Recreational Fishing Technical Report

CARIBBEAN REGIONAL OCEANSCAPE PROJECT (CROP)

Dominica, Grenada, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines

Component 2; Subcomponent 2.1

Expanding Marine Data Aggregation and Analytic Tools

Photo credit: Antonio Scant/UnSplash

RFP Reference No.: *LC-OECS COMMISSION-18987-CS-QCBS*

Loan No./Credit No./ Grant No.: TF05428

Country: Organisation of Eastern Caribbean States

Output #6 Final Report Submitted by The Nature Conservancy to the Organisation of Eastern Caribbean States on December 11, 2020

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Acknowledgements

This report was co-authored by Dr. Mark Spalding, Kate Longley-Wood, & Valerie McNulty from The Nature Conservancy. AI/ML analyses was led by Aaron Cole (University of Southern California Santa Cruz) and Darren Tanner (Microsoft), and supported by Barry Nickel (UCSC), Zach Ferdana (TNC), and Francesco Tonini (TNC). Stakeholder engagement support was led by Dr. Sherry Constantine (TNC) and Dr. Steve Schill (TNC) provided additional scientific and technical guidance. Other TNC staff supporting stakeholder engagement includes Petra MacGowan, Cherie Wagner, Amrita Mahabir, Allena Joseph, Anicka Phillip, Giselle Hall, Dr. Montserrat Acosta-Morel, and Ezra Campbell. In-country data collection support was provided by Kendon James, Tasia Jones, Clonesha Romeo, Margaret Straughn, and Makeda Warner. We are grateful for additional modelling and data advice provided by Nicholas George and Nikoyan Roberts. Finally, we could not have completed this work without the numerous stakeholders from the region who provided advice, data, and feedback.

Executive Summary

Under the Caribbean Regional Oceanscape Project (CROP) Subcomponent 2.1, the Organisation of Eastern Caribbean States Commission (OECSC) engaged The Nature Conservancy (TNC) to develop ecosystem service (ES) models for five countries in the Eastern Caribbean using methodologies developed under TNC's Mapping Ocean Wealth (MOW) initiative, and to develop training and resources to improve data access for decision-makers. This report outlines the activities under Output 6 of the project.

The Caribbean is more dependent on the travel and tourism sector than any other region worldwide. This sector is almost entirely focused on coastal areas, notably through beach-based activities, cruise tourism and in-water activities including sailing, and diving, and other vessel-based activities. There has been intentional development of the recreational fisheries sector as an activity for tourists visiting the region and today, much of the recreational fishing in the region takes place from private or chartered vessels or during fishing tournaments. However, historical attempts to collect standardized data on this sector at a regional level have been limited, and spatial characterization of this activity has been especially lacking.

Under this output, TNC addresses the spatial data gap associated with this activity using a combination of image analysis applied to crowd-sourced data from Flickr and TripAdvisor, complemented by participatory mapping and survey data from charter vessel operators, as well as other stakeholder-provided information and guidance. The result is a map of recreational fishing intensity for CROP countries, as well as several complementary summary statistics intended to further emphasize the importance of this sector to the region's economy.

The maps show how widely dispersed recreational fishing is across each of the CROP countries, with both nearshore fishing and quite heaving offshore fishing in deep waters in the more southerly countries. The more exposed windward shores are the only areas where fishing is often absent.

While the financial assessment is drawn from a relatively small sample size, the results indicate a direct expenditure of over $US 6.8 million per year. On a per country basis, the estimated expenditures are as follows:

Dominica	$360,000
Grenada	$1,060,800
Saint Lucia	$2,777,600
St. Kitts & Nevis	$2,407,200
St. Vincent & the Grenadines	$230,400

These figures capture payments from tourists to the operators themselves; however, there are likely to be many associated expenditures, and future iterations of this model would be strengthened by an effort to incorporate more data from private fishing vessels, including those operating within the countries.

Some tourists even selecting destinations based on fishing opportunities, as reviews of exit polls and motivation surveys regularly show fishing to be an activity highlighted as a key or prime motivator for between one and six percent of tourist arrivals in the small island states of the Caribbean. Given this, it might be reasonable to conjecture that such visitors might move elsewhere if the quality of fishing was diminished, and further thought could usefully be given to how to strengthen recreational fisheries as a sector in the region. This is clearly a very high-value activity, and most participants, particularly the more regular fishers are generating high expenditure overall on their visits.

This is the first time that this activity has been so extensively mapped at the regional scale. We believe that the results are of considerable use for better understanding the value nature-based tourism, applicable to management, that they will enable a broad range of users from the public to industry to government to better plan and manage both the tourism industry and any other active sectors within the blue economy.

Introduction

Overview

Ocean resources in the Caribbean have the potential to make a much greater contribution to poverty reduction and shared prosperity for the region's growing population of 40 million than they do currently, and to increase the resilience of people to climate change. The Caribbean region has been at the forefront of a movement towards the development of the blue economy and is home to a growing number of developing states that share the Caribbean Sea and have embraced the concept as the centerpiece of future growth strategies.

Given the value of the region's marine space and its resources, with support from the Global Environment Facility (GEF), the Organisation of Eastern Caribbean States (OECS) Commission, in partnership with the World Bank, is implementing the Caribbean Regional Oceanscape Project (CROP) to improve systems and put relevant structures in place in an effort to foster a Blue Economy and to promote greater consideration of the ecosystem functions and services, which the ocean provides for member states.

Under this project, The Nature Conservancy (TNC or "the team") is using the Mapping Ocean Wealth (MOW) approach to develop ecosystem service models and maps at the scale of the Eastern Caribbean in support of the CROP. The theory of change behind the MOW approach is that developing and improving access to accurate and spatially explicit metrics of the value of natural ecosystems could provide a critical tool in encouraging efforts to use nature sustainably, and work towards its protection, maintenance or restoration. These data will support the CROP countries (Dominica, Grenada, Saint Lucia, St. Kitts & Nevis, and St. Vincent & the Grenadines) in ongoing and future marine spatial planning through the direct provision of spatially explicit information on their ecosystem service values, particularly relating to fisheries and nature-based tourism. This will include existing information, new information generated locally, and the provision of both tools and training to enable practical use and application of ecosystem services values into planning. This report constitutes the first primary deliverable associated with Output 6 of the consultancy, providing a first full summary of the approach and results of a modelling exercise to describe the extent, intensity, and, to a certain degree, value of recreational fishing in the region.

Recreational Fishing

Recreational fishing is a popular activity for tourists visiting coastal destinations. Generally, recreational fishing is defined as fishing activity where the sale or consumption of the catch itself is not a primary objective. Globally, recreational fisheries are of considerable value. Over ten years ago they were estimated to generate an estimated US$39.7 billion in expenditures annually, supporting at least 954,000 jobs Cisneros-Montemayor & Sumaila (2010).

The Caribbean is more dependent on the travel and tourism sector than any other region worldwide, accounting for over 10% of GDP, and 15.2% of jobs in the region (WTTC 2019). This sector is almost entirely focused on coastal areas, notably through beach-based activities, cruise tourism and in-water activities including sailing, and diving. There has been a historical push to develop the recreational fisheries sector to maintain the appeal of the region to visitors from the US (Schmied 1989).

Most recreational fishing in the region takes place from private or chartered vessels, rather than from on-shore locations, and is frequently termed deep sea, sport, or game fishing. These vessels typically take fishers to deeper offshore waters where target species are pelagic fish, such as dolphinfish, wahoo, king mackerel, serra Spanish mackerel, yellowfin tuna, sailfish, blue marlin, white marlin and blackfin tuna, with other species, such as a barracuda, caught incidentally (Mohammed 2012). Many sportfishing charter operators diversify their services, offering other vessel-based activities such as diving in addition to fishing charters. Fishing tournaments also play a role in the sector. The Spice Isle Billfish Tournament, operated by the Grenada Yacht Club, is the largest billfish tournament in the southern Caribbean, and in 2012, generated EC$ 2,330,031 in economic activity (Charles & Associates 2012). Saint Lucia also hosts a yearly tournament out of Rodney Bay, and historically the Nevis Sportfishing Tournament has taken place at Oualie Beach (Mohammed 2012); however, it does not appear to have taken place in recent years. Overall, the sector has benefited local economies, and has also contributed to conservation scientific efforts; however, more information is needed to ensure that the sector can continue to operate sustainably (Mohammed 2012).

In the Eastern Caribbean, Mohammed (2012) compiled available data on recreational fisheries, including catch, landings, and socioeconomic data (e.g, employment, revenues, costs of operation), and other trends associated with the sector. Similarly, there are several studies available for select CROP countries (Scott 1994; Gentner & Obregon 2018); however, as noted in Mohammed (2012), the data needed to inform management and decision making around the recreational fisheries sector are typically not available for most countries in the Eastern Caribbean, and map-based data depicting the spatial footprint of the fishery are particularly lacking.

The primary purpose of this project is to address the spatial data gap associated with this activity. For the purpose of this project, we are primarily focusing on charter vessels catering to tourists, rather than activities by individual fishers, including locally-based recreational fishers, although there is likely considerable overlap between the two. The map also accounts for fishing activity taking place during major fishing tournaments. We created this map using a combination of image analysis applied to crowd-sourced data from Flickr and TripAdvisor, complemented by participatory mapping and survey data from charter vessel operators, as well as other stakeholder-provided information and guidance. By applying a series of geospatial processing techniques, informed by stakeholder input, the team has developed a map of recreational fishing intensity for CROP countries, as well as several complementary summary statistics intended to further emphasize the importance of this sector to the region's economy.

This mapping effort represents a slight divergence in technique from previous MOW projects, which typically link values to a specific, discrete habitat (e.g., coral reefs, beaches). Because recreational fishing takes place over a wide array of benthic and pelagic habitat, the team deemed it inappropriate to spread economic value across the entire intensity map, and this assumption was validated during stakeholder review workshops. As the first recreational fishing intensity map for the region, we believe that it provides substantial value in informing management and decision-making in the region.

Overall, the results of this project are intended to support CROP priorities of strengthening capacity for ocean governance, and coastal and marine geospatial planning in the participating countries. The project team also anticipates that the maps and data may have broader scale utility for the tourism industry and to help advance sustainable practices for the tourism and fisheries industries that enhance the value of the tourism industry in the region.

Methods

General data sources, data collection, and preparation

In order to develop a map of recreational fishing we drew on a number of different and independent sources to devise a composite map of recreational fishing intensity. We identified five broad classes of input data, summarized in Table 1.

Table 1. Summary of data input sources for recreational fishing model

Data Layer	**Source**
Onshore operators	TripAdvisor & local directory listings provided by TNC Caribbean Division
Participatory mapping points and tracks	Survey and in-person mapping conducted by TNC staff in February 2020
Photos	Flickr & TripAdvisor
Fishing aggregation devices (FAD)	Departments of Fisheries and/or Natural Resources in Dominica, Saint Lucia, and St. Vincent & the Grenadines

Deep-sea fishing derived from bathymetric contours	Bathymetric contours were derived from bathymetric sounding points digitized from British Admiralty nautical charts by TNC for the ECMMAN project in 2013.

TripAdvisor Data. Data were kindly provided by TripAdvisor for all attractions (points of interest, tour operators, hotels, holiday rentals, and restaurants), including both member reviews and uploaded images. Images and photographs were analyzed using AI/ML methods described below.

With photos it is important to avoid bias that would be introduced by multiple image uploads by a single person for a single location. For this purpose we were able to devise a metric of photos by attraction by member (PAM) where one user (member) can only record one photo for any search class for any location (attraction).

Onshore operators. The search of TripAdvisor data identified an initial list of 247 attractions with either reviews or PAMs suggesting an association with recreational fishing. Only a small proportion of these are likely to be recreational fishing operators, while there was also a risk of some misidentification, but these provided a start point from which we removed any attraction only identified in one single PAM or review. Further checks removed all restaurants and most hotels (unless the web-site confirmed the organisation of recreational fishing by the hotel). This gave a final list of 73 operators identified through TripAdvisor, each with an indication of size of operation measured through the number of PAMs and reviews.

This layer was enhanced by data from local sources across the region, adding to data to multiple of the TA operators, and adding a further seven operators, giving a final total 80 operators. We used the total PAMs and reviews to provide a simple weighting for likely fishing intensity score between 1 and 3 for each metric. For the seven operators with no TA data we elected to class them all as having the mean value of 2.

This listing of operators gives no direct indication of where fishing activities are taking place, however it is an important, weighted measure for departure points for recreational fishing. These are also the key points of spending, and hence local socio-economic influence.

Participatory Mapping. In February 2020, members of the project team travelled to each of the CROP countries in order to conduct informational interviews and participatory mapping exercises with charter operators who lead sportfishing and/or whale watching tours. 31 operators, 23 of whom offer sportfishing trips participated. Most participants filled out both the surveys and participated in the mapping exercise. In the structured survey, most participants provided data on the number, length, and cost of trips, as well as departure points, target species, and other information influencing the features of their trips. The questionnaire template and responses can be found in Annex A. In the participatory mapping exercise, participants were also asked to place adhesive dots on a map to indicate significant locations for sportfishing (Figure 1). These dots were annotated with qualitative or other descriptive information. Separate from this process, a further point was added – this was a remote seamount off the southwest coast of Grenada, singled out for its intense use, notably during an annual fishing tournament (Nicholas George, pers comm.). The points were georeferenced and digitized using ArcGIS software, and in some cases underwent further processing (e.g., connecting points to describe a route; buffering a point to widen the area) based on the annotations.

Figure 1. Example output of participatory mapping exercise in St. Vincent. Green dots represent recreational fishing points of importance. Red dots indicate whale/dolphin watching points of importance to be used in a separate analysis.

Fish Aggregation Devices (FADs). Through regional consultation processes we were also made aware that quite a number of the recreational fishing operators travel to fixed fish attracting devices (FADs) which have been secured in a number of offshore locations around the CROP countries. Government ministries[1] provided with locational data for Dominica, Saint Lucia, and St. Vincent and the Grenadines. countries and these too were added to our fishing locations layer. FAD data were not available for St. Kitts and Nevis or Grenada.

Bathymetric Contours. Detailed discussions on the most popular deep sea fishing techniques was provided, informing us of the widespread practice of vessels heading offshore and then fishing along a bathymetric contour, with shorter (half day) trips generally staying closer to shore in slightly shallower water than full day trips. The former typically concentrate around the 1000m contour for half day trips,

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[1] Dominica Ministry of Environment, Natural Resources, Physical Planning and Fisheries; Saint Lucia Department of Fisheries, Ministry of Agriculture, Fisheries, Natural Resources and Co-operatives) and St. Vincent & the Grenadines Fisheries Division, Ministry of Agriculture, Forestry, Fisheries, Rural Transformation, Industry and Labour

while the full day trips typically fish out to the 2000m contour. To conduct our analysis based on this information, we used bathymetric contours that were derived from bathymetric sounding points digitized from British Admiralty nautical charts by TNC for the ECMMAN project in 2013.

Other fishing location data. Relatively few (13) recreational fishing photos were identified from Flickr through the image recognition API and keyword searches of photo tags, but as geolocated points these were added to our compilation of fishing locations.

Modelling and geospatial processing

TripAdvisor and Flickr data analyses

This model incorporated AI/ML techniques and methodologies applied to Flickr and TripAdvisor photos, as well as TripAdvisor reviews. Under this approach, we developed a training data by selecting images (from Flickr and TripAdvisor) and text (from TripAdvisor reviews) that best represented the elements we wished to capture in our models. For example, we selected pictures of people holding trophy fish on boats and docks. In order to supplement the training data, we also employed Google image searches to supplement the training imagery. Once sufficient training photographs had been compiled, the team used Microsoft's the Azure Custom Vision service to classify the remainder of the photos from Flickr and TripAdvisor and return a list of photos that best matched the criteria from the training data. The images returned were then standardized to PAM point features, as described in previous paragraphs, and plotted on a map. As very few images were returned from Flickr, it was not necessary to standardize these to photo user days and each uploaded image provided a single georeferenced fishing location.

Similarly, we used the web-based tool LightTag to label over 2,000 TripAdvisor reviews according to activities and elements described in each review. As we were using these approaches to develop data for several different nature-dependent tourism models, each review might have had multiple labels. For example, a review describing a trip to the fishing grounds where barracuda were caught, followed by a snorkeling excursion would be classified as both "recreational fishing" and "on-reef" tourism. An expert team from Microsoft then applied a random-forest regression model to automatically classify the remainder of the reviews and return a list of reviews that matched each set of criteria. These could then mapped as points based on the attraction to which they were linked.

The AI/ML models were evaluated based on two major metrics: precision indicates the model's ability to accurately predict which images are positive for the category (i.e. good precision means the model delivers very few incorrect identifications); recall indicates the model's ability to find the images in a category (i.e. good recall means few positive images are overlooked by the model). For this work we sought to prioritise precision over recall as false identifications would lead to misleading information on the maps.

The image recognition model had a precision score of 100% and a recall score of 71%, indicating virtually no erroneous images, but almost 30% of positive images were likely missed. Nevertheless, the model was considered of sufficient quality to include the results.

More details on these AI/ML methods and outputs can be found in Appendix B.

Table 2. Summary of data inputs by country included in the model

Country	**# of TA Photos**	**# PAMs**	**# Reviews**	**# Mapping Exercise Participants**	**# Onshore Operators**	**#FADs**
Dominica	20	4	18	2	6	22
Grenada	40	23	121	5	22	N/A
Saint Lucia	245	113	100	6	46	2
St. Kitts & Nevis	72	25	727	6	23	N/A
St. Vincent & the Grenadines	22	10	50	4	7	6
Total	**399**	**175**	**1,016**	**23**	**104**	**30**

Developing use intensity maps

Each of the points and tracks recording fishing places or departure points is indicative of a larger area of fishing and a range of approaches were developed to expand these points or track data into appropriate extents, and then to develop weightings. These approaches are laid out in the table below:

Table 3. Summary of data processing steps applied to various inputs for recreational fishing model

Layer	Buffers	Weights
Onshore operators	10km	Weighted using the PAM and review scores (scoring 1-3 for each depending on number of reviews, then summed, so a maximum score of 6 points), the seven operators with no TA data were given a score of 4 points. Scores were then spread across a buffer around the onshore operators and out across the deep-sea fishing layers.

Layer	Buffers	Weights
Participatory mapping points	10km around all points and lines, unless specified by data provided to a different area.	All given an equal weight of 1.
Flickr photos	10km	All given an equal weight of 1.
Fishing aggregation devices (FAD)	2km, based on the assumption that fishing is highly localized around the FADs	Weighted based on distance from onshore operators: FADs within 0-20km of onshore operators were given a score of 3, within 20-40km a score of 2, and more than 40km a score of 1.
Deep-sea fishing derived from bathymetric contours	None	PAM weights from TA for onshore operators were spread to the deep-sea fishing layer using 20km and 40km buffers.

Based on the information we obtained regarding fishing patterns along contour lines, we developed an input deepsea fishing layer using bathymetric charts and by buffering 1000m and 2000m contours to cover depths from 800m to 2200m. (See Appendix C for more details).

Clearly there is likely to be diminishing fishing effort with distance from shore, and while the participatory mapping points and Flickr images represent known fishing locations, the onshore operators, FADs and preferred deepsea fishing grounds do not. For the onshore operators, we spread to their associated fishing intensity weightings between an immediately adjacent fishing area (up to 10km), and were further distributed to the deep-sea fishing layer in an effort to spread the density of activities from the operator locations to the offshore locations where fishing is occurring. For FADs we likewise developed a distance weighting for likely fishing intensity, using the assumption that FADs located further offshore are likely to attract less recreational fishing effort.

Each of the resulting layers was combined and their fishing weightings summed to develop a merged layer of fishing intensity. These final maps were then smoothed across a zone of 2.5km, using a focal statistics tool to better represent the likely blurred boundaries expected in open water fishing.

Economic value

Data gathered during the participatory mapping exercise also enabled us to generate approximate data on tourism spending. From the survey results, we calculated for each country the average # of trips per week in both the high and low seasons and the number of months in the high and low seasons. By multiplying these values, we estimated the number of trips/year/operator. We then multiplied these by the average cost/trip recorded from the survey, and then that number by the number of operators by country (from the totals in Table 2), in order to estimate the annual charter sportfishing tourism expenditure, in $USD. The results are reported in the following section. Unlike other Mapping Ocean Wealth data products, we elected not to distribute these values across the intensity maps. This was based on the fact that the activity takes places across a variety of benthic and pelagic habitats, rather than being tied to one specific habitat. Stakeholder consultations confirmed that this approach was appropriate.

Results and discussion

The final recreational fishing map for the region is presented on the next page, with individual maps for each country presented in Appendix D.

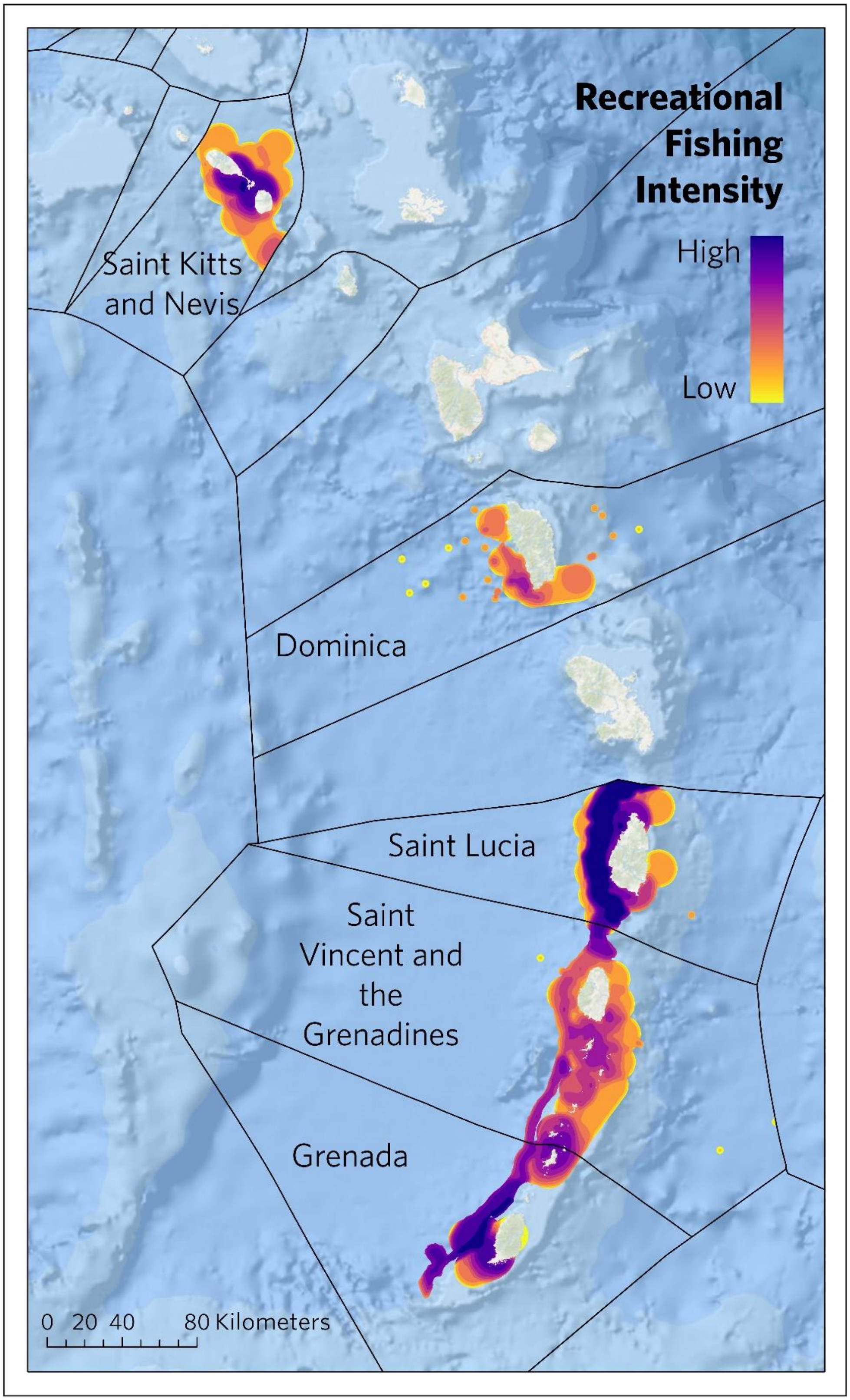

Figure 2. *Map of recreational fishing intensity across the study area. Values are unitless and represent a relative range of intensities*

These maps show how widely dispersed recreational fishing is across each of the CROP countries, with both nearshore fishing and quite heaving offshore fishing in deep waters in the more southerly countries. The more exposed windward shores are the only areas where fishing is often absent.

An estimated calculation of tourism expenditure for each country is given below in Table 4.

Table 4. Estimated annual tourism expenditures on recreational fishing trips

Country	**Cost/trip ($USD)**	**#Trips/year /operator**	**# Trips/year**	**Estimated Tourism Expenditure ($USD)**
Dominica	600	120	600	$360,000
Grenada	600	136	1768	$1,060,800
Saint Lucia	775	224	3584	$2,777,600
St. Kitts & Nevis	850	236	2832	$2,407,200
St. Vincent & the Grenadines	600	128	384	$230,400

Conclusions

The recreational fishery in the CROP countries is both widespread and important – as described here it is a multi-species fishery, and likely incorporating small amounts of near-shore fishing for benthic and demersal species, but most concentrated in offshore waters. We estimate that the operators listed here may be generating over 9000 fishing trips per year, likely including a mix of both opportunistic and one-off trips for inexperienced fishers and many that are keen recreational fishers for whom the experience is a core element of a vacation.

The final maps presented here received positive feedback from a stakeholder survey and we believe that our overall approach of using multiple data sources to triangulate towards an overall map of recreational fishing is powerful. Future iterations of this model would be strengthened by an effort to incorporate more data from private fishing vessels, including those operating within the countries, but also those coming from further afield: as an example the tournament-associated fishery in Grenada is heavily dominated by private vessels and the intensity of fishing from these may not be captured here.

Our financial assessment is drawn from a relatively small sample size and could be improved with a more in-depth survey of the sector including, as mentioned, an effort to include private vessels. The results indicate a direct expenditure of over US$6.8 million per year, but these represent only the payments to the operators themselves, while there are likely to be many associated expenditures, with some tourists even selecting destinations based on fishing opportunities. Our earlier reviews of exit polls and motivation surveys regularly show fishing to be an activity highlighted as a key or prime motivator for between one and six percent of tourist arrivals in the small island states of the Caribbean and it might be reasonable to conjecture that such visitors might move elsewhere if the quality of fishing was diminished.

Further thought could usefully be given to how to strengthen recreational fisheries as a sector in the region. This is a very high-value activity, and most participants, particularly the more regular fishers are generating high expenditure overall on their visits (Gentner and Obregon, 2018). There is good evidence that fishers are willing to pay well and a system of licensing may support the growth of this sector, while other management efforts, such as catch and release or other catch restrictions, combined with appropriate management of commercial fisheries might be considered to enhance recreational fisheries if this was considered a key sector for development.

Given the diffuse nature of this activity, and its lack of a direct link to any physical habitat we do not feel it would be helpful to try to spread economic value to the fishing areas. Future maps might, however attempt to show these values at the points of departure/landing.

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Appendices

Appendix A. Stakeholder Survey Data

Survey responses from charter operators are provided below. Due to its size, the table is broken up into multiple table, with the Participant ID field in the first column allowing for the linkage of responses among separate tables. Some of the data collected in this survey was used to estimate national tourism expenditures on recreational fishing; however, the small sample size may lead to bias.

1. Survey Instrument & Responses

Participant ID	**Location**	**3. Please select the activity your business offers**	**4. How many days of the week do you operate?**	**5. How many vessels are in your fleet?**
1	St. Vincent and the Grenadines	Whale watching tours, snorkeling, coastal cruise	3	2
2	Dominica	Whale watching tours, swimming with whales. diving, snorkeling, sea tours	2	1
3	St. Vincent and the Grenadines	Whale watching tours, snorkeling, island tours, scuba diving	6	1
4	Dominica	Recreational/sport fishing, Whale watching tours, swimming with whales, snorkeling, day charters	3	1
5	Dominica	Recreational/sport fishing, Whale watching tours, snorkeling	7	3

6	Dominica	Whale watching tours, diving, snorkeling	7	5
7	St. Vincent and the Grenadines	Whale watching tours, snorkeling, land and sea tours, coastal cruises	2	3
8	Grenada	Recreational/sport fishing, water tours, snorkelling, free diving	3	1
9	Grenada	Recreational/sport fishing, Water Tours, snorkelling	4	3
10	Grenada	Recreational/sport fishing	2	2
11	Grenada	Recreational/sport fishing	5	1
12	Saint Lucia	Recreational/sport fishing, Whale watching tours, coastal tours	7	7
13	Saint Lucia	Recreational/sport fishing, Whale watching tours, Private coastal charters	5	3
14	Saint Lucia	Recreational/sport fishing	7	1
15	Saint Lucia	Recreational/sport fishing, Whale watching tours, snorkeling, sunset cruise. sailing, charters	7	7
16	Saint Lucia	Recreational/sport fishing, snorkeling, charters, catch, clean and cook	2	3
17	Saint Lucia	Recreational/sport fishing, Whale watching tours, snorkeling, sunset cruise, interisland tours	3	1

18	St. Kiits and Nevis	Recreational/sport fishing	4	2
19	St. Kiits and Nevis	Recreational/sport fishing, snorkeling, water taxi	4	1
20	St. Vincent and the Grenadines	Whale watching tours	2	2
21	St. Kiits and Nevis	Recreational/sport fishing	2	1
22	St. Kiits and Nevis	Recreational/sport fishing	3	1
23	St. Kiits and Nevis	Recreational/sport fishing, snorkeling, coastal tours	4	1
24	St. Kiits and Nevis	Recreational/sport fishing	3	1
25	St. Vincent and the Grenadines	Recreational/sport fishing	3	1
26	St. Vincent and the Grenadines	Recreational/sport fishing, snorkeling, water taxi	5	1
27	St. Vincent and the Grenadines	Recreational/sport fishing, Whale watching tours, snorkeling, land and sea tours, semi-commercial fishing	1	2
28	Dominica	Whale watching tours, snorkeling, land tours	4	1
29	St. Vincent and the Grenadines	Recreational/sport fishing, Whale watching tours, snorkeling, coastal cruise	3	1

Participant ID	**6. How many persons are employed with your organisation? (including yourself)**	**7. Where do you depart from?**	**8. What is the average distance (miles) you travel to get to the fishing site(s)?**	**9. What is the average length of your trip? (from your departure to return)**

1	2			
2	6			
3	4			
4	6	Newtown Fishery Roseau Ferry Terminal	7 - 10 miles	4 hrs - 1/2 day 8 hrs - full day
5	6	Roseau, Portsmouth	5-8 miles	4 hrs (1/2 day) 6 hrs (3/4 day) 8 hrs (full day)
6	14			
7	3			
8	3	Windward	2-10	4- 6 hours
9	5	Harvey Vale, Hillsbourough	5	4
10	2	The Grenada Yacht Club, St. George's	10	full day (6-8hrs) 50 miles half day (4-6hrs) 30 miles
11	2	Port Louis Marina and St. George's	5 mile usually but up to 20-25 miles	1/2 day - 4 hr 3/4 day - 6rs full day - 8 hrs
12	21	Vigie Marina Rodney Bay Marigot Soufriere	2 -10	half day - 4 hrs full day - 8 hrs
13	11	Vigie Marina, Ganters Bay	2	3-4 hrs
14	2	Laborie	1/2	2 1/2 hours
15	22	Soufriere Marigot Marina Rodney Bay Marina Castries Port	3 - 12	4 hrs 6 hrs 8 hrs
16	3	Vieux Fort Port Laborie	5	4 hrs - half day 7 hrs - full day
17	4	Vieux Fort Soufriere Castries	5 - 7	half day - 4.5 hrs full day - 8.5 hrs
18	5	Oualie Beach Four Seasons Park Hyatt Port Zante Reggae Beach	5	4 hrs (1/2 day) 6-8 hrs (full day)
19	2	Oualie Beach Four Seasons Charlestown Port Zante Reggae Beach	2hrs - 1/2 mile (bottom fishing for kids); 4 hrs - 1.5 - 2 miles; 6 hrs - 15	2, 4, 6 and 8 hrs

		Park Hyatt Christophe Harbour	miles; 8 hrs - 20 miles	
20	2			
21	2	Port Zante Marina	10 - 12	4 hrs
22	2	Oualie Beach Four Seasons Park Hyatt Reggae Beach	2.5 - 3	2 hrs 4 hrs - half day 6-8 hrs - full day
23	2	Port Zante Four Seasons Frigate Bay Turtle Bay	4 - 6	half day - 4 hrs full day - 8 hrs
24	3	Oualie Beach Reggae Beach Crystal Habour	2 -4	4 hrs - half day 6-8 - full day
25	2	Canouan Petit St. Vincent (PSV)	5 - 40	4 hrs 8 hrs
26	3	Admiralty Bay Harbour, Port Elizabeth, Bequia	5 - 10	half day - 4 hrs full day - 7-8 hrs
27	4	Blue Lagoon Marina	6 - 12	5 hrs - half day 8 hrs - full day
28	6			
29	2	Villa	5	4 hrs - half day 6-8 hrs - full day

Participant ID	10. What is the average cost per tour? ($USD)	11. Please select your peak month(s) where you have the most customers.	12. What are your average number of tours per week for your (i) peak season (ii) low season [Peak season]	12. What are your average number of tours per week for your (i) peak season (ii) low season [Low season]
1				
2				
3				
4	4 hrs - 1/2 day - 600 8 hrs - full day - 1200	January, February, March, April, November, December	<5	<5
5	4 hrs (1/2 day) - 600 6 hrs (3/4 day)	January, February, March,	<5	<5

	- 800 8 hrs (full day) - 1100	November, December		
6				
7				
8	$500- $1000 with a max of 10 persons. $500 for max of 2 person	January, February, March, April, May, December	<5	<5
9	$400 (half day tour). $100 per hour for longer trips	January, February, March, April, November, December	<5	<5
10	half day - 600 full day - 1000	January, February, March, December	<5	<5
11	1/2 day - 550 3/4 day - 725 full day - 900	January, February, March, April, November, December, Peak months during peak season are February and March	5-7	<5
12	half day - 600 full day - 1500 100 per persons from cruise ships	January, February, March, April, November, December	>12	7-9
13	100 per person 600-900 to charter the boat	January, February, March, November, December	5-7	<5
14		March	5-7	<5
15	4 hrs - 550/660 6 hrs - 660/880 8 hrs - 880/1100 **dependent on boat 31ft/38ft	January, November, December	7-9	<5
16	half day - 350-500 full day - 400 - 800	January, February, December	<5	<5

	**dependent on number of guests **270-370 local rate			
17	half day - 550 full day - 1200	January	<5	
18	4 hrs (1/2 day) - 600 6-8 hrs (full day) - 1200	January, February, December	5-7	<5
19	2 hrs - 300 4 hrs - 650 6 hrs - 950 8 hrs - 1400	January, February, March, November, December, March is peak for kids	5-7	<5
20				
21	600 (foreigners rate) 550 (local rate)	January, February, March, April, December	5-7	<5
22	2 hrs - 300 4 hrs - 600 6-8 hrs - 1200	January, February, March, April, May, November, December	5-7	<5
23	half day - 600 full day - 1200	January, February, March, April, December, last 2 weeks of December is the peak	5-7	<5
24	4 hrs - 600 6-8 hrs - 1200	January, December	10-12	<5
25	4 hrs - 200 8 hrs - 400	December	5-7	<5
26	half day - 600 full day - 1000	January, February, March, April, November, December	<5	<5
27	half day - 500 full day - 800	January, February, December	<5	<5
28				
29	half day - 400 full day - 700	January, February, March, April,	<5	<5

		November, December		

Participant ID	13. What are the species of fish caught?	14. Which are the most abundant of the species caught?	15. Do you do any catch and release? If yes, what species?	16. What is the estimated percentage of customers who are local vs foreign?
1				
2				
3				
4	Barracuda, Sailfish, Dolphin, Blue Marlin, White Marlin, Wahoo, Yellowfin Tuna, Skipjack Tuna, Rainbow Runners, kingfish, spanish mackerel, sero mackerel	Barracuda, Blue Marlin, Wahoo	No	100 foreign
5	Dolphin, Wahoo, Yellowfin Tuna, Skipjack Tuna, Rainbow Runners, snapper, grouper	Yellowfin Tuna	Yes, sailfish, marlin	90% foreign
6				
7				
8	Barracuda, Dolphinfish, Cavalli, spanish mackerel, kingfish	Barracuda, Cavalli	No	80% Foreign : 20% Local
9	Barracuda, Yellowfin Tuna, Skipjack Tuna, Rainbow Runners, cavalli	Yellowfin Tuna, Skipjack Tuna	No	100%
10	Barracuda, Sailfish, Dolphin, Blue Marlin, White Marlin, Wahoo, Yellowfin Tuna,	Barracuda, Sailfish, Wahoo, Yellowfin Tuna	Yes, billfish	90% foreign and 10% local

	Skipjack Tuna, Rainbow Runners, snapper, grouper			
11	Barracuda, Sailfish, Dolphin, Blue Marlin, White Marlin, Wahoo, Yellowfin Tuna, Skipjack Tuna, Rainbow Runners	Barracuda, Sailfish, Dolphin, Wahoo	Yes, All billfish	5% local, 95% foreign
12	Barracuda, Sailfish, Dolphin, Blue Marlin, White Marlin, Wahoo, Yellowfin Tuna, Skipjack Tuna, kingfish, snapper, grouper, cavalli, amber jack	Barracuda, Sailfish, Dolphin, Blue Marlin, Wahoo, Yellowfin Tuna	Yes, billfish	95% foreign and 5% local
13	Barracuda, Sailfish, Dolphin, Blue Marlin, White Marlin, Wahoo, Yellowfin Tuna, Skipjack Tuna, Rainbow Runners, mackerel, red snapper, jacks, cavali, grouper	Barracuda, Sailfish, Dolphin, Wahoo, Yellowfin Tuna	Yes, Billfish	80% foreign and 20% local
14	Barracuda	Barracuda	Yes	10
15	Barracuda, Sailfish, Dolphinfish, Blue Marlin, Wahoo, Yellowfin Tuna, snapper, spanish mackerel, cavalli	Barracuda	Yes, billfish	95% foreign and 5% local
16	Barracuda, Dolphinfish, Blue Marlin, Wahoo,	horse-eye jack	No	55% local and 45% foreign

	Yellowfin Tuna, Skipjack Tuna, Rainbow Runners, cavalli, horse-eye jack, snapper, grouper			
17			Yes, billfish	
18	Barracuda, Dolphin, Blue Marlin, Wahoo, Rainbow Runners, blackfin	Barracuda, Dolphin, Yellowfin Tuna	Yes, billfish	95% foreign
19	Barracuda, Sailfish, Dolphin, Blue Marlin, Wahoo, Skipjack Tuna, blackfin, spanish mackerel, bonito	Barracuda, Dolphin, Wahoo	Yes, billfish	100% foreign
20				
21	Barracuda, Sailfish, Dolphin, Blue Marlin, White Marlin, Wahoo, Yellowfin Tuna, Skipjack Tuna, Rainbow Runners	Barracuda, Dolphin, Wahoo	Yes, Billfish	80% foreign
22	Barracuda, Dolphinfish, Wahoo, Yellowfin Tuna, Skipjack Tuna, Rainbow Runners, Bonito, spanish mackerel	Barracuda, Wahoo	Yes, billfish	95% foreign and 5% local
23	Barracuda, Dolphinfish, Wahoo, Skipjack Tuna, blackfin tuna. king fish, spanish mackerel	Dolphinfish, Wahoo	Yes, billfish and juvenile dolphinfish	95% foreign and 5% local

24	Barracuda, Dolphinfish, Wahoo, Yellowfin Tuna, Skipjack Tuna, kingfish, billfish	Barracuda, Wahoo	Yes, billfish	100% foreign
25	Barracuda, Dolphin, Blue Marlin, Wahoo, Yellowfin Tuna, Skipjack Tuna	Barracuda, Dolphin, Yellowfin Tuna	Yes, Flyfishing bonefish permit and tarpon	100% foreign
26	Barracuda, Sailfish, Dolphinfish, Blue Marlin, Yellowfin Tuna, Skipjack Tuna, cavalli	Barracuda	No	95% foreign and 5% local
27	Barracuda, Sailfish, Dolphinfish, Blue Marlin, Wahoo, Yellowfin Tuna, Skipjack Tuna, Rainbow Runners, snapper, amber jack, grouper	Barracuda, Wahoo	Yes, billfish	70% foreign and 30% local
28				
29	Barracuda, Dolphinfish, Blue Marlin, White Marlin, Wahoo, Yellowfin Tuna, Skipjack Tuna, spanish mackerel, cavalli	Barracuda, Yellowfin Tuna, Skipjack Tuna, cavalli	No	100% foreign
Participant ID	**17. Where do you depart from?**	**18. What is the length of your whale watching tour? (You may select more than if you offer different packages)**	**19. What is the average distance (miles) you travel on a tour?**	**20. What is the average cost per tour? ($USD)**
1	Barrouallie	2-4 hrs	2	100

2	Portsmouth Beach Hotel Dock Longhouse Roseau Ferry Terminal	4-6 hrs, swim with the whales - 8 hrs	3 miles out and traverse 30-40 miles	100
3	Kingstown but can depart from Bequia or other Grenadines islands if required	2-4 hrs	7	1000 to charter boat; 120 per person for cruise ship passengers
4	Newtown Fishery Roseau Ferry Terminal	2-4 hrs, 3 hrs	1/2 - 10 miles	70
5	Fort Young Castle Comfort/ Dive Dominica Jetty Anchorage, Roseau	2-4 hrs, 2.5 - 3 hrs	5 - 8 miles	89
6	Roseau Ferry Terminal, Castle Comfort/Dive Dominica Jetty	2-4 hrs, 3.5hrs	1/4 - 15 miles	69
7	Villa Beach Kingstown Cruise Birth	2-4 hrs	15-20	60
8				
9				
10				
11				
12	Vigie Marina Castries Port	2-4 hrs, 3 - 3.5 hrs	3-5 miles	55
13	Ganters bay	2-4 hrs	2.5 - 3	60
14				
15	Soufriere Castries (for cruise ship passengers)	2-4 hrs	1 - 5	66 - adult, 44- children (local rates 30 and 15 for adult and children respectively)
16				
17	Vieux Fort Soufriere Castries	2-4 hrs		550
18				
19				
20	Barrouallie	2-4 hrs	12	40
21				

22				
23				
24				
25				
26				
27	Blue Lagoon Marina	4-6 hrs, usually whale watching is coupled with other activities such as snorkeling, beach visits and coastal tours	3	500 to charter boat (max of 8 guests)
28	Roseau Ferry Terminal, Roseau Woodbridge	2-4 hrs	3 - 12 miles	60 b
29	Villa Kingstown Cruise Birth Young Island Dock	4-6 hrs, whale watching is coupled with other activities such as snorkeling and beach tours	5 - 10 miles	400 to charter the boat; 50 person person (if over 8 persons)

Participant ID	21. Please select your peak month(s) where you have the most customers.	22. What are your average number of tours per week for your (i) peak season (ii) low season [Peak season]	22. What are your average number of tours per week for your (i) peak season (ii) low season [Low season]	23. What is the average number of guests per tour during your peak and low season? [Peak season]
1	January, February, March, April, May, June, July, August, October, November, provide tours to schools and partners/affiliates of the St. Vincent and the Grenadines Environmental Fund (SVGEF) year round	<5	<5	>10

2	January, February, March, April, December	5-7	<5	>10
3	January, February, March, April, November, December	5-7	<5	>10
4	January, February, March, April, November, December	5-7	<5	>10
5	January, February, March, November, December	5-7	<5	7-9
6	January, February, March, November, December	>12	7-9	>10
7	January, February, March, November, December	<5	<5	>10
8				
9				
10				
11				
12	January, February, March, April, November, December	>12	5-7	>10
13	January, February, March, November, December	<5	<5	>10
14				
15	January, December	<5	<5	7-9
16				
17				
18				
19				

20	January, February, March, April	<5	<5	5-7
21				
22				
23				
24				
25				
26				
27	March, April, August	<5	<5	3-5
28	January, February, March, November, December	7-9	<5	>10
29	January, February, March, April, November, December	<5	<5	7-9

Participant ID	**23. What is the average number of guests per tour during your peak and low season? [Low season]**	**24. What are the species of whales and dolphins seen?**	**25. What are the most common species of whales and dolphins seen?**	**26. What is the estimated percentage of customers who are local vs foreign**	**27. Please feel free to share any other comments or information about your whale watching and/or recreational/sport fishing activities that you deem relevant to this exercise.**
1	3-5	Sperm whale, Short-fin pilot whale, Killer whale, Humpback whale, Bottle-nose dolphin,	Short-fin pilot whale, Bottle-nose dolphin	85% foreign and 15% local	

		risco/grampus dolphin			
2	5-7	Sperm whale, Short-fin pilot whale, Pygmy killer whale, Cuvier beaked whale, Humpback whale, Dwarf sperm whale, Fraser's dolphin, Bottle-nose dolphin, Rough tooth dolphin	Sperm whale, Pan tropical spotted dolphin	90% foreign	Runs a 5 days ocean programme which includes watching and swimming with whales.
3	>10	Sperm whale, Short-fin pilot whale, Humpback whale, Pan tropical spotted dolphin, Bottle-nose dolphin	Sperm whale, Short-fin pilot whale, Pan tropical spotted dolphin, Bottle-nose dolphin	100% foreign	
4	5-7	Sperm whale, Short-fin pilot whale, Killer whale, False killer whale, Pygmy killer whale, Humpback whale, Dwarf sperm whale, Pygmy sperm whale, Pan tropical spotted dolphin, Fraser's dolphin,	Sperm whale, Short-fin pilot whale, Pan tropical spotted dolphin, Bottle-nose dolphin	100 foreign	

		Bottle-nose dolphin, Rough tooth dolphin, Long-snouted spinner dolphin			
5	3-5	Sperm whale, Humpback whale, Bottle-nose dolphin, Long-snouted spinner dolphin	Sperm whale, Bottle-nose dolphin, Long-snouted spinner dolphin	90% foreign	
6	>10	Sperm whale, Short-fin pilot whale, Killer whale, False killer whale, Melon-headed whale, Pygmy killer whale, Cuvier beaked whale, Humpback whale, Bryde's whale, Dwarf sperm whale, Pygmy sperm whale, Pan tropical spotted dolphin, Fraser's dolphin, Bottle-nose dolphin, Rough tooth dolphin, Long-snouted	Sperm whale, Short-fin pilot whale, Pan tropical spotted dolphin, Fraser's dolphin, Bottle-nose dolphin	90% foreign	During peak season, 3 vessels are in operation. At full capacity (cruise ship season particularly the months Nov-Feb), each tour can be as much as 270 guests. Tours are run on Sundays specifically for locals.

		spinner dolphin			
7	7-9	Sperm whale, Short-fin pilot whale, Humpback whale, Bottle-nose dolphin, spinners	Short-fin pilot whale, Bottle-nose dolphin	95% foreign and 5% local	
8					
9					
10					guest preference is the major influence as to where I would go for fishing. Eg. Tours with young passengers will be focused closer to shore within the inner bay, whereas more experienced passengers would prefer longer tours further out at sea. Bottom fishing for snapper and grouper will normally take place around rein deer shallows which would range from 40 to 100/150ft in depth. 5 miles off rein

					deer shallows one can find an under water mountain where most of trolling would take place for yellow fin tuna.
11					- Usually fish in areas with a depth of between 1000-2000m but can travel to areas with 8000m depths. - The western side of the island with its calmer water is best for fishing particularly when winds are coming in from the East. Worst conditions are usually when winds are coming in from the North. Very rarely do wind come from South (would not go out in these cases)
12	>10	Sperm whale, Short-fin pilot whale, Melon-headed whale, Humpback	Sperm whale, Short-fin pilot whale, Pan tropical spotted dolphin, Fraser's	90% foreign and 10% local	

		whale, Pan tropical spotted dolphin, Fraser's dolphin, Bottle-nose dolphin, milke, grampus, spinner dolphin	dolphin, Bottle-nose dolphin		
13	>10	Sperm whale, Short-fin pilot whale, Killer whale, False killer whale, Humpback whale, Pan tropical spotted dolphin, Fraser's dolphin, Bottle-nose dolphin, spinners, grampus	Sperm whale, Short-fin pilot whale, Pan tropical spotted dolphin, Bottle-nose dolphin	80% foreign and 20% local	
14					
15	3-5	Sperm whale, Short-fin pilot whale, Humpback whale, Pan tropical spotted dolphin, Fraser's dolphin, Bottle-nose dolphin, spinner dolphin	Short-fin pilot whale, Pan tropical spotted dolphin, Bottle-nose dolphin	65% foreign and 35% local	
16					
17					UB Tours is a new provider operating for 2 months
18					

19					
20	<3	Sperm whale, Short-fin pilot whale, Humpback whale, Bottle-nose dolphin	Short-fin pilot whale, Bottle-nose dolphin	80% local and 20% foreign	
21					
22					
23					
24					
25					Wish people could fish a little more sustainable and stop the swine nets on beaches which are completely ruined the country...if you remove the bait you kill the rest of the food chain
26					
27	<3	Sperm whale, Short-fin pilot whale, Killer whale, False killer whale, Humpback whale, Pan tropical spotted dolphin, spinner dolphin	Short-fin pilot whale, Pan tropical spotted dolphin, spinner dolphin	100% foreign	
28	>10	Sperm whale, Short-fin pilot whale, Humpback whale, Bottle-nose dolphin,	Sperm whale, Bottle-nose dolphin	98% foreign	

		Rough tooth dolphin			
29	3-5	Sperm whale, Short-fin pilot whale, Killer whale, False killer whale, Humpback whale, Dwarf sperm whale, Pygmy sperm whale, Pan tropical spotted dolphin, Fraser's dolphin, Rough tooth dolphin, spinner dolphin	Short-fin pilot whale, Pan tropical spotted dolphin, Fraser's dolphin, spinner dolphin	90% foreign and 10% local	

Appendix B. Artificial Intelligence and Machine Learning Technical Overview

Overview

For the image classification component of this research we used the Azure Custom Vision service from Microsoft to rapidly develop images classification models and classify publicly available, geotagged images from the photo sharing website Flickr and user-uploaded images provided by TripAdvisor. In total, five classifiers were developed and implemented to classify images into four categories: on-reef/underwater, reef-adjacent, recreational fishing, and kayaking/stand-up paddleboarding. This section is largely specific to the recreational fishing model but references other models as examples of methodologies common to all approaches.

Image Sources

Flickr

The image sharing platform, Flickr, provides an API that can be used to query image metadata for publicly shared images. This metadata includes many attributes including the images publicly available URL (used to view and analyze images), coordinates, title, tags (text keywords assigned by the photo's owner), the image date, among many others.

TripAdvisor

TripAdvisor provided a table that included records with URLs for 212,709 images. Some of these images were no longer available, and some were too large to send to the Cognitive Services API, so they were removed from the pool. 190,509 images fit the criteria for analysis.

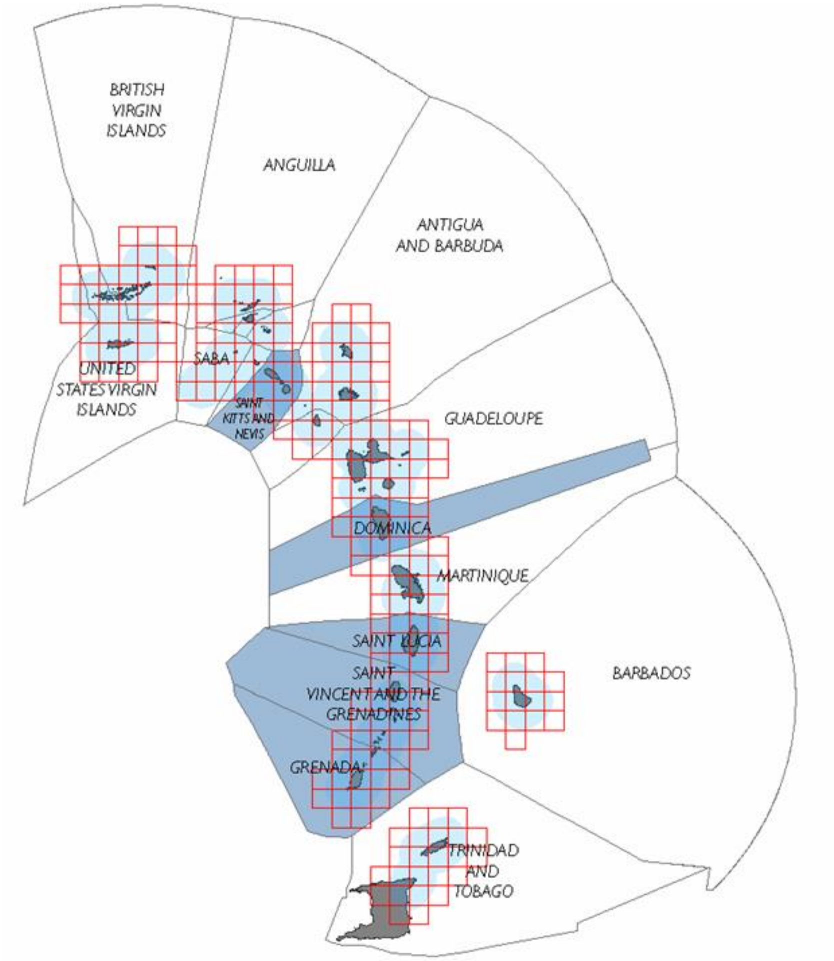

Figure B1. *Flickr Search Extents*

Software/Tools

Microsoft Azure Cognitive Services

Azure Cognitive Services are a suite of tools from Microsoft that use machine learning and AI algorithms for various applications including language, speech, and vision. The Computer Vision API analyzes images using a predefined classifier that returns image labels with a confidence score (e.g. name: fishing, confidence: 0.85; name: boat, confidence: 0.83), and a list of descriptors (person, outdoor, water, fishing, etc.). For the purposes of this research, however, we needed to classify images into very specific categories, (e.g. differentiating a reef-adjacent beach to a non-reef-adjacent beach) which isn't possible using the standard Azure Computer Vision service, so instead, we used the Azure Custom Vision service, which allows users to build, deploy, and improve their own classifiers for specific scenarios.

Azure Custom Vision Web Portal and SDK

The Custom Vision service has a web portal that can be used to create new classifiers, upload and tag images, train classifiers, evaluate classifier performance, and 'quick test' on single images. To facilitate the development and implementation of our classifiers, we used the Custom Vision Python SDK (https://docs.microsoft.com/en-us/python/api/overview/azure/cognitive-services?view=azure-python), which enabled the rapid development of five unique classifiers, uploading of thousands of tagged images, and more than one million image classification operations. We found the web portal most useful for 'one-click' operations like initiating model training, publishing models for analysis, and testing classifier performance on single images. While it is possible to use the web portal to upload and tag images, we found it very advantageous to do so programmatically, using the SDK. To better manage the training and tagging of images as well as reviewing classifier results, Google Sheets spreadsheets were used.

Google Sheets

Google Sheets is a free spreadsheet program offered by Google as a component of its Google Drive service and was used extensively for this project. Most importantly, the IMAGE function, which inserts an image into a cell using a URL, allowed us to view images directly in the Flickr and TripAdvisor spreadsheets so we could view the images themselves. This allowed us to use the spreadsheets not only for tracking purposes, but also for tagging positives and negatives and reviewing and validating the classification results. As an added benefit of using a cloud-based service, team members all over the world could collaborate on shared documents without the hassle of implementing an enterprise system or sharing static files. The gspread Python library (https://github.com/burnash/gspread, version 3.1.0) was utilized to read data directly from our Google sheets for uploading into the classifiers in the Custom Vision platform. Prior to using the gspread module to access the Google Sheets API, the application needs to be authroized and API access enabled (https://gspread.readthedocs.io/en/latest/oauth2.html.)

Methods

Downloading Flickr Images

We used the flickrapi Python library (https://pypi.org/project/flickrapi, version 2.4.0) to query the Flickr API to identify all images in the Eastern Caribbean from 2005 through August 2019. Any of the fields in the Flickr data schema can be queried, which allowed us to easily construct spatiotemporal queries. We noticed some inconsistencies when querying large numbers of images at once (for example the entire island of St. Lucia), so to ensure a complete dataset was returned, we used ¼ degree bounding box spatial queries combined with monthly date range temporal queries (looping through each ¼ degree cell for each month) and then compiled the results into a table. The bounding boxes were limited to covering an area of 30 meters from coral reefs for the area of interest (Figure 1). This data was saved into a CSV table, yielding a total of 174,288 images. Of these, 40,568 were within the Exclusive Economic Zone (EEZ) of the five countries studied for this project. The remaining images from non-OECS countries were used to train the computer vision classifiers.

Image Classifier Development

To rapidly deploy custom classifiers, our workflow followed a specific routine:

1. Create a simple classifier with 20-30 positive images and run on all training images
2. Load preliminary results into Google Sheets spreadsheet and create image tag fields
3. Sort through spreadsheet to identify and tag false positives and tag additional images in positive class
4. Use gspread Python module and the custom vision Python API to load training data from spreadsheet into a new classifier iteration
5. Train and run classifier on OECS images
6. Evaluate performance

Design

Our approach to developing the classifiers was to create simple, focused binary models, with the notion that we could implement more than one model per category if necessary. Each classifier was developed with a single positive class containing representative images (e.g. reef-adjacent) and a single negative class containing non-representative images (e.g. non reef-adjacent). The non-representative images in the negative class for each classifier were very carefully selected to include only specific images that had the highest probability of being a false positive for that particular category. It is unnecessary to include images in the negative class that would otherwise have a low confidence score. For example, the recreational fishing model would score a picture a person on a boat high since model was trained with similar images. So, images of people on boats that were not holding fish were included in the negative class. However, the model would not score a picture of a cityscape with a high probability, since no such images were used for training, so it was unnecessary to include urban landscape pictures in the negative class. This design principle was used for all model development.

In all of our use cases, representative pictures were extremely variable. We found the single most important concept for creating successful classifiers was to ensure the use of varied training images that represented the category of interest. For example, a positive reef-adjacent image could be nothing more than white sand and turquoise water or it may include boats, palm trees, beachgoers, buildings etc. The ability in developing successful models—both the positive and negative classes—lies in not overemphasizing any one particular feature in either class. For example, when developing the reef-adjacent model, images of palm trees without any ocean visible were yielding high confidence scores because so many palm trees were included in the images in the positive class. To counteract this in the model, non-reef-adjacent images with palm trees were added to the negative class. This concept carried through the entire training process for each model we developed. Microsoft recommends selecting images that vary by camera angle, lighting, background, and visual style. In practice, we found these concepts to be the most important aspect of the training process.

Additionally, the classifiers needed to be trained according to the images that we needed to classify. When we first began this research, there was discussion of using Google or Bing image searches to train models. At this time we were solely focused on the on-reef/underwater model. We came to quickly realize that popular images of coral reefs show vibrant underwater landscapes full of many species of coral, fish, and other marine life. In application, however, most images in Flickr and TripAdvisor are not nearly as impressive. It was decided to use training images from the same platform as the images we were analyzing for this reason.

It is recommended by Microsoft to have an even distribution of images, however, in all of our models, there are more negative images than positives. This is due largely to the fact that the categories of activities we were classifying were dynamic and we needed extensive and varied negative classes to counterbalance the false positives we were getting. In our case, we didn't have an unlimited supply of training data, so we made sure to only include category-positive images that were truly representative. Rather than dilute the quality of images in the positive classes we chose to proceed with unequally sized classes.

Creation

Classifiers are simple to create in the Custom Vision service, whether using the GUI or the SDK. There are two project types available: object detection and classification. Object detection finds the location of content within images, whereas image classification, the method we utilized, labels whole images. The Custom Vision service also offers two types of classifiers: multilabel and multiclass. The multilabel classification type allows for an image to be assigned to one or more tags whereas the multiclass type each image must be assigned to only one type. Since all of our classifiers are binary, the classification type was irrelevant. Once a new classifier is created, it is ready to be trained with tagged images.

Training

Training and evaluating the classifiers was by far the most time consuming part of this work. The image classifiers were all trained using Flickr images from non-OECS countries in the Caribbean. Initially, rather than searching through tens of thousands of predominantly irrelevant pictures, a text query was applied to the tags in the Flickr training images to identify several dozen clearly representative images for each category. Then, a simple classifier was created with a single positive class, trained, and run against all the training data. These results were saved as a CSV and loaded into a Google Sheets spreadsheet and sorted by confidence level in descending order. The image field (to view the images in line in the spreadsheet) and a tag field were added to the spreadsheet, then we tagged true positives and false positives from the list for the development of what we considered the first complete iteration of a classifier. When we had a sufficient amount of varied images in both the positive and negative classes, making sure to account for the types of false positives in the initial iteration, the gspread Python module and Custom Vision Python SDK were used to load the tagged images into a new model iteration.

The classifiers were trained using the advanced training type in the Custom Vision web portal and published for analysis. There is also the option for a simpler quick training that was not used. Even with a potential training time budget of 24 hours for the advanced training, the trainings typically took between 5 and 10 minutes to complete. When a classifier is published, that particular iteration becomes available at the URL endpoint for that model and is ready to receive requests from the SDK. Using the Python SDK, the classifier was then run on the OECS Flickr data for review. With each iteration, we added and/or removed particular images from the positive and negative classes in the training data to tune the classifier for better performance based upon reviewing the previous iteration until a sufficient model was developed.

Evaluation

Our focus was to develop precise classifiers rather than models that identified more of the target images, but did so with less accuracy. The Custom Vision classifier output is simply a confidence score per image. Per our workflow, the results were compiled into a CSV file and loaded into Google Sheets for review. Precision and recall are two standard image classification evaluation metrics, which we calculated in some cases on a subset of results. Precision specifies how accurate model predications are, or what percentage of time the model is correct in its predictions. For example, if the model found 100 underwater images and 95 were correct, the precision would be 95%. Recall indicates the percentage of all images that were classified, that is, how well the model was able to find all the images of a certain category. For example, if there were 100 reef-adjacent images in the pool of images and the model found 90, the recall would be 90%. Precision and recall are calculated based upon the selected predicted value, or confidence score.

While the Custom Vision web portal does calculate precision and recall on the training data using a k-fold cross validation technique (Table 1), in practice we found these numbers to not be fully representative of the data being classified. For example, for the reef-adjacent model we tagged 714 images in the Flickr results as being positive or negative. At a 99% confidence level, our metrics showed a 95.7% precision and 68% recall, whereas the metrics calculated by the Custom Vision web portal demonstrated a 100% precision and 85% recall. We attributed the difference to the fact that even with extensive improvement, the training data is still not fully representative of the entire population of images, and the nuance in the concept of reef-adjacency and the similarity between positive and negative images.

Models

The inputs and outputs from the classifier are described in Table A1.

Table B1*. Computer Vision Model Descriptive Statistics*

# Positive training images	# Negative training images	Threshold for inclusion	Custom Vision Precision	Custom Vision Recall	Flickr Identified	% of Total Flickr	TripAdvisor Identified	% of Total TripAdvisor
68	128	90%	100%	71.40%	8	0.02%	321	0.17%

Recreational Fishing

Positive recreational fishing image are predominated by pictures of people holding trophy fish on boats and docks. At the outset, we felt the recreational fishing model was going to be straightforward and simple. However, the variation in positive images and nuanced similarities between the positive and negative classes, similar to the reef-adjacent model, proved the task more challenging than initially forecast. As such, the negative class includes many pictures of boats without fishing, fish that aren't being displayed as a catch (either underwater or already caught), and people standing on boats or near water that aren't fishing or holding fish.

The false positives in this model remained fairly persistent even after continuing to add images into the negative class. Namely, images of people on boats continued to receive high confidence scores even after including many such images in the negative class. Model improvement would have been likely given additional development time, including the possibility of developing an additional model to capture people fishing with fishing poles, but was outside the scope of this project, especially given the limited number of fishing images in the Flickr and TripAdvisor datasets.

The final iteration of the recreational fishing model had 68 positive images and 128 negative images, and yielded only 8 Flickr images and 321 TripAdvisor images using a 95% confidence threshold.

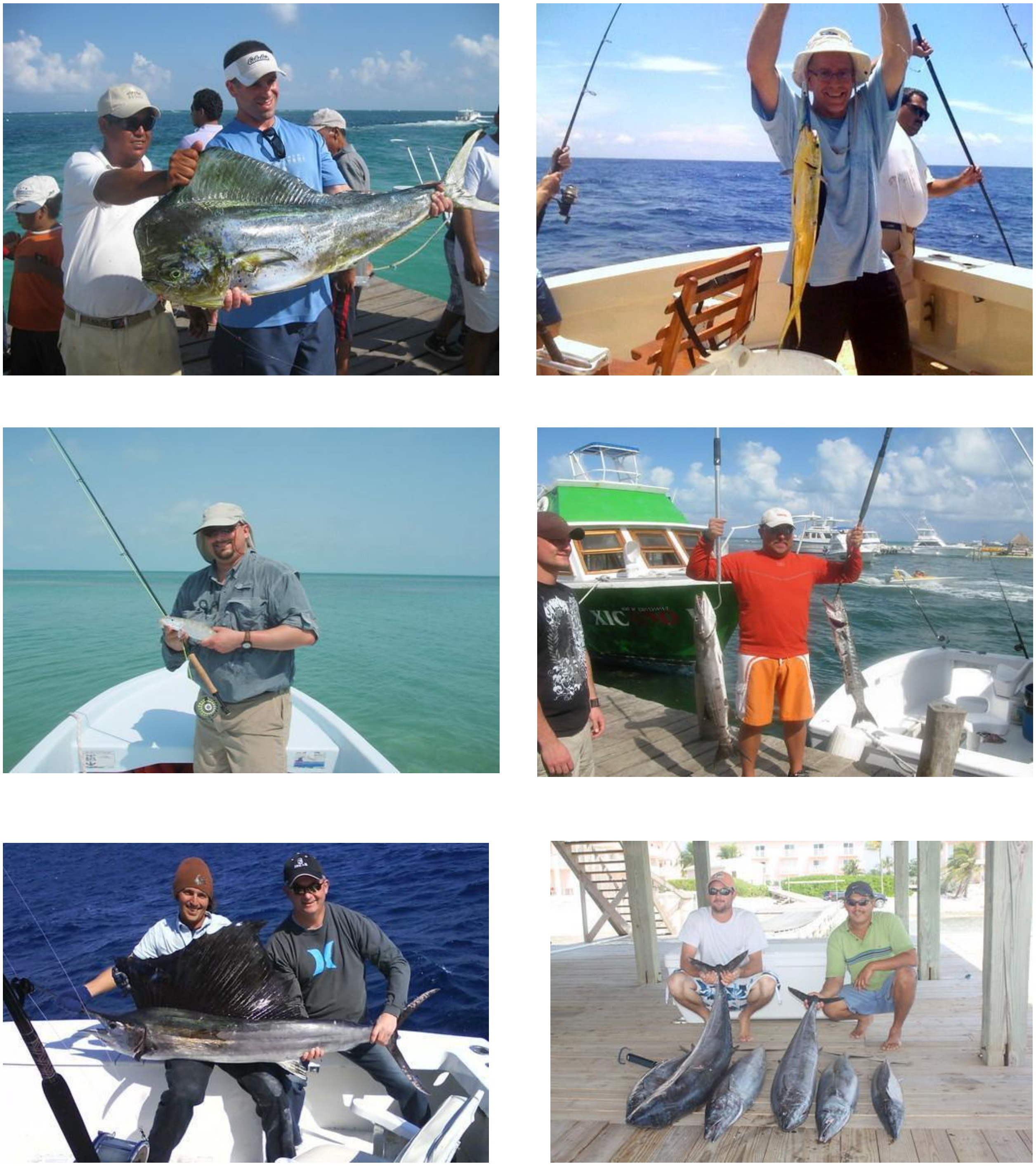

***Figure B2**. Sample of Recreational Fishing Positive Images*

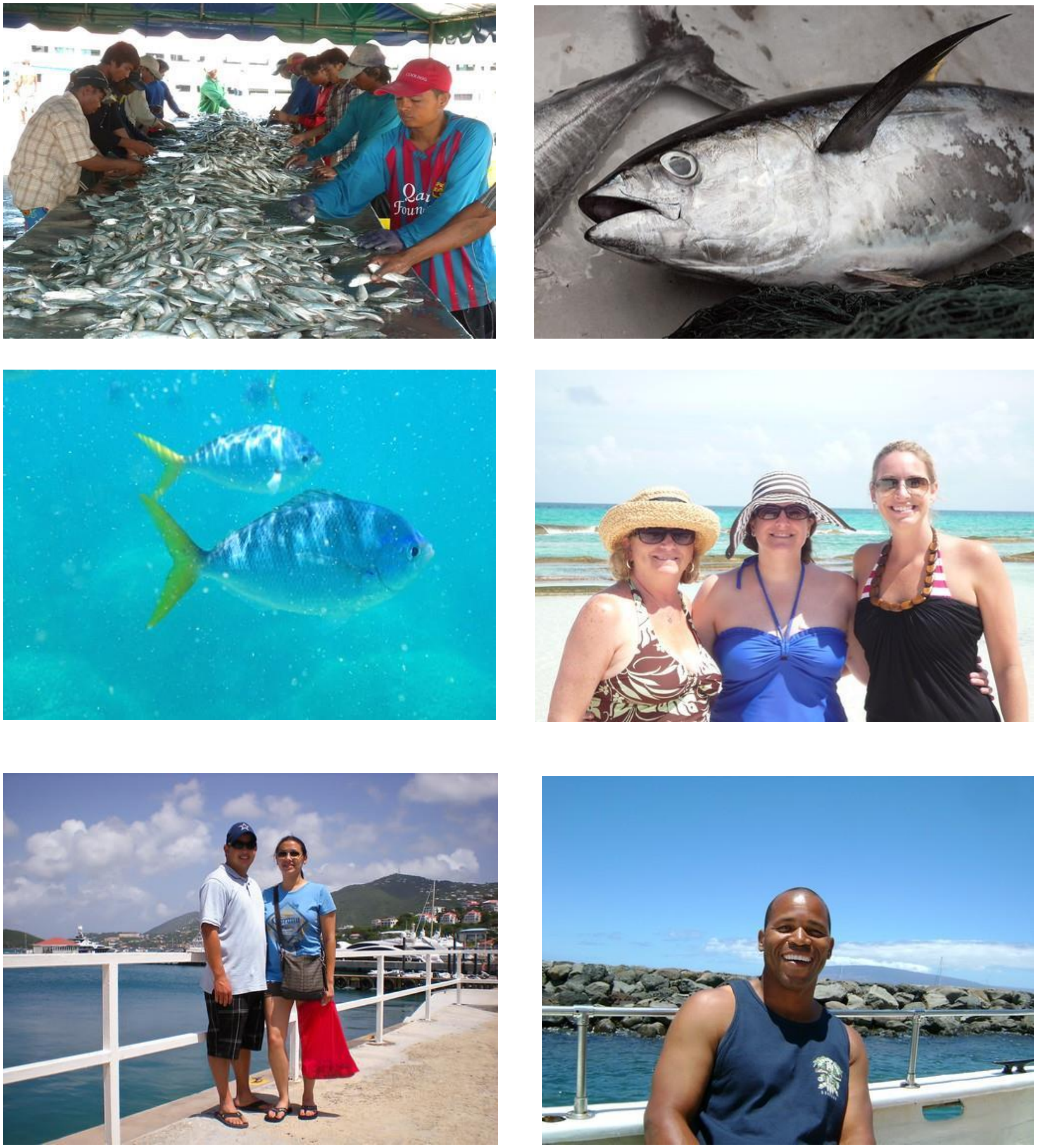

Figure B3*. Sample of Recreational Fishing Negative Images*

Discussion

This research demonstrates the validity of leveraging a COTS (commercial off the shelf) computer vision service, like Microsoft's Azure Custom Vision, to rapidly train image classifiers and analyze large sets of images. The approach we took to developing the computer vision models was based upon our previous experience and recommendations from Microsoft. Exhaustively testing the development methodology or model performance of any individual model was outside the scope of this work. While our experiences and many best practices learned during this project are detailed in the methods section of this write-up, the following content contains recommendations and discussion points for future work in this area.

Developing Models

- Ensure the subject/category of interest suitable for a computer vision/image classification solution
    - Using this project as an example, the underwater, recreational fishing, and paddling categories all have distinct differences between the representative positive and negative images. However, positive and negative reef-adjacent images often look very similar, which can make automated image classification difficult.
- Confirm you have an image repository with enough images for training and classification
- Train model for the images being analyzed
    - We trained our models using Flickr images from non-OECS Eastern Caribbean countries so that we made sure to have the most representative data possible.
    - There may be regional or other differences in your data to take into consideration when developing models with different applications.
- Ensure the use of an adequate number of images in each class

Considerations for Future Work

- Combining classes/categories into a single model
    - We implemented individual binary models for each image category and did not explore creating one large model with multiple classes. It is unknown whether this would have an impact on individual model performance.
- Pixel resolution of training images
    - We used Flickr images with medium resolution for training and analysis, which are universally available for each Flickr image. Flickr creates thumbnails of different sizes for each user image uploaded to the platform, but not all resolutions are available for all images, hence our decision to use the medium resolution images. Additionally, the upper limit for the Custom Vision platform per image is capped at 4MB. The impact of using higher resolution images for training and analysis remains unknown, but should be explored if warranted for a given application. For this research, the TripAdvisor images had variable resolution, including images with higher resolution, however, quantitatively comparing results independently by image source (e.g.

Flickr performance vs. TripAdvisor performance) was outside the scope of this work.

- Platform Selection
    - This work exclusively used the Microsoft Cognitive Services platform, taking advantage of an in-kind software grant from Microsoft. In the absence of having unrestricted access to a computer vision service, other computer vision platforms and/or the development of a custom classifier ought to be explored for performance, cost, and ease of use.
- Attempt to use an even number of images in each class
    - All of our models had more negative images than positive training images. This was due to the fact that our models had varied categories of false positives that needed to be trained into the model, while the positive class was more focused in scope. Given more time and a larger image repository, the impact of implementing evenly sized classes could have been explored in-depth.
- Develop a consistent control dataset to evaluate model performance
    - We did not employ a consistent control dataset across all of our models to evaluate the performance of each model iteration. Instead, we relied on the metrics calculated in the Custom Vision portal and a visual review of the outputs. While our approach allowed us to rapidly develop five models over the duration of the project, if we were to repeat this work we would take the time at the project outset to create a consistent control set of images.

Text Classification

The team defined and developed criteria for nine different categories related to nature-dependent tourism by which to classify TripAdvisor attraction reviews. For the purpose of the models described in this report, the categories and criteria were as follows, although we used this tool to identify other categories of tourism not described in this report.

When looking to classify reviews as positive for this category, we were looking for any indication that recreational fishing was undertaken, or was available, to the person making the review. They do not have to have caught anything, or have enjoyed it! If it is mentioned that it was available, even if they didn't do it, it still counts as they clearly registered its existence which is a (small) indication of its value.

- Game-fishing
- Sport fishing
- Deep sea fishing
- Fly fishing
- Trolling

- Offshore fishing
- Fishing charter

PLUS

Any of these fish:

- Mahi mahi
- Wahoo
- Sailfish
- Marlin
- Barracuda
- Kingfish
- Tuna
- Bonefish
- Jacks
- Snapper
- Trevally
- Grouper

With any of these terms:

- Catch
- Caught
- Landed
- Capture/Captured

We used the free, web-based tool LightTag to classify reviews that met the criteria described above, as well 7 other aspects of nature-dependent tourism, to be used in other models. The team would read reviews one at a time, and select from a drop-down menu any of the activities that the review described (Figure B4).

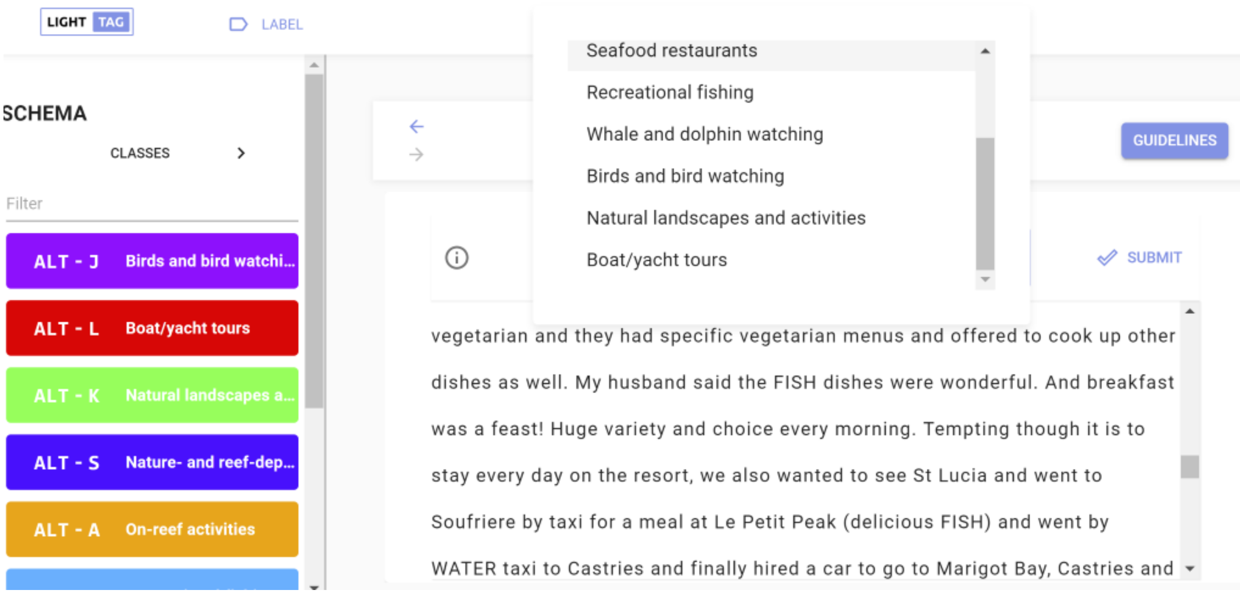

Figure B4. *Screen shot of LightTag API interface*

Based on the training data, the remainder of the reviews fed into a random forest machine learning algorithm, which analyzes patterns of language to identify reviews with a high likelihood of meeting each category's criteria. The algorithm also calculates a score for model quality according to several metrics:

- **Precision**: of the reviews that the model predicted are positive for the category, what proportion actually are positive (low scores mean lots of false positives)
- **Recall**: of the reviews that actually are positive for the category, what proportion did the model correctly predict (low scores mean lots of false negatives)
- **F1 score**: The harmonic mean of precision and recall = 2*(precision * recall)/(precision + recall) -- (essentially, in order to have high F1, you not both high precision and recall – having either one of those be poor will push the F1 score toward 0, because of the multiplication of the two proportions in the numerator)

As seen in Table B2, recreational fishing had high precision but low recall.

Table B2. Descriptive statistics for text analysis models

	f1-score_rf	precision_rf	recall_rf
On-reef activities	0.932692	0.910798	0.955665
Seafood restaurants	0.833333	0.863636	0.805085
Nature- and reef-dependent beaches	0.455446	0.638889	0.353846
Reef-adjacent activities	0.893617	0.933333	0.857143
Whale and dolphin watching	0.891304	0.836735	0.953488
Birds and bird watching	0.852459	0.812500	0.896552
Boat/yacht tours	0.697917	0.807229	0.614679
Natural landscapes and activities	0.824281	0.796296	0.854305
Recreational fishing	0.727273	0.909091	0.606061

Appendix C. Detailed data source and processing notes

Development of deep sea bathymetric contours

Deep-sea fishing layers were derived from bathymetric contours data based on guidance from local sportfishing experts. Bathymetric sounding points were converted into a bathymetry TIN layer, which was then used to derived contours at 100m intervals.

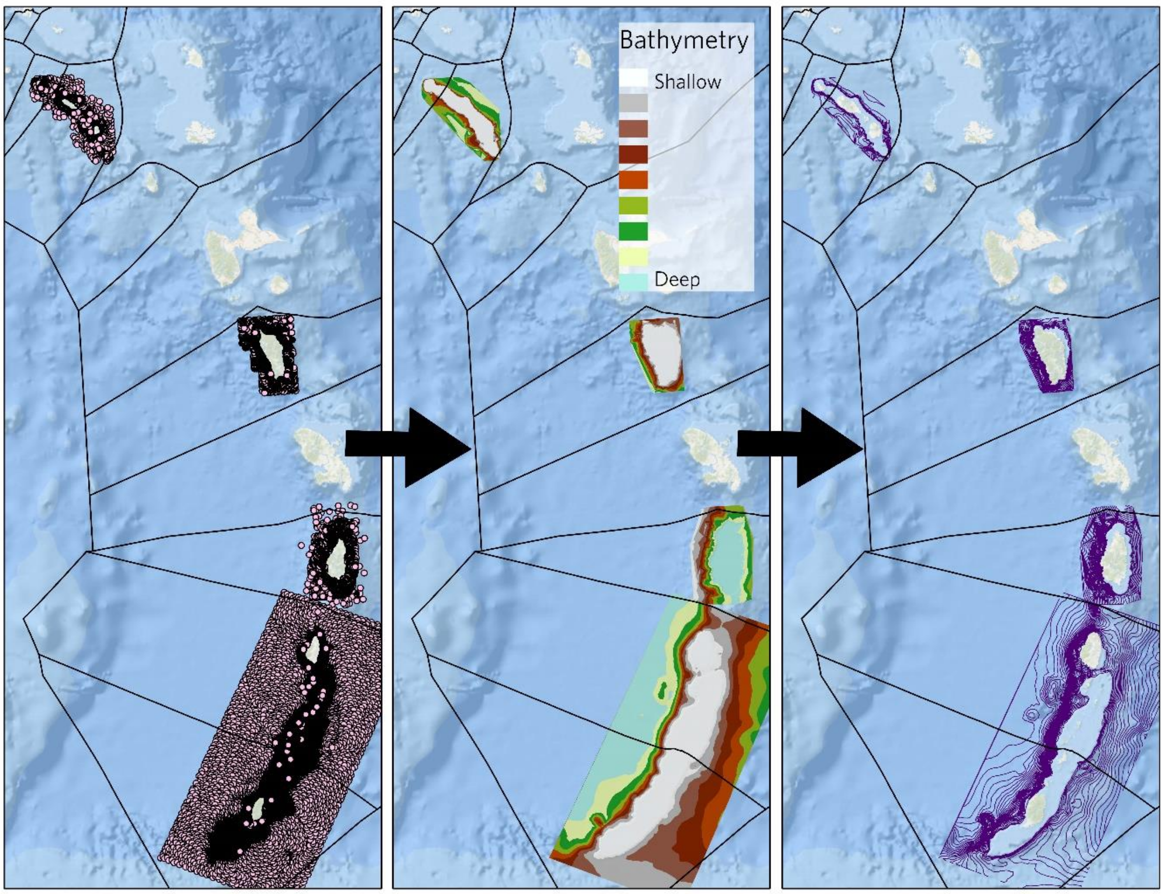

Figure 2. Derivation of bathymetric contours from sounding points.

Participatory mapping

Participatory mapped points were translated into boat path-lines and polygons where applicable, based on the participant's description of activities. Buffers and weights were assigned differently to each of these input layers.

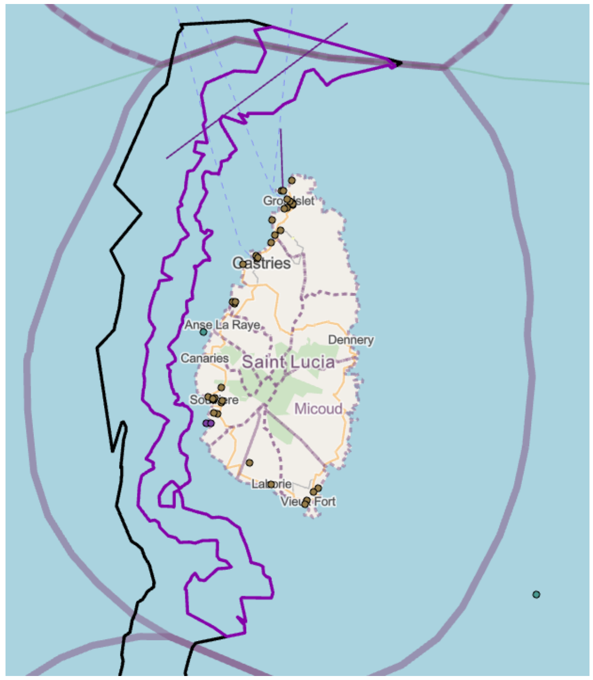

Figure 3. All 5 input layers for Saint Lucia.

Processing of deepsea fishing

The fishing intensity weightings from the onshore operators were spread from to the deep-sea fishing layer in an effort to spread the density of activities from the operator locations to the offshore locations where fishing is occurring. This was done using a Python script that buffered each onshore operator point individually at 10km, 20km, and 40km, then erased the 10km buffer from the 20km and the 20km from the 40km, creating donut hole buffers so that the buffers of each individual point did not overlap.

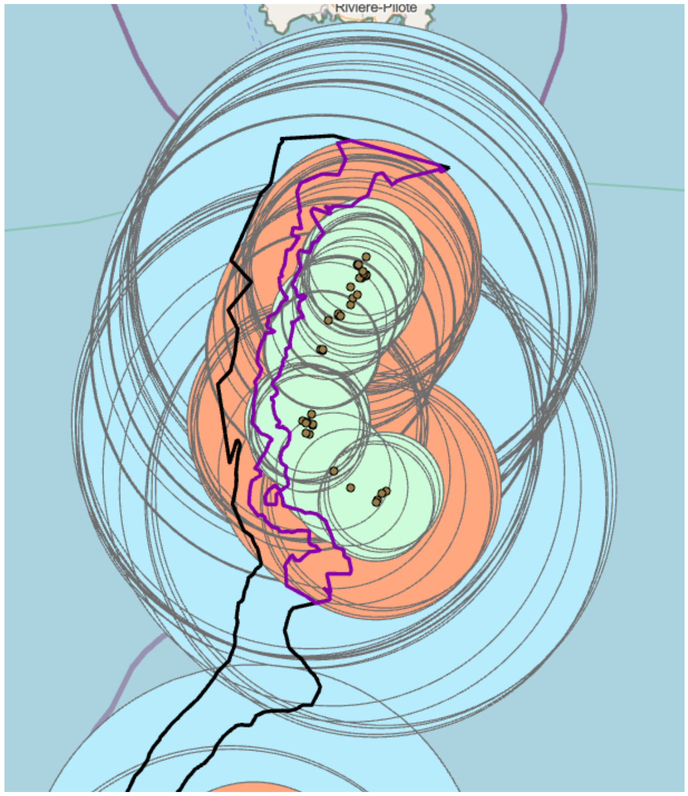

Figure 4. Donut hole buffers spreading the PAM weights from the onshore operators to the deep-sea fishing zones. Green buffers are 0-10km around each operator, orange 10-20km, and blue 20-40km.

The fishing intensity weights were then split between the 10km buffers and any buffers that overlapped with the deep-sea fishing zones (i.e. if the 20 and 40km buffers overlapped with the deep-sea fishing zones, the PAM weight was divided by 3; if only the 40km buffer overlapped, the weight was divided by 2). The resulting buffers were then clipped to the full-day and half-day deep-sea fishing zones.

Merging data layers

This resulted in 6 data layers which were then combined: buffered FADs, buffered participatory mapping data, buffered onshore operators, half-day deep-sea fishing trips zone, full-day deep-sea fishing trips zone, and buffered Flickr photo locations. Overlaps between individual buffers and data layers were summed so that if two layers with a score of 2 and 3 overlapped, the overlapping section would be given a score of 5. This was done by applying a union, creating a unique ID for each location using the X and Y centroid values concatenated, and applying a dissolve by XY ID while summing the weight field. The land vector (National Geospatial-Intelligence Agency Global Shoreline) was then erased from the resulting layer.

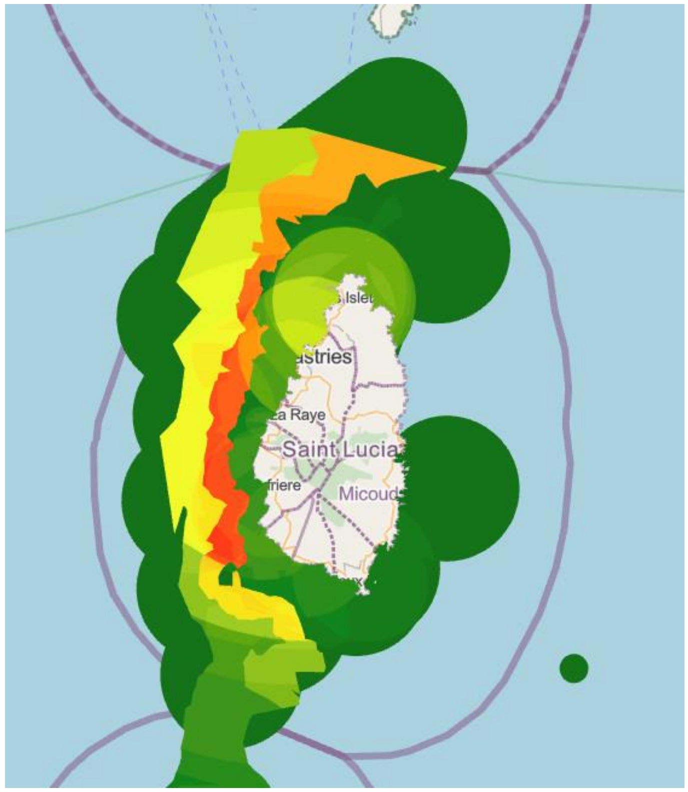

Figure 5. Resulting vector data representing recreational fishing in Saint Lucia.

In order to smooth the dataset, it was converted to a raster using the feature to raster tool with the weight field representing raster values and a cell size of 50m. A constant raster of zero value was created around all 5 countries and added to the recreational fishing raster using the cell statistics tool before blurring to eliminate hard edges. To blur the raster, the focal statistics tool was run on it for a circular neighborhood with a radius of 50 cells (2.5km) using mean statistics. The final raster was clipped to the footprint of the original output vector data and the exclusive economic zone (EEZ) boundary for each country.

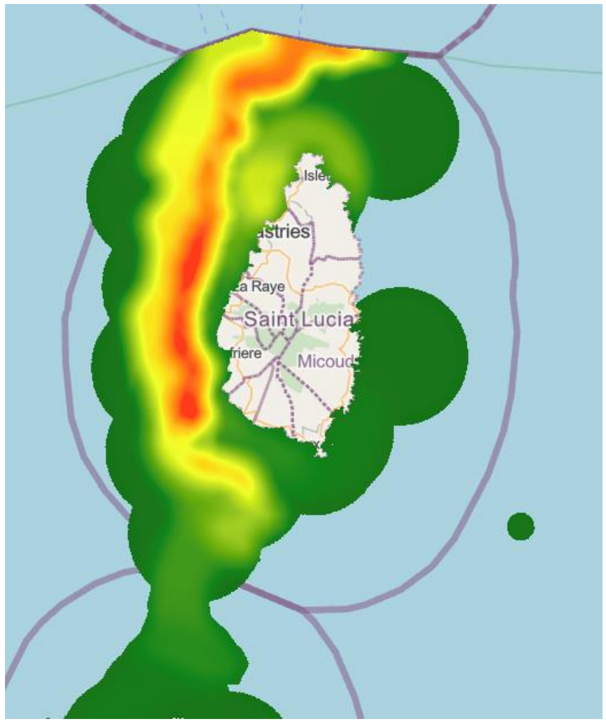

Figure 6. Final result: smoothed raster data representing recreational fishing in Saint Lucia.

Appendix D Maps by country (results rescaled)

Images D1 – D5 Depict total recreational fishing intensity for the region. Results are rescaled for each country, so color ramps may reflect different value ranges across countries. Values are mapped at a 100m resolution.

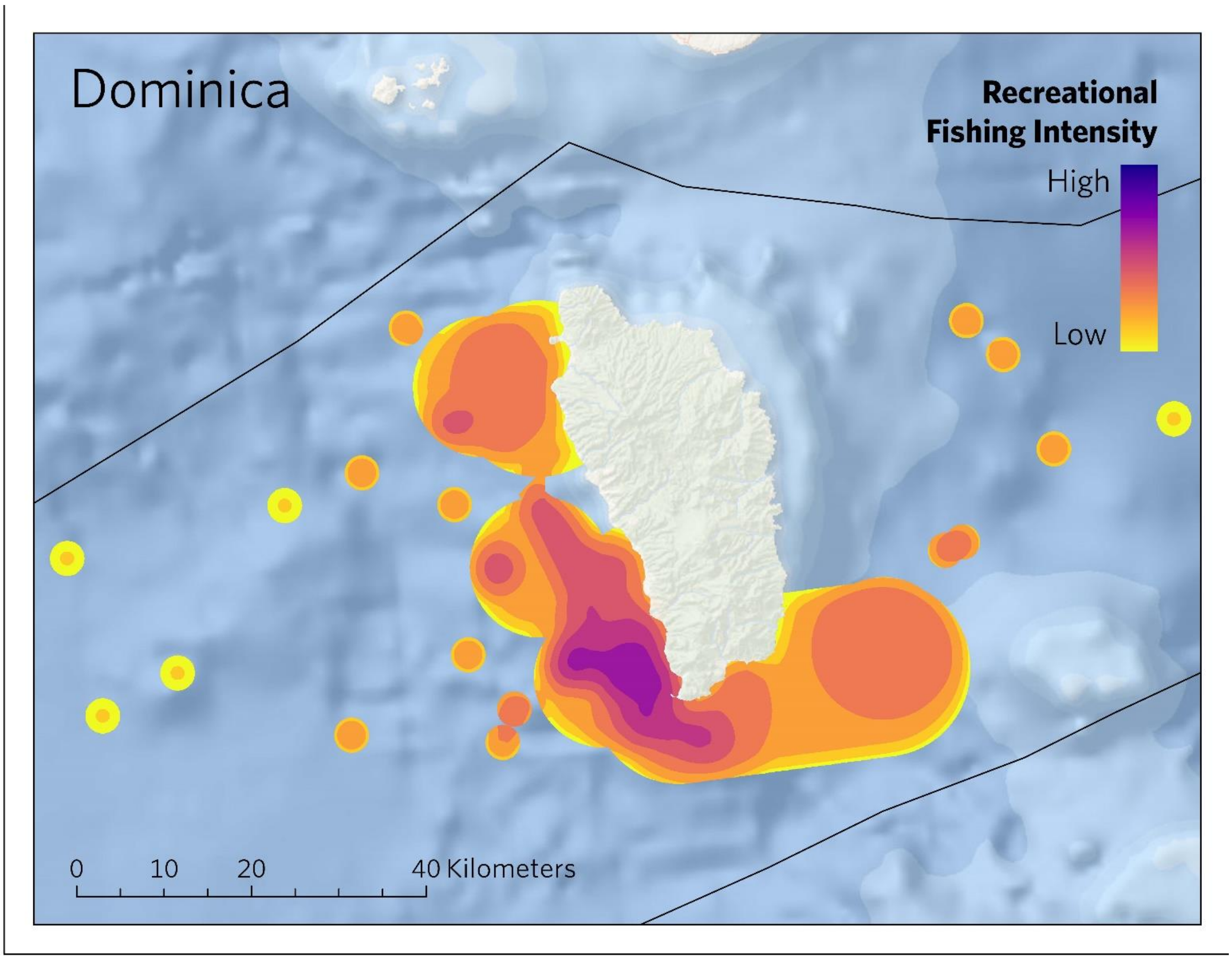

Figure D1. *Recreational Fishing Model – Dominica*

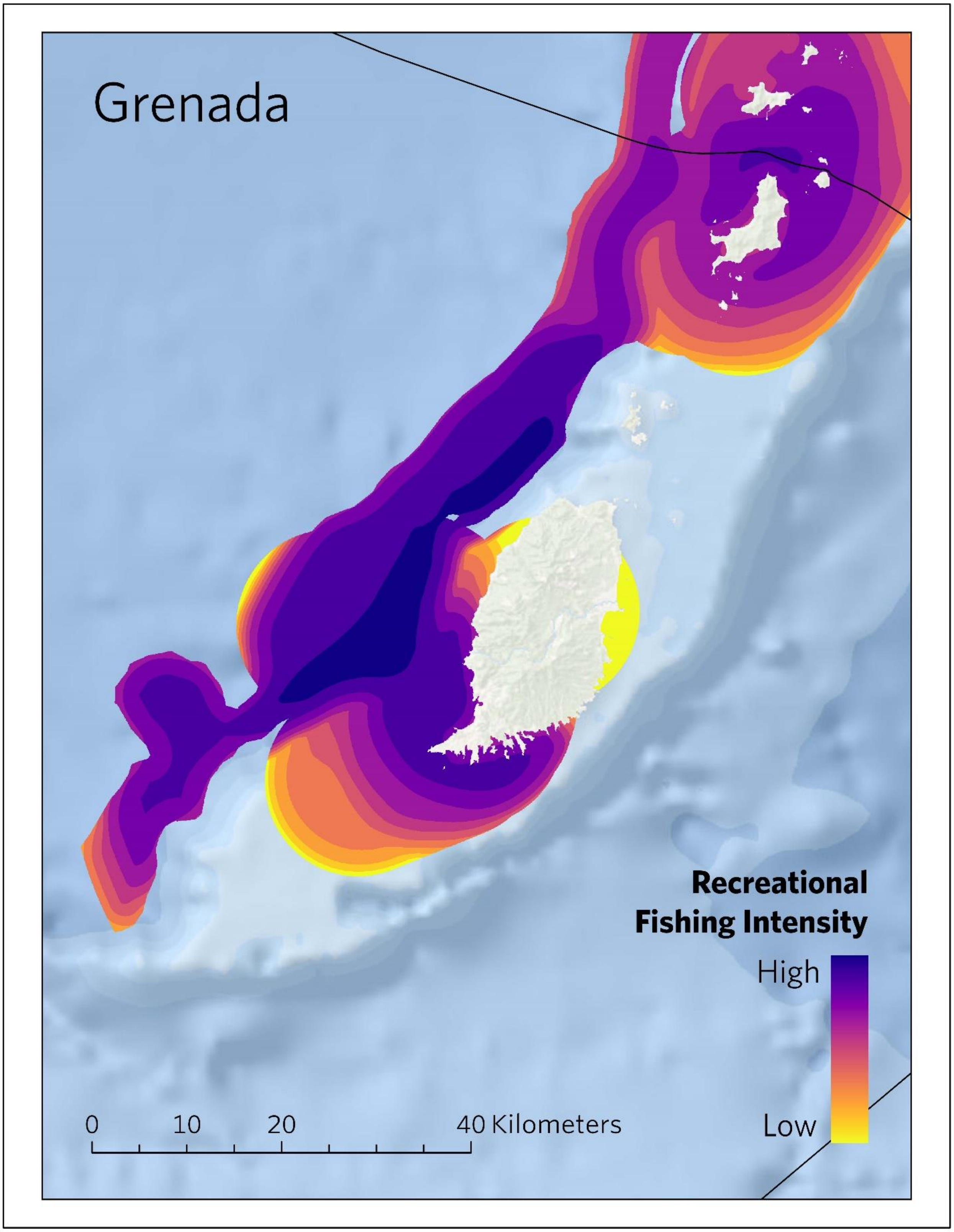

***Figure D2**. Recreational Fishing Model – Grenada*

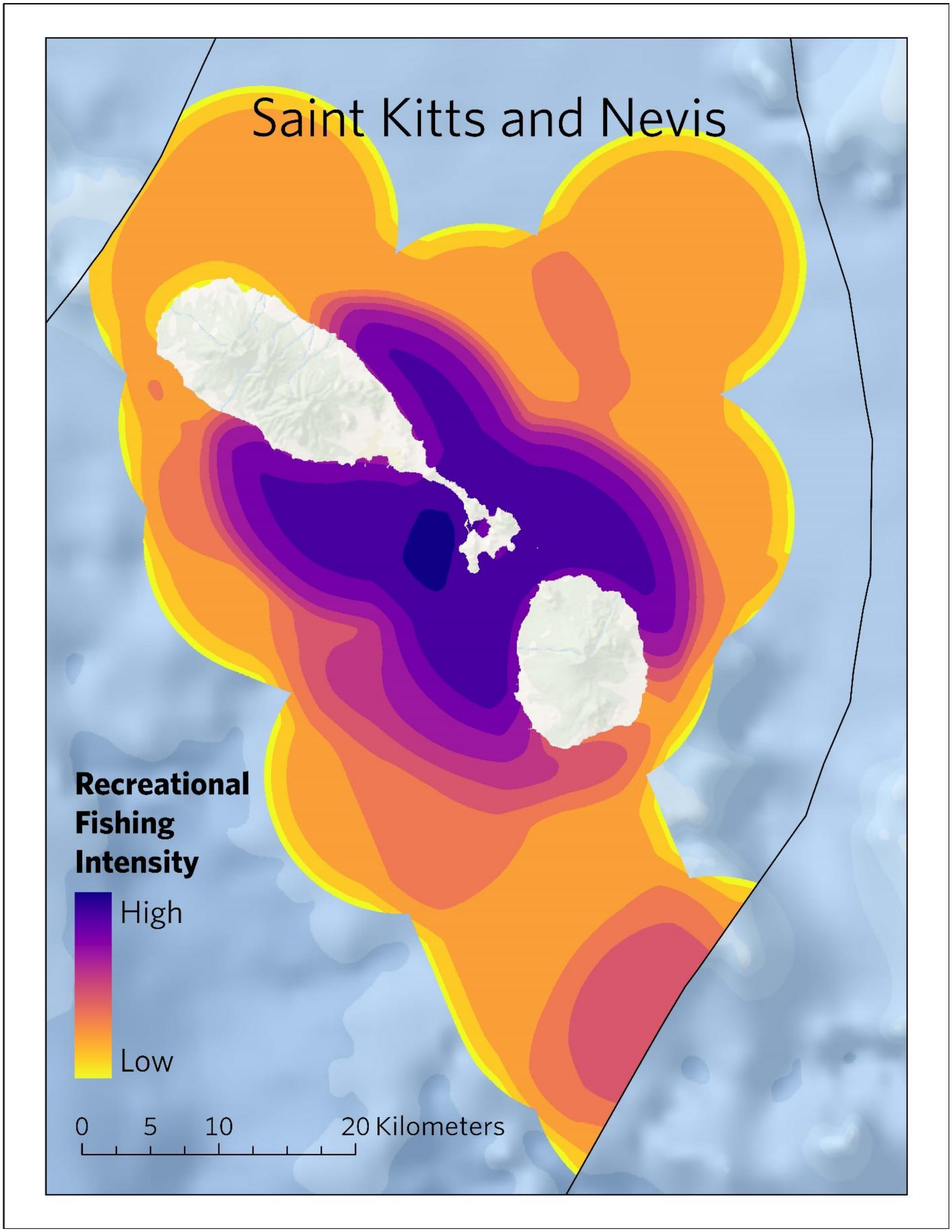

Figure D3. *Recreational Fishing Model – Saint Kitts and Nevis*

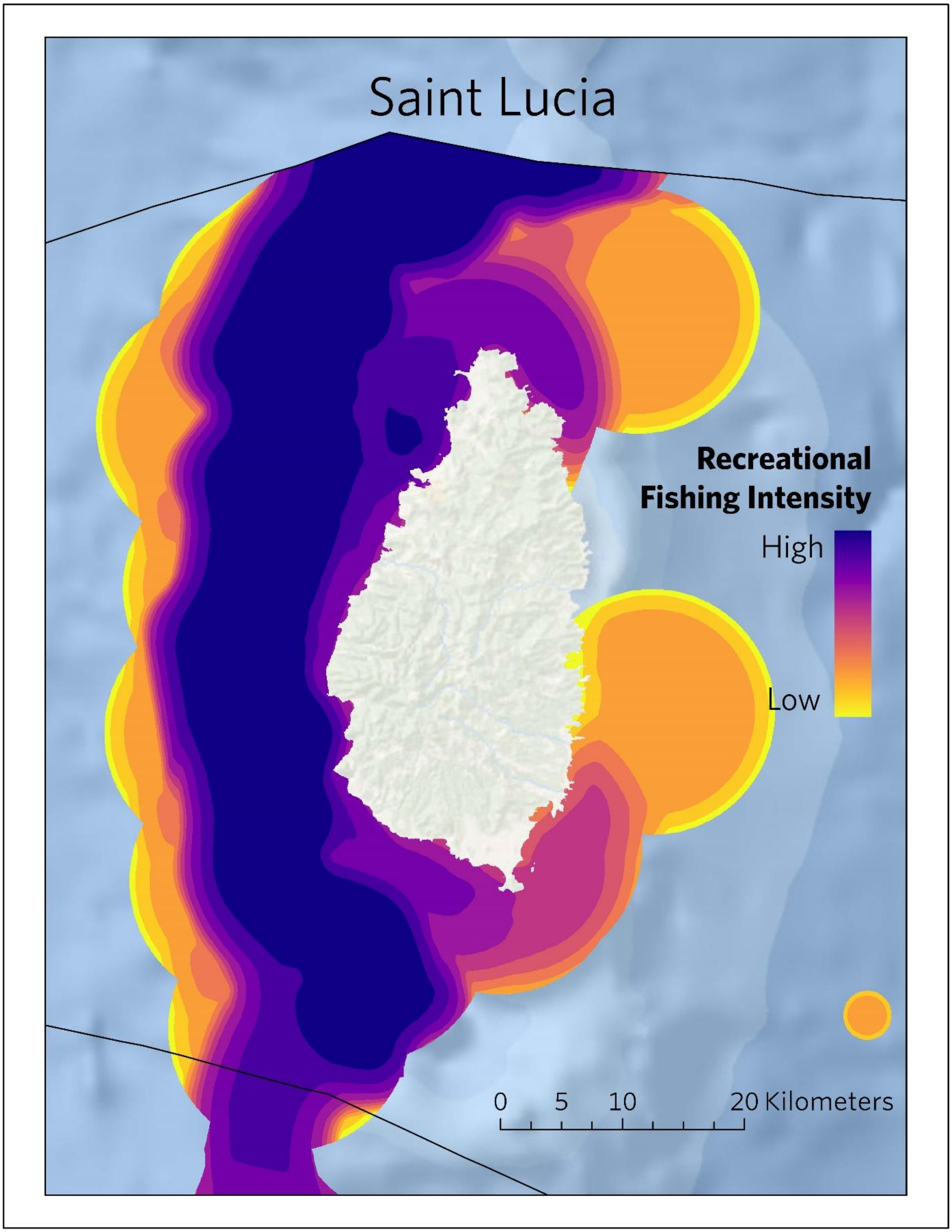

Figure D4. *Recreational Fishing Model – Saint Lucia*

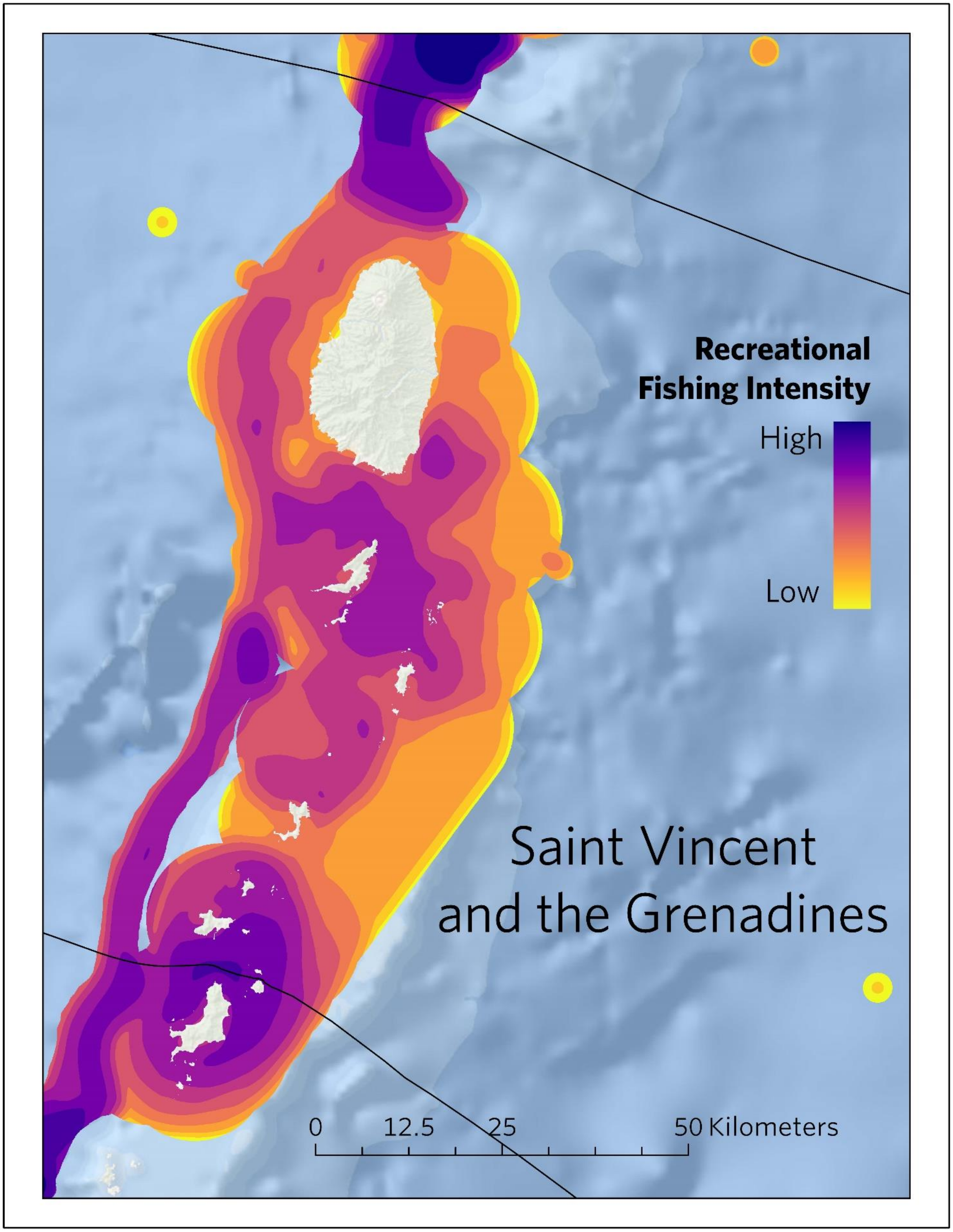

***Figure D5**. Recreational Fishing Model – Saint Vincent and the Grenadines*