INTEGRATION OF STUMPF'S RATIO MODEL AND RANDOM FOREST FOR SATELLITE-DERIVED BATHYMETRY ESTIMATION

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ABSTRACT:

The development of remote sensing for coastal and marine environment mapping has significantly enhanced our understanding of these ecosystems, enabling improved mitigation strategies against the impacts of human activities. However, remote sensing must consider the complex interplay of the atmosphere and water column. Ongoing research focuses on refining water column correction techniques, including Depth Invariant Indices (DII), Radiative Transfer models, and bathymetry models. This study specifically aims to enhance the Stumpf's Ratio model (SRM) for bathymetry by employing the Random Forest (RF) machine learning regression algorithm. The resulting bathymetry model, which incorporates visible bands from a Sentinel-2 MSI image, and their Stumpf's ratios, outperforms other methods, yielding the highest accuracy with RMSE and R^2 values of 1.25 m and 0.854, respectively. This was followed by the multivariate SRM with RMSE and R^2 values of 2.196 m and 0.554 respectively These findings demonstrate the promising potential of using RF machine learning regression with SRM for bathymetry modelling.

1. INTRODUCTION

An important factor to understand coastal and marine ecosystems is their morphological characteristics. Aside from simply knowing the resources which are found in such ecosystems, understanding their morphological dynamics in terms of geospatial context allow further comprehension and analysis not just of their interrelationship within their environment but also with respect to the adjacent terrestrial environments. In this regard, the increasing anthropogenic effects necessitates better understanding of marine environments in order to develop effective mitigation measures to ensure not just their well-being but also of the terrestrial environment. With this, resource mapping plays an important role.

Mapping of marine resources is generally done through exhaustive and expensive surveys such as transect and manta tow. However, with the development of Earth observation satellites which have the capability to capture the Earth's surface including those beneath shallow coastal regions, remote sensing has been long considered an alternative due to it being effective. But it is undeniable that mapping marine environments using remotely sensed data is rather challenging mainly due to the sensor limitations and the variable effects of both the atmosphere and water column attenuation thus the ongoing attempts of improving its use.

The main consideration when mapping marine resources using remote sensing techniques is the correction of the effects of water column attenuation. Due to the water acting as a medium which light has to pass through before going back to the sensor, information about the surface beneath is heavily attenuated. Because of this, different techniques of modelling the effects of water column are being developed and explored such as Depth Invariant Indices (DII) by Lyzenga, Radiative Transfer models, and bathymetry models (Tamondong et al, 2014).

Lyzenga's DII addresses the effects of the water column by normalising spectral response values of pixels relative to a reference depth thus extracting reflectance or radiance values of specific bottom features at shallow and deep regions (Lyzenga, 1978). Using spectral information at these depths, an attenuation coefficient is linearly estimated from the absorption properties of the spectral bands using a regression technique which is then used to fit the spectral values for the other pixels (Lyzenga, 1978; Tamondong et al, 2014). This method however is dependent on the bottom type based on their albedo. Due to this, following this method would require generating different sets of DII for different bottom classes (Lyzenga, 1978). Moreover, this method relies on the clarity of the water making it susceptible to variable water conditions (Lyzenga, 1978; Tamondong et al, 2014).

Radiative Transfer Model requires the diffuse attenuation coefficient in order to model the propagation of light from the surface, down to the bottom and back to the surface (Maltese et al, 2008; Tamondong et al, 2014). This method is based on the idea that the reflectance value observed at the surface of the water is the combined attenuated reflectance of the bottom feature and the diffuse reflectance due to the water column (Maltese et al, 2008; Tamondong et al, 2014). In this regard, *in situ* information about the diffuse attenuation coefficient is therefore required to model the water column corrected spectral reflectance of bottom features hence the *in-situ* irradiance measurement in the study of Tamondong et al (2014).

For bathymetry models, the Stumpf's Ratio Model (SRM) has become a commonly used method. Unlike DII and radiative transfer, this method was developed to estimate water depth by correlating it to the spectral reflectance values (Stumpf et al, 2003). This method assumes a linear relationship between the ratio of the log-transform of high and low absorption bands and the water depths. Although this method follows the same principle as DII, using the ratio of the high and low absorption bands allowed this model to be less susceptible to bottom feature

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and water condition variability (Lyzenga, 1978; Stumpf et al, 2003; Tamondong et al, 2014).

In Tamondong et al. (2014) which compared these three methods, it was found out that SRM is an effective and efficient water column correction method. Although the radiative transfer model produced the best results based on their study, it required extensive *in situ* data collection of water irradiances at different water depths whereas bathymetry only required a sufficient sample of water depths for the modelling process (Tamondong et al, 2014). DII produced the lowest accuracy among the three. Aside from being computationally sophisticated, the method is susceptible to bottom variability requiring creation of different sets of DII for every benthic feature thus making it computationally expensive as well (Tamondong et al., 2014). Among these three, bathymetry as a water column correction is therefore highly suggested.

2. RESEARCH BACKGROUND

In Tamondong et al. (2014), the Stumpf's ratio model (SRM) was used to create a bathymetry model which was added to the benthic classification process as an additional water variable. However, this model can be considered limited due to it being linear only. In this regard, this study aims to improve the model by utilising machine learning techniques in the modelling process. This goal will be implemented through the following objectives:

- Generate bathymetry model using different variations of linear regression including multivariate and SRM.
- Develop bathymetry using machine learning, specifically Random Forest regression technique.
- Implement comparative analysis of the generated bathymetry models using RMSE and R^2 values.

By improving SRM for bathymetry modelling, this study will not only create an alternative water depth estimate which can be used in navigation and fishing but ultimately, it will contribute in the development of an accurate water column correction model alternative which can be used to enhance the study of marine and coastal ecosystems.

3. DATA AND METHODS

3.1 Study area and data

The bathymetry data of Bolinao, Pangasinan, composed of 2,293 points measured using a Lowrance single-beam echosounder in Tamondong et al. (2014) was used in this study. For the satellite data, Tamondong et al., (2014) used a Worldview-2 image, a commercial high-resolution image having a spatial resolution of 1.84m. In this case however, a Sentinel-2 MSI image was used instead to explore as well its capability given that it is open-source. According to Hedley, et al., Sentinel-2 MSI serves as a better alternative to other open-source satellite images for coastal remote sensing applications with its relatively higher spatial resolution of 10m, more frequent repeat-cycle and narrower band widths making it more capable at capturing benthic features (2018).

Google Earth Engine (GEE) was used for processing the images mainly due to it being a cloud-computing platform. The Sentinel-2 MSI image used in this study was also obtained using GEE since it has access to petabytes worth of open-source Earth observation data including Landsat and MODIS as well (Gorelick et al, 2017). An advantage of using GEE is that the users have the option to access pre-processed optical images such as the case for the Sentinel-2 MSI scene used in this study which was pre-processed using the Sen2Cor preprocessing toolbox (Gorelick et al, 2017). Moreover, various remote sensing tools and functions are already available in GEE making it a considerably stand-alone remote sensing tool (Gorelick et al, 2017).

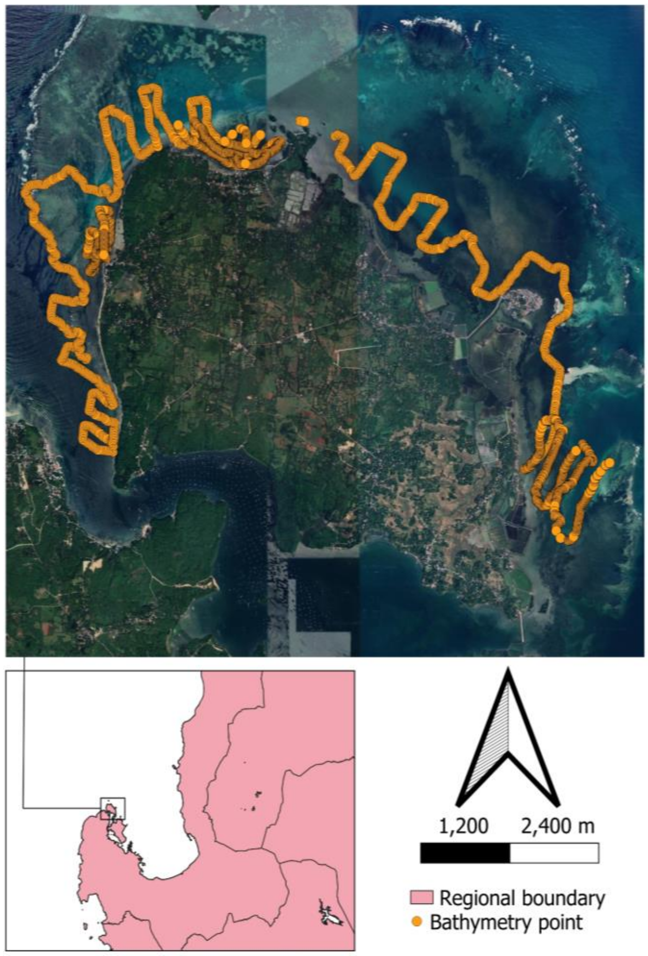

Figure 1. Bolinao, Pangasinan overlaid with points representing bathymetric measurements using a single-beam echosounder.

The use of GEE was further leveraged in this study by using the GEEMAP, a Python-based API allowing usage of GEE products and functions using Python. This was then integrated with Python-based data analytics libraries such as Numpy, Scikit-Learn and Pandas which enabled regression and machine learning implementations.

3.2 Methodology

The main goal of this study is to improve SRM by using machine learning regression, specifically using Random Forest (RF). RF is a robust nonparametric machine learning algorithm which is flexible at handling multi-dimensional and non-normalized data (Breiman, 2001). This algorithm is used in this study due to its capability for regression analysis. Moreover, its nonparametric nature based on decision trees could better model the relationship between spectral response and water depth compared to linear models. Comparing with other machine learning models, RF is capable of generating precise outputs allowing it to produce

robust, consistent and more accurate models compared to other algorithms such as Support Vector Regression (SVR) and Artificial Neural Networks (ANN) (Zhou et al., 2016).
SRM is shown in equation 1. Generally, this is applied to blue and green bands due to their penetrability to coastal environments compared to red band which is easily scattered and therefore diffused by the water media. However, there are studies which utilized the red band as well (Stumpf et al., 2003; Caballero & Stumpf, 2019).

$$SRM = a * \left[\frac{\log(b1)}{\log(b2)}\right] + c \qquad (1)$$

Where:

a = value of slope resulting from the linear regression;
$b1$ = spectral reflectance of lower absorption
$b2$ = spectral reflectance of higher absorption
c = intercept resulting from the linear regression

Other empirical methods which are linear in nature were also implemented in this study such as multivariate regression model which is a straightforward linear regression analysis between the RGB bands of the Sentinel-2 image, multivariate SRM regression which is similar to the previous but following SRM and lastly, Li et al.'s automatic global shallow water bathymetry (Li et al, 2021; Evagorou, et al., 2022). The multivariate linear regression of visible bands and the multivariate regression using SRM were included to also demonstrate the capabilities of the different visible bands for bathymetry.

Li et al. 's implementation of a satellite-derived bathymetry simply follows SRM which was modelled using *in situ* water depth data obtained from six globally diverse coastal sites (Li et al, 2021). This study produced RMSE values ranging from 1.2 m to 1.9 m suggesting its applicability around the world.
The methodology of this study is a straightforward regression analysis to develop a bathymetry model using the *in-situ* water depth data and the RGB bands of the Sentinel-2 MSI image following different empirical models as listed below:

- SRM using green and blue bands only
- Multivariate SRM using red, green and blue bands
- Multivariate linear regression using red, green and blue bands
- Li et al.'s automatic global shallow water bathymetry
- Multivariate regression of spectral reflectance (RGB) and SRM (B/R, G/R, and B/G) using RF machine learning regression

Figure 2 shows the general workflow of this study. The flowchart is a generic framework applied to the different models implemented in this study. The case of Li et al.'s model however did not include training but simply proceeded to validation.

3.3 Image processing in GEE

Using the Earth Engine library, an image collection of Sentinel-2 was accessed which was filtered by date and using a geometry which bounds Bolinao, Pangasinan. Land features were then masked out using Hansen et al. 's, Global Forest Change dataset land mask of 2015 which was also available in GEE's cloud repository. After masking, logarithmic-ratios of the visible bands were then derived, adopting the SRM (Stumpf et al., 2003). A new stack was created consisting of 6 variables, the visible bands and their logarithmic-ratios. After this, spectral and logarithmic-ratio values were sampled using the bathymetry point data in .csv format - which is composed of a total of 2293 samples surrounding the whole Bolinao island as shown in the following figure - using GEE's ee.Image.sampleRegions() method. This generates a collection of features having additional attributes extracted from an image, in this case the newly created stack. This feature collection was converted to a dataframe for the regression analysis which was done mainly using Numpy and Scikit-Learn's LinearRegression() method. For the machine learning model, GEE also includes a set of machine learning-based image classifiers such as RF which was used in this study.

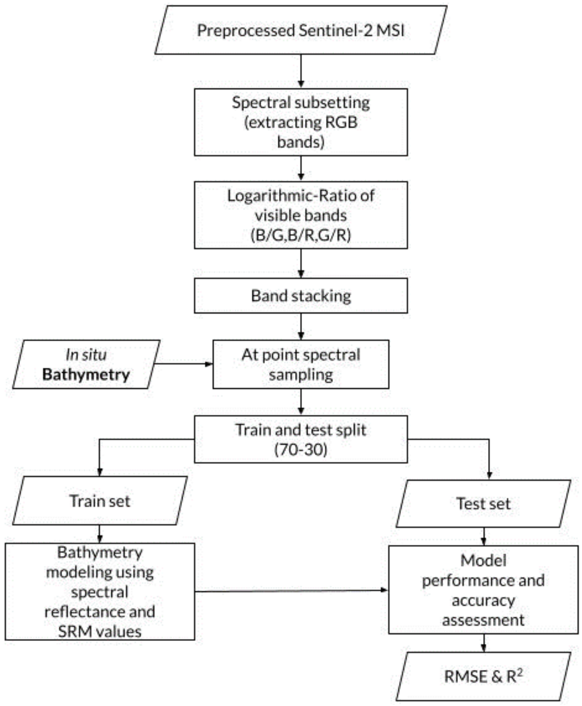

Figure 2. General framework for bathymetry modelling applied to different the linear and machine learning models.

3.4 Accuracy assessment

For the accuracy assessment of the generated bathymetry models, Root Mean Square Error (RMSE) and the coefficient of determination (R^2) were computed using statistical aggregation and linear fitting respectively. The RMSE was used to indicate the models' accuracy and precision as it computes for the mean residual between the true and modelled measurements. The R^2 on the other hand was used to compare the model and the true values by measuring their fit on a scatter plot. Furthermore, these two indicators were computed from two sets of data, first is the training dataset which is 70% of the total number of data and second is the validation dataset which is 30% of the total bathymetry points.
By assessing the accuracy of the model based on the training dataset, model performance can be assessed in terms of how well it is able to correlate the independent variables from the dependent variable, in this case the spectral reflectance and water depth respectively. Assessing the accuracy using a separate set of ground truthed data will provide insight as to how the produced model will hold true when applied to a different set. This is done to show as well if the model created is applicable to a different set of data which is not known to the model.
For the machine learning model however, hyperparameter tuning was not included in the scope of this study. Aside from the

number of trees, which was set to 1000 for this study, other parameters were set to default values only.

4. RESULTS AND DISCUSSION

4.1 Correlation of water depth and Surface Reflectance and SRM

When comparing the correlation of water depths with surface reflectance values only and SRM values, the latter produced better results having correlation values which are approximately 67% better than that of the surface reflectance values only. The multivariate linear model only correlated the spectral reflectance per band with the water depths which failed to address the exponential decrease of light penetration in water bodies as the depth-increases (Stumpf et al, 2003; Tamondong et al, 2014). Unlike spectral reflectance only, using the logarithmic-ratio of two bands or the SRM as suggested by Stumpf et al. is able to normalise that non-linear relationship between depth and the spectral reflectance producing a linear-like correlation thus reducing the RMSE and resulting in a better model fit (2003). This linear-like relationship can be inferred from figure 3 which shows a comparison of the scatter plots of the reflectance and SRM values to the water depths. This linear-like trend is most noticeable using the SRM for blue and green bands.

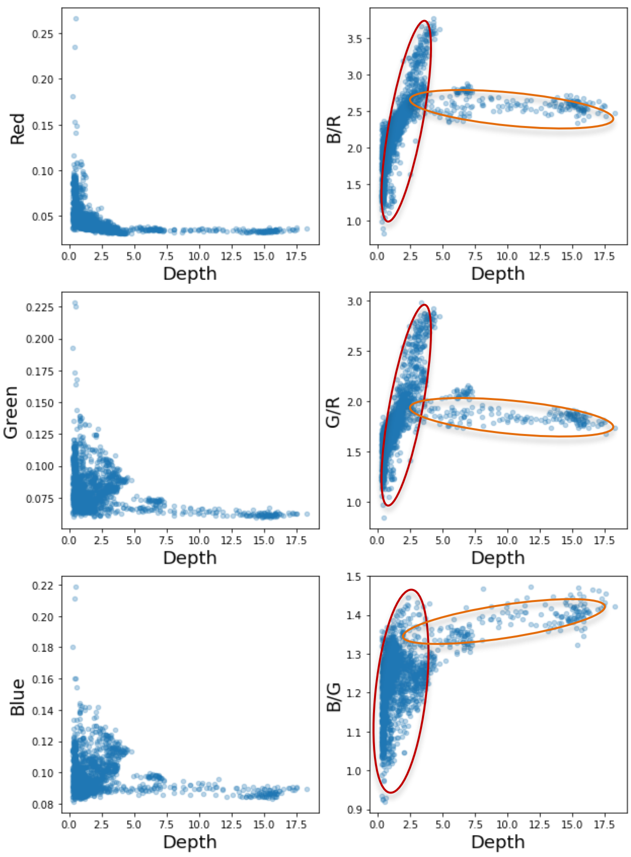

Figure 3. Scatter plots comparing reflectance values (left column) and logarithmic-ratios of the reflectance values (right) and water depth.

In figure 3, the scatter plots for SRM vs water depths showed clustering of samples as bounded by the red ellipse which have linear relationship; however, there is a secondary clustering that can be extracted from the plot bounded by the orange ellipse which is relatively lesser than the previous. This can be attributed to the variable bottom features in terms of albedo (Lyzenga, 1978; Stumpf et al, 2003). This is most prominent in the band ratios with the red band due to its low penetrating capability unlike blue and green bands (Lyzenga, 1978). Although the use of blue and green bands reduced this non-linear characteristic due to variable bottom features, table 1 summarizes the different R-square values produced when fitting non-linear models such as logarithmic, exponential and quadratic functions. Based from the table, non-linear models such as logarithmic and quadratic models produced better fit between SRM and water depths compared to linear models even when using the SRM for blue and green bands. This therefore suggests the use of non-linear approach in modelling water depths when using remote sensing data thus this study's attempt to analyse the applicability of a machine learning technique.

Looking at the R-square values for surface reflectance of the visible bands and water depths, the generally low R-square values indicate low correlation between the two variables. This implies that the use of empirical models with surface reflectance values only is significantly inferior to SRM.

	R^2			
	Linear	**Logarithmic**	**Exponential**	**Quadratic**
R	0.1123	0.2739	0.1297	0.2976
G	0.0702	0.061	0.0695	0.0712
B	0.0149	0.0011	0.0144	0.0512
B/R	0.2072	0.5613	0.1722	0.58
G/R	0.0998	0.4143	0.0842	0.51
B/G	0.2935	0.3555	0.2885	0.3246

Table 1. Non-linear fitting of water depth values with surface reflectance and SRM values.

4.2 Random Forest-derived bathymetry

Comparing the RMSE and R-square values of the different models developed in this study, RF produced superior results with RMSE of 1.26 m using the validation dataset. This implies that RF was able to best minimise the error of the model compared with the other models. The RMSE of the RF model is 51% less than the mean RMSE of the three linear models, not including the model of Li et al (2021). As for the linear fit of the modelled and actual values, the RF model produced an R-square value of 0.85 which does not only show strong fit between the model and the true values, but it is also 56% greater than the other three linear models. Based on these results, there is a significant improvement in the model when using RF.

Model	**Training Dataset**		**Validation Dataset**	
	RMSE	R-squared	RMSE	R-squared
Multivariate Linear Model	2.53	0.29	2.81	0.27
SRM (B/G)	2.56	0.27	2.77	0.29
Multivariate SRM	2.08	0.52	2.20	0.55
Li et al (2021)	-	-	4.60	-0.96
Random Forest Regression	0.86	0.92	1.26	0.85

Table 2. RMSE and R-squared values obtained using various models.

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As for the other linear models, the multivariate SRM also showed significant improvement in terms of fit between the modelled and actual values. In terms of the RMSE, while the error was reduced, it was still greater than 2 m which is a significant magnitude especially for shallow water regions. Nevertheless, using a multivariate SRM showed significant improvement as compared to the multivariate linear model only and SRM using blue and green bands only.

For the case of Li et al.'s variation of SRM, results showed that the model performed the weakest. Despite the use of training data sampled in six diverse coastal sites around the world, the model has been constrained to those areas only suggesting that bathymetry models derived from remotely sensed data are location specific. Moreover, the strong variability of environmental conditions can significantly affect the modelling process as well. Figure 4 shows a scatter plot of modelled water depth and actual depth using Li et al.'s version of SRM. The inverse proportionality and negative correlation therefore prove that their model is not applicable to all coastal regions, thus the automatic shallow bathymetry model's weak performance in this study.

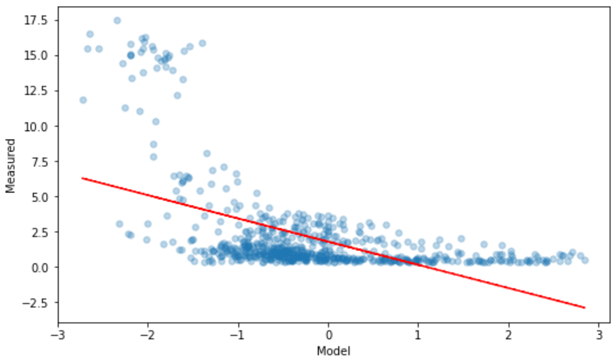

Figure 4. Li et al.'s modelled water depth vs actual water depths.

Figure 5 shows the scatter plots of the different bathymetry models using the independent validation set. Generally, the models generated positive correlation between modelled and actual values but the RF model produced the best fit. This can be explained by its non-parametric nature which allowed it to model non-linear relationships such as the case of spectral reflectance, SRM and water depth. Moreover, looking at the range of values for the modelled and measured there is significant difference between the performance of RF and the other linear models. RF was able to model a similar value range whereas the linear models underestimate the values at deep regions. This suggests that the RF model have exhibited sensitivity to minute value changes unlike the linear models which were not able to capture the exponential decrease of reflectance values at deep values, despite the use of the SRM or the logarithmic-ratio which is supposed to emphasize minimal changes in values (Tamondong et al, 2014; Stumpf et al, 2003). This exponential decrease has been exhibited by the scatter plots of the visible bands versus water depth values in figure 3.

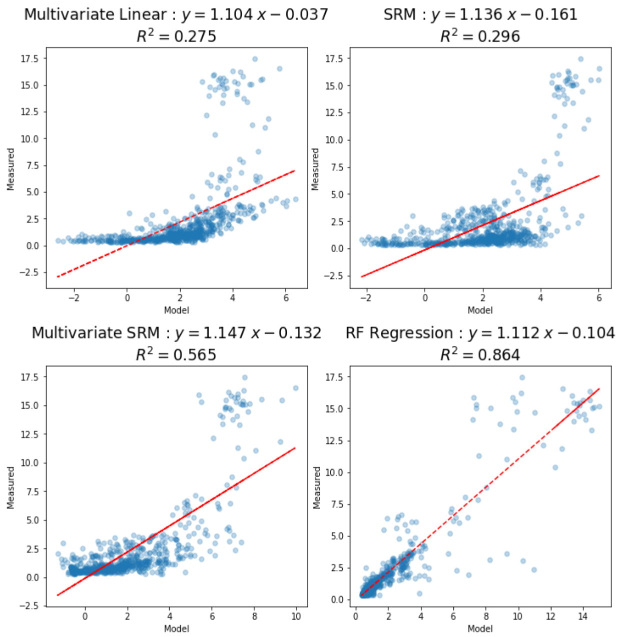

Figure 5. Scatter plots of modelled and actual water depth values.

Lastly, an advantage of using RF as a machine learning algorithm is its capability to evaluate the importance of the variables used in the process. For this study, multivariate regression was implemented using RF where all the variables from the stacked image, that is composed of the bands and their logarithmic-ratios resulting in a total of six variables, were included in the regression. Figure 6 shows the variable importance for this study in increasing order.

Consistent with Stumpf, et al., (2003) the logarithmic-ratio of the blue and green bands are the best variables for modelling water depth. From the six variables used for the RF model, the blue-green logarithmic-ratio contributed most in the regression process. Figure 7 shows a scatter plot showing the fit of the generated model using only the blue-green logarithmic-ratio. From this plot, there is a decrease when only using this variable but this result is still superior than the other linear models.

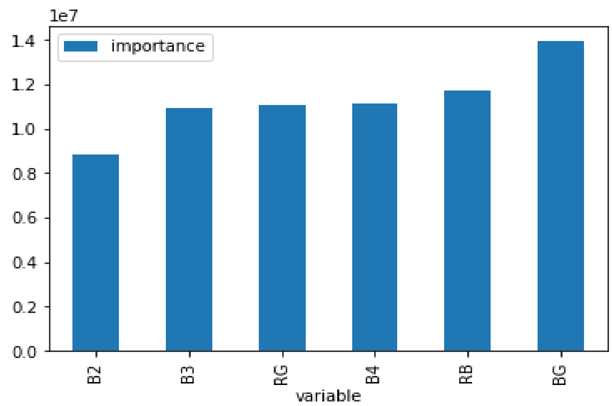

Figure 6. RF variable importance.

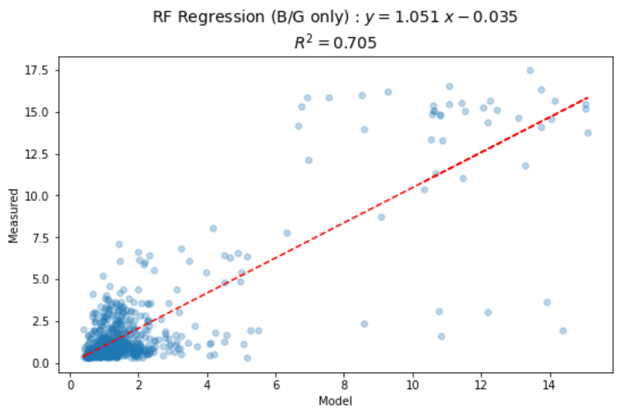

Figure 7. Scatter plot of modelled and actual water depth values for RF regression using SRM for blue and green bands only.

5. CONCLUSION AND RECOMMENDATIONS

This study demonstrated the use of machine learning in modelling bathymetry from remotely sensed data, specifically using Sentinel-2 MSI image. Aside from deriving bathymetry models, a comparative analysis of using linear models including SRM and non-parametric models using machine learning was also implemented in this study. Based on the results, the use of machine learning can significantly improve SRM for bathymetry modelling, in this case reducing SRM's RMSE by 51% and increasing correlation between modelled and actual depths by 56%. This does not only mean more accurate water depth estimates, but further improvement of this method could help develop a better alternative to addressing the effects of water column to spectral reflectance information. By doing so, coastal and marine mapping and other studies can also be improved, helping better address the current problems that such an environment is facing.

However, some recommendations for this study would include, first, considering other alternatives for preprocessing of the satellite data which are more focused for coastal applications. Second is the use of the same satellite data which this study was derived from to ensure temporal consistency with the *in-situ* data. Lastly, implementing hyperparameter tuning for the machine learning model used in this study is recommended. Despite these recommendations, this study nevertheless showed the potential of machine learning, specifically RF, for bathymetry modelling.

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