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Ground Truthing Strategies for Automatic Tree Crown Segmentation of Mangrove Forests Along the Batangas Coastline, Philippines using High-Resolution Imagery and Deep Learning

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Abstract

Mangrove forests play a critical role in protecting tropical coastlines, storing carbon, and supporting marine life, yet mapping their fine-scale canopy structure remains difficult. This study introduces a structured ground-truthing strategy for automatic tree crown delineation of mangrove forests using high-resolution UAV imagery and deep learning. UAV-derived RGB orthomosaics from the Batangas coastline, Philippines, were manually annotated into three canopy classes: Individual Crowns (IC), Crown Clusters (CC), and Canopy Gaps (CG), which form the reference foundation for model training. A multi-head DeepLabV3–ResNet50 network was developed to jointly predict canopy masks and distance maps that capture crown geometry and spatial relationships. From these distance surfaces, local maxima were extracted as potential crown centers, and a Voronoi-style watershed segmentation was applied to delineate discrete crown units. An adaptive merging rule, based on peak prominence and spatial proximity, refined the segmentation by merging coalescent crowns while preserving distinct individuals. The results show interpretable delineation of crowns across varying canopy densities and environmental contexts, from isolated individuals in coastal fringes to coalescent crowns in mature stands. High-prominence peaks corresponded to dominant crowns, while moderate peaks represented subordinate or merging individuals. The framework integrates manual annotation with automation through deep learning models, establishing a reproducible foundation for crown-level mapping and long-term monitoring of mangrove canopy dynamics.

1. Introduction

Mangrove forests are among the most productive and carbon-dense ecosystems, providing shoreline stabilization, long-term carbon storage, and nursery habitats that sustain coastal biodiversity. In the Philippines, mangroves mitigate storm surge and erosion while supporting fisheries and local livelihoods. Decades of land conversion, aquaculture expansion, and altered hydrology have fragmented many stands into mosaics of degraded, regenerating, and mature zones. Monitoring these structural variations is essential for understanding recovery trajectories; although high-resolution drone imagery has improved coastal characterization (Pe et al., 2024), crown-level reference data for the area remain sparse. Conventional field surveys yield accurate structural measurements but are labor-intensive and spatially limited in tidally inundated terrain. Satellite remote sensing enables wide-coverage mapping yet typically lacks the detail to resolve crown boundaries in dense mangroves. Unmanned Aerial Vehicles (UAVs) bridge this gap by providing centimeter-level RGB orthomosaics suitable for canopy-scale analysis. However, the absence of standardized, high-resolution reference annotations has constrained the training and validation of automated tree-crown delineation models on mangrove imagery. Object-based and deep learning methods have advanced tree crown delineation in forests since architectures such as U-Net, DeepLab, and Mask R-CNN report strong performance in open or homogeneous canopies (Lassalle et al., 2022, Lassalle and Souza Filho, 2022, Tong and Zhang, 2025, Li et al., 2023, Lu and Wang, 2024). Their transfer to mangroves remains challenging due to lateral crown interlocking that weakens boundary gradients and spectral homogeneity over foliage and shadowed water backgrounds. Ecologically, mangrove canopy organization is not binary. Under high stand density, crowns coalesce into crown clusters with limited visual separation; conversely, disturbance and self-thinning generate canopy gaps that facilitate recruitment and succession (Duke, 2001, Wannasiri et al., 2013). Prior mangrove mapping commonly emphasizes crowns and gaps (Kamal et al., 2015, Lassalle and Souza Filho, 2022, Lassalle et al., 2022, Tong and Zhang, 2025) but typically

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omits an explicit cluster class, despite evidence that trees are frequently aggregated rather than randomly distributed (Hanifa et al., 2024) and that foliage clumping occurs across hierarchical levels of tree structure (Niu, 2021, Vovides et al., 2018). When clustering is not explicitly labeled, dense, interlocking canopies are treated the same as isolated crowns. This removes important structural cues related to canopy closure and stand maturity, reducing the model's ability to generalize across varying canopy densities and obscuring ecological patterns of competition and regeneration that are fundamental to mangrove dynamics. Rule-based delineation tailored to mangroves has shown promise but also highlights limitations. For example, (Kamal et al., 2019) found that multi-canopy large trees were sometimes split into multiple crowns and replicability across sites remained an open question. These outcomes highlight the need for ground truth that encodes other canopy configuration and provides geometric cues to separate overlapping crowns. Mangrove crown delineation is constrained by two limitations: (i) the lack of consistent, high-resolution ground-truth datasets that represent canopy structure characterization other than individual trees and gap cover; and (ii) the difficulty of separating overlapping or coalescent crowns using purely spectral or texture cues. Traditional approaches to tree crown delineation typically rely on automated algorithms such as local maxima or minima detection (Suhardiman et al., 2016). While these methods can identify general canopy patterns, they often fail to accurately locate separate individual trees in dense, overlapping vegetation. To address these, the present study employs a framework that combines manual annotation with a deep learning model capable of learning mangrove crown geometry directly from UAV RGB imagery. The approach establishes a ground-truthing strategy that (a) formalizes three-class canopy labels: Individual Crowns (IC), Crown Clusters (CC), and Canopy Gaps (CG), and (b) trains a model to predict distance and boundary maps that guide instance-level crown delineation even in dense mangrove stands.

2. Study Area

The study area is located along the mangrove coastline of the Province of Batangas, Philippines. The site represents a heterogeneous intertidal landscape composed of mature, closed-canopy stands with regenerating patches and canopy gaps formed by natural disturbance and variable hydrological regimes. Tidal amplitude and salinity gradients exert a strong control on species distribution and crown architecture, producing short, symmetric crowns in frequently inundated or saline microsites and broader, interlocking canopies at slightly elevated, less saline elevations. These contrasts make the locality suitable for evaluating crown delineation methods under dense-canopy and overlap conditions while remaining logistically accessible for repeated flights. Figure 1 and 2 illustrates the location of the flight area and data collection using UAV. The flight mission was conducted under stable illumination and low wind conditions to minimize geometric distortion and shadow variability. High-resolution RGB orthomosaics were captured using a DJI Mavic 3, with a flight altitude of 30 m and an overlap configuration of 80% forward and 70% lateral, which yielded a ground sampling distance (GSD) of approximately 1.33 cm/pixel, sufficient to resolve individual crown textures and small canopy gaps. The rationale behind this configuration was to achieve spatial resolution adequate for tree-crown scale delineation while maintaining efficient coverage. The key flight parameters are summarized in Table 1.

Figure 1. The Study Area.

Figure 2. UAV-based data collection along the Batangas mangrove coastline using the DJI Mavic 3.

Parameter	Value
Terrain follow height	30 m
Flight speed	2.4 m/s
Ground Sampling Distance (GSD)	1.33 cm/pixel
Image overlap (frontal / side)	80% / 70%
Total images captured	264
Covered area	15,520 m^2
Camera type	RGB (20 MP)

Table 1. UAV flight configuration and data acquisition parameters.

3. General Workflow

The overall workflow of the proposed framework (Fig. 3) integrates manual annotation, deep learning model training, and rule-based crown evaluation into a process for generating and refining mangrove crown labels. The orthomosaics constitute the primary input for manual annotation and model training, and was subdivided into 512×512 px tiles with 10% overlap. Each tile was manually annotated into three canopy structure classes: Individual Crowns (IC), Crown Clusters (CC), and Canopy Gaps (CG), then the annotations were exported in COCO format. Figure 4 shows the obtained orthomosaic and sample patch. The annotated image tiles were used to train a multi-head DeepLabV3 network with a ResNet-50 backbone. The model was designed to learn two complementary outputs: a binary canopy mask that distinguishes vegetation from background, and a continuous distance map that encodes the distance of each pixel to the nearest crown boundary. These outputs together enable the network to capture both the extent and

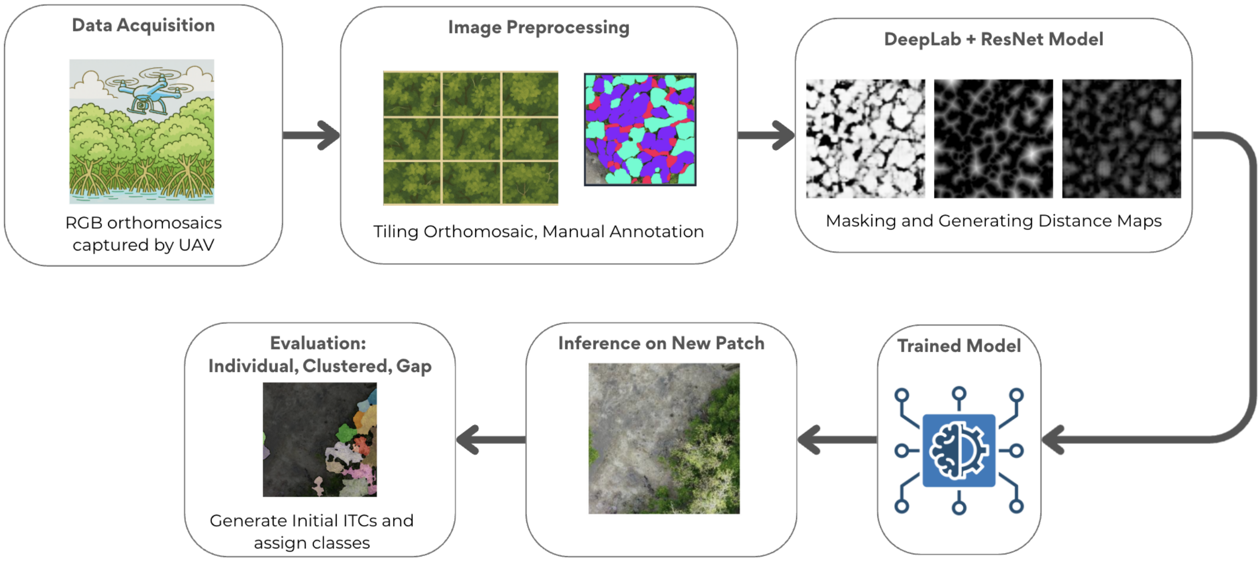


Figure 3. Workflow of Mangrove Crown Ground Truthing Strategy.

internal geometry of each crown. Training was guided by a composite loss function involving binary cross-entropy with an L1 loss. Once trained, the model was applied to new UAV image patches to generate predicted canopy masks and distance maps. From each distance surface, local maxima were extracted as potential crown centers, each representing a candidate tree apex. These detected peaks served as markers for a watershed segmentation applied to the inverse of the distance map, partitioning the canopy into discrete crown units. This process produces crown delineations that arise from the learned canopy geometry rather than from color or texture differences alone. The resulting crown polygons were then evaluated using peak prominence and spatial proximity to categorize each unit as *Individual*, *Clustered*, or *Gap*. High-prominence peaks corresponded to dominant, well-defined crowns, while moderate peaks located near other peaks of similar strength indicated coalescent or overlapping crowns. These three structural classes were not defined solely for visual segmentation but to represent distinct ecological states and competitive relationships within mangrove stands. Figure 5 illustrates how these canopy classes appear.

Figure 4. Orthomosaic and Sample Tile.

An Individual Crown (IC) represents a tree whose canopy is morphologically separable from its neighbors, characterized by a convex outline and a single dominant apex. Ecologically, these crowns correspond to mature or late-successional individuals that have established dominance within the stand. Such trees exhibit stable, well-defined canopy shapes and often occur at forest margins or in gaps where lateral growth is unconstrained. Crown Clusters (CC) denote regions where multiple crowns have coalesced into contiguous canopy masses with limited visual separation (Wannasiri et al., 2013). These clusters are a defining characteristic of dense, undisturbed mangrove stands where lateral branch interlocking and competition for light result in shared canopy surfaces. From an ecological perspective, clusters represent areas of high canopy closure and structural maturity, where individual-level discrimination becomes ecologically less meaningful than stand-level properties such as canopy connectivity and closure fraction. Including this class in the ground-truth dataset acknowledges the natural continuum between discrete and merged crowns and provides models with explicit examples of canopy overlap, improving generalization in complex forests. Canopy Gaps (CG) correspond to open areas devoid of closed canopy cover, often caused by natural disturbances such as branch fall, wind damage or anthropogenic clearing. Gaps are critical indicators of regeneration dynamics and stand turnover (Amir, 2012) so identifying these areas within the ground truth supports the integration of structural monitoring with ecological recovery studies. The adoption of these three structural classes formalizes a multi-level ground-truthing strategy. Instead of treating all canopy regions as equal segmentation targets, the framework captures the ecological hierarchy of the mangrove forest: individual trees as functional units, clusters as mature stand structures, and gaps as regenerative or disturbance-related zones.

4. Results and Discussion

The proposed framework produced interpretable crown delineations across the test sites along the Batangas coastline. Beginning with high-resolution UAV imagery, the network generated smooth distance surfaces that captured canopy geometry even in visually complex areas. From these predicted distance maps, crown centers were detected as local peaks, each representing the most convex point of a crown in geometric space. Figure 6 illustrates this process and the transition from raw imagery to structured crown instances. In the first panel, the RGB

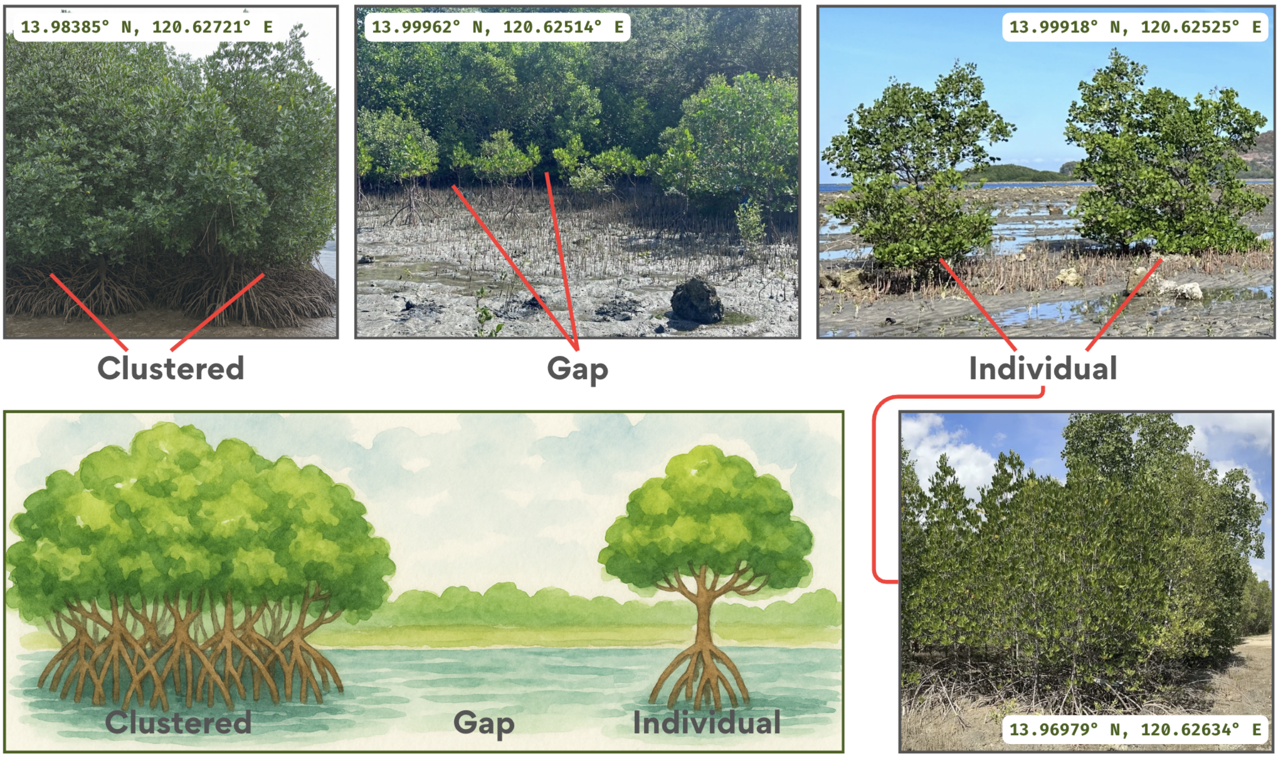


Figure 5. Illustration of annotation classes: Clustered, Individual, and Gap, using field photographs from the Batangas coastline study site (taken January 2025). A schematic illustration in the lower left panel provides a simplified depiction of each class.

orthomosaic shows a dense mangrove canopy with minimal visible separation between neighboring crowns. The second panel presents the corresponding distance map overlaid with detected peaks where bright regions indicate canopy centers. Green markers denote high prominence peaks associated with dominant, well-defined crowns, while yellow markers represent moderate prominence peaks typically found within coalescing or transitional crowns. These peaks provides a foundation for partitioning the canopy into crown units even when visual boundaries in the RGB data are faint or overlapping. The third panel shows the intermediate Voronoi diagram generated from these detected peaks. Each peak serves as a seed point, defining a region of spatial influence within the canopy mask. This tessellation approximates how crowns occupy space relative to their neighbors, effectively capturing canopy competition and spacing patterns. However, dense stands can produce many small adjacent cells and over-segmentation in areas where multiple peaks occur within a single, merged canopy. To resolve this, a merging step is applied, shown in the final panel. Adjacent cells with Moderate–High or Moderate–Moderate peak combinations are fused into single polygons, representing crown clusters or shared canopy zones. Isolated High–High pairs remain separate, marking distinct, dominant crowns. The process leading up to this reconstruction is detailed in Figure 7. The predicted distance surface (bottom right) provides a continuous measurement of canopy geometry, where each pixel's value represents its distance to the nearest crown boundary. Brighter regions correspond to canopy centers, while darker ridges mark dividing boundaries between adjacent crowns. The top-right panel shows the same surface overlaid with detected peaks, which act as the seed points for subsequent crown delineation. Each peak is assigned a prominence class based on its amplitude relative to the local maximum: high-prominence peaks (green) correspond to dominant crowns with well-defined convexity, while moderate peaks (yellow) indicate overlapping or transitional crowns within shared canopy areas. The bottom-left panel shows the initial tessellation of Voronoi polygons derived from these peaks, demonstrating how the canopy is spatially partitioned based on geometric distance rather than spectral contrast.

The merged Voronoi clusters in Figure 8 highlight how crown-level interactions manifest in dense mangrove stands. Areas where High–High peaks occur in close proximity generally represent distinct, dominant trees separated by narrow canopy divides, whereas Moderate–High and Moderate–Moderate pairs often indicate overlapping crowns. The proximity and prominence relationship between peaks thus provides a practical basis for distinguishing crown clusters from individual trees. In this study, a fixed distance threshold was used to merge neighboring polygons, prioritizing the preservation of true individual crowns while allowing reasonable aggregation within dense canopy zones. However, determining the optimal merging criteria remains dependent on context: too narrow a threshold risks underestimating cluster extent, while overly permissive merging may mask individual crown boundaries. Future refinements could employ adaptive spatial thresholds that vary with local canopy density, crown size distribution, or peak prominence gradients derived from the distance field. Several representative results from various canopy conditions are presented in Figure 9.

In the top row, individual crowns along open coastal margins are clearly separated, and the reconstructed polygons align closely with single trees, with crown areas ranging from approximately 270 to 1,500 pixels. In the middle row, the method delineates multiple crowns within dense, multi-layered stands. Despite limited visual contrast, the model preserves the internal crown structure and differentiates dominant (high-prominence) from subordinate (moderate-prominence) crowns. These results are

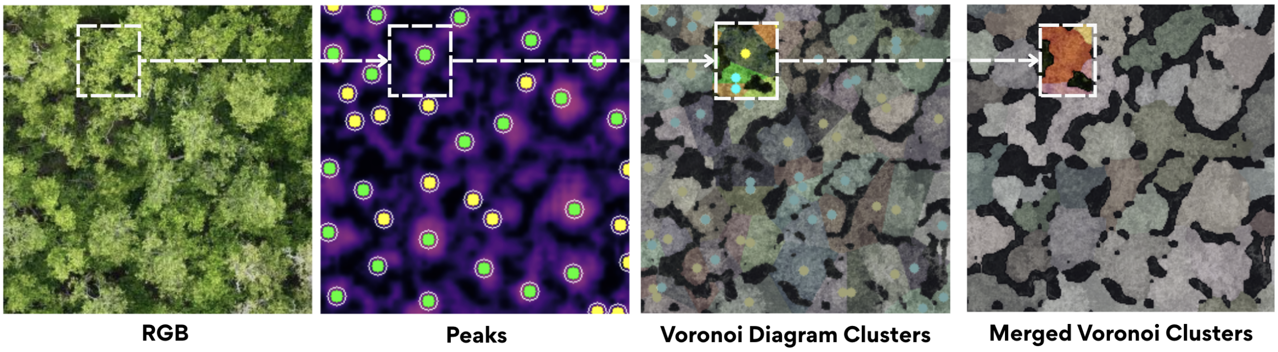


Figure 6. Voronoi-based crown reconstruction and merging. Detected peaks are converted into Voronoi cells that approximate crown influence zones. Neighboring cells with moderate–high or moderate–moderate peak pairs are merged into clusters, while isolated high–high pairs remain as individual crowns.

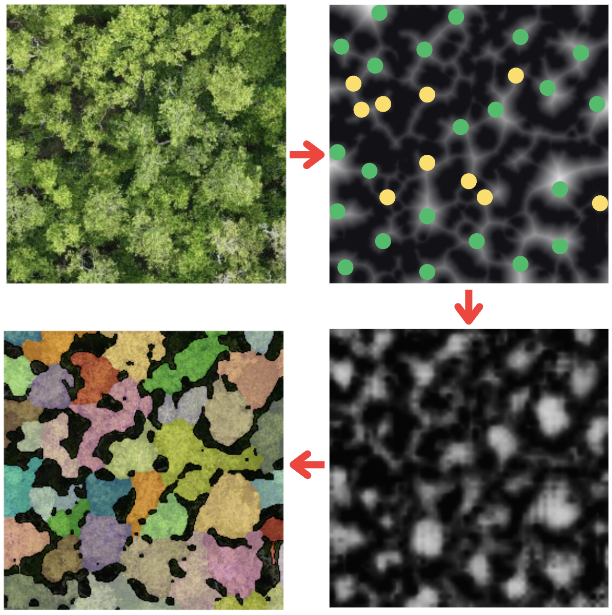


Figure 7. Predicted distance surface and peak detection. Bright regions indicate canopy centers, while darker ridges mark boundaries. Green and yellow markers (high- and moderate-prominence peaks, respectively) act as seeds for crown reconstruction.

consistent with ecological expectations for mixed-age stands transitioning between regeneration and closure phases. The bottom row shows an isolated mangrove growing in shallow water, where two distinct peaks correspond to a main and a smaller crown. Even in homogeneous backgrounds, the segmentation remains stable and avoids false boundaries, illustrating the framework's adaptability to varying canopy densities. Across all examples, peak prominence serves as a concise measure of canopy dominance and clustering. High peaks correspond to large, convex crowns that represent structural dominance, while moderate peaks are typically found at canopy edges or within clusters. Figure 10 illustrates typical edge cases occurring along the mangrove–shore transition where vegetation coexists with exposed substrate, rocks, or shallow water. These boundary environments present a challenge for canopy delineation because of the low spectral contrast between vegetation and background and the fragmented nature of crown cover. Crown polygons adhere closely to real canopy patches and rarely extend into surrounding rocky or water surfaces. This performance reflects the capacity of the learned distance field to encode canopy structure independently of local variation. Nevertheless, several limitations arise in these edge scenarios. Where vegetation is highly fragmented, the process can produce noisy masks as the gradient cues become weak near the boundary of the vegetation mask. Third, the absence of height information limits the model's ability to distinguish short, regenerating shrubs from background clutter such as driftwood or algae mats, especially

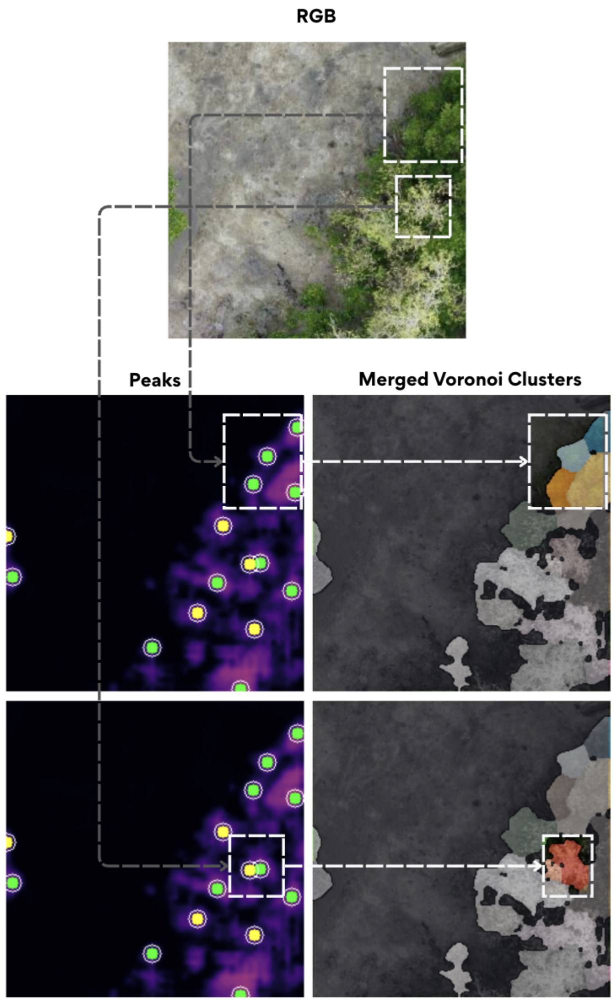
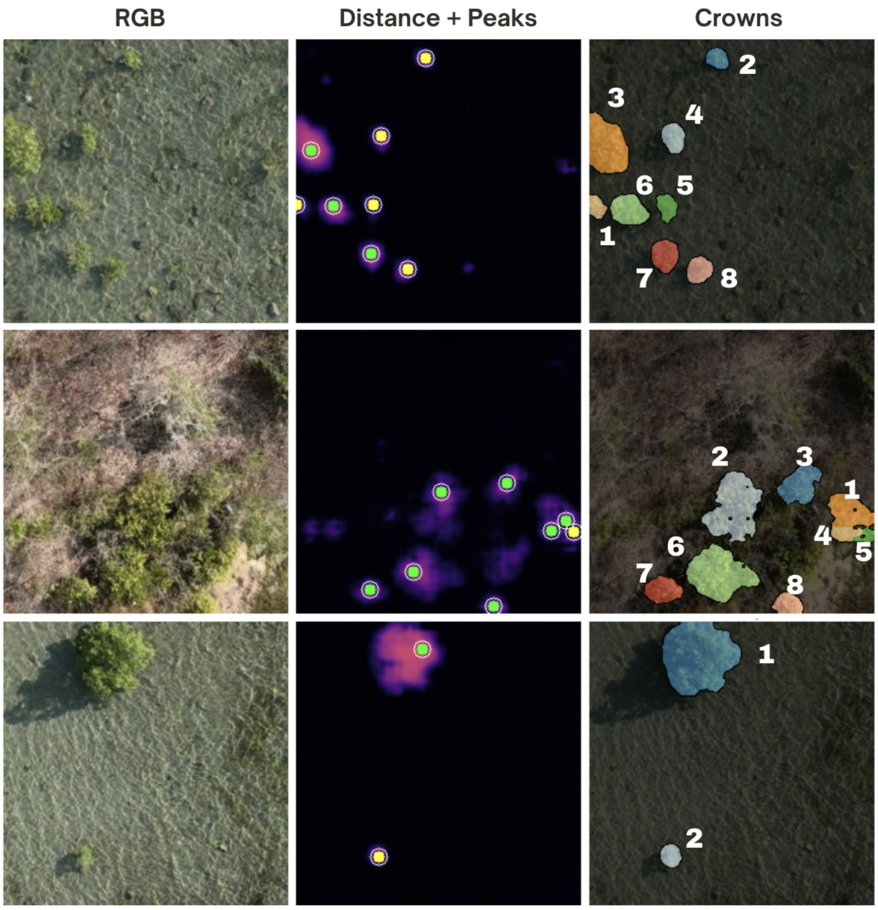


Figure 8. High Peaks and Moderate-High Peaks in Close Distance: Implies Distinct Under-Vegetation Overlap and Inter-Vegetation Overlap.



ID	Area (px)	Peak Class
1	327	Moderate
2	477	Moderate
3	1562	High
4	271	Moderate
5	368	Moderate
6	766	High
7	601	High
8	473	Moderate

ID	Area (px)	Peak Class
1	997	High
2	2242	High
3	957	High
4	311	High
5	178	Moderate
6	2139	High
7	668	High
8	429	High

ID	Area (px)	Peak Class
1	3636	High
2	338	Moderate

Figure 9. RGB Image, Distance Map + Peaks, and Identified Crown Boundaries.

under similar color tones. These limitations suggest the need to integrate additional cues such as elevation, multispectral indices, or multi-temporal imagery to improve discrimination at mangrove boundaries. Overall, while the framework can extract meaningful crown separation even where spectral signals are ambiguous, it remains sensitive to incomplete or low-contrast canopy structure near transitional boundaries.

5. Conclusion and Recommendations

This work takes a step toward rethinking how ground truthing is done for mangrove canopies. Rather than treating it as a one-time, manual task, the process here is built as a connected sequence where manual annotation and automation work together. Manual crown delineation on UAV orthomosaics remains essential but relying on it alone can be slow, subjective, and difficult in places where crowns overlap or merge into dense clusters. The framework developed in this study builds on that foundation, aiming to make ground truthing more consistent and scalable without losing its ecological implication. At its core, the workflow begins with clear manual labeling of three canopy structures to capture how mangrove stands naturally organize and regenerate. These annotations are then used to create distance maps that trains a multi-head DeepLabV3–ResNet50 model to recognize not only canopy edges but also internal crown geometry. The model's output is transformed into crown instances through a Voronoi-style reconstruction that considers the prominence and spacing of detected peaks. In this final step, neighboring Moderate–High peaks are interpreted as clustered

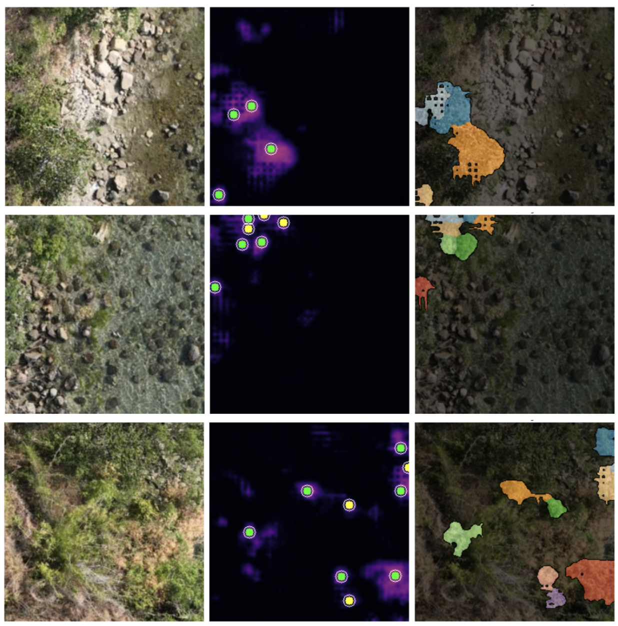


Figure 10. Edge Cases of Mangrove Crown Identification.

crowns, while well-separated High–High peaks represent individual trees. Ultimately, the approach improves boundary delineation in visually uniform and dense mangrove canopies. Several key insights emerge from the results. First, high prominence peaks consistently corresponded to dominant crowns with

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coherent geometry, while moderate peaks identified subordinate individuals or transitional overlaps. Second, adaptive merging of Voronoi cells based on spatial proximity allowed the model to distinguish clusters from individuals. Third, the resulting crown polygons reflected canopy organization observed in the field. Despite its potential, the framework still faces practical limitations. The analysis relies solely on single-date RGB imagery, which limits its ability to capture spectral variation, species differences, and vertical canopy layering. Integrating multispectral or LiDAR data could improve detection of overlapping crowns and enrich three-dimensional structure representation. The geographic scope is also confined to mangrove stands in Batangas; applying the same protocol to other Philippine sites or regional mangrove systems would help test model transferability and promote standardized benchmarks. Lastly, while the present framework provides static delineations, applying it to multi-temporal UAV datasets could reveal how crowns expand, merge, or regenerate following disturbance, transforming this workflow into a dynamic monitoring tool. In sum, the work establishes a reproducible foundation for crown-level ground truthing in mangrove forests and shows that a combination of manual annotation and deep learning techqnies can produce crown delineations that are consistent. As mangrove restoration and monitoring efforts expand, frameworks like this can bridge manual expertise and automated mapping, ensuring that data-driven models remain faithful to the complex, living structure of these coastal forests.

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Author Contribution Statement

Jazzie R. Jao: Writing (original draft); Writing (review & editing); Visualization; Software and Model Training; Methodology; Conceptualization; Investigation; Formal analysis; Supervision; Data acquisition; Data curation; Data Annotation; **Amelia Abenoja**: Software; Investigation; Data curation; Formal analysis; Data Annotation. **Miguel Gonzales**: Software, Investigation; Data curation; Formal analysis; Data Annotation. **Eryl Larido**: Software, Investigation; Data curation; Data acquisition; Data Annotation. **Waynes Wu**: Software, Investigation; Data curation; Formal analysis; Data Annotation. **Edgar Vallar**: Writing (review); Formal Analysis; Funding acquisition; Data acquisition; Project administration; Resources; Supervision, Validation. **Jejomar Bulan**: Data acquisition. **Jumar Cadondon**: Data acquisition. **James Roy Lesidan**: Data acquisition. **Steven Pe**: Data acquisition. **Maria Cecilia Galvez**: Funding acquisition; Project administration. **Arnel Beltran**: Funding acquisition; Project administration; Resources. **Aileen Orbecido**: Funding acquisition; Project administration; Resources. **Myriam Prasow Emond**: Data acquisition; Project administration. **Pablo Brito-Parada**: Funding acquisition; Writing (review); Project administration. **Yves Plancherel**: Funding acquisition; Resources; Project administration.

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