Extracting shallow bathymetry from very high resolution satellite spectral bands and a machine learning algorithm

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Summary
As a useful proxy for marine biodiversity, bathymetry in shallow coastal and estuarine areas remains difficult to map using shoal-limited waterborne or costly airborne survey systems. Recent advances in spaceborne sensors may address these issues by providing sub-meter optical information across regional areas. Here we evaluated the joint capabilities of the newest very high resolution multispectral sensor Pléiades-1A (blue, green, red wavebands at 0.5 m pixel size) and an optimizing machine learning algorithm (neural network) to retrieve shallow bathymetry over a structurally-complex reef area over the whole island of Moorea, French Polynesia. As ground-truth data, >15,000 acoustic depth soundings were measured in situ ranging from 0 to 20 m. Agreements between actual and modelled water depths derived from ratio transform (RT) and neural network (NN) models applied to three multispectral visible datasets (digital number, radiance, reflectance) were compared using several measures of accuracy. Results showed the NN outperformed RT models, and could accurately render the actual water depths ($R^2=0.89$, $R^2=0.8$ and RMSE=2.44). This innovative method enabled the coastal gap to be reliably filled at a sub-meter spatial resolution, thus opening new research avenues to map shallow habitats at a finer scale.

Introduction
Water depth is a crucial factor in explaining interactions between spatial patterns in marine habitat / life and ecological processes. Bathymetry is correlated with primary physical drivers, such as pressure, water motion, temperature and light, which in turn strongly affect spatial patterns in biodiversity. However, obtaining accurate, fine-scale but extended bathymetry in shallow waters remains hazardous and/or expensive using water- and airborne systems. Using the spatial and spectral capabilities of very high resolution spaceborne sensors has permitted recovery of bathymetry over clear waters with satisfactory accuracy ($R^2=0.7$, Collin and Planes 2012). Herein we examine whether a NN machine learner approach may improve bathymetry retrieval relative to the RT model.

Materials and Methods
The study area encompasses Moorea Island (189 km², 17°29’31″S, 149°50’08″W), Tahiti’s old sister, in French Polynesia. A waterborne survey for ground-truthing was conducted on 4-18 January 2011 with a 200-kHz digital sonar combined with a 12-channel GPS receiver mounted on a small boat. An array of 15,777 soundings ranging from 0 to 20 m, with 0.2-m vertical accuracy, was collected. The spaceborne imagery was taken on 23 June 2014 with the Pléiades-1A sensor, delivering a 2-m-pixel-sized optical dataset (blue, green, red and near-infrared) and a 0.5-m-pixel-sized panchromatic band. Rigorous orthorectification of both datasets was carried out before running a pansharpening procedure (Gram-Schmidt sharpening followed by a cubic convolution resampling) so that the spatial resolution of the four-banded optical dataset reached that of the panchromatic band, i.e. 0.5 m. The digital number dataset was then radiometrically-corrected to a primary radiance dataset, by using the sensor calibration coefficients, and to a secondary reflectance dataset, by correcting for the atmosphere light attenuation. The resulting three datasets (digital number, radiance and reflectance) were subject to two various methods aimed at empirically modelling the bathymetry: the RT (Stumpf et al. 2003) and the proposed NN. The RT model, based on the differential light absorption as a function of the optical wavelength, was built from the three sub-ratios involving the blue, green and red wavebands.
The RT created a relative digital depth model that needs to be calibrated by 2/3 of the ground-truth data (Collin and Planes 2012). The NN model, as a connected three-layer perceptron, exploits the blue, green and red wavebands as input factors explaining the 2/3 of the actual bathymetry response. By computing three “hidden” neural bands, the NN model predicted the absolute digital depth model. Finally, both modelled series were implemented on the 37,875×30,326-pixel spatial domain covering the entire island and validated by the remaining 1/3 of the ground-truth response in the form of Pearson’s correlation coefficient (r), coefficient of determination of the best fitted model (R²) and the inherent root mean square error (RMSE).

Results and Discussion

The comparison between actual and modelled bathymetry showed that NN models outperformed the RT models across the three pixel unit modalities. The most and least accurate RT models reached R² values of 0.67 (radiance) and 0.26 (reflectance), while the NN models gave 0.74 (digital number) and 0.8 (reflectance), respectively (Table 1). The best RT model suitably corroborated the results found in previous analogous studies with a R² value of 0.7 (Collin and Planes 2012; Collin et al. 2014). However it is noteworthy that all NN models produced very high measures of accuracy, compared to the traditional approaches to multispectral-based bathymetry retrieval.

The NN model provided with the best agreement was selected so that the mathematical formulae of the three “hidden” neural bands could be calculated and then unified in the predicted digital depth model spanning the whole Moorea Island (Figure 1).

Table 1. Measures of accuracy as functions of the model and pixel unit. Blue-to-red color gradients illustrate the increase in Pearson’s correlation coefficient (r) and coefficient of determination (R²) and decrease in root mean square error (RMSE).

<table>
<thead>
<tr>
<th>Ratio</th>
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<th>RMSE</th>
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<td>Digital Number</td>
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</table>

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Figure 1. Flowchart composed of the three visible spectral bands (blue, green and red), as explanators of the actual bathymetry response, feeding the three “hidden” neural bands, which in turn produced the predicted bathymetry.

References