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USING DEEP LEARNING AND UAV IMAGERY TO DETECT ELKHORN CORAL IN ST. CROIX'S EAST END MARINE PARK

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USING DEEP LEARNING AND UAV IMAGERY TO DETECT ELKHORN CORAL IN ST. CROIX'S EAST END MARINE PARK

by

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ABSTRACT

Elkhorn coral, or *Acropora palmata*, is an important reef building species that promotes species abundance and other ecological services to the communities in the US Virgin Islands. We captured high resolution imagery of a reef in St. Croix's East End Marine Park using a Wingtra One UAV. We then used deep learning techniques to detect individual coral colonies. We compared two deep learning models, FasterRCNN and MaskRCNN, and found that the models achieved accuracy shores up to 0.78. These scores improved when examining only larger corals in shallow waters. The model was able to both detect Elkhorn coral and distinguish it from other corals and features. This will be a useful method for measuring coral abundance and monitoring the success of restoration efforts.

ACKNOWLEDGMENTS

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LIST OF ABBREVIATIONS

ABC	The Alp
CNN	Convolution Neural Network
DEM	Digital Elevation Model
FN	False Negative
FP	False Positive
GNSS	Global Navigation Satellite System
NOAA	National Oceanic and Atmospheric Administration
PPK	Post Processed Kinematic
SCEEMP	St. Croix East End Marine Park
SML	Supervised Machine Learning
TNC	The Nature Conservancy
TP	True Positive
UAV	Uncrewed Aerial Vehicle
UUV	Uncrewed Underwater Vehicle

CHAPTER I – INTRODUCTION

Coral reefs are subject to many stressors, such as higher sea temperatures, rising sea level, increasing storm intensity, and increased sedimentation, brought on by anthropogenic climate change (Hoegh-Guldberg 2011; Rogers 1990). Hughes and others (2018) found the intensity and frequency of coral bleaching events have risen dramatically in the past three to four decades. In 2008, Conservation International estimated the global value of coral reefs to be $29.8 billion and the worth of coral reefs in the Caribbean to be $3.1 billion - $4.6 billion based on their ecosystem services related to tourism, fisheries, coastal protection, biodiversity, and carbon sequestration. Because corals are both socioeconomically and ecologically important, they need to be conserved and managed appropriately at local and regional scales (Costanza et al. 2014; Hughes et al. 2018; Schill et al. 2015).

Technologies such as remote sensing and machine learning are important, widely used tools in environmental research and conservation (Crisci et al. 2012, El Mahrad et al. 2020). Advancements in remote sensing allow researchers to capture data at greater radiometric resolution, spatial resolution, and over greater extents. Machine learning and other computational techniques provide ways to analyze data that would otherwise be too vast to study thoroughly (Fallati et al. 2020).

1.1 Elkhorn Coral

Elkhorn coral, or *Acropora palmata* (Lamarck, 1816), is important to the structure of coral reefs in the Caribbean (Lirman 1999). It was fundamental to building the coral reefs in the Caribbean Sea over the last 5000 years, supports broad biodiversity, absorbs wave energy thus protecting coastlines and habitats like seagrass beds and mangroves

(NOAA 2003; NOAA n.d.). Gladfelter and Gladfelter (1978) along with Nagelkerken and Nagelkerken (2004) have found that the structural complexity of *A. palmata* benefits other marine life, providing suitable habitat for a variety of fish which in turn can populate important fisheries (NOAA 2013). Few other coral species exist in the shallow areas and places with the fluctuating conditions in which Elkhorn corals thrive, and without it Caribbean islands would likely face increased coastal erosion (NOAA 2003, Andres and Witman 1995).

1.1.1 Importance to St. Croix

Elkhorn coral provides many ecosystem services for the islands its reefs border (Moberg & Folke 1999, Mumby et al. 2008). Mumby and others (2008) found that *A. palmata* contributed to the generation of sand, increased the density and value of several important species for fisheries, and promoted tourist and educational activities like bonefishing, snorkeling and the sale of curios and jewelry. While Mumby and his co-authors determined *Montastraea* reefs were the most valuable to the Bahamas, that genus is sparse in St. Croix, and *A. palmata* would provide most of *Montastraea's* services for Cruzans (Yee et al. 2014).

Stoffle and others describe in their NOAA report (2009) the complex interdependence of St. Croix's fisheries with the community and coral reefs surrounding the island. Fishing depends on healthy coral reefs to act as nurseries and continuously supply fisheries, but overfishing damages reefs (NOAA 2010).

In interviews with fishermen found in a NOAA report (2009), Stoffle and others found 72% of those interviewed considered finding any job outside of fishing at least 'fairly difficult'. They also recorded interviews where Cruzan residents note fish as a driving force of the island's hospitality economy. Tourists come to St. Croix to both see exotic fish while diving and consume low-cost, high-quality seafood. In this way fish population and species density directly impact both fishing and tourism/hospitality industries and indirectly impact other businesses like markets which sell curios and gifts to tourists and mechanics who repair fishing equipment. They also found that nearly all fish caught remain on St. Croix with 68% going to market, 18% consumed at home, and 9% being given to customers, crew, or others in the community. Fish and the money they generate tend to stay on St. Croix like a true island economy. A breakdown of the fishing industry would be felt in all facets of the island's economy, and fishing depends on healthy coral reefs.

1.1.2 Characteristics of *Acropora palmata*

Elkhorn coral is characterized by its light brown to orange color and branching, antler-like shape, found in clear waters at depths of 0.5 - 4.5 meters (see Figure 1.1C). It is a fast-growing species; an individual coral can grow 5 to 10 cm in a single year, and *A. palmata* reproduces both sexually through external fertilization of eggs by sperm in the water column and more commonly asexually through fragmentation (NOAA 2003; Gladfelter et al. 1978; Highsmith 1978; Shinn 1976). Bruckner, in his NOAA report, (2003) noted that its rapid growth allows it to outcompete other corals, by growing above them and blocking out sunlight. Additionally, Bak (1983) found *A. palmata* regenerates quickly after damage to tissue or skeleton. These traits make it a good candidate for repopulating damaged reefs. Elkhorn coral, like other acroporids, tends to form dense monospecific thickets (NOAA 2003). It is only found in the Caribbean from southern Florida and the Bahamas to Trinidad and Tobago, Venezuela and Colombia and is predominantly in areas with moderately high wave energy on the windward side of islands (see Figure 1.2) (NOAA 2003).

Figure 1.1 *Elkhorn Coral Imagery Captured with Different Sensors*

(A) Imagery obtained using Wingtra fixed wing vertical-takeoff-landing (VTOL) UAV. Two mature A. palmata, one young A. palmata, and one Millepora are visible. (B) imagery of the same area as 2A, but at higher resolution, obtained using Mavic multi-rotor UAV. (C) Underwater photo of Elkhorn coral captured by James St. John (2010) and is licensed under the Creative Commons Attribution 2.0 Generic license.

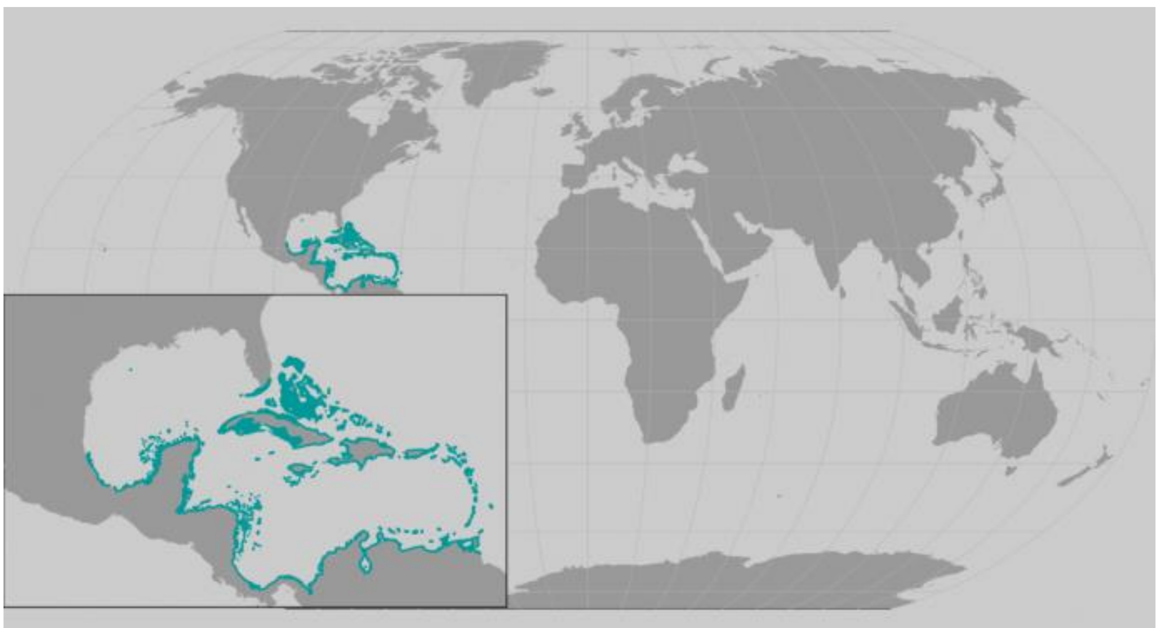

Figure 1.2 *Elkhorn Coral Extent*

Map showing the extent of *A. palmata* obtained from NOAA at https://www.fisheries.noaa.gov/species/elkhorn-coral#overview

Compared to other acroporids, *A. palmata* has been particularly susceptible to disease. Elkhorn coral is affected by Black band disease, Shut-down reaction, Skeletal anomolies, White band disease, and White pox disease (Sutherland et al. 2004). Most corals of the same genus are affected by only one disease, and just one other species, *A. clathrata*, is also affected by five.

1.1.3 Threats to *Acropora palmata*

Despite its historic dominance in the Caribbean, bleaching events and other stressors like white band disease have reduced its presence by more than 90% since 1980 (Hughes et al. 2018). Disease, sedimentation, tropical storms and other breakage events, and predation are the main threats to Elkhorn corals (NOAA 2005, NOAA 2003). In 2006, *Acropora palmata* was added to the list of threatened species under the Endagered Species Act, and in 2014 NOAA Fisheries reaffirmed the endangered status of *A. palmata* and *A. cervicornis* (NOAA 2005, NOAA 2019). In 2005 Boulon and others noted in their NOAA report, the rapid decline from super abundance and little evidence of recovery but did not believe the species was currently in danger of extinction, although it could become so in the foreseeable future.

The number of documented coral diseases has grown exponentially since 1965 (see Figure 1.3), and the fossil record indicates that White band disease, which was responsible for the greatest loss of *A. palmata*, is an emergent rather than cyclical disease (Aronson & Precht 2001; Sutherland et al. 2004). Sutherland and others (2004) explain abiotic stressors linked to human activity, like sedimentation, pollution, and increased temperature, increase severity and rates of diseases that threaten *A. palmata*.

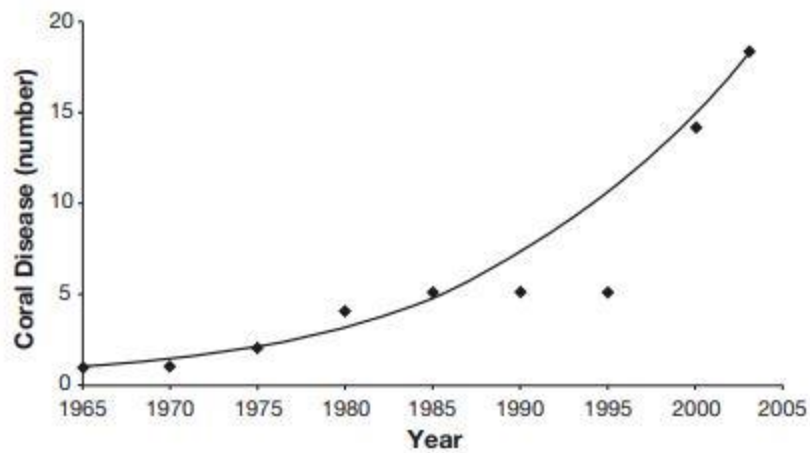

Figure 1.3 *Coral Diseases over Time*

Chart showing number of known coral diseases from 1965-2004. Created by Sutherland et al. (2004).

1.2 Remote Sensing and UAVs

Satellites and their sensors were once designed before all their uses were imagined, but after decades of remote sensing research, satellites and sensors are being created to serve specific research purposes (Oullette & Getinet 2016). Similar to the change in satellite remote sensing, UAVs were originally used in military surveillance, but in the past decades they have been applied to many different fields of research including coastal and marine studies (El Mahrad et al. 2013). New technologies for manufacturing aircraft, flight control and navigation, energy and power, and payload or sensor capability allow UAVs to be applied in an increasing number of fields (Fan et al. 2020).

1.2.1 Remote Sensing of Corals and Marine Environments

Remote sensing has become a popular tool for marine research and is well suited to help study and protect important coral reefs and species (Madin et al. 2019). El Mahrad and others (2020) report on the remote sensing technologies and applications for marine research. They discuss six categories of technologies: (1) Satellite Remote

Sensing, (2) Aerial Remote Sensing or Crewed Aircraft, (3) Uncrewed aerial vehicles, (4) Uncrewed Surface Vehicles, (5) Uncrewed Underwater Vehicles, and (6) Static Sensors. These various technologies are used to collect climatological, radiometric, bathymetric, and ecological data at spatial and temporal scales that would be prohibitively time consuming and expensive through other methods such as point sampling.

Researchers use remote sensing technologies to monitor marine environments, prevent or mitigate hazards, and assess marine environments following a hazard or other event to evaluate its impact (Oullette & Getinet 2016). Ferreira et al. (2012) used satellite remote sensing to create maps of intertidal and subtidal habitats on the coasts of Tanzania and Mozambique. Passive microwave sensors can detect sea surface salinity which can be used to determine ocean acidification; monitor hurricanes, estimate ocean rainfall, and predict unusually high or low precipitation (Land et al. 2015; Vinogradova et al. 2019). Static sensors can measure water qualities like turbidity or the presence of oil and measure upwelling (Hu et al. 2019; Parra et al. 2018). Our study falls under the category of environmental monitoring and uses multispectral remote sensing.

Because coral reefs may extend up to tens of kilometers and have processes occurring at both much smaller and larger scales, researchers need synoptic data to accurately assess and monitor them (Hatcher 1997; Mumby et al. 2004; Fallati et al. 2020). Reshitnyk and others (2014) along with Collin and Hench (2012) have used satellite remote sensing to study coral reefs, but the spatial resolution (0.5 m at its sharpest) is insufficient to identify individual corals. Madin and others (2019) suggest a coordinated collection of data using satellites, UAVs, static sensors, and UUVs to study coral reefs at multiple sites, depths, and spatial scales. They also note that improvements in sensors enable researchers to obtain more accurate and more frequent, possibly real-time, data on environmental conditions.

1.2.2 Uncrewed Aerial Vehicles

UAVs have been used to monitor marine wildlife and vegetation, aid in disaster response, and many other applications (Murphy et al. 2008; Göktogan et al. 2010; Ma et al. 2013; Li et al. 2021). Li et al. (2021) successfully used UAVs to detect sea cucumbers, which exist at a similar spatial scale to Elkhorn coral. Ma and others (2013) discuss several advantages of UAVs over satellites and manned flights for image collection: (1) by flying at lower altitudes, they capture imagery of higher spatial resolution than satellites and ignore most negative effects of atmospheric interference and cloud cover, a common problem in the Caribbean; (2) because there is no pilot on the platform, UAVs are cheaper to operate and can fly in areas that would be unsafe for crewed flights. UAVs reduce barriers to coral reef conservation by allowing greater access to difficult to reach areas and providing a relatively cheap and easy way to gather large amounts of data quickly (Madin et al. 2019).

Ma et al. (2013) summarized a common three-stage framework for research using UAVs. The first step is data acquisition and includes steps like flight planning. The second step is data processing where the researcher ensures the pixels correspond to their true location, corrects the values of the pixels if needed, and creates the mosaic or whatever intermediate product needed. The final step is applying the product to the research question. The authors provide examples like monitoring hazards. In this research, a partial extent of the orthomosaics will be used to train a deep learning model, and the entire orthomosaics will be used to run the model.

UAVs have limited battery life which puts restraints on the duration and sensor payload of missions and must be accounted for when designing a study (Ma et al. 2013). Similarly, Fallati and others (2020) discuss the poor GNSS accuracy of UAVs in their study and corrected for it through the combined use of real-time kinematic processing and ground control points. This study used imagery collected using both a fixed-wing UAV with PPK corrections and a quadcopter. The fixed-wing Wingtra One can fly longer missions and collect data over a greater extent and the quadcopter would be used to collect higher resolution imagery over a smaller extent to be used in accuracy assessments (see Figures 1.1 and 1.4).

Figure 1.4 *Wingtra One UAV Take-off*

TNC researcher operating Wingtra One, a fixed-wing, vertical take-off and landing UAV on the northeast coast of St.Croix.

1.3 Deep Learning

Deep learning, like remote sensing and UAVs, is a developing tool with great potential for geographers and other researchers. It is a type of machine learning that uses multiple layers to recognize hierarchical representations or features in n-dimensional arrays (Bau et al. 2020; LeCun et al. 2020).

1.3.1 Supervised Machine Learning in Marine Research

Crisci and others (2012) explain that machine learning is a novel tool for common statistical problems such as classification and regression. They further explain that Supervised Machine Learning models receive training data and create regressions or classifications derived from labels from the training data, as opposed to unsupervised processes which seek naturally occurring divisions within the data. Most current machine learning applications and research, including our study, use SML, but LeCun and others (2015) believe unsupervised learning will become increasingly important in deep learning because it more closely resembles human and animal learning.

Deep learning has recently been used to detect sea cucumbers, produce habitat suitability maps, monitor the effects of coral bleaching, and even classify corals into categories such as ‘branching’ and ‘mounding’ (Chirayath & Instrella 2019; Fallati et al. 2020; da Silveira et al. 2021; Li et al. 2021). These studies and our study all employ SML to detect or classify some object or field. I believe deep learning techniques can be used to detect individual corals on a species level with imagery of a sufficient spatial resolution. Where Kutser & Jupp (2006) concluded that spectral data alone was not enough to classify corals on a species, or even genus level, deep learning models may be able to utilize both radiometric and geometric techniques to detect Elkhorn corals and distinguish them from other species.

1.3.2 Convolution Neural Networks

Although there are seemingly innumerable applications for deep learning from fields such as medicine, genetics, linguistics, and physics, Yuan and others (2020) describe four ways deep learning can be used in environmental remote sensing, namely land cover mapping, environmental parameter retrieval, data fusion and downscaling, and finally information construction and prediction (LeCun et al. 2015). Object detection (or target recognition), the deep learning application this project is concerned with, and image classification both fall under the umbrella of land cover mapping, and generally use convolution neural networks.

CNNs use both geometric and algebraic (for remotely sensed images this means both the shape and radiometric or pixel values of an object) methods to identify features (Crisci et al. 2012; Fallati et al. 2020, Rassakovsky et al 2015). These methods are implemented through convolution, pooling, and activation layers (see Figure 1.5) (Bau et al. 2020, LeCun et al. 2015, Yuan et al. 2020). Initially, convolution layers use a pass filter to exaggerate low level features like edges. Then pooling layers are used to preserve the most important aspects of features and remove less important data. When done properly, this both improves computing speeds and inhibits overfitting. Finally, an activation layer performs non-linear operations to detect features that provide the most meaning in the image and create a feature map. These repeated steps can eventually identify high level features such as eyes in applications like facial recognition (Bau et al. 2020). CNNs became increasingly popular in the field of computer vision after they outperformed other deep learning methods at the 2015 Imagenet competition for both object detection and classification (Rassakovsky et al. 2015).

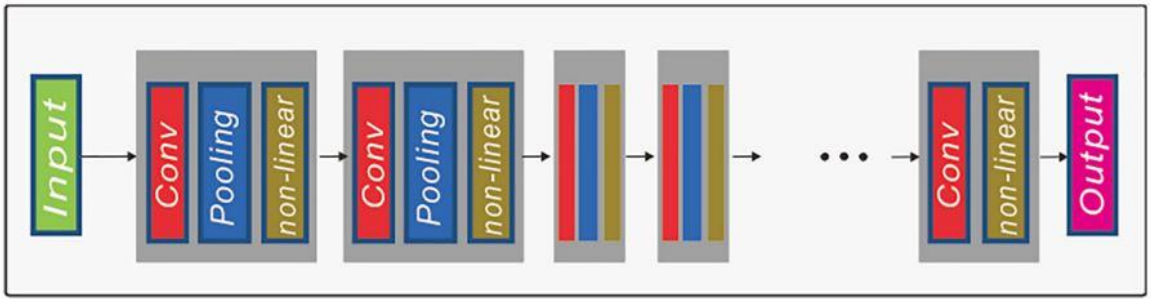

Figure 1.5 *Model of CNN Deep Learning Structure*

Model of CNN structure created by Yuan et al. (2020).

Bau and others (2020) found that the object detection units developed by CNNs create classes although they are not specifically trained to do so, and these units vary in importance in producing accurate outputs. In their study they found that an image classifier trained to recognize ski resorts created 512 detection units and of those units four accounted for 17% of the model's ability to recognize a scene correctly. These four units detected high level features of 'snow', 'mountain top', 'house', and 'tree top'. In this way, deep learning CNNs behave like unsupervised machine learning models, which create classes for unlabeled features they detect, and mimics human learning.

This study would use ESRI's deep learning functions in ArcGIS Pro. These tools use a three-step process to classify pixels, classify objects or detect objects (ESRI, n.d.). The first step is the creation of training data. It is important that the training data is accurate and complete, simultaneously maximizing identifying variables of the desired classes and minimizing characteristics shared between classes (Crisci et al. 2012; da Silveira et al. 2021). For this study, training data should cover all depths at which *A. palmata* is found and include examples of mature and young corals to ensure the model will detect as many corals as possible. This training data is used to create image chips or samples compatible with Python based, open-source deep learning libraries like Keras, PyTorch and TensorFlow (ESRI n.d.). Second, these libraries use image chips to train a model to detect objects that resemble the input data. Finally, the trained model takes raster layers as inputs and outputs a shapefile with detected objects, in this case, Elkhorn corals. One benefit of using ArcGIS Pro rather than the deep learning libraries directly is the product will be georeferenced and ready to use as a feature class (ESRI n.d.).

1.4 Study Area: St. Croix East End Marine Park

Our study area is a coral reef north of Yellowcliff Bay and Teague Bay on the northeastern part of St. Croix (U.S. Virgin Islands). It contains rich species diversity and supports A. palmata, Acropora millepora, and other mounding corals (Mateo et al. 2001; NOAA 2013). The site's clear waters and various corals are well suited to this study.

The study area is completely within the St. Croix East End Marine Park (see Figure 1.6). This multiuse marine park was the first of its kind in the U.S. Virgin Islands and protects over 150 square kilometers of marine habitat including the largest barrier reef system in the Caribbean (Dorfman et al. 2015). Dorfman and others (2015) found that Teague (alternatively Tague) Bay had the greatest density of hard coral within SCEEMP. They also estimate that runoff caused by land development and dirt roads in the Yellowcliff Bay watershed is a 'high threat' to the six sensitive species of corals, including A. palmata found there. Our study area is also categorized as a 'No Take Zone' meaning no commercial or recreational fishing is allowed.

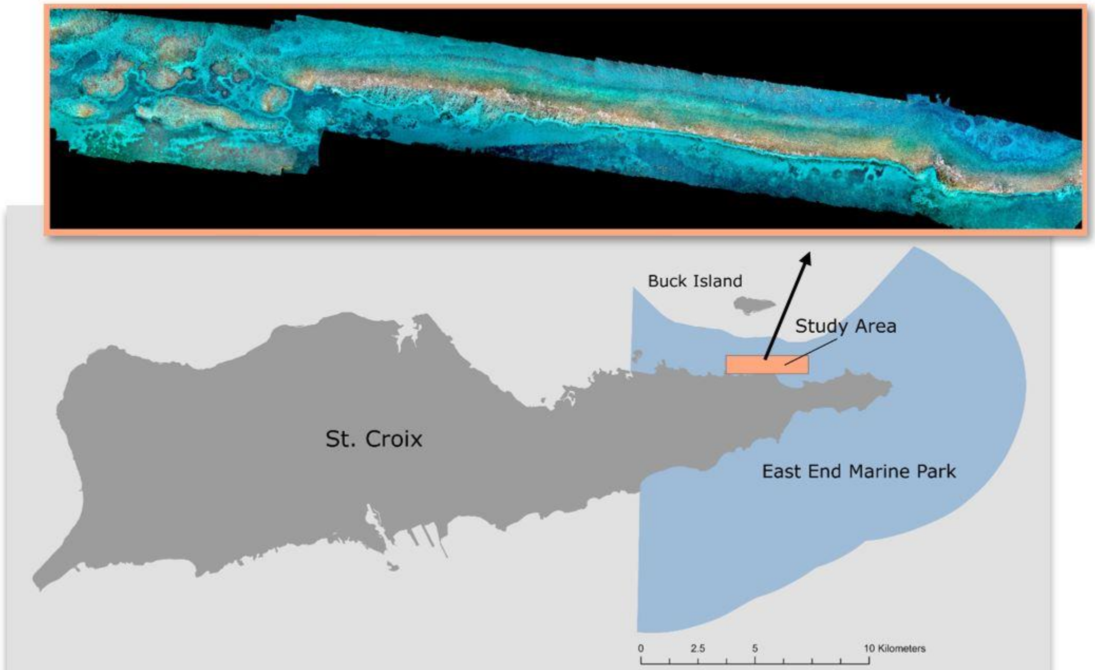

Figure 1.6 *Map of SCEEMP and Study Area*

Orthomosaic of the reef TNC researchers flew over and a map showing boundaries of marine protected area, the islands of St. Croix and Buck Island, and the study area.

Additionally, the site is part of an ongoing conservation effort by The Nature Conservancy in partnership with other organizations to repopulate Elkhorn coral in the U.S. Virgin Islands and throughout the Caribbean (Griffin 2014; TNC 2020). In 2009 The Nature Conservancy began outplanting *A. palmata*, or reintroducing juvenile Elkhorn corals, to areas that historically had the species or reefs that were damaged recently including Teague Bay, part of our study site. In 2017 TNC scientists implemented new techniques of microfragmentation and facilitated sexual reproduction to grow the Elkhorn coral population on St. Croix's reefs (TNC 2020). Alexandra Gutting, a TNC scientist leading the coral restoration work, shared with me in an email on November 10, 2021 that the most recent *A. palmata* outplanting took place in July of 2020. Since 2012, The

Nature Conservancy has outplanted 1525 *A. palmata* in St. Croix's reefs. The active efforts to increase the *A. palmata* population in the area makes our study even more timely and needed.

CHAPTER II – METHODOLOGY

2.1 Data Acquisition

Researchers from The Nature Conservancy captured imagery of the coral reef using a Wingtra UAV with fixed wings and vertical take-off and landing (Figures 1.1A and 1.4). Ten missions were flown from the 25th of May through the 2nd of June 2021. The imagery covered an area of 1,480,000 meters^2 or 1.48 kilometers^2 and had a nominal resolution of 1-1.8 cm depending on the altitude of the missions. A secondary set of imagery with higher spatial resolution (< 1 centimeter) was collected over a smaller extent (13,800 meters^2 or 0.93% of the primary imagery's extent) using a DJI Phantom 4 Quadcopter (Figure 1.1B). Imagery was collected in the mornings and evenings while the sun was less than 30 degrees above the horizon to minimize sun glint. A TNC diver collected georeferenced photographs of Elkhorn coral and created a point shapefile of corals later used to create training data for the deep learning model.

2.2 Data Processing

The imagery was georeferenced through PPK corrections, rather than traditional ground control points. A survey grade GNSS receiver was used to get an accurate position with which we corrected the flight data. We used Drone Deploy to create orthomosaics and digital elevation models from the UAV imagery. The orthomosaics had a resolution of 1.8 cm, and the DEMs had a resolution of 8 cm.

The images and DEMs were resampled to a resolution of 1 cm and aligned so the cells for each are in consistent locations. Next, we used the composite bands (data management) tool in ArcGIS Pro to combine the layers to create a four band raster consisting of elevation data and blue, green and red light. We converted the negative elevation values to positive integer depth values, reducing the disk size and making the data for depth more intuitive.

ESRI's deep learning functions in ArcGIS Pro use a three-step process to classify pixels, classify objects or detect objects (ESRI, n.d.). For our purposes, object detection is the appropriate deep learning method. First, we created training data by drawing polygons around corals we manually identified in the low-resolution imagery and checked against the higher resolution imagery to verify the coral type in the lower resolution imagery (Figure 2.1). Although our purpose is to detect *A. palmata*, we decided it would be useful to train the model on the other types of coral in the scene to prevent the misidentification of other coral types as *A. palmata*. In a similar fashion, we created point data for all the corals visible in the high-resolution imagery to use in an accuracy assessment.

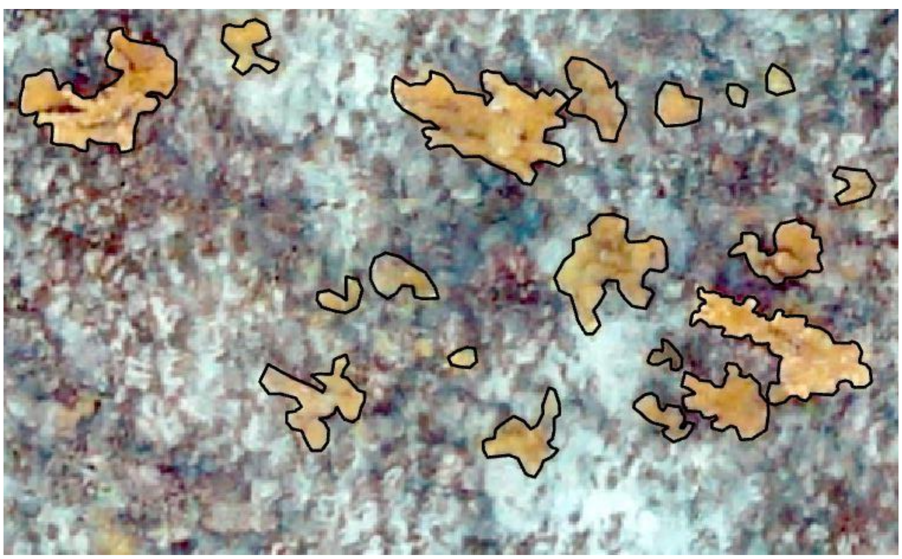

Figure 2.1 *Manually Created Training Data*

We created training data for the deep learning model by digitizing corals throughout the entire reef. Each polygon was given an attribute of A. palmata, A. millepora, or mounding coral.

The point data included three categories of corals *A. palmata, Acropora millepora,* and mounding corals and values for coral width and depth, which was extracted from the DEM.   Next, we trained a FasterRCNN deep learning model using RCNN masks and image chips of the training data. FasterRCNN is used for object detection and creates bounding boxes and masks for every instance of an object in the image. Finally we used the trained model on an input raster, the lower resolution, greater extent imagery to detect Elkhorn corals.

We also trained MaskRCNN models with three different levels of convolution depth: resnet50, resnet101, and resnet152 using the same training data as the FasterRCNN model. Rather than the bounding boxes created by FasterRCNN, MaskRCNN outputs polygons that outline the detected features. Because the output is polygons in the shape of the targets rather than bounding boxes, we learn more about the size of the corals and the total area they cover (see Figure 2.2). Finally, we took the output of the MaskRCNN medium depth model and used it to enhance our training data. We retrained the model and ran it again at the same convolution depths as the previous outputs. Because the outputs of both the FasterRCNN and MaskRCNN models created many overlapping polygons, we dissolved the output polygons by the coral type. This made our accuracy assessments more reliable because we did not have multiple polygons intersecting a single identified coral, which would have inflated the precision scores by exaggerating the number of true positive outputs. Finally, we used Zonal Statistics to calculate the mean depth for each polygon in the MaskRCNN output. After creating the different outputs and having data for coral size and depth for both the corals identified by ourselves and the corals detected by the deep learning model, we could perform accuracy assessments.

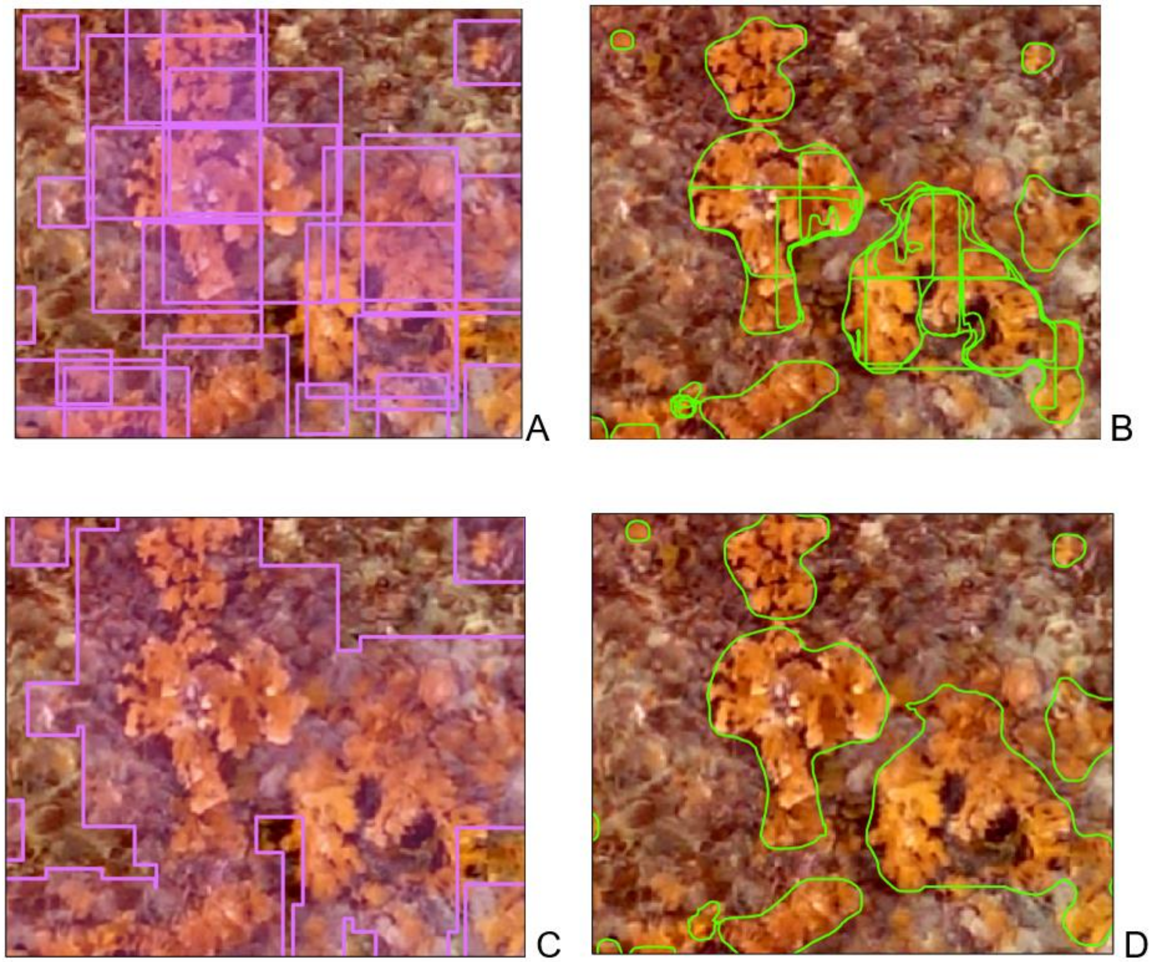

Figure 2.2 *Deep Learning Model Outputs*

All images are at the same resolution and of the same location. (A) FasterRCNN output before the polygons are dissolved. (B) MaskRCNN output before the polygons are dissolved. (C) FasterRCNN output with dissolved polygons. (D) MaskRCNN output with dissolved polygons.

2.3 Accuracy Assessment

After we used the deep learning tools to detect corals, we used a combination of the in-situ data gathered by the TNC and a second set of UAV imagery of higher spatial resolution but smaller extent (see Figure 1.1) to conduct accuracy assessments and report the potential for deep learning object detection for the mapping of corals. We found both the false positives (FP), where the model detected a coral, but there was no coral present identified by a person, and false negatives (FN), where a coral was identified by a person but not detected by the model, and used those values to calculate Precision, Recall and an F1 score (see Figure 2.3). Precision measures the models' tendencies to include false negatives, or how often the outputs contained superfluous corals. Recall measures the models' tendencies to not detect coral identified by a human. The F1 score indicates how well a model did overall considering both precision and recall. We used the FasterRCNN model on the 10 different datasets, and then used the imagery that produced the best F1 score for further analyses (Table 2.1).

$$Precision = \frac{TP}{TP+FP} \qquad Recall = \frac{TP}{TP+FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Figure 2.3 *Accuracy Assessment Formulas*

Formulas used in accuracy assessments. TP represents true positives; for Precision this value is the number of identified corals that intersect with the model's output, and for Recall this value is the number of output polygons that intersect manually identified corals. FP represents false positives, and FN represents false negatives. Figure credit: Li et al. 2021

Table 2.1 *Accuracy Scores by Imagery Dataset*

Dataset	Recall	Precision	F1
May 25 – PM – Partly Cloudy – 75m	0.90	0.61	0.73
May 26 – AM – Clear – 75 m	0.91	0.48	0.63
May 27 – PM – Clear – 75 m	0.91	0.56	0.70
May 27 – PM – Clear – 90 m	0.92	0.55	0.70
May 28 – AM – Mostly Sunny – 90 m	0.89	0.52	0.66
May 28 – AM – Clear - 90 m	0.84	0.57	0.68
May 28 – PM – Clear - 120 m	0.94	0.51	0.66
May 30 - PM - Clear 120 m	0.90	0.53	0.67
May 31 – AM – Clear - 70 m	0.84	0.27	0.41
June 2 – AM – Clear - 120 m	0.95	0.58	0.72

Note: Datasets represented by time they were collected, weather conditions and altitude. All accuracy scores are based on FasterRCNN outputs trained on the same data.

We also binned the data into groups based on coral size and depth and found the accuracy of those groups. For coral size, there were 25 groups. The group of the narrowest corals is between 0 and 10 cm wide, and the width increased by a uniform 10 cm for each subsequent group making the final group corals between 240 and 250 cm. For depth, the groups were divided by a step of 25 cm from a range of 50 to 225 cm, making 7 groups.

CHAPTER III – RESULTS AND DISCUSSION

3.1 Assessing the Imagery

We used the FasterRCNN trained on the original training data to determine which imagery produced the best results. We found the imagery captured on May 25, 2021 gave the best results with a recall score of 0.90, a precision of 0.61 and an F1 score of 0.73, and all further analyses and results will be determined using this imagery (see Table 2.1). Across all the imagery, recall scores remained consistently high, with the lowest being 0.84. However, precision scores varied much more with the lowest being 0.27.

Although the flights were conducted at different altitudes and in various amounts of cloud cover, these factors did not seem to have a meaningful influence on the deep learning output. While the greatest F1 score came from imagery collected at 75m above sea level in partly cloudy skies, the next best results came from imagery captured at 120m above sea level and in clear skies. Conversely the worst F1 score came from imagery collected at 70m above sea level in clear skies.

3.2 Comparing FasterRCNN and MaskRCNN

As its name suggests, FasterRCNN was able to create a deep learning model faster than MaskRCNN. We used a computer with an RTX 3090 GPU with 24 GB vRAM, 64 GB RAM, and an i9-12900KF CPU to train and run the deep learning models. For the FasterRCNN model, it took around 21 minutes to process the small area used for accuracy assessments; for the MaskRCNN model it took 24 minutes. While this difference is small, it may be exacerbated on less powerful hardware or on larger datasets. If time and computing power are both limited, FasterRCNN would likely be preferable to MaskRCNN for similar projects.

Initially MaskRCNN methods did not produce better recall or F1 scores than FasterRCNN methods. On the same training data as the FasterRCNN, the MaskRCNN model achieved recall scores similar to the 10 FasterRCNN outputs, but the precision and F1 scores were generally lower. However, when we took the output from the initial MaskRCNN model and used that as training data for another model, the accuracy surpassed that of the FasterRCNN model (Table 3.1). In addition to having the greatest accuracy, the MaskRCNN outputs provide more data and detail about the number of individual colonies and their size because they are polygons drawn to the shape of the target rather than bounding boxes. This information would be useful when conducting a census of coral colonies or determining what percent of the seafloor is covered with corals.

Table 3.1 *Accuracy Scores by Convolution Layers for MaskRCNN Outputs Compared to the Highest FasterRCNN Accuracy Score*

Deep Learning Model	Recall	Precision	F1
Shallow	0.96	0.42	0.59
Mid	0.92	0.5	0.65
Deep	0.86	0.57	0.68
Reseed - Shallow	0.76	0.82	0.78
Reseed - Mid	0.86	0.68	0.76
Reseed - Deep	0.93	0.62	0.74
FasterRCNN	0.90	0.61	0.73

Note: Shallow, Mid, and Deep correspond to resnet 50, 101, and 152 architectures respectively. Reseeded indicates the model was trained with the output from the initial MaskRCNN model. The final row is the best result achieved using the FasterRCNN model.

3.3 Coral Size and Depth

After finding the model that produced the best outputs, we organized the deep learning output polygons and the point data used to check the accuracy into bins according to the size of the coral and its depth. We then used the same accuracy assessments as before to calculate recall and precision for each individual group. These results are from the reseeded MaskRCNN model with the shallowest convolution layers (see Table 3.3).

The identified corals represented by point data ranged from 0.08m to 2.52m in width, and the model's output ranged from $.02m^2$ to $4.48m^2$ in area. Finding the precision values for the different groups based on size proved challenging because the data for identified corals did not include the area of the coral but rather the width of the coral, and the deep learning model's output are polygons which have a 'Shape_Area' attribute measured in square meters. If this study was to be replicated, we would recommend using polygons to check the accuracy of the models rather than points to make interpreting the impact coral size has on accuracy easier. However, we ultimately discovered there was a threshold where the model greatly increased in accuracy for corals above 0.3m in width (see Figure 3.1). We decided that the corresponding area should be $0.07m^2$, or $\boldsymbol{\pi}r^2$, where r is 0.15m. Recall scores increased dramatically after crossing the 0.3m threshold from 0.54 to 0.90. Precision scores also improved from 0.52 to 0.72 when the size of the corals changed from less than $0.07m^2$ to greater than $0.07m^2$, and F1 scores increased from 0.53 to 0.80.

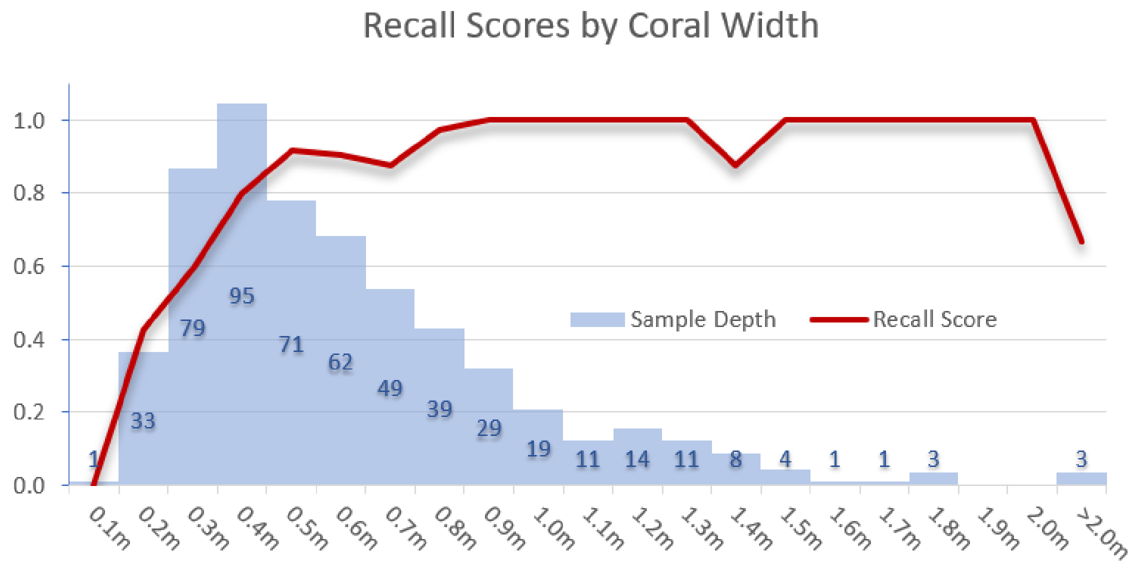

Figure 3.1 *Recall Scores by Coral Width*

Recall scores and sample depth for each group of corals. Groups were organized into 10cm bins with the lower value being inclusive and the upper value being exclusive.

For depth, the identified corals ranged from 0.6 to 2.2m, and the output from the model ranged from 0.6m to 3.7m in depth, however only three detected corals were at depths greater than 2.2m, the outer limit of identified corals. Depth had a particularly strong influence on precision (see Figure 3.2). For depths less than 1.5m the model had a precision score of 0.75, and for depths greater than 1.5m the precision score was 0.36. Recall scores remained high across all depths, but the F1 score dropped from 0.78 for depths less than 1.5m to 0.51 for depths greater than 1.5m as a result of the poor precision values in deeper water (see Table 3.2).

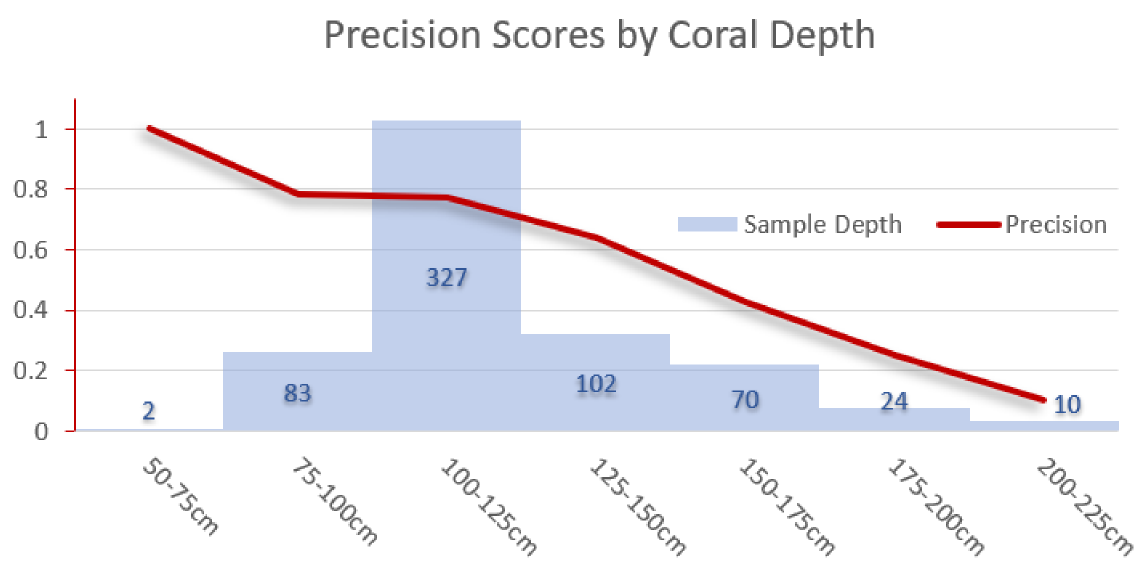

Figure 3.2 *Precision Scores by Coral Depth*

Precision scores and sample depth for each group of corals. Groups were organized by depth into 25cm bins with the lower value being inclusive and the upper value being exclusive.

MaskRCNN Reseeded-Shallow	Recall	Precision	F1
Size < 0.3m or 0.07m²	0.54	0.52	0.53
Size > 0.3m or 0.07m²	0.90	0.72	0.80
Depth < 1.5m	0.82	0.75	0.78
Depth > 1.5m	0.89	0.36	0.51

Table 3.2 *Accuracy by Coral Size and Depth*

Note: Accuracy scores for the Reseeded MaskRCNN (resnet50) model showing the Recall, Precision, and F1 scores for above and below thresholds in coral size and coral depth.

Spatial resolution is one of the most important factors in determining how well deep learning object detection will identify corals. A more powerful sensor that can produce clear images of corals less than 30cm across would likely improve the results of this study. It is more difficult to gauge the importance of depth because *A. palmata* only grow in shallow waters causing the sample size drops off drastically after depths of

150cm, but it appears the model overestimates the number of corals in deeper water. It is also interesting that Recall improved at depths greater than 150cm, from 0.82 to 0.89, showing the model still efficiently detects corals in deeper water even if the overall accuracy decreases.

3.4 Inaccuracies of Accuracy and Improving the Model

While examining the results, we found ways to improve this process on subsequent studies or applications. One issue previously mentioned was using polygon rather than point data to check the accuracy. While accuracy assessments themselves do not impact how well the model worked, good accuracy assessments help researchers and policy makers understand the reliability of the data they use. As we looked at our results, we found several instances where the accuracy assessment was misleading because we used point data rather than polygons to represent the presence of real corals (see Figure 3.3). Using polygons rather than points to represent observed coral would eliminate many of these kinds of errors where the model seems to have correctly identified *A. palmata* colonies, but the output polygon does not intersect the point representing a manually identified coral.

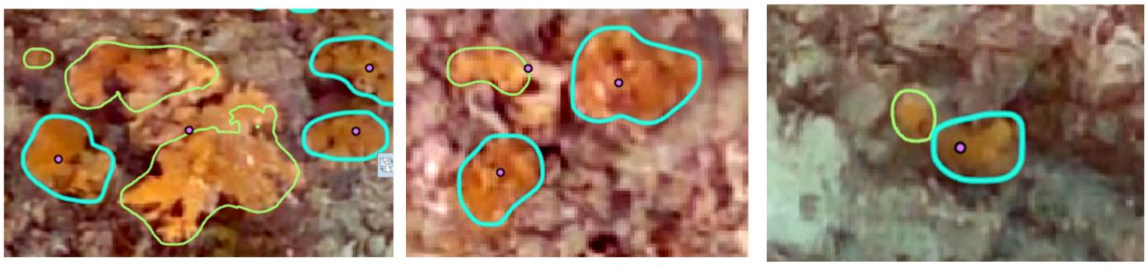

Figure 3.3 *Trouble with the Accuracy Assessment*

These images show three instances of the model correctly detecting *A. palmata*, but the accuracy assessment considered them to be false positives (and false negatives in the first two images) because the point representing the coral (the pink dot) does not intersect with the output polygons (the green outlines). Blue polygons represent TPs, green represent FPs, and pink dots with no blue circle represent FNs.

Another concern with our accuracy measurements is FPs are difficult to verify in many instances. We observed that precision was much lower for corals less than 30cm across and greater for larger corals, but in several instances, it seems the model detected true corals where we did not find them as we created the accuracy assessment data (see Figure 3.4). In addition to finding corals we simply missed, there were many times we were unsure whether an object was a coral or not when we created the data because the objects were too small to be certain even with sub-centimeter resolution. Although these detected objects are counted as FPs, we cannot be sure they truly are with the data available to us. However, all these problems, the FPs and FNs as a result of the point data and polygon data not intersecting when both represent the same coral and the uncertainty of FPs on very small corals would lead us to underestimate the effectiveness of the remote sensing model. Our accuracy scores are likely more conservative than the reality of model.

Figure 3.4 *Inaccurate False Positive Results*

The above images show two instances where the deep learning model likely found *A. palmata* that we missed when creating the point data of all corals in the testing areas. These are counted as FPs because we didn't identify them as coral, but they are likely TPs.

Finally, we had an unexpected problem of Sargassum, a macroalgae common to the Caribbean, being recognized as *A. palmata* by the model (see Figure 3.5). This demonstrates the need to carefully examine the imagery for unexpected problems when training a deep learning model. If we had created training data for Sargassum like we did with *A. millepora* and mounding corals, the model may not have produced these false positive outputs. The sargassum only contributed to a handful of false positive outputs, but if it had been more prevalent in the scene, it could have had a larger impact on our results.

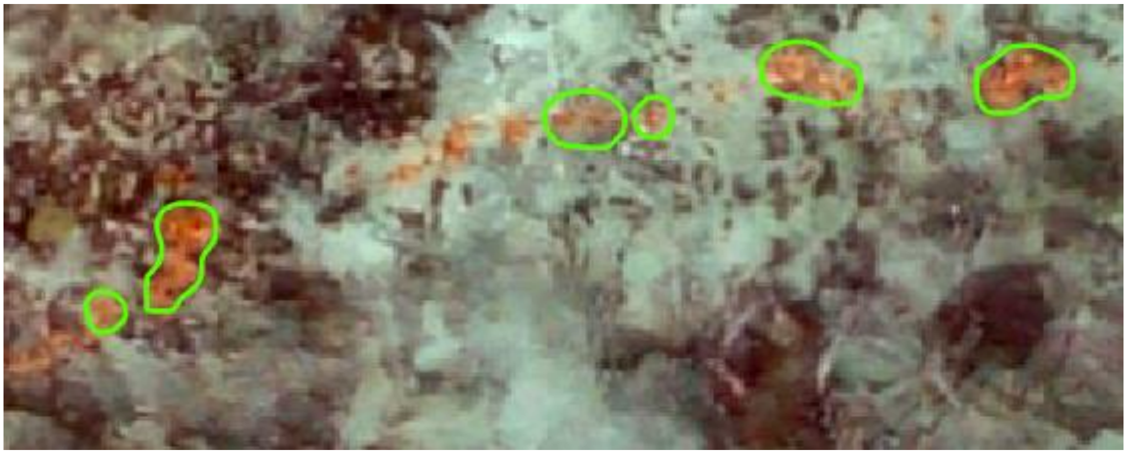

Figure 3.5 *Sargassum Incorrectly Identified as Coral*

Because of its similar size, shape, and color, sargassum was incorrectly identified as *A. palmata*. In future applications of this process, users should account for all likely sources of confusion for the model.

3.5 Applications and Further Study

Deep learning methods for detecting A. palmata are faster than in-situ surveys and produce reliable results. These methods can be used to gauge the success of outplanting efforts, measure coral growth and abundance, measure damage after storms or other breakage events, and possibly monitor disease. Monitoring corals at this scale may help with early detection of disease or other hazards and will supplement coarser observation from satellite imagery to help researchers and managers understand the state of coral reefs across all spatial scales (see Figure 3.6).

Below we can see a comparison between a density map created using the output from the deep learning model and a density prediction map created by NOAA based on environmental covariates like depth and rugosity. The NOAA map predicts the abundance of coral based on how suitable the habitat is, and our map was created by calculating the sum of the 'Shape_Area' field for *A. palmata* polygons in each cell. While we designed the final map to be at a similar spatial scale as the NOAA product (roughly 20m cells), our map has more detail as a result of the scale at which we initially collected data. These maps demonstrate the information that is lost when spatial data is represented at coarser scales.

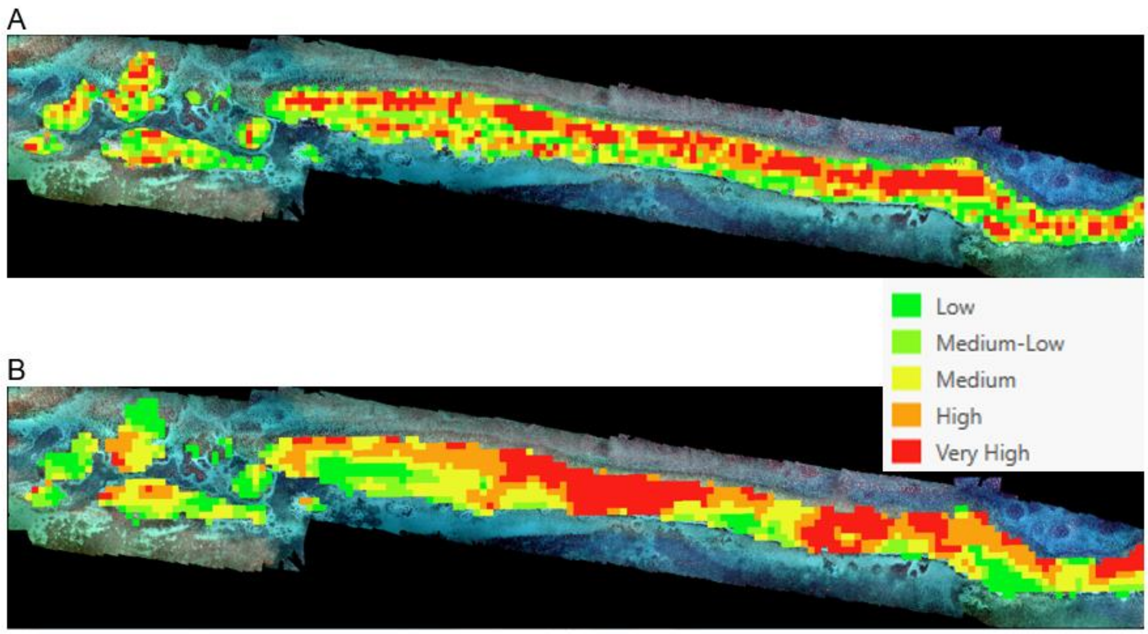

Figure 3.6 *Elkhorn Coral Density Maps*

Maps showing the density of A. palmata in the study area. Map (A) shows the sum of the area covered by the coral in each cell as detected by the deep learning model and has finer spatial resolution. Map (B) shows a prediction of coral density based on environmental factors and was created by NOAA. NOAA data can be found at https://gis.ngdc.noaa.gov/arcgis/rest/services/nccos/BiogeographicAssessments_NCCOS_StCroix/MapServer

Deep learning techniques have been used to identify sea cucumbers, and further research should be done to determine which other sessile organisms, like sea anemones or other coral species, can be detected with these techniques (Li et al. 2021). Although it would be difficult to measure them over time, shallow water species such as batoids (rays) and medusozoans (jellyfish) could likely be detected from UAV imagery using similar methods.

CHAPTER IV – CONCLUSION

Corals provide socio-economic and ecological benefits, and their continued preservation will help the Caribbean communities they serve. An important first step in their conservation is monitoring, which can be costly, difficult, and time-consuming using traditional survey methods. UAV imagery and deep learning techniques provide a faster, cheaper avenue for coral monitoring and can help researchers and managers have more accurate information to make more informed decisions.

Our study demonstrates FasterRCNN and MaskRCNN are both viable deep learning methods depending on the needs of the user. With FasterRCNN and MaskRCNN we were able to achieve overall accuracy scores of 0.73 and 0.78 respectively. While this study had the best results detecting large corals in shallow waters, improvements to the spectral and spatial resolution of the sensor may allow for smaller, deeper corals to be accurately detected.

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