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Research article

Nature dependent tourism – Combining big data and local knowledge

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ABSTRACT

The ability to quantify nature's value for tourism has significant implications for natural resource management and sustainable development policy. This is especially true in the Eastern Caribbean, where many countries are embracing the concept of the Blue Economy. The utilization of user-generated content (UGC) to understand tourist activities and preferences, including the use of artificial intelligence and machine learning approaches, remains at the early stages of development and application. This work describes a new effort which has modelled and mapped multiple nature dependent sectors of the tourism industry across five small island nations. It makes broad use of UGC, while acknowledging the challenges and strengthening the approach with substantive input, correction, and modification from local experts. Our approach to measuring the nature-dependency of tourism is practical and scalable, producing data, maps and statistics of sufficient detail and veracity to support sustainable resource management, marine spatial planning, and the wider promotion of the Blue Economy framework.

1. Introduction

This work describes a new effort to model, measure and map the value of nature in tourism across five small island nations in the Eastern Caribbean. While previous work has described multiple techniques and approaches in this field, the current work provides a more holistic appraisal. It combines multiple approaches, including artificial intelligence to utilise "big data" sources and local input in model design, data enhancement, review, and participatory mapping. The outputs can support planning within the sector and will provide key inputs to wider marine spatial planning and ocean accounting (Gacutan et al., 2022).

The natural environment is an essential part of the tourism product at destinations around the world. Images of nature can greatly influence tourists' perceptions and destination choices, and interactions with nature provide important sources of recreation and enjoyment that contribute to visitor satisfaction and loyalty. Understanding and mapping the contributions of natural resources to tourism value is a prerequisite for managing such resources, and in planning for sustainability or future utilization. An empirical approach is required to move beyond generic concepts of value towards quantified, spatially explicit

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knowledge. This work provides a broad, multi-faceted, example of how such information can be developed using existing information and tools.

To date, much of the effort to quantify natural values in tourism has had a relatively narrow focus. Direct uses or interactions with the natural world such as scuba-diving or birdwatching, have been assessed in studies of "nature-based tourism" (Balmford et al., 2009; Cisneros-Montemayor et al., 2020) and "wildlife tourism" (WTTC, 2019). More indirect natural values have also been considered, including the role of nature in views (Mendoza-González et al., 2018); the formation of destination image (San Martín and Rodríguez del Bosque, 2008; Beall et al., 2021; Gössling, 2021), and the use of nature imagery in destination marketing (Avau et al., 2011).

Other indirect contributions from nature to tourism associated with supporting, regulating, and provisioning ecosystem services have received much less attention. Coral reefs, for example, generate beach sand (Perry et al., 2015), contribute to beach stability and provide clear, calm shallow waters appreciated by many beachgoers. Healthy reefs, mangroves, saltmarshes, and seagrass ecosystems contribute to the production of fresh seafood and protect critical tourism infrastructure against damage from storms and flooding (Del Valle et al., 2020; Guannel et al., 2016; Sheaves et al., 2015). The idea of *nature-dependency* (Spalding et al., 2020) captures these multi-dimensional aspects of the natural environment in supporting tourism and provides a broad and flexible framework for evaluating nature's contributions to human wellbeing.

The study of nature's contributions to tourism has often utilised revealed and stated preference methods that rely on primary data (e.g. Lee, 1997; Mendoza-González et al., 2018), and on the aggregation of value estimates from other sites or secondary data (e.g. Heck et al., 2019). The utilization of "big data" – the large volumes of diverse and often highly up-to-date digital information now widely available (Li et al., 2018; Xu et al., 2020) – provides an alternative approach. Within this information array, user-generated content (UGC) – information prepared and shared by a broad body of public users via internet platforms and social media (Mariani and Borghi, 2021) – is becoming particularly valuable (Ghermandi, 2022). Although there are challenges in using UGC data (Tenkanen et al., 2017; Heikinheimo et al., 2017; Monkman et al., 2018), errors and bias can be reduced through various analytical stages of data acquisition, storage, cleaning, filtering, and transformation (Crampton et al., 2013; Toivonen et al., 2019). In this way, UGC can be used to generate large datasets to reveal complex geospatial patterns and insights (Fisher et al., 2018; Teles da Mota and Pickering, 2020).

Initial work in the analysis of UGC in this field included the use of geotagged photos, with keyword searches or other manual screening approaches (Wood et al., 2013; Spalding et al., 2017; Silva et al., 2019), but more recent studies have applied artificial intelligence and machine learning techniques to mine content in other ways (Richards and Tunçer, 2018; Alaei et al., 2019; Lee et al., 2019). There are also now some examples of work that combines UGC datasets with "small data" in a more mixed methods approach (Xu et al., 2020).

The five countries described in this study are some of the most tourism dependent economies in the world, with pre-pandemic tourism in 2019 estimated to contribute from 36 to 80% of employment and from 33 to 68% of GDP (both statistics are for Dominica and Saint Lucia respectively) (WTTC, 2022a). As a contribution to the Caribbean Regional Oceanscape Project (CROP), led by the OECS (Organisation of Eastern Caribbean States, 2020), the primary motivations for this research are to produce data, maps and statistics of sufficient detail and veracity to support policy for sustainable resource management, the development of blue growth and marine spatial plans, and to promote Blue Economy and Natural Capital Accounting frameworks in these countries (Patil et al., 2016; see also Clegg et al., 2020).

This work develops seven models to describe multiple aspects of nature dependency. It draws data from several UGC sources (Methods: 2.1), using artificial intelligence to review and filter information (2.2). This data is enhanced both through other regional and global "big data" sources, and through local data and local engagement (2.2). The derived data from this work is used to generate baseline maps of relative nature dependency (2.3). For two of the more data rich and high-value components of nature dependency (beaches and reef-associated activities) additional modelling is then undertaken to generate direct metrics of value around visitor numbers and expenditure (2.4).The findings highlight new and important patterns of how nature influences and supports tourism activities in the Eastern Caribbean, including the extent of the spatial footprint of nature dependency and the focus of tourist activity on particular ecosystems. Beyond these important applications to sustainable tourism policy at the study sites, we illustrate a practical and scalable approach to measuring the nature-dependency of tourism that may be of considerable utility in future research.

2. Methods

This work is focused on five island nations: Dominica, Grenada, Saint Kitts and Nevis, Saint Lucia, and Saint Vincent and the Grenadines. In these countries, seven models were developed to describe different aspects of nature dependency. Here we briefly describe the models; then the key data sources that were utilised; before providing a sequential description of the key modelling steps which were broadly common to all models.

2.1. Model selection and data sources

An initial workshop in Saint Lucia, held in May 2019, included 36 natural resource professionals from nine countries in the region (see Supplementary Material). This workshop led to the development of a range of proposed models, methodologies, and potential data sources for the quantification of nature-dependent tourism. A final list of seven models was selected based on feasibility and on synergies which could be achieved within the proposed approaches (Table 1).

Prior to building these models, data availability was assessed. Three key sources of information were utilised, prior to and during model building:

Big data: UGC was seen as a key primary source, to be reviewed using artificial intelligence and machine learning on images and/or text sources (see below). Key sources included TripAdvisor (reviews and

Table 1
The final list of models selected for development in this study. See Supplementary Material for a list of these and other proposed models that were initially considered for inclusion.

Final models for nature dependency	Notes
On-reef activities	Snorkeling and diving activities only
Nature-dependent beaches	Capturing the natural value perceived by visitors, driven by landscape and seascape features, notably clear waters with offshore reefs; clear, bright and uncluttered sand; and adjacent or distant vegetated landscapes dominating beach views.
Paddle sports	Kayak, canoe and paddle-boarding activities, considered nature-dependent because many involve long-shore exploration and demand clear and clean water and actively avoid urban and port settings.
Recreational Fishing	Fishing for recreational/pleasure purposes, focused on fishing from charter vessels and during tournaments. This term covers variously named "game", "deep sea", and "blue water" fishing
Wildlife viewing:	
Whale and dolphin watching	Boat-based trips
Birdwatching	Model was developed, although this activity was not necessarily marine or coastal
Seafood restaurants	Targeting both independent and hotel-based establishments where locally caught or "fresh" seafood is on the menu

images); Flickr; eBird; and Diveboard. A range of additional "big data" sources informed the models or helped to frame and constrain the outputs. These included tourism arrivals and expenditure, cruise tourism statistics, lists of top tourist attractions, accommodation data, and dive shop listings. Base maps for the models included protected areas, bathymetric contours, and satellite-derived maps of coral reef habitats and sandy beaches.

Local expertise: Industry and government partners helped to inform and to guide the model-building, and to locate additional data sources. A process of participatory mapping was used to create maps of whale and dolphin watching and recreational fishing. In total, further input was received after the initial workshop from at least 87 individuals and 81 organizations in the region.

Local data: In almost all cases, UGC data were enhanced or modified with locally-sourced datasets. These included information on dive sites and dive shops; key fishing locations; cruise ship visitor destinations; and key birdwatching sites and species.

Full lists of data and sources are listed in the Supplementary Material. Fig. 1 provides examples of some of the input layers which informed model building.

For each model, data development and mapping followed a similar approach, represented in Fig. 2. Full details for each of the seven models are available in the Supplementary Material, while the following sections describe the key stages of data development.

2.2. *Artificial intelligence and machine learning*

The first step of the modelling process involved identifying patterns of activity by applying Artificial Intelligence and Machine Learning (AI/ML) protocols to data from Flickr and TripAdvisor.

Metadata around Flickr images typically includes georeferenced information linked to the location where the image was taken. TripAdvisor data (both text and images) is geospatially linked to "destinations", which include hotels, restaurants, and attractions.

A total of over 190,000 images and over 364,000 reviews from TripAdvisor were utilised; together with over 40,000 images from Flickr. These data cover the history of these two platforms going back as far as 2006 and up to the end of 2018. The exponential growth of these two platforms means that they are dominated by data from 2013 to 2018 (56% for Flickr and 78% for TripAdvisor).

Image and text classification models were developed using training layers, testing performance using precision (positive prediction) and recall (sensitivity), in an iterative process with initial training layers expanded to improve accuracy in some cases. Given the very large

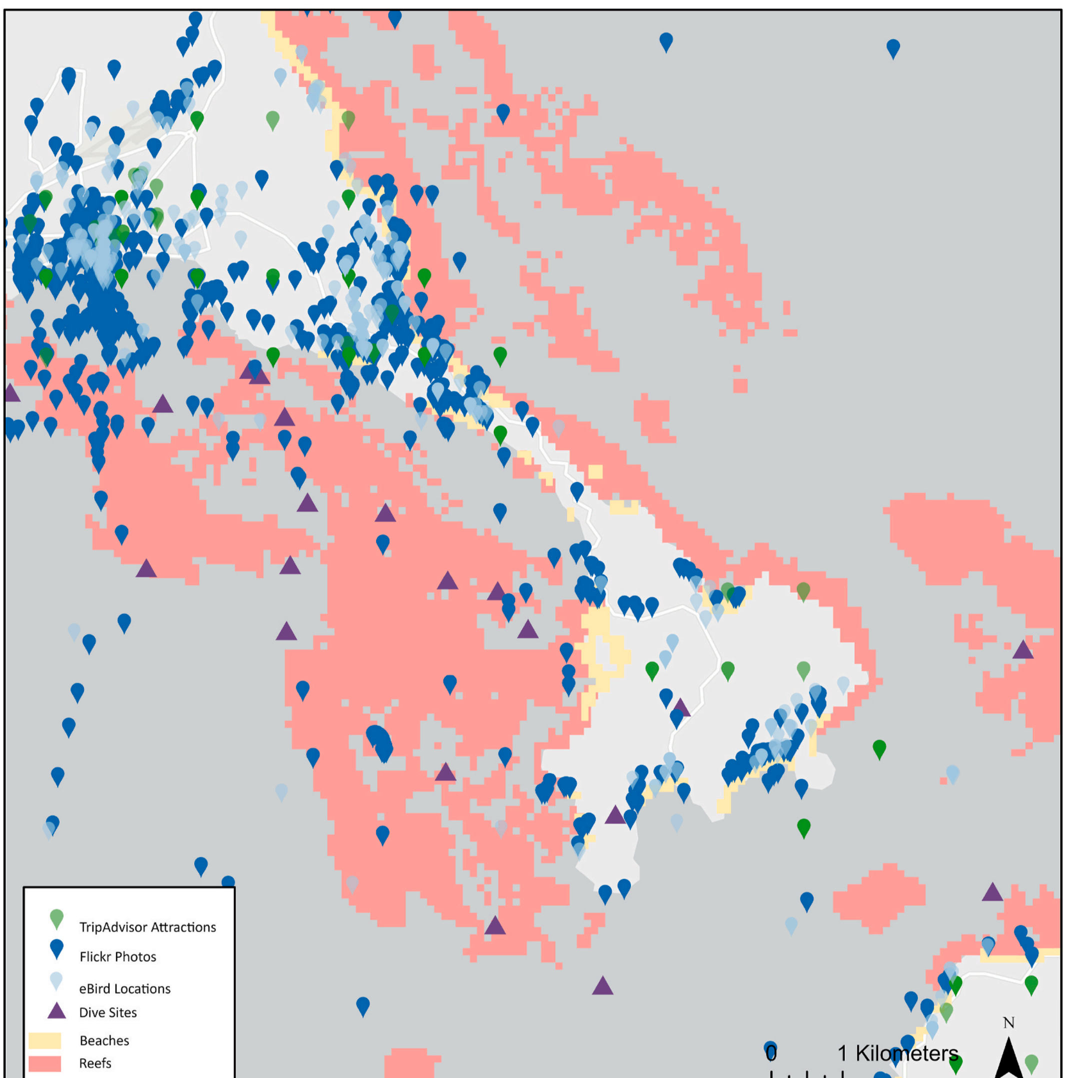

Fig. 1. Sample of UGC and local input layers for southern Saint Kitts and north-west Nevis, including dive sites, Flickr images, TripAdvisor attractions and eBird observations. Coral reef and beach areas derived from high-resolution satellite imagery are also mapped. All data points have associated data, which provided key raw material for building subsequent models.

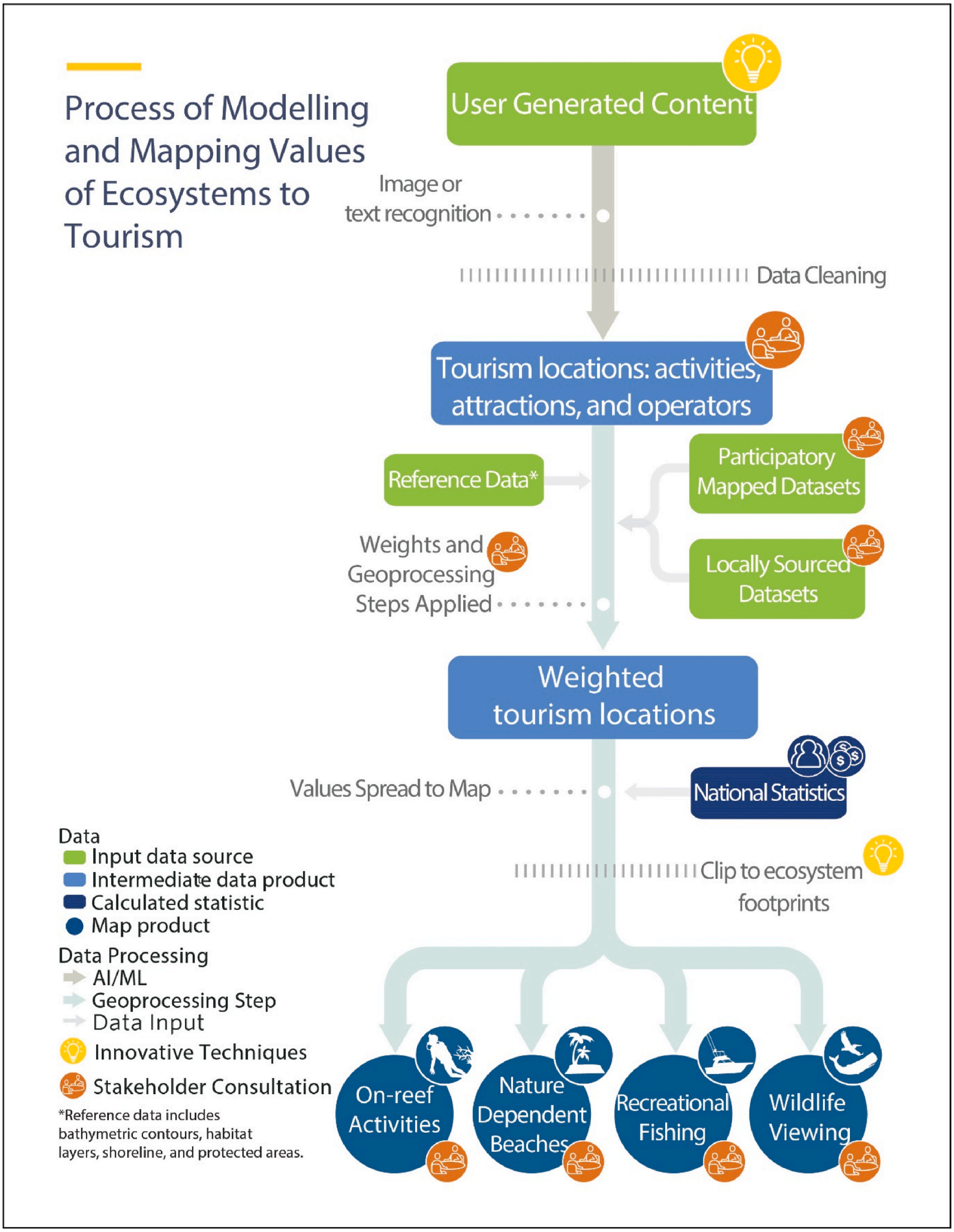

Fig. 2. Flow chart outlining the general modelling process. Although not represented here, analysis of paddle sports and seafood restaurants also followed this broad process.

source datasets, and a desire to avoid errors of inclusion (false positives), we prioritized precision over recall, meaning that results would be conservative in terms of total positives, with a risk of some omissions of locations, but very few incorrect locations.

Image recognition largely utilised Microsoft's Azure Custom Vision service. Initial reviews of available imagery suggested that despite overall high numbers, there were insufficient images for all proposed models. Efforts were focused on reefs, beaches, fishing, and paddle sports. Following training we were able to set precision thresholds of 90–99% across models. In evaluating the final outputs, the process of manual verification was sufficiently rapid that all images were checked with the final selection having 100% precision.

Text modelling involved developing a series of classifier models, one for each focus area described in Table 1, using a subset of reviews from the full TripAdvisor corpus. Each of these models was constructed as a binary classifier to identify whether the respective model category was described in a given text. Two authors of this paper provided binary labels for a total of 2719 text reviews, where positive labels indicated that an activity related to one of the focus areas was described in the text and negative labels indicated that none of the activities were in the text. As such, individual texts could have between zero (no activities mentioned) and seven (all activities mentioned) positive labels. Each model was trained as a binary classifier using the relevant label as an indicator for the corresponding focus area. Modelling experiments assessed the performance of two classification algorithms (logistic regression and random forests) with three text vectorization approaches (bag of words, term frequency-inverse document frequency (tf-idf), and document-mean tf-idf weighted word embeddings, where embeddings were estimated using a custom-trained word2vec model) (Mikolov et al., 2013). Based on metrics obtained with a 6-fold cross-validation on an initial training subset of the labelled texts, the random forest models using the bag of words vectors were selected for their performance and interpretability (see Supplementary Material). Metrics described in Table 2 reflect classification performance on a hold-out dataset (30% of data) not used during initial cross-validation and training. The resulting random forest models were then used to classify the remaining unlabelled texts.

Some users of Flickr and TripAdvisor upload multiple images for the same location, but the objective was to utilise users as single units of activity in a place and so it was necessary to count users not images. To achieve this, for Flickr we used the Photo User Day (PUD) approach where a person's images in a single location can only score as a single observation per day (Wood et al., 2013). A similar approach was developed for TripAdvisor images where only one photo per attraction per member (PAM) could be scored. With both PUDs and PAMs any photo could be used to develop the score, so any location can still score in multiple models from the set of uploaded images by a single photographer. This replication risk was not considered an issue for TripAdvisor reviews where members submit a single (often wide-ranging) review per destination.

In all cases the number of identifications (by unique users) in any location was used to provide a score of the relative level of demand for any nature dependent activity or benefit in that location, a metric which we describe as "use intensity" (Spalding et al., 2017).

A summary of some of the data findings from the machine learning process, including information on precision and recall is provided in Table 2.

2.3. Additional data sources

Alongside the data gathered from the AI/ML work, several additional datasets were developed to enhance or in some cases be the primary source for particular models. These are outlined below:

On-reef Activities: Locational data for dive sites was initially pulled from a global, user-built dive site database, Diveboard (2020). This layer was greatly enhanced with the addition of data from five other global databases and 23 local industry sources. Of the 314 dive sites provided by these sources, 77% had recorded the number of dives logged at the site, which was used to give a partial weighting for use intensity (low-medium-high-very high).

Recreational Fishing: Given insufficient spatial UGC data for fishing locations, local outreach and a participatory mapping programme were used to generate a recreational fishing map, together with information on travel distances and user preferences. This map was then further weighted by an offshore buffering process from coastal locations of fishing operators identified by the AI/ML data (see Supplementary Material).

Whale/dolphin watching: As with fishing, a local outreach and participatory mapping programme identified whale and dolphin watching locations, and information on travel distances and user preferences. This was enhanced by offshore buffering of data from onshore operators (see Supplementary Material).

Birdwatching: The online database associated with eBird, a semi-structured citizen science programme of birdwatching observations, was used as a primary source of birdwatching observations (Johnston et al., 2019; eBird, 2020). Data for the five countries in this study come from 1400 observers with some 73,000 data points and include observations on 212 species.

2.4. Mapping use intensity

As mentioned, both the UGC and additional data sources provided data on both location and use intensity. Such activities are dependent on diverse natural resources – some confined to distinct habitats such as beaches and coral reefs, others more spatially diffuse or linked to multiple ecosystems.

For beaches and coral reefs, use intensity scores were linked to high resolution maps of these ecosystems, following a two-step process. First, use intensity scores (PUDs, PAMs, numbers of reviews, numbers of dives) were buffered by 1 km from their point locations to allow for potential errors in the input layers, and to enable TripAdvisor attractions to connect to the activity or benefit being assessed (e.g. adjacent beaches). These relative scores were summed for each model.

Second, the scores were spread across the extent of relevant habitat with which they overlap, ensuring that the total score value is captured within the spatial extent of that habitat. In this way, a high scoring buffer will create a high value per unit area if the total overlapping habitat is small, but a smaller value per unit area if a large extent of habitat is included within the buffer.

Fishing and whale-watching are more broadly linked to pelagic and coastal waters. Intensity was modelled using a distance decay function from the known and weighted scores of operators (attractions), spreading these unitless scores across the preferred fishing or whale-watching areas.

Table 2
Summary of the precision and recall scores for the final IR and TR models, with total numbers of identified images or reviews. Note that the poor recall and precision associated with nature dependent beach texts led to the decision to use only images in this model.

	Image recognition						Text recognition		
	Model precision	Model recall	No. Flickr images Identified	Total PUDs	No. TripAd-visor images identified	Total PAMs	Model precision	Model recall	No. of reviews identified
On-reef	100.0%	92.9%	1496	161	3876	1446	91.1%	95.6%	37,948
Beach	100.0%	84.8%	615	195	3209	2423	63.9%	35.4%	5916
Fishing	100.0%	71.4%	8	8	321	175	90.9%	60.6%	1016
Paddle sports	94.7%	100.0%	25	N/A	340	225	93.3%	85.7%	6321
Whale/dolphin watching	N/A	N/A	62	24	N/A	N/A	83.7%	95.3%	1964
Restaurants	N/A	N/A	N/A	N/A	N/A	N/A	86.4%	80.5%	30,314

Paddle sports are linked to onshore attractions and may benefit from a range of coastal habitats. For this layer we therefore buffered the values, with a distance decay, over the adjacent coastal waters. Birdwatching data, after cleaning, was considered to have high spatial accuracy and was fitted to a 500 m grid where cells may incorporate many different habitats, from hotel gardens to rainforests to offshore waters. Seafood restaurants were the only locations that we were unable to link to natural habitats providing benefits and were simply plotted as buffered points.

A summary of the seven models is provided in Table 3, and further details are provided in the Supplementary Material. In each case the use-intensity map provides a unitless, but scaled measure of importance of value, and although these are in many ways the key output, a combined map to illustrate the overall distribution of nature dependency was also developed. The variable metrics covered by the maps were converted into quantiles and scored. The high contribution derived from beaches and from on-reef activities were converted to deciles, and scored from 1 to 10 (low to high), while the remainder were converted to terciles (scored from 1 to 3). These individual values were summed, and the resulting layer was summarised into a hexagonal grid (1 km^2) to provide a consistent and easy-to-visualize scale, with the highest score at any point in a hexagon giving the final score to that hexagonal cell.

Table 3
Sources and modelling approaches used for each of the seven models. IR – image recognition. TR – Text recognition. TA – TripAdvisor.

Model	Key sources	Weighting	Modification	Mapped to
On-reef activities	IR on Flickr, TA; dive sites.	Image density, dive intensity. Relative concentration of images plus dive centres used to inform national weighting for overall value.	Buffered points, summed and spread to available habitat	Coral reef habitats
Nature-dependent Beaches	IR on Flickr, TA	Image density. Relative importance of natural images used to information national weighting for overall value.	Buffered points, summed and spread to available habitat	Sandy Beaches
Paddle sports	IR on Flickr, TA; TR on TA reviews	Image/review density	Buffered points, summed	Attractions (operators and hotels)
Fishing	IR on TA; TR on TA reviews; participatory mapping and local input for actual fishing locations	Operators weighted by reviews. Preferred fishing areas then weighted by values of onshore operators x distance		Open water areas
Whales/ dolphins	IR on Flickr, TA; TR on TA reviews; participatory mapping and local input for actual viewing locations	Operators weighted by reviews. Preferred viewing areas then weighted by values of onshore operators x distance		Open water areas
Birdwatching	eBird user database	User observations x day; observations x "important" bird species		Observation locations, protected areas
Restaurants	Text recognition	Attractions weighted by number of seafood reviews		Attractions (restaurants and hotels)

2.5. Enumerating value

In addition to simple use intensity, for coral reefs and beaches, estimates of value in terms of visitor numbers and expenditure were modelled. As a starting point, an estimate of the proportion of total national tourism arrivals and expenditure that could be linked to these habitats was calculated from two classes of information:

- Literature: a review of academic literature, reports and industry data (e.g., exit surveys), was compiled from within and beyond the region to benchmark our estimates. For reefs, this literature guided an estimate of likely proportional spend for on-reef activities. For beaches a key input was the prior work on beach tourism values in Grenada and Barbados (Schuhmann et al., 2019), giving an indication of likely overall beach dependency for tourism, and an estimated decline in returning tourism arising from environmental degradation.
- National data: several metrics were derived which could inform the relative importance of these activities for each country. These included: the proportion of total PUDs and PAMs that were nature dependent (underwater or natural beach); the proportion of reviews that mentioned these activities; the proportion of attractions with these activities; and, for reefs, the ratio of dive centres to hotel rooms (these latter statistics derived from the Global Accommodation Reference Database (DELTA CHECK, 2019), TripAdvisor and national data sources, see Supplementary Material).

Using this information, an estimate of the proportion of total national statistics which could be assigned to nature dependence for both reefs and beaches was assigned based on expert-judgement. Based on the limitations of the input data, the proportional scores describe different aspects of value for reefs and beaches. Reef numbers represent a simple proportion of total expenditure/engagement which can be assigned to on-reef activities; beach numbers represent the proportion by which total expenditure/engagement would likely decrease following environmental degradation. As a result, the estimates of absolute values between reef and beach activities are not directly comparable.

As a final step, cruise tourism was differentiated from overnight tourism using general tourism statistics and cruise industry datasets (FCCA and BREA, 2018; ECCB, 2020). Cruise passengers average 72% of arriving individuals in these countries, but only generate some 8% of expenditure. About 87% of cruise passengers disembark at their destinations, but they are time limited and cannot visit all areas of a country. To account for these differences, we separated arrivals and expenditure data for cruise passengers, modifying arrivals to account only for disembarking passengers. We created a spatial footprint for the more limited movements of these passengers (see Supplementary Material).

Finally, the differentiated data for overnight and cruise statistics were separately distributed across each country following the use-intensity maps, with the cruise data restricted to their narrower spatial footprint.

For the remaining models, there was insufficient data to apply monetary or other values to our use intensity maps. Nevertheless, as part of the participatory mapping work, information on annual expenditure and visitation rates were gathered from charter operators for recreational fishing and whale and dolphin watching (Supplementary Material).

3. Results

Following cleaning and removal of duplications, we obtained data describing nature dependency for some 90,000 independent data points, largely derived from automated extraction from UGC (Table 3), but with critical expert additions and review.

These datasets were used to generate maps of use intensity for seven nature-dependent activities, with two of these models further refined to show modelled values in terms of visitor numbers and expenditure linked to that use intensity. Summary maps for five of these models are presented in Fig. 3. More detailed maps are presented in the Supplementary Material and can also be viewed online at https://maps.oceanwealth.org/oecs.

Each map shows a highly heterogeneous pattern of values. Fig. 4 shows the synthesis map for all seven models in which the overall coastal dominance is clear, but with a more diffuse spread of values into offshore waters. The maps also show variability along different coasts, with notably lower values, for example on many windward (eastern) shorelines.

The number of attractions or locations involved in each of the models gives some indication of the importance of different activities and their distribution between countries. A number of these are presented in Table 4.

Numerical values for visitation and expenditure are provided in Table 5. Reef-based activities are estimated to account for 8% of all tourism expenditure. For beaches, the model estimates that 22% of all tourism expenditure is dependent on the current natural values associated with beaches – a value that could be lost with just a 5% decline in water quality or similar environmental changes (Schuhmann et al., 2019). The same applies for visitation statistics where the numbers in

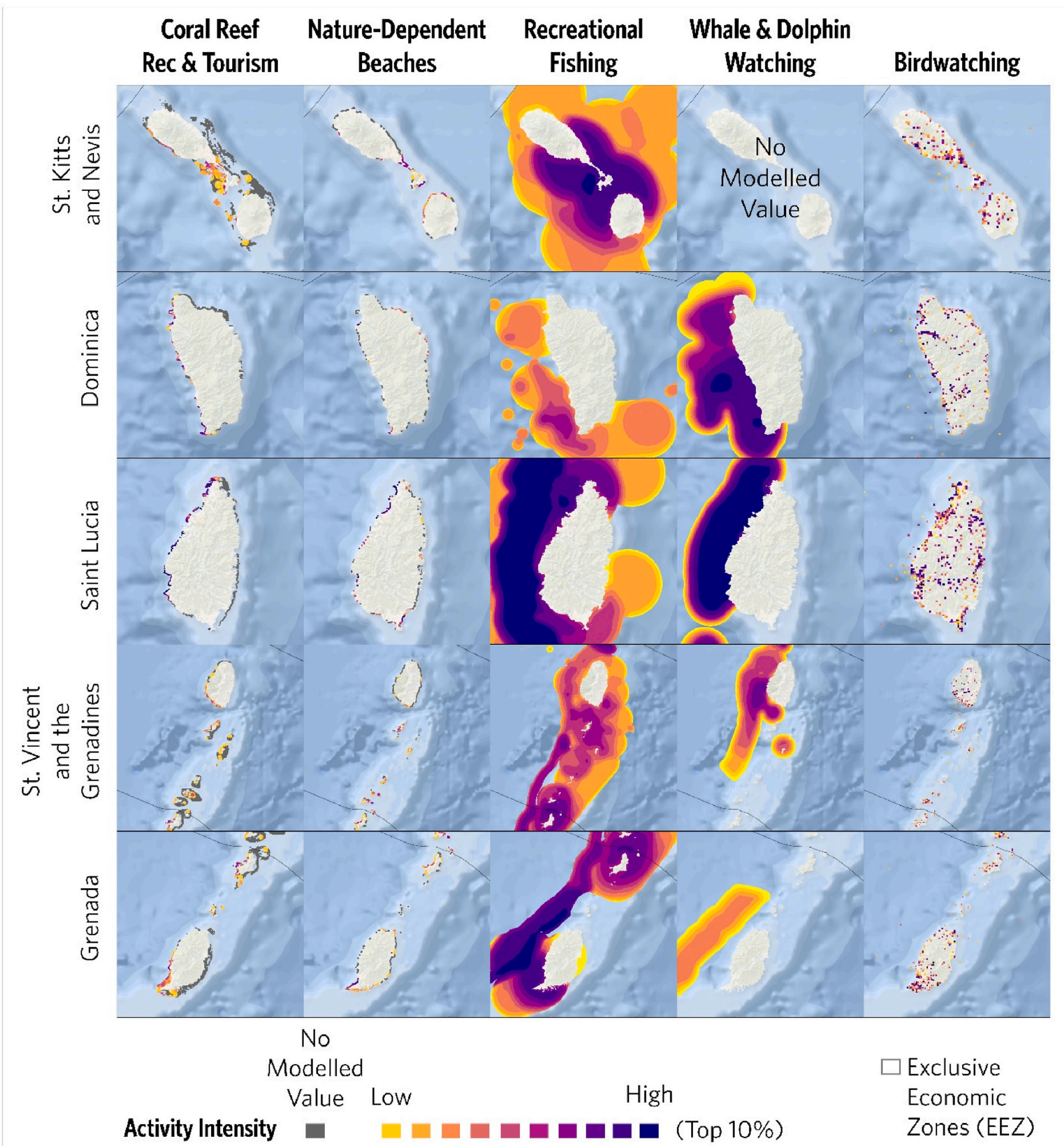

Fig. 3. Summary maps from five of the seven models described. In all cases, model values have been sorted into deciles at the regional scale. More detailed maps, as well as maps for seafood and paddle sports can be found in the Supplementary Material.

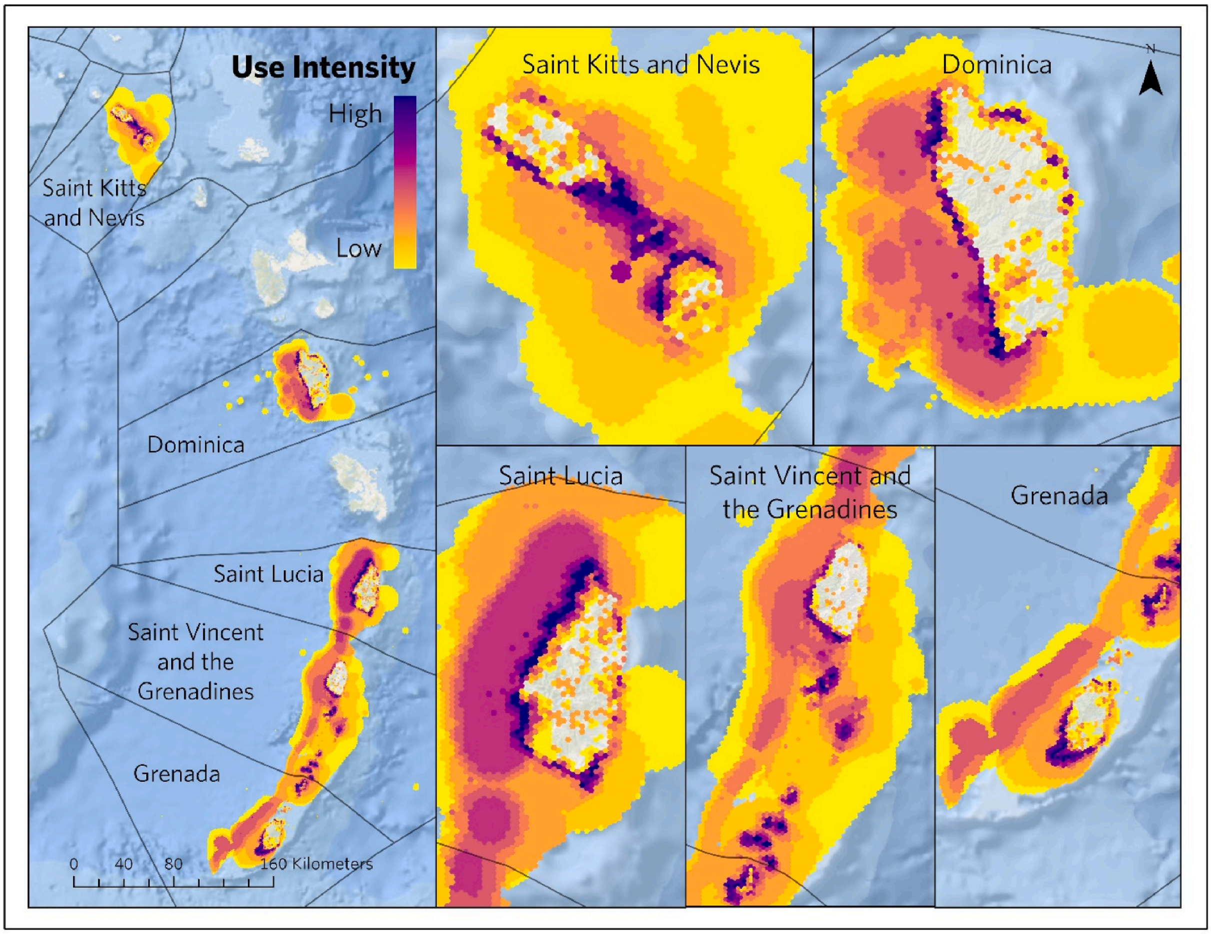

Fig. 4. The combined value of nature to tourism from all models. Highest quantile scores for each model in any cell are summed generating a combined score ranging from 1 to 35 per cell.

Table 4
Summary data from all models indicating the number of operators, attractions or points of observation.

	Dominica	Grenada	St. Kitts and Nevis	Saint Lucia	St. Vincent & the Grenadines	TOTAL
Beaches with nature dependency scores	39	105	80	163	72	459
Dive sites	55	92	36	43	88	314
Dive Centres	12	13	9	21	10	65
Recreational fishing operators	15	13	12	16	3	49
Paddle sports operators	30	86	65	166	60	407
Whale/dolphin watching operators	7	2	1	15	5	30
Restaurants	133	200	185	393	163	1074
Birdwatching observers	254	257	253	492	158	1414
Birdwatching location observations (500 m grid)	2084	1512	781	2289	811	7477

Table 5
Numerical values for expenditure and visitation derived from the reef and beach models (See Section 2.5). For reefs, the numbers represent all associated expenditure or visitation. For beaches the numbers represent the likely drop in expenditure or visitor returns expected from limited environmental degradation. Visitor values are not corrected by length of stay, hence, for example, the apparently high numbers for Saint Kitts and Nevis, in terms of visitors, do not show up in expenditure as almost 90% are short-stay cruise passengers. Monetary values are expressed in 2019 US dollars (see Supplementary Material).

	Dominica	Grenada	St. Kitts and Nevis	Saint Lucia	St. Vincent & the Grenadines	TOTAL
Total tourism expenditure	$100,874,168	$162,811,879	$165,229,932	$870,950,990	$105,298,900	$1,405,165,869
Total nature dep. beach expenditure	$8,971,862	$39,634,719	$35,589,482	$207,227,645	$26,670,739	$318,094,447
Total on-reef expenditure	$11,382,075	$13,097,875	$6,667,569	$76,963,697	$10,206,966	$118,318,182
Total visitors	313,670	468,527	1,099,944	1,125,962	282,952	3,291,055
Total nature dep. beach visitors	27,945	85,092	180,406	211,423	60,198	565,064
Total on-reef visitors	19,389	22,732	22,444	59,536	18,999	143,100

Table 5 represent visitor-equivalents, or the number of visitors whose visit is dependent on beaches and reefs (recognizing that, for most visitors, destination choice is a complex of multiple influencing variables).

Further breakdown of these statistics (see Supplementary Material) shows the very different patterns between cruise tourism and overnight stays. Cruise tourism generates 70% of all visitors across these countries, and cruise visitors contribute 62% and 42% of nature dependent beach and on-reef visitor numbers respectively. When such numbers are corrected for length of stay (cruise visitors stay on average only one day per country), they comprise 14% and 7% of nature dependent beach and on-reef visitors per day. With restaurants and accommodation on-vessel, they also spend relatively little. In our models, their expenditure represents only 5% and 2.3% of total expenditure for beaches and on-reef activities respectively. It is further notable that the nature dependency of cruise tourism is lower than for overnights: 15% of cruise expenditure is linked to nature dependent beaches, and only 2.5% to on-reef activities, compared to 23% and 9% respectively for overnight visitors.

National estimates of expenditure from recreational fishing and whale and dolphin watching are presented in the Supplementary Material. These represent smaller components of the overall tourism industry. It should be noted that the values presented consist of direct expenditure only – the full associated expenditure would include travel, accommodation, or food which may also have some dependence on these activities.

4. Discussion

This work represents a comprehensive approach to understand and map nature dependency in the tourism sector at a regional scale. By combining a wide array of information sources; and by focusing on developing maps of "use intensity" rather than attempting to force diverse findings into a single metric, such as monetary value, we have developed a series of unique but compatible models. These not only highlight new and important patterns of how nature influences tourism preferences and activities in the Eastern Caribbean, they also draw attention to methodological approaches that may be of considerable utility in future research and practical applications.

4.1. Nature dependency in caribbean tourism

The critical importance of tourism to the economies of Eastern Caribbean countries already informs and drives policy and governance. While the role of nature in this tourism has received some recognition for decades (Bacon, 1987; Weaver, 1993; Schuhmann et al., 2016), it has rarely been fully accounted. Existing studies have focused on specific nature-based activities, without considering the contribution of nature to more mainstream components, such as the enjoyment of beaches, views, or seafood (Carr and Heyman, 2009; van Beukering et al., 2015).

The maps presented here show that nature influences tourism value over a large spatial footprint, but also that there is considerable variation in the intensity of those values. The combined map of use-intensity (Fig. 4) highlights the particularly high value of coastlines (especially leeward coastlines) and their landwards and seawards margins – where it is possible for almost all of our values to co-occur. The considerable spread of values across ocean space up to 40 km from shore is notable. While such values are diffuse, the species which underpin both fishing and wildlife watching are highly mobile and rely on extensive areas of pelagic waters, and any management in support of these activities must be equally wide-ranging. Birdwatching shows a more heterogeneous distribution across inland and upland areas, but again many species are dependent on wider expanses of natural habitats and have similar needs for broad-scale management.

Within the general assessment of value and nature dependency, the spatial variation is important. Nature-dependent beach values, for example, are concentrated towards a relatively small proportion of all beaches, with only 5% of beaches generating 68% of the total nature-dependent beach expenditure. Most beaches have at least some nature-based tourism values, but some 50% have no registered value in our model – many are on more exposed windward shores, far from any tourism accommodation or infrastructure, and not easily accessible. Generally, paddle sports are focused on some of the same beaches, but are more constrained, perhaps because these activities are not offered in all beach settings.

Although often adjacent to valuable beaches, on-reef activities also draw values to new areas, such as along the central-west coasts of both Saint Vincent and Grenada. Yet, only 35% of mapped coral reefs are used for on-reef activities, and 80% of this value is attributable to just 5% of coral reefs. Seafood restaurants are more widespread – likely reflecting both travel by tourists to visit these establishments, and possibly more local usage of TripAdvisor for restaurant reviews.

The potential losses from declines in the natural values of beaches are high: environmental declines could amount to a fall in over 17% of current visitors and over 22% of expenditure. These values are relatively homogenous across countries (22% of expenditure for Saint Kitts and Nevis to 25% for Saint Vincent and the Grenadines), with the exception of Dominica, where natural beach values are associated with only 9% of expenditure. (Dominica has mainly black sand beaches which are considered less attractive to tourists, and tourism marketing has focused on terrestrial activities, diving, and whale-watching.) Both visitor and spending values point to a level of nature dependence that is likely to be of central importance to socio-economic stability in the islands.

For reef values, the estimates for both expenditure and visitor numbers are high, though we note that these are measures of total value rather than likely decline from environmental degradation, and so are not comparable to the beach statistics. On-reef activities drive over 4% of visitors and over 8% of annual expenditure, with considerable variation between countries: Dominica, a well-known diving destination, dominates the proportional values, with 11% of expenditure coming from this sector while the figure for Saint Kitts and Nevis is only 4%.

The apparently lower dependency of cruise tourism on nature is not surprising: cruise visitors are restricted by port schedules, limiting their ability to access nature dependent activities. Spatially, they can, on average, access only 36% of the total extent of beaches and reefs reached by tourism overall, a value that may be an overestimate, given the very limited movement dynamics of cruise tourists reported from other studies (Jaakson, 2004; Brida et al., 2012), and the concentration of onshore activities to a relatively limited number of operators. Yet, our models may also underestimate nature dependency in the cruise sector. By focusing on activities, we may underplay the role of destination image and perception in this industry. Virtually all publicity associated with the cruise sector in these islands relies on nature to attract visitors using iconic nature-centric imagery and texts to describe their destinations, suggesting a high appeal of natural values even if visitor participation is lower than that of overnight visitors.

Taken together, these findings add to the growing body of literature addressing the spatial distribution and value of coastal and marine ecosystem services. While the novelty of our approach precludes direct comparison with most studies, our results confirm previous findings of high spatial variability in ecosystem service values (e.g., Burke et al., 2008; de Gauna et al., 2021), the spatial concentration of high-value areas (e.g., Nahuelhual et al., 2017; Vergara et al., 2021), and the importance of geophysical, ecological and socioeconomic factors that affect access to nature and the resulting distribution of value (Arkema et al., 2015).

4.2. Combining UGC with local input

One of the more unique features of this work is the broad utilization of UGC from several platforms, alongside both large-scale and local sources, and the incorporation of machine learning approaches to process such data. Our work highlights multiple uses, but also some caveats. Even with the very large size of input layers, sample size can still be limiting: for image recognition, the pool of training images was, in some cases, expanded to adjacent Eastern Caribbean islands, and while we obtained effective algorithms for image identification for most areas of interest, the total number of images identified was still small, highlighting the high data volumes required for this work. With seafood, which generates a diverse range of visual images, we were unable to develop a large enough training array. These challenges were to some degree overcome by the complementary use of text recognition. Thus, text-based information proved effective at identifying fresh seafood restaurants (precision = 0.86, recall = 0.81) where image recognition could not be used. By contrast, text recognition was a poor tool for assessing nature dependency of beaches (precision = 0.63, recall = 0.35), where image recognition was highly effective.

The use of UGC offers other potential opportunities that could provide a highly effective component of future work. Large, continually updated information sources would enable researchers to consider change through time, and even provide opportunities to work in near real time, to understand trends in tourism and the drivers of those changes. User preferences, opinions, and sentiments are also of considerable interest and are already being used to understand perceptions of environmental quality, management, and sustainability by travellers (Saura et al., 2018; Yang et al., 2022). A more automated approach to sentiment analysis may prove even more effective at removing bias from user-ratings (Al-Natour and Turetken, 2020) although there remain significant challenges, and such approaches may require even larger datasets than those described here (Alaei et al., 2019).

Error is a particular concern in using crowd-sourced data. As noted earlier, we prioritized precision over recall, preferring to lose sample points over the risk of influencing our maps with false positives. One key challenge with TripAdvisor is locational accuracy – the locational details for attractions are generally reliable, however it cannot be assumed that the attraction location represents the location of the particular benefit. In many cases there is a simple offset (the beach is adjacent to the hotel), but in a few cases, notably for excursions, the activities described take place at a considerable distance from the reported attraction location. Future work should attempt to assess the scale of this error and should consider the means to correct such data.

TripAdvisor was not the sole source of UGC. Flickr remains a rich resource for imagery, with relatively high geospatial accuracy of image locations. Unfortunately, it appears to be declining in popularity and returned a relatively small number of images. Birdwatching information benefitted from a crowd-sourced platform with a highly informed user-base. Similar special-interest platforms for the diving community were equally important, although the data required cleaning and were less reliable spatially. While prominent social media platforms like Twitter, Instagram, and Flickr restrict use of their data for these purposes, future work could assess how other sources of UGC associated with nature could be used to infer dependency and value, including fitness trackers, hiking apps and reservation systems (Teles da Mota and Pickering, 2020; Lawson, 2021; Rice and Park, 2021).

The importance of local input in developing policy-relevant maps of nature dependency is critical. Local engagement from both government and industry representatives helped in prioritizing the targets and modelling approaches. Input from these and other experts played a key role in defining and reviewing the modelling and in helping to review and clean the input layers. In most cases, locally-derived data were added into the models, an essential step for models where UGC returns were low, notably recreational fishing and whale and dolphin watching.

One of the challenges of a multifaceted model of natural values is the provision of clear and comparable metrics. The monetization of values has often been used for this purpose, however such values have limits, and there is growing interest in measuring “nature’s contribution to people” more broadly (Díaz et al., 2018). In the case of tourism, value can take many forms: even monetary value will look very different from the perspectives of governments, international corporations, and local populations. Given the highly varied input metrics and lack of reliable data to convert many of our use intensity models to concrete metrics of monetary value or visitor numbers, we took the conscious decision not to attempt such transformations for most of our layers. This puts more weight on users to understand how to utilise the data but can also empower them. Use intensity maps are not simple reflections of economic value, but also describe patterns of cultural influence and impacts, employment, access and displacement, competition, opportunity costs, even votes - all of which have a part to play in informing management (Díaz et al., 2018; Pennino et al., 2021).

4.3. Practical applications

A key purpose for this research and data is to support ongoing management and future policy and development. Ecosystem services make vast contributions to human wellbeing and their diminution or loss can have considerable direct, downstream, and intergenerational impacts. Understanding these costs and benefits is critical for both governmental and sectoral planning.

By distinguishing multiple components of nature dependency, the datasets enable a detailed and pragmatic approach to incorporating nature into planning. As such, these maps can provide an important contribution to marine spatial planning (MSP) (Ehler and Douvere, 2009), a process that is likely to form a central role in the development of the Blue Economy in the five countries considered here (Organisation of Eastern Caribbean States, 2020).

By focusing on use intensity, and by disaggregating overall values into multiple components, stakeholders can more readily understand the role of ecosystems in terms of their own livelihoods. Maps also provide a common tool for combining information from other sectors, enabling a more realistic consideration of tradeoffs, conflicts, and synergies between stakeholders (Arkema et al., 2015; Guerry et al., 2015). Beyond this, the involvement of local people and knowledge in the mapping process not only increases the quality of the resulting data but can improve stakeholder buy-in and acceptance of the maps, and collaboration in the MSP process (Friedrich et al., 2020).

Beyond MSP, ecosystem services valuations have been widely used in more specific applications, including the identification and prioritization of conservation actions, the establishment of user fees for protected areas, and the establishment of fines for boat groundings (Waite et al., 2015). Further, maps and models can enable future visioning: risks and opportunities can be predicted by looking at current patterns of use intensity, allowing the development of realistic inferences about the costs and benefits of development, or the impacts of investments and interventions. Such insights can improve the efficiency of public spending on conservation and may allow for the identification of new revenue streams from related markets, concessionaire fees, or access fees.

There are growing efforts to incorporate ecosystem services into national income accounting using frameworks such as the UN System of Environmental and Economic Accounts (SEEA) which allows for the incorporation of monetary values and for a broader accounting of ecosystem services, extent and condition (United Nations Statistical Commission, 2021). The integration of ecosystem service accounting into national Tourism Satellite Accounts (TSAs) can support the measurement of tourism sustainability (Frechtling, 2010; UNWTO, 2019). Critical steps toward adopting the SEEA approach and integration of the SEEA with TSAs include identifying the scope and location of ecosystem assets of primary interest to tourism, understanding the flows of ecosystem services that are directly related to businesses, and associating ecosystem assets with human use and pressure (UNWTO, 2019).

In order to support these and other uses, the work presented here has been widely shared with stakeholders in the region and can be viewed on an online platform (https://oceanwealth.org/project-areas/caribbean/crop/).

4.4. Future opportunities

From a methodological perspective, the potential for expanding these approaches is considerable, including the utilization of other platforms such as social media for sourcing data (Tenkanen et al., 2017; Teles da Mota and Pickering, 2020; Arefieva et al., 2021). Given the relatively automated nature of machine-learning approaches, future work could include the development of live data harvesting or data stream processing, including geoprocessing; and the potential to continuously track trends through space and time. Challenges will likely arise from the dynamic nature of UGC: changes in platform structure, market utilization and regulatory frameworks could limit consistency in data access and comparisons over time.

By building in temporal dimensions to studies of this sort it may also be possible to better understand drivers of change, such as the role of ecosystem quality on human benefits, or, conversely, the influence of human activity on ecosystem function. Such quantitative and dynamic tracking of ecosystem condition and human activity could greatly support the development of actionable insights regarding resource management.

While the approaches described here are comprehensive, there are still gaps. For example, one key tourism activity requested by stakeholders in the region was that of boat tours and sunset cruises, which are popular and have a clear component of nature dependency. While some of this activity is captured – in our models for on-reef activities, whale and dolphin watching and recreational fishing – our approach made it difficult to separate the nature-based component of other boat trips. Likewise, there are many land-based nature dependent activities – hiking, zip-lining, off-road driving, visits to volcanic landscapes, mangrove forests, and waterfalls – that future work could usefully explore and incorporate into models of nature dependence. Further, by focusing our work on place-based activities, we have not accounted for the role that nature plays in destination choice through formal publicity and peer-to-peer transmission of sentiments and memorable tourism experiences (Kim, 2018; Al-Natour and Turetken, 2020). While such elements would provide a valuable addition, we expect that they would to some degree replicate the findings of our activity-based approach.

The impact of the Covid-19 pandemic was not covered under the timeframe of our data sources but has had an enormous impact on tourism world-wide. From 2019 to 2020 one third of all jobs in the sector were lost in these countries, with a 68–76% drop in international tourism receipts (WTTC, 2022a). While numbers are fast returning (WTTC, 2022b), it seems likely that recovery will not necessarily mean a simple return to pre-pandemic travel patterns and choices (Bulchand-Gidumal, 2022). For example, it has been suggested that many tourists may prioritise less crowded destinations and activities (Spalding et al., 2020; Park et al., 2021). Over-tourism has already become a concern in many destinations, and post-pandemic recovery could be helped by shifts in tourism management away from maximizing visitor numbers towards more stable and sustainable revenue generation (Peterson, 2020).

In the Caribbean especially, nature is likely to play a critical role in supporting low-volume high-income tourism management strategies. Such strategies may further confer future resilience to the industry in the face of threats posed by climate change and shifts in travel patterns that result from efforts to curtail emissions. Models like ours may be crucial in helping to view and to plan such strategies, not only by providing over-arching statistics but through the spatial delineation of values and pressures that can support detailed planning and the development of future projections.

Credit author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.117696.

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