Mask R-CNN and U-Net model and output of coral reef halo measurements based on global multispectral satellite imagery

Website: https://www.bco-dmo.org/dataset/943698
Data Type: model results
Version: 1
Version Date: 2024-12-18

Project
» CAREER: Decoding seascape-scale vegetation patterns on coral reefs to understand ecosystem health: Integrating research and education from organismal to planetary scales (Coral Reef Halos)

Contributors	Affiliation	Role
Madin, Elizabeth	University of Hawaiʻi at Mānoa (HIMB)	Principal Investigator, Contact
Franceschini, Simone	University of Hawaiʻi at Mānoa (HIMB)	Scientist
Soenen, Karen	Woods Hole Oceanographic Institution (WHOI BCO-DMO)	BCO-DMO Data Manager

Abstract
Reef halos are rings of bare sand that surround coral reef patches. Halo formation is likely to be the indirectly result of interactions between relatively healthy predator and herbivore populations. To reduce the risk of predation, herbivores preferentially graze close to the safety of the reef, potentially affecting the presence and size of the halo. Reef halos are readily visible in remotely sensed imagery, and monitoring their presence and changes in size may therefore offer clues as to how predator and herbivore populations are faring. However, manually identifying and measuring halos is slow and limits the spatial and temporal scope of studies. There are currently no existing tools to automatically identify single reef halos and measure their size to speed up their identification and improve our ability to quantify their variability over space and time. Here we present a set of convolutional neural networks aimed at identifying and measuring reef halos from very high-resolution satellite imagery (i.e., ~0.6 m spatial resolution). We show that deep learning algorithms can successfully detect and measure reef halos with a high degree of accuracy (F1 = 0.824), thereby enabling faster, more accurate spatio-temporal monitoring of halo size. This tool will aid in the global study of reef halos, and potentially coral reef ecosystem monitoring, by facilitating our discovery of the ecological dynamics underlying reef halo presence and variability.

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Methods & Sampling

The Mask R-CNN model was trained using the training data set, thereby automatizing the identification of reef halos from the test set of satellite images and extracting the shape of the reef halos from the imagery background (i.e., extracting both the patch reef and its surrounding halo). The Mask RCNN was trained with 3322 reef halos from 13 AOIs, while the remaining 805 halos from seven AOIs were kept to evaluate the model's performance.

After object extraction, we automated halo measurement using a U-Net pixel classification model which discriminated the halo (sand ring) from the interior reef patch. A total of 6428 annotations from the training set were used for model training. Annotations consisted of pixel areas manually classified by users, divided into "patch reef" and "halo" classes, respectively.

The total of 6428 annotations used for the classification model was derived from splitting some of the 4127 original annotations (see related dataset). This process was implemented as part of the model training to improve pixel classification by creating diverse and multiple samples.These shapefiles were created as part of the training process and can be recreated from the original annotations already provided by processing them within the ArcGIS using the .dlpk model (as explained also in the github tensorflow).

Data Processing Description

Both the Mask R-CNN and U-Net models were developed using Tensorflow (ver. 2.5.1), Keras (ver. 2.4.3), and PyTorch (ver. 1.8.2) libraries in Python (ver. 3.9) and ArcGIS (ver. 2.9.1.) The machine running the deep learning model had an Intel® Core™ i9-9900K CPU @3.60 GHz processor with 128 GB of installed RAM and a PNY NVIDIA Quadro A6000 GPU.

The areas of both reefs and halos were calculated by counting the number of pixels assigned to the respective "reef" and "halo" classes. The total area for each spatial object was estimated with the known size of a pixel.

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Data Files

File
943698_v1_modelstats.csv (Comma Separated Values (.csv), 50.73 KB) MD5:b49c785f920289b09b09ef0156144660 Primary data file for dataset ID 943698, version 1

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Supplemental Files

File
Mask R-CNN model filename: MASKRCNN_model.zip (ZIP Archive (ZIP), 189.89 MB) MD5:53ab64b0a4b3b399fecdda54427bced6 Mask R-CNN Model: Mask R-CNN model for automatized identification of reef halos and extraction the shape of the reef halos from the imagery background (i.e., extracting both the patch reef and its surrounding halo). Provided as .dlpk and .emd files. They represent the trained model and can be used with any Python machine learning suite (e.g., TensorFlow, Keras, PyTorch) or within ArcGIS. These files are the only inputs required for predicting new objects in machine learning tools or ArcGIS. This allows any ArcGIS or Python user to replicate our model and predict potential halos in any geographic area.
U-Net model filename: U_NET_model.zip (ZIP Archive (ZIP), 145.96 MB) MD5:5651d7be9b83a2102fe815f2a7172328 U-NET Model: U-Net pixel classification model for automated halo measurement after object extraction, which discriminated the halo (sand ring) from the interior reef patch. Model provided as .dlpk and .emd files. They represent the trained model and can be used with any Python machine learning suite (e.g., TensorFlow, Keras, PyTorch) or within ArcGIS. These files are the only inputs required for predicting new objects in machine learning tools or ArcGIS. This allows any ArcGIS or Python user to replicate our model and predict potential halos in any geographic area.

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Related Publications

TensorFlow Developers. (2021). *TensorFlow* (Version v2.5.1) [Computer software]. Zenodo. https://doi.org/10.5281/ZENODO.5177380 https://doi.org/10.5281/zenodo.5177380
Software

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Related Datasets

IsDerivedFrom

Madin, E., Franceschini, S. (2024) **Manually annotated reef halos based on sattelite imagery from 6 study areas as training and test data for a deep learning model.** Biological and Chemical Oceanography Data Management Office (BCO-DMO). (Version 1) Version Date 2024-12-18 doi:10.26008/1912/bco-dmo.932211.1 [view at BCO-DMO]
Relationship Description: Manually annotated reef halos as input data (training & test) for Mask R-CNN and U-Net model.

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Parameters

Parameter	Description	Units
AOI	Area of interest. Twenty areas in total. Country codes: AUS = Australia, BHS = Bahamas, BLZ = Belize, EGY = Egypt, SAU = Saudi Arabia, USA = United States of America (Florida)	unitless
object_id	The object ID was used to relate the halo area of each object to its reef patch to get a ratio, not to relate them to the test data set,	unitless
hArea_m2	Halo area	square meter (m2)
rArea_m2	Reef area	square meter (m2)
log_hArea_m2	Log-transformed halo area	square meter (m2)
log_rArea_m2	Log-transformed reefarea	square meter (m2)

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Project Information

CAREER: Decoding seascape-scale vegetation patterns on coral reefs to understand ecosystem health: Integrating research and education from organismal to planetary scales (Coral Reef Halos)

Website: http://oceansphere.org

Coverage: Hawai'i (field components) and global (synthetic components)

NSF Award Abstract:
Coral reefs worldwide are under increasing threat from a range of human-induced stressors. Climate change is understood to be a key global stressor threatening reefs, but the only proven levers for ecosystem managers to increase reef resilience is to mitigate local and regional stressors such as fishing pressure. A vexing question persists, however, which is how to measure the effects of fishing on ecosystems, particularly over the large spatial (e.g., >10s of meters) and temporal (multi-year) scales over which fishing occurs. One promising approach to doing so is using the large-scale vegetation patterns found on coral reefs globally, called “halos”, to remotely observe when, where, and to what extent fishing pressure is affecting community structure and function. This program combines lab- and field-based experiments with cutting-edge satellite imaging technology and computer science approaches to provide a leap forward in our understanding of how species-level interactions can scale up in space and time to shape coral reef seascapes around the world. By drawing on these approaches, the synergistic education program: 1) integrates science and art (i.e., murals and satellite imagery) to educate and inspire Hawaiʻi’s students and general public about coral reef ecology; 2) builds technological capacity in Hawaiʻi’s underrepresented minority high school to graduate students, and 3) empowers these students with science communication skills to communicate with diverse audiences. By leveraging this research program and the cutting-edge technologies it will involve, the investigator establishes a strong foundation for long-term teaching and mentoring activities focused on increasing capacity within STEM-underrepresented minorities with Hawaiian and other Pacific Islander backgrounds. Decoding what coral reef halos can tell us about the effects of fishing on reef ecosystem health provides valuable knowledge to reef ecosystem managers and conservation practitioners as reefs continue to rapidly change due to human stressors.

This project combines lab- and field-based experiments with cutting-edge satellite imaging technology and computer science approaches to address the goals of: 1) determining the mechanisms that create the “halos” that form around coral patch reefs, and 2) testing the predictions arising from these mechanisms in a global arena. This project uses a transdisciplinary approach – spanning ecology, oceanography, geospatial science, and computer science – to address these goals. This program has three scientific objectives: to determine 1) which species interaction mechanisms and environmental factors cause reef halos and what their relative importance is; 2) whether these mechanisms are globally consistent or vary geographically; and 3) whether halos can therefore be used as an indicator of aspects of coral reef ecosystem health. In the process, this research advances our understanding of how remote observation tools (satellite and drone imagery; camera traps) can be integrated with computer science (machine learning) and ecological approaches (mechanistic experiments) to generate emergent insights that would not otherwise be possible.

This project is jointly funded by the Biological Oceanography Program, the Established Program to Stimulate Competitive Research (EPSCoR), and Ocean Education Programs.

This award reflects NSF's statutory mission and has been deemed worthy of support through evaluation using the Foundation's intellectual merit and broader impacts review criteria.

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Funding

Funding Source	Award
NSF Division of Ocean Sciences (NSF OCE)	OCE-1941737

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