Validating The Philippine Mangrove Map 2023 through Capacity Building and Crowdsourcing

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Keywords: Accuracy Assessment, Citizen Science, Participatory GIS, Nationwide Mangrove Mapping, ODK Collect

Abstract

Mangroves are crucial coastal ecosystems. They provide numerous ecological and socio-economic benefits – shoreline protection, carbon sequestration, food security, and biodiversity conservation. The Philippine Mangrove Map 2023, generated through Machine Learning, improves understanding, accounting, and conserving these vital habitats. However, ensuring the accuracy and reliability of maps is imperative for informed decision-making and effective conservation efforts. Various validation methods were reviewed to develop a nationwide approach integrating practicality and statistical rigor, incorporating multiple data sources such as satellite and airborne imagery and GPS points from the government, civil society, and citizens. Capacity building enabled large-scale citizen science collaboration to gather quality datasets and foster reciprocal learning between scientists and local citizens. This collaborative effort aims to improve the quality of datasets and ultimately enhance the accuracy of the Philippine Mangrove Map 2023 and succeeding mangrove extents maps.

1. Introduction

Mangroves are crucial coastal ecosystems that provide numerous ecological, economic, and societal benefits. More than half of the cities and municipalities in the Philippines are coastal and vulnerable to the impacts of frequent typhoons and rising sea levels (Department of Environment and Natural Resources [DENR], 2001). Mangrove forests serve as natural barriers, safeguarding these communities against the destructive forces of storm surges, floods, and coastal erosion. Each year, they protect approximately 613,000 individuals, including a significant portion (23%) who are impoverished (Beck & Lange, 2017). These vegetation are not only crucial for the safety of human lives but also for the preservation of marine biodiversity, acting as havens that sustain marine life, which are integral to the nation’s food supply and the economic stability of coastal regions (Arceo-Carranza et al., 2021). Additionally, mangroves are key players in the blue carbon ecosystem, capturing substantial amounts of carbon dioxide (Inoue, 2019), thus contributing to the Philippines’ climate change adaptation efforts.

The Philippines experienced substantial mangrove loss from the 1950s to the 1970s, mainly attributable to the conversion of mangrove areas into aquaculture ponds (Primavera, 2000). This trend of mangrove deforestation persists, as evidenced by an estimated loss of 29,000 hectares across 12 of 17 Philippine regions from 2000 to 2020 (Baloloy et al., 2023). On a global scale, there is cause for concern as approximately 287 km^2 of mangroves are lost annually from 1990 to 2020 (Bhowmik et al., 2021). A study has shown that regions with significant mangrove deforestation tend to experience more rainfall, warmer ocean temperatures, and an increase in severe weather occurrences, all of which are associated with the broader effects of climate change (Baloloy et al., 2023).

Mangrove conservation efforts include various strategies, including governmental designation of protected areas, scientist-led monitoring technologies, and restoration projects by multiple organizations. Just this May 2024, the Philippines has enacted the Philippine Ecosystem and Natural Capital Accounting System (PENCAS) Act. This law supports the systematic and nationwide physical assessment of the country’s natural resources and the contributions of different ecosystems to economic development. Determining the physical account (cover/extent, conditions, flow of ecosystem services) and monetary account (economic value) of a natural resource such as a mangrove forest not only informs development planning and policy analysis on the sustainable use of resources but brings the country closer to achieving international and local agendas on biodiversity, climate, Blue Economy, Sustainable Development Goals and Green Recovery.

Satellite imagery allows extensive monitoring and mapping of the Philippines' forests on a large scale. In the context of the PENCAS law, spatial mapping can play a major role in natural capital accounting. The National Mapping and Resource Information Authority (NAMRIA), an attached agency of the DENR, produced the Coastal Resource Management Map (CRM) of 2020, which is derived from extensive fieldwork and analysis of a compilation of Sentinel-2 satellite images taken from 2016 to 2021. The CRM map shows the extent of corals, seagrass/seaweeds, and mangroves across the nation. To further supplement and update the mangrove resource data, the Philippine Space Agency (PhilSA) and the Department of Environment and Natural Resources (DENR) collaborated to produce the Philippine Mangrove Map of the year 2023. This map was developed by integrating artificial intelligence (AI) with remote sensing data, aiming to automate the process to produce annual mangrove extent maps efficiently. To ensure its reliability, the map is undergoing rigorous on-the-ground validation, aimed at refining both its accuracy and the underlying machine-learning (ML) algorithm for mangrove mapping. This study will discuss the method developed to validate the Philippine Mangrove Map 2023.

https://doi.org/10.5194/isprs-annals-X-5-2024-243-2024

2. Review of Validation Methods

2.1 Satellite Image Interpretation

The accuracy of satellite image classification maps is commonly assessed by interpreting the true class from similar or higher spatial resolution satellite images (Lyons et al., 2018). Bunting et al. (2018) used this method in their 2010 global mangrove forest baseline of the Global Mangrove Watch. 53,000 cumulative stratified point samples of water, mangrove, and terrestrial non-mangrove classes were generated within a defined mangrove habitat zone. They limited the accuracy assessment to 17 sites (countries/states) with available local knowledge. Landsat, ALOS PALSAR, and high-resolution (including from Google Earth) imagery were used as references for accuracy assessment operators. Bunting et al. (2021) revised the 2010 baseline to version 2.5, generating 50,750 stratified random points, now limited to mangroves and non-mangroves, across 60 sites around the globe, including the Philippines. Sentinel-2, Bing, and Mapbox imagery were added as additional references.

Local and national mangrove maps also utilize satellite image interpretation for accuracy assessment (Cissell et al., 2020; Huang et al., 2022; Zablan et al., 2023a; Zablan et al., 2023b). Since image interpretation is subjective, multiple references are considered to avoid introducing labeling errors. This includes using false color combinations from multispectral bands to highlight specific image features (Ghorbanian et al., 2020; Lillesand et al., 2015). Baloloy et al. (2020) used Sentinel-2 false color combination B11 (SWIR1) - B8 (NIR) - B4 (Red) to highlight mangrove forests (Figure 1). Additionally, six distinct indices have been developed to help extract mangrove features from images, each specifically designed and tested to delineate mangrove forests and differentiate them from non-mangroves (Baloloy et al., 2020; Huang et al., 2022; Suryarso, 2022; Zablan et al., 2023a; Zablan et al., 2023b).

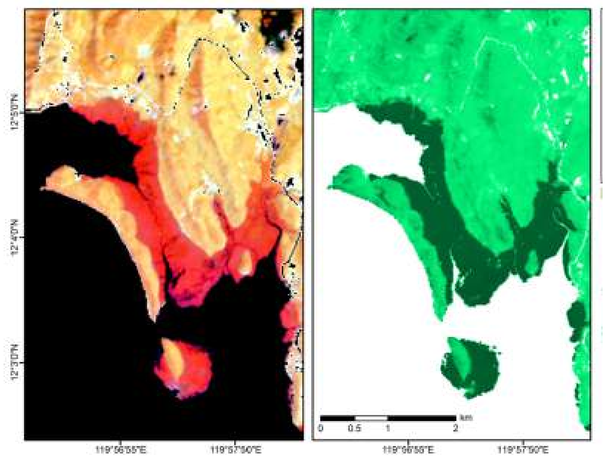

Figure 1. B11-B8-B4 False Color Composite (left) and Mangrove Vegetation Index (MVI) visualization (right) from Sentinel-2 images. Pixels in red-orange in the false color and dark green in the MVI images potentially indicate the existence of mangroves. (Image source: Baloloy et al., 2020)

2.2 Field Data Points

The second most popular way of validating classification maps is in-situ field data collection, often using GPS (Lyons et al., 2018). Many mangrove mapping studies using in-situ data typically focus solely on a limited geographical scope. (Giardino et al., 2015; Mensah et al., 2015; Salam et al., 2007). However, an ambitious nationwide mangrove mapping study in China used in-situ data from multiple sources and combined it with satellite image interpretation to create a substantial amount of training and validation samples (Chen et al., 2017). This study also used citizen science data from the China Mangrove Conservation Network (CMCN). Still, Lyons et al. (2018) observed that older studies utilized this method and reported a decline in the use of resource-intensive field data for validating classification maps, attributing it to the growing availability of very high-resolution (VHR) imagery for remote interpretation. Other studies similarly utilize combinations of different data sources and types for mangrove map validation (Baloloy et al., 2020; Giardino et al., 2015; Huang et al., 2022).

Field data collection experience can be improved by using e-survey forms like ODK Collect, an offline-ready mobile data collection platform designed for efficient field data gathering (e.g., GPS, bearing, photos, texts, videos, and others) in developing regions (Hartung et al., 2010). ODK Collect has been used for agricultural monitoring, deforestation tracking, and crime recording (Anokwa et al., 2009). Campus et al. (2020) evaluated ODK to be a reliable tool for forest data collection as it improves coherence and completeness. Jones et al. (2016) recommended its usage for community-based measurement of mangrove forest carbon stock.

2.3 Airborne Image Interpretation

Unmanned Aerial Vehicles (UAVs), or drones, are used to acquire ultra-high-resolution imagery. This commonly serves as "ground truth" for validating satellite data products, replacing costly in-situ observations, and providing detailed information over large areas quickly, even in inaccessible terrain (Alvarez-Vanhard et al., 2021). UAV imagery offers an alternative to satellite-based mapping methods for mangrove mapping. For example, Baloloy et al. (2020), utilized field data points and drone orthomosaic imagery with 3 to 5 cm spatial resolution to validate the mangrove maps they produced. Drone surveys conducted in 11 sites across the Philippines and 1 in Japan gathered around 500 randomly selected validation points from the orthomosaics produced.

In Ruwaimana et al. (2018), DJI Phantom 2 drone imagery was compared with Pleiades VHR satellite imagery. The former exhibited superior mapping performance and the ability to provide timely data, even on cloudy days. However, they noted limitations, such as longer processing times and suitability primarily for long-term monitoring of small areas. Despite these drawbacks, low-cost drones are practical for accurately mapping physically difficult-to-access coastal ecosystems (Kabiri, 2020). Comparing a map with a more accurate map is, after all, a reasonable validation option (Lyons et al., 2018).

Interestingly, airborne image-based validation methods, as demonstrated in a nationwide mangrove mapping study of Mexico (Acosta-Velázquez et al., 2009), do not necessarily require orthomosaics. Instead, the Mexican Marine Defense Secretary creatively mounted digital cameras and GPS on helicopters. Systematic sampling of airborne photos from these flights yielded 5,743 validation points, which were interpreted by external specialists with regional expertise.

This contribution has been peer-reviewed. The double-blind peer-review was conducted on the basis of the full paper.
https://doi.org/10.5194/isprs-annals-X-5-2024-243-2024

3. Discussion of Validation Approach

3.1 Comparison of Validation Methods

Using satellite imagery as a validation reference is practical for large-scale studies due to the availability of free global satellite imagery, such as Sentinel-2 and Google Earth. This method allows for substantial data point collection and easy randomization, which helps reduce classification bias (Zhen et al., 2013). However, the subjectivity of image interpretation may introduce bias. This can be addressed by introducing multiple references, especially equal or higher-resolution satellite imagery (Lyons et al., 2018). However, Google Earth and Bing Maps VHR imagery are not spatiotemporally homogenous. They consist of a patchwork of images (of resolution ranging from 15m to 10 cm) taken at different times from various satellite or airborne image providers (Lesiv et al., 2018). Lesiv et al. (2018) found that the most recent Google Earth image might be 1-4 years old, leading them to conclude its usage is inadequate for monitoring protected areas and deforestation. This lag can result in labeling points as mangroves based on outdated imagery, potentially missing recent deforestation. Moreover, the spatial resolution may be insufficient to visually interpret mangrove features from other similar vegetation. To address the temporal resolution issue, freely available medium-resolution imagery, like Sentinel-2, can be used. However, this does not solve the spatial resolution issue, which requires proprietary VHR imagery, at a potentially high cost.

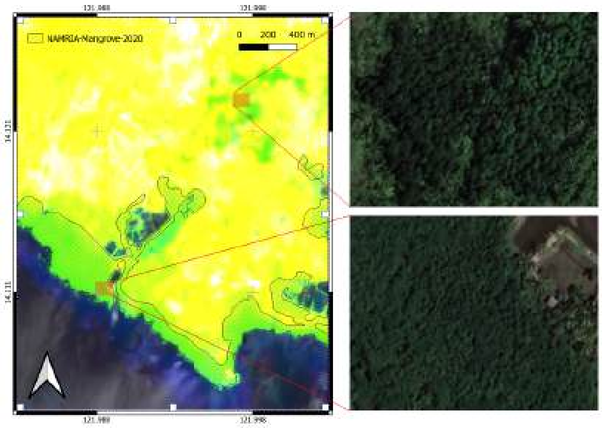

Figure 2. B11-B8-B4 False Color (left) and MVI visualization (right) from Sentinel-2 images of a portion of Alabat Island, Quezon. Pixels in green are potentially mangroves. Inset maps showing Google Earth VHR images of these potential mangrove forests.

Another solution is to refer to false color composites, indices, or other maps. However, as seen in Figure 2, this can still be difficult and inconclusive due to conflicting information. For instance, the false color composite should highlight the mangrove forest in green, but it highlighted a patch of vegetation outside the 2020 NAMRIA CRM. From the VHR imagery, the canopies of the patch (top inset map) appear darker in color and larger via texture compared to the “mangroves” (bottom inset map) identified by NAMRIA. This patch may be a different kind of mangrove species, like landward-type mangroves, and cannot be ruled out merely from the canopy. Moreover, it may be just an issue of spatiotemporal inhomogeneity of Google Earth VHR imagery. Thus, a definitive conclusion requires on-the-ground data.

Field data, whether in-situ or airborne, provide on-the-ground detailed information capturing leaves, roots, fruits, and other vegetation details, which are difficult for satellites to detect. However, mangrove forests, often located in inaccessible inter-tidal zones, can pose challenges for in-situ data collection using GPS, making it labor-intensive and prone to sampling bias (Ghorbanian et al., 2020). Randomization is difficult as some areas may be genuinely inaccessible. Airborne methods, such as UAVs, provide a balance between the wide coverage of satellite imagery and the detailed information from in-situ data. While interpretation of airborne imagery may still introduce bias or error, these issues are minimized by higher spatial resolution. Additionally, UAVs are not affected by cloud cover, unlike satellite imagery. Weather conditions, such as strong winds, can pose challenges, but adjustments can be made to the acquisition date to accommodate local weather (Guimarães et al., 2019; Ruwaimana et al., 2018). Both Guimarães et al. (2019) and Ruwaimana et al. (2018) highlight the potential of aerial imagery in sustainable forest monitoring and management, especially as drone technology evolves. While procuring UAV equipment requires investment, Ruwaimana et al. (2018) argue it is a worthy one-time expense, as continuous monitoring can ultimately yield cost-effective data.

3.2 Validation Method for the Philippine Mangrove Map

Balancing statistical rigor (or adherence to probabilistic methods) with practicality is essential for an effective accuracy assessment (Stehman, 2001). Building upon this principle, the Philippine Space Agency has devised a comprehensive validation approach that harmonizes the quantity and quality of data collected.

Figure 3. Purposively sampled points that were fed to the mangrove mapping machine learning model.

3.2.1 Initial Validation: Purposive sampling was employed to select 49 mangrove and 43 non-mangrove vegetation regions of interest (ROIs) using a combination of local expertise and available resources (Figure 3). The selection process involved cross-referencing various references, including VHR images from Google Earth, ESRI, and Planet; the 2020 Mangrove Maps from Global Mangrove Watch, NAMRIA, and BlueCARES Project; and Google Street View imagery. This approach ensures that the datasets provided to the model are both abundant and of high quality, generating 461 mangrove and 922 non-mangrove vegetation points from the polygons.

The dataset was split into two parts: 70% of the points were used to train the model and 30% were used to initially validate the results. This yielded an overall accuracy (OA) of 99.93% and a kappa statistic (κ) of 0.9984 (Table 1). Despite these impressive numbers, there's a possibility of bias stemming from the nonprobabilistic sampling method of the ROIs, even with the introduction of randomization through dataset splitting.

		Predicted	
		NM	*M*
Actual	*NM*	907	0
	M	1	497

Table 1. Confusion Matrix of Initial Validation Results with Satellite Image Analysis

A notable challenge is that many identified mangroves are seaward mangroves, which are relatively easy to distinguish. In contrast, landward mangroves pose a more significant hurdle due to their spectral and canopy similarities with other vegetation types. Furthermore, landward mangroves often mix with adjacent vegetation, such as beach forests, further complicating accurate identification. This complexity in delineating mangrove boundaries is a common issue faced by numerous mangrove mapping organizations, leading to discrepancies in the depiction of 2020 mangrove extents (Figure 4). Hence, for proper mangrove resource accounting, on-the-ground validation is needed to complement remote sensing-based approaches and ensure accurate mapping of mangrove ecosystems.

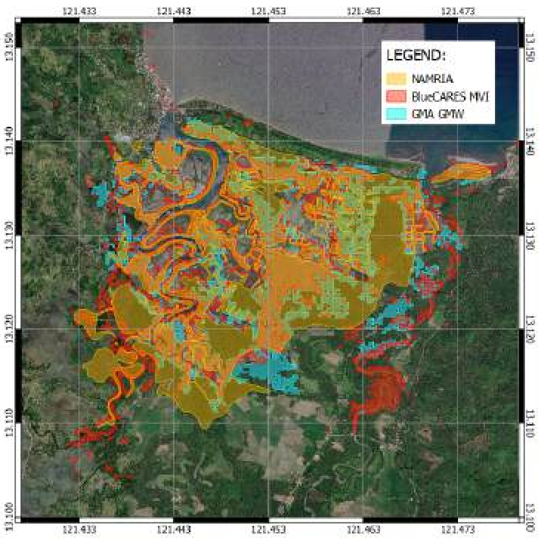

Figure 4. 2020 Mangrove Extent Maps of a portion of Pola, Mindoro from NAMRIA, BlueCARES, and GMW, revealing varying delineations, particularly in the landward zones.

3.2.2 On-the-ground Validation Methodology: To validate this nationwide mangrove map, synergistic use of the three validation methods is employed. First, ODK Collect will be utilized to accessibly gather a diverse on-the-ground dataset essential for nationwide map validation. The questionnaire form in ODK Collect will capture the following data:

1. **(Optional) Affiliation:** For crediting contributors and fostering a spirit of competition.
2. **Photographs:** Pictures of the immediate area with a significant presence of vegetation. Optional photos of leaves, flowers, fruits, canopies, and trunks can also be included.
3. **Point Location:** Record the location using the phone's GPS.
4. **Vegetation Classes:** Identify the classes of vegetation present in the immediate area (e.g., mangrove trees, nipa palms, coconut trees, and/or others).
5. **Canopy Density:** Assess the density of the mangrove forest canopy.
6. **(Optional) Mangrove Species:** Identify the mangrove species present (if known).

It must be noted that ODK is currently only available for Android users, which may limit its accessibility to some validators using other operating systems. Inundated regions are expected to be avoided by contributors for safety reasons. Thus, the second method is using drone orthomosaic imagery to delineate mangrove extents, especially for those with the necessary resources and capacity. This method provides a balanced approach to obtaining both data quantity and quality. 5-10 validation points per hectare will be generated from the drone-based delineated areas. The recommended specifications for the flight plan are as follows:

- Minimum Flying Height: 80 meters
- Coverage: At least 10 - 25 hectares
- Camera Angle: NADIR (directly downward-looking)
- Overlap: 70% overlap in both forward and side directions

This synergistic approach considers the diverse resources and capacities of citizen scientists to be tapped across the nation. It offers them the option to use the more accessible, though physically demanding, ODK Collect, or the costlier drone-based method, which promises faster and larger-scale data collection.

3.2.3 Capacity Building for Citizen Science: Last February 28, 2024, PhilSA, along with the Geospatial Database Office (GDO) and the Biodiversity Management Bureau (BMB) of the DENR, capacitated the public, DENR offices, local government units, nongovernmental organizations, and other stakeholders on validating the mangrove map. This included a hands-on activity on using ODK for field data collection (Figure 5). A short manual (https://bit.ly/Mangrove2023Validation) and a Facebook Reel video (https://bit.ly/HowToValidateMap) were created and shared for further capacitation and dissemination on the methodology (Figure 6). DENR’s capacitated offices were deployed for fieldwork. To ensure statistical rigor and practicality, approximately ten (10) barangays per province will be randomly chosen for in-situ data collection until June (Figure 7). The 611 selected barangays, located along the coast, host mangrove forests according to the NAMRIA 2020 CRM.

The offices are instructed to either use ODK Collect or drones to gather data. 25 Mangrove and 25 Non-Mangrove ODK points per barangay are set as the ideal sample size, totaling approximately 30,000 points for the whole country. However, a soft target of 5 mangrove and 5 non-mangrove points is set to consider the varying resources of different offices. The complete list of selected barangays can be accessed through the following links:

- Visayas: https://bit.ly/VisayasSites
- Luzon: https://bit.ly/LuzonSites
- Mindanao: https://bit.ly/MindanaoSites

Figure 5. Presenting the AI-Powered Philippine Mangrove Map of 2023 alongside insights into the significance and methodologies for validating the map.

Figure 6. Mangrove Validation Video Demonstration shared on Facebook by DENR. (https://bit.ly/HowToValidateMap)

Figure 7. Selected barangays for in-situ mangrove data collection.

PhilSA has been holding workshops for various locations in the Philippines under the PhilSA Integrated Network for Space-Enabled Actions towards Sustainability (PINAS) project that was launched in October 2022 with hopes of promoting sustainability through space data utilization. The mangrove map validation presentation and hands-on ODK collection tutorial were extended locally through the PINAS Zamboanga Workshop held in Zamboanga City from 19 to 20 March 2024 (Figure 8). Participants from Zamboanga Peninsula, Basilan, Sulu, and Tawi-Tawi, representing academia, government, and other organizations, attended.

Figure 8. PhilSA personnel training participants of PINAS Zamboanga on collecting in-situ data using ODK.

To ensure truthfulness, crowdsourced data obtained via ODK or drones will undergo quality checks. This involves cross-referencing select points using ground-level imagery along with other sources like satellite imagery, existing mangrove maps. Mangrove experts will also be consulted.

3.2.4 Reciprocal Learning: After the PINAS Zamboanga Workshop, PhilSA, along with personnel from Mindanao

Development Authority and local government, collected field data from Sta. Cruz Island, Zamboanga City using drones and ODK. PhilSA also trained local personnel to utilize these technologies for in-situ field data collection. Concurrently, local foresters shared their knowledge regarding the diversity and status of the mangrove forest on the island. This reciprocal learning approach facilitated the exchange of expertise between parties. During this interaction, the space scientists were introduced to *Pemphis acidula*, locally known as Bantigi (Figure 9), a mangrove species typically found in landward zones of mangrove forests and sheltered beaches (Wang et al., 2011). Notably, this species is classified as rare and threatened by the Department of Environment and Natural Resources (DENR) due to its exploitation for bonsai purposes (Evangelista, 2018). This highlights the necessity of field activities as they offer access to noting landward-type mangroves, addressing the current lack of data in these areas.

Figure 9. Local forester teaching PhilSA personnel about *Pemphis acidula*.

The Bantigi patch found on the island escaped the notice of bo, highlighting the importance of incorporating local knowledge and expertise into mapping efforts. This emphasizes the need for on-the-ground validation and increased collaboration with local stakeholders to ensure accurate and complete mangrove maps. Additionally, probabilistic sampling may overlook rare species like Bantigi without sufficient random data, emphasizing the need for practical considerations in accuracy assessment methods.

3.2.5 Crowdsourcing: Citizens are not obligated to collect in-situ data from the randomly chosen barangays illustrated in Figure 6. Nonetheless, they are encouraged to volunteer geographic information, especially if they live near mangroves. They may also remotely contribute existing data they collected (e.g., shapefiles, drone imagery) to sdmad@philsa.gov.ph. Moreover, people can view the the initial 2023 Philippine Mangrove Map through the webmap app that is developed using Google Earth Engine Javascript API for this research activity. The app allows them to remotely share their local knowledge through the feedback button (Figure 10). Data gathered will be evaluated for validity and will be used to refine the model and the validation process.

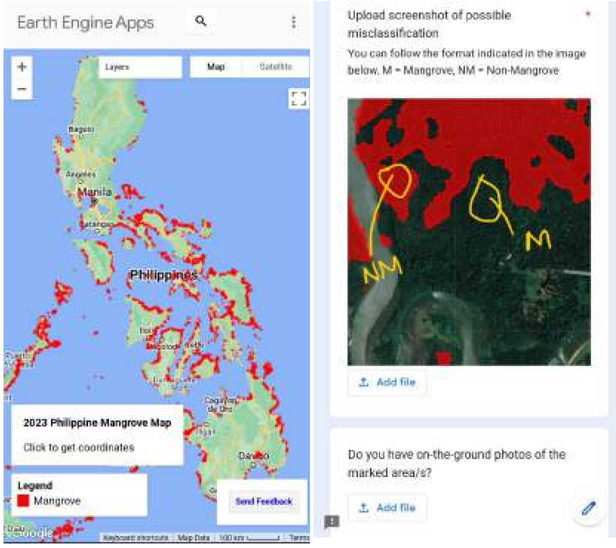

Figure 10. 2023 Philippine Mangrove Map Web App (https://cczablan1.users.earthengine.app/view/philsa-2023-mangrove-map-beta)

The primary concern with crowdsourcing is incorporating randomization to data from areas outside the randomly selected barangays in Figure 7. Nevertheless, their contributions remain valuable for instructing and validating the model. For example, a citizen provided an ODK entry indicating the presence of *Heritiera littoralis*, locally known as Dungon, a mangrove associate (Figure 11). This species typically inhabits inter-tidal and landward areas, occasionally intermixed with terrestrial vegetation (Jian et al., 2010). This species escaped the notice of both NAMRIA and PhilSA but provides valuable local knowledge to improve the map. This highlights the need for crowdsourced, non-probabilistic data to complement probabilistic samples, serving as a practical means of map validation.

Figure 11. ODK picture entry by a citizen showing the presence of Dungon or *Heritiera littoralis*.

3.2.6 Storage, Updating, and Retrieval of Information: All ODK entries sent over the web are uploaded to the Philippine Space Agency cloud server. ODK entries collected offline are uploaded once the device reconnects to the internet. The Philippine Space Agency server includes ODK Central (PostGIS and Google Cloud bucket), and API endpoints for filtering and accessing information.

A live tracker linked to ODK Central for submissions was developed to retrieve and monitor the flow of crowdsourced geospatial data. This aims to identify areas requiring additional validation data, aiming to stimulate competition and increase participation among partners and volunteers. By providing real-time feedback and visualization, the tracker enhances transparency and motivates contributors to engage more actively.

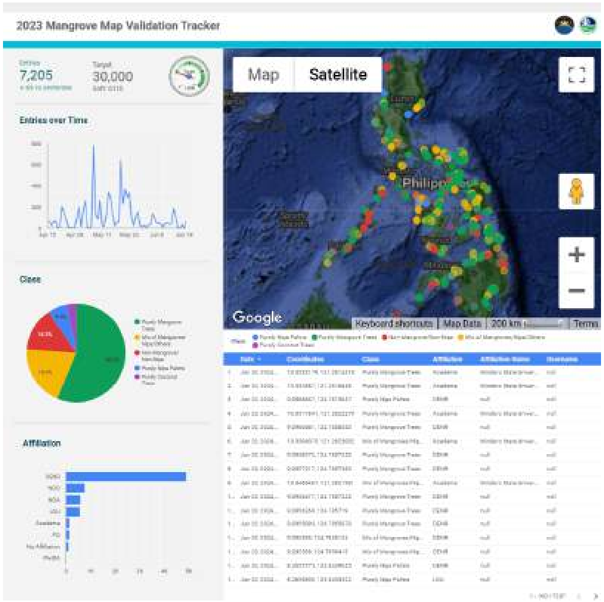

Figure 12. Live tracker showing ODK Entries as of June 20, 2024 (https://bit.ly/MangroveValidationTracker)

4. Future Plans

ODK points will serve as supplementary data for better satellite image interpretation in retraining the model, especially in areas identified as potential misclassifications. This is due to ODK’s spatial accuracy limits, e.g., some mangrove points are taken in rivers due to accessibility issues in inundated areas. Then drone-based validation data will be used to compute the accuracy metrics for both the initial and improved maps.

Ideally, the collection of validation data should be done within the mapping year to prevent a delay in the release of the final map. PhilSA will be addressing this in future mapping activities. PhilSA, in cooperation with the European Union (EU), is currently generating annual land and forest cover maps under the Copernicus Capacity Support Action Programme for the Philippines (CopPhil) that was launched on April 24, 2023 (Arayata, 2023).

5. Conclusion

The development of the Philippine Mangrove Map 2023 represents a significant step towards understanding and conserving these vital ecosystems. Concretely, the map will inform the DENR of the areas where mangrove forests have progressed, remained static, or declined for the implementation of context-based mangrove rehabilitation and protection efforts. This map shall also serve as a support in establishing natural capital accounts for integrating key ecosystems like mangrove forests into national and local plans and policies. Moreover, the Philippine Mangrove Map 2023 represents a major stride in DENR’s efforts to create a blue carbon action partnership and a Marine Protected Area Network across the archipelago or the Great Blue Wall initiative. This initiative aims to secure tangible benefits from biodiversity conservation actions, ensure the sustainability of coastal and marine ecosystems, and foster a blue economy, especially in the coastal communities.

Ensuring the precision of such maps is essential for optimizing their utility and effectiveness in decision-making and policy formulation for the DENR and stakeholders alike. The validation process serves as a critical step in achieving this goal. The validation process incorporated multiple data sources, including satellite and airborne imagery, and GPS points, to achieve a balance between quantitative and qualitative validation datasets. Capacity building was necessary to ensure the acquisition of a sizable amount of quality data necessary for a nationwide study. Additionally, the inclusion of local crowdsourced data was also key in enabling the discovery of previously unmapped mangrove forests.

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