# Toward regional hazard risk assessment: a method to geospatially inventory critical coastal infrastructure applied to the Caribbean

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## Abstract

Hurricanes and sea level rise pose significant threats to infrastructure and critical services (e.g., air and sea travel, water treatment), and can hinder sustainable development of major economic sectors (e.g., tourism, agriculture, and international commerce). Planning for a disaster-resilient future requires high-resolution, standardized data. However, few standardized approaches exist for identifying, inventorying, and quantifying infrastructure lands at risk from natural hazards. This research presents a cost effective, standardized and replicable method to geospatially inventory critical coastal infrastructure land use and components, for use in risk assessments or other regional analyses. While traditional approaches to geospatial inventorying rely on remote sensing or techniques, such as object-based image analysis (OBIA) to estimate land use, the current approach utilizes widely available satellite imagery and a "standard operating procedure" that guides individual mappers through the process, ensuring replicability and confidence. As a pilot study to develop an approach that can be replicated for other regions, this manuscript focuses on the Caribbean. Small islands rely heavily on a small number of critical coastal infrastructure (airports, seaports, power plants, water and wastewater treatment facilities) and climate related hazards threaten sustainable development and economic growth. The Caribbean is a large and diverse area, and gaps exist between countries in the resources required for planning but much of the region lacks a comprehensive inventory of the land, infrastructure, and assets at risk. Identifying and prioritizing infrastructure at risk is the first step towards preserving the region's economy and planning for a disaster resilient future. This manuscript uses high resolution satellite imagery to identify and geo-spatially classify critical infrastructure land area and assets, such as structures, equipment, and impervious surfaces. We identified 386 critical coastal infrastructure facilities across 28 Caribbean nations/territories, with over 19,000 ha of coastal land dedicated to critical infrastructure. The approach establishes a new standard for the creation of geospatial data to assess land use change, risk, and other research questions suitable for the regional scale, but with sufficient resolution such that individual facilities can utilize the data for local-scale analysis.

**Keywords:** Critical infrastructure, Geospatial data development, Risk assessment, Caribbean, Regional assessments, Heads-up digitizing, Land use and land cover

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## Highlights

- Created a cost effective, standardized, and replicable method to geospatially inventory critical coastal infrastructure land use
- The approach improves on other geospatial data collection approaches where land use data is required for conducting regional assessments of storm risk, climate risk, or economic projections
- Pilot study of Caribbean shows 19,000 ha of coastal land dedicated to critical infrastructure
- Developed an inventory of Caribbean critical infrastructure assets (buildings, paved surfaces, industrial structures, etc.) at a regional scale
- The results of this study can be used to track land use change over time and provide guidance for urban planning in coastal regions with limited land area for development

## Introduction

Planning for a disaster-resilient future requires high-resolution, standardized data on a regional scale in order to properly assess risk. However, few standardized approaches exist for identifying, inventorying, and quantifying regional land and infrastructure at risk from natural hazards. Hurricanes and sea level rise pose a significant threat to infrastructure and critical services that were built in harm's way, such as water telecommunications, energy, and international commerce. These threats hinder sustainable development of major economic sectors, such as tourism, agriculture, and international commerce. They also pose significant threats to fragile coastal ecosystems, as infrastructure-related disasters can result in the release of hazardous materials [1–3]. While individual islands, nations, or local governments may already possess such datasets for their specific location, access to and consistency between such datasets remains a significant challenge for researchers wishing to conduct regional studies [4, 5]. Due to the varying nature of coastal infrastructure, this last piece presents unique challenges. This research develops a standardized and replicable method to geospatially inventory critical coastal infrastructure land use and components. The resulting data can be used for natural hazard vulnerability assessment, tracking land use change over time, as well as other applications, on a regional scale.

As a pilot to develop an approach that can be replicated for other regions, this manuscript focuses on the 28 island nations and territories in the Caribbean. Island economies such as those in the Caribbean rely on their critical coastal infrastructure, such as airports, seaports, power plants, water and wastewater treatment facilities. Due to its geographic location and topography, the Caribbean is one of the most natural-disaster prone

regions worldwide [6] and climate related hazards threaten sustainable development and economic growth [7, 8]. While climate related hazards pose a significant threat to critical infrastructure, like many areas around the world, the region lacks a comprehensive inventory of the land, infrastructure, and assets at risk. Identifying and prioritizing infrastructure at risk is a first step towards preserving the region's economy and planning for a disaster resilient future [9, 10].

Using the most up-to-date high-resolution satellite imagery, this manuscript employs heads-up digitizing, a method of manually tracing geographic features using aerial imagery, to identify and geo-spatially classify critical infrastructure land area and assets, such as buildings, industrial structures, and impervious surfaces. This approach establishes a standard for the creation of geospatial data that can be used to assess land use change, hazard risk, and other research questions suitable for the regional scale, but with sufficient resolution such that individual facilities can utilize the data for local-scale analysis.

This paper begins with a discussion of various approaches to the creation and classification of geospatial data that could be used for analyzing environmental risks and answering other questions about intra-regional challenges. It then provides our justification for focusing on the Caribbean as a pilot study to develop a new methodology for creating regional land use inventories. Next, the methodology and "standard operating procedure" is laid out in detail. We tested our approach in a validation exercise to explore how well our methodology worked when followed by different mappers. The results section summarizes the total coastal land area in the Caribbean that is devoted to critical coastal infrastructure. Finally, the discussion section addresses the implications, shortcomings, and next steps for this work.

## Background – geospatial data and its implications for storm assessments and land use planning

Hurricanes and sea level rise pose a significant threat to infrastructure and critical services and can hinder sustainable development of major economic sectors [11]. Planning for a disaster-resilient future requires high-resolution, standardized data on a regional scale [12]. For example, ocean scientists rely on high-resolution bathymetry and elevation data sets to develop models of sea level rise, storm surge, waves, and riverine flooding [13]. The impacts of these hazards on society and the environment, however, depend on what lies in harm's way. While advances in regional storm modeling have resulted in more reliable projections of climate hazards, few standardized approaches exist for identifying, inventorying, and quantifying regional land and infrastructure at risk from episodic coastal flooding and/or chronic sea level rise. While there are numerous methods to assess

vulnerability and risk at the micro and meso-scale, critical infrastructure are not typically included [14] and when they are, risk is typically assessed only to one XY coordinate (a "point") as opposed to the land occupied by the entire facility (See e.g., [12, 15, 16]). Developing countries are expected to experience the greatest impacts of climate change to their economies and livelihoods [17, 18] and limited access to resources constrains their ability to adapt in the face of more frequent storm events and a changing climate [17]. While a vast amount of geospatial data has been created over the last several decades at almost every scale, there remains a dearth of high-resolution land use classification data at the regional scale that can be used for environmental risk and vulnerability assessments of coastal infrastructure. The rest of this section describes some of the techniques to create and classify data.

## Land use and land cover data

Vegetated, non-vegetated, and man-made features are ubiquitous throughout the Earth's landscape. High spatial and temporal resolution satellite imagery have improved researchers' ability to classify land use and land cover (LULC). Most notably, the Landsat satellite program (www.nasa.gov/mission_pages/landsat/) sparked a surge in the development of remote sensing techniques to comprehensively characterize, quantify, and monitor the Earth's surface [19, 20]. Land cover characterizes the physical materials covering the landscape, such as forest, grass, or open water while land use represents the function land serves, such as commercial, residential, or agricultural [21]. LULC information play an important role for addressing environmental issues, such as monitoring LULC change [22–24] and modeling the impacts of urbanization [25, 26]. Seto et al. [27] estimated that global urban land cover will increase by 1.2 million $km^2$ by 2030, a 185% increase from the year 2000. Increased urbanization will likely threaten biodiversity, result in the loss of fertile crop land [28] and exacerbate the impacts of climate change [29]. While only 1.8% of world land, excluding Antarctica, is located in the low elevation coastal zone (LECZ), a full 10% of the world population lived in this zone in 2010. Density is expected to increase from 288 inhabitants/$km^2$ to 455 inhabitants/$km^2$ by 2100 [30]. High concentrations of people, industry, assets, and infrastructure in urban areas, like major cities located in the LECZ, are at the greatest risk to the effects of climate change and natural disasters [31].

## Automated and machine learning LULC classification

Identifying, extracting, and classifying detailed and nuanced features in urban areas requires high spatial resolution (HSR) satellite imagery [32, 33]. However, HSR is not available in all regions of the world and lower resolution imagery lacks the level of detail necessary to extract detailed urban LULC [34]. Automated classification techniques like object-based image analysis (OBIA), a method that groups pixels into objects with similar spectral characteristics, are promising approaches for higher accuracy land use and land cover classification [35, 36]. However, OBIA is not effective for classifying the urban landscape [37]. OBIA relies on the segmentation of pixels into groups, limiting the ability to differentiate objects constructed of materials with similar spectral characteristics, such as impervious surfaces and buildings [35]. Pixel based urban land-use classification has a similar problem. Even with high resolution satellite imagery, the heterogeneity of the landscape is too complex for accurate classification. Machine learning techniques, such as Convolution Neural Networks (CNN) and Random Forest (RF), have also been applied to improve accuracy of automated land cover classification [38, 39]. However, these methods present similar limitations of classifying urban land-cover, such as misidentifying features with similar spectral characterizes and requiring large amounts of training data for high accuracy classification, in addition to requiring a reasonably high skill set to properly implement [38–40].

## Open street maps

Open Street Maps (OSM) is a web-based platform for crowd-sourcing of publicly available spatial data generated by users all over the world, commonly referred to as volunteered geographic information [41]. OSM collected data has been integrated in a number of applications including LULC mapping [42] and urban planning [43]. Due to the high cost of collecting and maintaining geo-spatial data, OSM provides a free alternative mapping service for the aggregation and distribution of spatial data. While OSM data is extensive, particularly in densely constructed urban areas, the contribution of individuals lacking a formal training in geographic information systems can lead to the generation of data that is of lower quality and accuracy compared to authoritative databases generated by local, state, and national agencies [44, 45]. For example, a comparison of OSM building footprint data to an authoritative reference dataset in Munich, Germany identified that while OSM derived geospatial data had a high area completeness, many of the buildings included in the authoritative dataset were not mapped in OSM dataset [4]. In addition, buildings in dense urban areas were grouped together and lacked rich building attribute information. Other studies comparing OSM derived data to authoritative databases have identified similar limitations, such as a lack of detailed attributes and lower accuracy and completeness in rural areas [45].

### Heads-up digitizing

Heads-up digitizing refers to a method of manually transposing information from an image into points, lines, and polygons in a digital file typically called a shapefile. The user looks at an image, such as an orthophotograph, on a computer screen and traces the features of interest into a new digital file. The technique is more labor intensive than automated classification used in remote sensing, but is still used for many applications, especially when data are not conducive to an algorithm for making classification decisions. Many digital maps currently in wide use were created using this process.

### Limitation of risk/vulnerability assessment

The frequency of coastal flooding due sea level rise is expected to double in the coming decades [46]. High accuracy spatial resolution Light Detecting and Ranging (LIDAR) and Digital Elevation Models (DEMS) have allowed for greater detailed flood risk mapping and vulnerability assessments [47, 48]. However, varying DEM sources and their associated elevation error can impact the ability to predict coastal flooding and its risk [49]. For example, a study comparing LiDAR derived DEMs to publicly available DEMs concluded that publicly available DEMs did not meet the level of accuracy necessary for flood risk assessment, particularly at a greater spatial scale [50]. Risk and vulnerability assessments are used in coastal regions throughout the world to aid in understanding the impacts of major storm events and future sea level rise scenarios [51–53]. High-resolution modeling, such as the Advanced Circulation Model for Shelves, Seas, and Estuaries (ADCIRC), has allowed for a comprehensive and informative assessment of flooding risk [54, 55]. Increasing development in coastal regions coupled with more frequent and intense extreme weather events has increased exposure and vulnerability to people, assets, and infrastructure [56].

### Methods

The approach used in this manuscript establishes a standard for the creation of geospatial data that can be used to assess land use change, risk, and other research questions suitable for the regional scale, but, with sufficient resolution such that individual facilities can utilize the data for local-scale analysis. This manuscript builds on work that developed the first geospatial inventory of Rhode Island's (USA) commercial ports and harbors [57]. It introduces a "standard operation procedure" (SOP) to employ a heads-up digitizing approach to identify and geo-spatially classify critical infrastructure, their land area and assets, such as buildings, industrial structures and impervious surfaces. Serving as a guide for a reliable and repeatable approach for the creation of geospatial data for critical infrastructure using heads-up digitizing, the SOP consists of decision-making criteria mappers can use to determine critical infrastructure facility land use boundaries and key features to digitize, as well as outlining the digitizing procedure and a number of "what-if" scenarios that a mapper might encounter.
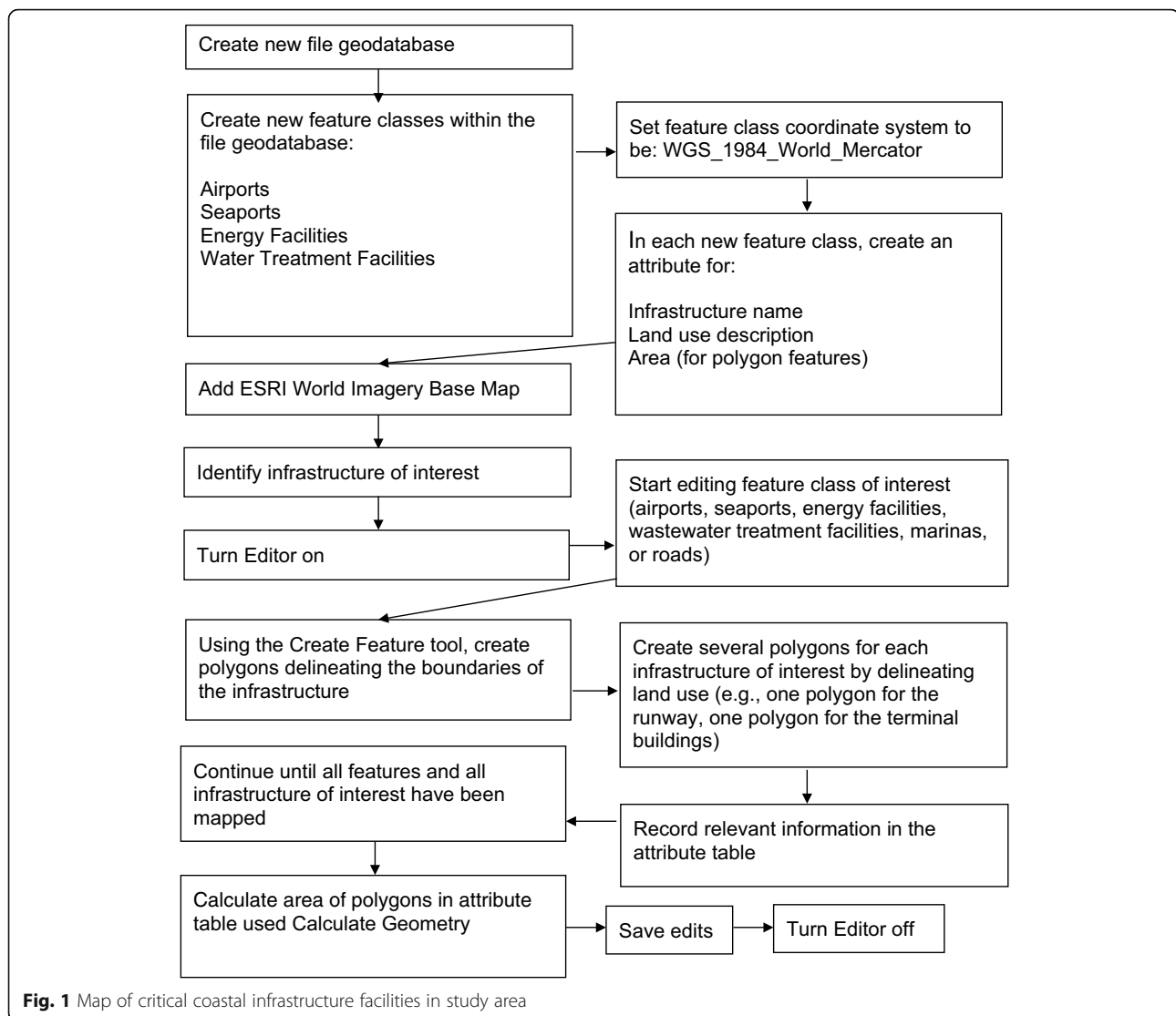
### Caribbean as a case study

In this paper, we use the Caribbean region as a case study (Fig. 1 and Table 1). This collection of island nations faces a unique set of economic, social, and environmental challenges. Island economies such as those in the Caribbean heavily rely on critical infrastructure and the services they provide. With much of the region's infrastructure located in the coastal zone, the impacts of climate change are expected to disrupt the regions tourism economy and commerce [58]. The Inter-American Development Bank projects that the Caribbean could face climate-related losses in excess of $22 billion annually by 2050 [59]. Due to the relative isolation of the islands and lack of natural resources, airports and seaportsare important links for socio-economic development and connectivity between islands in the region and the global economy. In addition, seaports and airports are lifelines for goods such as energy resources, food, potable water (and nearly all of the other imported goods that are part of modern life). Energy facilities and water treatment provide electricity and potable water, necessities that modern day cities cannot do without. Under current climate change projections plus continued development in the coastal zone which is often improperly regulated, critical infrastructure in the region may face more frequent flooding and operational disruptions as early as the 2030s [60]. While climate related hazards pose a significant threat to critical infrastructure, like many areas around the world, the region lacks a comprehensive inventory of the land, infrastructure, and assets at risks.

In this pilot study, mapped infrastructure meets the following criteria: 1) it is an airport, seaport, water treatment, or energy facility, 2) it is located within 1 km of the coastline, and 3) it must be currently in use All facilities were also cross-referenced through Google searches.

### Existing databases of infrastructure

In order to create the inventory, we first searched for existing datasets of infrastructure. Limited critical infrastructure databases exist in this region and throughout the world. Those that do exist are almost exclusively "point datasets," meaning that each facility is identified as one XY coordinate, with information provided about aspects of that facility, such as depth of water if a seaport or airport code if an airport. The single XY point coordinate associated with each facility may or may not be geographically located on the facility itself, though it usually is in close proximity. Our manuscript recognizes

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**Fig. 1** Map of critical coastal infrastructure facilities in study area

the need for "polygon" datasets, which allow for a more nuanced analysis of land use and risk.

That said, we relied upon several worldwide databases (Table 2) and online sources to first identify and inventory critical infrastructure points. Seaports were identified from the World Port Index [61] prepared by the National Geospatial–Intelligence Agency and Countries with ports in the Caribbean prepared by World Port Source [62]. These databases include port name, latitude and longitude, and port characteristics (e.g., facilities and services offered). Seaport types within our database included cruise ports, container ports, oil terminals, and general purpose ports. Airports were identified from OpenFlights Airport Database [63] and World Airport Database [64]. These databases included airport name, longitude and latitude, and airport ID. We were unable to locate regional databases for water and wastewater treatment facilities and energy facilities. Instead, both

facility types were identified through a google search using terms such as "Caribbean Power Plants" of "Caribbean Water Treatment Facilities". Energy facilities were categorized by their fuel source, and included power plants (natural gas, coal, etc.,), oil refineries, nuclear power plants, and solar and wind farms. Water and wastewater treatment facilities included water treatment facilities, desalination plants, and wastewater treatment facilities. We aggregated critical infrastructure facilates identified from existing databases and google searches into an individual inventory for each facility type in a point shapefile containing facility name, facility type, location, and coordinates.

## Satellite imagery

In order to create polygons for land uses and facility assets, we relied on satellite imagery to recognize key features. Base imagery used to digitize critical infrastructure

**Table 1** Study area characteristics

| Country | Total Land Area (km²) [a] | Population (2020) [a,b] | GDP (US$M) [a,b] | # of Airports[a] | # of Seaports[a] | # of Energy Facilities[a] | # of Water Treatment Facilities[a] |
|---|---|---|---|---|---|---|---|
| Anguilla[s,u,oe] | 91 | 18,090 | 175.4 | 1 | 1 | 1 | 1 |
| Antigua and Barbuda[s,u, oe] | 442.6 | 98,179 | 1.5 | 2 | 1 | 3 | 1 |
| Aruba[s] | 180 | 119,428 | 2700 | 1 | 4 | 3 | 3 |
| The Bahamas[s,u] | 10,010 | 337,721 | 12,060 | 9 | 8 | 3 | 0 |
| Barbados[s,u] | 430 | 294,560 | 4990 | 1 | 1 | 3 | 3 |
| Bermuda[s,] | 54 | 71,750 | 6127 | 1 | 4 | 2 | 2 |
| Bonaire | 228 | 25, 897 | 428 | 1 | 2 | 2 | 1 |
| British Virgin Islands[s,oe] | 151 | 37,381 | 1028 | 2 | 1 | 1 | 0 |
| Cayman Islands[s] | 264 | 61,944 | 2250 | 3 | 2 | 2 | 5 |
| Cuba[s,u] | 110,860 | 11,059,062 | 93,790 | 6 | 31 | 12 | 0 |
| Curaçao[s] | 444 | 151,345 | 5600 | 1 | 4 | 4 | 1 |
| Dominica[s,u,oe] | 751 | 74,243 | 557 | 2 | 3 | 2 | 1 |
| Dominican Republic[s,u] | 48,760 | 10,499,707 | 76,090 | 7 | 16 | 8 | 0 |
| Grenada[s,u,oe] | 344 | 113,094 | 1119 | 2 | 1 | 1 | 0 |
| Guadeloupe[s,oe] | 1628 | 400,139 | – | 2 | 4 | 4 | 2 |
| Haiti[s,u] | 27,750 | 11,067,777 | 8608 | 2 | 10 | 3 | 1 |
| Jamaica[s,u] | 10,991 | 2,808,570 | 14,770 | 5 | 12 | 7 | 3 |
| Martinique[s,oe] | 1128 | 376,400 | – | 1 | 2 | 3 | 3 |
| Montserrat[s,oe] | 102 | 5373 | 167.4 | 0 | 1 | 1 | 0 |
| Puerto Rico[s] | 8959 | 3,189,068 | 104,200 | 5 | 18 | 13 | 8 |
| Saint Lucia[s,u] | 606 | 166,487 | 1686 | 1 | 3 | 0 | 0 |
| Saint Martin[s] | 54.4 | 32,556 | 561.5 | 2 | 4 | 3 | 1 |
| Sint Eustatius[s] | 21 | 3140 | 108 | 1 | 1 | 1 | 0 |
| St. Kitts and Nevis[s,oe] | 261 | 53,821 | 964 | 2 | 2 | 3 | 1 |
| St. Vincent & Grenadines[s,u,oe] | 389 | 101,390 | 785 | 5 | 6 | 1 | 0 |
| Trinidad & Tobago[s,u] | 5128 | 1,208,789 | 22,780 | 1 | 10 | 4 | 3 |
| Turks and Caicos Island[s] | 948 | 55,926 | 632 | 3 | 3 | 2 | 1 |
| U.S. Virgin Islands[s] | 346 | 106,235 | 5182 | 2 | 15 | 6 | 6 |

[a] Facilities within 1 km of the coastline and currently active; [b]The WorldFactBook (https://www.cia.gov/library/publications/resources/the-world-factbook/); [c] Statista (https://www.statista.com/); [s]Small Island Developed State; [u]United Nations Member;;[oe] Organsation of Eastern Caribbean States (OECS) member

boundaries and assets needs to be up-to-date and high resolution. Availability of recent high-resolution satellite imagery varies depending on geographic location. While sources for high-resolution imagery, such as Planet, Inc. (https://www.planet.com/) and Satellite Imaging Corp (https://www.satimagingcorp.com/), are available for some regions throughout the world, acquiring regional scale imagery can be costly. Publicly available imagery, such as ESRI World Imagery, is a cost-effective source of high-resolution imagery for detailed feature extraction. Last updated in 2020, ESRI World Imagery provides 1 meter or better satellite and aerial images worldwide, including 15 m Terra Color Imagery at small and mid-scales (~ 1:591 M down to ~ 1:72 k) and 2.5 m SPOT Imagery (~ 1:288 k to 1:72 k) and typically captured within the last three to 5 years. To be considered suitable for this project, imagery used must have been the most up-to-date and captured after 2010. Imagery resolution ranged between 0.31–0.50 m with the date of imagery ranging from 03/09/2011 to 12/10/2019. We defined an imagery scale range of 1:1000–1:8000, allowing for the digitization of larger features and parcel boundaries while ensuring that smaller features could be captured accurately. In some instances, imagery was either

**Table 2** Databases used to locate critical infrastructure facilities

| Facility Type | Main Source | Specific Source | URL | Data Type | Description |
|---|---|---|---|---|---|
| Ports | World Port Index | WPI_ Shapefile | https://msi.nga.mil/ Publications/WPI | Shapefile | Shapefile with points for each terminal. Multiple terminals per port. |
| Ports | World Port Source | Countries with ports in the Caribbean | http://www.worldportsource. com/ports/region.12.php | Shapefile | Breakdown of ports by country. Port icons are coded by size. |
| Airports | OpenFlights Airports Database | OpenFlights Airport Database | https://openflights.org/data. html#airport | Spreadsheet File | As of January 2017, the OpenFlights Airports Database contains over 10,000 airports |
| Airports | World Airport Database | World Airport Database | http://www.world-airport-database.com/database.html | Spreadsheet File | One of the largest airport databases in the world with information on 33,539 airports in 228 countries. A satellite map of more than 31,000 airports is also available. |
| Water and Wastewater Treatment Facilities | Google | Google Maps | https://www.google.com/ maps | N/A | *Key Search Terms: Water treatment plant; Wastewater Treatment Plant; Sewage Treatment Plant; Desalination plant; Water Authority* |
| Energy Facilities | Google | Google Maps | https://www.google.com/ maps | N/A | *Key Search Terms: Power Plant; Power Station; Nuclear Power Plant; Wind Farm; Solar Farm* |
| All | ArcGIS | Basemap – World Imagery | https://www.arcgis.com/ home/item.html?id=10df22 79f9684e4a9f6a7f08febac2a9 | Orthoimagery | World Imagery, last updated August 2020, provides one meter or better satellite and aerial imagery in many parts of the world and lower resolution satellite imagery worldwide. The map includes 15 m TerraColor Imagery at small and mid-scales ((~ 1:591 M down to ~ 1:72 k) and 2.5 m SPOT Imagery (~ 1:288 k to ~ 1:72 k) for the world. |
| All | Google Earth | Google Earth | https://support.google.com/ earth/answer/148094?hl=en | Orthoimagery | Google Earth contains a large collection of imagery, including satellite, aerial, 3D, Street View, as well as historical images. Images are collected over time from providers and platforms. |

of low resolution or had significant cloud cover over a facility. In these situations, we were unable to extract features from the imagery.

**Creation of a standard operating procedure (SOP)**

To standardize an approach for geospatially inventorying critical coastal infrastructure, we developed a Standardized Operating Procedure (SOP) for digitizing critical coastal infrastructure in ArcMap (Fig. 3). The SOP lays out clear guidelines and directions for different mappers to develop similar geospatial data. While the methodology developed is specific to ArcMap, it can be easily be adapted for use on any platform or open source application (e.g., QGIS). For each facility type, mappers create a polygon feature class projected using WGS 1984 Web Mercator (Auxiliary Sphere) within a file geodatabase in ArcMap. The digitization process followed these three basic steps (further details may be found in the Additional file 1):

Step 1: The first step in our digitization process was to define the parcel boundary for a facility, which we defined as the entire land area owned by the facility that encompassed all assets owned by the facility. With

many of the critical coastal infrastructure located in highly developed areas, determining the facility boundary could be challenging, particularly in regions with lower resolution imagery. To guide boundary delineation, we used linear structures, such as roads and fences surrounding a facility to determine the land area covered by the facility.

Step 2: Next, polygons of key assets for each facility type, such as buildings, liquid bulk storage tanks, and runways were delineated from the imagery. Mappers used the snapping toolbar in ArcMap to prevent adjacent features, such as buildings in close proximity, from overlapping.

Step 3: For each feature digitized, detailed information, such as the feature type, facility name, facility type, location, the date and resolution of the imagery used were recorded in the attribute table. This process was completed for each facility type, and each database was checked for quality assurance and consistency.

Because decisions about boundaries and classifications are subjective to the mapper's perceptions, the SOP describes in detail how decisions should be made regarding drawing lines, classification, and scale. Within the SOP,

we developed a set of systematic and repeatable procedures, such as defining an imagery scale range for heads-up digitizing, to guide a mapper in the creation and classification of uniform polygon features for critical coastal infrastructure (Fig. 2). For each facility type, we outlined a standardized inventory of features to be mapped, such as runways for airports, for the mappers to reference as a guide in making decisions about extracting features from satellite imagery (Fig. 3).
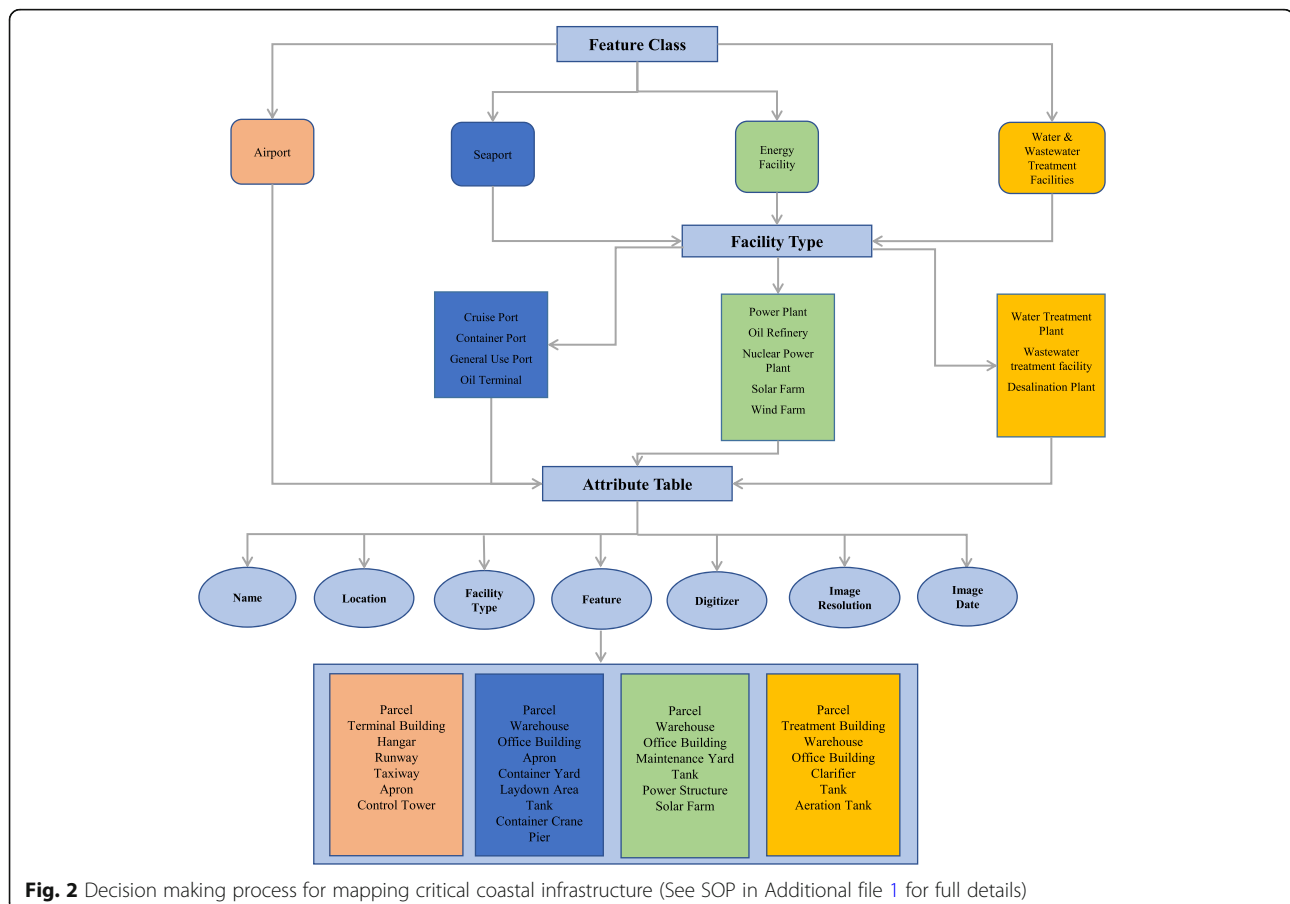
Given the lack of publicly available imagery in certain regions and the geospatial circumstances for some critical infrastructure facilities, such as facilities located in densely constructed urban vs. less developed rural areas, mappers may be confronted with circumstances that complicate the process of heads-up digitizing critical coastal infrastructure. To meet this challenge, we created "what-if" scenarios (see SOP Section 4.1) to augment the set of rules and provide mappers with guidance on how to proceed under different circumstances. For example, the "what ifs" can help the mapper determining a parcel boundary that is not immediately obvious or select the appropriate imagery to use when the imagery and image date changes at different scales.

## Results

Results of this pilot study allow for a macro-level analysis of infrastructure land use in the Caribbean Islands region. In total, we identified 566 critical infrastructure facilities in the Caribbean across the 28 island nation territories. Of that, approximately 65% ($n = 386$) of the facilities were within 1 km of the coast and satisfied the requirements as critical coastal infrastructure, thus we included in our analysis. These facilities encompass a total land area of 19,118 ha of land area in the Caribbean (Table 3). This section first describes results for each critical infrastructure category, as well as the results of a validation exercise. It then provides some key findings about the methodological approach itself.

### Airports

Island economies such as those in the Caribbean depend on airports for trade, food, and energy needs. Additionally, a majority of Caribbean Island GDP is directly dependent on tourism, for which airports are a critical component. Airports in the Caribbean are frequently sited along the coast, as coastal land offers large expanses of flat space and an approach by sea that makes takeoff and landing easier



**Fig. 2** Decision making process for mapping critical coastal infrastructure (See SOP in Additional file 1 for full details)
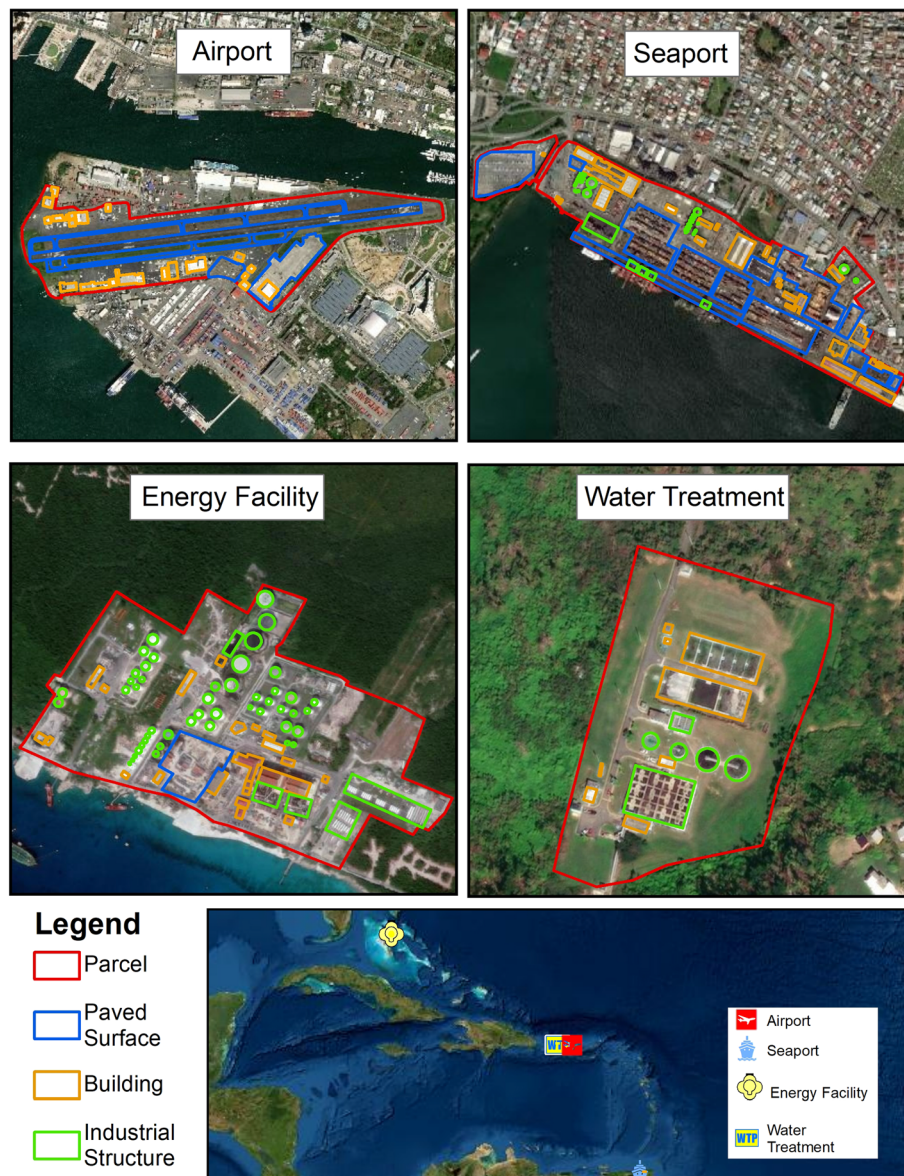
**Fig. 3** Example mapped critical infrastructure facilities and key features. **a** Fernando Luis Ribas Dominicci Airport, Puerto Rico; **b** Port of Spain, Trinidad and Tobago; **c** Bahama Light and Power Clifton Pier, The Bahamas; **d** Planta De Tratamiento De Aguas Negras, Puerto Rico

for pilots. Rising air temperatures and decreasing air density over the coming century will impact airplane takeoff, resulting in the need for longer runways. Increasing heat can buckle pavement, reduce payload limits, and lead to other health and safety risks. Sea level rise and storm surge further threaten airstrips that often extend directly over the sea on filled land [65]. We identified 71 airports in the Caribbean that meet the criteria of coastal critical infrastructure, covering 10,588 ha of land (Table 4). At each airport, we mapped paved surfaces including runways, aprons, taxiways, and parking areas, as well as building, including terminal buildings, hangars, and control towers. An example of a mapped airport is included in Fig. 3a.

Among the critical infrastructure facility types we digitized, airports by far had the largest footprint in the Caribbean in coastal regions. Depending on the size of the airport and the requirements of the planes landing there, runways alone can require a large amount land. For example, the United States Department of Transportation recommends a runways length of 9000 ft for a Boeing 737 [66]. Larger airports may have more than one runway, in addition to taxiways, aprons, and land area dedicated to terminal buildings and parking areas for travelers. Given current climate conditions and the associated need for longer runways, our inventory could be a useful tool to aid planners in designing and

**Table 3** Number of coastal critical infrastructure facilities and total land footprint in the Caribbean

| Infrastructure Type | # of Facilities Identified | # of Facilities within 1 km of Coast | Total footprint (ha.) | | # of features mapped | |
|---|---|---|---|---|---|---|
| | | | Parcels | Paved Surfaces | Buildings | Tanks |
| Airports | 147 | 71 | 10,589 | 1876 | 671 | N/A |
| Seaports | 210 | 170 | 3704 | 792 | 1494 | 735 |
| Energy Facilities | 136 | 98 | 4619 | 90.5 | 1718 | 2280 |
| Water & Wastewater Treatment Facilities | 73 | 47 | 206 | 0.3 | 174 | 81 |
| Total | 566 | 386 | 19,118 | 2759.52 | 4057 | 3096 |

**Table 4** Airports results summary

| Total footprint (ha.) | | | | # of features mapped | | |
|---|---|---|---|---|---|---|
| Parcel | Runways | Aprons | Taxiway | Buildings | Terminal Buildings | Hangars |
| 10,588.5 | 924 | 493 | 411 | 539 | 36 | 87 |

**Table 5** Seaports results summary

| Seaport Type | # of facilities | Total footprint (ha.) | | | | # of features mapped | |
|---|---|---|---|---|---|---|---|
| | | Parcel | Apron | Container Yard | Laydown Area | Buildings | Tanks |
| General Cargo | 101 | 1668.9 | 39.6 | 151.4 | 85.1 | 886 | 322 |
| Container Port | 25 | 1154.1 | 27.8 | 353.7 | 60.5 | 407 | 100 |
| Oil Terminal | 19 | 826.8 | 0.65 | – | 5.5 | 115 | 313 |
| Cruise Port | 25 | 54.5 | 3.4 | – | 2.2 | 86 | – |
| Total | 170 | 3704.3 | 71.5 | 505.1 | 153.1 | 1494 | 735 |

adapting airports in the coastal regions, where undeveloped land area is already scarce, and will become increasingly scarce with a changing climate.

### Seaports

Seaports serve as the economic lifeblood of island nations, many of which are served by only one seaport which imports all materials and supplies that would be too expensive to transport via air. Island economies depend on cruise ports for tourism, container ports for imports/exports and transshipment, and bulk ports for the import/export of raw materials. Additionally, energy ports import valuable petroleum products needed for road and air transport, as well as general power for the electric grid that powers other critical infrastructure facilities including desalination plants, water treatment plants, and telecommunication systems. Across the 28 island nations in this study, we identified 170 individual seaports, which includes: container ports, cruise ports, oil terminals, and general cargo ports (Table 5). We mapped the full outline of the parcel, the individual buildings, key paved surfaces, and tank used to store petroleum or other liquid products. An example of a mapped seaport is include in Fig. 3b. Results show that 3704 ha of Caribbean land was devoted to seaport infrastructure.

### Energy facilities

Energy facilities play an important role in supplying power to the industries that drive economic growth and development, in addition to powering homes and business. With increased urban development in coastal regions, the placement of energy facilities is critical for supplying power to a growing population. In addition, energy facilities need access to a water source for cooling, with sea water being a common source utilized due to its high availability. For Island nations, reliance on reliable energy infrastructure that supplies consistent power is a vital function for maintaining health and well-being among the residents of island nations, as well as ensuring these countries can produce goods and services

that can be distributed between islands and the global economy.

In total, we located and mapped 98 energy facilities throughout the Caribbean region, including: fossil fuel power plants, nuclear power plants, oil refineries, solar farms, and wind farms (Table 6). We mapped the facility land area, buildings, structures dedicated to generating power, and tank farms used to store fuel. An example of a mapped energy facility is included in Fig. 3c. In total, energy facilities covered 4619 ha of the coastal land in the Caribbean region. Not surprisingly, as the size of the country and its population increased, so did the number of facilities and land area dedicated to generation of power and the storage of fuels such as oil, petroleum, or natural gas. Of the 98 facilities mapped, only 8 used a renewable fuel source such as solar or wind, with the rest relying on fossil fuel as a primary fuel source to produce power. The reliance on fossil fuel power plants as a primary fuel source may be indictive of a level of reliability and consistent power supply associated with these fuels sources, in addition to supplying large quantities of power with a relatively small footprint on islands with limited land area to produce enough power to supply a growing population and economy.

### Water & Wastewater Treatment Facilities

Society depends on safe, clean, treated water to prevent disease and maintain health. Properly treated wastewater protects the environment and similarly prevents disease in humans. Many water and wastewater treatment facilities are located in the coastal zone, as they either rely on seawater as a source (e.g., for a desalination plant) or a destination for treated water [15]. Though such facilities are not limited to coastal locations, such locations are often more cost effective, as the low elevation reduces the need for expensive pumping systems. In this study, we identified 47 water treatment, wastewater treatment, and desalination facilities, encompassing 206 ha of coastal land (Table 7). The limited number of water and wastewater treatment facilities inventoried

**Table 6** Energy facilities results summary

| Energy Facility Types | # of facilities | Total footprint (ha.) | | # of features mapped | | |
|---|---|---|---|---|---|---|
| | | Parcel | Paved Surfaces | Buildings | Power Structures | Tanks |
| Fossil Fuel Power Plant | 66 | 1308.1 | 44.0 | 876 | 116 | 594 |
| Nuclear Power Plant | 1 | 15.0 | 1.1 | 15 | 7 | 38 |
| Oil Refinery | 23 | 3155.4 | 45.4 | 824 | 62 | 1658 |
| Solar Farm | 4 | 103.6 | – | 3 | – | – |
| Wind Farm | 4 | 36.9 | – | – | – | – |
| Total | 98 | 4619 | 90.5 | 1718 | 185 | 2280 |

**Table 7** Water and wastewater treatment facilities results summary

| Water Treatment Facility Types | # of facilities | Total footprint (ha.) | | # of features mapped | | |
|---|---|---|---|---|---|---|
| | | Parcel | Paved Surfaces | Buildings | Clarifiers | Tanks |
| Water Treatment Plant | 16 | 55.2 | – | 69 | 21 | 30 |
| Wastewater Treatment Plant | 27 | 119.5 | 0.32 | 77 | 64 | 29 |
| Desalination Plant | 4 | 31.4 | – | 24 | – | 22 |
| Total | 47 | 206.1 | 0.32 | 170 | 85 | 81 |

may be a result of the lack of a regional database and the challenges of locating these facilities. However, the Caribbean region does suffer for a lack of adequate resources to treat water, with only 17% of the homes in the region directly connected to a form of water treatment (Fluence News [67]).

### Validation exercise/accuracy assessment

One of the potential applications for this approach is tracking land use over time. For example, researchers could conduct an inventory every five years in order to monitor how infrastructure land use is growing or shrinking for a particular region. To this end, the approach must be replicable such that different individual mappers would make the similar choices with respect to boundaries and classifying assets. To assess the accuracy and replicability of the methodology, we hosted a validation exercise to compare results obtained by independent mappers for a subset of facilities within our database. We recruited 11 volunteer mappers with basic GIS skills. Using a random name generator, two facilities for each facility type (eight facilities in total) were selected for testing. Facilities represented areas from a variety of built-environment densities and had varying resolution satellite imagery. Prior to digitizing the facilities, mappers reviewed our SOP and partook in a two-hour training exercise. Once they reviewed the materials, each mapper was assigned four facilities and tasked with determining and digitizing the parcel boundary, buildings, and other features for each facility. We then compared the percent overlap between polygon boundaries to determine the effectiveness of our methodology in guiding mappers to create a dataset that matched the one created by our research team. In addition, we made comparisons to data derived from OpenStreet-Maps (OSM) for the same subset of facilities. However, of the eight facilities selected for the validation exercise, only four were mapped in OSM for comparison.

To determine the percentage of parcel polygon overlap between our dataset and the participants dataset, we applied the Union tool in ArcMap to join the sample polygon features for each mapper with those in the researcher dataset. We then divided the area that intersected by the total area (i.e., intersecting + non-intersecting) of the joined polygons. In comparison of the polygon overlap for parcels, we found that an average of 83.6% of the polygon area from the volunteer mapper derived dataset overlapped with our polygon parcels (Table 8). After the exercise, we survey the mappers to identify the components that the participants struggled the most with when completing the exercise. The most common challenges of the exercise identified from the feedback was determining the boundary that surrounded a facility, particularly for facilities that were in densely developed areas. Three of the facilities that were mapped were problematic for participants, with variability in the percentage overlap among mappers (Fig. 4). In comparison to OSM, we found an average of 82.8% overlap of polygon area between our dataset and the facilities mapped in OSM. Analysis shows that the variation may be indicative of the geographic location of the facility, such as facilities in highly developed regions or areas with lower resolution imagery available, as well as the experience level mappers have with GIS and the efficacy of the methodology we have developed. Overall, the results of this exercise suggest that our approach and SOP provide enough instruction such that different mappers could obtain similar results, though additional training would be helpful to boost replicability. This validation exercise lends confidence to the replicability of this method for conducting such geospatial analysis.

**Table 8** Results of the validation exercise and comparison with Open Street Maps

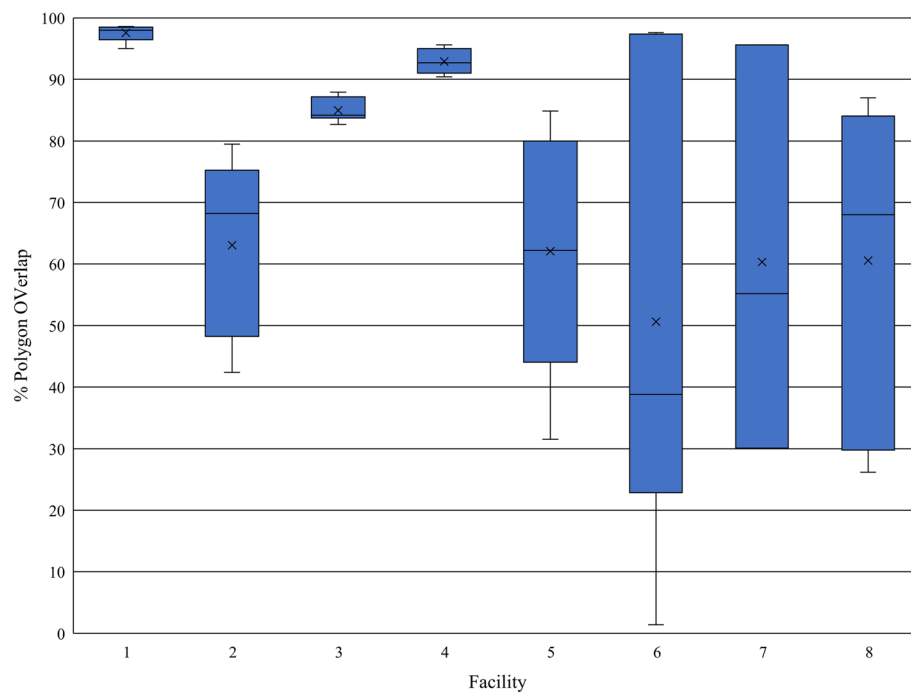| % Polygon Overlap | | | |
|---|---|---|---|
| Dataset | Mean | Range | SD |
| Validation Exercise (# of mappers = 11, # of facilities = 8) | 83.6 | 45.4 | 14.1 |
| OSM (# of facilities = 4) | 82.8 | 38.1 | 18.1 |

**Fig 4** Validation exercise comparison of polygon overlap among eight mappers for each facility type

## Discussion and implications

The primary purpose of this manuscript was to develop a standardized, replicable approach to mapping critical coastal infrastructure using the most-up-to date satellite imagery. The resulting data can be used for a variety of applications. For example, by running a regional sea level analysis, researchers can quantify the amount of critical infrastructure at risk from inundation or storm surge on a more granular level than by simply using point datasets. It could also be used for analysis of other regional trends, such as tracking coastal land utilization over time, regional economic studies, or planning. The approach developed here provides empirical data that has a higher level of precision than estimates based on more generic land use. For example, Dronkers et al. [68] developed an approach to estimate land use for ports based on cargo throughput. This approach was subsequently improved by Hansen and Nicholls [69] for a study that projected 2050 port land use demands based on a variety of economic and climate scenarios. The data resulting from the approach described in this study could allow for validation, as well as for including a wider variety of coastal infrastructure. Additionally, this data could be used to identify facilities and infrastructure storing hazardous materials, such as oil refineries and power stations, that could potentially release pollutants into the surrounding ecosystem similar to what occurred in Galveston Bay during Hurricane Harvey [2].

While the Caribbean was used as a case study for this pilot, there are many other regions throughout the world with finite land area and infrastructure located in low-lying coastal areas. Many will likely experience similar climate related challenges. For example, island nations located in the South Pacific are particularly susceptible to climate related hazards. A recent study on the exposure of infrastructure to climate risks in the South Pacific estimate that 57% of the infrastructure is located with 500 m of the coastline [12]. While this study was one of the first to develop a comprehensive assessment of the infrastructure assets vulnerable to climate risk, a point database was used to identify infrastructure, thus limiting the ability to determine the assets at greatest risk. The methodology we outline in this paper provides an opportunity to develop more detailed geodatabases that could be used for a comprehensive analysis of the assets and infrastructure at greatest risk in regions like the South Pacific. While other mapping techniques are available, the SOP standardizes the process of creating spatial data for critical infrastructure features in a way that is cost effective, fast, and useful for projects relying on participatory mapping to generate spatial data. The SOP can also be used as a complimentary guide pre-existing mapping techniques as well as for the creation of geospatial data using OSM or other open source mapping applications. Additionally, the SOP can be utilized to allow for revisions as satellite imagery is updated.

Next steps for this work include an expansion of the approach to include other types of coastal land use (e.g., marinas and emergency facilities), expanding the SOP to include standardized approaches for mapping other critical infrastructure features, such as roads, bridges, and railways within close proximity to coastal infrastructure facilities, as well as conducting the study in other regions around the world (e.g., the South Pacific). In addition, the data could be used to conduct a regional analysis of Caribbean coastal infrastructure at risk from storm surge, similar to methods described in a pilot study we conducted for the U.S. Virgin Islands [70].

### Limitation of this approach
There are a few challenges and limitations to this approach that warrant discussion. This section describes some of the larger issues.

#### Identifying facilities
This manuscript relies on existing point datasets and Google searches to identify where facilities are located along the coast. It then develops those point datasets into polygon datasets to allow for a more nuanced understanding of land use. For ports and airports, we were able to find comprehensive datasets. However, for water treatment and energy facilities, we relied more on Google searches to identify where on each island these facilities could be found. As such, it is possible that some facilities were missed. In next steps, we plan to expand our approach to include other types of uses, such as marinas, hospitals, emergency facilities, and bridges. Some of these, such as marinas, have likely been assembled into databases that can be used to identify locations. Others, however, will rely on a more hands-on approach through Google or other search engines.

#### Determining parcel boundaries
"Parcel" generally describes the boundaries of a piece of land held by a particular owner. Delineating such ownership boundaries through an inspection of satellite imagery would be an impossible task. For this project, we consider the parcel to be the land area devoted to a particular infrastructure use. In some cases, identifying this boundary was relatively straightforward, such as for a river or a road. However, in other cases, the mapper needed to use their best judgement to determine where a parcel boundary should be drawn. Though we included several "what if" instructions in the SOP, this type of decision making could lead to errors in the dataset.

#### Limitations in publicly available imagery
Acquiring high resolution satellite imagery at the regional scale from a private company could be costly, thus for purposes of this study, we relied on publicly available satellite imagery provided by ESRI. While the cost associated with accessing publicly available data was negligible, a reliance on this imagery presents several limitations as compared to formal imagery sources. For one thing, cloud cover sometimes presented challenges in identifying infrastructure. In addition, the date of the imagery may vary with scale, meaning that as a mapper zooms in on a piece of infrastructure the image date at a higher resolution could be several years earlier or later than that of the image at a smaller scale.

### Conclusion
This paper describes a cost effective, precise and standardized approach to inventory critical infrastructure on a regional scale. Using a heads-up digitizing approach, the methods outlined in this paper can be used to create a high-resolution dataset for the land and key features dedicated to critical infrastructure. The dearth of such datasets has been identified as a barrier to conducting research to understand a variety of issues, especially in developing nations such as many of the islands in the Caribbean. Along with high-resolution bathymetry and elevation data, land use data such as developed in this manuscript is the third major category of data necessary to assess storm surge and sea level rise impacts to the coast at the local and regional scale. Using the 28 islands in the Caribbean region to pilot the approach, we identified 386 critical coastal infrastructure facilities, with over 19,000 ha of coastal land dedicated to critical infrastructure. This data can be available to other researchers who wish to conduct regional-scale work on climate vulnerability or other applications. Such geospatial datasets are necessary for a variety of analyses, including risk assessment and tracking land use change over time for a region. While other approaches to inventorying rely on complex or automated remote sensing or techniques to estimate land use, this approach utilizes satellite imagery and a "standard operating procedure" that guides individual mappers through the process, ensuring replicability and confidence. The approach will be expanded and the SOP further developed to include other regions, such as the South Pacific, and additional types of infrastructure.

### Supplementary Information
The online version contains supplementary material available at https://doi.org/10.1186/s43065-021-00019-0.

| Additional file 1. |
| --- |

**Availability of data and materials**
The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. The data has been made available to view through the University of Rhode Island ArcGIS Online page at https://tinyurl.com/amd746ey.

## Declarations

**Competing interests**
The authors declare that they have no competing interests.

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