# Mangrove Ecosystem Detection using Mixed-Resolution Imagery with a Hybrid-Convolutional Neural Network

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## Abstract

Mangrove forests are rich in biodiversity and are a large contributor to carbon sequestration critical in the fight against climate change. However, they are currently under threat from anthropogenic activities, so monitoring their health, extent, and productivity is vital to our ability to protect these important ecosystems. Traditionally, lower resolution satellite imagery or high resolution unmanned air vehicle (UAV) imagery has been used independently to monitor mangrove extent, both offering helpful features to predict mangrove extent. To take advantage of both of these data sources, we propose the use of a hybrid neural network, which combines a Convolutional Neural Network (CNN) feature extractor with a Multilayer-Perceptron (MLP), to accurately detect mangrove areas using both medium resolution satellite and high resolution drone imagery. We present a comparison of our novel Hybrid CNN with algorithms previously applied to mangrove image classification on a data set we collected of dwarf mangroves from consumer UAVs in Baja California Sur, Mexico, and show a 95% intersection over union (IOU) score for mangrove image classification, outperforming all our baselines.

## 1 Introduction

Mangrove forests are coastal ecosystems that are highly effective at inhibiting the causes of climate change through carbon sequestration, storing approximately twice as much carbon per cubic meter in their biomass as that of tropical rainforests [20], and 14% of "blue carbon" in our oceans [14]. Therefore, mangrove forests prove to be useful tools for national governments to reduce their individual contributions to global climate change, as over 45 countries specifically mention mangroves in their Nationally Determined Contributions (NDCs) towards meeting the goals of the Paris Climate Agreement [15].

These forests not only help prevent the causes of climate change, but are key in mitigating climate change impacts. Climate change increases the intensity and frequency of tropical storms [12], leading to larger storm surges [10] and higher levels of coastal erosion [16]. Mangroves act as natural storms breaks that mitigate the physical impact of tropical storms on communities near mangrove forests by reducing erosion through lessening wave energy [4]. Because of this, mangrove forests serve as an important resource for local decision makers to protect their constituents.

The ecosystem services of mangroves forests are estimated to provide 33-57 thousand USD per hectare per year to associated local economies. Despite the benefits that mangroves provide, they are at risk due to human activity, declining at a rate of 2% per year [19] and could release an estimated 4.2 billion tons of carbon dioxide into the atmosphere if deforestation continues at current rates [6].

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Therefore, such deforestation impacts not only affects global climate, but regional economies, so [17] tracking extent and associated ecosystem services of mangroves an important metric to measuring their economic and societal value.

Many previous methods developed to track the extent mangrove ecosystems utilize single sources of data of lower resolution, with algorithms developed for predictions dependent on hyperspectral bands [9] or vegetation indices [21]. Most notably, Global Mangrove Watch (GMW) utilizes ALOS PALSAR and Landsat Satellite Imagery to estimate global coverage of mangroves at a 25m resolution with a variant of Random Forest, the Extremely Randomized Tree classifier trained from 53,878 manually labeled points [2]. These prediction maps can be useful for global and national decision makers; but predictions from GMW are lower resolution and temporally sparse with the most recent predictions created in 2016, leaving many local decision makers with outdated and imprecise statistics.

On the other hand, to avoid the lower resolution and temporal frequency that satellite images provide, remote sensing using consumer UAVs has emerged, allowing remote sensing scientists to resolve details in imagery not visible from satellites, and record these images more frequently. Although these methods require in-situ surveys, UAVs show a large amount of promise for ecology and remote sensing tasks [13] such as crop monitoring [1] and forest management [5]. UAVs have even been used to record high resolution images to measure mangrove extent, but are often dependent on expensive hyperspectral sensors [3] to achieve high performance using images sourced from UAVs alone.

To further aid in the conservation of mangrove forests, we aim to combine the advantages of satellite and UAV remote sensing to create more accurate mangrove extent maps. In this paper, we propose a novel Hybrid CNN deep learning network that can be used to measure the extent of mangroves using a combination of medium resolution 4-band Planetscope satellite and UAV imagery. We also describe methods used to acquire our dataset of mangrove imagery and labels and compare our mangrove classification network to baseline models and labels from previous related works. Lastly, we provide pathways for future development for the remote sensing of mangrove ecosystems to aid in the fight against climate change.

## 2 Methodology

**Image Data** To predict mangrove area we relied on high resolution UAV imagery sourced from our in-situ surveys and medium resolution satellite imagery. For our UAV imagery, we surveyed mangrove sites in Baja California Sur between July 2018 and March 2020 using a DJI Phantom 4 Pro UAV, chosen for its high image quality and affordability. These images were taken using the onboard RGB camera at a resolution at 4K resolution(3840 x 2160 pixels) at an altitude of 120m with DJI GroundStation Pro. The images were then orthorectified using Agisoft Photoscan with a final resolution of 3cm/pixel. More information on our UAV surveying procedure is documented in Hsu et al. [7]. We also acquired corresponding Planetscope Imagery at 3m resolution for each area of interest surveyed using our UAVs. This imagery contained Red, Green, Blue, and Near-Infrared Bands (R, G ,B, and NIR, respectively) using the same bounds of our UAV imagery with no cloud cover and captured closest to our original UAV survey date.

We generated additional features for each pixel in our satellite imagery, including the normalized difference vegetation index (NDVI) and the normalized difference water index (NDWI) as shown in Fig. 1d and Fig. 1e, respectively, to aid in the classification of vegetation and water areas . These generated features were appended to each satellite pixel to be inputted into our models.

$$NDVI : \frac{(NIR - R)}{(NIR + R)} \qquad NDWI : \frac{(G - NIR)}{(G + NIR)}$$

**Label Data** Using the high resolution mangrove images, labels were created by hand from trained annotators used as inputs for our image classification models. These labels were generated in QGIS in the form of polygons and then reviewed by subject matter experts to verify their accuracy. 1500 person-hours among 11 trained individuals generated our labels, totaling 719 hectares, or $1.1\ x\ 10^6$ labeled Planetscope satellite pixels when rasterized.

**Hybrid CNN** To take advantage of the high resolution features of our UAV imagery, we utilized a pretrained Efficientnet-b0 feature extractor [18] to extract implicit features from square sections of

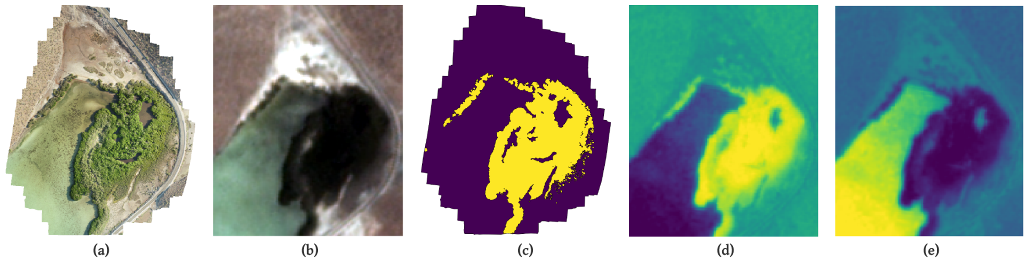


Figure 1: Example images from data sources, image labels, and extracted vegetation indice features. (1a) UAV Image. (1b) Planetscope Image (RGB Shown). (1c) Hand-labels. (1d) Generated NDVI feature. (1e) Generated NDWI feature.

our imagery. Such feature extractors are exceptional at extracting implicit image features, avoiding the need for any explicit feature engineering. For a standard image classification network, the outputs of this feature extractor would be inputted to another densely connected layer to generate predictions [11]. However, this network on its own cannot input single lower resolution hyperspectral pixels that aid in the classification of mangroves. We modified this standard image classifier to utilize lower resolution hyperspectral features by using another input densely connected layer which inputs satellite pixels. We then constructed the Hybrid CNN network by concatenating the outputs of the densely connected layer and inputted to a final densely connected neuron layer which outputs predictions. This method effectively fuses our high resolution UAV images and lower resolution satellite pixels, to take advantage of both the high resolution image features present in our UAV imagery and the hyperspectral bands present in our satellite imagery.

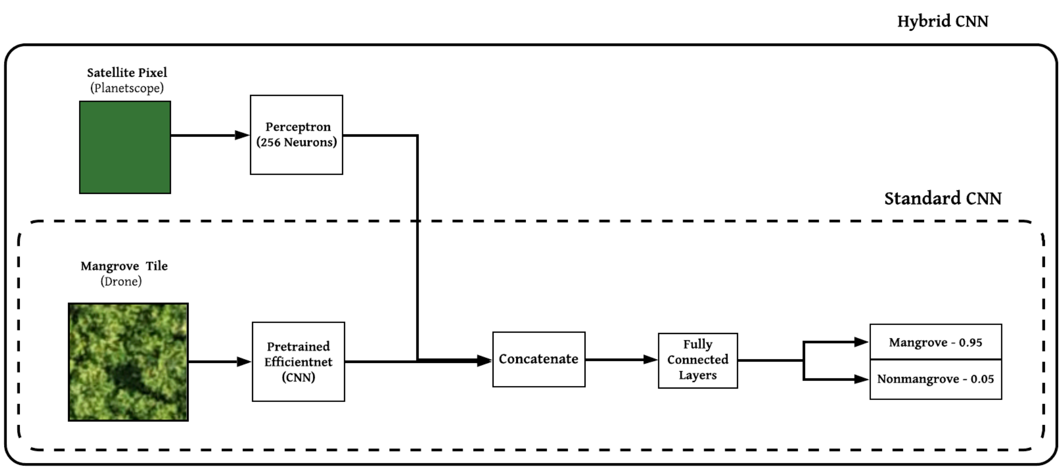


Figure 2: Illustration of Hybrid CNN architecture showing the flow of features from the Efficientnet-b0 feature extractor and intermediate densely connected layers used for mangrove image classification

**Baselines** To measure the effectiveness of our Hybrid-CNN architecture, we established baselines by utilizing methods from literature and experimentation to prove the utility of the input satellite features in combination with a CNN feature extractor. We created a baseline using only a pretrained Efficientnet-b0 feature extractor trained on UAV imagery alone. We also used a random forest model trained on Planetscope RGB/NIR pixels with generated NDVI features [8], and a model trained on NDVI features alone [21]. Lastly, we obtained GMW Labels [2] and rasterized them to the resolution of our Planetscope imagery to compare them directly to our ground truth labels.

## 3 Experiment and Results

**Results** With our baselines and Hybrid CNN, we validated these models to verify their performance. We tested our entire labeled dataset rasterized at the resolution of our Planetscope imagery to derive mean accuracy and mean intersection over union metrics (IOU) using a 5-fold cross validation for all methods. Our experiments show that the Hybrid CNN network has higher performance compared to our baseline models, with the highest accuracy and IOU compared to our baseline methods.

| Model | Mean IOU | Mean Accuracy |
|---|---|---|
| Hybrid CNN | **0.953** | **0.967** |
| Efficientnet-b0 CNN | 0.898 | 0.954 |
| GMW Labels | 0.662 | 0.794 |
| Random Forest (NDVI) | 0.730 | 0.913 |
| Random Forest (RGB/NIR + NDVI) | 0.824 | 0.919 |

Table 1: Model performance of Hybrid CNN and Baseline algorithms

From visual inspection, we can see that a CNN without hyperspectral satellite image features and containing only the Efficientnet-b0 layers trained on UAV imagery performs worse compared to our Hybrid-CNN. Also, our baselines utilizing only satellite features also have a worse performance to our Hybrid CNN, vastly overestimating as seen in Fig. 3e, or underestimating extent by as seen in Fig 3f. Lastly, although GMW labels capture the general area of the mangrove ecosystem, as shown in Fig. 3d, the poor resolution and precision of these labels render it difficult to capture the true extent, resulting in the worst performance compared to our other baseline methods and Hybrid CNN.

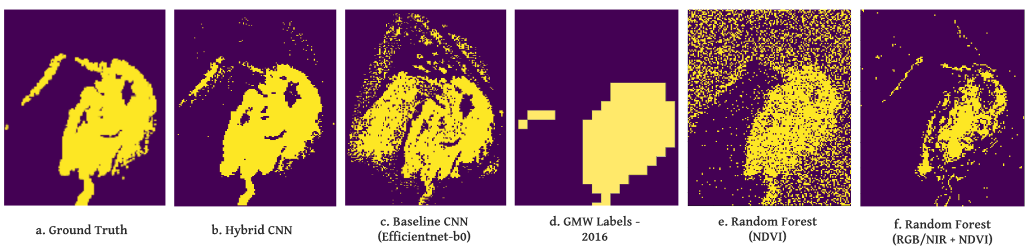


Figure 3: Visualizations of ground truth and each image classification method on a test site (Mangrove - Yellow, Nonmangrove - Purple)

## 4 Discussion and Conclusion

This paper outlines the ability of our Hybrid CNN to effectively detect mangrove areas at high resolutions and IOU through the use of medium resolution satellite and high resolution drone imagery. We compared our Hybrid CNN network to baseline methods used to previously classify mangrove extent and found that our Hybrid CNN network outperformed these baseline methods by up to 30% increase in mean IOU when measured against GMW labels.

One notable weakness of methodology is that our Hybrid CNN methodology must require both drone and mangrove imagery, limiting its scalability. To address this limitation, we plan to implement a weakly-supervised image classifier to classify satellite imagery at performances comparable to our current Hybrid CNN method. We also aim to provide open access to our dataset of high resolution mangrove images and labels so other researchers can build upon our methods.

Our current method can create accurate high resolution classifications of mangrove extent, allowing decision makers to have more frequent and recent statistics to guide decision-making for mangrove forest management and climate policy. Better local conservation of mangrove forests driven by our methods enables relevant nations to hasten the completion of their Paris Accord NDCs, and benefit humanity through helping limit global warming to 2.0°C. Further improving current issues of scalability will further enable the application of our methods to other geographic regions and at the local, national, and international scale to better monitor mangroves as a nature-based solution for our climate crisis.

# 5 Appendix

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