Organisation of Eastern Caribbean States

Coral Reef Recreation and Tourism 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: Lorenzo Mittiga/TNC Photo Contest 2019

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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 4 of the project.

The Caribbean is highly dependent on coastal and marine tourism activities, many of them associated with coral reefs, either directly ("on-reef" e.g., SCUBA, snorkeling) or indirectly (e.g., beach-related activities, access to fresh seafood). While previous studies have quantified and mapped the value of coral reefs to tourism at the Global scale, downscaling these analyses to the regional and local levels afford an opportunity to integrate emerging artificial intelligence and machine learning (AI/ML) technologies, incorporate data from local sources, and engage with stakeholders who can guide additional refinements to the methodologies.

Under this output, TNC improved its global estimates of on-reef tourism expenditure and visitation estimates by integrating fine-scale benthic habitat data, cross-referencing global tourism datasets with local sources of information on dive sites, dive shops, and hotels, and applying AI/ML methodologies to photos and reviews kindly provided by TripAdvisor to further highlight patterns of reef-related tourism. We have also linked values directly to beaches themselves, rather than nearby reefs, focusing value on a range of natural factors that draw tourists to these areas. Maps of paddle sport activities (e.g., kayaking, stand-up paddleboarding) and seafood also provide supplementary information about the influence of coastal habitats on tourism activities in the region.

Across the combined CROP countries, tourism expenditure directly linked to on-reef activities is estimated at US$118 million annually. This can also be expressed in terms of visitor numbers, with 83,000 overnight visitors and 60,000 cruise visitors choosing these islands for their on-reef activities. Natural values of the beaches in the CROP countries are estimated to be generating some US$318 million of tourism expenditure annually with 143,000 overnight visitors and 565,000 cruise visitors who are attracted specifically to the pristine, natural aspects of the region's beaches. These figures, broken down by country are as follows:

Country	On-Reef Tourism		Nature-Dependent Beach Tourism		Total	
	Expenditures ($USD)	***Visitors (# people)***	***Expenditures ($USD)***	***Visitors (# people)***	***Expenditures ($USD)***	***Visitors (# people)***
Dominica	$11,382,075	19,389	$8,971,862	27,945	$20,353,937	47,334
Grenada	$13,097,875	22,732	$39,634,719	85,092	$52,732,594	107,824
Saint Lucia	$76,963,697	59,536	$207,227,645	211,423	$284,191,342	270,959
St. Kitts & Nevis	$6,667,569	22,444	$35,589,482	180,406	$42,257,051	202,850
St. Vincent & the Grenadines	$10,206,966	18,999	$26,670,739	60,198	$36,877,705	79,197
Total	**$118,318,182**	**143,100**	**$318,094,447**	**565,064**	**$ 436,412,629**	**708,164**

Both on-reef and nature-dependent beach values are generally concentrated along the leeward side of the islands, reflecting calmer sea conditions. During consultations, stakeholders generally agreed that these patterns reflected on-the-ground conditions. From the perspective of the specific layers, the very high value of nature to tourism across the five CROP countries is apparent. On-reef activities are widespread in most reefs, especially near diving centers such as those in southern St Vincent, southern Grenada, the Tobago Cays, Monkey Shoals (St Kitts and Nevis). The highest value reefs in Dominica and Saint Lucia are generating expenditure of over one quarter of a million dollars per hectare of reef every year. These highest value reefs should be a particular target of conservation attention, while the potential of reefs to generate such values might be an inspiration to encourage further coral reef tourism investment in other areas.

The very high natural values of beaches overall is not surprising. There are many beaches where natural values are considered to be critical to the overall beach value, generating many millions of dollars of expenditure annually – these include beaches such as South Peninsula Beach in St. Kitts, Grand Anse in St. Vincent and several beaches in Saint Lucia such as the very small beaches La Toc, Anse Chastenet and Jalousie. As with coral reefs, the highest values of all occur where the beach itself is small but attracts high use.

For paddle sports, the overall geographic distribution is a little more restricted but is nonetheless found across all countries. Seafood, by contrast appears to closely track tourism more generally. Further analysis and interpretation of these maps will require higher resolution exploration of the data in each country.

This is the first time that these components of nature-based tourism associated with coral reefs have been so extensively mapped and analysed at these resolutions. We believe that the results are of considerable use for understanding the value of coral reefs and coastal ecosystems at local scales, 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.

The maps are also valuable for future planning and in this sense it is useful to look at places both within countries and between countries which might provide models for future natural resource management, for example in restoring natural values as a means to generate new future benefits.

What is clear from our work is that the current model of tourism in the CROP countries is indeed highly nature-dependent. Our maps are modelling the natural values perceived by the current visitors to these islands. Environmental degradations, it follows, would generate the risk of losing the current "type" of visitor and the benefits they provide to the local economy.

Given the current impact of Covid-19 on tourism in the Caribbean, and especially the likely changes in demands coming from a recovering tourism sector it is highly likely that future tourism will have, if anything, a greater dependency on natural values and lower density locations and so our sites of high natural value will likely show an increasing proportional relevance for the recovering sector.

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 4 of the consultancy, providing a first full summary of the approach and results of a modelling exercise to describe the extent, intensity, and value of coral reef recreation and tourism in the region.

Nature-dependent coastal recreation and tourism

In 2017, The Mapping Ocean Wealth team, including partners The World Resources Institute, the Natural Capital Project, University of Cambridge, and University of Edinburgh, published a study and global map describing worldwide patterns of coral reef tourism and related expenditures (Spalding et al. 2017). This map was built using a unique and highly innovative approach that involved aggregating multiple large datasets which were then used, in combination with expert input and published literature, to build up value estimates for coral reef related visitation and expenditure. Those values were linked directly to those reefs that were responsible for generating them.

Two components of coral reef value were differentiated in this initial study: those of "on reef" activities, essentially diving and snorkeling, and occasional other in-water activities such as glass-bottom boats or submarines; and also a broader class of "reef adjacent" activities – a term intended to capture many indirect values deriving from the presence of coral reefs, including reef views, white sand beaches, clear calm waters and fresh seafood.

The results from this work showed that coral reefs contribute to $36 billion dollars of tourism spending annually, and drive almost 70 million visits per year, worldwide. Closer examination revealed the particularly heavy dependence of many developing economies, including Small Island Developing States (SIDS) on coral reefs. Some of these countries have limited options for economic development; and for many, tourism is a lifeline, generating livelihoods, wealth and foreign exchange. This initial work helped to build a much clearer understanding of the dependence of many of these nations on coral reefs, and the resolution of the work was already sufficient to support the management of these fragile ecosystems in some countries.

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. Coral reefs encircle most islands and make a critical contribution to this tourism. For the five CROP countries in this report it was estimated that they were responsible for generating over US$140 million of total tourism expenditure annually (Spalding et al. 2017).

In 2018, JetBlue and the World Travel and Tourism Council supported the MOW team in refining aspects of the global coral reef recreation and tourism model for the Caribbean, specifically around refining the estimates of reef-adjacent tourism. This project enabled the team to refine the global approach, a much needed change, particularly for the Caribbean where beach tourism is such a critical economic pillar. The new approach used a combination of social media content; data from government agencies and the tourism industry (e.g., exit surveys) to refine estimates of reef adjacent tourism that vary by country. Using these new models, the annual value of coral reefs for CROP countries was re-assessed at $223 million per year (Spalding et al. 2018).

This latter work provided proof of concept for two key advances that are built into the Mapping Ocean Wealth Project under CROP (MOW/CROP). The first is that national and regional reports and datasets are widely available and can be critical in informing the downscaling of models from global to national/regional scales. The second was that applying emergent Artificial Intelligence/Machine Learning (AI/ML) technologies and methodologies to crowd-sourced data sources can yield robust datasets that can be used as data inputs into the ecosystem service models, especially when compared to traditional keyword searches used in previous studies.

In this project, we apply some of our existing techniques to further enhance the mapping and valuation of coral reefs to tourism for the CROP countries. For on-reef tourism the approach is largely unchanged although we have incorporated better input maps and data and improved the resolution. Importantly, we have modified the refined the approach for valuing reef-adjacent tourism, modelling and evaluating various sub-components separately in a way that we believe will be more helpful for the public, industry and governments to consider and manage natural resources for the benefits of both the industry and nature. In doing this we have shifted our focus away from a strictly reef-centric approach to one where natural values are more broadly interpreted. This is because it is both challenging and to some degree misleading to focus attention solely on coral reefs when natural values are much more broadly derived from an array of coastal and nearshore ecosystems, that are themselves tightly interconnected.

The highest value component of these new datasets is the map of nature-dependent beach tourism. Here we have linked natural values (expressed as both visitation and expenditure) directly to the beaches themselves, rather than nearby reefs, focusing value on a range of natural factors including the beach itself alongside adjacent waters, reefs and also the naturalness of adjacent land areas.

Using the results of AI/ML methodologies, we have also developed heat maps of non-motorized water sport activities (e.g., kayaking and paddleboarding) that are often reef-associated and clearly depend on healthy natural coastal waters. We have also developed maps of the location of seafood restaurants, as these are often largely dependent on the ability to serve fresh fish that were caught on or adjacent to reef habitats.

This work has benefitted greatly from direct and extensive regional engagement. Local data collectors have helped to obtain country-level data from government agencies, scientists, and other sources. We have been able to conduct the type of robust stakeholder engagement activities that are not feasible when conducting modeling activities at the global, or even regional scale. Stakeholder workshops and webinars have bought together experts who have deep familiarity with data inputs, as well as the locations being characterized, have allowed the team to refine our methodologies and data products in way that are directly responsive to the needs of those individuals who could ideally use this information in support of their own work.

This report is intended to provide an in-depth technical description of the data sources, methodologies, detailed results and conclusions for this work. A high level of detail is provided in order to document key data sources, assumptions, modeling steps, and other considerations. Under this project, the TNC team will be developing additional data products, syntheses, communications and other resources intended to support the CROP objectives and future work in the region. Forthcoming products include:

- Map, model, and technical report describing recreational fishing
- Map, model, and technical report describing coral reef fisheries
- Map, model, and technical report describing other nature-dependent tourism
- Country-specific summary reports describing all model outputs and highlighting key results
- Summaries for all models and findings
- Data and statistics integrated into web-based tool and mobile app
- Final project report

These products can be found at Oceanwealth.org/Caribbean and at maps.oceanwealth.org/project-areas/OECS as they become available.

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 coral reefs and other habitats that enhance the value of the tourism industry in the region.

Methods

There are four components to our work:

- On-Reef Activities
- Nature-Dependent Beaches
- Paddle Sports
- Seafood Restaurants

For each of these models we developed a spatial model and map of “use intensity”, showing the spatial patterns of importance of these component parts. These maps indicate value, but do not convert that value into monetary or other units.

For on-reef activities and nature-dependent beaches, data were considered sufficiently reliable to build a direct model of value, developing a national level estimate of importance to be expressed both as tourism numbers and expenditure. These quantitative values were then linked to the maps of use-intensity to spread actual values to coastal areas or ecosystems.

The process of generating models and maps for each of these has drawn on some common datasets and so we first describe these, and the general processes by which they were derived before describing the individual approaches for modelling and mapping the four sub-components.

General data sources, data collection and preparation

Table 1 gives an overview of the key data inputs and sources utilised in the four components of this work

Data inputs are derived from a mix of large-scale (global and regional) datasets, from which data for the CROP countries were extracted and in some cases enhanced; and local datasets obtained from partners within the CROP region. Following Workshop 1, the Consultant used feedback from the workshop to engage in-country data collectors to obtain and compile the local and regional-scale datasets identified in the workshop. Data collectors reached out to Ministries of Tourism, Hotel and Tourism Associations, and local dive associations to request names and locations of dive sites, dive shops, and hotels, as well as statistics and reports on tourism arrivals, expenditures, and reef-related activities.

In most cases the local and large-scale data sources were combined, with local data used to enhance large-scale input layers.

Table 1. Summary of data inputs for coral reef recreation and tourism models

Model	Data input	Source(s)
On-Reef Recreation & Tourism	PUDs (Underwater Photos)	Flickr
	PAMs (Underwater Photos)	TripAdvisor
	Dive Sites	Diveboard, TNC, St. Kitts and Nevis Department of Marine Resources/Ministry of Tourism, Saint Lucia Ministry of Fisheries, Marine Resource Management Unit
	Dive Shops	Diveboard, Diveary, Saint Lucia Ministry of Fisheries, Marine Resource Management Unit, Grenada Tourism Authority, TNC, St. Kitts and Nevis Department of Marine Resources
	Hotels	GARD, TripAdvisor, TNC, Grenada Hotel and Tourism Assoiation, St. Kitts & Nevis Ministry of

Model	Data input	Source(s)
		Tourism, Saint Lucia Hotel and Tourism Association, Dominica Hotel and Tourism Association
	Coral Reef Habitat	TNC
	Tourism Arrivals & Expenditures	ECCB
	Cruise Arrivals & Expenditures	BREA
	Cruise Activities	Port guides and other web-based cruise guides (see Annex A for details)
Nature-Dependent Beaches	PUDs (Beaches)	Flickr
	PAMs (Beaches)	TripAdvisor
	Beach Habitat	TNC
	Beach locations	TripAdvisor
	Tourism Arrivals & Expenditures	ECCB
	Cruise Arrivals & Expenditures	BREA
	Cruise Activities	Port guides and other web-based cruise guides (see Annex A for details)
Paddle Sports	PUDs (Underwater Photos)	Flickr
	PAMs (Underwater Photos)	TripAdvisor
	Reviews	TripAdvisor
Seafood Restaurants	Reviews	TripAdvisor

Base layer maps and data

A summary of model inputs by country can be found in Appendix A, and additional information about model inputs and data cleaning can be found in Appendix B.

Reef maps. Base maps of coral reefs were created by The Nature Conservancy under the ECMMAN Project. They are derived from satellite imagery and were ground-truthed by surveys. They included a combination of habitat classes which had a likely structural reef or hard coral component, and have a basic 5m resolution. Minor modifications were made to these as described in the annex.

Beaches. Base maps of beaches had been mapped as polygons by The Nature Conservancy. The original layer was created by TNC for the CLME project in 2013 under a grant from UNESCO. These were enhanced and where available annotated with beach names from TripAdvisor where possible.

Baseline tourism statistics. Tourism values can be expressed in terms of numbers of visitors or expenditure. Both sets of statistics are collated annually by the Eastern Caribbean Central Bank (ECCB 2020). For this work we used averaged values for the five years up to and including 2019. EC Dollar values were converted to USD$ and using a currency deflator averaged to 2019 US Dollar equivalents.

Cruise and overnight passengers (including excursionists in the former and yacht-based tourists in the latter where possible) were separated, however for cruise expenditure we had to utilize national government statistics, with cruise industry statistics for St Vincent and The Grenadines. Summary statistics are provided below.

Table 2. Baseline model input tourism statistics

	St Kitts and Nevis	**Dominica**	**Saint Lucia**	**St. Vincent & the Grenadines**	**Grenada**
VISITOR NUMBERS:					
Total cruise/excursionist	976,546	228,128	696,642	153,001	301,638
Total overnights + yachts	123,398	85,542	429,320	129,951	166,889
TOTAL visitors	1,099,944	313,670	1,125,962	282,952	468,527
EXPENDITURE (2019 US$)					
Total expenditure cruise	$47,815,455	$9,034,862	$23,697,021	$12,133,948	$13,078,192
Total expenditure overnights + yachts	$117,414,477	$91,839,306	$847,253,969	$93,164,952	$149,733,686
TOTAL expenditure	$165,229,932	$100,874,168	$870,950,990	$105,298,900	$162,811,879

It is important to note that cruise passengers and excursionists typically stay one day in any country while average stays of overnight tourists range from 8 to 13 days and so total visitor numbers may in some cases be less useful than visitor days – making overnights a far larger number contributor to tourist footfall than simple arrival numbers.

Thus, cruise ships generate 72% of all arriving individuals, but only 8% of expenditure. Overnight stays spend around 23 times more per passenger, but even when converted to daily spend this number still equates to overnight visitors are spending around 2.5 times more per day than cruise passengers.

Cruise passengers also behave, move and spend differently from overnight stays (see below).

Hotels. A detailed hotel layer was provided by Delta Check from their Global Accommodation Reference Database, GARD, which provided location details for 446 hotels (with hotel size indicated by number of rooms) (DELTA CHECK 2019). This was enhanced by data from TripAdvisor following considerable checking and cross-referencing to remove "vacation rentals". This process enabled some name and location correction of GARD data, but also enabled the adding of 305 further properties. Some additional information from the region was reviewed and enabled minor modifications. Where no size data (e.g., number of rooms and beds) were available from any sources it was clear that they were typically very small hotels and these were not given any size weighting. The final hotel layer contains 782 hotels across the five countries, with 13,580 rooms.

Cruise tourism distribution. Cruise passengers behave, move and spend differently from overnight stays. A key source for the general patterns of activities and expenditure was the industry itself and particularly the 2018 report based on passenger surveys (FCCA and BREA 2018b). Given that movements of cruise passengers are restricted we developed a simple map of cruise passenger footprints to encompass the likely area where cruise passenger activity and expenditure would be restricted. This cruise footprint encompassed a radius around the cruise ports combined with an extended area derived from multiple cruise industry excursions that were plotted following an internet-based search of the places they encompass.

TripAdvisor. 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. These were used in all of the work outlined below to identify areas of highest popularity for key activities.

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).

Table 3. Summary of TripAdvisor data inputs, by country, used in models

Country	# Photos (Total)	# PAMs	# Reviews
Dominica	12,739	3,307	22,432
Grenada	27,656	6,759	54,132
Saint Lucia	107,091	24,054	202,638
St. Kitts & Nevis	28,921	8,075	63,156
St. Vincent & the Grenadines	13,884	3,395	21,795
Total	**190,291**	**45,590**	**364,153**

The spatial location of TripAdvisor information is always linked to the "attraction" where the reviews or photos were uploaded. In some cases these are appropriate geolocators, but for many others they are more appropriately considered as giving only a broad geolocation and cannot be used to pinpoint activities such as dive-sites or sites visited during tours.

Flickr. The popular crowd-sourced photo upload site Flickr is one of the few open-access data sources generating large volumes of spatially referenced data. All data were downloaded from the entire eastern Caribbean using a 500m grid. As with TA photographs it is important to avoid bias introduced by multiple image uploads from a single user in a single location and so the Photo User Day (PUD) approach is used which only allows the counting of one image per user per grid cell on any day (Wood et al. 2013).

Flickr data generally give high apparent accuracy geolocations; however, PUDs that were not within 500m of the reef habitat footprint were removed from the analysis.

Table 4. Summary of Flickr data inputs, by country, used in models

Country	# Flickr Photos (Total)	# PUDs
Dominica	5,301	1,661
Grenada	8,700	2,478
Saint Lucia	15,023	4,609
St. Kitts & Nevis	6,157	1,713
St. Vincent & the Grenadines	5,385	1,698
Total	**40,566**	**12,159**

Diving information. Initial data on the distribution of dive centres and dive sites were generously provided through the global database DiveBoard

For dive sites, the original Diveboard data was corrected and enhanced with reference to a large number of other databases and local data sources (see Appendix B). The final layer consisted of 315 sites, of which 242 were from Diveboard.

A separate dataset of dive centres was compiled using data from Diveboard, TripAdvisor and a small number of other sources. The final layer consists of 52 dive centres across the region.

Local and regional input. As indicated, experts from the region played a critical role in informing and reviewing our work and generating many of the corrections for all layers. In May 2019, a stakeholder workshop was held where the proposed methodology for developing the map was introduced to stakeholders, who then provided feedback and suggested possible sources of data to integrate into the model.

In May 2020, draft use-intensity maps were presented to stakeholders for review and feedback via webinars. In general, stakeholders agreed that the maps accurately represented diving and snorkeling activities in their respective countries, and suggested a several additional sources of information.

During these webinars, stakeholders also echoed feedback from the May 2019 workshop that cruise ship passengers are likely to engage in these types of activities at a different level of intensity, and that their contribution to coral reef recreation and tourism should be considered separately.

Modelling and geospatial processing

TripAdvisor and Flickr data analyses

Each of the models incorporated the results of AI/ML techniques and methodologies applied to Flickr and TripAdvisor photos, as well as TripAdvisor reviews. For all of this work, an initial stage requires the development of training data which supports the "learning" and enables a subsequent process of testing for accuracy. Training layers are built 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, for on-reef recreation and tourism, we selected photographs that depicted underwater scenes or reviews that describe diving or snorkeling experiences; for beaches, we selected images of beaches where natural elements were dominant (e.g., white sands, turquoise waters, vegetation).

Image recognition. Once sufficient training photographs had been compiled, the team used Microsoft's Azure Custom Vision (https://azure.microsoft.com/) 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 actual process was somewhat iterative, with the gradual refinement of training layers until high levels of accuracy were obtained. The images returned were then standardized to PUDs and PAM point features, as described in previous paragraphs, and plotted on a map.

Text recognition. We used the web-based tool LightTag to label over 2,000 TripAdvisor reviews according to activities and elements described in each review. For example, a review describing a visit to a resort where the visitor ate delicious red snapper and rented a kayak would be tagged as both "seafood" and "reef-adjacent activity". 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 were 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 that the search finds few false negatives); recall indicates the model's ability to accurately capture all images in the class (i.e. good recall means that the search finds most of the positive examples that exist in the dataset).

Each data category (e.g., on-reef, nature-dependent beach, paddleboard, seafood) and input (e.g., photo or text) then has its own unique Application Programming Interface (API) that can analyze photos or reviews and produce outputs that can be spatially referenced. We used this process for all data searches, not only for efficiency, but also to deliver a series of APIs that can be re-used, either in the future, or for other countries with minimal modification.

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

In the following section we describe the methods for each of the four tourism models in more detail.

On-reef recreation and tourism

On-reef tourism describes non-extractive activities undertaken in the water around coral reefs – essentially diving and snorkelling although in some countries it might also include glass-bottomed boat or recreational submarine trips.

Two key sources for quantifying and locating on-reef tourism were underwater images and a large number of such images were obtained through image recognition software, with the training of specific algorithms to identify underwater imager.

Use intensity mapping

Locations of in-water activities (diving and snorkelling) were located using underwater photos from Flickr and the dive sites dataset. The AI/ML API on Flickr imagery identified a total of 161 UW PUDs with values ranging from 1-10 (mean 1.88, precision = 100%, recall = 92.9%), which were kept as a direct metric of use intensity. There were 314 dive sites, of which about one third had a record for the number of dives – these were grouped into quantiles and use-intensity scores between 1 and 4 were assigned as follows:

No of dives	
0-1	1
2	2
3-8	3
9-38	4

Due to the dive sites having a relatively low locational accuracy dive sites were buffered to a 1km radius. The same buffer was applied to the PUDs to account for a broader area over which the on-reef activity was likely to take place

The buffered points were then joined to the reef map (100m resolution) and the use-intensity of each buffered point was spread across the reef extent within that same buffer. These reef scores were then summed for all the points to give a unitless map of reef use intensity.

Estimated national, on-reef, values

To develop a credible metric for the proportion of persons enjoying on-reef activities or their equivalent spending, we assessed three broad approaches

1. Literature review. Despite a thorough literature search we only found very oblique references to diving, nothing of sufficient to generate any clear statements on value.

2. Direct national metrics. Building on prior work (Spalding et al. 2018) we amassed assessments of visitor activities, largely derived from exit polls for three CROP countries, as well as a number of statistics for nearby and socio-economically similar small island states. Although providing a useful guide, there is rarely sufficient data to know the detailed questions that were asked and further very little consistency between approaches. These data were thus useful as a guide, but insufficient to determine an appropriate measure of value

3. Proxy indicators. Our final source of information to understand the relative importance of on-reef activities in these countries were the multiple input layers we had gathered – dive-centres, photographs from Flickr, and TripAdvisor reviews and photos (1,496 Flickr photos, 3,876 TripAdvisor photos, 37,954 TripAdvisor reviews). In each case we derived a metric to show the proportional importance of on reef activities in relations to the overall dataset. With dive sites we used the same approached developed in the global assessment, measuring the number of dive centres per 1000 hotel rooms.

Given that neither literature sources or nationally derived values were directly useable for the CROP countries it was determined to use the proxy metrics to determine relative values, and then to use additional regional information from literature and national statistics to convert these relative values to actual values (percentages of national tourism values).

Four final proxy metrics were used (Table 5) and the countries were ranked for each. There was broad agreement across these rankings and they were then combined into an average rank for each country to give the final relative values.

These average ranks were converted to proportional reef values by country. The spread for these values was assessed as being a range from 5% to 12% of total tourism spending. The lower level was set conservatively to be a little higher than countries such as Sint Maarten (4%) where on-reef activities are rare. The upper limit was set, also conservatively, to fall considerably below other nearby destinations which are more tightly focussed on diving and snorkelling (Saba, Cayman Islands). Proportional values for the remaining countries were spread between these lowest and highest scores using a linear interpolation from the average rank scores.

Table 5. Calculation of reef tourism percentage value by country

Country	PUD Ratio	Rank	Dive centres to 1000 hotel rooms	Rank	TA Review Ratio	Rank	TA PAMs Location Ratio	Rank	Av from ratios	Av rank	Scaled 5-12%*
DMA	6.1%	2	9.4	1	11.0%	2	12.1%	1	9.6%	1.50	12.0%
GRD	5.4%	4	5.1	3	10.2%	4	11.8%	2	8.1%	3.25	8.5%
KNA	3.7%	5	3.3	5	8.0%	5	8.5%	5	5.9%	5.00	5.0%
LCA	6.0%	3	3.6	4	11.2%	1	10.3%	4	7.8%	3.00	9.0%
VCT	6.6%	1	8.6	2	10.4%	3	10.9%	3	9.1%	2.25	10.5%

Cruise ship passengers

As cruise ship passengers are time-limited, and do not have access to all parts of the countries they visit, it is assumed that their access to particular activity-based excursions will be more limited. Industry data was insufficient, but it was noted that and average of 7% of all passengers partake in "soft water" excursions – given that these include multiple activities it seems likely that snorkelling would make up about a quarter of this statistic. Allowing for a similar small proportion of the non-excursion passengers to also undertake on-reef activities we would estimate that perhaps only 2-5% of all passengers would choose on-reef activities.

Separately, the only study we were aware of that used standardised exit surveys for both overnight and cruise tourists showed that in Sint Maarten cruise passenger participation in most on-island activities other than shopping was between one quarter and one third of that of stayover arrivals (Sint Maarten Department of Statistics 2019). Although not one of the CROP countries, it seems likely that similar numbers would carry over for CROP countries, particularly because on-reef activities such as diving are time-consuming and logistically more complex than many other activities.

Without further information it was therefore decided to apply a two-thirds reduction to the values assigned above for overnight stays for assessing likely cruise passenger participation in on-reef activities. This approach delivers estimates of 1.7 to 4%.

Mapping values to reefs. In the final stage it was then possible to use the national on-reef values as multipliers for the national tourism statistics to generate final value scores which were then distributed across coral reefs utilising the use intensity maps.

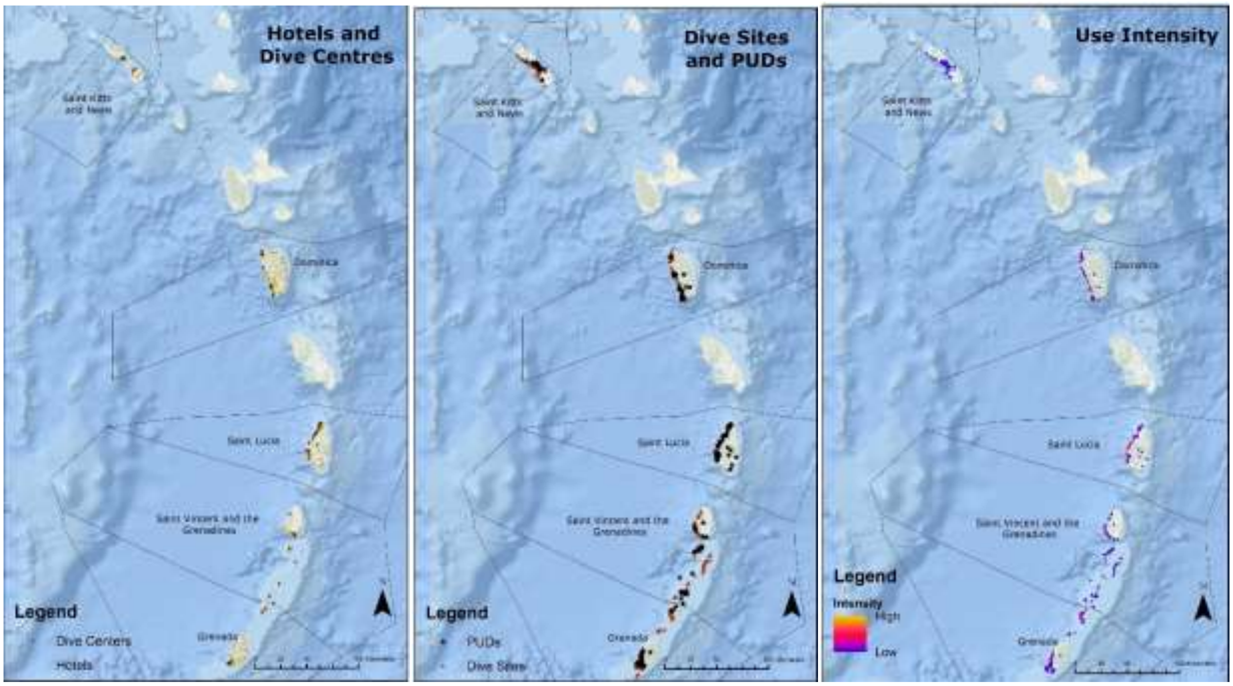

Figure 1*. Input data to on-reef recreation and tourism model. Hotels and dive sites in panel 1 were used to estimate the percentage of tourism activity that could attributed to on-reef tourism. The second panel shows the features used to distribute these values across the study area. The third panel shows the PUDs and dive sites buffered and summed to provide a use intensity map before it was extracted to the reef area.*

Nature-dependent beaches

Past work in this area has focused on "reef adjacent" values in a broadly but to some degree vaguely defined approach which sought to capture values ranging from seafood to reef-generated beaches (Spalding et al. 2017, Spalding et al. 2018). In this work we were presented the opportunity to explore these values more thoroughly and at greater resolution. As we did so it quickly became clear that perhaps the most important single element, beach tourism, could be only be linked to reefs in a very loose manner, but that the importance of nature more generally was widely apparent. As we explored further we began to develop the idea of nature-dependency in place of reef-dependency. Nature-dependency describes the level of dependence that any beach tourism may have on key natural values. Such values include:

- White sand (coral-derived)
- Natural vegetation adjacent to, or dominating views from the beach
- Turquoise and/or dappled clear water

The identification of such elements is to some degree subjective, however it is clear (See Appendix C) that both visual images and text-based phrases can be defined and such approaches were used to train machine-learning algorithms which were then applied to PUDs, PAMs and TripAdvisor reviews. For each image and review the result was a binary yes-no assignment, however for our work it is the combination of thousands of such data points that gives a sense of relative natural value.

Use intensity mapping

Locations of nature-dependent beaches were located using photos from Flickr and TripAdvisor. The AI/ML imagery API identified a total of 414 nature-dependent beach PUDs with values ranging from 1-14 (mean 2.1) and 3,194 nature-dependent PAMs (mean =7.8), (precision = 100%, recall = 84.8%), which were kept as a direct metric of use intensity.

Images and reviews from all sources amounted to over 9,000 positive identification of nature-dependent beaches, covering some 600 locations across the CROP countries.

Table 6. AI/ML derived model inputs to nature-dependent beach model

Source	Locations	Units (PUDs, PAMs)	Max value	Mean
Flickr	195	414	14	2.1
TA images	412	3194	283	7.8

Each image represents a unique observation and so these values could simply be combined to give an intensity of nature importance score. Although it would be possible to get weighted importance of beaches by using total numbers (PUDs, PAMs as the denominator), this was not considered necessary for the current work as we were simply looking to develop a map of intensity of nature dependency.

Finally, as with the on-reef use intensity mapping, the points representing the total scores of nature dependency per location were buffered to a 1km radius and the total value of each buffer was spread evenly across all beach areas within that buffer. The larger area of beach within a buffer, the more broadly the value would be spread. Finally each of values per beach were summed to give total values.

Estimating national nature-dependent beach values

In order to understand the relative importance of nature to beach tourism at the national level we undertook a three-step process:

1 Firstly we developed an estimate of **overall beach utilisation** for the region. Originally we had hoped to develop country-specific scores, informed by our earlier work (Spalding et al. 2018) and an extended search for similar data from exit surveys. Finally it was determined to use

an averaged score (77% of all tourism value) from multiple exit surveys of similar islands in the region for four of the countries and a lower score (30%) for Dominica (see Appendix B for further details).

2 Secondly we developed an estimate of the relative contribution of natural values to this tourism. The work of Peter Schuhmann in Barbados (Schuhmann et al. 2019a) and Grenada (unpublished) projected declines in visitor returns based on environmental degradation. We therefore decided to use the same numbers to project likely losses from a 5% decline in water quality as a metric for **current natural beach value.** Based on this work we would project a 31.2% loss of returns (Schuhmann, per comm) and we used this number to calculate current natural values.

3 Finally we developed **national modifiers.** The data from PUDs, and TA reviews suggest that the importance of nature to beaches in the five CROP countries varies notably. NDBs make up 13% of PUDs, and 2.7% of reviews for St. Vincent and the Grenadines, but only 2% and 0.5% respectively for Dominica. Such modifiers were dependent on expert judgement, informed by the national numbers of nature-dependent images and reviews as a proportion of national totals.

These three steps were applied to overnight tourists. Beach visitation by cruise ship passengers may be different from overnight stays. Data from (FCCA and BREA 2018b) suggests that across the CROP countries an average of 87% of passengers disembark. A little half of these take formal excursions, but only a very small proportion are beach focused, and we estimated values of 18-28% beach utilisation for excursion passengers. For the remainder we had no further data on activities and so we used the same proportions of beach use that we used for overnight visitors (77%, or 30% for Dominica). Following this we used the same modifier for natural beach value (31.2% of total beach value), and the same national modifiers to these.

Mapping values to beaches. In the final stage it was then possible to use the proportional values described above to obtain actual values for nature-dependent beaches by country. These values were then distributed across the beach layers using the use intensity maps.

Paddle sports

The role of nature and natural ecosystems in supporting coastal sports and activities is of course well understood. Diving and snorkeling are already addressed in our on-reef mapping work, but under the current work, we decided to assess the feasibility of quantifying a variety of other sports, including open water swimming, kayaking, stand-up paddleboards, small boat sailing, and kite surfing.

Early exploratory work with image analysis showed that there were simply insufficient data to train AI/ML approaches for most of these, however we had considerable success with the identification of kayaking/canoeing and stand-up paddleboarding.

As with the work on beaches, the approach represents a departure from our earlier efforts which focus entirely on reef dependence. These sports may benefit from the proximity of reefs, generating calm and sheltered waters, however they are also popular in natural inlets, mangrove and seagrass areas and so the term we do not see them as reef adjacent or reef dependent. At the same time, while healthy natural ecosystems are not a pre-requisite for these activities it is clear that most users enjoy them because of a proximity to nature.

The final API developed (precision = 94.7%, recall = 100%) selected some 340 images on TA, of which some 10% were errors, with a further 7% being "acceptable errors" including inflatables, snorkeling and kite-surfing. With multiple uploads these became 225 PAMs.

The same API located a further 25 images from the Flickr data.

The TA review data located 6,321 reviews relating to paddling sports.

The point data from TA attractions (Reviews and PAMs) and PUDs were buffered using a point statistics function and then summed together. The results were then smoothed using focal statistics to generate a simple use-intensity map. This was clipped exclude any areas more than 500m inland. Unlike the on-reef tourism and nature-dependent tourism models, we did not extract this use-intensity layer to a habitat footprint based on stakeholder advice, and due to the fact that this activity is not likely to be tied to a single habitat type.

Seafood restaurants

Efforts to develop image recognition algorithms for seafood were unsuccessful and so the identification of these places was dependent on the text-based processing. The training process involved identifying reviews which mentioned seafood in many different forms, although non-local seafood was excluded from the training layers (e.g. salmon, oysters, mussels, tuna).

The final API had relatively good accuracy (Precision - 0.86, Recall - 0.81, F1 - 0.83), and identified over 30,000 reviews (8.3% of all reviews) which mentioned seafood.

These were linked to 1,074 attractions locations, each of which were weighted by the total number of seafood reviews.

In developing a use-intensity map these points were buffered using a point statistics function and then smoothed using focal statistics to generate a simple use intensity map. The focal statistics were then used to smooth the resulting map which is intended only to indicate approximate locations of seafood importance rather than particular restaurants. This map was then clipped to exclude open water.

Results and Discussion

A summary of model outputs by country can be found in Appendix A.

On-reef recreation and tourism

Across the combined CROP countries tourism expenditure directly linked to on-reef activities is estimated at US$118 million annually. This can also be expressed in terms of visitor numbers, with 83,000 overnight visitors and 60,000 cruise visitors choosing these islands for their on-reef activities.

Table 7. Estimated values of on-reef tourism for overnight and cruise passengers in terms of 2019 US dollar expenditure and visitor numbers.

	St. Kitts & Nevis	Dominica	Saint Lucia	St. Vincent & the Grenadines	Grenada
Overnight visitors:					
National modifier	*5.0%*	*12.0%*	*9.0%*	*10.5%*	*8.5%*
FINAL value	*6,170*	*10,265*	*38,639*	*13,645*	*14,186*
Overnight expenditure					
National modifier	*5.0%*	*12.0%*	*9.0%*	*10.5%*	*8.5%*
FINAL value	*$5,870,724*	*$11,020,717*	*$76,252,857*	*$9,782,320*	*$12,727,363*
Cruise visitors					
National modifier	*1.7%*	*4.0%*	*3.0%*	*3.5%*	*2.8%*
FINAL value	*16,274*	*9,124*	*20,897*	*5,354*	*8,546*
Cruise expenditure					
National modifier	*1.7%*	*4.0%*	*3.0%*	*3.5%*	*2.8%*
FINAL value	*$796,845*	*$361,358*	*$710,840*	*$424,646*	*$370,512*

Figures 2 & 3 reflect total on-reef recreation expenditures and visitation for the region. Maps at the country-level, separated by cruise and overnight visitors, can be found in Appendix E.

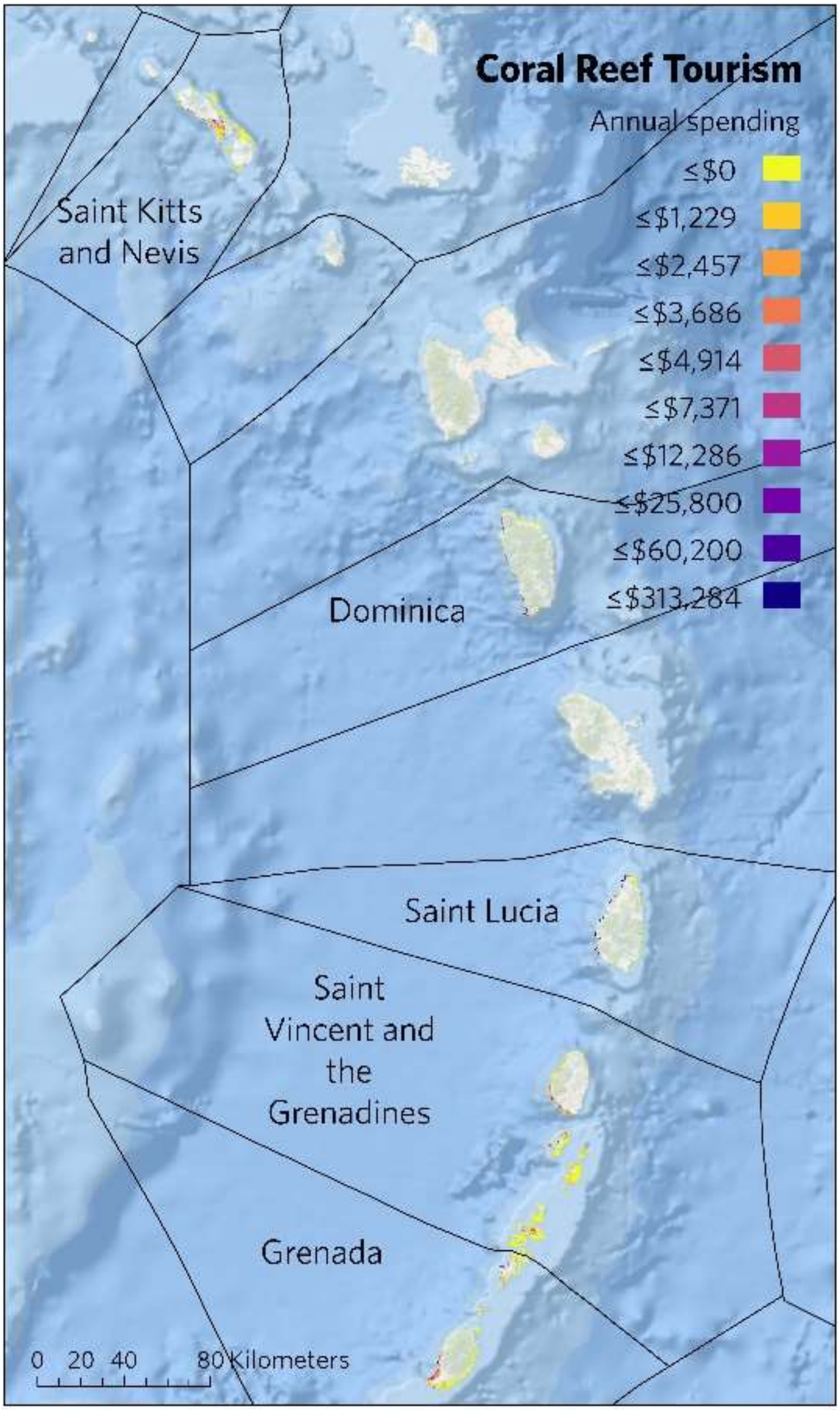

Figure 2. *Coral reef recreation and tourism expenditures in CROP countries. The values are mapped to a map of coral reef and reef-like habitat at 100m resolution, and values reflect expenditure per hectare.*

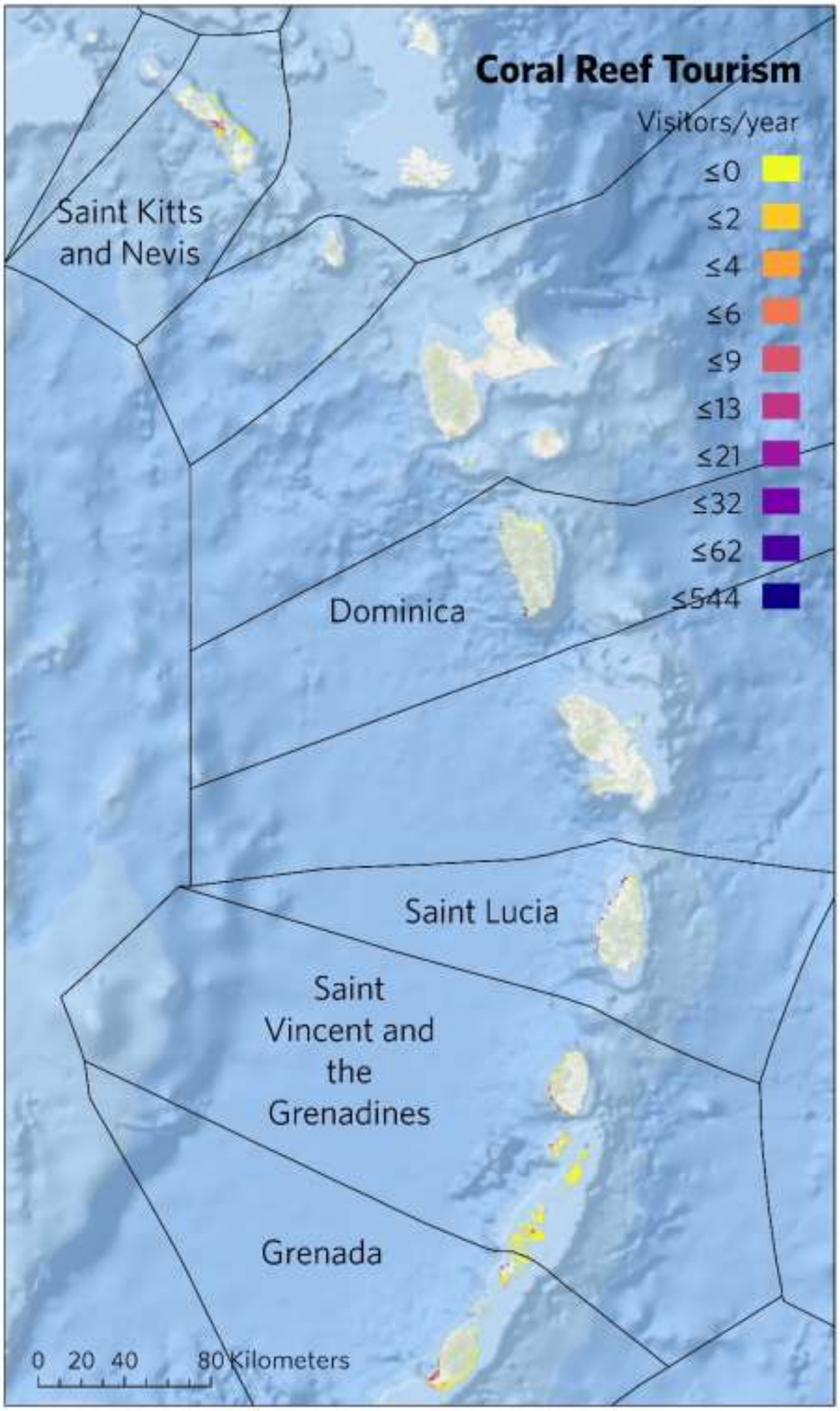

Figure 3*. Coral reef recreation and tourism visitation in CROP countries. The values are mapped to a map of coral reef and reef-like habitat at 100m resolution, and values reflect visitation per hectare.*

Discussion:

The maps show the wide spread of values across leeward reefs in each country. At the same time there is variation, with strong concentrations of high value reefs in certain areas, and some quite extensive reefs with zero or low values. Most of the latter are restricted to high energy windward reefs which are largely inaccessible to tourism, but in a few areas it would appear that reefs are simply remote from tourism centres.

The on-reef values explored here are considerably higher than those projected from the 2017 global assessment which estimated a total value of US$73 million per year. This increase is largely driven by increases in both arrivals and expenditure in the increases in both tourism arrivals and expenditure between these two studies, including a particularly increase in tourism expenditure for Saint Lucia.

Nature-dependent Beaches

Natural values of the beaches in the CROP countries are estimated to be generating some US$318 million of tourism expenditure annually, a number that is almost entirely ($302 M) driven by overnight visitors . In terms of visitors these numbers can be expressed as some 215,000 overnight visitors and 348,000 cruise passengers who chose these islands because of the natural values of their beaches.

Table 8: Results of nature-dependent beach values for overnight stay visitors

	St Kitts & Nevis	**Dominica**	**Saint Lucia**	**St. Vincent & the Grenadines**	**Grenada**
Overnight visitors:					
Beach use/dependency (77% or 30% for Dominica)	*95,017*	*25,663*	*330,576*	*100,062*	*128,504*
Natural value modifier (value x 0.312)	*29,645*	*8,007*	*103,140*	*31,219*	*40,093*
National modifier	*1*	*0.95*	*1*	*1.1*	*1.05*
FINAL value	***29,645***	***7,606***	***103,140***	***34,341***	***42,098***
Overnight expenditure					
Beach use/dependency (77% or 30% for Dominica)	*90,409,147*	*27,551,792*	*652,385,556*	*71,737,013*	*115,294,939*
Natural value modifier (value x 0.312)	*28,207,654*	*8,596,159*	*203,544,293*	*22,381,948*	*35,972,021*
National modifier	*1.00*	*0.95*	*1.00*	*1.10*	*1.05*
FINAL value	***$28,207,654***	***$8,166,351***	***$203,544,293***	***$24,620,143***	***$37,770,622***

Table 9: Results of nature-dependent beach values for cruise passengers

	St. Kitts & Nevis	Dominica	Saint Lucia	St. Vincent & the Grenadines	Grenada
Beach utilisation - excursion pax	22%	20%	28%	20%	18%
Beach utilisation - non-excursion pax	27%	10%	22%	29%	25%
Combined beach utilisation	49%	30%	50%	49%	44%
Natural beach visitation value	150,761	20,339	108,283	25,857	42,994
Natural beach linked expenditure value	$7,381,828	$805,511	$3,683,352	$2,050,596	$1,864,097

Figures 4 & 5 reflect total nature-dependent beach expenditures and visitation for the region. Maps at the country-level, separated by cruise and overnight visitors, can be found in Appendix E.

Broadly speaking the patterns of natural value follow the patterns of tourism more generally. One important observation is the extraordinary value of nature for some beaches, with small beaches linked to very high natural values in particular generating values as high as US$3 million per hectare per year (Saint Lucia). These beaches in particular should be areas of particular attention to ensure that natural values are in no way compromised.

Because this mapping approach has diverged considerably from earlier studies, the findings are no longer comparable with the “reef adjacent” values of the earlier work.

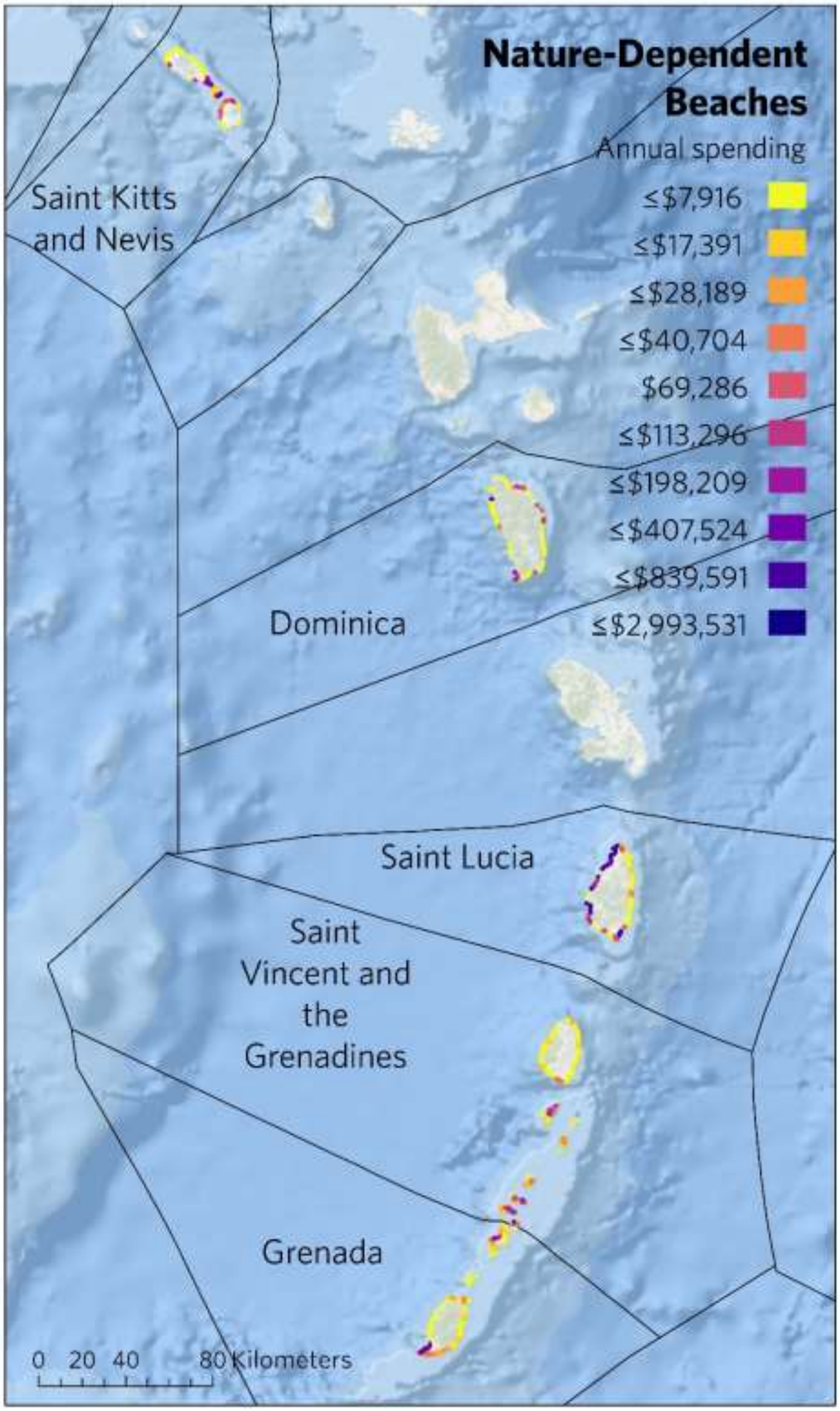

Figure 4. *Nature-dependent beach tourism expenditures in CROP countries. The values are mapped to a map of beaches at 100m resolution, and values reflect expenditure per hectare.*

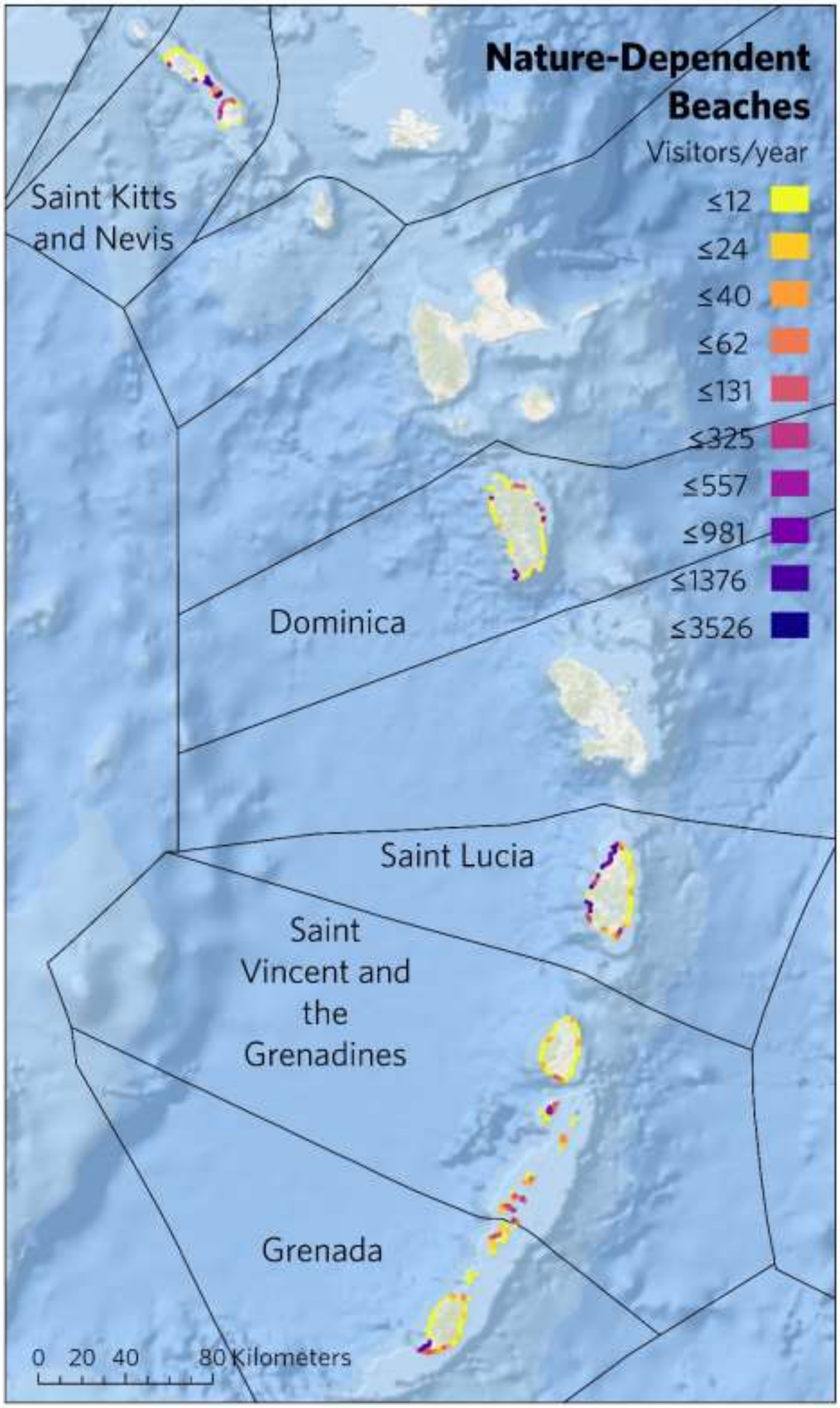

Figure 5. *Coral reef recreation and tourism visitation in CROP countries. The values are mapped to a map of beaches at 100m resolution, and values reflect visitation per hectare.*

Paddle sports

The 407 attractions that we located with kayaking and SUP activities, weighted by use intensity are shown in the maps below and described in Table 10.

Table 10. Paddle sport input data by country

Country	# Attractions	# Images	#PAMs	# Reviews
Dominica	30	19	14	209
Grenada	86	110	41	898
Saint Lucia	166	120	106	4371
St. Kitts & Nevis	65	73	49	538
St. Vincent & the Grenadines	60	18	15	305
Total	**407**	**340**	**225**	**6,321**

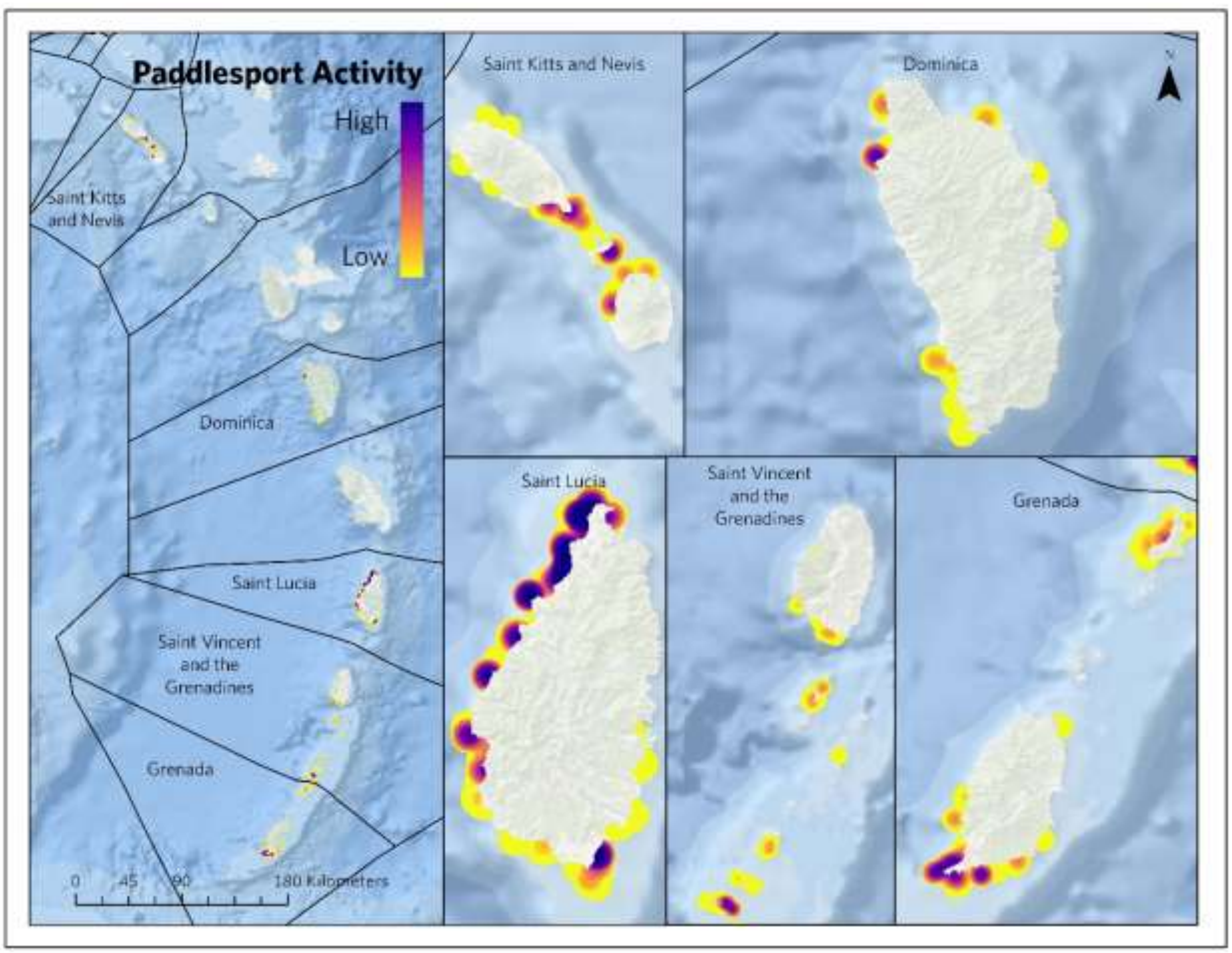

Figure 6. *Use intensity map of paddle sport activities in CROP countries. Values are unitless.*

Seafood restaurants

The 1,074 attractions that we located with seafood, weighted by use intensity are shown in the maps below and described in Table 11.

Table 11. Seafood-related input data by country

Country	# Attractions	# Reviews
Dominica	133	1288
Grenada	200	5469
Saint Lucia	393	12538
St. Kitts & Nevis	185	8479
St. Vincent & the Grenadines	163	2540
Total	**1,074**	**30,314**

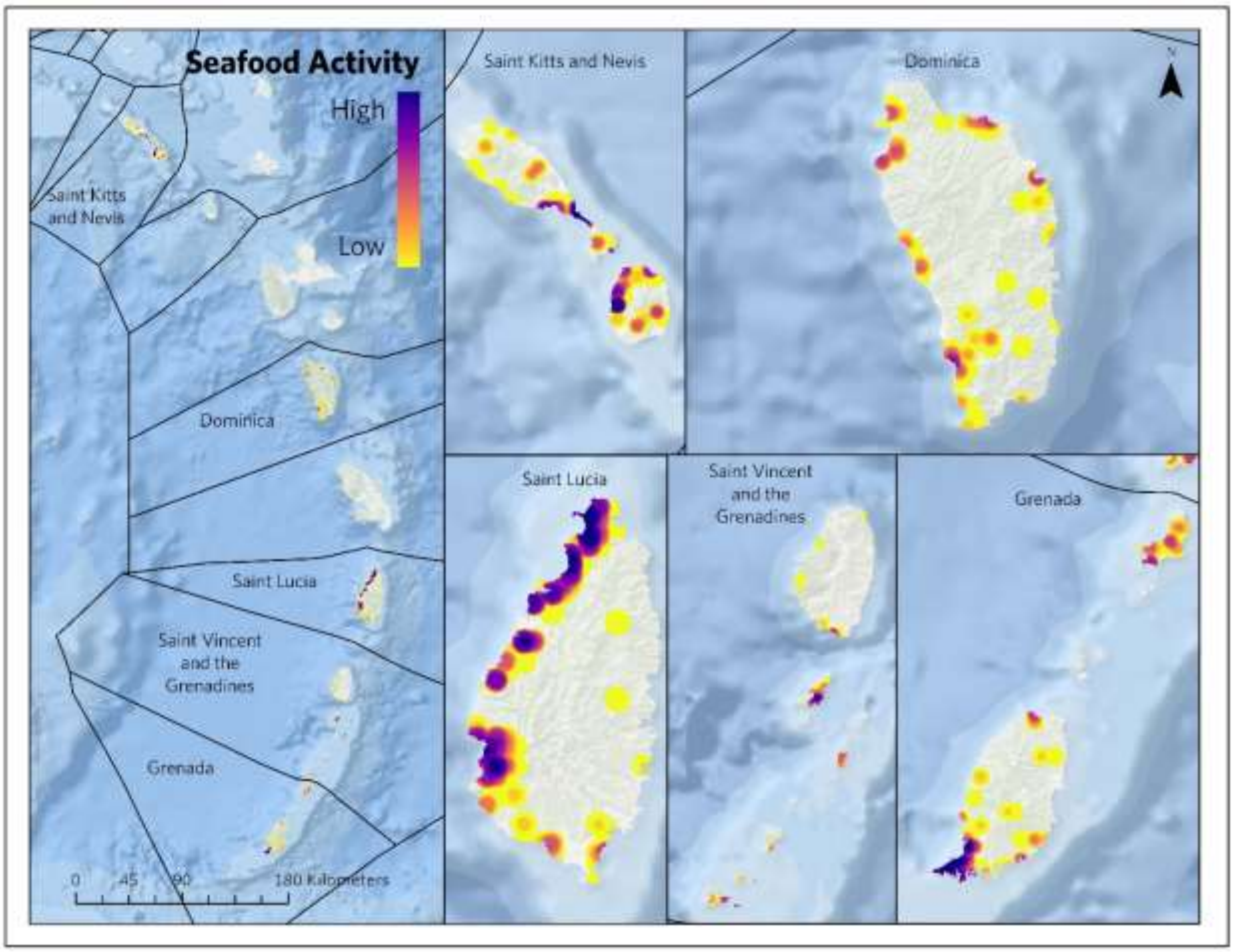

Figure 7*. Intensity map of seafood associated attractions in CROP countries. Values are unitless.*

Conclusion

This is the first time that these components of nature-based tourism associated with coral reefs have been so extensively mapped and analysed at these resolutions. We believe that the results are of considerable use for understanding the value of coral reefs and coastal ecosystems at local scales, applicable to management. They should support a broad range of users from the public to industry to government to better plan and manage both the tourism industry and any other sectors whose actions could either support or jeopardise these values. The maps are also valuable for future planning and in this sense it is useful to look at places both within countries and between countries which might provide models for future natural resource management, for example in restoring natural values as a means to expand natural benefits to new locations.

This work has drawn heavily from two earlier studies that focused on coral reef tourism both globally (Spalding et al. 2017) and for the Caribbean (Spalding et al. 2018). At the same time this work presents a major departure, both in terms of the utilization of AI/ML to retrieve large volumes of data, but also because of the very high levels of local engagement, in data supply building the models and reviewing the findings.

In the process of increasing the resolution of our work we have broken down the focus of earlier work have differentiated a several components of ecosystem benefits. This has been highly successful, as can be seen in this report with the differentiation of beach dependency, paddling and seafood, but it is also reflected in the separate report on recreational fishing and with ongoing work on other aspects of nature dependency. In undertaking this finer categorization, it quickly became clear that the differentiation of coral reefs from other ecosystems in terms of the provision of benefits was potentially more distracting than helpful. For this reason we have moved towards using the term nature dependency as opposed to coral reef dependency for all of the “reef adjacent” benefits.

From the perspective of the specific layers, the very high value of nature to tourism across the five CROP countries is of course highly apparent. On-reef activities are widespread in most reefs. The highest value reefs should be a particular target of conservation attention. These include many reefs near the diving centres in southern St Vincent, southern Grenada, the Tobago Cays, Monkey Shoals (St Kitts and Nevis). Some of the highest values of all are recorded in places where overall reef area is limited and diving is popular - small areas of reef in Dominica and Saint Lucia are generating expenditure of over one quarter of a million dollars per hectare every year. Not only should such areas be afforded the best possible management, governments would be wise to consider options to spread such value, both to provide alternative areas in event of damage, but more positively as opportunities to replicate such benefits through careful and sustainable investment.

The very high natural values of beaches overall is not surprising. As with on reef tourism, the highest values of all occur where the beach itself is small, but attracts high use. There are many beaches where natural values are considered to be critical to the overall beach value, generating many millions of dollars of expenditure annually – these include beaches such as South Peninsula Beach in St Kitts, Grand Anse in St Vincent and several beaches in Saint Lucia such as the very small beaches such as La Toc, Anse Chastenet and Jalousie. The proportional value of nature to these beaches varies of course, and it is notable that even in quite developed beach areas, such as the Pigeon Island to Rodney Bay beaches in Saint Lucia, nature is still an important component, even if its proportional contribution to value may be lower than others.

Although individual highest value are of interest, in many settings across the CROP countries it is low density, more exclusive tourism that provides a critical attraction both in terms of on-reef and nature-dependent beaches. There is a strong risk in seeking to build towards the highest values, and over-tourism is a growing concern both for destinations and for the industry as a whole (van Beukering et al. 2015, Peterson 2020). For this reason, overall values may be more valuable metrics and indeed maps showing a well-distributed spread of values across a country may be more indicative of a healthy industry with distributed benefits, and indeed distributed impacts.

For paddle sports, the overall geographic distribution is a little more restricted but is nonetheless found across all countries. Seafood, by contrast appears to closely track tourism more generally. Further analysis and interpretation of these maps will require higher resolution exploration of the data in each country.

The use of user-generated content from very large crowd-sourced datasets such as Flickr and TripAdvisor is clearly a very powerful tool for understanding relatively fine-scale patterns in tourism. Concerns have been raised about accuracy and bias, and it is clear that any public sourced datasets have a high ratio of errors. In reality it is the high volume of data that is what makes these datasets so valuable, enabling us to smooth over the occasional errors. Beyond this of course, we also made considerable efforts to clean the data. One particularly powerful element of the current work is the high degree of local engagement which has enabled us to greatly enhance the data from these more international sources, and to proof, corroborate or correct the final models and output maps. We recognize that other platforms, notably social media platforms would represent another rich source of data however such platforms do not allow large-scale data extraction and cannot at present be used for data mining in this way.

Estimating values is built on a series of assumptions, key among which is that the loss of natural values would imply a direct and immediate change in tourism arrivals and expenditure. In reality, such a relationship would be very hard to prove, and indeed there are many different modalities to tourism across the Caribbean, with some areas appearing to thrive on mass tourism with relatively low natural values. Whether such tourism models could be transferred to the CROP countries is debatable, but what is clear from our work is that the current model of tourism in the CROP countries is indeed highly nature-dependent. Our maps are modelling the natural values perceived by the current visitors to these islands. Environmental degradations, it follows, would generate the risk of losing the current "type" of visitor and the benefits they provide to the local economy.

Given the current impact of Covid-19 on tourism in the Caribbean, and especially the likely changes in demands coming from a recovering tourism sector it is highly likely that future tourism will have, if anything, a greater dependency on natural values and lower density locations (Spalding et al. 2020) and so our sites of high natural value will likely show an increasing proportional relevance for the recovering sector.

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Appendices

Appendix A. Summary of Model Inputs and Results

Table A1. Summary of model inputs and results, by country

	St Kitts and Nevis	Dominica	Saint Lucia	St. Vincent & the Grenadines	Grenada	Totals
# Hotels	67	183	262	114	156	782
# Hotel Rooms	2,731	1,281	5,836	1,164	2,564	13,576
# Dive Sites	36	55	43	88	92	314
# Dive Centres	9	12	21	10	13	65
Reef Area* (km^2)	93.4	31.1	30	212.1	115.8	482
Beach Area* (km^2)	7.2	4	6.4	13	10.1	41
Overnight Tourist Expenditures ($USD)	$117,414,477	$91,839,306	$847,253,969	$93,164,952	$149,733,686	$1,299,406,390
Overnight Visitors (# Tourist Arrivals)	123,398	85,542	429,320	129,951	166,889	935,100
Cruise Tourist Expenditures ($USD)	$47,815,455	$9,034,862	$23,697,021	$12,133,948	$13,078,192	$105,759,478
Cruise Visitors (# Tourist Arrivals)	976,546	228,128	696,642	153,001	301,638	2,355,955
Total Tourism Expenditures ($USD)	$165,229,932	$100,874,168	$870,950,990	$105,298,900	$162,811,878	$1,405,165,868
Total Visitors (# Tourist Arrivals)	1,099,944	313,670	1,125,962	282,952	468,527	3,291,055
On-Reef Overnight Tourist Expenditures ($USD)	$5,870,724	$11,020,717	$76,252,857	$9,782,320	$12,727,363	$115,653,981
On-Reef Overnight Visitors (# Tourist Arrivals)	6,170	10,265	38,639	13,645	14,186	82,905
On-Reef Cruise Tourist Expenditures ($USD)	$796,845	$361,358	$710,840	$424,646	$370,512	$2,664,201
On-Reef Cruise Visitors (# Tourist Arrivals)	16,274	9,124	20,897	5,354	8,546	60,195
Total On-Reef Tourist Expenditure ($USD)	$6,667,569	$11,382,075	$76,963,697	$10,206,966	$13,097,875	$118,318,182
Total On-Reef Visitors (# Tourist Arrivals)	22,444	19,389	59,536	18,999	22,732	143,100
Nature-Dependent Beach Overnight Tourist Expenditures ($USD)	$28,207,654	8,166,351	$203,544,293	$24,620,143	37,770,622	$302,309,063
Nature-Dependent Beach Overnight Visitors (# Tourist Arrivals)	29,645	7,606	103,140	34,341	42,098	216,830
Nature-Dependent Beach Cruise Tourist Expenditures ($USD)	$7,381,828	805,511	$3,683,352	$2,050,596	1,864,097	$15,785,384
Nature-Dependent Beach Cruise Visitors (# Tourist Arrivals)	150,761	20,339	108,283	25,857	42,994	348,234

	St Kitts and Nevis	Dominica	Saint Lucia	St. Vincent & the Grenadines	Grenada	Totals
Total Nature-Dependent Beach Expenditure ($USD)	$35,589,482	$8,971,862	$207,227,645	$26,670,739	$39,634,719	$318,094,447
Total Nature-Dependent Beach Visitors (# Tourist Arrivals)	180,406	27,945	211,423	60,198	85,092	565,064
Total Coral Reef Expenditure ($USD)	$42,257,051	$20,353,937	$284,191,342	$36,877,705	$52,732,594	$436,412,629
Total Coral Reef Tourism Visitors (# Tourist Arrivals)	202,850	47,334	270,959	79,197	107,824	708,164
# Trip Advisor Hotels**	660	598	2739	1503	984	6,484
# Trip Advisor Restaurants	268	151	402	192	410	1,423
# Trip Advisor Other Attractions	425	232	1181	244	360	2,442
Total # Trip Advisor Locations	1353	981	4322	1939	1754	10,349
Total Nature-Dependent Beach TripAdvisor Attractions***	80	39	163	72	105	459
Total Paddle Sports Trip Advisor Attractions	65	30	166	60	86	407
Total Seafood Trip Advisor Attractions	185	133	393	163	200	1,074
# Trip Advisor Images	28,921	12,739	107,091	13,884	27,656	190,291
# Trip Advisor PAMs	8,075	3,307	24,054	3,395	6,759	45,590
# Trip Advisor PAMs - Nature-Dependent Beaches	62	23	154	89	84	412
# Trip Advisor PAMs - Paddle Sports	49	14	106	15	41	225
# Trip Advisor Reviews	63,156	22,432	202,638	21,795	54,132	364,153
# Trip Advisor Reviews - Paddle Sports	538	209	4,371	305	898	6,321
# Trip Advisor Reviews - Seafood	8479	1,288	12,538	2,540	5,469	30,314
# Flickr Images	6,157	5,301	15,023	5,385	8,700	40,566
# Flickr PUDs	1,713	1,661	4,609	1,698	2,478	12,159
# Flickr PUDs - On-Reef Tourism	17	35	47	34	28	161
# Flickr PUDs - Nature-Dependent Beaches	24	10	53	66	42	195

*Based on original habitat data converted to 100m resolution

**Prior to data cleaning; may include vacation rentals and/or duplicates

*** Does not include restaurants

Appendix B. Technical and Geoprocessing Notes

Coral reef maps

Source maps are based on satellite-derived benthic habitat compiled by TNC Caribbean Team under the ECMMAN project from the following sources:

Table B1. Satellite imagery used to develop benthic habitat maps, by country

Country	Satellites
Dominica	WorldView-2, Pléiades
Grenada	WorldView-2, Pléiades
Saint Kitts and Nevis	IKONOS, QuickBird
Saint Lucia	Pléiades
Saint Vincent and the Grenadines	WorldView-2, Pléiades

Steve Schill & George Raber conducted ground truth surveys. Contractor Sam Purkis (spurkis@rsmas.miami.edu) created the benthic products at a 5m resolution.

An initial reef map was prepared from the TNC Caribbean habitat maps. A broad interpretation of the available classes was used to incorporate all possible reef habitat types. These were: coral framework; hard coral framework; reef rubble; "rocky outcrop with corals; and "any categories with named genera (*Acropora, Montastrea, Porites*), including "*A palmata* stumps".

A number of non-wreck dive-sites were distant from these reefs, but on investigation were also focused on reefal or coral dominated habitat, and this was confirmed for two important areas from secondary literature (Central West Dominica, described by Steiner 2015 as "the reefs with the highest species richness, live coral cover and architectural diversity"; and West Bequia, where Copland 2009 also provides a map showing reefs on this coast where none are noted in the TNC map). In some cases these apparent errors may simple relate to the relatively low resolution of the dive-sites information; however it is likely that some reefs have not been mapped either due to depth, small spatial extent or high substrate heterogeneity, but rather than lose such data we decided to utilise the presence of non-wreck diving to enhance our base-map of reefs using the following approach:

1 – Select all non-wreck dive sites >1km from primary coral reefs (narrow definition, above) that were not wrecks

2 – Buffer 1km from these reefs and select all hardground habitat polygons that intersect with this buffer (Class: Hardground with gorgonians; boulders/rocks,

rugose gorgonian slope, semi-consolidated rubble) as these are likely to be places where coral communities could be present, and provide habitat attractive to divers.

3 – Add these polygons to the final reef habitat map.

A final additional edit was to include the reef area of the Monkey Shoals in St Kitts and Nevis. This is a popular diving area, but lay beyond the extent of the TNC habitat maps. While we were unable to locate a detailed habitat map from any secondary source, this is a relatively small area and we had confirmation that a well-developed reef system encircles the perimeter, sloping gradually from about 15 m depth to a sand terrace at 30-40 m depth (https://www.livingoceansfoundation.org/exploring-monkey-shoals/). Given the small overall extent of this shallow bank we opted to use a simple 20m bathymetric contour to define a bounding polygon for these reefs (the 20m cutoff being broadly equivalent to that used in other maps and also equating to typical safe diving limits for recreational diving).

In a final processing these reefs were gridded to 100m, which has the effect of greatly increasing total reef area, but represents the broader area around which on-reef tourism activities are likely to take place.

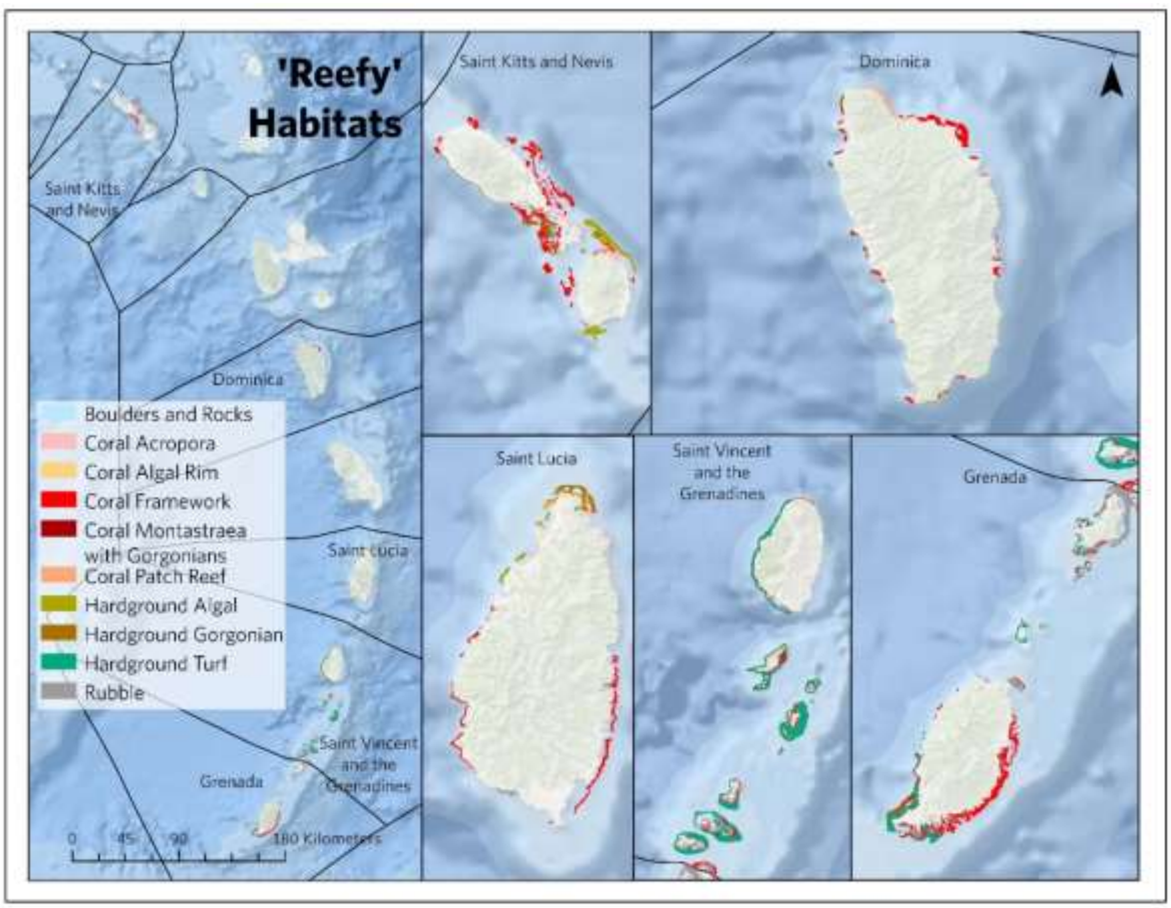


Figure B1. Reef and reef-like habitat map used for ecosystem service modeling

Beach maps

In 2013 TNC developed a map with polygon beach extents for most beaches in the Eastern Caribbean under the CLME project under a grant from UNESCO. The beaches were hand-digitized from a several high-resolution satellite imagery sources.

Under this project, this map was further annotated with beach names derived from any named beach attractions from TripAdvisor.

Further beaches were hand-digitised using satellite imagery to fill a small number of gaps in this layer.

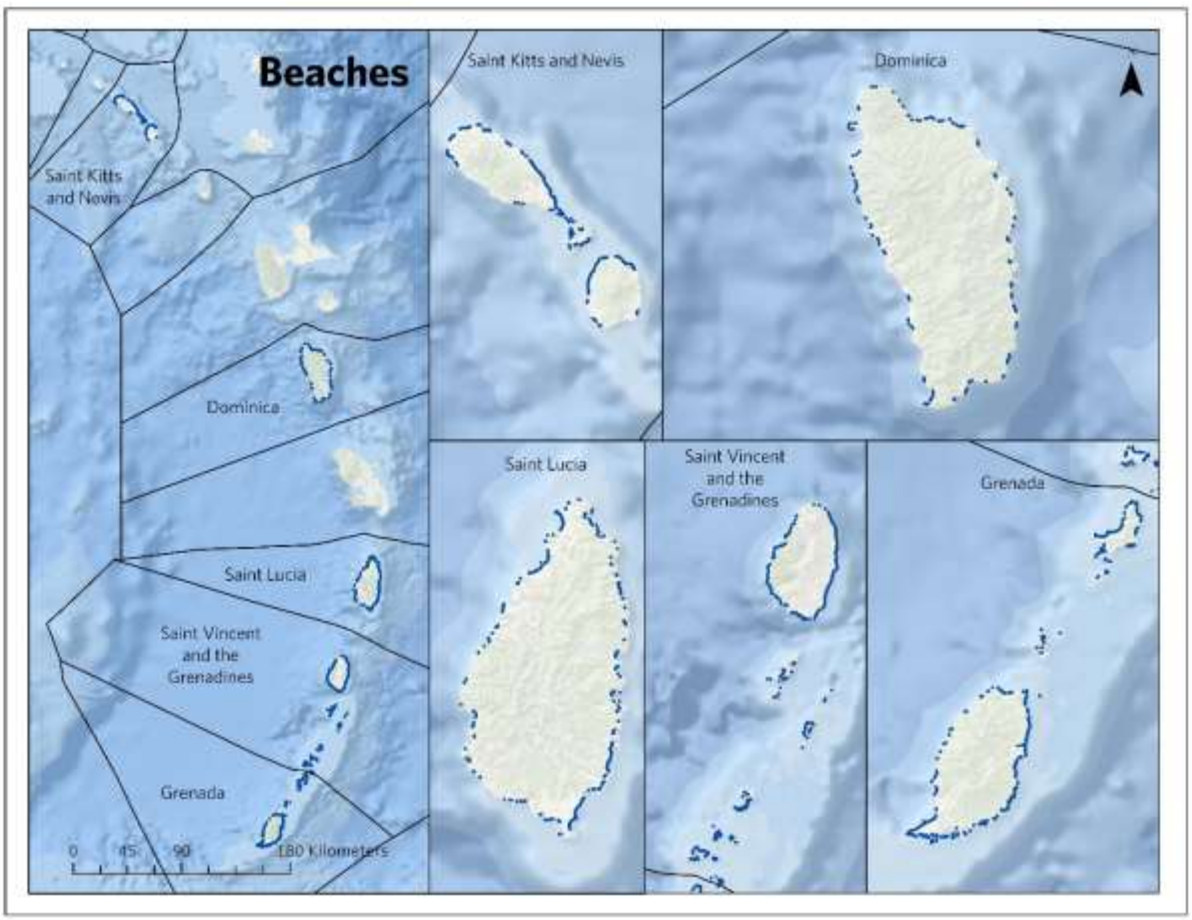


Figure B2. Beach map used for ecosystem service modeling

Tourism arrivals and expenditure

Various sources were available at national and regional levels for tourism numbers. Our key sources were:

- Eastern Caribbean Central Bank (ECCB) – annual tourism statistics. Taken average values for 5-year 2014-2019. https://www.eccb-centralbank.org/statistics/tourisms/comparative-report (ECCB 2020)
- (FCCA and BREA 2018a, b) – Data gathered from the cruise-ship industry
- Various national statistics derived from government sources and provided data covering various periods between 2014 and 2018. Where average values were derived from these they took all years available between 2014-2018.

Visitors fall into four classes: cruise passengers, overnight stays, excursionists (not staying the night), and yacht passengers. The first two dominate the statistics, although yacht passengers are also large numbers in the south of the region. Wherever information was available we combined excursionists with the cruise passengers, and yacht passengers with the overnight (yacht passengers typically spend multiple nights, and while they may not be using accommodation, many of the yachts are rented from local companies). In both cases the numbers made a very small proportion of the total visitor and expenditure and so for the few cases where such numbers were not available it is unlikely that they would change any overall statistics significantly.

Expenditure figures have all been converted to 2019 US$. This involves two steps. Firstly the annual totals were converted from EC$ to US$ for the mid-point (30 June) of the year for which they were collated using historical currency rates (using xe.com, accessed 16/9/2020). These dollar values were then corrected for inflation using a GDP deflator (World Development Indicators, https://data.worldbank.org/indicator/NY.GDP.DEFL.ZS?locations=US) to give a 2019 US$ equivalent. Averaged values were generated from these 2019 US$ equivalent numbers.

Some further details are provided below:

Table B2. Detailed tourism statistics provided by ECCB

	St. Kitts & Nevis	Dominica	Saint Lucia	St. Vincent & the Grenadines	Grenada
Total cruise/excusionist	976,546	228,128	696,642	153,001	301,638
Total overnights + yachts	123,398	85,542	429,320	129,951	166,889
TOTAL visitors	1,099,944	313,670	1,125,962	282,952	468,527
Proportion of visitors which are cruise	89%	73%	62%	54%	64%
Total expenditure cruise	$47,815,455	$9,034,862	$23,697,021	$12,133,948	$13,078,192
Total expenditure overnights + yachts	$117,414,477	$91,839,306	$847,253,969	$93,164,952	$149,733,686
TOTAL expenditure	165,229,932	100,874,168	870,950,990	105,298,900	162,811,879

	St. Kitts & Nevis	Dominica	Saint Lucia	St. Vincent & the Grenadines	Grenada
Proportion of Expenditure by cruise pax	29%	9%	3%	12%	8%
Cruise spend per pax	$48.96	$39.60	$34.02	$79.31	$43.36
Overnight spend per pax	$951.51	$1,073.62	$1,973.48	$716.93	$897.21
Number of stayover nights	1,233,983	855,418	3,589,114	1,715,349	1,522,026
Total "nights" stayover plus cruise	2,210,529	1,083,546	4,285,756	1,868,350	1,823,664
Proportion of visitor nights which are cruise	44%	21%	16%	8%	16%
Overnights spend per day	$95.15	$107.36	$236.06	$54.31	$98.38

Hotels

Two key sources were available for the mapping of accommodation:

Global Accomodation Reference Database, GARD (DELTA CHECK 2019). Although a global database this has considerable detail in terms of both location and notes on size (number of rooms being the most reliable indicator, but also number of beds for many). While mostly accurate GARD is not always most up-to-date and with villa rentals it tends to list number of properties instead of number of rooms. This listed 450 hotels with total of 11514 rooms (average 26, median 8): c.240 of these were also on TA I think (they all have a "no of reviews TA" filled in). Only 26 have no size information (# rooms).

TripAdvisor. Accommodation data in the original dataset provided listed 3025 properties, most with no relevant size information. This listing included hotels and vacation rentals, initially indistinguishable. This dataset is less curated, and generated multiple challenges:

- In some cases, individual rooms, suites and villas belonging to single management agencies are listed (extreme example: Palm Island is one property, TA lists 14 including villas and suites which are all part of the same property).
- Double entries: many vacation rentals are listed two or more times with different names even after cleaning and this is impossible to fully resolve. Estimated an average of 2 entries per accommodation.
- Spatial accuracy is good, overall. In some cases better than GARD (e.g. Mustique Island where GARD lists 80 rooms there are in fact about 80 private villas all up for rent through various agencies.)

- In quite a few cases the TA hotels are more up-to-date in terms of re-named hotels and new developments.

In addition to these sources, we were provided some limited information from local sources and from an older WWF/TNC dataset, both were very limited in scope and found to have considerable inaccuracies and so were not used beyond some small elements of data verification.

Data cleaning

The initial TA dataset included an indistinguishable mix of Hotels and Vacation Rentals. Subsequent support from TA enabled us to quickly remove some 896 Vacation Rentals, but this was still only a small proportion and so it was determined to manually remove all other likely VR or ultra-small establishments.

This cleaning process involved an initial identification of likely-VR properties, highlighting any property:

- with unusual descriptors in the "name" (lovely, luxury, 2-bedroom...), or unlikely names (Clementine, Seabiscuit, Oasis); and
- without "hotel", "guest house", "B&B", "inn" etc. in name;
- with a singular unit of accommodation in the name (e.g. villa, but not villas; apartment, suite, cottage...etc).

These likely VR properties were then reviewed further: any properties with >3 rooms were reinstated, while individual properties with >10 reviews were also investigated and some were reinstated where there was a clear sign that they were larger, fixed accommodations.

Removing duplications: Most of the hotels in TA are duplications of those in GARD and the latter, with its size information was considered our primary source. Clear duplications were simply removed. Unfortunately many hotels, including the larger hotels, are regularly renamed, bought and sold, or even demolished and re-built so quite a lot are in twice with different names. It would be impossible within the bounds of this work to check all hotels, however we selected the largest (focusing on those with more than 50 rooms) and explored for similarities in names, sizes and locations, where necessary searching online for the hotels themselves. This process led to the removal of a further 24 properties (2455 rooms) out of 82 checked.

The final hotels layer (Hotelsv3) includes 782 properties. Of which

- GARD = 446 hotels, 10858 rooms, average 24 (a small number of hotels have many beds few rooms, but this is too few to be worth correcting, as it would only add about 80 rooms)
- TripAdvisor – 336 hotels, 2722 rooms, average 8 rooms.

Some 305 properties have been assigned 1-room. Most of these (230) are from TripAdvisor and the room number has been assigned by default: the majority are indeed very small properties (a few with >100 reviews were revised and rooms assigned from tertiary sources). Although it might be possible to estimate approximate room numbers for some of these[1] it was felt that the overall improvement would be negligible and this was not done.

The separated layer of ultra-small accomodations and vacation rentals originating from TripAdvisor data includes 2664 properties. Accommodation size is not available. Many of the properties are private rentals such as AirBnB properties. In some places, e.g. on several small and exclusive islands in the Grenadines, such properties make up the dominant form of available accommodation.

Unfortunately, this layer includes considerable repetition with single properties occurring in multiple entries based on individual reviewer uploads. It also contains reviews of singular properties (suites, apartments and villas) within established hotels already listed in the hotels database

This layer could still have some value but has not been used further in the current work.

Cruise tourism

Cruise passengers behave, move and spend differently from overnight stays. For many, the boat is the destination (Whyte et al. 2018), while even onshore visits are highly controlled and contained (Weaver 2005, Gutberlet 2019), and while most do disembark at each port-of call, they don't use hotels, and would likely only have limited (lunchtime) use of restaurants. Many tend to remain within an easy reach of the cruise port, some only undertaking urban activities and shopping. Average stay onshore may be limited although excursions are also popular, and in the Caribbean activities such as snorkeling and scuba diving are highly rated (Whyte et al. 2018). Such excursions are often also highly controlled by the cruise company, with few tourists making independent bookings, and this is likely to lead to a relatively constrained range of activities undertaken and places being visited (Lopes and Dredge 2018).

(FCCA and BREA 2018b) give breakdown of some activity and expenditure for all countries except Dominica. These data provide the primary information for assessing nature dependency of cruise passengers.

Working from industry-produced data online a review of excursion options was developed.

Most companies list (often for pre-booking) their "top 10" excursions. In this work information was taken from five cruise companies working in the region (Carnival, Royal Caribbean, Norwegian Cruise Line, Princess, and Celebrity Cruises), giving a

[1] We plotted the room numbers for those hotels where there was also a TA number of reviews and found an approximate correlation (#reviews = 13.7*#rooms. $R^2 = 0.598$).

total of 163 excursions (many are repeated or similar between companies). Additionally, port guides were used for: Dominica, Grenada, Saint Kitts, Nevis, Saint Lucia, Saint Vincent, and Bequia.

These sources were translated into data points when possible, then buffered by 1km. Where the excursions described a scenic drive along the coast or a catamaran tour along the coast between two points of interest, a 1km buffer from the coastline was applied. If the lists mentioned specific marine reserves for diving or snorkeling, these areas were included in the layer using data from The Nature Conservancy in the Caribbean's marine protected area shapefile.

Many of the non-excursion passengers take a taxi or water taxi to a beach or sometimes to other attractions ("All cruise terminals have taxi stands outside them where taxis congregate and then take the tourists to the beaches. Each island has very popular beaches that are overrun with tourist on cruise ship days" Sherry Constantine pers comm 14 Aug, 2020). Port data points were compiled at a country-by-country level through in-country data collection and existing TNC shapefiles compiled during past projects including At the Water's Edge and Sustained Marine and Coastal Biodiversity Threat Abatement in the Eastern Caribbean. Cruise ports were identified from WhatsInPort.com and selected out from the ports point layers. These cruise ports were then buffered by 5km to account for tourist activity around the ports.

Table B3. Summary of data sources for cruise ship passenger footprint layer

Country	Top 10/Excursions Lists	Port Guides
Dominica	Carnival – Shore Excursions Princess – Excursions Royal Caribbean – Things to Do in Roseau	The Telegraph – Dominica
Grenada	Carnival – Shore Excursions Carnival – Top 7 Things to Do in Grenada Princess – Excursions Royal Caribbean – Shore Excursions	The Telegraph – Grenada
Saint Kitts and Nevis	Carnival – Shore Excursions Carnival – Top 10 Things to Do in Saint Kitts Princess – Excursions Royal Caribbean – Shore Excursions	The Telegraph – Saint Kitts The Telegraph – Nevis
Saint Lucia	Carnival – Top 10 Things to Do in Saint Lucia Norwegian Cruise Line – Shore Excursions	The Telegraph – Saint Lucia

Country	Top 10/Excursions Lists	Port Guides
	Royal Caribbean – Shore Excursions	
Saint Vincent and the Grenadines	Celebrity Cruises – Shore Excursions	The Telegraph – Saint Vincent The Telegraph – Bequia

The excursions and port datasets were combined and dissolved to create a single mask layer of cruise ship passenger activities. (While the separate tour layers could have been combined to give an intensity metrics this was unlikely to be reliable as there was no weighting for popularity of different tours, while at the same time our use intensity metrics from attractions and photos provides an independent indicator of likely use intensity which is at least partly informed by cruise passengers).

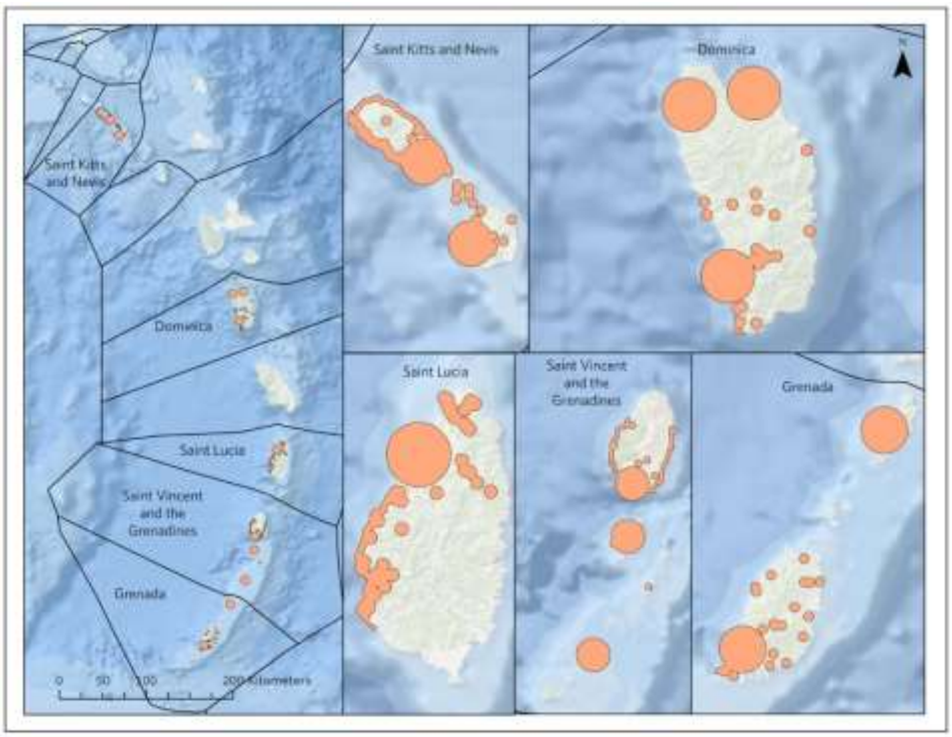


Figure B3. *Spatial footprint of cruise passenger activity used in models*

Dive sites and dive centres

Two datasets were developed: dive sites and dive centres. The primary source for both of these was the global diving database https://www.diveboard.com/ (Diveboard 2020). Data were generously provided and used in combination with a large number of secondary sources from other global and regional sources as well as from local operators. The full process is described in a separate document (diving data methods.doc), but this is summarised with some detail below

Diveboard Dive Spots. These are identified and (usually) named locations where diving has taken place. Although we were given the entire database, only about 10% of the total dive-spots have been verified (flag_moderate_private_to_public is "nil"). This is a best layer and forms our starting point (DB1). For CROP countries it contains 235 spots.

Most of the remainder are simply unchecked and may be valid (flag_moderate_private_to_public is "true"), indeed many are identical sites to those already held in DB1. However it also includes some that have been checked and excluded or re-combined with other sites. This subset (DB2) was only used for cross-checking.

DB1 was first enhanced by bringing in data from sites in DB2 that had the same ID or name as sites in DB1 – this enabled us to increase the number of recorded dives, but did not add sites.

A small number of Diveboard sites were multi-site references with multiple names listed in the name field: where possible these were split and re-located, with number of dives spread evenly across sites.

Additional data sources: numerous other sources were available. Given the apparent accuracy of Diveboard, and in order to avoid duplication of sites due to alternative names or spellings, we decided only to bring further sites in where the source is local, reliable and recent OR if it is found in 2 other sources. DB2 data was held in the background as a potential source to be cross-checked against these tertiary sources. The sources used are listed below:

Global dive-data maps:

https://www.diveboard.com/explore
https://dive.site/
https://www.plongeur.com/
https://scubadivingresource.com/ - no map but MANY site descriptions
https://www.deepblu.com/planet
https://www.wannadive.net/

St Kitts:

- https://prodiversstkitts.com/pages/sites.html, https://www.ebay.com/itm/Franko-Maps-St-Kitts-Nevis-Coral-Dive-Creature-Guide-5-5-X-8-5-Inch-/263407191956
- https://www.plongeur.com/ville/134987-saint-christophe

Dominica:

- https://www.scubatravel.co.uk/dominica/dominicadive.html; https://images-na.ssl-images-amazon.com/images/I/51L3DVL-1bL._SX326_BO1,204,203,200_.jpg (Franko Maps)
- https://scubadivingresource.com/destinations/caribbean/dominica/dive-sites/, https://cabritsdive.com/diving-in-dominica/
- https://myscubadivinggearguide.com/wp-content/uploads/2019/01/domnature.jpg

Saint Lucia:

- http://serenityvacations.convergesolve.com/demo/things-to-do/diving/
- https://store.yellowmaps.com/products/2126619m-st-lucia-reef-creatures-fish-card-by-frankos-maps-ltd?utm_source=Pinterest&utm_medium=Social
- http://www.scubabooksonline.com/Caribbean/diveSaint Luciasites.htm
- divesaintlucia.com/dive-map/
- https://tikaye.com/diving/dive-sites/
- https://diveary.com/site/roseman-s-trench-2680
- https://www.divefairhelen.com/st-lucia-dive-sites.htm, https://www.discovereef.com/

St Vincent:

The diving industry on the main island are highly sensitive about sharing dive-sites locations and we should be very cautious that we do NOT share the raw data. The only locational data found online for these is here: http://www.discoversvg.com/index.php/en/about-svg/downloads/category/16-magazines (Also here - http://www.tourism.gov.vc/tourism/images/stories/PDF/Tourism_Higlight_-_Issue_2.pdf)

Lists found here:

- http://www.scubabooksonline.com/Caribbean/divestvincentsites4.htm
- https://scubadivingresource.com/destinations/caribbean/st-vincent-the-grenadines/
- http://www.divestvincent.com/DiveSites2.html

Grenada:

- https://www.ecodiveandtrek.com/about-us/dive-sites/
- http://www.deeferdiving.com/carriacou-scuba-diving.html
- https://www.deepblu.com/planet/region/Caribbean%20Sea%20-%20Carriacou/GD/59f01fe06dddf779fcea97a4/,

Best Dives of Grenada, St. Vincent & the Grenadines https://books.google.it/books?id=ke0h_b2m8BgC&pg=PT10&lpg=PT10&dq=halifax+wall+grenada&source=bl&ots=qK3pseWOgz&sig=ACfU3U2bYefDw2zNbSeEBCkf40uszCDOjw&hl=en&sa=X&ved=2ahUKEwiG_uKx47DoAhXRbsAKHeG2DmMQ6AEwAHoECAgQAQ#v=onepage&q&f=false

One important component of the Diveboard data is that numbers of dives are available for many sites and this was used to give a light weighting to use intensity as follows:

No of dives	Weighting
0-4	1
5-9	1.5
10-20	2
>20	3

Buffering:

The location of dive sites is annotated by users and likely to be of low accuracy. Indeed it was notable that many dive sites are placed too far from shore (in very deep water) – and this was corroborated by the fact that may of the PUD locations are far closer to shore. It was thus decided to buffer the dive sites into an area of 1km radius from apparent location.

Final data layer

- In total the final layer has 314 dive-sites.
- Of these 242 have a Diveboard count of numbers of dives.
- There are 44 wrecks – this is based on the name, description in Diveboard and/or during the data verification process. It is likely that some wreck sites have not been identified. It is noteworthy that some of the wrecks listed in Diveboard are also counted as reefs, so the terms are not mutually exclusive.

Dive centres

The “dive shops” listed from Diveboard DB1 and DB2 were identical, and were pooled to generate a single list, pulling data from the different entries as needed.

Data was cleaned, ideally finding correct locations, but particularly targeting obvious errors (mountainous or offshore dive shops). Although a useful layer, the Diveboard data was incomplete and additional data was sourced from multiple locations, notably TripAdvisor – these were thoroughly reviewed by one of us (MDS)

In the final dataset there are 52 Dive shops, including 26 from Diveboard and 18 from TripAdvisor.

Nature-dependent beach calculations

1. Beach Utilisation

We found that there were methodological inconsistencies making comparison of exit survey data difficult. In particular, some surveys where participants can only assign one choice, beach becomes a very low proportion (St. Kitts & Nevis becomes 18%). In other surveys where participants can list multiple activities: beach becomes highly predominant (87% of Grenada tourists), but if we normalise it again drops right off (Grenada becomes 20%). Seems very likely that most tourists in CROP countries would do "beach plus" therefore non-normalised value of beach visitation is appropriate to get an estimate of beach use. The veracity of this is perhaps emphasised for Anguilla where beach-focused activity is the absolute core of the industry, but which the single choice survey would suggest beaches are only 30% of activities – clearly very wrong! Schuchman (Schuhmann et al. 2019b) makes it clear that such numbers are total proportion of people visiting the beach (92% in Barbados).

Given the lack of data for 4/5 CROP countries, but the widespread knowledge that beaches are a critical component across most E Carib Islands we amalgamated available data for similar, small island states in the region, and opted to use the average for these to inform a single regional beach importance.

Table B4. Summary of sources used to estimate beach tourism

Country	%	Source
Barbados	92%	(Schuhmann et al. 2019b)
Cayman Islands	88%	https://www.visitcaymanislands.com/Visitcaymanislands.com/media/Documents/BI-Annual-Statistics-Report-January-to-June-2016-v2.pdf
Grenada	87%	http://www.widecast.org/Resources/Docs/RARE_2004_Assessing_Small_Scale_Tourism_in_Grenada.pdf
Guadeloupe	77%	https://www.regionguadeloupe.fr/fileadmin/Site_Region_Guadeloupe/Mediatheque/Brochures_et_publications/ORT_Newsletter_mars_2018_Les_touristes_recepteurs.pdf
Martinique	69%	http://martinique.media.tourinsoft.com/upload/SYNTHESE-BILAN-TOURISME-2017-3.pdf
St. Eustatius	60%	(van de Kerkhof et al. 2014)
St. Maarten	68%	http://www.stat.gov.sx/downloads/Tourism_Exit_Survey_Results_2013.pdf

The mean values for these numbers is 77% and it was decided to apply this value to all CROP countries other than Dominica. For Dominica where narrow black-sand beaches predominate around much of the coast there is a strong focus on other aspects of tourism, notably cultural and terrestrial nature-based activities, together with some diving (CHL Consulting Company Ltd. 2013). Beaches are not unimportant, but the value is likely to be much lower. The only input data for Dominica suggests that 61% of visitor undertake “general/leisure/VFR stay” and “nature tourism/leisure” (CHL Consulting Company Ltd. 2013), given the strong focus of such activities on non-beach activities it seems not unreasonable to assume that perhaps half of this number would encompass beach visits. Our final input figures for beach visitation would therefore stand at:

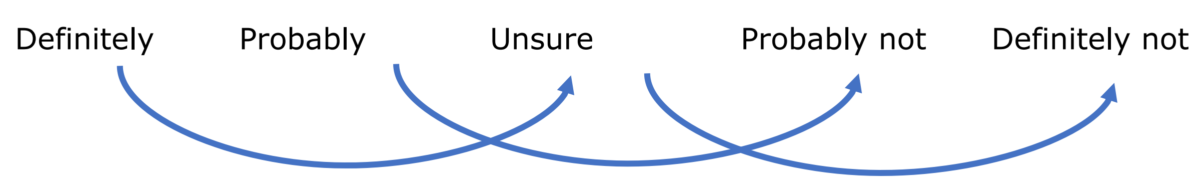
Beach Utilisation by visitors to CROP countries:

- Grenada, St Kitts and Nevis, Saint Lucia and St Vincent and the Grenadines – 77%
- Dominica – 30%

2. Current natural beach value

This has been based on (Schuhmann et al. 2019a), where visitors were asked to assess there likelihood of return following various aspects of environmental degradation. All of the elements of degradation considered in this paper could be considered relevant to natural values of beaches (water quality, fish-life, coral health and beach width). We therefore consider that such values would provide a direct metric for assessing natural values, and that we can use, without further modification, the stated likely reduction in returns following environmental degradation to provide an indication of current natural values.

The paper provides a range of options. For our work we considered a loss of returns to encompass all respondents whose likely return response moved by two or more steps in the scale of return likelihood (see figure below), based on ANY ONE of the environmental changes.



For this work then, Schuhmann revisited the data from this paper and drew up the following matrix for the reduction in visitor returns related to environmental degradation

Table B5. Environmental factors considered in Schuhmann et al. 2019a

2- or 3-Point Changes in Stated Probability of Return (% of respondents)				
ENV CHANGE	WATER QUALITY	BEACH WIDTH	MARINE LIFE	CORAL HEALTH
-50%	62.3%	15.7%	20.7%	14.2%
-25%	45.3%	10.8%	15.5%	12.4%
-10%	34.9%	6.4%	12.4%	9.0%*
-5%	31.2%	5.5%	12.3%	9.9%*

* The apparent inverse direction in the return likelihoods for these numbers is not statistically significant (chi square test).

For this work we have taken the highest value across declines, based on the argument that, while not additive, most declines would be simultaneous, and there may be some additionality because visitors may have different sensitivities to different aspects of environmental decline. At the same time we have taken the lowest level of decline (5%) as this is perhaps a more likely scenario in short-term planning. Therefore, we take the drop in returns associated with a 5% decline in Water Quality for our model, indicating a 31.2% drop in returns.

The advantage of this matrix is that it could enable further re-programming of the model to develop a dashboard where users can investigate costs of different degrees of degradation and different components of such degradation.

3. National modifiers

The data from PUDs, and TA reviews suggest that the importance of nature to beaches in the five CROP countries varies notably. NDBs make up 13% of PUDs, and 2.7% of reviews for St Vincent, but only 2% and 0.5% respectively for Dominica.

These numbers suggest a real and consistent variation in the appreciation of natural values between countries which might, in reality, alter the natural beach value described above, based on a survey of tourists in Barbados. The only means we were aware of that be used to alter such a value, however, was informed expert judgement. Barbados is a slightly more developed and urbanised country than the CROP countries, and while it is particularly known for its beaches it is likely that other elements of tourism might draw some value away from beaches. With this in mind we developed a simple modifier, lifting the relative value of two countries, keeping two unchanged and lowering the value of Dominica.

Table B6. Nature-dependent Beach Modifiers by Country

Country	PUD Ratio	TA PAM Ratio	Suggested modifier to natural beach value
Dominica	2%	1.1%	-5%
Grenada	8%	8.7%	5%
St Kitts and Nevis	5%	4.0%	0%
Saint Lucia	7%	3.8%	0%
St. Vincent & the Grenadines	13%	16.5%	10%

Other statistics support the general patterns shown in the PUD and TA PAMs, including the rankings of nature dependency reviews for only beach attractions, the proportion of non-restaurant attractions that had nature-dependent beaches, and the rankings from TA Reviews.

Appendix C. 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.

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.

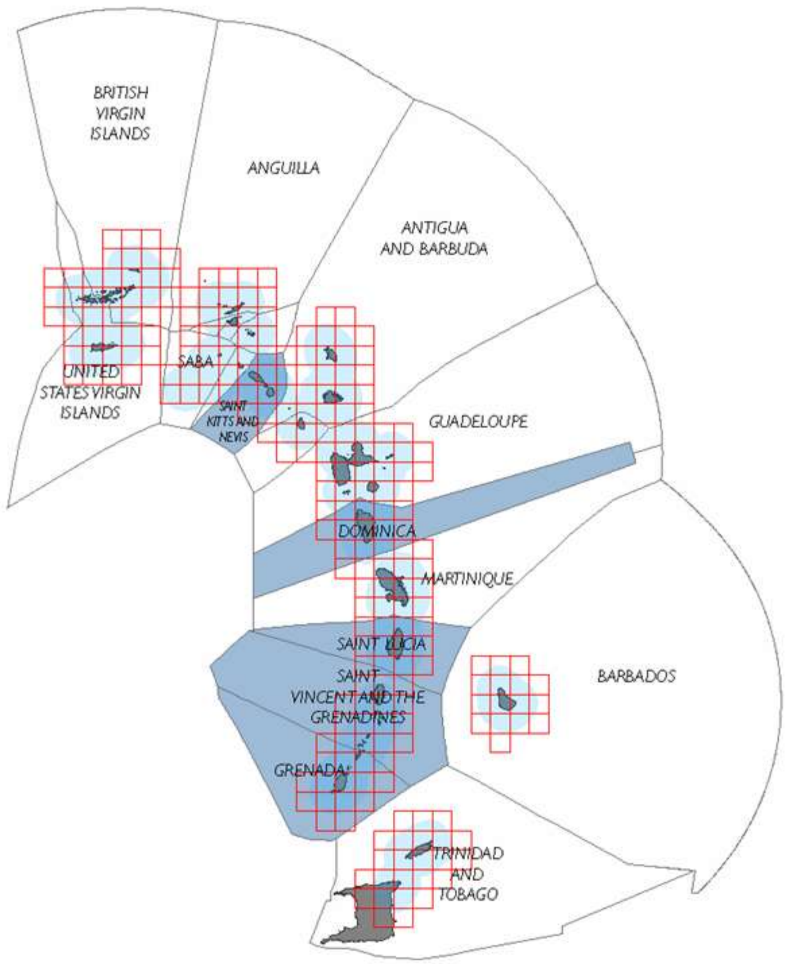


Figure C1. Flickr Search Extents

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 Saint 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.

We did end up developing two models for the on-reef/underwater category, since creating a single model to try and classify the variation in all the representative images would have been more difficult. In that particular case, we developed one model to identify underwater images where the blue hue of the water wasn't apparent. For example pictures taken with a flash, or up close of coral reef. The other class was used to identify underwater images that had a blue hue and looked more of what you might expect an underwater image to look like. These models were used in conjunction and both run on the image datasets to identify underwater images. This logic could have easily extended to other categories, had the scope permitted. For example, models could be developed to identify common false positives and run in conjunction with category-specific models as a filter. For example, swimming pools are a typical false positive for the reef-adjacent classifier and are included in the negative class. Instead of using swimming pools as a negative for the reef-adjacent model, we could have developed a model to classify swimming pools as a means to filter out the false positives.

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. In the reef-adjacent model, the more images we added into the positive category, the worse the model started performing. We believe this to be in large part due to reducing our threshold of what constituted reef-adjacency, and the ultimate confusion of the model to differentiate between the positive and negative images in the training data.

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

We developed five classifiers in a short time span representing the four categories of interest, using two models for the underwater/on-reef category, and a single one for each of the other categories.

Table C1. Computer Vision model descriptive statistics

Model	Underwater		Reef Adjacent	Recreational Fishing	Kayaking / Paddling
	Underwater Clear	Underwater Blue			
# Positive Training	70	70	166	68	88
# Negative Training	50	50	241	128	190
Threshold Pct	90%	90%	99%	90%	95%
Custom Vision Precision	100%	100%	100%	100%	94.7%
Custom Vision Recall	92.9%	92.9%	84.8%	71.4%	100%
Flickr Identified	1,496		615	8	25
Flickr Ratio	3.69%		1.52%	0.02%	0.06%
TripAdvisor Identified	3,876		3,209	321	340
TripAdvisor Ratio	2.03%		1.69%	0.17%	0.18%

On-Reef/Underwater

Throughout this work we noticed that there are two distinct types of underwater images, those with dominant blue hues, and those without. Rather than attempting to create a single model to represent both of these types of images, and building upon our work from 2018, we developed two independent binary models to classify underwater images. Each underwater model contained 70 positive images and 50 negative images. After careful review, we decided on a threshold of 90% for either model to classify the images, that is, if either on-reef model predicted greater than 90% we classified the image as underwater. At this confidence level, 1,496 images were identified in the Flickr dataset, and 3,876 images in the TripAdvisor dataset were classified as underwater.

The underwater blue model is comprised of underwater images where the water itself is clearly visible. To ensure variation in the training images in the positive class, we made sure to include images that contained people, reef, a variety of sea life, and open ocean. The underwater clear model contains images where either no or a minimal amount of blue hue is detected, including mostly close-up shots of coral reef, fish, and other marine life. The negative class for both models is the same, and includes all above-water images that were flagged as false positives in the first iteration, including some images with beaches, water shots with no beach visible, distant aerial images of the ocean, rocky intertidal zones, and images of the sky.

Figure C2. Sample of Underwater Blue Positive Images

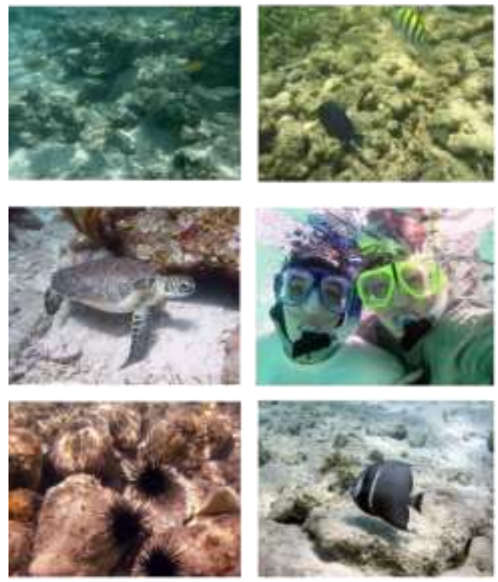


Figure C3. Sample of Underwater Clear Positive Images

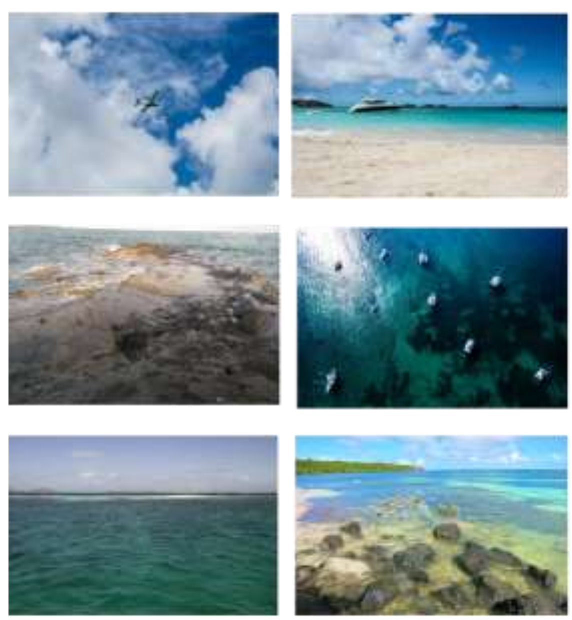


Figure C4 . Sample of Underwater Negative Images

Reef-Adjacent (i.e. nature-dependent)

Reef-adjacent beaches typically have white sand, non-turbid turquoise water, minimal nearshore waves, and often green vegetation nearby. However, beaches in general, whether reef-adjacent or not, share many characteristics. In addition to the obvious (water, sand, waves, shoreline, palm trees, vegetation, etc.) the time of day, sun reflection off the ocean, and exposure level of the image all play a big part in being able to positively identify a reef-adjacent beach, thus making the development of a classifier to distinguish between the two quite challenging.

If our objective were to just classify a beach or shoreline, the development process would be inherently simple, and the false positives would likely be things like swimming pools and palm trees, both of which would be relatively easy to train the classifier to identify. However, our model needed to be able to make the distinction between types of beaches, so the training data had to be very carefully selected. As such, we ended up running six iterations of this classifier, before ultimately settling on the fourth iteration. There are 166 images in the positive class and 241 in the negative class. As images were added into subsequent iterations, the classifier's precision and recall began to decrease in tandem, likely due to the similarities between the positive and negative classes. Thusly, increasing the training size resulted in poorer classifier performance as the model was less able to distinguish between the positive and negative classes. With a focus on precision rather than recall, a threshold of 99% was selected, which yielded 615 Flickr images and 3,209 TripAdvisor images.

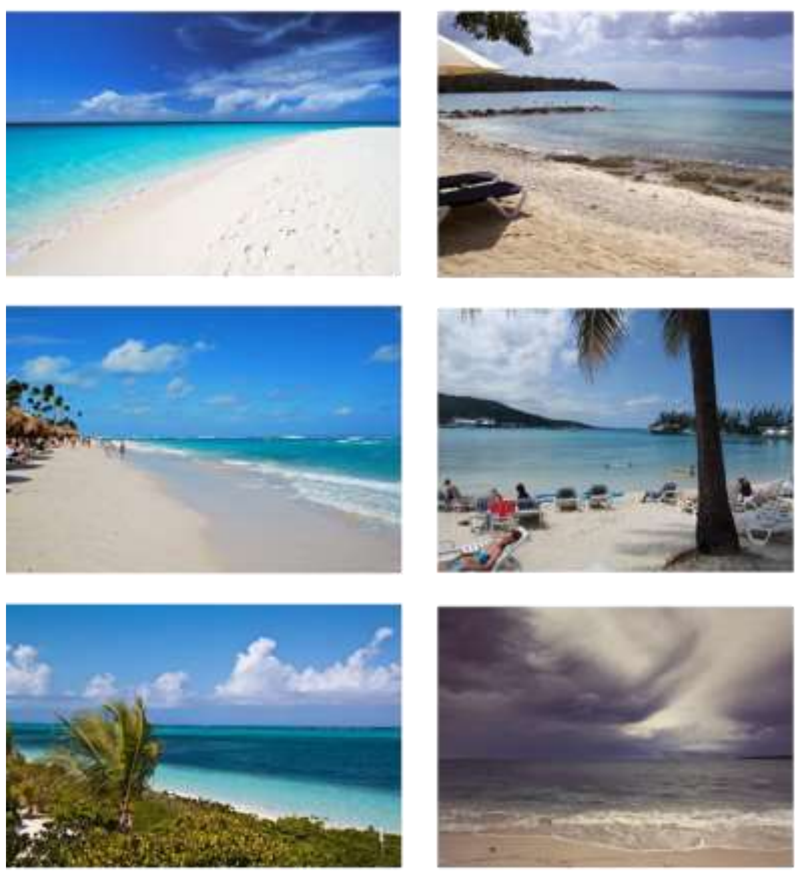


Figure C5. Sample of Reef-Adjacent Positive Images

Figure C6. Sample of Reef-Adjacent Negative Images

Paddle sports

The positive class of the paddle sports model consists of images of people paddling kayaks and paddleboards on the water. To our surprise, the paddling model has by far the widest variety of false positives of any of the models. The obvious false positives included above-water images without kayaking or paddleboarding, pictures of motorboats and smaller watercraft, surfing, boogie boarding, and jet skiing. These common and logical false positive categories were included in the negative class. Interestingly—and likely due to the prevalence of paddles in the images—pictures of people holding fishing rods, skydiving, and golfing were identified as false positives and needed representation in the negative class. Had more time permitted, we would have likely developed specific models for each type of paddling activity, though the effectiveness of this approach is unknown, given the prevalence of false positives in the model that was developed.

The final iteration of the paddling classifier included 88 positive images and 188 negative, and like the recreational fishing model, also yielded a small percentage of images. 25 Flickr images and 340 TripAdvisor images were classified using a 90% probability threshold.

Figure C7. Sample of Paddling Positive Images

Figure C8. Sample of Paddling 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 overview

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.

1. Reef-adjacent activities

This is to define the presence of specific activities that are likely to be highly dependent on nearby reefs for creating conditions for the activity. Look for reviews that mention any of the following terms:

- Kayak
- Canoe
- Paddleboard
- Paddle board
- Kitesurf
- Kite surf
- Windsurfing
- Pedalo

2. Seafood restaurants

This is to identify attractions where the presence of fresh seafood is a major draw for tourism activities. We are not going to be able to distinguish reef-fish from non-reef fish in the ML phase as there is too much noise. Thus we are just going to look for any mention of seafood. Look for reviews that mention any of the following:

- Seafood
- snapper
- spiny lobster
- lobster
- grouper
- lionfish / lion fish
- jack
- parrotfish / parrot fish

- conch (not as souvenirs)
- Mahi mahi
- Wahoo
- Sailfish
- Marlin
- Barracuda
- Kingfish
- Tuna
- Bonefish
- Trevally
- Fresh fish
- catch of the day

NOT

- shrimp
- scallop
- salmon
- tinned tuna

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 B9).

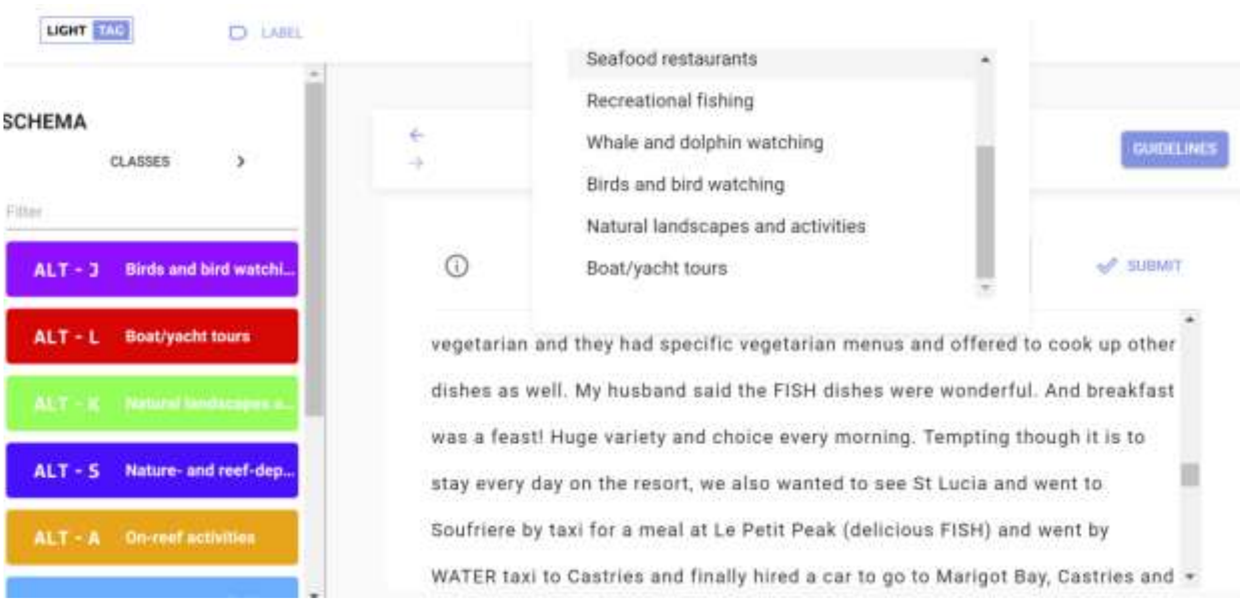


Figure C9. *Screen shot of LightTag API interface*

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, both seafood restaurants and reef-adjacent activities had overall high model quality metrics.

Table C2. 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 D. Geoprocessing Steps for Models

On-reef recreation and tourism

1. Prepare dive site map by selecting all dive sites that are not classified as wrecks.
2. Use the number of dives per year assigned to each dive site to assign a weight to each dive site (1 – 4)
3. Prepare initial reef map by selecting from benthic habitat map all features with the following categories: all named genera (Acropora, Montastrea, Porites), including "palmata stumps"; coral framework; hard coral framework; reef rubble and "rockyoutcrop with corals".
4. Select all hardground benthic habitat polygons (hardground with gorgonians; boulders/rocks, rugose gorgonian slope, semi-consolidated rubble) that are within 1km of the dive site layer prepared in Step 1 and add these polygons to the selection in Step 2.
5. Finalize the coral reef habitat layer by selecting the Monkey Shoals dive site in St. Kitts & Nevis, and digitize additional reef habitat in this location by tracing the 20 m depth contour around this dive site. Add this polygon to the reef layer from Step 3.
6. Finalize the reef habitat dataset by converting the polygon to a 100m resolution raster. The title of this dataset is "reefy_hab"; create a point layer based on this raster
7. Prepare the Underwater Photo User Day (PUD) datasets by aggregating the locations of all underwater Flickr photos within a 500m grid cast over the region of interest. The points are further dissolved by the date the photo was taken, and then by the Flickr member ID within each grid cell. The result is a point layer with a numerical score that reflects the total number of days, across all users, that each person took at least one photograph within each site, after Wood 2013.
8. Apply a 1km buffer to each PUD and Dive Site
9. Perform a spatial join between the buffered PUD and Dive Site and the reef point layer created in Step 6, such that each buffered point has a sum total of all of the reef tracts within 1km of their location; assign that total reef score to the corresponding Dive Site or PUD point via a spatial join
10. Create an intensity score for PUD and Dive Site point by dividing the PUD score (Step 7) or Dive Site weight (Step 2) by the Reef Score
11. Run a point density analysis on the PUD and Dive Site points, using the intensity score from Step 10 as the input value, with a 1km neighborhood and 100m resolution; snap the output rasters to the Reefy Habitat raster
12. Use the Cell Statistics tool to sum the PUD and Dive Site point density rasters

13. Extract this layer using the Reefy Habitat raster as a mask. The resulting layer is the Coral Reef Use Intensity raster
14. Obtain the sum of all of the cells in the use intensity raster; divide both the overnight tourism expenditure and visitation input values by this sum.
15. Use the raster calculator to multiply the Coral Reef Use Intensity Raster by the values obtained in Step 14 to spread the expenditure and tourism values to the coral reef, weighted by the use intensity.
16. Use the Cruise Footprint polygon to clip the Coral Reef Use Intensity layer to derive a Coral Reef Use Intensity raster specific to cruise passengers
17. Repeat steps 14 and 15 using the cruise tourism expenditure and visitation input values

Nature-dependent beaches

1. Prepare beach layer by converting the beach polygon layer to a raster with 100m resolution; create a point layer based on this raster
2. Prepare the Nature-Dependent Beach Photo User Day (PUD) dataset by aggregating the locations of all nature-dependent beach Flickr photos within a 500m grid cast over the region of interest. The points are further dissolved by the date the photo was taken, and then by the Flickr member ID within each grid cell. The result is a point layer with a numerical score that reflects the total number of days, across all users, that each person took at least one photograph within each site, after Wood 2013.
3. Prepare the Nature-Dependent Photo by Attraction by Member (PAM) by dissolving all TripAdvisor photos and their locations by the MemberID field, such that each point represents a TripAdvisor attraction and has a value corresponding to the number of TripAdvisor users posting a nature-dependent beach photo at that location
4. Apply a 1km buffer to each PUD and PAM
5. Perform a spatial join between the buffered PUD and PAMs and the beach point layer created in Step 1, such that each buffered point has a sum total of all of the beach units within 1km of their location; assign that total beach score to the corresponding PUD or PAM point via a spatial join
6. Create an intensity score for PUD and PAM points by dividing the PUD score (Step 2) or the PAM score (Step 3) by the beach score (Step 5)
7. Run a point density analysis on the PUD and PAM points, using the intensity score from Step 6 as the input value, with a 1km neighborhood and 100m resolution; snap the output rasters to the beach raster
8. Use the Cell Statistics tool to sum the PUD and PAM point density rasters
9. Extract this layer using the beach raster as a mask. The resulting layer is the Nature-Dependent Beach use intensity raster
10. Obtain the sum of all of the cells in the use intensity raster; divide both the overnight tourism expenditure and visitation input values by this sum.

11. Use the raster calculator to multiply the use intensity raster by the values obtained in Step 10 to spread the expenditure and tourism values to the beaches, weighted by the use intensity.
12. Use the Cruise Footprint polygon to clip the Nature-Dependent Beach Use Intensity layer to derive a Nature-Dependent Use Intensity raster specific to cruise passengers
13. Repeat steps 10 and 11 using the cruise tourism expenditure and visitation input values

Paddle sports

1. Prepare the Paddle Sport Photo by Attraction by Member (PAM) by dissolving all TripAdvisor photos and their locations by the MemberID field, such that each point represents a TripAdvisor attraction and has a value corresponding to the number of TripAdvisor users posting a nature-dependent beach photo at that location
2. Select from the TripAdvisor Review point layer all of the points that have a non-zero value for Activities
3. Use the Point Density tool with a 1km neighborhood on the point layers from Steps 1 & 2 to derive a density map from each point layer
4. Use the cell statistics tool to sum the two layers
5. Use the focal statistics tool with a neighborhood of 1km and a Mean statistics type to smooth the layer for improved visualization
6. Create a 500m inner buffer of the shoreline
7. Use the inner buffer from Step 6 to erase a polygon outline of each island's shoreline
8. Convert the resulting polygon from Step 7 to a raster
9. Use the raster from Step 7 to erase the layer from Step 5 (using raster calculator) in order to only show to eliminate all values more than 500m inland from the shoreline

Seafood restaurants

1. Select from the TripAdvisor Review point layer all of the points that have a non-zero value for Seafood
2. Use the Point Density tool with a 500m neighborhood on the point layers from Steps 1 to derive a point density map
3. Use the focal statistics tool with a neighborhood of 500m and a Mean statistics type to smooth the layer for improved visualization
4. Use a shoreline polygon layer depicting each island to clip the layer from Step 3 such that all values fall on land.

Appendix E. Maps by Country

On-reef tourism – Annual overnight and cruise tourism expenditure by country

Images E1 – E5 Depict total annual on-reef tourism expenditures (overnight and cruise tourism). Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

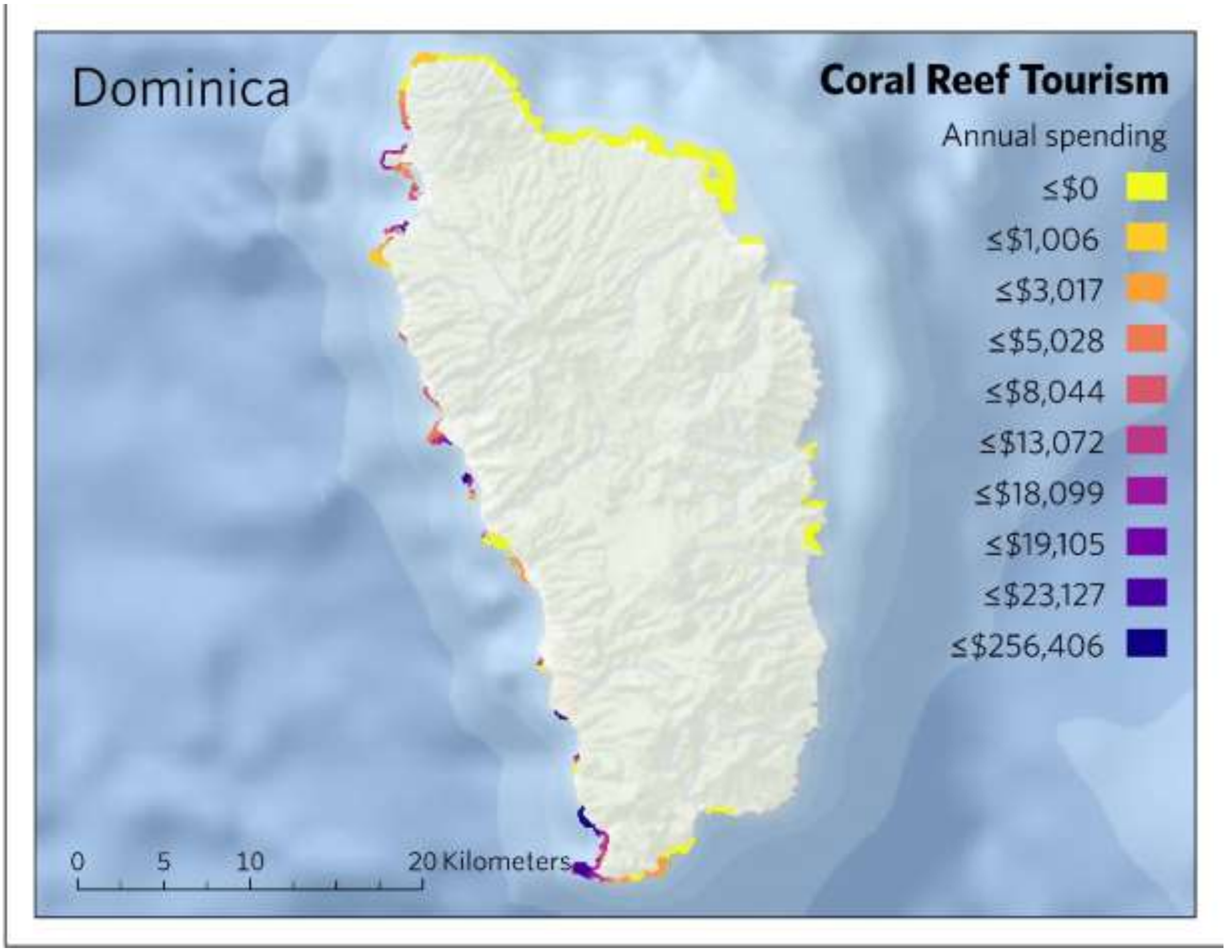


Figure E1. *Total annual on-reef tourism expenditures (overnight and cruise visitors) for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

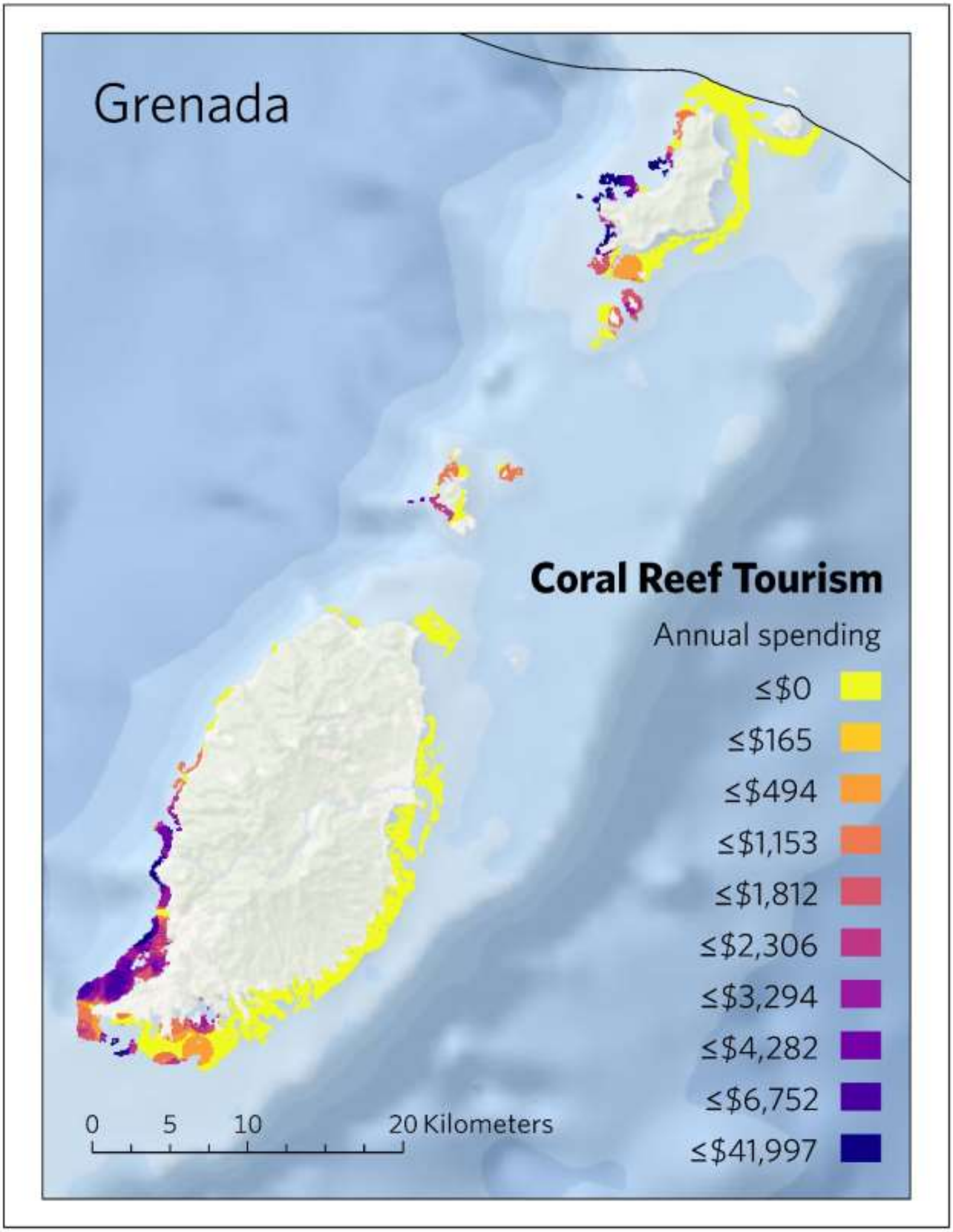


Figure E2. *Total annual on-reef tourism expenditures (overnight and cruise visitors) for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

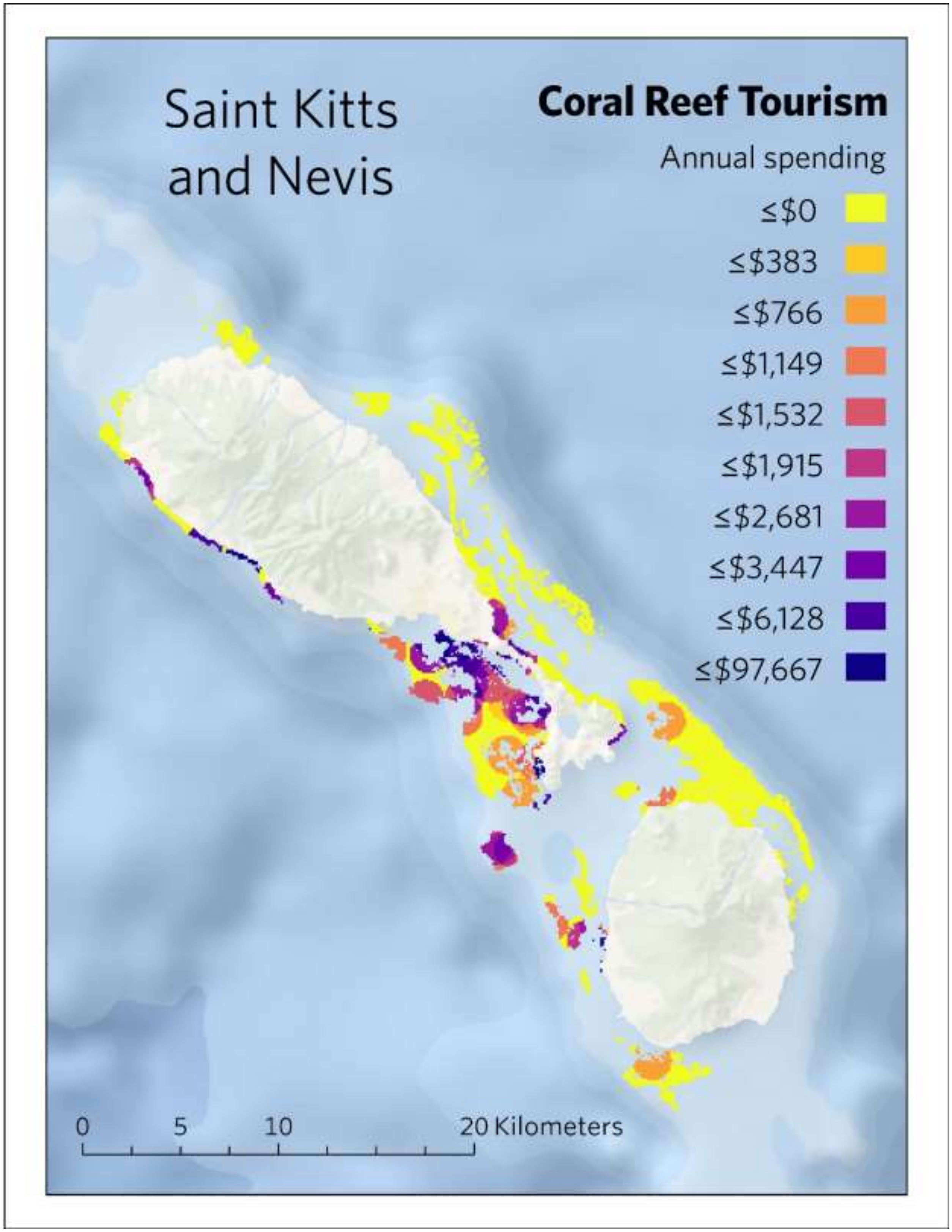


Figure E3. *Total annual on-reef tourism expenditures (overnight and cruise visitors) for St. Kitts & Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

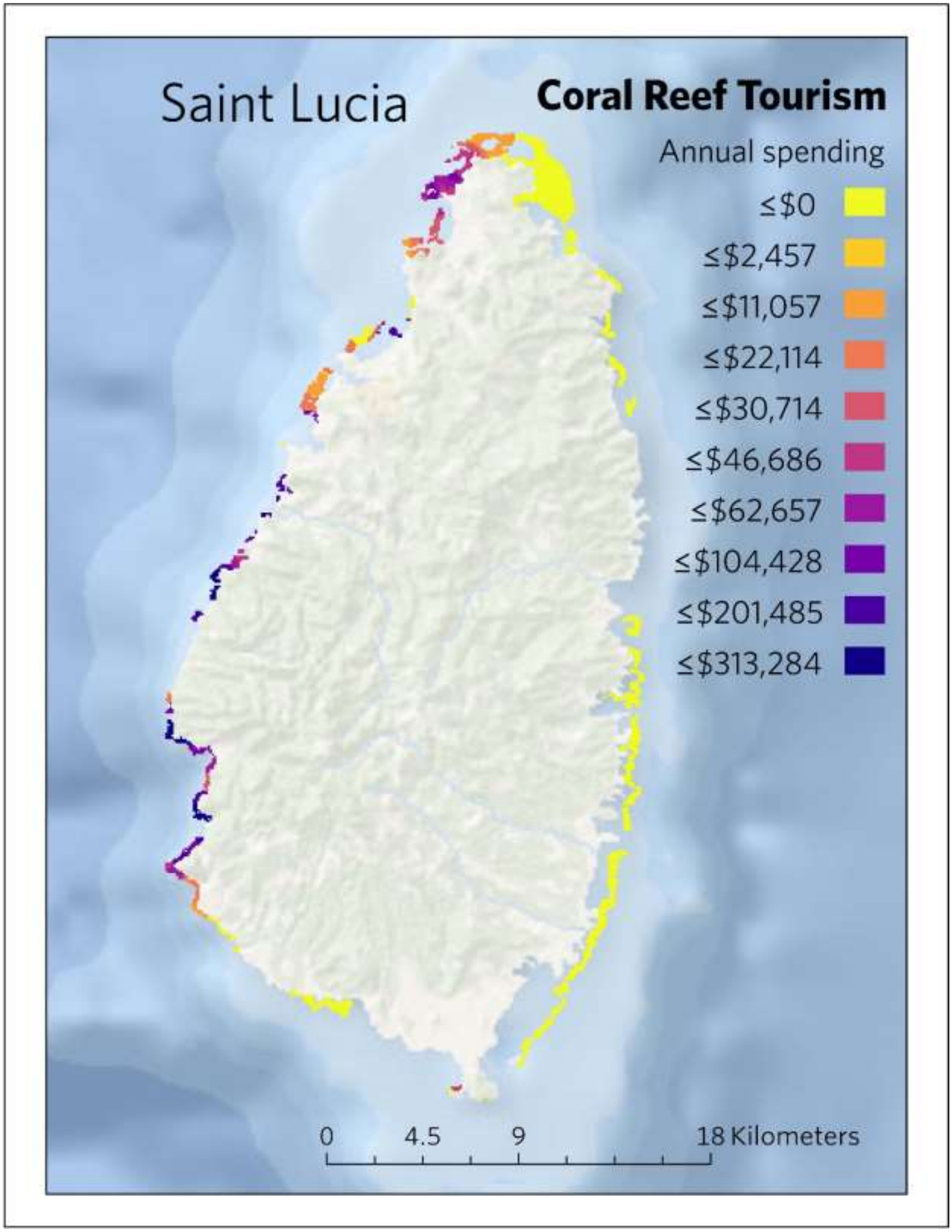


Figure E4. *Total annual on-reef tourism expenditures (overnight and cruise visitors) for Saint Lucia. Values are mapped to a 100m resolution reef habitat map,and are expressed at the scale of 1 hectare.*

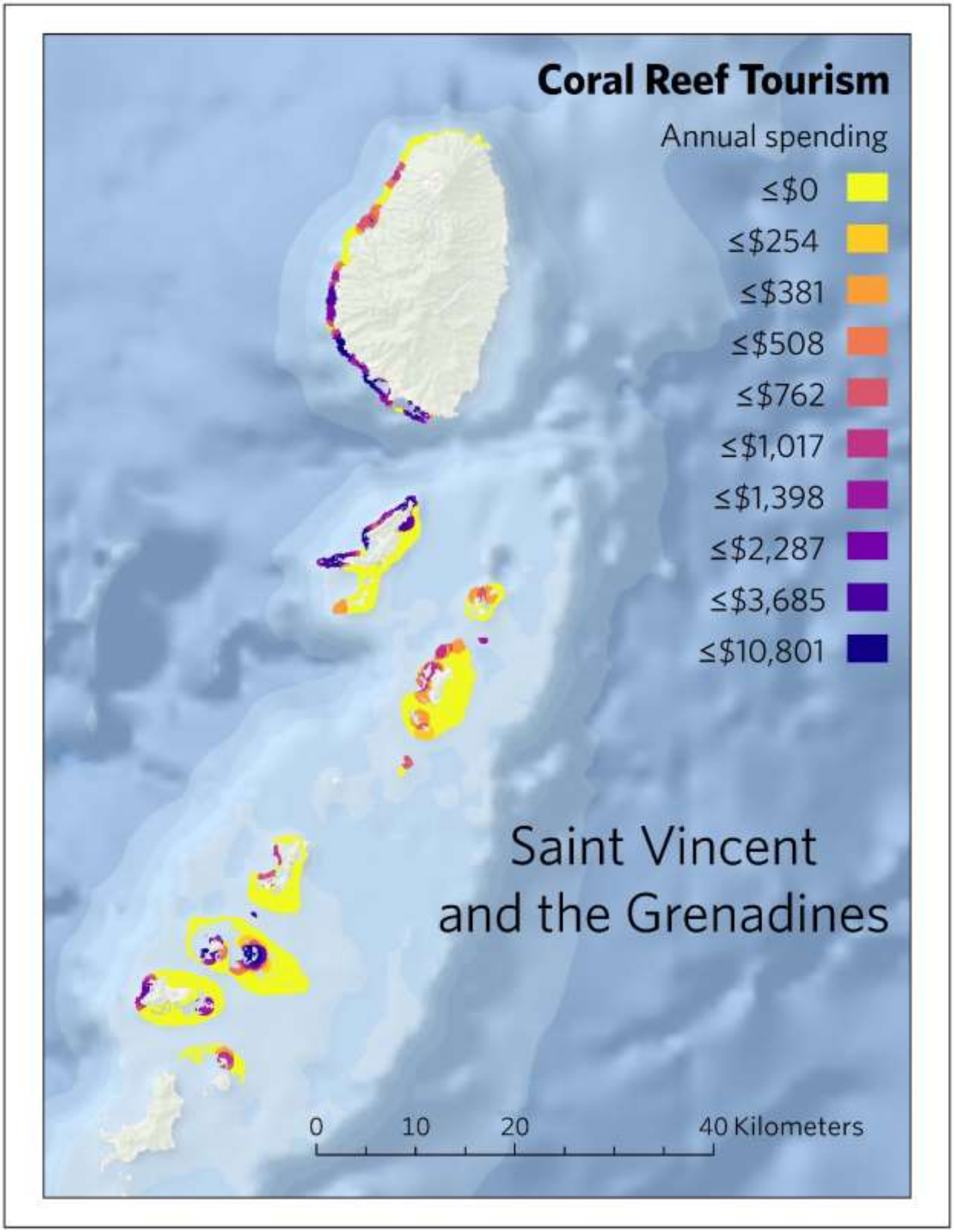


Figure E5. *Total annual on-reef tourism expenditures (overnight and cruise visitors) for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

On-reef tourism – Annual overnight visitor tourism expenditure by country

Images E6 – E10 Depict total annual on-reef tourism expenditures for overnight visitors. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

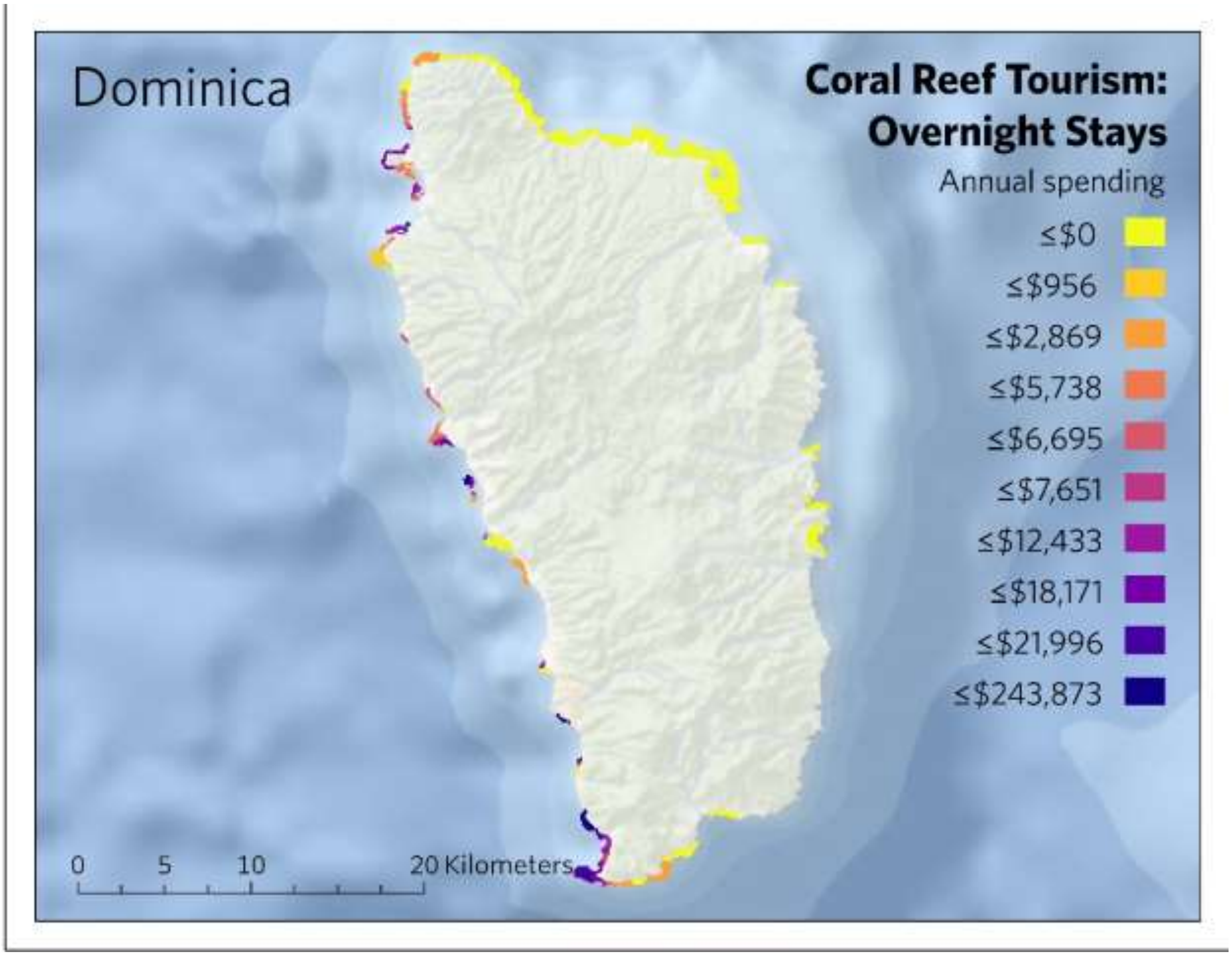


Figure E6. *Total annual on-reef tourism expenditures by overnight visitors for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

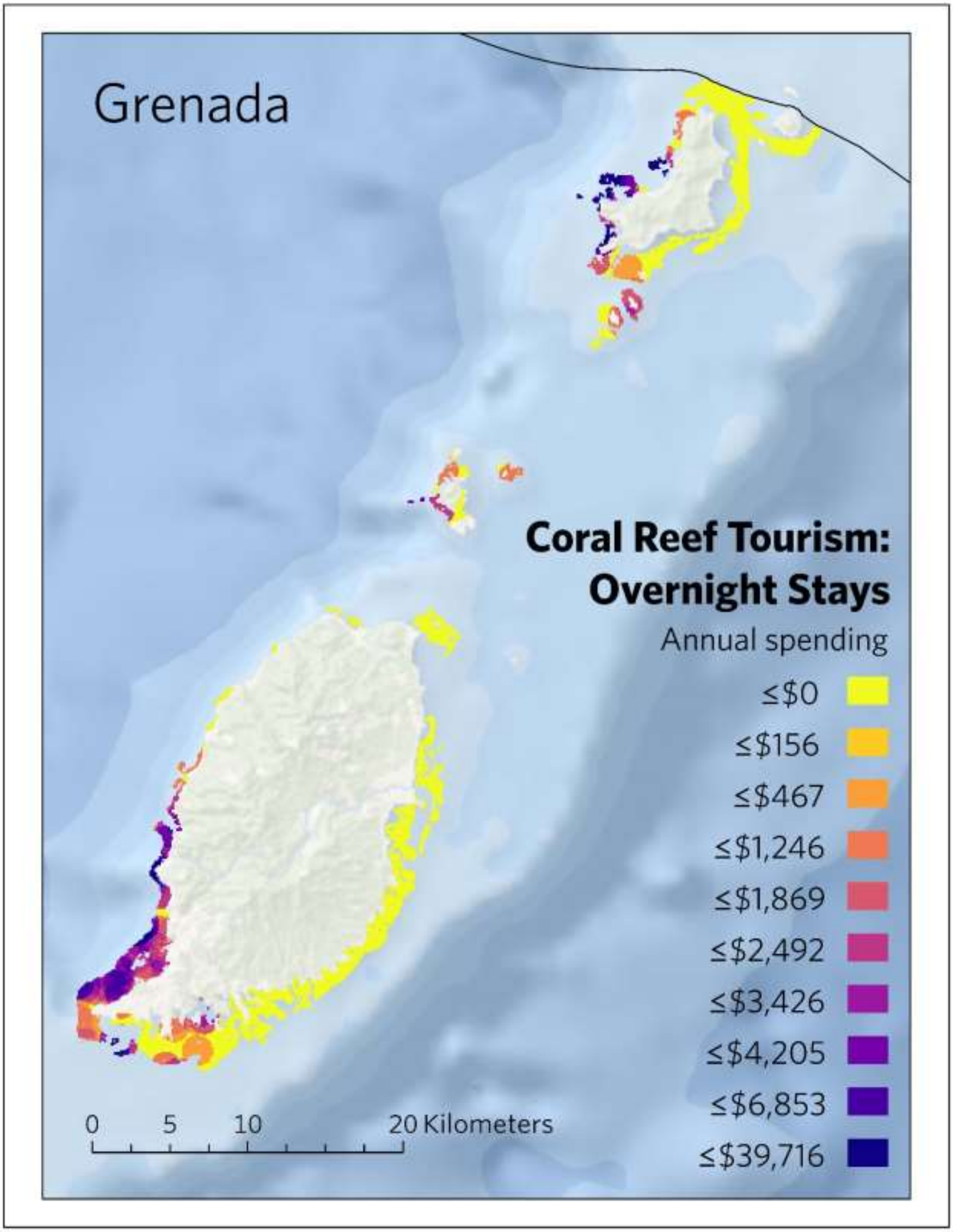


Figure E7. *Total annual on-reef tourism expenditures by overnight visitors for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

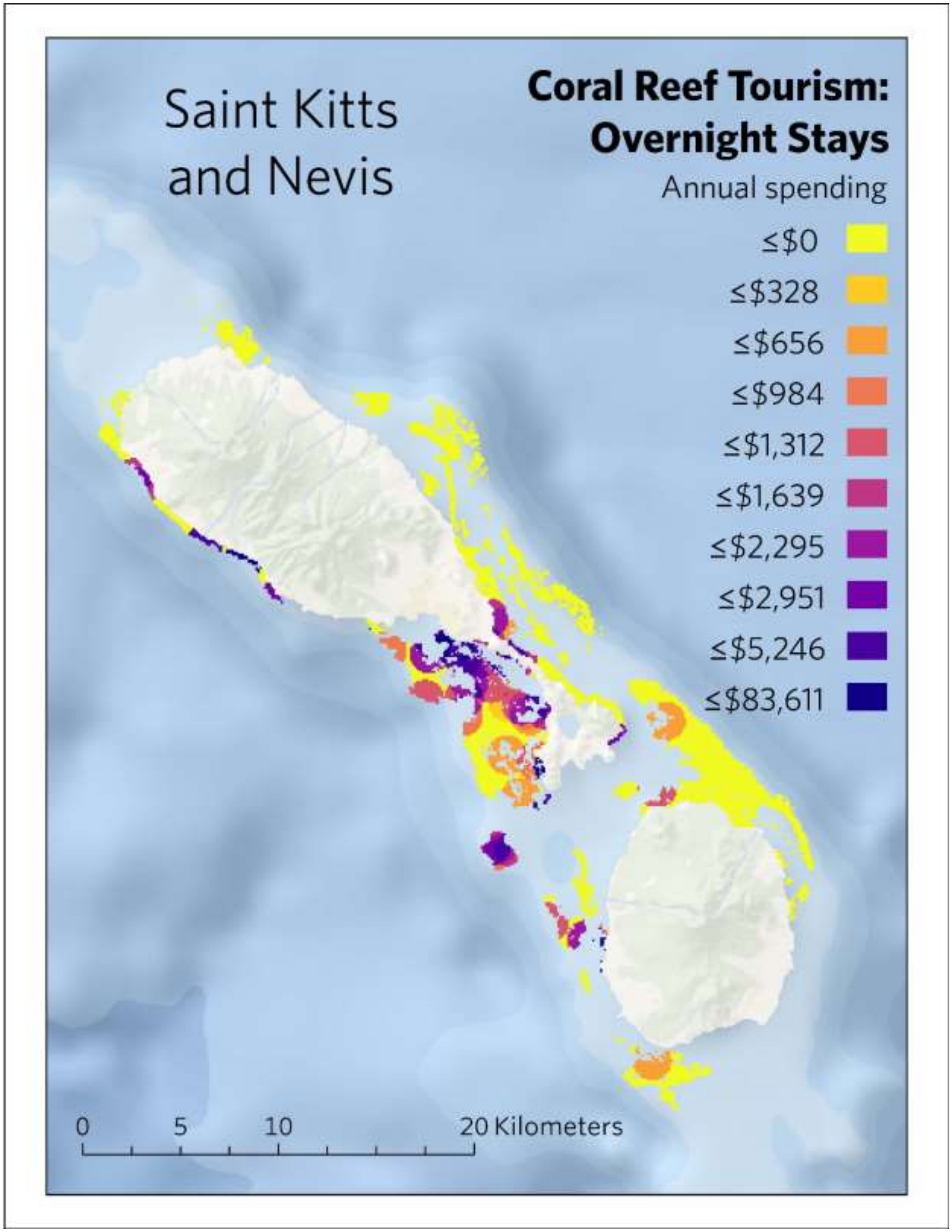


Figure E8. *Total annual on-reef tourism expenditures by overnight visitors for St. Kitts & Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

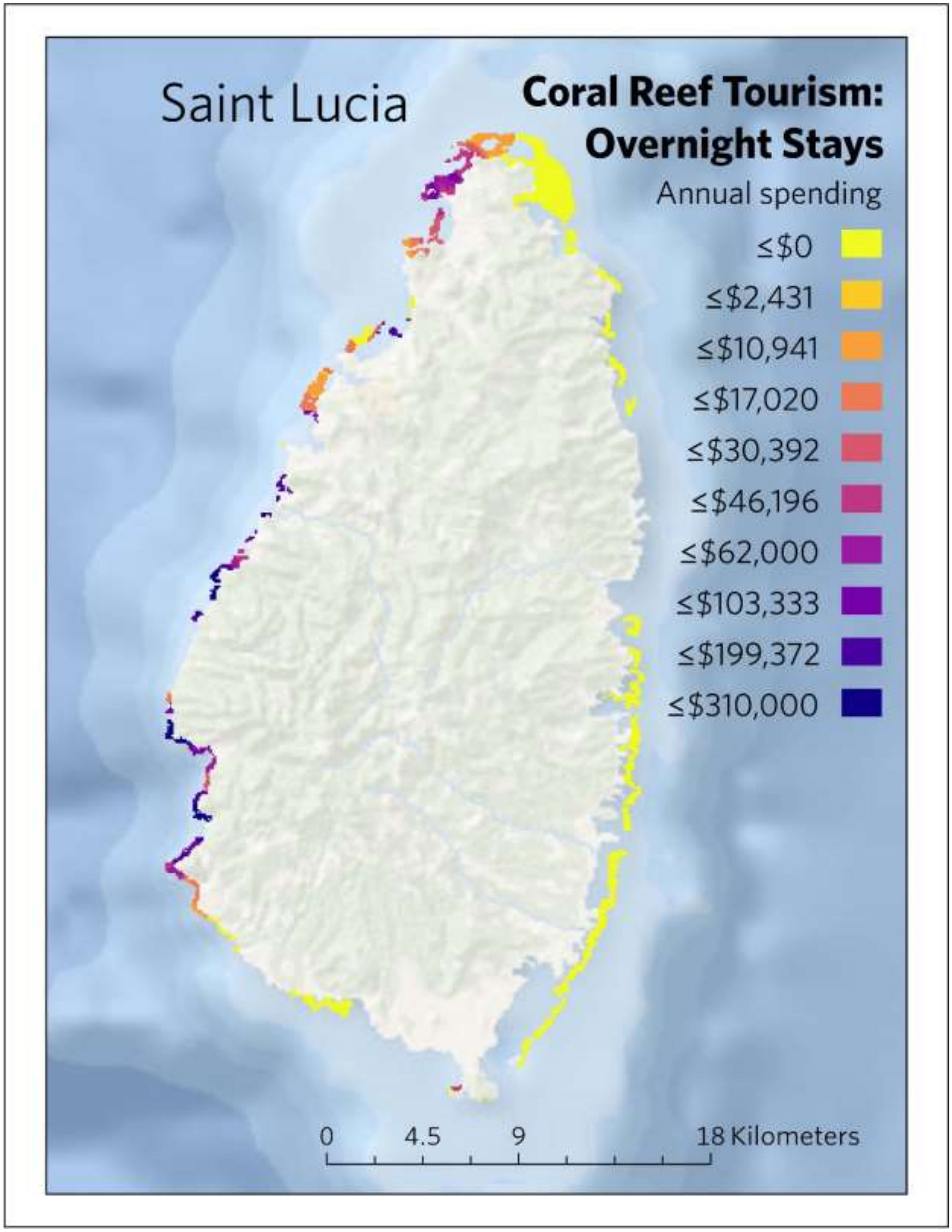


Figure E9. *Total annual on-reef tourism expenditures by overnight visitors for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

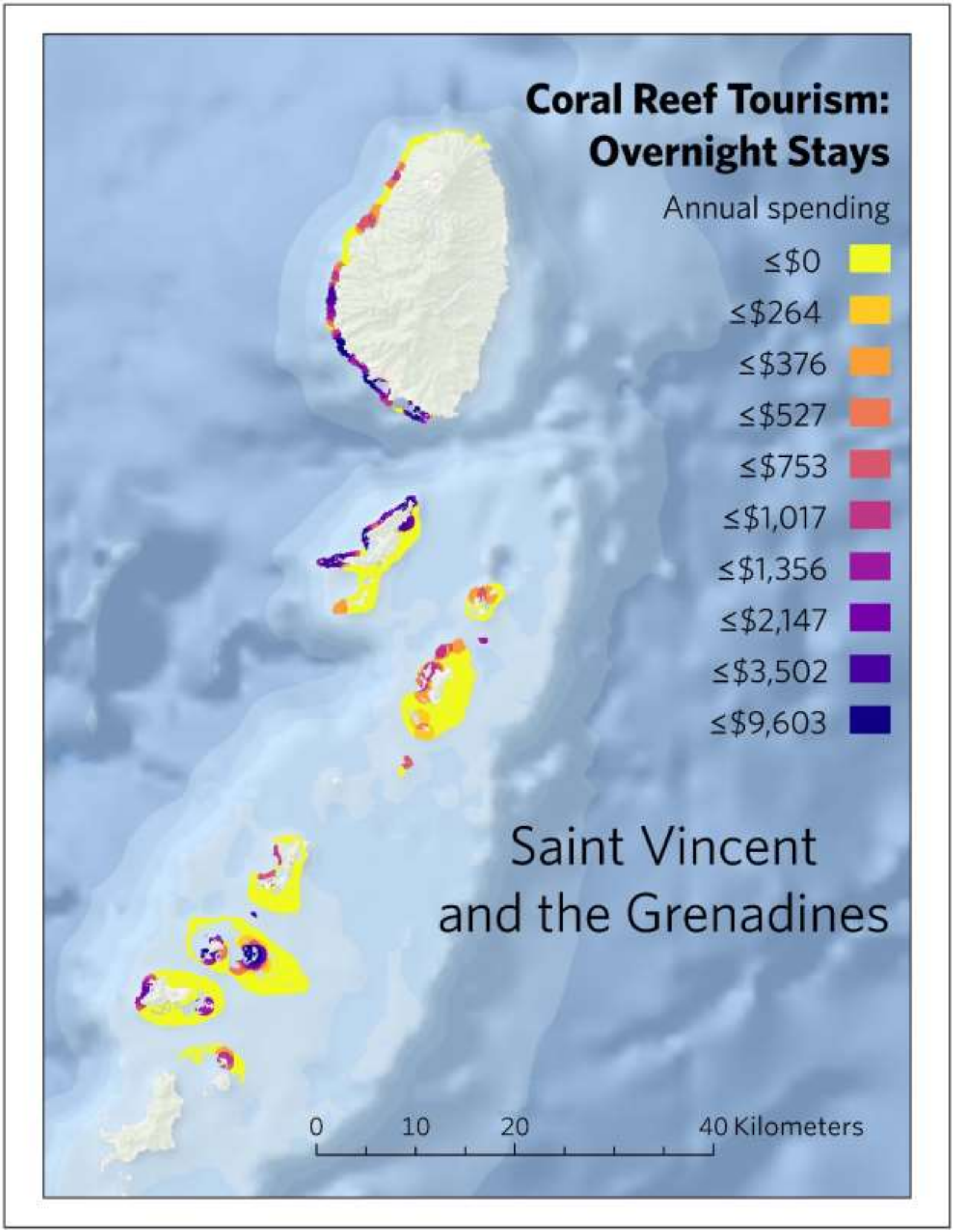


Figure E10. *Total annual on-reef tourism expenditures by overnight visitors for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

On-reef tourism – Annual cruise visitor tourism expenditure by country

Images E11 – E15 Depict total annual on-reef tourism expenditures for cruise visitors. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

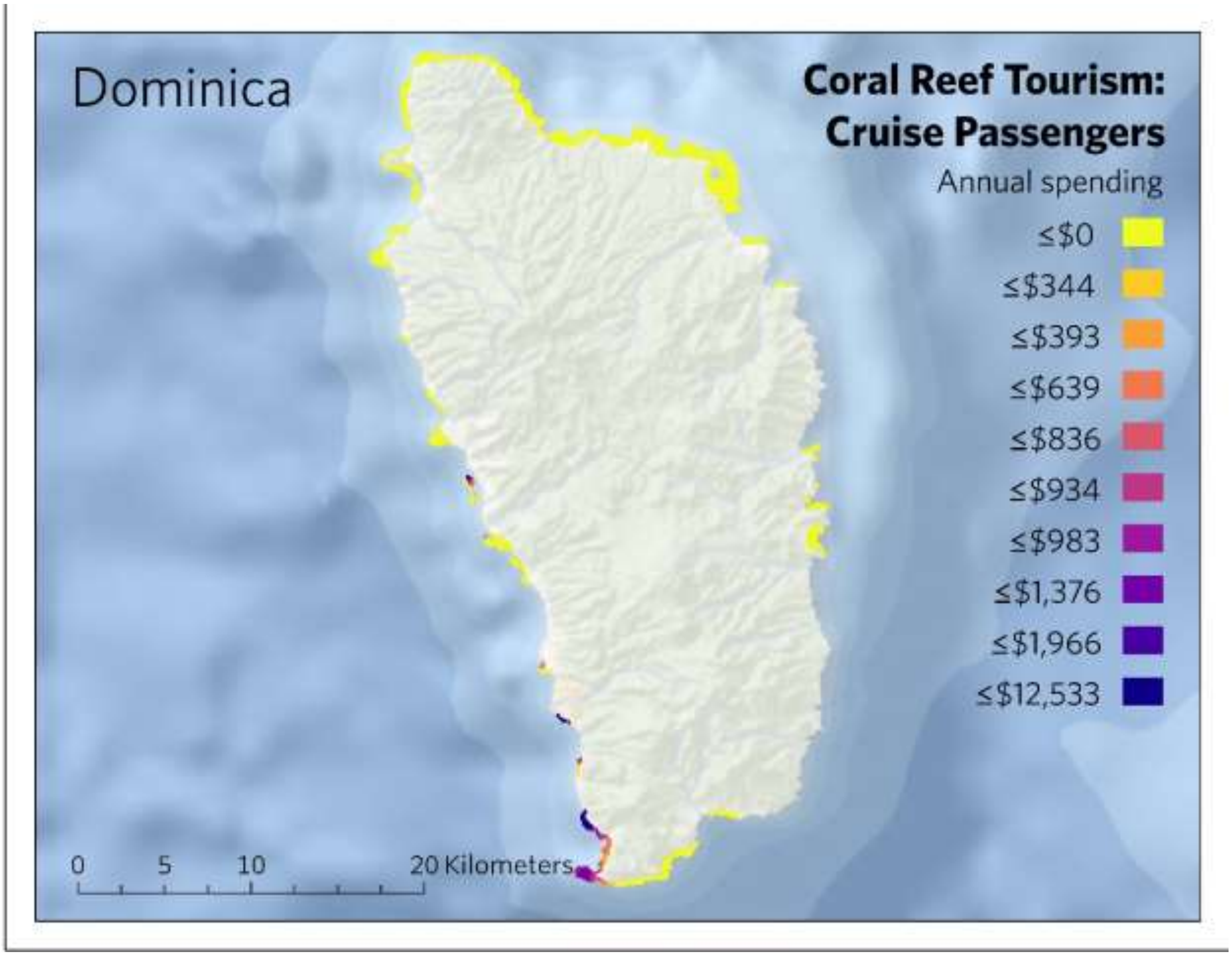


Figure E11. *Total annual on-reef tourism expenditures by cruise visitors for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

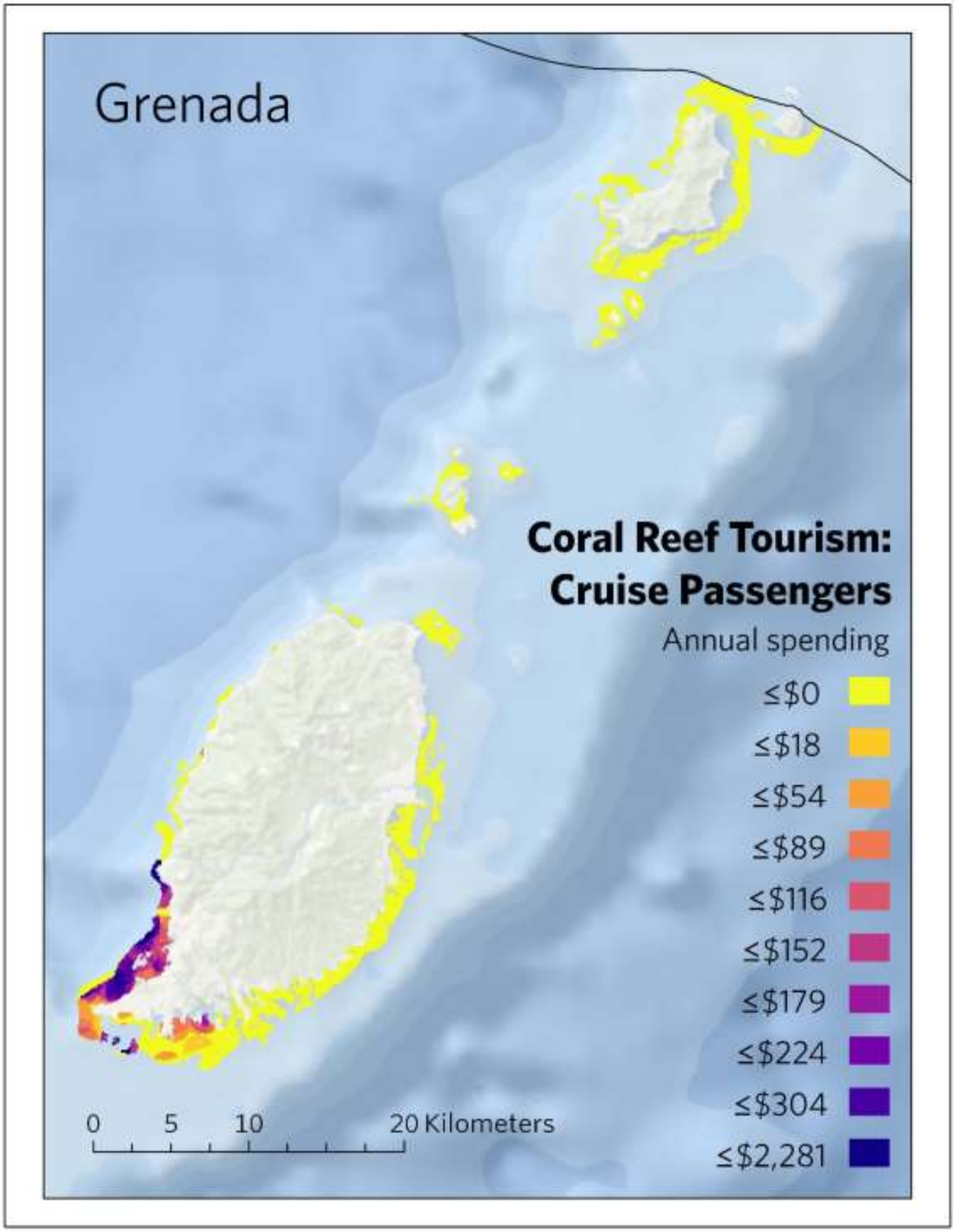


Figure E12. *Total annual on-reef tourism expenditures by cruise visitors for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

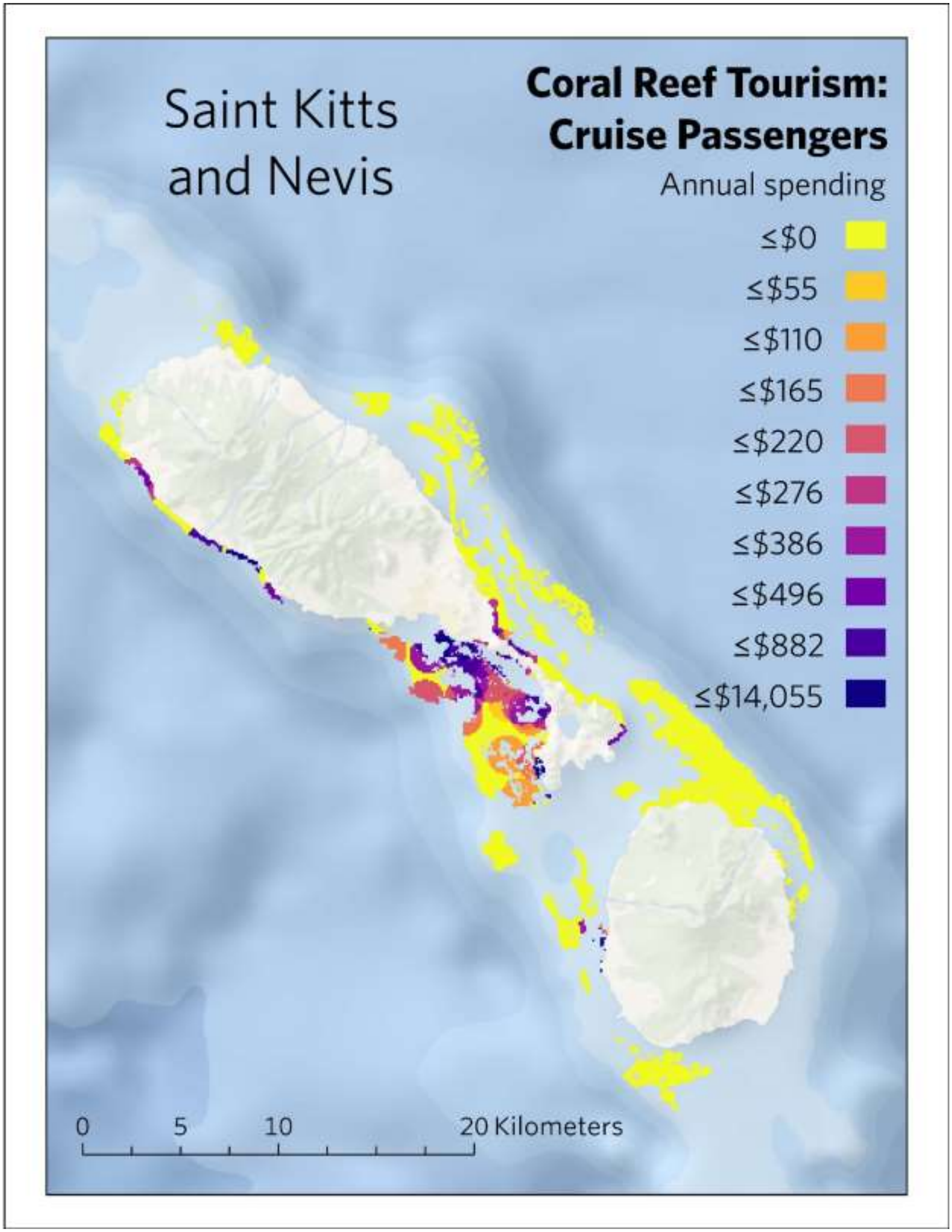


Figure E13. *Total annual on-reef tourism expenditures by cruise visitors for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

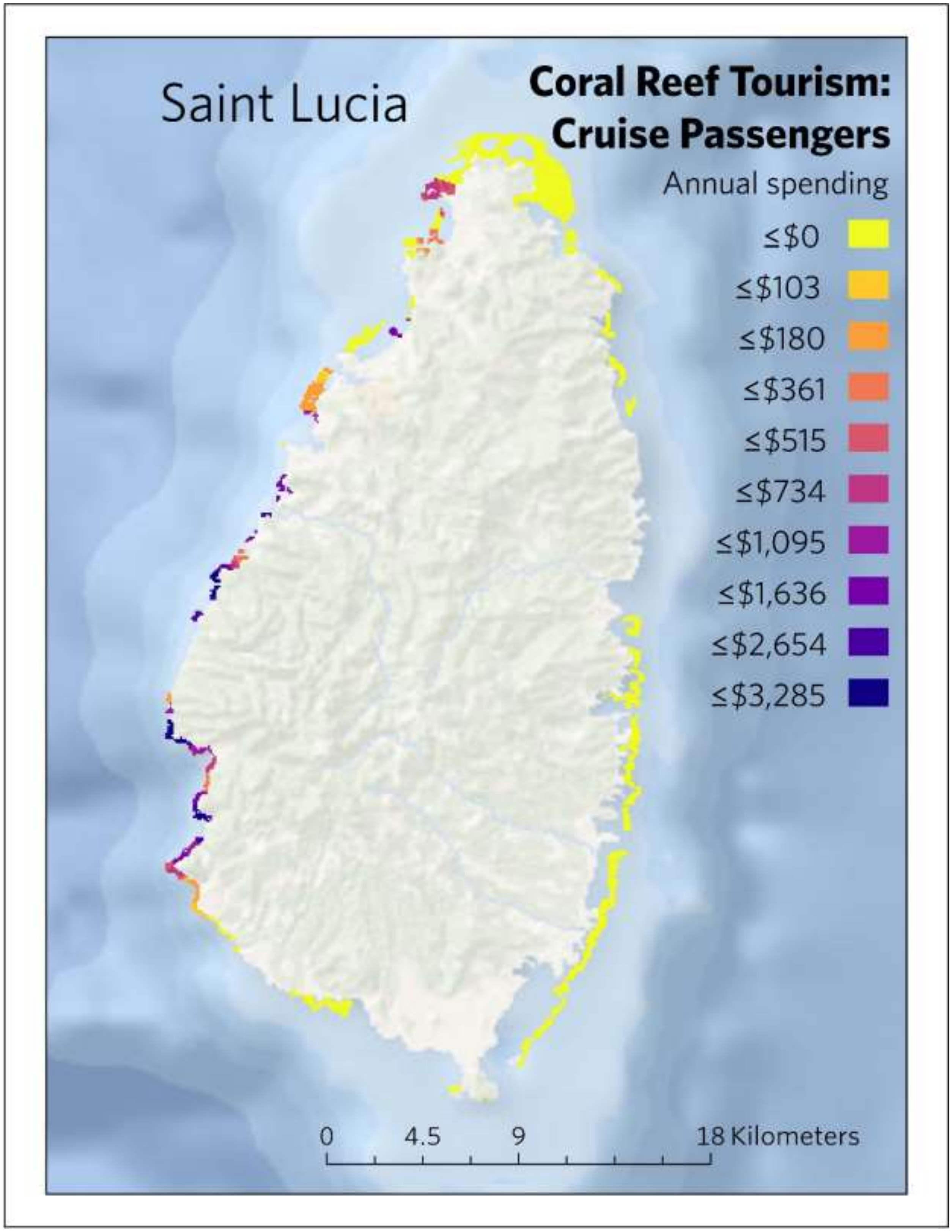


Figure E14. *Total annual on-reef tourism expenditures by cruise visitors for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

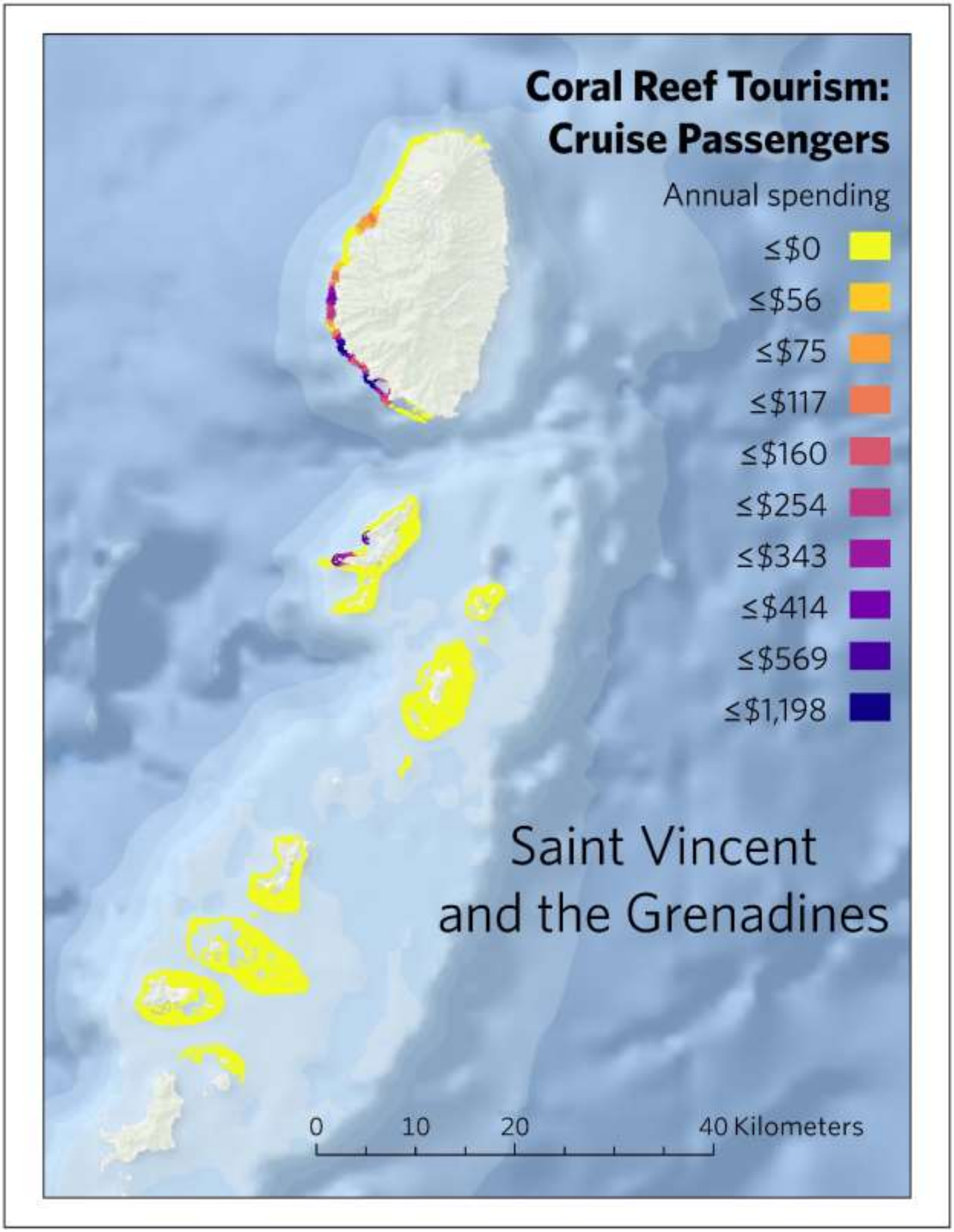


Figure E15. *Total annual on-reef tourism expenditures by cruise visitors for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

On-reef tourism – Annual overnight and cruise tourism visitation by country

Images E16 – E20 Depict total annual on-reef tourism visitation (overnight and cruise tourism). Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

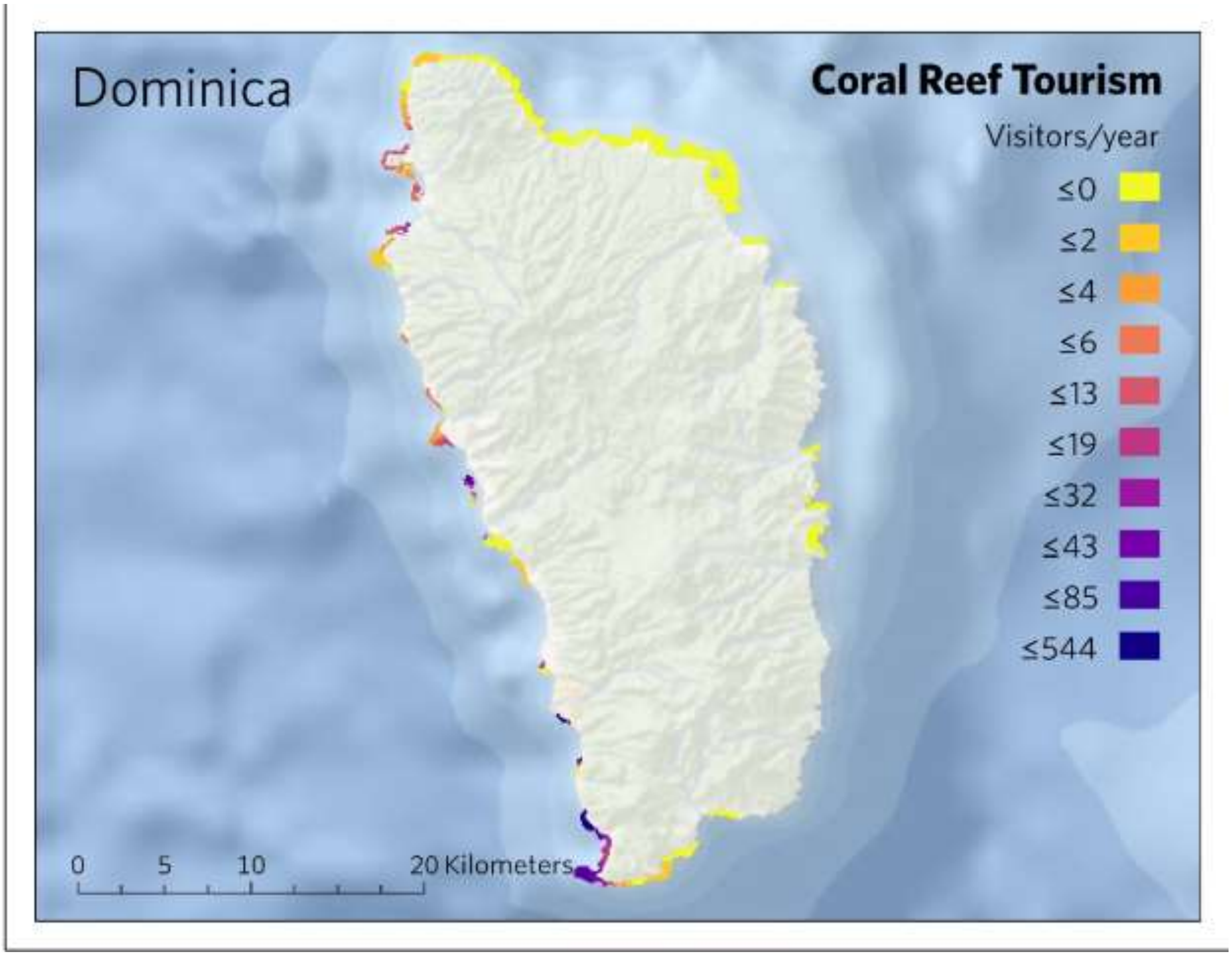


Figure E16. *Total annual on-reef tourism visitation (cruise and overnight) for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

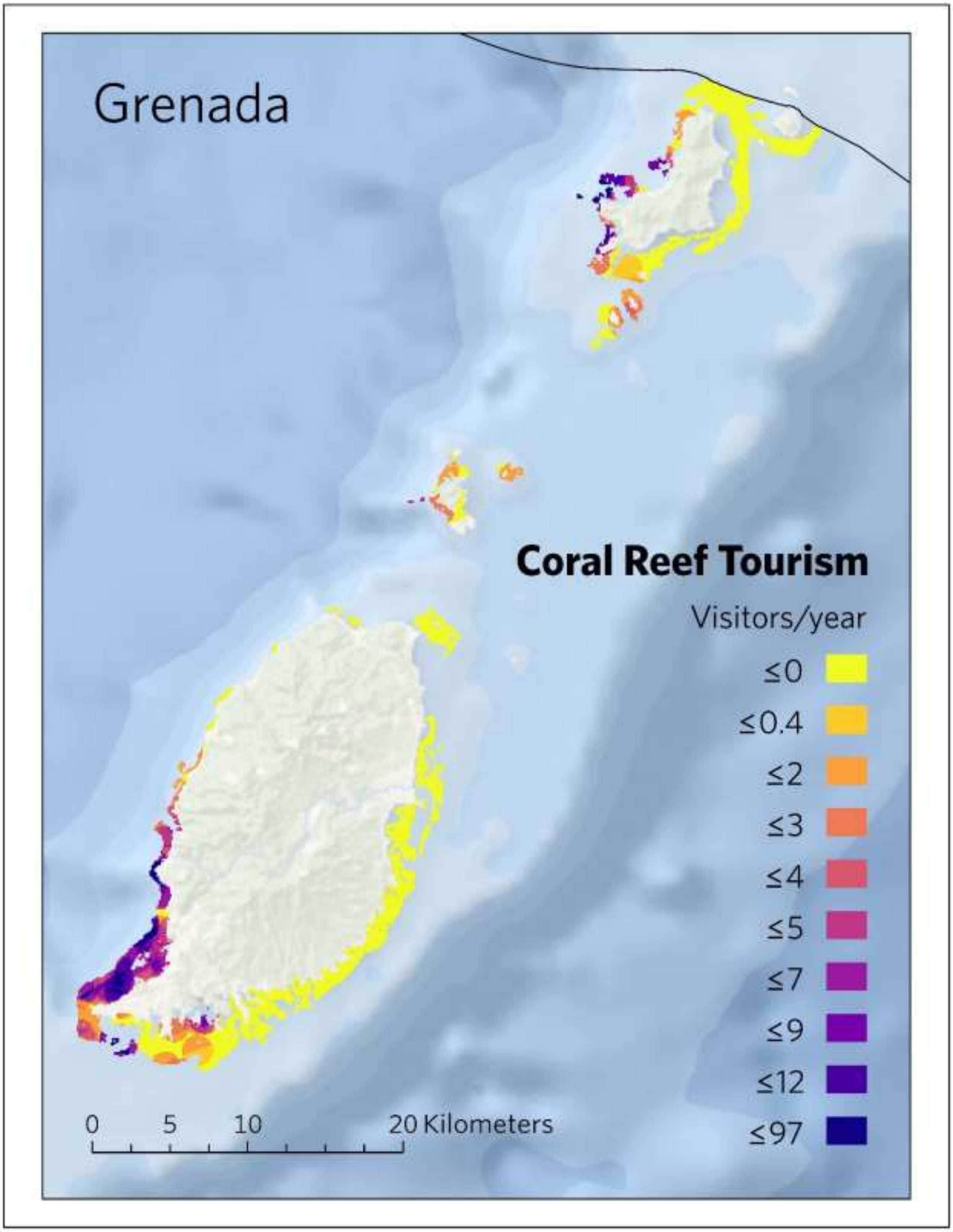


Figure E17. *Total annual on-reef tourism visitation (cruise and overnight) for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

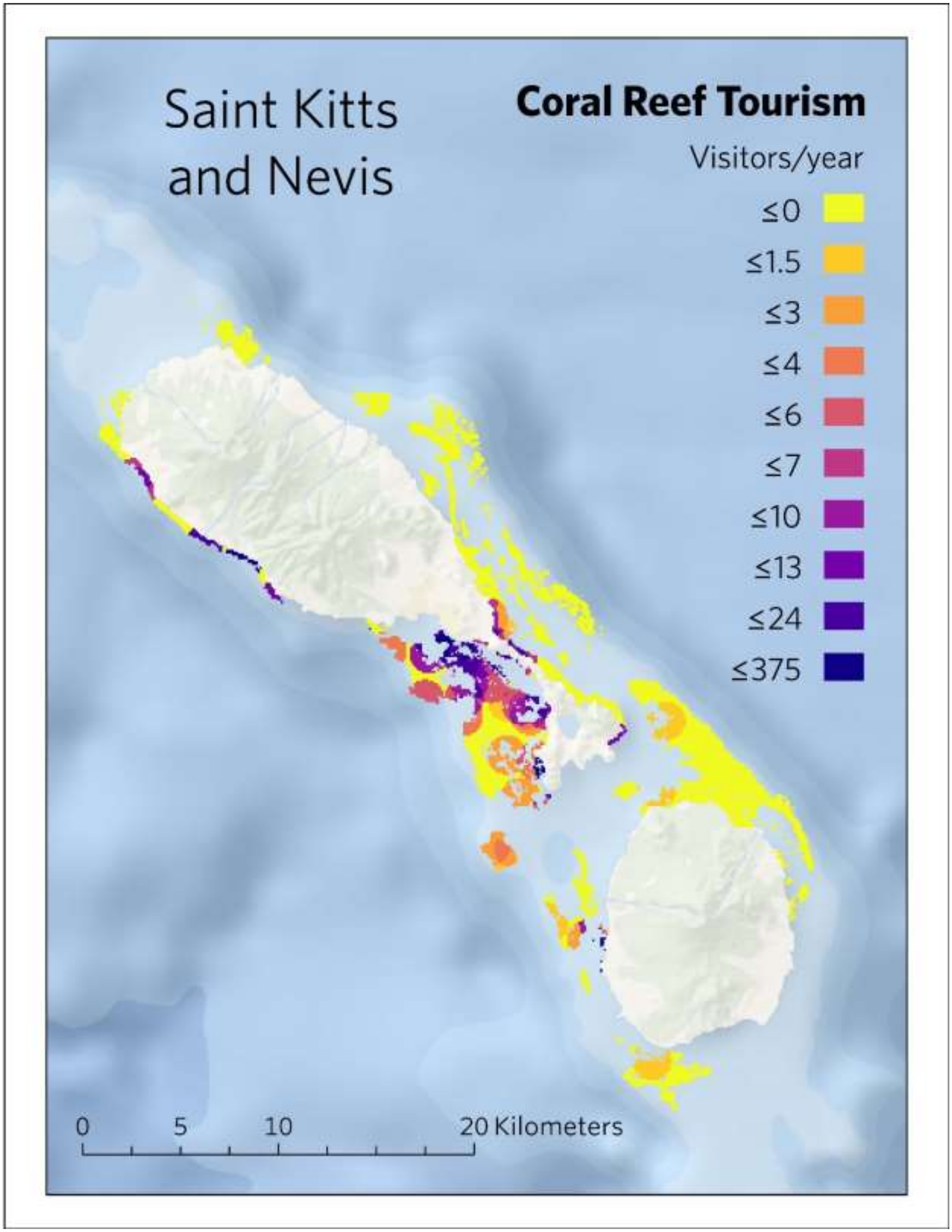


Figure E18. *Total annual on-reef tourism visitation (cruise and overnight) for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

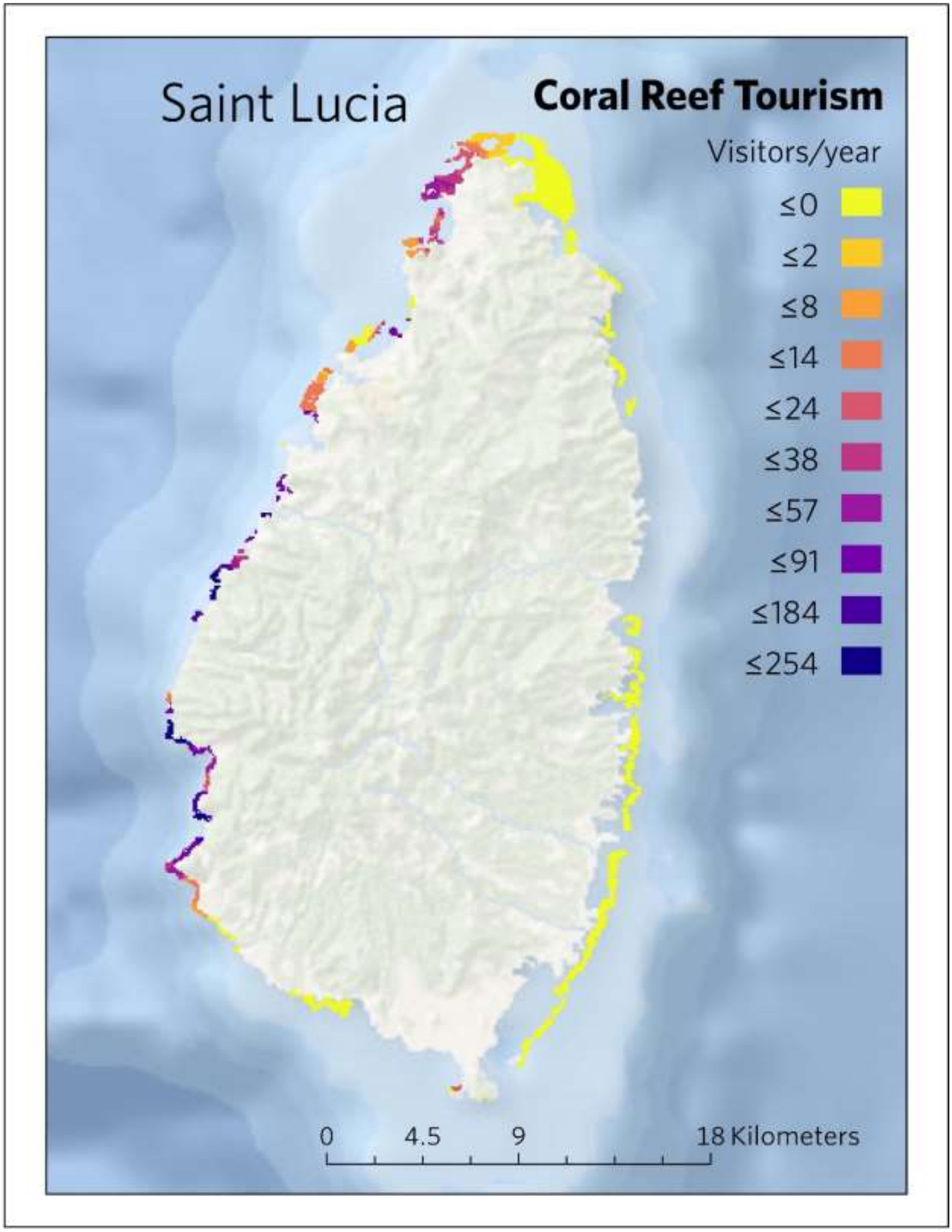


Figure E19. *Total annual on-reef tourism visitation (cruise and overnight) for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

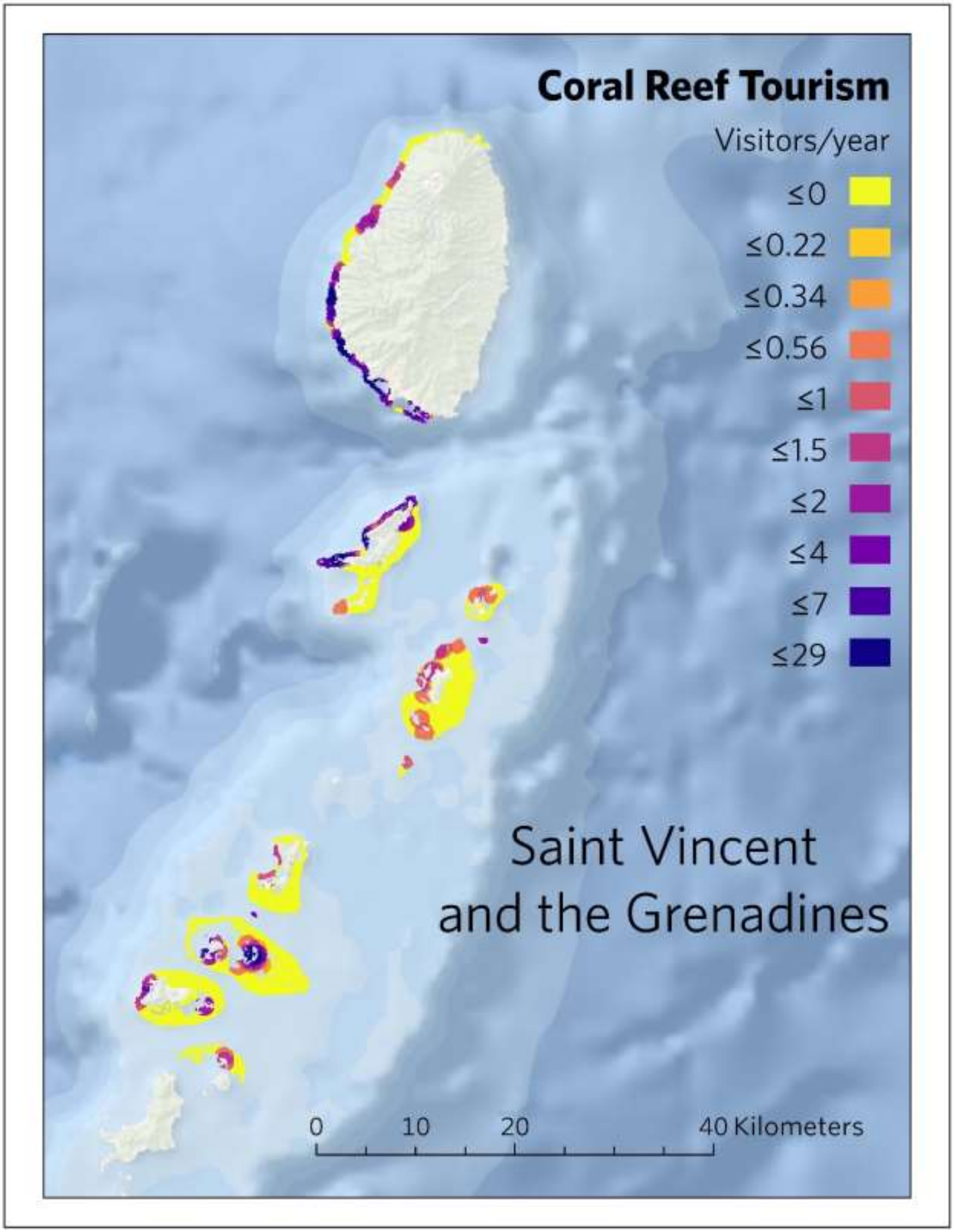


Figure E20. *Total annual on-reef tourism visitation (cruise and overnight) for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

On-reef tourism – Annual overnight tourism visitation by country

Images E21 – E25 Depict total annual on-reef overnight tourism visitation. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

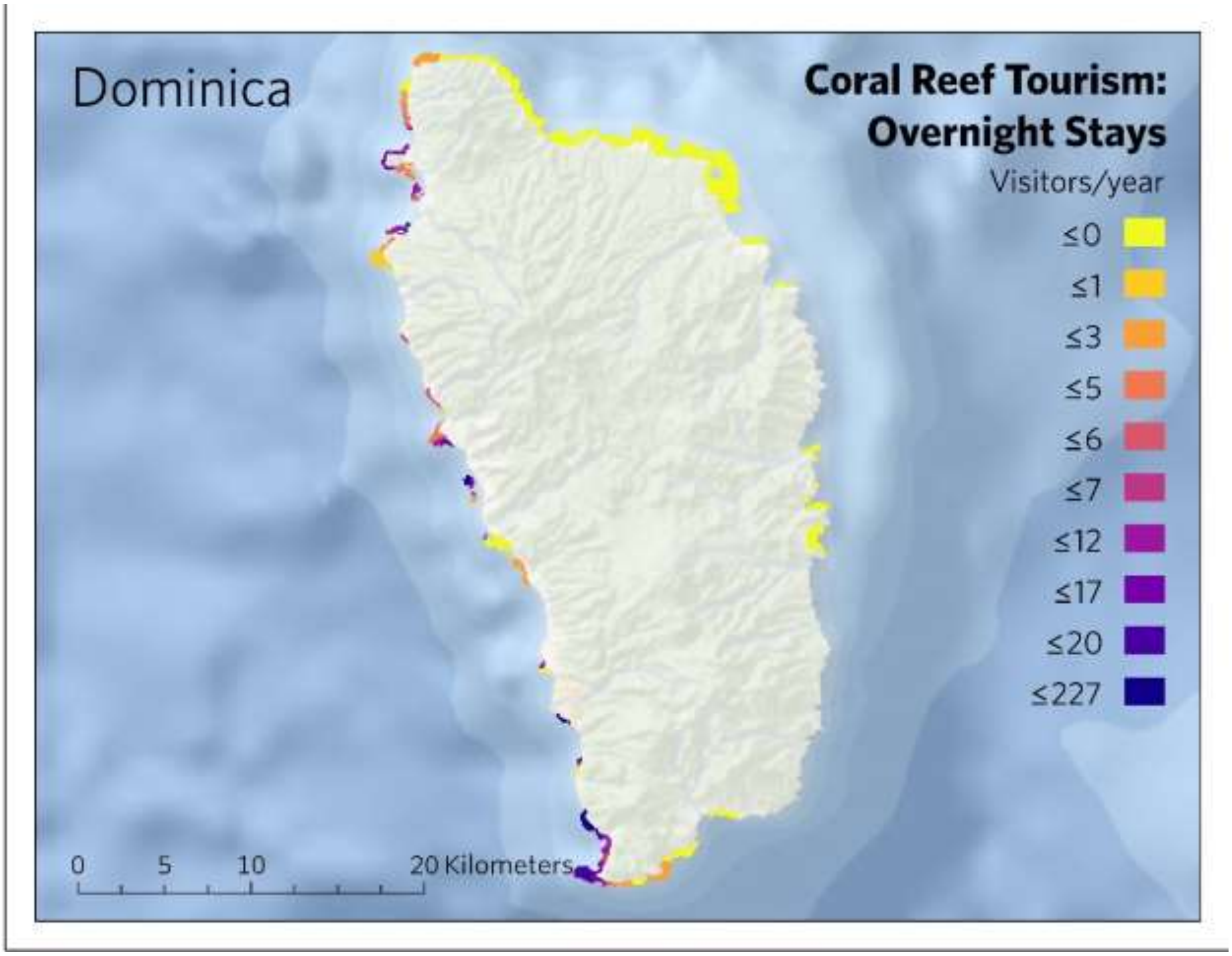


Figure E21. *Total annual on-reef overnight tourism visitation for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

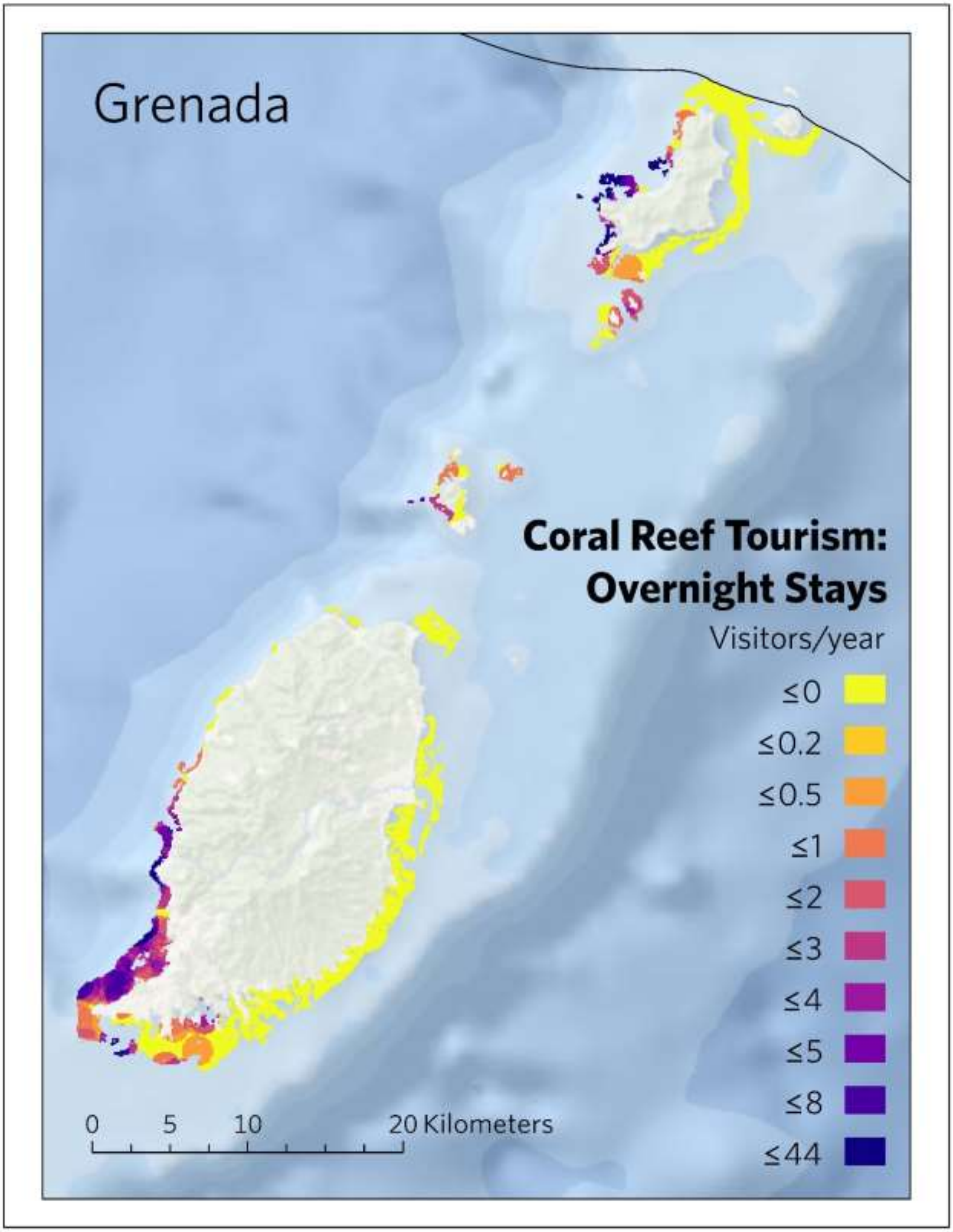


Figure E22. *Total annual on-reef overnight tourism visitation for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

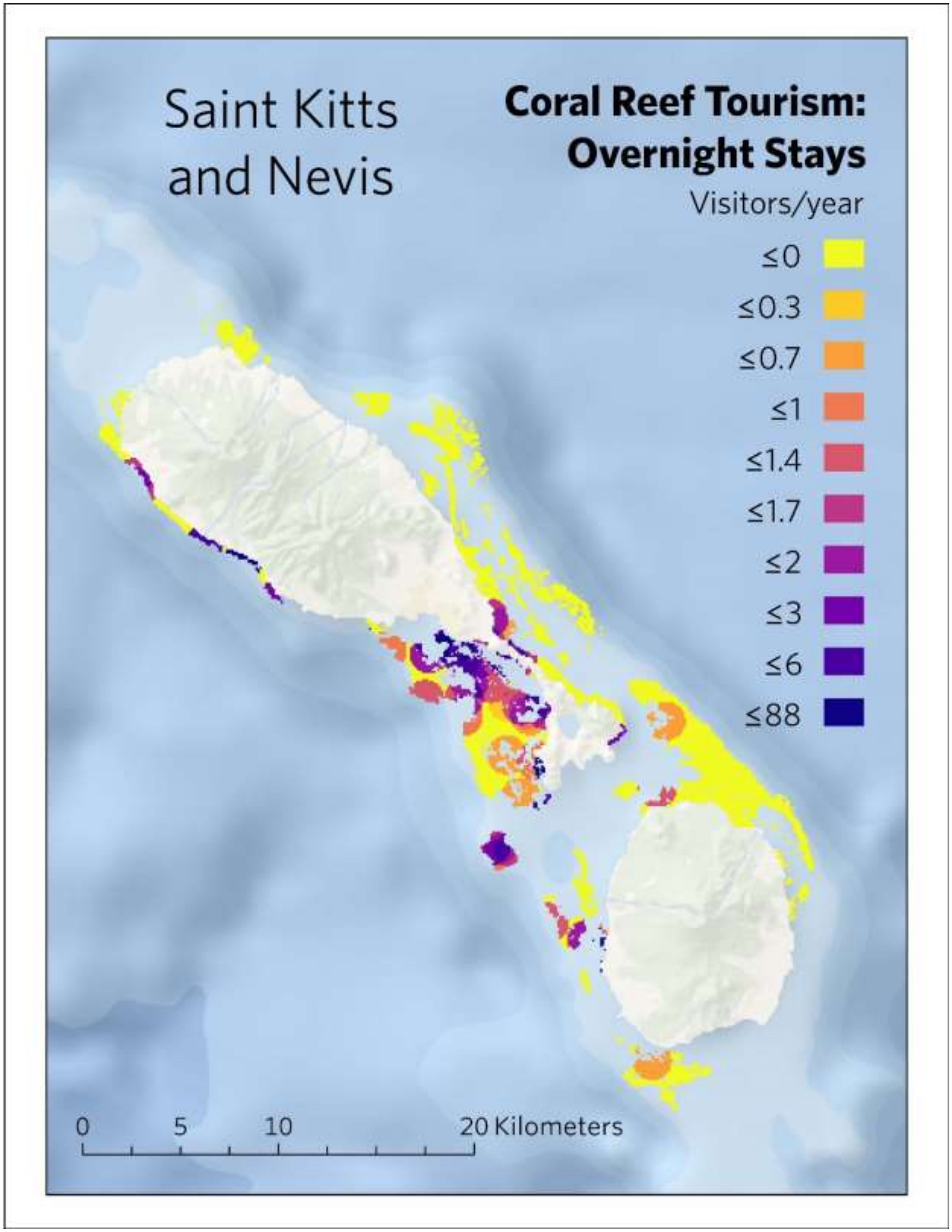


Figure E23. *Total annual on-reef overnight tourism visitation for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

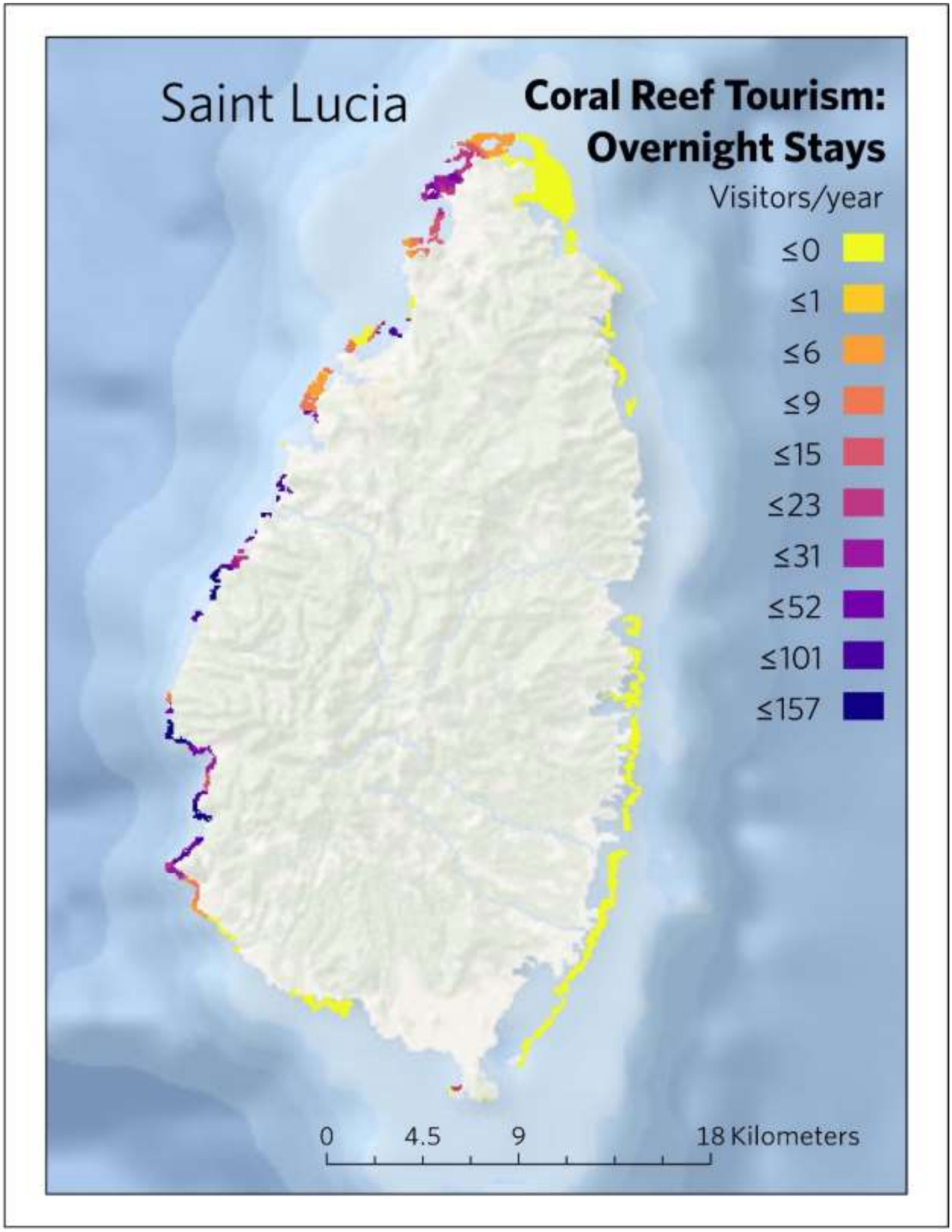


Figure E24. *Total annual on-reef overnight tourism visitation for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

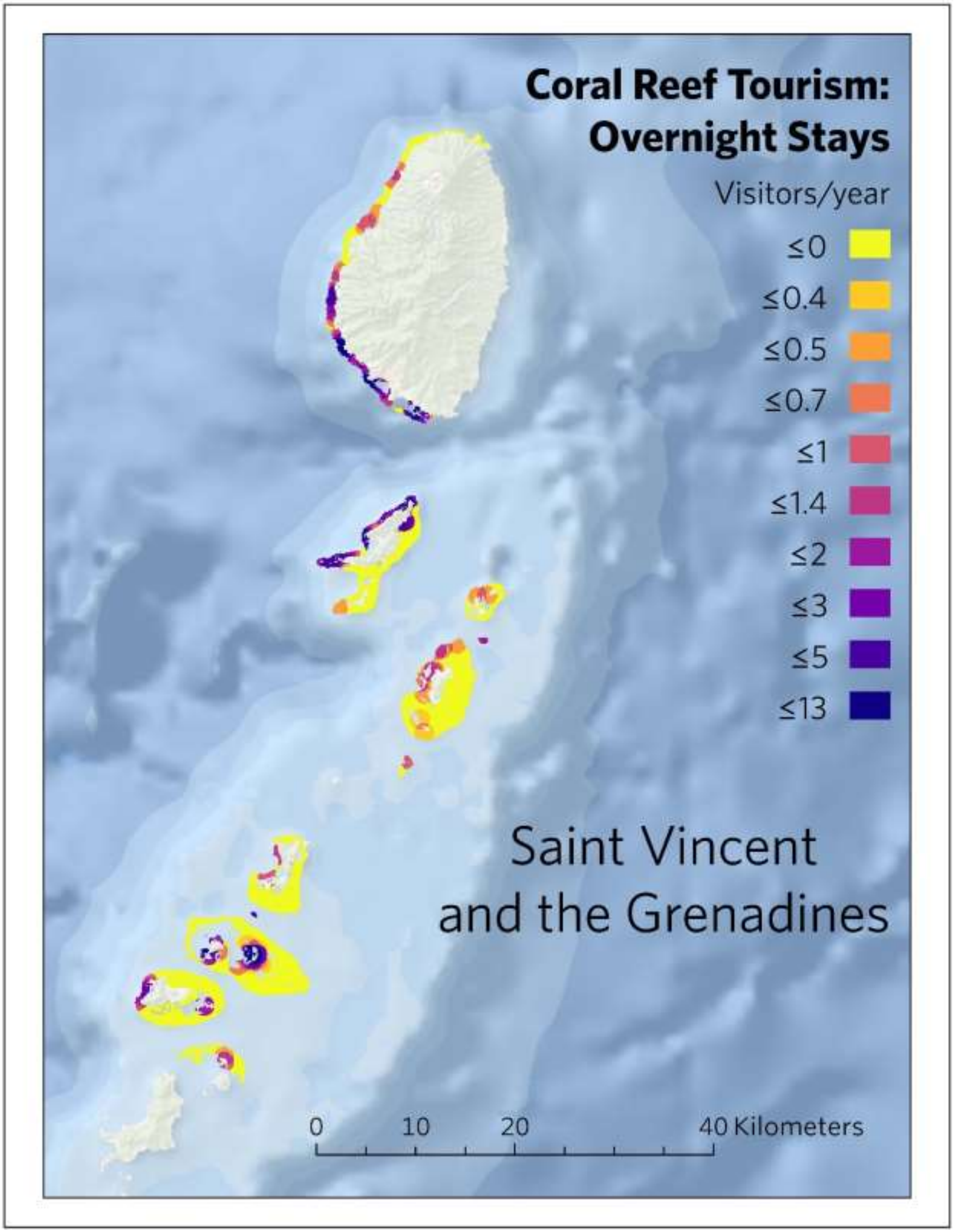


Figure E25. *Total annual on-reef overnight tourism visitation for Saint Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

On-reef tourism – Annual cruise tourism visitation by country

Images E26 – E30 Depict total annual on-reef overnight tourism visitation. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

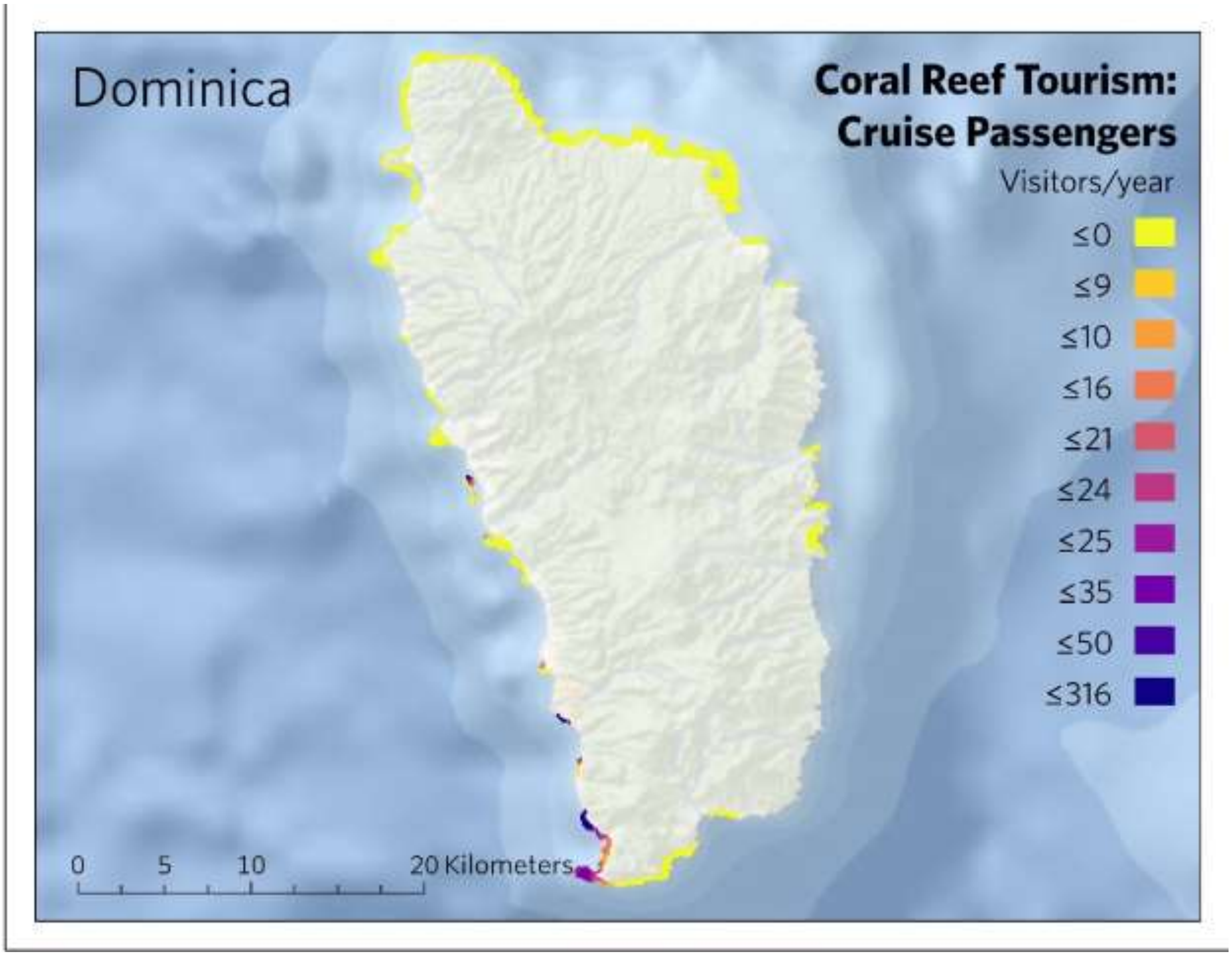


Figure E26. *Total annual on-reef cruise tourism visitation for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

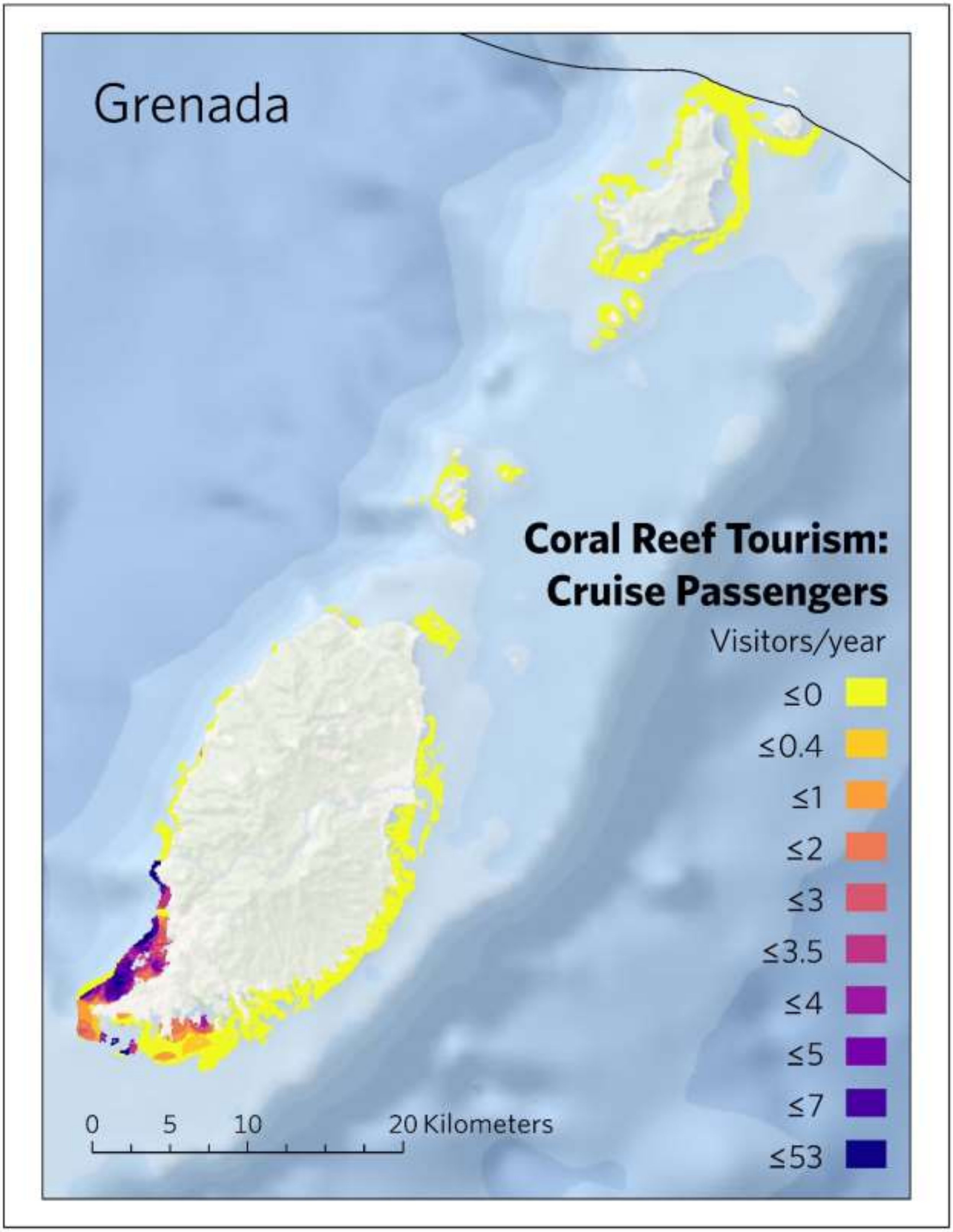


Figure E27. *Total annual on-reef cruise tourism visitation for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

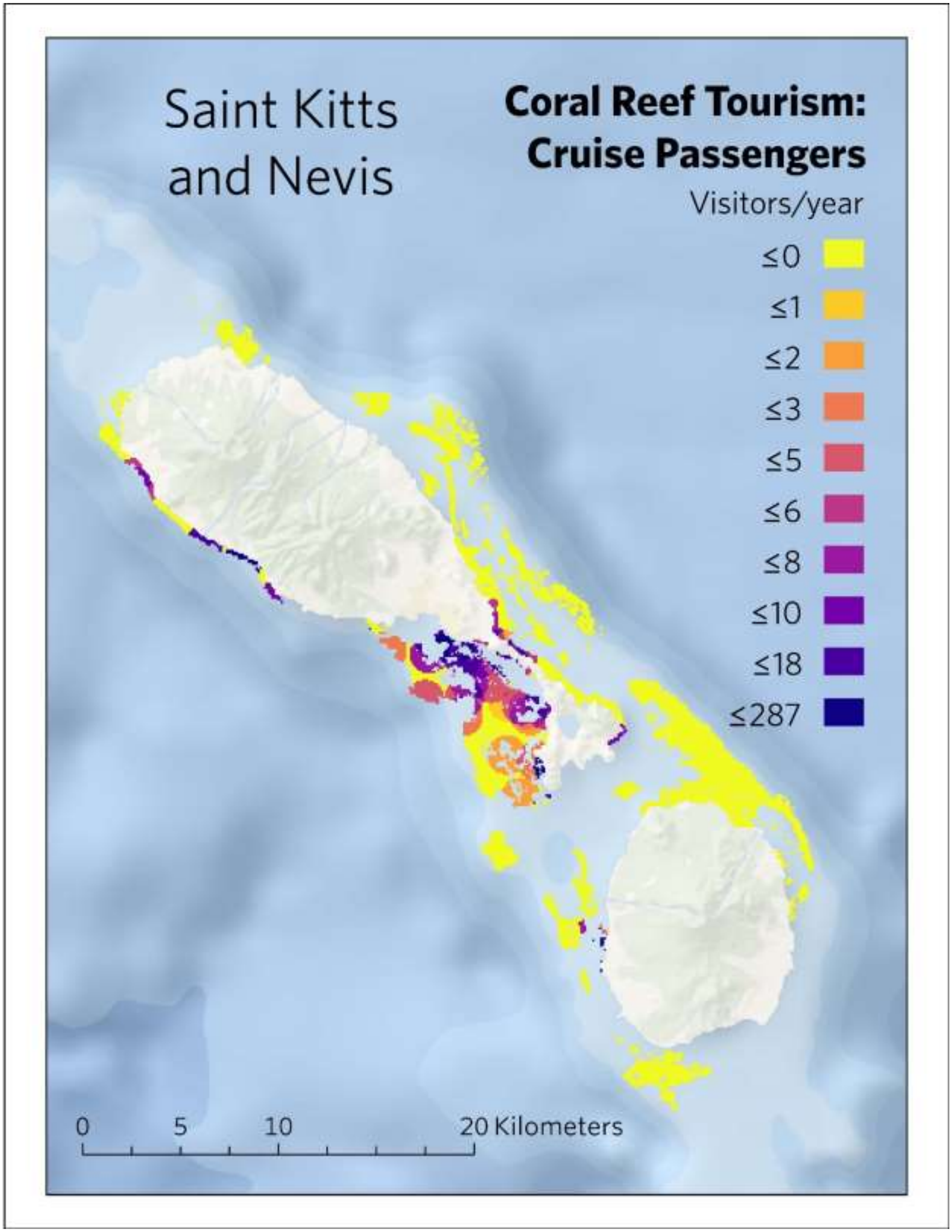


Figure E28. *Total annual on-reef cruise tourism visitation for St. Kitts & Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

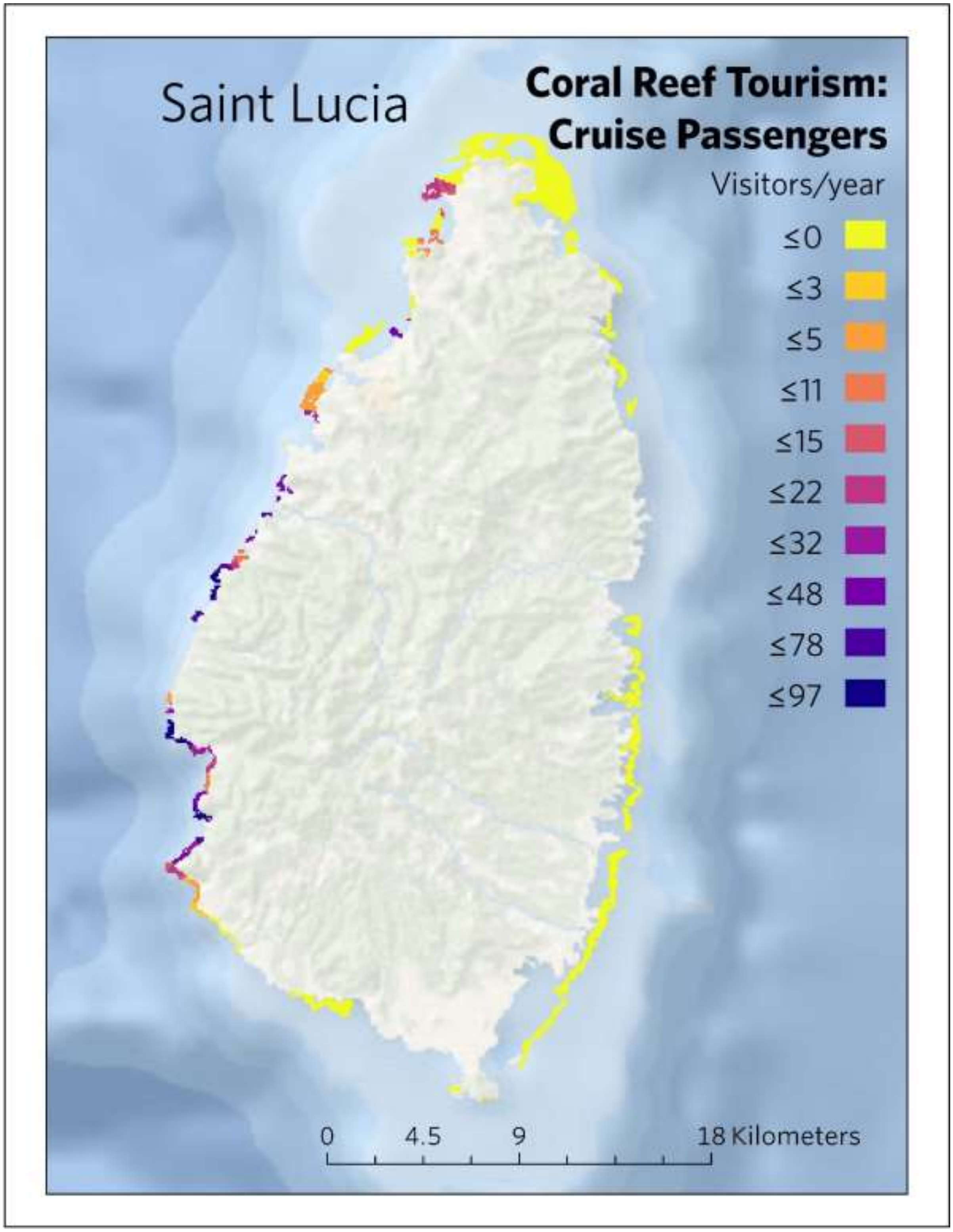


Figure E29. *Total annual on-reef cruise tourism visitation for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

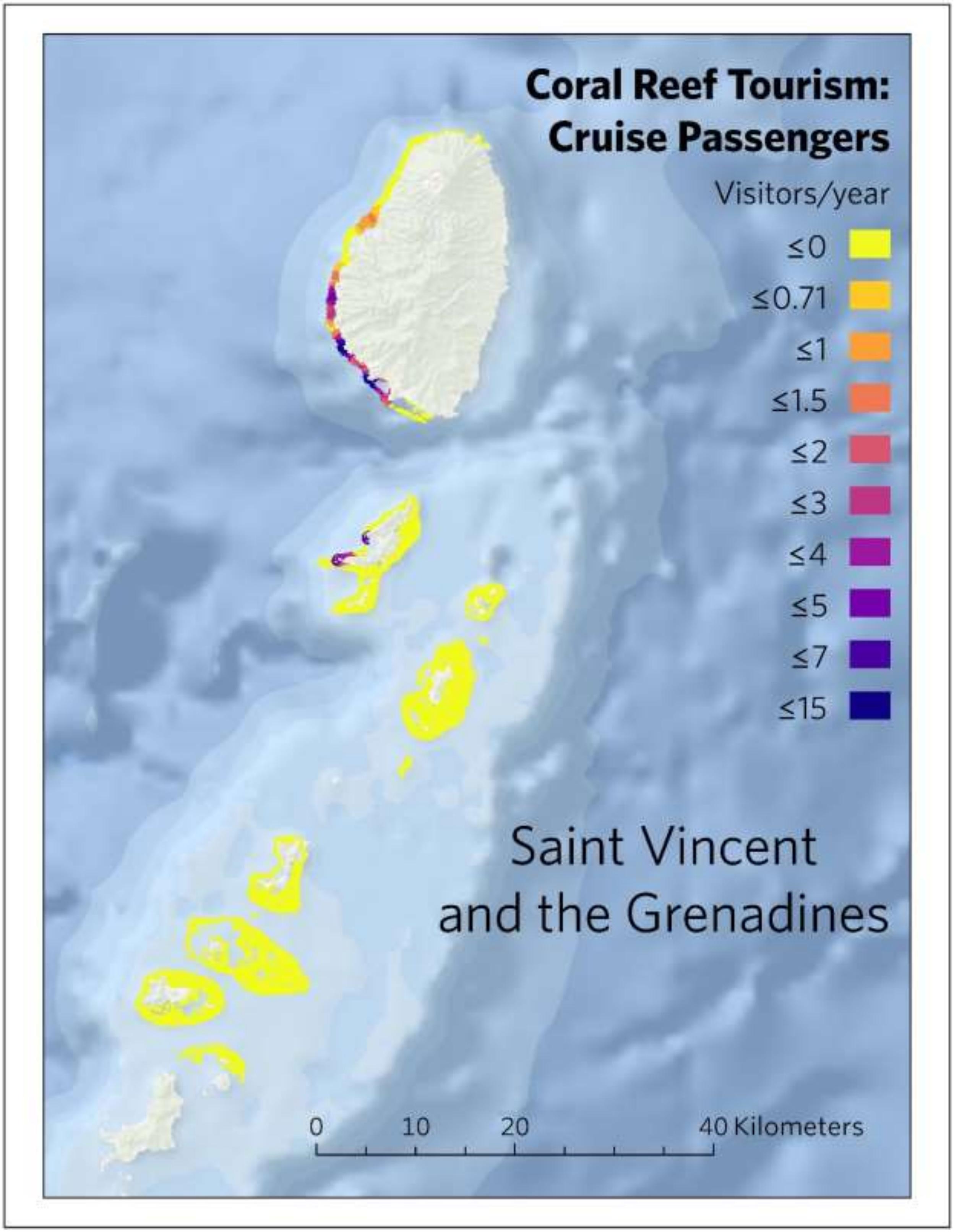


Figure E30. *Total annual on-reef cruise tourism visitation for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

Nature-dependent beaches – Annual overnight and cruise tourism expenditure by country

Images E31 – E35 Depict total annual nature-dependent beach tourism expenditures (overnight and cruise tourism). Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

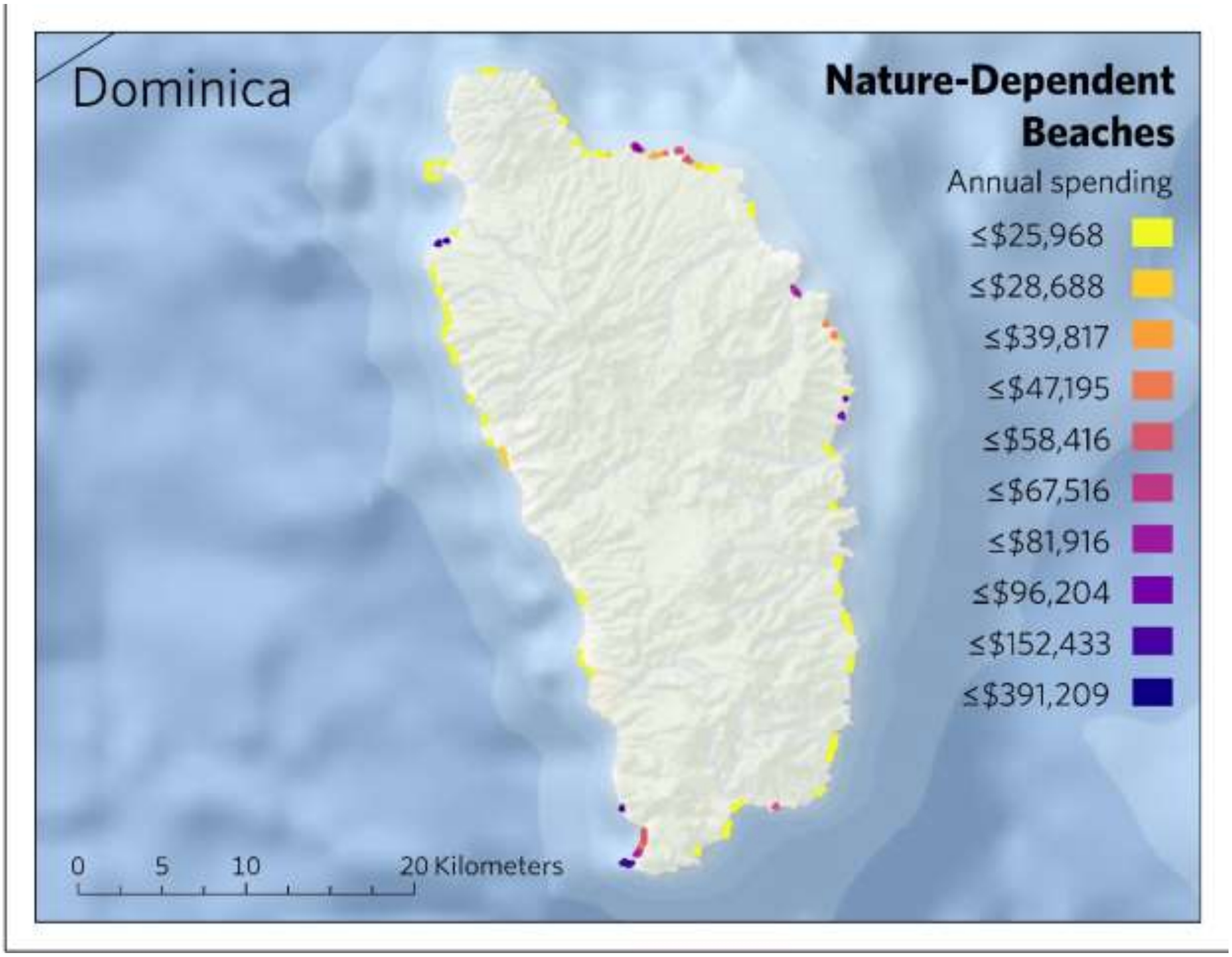


Figure E31. *Total annual nature-dependent beach tourism expenditures (overnight and cruise visitors) for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

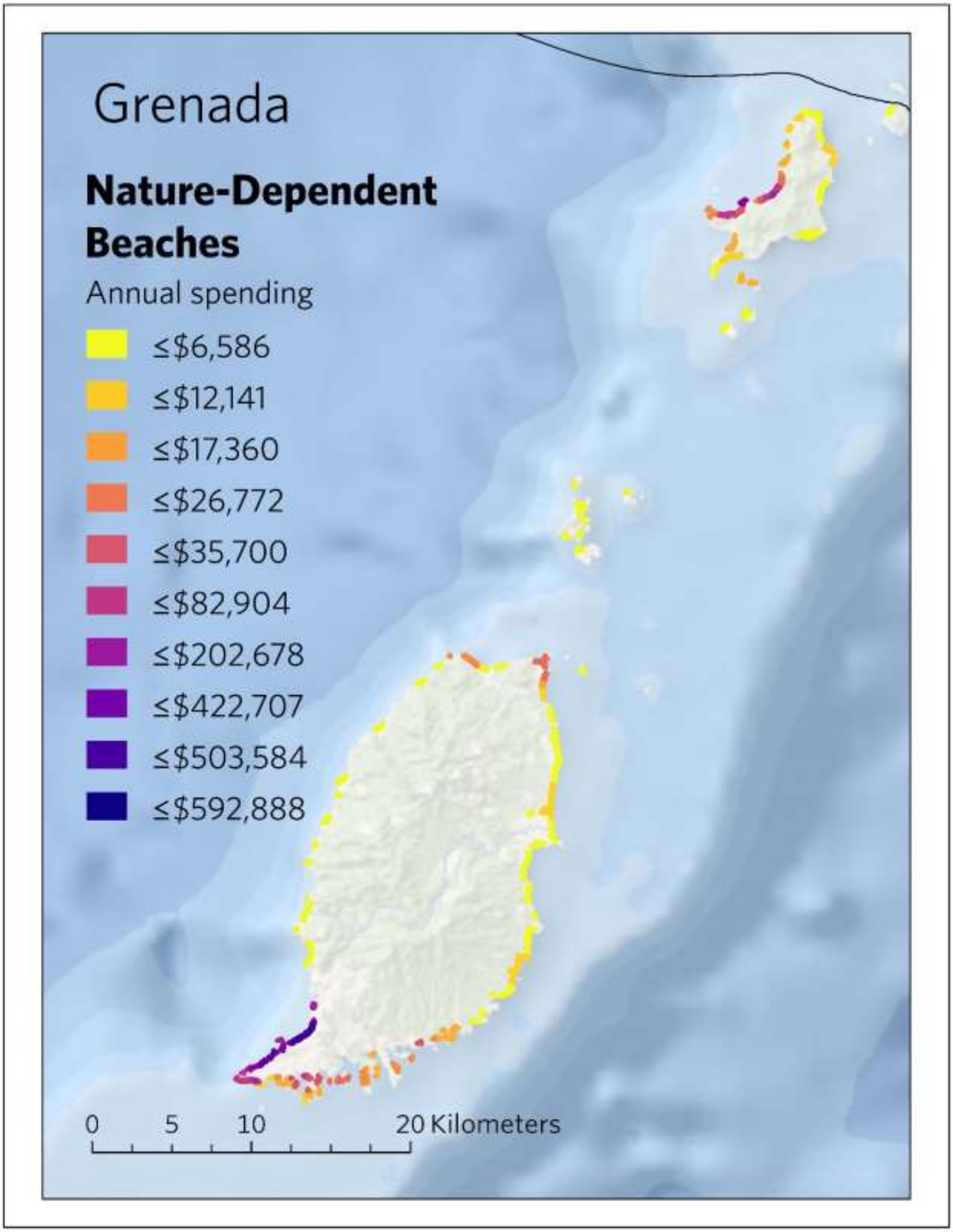


***Figure E32**. Total annual nature-dependent beach tourism expenditures (overnight and cruise visitors) for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

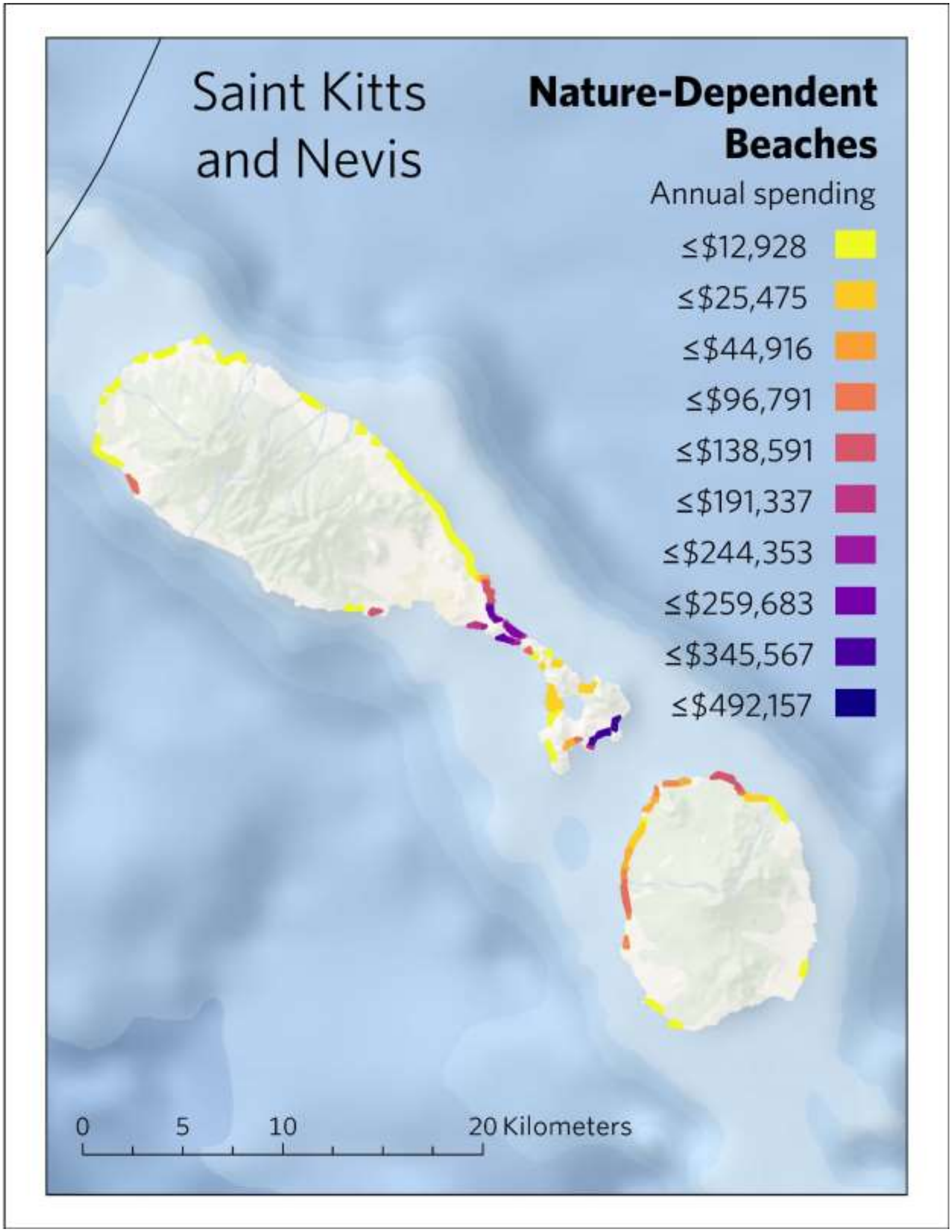


***Figure E33**. Total annual nature-dependent beach tourism expenditures (overnight and cruise visitors) for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

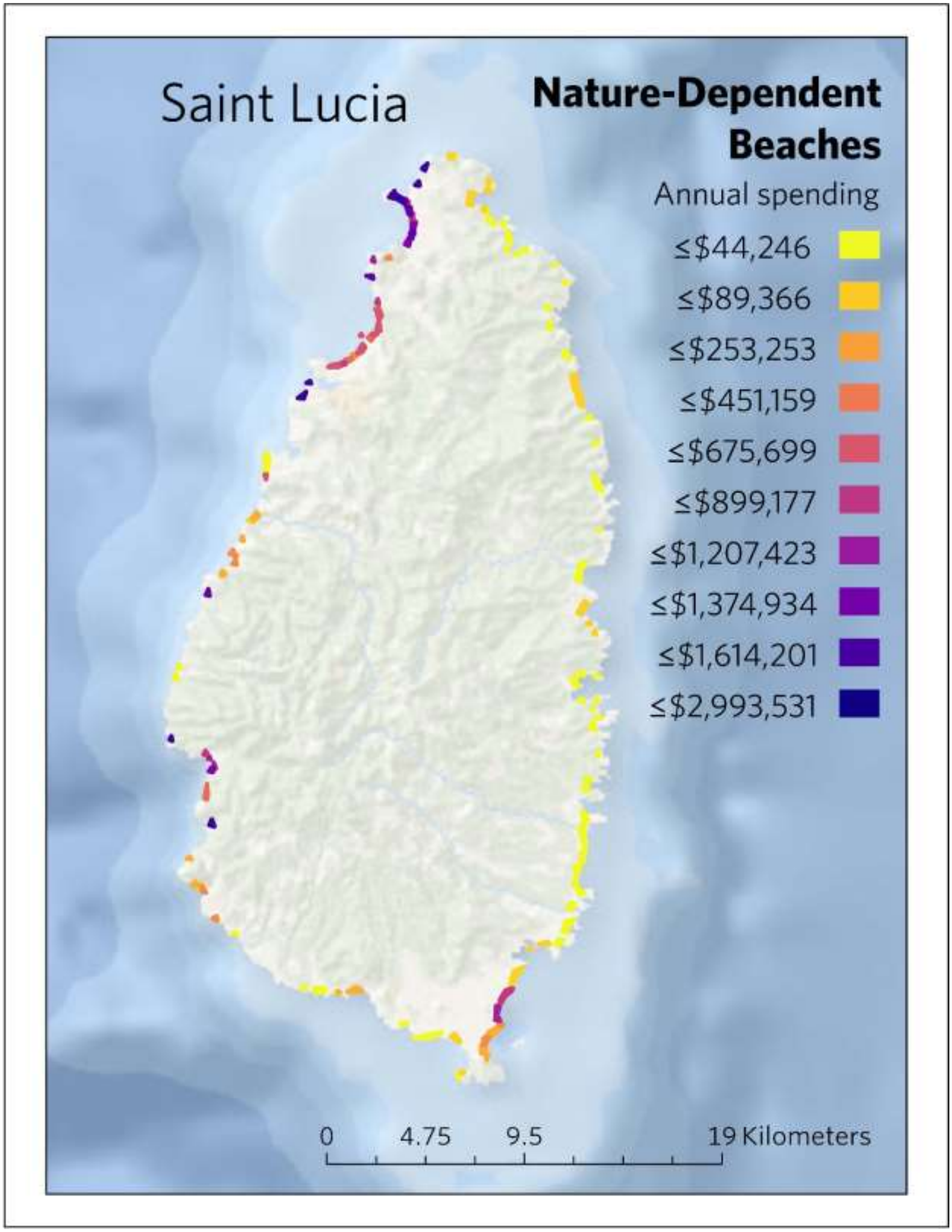


Figure E34*. Total annual nature-dependent beach tourism expenditures (overnight and cruise visitors) for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

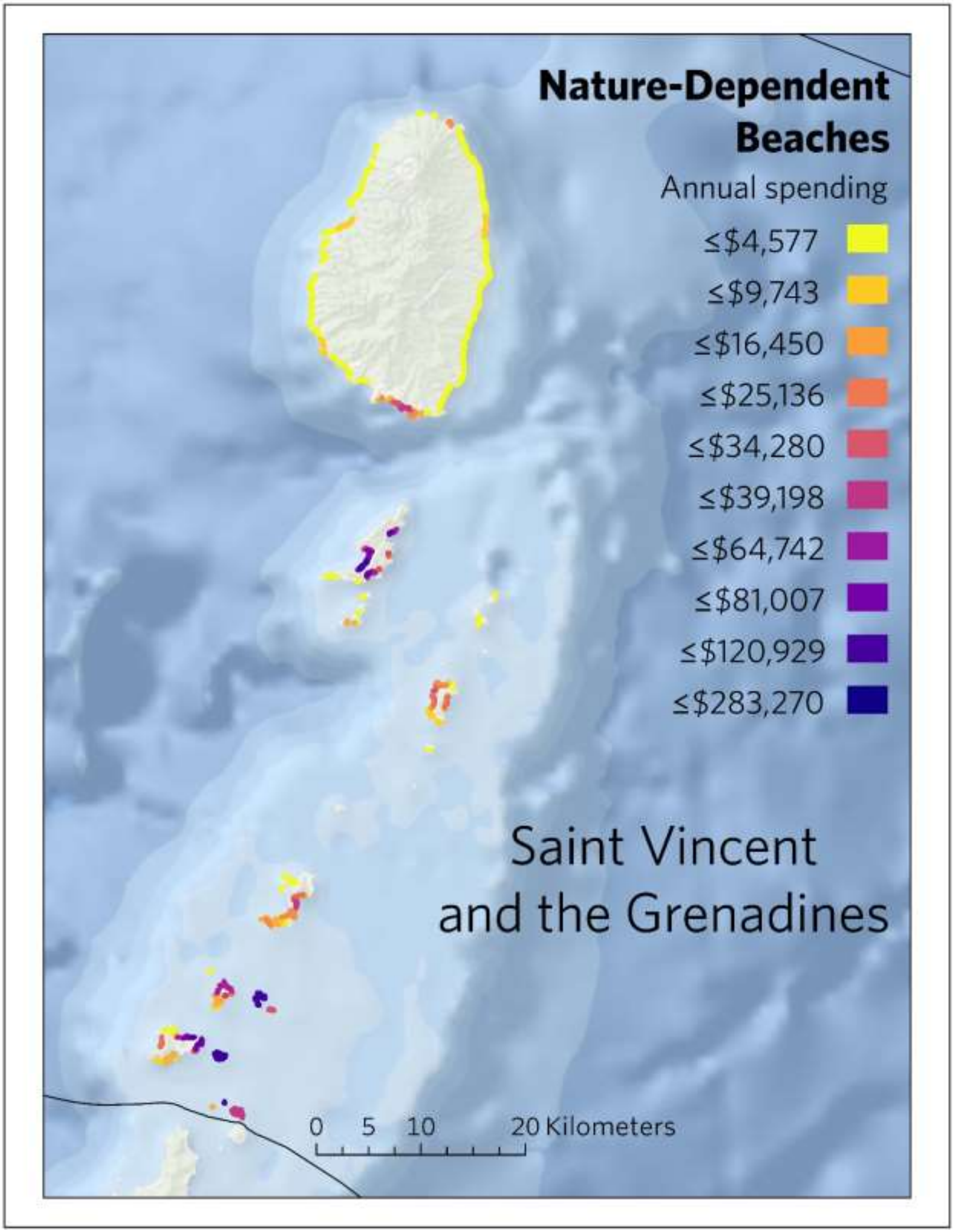


Figure E35*. Total annual nature-dependent beach tourism expenditures (overnight and cruise visitors) for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

Nature-dependent beaches – Annual overnight tourism expenditure by country

Images E36 – E40 Depict total annual nature-dependent beach tourism expenditures for overnight visitors. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

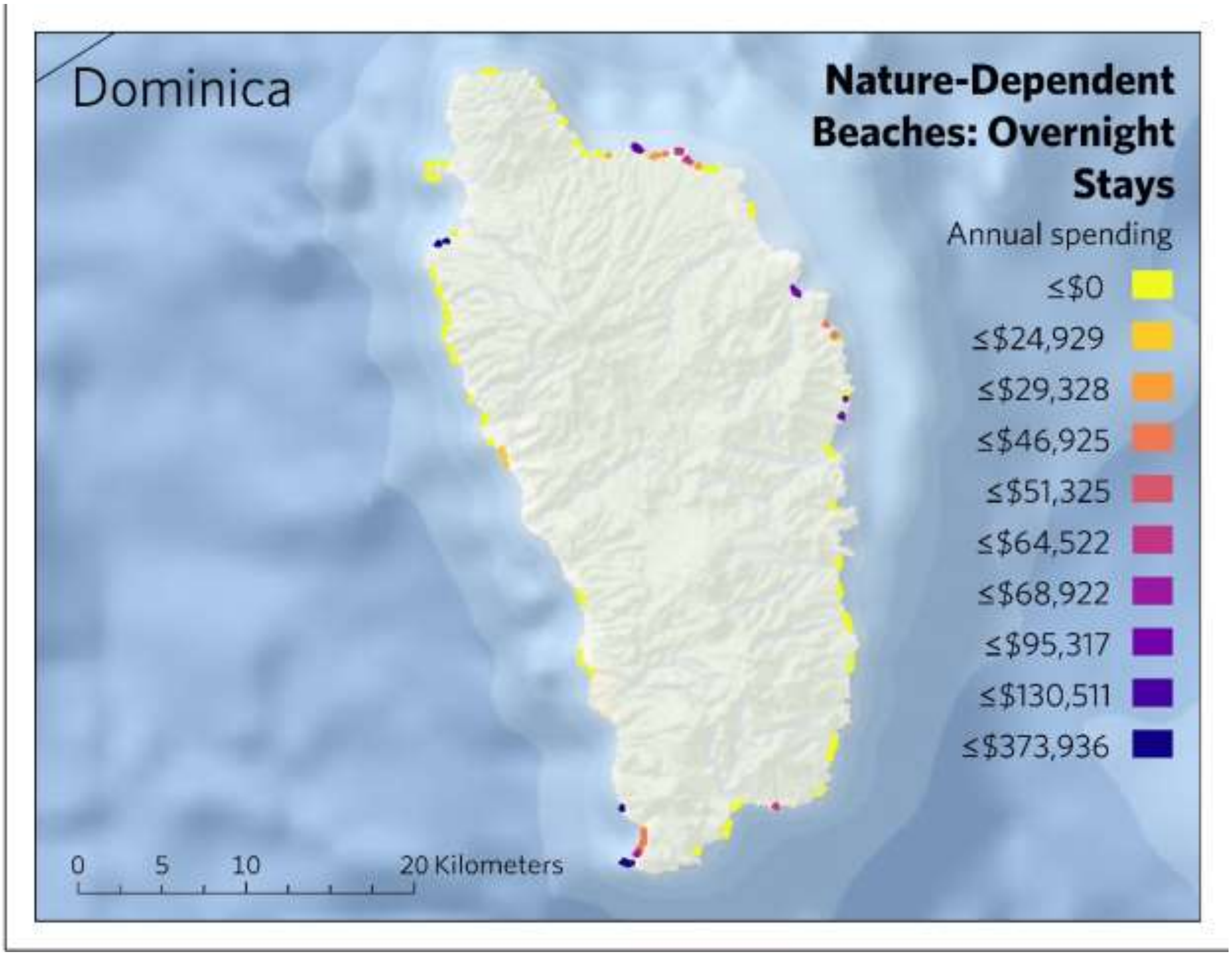


Figure E36. *Total annual nature-dependent beach tourism expenditures for overnight visitors for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

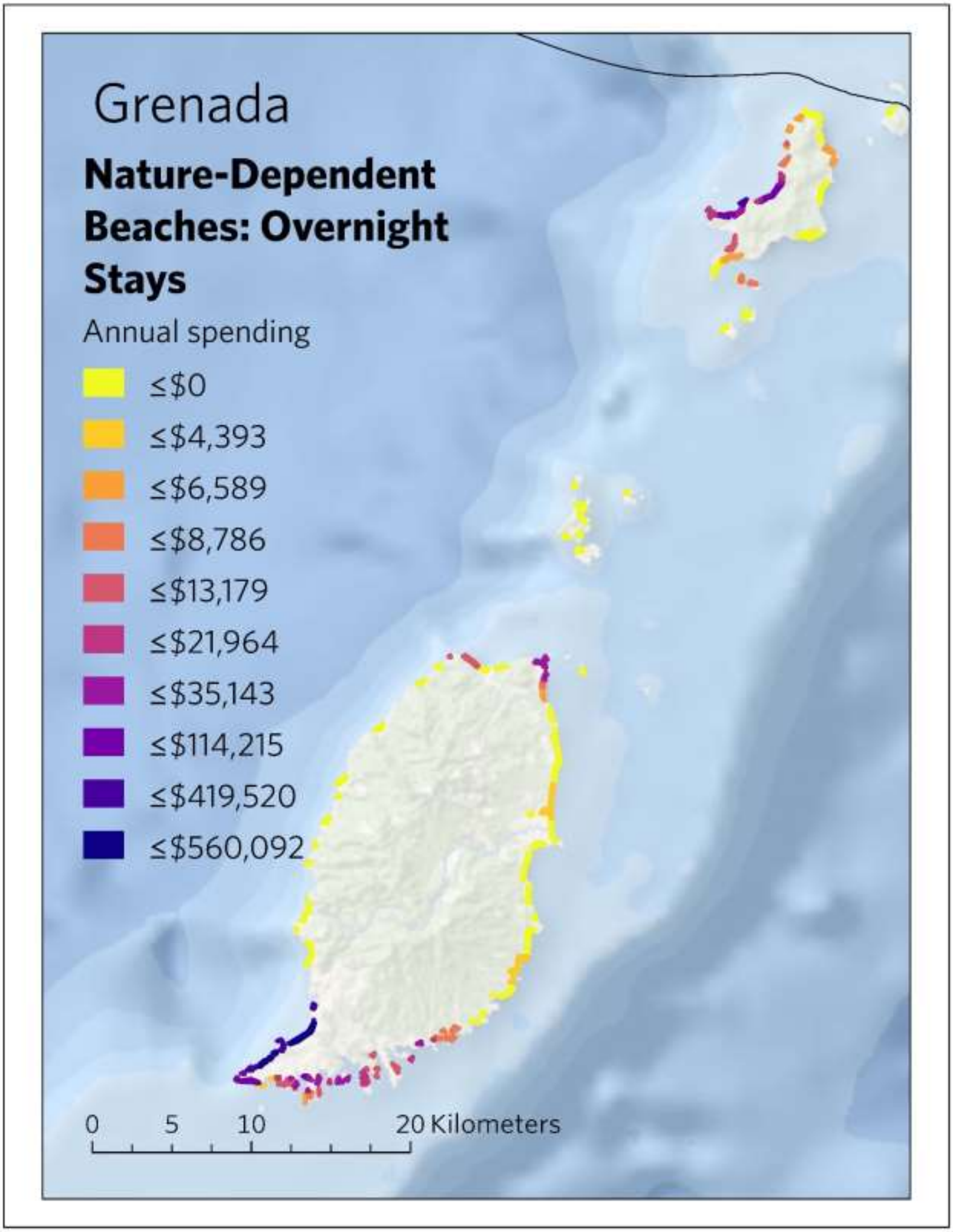


Figure E37. *Total annual nature-dependent beach tourism expenditures for overnight visitors for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

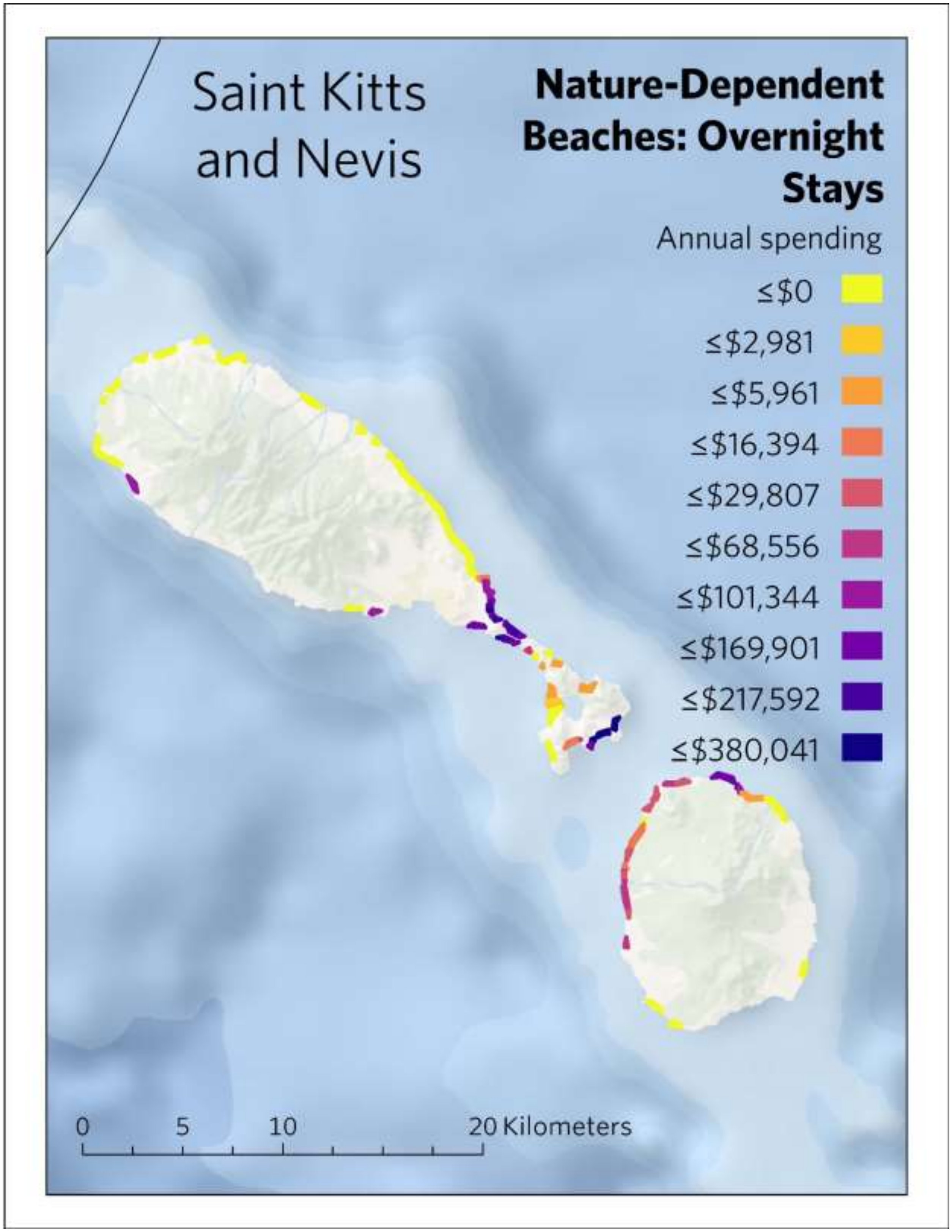


Figure E38. *Total annual nature-dependent beach tourism expenditures for overnight visitors for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

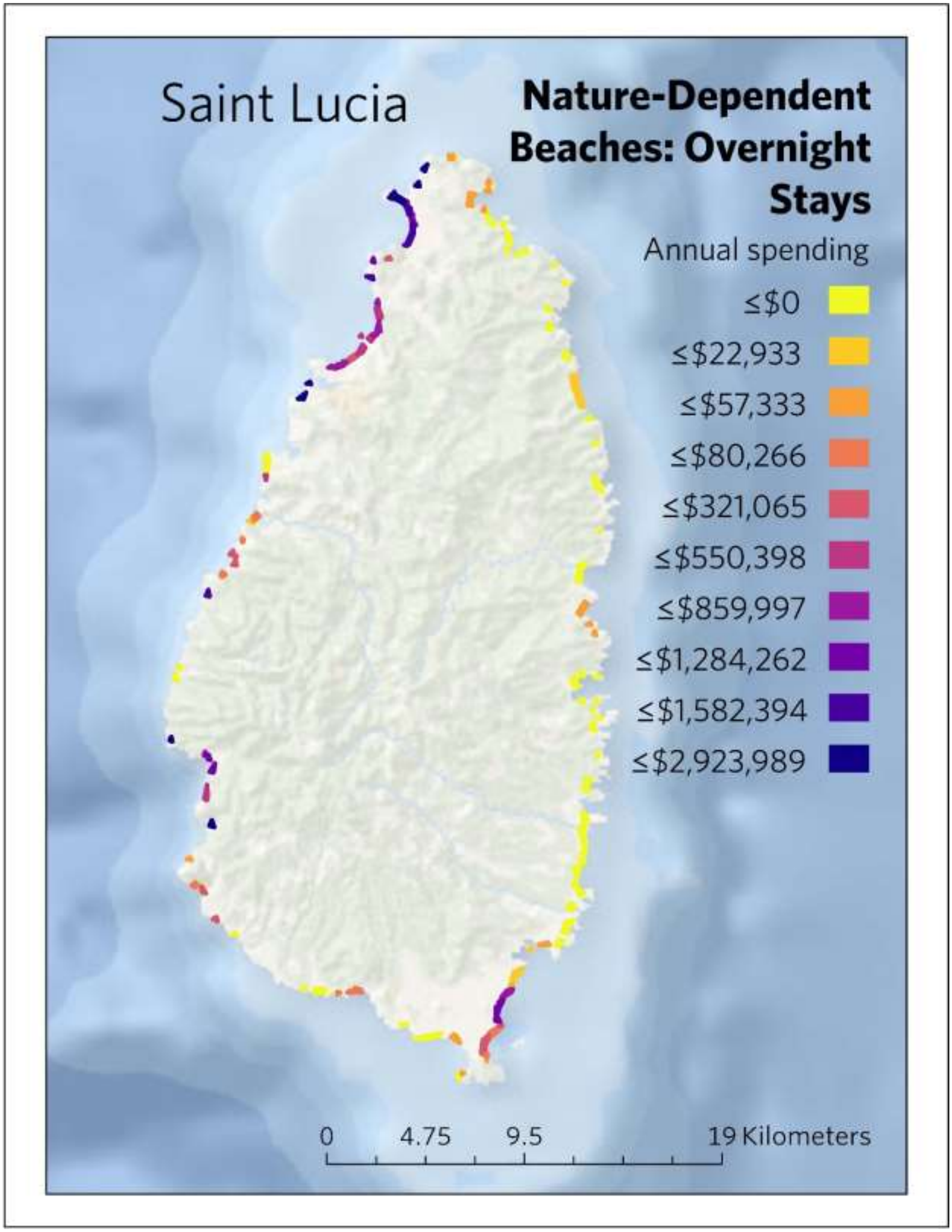


Figure E39. *Total annual nature-dependent beach tourism expenditures for overnight visitors for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

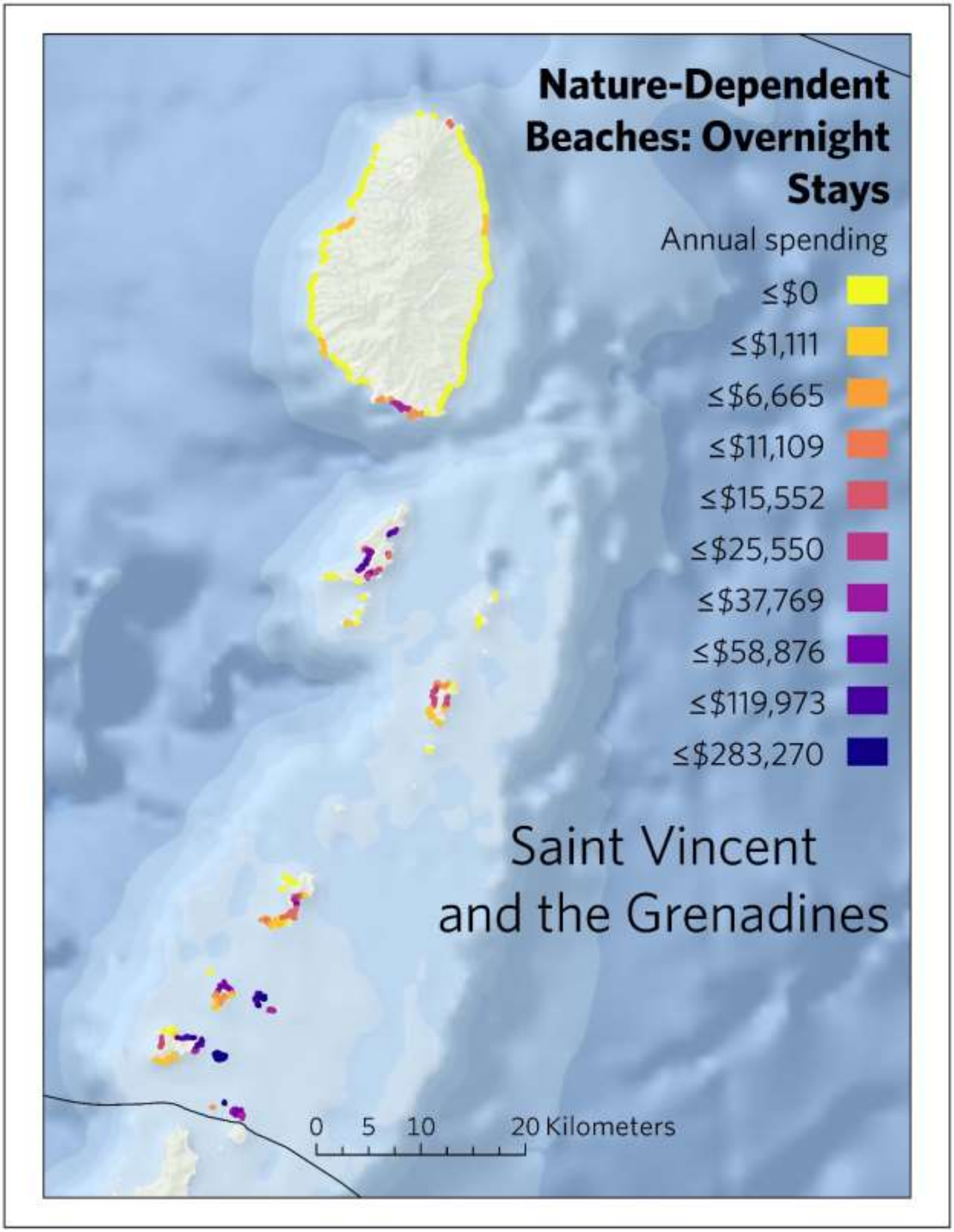


Figure E40. *Total annual nature-dependent beach tourism expenditures for overnight visitors for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

Nature-dependent beaches – Annual cruise visitor tourism expenditure by country

Images E41 – E45 Depict total annual nature-dependent beach tourism expenditures for cruise visitors. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

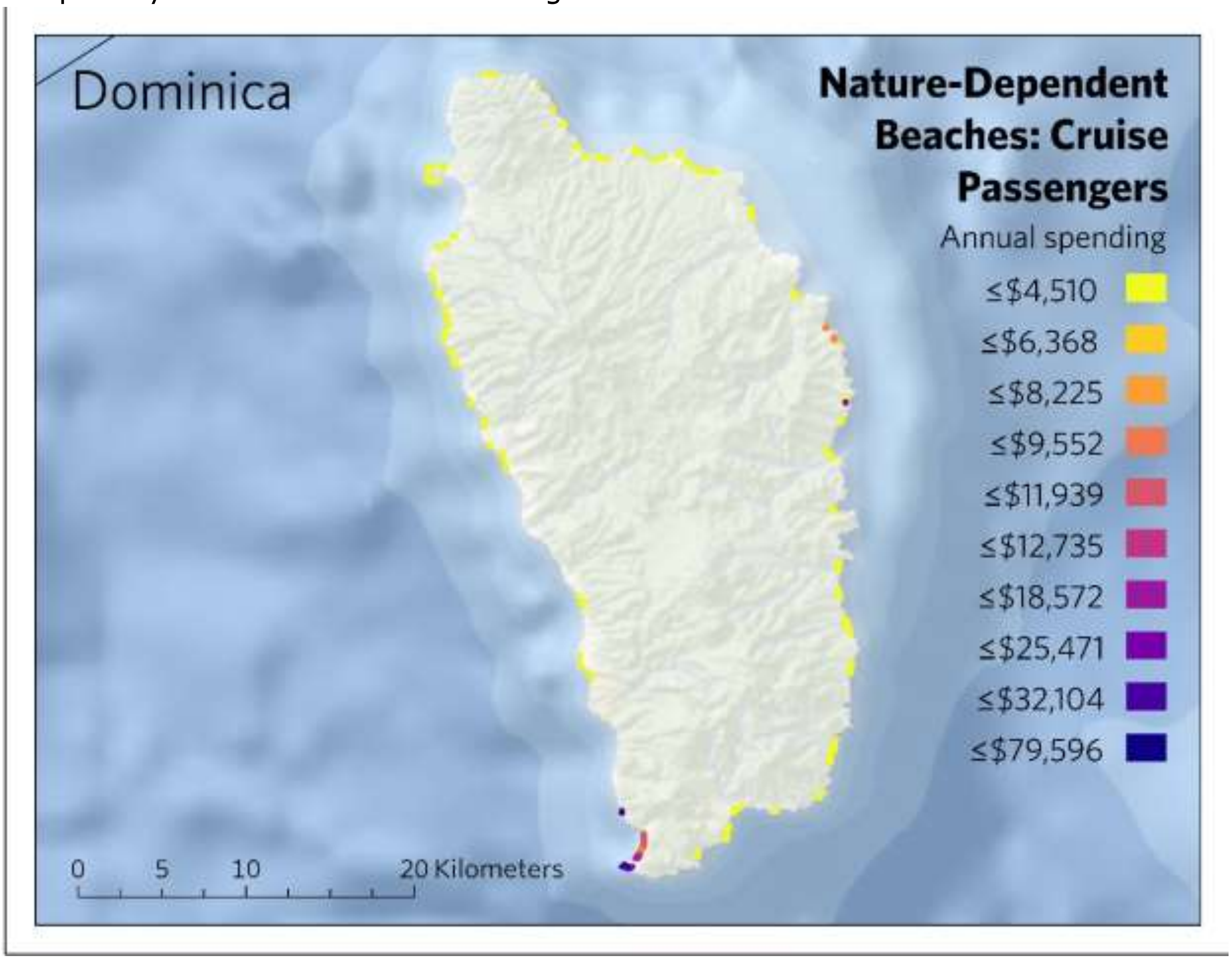


Figure E41. *Total annual nature-dependent beach tourism expenditures for cruise visitors for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

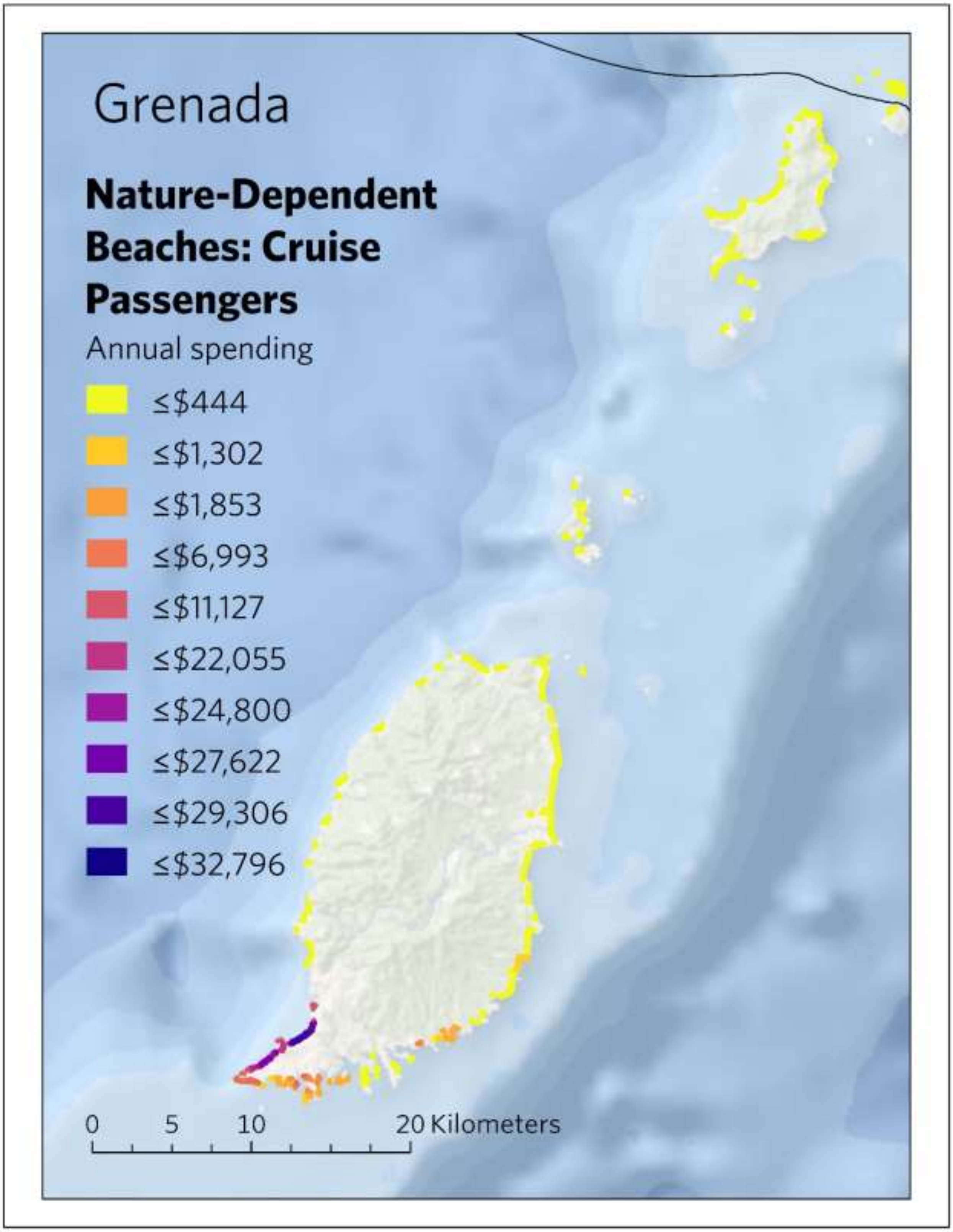


***Figure E42**. Total annual nature-dependent beach tourism expenditures for cruise visitors for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

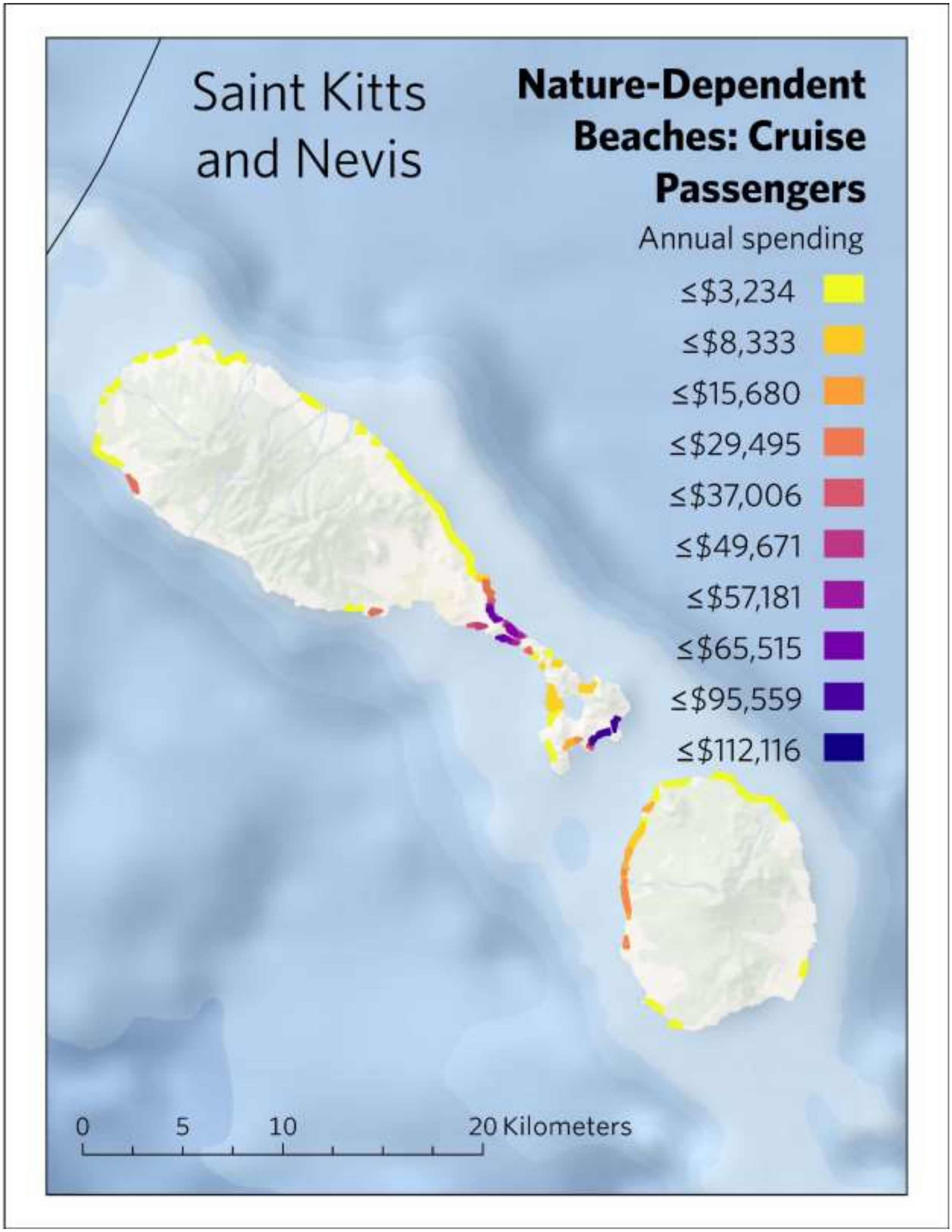


Figure E43*. Total annual nature-dependent beach tourism expenditures for cruise visitors for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

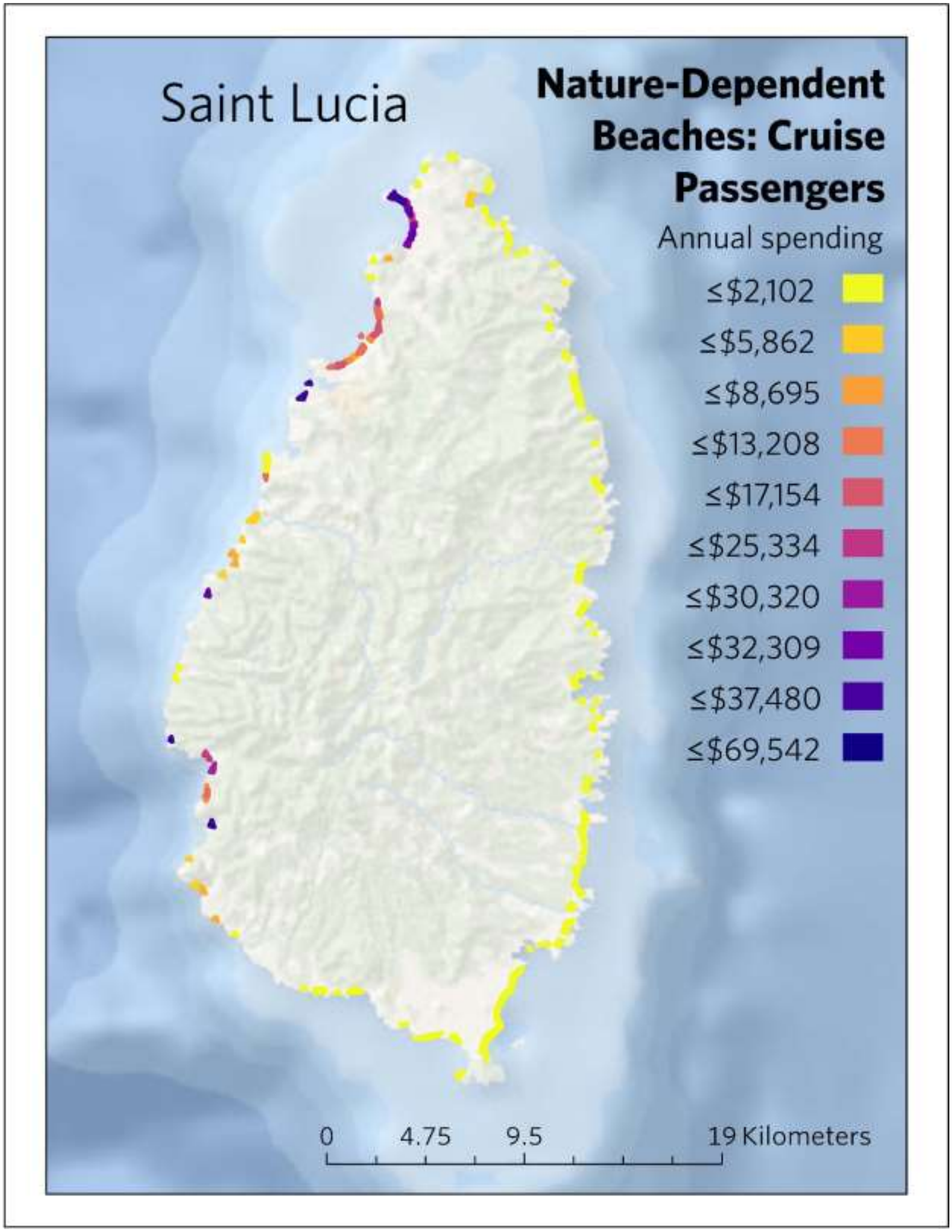


Figure E44. *Total annual nature-dependent beach tourism expenditures for cruise visitors for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

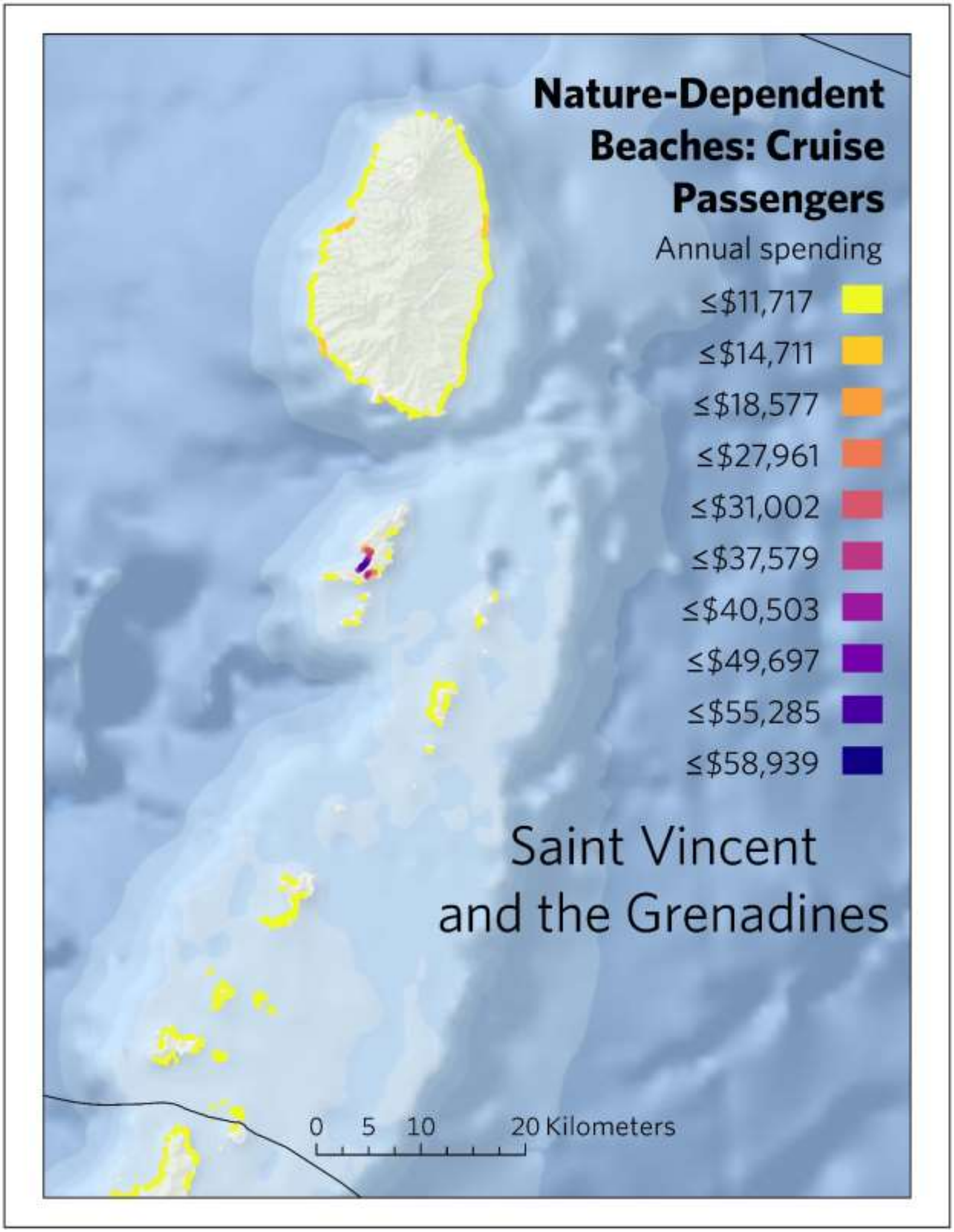


Figure E45. *Total annual nature-dependent beach tourism expenditures for cruise visitors for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

Nature-dependent beaches – Annual overnight and cruise tourism visitation by country

Images E46 – E50 Depict total annual nature-dependent beach tourism visitation from overnight and cruise tourism. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

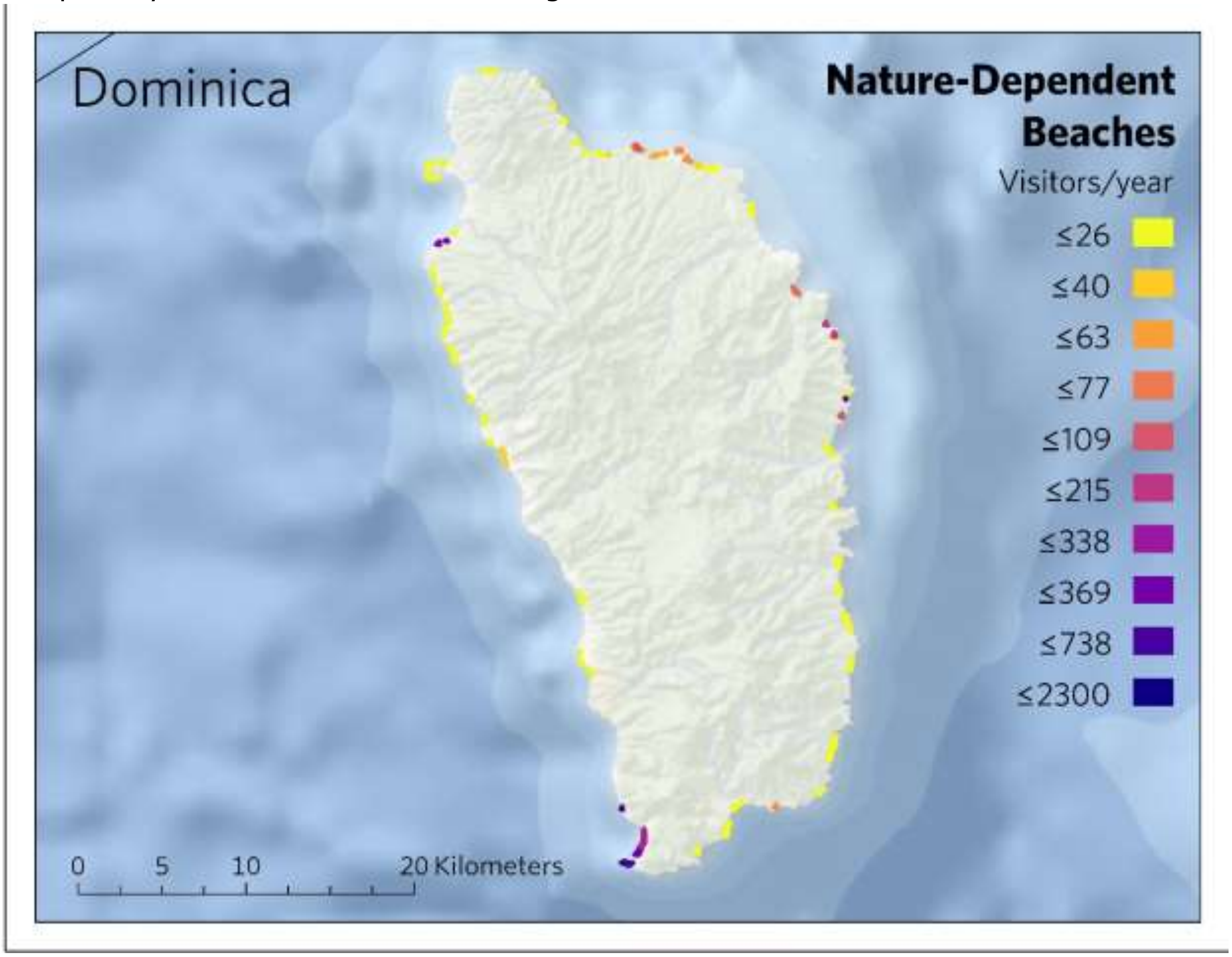


Figure E46. *Total annual nature-dependent beach tourism visitation (cruise and overnight) for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

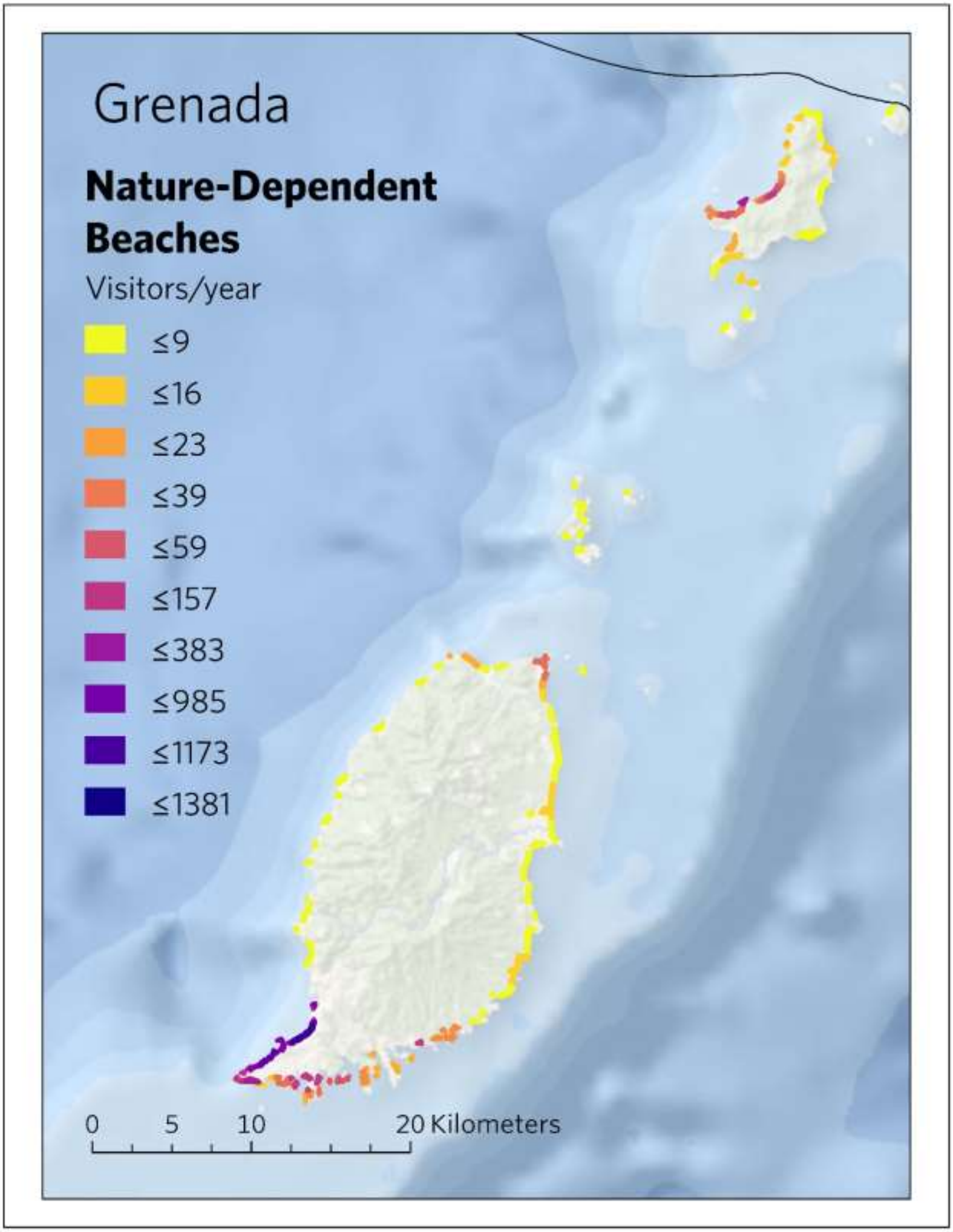


Figure E47. *Total annual nature-dependent beach tourism visitation (cruise and overnight) for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

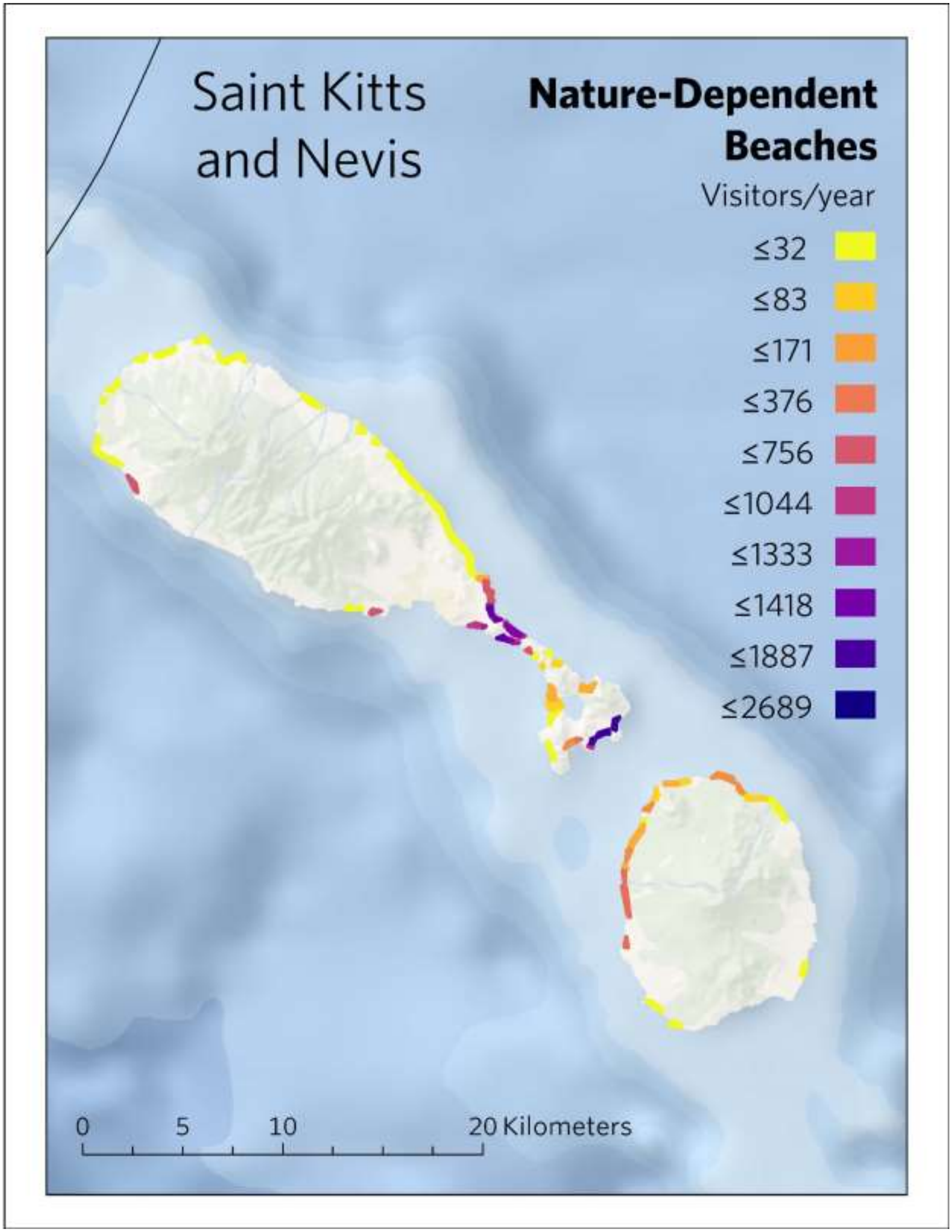


Figure E48. *Total annual nature-dependent beach tourism visitation (cruise and overnight) for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

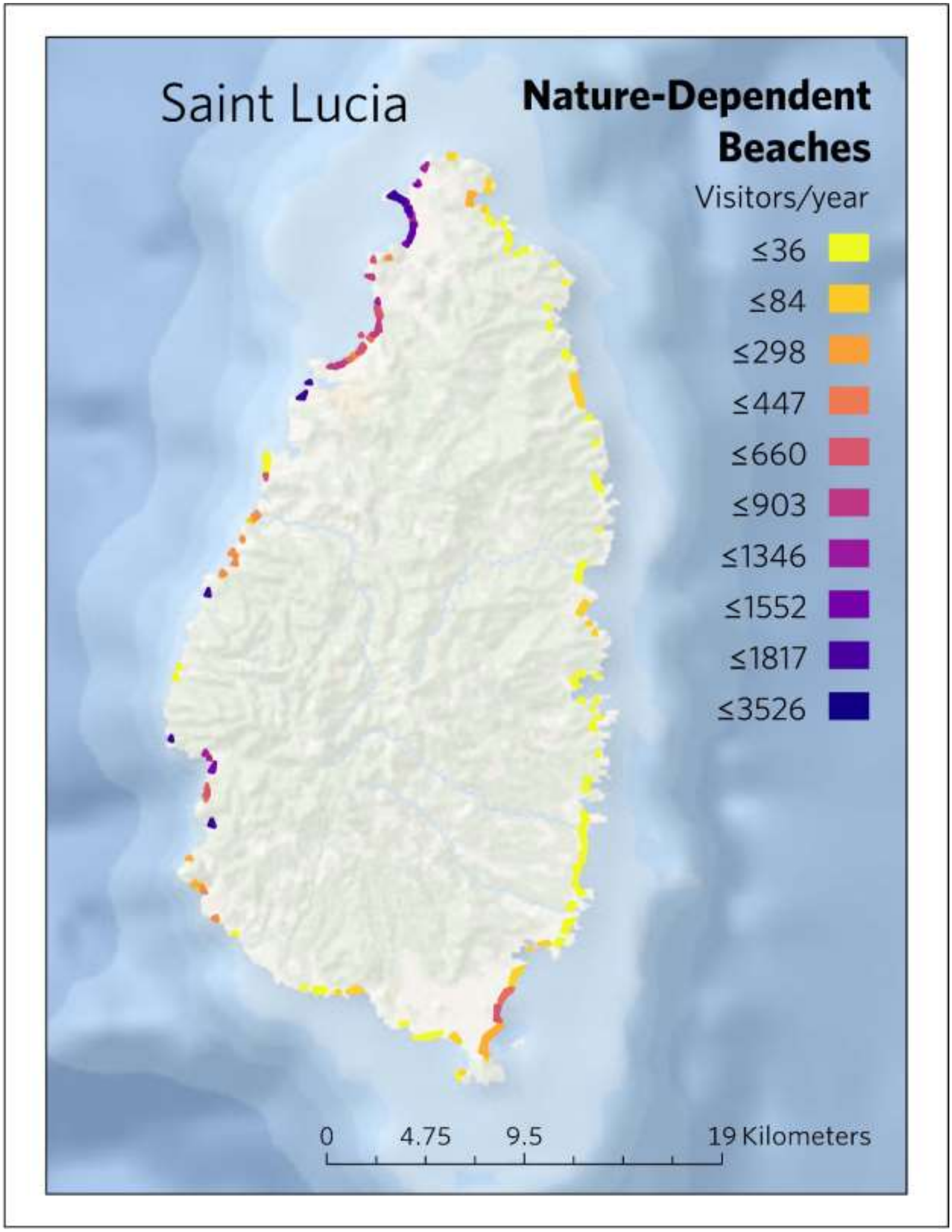


Figure E49. *Total annual nature-dependent beach tourism visitation (cruise and overnight) for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

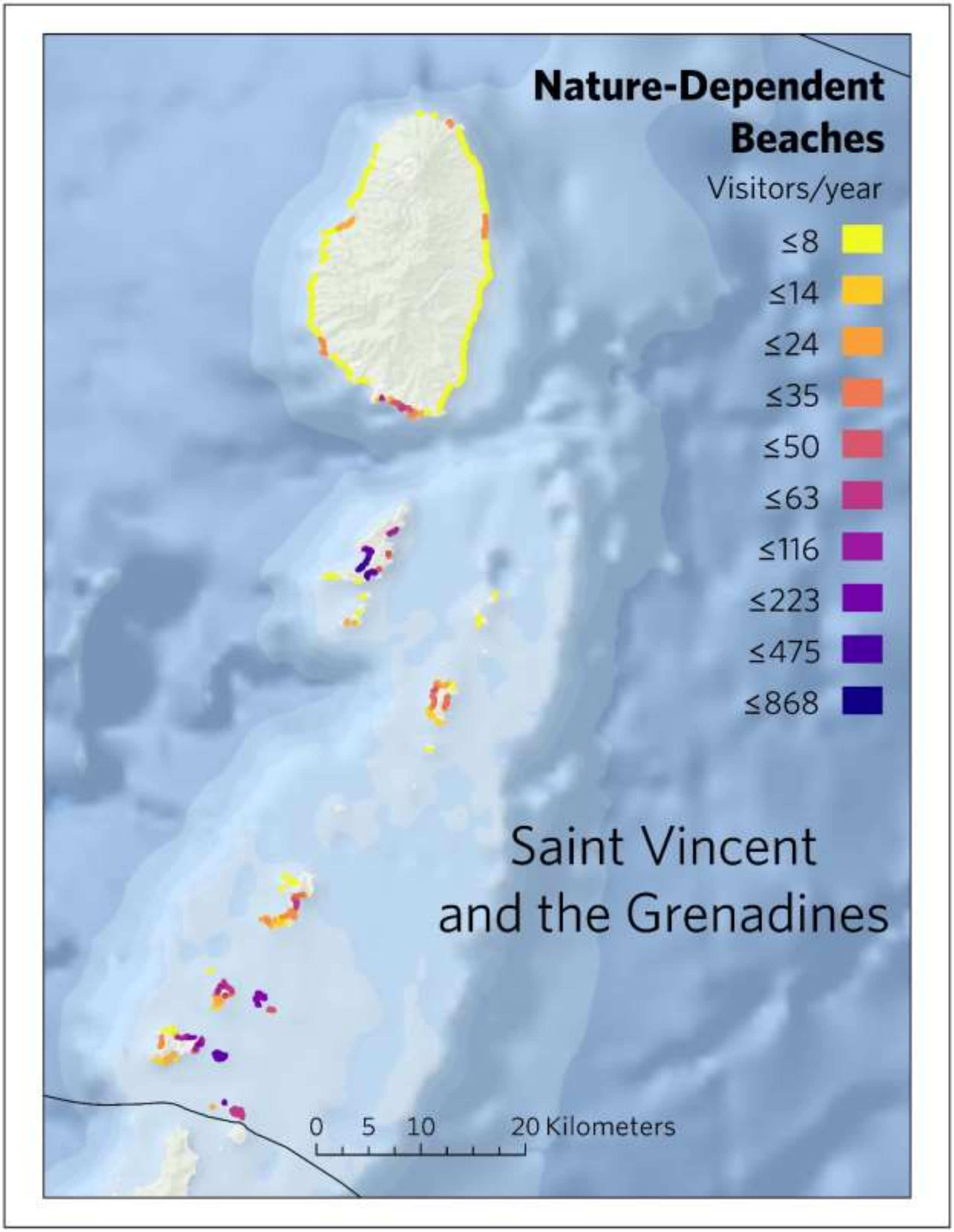


Figure E50. *Total annual nature-dependent beach tourism visitation (cruise and overnight) for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

Nature-dependent beaches – Annual overnight tourism visitation by country

Images E51 – E55 Depict total annual nature-dependent beach overnight tourism visitation. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

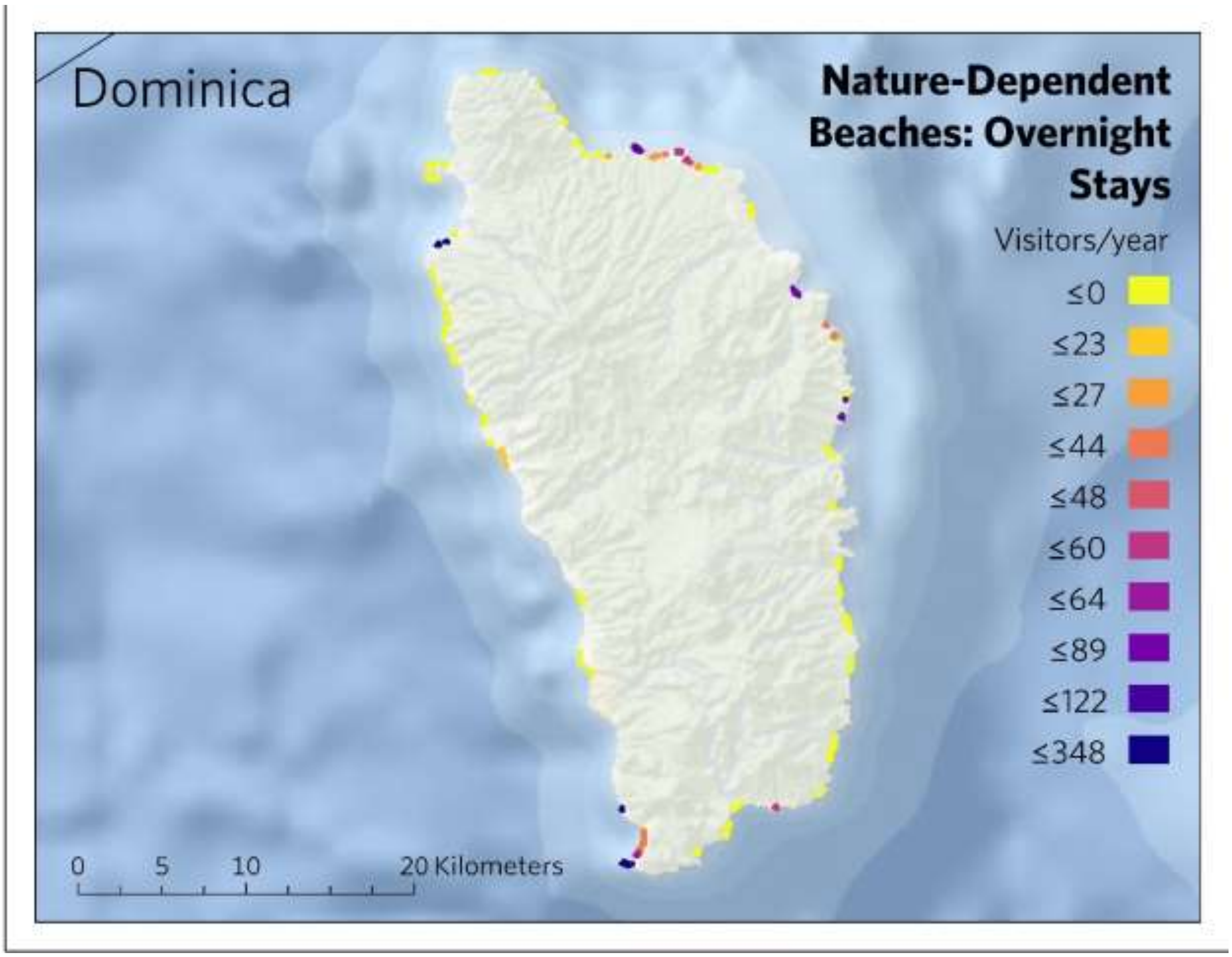


Figure E51. *Total annual nature-dependent beach tourism overnight visitation for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

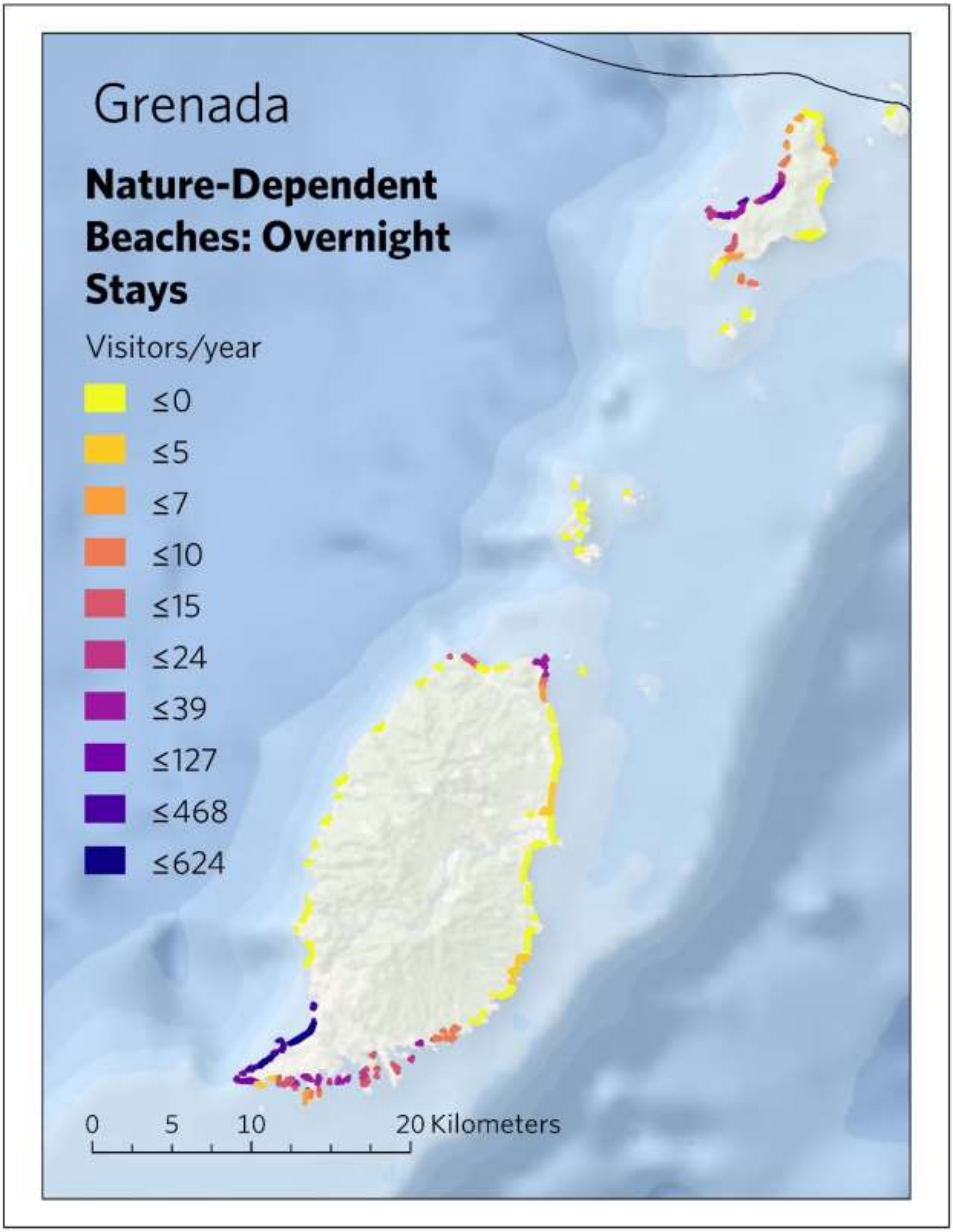


Figure E52. *Total annual nature-dependent beach tourism overnight visitation for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

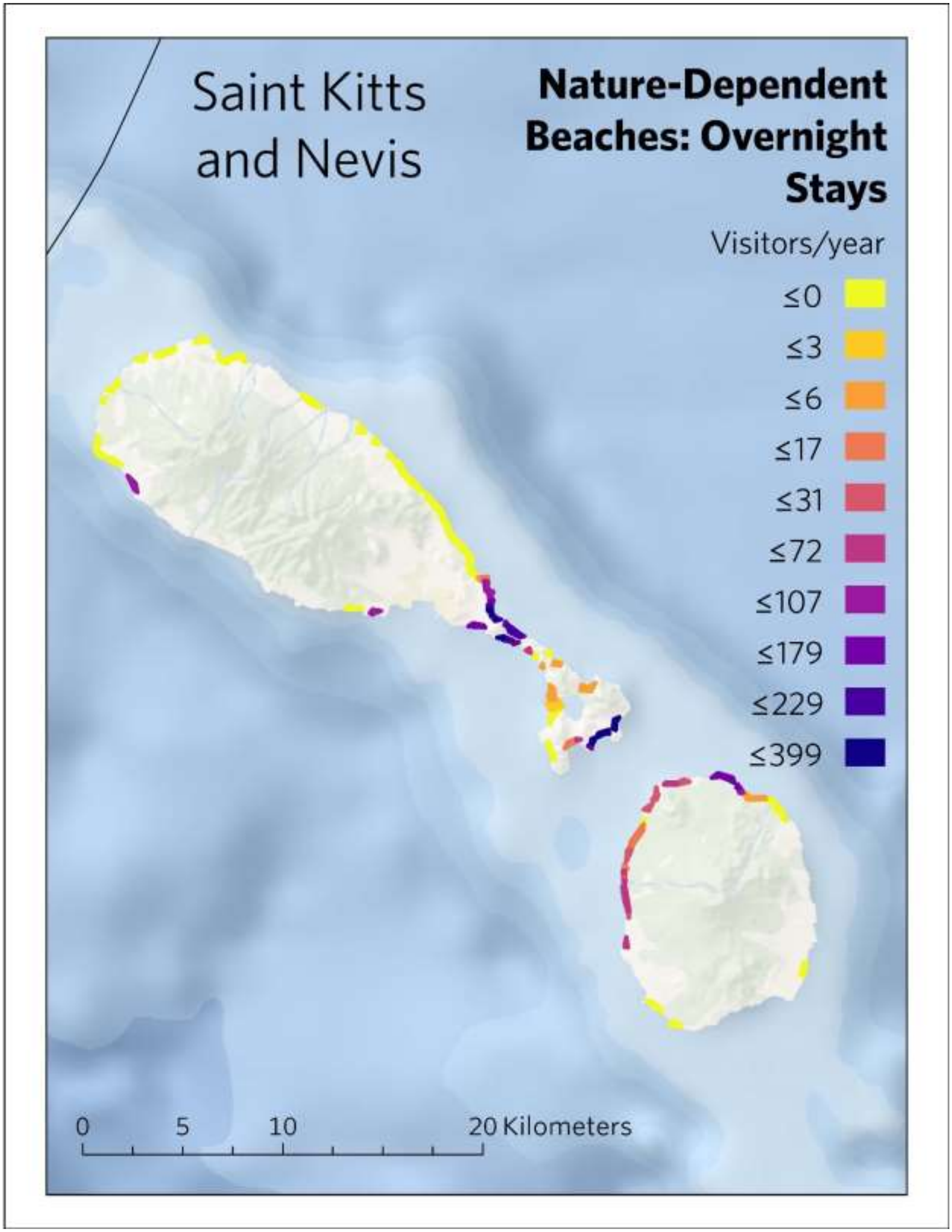


Figure E53. *Total annual nature-dependent beach tourism overnight visitation for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

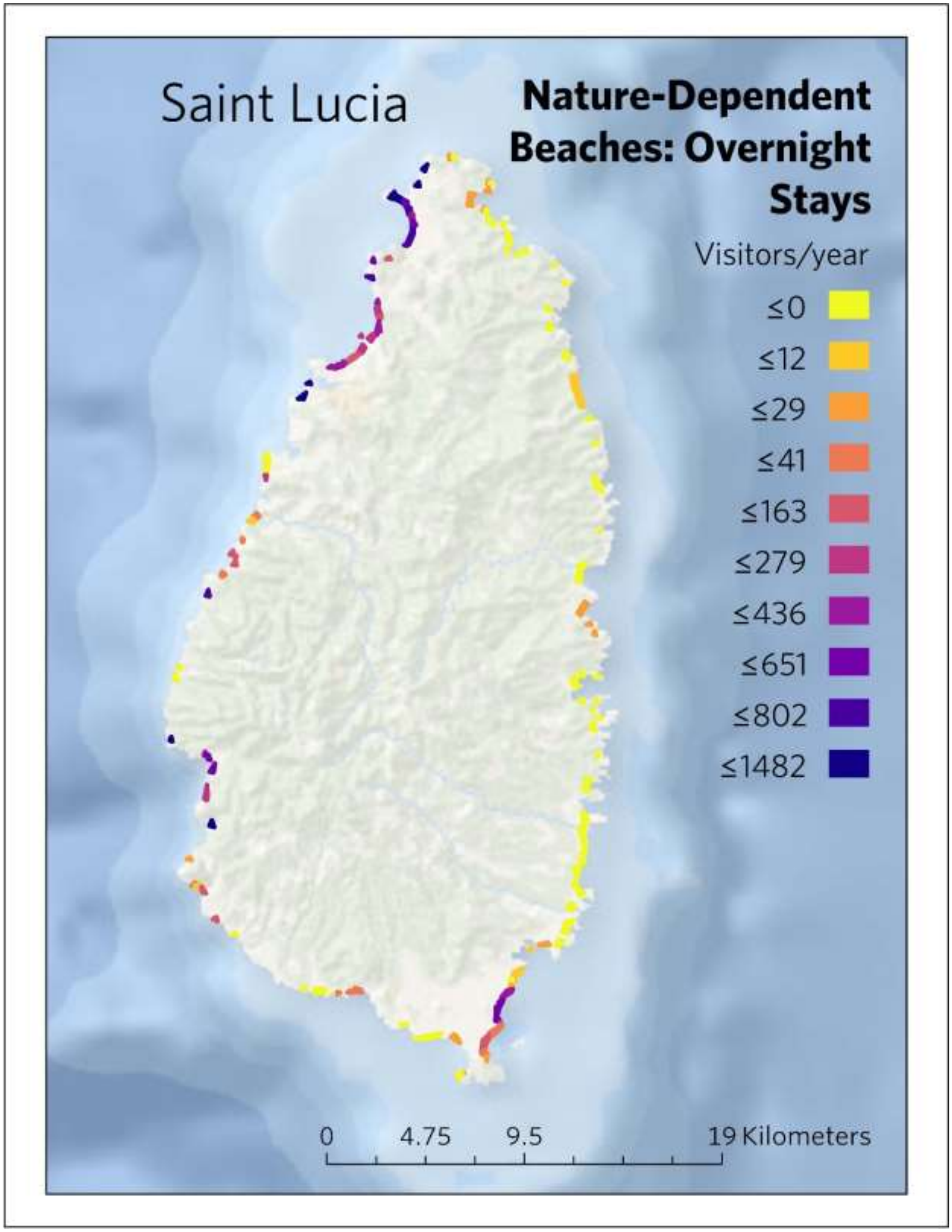


Figure E54. *Total annual nature-dependent beach tourism overnight visitation for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

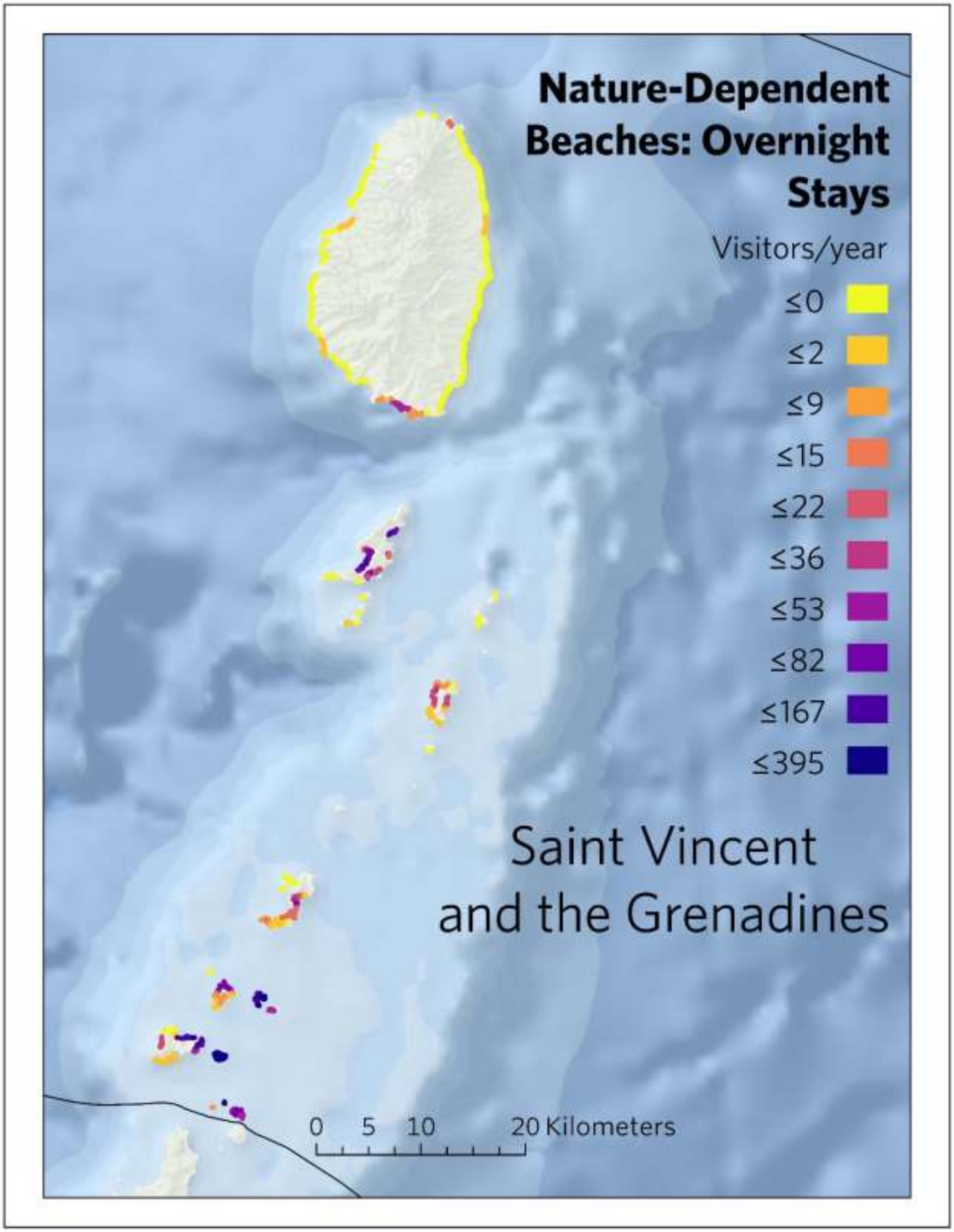


Figure E55. *Total annual nature-dependent beach tourism overnight visitation for St. Vincent and the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

Nature-dependent beaches – Annual cruise tourism visitation by country

Images E56 – E60 Depict total annual nature-dependent beach cruise tourism visitation. Results are rescaled for each country, so color ramps may reflect different value ranges across countries.

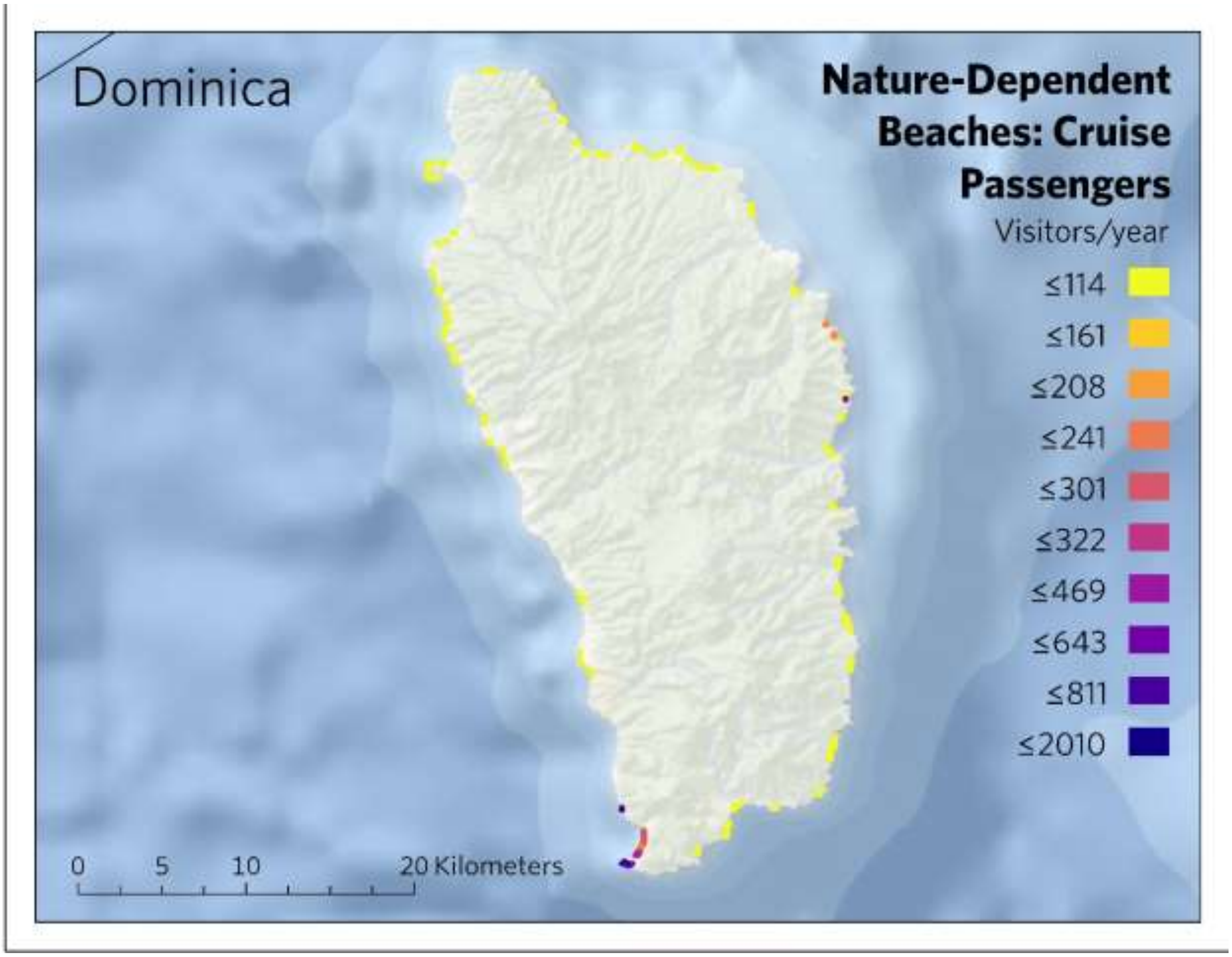


Figure E56. *Total annual nature-dependent beach tourism cruise visitation for Dominica. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

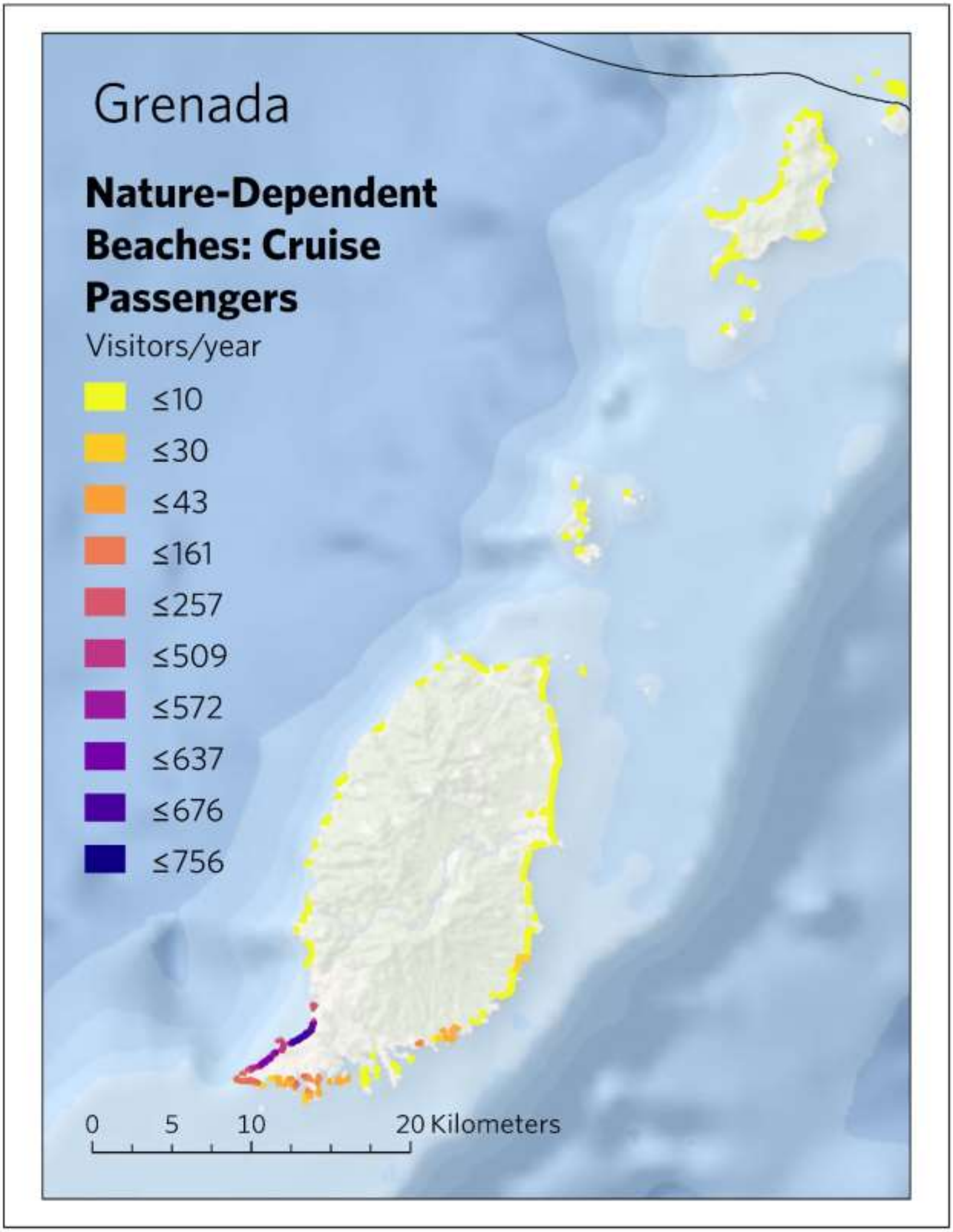


Figure E57. *Total annual nature-dependent beach tourism cruise visitation for Grenada. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

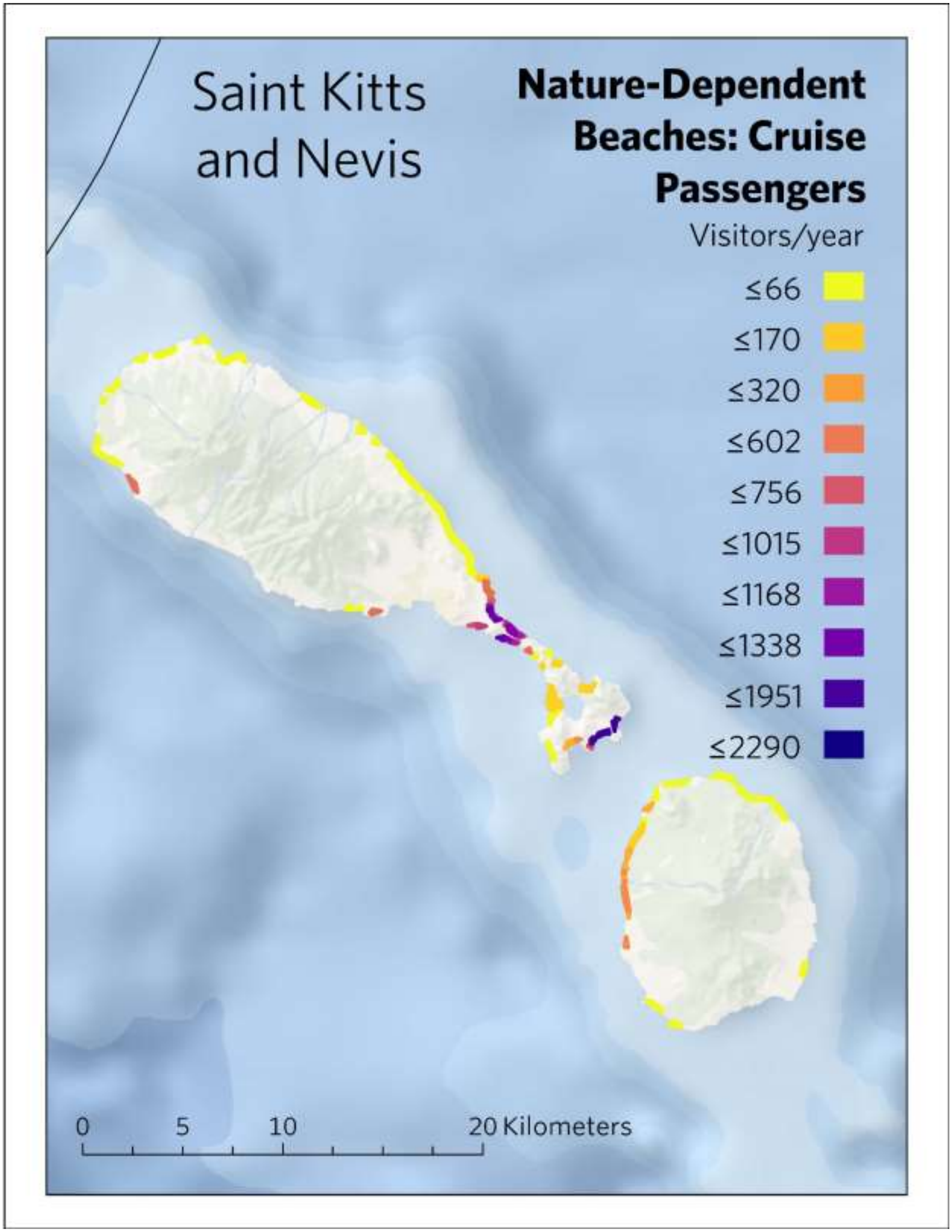


Figure E58. *Total annual nature-dependent beach tourism cruise visitation for St. Kitts and Nevis. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

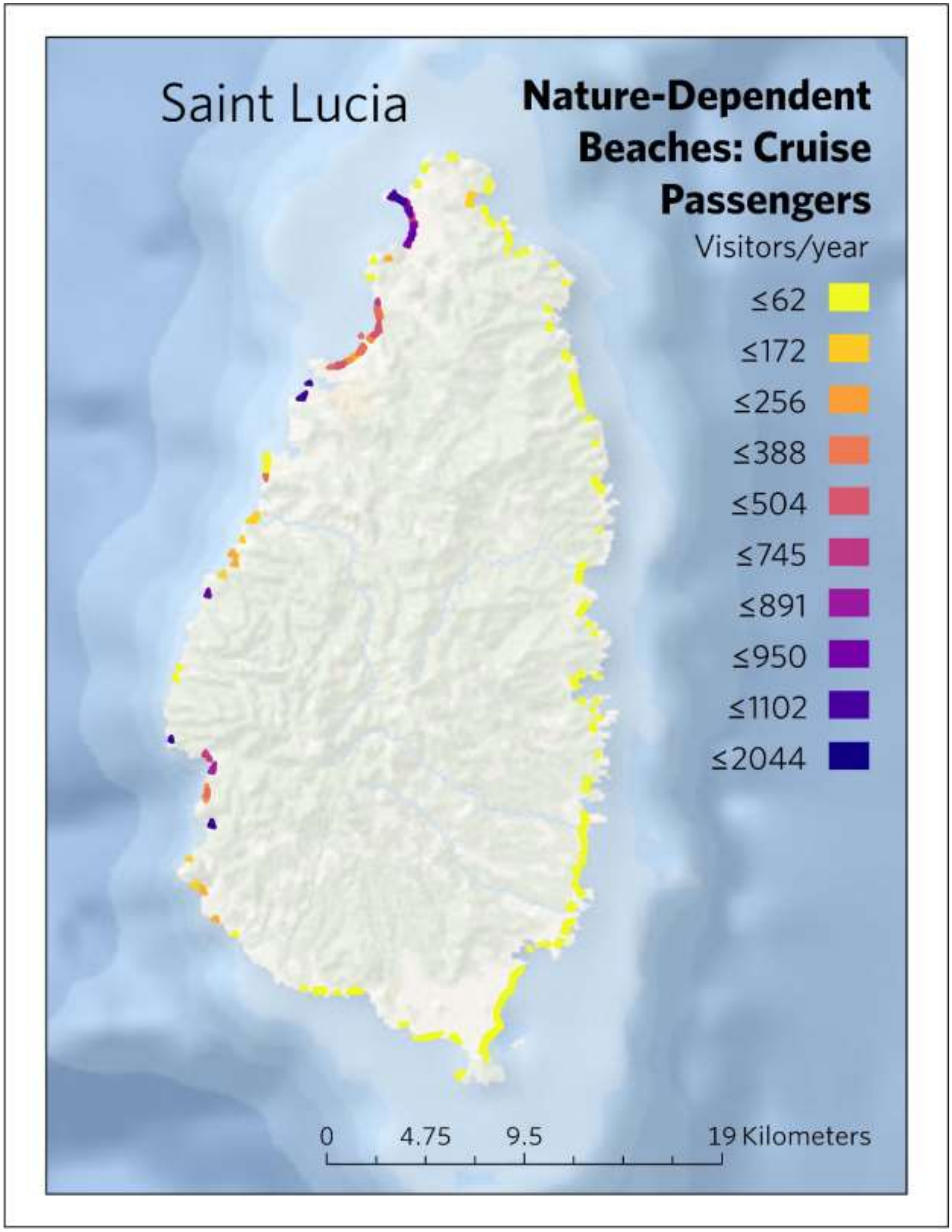


Figure E59. *Total annual nature-dependent beach tourism cruise visitation for Saint Lucia. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*

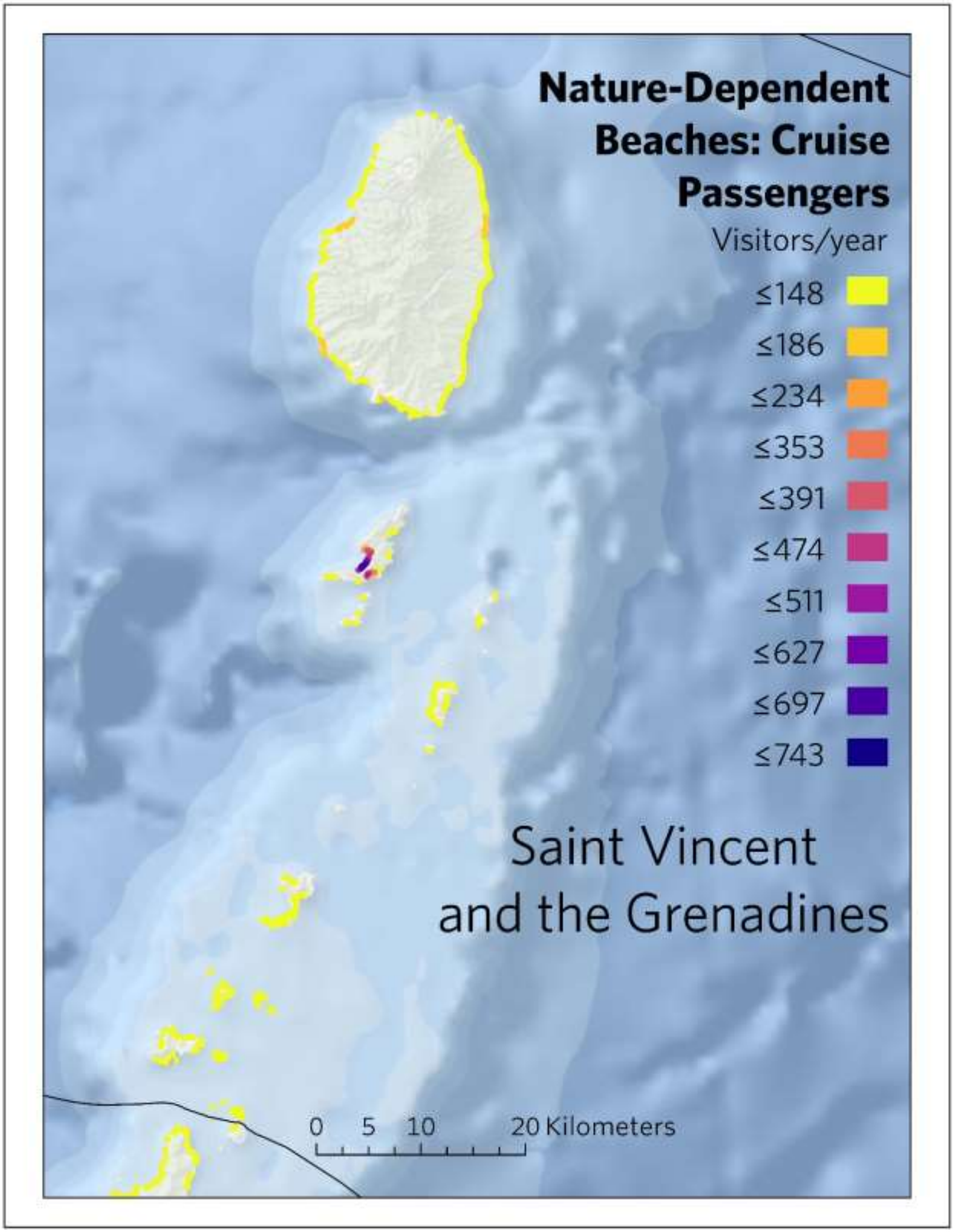


Figure E60. *Total annual nature-dependent beach tourism cruise visitation for St Vincent & the Grenadines. Values are mapped to a 100m resolution reef habitat map, and are expressed at the scale of 1 hectare.*