remote sensing

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Technical Note

Development of a Google Earth Engine-Based Application for the Management of Shallow Coral Reefs Using Drone Imagery

Paula A. Zapata-Ramírez [1], Hernando Hernández-Hamón [1], Clare Fitzsimmons [2], Marcela Cano [3], Julián García [1], Carlos A. Zuluaga [1] and Rafael E. Vásquez [1,*]

[1] School of Engineering, Universidad Pontificia Bolivariana, Medellín 050031, Colombia; paula.zapataramirez@upb.edu.co (P.A.Z.-R.); hernando.hernandezh@upb.edu.co (H.H.-H.); julian.garciac@upb.edu.co (J.G.); carlos.zuluaga@upb.edu.co (C.A.Z.)
[2] School of Natural & Environmental Sciences, Newcastle University, Newcastle upon Tyne NE1 7RU, UK; clare.fitzsimmons@newcastle.ac.uk
[3] Parques Nacionales Naturales de Colombia, Bogotá 110221, Colombia; marcela.cano@parquesnacionales.gov.co
* Correspondence: rafael.vasquez@upb.edu.co

Abstract: The Caribbean is one of the world's most vulnerable regions to the projected impacts of climate change, and changes in coral reef ecosystems have been studied over the last two decades. Lately, new technology-based methods using satellites and unmanned vehicles, among others have emerged as tools to aid the governance of these ecosystems by providing managers with high-quality data for decision-making processes. This paper addresses the development of a Google Earth Engine (GEE)-based application for use in the management processes of shallow coral reef ecosystems, using images acquired with Remotely Piloted Aircraft Systems (RPAS) known as drones, at the Old Providence McBean Lagoon National Natural Park; a Marine Protected Area (MPA) located northwest of Old Providence Island, Colombia. Image acquisition and processing, known as drone imagery, is first described for flights performed using an RTK multispectral drone at five different monitoring stations within the MPA. Then, the use of the GEE app is described and illustrated. The user executes four simple steps starting with the selection of the orthomosaics uploaded to GEE and obtaining the reef habitat classification for four categories: coral, macroalgae, sand, and rubble, at any of the five monitoring stations. Results show that these classes can be effectively mapped using different machine-learning (ML) algorithms available inside GEE, helping the manager obtain high-quality information about the reef. This remote-sensing application represents an easy-to-use tool for managers that can be integrated into modern ecosystem monitoring protocols, supporting effective reef governance within a digitized society with more demanding stakeholders.

Keywords: remote sensing; coral reefs; google earth engine; marine ecosystem management; drone imagery; machine learning; environmental monitoring

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1. Introduction

As the human population has increased [1], natural resources have become crucial for the sustainable development of humanity. The ocean plays a key role in blue growth and blue economy strategies since marine ecosystems provide assets, goods, and services [2,3] that can be capitalized on sustainably, as guided by the United Nations 2030 Agenda [4]. However, the view of the ocean as a new frontier for economic development poses challenges and potential harm for marine ecosystems that must be addressed [5]. Human activities have been increasing the rate of anthropogenic climate change [6] and have induced accelerated ocean biodiversity loss and associated impacts on the planet's health [7]. The Caribbean is one of the world's most vulnerable regions to the projected impacts of climate change [8], and changes in coral reef ecosystems have been consistently demonstrated across the last two decades [9,10]. Within this region, insular areas such as the Archipelago of San Andrés, Providencia, and Santa Catalina will be more exposed to increasingly frequent extreme weather events as the ones seen in recent years (e.g., category 5 Hurricane Iota in 2020 and most recently category 1 Hurricane Julia in 2022). The projected future impacts of climate change are expected to further accelerate the deterioration of Caribbean coral reefs [11] and exacerbate the effects of local stressors (e.g., overfishing, and diving pressure, among others). Along with these factors, the new lethal disease "Stony coral tissue loss disease" (SCTLD), first reported in Florida in 2014, is threatening the existence of at least 30 coral species, especially brain, pillar, star, and starlet corals in the Caribbean [12,13]. This was recorded for the first time at the Archipelago of San Andrés, Providencia, and Santa Catalina in April 2022.

Climate change effects on coral reef ecosystems pose challenges for management, since those ecosystems are complex and can exhibit changes at different scales, requiring the inclusion of several stakeholders in decision-making processes to identify how society can sustainably use such marine resources [14–16]. Lately, new technology-based methods (e.g., satellites, and unmanned vehicles, among others) have emerged as tools to support the management of these ecosystems, increasing optimism about management results in large marine areas [17]. Traditional methods (mostly based on human divers) usually collect data on abundance, community composition, and species richness, using transects or quadrants that generally follow the reef zonation, which is expensive and labor-intensive. Such new technologies can make data collection quicker, cheaper, and more extensive, helping to provide high-quality data to expand our understanding of coral reefs. This will help address the multi-dimensional interactions between reefs and humans [18], facilitating management processes in a digitized society with more demanding stakeholders, and building appropriate capacities to steer reef governance by improving monitoring and assessment [19]. The new governance paradigm needs better understanding at large-time/space scales [20], to create pathways and achieve targets for recovery and climate adaptation, which require globally coordinated actions [21]. Remote-sensing techniques play a crucial role in the modernization of management processes since spatial resolution has increased significatively since the 1960s, and emerging tools such as artificial intelligence show promise for the coral reef remote-sensing specialists due to the emergence of machine-learning algorithms for mapping and feature detection from drone imagery of marine environments [22]. Recently, Cowburn et al. [23] demonstrated how ecosystem-based management (EBM) strategies can benefit from remote-sensing techniques; they addressed big-data sources, remote techniques to complement fieldwork, collaboration, and communication using virtual platforms, and toolboxes to be used by a modern coral reef scientist.

Remote-sensing techniques have been extensively used for coral reef monitoring and management during the last two decades, taking advantage of improvements in sensor technologies and processing algorithms, as described by Hedley et al. [24] and Lyons et al. [25], starting from satellite images and more recently with the use of images acquired using Remotely Piloted Aircraft Systems (RPAS), known as Unmanned Aerial Vehicles (UAVs) or drones. Casella et al. [26] proposed a novel technique to measure three-dimensional features in a shallow-water coral reef using a small drone with a consumer-grade camera, and data processing with structure from motion (SfM) algorithms at the inner lagoon of Tiahura, Moorea, French Polynesia. Lopera-Gil et al. [27] described the initiative to use consumer-grade drones as potential instruments to increase the quality of information needed in decision-making processes regarding ocean space utilization in shallow coral reefs within a Marine Protected Area (MPA) of Providence Island, Colombia. Bennett et al. [28] developed a semi-automatic workflow to process drone imagery with Google Earth Engine (GEE) and free open-source software to analyze images at Heron Reef, Australia. Sierra-Escrigas et al. [29] analyzed remotely sensed aerial images to report the status of some of Isla Arena's reef ecological units and to make a spatial analysis of the reef formation. Fallati et al. [30] employed a consumer-grade drone, coupled with SfM and object-based image (OBI) analysis to monitor changes in composition and the associated deterioration in shallow-water reef environments of Maldives. Kennedy et al. [31] developed a classification system, named

Reef Cover, to produce and deliver globally applicable coral reef mapping products using data from remote sensors. Nababan et al. [32] used drone imagery and OBI analyses to map shallow-water benthic habitats in the region of Wangiwangi, Wakatobi District, Indonesia. Borges et al. [33] compared four different machine-learning methods in the classification of an intertidal reef using a commercial drone equipped with RGB and multispectral sensors. Mat-Zaki et al. [34] presented and optimized workflow using Agisoft PhotoScan Pro for coral reef habitat mapping using drone imagery. Nieuwenhuis et al. [35] incorporated geomorphometric variables derived from Digital Elevation Models (DEM) and spectral information to increase the accuracy in habitat classification processes, using drone imagery from an RTK-ready (Real-Time Kinematic) aerial vehicle. Alevizos and Alexakis [36] developed a novel approach to describe shallow bathymetry changes using drone multispectral imagery.

Although much progress has been made in the use of remote-sensing data for coral reef mapping, taking advantage of such resources and quality of information still requires high levels of technical expertise and efforts and high-performance computing facilities [37], limiting the reach of the benefits to researchers and managers. Google Earth Engine (GEE) [37,38], a cloud-based computing platform for geospatial analysis, has been developed as a resource to support a variety of high-impact societal issues using data from remote sensors within several disciplines [39–43]. Several recent works focus on marine ecosystems. Bennett et al. [28] used GEE to develop a semi-automatic workflow to process drone imagery from Heron Reef in Australia. Yancho et al. [44] presented the Google Earth Engine Mangrove Mapping Methodology (GEEMMM), a platform designed to be intuitive, accessible, and replicable, for a wide audience of non-specialist managers and decision-makers. Williamson et al. [45] used GEE to develop the Coral Reef Stress Exposure Index (CRSEI), for remotely monitoring coral reef exposure to environmental stressors. de Lima et al. [46] developed and validated two models for sea-level rise prediction using GEE. Li et al. [47] developed an automated approach to perform bathymetry mapping using the Sentinel-2 surface reflectance dataset in GEE. Callejas et al. [48] presented a direct workflow based on GEE to monitor water temperature to study its effects on the coral reef’s health at several MPAs in the Caribbean.

In the case of Colombia, shallow-water coral reefs have been assessed and monitored since 1998 [49], however, ecosystem management and scientific hypothesis are often based on large and disparate datasets, which are mostly geographically limited or with low resolution. As a result, coral extent and distribution at large scale have not been sufficiently inventoried in most reefs around the country. There is, therefore, a high degree of urgency to take advantage of modern technology-based tools to map reefs and to improve the monitoring systems at appropriate scales, not only for the conservation and understanding of the natural spatial extent, temporal variability, and resilience but also to enhance communication and participation with reef dependent communities. The resulting improvement in the scientific background will underpin policy decisions concerning sustainable reef management within modern governance schemes. The contribution of this work is based on the development of an accessible Google Earth Engine-based application for shallow coral reef ecosystems using drone imagery, which can be easily used by managers and decision-makers. The work was conducted and validated for shallow coral reefs at the Old Providence McBean Lagoon National Natural Park, a Marine Protected Area (MPA) located northwest of Old Providence Island, Colombia, which is the only protected area in the System of National Natural Parks located in the Colombian insular Caribbean region [27].

This paper is organized as follows. Section 2, contains the description of the study site and the development of the GEE application. Section 3 shows the coral reef classification based on the results obtained with different machine-learning algorithms. Section 4 contains the discussion with the benefits and drawbacks of the application to be used by managers, and finally, some conclusions are presented in Section 5.

2. Materials and Methods

2.1. Study Site

The Old Providence McBean Lagoon National Natural Park is one of the most pristine reef ecosystems in the Caribbean and the only protected area in the System of National Natural Parks within the Colombian insular Caribbean [27]. The island extends 7.2 km across from N-S among oceanic islands, atolls, and banks of the Archipelago of San Andrés, Providencia, and Santa Catalina, Figure 1. The barrier reef is a calcareous platform that stretches over 32 km, the second-largest barrier of the S-E Caribbean [50,51]. A submerged elongated ridge in a shelf-margin position is situated at more than 25 m depth and perhaps a drowned shelf-edge barrier reef. The geomorphology of the reef complex was described by Geister [52] and Geister and Díaz [53]: the lagoon platform is occupied by extensive semi-closed and gently sloped terraces up to 14 m deep with 2–6 m wide areas that are occupied by an extensive shallow lagoonal terrace. In front of the shallow peripheral reef, there is a fore-reef terrace (Front Reef) up to several meters wide, which slopes gently to the Rock Terrace. A major part of the barrier reef is formed by a wide belt consisting of numerous patch reefs, most of the pinnacle type, which rises from the seafloor at −6 to −8 m reaching the low-tide level. Sporadic storms with westerly or north-westerly attaining speeds over 20 m/s do occur, mostly in the second half of the year [53]. The mean annual air temperature is 27 °C, with a 1 °C range between monthly values. Rainfall is irregular and varies from one year to another. According to Geister and Díaz [53], the surface persistent northward flow of the Caribbean Current through large gaps and narrow open seaways across the top of the Nicaraguan Rise controls sedimentation processes in the area.

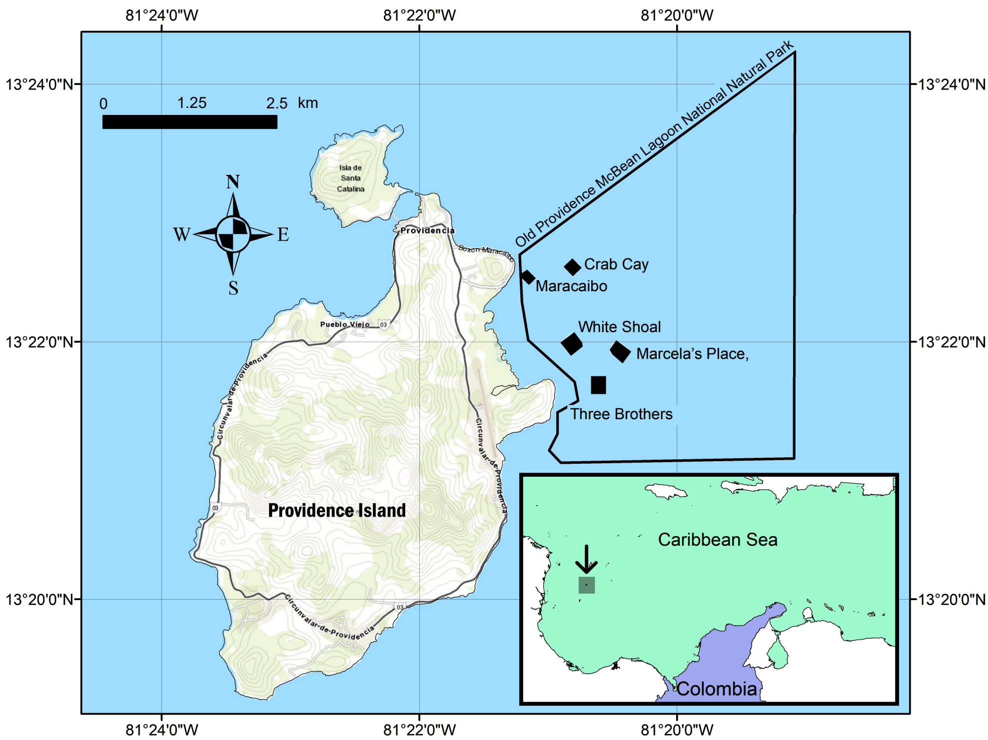

Figure 1. Study sites within the Old Providence McBean Lagoon National Natural Park

The park monitors the coral formations at permanent stations, using the condition-trend indicator protocol of coral areas (ICTAC) proposed by Rodríguez-Ramírez et al. [54], which employs permanent transects to evaluate the variables: alive hard coral cover, leafy macroalgae cover, and algal carpet, biomass of herbivorous fish, and biomass of carnivorous fish. The reefs in the park offer a range of critical co-benefits to the coastal communities of these islands, including protection against storm surges, prevention of coastal erosion, habitat for commercially important species, and recreational sites.

2.2. Data Acquisition

Multispectral aerial imagery was collected over five monitoring reef stations (Marcela's Place, Three Brothers, White Shoal, Crab Cay, and Maracaibo) at Old Providence McBean Lagoon National Natural Park using a DJI Phantom 4 RTK multispectral drone [55,56]. The RTK-GPS measurements provide high spatial accuracy (<10 cm), which is essential when processing drone-based imagery with a pixel resolution of a few centimeters. Based on the methodology proposed by Lopera-Gil et al. [27], each flight plan was designed using Pix4DCapture with existing extent data provided by the Caribbean Center for Oceanographic and Hydrographic Research-CIOH, which is part of the Colombian Maritime Directorate (DIMAR); WorldView-3 satellite images from previous surveys undertaken at the same reefs were used also for this matter. Each mission was conducted employing a detailed flight plan concerning the exact flying orientation, route, number of lines, number of images, end laps, and side laps, using the DJI GS RTK app. Once the area was delimited, the AUV's flights were programmed in a polygon, grid, or double-grid mission pattern as in [27]; we planned double-grid missions to obtain a 200% overlap. Flights were performed along parallel tracks at 50–60 m altitude above sea level, with the camera oriented at the nadir. The flight time was around 18 min (saving 15% of battery for landing), and we were able to cover approximately an area of 320 m × 320 m in grid mode, and 210 m × 210 m in double-grid mode. All flights took place early in the morning (6:00 a.m.–7:00 a.m.) when the sun elevation was lower than 30 degrees from the horizon and the sea state was calm. Furthermore, flights were conducted on days with no or little wind (less than 5 m/s) since waves influence the capacity to map benthic communities. Drone flights and ground truth data were collected between the 10th and the 21st of June 2022. Training and validation were performed later between July and August of the same year, which represents a short period of time that provided a stable behavior of the reef with no extreme events recorded.

2.3. Data Processing

Images collected from the drone flights were imported to Agisoft Metashape 1.7 [57], a commercial structure from motion (SfM) software that offers a user-friendly workflow providing good quality outputs. From the overlapping photographs we performed four main steps: (i) alignment of the photos using a high-accuracy setting, (ii) the creation of a sparse point cloud; (iii) generation of a dense point cloud with an aggressive filter setting; and (iv) creation of high-resolution orthomosaics [30] of the five monitoring stations that were saved in `.tif` format.

2.4. Ground Truth Verification points

Sufficient ground control points for image rectification/registration were needed to test the accuracy of the information collected with the drone. Ground truth samples of benthic habitat classes were then taken at each of the monitoring stations in the study area. These were collected at traditional reef monitoring stations along 10 m belt transects running from the back reef to the shoreline. Four categories were considered: coral, macroalgae, sand, and rubble. We also collected underwater photos and videos along the transects and recorded the coordinates on the extremes of each transect to allow the co-location within the RTK drone orthomosaic. The number of pixels in each ground truth point at each monitoring station is provided in Table 1.

Table 1. Number of pixels that represent ground truth points at each monitoring station

Class	White Shoal (px)	Maracaibo (px)	Three Brothers (px)	Marcela's Place (px)	Crab Cay (px)
Coral	695	48	160	730	124
Sand	958	115	2122	3226	1312
Macroalgae	287	22	6	408	28
Rubble	79	55	35	7	180

2.5. Reef Habitat Classification through GEE

An app was developed within GEE using a JavaScript API to (i) automatically classify the coverage associated with the four established classes in a supervised way, (ii) obtain the thematic accuracy metrics, and (iii) calculate the areas corresponding to the four selected classes. The app was developed to make the mapping and monitoring of reef ecosystems easy for managers in Colombia, and highlight the potential for their development anywhere in the world, without requiring a dedicated in-house geospatial expert. Users do need basic computer skills and an understanding of the key steps involved in mapping reefs, but they are not expected to have advanced skills in remote sensing, geospatial analysis, and/or coding. Development phases included the selection of multispectral and RGB scenes, the selection of clipping areas within the scenes, and the location and selection of polygons established as training zones to obtain the images corresponding to the result.

The `.tif` orthomosaics from each of the five sites were uploaded as an image collection asset into GEE, see Figure 2. The four categories (coral, macroalgae, sand, and rubble) were chosen, because these substrates were most easily recognizable in the drone imagery. It should be noted that the rubble class includes epilithic algae matrix and dead hard coral. In addition to the ground truth verification points, we also used the drone images to complement the visual identification of the four classes of substrate types, which according to Bennett et al. [28] are acceptable to use as reference data for training the classifier and accuracy assessment. As a result, areas that best represent each class were visually identified in the drone orthomosaics in GEE.

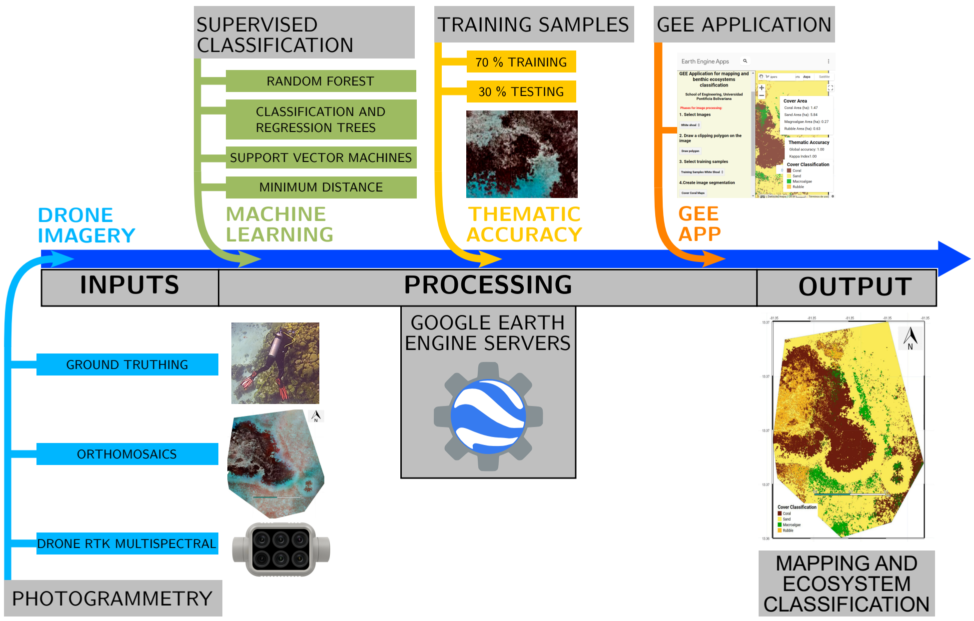

Figure 2. GEE application for mapping and benthic ecosystems classification workflow

The steps to obtain the classified maps from the GEE App control panel are described as follows, Figure 3:

1. The first section of the panel is to **Select images**. The user chooses one of the five monitoring reef stations, and the relevant previously imported orthomosaic is called to the platform with the asset tool.
2. Next, a **Draw polygon** button is presented for the selection or definition of the evaluation areas, corresponding to the user's desired coverage(s). The user can select the areas by creating a Feature Collection and using the `.clip()` function to convert an image into a Geometry.
3. The **training sample** is created using photos interpreted directly from the API by drawing polygon geometries for each class. These polygons are joined using the `.merge()` function and then used to train the algorithms. We tested the performance

of several algorithms (Random Forest—RF; Minimum Distance—MD; Classification and Regression Trees—CART; and Support Vector Machines—SVM) for habitat reef classification. All the algorithms can be run in the app, but for this work, we chose to show the results of the RF algorithm as an example. RF has been widely used to map reefs in different locations with high accuracy [28,58].

4. Finally, in the section on creating image segmentation, the **Cover Coral Maps** button runs the whole process of classification and obtaining thematic accuracy metrics including the Kappa index and the global precision from the confusion matrix obtained with the `.ConfusionMatrix()` function. The area of each class is calculated by counting the number of pixels and converting them to hectares.

The app provides the option to compare four different classification algorithms (random forest, regression trees, support vector machine, and minimum distance). These supervised classification methods have been widely used for the classification of reef habitats [25,28,59] and are increasingly popular techniques for analyzing ecological datasets. For instance, random forest is a decision tree method, where multiple decision trees are created, and the final prediction is the mode of the prediction from all trees. The algorithm has been also used in conjunction with GEE to classify reef geomorphology in Australian reefs [25]. De'Ath and Fabricius [59] used regression trees to analyze survey data from the Australian Central Great Barrier Reef, comprising abundances of soft corals and physical and spatial environmental information. The authors highlight the capabilities of the algorithm such as the flexibility to handle a broad range of response types, including numeric and categorical ratings, the invariance to monotonic transformations of the explanatory variables, and the ease and robustness of construction, among other capabilities. On their part, support vector machine algorithms are binary classifiers based on the construction of optimal hyperplanes in a high-dimensional space between a nearby training sample and the separation hyperplane [60]. The algorithm estimates the optimum separating hyperplane that maximizes the margin between two classes. It has been applied to map cold water corals for its advantages when regularizing the parameters, allowing the user to control over-fitting, the kernel trick, and the convex optimization problem [61]. It also can be computationally faster than other classifiers [62]. Finally, the minimum distance is a frequently used classifier that can be used with minimal modification even though it is insensitive to the degree of variance in the spectral response of the data [63]. The algorithms were used in Fiji coral reefs [63] to isolate the controls that the environmental features in each scene and the sampling design used for the collection of calibration and validation data, had on the accuracy levels of each map of the resulting study. A key advantage of all the algorithms used in the current study is the fact that they can achieve moderate to high overall accuracies with only small amounts of training data [60].

2.6. Accuracy Assessment

To assess the accuracy of the resulting classifications for the five monitoring reef stations, we used 30% of the validation points to extract pixel classification information at each station as done by [28]. The confusion matrix was used to compare how the classifier performed using the validation points with the reference classification, and the overall accuracy was obtained by dividing the total number of correctly classified pixels by the total number of reference pixels sampled at each station. The Kappa index was calculated by the correspondence between the classified image and the reality, according to the accuracy of the classification and eliminating the random component. Both metrics are commonly used from the GEE platform in supervised classification studies using machine learning [64]. Accuracy here represents the possibility that the class, which has been classified on the map, represents that class in the field [28,65].

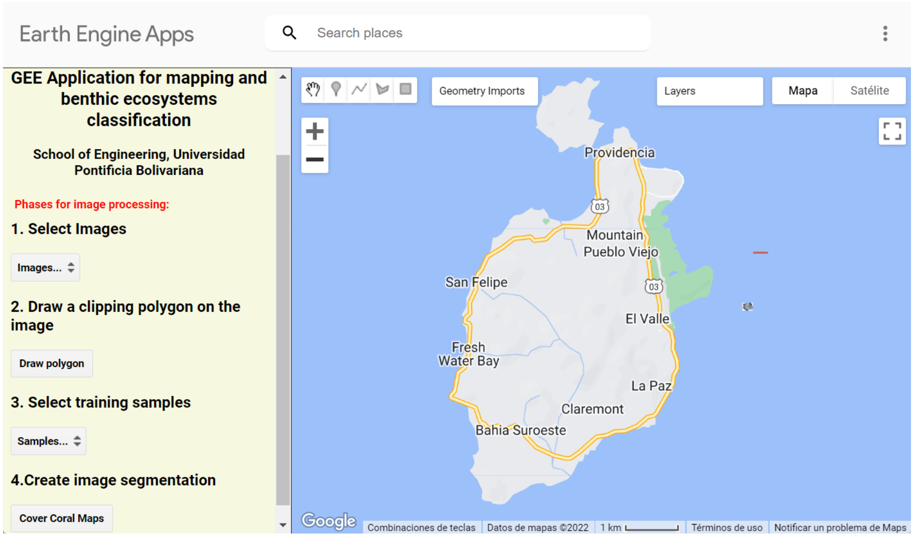

Figure 3. GEE App initial panel and steps to be executed by the user. It can be accessed in [66]. Visit https://nandoceanos.users.earthengine.app/view/coralclass, (accessed on 15 November 2022).

3. Results

3.1. Drone Imagery

As has been described in Section 2, orthomosaics were obtained for all five stations using Agisoft for the five monitoring reef stations (Marcela's Place, Three Brothers, White Shoal, Crab Cay, and Maracaibo) at Old Providence McBean Lagoon National Natural Park that were collected using a DJI Phantom 4 RTK multispectral, Figure 4.

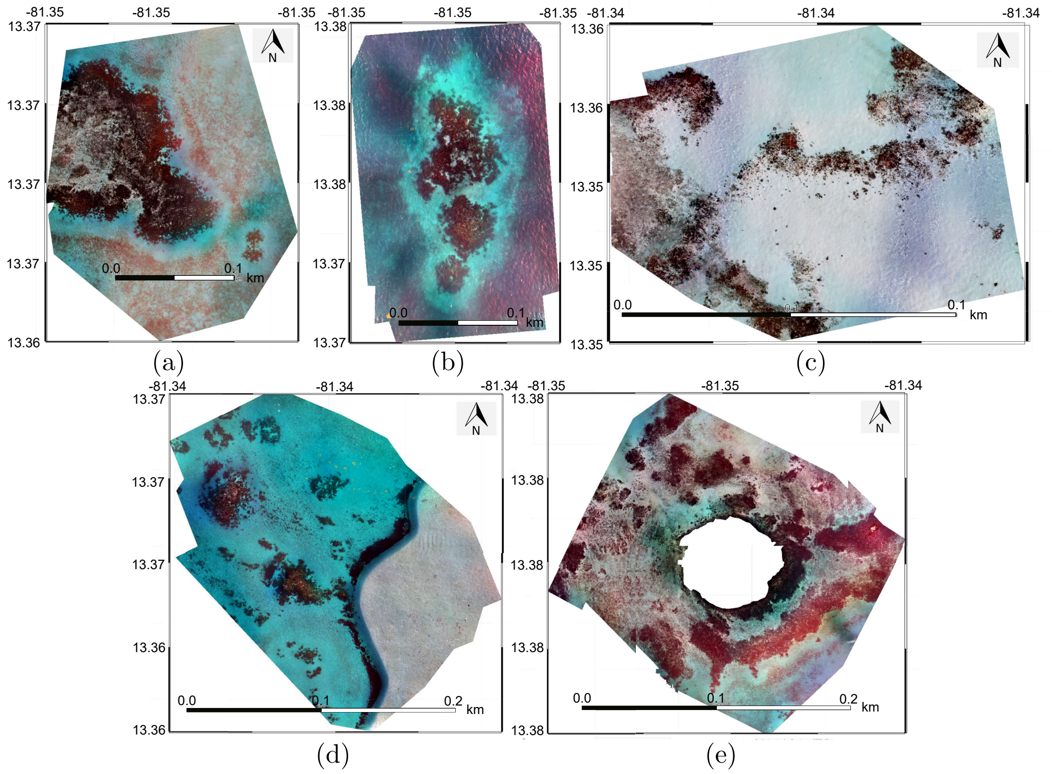

Figure 4. Orthomosaics for the five stations. (**a**) White Shoal, 702 photos, 59,115 m^2 (5.91 ha). (**b**) Maracaibo, 609 photos, 34,313 m^2 (3.43 ha). (**c**) Three Brothers, 545 photos, 22,447 m^2 (2.24 ha). (**d**) Marcela's Place, 517 photos, 71,576 m^2 (7.16 ha). (**e**) Crab Cay, 930 photos, 71,021 m^2 (7.10 ha).

3.2. GEE Application Use

When the user opens the browser and goes to the GEE application for mapping and benthic ecosystems classification [66] the interface shown can be seen in Figure 3. Then, as described in Section 2, the first step corresponds to the image selection, as seen in Figure 5. The second step draws the desired polygon, see Figure 6. The third step asks the user for the training set that will be used for the classification, Figure 7. Finally, when the user presses the last button, results are produced, as shown in Figure 8, which contains: the coverage areas for coral, sand, macroalgae, and rubble; the classification accuracy; and the classification result (class).

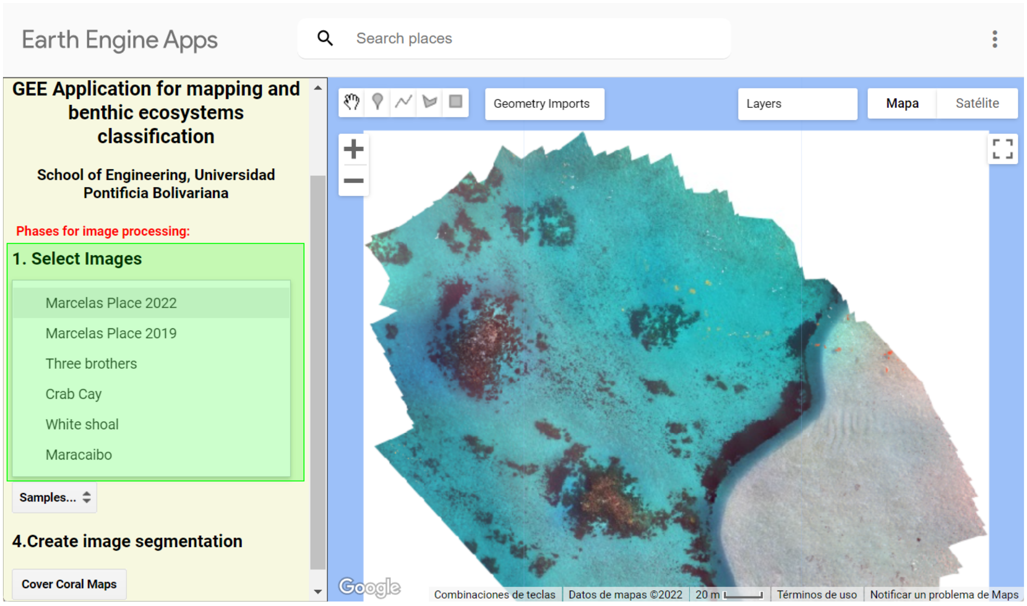

Figure 5. GEE App Step 1. Selection of the orthomosaic in the desired station.

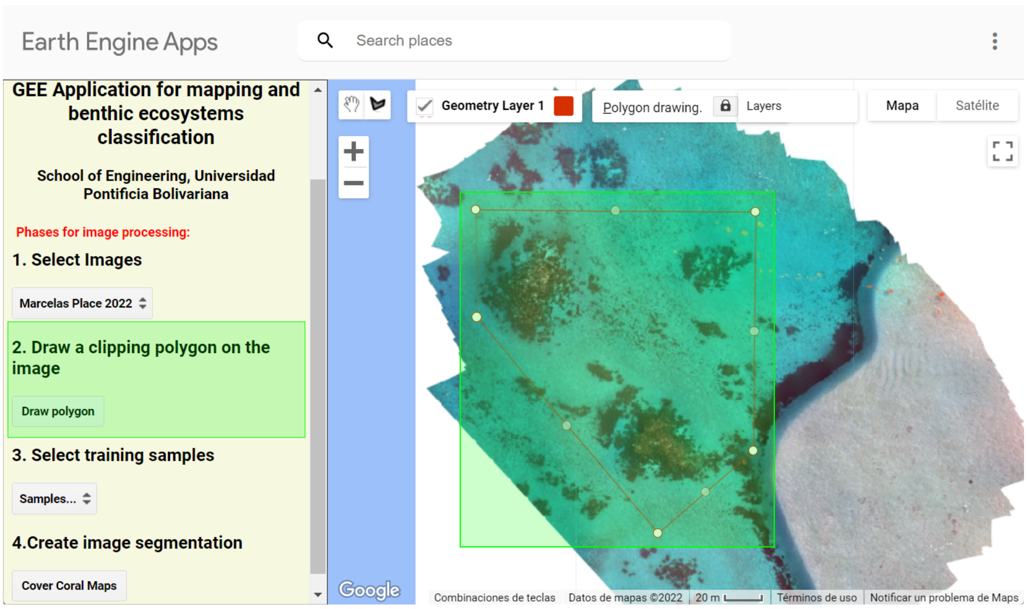

Figure 6. GEE App Step 2. Polygon drawing over the orthomosaic.

The developed GEE app successfully generated the classification maps of the five reef monitoring stations at the Old Providence McBean Lagoon National Natural Park, using the orthomosaics shown in Figure 4. Figure 9 shows the results obtained for the five selected stations, using Random Forest as the classifier in the GEE app.

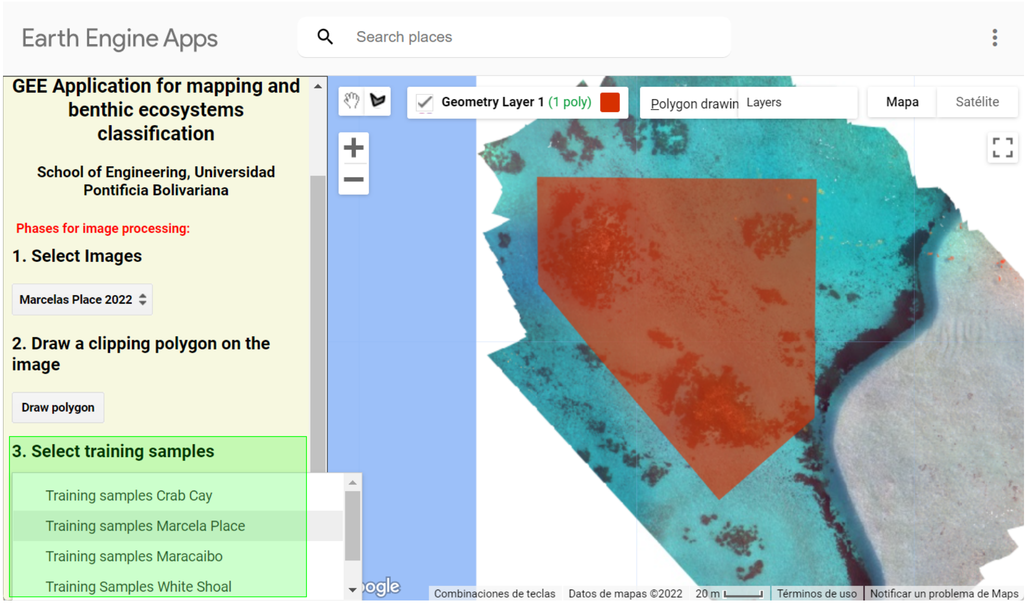

Figure 7. GEE App Step 3. Training set selection for the desired station.

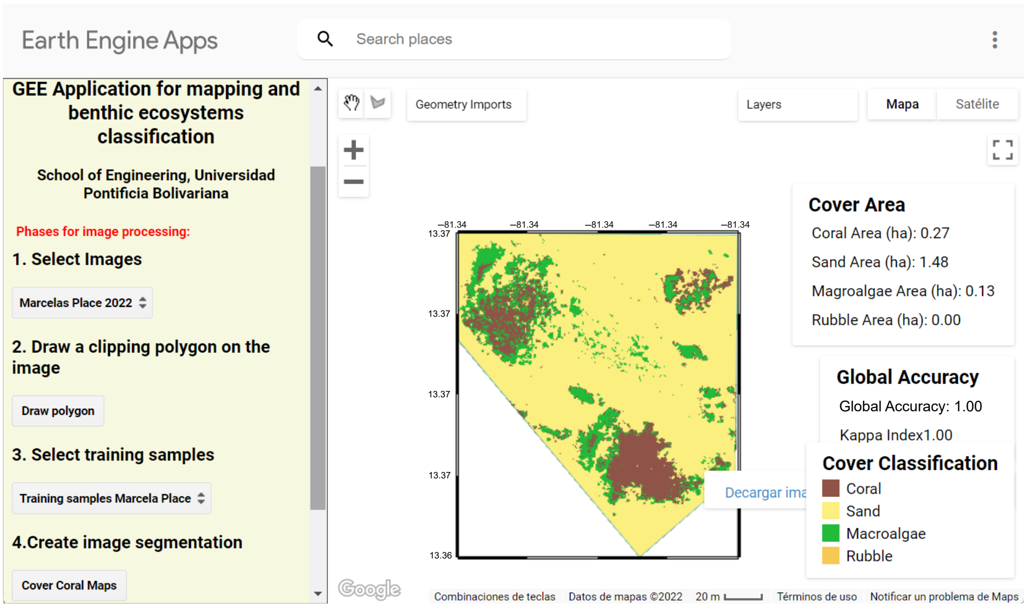

Figure 8. GEE App Step 4. Classification results for the desired station.

To assess accuracy, we generated 20 maps in total, classifying each of the five orthomosaics using the four algorithms described above. A consistently high overall accuracy was achieved (above 0.8), except for the Minimum Distance algorithm, which achieved an accuracy of less than 0.6 at Three Brothers. Table 2 shows the results achieving the minimum requirement for mapping, as stated by Mumby [67] who established that where habitat maps are used to provide a general inventory of resources as background to a management plan, a thematic minimum accuracy of 60% is probably as useful as 80%. We classified the following areas for the Old Providence McBean Lagoon National Natural Park within the monitoring stations: coral 4.02 ha, sand 11.36 ha, macroalgae 1.45 ha, and rubble 6.75 ha, see Table 3 and Figure 9.

Table 2 shows the performance results of the accuracy assessment for the different classification algorithms evaluated for the five reef monitoring stations. The CART algorithm achieved the highest accuracy (1), followed by RF with 0.99. The remaining classifiers ranged from 0.93 for the SVM and finally, MD ranges between 0.94 and 0.52, respectively.

As previously mentioned, Figure 9 shows the results obtained for the five selected stations using the Random Forest classifier.

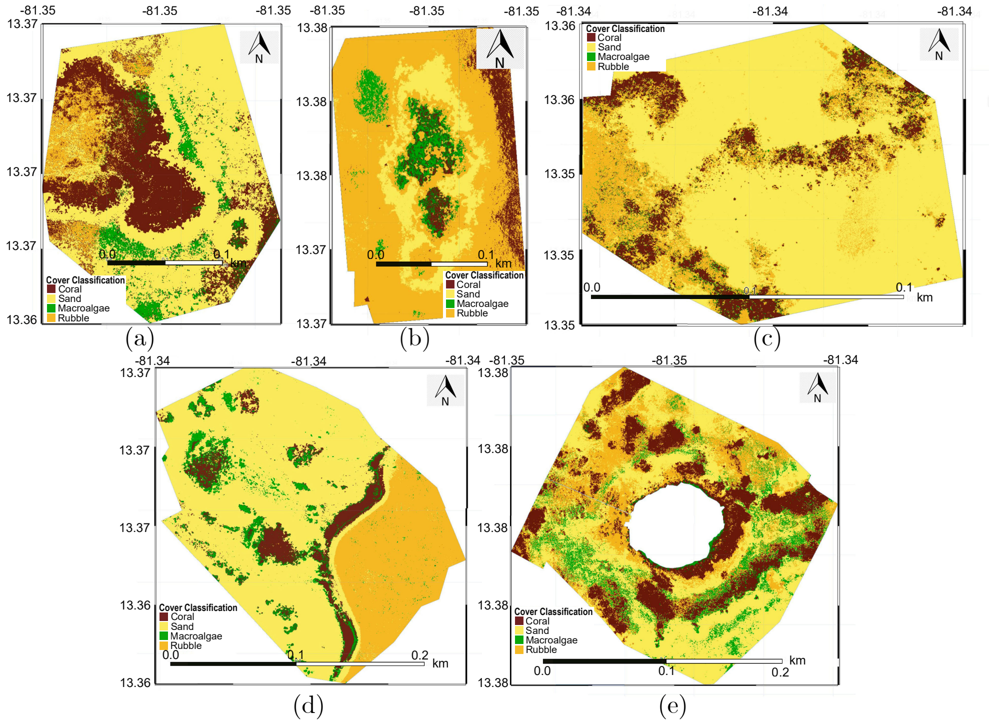

Figure 9. Classification results for the five stations using Random Forest. (**a**) White Shoal. (**b**) Maracaibo. (**c**) Three Brothers. (**d**) Marcela's Place. (**e**) Crab Cay.

Table 2. Accuracy assessment for the different algorithms provided in the GEE app for the five monitoring reef stations

Site	Index	MD	RF	CART	SVM
White Shoal	Kappa	0.8138	0.9961	1.0000	0.9394
	Precision	0.8752	0.9975	1.0000	0.9394
Maracaibo	Kappa	0.9197	1.0000	1.0000	1.0000
	Precision	0.9458	1.0000	1.0000	1.0000
Three Brothers	Kappa	0.5275	0.9993	1.0000	0.9617
	Precision	0.7216	0.9991	1.0000	0.9256
Marcela's Place	Kappa	0.5275	0.9984	1.0000	0.9617
	Precision	0.7216	0.9984	1.0000	0.9839
Crab Cay	Kappa	0.7351	0.9982	1.0000	0.9664
	Precision	0.8996	0.9994	1.0000	0.9664

Table 3. Total class areas coverage estimated by the RF classifier at the five reef monitoring stations

Class	White Shoal (ha)	Maracaibo (ha)	Three Brothers (ha)	Marcela's Place (ha)	Crab Cay (ha)
Coral	1.64	0.28	0.22	0.62	1.26
Sand	2.85	0.45	1.39	4.27	2.40
Macroalgae	0.20	0.17	0.01	0.38	0.69
Rubble	0.59	2.02	0.53	1.68	1.93

From these results, the selected example with RF algorithm (Table 2 and Figure 9) shows that each of the four focal reef classes can be mapped well. In particular, the Sand class, where all pixels were well classified, followed by Coral (99.99%) and finally by Macroalgae (99.99%) and Rubble (99.98%), respectively. Table 4 shows the comparison of the four class assignments by the RF classifier (rows) with class assignments of reference points (columns) at the five monitoring reef stations, also known as confusion matrices. Values shown are numbers of pixels, with bold numbers representing correctly classified pixels.

Table 4. Confusion matrices for the five reef monitoring stations. Classes are identified as Coral (C), Sand (S), Macroalgae (M), and Rubble (R).

	White Shoal				Maracaibo				Three Brothers				Marcela's Place				Crab Cay			
	C	**S**	**M**	**R**	**C**	**S**	**M**	**R**	**C**	**S**	**M**	**R**	**C**	**S**	**M**	**R**	**C**	**S**	**M**	**R**
C	694	1	0	0	124	0	0	0	160	0	0	0	729	0	1	0	124	0	0	0
S	0	958	0	0	0	1312	0	0	0	2102	0	0	0	3226	0	0	0	1312	0	0
M	1	0	286	0	0	0	28	0	0	0	6	0	2	0	406	0	0	0	28	0
R	2	1	0	76	0	0	1	179	0	2	0	33	0	0	0	7	0	0	1	179

4. Discussion

This work has demonstrated GEE to be an easy-to-use tool that can efficiently and accurately analyze data gathered using commercial drone technology and standard algorithms. This will allow managers to directly integrate the approach into modern coral reef monitoring protocols. Applications are many, but improvements are always possible. Both are discussed below, in the context of the case study presented.

Recent reports established that Old Providence McBean Lagoon National Natural Park has recently experienced loss in reef cover due to the passage of the Iota Hurricane as reported by Hernández, H. et al. [68]. However, comparisons from before and after such events are difficult due to the lack of high-resolution information that could help managers track recoveries or declines. The GEE app has proven to be a robust platform to support this, and its utility is only likely to grow in line with predicted increases in extreme events such as hurricanes and tropical storms in the upcoming years for the insular areas in the Caribbean, such as in Old Providence Island [69]. The resulting GEE app represents a good contribution in a time where real-time thematic mapping for reef monitoring is increasing [25]. In this case, it has allowed a baseline to be established for information about reef status that can be integrated into an active monitoring protocol for Old Providence Island.

Although the app performs well, there are always possibilities for improvements. Integration of orthomosaic processing into the app would allow managers to upload simple drone images into the app and run the complete procedure on the same platform. In addition, as indicated by Yancho et al. [44] the usage of GEE-based tools requires a relatively stable and reasonably strong internet connection, especially to view images and products. Therefore, there are limitations for areas such as Old Providence Island, where internet service is not very stable.

Additionally, we used the accuracy tool, provided in the GEE library, and, in general terms, it performs very well for four simple classes when the error matrix is analyzed. Nonetheless, when some of the output maps were reviewed, some of the class distributions seemed to be less accurate with some classification algorithms than others. This could be related to the high complexity of the reef environment in the park, the number of checkpoints of each class within the five monitoring stations, and the spectral similarity among the classes. In particular, the rubble class includes an epilithic algae matrix that, in some cases, can be confused with the macroalgae class. Similar difficulties have also been found in similar works. Similar difficulties have also been found in similar works [32].

Finally, when acquiring images with adequate illumination, guidance could minimize the difficulty of image segmentation by allowing the model to identify relevant features and make accurate predictions. On the other hand, from GEE it is possible to make a direct choice and adjustment of the hyperparameters, which can also determine an efficient performance of the model. Other uncertainties could be related to the classification accuracy due to similar spectral responses between some benthic components of the reef such as algae vs. corals as addressed by Zapata-Ramírez et al. [70].

5. Conclusions

This paper successfully demonstrated the development of a Google Earth Engine (GEE)-based application for habitat classification within management processes of shallow coral reef ecosystems. The GEE-based app uses images acquired with Remotely Piloted Aircraft Systems (RPAS) known as drones at the Old Providence McBean Lagoon National Natural Park; a Marine Protected Area (MPA) located northwest of Old Providence Island, Colombia. The image acquisition/processing process was described for flights performed using an RTK multispectral drone at five different monitoring stations within the MPA. The GEE app yields the reef habitat classification in four categories: coral, macroalgae, sand, and rubble, at each of the five monitoring stations. The app correctly classified these categories for the reef ecosystem, demonstrating that the tool can help the manager obtain high-quality information about the reef and improve our understanding of such an important ecosystem for the Caribbean region.

We have shown the power of GEE as a geospatial analysis platform to process and analyze geospatial data useful for reef monitoring. However, it requires computer and programming skills that managers normally do not have. Our app provides an easy way to automatically classify and straightforwardly analyze reef coverage, without the need to run complex algorithms since the app already contains all the information needed to run the analysis. In addition, since it is cloud-based, it is possible to import higher-resolution images, such as the ones provided here that are not available in the GEE big-data catalog. Thus, making them available as input variables in the application scripts [37]. Parallel processing is agile and depends only on the internet speed saving processing time and increasing the computational power needed to obtain the final thematic cartography [71].

This remote-sensing application represents an easy-to-use tool for managers that can be integrated into modern ecosystem monitoring protocols, helping to steer reef governance in the right direction within a digitized society with more demanding stakeholders. However, future work could address limitations such as the fact that drone imagery must be previously done with image-processing software and that internet connections on small islands such as Old Providence Island can be unstable and limit real-time utility. Nonetheless, this development can make the use of remote-sensing technology significantly easier for non-specialist users, supporting access for managers and decision-makers by increasing their understanding of phenomena and processes with data that benefit from higher spatial and temporal resolutions. Furthermore, GEE can be used for the fusion of images with different spatial and temporal resolutions [72], to extend the capabilities of the app we developed that uses centimeter-resolution drone-acquired imagery to study local scales in combination with meter-resolution satellite imagery, which would allow incorporating global and regional scales into decision-making processes of the marine protected area.

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