai shallow water area in Indonesia to apply GAM in deriving depth information. We found that higher image spatial resolution results in higher mapping accuracies. This study highlights the potential of selected images and mapping techniques for deriving bathymetric data.

1. Introduction
Bathymetric map is one of a basic geospatial information which utilized in a wide range of applications, such as scientific and practical uses. However, mapping the depth in a shallow water area using conventional method (e.g. echo-sounding) is relatively difficult and could be dangerous. To overcome this problem, the remote sensing methods have been proposed. One of the most widely used method is Lyzenga’s method [1]. This method utilizes the dependency of the in-water volume scattering and bottom reflection components of the observed radiance on the water depth to estimate it [2].

The utilization of remote sensing data to model shallow water bathymetry has been developed more due to advancing technology of satellite sensors and computing algorithm. Multispectral satellite sensors already available in a high spatial resolution. One example is Worldview 2 satellite which has 2 m spatial resolution for its multispectral data and 0.5 m for the panchromatic type. Prior to Worldview 2, Sentinel 2A by European Space Agency (ESA) provided free top of atmospheric reflectance data (level 1C) for worldwide coverage. With its 10 m spatial resolution, this type of remote sensing data can be used as main input of bathymetry modelling at intermediate scale. Another widely known multispectral sensor is Landsat 8 OLI which has the lowest spatial resolution compared to Worldview 2 and Sentinel 2A. However, its 30 m spatial resolution is essential for earth dynamic modelling, including bathymetry, at regional to global scale.
In term of computing methods, the development of machine learning algorithms had made satellite derived bathymetry (SDB) modelling a challenging topic for many researchers. Manessa et al. utilized random forest (RF) algorithm to make SDB model from Worldview 2 imageries [3]. Based on Manessa’s research, the root mean square error (RMSE) of RF algorithm ranged from 0.75 – 3.70 m in two different sites in Indonesia. Another exercise of RF algorithm in SDB was made by Sagawa et al., which concluded that the RMSE of the estimated water depth over five test areas was 1.41 m for depths of 0 to 20 m [4].

Besides the RF algorithm, there is empirical algorithm which has simplistic approach to compute water depth. The empirical algorithm employs direct observations of water depth in the study area to calibrate the reflectance-to-depth relationships [5]. A comprehensive assessment of the best method among widely used empirical algorithms was done by Manessa et al [6]. The research indicated that semiparametric regression by using combination of depth independent variables and spatial coordinates gave the best accuracy. However, the use of spatial coordinate alone without combining it with depth independent variables gave a slightly less accurate result than the combined one.

Based on Manessa’s research, this paper will examine the semiparametric regression using spatial coordinates as described in Kanno et al [2]. By using that single algorithm, this research will compare the SDB models’ performance over three different spatial resolutions of satellite imageries (Landsat 8 OLI, Sentinel 2A, and Worldview 2). Furthermore, the utilization of different number of bands and training data will also be examined to get more thorough analysis.

2. Study area
Area of interest of this study desired to be a shallow clear water area which also has in situ depth measurement. Morotai Island in North Maluku Province in Indonesia has been chosen as study area because of its qualified attributes. This research will focus on this single study area, located across 2° 8.80884’ - 2° 6.17581’ N and 128° 12.85289’ - 128° 13.93326’ E. Figure 1 below shows the study area of this research.
3. Echo sounder data
The in-situ depth measurement was organized by the Centre for Marine and Coastal Mapping, Geospatial Information Agency by using both Single Beam Echo Sounder (SBES) and Multi Beam Echo Sounder (MBES). Total depth measurement is 55,913 points which covers an area of 9.767 km$^2$. Before taken into further processing, the echo sounder data have been corrected to transform them into mean sea level (MSL) reference rather than momentary sea level surface. Tidal correction parameter was generated from http://tides.big.go.id.

![Figure 2. In situ depth measurement by echo sounder (red dots).](image)

4. Satellite imageries
To satisfy this research objective, three different spatial resolutions of satellite imageries were chosen. Those spatial resolutions are 30 m, 10 m and 2 m. Landsat 8 OLI image was chosen to represent the 30 m pixel size, while Sentinel 2A and Worldview 2 represent 10 m and 2 m resolution respectively. Table 1 below describes the attributes of each satellite used as main input data in this research.

|                  | L8     | S2A    | WV2    |
|------------------|--------|--------|--------|
| Spatial Resolution (m) | 30     | 10     | 2      |
| Blue band (μm)    | 0.435 - 0.512 | 0.496 | 0.450 - 0.510 |
| Green band (μm)   | 0.533 - 0.590 | 0.56  | 0.510 - 0.580 |
| Red band (μm)     | 0.636 - 0.673 | 0.6645 | 0.630 - 0.690 |
| NIR band (μm)     | 0.851 - 0.879 | 0.8351 | 0.770 - 0.895 |

Landsat 8 Operational Land Imager (OLI) is a successor of Landsat 7 which provides more band than its predecessor. Landsat 8 OLI provides two brand new bands to improve the data performance in term of ocean color observations and thin clouds detection. Overall there are 9 OLI bands with spatial resolution of 30 m, except for two panchromatic bands (band 10 and 11) which have 15 m resolution [7]. The used Landsat 8 OLI data was L1TP which is the highest quality Level-1 Precision Terrain data. Before being used in the processing step, the data was pre-processed to convert digital numbers (DN)
into surface reflectance. The pre-processing step was done by applying dark object subtraction correction [8]. Sentinel-2A is a European Space Agency (ESA) satellite mission which provides 10 m spatial resolution at 4 visible bands (red, green, blue and near infrared/NIR). Since December 2018, ESA produces globally coverage of level 2A (L2A) data which provides bottom of atmosphere (BOA) reflectance [9]. This research used the L2A data provided by ESA, no pre-processing step needed as the data already atmospherically corrected.

Worldview 2 is a satellite mission organized by DigitalGlobe which provides 2 m spatial resolution for multispectral images. Total available bands are 9, consists of 8 multispectral bands and a panchromatic band. This research utilized ortho-ready standard 2A image (OR2A). The OR2A has no topographic relief applied, making it suitable for custom orthorectification. The pre-processing step has been done using dark object subtraction to generate surface reflectance. Further reading about Worldview 2 data can be found in [10].

5. Semiparametric regression using spatial coordinates
The method was first derived by Kanno et al. by a statistical combination of Lyzenga’s method and a spatial interpolation method [11]. Further improvement was made by modelling the error term in Lyzenga’s method based on its spatial dependency [2]. Then, the semiparametric regression can be written as Eq. (1) [2,12].

\[ h = X\beta + t(z) + \varepsilon' \]  

where \( X \) and \( \beta \) are the Lyzenga’s estimators derived from in situ depth measurement and satellites visible bands. Meanwhile, \( t(z) \) is a smooth nonparametric function of the two-dimensional coordinate vector \( z \) and \( \varepsilon' \) is a zero mean random variable [2]. To implement this equation, we used penalized thin-plate regression spline available in ‘mgcv’ package of R statistical software. The full explanation of this algorithm can be read in [2].

6. Bathymetry models
As mentioned above, the implementation of Eq. (1) has been done by using mgcv package, especially the Generalized Additive Model (GAM) smoothing function. This research used the smooth term function ‘s’ which optimized by Generalized Cross Validation (GCV) and regression splines with fixed degrees of freedom. Essential step in making the model is defining the degrees of freedom or in practical mgcv package was written as k. The value of k should be neither too large nor too small. In practice, the trial and error procedure were done in defining k value to produce models with \( R^2 \) value more than 0.90. More complete explanation of GAM function can be found in [13,14].

In term of modelling the depth, we used 4, 3 and 2 bands each satellite to identify which band gives the better result. In 4 bands models, all visible bands (blue, green, red, NIR) were utilized. Meanwhile, the 3 bands models not using the NIR band and the 2 bands models only using blue and red bands.

Besides the using of different number of bands, this research also used different number of training data. Of the available in situ depth data, we tested the performance of training data number = 75%, 50% and 25%. Before taken into the processing step, the bathymetry data were filtered to have maximum depth of 30 m. To analyze the performance of the models, we split the depth range into 0 - 5 m and 0 – 30 m. The setting of this research was intended to determine the most optimum satellite derived bathymetry models. To accommodate the computation process, a high-performance computer (HPC) was used.

7. Assessment of SDB models
As mentioned in previous section, all produced models already have \( R^2 \) values larger than 0.90. Then, to assess the performance of each model we used mean absolute error (MAE) value. MAE value has been chosen as the measure of average model error because of it is a more natural measure of average
error, and unlike root mean square error (RMSE) is unambiguous [15]. MAE values were calculated using Eq. (2).

\[ MAE = \frac{1}{n} \sum_{i=1}^{n} |x_i - \hat{x}_i| \] (2)

8. Results and discussion

This research indicates an unexpected result. The SDB models derived from Landsat 8, which has the coarsest spatial resolution among the tested satellites, have the best accuracy (the lowest MAE value) for the shallow water region (0 - 5 m). Landsat 8 (L8) MAE values ranged from 0.468 – 0.484 m. Meanwhile Sentinel 2A (S2A) and Worldview 2 (WV2) MAE values ranged from 0.515 – 0.583 m and 0.490 – 0.564 m respectively. This result shows that coarser resolution could avoid appearance of high frequency noises. As a note, the noises/errors are not only caused by the sensor images, but also by the in-situ data as they have a dense spacing (~ 2.8 m along-track).

The second finding is the use of 2 bands (red and blue) in shallow water area gives the best accuracy compared to 4 and 3 bands among all tested satellites. This indicates that in the study area, the green and NIR frequencies have more noises than the other two bands. Furthermore, the number of training data equals to 75% of dataset does not give the best performance over the shallow water area. S2A and WV2 only need 25% of dataset used as training data to achieve the best accuracy, while the L8 needs 50% of it. Full list of results in 0 – 5 m depth area shown in Table 2, Table 3 and Table 4. This result affirms the presumption that the in-situ depth data have many errors (probably systematic errors) therefore need to be corrected by more than just tidal correction.

| Table 2. MAE of training data size = 75% of dataset at 0 -5 m depth |
|--------------------------|----------|----------|
| L8 | S2A | WV2 |
| 4 bands (m) | 0.484 | 0.583 | 0.555 |
| 3 bands (m) | 0.484 | 0.583 | 0.541 |
| 2 bands (m) | 0.480 | 0.545 | 0.490 |

| Table 3. MAE of training data size = 50% of dataset at 0 -5 m depth |
|--------------------------|----------|----------|
| L8 | S2A | WV2 |
| 4 bands (m) | 0.472 | 0.572 | 0.564 |
| 3 bands (m) | 0.472 | 0.572 | 0.564 |
| 2 bands (m) | 0.468 | 0.529 | 0.514 |

| Table 4. MAE of training data size = 25% of dataset at 0 -5 m depth |
|--------------------------|----------|----------|
| L8 | S2A | WV2 |
| 4 bands (m) | 0.479 | 0.554 | 0.550 |
| 3 bands (m) | 0.479 | 0.554 | 0.548 |
| 2 bands (m) | 0.475 | 0.515 | 0.492 |

Besides statistical approach, we also use the visual interpretation of SDB models. The simplest way is by extracting the zero-depth contour from the SDB models. Zero-depth contour line is an indication of the models’ ability to distinguish land and water area. To compare each satellite, we plot zero depth contour over the SDB models utilized 4 bands at 75% training data. Figures 3, 4 and 5 below indicate that WV2 derived bathymetry model is the only image which able to preserve the existence of the southern island. Moreover, it also gives the most detailed contour line.
Figure 3. Landsat 8 derived bathymetry of the area of interest, black line depicts the zero-depth contour.

Figure 4. Sentinel-2A derived bathymetry of the area of interest, black line depicts the zero-depth contour.
9. Conclusion
SDB models based on Landsat 8 OLI images gave the best accuracy. This probably caused by its coarse resolution could avoid high frequency noises came from both the sensor and the in-situ depth data. In the study area, Morotai Island, red and blue bands performed better than the other two multispectral bands. Besides the sensors’ performance, the quality of in situ depth data should also be noticed. Any other systematic errors (sound velocity, aeration, stylus speed and multiple echoes) than tidal factor should be removed from the echo-sounder data.

Despite its good performance in statistical assessment, Landsat 8 OLI image gave a poor performance in determining the land and sea area. Overall, the SDB approach still remains insufficient for mapping the shallow water (0 - 5 m) area as it has 10% - 50% depth error relative to the measured depth.

Acknowledgement
The authors would like to thank Center for Marine and Coastal Mapping, Geospatial Information Agency for providing the in-situ depth measurement data. Furthermore, we also acknowledge Ms. Masita Dwi Manessa for the technical scripting support.

References
[1] Lyzenga D R, Malinas N P and Tanis F J 2006 Multispectral bathymetry using a simple physically based algorithm IEEE Trans. Geosci. Remote Sens. 44 2251–9
[2] Kanno A, Koibuchi Y and Isobe M 2011 Shallow Water Bathymetry from Multispectral Satellite Images: Extensions of Lyzenga’s Method for Improving Accuracy Coast. Eng. J. 53 431–50
[3] Manessa M D M, Kanno A, Sekine M, Haidar M, Yamamoto K, Imai T and Higuchi T 2016 Satellite-Derived Bathymetry Using Random Forest Algorithm and Worldview-2 Imagery Geoplanning J. Geomatics Plan. 3 117
[4] Sagawa T, Yamashita Y, Okumura T and Yamanokuchi T 2019 Satellite Derived Bathymetry Using Machine Learning and Multi-Temporal Satellite Images Remote Sens. 11 1155
[5] Geyman E C and Maloof A C 2019 A Simple Method for Extracting Water Depth From Multispectral Satellite Imagery in Regions of Variable Bottom Type Earth Sp. Sci. 6 527–37
[6] Manessa M D M, Haidar M, Hartuti M and Kresnawati D K 2018 Determination of the Best Methodology for Bathymetry Mapping Using Spot 6 Imagery: a Study of 12 Empirical Algorithms Int. J. Remote Sens. Earth Sci. 14 127
[7] Department of the Interior U.S. Geological Survey 2019 LANDSAT 8 (L8) DATA USERS HANDBOOK Version 4.0 April 2019 Dep. Inter. U.S. Geol. Surv. 4

[8] Chavez P S 1988 An improved dark-object subtraction technique for atmospheric scattering correction of multispectral data Remote Sens. Environ. 24 459–79

[9] ESA 2015 SENTINEL-2 User Handbook Sentinel-2 User Handbook SENTINEL-2 User Handbook Title Sentinel -2 User Handbook SENTINEL-2 User Handbook 1–64

[10] Updike T and Comp C 2010 Radiometric Use of WorldView-2 Imagery Technical Note DigitalGlobe 1–17

[11] Kanno A, Koibuchi Y K, Takeuchi W And Isobe M 2009 A Generalized Satellite-based Method of Water Depth Mapping with a Semiparametric Optical Model J. Remote Sens. Soc. Japan 29 459–70

[12] Kanno A, Koibuchi Y and Isobe M 2011 Statistical combination of spatial interpolation and multispectral remote sensing for shallow water bathymetry IEEE Geosci. Remote Sens. Lett. 8 64–7

[13] Wood S N 2017 Generalized additive models: An introduction with R, second edition

[14] Pya N and Wood S N 2016 A note on basis dimension selection in generalized additive modelling 1–8

[15] Willmott C J 2005 Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance Clim. Res. 30 79–82