Comparison of Flickr and Public Participation GIS to characterise the types, spatial patterns and socio-ecological drivers of social values for the Kimberley region

By

Tahlia Daymond

This thesis is presented for the Degree of Honours in Environmental Management and Sustainability

College of Science, Health, Engineering and Education

Environmental and Conservation Sciences

Murdoch University, 2020

Declaration

I declare this thesis is my own account of my research and contains as its main content, work which has not previously been submitted for a degree at any tertiary education institution.

……………………………………………………..

Tahlia Daymond

2nd November 2020

Abstract

Coastal and marine environments are highly valued for the resources and services they provide. To sustainably manage these environments, we need to understand what people value and where these values occur, but spatial data is not always easily obtainable. Crowdsourcing methods such as the retrieval of geotagged photographs from the photo-sharing social media platform Flickr and Public Participation GIS (PPGIS) that use field-based or online mapping techniques enable the identification, quantification and mapping of social values. This study compared these methods to evaluate whether Flickr provides similar data to PPGIS about values and where they are likely to occur.

A total of 5,293 geotagged Flickr photographs of the natural environment were retrieved for the Kimberley region in Western Australia. The relative abundance of the ten evaluated value types differed between Flickr and two previously published PPGIS datasets involving field-based interviews ($p < 0.001$) and an online survey ($p < 0.001$), but *scenic/aesthetic* and *nature appreciation* were highly valued in all studies. There were clear distinctions in the spatial patterns of where values were recorded; Flickr users tended to take photographs near easily-accessible locations, whereas PPGIS participants mapped values across most of the Kimberley coastline. Spatial modelling performed to investigate the distribution of value types revealed accessibility was the main driver to where Flickr users were likely to take photographs within the Kimberley region. In contrast, values mapped by PPGIS participants were more broadly distributed and therefore the models were less able to identify strong relationships with the evaluated drivers. Despite this, value types mapped by both methods were concentrated near the coastline and the few major towns of the region, likely due to these being familiar places and popular tourism destinations.

Values crowdsourced through Flickr and PPGIS can be used together to take advantage of their reinforcing and complementary information. Whilst PPGIS enabled more value types to be identified within the study area and over a greater spatial distribution, Flickr can be used to provide further depth of information, such as insight into certain value types through photograph content analysis and by highlighting locations of visitation that may need management. The findings of this study can be valuable to inform future planning and management of coastal and marine environments, especially where spatial data may be limited.

Table of contents

List of figures

List of tables

List of acronyms

API	Application Programming Interface
AUC	Area under the receiver operating characteristic (ROC) curve
GIS	Geographical Information System
GPS	Global Positioning System
PPGIS	Public Participation GIS
Maxent	Maximum entropy

Acknowledgements

I would like to thank my two supervisors, Dr Margaret Andrew and Dr Halina Kobryn for their knowledge, expertise and guidance throughout this entire year. I'm not sure I could have made it through to the end without your support.

I also want to acknowledge the two wonderful people I had the chance to share an office and this roller coaster journey of a year honours was, Danielle Godwin and Christina O'Donnell. This year would have been much harder without your support, motivation and most importantly, snacks.

Thank you to the spatial environmental science group, namely Dr Margaret Andrew, Dr Halina Kobryn, Danielle Godwin, Christina O'Donnell and the late addition of Dr Mike Hughes. Reading and discussing journal articles every week was a highlight of this year and I learnt a lot of new things outside of my research area.

Thank you to my family and friends who have supported me throughout my studies. Finally, thank you to my partner Nick, this year was very challenging, and your unending patience and support kept me sane. I can always trust you to make me smile and laugh.

1. Introduction

Coastal and marine environments are highly valued by human societies; they provide meaningful places to experience aesthetic landscapes, wildlife, cultural heritage and recreation opportunities (Johnson et al., 2019; Retka et al., 2019) that directly and indirectly contribute to human well-being (Pascoe et al., 2017). Sustainable management of these ecosystems needs to take into account environmental, economic, cultural and social values to ensure natural resources are not overexploited and to flag and address potential conflict between alternative values (Crain et al., 2009; Fulton et al., 2017; Moore et al., 2017). It also needs to consider the relationships between these values and coastal and marine environments to understand the factors influencing a value and to ensure that people's values can be fulfilled (Garcia Rodrigues et al., 2017; Le Cornu et al., 2014). Therefore, it is necessary to understand these values for informed management and to balance between human use and preservation of the environment (Crain et al., 2009; Le Cornu et al., 2014).

1.1. Social values

Social values are defined as the importance of places and the resources or services they provide as characterised by people's perceptions and attitudes (Lockwood, 1999). Data about values provide insight and understanding into what people value about the environment and offer the opportunity to better incorporate social dimensions into planning and decision-making processes for coastal and marine environments (Voyer et al., 2012). They can draw together social, environmental, economic and cultural values enabling a multidisciplinary conceptual tool useful for natural resource management, planning and decision-making (Brown & Weber, 2013; Seymour et al., 2010; Tadaki et al., 2017).

1.2. Passive and active crowdsourcing of values

Spatial data, or data that captures the locations where values occur, can enable highly valued places to be identified. This can be valuable to improve and rationalise the planning and management of specific places. However, value datasets with geolocated information are often scarce for planning, management and decision-making processes, such as marine spatial planning (Garcia Rodrigues et al., 2017; Le Cornu et al., 2014; Martin et al., 2016; Voyer et al., 2012). Despite this, there is a wide range of methods that can be used to gather spatial data about values, such as field-based techniques, online mapping interfaces and more recently, social media.

The passive crowdsourcing of geotagged photographs is a relatively recent and increasingly popular method of gathering information about values volunteered by social media users (Ghermandi & Sinclair, 2019). Geotagged photographs retrieved from photo-sharing platforms such as Flickr contain geolocated information and have been used to monitor visitation patterns in protected areas (Sessions et al., 2016; Tenkanen et al., 2017; Walden-Schreiner et al., 2018; Wood et al., 2013). The locations of geotagged photographs can be used as a proxy for the location of values held by contributors of the photographs and have been used in spatial assessments for recreation, nature-based tourism and landscape aesthetics (Casalegno et al., 2013; Figueroa-Alfaro & Tang, 2017; Wood et al., 2013; van Zanten et al., 2016). In addition to simply providing the location of a value, the type of value may be interpretable from the photograph itself. However, content analysis of contributed geotagged photographs is not yet common.

Public Participation GIS (PPGIS) is an active crowdsourcing approach that uses field-based techniques such as interviews (Moore et al., 2017) or online mapping interfaces for surveys (Brown et al., 2016). PPGIS relies on participants to actively contribute values using non-digital or digital mapping. PPGIS methods have been used in support of a broad range of applications, such as natural resource management (Brown, 2004; Brown & Weber, 2011) and coastal and marine spatial planning (Klain & Chan, 2012; Strickland-Munro et al., 2016a).

1.3. Spatial modelling of values

The values people hold for places accompanied with social and ecological data, such as the proximity of a value to infrastructure or natural features, can be used to understand the spatial associations between human uses and the environment using tools such as distribution modelling. Distribution models can be used to understand and predict the occurrence of values across an area and capture complex associations of values with the environment (e.g. Clemente et al., 2019; Muñoz et al., 2020; Richards & Friess, 2015). The associations between socio-ecological characteristics and values that are identified by distribution models can be used to infer the features and processes that drive the occurrence of the values. This information can be used by managers to understand environmental preferences people have for places, as well to generate maps predicting where values can occur for scenario planning.

1.4. Project rationale and aims

Data about values crowdsourced from Flickr and PPGIS can provide insight and understanding into values, and the data can be analysed to quantify and predict their relationships with the environment. However, there are advantages and limitations unique to each method (for a more extensive comparison refer to the literature review in Appendix A). For example, methods of PPGIS such as interviews can be time consuming and costly. They require considerable human effort to actively solicit values from participants but also provide rich insight into the values people hold for a particular place. Online surveys are a less costly and more time efficient method of PPGIS, but do not provide insight into values to the same degree. On the other hand, social media is becoming an attractive method of crowdsourcing values that does not require any interactions between researchers and users and is considered quick and inexpensive (Ghermandi & Sinclair, 2019). There are however trade-offs to using social media. Whilst the availability of geotagged photographs is likely to increase (Alivand & Hochmair, 2017), and therefore the opportunity to retrieve and identify values from their content will also increase, this method provides less information into values and the users themselves compared to methods of PPGIS.

Although the advantages and limitations of these approaches have been reported independently (e.g. Brown & Kyttä, 2014; Ghermandi & Sinclair, 2019), so far few studies have rigorously compared them. Muñoz et al. (2020) is the only known published study that has compared information from geotagged Flickr photographs and PPGIS about human use of the environment. These authors assessed the spatial distribution of values to understand the similarities and differences in the data captured by the two methods and reported on the advantages and limitations of each method. Their study evaluated the values of people and their relationships with environmental characteristics of Southern Norway and found large differences in the spatial distribution and associations with the environment depending on whether the data about values was collected using Flickr or PPGIS. Where Muñoz et al. (2020) evaluated two online PPGIS surveys compared to Flickr, the present study evaluated data gathered about values from two PPGIS methods involving interviews and an online survey that related to coastal and marine environments of the Kimberley region of Western Australia and compared these to values derived from the content of geotagged Flickr photographs.

The Kimberley region is a vast and remote area located in the north of Western Australia. In 2011, the Western Australian government introduced the *Kimberley science and conservation strategy* committed to plan, implement and extend marine protected areas in the Kimberley region (Government of Western Australia, 2011). The planning and the implementation of specific management plans for marine protected areas was supported by spatial data about social values (Spencer-Cotton et al., 2016; Strickland-Munro et al., 2015, 2016b, 2016c). PPGIS methods were employed to gather this data, however geotagged photographs retrieved from popular social media platforms such as Flickr may provide another method to obtain similar data about social values.

Hence, the overall aim of this study was to evaluate whether social values derived from the content of geotagged Flickr photographs can provide reinforcing and complementary perspectives on the social values of the Kimberley region compared to previously published PPGIS datasets (Strickland-Munro et al., 2015, 2016b) to answer the following research questions:

- What social values do geotagged Flickr photographs depict about the natural environment of the Kimberley Region and how does this compare to social values previously mapped through PPGIS?
- Where do social values mapped through Flickr commonly occur and how does this compare to social values previously mapped through PPGIS?
- Do social values mapped through Flickr have similar associations with socio-ecological drivers to social values previously mapped through PPGIS?

2. Methods

2.1. Study area

The Kimberley region of Western Australia extends from the western end of Port Hedland to the Northern Territory Border (Figure 2.1), with a coastline of approximately 13,000 km. The study itself focuses on the coastal and marine environments, extending seawards from the coastline into the Indian Ocean and Timor Sea, and inland approximately 25 km, drawing on previous work that guided planning and management of marine protected areas in the Kimberley (further discussed in *section 2.3.2*).

The Kimberley presents unique tourism and wilderness experiences due to the rich biodiversity, cultural heritage and recreational opportunities it contains (Larson & Herr, 2008; Pearce et al., 2016). The coastal and marine environments are in good ecological condition (Halpern et al., 2008) offering renowned natural attractions, such as migrating humpback whales, gorges and waterfalls (Scherrer et al., 2011). The Kimberley is rich in cultural history with evidence of Aboriginal people occupying the land for at least 40,000 years through Indigenous rock art in the region (Morwood, 2002).

The population of the Kimberley region is sparse, comprising of approximately 35,000 people spread across 423,500 km^2, of which ~40% of the population is of Aboriginal heritage (Australian Bureau of Statistics, 2020). Much of the Kimberley region comprises of Indigenous country with access to many areas restricted, thereby individuals and tourism operators require permits or permission from traditional owners for access (Kimberley Land Council, 2004; Scherrer & Doohan, 2011; Smith et al., 2009). Access is also limited by the scarcity of sealed roads connecting the few major towns of Port Hedland, Broome and Derby, and most of the coast is only accessible by four-wheel drive vehicles and boats, including expedition cruises (Collins, 2008; Scherrer et al., 2011; Smith et al., 2009). The Kimberley has the second largest tides in the world ranging up to 11 m daily during spring tides (Wolanski & Spagnol, 2003), further limiting coastal access. Yet the coast presents a plethora of recreational opportunities for activities such as four-wheel driving, camping and fishing (Collins, 2008; Larson & Herr, 2008).

Visitation to the Kimberley peaks during the dry season (May to October) as the monsoonal climate brings high rainfall, storms and tropical cyclones in the wet season (September to April) causing most of the region to be inaccessible (Brocx & Semeniuk, 2011; Lough, 1998). The pattern of visitation is seasonal, yet tourism comprises one of the major economic contributions to the region, attracting approximately 412,000 visitors each year (Tourism WA, 2019). Other major economic activities include commercial fishing, pearling and aquaculture, oil and gas extraction and mining (Government of Western Australia, 2011).

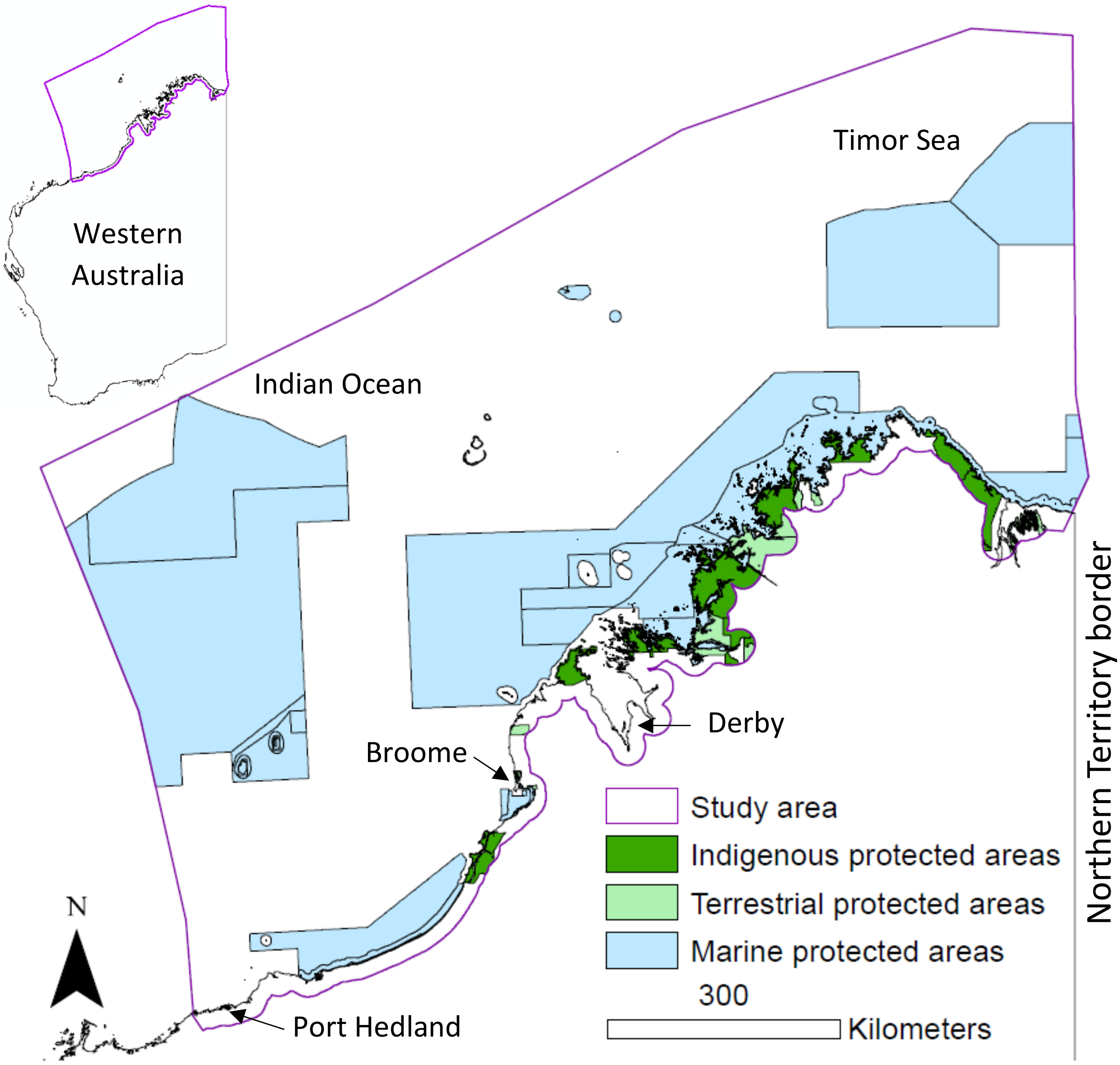


Figure 2.1. Map of the Kimberley study area with terrestrial and marine protected areas. The study area extends from the western end of Port Hedland to the Northern Territory border, from approximately 25 km inland and seawards into the Indian Ocean and Timor Sea.

2.2. Workflow

This research used geotagged Flickr photographs to identify, investigate spatial patterns, and model the association of values with socio-ecological drivers, and compared this to previous published PPGIS datasets (Strickland-Munro et al., 2015, 2016b) to evaluate whether geotagged Flickr photographs can provide reinforcing and complementary perspectives to values mapped through PPGIS. Geotagged photographs were retrieved from Flickr, validated and their content was classified to identify the values they represented, and PPGIS datasets were prepared from previous work in the Kimberley region. A set of socio-ecological drivers were selected based on relevance to the study area. Next, the relative abundance of value types was statistically compared between Flickr and PPGIS and the relative spatial patterns were investigated using kernel density analyses. Lastly, social values were modelled using Maxent (Phillips et al., 2005) to investigate the occurrence of values and their associations with socio-ecological drivers.

2.3. Datasets

2.3.1. Flickr

2.3.1.1. Retrieval of geotagged photographs

Flickr is a major photo-sharing social media platform with over 90 million monthly active users worldwide, as reported in Di Minin et al. (2015) and Toivonen et al. (2019). Flickr supports sharing of geotagged photographs that can be retrieved using the publicly available Flickr Application Programming Interface (API). Operating under accordance with the Murdoch University Human Ethics Committee (Approval 2020/030), the Flickr API was accessed on April 6 2020 to retrieve all publicly shared geotagged photographs uploaded until this date within geographic bounding boxes spanning the study area. A total of 6,320 geotagged photographs were retrieved using an R code adapted from Richards and Friess (2015), and the following metadata recorded and organised into an Excel spreadsheet: unique user identifier;

photograph ID; latitude and longitude; spatial accuracy of the photograph coordinates; date and time the photograph was taken; title, description and tags of the photograph as generated by the user; and a URL to view the photograph as posted on the user's Flickr page.

2.3.1.2. Content analysis and classification of geotagged photographs

Geotagged photographs were accessed using the photograph URL embedded in the retrieved metadata. A set of social values was developed guided by previous publications for the study area (Strickland-Munro et al., 2015, 2016b) and similar studies performing content analysis on geotagged photographs (Table 2.1; Clemente et al., 2019; Muñoz et al., 2020; Richards & Friess, 2015; Tenerelli et al., 2016). Henceforth, 'individual values' will be used to refer to the individual records of values, and 'value type(s)' will be used to refer to discrete categories of values. An initial review of a subset of 100 randomly selected photographs was conducted to observe emergent value types and refine the ruleset used to classify photos. The ruleset was applied by several independent researchers to validate value types and minimise ambiguities, potential inconsistencies and interpretation bias. The content of all geotagged Flickr photographs was then analysed and classified according to the finalised ruleset (Table 2.1; for a more detailed description see Appendix B). This involved the photograph first being screened to establish the content was of the natural environment or a natural resource. Photographs included for analysis were then assigned one or more value types to ensure all types of values observed in the photograph were represented. To assist interpretation of photograph content and familiarisation with the study area, text generated by the user (e.g. title, descriptions and tags) and geographic coordinates were used to search for information to provide background, and to identify and confirm objects and locations within the study area.

Table 2.1. Ruleset used to classify social value types captured by geotagged Flickr photographs that refer to the natural environment or natural resources of the Kimberley region, definition of the value type, and examples of photograph content applied to each value type (for a more detailed description see Appendix B).

Social value types	Definition	Examples
Direct use, non-consumptive		
Scenic/aesthetic	Landscapes or attractive scenery	Gorges, waterfalls, caves, islands, beaches, sunrise/sunset, aerial view over the landscape, moon or stars, natural processes such as fire or lightning
Aboriginal culture/heritage	Reflect Aboriginal history or connection with coastal and sea country	Rock art, paintings, artwork
European culture/heritage	Reflect European history	World War Two artefacts, exploration, pastoralism
Learning/research	Enable learning through observation or study	Clipboards, art centres, museums
Spiritual	Sacred, religious or spiritually special places	Churches, graveyards
Recreation	Outdoor recreation activities	Off-road vehicles, bicycles, camping gear, sunbathing/swimming, hiking, riding, diving, snorkelling, surfing, social activities such as bonfires and picnics
Direct use, consumptive		
Fishing (recreational)	Fishing for fish or other marine life	Fishing rods, crab pots
Economic (non-tourism)	Natural resources which can be used by people and transportation of these resources	Oil/gas, mining, minerals, pastoralism, commercial vessels, trucks, trains
Nature-based tourism	Tourism opportunities in the natural environment	Tourism infrastructure, accommodation, cruises, cave systems, gorges, rivers, waterfalls, wildlife observation, statues or sculptures, information signs
Indirect use		
Nature appreciation	Living organisms	Animals, plants, habitats such as reefs and mangroves

2.3.2. Public Participation GIS (PPGIS)

The Kimberley Research Node Project *2.1.2. Values and aspirations for coastal waters of the Kimberley* funded by the Western Australian Marine Science Institution (WAMSI) identified and analysed the types of values people associated with existing and proposed marine protected areas in support of marine spatial planning and management (Spencer-Cotton et al., 2016; Strickland-Munro et al., 2015, 2016b, 2016c). That project was the source of the PPGIS data used in this study. The PPGIS datasets that were compared to Flickr were collected through interviews and participatory mapping (Strickland-Munro et al., 2015), and a follow up online survey (Strickland-Munro et al., 2016b).

2.3.2.1. Interview PPGIS

Strickland-Munro et al. (2015) conducted interviews and participatory mapping (henceforth referred to as interview PPGIS) to identify emergent value types of stakeholders associated to Kimberley coastal and marine environments (Moore et al., 2017). Participants were asked to draw polygons around valued places onto hard copy base maps and interviews were digitally recorded, transcribed and analysed to identify value types. A total of 15 value types were revealed and grouped into non-consumptive direct use, consumptive direct use, indirect use, and non-use values (Table 2.2). Drawn polygons were aggregated and up to nine value types were attributed to individual polygons, resulting in a total of 2,788 individual values assigned to 986 polygons.

2.3.2.2. Online PPGIS survey

Strickland-Munro et al. (2016b) conducted an online survey (henceforth referred to as online PPGIS survey) to extend and validate values and to explore the management preferences of stakeholders associated with Kimberley coastal and marine environments. The online PPGIS survey consisted of a set of questions and a mapping component. Participants were asked to place digital markers representing value types and, separately, management preferences through a Google Maps interface. A list of 14 pre-determined value types and 13 management preferences were provided (Table 2.2). Participants could zoom in and out to orientate themselves, although markers could not be placed unless zoomed into a minimum resolution (≤ 10 km) to ensure mapping accuracy. Only one value type was assigned per marker, however there were no limitations to the number or proximity of markers that could be placed. As with interview PPGIS, value types were grouped into use themes. A total of 19,157 markers were placed, with 13,756 of these values and 5,401 management preferences.

Table 2.2. Summary of data collected using Flickr, interview PPGIS (Moore et al., 2017; Strickland-Munro et al., 2015) and the online PPGIS survey (Strickland-Munro et al., 2016b), including the dates of data collection, number of users/participants, method of participant recruitment, number of social value types and the total number of individual spatial features for each method.

	Flickr	**Interview PPGIS**	**Online PPGIS survey**
Date	April 6 2020*	2013	April – July 2015
Users/participants	445	232	372
Participant recruitment	No recruitment, photographs accessed through the Flickr API (no contact required)	Personal contact, email, recommendations from organisations and respondents	Personal contact, postal invitation, email, social media, local media, survey information cards, newsletters
Social value types	10	15	14
Spatial features	6,320 photographs	986 polygons	13,756 points

** Date of download.*

2.3.3. Socio-ecological driver variables

Assessing the associations between value types and socio-ecological drivers required the development of spatial data layers for the predictor variables. Socio-ecological drivers were selected based on knowledge of the study area obtained through content analysis of geotagged photographs and the literature regarding values. Variables included environmental, infrastructure, and management features (Table 2.3). Environmental features were expected to be related to value types because natural attractions may draw people to those locations. These included distance from water bodies, geological features and waterfalls, distance inland and seawards from the coastline, as well as variation in topography, vegetation diversity and coastal geomorphology. Infrastructure constrains whether people can access and experience a type of value in a particular place and thus influences if they hold a value for that place. Therefore, infrastructure variables included distance from major roads, minor roads and tracks, major towns and coastal access points. Management variables influence the activities and the types of values people associate with a given place. These included the protection status, or IUCN category, of protected areas.

Table 2.3. Description of environmental, infrastructure, and management socio-ecological driver variables for the Kimberley region and the data sources from which they were derived. The scale of the original data sources are provided. All distance variables were calculated as Euclidean distance. Type describes whether the variable was considered marine, terrestrial, or both. Variables excluded from the final model due to intercorrelations are italicised (see section *2.4.3.1*).

Variables	**Description**	**Type**	**Source and scale of source data**
Environmental			
Distance seawards	Distance seawards from the coastline. Coastline defined as mean high-water mark.	Marine	*GEODATA COAST 100K* (Geoscience Australia, 2004) Scale: 1:100,000
Distance inland	Distance inland from the coastline. Coastline defined as mean high-water mark.	Terrestrial	*GEODATA COAST 100K* (Geoscience Australia, 2004) Scale: 1:100,000
Distance from waterbodies	Waterbodies include lakes, rivers, streams and creeks. Waterbody features converted from polygons to points using polygon centroids as features too fine at 2 km resolution.	Terrestrial	*GEODATA TOPO 250K series 3* (Geoscience Australia, 2006) Scale: 1:250,000
Topographic rugosity	Topographic rugosity showing the terrain variation across a landscape calculated via Benthic Terrain Modeler (Walbridge et al., 2018) using neighbourhood size of 65 (~ 1.95 km).	Terrestrial	*USGS Digital Elevation SRTM 1 Arc-Second Global* (USGS, 2000) Scale: 1 s (~30 m) pixels
Vegetation diversity	Vegetation diversity calculated using standard deviation and 19 x 19 (~ 2 km) moving window. Vegetation groups native to Australia reclassified from 33 groups into 12 major groups including no data, rainforests, forests, woodlands, forests and woodlands, shrublands, grasslands, woodlands and shrublands, mangroves, inland aquatic, naturally bare, and cleared.	Terrestrial	*Australia present major vegetation groups* (Department of Agriculture, Water and the Environment, 2018a) Scale: 1:25,000 to 1:5,000,000
Distance from geological features	Geological features include caves, cliffs, capes and outcrops. Outcrops converted from polygons to points using polygon centroids as features too fine at 2 km resolution, and cliffs converted from lines to points by extracting vertices so all features could be combined into one variable.	Terrestrial	*GEODATA TOPO 250K series 3* (Geoscience Australia, 2006) Scale: 1:250,000
Distance from waterfalls	Waterfalls defined as the sudden decent of water into a waterbody.	Both	*GEODATA TOPO 250K series 3* (Geoscience Australia, 2006) Scale: 1:250,000
Coastal geomorphology	Coastal geomorphology includes beach, beach/rocky shore, mangal, mud/salt marsh, rocky shore, rocky shore/mangal, unclassified island and developed.	Both	*Western Australia coastal waterways geomorphic habitat mapping* (Geoscience Australia, 2016) Scale: 1:100,000

Table 2.3. Continued.

Variables	Description	Type	Source and scale of source data
Infrastructure			
Distance from major roads	Major roads defined as sealed bitumen surfaces.	Terrestrial	*Road hierarchy* (Main Roads Western Australia, 2017) Scale: 1:100,000 to 1:400,000
Distance from minor roads and tracks	Minor roads defined as gravel surfaces usable by two-wheel drive vehicles, and tracks defined as unconstructed, unformed roads created by off-road vehicles.	Terrestrial	(Kobryn et al., 2018) Scale: Not reported. Digitised from high resolution imagery.
Distance from major towns	Major towns defined as areas where buildings are close together and there is an associated road network and include Port Hedland, Broome and Derby. Major towns converted from polygons to points using polygon centroids as features too fine at 2 km resolution.	Terrestrial	*GEODATA TOPO 250K series 3* (Geoscience Australia, 2006) Scale: 1:250,000
Distance from human settlements	Human settlements include populated places with more than 200 people but not considered a built-up area, homesteads (i.e. permanent residence buildings in rural locations) and Aboriginal communities. Aboriginal communities defined as housing or infrastructure that is inhabited or intended to be inhabited predominately by more than 50% of the usual residents and by Aboriginal or Torres Strait Islander peoples.	Terrestrial	*GEODATA TOPO 250K series 3* (Geoscience Australia, 2006) Scale: 1:250,000 *Aboriginal communities and town reserves* (Department of Planning, Lands and Heritage, 2016) Scale: 1:5,000,000
Distance from aircraft facilities	Aircraft facilities includes airports, helipads, and paved or cleared landing grounds.	Terrestrial	*GEODATA TOPO 250K series 3* (Geoscience Australia, 2006) Scale: 1:250,000
Distance from roadhouses	Roadhouses defined as petrol stations on major roads that have an attached restaurant or café.	Terrestrial	*Roadhouse map* (Freight and Logistics Council of WA, 2020) Scale: Not reported
Distance from coastal access	Coastal access includes ports and boat ramps.	Both	*Coastal infrastructure* (Department of Transport, 2017) Scale: Not reported *Major ports* (Geoscience Australia, 2014) Scale: 1:15 to 1:250

Table 2.3. Continued.

Variables	Description	Type	Source and scale of source data
Management			
Marine protected areas	IUCN category of marine protected areas and include protected areas in both state and commonwealth waters.	Marine	*CAPAD marine* (Department of Agriculture, Water and the Environment, 2018b) Scale: 1:1,000 to 1:500,000
Terrestrial protected areas	IUCN category of terrestrial protected areas.	Both	*CAPAD terrestrial* (Department of Agriculture, Water and the Environment, 2018c) Scale: 1:1,000 to 1:500,000
Indigenous protected areas	IUCN category of Indigenous protected areas. Indigenous protected areas dataset is from 2016 as the Australian Government introduced the *New Indigenous Protected Areas Program* to increase the land and sea areas dedicated for Indigenous Protected Areas in 2017. As data for both methods of PPGIS was collected prior to 2017, the 2016 dataset was more appropriate to use as it was more representative.	Both	*Indigenous Protected Areas* (Department of Agriculture, Water and the Environment, 2016) Scale: 1:1,000 to 1:500,000

2.4. Data analyses

2.4.1. Relative abundance of value types between Flickr and PPGIS

Chi-square tests of independence were performed to determine whether the relative abundance of value types significantly varied between Flickr and PPGIS. Following a significant finding, standardised residuals were calculated to determine which value types were the major contributors to the overall difference. Standardised residuals less than -2.0 indicated observed counts less than expected, and greater than 2.0 indicated observed counts greater than expected. The greater the absolute value of standardised residuals, the stronger the difference between observed and expected counts.

2.4.2. Spatial patterns

The spatial patterns of value types mapped through Flickr and PPGIS were generalised using kernel density layers and compared. Kernel density layers were used to produce maps of relative hotspots showing the locations where values were more commonly mapped through Flickr than the online PPGIS survey, and vice versa. Kernel density layers were generated for each value type in ArcGIS 10.6 based on the quartic kernel function (Silverman, 1986). This function calculates densities of point or line spatial features within a defined area and produces a smooth, continuous surface. As kernel density layers can only be calculated using point or line spatial features, the following analyses were performed only for Flickr and the online PPGIS survey as these methods utilised the same spatial feature (i.e. points). Not only were these methods comparable, they also shared similarities in how they were collected requiring the use of the internet and therefore were also similar in approach. Kernel density maps were generated using 2 km x 2 km grid cells and a 20 km search radius, parameters suitable for the analysis given the size of the study area (Munro et al., 2017). Kernel densities were standardised so the density estimates could be directly compared given the different levels of mapping effort between the two datasets. Standardised kernel densities were calculated for Flickr (1) and the online PPGIS survey (2) using the following equations, where *STD* indicates the standardised kernel density layer, *KD* indicates the raw kernel density layer, and *n* indicates the number of individual value points used to generate the kernel density layer:

$$STD\_Flickr = KD\_Flickr * n\_OnlinePPGISSurvey \quad (1)$$

$$STD\_OnlinePPGISSurvey = KD\_OnlinePPGISSurvey * n\_Flickr \quad (2)$$

Standardised kernel densities were then subtracted to show relative hotspots of value types between Flickr and the online PPGIS survey.

2.4.3. Maximum entropy modelling

2.4.3.1. Final processing of socio-ecological driver variables

A set of 18 variables were selected as the most relevant drivers to predict the occurrence of value types within the study area (Table 2.3). All pre-processing and preparation of variables was performed in QGIS 3.4.15. This included reprojecting to a UTM coordinate system and converting all variables to raster format using 2 km x 2 km grid cells, a resolution consistent with the extent of most geographic features of interest within the study area (Strickland-Munro et al., 2016a).

It is best practice to screen for intercorrelations of socio-ecological driver variables to ensure robust conclusions from the Maxent models (Phillips et al., 2005). Correlations between the 18 variables were evaluated for the study area as a whole (Appendix C). Because separate models were constructed for terrestrial and marine parts of the study area, correlations between terrestrial variables were also assessed just over the terrestrial part of the study area (16 variables; Appendix C). Three variables were excluded because they had correlation coefficients greater than 0.8 or less than -0.8 with one or more variables in both sets of correlation analyses and were considered less important to predict the occurrences of values than the variables they were correlated with (Elith et al., 2011). These variables were 'distance from aircraft facilities', 'distance from human settlements' and 'distance from roadhouses'. Therefore, a final set of 15 socio-ecological drivers were included for further analyses.

2.4.3.2. Associations with socio-ecological drivers

Maxent models were used to explore the potential distribution of value types and associations with socio-ecological drivers. The potential distribution describes the areas predicted to be suitable for a given value to occur. Maxent utilizes known point occurrence locations (i.e. presence only data) and empirically estimates associations with the provided socio-ecological drivers to understand and predict the spatial distribution of a phenomenon (Elith et al., 2011; Franklin, 2010). Although most commonly used to model species distributions (Phillips et al., 2006; Phillips & Dudík, 2008), Maxent is a general technique that can be used to model the distribution of human values (Sherrouse et al., 2011). Maxent is able to capture the relationships between types of values and the most important socio-ecological drivers, which are illustrated with response curves (Elith et al., 2011; Phillips & Dudík, 2008). This can be used to generate predictive maps of the potential distribution of values types. Similarly to kernel density analyses, Maxent requires point occurrence locations and therefore models were only generated for value points from Flickr and the online PPGIS survey. Models were also performed separately for marine and terrestrial parts of the study area as preliminary analyses suggested this would better facilitate model interpretation.

Occurrence data used in Maxent models may exhibit spatial biases as they are typically taken near accessible locations (Phillips et al., 2009; Reddy & Dávalos, 2003), which is particularly true for geotagged Flickr photographs. Models can be confounded by the sampling bias which may cause inaccurate interpretations of response curves and spatial predictions. Preliminary analyses suggested models may be confounded by this bias, and therefore a bias file was developed to account for the spatial patterns of sampling intensity (Elith et al., 2010; Phillips & Dudík, 2008; Phillips et al., 2009). Bias files were generated separately for Flickr and the online PPGIS survey using kernel density analyses. The total set of geotagged photographs for Flickr and points for the online PPGIS survey were used to calculate kernel densities based on 2 km x 2 km grid cells and a 100 km search radius. The bias file was normalised to scale values between 0 and 1, then multiplied by 100 and all values greater than 1 set to 1 to minimise the skewness of extreme densities (Elith et al., 2010).

Models were generated using a random subsample of 70% of the occurrence points for each value type (training), with 30% withheld for model validation (test) and a random set of 10,000 background points (Barbet-Massin et al., 2012). The test data provides independent samples from the training data and enables more accurate estimates of model performance. The output was calculated as the average of ten replicates using different training/test splits and background points. Model features were restricted to linear, hinge and product, and the regularization multiplier was set to 3, to minimise model overfitting and reduce model complexity (Merow et al., 2013; Phillips et al., 2006; Radosavljevic & Anderson, 2014).

Model performance was evaluated using the area under the receiver operating characteristic (ROC) curve (AUC). AUC values indicate how well the model distinguishes between the occurrence points of values and background points (Merow et al., 2013). AUC values greater than 0.5 indicate model predictions were better than random, and values greater than 0.7 indicate model predictions were reasonable (Phillips et al., 2006).

To identify the drivers that best predict the spatial distribution of each value type, the variable permutation importance was examined. This assessment of variable importance randomly permutes the values of a given variable across the set of training and background points and provides a measure of how much the model relies on a given variable normalised to percentages. Univariate response curves for variables with greater than average importance (≥ 6.7%) were generated for each value type for Flickr and the online PPGIS survey to identify the association between values and the most important socio-ecological drivers. Univariate response curves plot the relationship between predicted suitability and a given driver variable, considering only the corresponding variable. Predictive maps of the potential distribution of values were also generated. These show the areas predicted suitable for value types to occur and range from 0 to 1, with 0 indicating a value will not occur at a given location, and 1 indicating a value will occur (i.e. perfect suitability).

3. Results

3.1. *Geotagged Flickr photographs*

From the 6,320 geotagged photographs retrieved from Flickr, a total of 5,293 photographs taken by 406 users were identified to represent the natural environment or a natural resource. The median number of photographs per user was 3 (range = 1 to 285), indicating that few users shared a large number of photographs. Moreover, of the 406 users, only seven users shared more than 100 photographs accounting for almost a quarter (23.5%) of the total number of photographs.

Despite Flickr being launched in 2004, retrieved photographs were taken between June 1962 and March 2020 (Figure 3.1). The number of photographs greatly increased from 2010, with over 90% of retrieved photographs taken between 2011 to 2019. Photographs were primarily taken between June and October, corresponding to the dry season and the peak visitation period to the Kimberley region (Figure 3.2). September and October were popular months of visitation to the region, likely due to the Australian school holidays occurring around this period. In contrast, fewer photographs taken between November and May were likely due to the wet season limiting accessibility to most of the region.

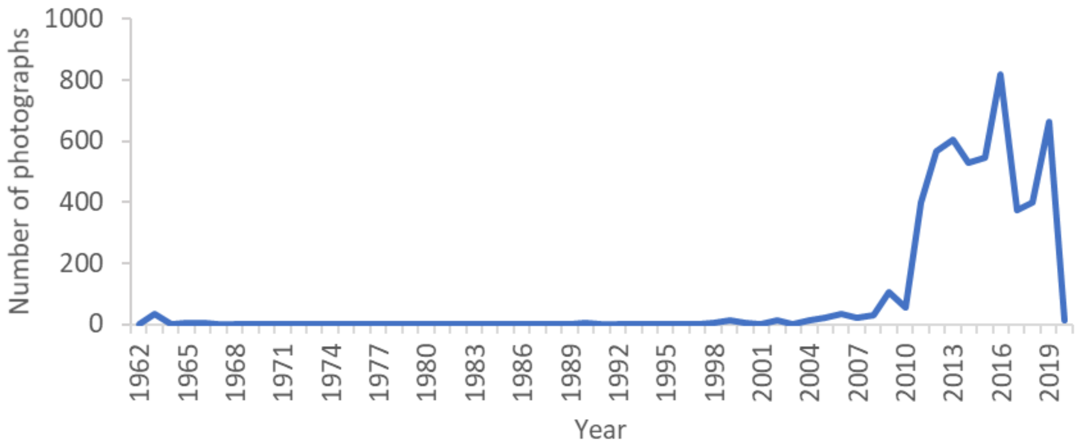


Figure 3.1. Total number of geotagged Flickr photographs representing the natural environment or natural resource by year. Photographs taken between 2011 to 2019 (n = 4,910) accounted for 90% of total photographs. There was a small number of photographs in 2020 (n = 15) as photographs were retrieved only up until April 2020.

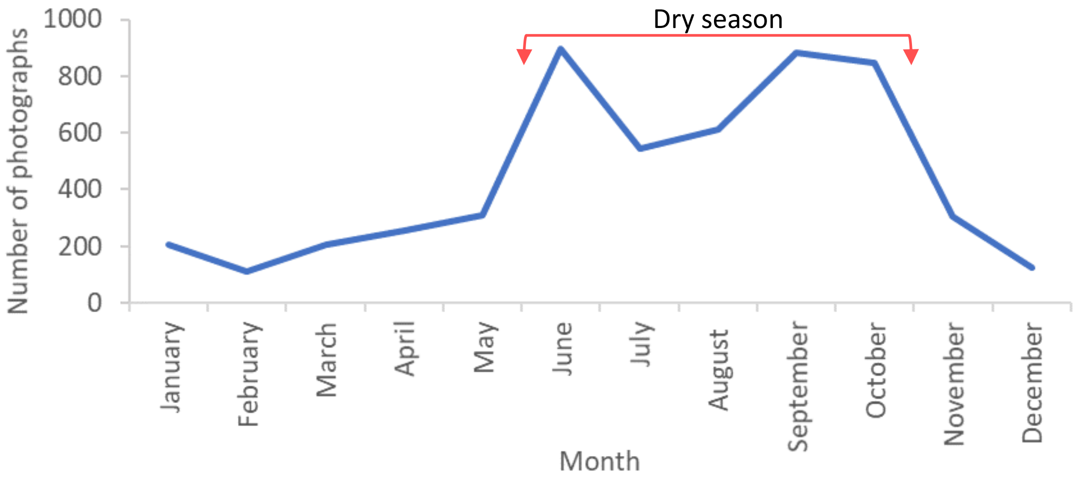


Figure 3.2. Total number of geotagged Flickr photographs representing the natural environment or natural resource by month. The dry season shown in red, also the peak visitation period, typically runs from May to October.

A total of 7,486 individual values were identified through the content analysis of photographs (Table 3.1). The number of value types assigned to each photograph ranged from 1 to 4 (average ± SD = 1.4 ± 0.6). Photograph content was skewed towards the value type *scenic/aesthetic* with over half of the retrieved photographs depicting landscapes or attractive scenery. The second most frequently observed value type was *nature appreciation*, followed by *nature-based tourism* and *recreation*. The least frequently observed value type was *fishing (recreational)*, which occurred in only 1% of photographs. Given the large number of photographs depicting landscapes or attractive scenery, it was unsurprising that photographs representing *scenic/aesthetic* were also shared by the greatest number of individual users. As with the frequency of value types, this was followed by *nature appreciation*, *nature-based tourism* and *recreation*.

Table 3.1. Number and percentage of social value types identified through content analysis of geotagged Flickr photographs and the users who contributed photographs for each type of social value organised in decreasing order of photograph frequency. The % photographs are the number of photographs for each value type divided by the total number of photographs (n = 5,293) and sums to > 100% as more than one value type could be assigned per photograph. The % users are the number of users for each value type divided by the total number of users (n = 406) and sums to > 100%.

Social value types	**Number of photographs**	**% photographs**	**Number of users**	**% users**
Scenic/aesthetic	3087	58.3	321	79.1
Nature appreciation	1390	26.3	222	54.7
Nature-based tourism	1169	22.1	198	48.8
Recreation	785	14.8	159	39.2
Economic (non-tourism)	467	8.8	97	23.9
Aboriginal culture/heritage	177	3.3	45	11.1
Learning/research	128	2.4	35	8.6
Spiritual	116	2.2	34	8.4
European culture/heritage	97	1.8	28	6.9
Fishing (recreational)	70	1.3	34	8.4
Total	**7486**		**406**	

3.2. Relative abundance of value types between Flickr and PPGIS

As with Flickr, *scenic/aesthetic* was the most frequent value type represented in interview PPGIS (Table 3.2) but the second most frequent represented in the online PPGIS survey (Table 3.3). Moreover, the relative frequency of *scenic/aesthetic* compared to the number of individual values in the Flickr dataset was more than double than in either of the PPGIS datasets (Figure 3.3).

Following *scenic/aesthetic*, the most frequent value types represented in Flickr was *nature appreciation*, *nature-based tourism* and *recreation*. The most frequent value types for interview PPGIS following *scenic/aesthetic* was *recreation*, *fishing (recreational)* and *nature appreciation*. For the online PPGIS survey the most frequent value type was *nature appreciation* followed by *scenic/aesthetic*, *fishing (recreational)* and *Aboriginal culture/heritage*. Whilst *scenic/aesthetic* and *nature appreciation* were highly represented across the three methods, *fishing (recreational)* was only highly represented in interview PPGIS and the online PPGIS survey, indicative of a difference between value types derived from Flickr versus PPGIS.

Comparison of the relative abundance of value types from Flickr to PPGIS revealed significant differences between Flickr and interview PPGIS (X^2 = 1841.4, df = 9, $p < 0.001$) and between Flickr and the online PPGIS survey (X^2 = 2842.2, df = 9, $p < 0.001$). According to the X^2 test statistic, this difference was greater between Flickr and the online PPGIS survey. Standardized residuals revealed large differences in the observed and expected frequencies for all value types but *nature appreciation* for Flickr compared to interview PPGIS and *spiritual* for both Flickr and interview PPGIS (Table 3.2). Large differences were also observed for most value types for both Flickr and the online PPGIS survey with the exceptions of *spiritual*, *recreation* and *nature appreciation* (Table 3.3).

Whilst the overall difference was greater between Flickr and the online PPGIS survey, these differences were driven by fewer but larger differences in the value types (Table 3.3). The standardized residuals were the largest for the value types *scenic/aesthetic*, *Aboriginal culture/heritage* and *fishing (recreational)*. They showed *scenic/aesthetic* to be significantly greater than expected for Flickr and significantly less for the online PPGIS survey. The opposite was shown for the value types *Aboriginal culture/heritage* and *fishing (recreational)*, which showed these value types to be significantly less than expected for Flickr, but significantly greater than expected for the online PPGIS survey. This pattern was also observed for interview PPGIS, but to a slightly lesser extent as indicated by the standardized residuals (Table 3.2). These differences are particularly evident in Figure 3.3 where *Aboriginal culture/heritage* and *fishing (recreational)* was significantly less frequent for Flickr compared to both methods of PPGIS.

Table 3.2. Chi-square test of independence results displaying the observed count and standardised residuals in brackets for the comparison between Flickr and interview PPGIS. The overall difference was significant ($X^2 = 1841.4$, df = 9, $p < 0.001$) and standardised residuals < -2.0 (orange) or > 2.0 (green) are highlighted.

Social value types	**Flickr**	**Interview PPGIS**
Direct use, non-consumptive		
Scenic/aesthetic	3087 (7.1)	407 (-13.3)
Aboriginal culture/heritage	117 (-8.9)	261 (16.6)
European culture/heritage	97 (-3.4)	78 (6.3)
Learning/research	128 (-3.4)	94 (6.4)
Spiritual	116 (-0.6)	41 (1.0)
Recreation	785 (-4.6)	403 (8.5)
Direct use, consumptive		
Fishing (recreational)	70 (-14.1)	348 (26.5)
Economic (non-tourism)	467 (3.3)	48 (-6.2)
Nature-based tourism	1169 (4.8)	139 (-8.9)
Indirect use		
Nature appreciation	1390 (1.6)	321 (-3.0)
Total	**7486**	**2140**

Table 3.3. Chi-square test of independence results displaying the observed count and standardised residuals in brackets for the comparison between Flickr and the online PPGIS survey. The overall difference was significant ($X^2 = 2842.2$, df = 9, $p < 0.001$) and standardised residuals < -2.0 (orange) or > 2.0 (green) are highlighted.

Social value types	**Flickr**	**Online PPGIS survey**
Direct use, non-consumptive		
Scenic/aesthetic	3087 (23.2)	2129 (-18.6)
Aboriginal culture/heritage	117 (-19.7)	1608 (15.8)
European culture/heritage	97 (-6.1)	358 (4.9)
Learning/research	128 (-5.5)	400 (4.4)
Spiritual	116 (-0.9)	208 (0.8)
Recreation	785 (0.7)	1173 (-0.6)
Direct use, consumptive		
Fishing (recreational)	70 (-24.8)	1849 (19.9)
Economic (non-tourism)	467 (9.4)	309 (-7.5)
Nature-based tourism	1169 (5.5)	1382 (-4.4)
Indirect use		
Nature appreciation	1390 (-0.9)	2259 (0.8)
Total	**7486**	**11675**

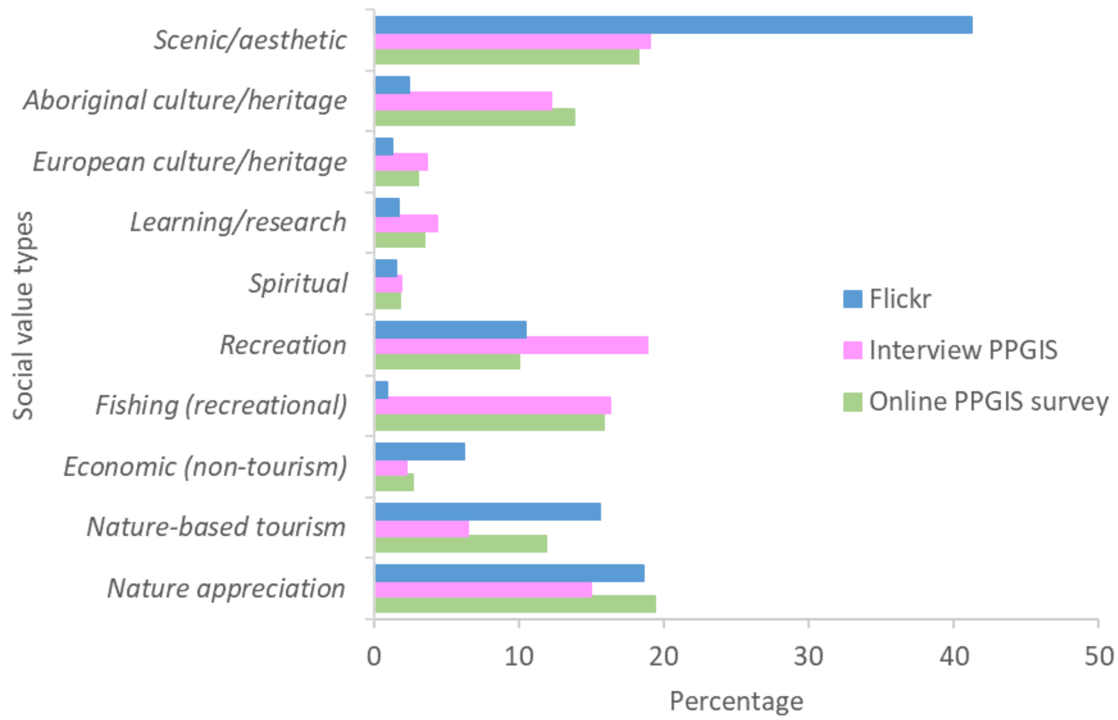


Figure 3.3. Relative frequency of value types identified through geotagged photographs retrieved from Flickr, mapped polygons from interview PPGIS and mapped points from the online PPGIS survey. The percentage is the observed count divided by the total number of individual values for Flickr (n = 7,486), interview PPGIS (n = 2,140), and the online PPGIS survey (n = 11,675).

3.3. Spatial patterns

Geotagged Flickr photographs, interview PPGIS polygons and online PPGIS survey points were first mapped to reveal any spatial patterns in their distribution within the study area (Figure 3.4).

Geotagged photographs were concentrated near the few major towns of Port Hedland, Broome and Derby (Figure 3.4a). Photographs in the northern Kimberley were sparse, likely due to limited accessibility to this part of the region. Within the marine environment, a small number of fairly evenly distributed photographs were taken off the northern Kimberley in the Timor Sea, yet only one photograph was taken off the western Kimberley in the Indian Ocean at Rowley Shoals.

Interview PPGIS and the online PPGIS survey showed the entire coastline to be valued (Figures 3.4b, 3.4c). Due to the density of polygons from interview PPGIS and points from the online

PPGIS survey, areas with especial concentrations could not be readily observed along the coastline. Within the marine environment, polygons from interview PPGIS tended to stay near the coastline with one exception located at Rowley Shoals (Figure 3.4b). For the online PPGIS survey, offshore clusters were located at Rowley Shoals, and Scott and Seringapatam Reef (Figure 3.4c).

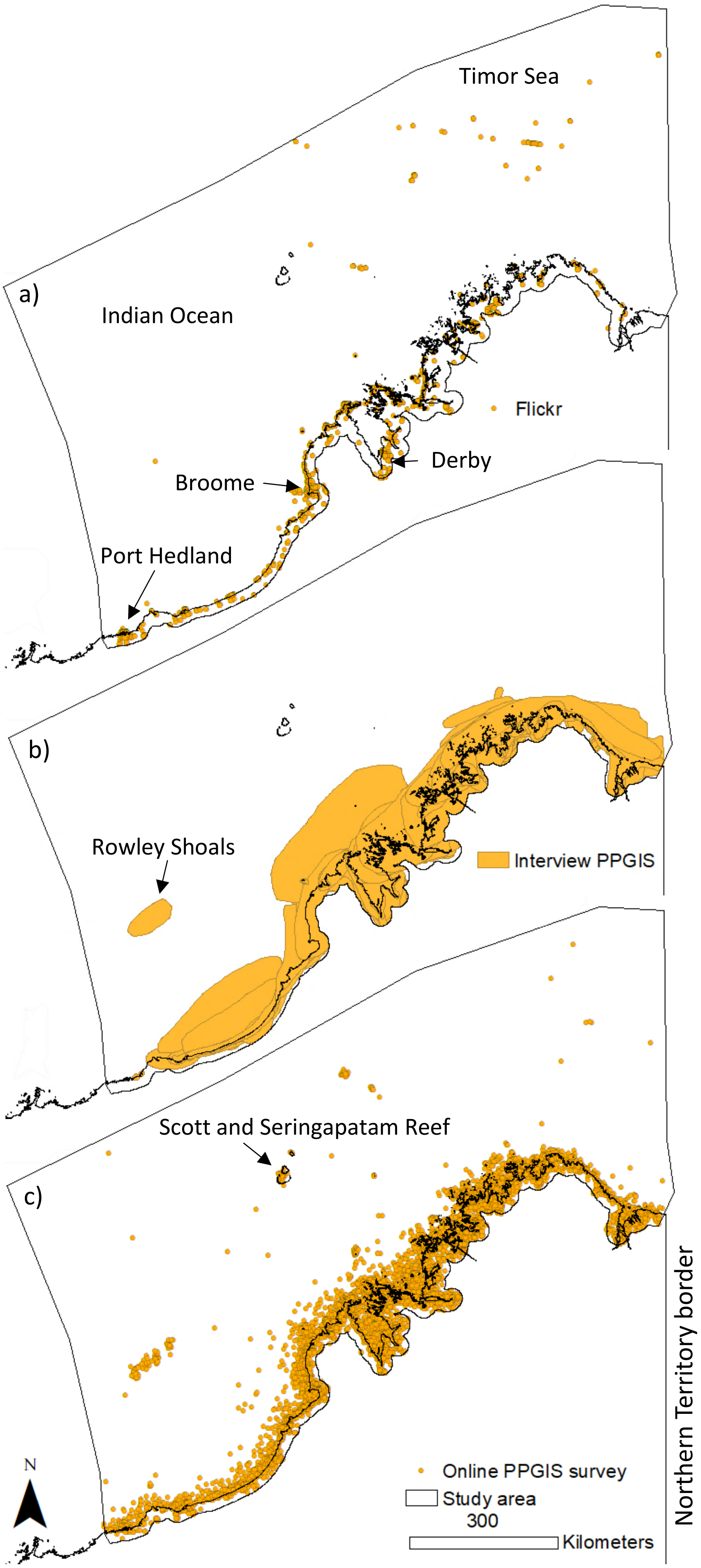


Figure 3.4. Overall distribution of a) geotagged Flickr photographs (n = 5,293), b) mapped interview PPGIS polygons (n = 986), and c) mapped online PPGIS points (n = 11,675) within the study area.

Analysis was then undertaken using kernel density layers to produce maps of relative hotspots showing the locations where value types were more commonly mapped through Flickr or the online PPGIS survey. Figure 3.5 depicts the relative hotspots for the four most frequent value types depicted by geotagged Flickr photographs as these were the most abundant between the methods to support analyses (for remaining social values see Appendix D).

There were distinct differences in relative hotspots for value types mapped through Flickr compared to the online PPGIS survey (Figure 3.5). Consistent with the previous observation for the spatial patterns of geotagged photographs (Figure 3.4a), relative hotspots tended to concentrate on specific locations. Specifically, relative hotspots of value types were recurrently more common for Flickr than the online PPGIS survey near the major towns of Port Hedland, Broome and Derby (Figure 3.5) with the exception of the value type *nature-based tourism* which showed Broome was not a notable hotspot mapped through Flickr relative to the online PPGIS survey (Figure 3.5c). Value types mapped through Flickr were also generally more common near the Eighty Mile Beach caravan park, except for the value type *nature-based tourism* (Figure 3.5). There were few to no relative hotspots for value types mapped through Flickr in the northern Kimberley region, apart from areas near the Mitchell Plateau and the town of Kalumburu (Figure 3.5). In contrast, relative hotspots for the online PPGIS survey were distributed less discretely along most of the coastline (Figure 3.5). Value types mapped through the online PPGIS survey were recurrently more common than Flickr in the northern Kimberley, likely due to this part of the region being largely remote from major roads and therefore access was limited for people to take photographs.

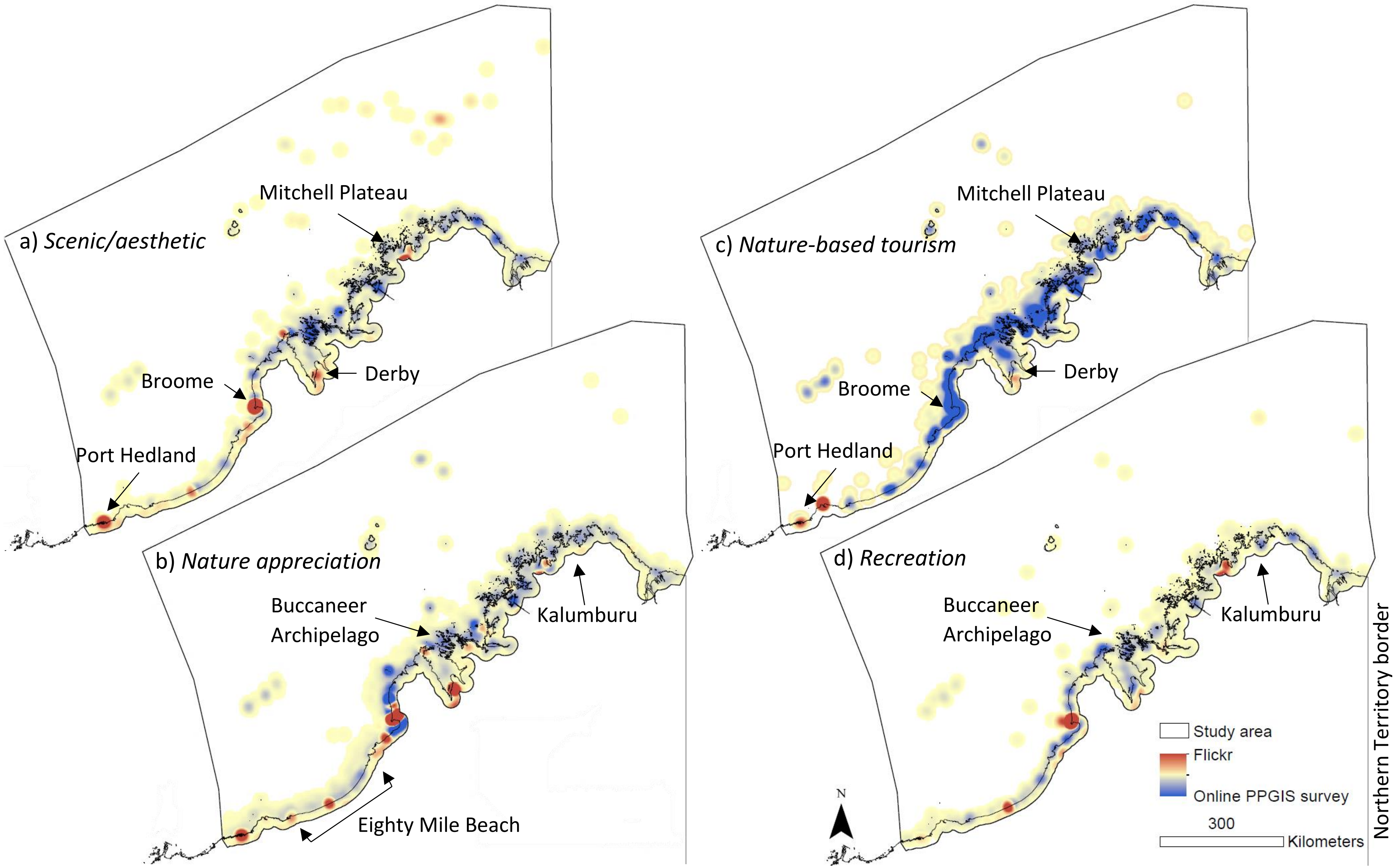


Figure 3.5. Kernel density maps depicting the relative hotspots of value types between Flickr and the online PPGIS survey for a) *scenic/aesthetic*, b) *nature appreciation,* c) *nature-based tourism*, and d) *recreation*. Red areas indicate where Flickr was more commonly mapped compared to the online PPGIS survey, blue areas indicate where the online PPGIS survey was more commonly mapped compared to Flickr, and yellow indicates areas that were similarly mapped between the two methods. The darker the colour, the greater the difference.

3.4. Associations with socio-ecological drivers

Maxent models were performed to explore the potential distribution of value types and associations with socio-ecological drivers. Models were performed for each value type mapped through Flickr and the online PPGIS survey, and separately for marine and terrestrial environments of the study area. The average area under the receiver operating characteristic (ROC) curve (AUC) for each model was greater than 0.7 (Table 3.4), indicating reasonable performance of all models to differentiate between occurrence points of values and background points.

The average AUC across all value types (i.e. column average) was slightly better for models performed for the marine environment using data from Flickr (0.935) compared to the online PPGIS survey (0.923; Table 3.4). In contrast, model performance for terrestrial models was generally worse for both methods, however models performed much better using data from Flickr (0.914) compared to the online PPGIS survey (0.781; Table 3.4). This was particularly evident for the online PPGIS survey which had the lowest average AUC values for terrestrial models with values less than 0.8 for all value types, with the exceptions of *nature-based tourism* and *fishing (recreational)*.

Model performance was greater for all value types (i.e. row average) mapped through Flickr compared the online PPGIS survey (Table 3.4). However, it is important to note that AUC values cannot be directly compared between methods as they were evaluated using different background points. There were no value types that clearly modelled better or worse for Flickr compared to the online PPGIS survey. However, *fishing (recreational)*, *European culture/heritage* and *learning/research* showed some of the highest average AUC values mapped by both Flickr and the online PPGIS survey. In contrast, the value types *scenic/aesthetic* mapped through Flickr and *nature appreciation* mapped through the online PPGIS survey showed the lowest average AUC values, surprising given these were the most abundant value types represented in Flickr and the online PPGIS survey.

Table 3.4. Average AUC for Maxent models performed for each social value type mapped through Flickr and the online PPGIS survey and separately for terrestrial and marine environments. The average AUC was based on models replicated 10 times and generated using a random subsample of 70% of occurrence points for training and 30% for test data. The row average shows the average AUC of each value type across terrestrial and marine models, and the column average shows the average AUC of all value types for terrestrial and marine models. NA indicates that no value points occurred within the marine environment for *European culture/heritage* mapped through Flickr.

	Flickr			**Online PPGIS survey**		
Social value types	**Terrestrial**	**Marine**	**Row average**	**Terrestrial**	**Marine**	**Row average**
Scenic/aesthetic	0.835	0.871	**0.853**	0.775	0.926	**0.851**
Aboriginal culture/heritage	0.881	0.982	**0.932**	0.731	0.948	**0.840**
European culture/heritage	0.940	NA	**0.940**	0.794	0.939	**0.867**
Learning/research	0.929	0.947	**0.938**	0.795	0.931	**0.863**
Spiritual	0.978	0.985	**0.982**	0.711	0.964	**0.838**
Recreation	0.885	0.954	**0.920**	0.796	0.919	**0.858**
Fishing (recreational)	0.940	0.970	**0.955**	0.851	0.908	**0.880**
Economic (non-tourism)	0.968	0.797	**0.883**	0.786	0.904	**0.845**
Nature-based tourism	0.898	0.947	**0.923**	0.802	0.903	**0.853**
Nature appreciation	0.888	0.958	**0.923**	0.770	0.884	**0.827**
Column average	**0.914**	**0.935**		**0.781**	**0.923**	

The spatial predictions of Maxent models described the potential distribution of values (i.e. the locations where a value type was predicted to occur) based on the associations with socio-ecological drivers identified from Maxent models. Figures 3.6 to 3.9 show the areas of predicted suitability for values to occur, referred to as the potential distribution, of the four most frequent values types depicted by geotagged photographs (for remaining value types see Appendix E). Maps were combined for each value type modelled for terrestrial and marine environments to show the potential distribution across the entire study area.

The potential distribution of value types mapped though Flickr and the online PPGIS survey showed some overlap in the areas predicted for values to occur. Value types were generally predicted to occur near the coast; this was especially true for values mapped through Flickr (Figures 3.6 to 3.9). There was one exception to this; the value type *scenic/aesthetic* was predicted to occur near the coast, then declined, and then the potential distribution increased again at farther distances to sea (Figure 3.6a). The potential distribution for the online PPGIS survey was less restricted and showed moderate suitability for value types to occur extending up to ~30 km offshore from the coast (Figures 3.6 to 3.9).

The potential distribution of value types also showed substantial differences in the predicted areas for values mapped through Flickr and the online PPGIS survey to occur. Value types mapped through Flickr were predicted to occur near the major towns of Port Hedland, Broome and Derby, as well as the top of the Dampier Peninsula and the Buccaneer Archipelago (Figures 3.6 to 3.9). The potential distribution of value types mapped through Flickr did not extend to the northern Kimberley region (showing little to no predicted suitability of occurrence), but rather was restricted south-westward of the Walcott Inlet. In contrast, value types mapped through the online PPGIS survey were predicted to occur near the major town of Broome, as well as near Derby for the value types *nature-based tourism* and *recreation*. Port Hedland did not prove to be a highly suitable location for the occurrence of value types for the online PPGIS survey, however there was low to moderate suitability slightly offshore. Furthermore, the potential distribution of value types mapped through the online PPGIS survey extended along the entire coastline, including the northern Kimberley region.

Scenic/aesthetic

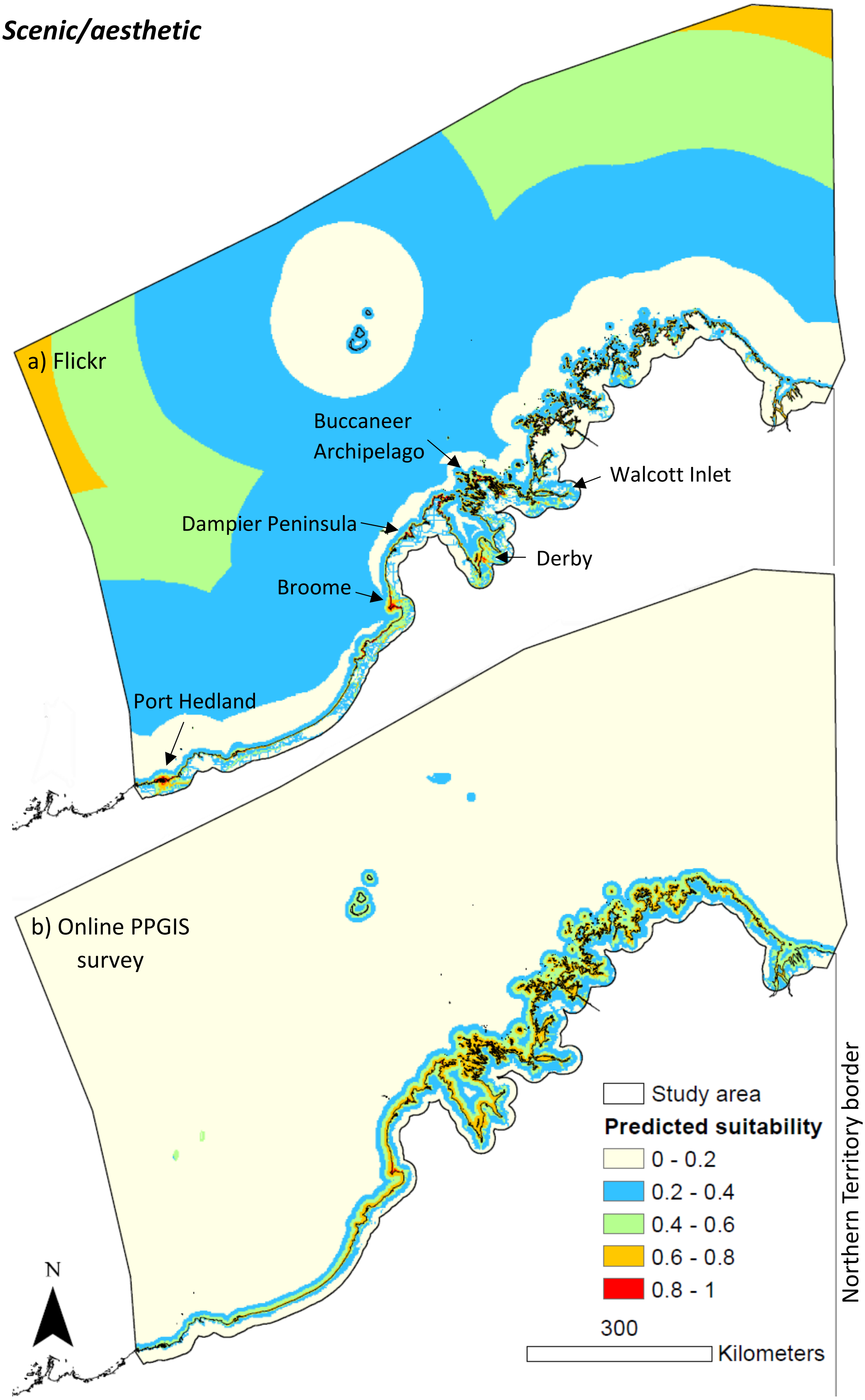


Figure 3.6. Areas predicted suitable by Maxent models for occurrence points for the value type *scenic/aesthetic* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

Nature appreciation

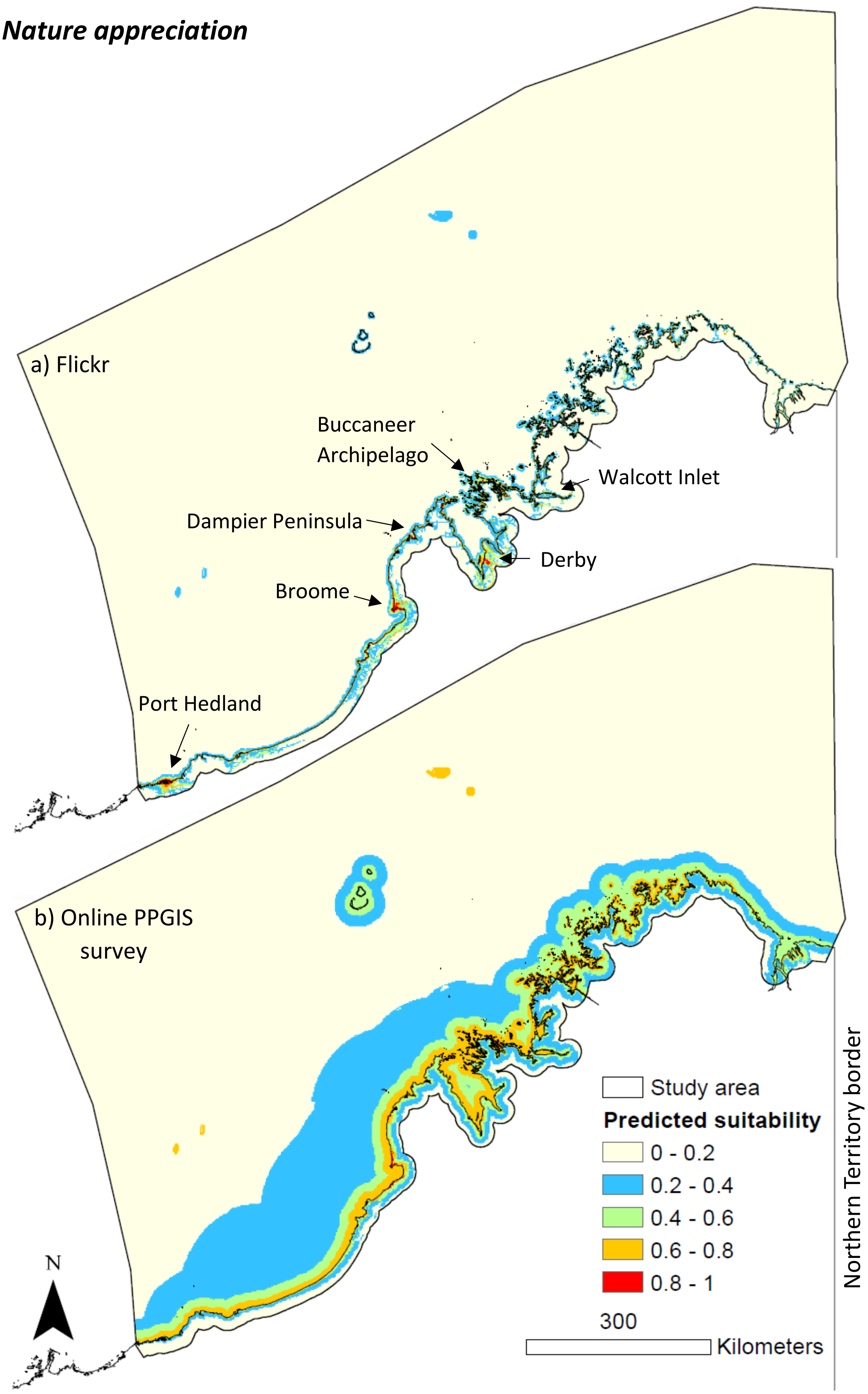


Figure 3.7. Areas predicted suitable by Maxent models for occurrence points for the value type *nature appreciation* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

Nature-based tourism

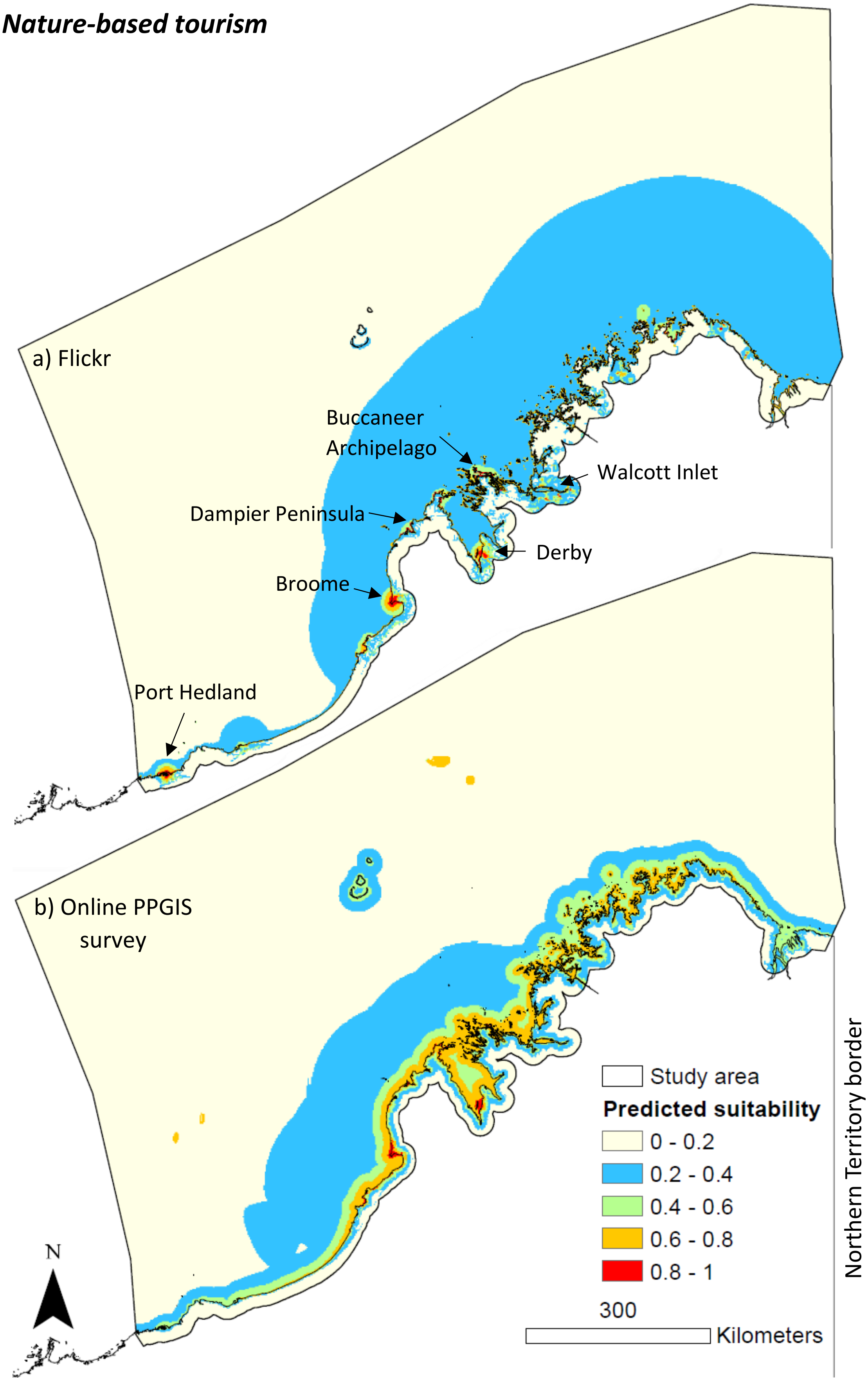


Figure 3.8. Areas predicted suitable by Maxent models for occurrence points for the value type *nature-based tourism* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

Recreation

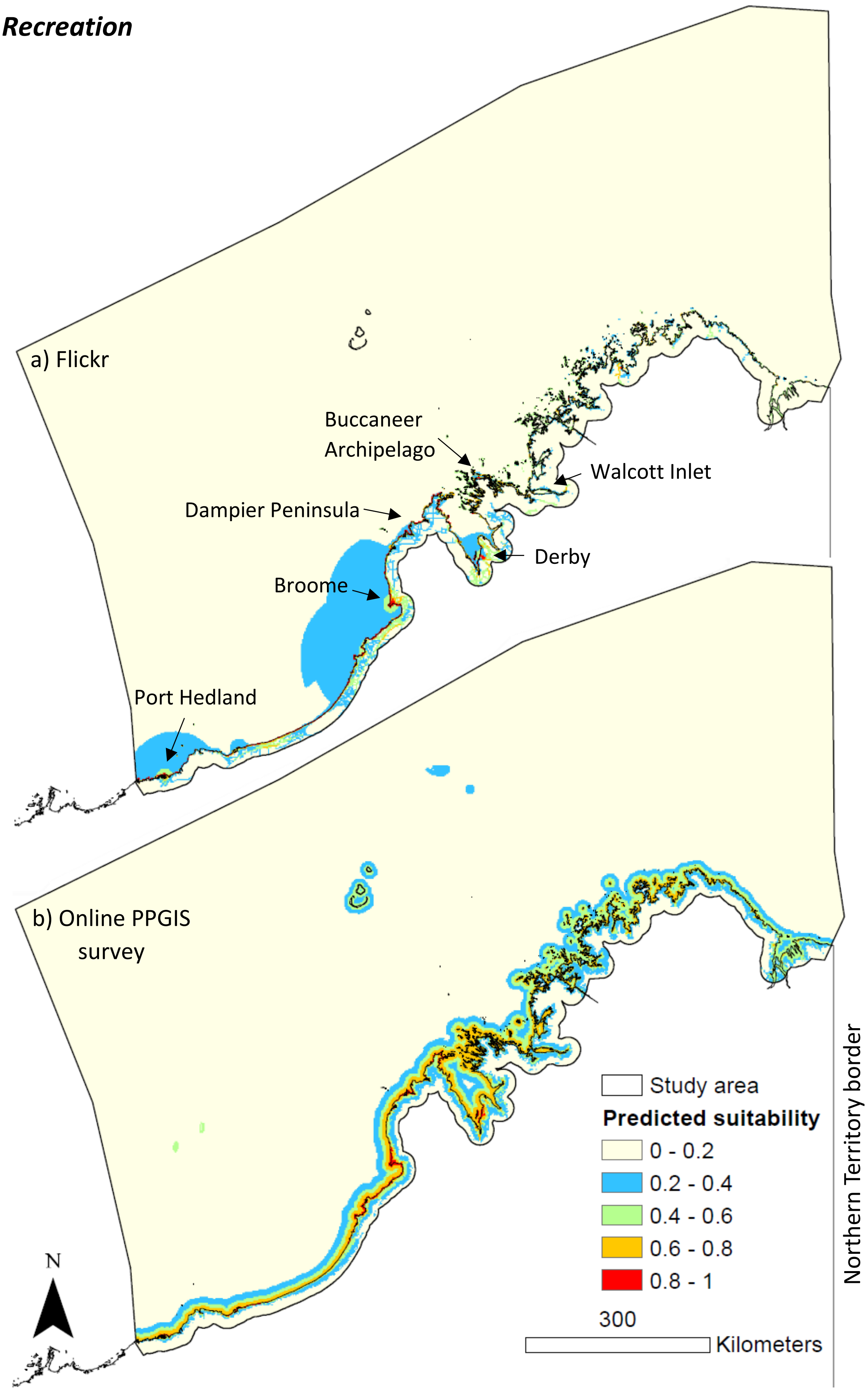


Figure 3.9. Areas predicted suitable by Maxent models for occurrence points for the value type *recreation* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

There was some disagreement in the socio-ecological drivers for models performed for each value type from the different methods of mapping values, which was reflected in the predictive maps of the potential distribution of values types. Infrastructure was found to be a major driver influencing all Flickr value types modelled for the terrestrial environment (Table 3.5). Distance from minor roads and tracks was an important driver for all value types mapped through Flickr with the occurrence of values likely to occur immediately adjacent to minor roads and tracks (Figures 3.10 to 3.13). Distance from major roads and coastal access was also important for most value types mapped through Flickr. Distance from major roads followed the same occurrence pattern to distance from minor roads and tracks, whereas the occurrence of values was likely to occur within the near vicinity (~10 km) from coastal access features (Figures 3.10 to 3.13). This indicates the occurrence of value types mapped through Flickr was largely influenced by the proximity to infrastructure features and that access is important.

The environmental variable distance seawards was found to be a major driver of marine models influencing value types mapped through both methods (Table 3.6). Whilst distance seawards was an important driver for five out of the ten value types mapped through Flickr, it was consistently the most important driver for determining all value types mapped through the online PPGIS survey. Value types mapped through Flickr followed a different pattern of occurrence to the online PPGIS survey and were more likely to occur within 20 km of the coast, whereas value types mapped through the online PPGIS survey were predicted to occur within 50 km (Figures 3.10 to 3.13). This difference of occurrence was reflected in Figures 3.6 to 3.9 that showed the potential distribution of value types mapped through the online PPGIS survey extended further offshore than value types mapped through Flickr. The chance of occurrence thereafter was similar between Flickr and the online PPGIS survey and declined slightly with increasing distance. One exception was the value type *scenic/aesthetic* mapped through Flickr which was predicted to occur immediately adjacent to the coast, then decreased, and then increased with increasing distance (Figure 3.10) and was reflected in the predictive map showing the potential distribution (Figure 3.6a).

Distance from major towns was also an important driver in terrestrial models for half of the value types mapped through the online PPGIS survey and for half of the value types mapped through Flickr in marine models, with values likely to occur within 10 km of a major town (Table 3.5 and 3.6; Figures 3.11 to 3.13). Major towns may provide a source of access or could indicate the occurrence of values is related to the size of the nearby population and the visitors that holds these values. Distance from coastal access points was also important for value types mapped through the online PPGIS survey in marine models whereas it was mainly important in terrestrial models for Flickr, with values more likely to occur within ~30 km of coastal access features.

Despite some disagreements in socio-ecological drivers, there were some consistencies between models performed for both methods which were reflected in Figures 3.6 to 3.9. There was at least one important variable that was common to all value types modelled for marine and terrestrial environment mapped through both methods, with only three exceptions for marine models; *European culture/heritage*, *recreation* and *fishing (recreational)* (Table 3.6). The environmental variable distance inland was an important driver for all value types in terrestrial models for the online PPGIS survey and was also important for most value types mapped through Flickr (Table 3.5). For both methods, value types were more likely to occur within 5 km inland from the coast (Figures 3.10 to 3.13).

Further points of commonalities was the value type *scenic/aesthetic* that was found to have an important association with distance from waterfalls and coastal geomorphology in terrestrial models and distance seawards in marine models for both Flickr and the online PPGIS survey (Figure 3.10); *nature appreciation* was found to have an important association with distance from waterfalls for terrestrial models and distance seawards for marine models (Figure 3.11); *nature-based tourism* an important association with distance from waterfalls for terrestrial models and distance from coastal access for marine models (Figure 3.12); and *recreation* an important association with distance from waterfalls for terrestrial models (Figure 3.13).

Similarly, values types mapped through both methods for terrestrial models were commonly influenced by the environmental variable distance to waterfalls (Figures 3.10 to 3.13). The modelled relationships showed a similar pattern of occurrence with the likelihood of values increasing slightly until ~300 km from a waterfall. Given these long distances, the waterfalls themselves were unlikely to drive the occurrences, rather it was likely co-occurring with another socio-ecological variable. Coastal geomorphology revealed all geomorphology types to be similarly important for *scenic/aesthetic* mapped through Flickr and the online PPGIS survey (Figure 3.10). The pattern of occurrence was also similar for distance from coastal access for the value type *nature-based tourism* mapped through both methods, with values more likely to occur within ~30 km from coastal access features and subsequently declining (Figure 3.12).

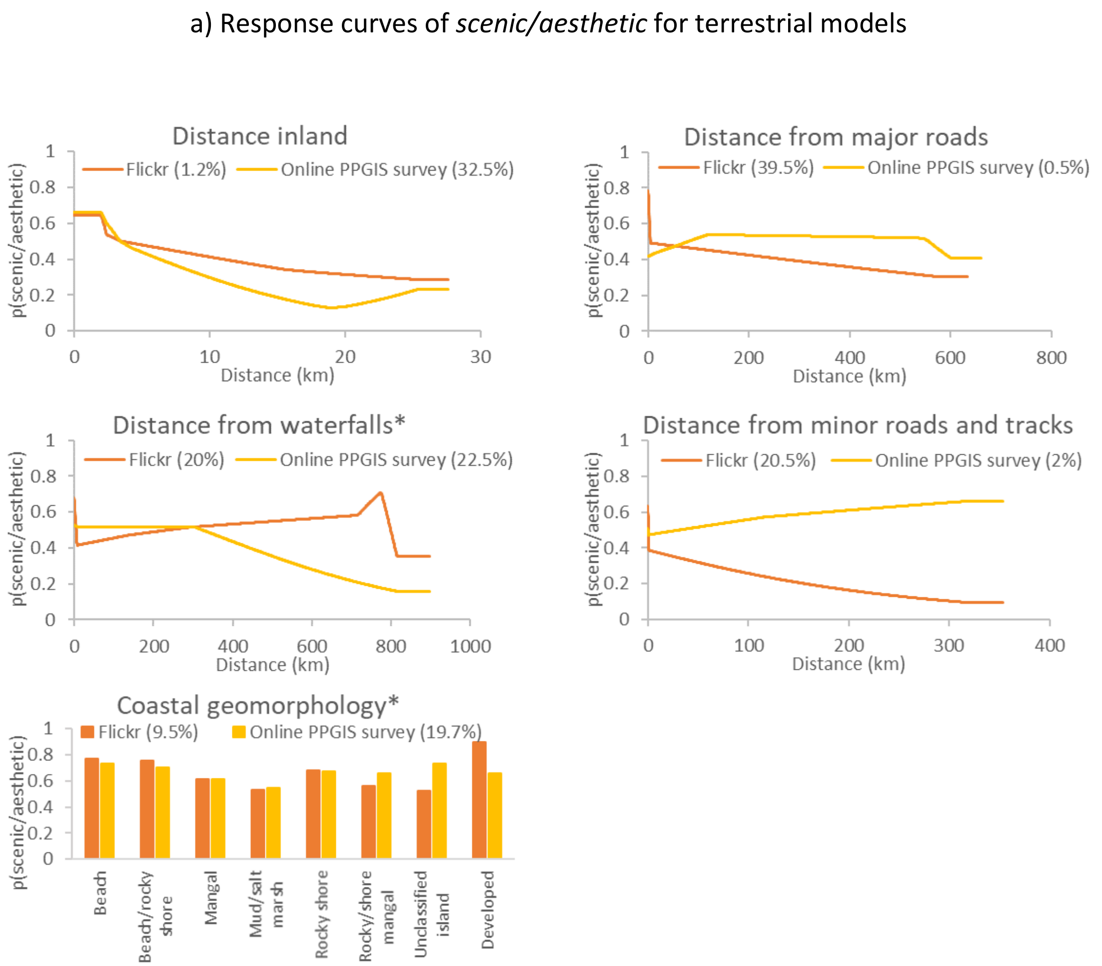
The associations with socio-ecological drivers illustrated with response curves suggests that values mapped through Flickr were more specialised in distribution. This was reflected in the model performance for Flickr being generally better than PPGIS, and the associations with socio-ecological drivers generally restricted within the close vicinity of features. In contrast, the lower model performance for the online PPGIS survey, that values types were not necessarily restricted to certain socio-ecological drivers and that the associations with socio-ecological drivers was suitable at greater distances from features, suggests that the online PPGIS survey follows a more generalised distribution.

Table 3.5. Importance of each socio-ecological driver to value types for terrestrial Maxent models for Flickr (F) and the online PPGIS survey (OS) expressed in percentage. Variable importances greater than average (6.7%) are bolded and variables with 0% importance in all models are not included.

	Scenic/ aesthetic		***Aboriginal culture/ heritage***		***European culture/ heritage***		***Learning/ research***		***Spiritual***		***Recreation***		***Fishing (recreational)***		***Economic (non-tourism)***		***Nature-based tourism***		***Nature appreciation***	
Variables	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**
Environmental																				
Distance inland	1.2	**32.5**	2.7	**36**	**24.7**	**34.6**	**7.4**	**40.1**	0.2	**19.5**	1.1	**32.3**	1.7	**41.7**	2.5	**14.2**	0.9	**44.2**	2.2	**52.9**
Distance from waterbodies	0	1.7	0.1	0.2	1	0.5	0	0.3	0.3	1.1	0.2	0.6	0	1.7	0.8	**7.6**	0.6	0.8	2.3	0.3
Topographic rugosity	2.1	0.1	1.9	0.6	1.4	**9.1**	0	1.3	2	4.1	0.6	4.3	0	0.3	0	5.1	1.3	0.4	2	0.5
Vegetation diversity	0.6	1	1.9	0.7	0.5	1.6	0.5	1.2	1.8	1.4	0.4	2.4	2	2.2	0.1	4.4	0.4	0.4	1.3	0.2
Distance from geological features	0.7	6.1	**13.4**	4	3.9	2.4	0.1	2.2	0.8	1.7	2.8	2.6	1.3	2.2	0.2	1.2	0.8	1.3	0.3	0.4
Distance from waterfalls	**20**	**22.5**	**26.6**	**26**	**13.5**	3.5	**15.8**	**12.7**	**13.4**	**46.2**	**17.9**	**13**	5.5	**10.6**	1.1	1.4	**35.1**	**18.7**	**9.5**	**18.8**
Coastal geomorphology	**9.5**	**19.7**	**14.1**	1.7	5.3	1.3	0	0.9	0.1	5.1	5.9	**7.8**	**12.9**	**9.1**	0.4	5	4.9	3.3	5.5	6
Infrastructure																				
Distance from major roads	**39.5**	0.5	1.6	3.9	0.1	1.5	**7.5**	0.7	0	**6.7**	**32.2**	1.3	**24.8**	**11.2**	**70.3**	**24.7**	**22.9**	4.3	**42.1**	1.3
Distance from minor roads and tracks	**20.5**	2	**20**	**10.3**	**25.8**	**16.6**	**25.8**	**9.7**	**55.6**	3.8	**37.5**	**8.9**	**23.5**	3.4	**16.9**	**19.7**	**17.6**	1	**30.6**	2.1
Distance from major towns	3.6	3.2	4.4	2.6	0.1	4.6	1	**13.8**	5.7	4.4	0.4	**17.6**	**28.3**	**14**	2.9	**7**	0.6	**10.4**	2.4	**6.9**
Distance from coastal access	1.4	5.3	**13.1**	4.8	**20.8**	**23.9**	**41.9**	1.9	**17.3**	2.1	0.2	2.4	0	0.8	4.2	**6.7**	**14.3**	5	1.2	0.5
Management																				
Terrestrial protected areas	0.2	4.1	0	6	2.5	0.1	0	**7.6**	1.2	2	0.4	4.4	0	1.2	0.3	0.3	0.3	**8.9**	0.3	**9.3**
Indigenous protected areas	0.7	1.3	0.2	3.2	0.5	0.1	0	**7.5**	1.7	1.9	0.5	2.5	0	1.5	0.1	2.7	0.2	1.2	0.3	0.9

Table 3.6. Importance of each socio-ecological driver to value types for marine Maxent models for Flickr (F) and the online PPGIS survey (OS) expressed in percentage. Variable importances greater than average (6.7%) are bolded and variables with 0% importance in all models are not included. NA indicates that no value points occurred within the marine environment for *European culture/heritage* mapped through Flickr.

	Scenic/ aesthetic		***Aboriginal culture/ heritage***		***European culture/ heritage***		***Learning/ research***		***Spiritual***		***Recreation***		***Fishing (recreational)***		***Economic (non-tourism)***		***Nature-based tourism***		***Nature appreciation***	
Variables	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**	**F**	**OS**
Environmental																				
Distance seawards	**27.3**	**89.2**	**44**	**87**	NA	**53.1**	**97.5**	**76.5**	**96**	**79**	2.3	**87.2**	5.7	**91.2**	0.9	**63.4**	5.2	**71.7**	**73.6**	**84.3**
Topographic rugosity	0.3	0	**52.8**	0	NA	0.8	0.1	0.9	3.5	0.7	0.1	0	0.1	0	0	0.4	0.3	0	0.1	0
Vegetation diversity	0	0	1.6	0	NA	0.2	0.2	0	0.1	0.3	0	0.1	0	0	0	0.1	0.2	0	0.2	0
Distance from waterfalls	4.6	1.9	1.6	3.7	NA	**7.9**	0	2.7	0.3	**7**	3.2	1.7	0.4	0.7	0	3.8	**9**	5.8	0.5	1.1
Coastal geomorphology	**37**	0.2	0	0.6	NA	1.2	0	0.3	0	0.2	**50.2**	0.1	**45**	0.1	0.1	1.2	**43.2**	0.1	5.8	0.2
Infrastructure																				
Distance from major towns	**20.9**	1.5	0	1.8	NA	5.8	0.5	**14.5**	0	**10.2**	**43.1**	1	**37.8**	2.1	**15.4**	**9.3**	5.5	6.5	**12.3**	2.1
Distance from coastal access	**9.4**	4	0	**6.8**	NA	**29.6**	0.5	0.4	0.1	2.1	0.6	**8.2**	0	3.8	**54.3**	**19.8**	**36.5**	**9.5**	3.7	6.2
Management																				
Marine protected areas	0.3	3.2	0	0	NA	1.4	1.1	4.6	0	0	0.1	1.6	0.3	2	**29.3**	1.9	0	6.3	3.8	6
Terrestrial protected areas	0.1	0	0	0	NA	0	0	0	0	0.1	0.2	0.1	**10.5**	0	0	0	0	0	0	0
Indigenous protected areas	0.1	0	0	0	NA	0	0	0	0	0.4	0.2	0	0.2	0	0	0	0	0	0	0



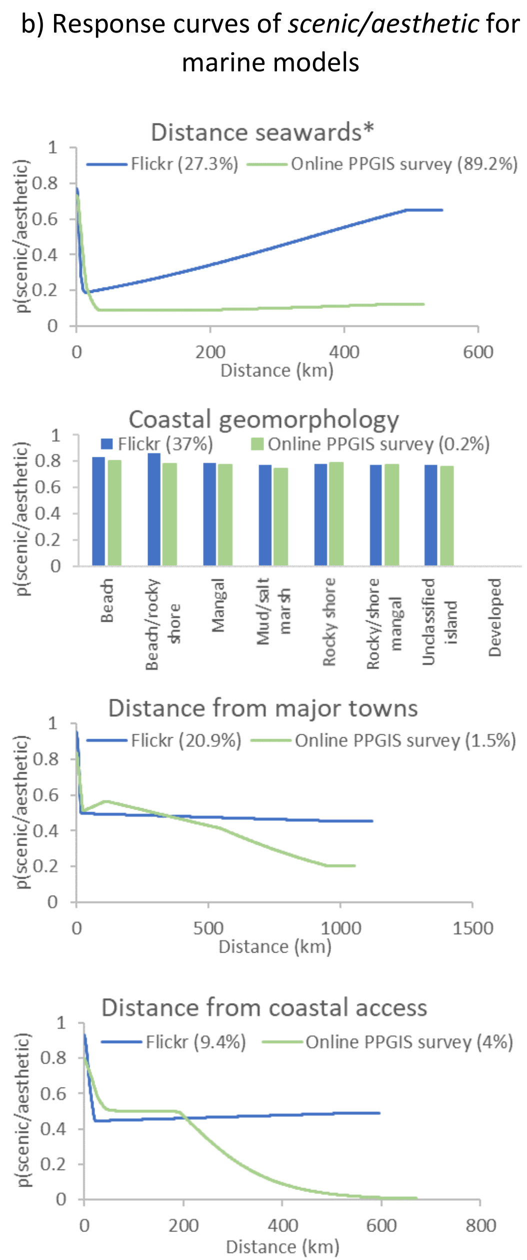


Figure 3.10. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *scenic/aesthetic* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above average in importance for both Flickr and the online PPGIS survey.

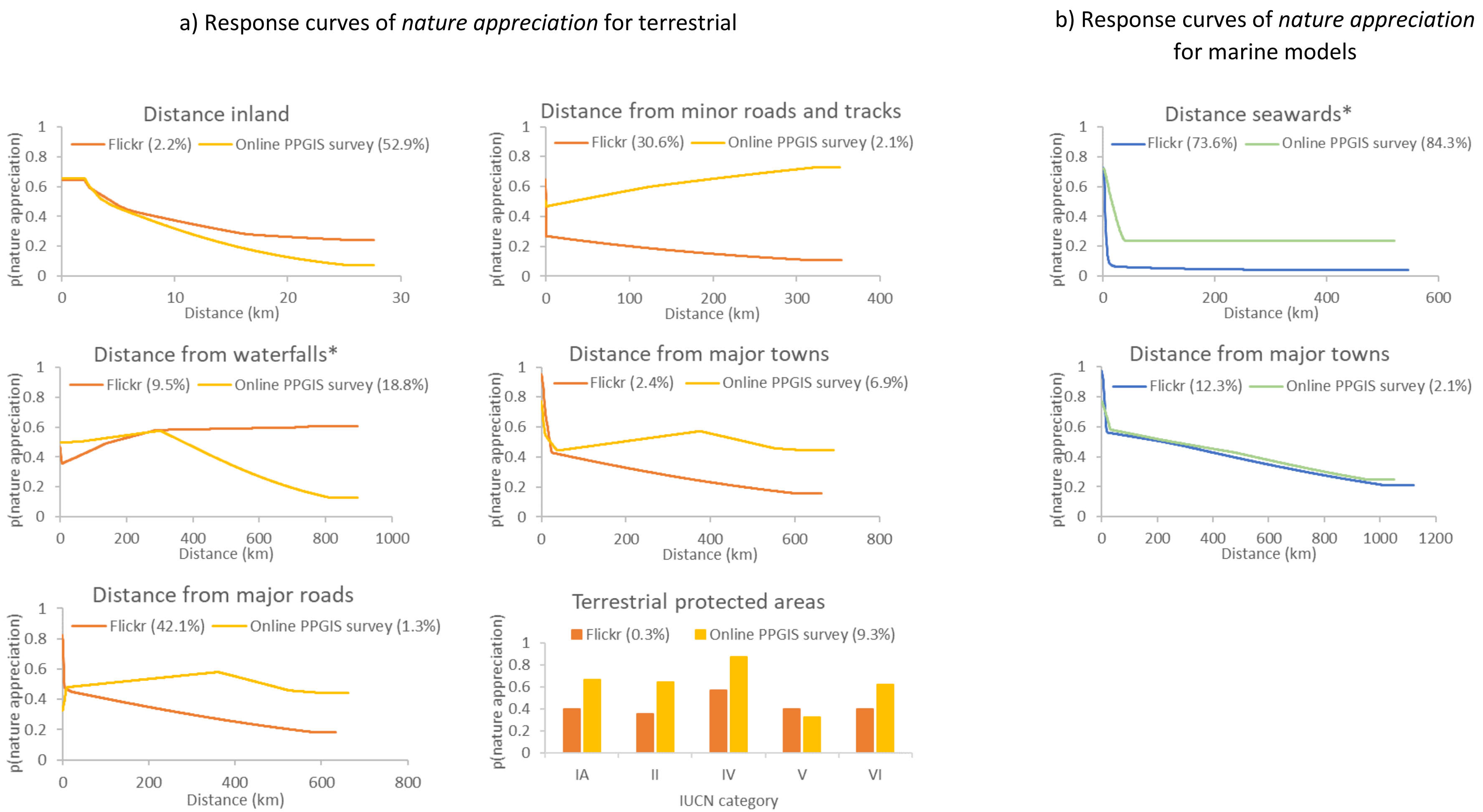
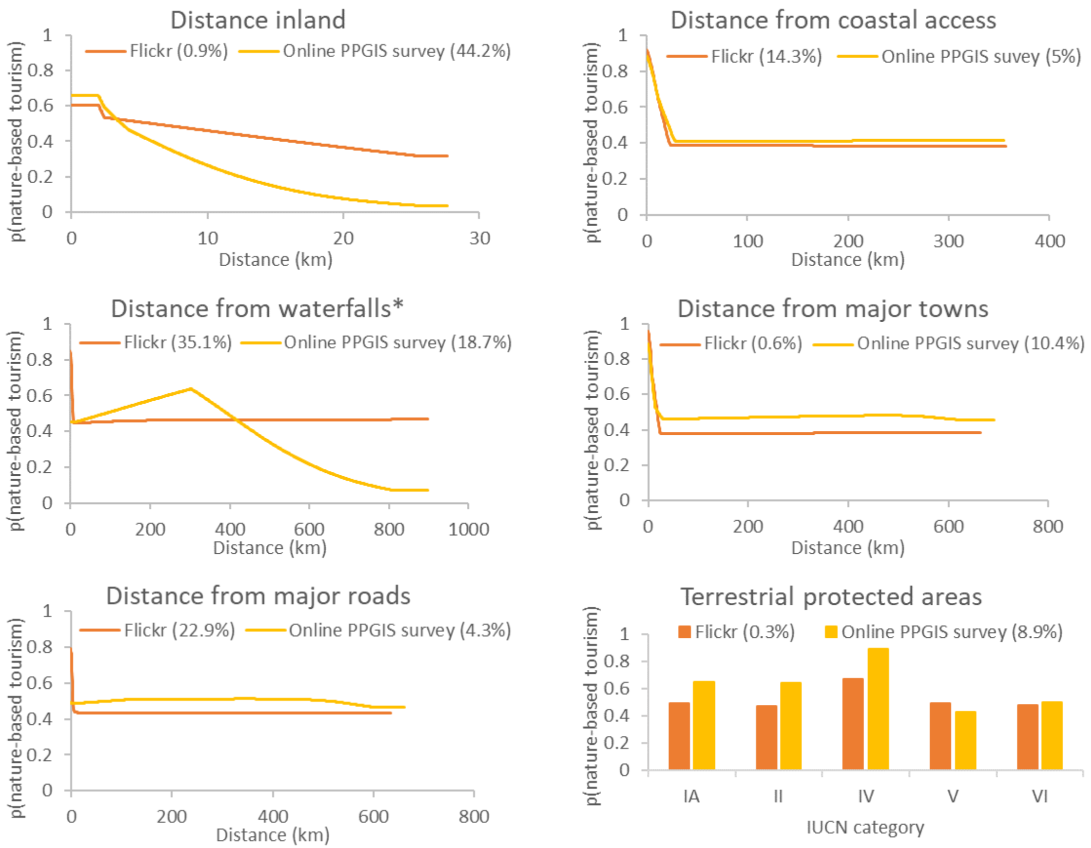
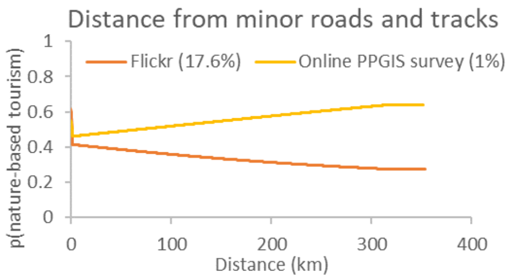


Figure 3.11. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *nature appreciation* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above average in importance for both Flickr and the online PPGIS survey.

a) Response curves of *nature-based tourism* for terrestrial models





b) Response curves of *nature-based tourism* for marine models

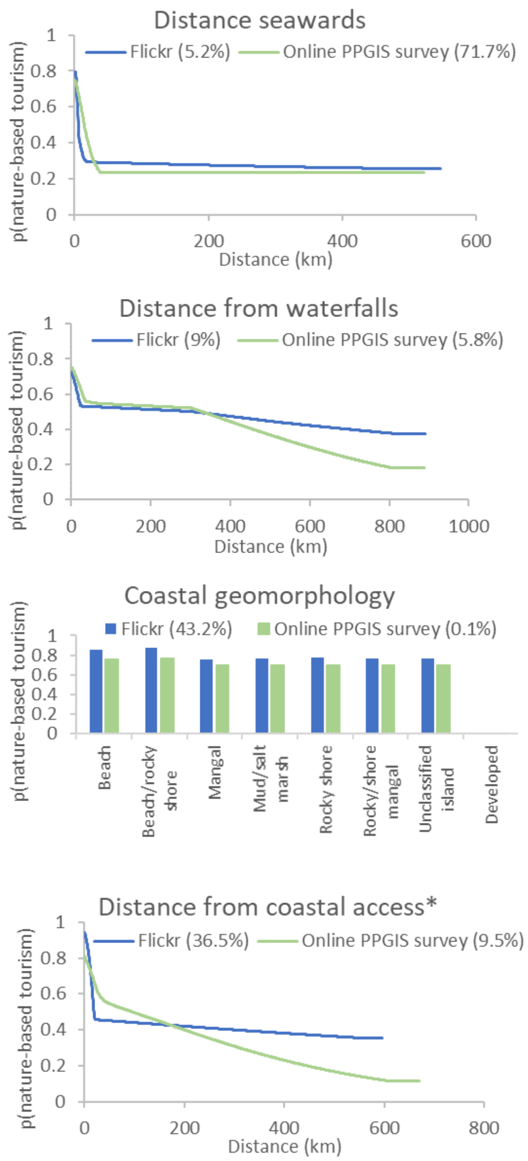
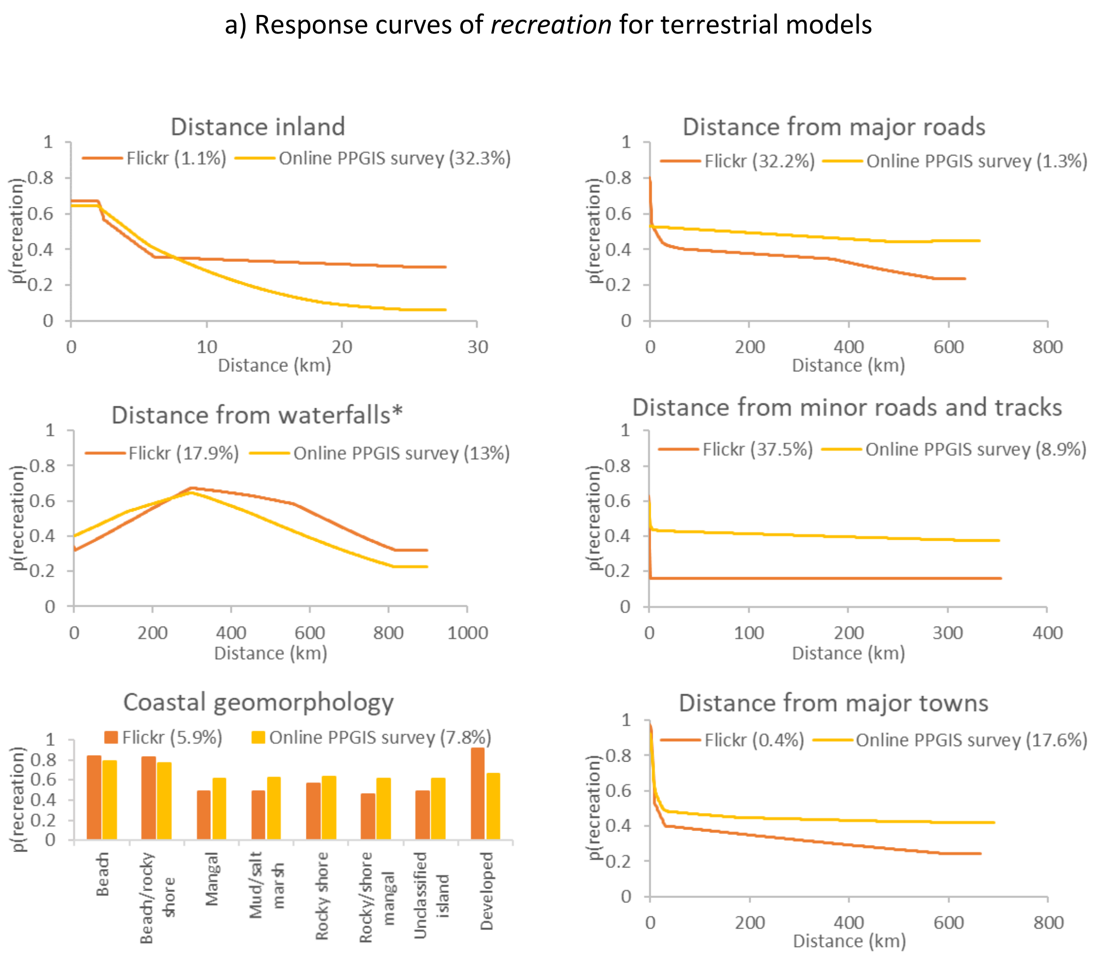


Figure 3.12. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *nature-based tourism* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above average in importance for both Flickr and the online PPGIS survey.



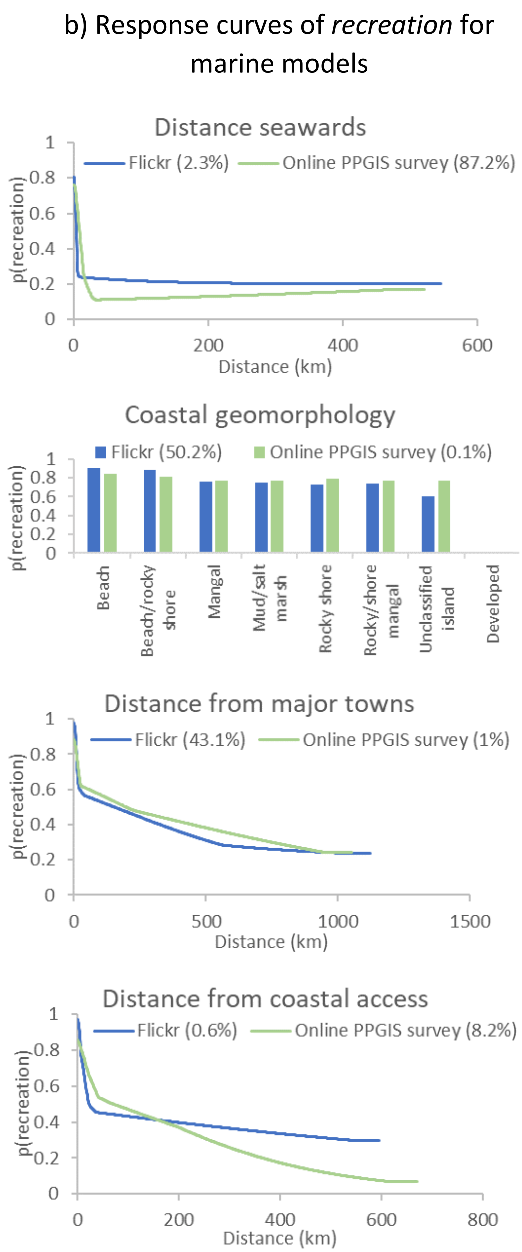


Figure 3.13. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *recreation* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above

4. Discussion

This study retrieved, validated and classified geotagged Flickr photographs to evaluate whether values identified from Flickr can provide reinforcing and complementary perspectives to values mapped through PPGIS. Statistical analyses were used to compare the relative abundance of value types. Spatial analyses were employed to identify hotspots, to investigate the socio-ecological associations, and to generate predictive maps of the potential distribution of value types. There were significant differences in the relative abundance of value types between Flickr and PPGIS and locations of relative hotspots. The potential distributions of value types and their associations with socio-ecological variables modelled by Maxent showed substantial differences between Flickr and PPGIS. However, there was some overlap in the areas predicted suitable for value types to occur mapped through Flickr and the online PPGIS survey, as well as associations with socio-ecological drivers that were common to both methods. Therefore, value types derived and mapped from geotagged Flickr photographs provide different, but complementary perspectives to the value types mapped through PPGIS.

4.1. Geotagged Flickr photographs

This study demonstrates that geotagged Flickr photographs can provide insight into social values for remote areas and coastal and marine environments. The number of geotagged photographs retrieved from Flickr was surprisingly high given the remoteness of the region and the study area largely encompassing the marine environment. This number was considerable compared to the numbers obtained in previous studies of remote regions (Rossi et al., 2020) and coastal and marine environments (Clemente et al., 2019; Retka et al., 2019; Richards & Friess, 2015). However, this discrepancy may be attributed to the large size of the study area.

Individual Flickr users contributed relatively few photographs, but there was a bias towards highly active users. The median number of photographs retrieved per user was three, yet almost a quarter of the retrieved photographs were shared by 7 of 406 users. This reinforces that social media may be biased towards a small number of highly active users (Tieskens et al., 2018; Yoshimura & Hiura, 2017). PPGIS also suffers from this potential bias (Brown, 2017). Precautions can be used to mitigate this, such as limiting the number of photographs retrieved per Flickr user, or limiting the number of polygons or point markers mapped per PPGIS participant. Due to the remoteness of the Kimberley and the number of Flickr users who contributed photographs, this approach would have considerably reduced the number of available photographs. As the distribution of photographs from the seven highly active Flickr users did not appear spatially biased or biased by value type, they were unlikely to distort any conclusions. Therefore, no limit was applied, and all retrieved photographs were retained.

4.2. Temporal information

Despite Flickr being launched in 2004, retrieved photographs were distributed across a 58-year timeline. Photographs were primarily taken within the last ten years, with over 90% taken between 2011 and 2019. Previous studies that have used Flickr for content analysis to identify values typically restricted photographs to be retrieved from 2010 or later (e.g. Clemente et al., 2019; Retka et al., 2019; Rossi et al., 2020; Tenerelli et al., 2016). Whilst no restriction was applied to this study, this was unlikely to influence the results given the predominance of photographs taken since 2010. By not restricting the period of retrieved photographs, the temporal extent of photographs taken within the study area could be identified. However, there are possible errors in the photograph date embedded in the metadata which may introduce uncertainty. Sources of uncertainty emerge from the device used to take the photograph, such as a camera for which the date may be set incorrectly, or from Flickr users manually entering the date when uploading their photographs. Therefore, the validity of these dates should be considered when interpreting the results.

Photographs were primarily taken in the months of peak visitation during the dry season. This result was expected due to the wet season limiting access to most of the Kimberley region. This finding reaffirms the potential of geotagged photographs to evaluate visitor movement and patterns of visitation (Levin et al., 2015; Tenkanen et al., 2017; Wood et al., 2013) and emphasises that geotagged photographs can be both spatially and temporally explicit (Levin et al., 2017; Walden-Schreiner et al., 2018).

The temporal information embedded in the metadata of geotagged Flickr photographs represents the direct experience of a value at a particular place and time (Retka et al., 2019). In contrast, PPGIS provides a different source of temporal information that may not necessarily provide the changes in value types over lengthy periods or correspond to actual visitation patterns. For example, interview PPGIS can be re-run in different seasons and years to gather temporal data, and online PPGIS surveys can be open for extended periods with a time stamp recorded for every marker placed. However, temporal information is readily available for most geotagged photographs and can be obtained in a timely manner to provide complementary data to supplement the temporal information of PPGIS.

4.3. Relative abundance of value types between Flickr and PPGIS

The data gathered through content analysis of geotagged photographs provided information about where and when photographs were taken and an insight into what people valued about the natural environment. The data gathered through PPGIS can also provide this information through drawn polygons and interviews with participants (interview PPGIS) and by markers representing value types placed through a digital mapping interface (online PPGIS survey). However, the relative abundance of value types derived from the content of geotagged photographs was significantly different from both methods of PPGIS. This difference was evident in the relative abundance of almost all value types represented in Flickr photographs compared to the value types represented in PPGIS, as revealed by the standardised residuals.

Photographs were highly skewed towards the value type *scenic/aesthetic*, consistent with findings from similar studies (Clemente et al., 2019; Figueroa-Alfaro, 2017; Martínez Pastur et al., 2016; Muñoz et al., 2020; Retka et al., 2019). The motivation behind why people take photographs is not well understood for social media users (Zhang et al., 2020) but it is suggested that people are more likely to take photographs of features they find visually appealing (Figueroa-Alfaro, 2017; Yoshimura & Hiura, 2017). Photographs also strongly represented the value types of *nature appreciation*, *nature-based tourism* and *recreation*. Similarly, *scenic/aesthetic* and *nature appreciation* were highly valued by PPGIS. However, the value type *scenic/aesthetic* was more than twice as abundant for Flickr than PPGIS, further indicating the potential bias that Flickr users tend to take photographs of landscapes or attractive scenery. The difference in relative abundance for *nature appreciation* was not as extreme. Notably, this was the only value type that did not reveal a significant standardised residual (i.e. large difference in the observed and expected count) for Flickr compared to interview PPGIS, or for both Flickr and the online PPGIS survey when compared.

Photographs depicting *scenic/aesthetic*, *recreation* and *nature appreciation* have typically been the most identified value types using content analysis in prior studies (Clemente et al., 2019; Martínez Pastur et al., 2016; Muñoz et al., 2020; Oteros-Rozas et al., 2018; Retka et al., 2019; Richards & Friess, 2015). The value type *nature-based tourism* was identified as highly valued within the content of photographs retrieved for the study area. *Nature-based tourism*, however, has scarcely been identified in previous studies using content analysis (e.g. Hausmann et al., 2018) despite the locations of geotagged photographs demonstrated to be a suitable proxy for *nature-based tourism* (Kim et al., 2019; Wood et al., 2013). However, this may simply be due to the definition of *nature-based tourism* in the ruleset used to classify photographs. Due to the prevalence of nature-based tourism activities in the Kimberley region, *nature-based tourism* was an independent category, but it can overlap with other value types such as *recreation*. This suggests previous studies may have not explicitly used the value type *nature-based tourism*, they may have accounted for this value within other value types such as *recreation*.

In contrast, some value types such as *economic (non-tourism)* and *fishing (recreational)* were easy to identify from photographs but were either not frequently photographed or not common within the study area. However, the latter is unlikely given the relative abundance of the value type *fishing (recreational)* for both methods of PPGIS, which indicated this to be highly valued within the study area. A study by Beckley (2015) also reported recreational fishing to be a popular activity along parts of the Kimberley coastline, such as Eighty Mile Beach. This suggests that *fishing (recreational)* was not frequently photographed by Flickr users. This is further supported in a study by Tonge et al. (2013), which reported that marine-based activities, such as fishing, were less likely to be captured by photographs compared to land-based activities. This study proposed the disparity may be due to the type of camera used to take photographs as marine-based activities may require a waterproof camera (Tonge et al., 2013). Within the present study, the standardised residuals revealed *fishing (recreational)* to be one of the largest contributors to the significant difference between Flickr and both methods of PPGIS. This further supports the concept that recreational fishing may be highly valued in the Kimberley region, but may not be accurately evaluated through photographs. Similar to the value type *fishing (recreational)*, *economic (non-tourism)* was infrequently photographed by Flickr users. Photographs publicly shared to social media platforms are likely to represent only certain aspects of people's lives (Cover, 2016). They are unlikely to be objective and representative of everything that Flickr users see or value in everyday life, or of the true occurrence of value types within the study area.

Other value types were not as easy to identify in the content of geotagged photographs and were inherently under-represented, such as *spiritual* and *culture/heritage*, likely due to the inability of photographs to relate these value types with the environment (Richards & Friess, 2015). These findings substantiate that Flickr users are more likely to take photographs representing specific types of values and the photographs themselves are limited in their ability to represent certain value types (Retka et al., 2019; Richards & Friess, 2015). Moreover, content analysis of photographs can introduce interpretation bias when classifying value types (Richards & Friess, 2015; Zhang et al., 2020). To minimise the bias of interpretation, a detailed ruleset was developed (Oteros-Rozas et al., 2018; Richards & Friess, 2015; Tenerelli, 2016). The ruleset was applied by several independent analysts to refine it for ambiguities, remove the potential for inconsistencies and individual-level biases.

The set of value types employed in this study was adapted from previous studies and specifically reflected values of stakeholders associated to coastal and marine environments of the Kimberley region (Spencer-Cotton, 2016; Strickland-Munro et al., 2015, 2016b, 2016c). It was only possible to detect ten types of values in the photographs compared to the 15 identified through interview PPGIS and 14 mapped through the online PPGIS survey. The additional value types not interpreted from Flickr were *therapeutic*, *social interaction and memories*, *experiential*, *subsistence*, *bequest* and *existence* for interview PPGIS, and *life sustaining*, *therapeutic/health*, *intrinsic/existence* and *wilderness/pristine* for the online PPGIS survey. These value types relate to the feelings and memories people associate with places. Therefore, these value types were unable to be interpreted from the content of Flickr photographs as they did not relate with the environment (Richards & Friess, 2015).

To ensure consistency between methods, one or more value type was assigned to each photograph. More than one value type was often assigned to polygons mapped through interview PPGIS, and there were no limitations to the number or proximity of value type makers mapped through the online PPGIS survey. This was inconsistent with previous studies employing content analysis to identify values that assigned only one value type per photograph (e.g. Richards & Friess, 2015; Muñoz et al., 2020). This, however, enabled real-world co-occurrence of value types to be established, rather than forcing only a single value. There were sets of value types that typically co-occurred in the same photograph. For example, *scenic/aesthetic* tended to co-occur with *nature-appreciation* due to the abundance of photographs taken of sunrises or sunsets over mangroves and may explain why some value types were more abundant than others.

4.4. Spatial patterns

Kernel density analyses revealed distinct differences in the relative hotspots of value types mapped through Flickr compared to the online PPGIS survey. The relative hotspots of value types mapped through Flickr reflected places people visited within the study area. Flickr users tended to take photographs representing values at popular tourism destinations that are easy to access (Antoniou et al., 2010; Li et al., 2013), unlike participants of the online PPGIS survey who were able to map values of inaccessible, yet familiar or known places. This was reflected in the relative hotspots for value types mapped though PPGIS occurring along most of the coastline, rather than at discrete locations.

Consistent with the relative hotspots of value types mapped through Flickr compared to the online PPGIS survey, Antoniou et al. (2010) found that geotagged photographs tended to cover a small percentage of the area and were confined near developed areas and popular tourist attractions. The relative hotspots mapped through Flickr therefore represent hotspots of actual visitation (Levin et al., 2017; Li et al., 2013; Retka et al., 2019). This likely resulted in places potentially not being photographed as Flickr users are limited to where they can visit, hence the scarcity of relative hotspots distributed across the entire study area. For example, relative hotpots mapped through Flickr were scarce in the northern Kimberley where access is limited compared to the online PPGIS survey where relative hotspots extended to this part of the region. The drivers behind the occurrence of value points based on the two data sources independently were further explored using Maxent and are discussed in the next section.

4.5. Associations with socio-ecological drivers

Whilst kernel density analyses were used to describe the relative hotspots of value types mapped through Flickr and the online PPGIS survey, the spatial predictions from Maxent described the potential distribution of values and associations with socio-ecological drivers. This supports the understanding of where value types will potentially occur within the study area based on the association with socio-ecological drivers. This type of knowledge is useful to relate values with the environment for sustainable management of resources and services.

The importance of accessibility for value types mapped through Flickr was reflected in the associations with infrastructure variables. Distance from minor roads and tracks, major roads, and coastal access were major drivers determining the occurrence of most values types mapped through Flickr. This finding was congruent with previous studies (Clemente et al., 2019; Muñoz et al., 2020; Richards & Friess, 2015) and is indicative that for places to be photographed and valued by Flickr users, they need to be accessible. The limited potential distribution of value types in the northern Kimberley can be attributed to these areas being largely remote due to the lack of access. It can also be attributed to much of the Kimberley region comprising of Indigenous country where access is restricted. People seeking to visit these areas, including both individuals and tourism operators, require permission from traditional owners (Kimberley Land Council, 2004; Scherrer & Doohan, 2011; Smith et al., 2009). This restriction may explain why Indigenous protected areas were revealed to be an unimportant driver to the distribution of value types but this result should not undermine the importance of these areas. In contrast, value types mapped through the online PPGIS survey were less reliant on accessibility as a driver to determine the occurrence of values (Brown, 2013; Brown & Brabyn, 2012). Rather the familiarity of the participant to the study area is the key determinant to where values are mapped (Brown & Kyttä, 2014; Levin et al., 2017). This was reflected in the actual and potential distribution of value types mapped through the online PPGIS survey extending into the northern Kimberley and shows that despite the lack of value types mapped through Flickr, this part of region is still highly valued.

Despite some differences, there was some overlap in the areas predicted suitable for value types to occur which was influenced by the somewhat consistent response curves of socio-ecological driver variables. Value types mapped through both methods were predicted to occur close to the coastline. This finding was consistent with previous studies and supports that value types identified by both methods are strongly related to proximity to the coast, as in other coastal regions worldwide (Clemente et al., 2019; Retka et al., 2019). Value types mapped through both methods were also predicted to occur near the major towns of Broome and Derby. Infrastructure, and specifically developed areas, have been demonstrated to be an important driver to the occurrence of values for both Flickr and PPGIS (Brown et al., 2012; Oteros-Rozas et al., 2018) which was also reflected in the relative hotspots of mapped value types. For value types mapped through Flickr, these areas are not only popular tourism destinations but serve as a hub for which people can travel from. Similarly, for value types mapped through the online PPGIS survey, some areas are well-known and were therefore more likely to be mapped.

Previous studies modelling the distribution of specialist and generalist biological species found that specialist species tended to be modelled more accurately (Evangelista et al., 2008; Tsoar et al., 2007). Specialist species are typically restricted to narrow niches and therefore the potential distribution of the species is easier to predict, whereas generalist species are less predictable as they are not reliant on the proximity to certain environmental characteristics (Evangelista et al., 2008; Franklin, 2010; Tsoar et al., 2007). Although the AUC values from models performed using data from Flickr and the online PPGIS survey cannot be directly compared because they were evaluated using different background points (Lobo et al., 2008), the higher AUC values obtained from models developed for value types mapped through Flickr suggest that Flickr followed a more specialised distribution. This was reflected in the associations with socio-ecological drivers, with value types mapped through Flickr typically restricted near features, such as minor roads and tracks, suggesting a narrow breadth of suitable conditions in which value types were predicted to occur. In contrast, value types mapped through the online PPGIS survey were modelled less accurately and showed a wider niche compared to values mapped through Flickr, suggesting the online PPGIS survey followed a more generalist distribution.

Maxent models have proven useful to describe the potential occurrence of value types and associations with socio-ecological drivers even when data is limited (Sherrouse et al., 2011). Maxent can form spatial predictions from a small number of occurrences (Phillips & Dudík, 2006) providing a useful tool for remote and coastal and marine environments. Maxent can also predict the future distribution of values (e.g. Elith et al., 2010). For example, with the current development of a sealed road (i.e. a major road) to connect Broome to Cape Leveque at the top of the Dampier Peninsula (Main Roads Western Australia, 2020), Maxent models could be performed to predict the future distribution of value types given the ease of access this infrastructure would provide once established. As this would likely influence a specific area, models could be performed at a finer resolution looking only at the Dampier Peninsula (e.g. Richards & Friess, 2015). The output from these models would likely provide different information for the two sources of occurrence data about values due to major roads influencing most value types mapped through Flickr but influencing only three value types mapped through the online PPGIS survey. Predictive maps generated from the Maxent output would likely show the potential distribution of almost all value types mapped through Flickr to increase near the road and at the top of the Dampier Peninsula due to the road facilitating access and likely linking to minor roads and tracks in this region. In contrast, predictive maps for value types mapped through the online PPGIS survey would be unlikely to change for most value types due to infrastructure influencing only a few value types. This would then support different inferences that the places valued by Flickr users in the Dampier Peninsula will likely increase yet remain relatively unchanged but still valued for the online PPGIS survey and is an example of the different but complementary information these methods can provide. This highlights that the use of spatial modelling techniques such as Maxent can provide a tool for integrated management. By predicting the occurrence of value types and drivers that influence this distribution, targeted management can be applied.

Models were performed separately for marine and terrestrial parts of the study area. Maxent has been found to perform well for both environments (Elith & Leathwick, 2009), however, there was no clear template to performing and evaluating models for this study area spanning both marine and terrestrial environments. For the most part, biological species are typically constrained to marine or terrestrial environments so previous studies were understandably restricted to one or the other. Although human values can occur in either environment, in practice it is hard to develop combined models because the socio-ecological drivers can be quite different between the two and not all drivers can feasibly be applied to both environments. Therefore, there were implications for some of the modelling choices, namely the selection, inclusion and resolution of socio-ecological variables. Models were performed including all socio-ecological variables for both environments. Points were evaluated as being terrestrial or marine at a coarse resolution (2 km), which may not have the necessary precision to accurately determine whether a point occurred on land or in the ocean. This caused some terrestrial drivers to be identified as important for the marine environment. For future analyses, it is recommended that models should be performed including only the predictor variables considered to belong to that environment and at a finer resolution (e.g. Richards & Friess, 2015). This would increase the precision to determine the environment a point occurred in, and to ensure the associations with drivers specific to terrestrial and marine parts are accurately modelled.

Another consideration of the modelling choices was the removal of socio-ecological variables. Variables were removed due to intercorrelations with other variables that were considered more important to predict the occurrences of values. The variable 'distance from human settlements' was removed due to intercorrelations with 'distance from aircraft facilities', 'distance from coastal access' and 'distance seawards', however given the relative hotspots near Kalumburu, a small settlement in the northern Kimberley identified in Figure 3.5, this variable may have been valuable. The choice to remove the other variables, 'distance from aircraft facilities' and 'distance from roadhouses', was deemed more appropriate as these were unlikely to provide additional information to the variables included in the models.

Lastly, geotagged Flickr photographs typically occurred near accessible locations. Of the known studies that used Maxent to model the spatial distributions of values, none have accounted for this potential bias (e.g. Clemente et al., 2019; Richards & Friess, 2015; Yoshimura & Hiura, 2017). Accessibility was considered as representing a type of bias in this study which could hinder the ability to understand the predicted distributions of value types more generally. Therefore, kernel density layers were generated to mimic the bias in the occurrence data of value types mapped through Flickr and the online PPGIS survey. Although Flickr is more likely to be a biased source of data for values than the online PPGIS survey due to the differences in how they collect data, for consistency, bias layers were developed for both methods. Compared to preliminary analyses, the explicit consideration of bias enabled models to be interpreted as if they were produced with unbiased data (Phillips et al., 2009) and is important for practice. For example, important variables differed slightly between models performed with and without considering bias for value types mapped through Flickr and the online PPGIS survey. The importance of variables increased for some infrastructure variables for value types mapped through Flickr when bias was considered, namely distance from minor roads and tracks and major roads. Contrary, the importance of the environmental variables distance inland and seawards from the coastline decreased when considering bias, enabling associations with other socio-ecological variables to be revealed. This indicated models without considering bias were likely to incorrectly predict the distribution of value types and associations with socio-ecological drivers (Fourcade et al., 2014; Kramer-Schadt et al., 2013). It is important that the information provided by these models are correct to inform effective planning and management as incorrect predictions could result in environmental usage to be unmanaged. Therefore, it is recommended that future studies evaluating values account for potential biases when performing models using Maxent.

4.6. Reinforcing and complementary information

The results from this study suggest value types mapped through Flickr and PPGIS can be used together to take advantage of their reinforcing and complementary information. Flickr can be used to augment the temporal information of PPGIS. Temporal data is generally available and embedded in the metadata of geotagged Flickr photographs and can be used together with PPGIS to provide timely insight to when a given value was experienced within the study area.

Flickr can be used to increase the abundance of certain value types in an assessment and provide visual insight into what people value about the environment. For example, the value type *nature appreciation* mapped through Flickr was highly valued near major towns, but what did people value? Photograph content revealed that people valued observing wildlife in the natural environment, as well as mangroves. In contrast, PPGIS enables more types of values to be represented and mapped, along with management preferences. Together, these methods represent different value types and abundance of value types that can be used to inform management. For example, if the value type *nature appreciation* mapped through Flickr and the online PPGIS survey, as well as a management preference to increase conservation and protection all occurred at the same location, this would provide a strong basis for targeted management at that location. Mapped values may also likely to be contributed by different socio-demographic groups. Socio-demographic information for Flickr users is generally unavailable due to privacy regulations (Lomborg & Bechmann, 2014; Oteros-Rozas et al., 2018) and the only known study to report on the socio-demographic characteristics of Flickr users was Li et al. (2013). This study inferred the characteristics of Flickr users by assessing photograph densities in California, USA, compared to census data. This study reported users were typically well-educated but were unable to accurately report on age or gender. An advantage of PPGIS is the ability to gather socio-demographic information from participants, such as age, gender and level of education (Brown & Kyttä, 2014). Participant characteristics generally vary between previous studies and between study areas, however previous PPGIS studies for the Kimberley region reported participants were typically older and well-educated and were relatively equivalent in gender (Brown et al., 2016; Moore et al., 2017; Munro et al., 2017; Pearce et al., 2016; Strickland-Munro et al., 2016a, 2016d). This suggests that together these methods may provide the opinion from a broader range of people and is more likely to include the 'silent majority' (Brown & Kyttä, 2014).

Flickr provides location-based data of places that are highly valued. Value types mapped through Flickr were influenced by infrastructure features and thereby were restricted near accessible locations. However, Flickr provides a useful method to easily identify high use areas that may require management (Levin et al., 2017; Retka et al., 2019). In contrast, value types mapped through the online PPGIS survey do not necessarily represent visited locations and can capture places that may be temporarily or permanently inaccessible. Together, these methods can describe places that are highly valued because they are accessible and places that are highly valued because they are meaningful to people. This was particularly evident for the northern Kimberley where geotagged photographs contributed by Flickr users were restricted in the number of photographs and value types mapped whereas the online PPGIS survey still showed this region to be highly valued. This was also evident when looking at specific places, such as Port Hedland, that was highly valued across most value types mapped through Flickr, but the opposite for the online PPGIS survey. Therefore, value types mapped through Flickr can provide a greater depth of information to the valued places mapped through the online PPGIS survey within the study area using different but complementary data and can reinforce the conclusions of PPGIS.

4.7. Future work

Future work into other popular photo-sharing social media platforms, such as Instagram and Panoramio accessible through the Google API, could be employed to increase the number of photographs with geolocated information (Tenkanen et al., 2017). Previous studies have found that certain types of values are better represented in some social media platforms compared to others (Hausmann et al., 2018; Oteros-Rozas et al., 2018; Toivonen et al., 2019). This suggests that crowdsourcing photographs across multiple platforms may be more likely to represent the true distribution and abundance of value types of the Kimberley region, further contributing to how these methods could be used for planning and management of coastal and marine environments.

To gather more information about Flickr users, future studies could evaluate whether users are residents or visitors (e.g. Antoniou et al., 2010; Muñoz et al., 2020). This knowledge can enable some level of identity to who Flickr users are and can assist with identifying and addressing potential conflict. Photograph content suggested some Flickr users may work for oil and gas companies within the region which typically involves fly-in fly-out (FIFO) work. FIFO work is common in the Kimberley region due to the availability of natural resources, such as iron ore and oil and gas. Future studies could seek to assess whether temporary residents (i.e. workers) can be identified based on the pattern of geotagged photographs taken in the Kimberley region and their typical place of residence.

Maxent has traditionally been used to model current and future distributions of biological species and is a new technique being used to model the distribution of values. To the best of my knowledge, Maxent has not been used to predict the future distribution of values. Therefore, Maxent models for future scenarios could be performed to evaluate the applicability of this approach in relation to values.

Lastly, this study was developed from an environmental management point of view and would have benefited from a social science perspective. Integration of social science into studies evaluating values is warranted to contextualise and further the understanding of how the resources and services of coastal and marine environments contribute to human well-being. This could also enable the behavior of Flickr users to be explored and understood.

5. Conclusions and implications for management

The availability of geotagged Flickr photographs will likely continue to increase (Alivand & Hochmair, 2017) along with the opportunities to use this data. The information embedded in the metadata of geotagged photographs enables data about values to be both spatially and temporally explicit. Content analysis of geotagged photographs can provide a useful method of identifying values that provides insight and understanding into what people value about the environment. The understanding of values can contribute to certain steps of planning and management processes, such as marine spatial planning. For example, in the process of stakeholder analysis, Brown et al. (2016) describe four steps. Firstly, identify stakeholders. Secondly, identify the type and quantity of values and management preferences. Thirdly, identify stakeholder preferences by place locations, and lastly, place-based integration by aggregation and weighting of stakeholder preferences. The results for Flickr found in this study can contribute to steps two and three. The data gathered from the content of geotagged photographs enabled value types to be identified and quantified for the Kimberley region. Value types mapped through geotagged photographs can also provide locational data to popular places people visit, or are likely to visit, within the study area. Therefore, geotagged photographs can prove to be a valuable data source that can enrich and expand on the value types mapped through PPGIS. Crowdsourcing geotagged photographs can also provide a more frequent and repeatable method to PPGIS to gather data about social values that are spatially and temporally explicit. Using value types mapped through Flickr together with the values mapped through PPGIS can better inform managers to the places people visit and of places that are highly valued. The use of Maxent can also enable planners and managers to integrate value types and socio-ecological drivers that can be used to predict where values are likely to occur and their associations with the environment. Therefore, planners and managers may be better equipped to sustainably plan and manage between use and preservation of coastal and marine environments.

6. References

Alivand, M., & Hochmair, H. H. (2017). Spatiotemporal analysis of photo contribution patterns to Panoramio and Flickr. *Cartography and Geographic Information Science, 44*, 170-184.

Antoniou, V., Morley, J., & Haklay, M. (2010). Web 2.0 geotagged photos: Assessing the spatial dimension of the phenomenon. *Geomatica, 64*, 99-110.

Australian Bureau of Statistics. (2020). *2016 census data*. https://quickstats.censusdata.abs.gov.au/census_services/getproduct/census/2016/quickstat/51001

Barbet-Massin, M., Jiguet, F., Albert, C. H., & Thuiller, W. (2012). Selecting pseudo-absences for species distribution models: How, where and how many? *Methods in Ecology and Evolution, 3*, 327-338.

Beckley, L. E. (Ed). (2015). *Human use patterns and impacts for coastal waters of the Kimberley.* Final Report. Kimberley Marine Research Program Node of the Western Australian Marine Science Institution. https://www.wamsi.org.au/sites/wamsi.org.au/files/files/Human%20use%20patterns%20and%20impacts%20for%20coastal%20waters%20of%20the%20Kimberley_WAMSI%20KMRP%20Report%202_1_1_Beckley%20L_E_%202015_FINAL.pdf

Bennett, N. J., Roth, R., Klain, S. C., Chan, K., Christie, P., Clark, D. A., Cullman, G., Curran, D., Durbin, T. J., Epstein, G., Greenberg, A., Nelson, M. P., Sandlos, J., Stedman, R., Teel, T. L., Thomas, R., Veríssimo, D., & Wyborn, C. (2017). Conservation social science: Understanding and integrating human dimensions to improve conservation. *Biological Conservation, 205*, 93-108.

Brocx, M., & Semeniuk, V. (2011). The global geoheritage significance of the Kimberley Coast, Western Australia. *Journal of the Royal Society of Western Australia, 94*, 57-88.

Brown, G. (2004). Mapping spatial attributes in survey research for natural resource management: Methods and applications. *Society and Natural Resources, 18*, 17-39.

Brown, G. (2013). The relationship between social values for ecosystem services and global land cover: An empirical analysis. *Ecosystem Services, 5*, 58-68.

Brown, G. (2017). A review of sampling effects and response bias in internet participatory mapping (PPGIS/PGIS/VGI). *Transactions in GIS, 21*, 39-56.

Brown, G., & Brabyn, L. (2012). The extrapolation of social landscape values to a national level in New Zealand using landscape character classification. *Applied Geography, 35*, 84-94.

Brown, G., & Kyttä, M. (2014). Key issues and research priorities for public participation GIS (PPGIS): A synthesis based on empirical research. *Applied Geography, 46*, 122-136.

Brown, G., Montag, J. M., & Lyon, K. (2012). Public participation GIS: A method for identifying ecosystem services. *Society and Natural Resources, 25*, 633-651.

Brown, G., Strickland-Munro, J., Kobryn, H., & Moore, S. A. (2016). Stakeholder analysis for marine conservation planning using public participation GIS. *Applied Geography, 67*, 77-93.

Brown, G., & Weber, D. (2011). Public participation GIS: A new method for national park planning. *Landscape and Urban Planning, 102*, 1-15.

Brown, G., & Weber, D. (2013). A place-based approach to conservation management using public participation GIS (PPGIS). *Journal of Environmental Planning and Management, 56*, 455-473.

Casalegno, S., Inger, R., DeSilvey, C., & Gaston, K. J. (2013). Spatial covariance between aesthetic value & other ecosystem services. *PLoS ONE, 8*, 1-5.

Clemente, P., Calvache, M., Antunes, P., Santos, R., Cerdeira, J. O., & Martins, M. J. (2019). Combining social media photographs and species distribution models to map cultural ecosystem services: The case of a natural park in Portugal. *Ecological Indicators, 96*, 59-68.

Collins, J. H. (2008). Marine tourism in the Kimberley region of Western Australia. *Geographical Research, 46*, 111-123.

Cover, R. (2016). *Digital identities: Creating and communication the online self.* London, UK: Elsevier.

Crain, C. M., Halpern, B. S., Beck, M. W., & Kappel, C. V. (2009). Understanding and managing human threats to the coastal marine environment. *Annals of the New York Academy of Sciences, 1162*, 39-62.

Department of Agriculture, Water and the Environment. (2016). *Indigenous Protected Areas (IPA) – Dedicated.* Canberra, Australia: Department of Agriculture, Water and the Environment.

Department of Agriculture, Water and the Environment. (2018a). *Australia – Present major vegetation groups – NVIS version 5.1 (Albers 100m analysis product).* Canberra, Australia: Department of Agriculture, Water and the Environment.

Department of Agriculture, Water and the Environment. (2018b). *Collaborative Australian Protected Areas Database (CAPAD) 2018 – Marine.* Canberra, Australia: Department of Agriculture, Water and the Environment.

Department of Agriculture, Water and the Environment. (2018c). *Collaborative Australian Protected Areas Database (CAPAD) 2018 – Terrestrial.* Canberra, Australia: Department of Agriculture, Water and the Environment.

Department of Planning, Lands and Heritage. (2016). *Aboriginal communities and town reserves.* Perth, Australia: Department of Planning, Lands and Heritage.

Department of Transport. (2017). *Coastal infrastructure DOT (DOT-020).* Perth, Australia: Department of Transport.

Di Minin, E., Tenkanen, H., & Toivonen, T. (2015). Prospects and challenges for social media data in conservation science. *Frontiers in Environmental Science, 3*, 1-6.

Elith, J., Kearney, M., & Phillips, S. (2010). The art of modelling range-shifting species. *Methods in Ecology and Evolution, 1*, 330-342.

Elith, J., & Leathwick, J. R. (2009). Species distribution models: Ecological explanation and prediction across space and time. *Annual Review of Ecology, Evolution, and Systematics, 40*, 677-697.

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions, 17*, 43-57.

Evangelista, P. H., Kumar, S., Stohlgren, T. J., Jarnevich, C. S., Crall, A. W., Norman Iii, J. B., & Barnett, D. T. (2008). Modelling invasion for a habitat generalist and a specialist plant species. *Diversity and Distributions, 14*, 808-817.

Figueroa-Alfaro, R. W., & Tang, Z. (2017). Evaluating the aesthetic value of cultural ecosystem services by mapping geo-tagged photographs from social media data on Panoramio and Flickr. *Journal of Environmental Planning and Management, 60*, 266-281.

Fourcade, Y., Engler, J. O., Rödder, D., & Secondi, J. (2014). Mapping species distributions with Maxent using a geographically biased sample of presence data: A performance assessment of methods for correcting sampling bias. *PLoS ONE, 9*, 1-13.

Franklin, J. (2010). *Mapping species distributions: Spatial inference and prediction*. Cambridge, UK: Cambridge University Press.

Freight and Logistics Council of WA. (2020). *Roadhouse map.* Perth, Australia: Freight and Logistics Council of WA.

Fulton, B., Smith, T., Sainsbury, K., & Haward, M. (2017). Managing multiple uses of our oceans. In B. D. Mapstone (Ed.), *Oceans: Science and solutions for Australia* (pp. 63-68). Clayton South, Australia: CSIRO Publishing.

Garcia Rodrigues, J., Conides, A. J., Rivero Rodriguez, S., Raicevich, S., Pita, P., Kleisner, K. M., Pita, C., Lopes, P. F. M., Alonso Roldan, V., Ramos, S. S., Klaoudatos, D., Outeiro, L., Armstrong, C., Teneva, L., Stefanski, S., Böhnke-Henrichs, A., Kruse, M., Lillebø, A. I., Bennett, E. M., Belgrano, A., Murillas, A., Sousa Pinto, I., Burkhard, B., & Villasante, S. (2017). Marine and coastal cultural ecosystem services: Knowledge gaps and research priorities. *One Ecosystem, 2*, 1-33.

Geoscience Australia. (2004). *GEODATA COAST 100K.* Canberra, Australia: Geoscience Australia.

Geoscience Australia. (2006). *GEODATA TOPO 250K series 3 user guide.* Canberra, Australia: Geoscience Australia.

Geoscience Australia. (2014). *Major ports.* Canberra, Australia: Geoscience Australia.

Geoscience Australia. (2016). *Western Australia coastal waterways geomorphic habitat mapping.* Canberra, Australia: Geoscience Australia.

Ghermandi, A., & Sinclair, M. (2019). Passive crowdsourcing of social media in environmental research: A systematic map. *Global Environmental Change, 55*, 36-47.

Government of Western Australia. (2011). *Kimberley science and conservation strategy*. https://www.dpaw.wa.gov.au/images/documents/conservation-management/kimberley/kimberley_science_conservation_strategy.pdf

Halpern, B. S., Walbridge, S., Selkoe, K. A., Kappel, C. V., Micheli, F., D'Agrosa, C., Bruno, J. F., Casey, K. S., Ebert, C., Fox, H. E., Fujita, R., Heinemann, D., Lenihan, H. S., Madin, E. M. P., Perry, M. T., Selig, E. R., Spalding, M., Steneck, R., & Watson, R. (2008). A global map of human impact on marine ecosystems. *Science, 319*, 948-952.

Hausmann, A., Toivonen, T., Slotow, R., Tenkanen, H., Moilanen, A., Heikinheimo, V., & Di Minin, E. (2018). Social media data can be used to understand tourists' preferences for nature-based experiences in protected areas. *Conservation Letters, 11*, 1-10.

Johnson, D. N., van Riper, C. J., Chu, M., & Winkler-Schor, S. (2019). Comparing the social values of ecosystem services in US and Australian marine protected areas. *Ecosystem Services, 37*, 1-11.

Kim, Y., Kim, C., Dong, K. L., Lee, H., & Andrada, R. T. (2019). Quantifying nature-based tourism in protected areas in developing countries by using social big data. *Tourism Management, 72*, 249-256.

Kimberley Land Council. (2004). *How traditional owners of the North Kimberley want to look after their country.* Department of Planning & Infrastructure North Kimberley Scoping Study Indigenous Consultations. https://www.dplh.wa.gov.au/getmedia/f6cbab7f-d18b-413c-a6b7-a8ee3b7ec0c0/KIM_Traditional_Owners_North_Kimberley

Klain, S. C., & Chan, K. M. A. (2012). Navigating coastal values: Participatory mapping of ecosystem services for spatial planning. *Ecological Economics, 82*, 104-113.

Kobryn, H. T., Brown, G., Munro, J., & Moore, S. A. (2018). Cultural ecosystem values of the Kimberley coastline: An empirical analysis with implications for coastal and marine policy. *Ocean and Coastal Management, 162*, 71-84.

Kramer-Schadt, S., Niedballa, J., Pilgrim, J. D., Schröder, B., Lindenborn, J., Reinfelder, V., Stillfried, M., Heckmann, I., Scharf, A. K., Augeri, D. M., Cheyne, S. M., Hearn, A. J., Ross, J., Macdonald, D. W., Mathai, J., Eaton, J., Marshall, A. J., Semiadi, G., Rustam, R., Bernard, H., Alfred, R., Samejima, H., Duckworth, J. W., Breitenmoser-Wuersten, C., Belant, J. L., Hofer, H., & Wilting, A. (2013). The importance of correcting for sampling bias in MaxEnt species distribution models. *Diversity and Distributions, 19*, 1366-1379.

Larson, S., & Herr, A. (2008). Sustainable tourism development in remote regions? Questions arising from research in the North Kimberley, Australia. *Regional Environmental Change, 8*, 1-13.

Le Cornu, E., Kittinger, J. N., Koehn, J. Z., Finkbeiner, E. M., & Crowder, L. B. (2014). Current practice and future prospects for social data in coastal and ocean planning. *Conservation Biology, 28*, 902-911.

Levin, N., Kark, S., & Crandall, D. (2015). Where have all the people gone? Enhancing global conservation using night lights and social media. *Ecological Applications, 25*, 2153-2167.

Levin, N., Lechner, A. M., & Brown, G. (2017). An evaluation of crowdsourced information for assessing the visitation and perceived importance of protected areas. *Applied Geography, 79*, 115-126.

Li, L., Goodchild, M. F., & Xu, B. (2013). Spatial, temporal, and socioeconomic patterns in the use of Twitter and Flickr. *Cartography and Geographic Information Science, 40*, 61-77.

Lobo, J. M., Jiménez-Valverde, A., & Real, R. (2008). AUC: A misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography, 17*, 145-151.

Lockwood, M. (1999). Humans valuing nature: Synthesising insights from philosophy, psychology and economics. *Environmental Values, 8*, 381-401.

Lomborg, S., & Bechmann, A. (2014). Using APIs for data collection on social media. *The Information Society, 30*, 256-265.

Lough, J. M. (1998). Coastal climate of northwest Australia and comparisons with the Great Barrier Reef: 1960 to 1992. *Coral Reefs, 17*, 351-367.

Main Roads Western Australia. (2017). *Road hierarchy.* Perth, Australia: Main Roads Western Australia.

Main Roads Western Australia. (2020). *Broome Cape Leveque road.* https://www.mainroads.wa.gov.au/projects-initiatives/projects/regional/broome-cape-leveque-road/

Martin, C. L., Momtaz, S., Gaston, T., & Moltschaniwskyj, N. A. (2016). A systematic quantitative review of coastal and marine cultural ecosystem services: Current status and future research. *Marine Policy, 74*, 25-32.

Martínez Pastur, G., Peri, P. L., Lencinas, M. V., García-Llorente, M., & Martín-López, B. (2016). Spatial patterns of cultural ecosystem services provision in Southern Patagonia. *Landscape Ecology, 31*, 383-399.

Merow, C., Smith, M. J., & Silander, J. A. (2013). A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter. *Ecography, 36*, 1058-1069.

Moore, S. A., Brown, G., Kobryn, H., & Strickland-Munro, J. (2017). Identifying conflict potential in a coastal and marine environment using participatory mapping. *Journal of Environmental Management, 197*, 706-718.

Morwood, M. J. (2002). *Visions from the past: The archaeology of Australian Aboriginal art*. Sydney, Australia: Allen & Unwin.

Muñoz, L., Hausner, V. H., Runge, C., Brown, G., & Daigle, R. (2020). Using crowdsourced spatial data from Flickr vs. PPGIS for understanding nature's contribution to people in Southern Norway. *People and Nature, 2*, 1-13.

Munro, J., Pearce, J., Brown, G., Kobryn, H., & Moore, S. A. (2017). Identifying 'public values' for marine and coastal planning: Are residents and non-residents really so different? *Ocean and Coastal Management, 148*, 9-21.

Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., & Plieninger, T. (2018). Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. *Ecological Indicators, 94*, 74-86.

Pascoe, S., Cannard, T., Stoeckl, N., Cresswell, I., Paredes, S., & Doshi, A. (2017). The oceans and our lives. In B. D. Mapstone (Ed.), *Oceans: Science and solutions for Australia* (pp. 63-68). CSIRO Publishing.

Pearce, J., Strickland-Munro, J., & Moore, S. A. (2016). What fosters awe-inspiring experiences in nature-based tourism destinations? *Journal of Sustainable Tourism, 25*, 362-378.

Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling, 190*, 231-259.

Phillips, S. J., & Dudík, M. (2008). Modeling of species distributions with Maxent: New extensions and a comprehensive evaluation. *Ecography, 31*, 161-175.

Phillips, S. J., Dudík, M., Elith, J., Graham, C. H., Lehmann, A., Leathwick, J., & Ferrier, S. (2009). Sample selection bias and presence-only distribution models: Implications for background and pseudo-absence data. *Ecological Applications, 19*, 181-197.

Phillips, S. J., Dudík, M., & Schapire, R. E. (2005). *Maxent software for modeling species niches and distributions (Version 3.4.1).* https://biodiversityinformatics.amnh.org/open_source/maxent/

Radosavljevic, A., & Anderson, R. P. (2014). Making better Maxent models of species distributions: Complexity, overfitting and evaluation. *Journal of Biogeography, 41*, 629-643.

Reddy, S., & Dávalos, L. M. (2003). Geographical sampling bias and its implications for conservation priorities in Africa. *Journal of Biogeography, 30*, 1719-1727.

Retka, J., Jepson, P., Ladle, R. J., Malhado, A. C. M., Vieira, F. A. S., Normande, I. C., Souza, C. N., Bragagndo, C., & Correia, R. A. (2019). Assessing cultural ecosystem services of a large marine protected area through social media photographs. *Ocean and Coastal Management, 176*, 40-48.

Richards, D. R., & Friess, D. A. (2015). A rapid indicator of cultural ecosystem service usage at a fine spatial scale: Content analysis of social media photographs. *Ecological Indicators, 53*, 187-195.

Rossi, S. D., Barros, A., Walden-Schreiner, C., & Pickering, C. (2020). Using social media images to assess ecosystem services in a remote protected area in the Argentinean Andes. *Ambio, 49,* 1-15.

Scherrer, P., & Doohan, K. (2011). Capturing intangible cultural impacts of tourism on aboriginal land in Australia's Kimberley region. *Tourism Recreation Research, 36*(3), 271-280.

Scherrer, P., Smith, A. J., Randall, M., & Dowling, R. (2011). Environmental and cultural implications of visitor access in the Kimberley region, Australia. *Australian Geographer, 42*, 257-271.

Sessions, C., Wood, S. A., Rabotyagov, S., & Fisher, D. M. (2016). Measuring recreational visitation at US National Parks with crowd-sourced photographs. *Journal of Environmental Management, 183*, 703-711.

Seymour, E., Curtis, A., Pannell, D., Allan, C., & Roberts, A. (2010). Understanding the role of assigned values in natural resource management. *Australasian Journal of Environmental Management, 17*, 142-153.

Sherrouse, B. C., Clement, J. M., & Semmens, D. J. (2011). A GIS application for assessing, mapping, and quantifying the social values of ecosystem services. *Applied Geography, 31*, 748-760.

Silverman, B. W. (1986). *Density estimation for statistics and data analysis* (Vol. 26.). New York, USA: Chapman and Hall.

Smith, A. J., Scherrer, P., & Dowling, R. (2009). Impacts on Aboriginal spirituality and culture from tourism in the coastal waterways of the Kimberley region, North West Australia. *Journal of Ecotourism, 8*(2), 82-98.

Spencer-Cotton, A., Kragt, M., & Burton, M. (2016). *Human values and aspirations for coastal waters of the Kimberley: Social values and management preferences using Choice Experiments.* Technical Report. Kimberley Marine Research Program Node of the Western Australian Marine Science Institution.
https://www.wamsi.org.au/sites/wamsi.org.au/files/files/WAMSI_Project_2_1_2_Technical_Report_3_final_March_2016.pdf

Strickland-Munro, J., Kobryn, H., Bayley, S., Moore, S., & Palmer, D. (2016c). *Human values and aspirations for coastal waters of the Kimberley: Port Smith (Purnturrpurnturr) visitor survey.* Technical Report. Kimberley Marine Research Program Node of the Western Australian Marine Science Institution.
https://www.wamsi.org.au/sites/wamsi.org.au/files/files/WAMSI_Project_2_1_2_Technical_Report_4_final.pdf

Strickland-Munro, J., Kobryn, H., Brown, G., & Moore, S. A. (2016a). Marine spatial planning for the future: Using public participation GIS (PPGIS) to inform the human dimension for large marine parks. *Marine Policy, 73*, 15-26.

Strickland-Munro, J., Kobryn, H., Brown, G., Pearce, J., & Moore, S. (2016b). *Human values and aspirations for coastal waters of the Kimberley: Social values and management preferences using Public Participation GIS.* Technical Report. Kimberley Marine Research Program Node of the Western Australian Marine Science Institution.
https://www.wamsi.org.au/sites/wamsi.org.au/files/files/WAMSI_Project_2_1_2_Technical_Report_2_final_April_2016.pdf

Strickland-Munro, J., Kobryn, H., Moore, S. A., & Brown, G. (2016d). Valuing the wild, remote and beautiful: Using public participation GIS to inform tourism planning in the Kimberley, Western Australia. *International Journal of Sustainable Development and Planning, 11*, 355-364.

Strickland-Munro, J., Moore, S., Kobryn, H., & Palmer, D. (2015). *Values and aspirations for coastal waters of the Kimberley: Social values and participatory mapping using interviews.* Technical Report. Kimberley Marine Research Program Node of the Western Australian Marine Science Institution.
https://www.wamsi.org.au/sites/wamsi.org.au/files/files/values_and_aspirations_for_coastal_waters_of_the_Kimberley.pdf

Tadaki, M., Sinner, J., & Chan, K. M. A. (2017). Making sense of environmental values: A typology of concepts. *Ecology and Society, 22*, 7.

Tenerelli, P., Demšar, U., & Luque, S. (2016). Crowdsourcing indicators for cultural ecosystem services: A geographically weighted approach for mountain landscapes. *Ecological Indicators, 64*, 237-248.

Tenkanen, H., Di Minin, E., Heikinheimo, V., Hausmann, A., Herbst, M., Kajala, L., & Toivonen, T. (2017). Instagram, Flickr, or Twitter: Assessing the usability of social media data for visitor monitoring in protected areas. *Scientific Reports, 7*, 1-11.

Tieskens, K. F., Van Zanten, B. T., Schulp, C. J. E., & Verburg, P. H. (2018). Aesthetic appreciation of the cultural landscape through social media: An analysis of revealed preference in the Dutch river landscape. *Landscape and Urban Planning, 177*, 128-137

Toivonen, T., Heikinheimo, V., Fink, C., Hausmann, A., Hiippala, T., Järv, O., Tenkanen, H., & Di Minin, E. (2019). Social media data for conservation science: A methodological overview. *Biological Conservation, 233,* 298-315.

Tonge, J., Moore, S. A., Ryan, M. M., & Beckley, L. E. (2013). A photo-elicitation approach to exploring the place meanings ascribed by campers to the Ningaloo coastline, north-western Australia. *Australian Geographer, 44*(2), 143-160.

Tourism, WA. (2019). *The Kimberley 2018 Visitor Factsheet.* https://www.tourism.wa.gov.au/Publications%20Library/Research%20and%20reports/2018/RDC%20Profiles%202018/Kimberley_2018%20Factsheet.pdf

Tsoar, A., Allouche, O., Steinitz, O., Rotem, D., & Kadmon, R. (2007). A comparative evaluation of presence-only methods for modelling species distribution. *Diversity and Distributions, 13*, 397-405.

U.S. Geological Survey (USGS). (2000). *Digital elevation SRTM 1 arc-second global*. Virginia, United States: U.S. Geological Survey.

van Zanten, B. T., Van Berkel, D. B., Meentemeyer, R. K., Smith, J. W., Tieskens, K. F., & Verburg, P. H. (2016). Continental-scale quantification of landscape values using social media data. *Proceedings of the National Academy of Sciences, 113*, 12974-12979.

Voyer, M., Gladstone, W., & Goodall, H. (2012). Methods of social assessment in marine protected area planning: Is public participation enough? *Marine Policy, 36*, 432-439.

Walden-Schreiner, C., Leung, Y.-F., & Tateosian, L. (2018). Digital footprints: Incorporating crowdsourced geographic information for protected area management. *Applied Geography, 90*, 44-54.

Wolanski, E., & Spagnol, S. (2003). Dynamics of the turbidity maximum in King Sound, tropical Western Australia. *Estuarine, Coastal and Shelf Science, 56*, 877-890.

Wood, S. A., Guerry, A. D., Silver, J. M., & Lacayo, M. (2013). Using social media to quantify nature-based tourism and recreation. *Scientific Reports, 3*, 1-7.

Yoshimura, N., & Hiura, T. (2017). Demand and supply of cultural ecosystem services: Use of geotagged photos to map the aesthetic value of landscapes in Hokkaido. *Ecosystem Services, 24*, 68-78.

Zhang, H., Huang, R., Zhang, Y., & Buhalis, D. (2020). Cultural ecosystem services evaluation using geolocated social media data: A review. *Tourism Geographies*, 1-23.

Appendix A. Literature review

Critical comparison of traditional participatory mapping approaches, Public Participation GIS and social media to identify, quantify and map values

1. Introduction

The natural environment is important to people for a diverse range of reasons, as the relationship between humans and the environment is highly interactive. Among the range of benefits they provide are the places for meaningful experiences, such as recreation or simply viewing wildlife in their natural habitat. Brown and Raymond (2007) found that these types of interactions which foster connection contributes to quality of life and well-being, enabling personal bonds and place attachments to develop.

Human experiences and perceptions of the environment can be evaluated using a variety of value typologies, many within environmental applications, such as landscape values, place-based values, social values and Cultural Ecosystem Services (CES) (e.g. Brown et al., 2020; Kenter et al., 2015; McLain et al., 2013; van Riper et al., 2012). These value typologies draw on the concept of 'sense of place', which refers to the meanings and values that people associate with places (Besser et al., 2014; Brown & Raymond, 2007; Brown et al., 2020). These values can be used inform social, ecological and economic concerns for the environment (Brown, & Weber, 2013).

The evaluation of values as a basis for human-environment interactions has become a powerful conceptual tool for planning, management and sustainability practices (Tadaki et al., 2017; Vihervaara et al., 2010). Data gathered about values can be used to identify the complex links between humans and the environment and to support human wellbeing (Bennett et al., 2017; Tadaki et al., 2017; Vihervaara et al., 2010). Practices such as protected area management, natural resource management, conservation management, impact assessments and decision-making processes for policy makers are increasingly recognising the importance of incorporating human dimensions through values and preferences (e.g. Brown et al., 2016; Strickland-Munro et al., 2016a).

Comparably, planners and managers need to know the advantages and limitations of different methods that can gather data about values to incorporate into practice. Participatory mapping, Public Participation GIS (PPGIS) and social media present three methods that can gather data about values as well as spatial data to where values occur. As the data that can be gathered through these methods allows values to be mapped, they enable robust approaches to understand the importance of places through the identification and quantification of values over a geographical area (Brown et al., 2020; Moore et al., 2017; Richards & Friess, 2015). Moran (2010) further supports this, stating that this type of data integrates social science and environmental science to present the human dimensions, or social layer, that is necessary for effective planning, management and sustainability.

This literature review addresses three methods that can be employed to gather spatial data to identify, quantify and map values: (1) participatory mapping through interviews, focus groups and workshops (henceforth referred to as traditional approaches), (2) internet-based PPGIS, and (3) social media. The advantages and limitations of each method will be presented individually and then compared (Figure 1.1) to provide recommendations regarding the choice of method considering the time, cost, scale of analyses, recruitment effort, response rates, sample sizes, ethical considerations, type of data that can be collected and mapped, and the mapping technique.

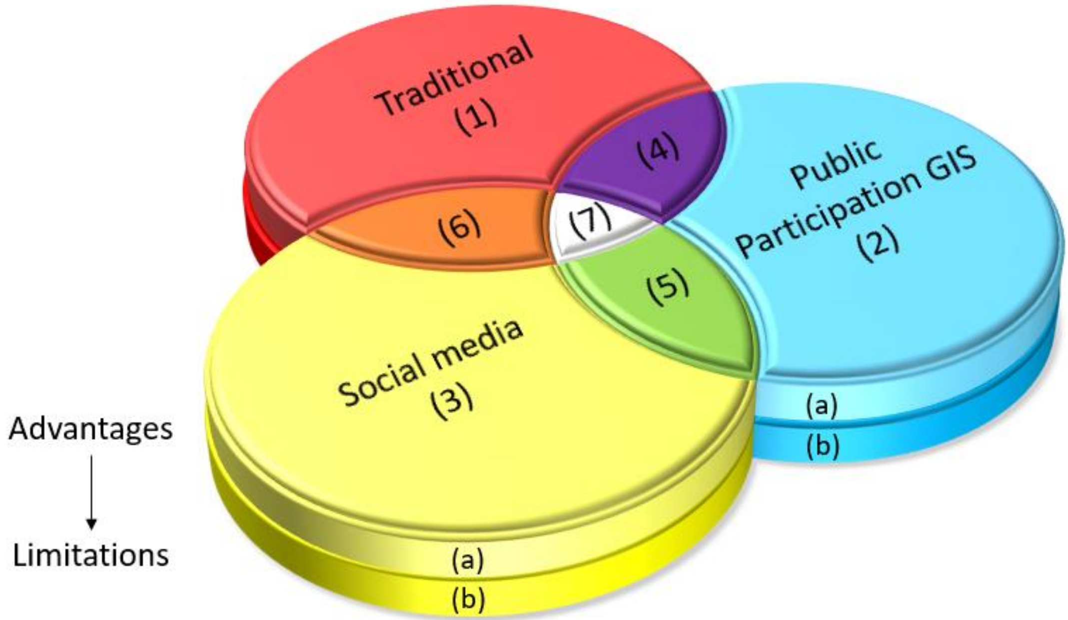


Figure 1.1. Venn diagram illustrating the advantages (a) and limitations (b) that are independent to each method (1, 2, 3) and the characteristics that are comparable between two (4, 5, 6) or all three (7) methods (Figure: author supplied).

2. Traditional approaches

Traditional approaches of identifying and mapping human values involve interviews, focus groups or workshops. Interviews, focus groups and workshops are semi-qualitative methods that provide an interpretive and inductive approach to participatory mapping, typically involving questions addressing socio-demographic characteristics and attributing values to places on a map. By utilising in-person data collection techniques, these more traditional approaches enable two-way interactions between participant(s) and researchers (Brown & Kyttä, 2014). Lowery and Morse (2013) indicated that the associated mapping component allows participants to provide meaningful knowledge, perspectives and experiences of places. Hence, the primary goal of these approaches is to provide comprehensive understanding for places of value that enables community engagement and empowerment (Brown & Kyttä, 2014).

Interviews, focus groups and workshops commonly involve open-ended questions relevant to the topic or study area. Open-ended questions enable participants to freely consider and articulate their values more deeply (Neuman, 2011). Using this approach, values and preferences within an area can be explored with or without pre-determined values. Where values are not pre-determined, interviews and discussions can be recorded and later transcribed to elicit values associated to mapped places (e.g. Lowery & Morse, 2013; Moore et al., 2017). Open-ended questions, such as ‘where are places you consider important?’, in addition to a spatial mapping component allows participants to identify important places and to articulate the importance of mapped places (Figure 2.1; Klain & Chan, 2013; Lowery & Morse, 2013; Moore et al., 2017). Important places are typically mapped by drawing polygon areas or placing sticker dots onto hard copy maps such as nautical charts, aerial images or topographical maps. The mapped places can then be discussed, elaborated, contested and negotiated providing comprehensive insights for place meanings and attachments. As such, follow up questions can be structured to describe certain values (Klain & Chan, 2012; Ramirez-Gomez et al., 2013), or to enable participants to reflect on the meaning of mapped places (Moore et al., 2017).

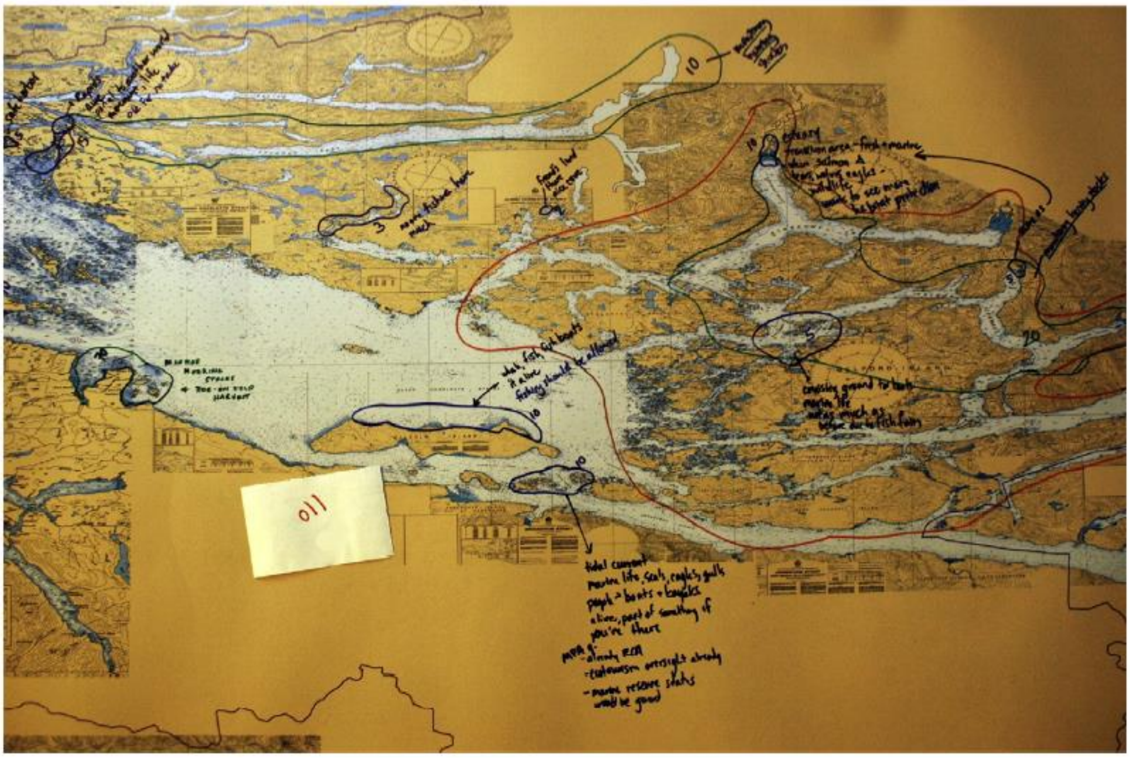


Figure 2.1. Example of a nautical chart base map displaying polygon areas drawn by participants representing monetary and non-monetary values gathered through interviews (reprinted with permission from Klain & Chan, 2013).

2.1. Advantages and limitations

2.1.1. Time, cost and scale

Previous studies found that in comparison to interviews, focus groups and workshops present the advantage of being a more time and sampling efficient approach, due to synergy among participants and sampling larger groups simultaneously (Besser et al., 2014; Lowery & Morse, 2013). However, these approaches are limited by the time and expense required to organise and conduct in-person interviews and discussions. Considerable human effort is required to contact participants, have participants agree to participate and to being recorded (where appropriate), organise when and where this will take place, and then conduct the interviews or discussions themselves. There may also be the additional material cost of printing potentially numerous paper maps (Brown & Fagerholm, 2015; Brown & Reed, 2009). There is also the added expense of travelling to the location to conduct the interviews, especially for rural or remote areas where access can be limited (e.g. Ramirez-Gomez et al., 2013, 2016).

After the mapping component is completed, maps need to be digitised before they can be analysed within a GIS. This is an additional and relatively time-consuming step that is not required for digital mapping (Brown & Fagerholm, 2015; Brown & Reed, 2009). Another labour-intensive component is the transcription and analysis of recorded interviews. In the case where values were not directly attributed during the interviews, these values cannot be elicited and attributed to polygons until this process is complete (Lowery & Morse, 2013). Therefore, due to the time and cost limitations required to implement these approaches, they are typically restricted to local or regional scales.

2.1.2. Recruitment, response and ethical considerations

A major limitation of these approaches is the low response rate from participants. Brown (2004) found that more traditional approaches require considerable time investment from participants and therefore tend to involve older and more educated people that often have a direct interest in the area. McLain et al. (2013) suggested that to increase response rates, certain groups can be targeted to encourage broader participation.

Despite low response rates, an advantage of traditional approaches is that they do not require access to the internet and may therefore appeal to a wide range of participants (Brown & Reed, 2009). McLain et al. (2013) report that through traditional approaches, researchers are able to target and recruit certain groups, such as underrepresented or disadvantaged communities. However, recruitment often requires time for relationships to be built and for trust to be established between the participant and the researcher (Neuman, 2011). Brown and Kyttä (2018) indicated that for some communities, such as Indigenous, this relationship is crucial as a lack of established trust poses a significant communication barrier.

Ramirez-Gomez et al. (2013, 2016) found that Indigenous communities are highly underrepresented in research, planning and management despite the recognised importance and contribution of their knowledge. These communities often hold different values to westernised communities and therefore the integration of Indigenous knowledge through participatory mapping can provide larger scale understanding of values and more beneficial outcomes.

Scepticism in participatory mapping approaches can arise when conducted from 'outsiders' (Brown & Kyttä, 2018). Despite agreeing to participate, Klain and Chan (2012) found that some participants may refuse to answer certain questions or participate in mapping. Because the elicitation of values using participatory mapping can be used to inform spatial planning and management, some participants may feel that by identifying specific areas of value, areas that are not identified will be seen as less important and therefore may be exploited (Brown & Kyttä, 2018; Klain & Chan, 2012). Brown and Kyttä (2014) indicated this may lead to the ethical considerations regarding the ownership and intellectual property of the data. They suggest it may be presumed that the data belongs to the participants that created it, which may be true in most cases. Regardless of the intent of the data, communication with participants prior, during and post interviews is evidently very important (Brown & Kyttä, 2018). Participant awareness of the intent and outcomes of their contributions is critical to conducting ethical research and can enable trust between the participant and the researcher (Brown & Kyttä, 2014, 2018).

2.1.3. Level of contribution

The relationship between the participant and the researcher, in addition to the participant's knowledge and interest in the study area, can influence how much participants contribute. McLain et al. (2013) suggest participant engagement in mapping and familiarity with an area produce greater contributions and outcomes. Besser et al. (2014) found the inverse to be equally true, where participants that are unfamiliar with the study area may be reluctant to map values as they are unable to identify features on the map and will therefore be less engaged in mapping.

Within group discussions, such as focus groups, workshops and in some instances interviews, some participants may be heard more than others. Participants with stronger personalities may step forward and take lead during discussions or mapping. Lowery and Morse (2013) point out the advantage of having discussions guided by a facilitator is that if one or more participant is observed to be dominating, the facilitator can ask to hear from other participants.

In many instances, discussions between participants is encouraged. Previous studies indicate that although disagreements may arise, participants are often able to come to a consensus when mapping values (Besser et al., 2014; Lowery & Morse, 2013). Therefore, a considerable advantage of this approach is the synergy between participants. This enables participants to identify more areas of importance and stimulates reflection on the meaning and values of the mapped area (Lowery & Morse, 2013; Moore et al., 2017), enabling greater levels of contribution.

2.1.4. *Precision and accuracy*

Workshops and interviews utilise relatively low-technological participatory mapping methods. Brown and Pullar (2012) state that these traditional methods do not require much skill from the participant, as it typically involves drawing polygons or placing sticker dots onto paper-based maps enabling the identification of spatially significant areas or places. However, the precision and accuracy of these methods can be quite variable and needs to be taken into consideration (Besser et al., 2014; Brown & Pullar, 2012; Lowery & Morse, 2013). Brown and Pullar (2012) suggest that mapped points through sticker dots are more concise and are less likely to overrepresent areas of value. However, it is widely agreed that the precision and accuracy of mapped values is also related to the scale and geographic detail of the maps (Besser et al., 2014; Brown, 2004). Having facilitators present during mapping activities to provide instructions, clarify and assist participants, can increase the accuracy of mapped values (Besser et al., 2014).

As Besser et al. (2014) point out, values mapped through these more traditional approaches require a level of interpretation when attributing values to polygons which can influence the precision of mapped values. This influence is even greater when values are elicited and attributed after the interviews have been conducted as the mapped values can no longer be confirmed with the participant (Lowery & Morse, 2013). Eliciting values rather than using pre-determined values introduces the assumption that the words used to describe values have the same meaning between participants. This requires some level of interpretation from the researcher regarding the participants understanding of the value (Besser et al., 2014).

Another concern is the digitizing of maps which provides more opportunity for spatial errors from potentially incomplete or overlapping polygons or points (Brown & Fagerholm, 2015; Brown & Reed, 2009). However, the opportunity for this type of spatial error can be eliminated by the direct entering of values which can be easily achieved through digital mapping (Brown & Fagerholm, 2015; Brown & Reed, 2009).

3. Public Participation GIS (PPGIS)

PPGIS is the application of GIS and spatial mapping to provide knowledge of a place (Sieber, 2006). PPGIS surveys differ from the more traditional approaches described above in that values are identified through digital, internet-based mapping with the goal of enhancing public participation (Brown & Kyttä, 2014; Brown et al., 2017).

PPGIS surveys ask participants to spatially identify places that are important to them using a digital map of a geographical area. From a list of pre-determined values or management preferences provided with operational definitions, participants are asked to identify and mark values or preferences onto places they consider important (Figure 3.1). PPGIS surveys are typically self-directed and completed individually using a computer (Brown & Fagerholm, 2015). The mapping interfaces are often customisable and therefore can capture a wide range of values. These interfaces also have the ability to incorporate management preferences that can be used to inform spatial planning and management (e.g. Munro et al., 2019; Strickland-Munro et al., 2016a).

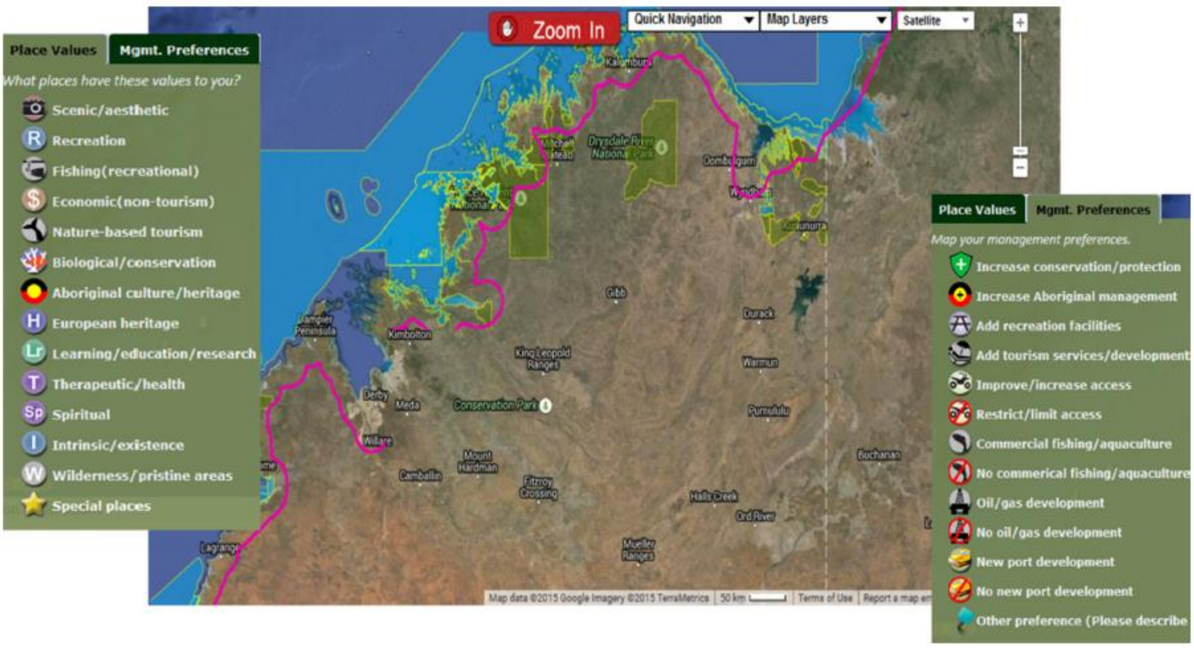


Figure 3.1. Example of a PPGIS mapping interface using Google Maps displaying place values and management preferences employed for the Kimberley coast, Western Australia (reprinted with permission from Strickland-Munro et al., 2016a).

An additional component of PPGIS is the ability to ask questions of participants prior to or post mapping. These questions can be related to the mapping activity, such as how often participants visited and what activities they undertake at the places they identified as valuable to them (e.g. de Vries et al., 2013). These questions can also be non-spatial, such as socio-demographic characteristics and participant knowledge of the study area (e.g. Brown & Brabyn, 2012; Brown et al., 2016).

3.1. Advantages and limitations

3.1.1. Time, cost and scale

PPGIS methods are more time and cost-effective compared to more traditional approaches as they take considerably less time to implement and conduct (Brown & Fagerholm, 2015). Brown and Fagerholm (2015) state that although PPGIS surveys can be time consuming to implement if researchers are unfamiliar with the interface, this time is minimal in comparison to the total time required to organise and conduct interviews, focus groups or workshops. Additionally, other studies have indicated that PPGIS is a more efficient approach of collecting, storing and analysing spatially explicit data about values as they are pre-determined and directly entered onto a digital map (Brown & Kyttä, 2018; Brown & Reed, 2009). Therefore, they require no additional data coding or entry such as the coding of values and digitising that is required for paper-based mapping. PPGIS surveys however do require the cleaning and verification of data which can be time consuming and costly (Tang & Liu, 2016). Brown et al. (2020), however, highlight the benefit of PPGIS is that it is not restricted to in-person interviews and discussions and can therefore be implemented at multiple scales. Although PPGIS is typically more effective at local to regional scales, it has the capability to be viable over relatively broad scales (e.g. Brown & Brabyn, 2012).

3.1.2. Recruitment, response and ethical considerations

Brown and Kyttä (2014) reported that similar to more traditional approaches, a limitation of PPGIS is the low recruitment rates of participants. Several studies have found that despite internet-based PPGIS surveys generally recruiting larger sample sizes than more traditional approaches, as PPGIS has transitioned from paper-based to internet-based methods response rates have declined (e.g. Brown, 2017; Pocewicz et al., 2012). In response to low response rates, some researchers have employed other methods of recruitment, including targeting online panels and stakeholder groups via email, and social media (Brown, 2017; Brown et al., 2012a; de Vries et al., 2013).

Providing rewards for participation, such as gift cards, has been observed to increase the number of participants in some instances, but can have negative implications regarding the people that are attracted to and participate in the survey. Strickland-Munro et al. (2016b) found that some participants complete the survey simply for the incentive of the reward and do not contribute meaningful data, likely as they have little to no knowledge of the study area. However, they found there are methods to identify these participants using the origin of their IP address. Further, there are preventative methods to hinder these participants from participating using targeted sampling (e.g. Muñoz et al., 2020).

Through survey questions, PPGIS can ask the socio-demographic characteristics of participants. Previous studies have found that PPGIS surveys typically recruit older and more educated men, potentially introducing sampling and response bias (Brown, 2017; Brown & Kyttä, 2014). However, Czepkiewicz et al. (2017) found that with the proliferation of social media, this too has become a viable method of recruitment that typically recruits younger and well-educated participants. Therefore, multiple recruitment methods should be employed to try and capture a broader representation of the community (Brown, 2017).

PPGIS utilises higher-technological methods than more traditional approaches and requires access to a computer and the internet. It also requires some level of understanding of how to use and navigate the PPGIS interface and therefore it can exclude some people and communities from participating (Besser et al., 2014; Czepkiewicz et al., 2017). PPGIS interfaces must be efficiently designed for easy access, use and navigation, and the content easy to follow and understand for participants to feel more comfortable to map values. Due to these reasons, PPGIS surveys typically provide detailed instructions that often makes the experience easier for participants (Brown et al., 2012b; Tang & Liu, 2016).

Despite attempts to ameliorate issues of exclusion, Brown and Kyttä (2018) reported a substantial limitation of PPGIS is the inability to reach underrepresented or disadvantaged communities. Although more traditional approaches are labour intensive, they can be implemented in areas with no or limited internet access, an option not applicable for internet-based PPGIS. Similarly to more traditional approaches, PPGIS is often used to inform spatial planning and management and therefore requires a level of trust from the participant that the information they provide will not be used to exploit places that may not be considered as highly valuable (Brown & Kyttä, 2018).

3.1.3. Level of contribution

Attracting people that do not contribute meaningful information is an example of how higher participation does not necessarily equate to more or better data. PPGIS requires sufficient spatial data to identify spatial patterns (Brown et al., 2020; Brown & Kyttä, 2014), however quantity does not necessarily equate to quality. The level of contribution is typically indicative of an participant's interest and enthusiasm in the PPGIS process, whether that is because they simply enjoy surveys or they have an interest in the planning and development for the study area (Brown, 2017; Brown & Pullar, 2012). Brown (2017) suggests that, in this context, participants with greater interest are likely to spend more time mapping and are more likely to contribute a greater number of values. However, Strickland-Munro et al. (2016b) found that participants that contributed large numbers of mapped values required additional analysis from the researcher to determine whether these markers were deliberately placed and meaningful.

Brown (2017) and Brown et al. (2012b) suggest that analysis of these mapped values may reveal no influence on the data, however the values mapped from these participants may be randomly thinned or removed altogether to limit the potential impact of outliers. These studies point out that preventative methods can be employed to limit the number of markers participants can place, however, are perceived to be counterproductive.

Consistent with more traditional approaches, PPGIS participants require some familiarity with the study area to confidently map values (Brown, 2012). Brown (2012) suggested that participants may be more reluctant to map values through internet-based surveys as they may feel mapping is beyond their capability. Equally, this study suggests less confident participants may be more likely to wrongly map values, therefore bringing the precision and accuracy of mapped values to question.

3.1.4. Precision and accuracy

As with more traditional approaches, the precision and accuracy of mapped values are a concern for PPGIS (Brown & Kyttä, 2014). Familiarity with the area is typically consistent with participants mapping more values that are likely to be more spatially accurate (Brown, 2012; Brown & Reed, 2009). Unlike more traditional approaches where values may not be pre-determined and are elicited during or after the interview requiring a level of interpretation, PPGIS surveys provide pre-determined values. To support the mapping of these values, PPGIS surveys provide operational definitions for each value. Brown and Pullar (2012) suggest that by including these definitions, this provides clarity to the meaning of each value, increasing the accuracy of mapped values.

As PPGIS typically utilises points as the mapping method, it tends to produce finer resolutions compared to more traditional approaches (Brown et al., 2017). As more traditional approaches use sticker dots which can ambiguously represent a place, the finer point location employed for digital mapping increases the precision of mapped values (Brown & Pullar, 2012; Pocewicz et al., 2012). Unlike more traditional approaches, PPGIS can provide a level of quality control by providing multiple maps, multiple map scales and enforcing a minimum zoom level at which participants can place values thereby increasing the precision and accuracy of mapped values (Brown & Pullar, 2012).

Both internet-based PPGIS and more traditional approaches require relatively intense active contributions from participants to map values. A relatively recent method and increasingly available method of mapping values is through social media. Social media users are able to share content that often contains spatially explicit information through the use of digital technology equipped with Global Positioning Systems (GPS), such as cameras and smartphones (Birenboim & Shoval, 2016), that provides an alternative method of identifying and mapping values from the data collected.

4. Social media

Social media provides a passive or opportunistic approach of retrieving data that can be used to identify and map values (Ghermandi & Sinclair, 2019). Passive data collection differs from the active contributions required for more traditional approaches and internet-based PPGIS in that it gathers user-generated content that is voluntarily shared to social media platforms and is typically independent of research or management purposes (Ghermandi & Sinclair, 2019). Cameras and smartphones equipped with Global Positioning Systems (GPS) provide opportunities for people to take photographs whenever and whenever they choose (Birenboim & Shoval, 2016; Goodchild, 2007). Using these devices, the time and geographical coordinates at which the photograph was taken can be recorded (Goodchild, 2007). The geographical location can also be manually entered by the user when sharing content using coordinates or by tagging place names (Li et al., 2013; Senaratne et al., 2017).

User-generated content includes text, tags, photographs and associated metadata containing geographical, time and user information (Figure 4.1). Crowdsourcing georeferenced content publicly shared to social media platforms is a relatively recent and increasingly available approach to identify values that are spatially explicit through the data retrieved (Di Minin et al., 2015; Ghermandi & Sinclair, 2019). Some social media platforms such as Flickr, Twitter, Instagram and Panoramio provide an Application Programming Interface (API) that can be used to retrieve georeferenced content, however the process and accessibility of the API and level of geographical information varies between social media platforms (Di Minin et al., 2015; Ghermandi & Sinclair, 2019; Lomborg & Bechmann, 2014; Toivonen et al., 2019).

Figure 4.1. Example of user-generated content shared to a social media platform displayed on a smartphone (Toivonen et al., 2019).

Photographs that contain georeferenced content (i.e. geotags) provide spatially explicit data that can be used to map the distribution of values. The spatial distribution and density of geotagged photographs can effectively be used as a proxy to estimate places of value for activities such as nature-based tourism (Wood et al., 2013), recreation (van Zanten et al., 2016), and of aesthetic value (Casalegno et al., 2013; Figueroa-Alfaro & Tang, 2017; Yoshimura & Hiura, 2017). However, to understand the complexity of human-environment interactions, the spatial distribution and photograph content of geotagged photographs should be combined. Previous studies have suggested that photograph content analysis provides a more powerful tool to identify the values people hold towards the environment as values can be directly observed rather than a proxy estimate (Richards & Friess, 2015; Tenerelli et al., 2016). This process involves assessing photographs based on criteria related to the content of the photograph using a pre-determined list of values (Clemente et al., 2019; Muñoz et al., 2020; Oteros-Rozas et al., 2018; Richards & Friess, 2015; Tenerelli et al., 2016).

4.1. Advantages and limitations

4.1.1. Time, cost and scale

Social media provides an effective method of identifying and mapping values where resources are limited (Di Minin et al., 2015). The passive collection of geotagged photographs using an API provides an easy, cheap and time efficient approach (Ghermandi & Sinclair, 2019; Lomborg & Bechmann, 2014; Toivonen et al., 2019), however, it is not entirely without time and expense. The identification of values requires the interpretation and classification of photograph content which can be laborious (Di Minin et al., 2015; Richards & Friess, 2015). However, in the cases where time limitations may be a concern, there are automatic image recognition techniques that are reasonably accurate and can be employed in place of manual content analysis (e.g. Richard and Tunçer, 2018).

The expansion of social media use has provided the capability to identify and map values over broad geographic scales (Wood et al., 2013; van Zanten et al., 2016) that is simply not viable for more traditional approaches and PPGIS surveys. However, due to the large availability of geotagged photographs from photo-sharing social media platforms (Wood et al., 2013) and the time investment of content analysis (Richards & Friess, 2015), this method is often restricted to regional scales (e.g. Clemente et al., 2019; Muñoz et al., 2020; Tenerelli et al., 2016).

4.1.2. Recruitment, response and ethical considerations

Unlike the previously described methods, social media does not rely on the recruitment and response of participants. Rather, social media relies on voluntary, user-generated content shared to social media platforms. This content can be accessed and collected through an API for any non-commercial use (Ghermandi & Sinclair, 2019; Toivonen et al., 2019). As Ghermandi and Sinclair (2019) point out, social media is also not subject to the low sample sizes that are observed for more traditional approaches due to the large availability of publicly shared content.

Social media requires users to have access to digital technology such as a camera, computer or smartphone along with internet access; therefore, data collected in this way is geographically biased towards more developed and populated areas (Di Mini et al., 2015; Oteros-Rozas et al., 2018). Despite the limited socio-demographic information available about users due to privacy regulations (Lomborg & Bechmann, 2014; Oteros-Rozas et al., 2018), photo-sharing users typically represent those that are familiar with technological devices, are highly educated and younger (Chen et al., 2018; Li et al., 2013). Therefore, social media users are unlikely to be representative of the population (Lomborg & Bechmann, 2014; Oteros-Rozas et al., 2018; Tenerelli et al., 2016). Social media is generally not used or available to certain people and communities, such as the elderly, ethnic minorities, and rural, remote and Indigenous communities (Clemente et al., 2019; van Zanten et al., 2016).

Social media, however, can enable users to freely share their experiences and values (Chen et al., 2018) and therefore considerations must be made regarding the legal and ethical implications of passively crowdsourced data. Certain social media platforms have their content ‘public’ by default and that must be considered when using or distributing user content (Lomborg & Bechmann, 2014). When signing up to social media platforms, users must accept the terms of use. This implicit consent often implies the platform can use and distribute user-generated content without any additional permissions from the user (Ghermandi & Sinclair, 2019; Lomborg & Bechmann, 2014). Similar to more traditional approaches and PPGIS, it is then the responsibility of the researcher to responsibly store, analyse and re-distribute the content to ensure the user remains anonymised (Zook et al., 2017).

4.1.3. Level of contribution

Whilst the availability of publicly shared content is considerably high, Di Minin et al. (2015) reported this content is typically biased towards a small number of highly active users. Similar to PPGIS, these users share a large number of photographs over small or broad areas which may cause potential outliers. Muñoz et al. (2020) suggested that the level of contribution is also likely due to interest in the area with non-residents, such as tourists, more likely to contribute a greater number of photographs. Highly active users are also more likely to share more information such as titles, descriptions and tags, providing more context behind the motivation of the photograph, therefore making the experience or value of the photograph clearer for interpretation.

4.1.4. Precision and accuracy

Interpretation is an inherent bias of content analysis due to subjective nature of researchers' capabilities to identify and assign values based on photograph content (Clemente et al., 2019; Oteros-Rozas et al., 2018; Richards & Friess, 2015). Increased accuracy of values can be achieved through a detailed classification approach; however, photograph content is commonly biased toward aesthetic values (Clemente et al., 2019; Martínez Pastur et al., 2016; Muñoz et al., 2020; Retka et al., 2019). Whilst the accuracy of assigning values may be open to interpretation, the embedded GPS devices are relatively accurate (Birenboim & Shoval, 2016; Goodchild, 2007). However, the precision and accuracy of social media data is considered questionable due to a lack of quality control (Goodchild, 2013). Georeferenced content can be captured from the device when a photograph is taken or can be manually entered when sharing content to social media platforms and therefore the spatial accuracy of geotagged photographs is dependent on the photograph and on the user (Li et al., 2013; Senaratne et al., 2017). Geotags represent visited locations where the photograph was taken rather than the subject of the photograph itself, however users can manually alter this location to represent the subject of the photograph (Senaratne et al., 2017). Previous studies have pointed out that this can cause concerns regarding the actual location of interpreted values (Muñoz et al., 2020; Oteros-Rozas et al., 2018).

5. Comparison of methods

As described in this review, there are advantages and limitations to each of the methods discussed (more traditional approaches, PPGIS and social media). Some of these advantages and limitations are independent as each method differs in the ability to identify and map values, however there are also similarities between the three methods (Table 5.1).

Table 5.1. Summary and comparison of the characteristics of traditional approaches, Public Participation GIS and social media discussed in this literature review.

	Traditional approaches	**Public Participation GIS**	**Social media**
Time required	High	Intermediate	Low
Expenses	High	Intermediate	Low
Scale	Local or regional	Local, regional or broad	Local, regional or broad
Recruitment effort	High	High	Low
Response rates	Low	Low	High
Sample sizes	Low	Intermediate	High
Ethical considerations	Ownership of the data, responsible storing and use, anonymity	Ownership of the data, responsible storing and use, anonymity	Responsible storing and use, anonymity
Consent	Explicit	Explicit	Implicit
Data collection	Intensive active collection	Intensive active collection	Passive collection
Range of contribution	Low to high	Low to high	Low to high
Mapping technique	Non-digital	Digital	Digital
Mapping method	Polygon or sticker dots	Points	Point coordinates or tagged places
Socio-demographic characteristics	Older, well educated	Older, well educated	Younger, well educated
Value typology	Pre-determined or elicited during interviews	Pre-determined	Pre-determined

As more traditional approaches and PPGIS require actively soliciting contributions from participants they are more costly and time consuming for both participants and researchers alike than the passive data collection of social media (Levin et al., 2017). More traditional approaches require comparatively greater human effort and resources, and they are therefore more difficult to gather data in a time and cost-efficient manner. Although PPGIS and social media present opportunities to gather similar data where resources are limited, they are not without time and expense. PPGIS can require substantial efforts to implement and clean the data prior to analysis and whilst the collection of social media data using an API is quick and cheap, photograph content analysis can involve substantial time demands.

As PPGIS and social media have the advantage of internet-based applications they are less restricted to the scale at which they can be implemented (Levin et al., 2017). However, there are limitations in that many communities have restricted access to the internet and technological devices. Through more traditional approaches that utilise in-person data collection methods and paper-based applications, disadvantaged or underrepresented communities can be reached and their values heard. In contrast, a major limitation of PPGIS and social media is the inability to reach these communities despite targeted sampling efforts (Brown & Kyttä, 2018).

The representativeness of participants and users of the general population is a concern for all three methods. Unlike more traditional approaches and PPGIS, socio-demographic information is generally unavailable for social media users and therefore issues regarding representativeness are not definitive, but are suspected to be skewed towards younger, more educated users (Oteros-Rozas et al., 2018). In contrast, participants of more traditional approaches and PPGIS tend to be older and more educated. Despite the common bias towards higher educated people, PPGIS and social media provide opportunities to reach and attract groups that more traditional approaches may not (Kahila-Tani et al., 2019). Additionally, each method differs slightly in its ability to capture and appeal to different socio-demographic groups. For example, some participants may feel uncomfortable participating through in-person approaches, such as interviews, focus groups and workshops, whereas others may feel discomfort and unfamiliarity navigating internet-based surveys and spatial mapping (Besser et al., 2014). Similarly, many people may feel discomfort using social media platforms.

Social media platforms present the opportunity to gather data without explicit consent from users. In contrast to more traditional approaches and PPGIS that require explicit consent from participants, social media relies on the assumption that publicly shared content provides implicit or implied consent. Irrespective of whether consent is explicitly or implicitly provided, researchers still have the responsibility to appropriately store and re-distribute content and ensure anonymity of users and participants.

In comparison to more traditional approaches and PPGIS, social media is typically not subject to recruitment, response and sample size limitations. Traditional approaches generally recruit low sample sizes and therefore struggles to represent the 'silent majority' (Brown & Kyttä, 2014). As PPGIS and social media provides the opportunity to reach much greater sample sizes, these methods are more likely to represent the 'silent majority' (Brown & Kyttä, 2014; Czepkiewicz et al., 2017; Kahila-Tani et al., 2019).

With increasing use of digital technology there is an increasing number of users that have access to the internet and are able to share content to social media platforms. This brings to light, however, the trade-off that PPGIS and social media may provide more data, but typically provide less information regarding values. This is not the case for more traditional approaches that provide rich understanding of the meaning of values. More traditional approaches have the ability to elicit values without pre-determined typologies, an approach which is far more difficult to implement for PPGIS and is not viable for social media. However, more traditional approaches and social media require a level of interpretation to identify values, whereas PPGIS simply provides the values and operational definitions for participants to place values. Additionally, for social media the interpretation of values is entirely subject to the researcher(s) which has the implication of interpretation bias towards certain values.

Although these values are identified through different methods, they reveal potential bias for over or underrepresenting certain values. For example, aesthetic and recreation are commonly observed to be the most frequently mapped values for all three methods whilst spiritual is mapped less frequently (e.g. Brown et al., 2020; Clemente et al., 2019; Moore et al., 2017). The understanding and decision behind mapped values must also be taken into consideration. Through more traditional approaches, the underlying context as to why mapped places hold meaning and value as well as ambiguous values such as 'spiritual' can be understood (Lowery & Morse, 2013), whereas this is not achievable in the case of PPGIS and social media.

Another similarity between these methods is the wide range in the levels of contribution from participants/users. People tend to contribute more mapped values or photographs if they have a direct interest in the study area. Additionally, PPGIS and more traditional approaches often observe that participants familiar with the area are more likely to contribute more or an extensive number of mapped values.

Lastly, although each method employs a different approach to map values using points, polygons, or coordinates or place tags, these methods are thought to converge on a common spatial agreement given enough observations (Brown et al., 2017; Brown & Pullar, 2012; Goodchild, 2013; Goodchild & Li, 2012). In contrast to more traditional approaches and PPGIS, social media, however, can only represent visited places and would require significantly more observations to converge with polygons and points. Additionally, the location of geotagged photographs can be manually entered by participants causing concerns whether the photograph represents the location the photograph was taken (i.e. the visited place) or the object of the photograph which may be kilometres away from the photograph location. As places need to be visited, social media is also unable to extensively describe an area like more traditional approaches and PPGIS can.

6. Conclusions and implications for management

The social dimensions around human-environment interactions is increasingly being recognised as a vital component for effective and informed planning and management. Data gathered from each of the three methods described in this review have the capacity to identify human-environment interactions through the experiences and values people hold towards the environment. Not only does the data gathered from these methods enable values to be identified, they are also able to gather spatial data through mapping activities or georeferenced content to map values. Values mapped through these robust methods provide insight and understanding to places of value by informing not only the 'what' but also the 'where'. Whilst each method has their limitations, they also provide many advantages and opportunities for managers. These could be used together to mitigate the limitations and provide a greater overview of the human-environment interactions for a given area. For example, response rates and sample sizes (i.e. number of participants) are a large concern and a limitation for traditional approaches and PPGIS. This is likely due to the active contribution required from participants to gather data. By contrast, the passive collection of data from social media requires no contact between users and the researcher, and typically results in a considerable number of individual users. These methods may also be inclusive of different socio-demographic groups. Together, these methods can provide values from a greater number and likely a more diverse population. Whilst the applicability of traditional approaches, PPGIS and social media will likely have to be evaluated for each situation, this literature review has critically compared the limitations and advantages that are independent and consistent between each method. This can assist planners and managers with the choice of method when considering the time, cost, scale of analyses, sample sizes, spatial features, type of data collection, and the mapping technique.

7. References

Bennett, N. J., Roth, R., Klain, S. C., Chan, K., Christie, P., Clark, D. A., Cullman, G., Curran, D., Durbin, T. J., Epstein, G., Greenberg, A., Nelson, M. P., Sandlos, J., Stedman, R., Teel, T. L., Thomas, R., Veríssimo, A., & Wyborn, C. (2017). Conservation social science: Understanding and integrating human dimensions to improve conservation. *Biological Conservation, 205*, 93-108.

Besser, D. T., McLain, R., Cerveny, L., Biedenweg, K., & Banis, D. (2014). Mapping landscape values: Issues, challenges and lessons learned from field work on the Olympic Peninsula, Washington. *Environmental Practice, 16*, 138-150.

Birenboim, A., & Shoval, N. (2016). Mobility research in the age of the smartphone. *Annals of the American Association of Geographers, 106*, 283-291.

Brown, G. (2004). Mapping spatial attributes in survey research for natural resource management: Methods and applications. *Society and Natural Resources, 18*, 17-39.

Brown, G. (2012). An empirical evaluation of the spatial accuracy of public participation GIS (PPGIS) data. *Applied Geography, 34*, 289-294.

Brown, G. (2017). A review of sampling effects and response bias in internet participatory mapping (PPGIS/PGIS/VGI). *Transactions in GIS, 21*, 39-56.

Brown, G., & Brabyn, L. (2012). The extrapolation of social landscape values to a national level in New Zealand using landscape character classification. *Applied Geography, 35*, 84-94.

Brown, G., & Fagerholm, N. (2015). Empirical PPGIS/PGIS mapping of ecosystem services: A review and evaluation. *Ecosystem Services, 13*, 119-133.

Brown, G., & Kyttä, M. (2014). Key issues and research priorities for public participation GIS (PPGIS): A synthesis based on empirical research. *Applied Geography, 46*, 122-136.

Brown, G., & Kyttä, M. (2018). Key issues and priorities in participatory mapping: Toward integration or increased specialization? *Applied Geography, 95*, 1-8.

Brown, G., Montag, J. M., & Lyon, K. (2012b). Public participation GIS: A method for identifying ecosystem services. *Society and Natural Resources, 25*, 633-651.

Brown, G., & Pullar, D. V. (2012). An evaluation of the use of points versus polygons in public participation geographic information systems using quasi-experimental design and Monte Carlo simulation. *International Journal of Geographical Information Science, 26*, 231-246.

Brown, G., & Raymond, C. (2007). The relationship between place attachment and landscape values: Toward mapping place attachment. *Applied Geography, 27*, 89-111.

Brown, G., & Reed, P. (2009). Public participation GIS: A new method for use in national forest planning. *Forest Science, 55*, 166-182.

Brown, G., Reed, P., & Raymond, C. M. (2020). Mapping place values: 10 lessons from two decades of public participation GIS empirical research. *Applied Geography, 116*, 1-8.

Brown, G., Strickland-Munro, J., Kobryn, H., & Moore, S. A. (2016). Stakeholder analysis for marine conservation planning using public participation GIS. *Applied Geography, 67*, 77-93.

Brown, G., Strickland-Munro, J., Kobryn, H., & Moore, S. A. (2017). Mixed methods participatory GIS: An evaluation of the validity of qualitative and quantitative mapping methods. *Applied Geography, 79*, 153-166.

Brown, G., & Weber, D. (2013). A place-based approach to conservation management using public participation GIS (PPGIS). *Journal of Environmental Planning and Management, 56*, 455-473.

Brown, G., Weber, D., Zanon, D., & de Bie, K. (2012a). Evaluation of an online (opt-in) panel for public participation geographic information systems surveys. *International Journal of Public Opinion Research, 24*, 534-545.

Casalegno, S., Inger, R., DeSilvey, C., & Gaston, K. J. (2013). Spatial covariance between aesthetic value & other ecosystem services. *PLoS ONE, 8*, 1-5.

Chen, Y., Parkins, J. R., & Sherren, K. (2018). Using geo-tagged Instagram posts to reveal landscape values around current and proposed hydroelectric dams and their reservoirs. *Landscape and Urban Planning, 170*, 283-292.

Clemente, P., Calvache, M., Antunes, P., Santos, R., Cerdeira, J. O., & Martins, M. J. (2019). Combining social media photographs and species distribution models to map cultural ecosystem services: The case of a natural park in Portugal. *Ecological Indicators, 96*, 59-68.

Czepkiewicz, M., Jankowski, P., & Młodkowski, M. (2017). Geo-questionnaires in urban planning: Recruitment methods, participant engagement, and data quality. *Cartography and Geographic Information Science, 44*, 551-567.

de Vries, S., Buijs, A. E., Langers, F., Farjon, H., van Hinsberg, A., & Sijtsma, F. J. (2013). Measuring the attractiveness of Dutch landscapes: Identifying national hotspots of highly valued places using Google Maps. *Applied Geography, 45*, 220-229.

Di Minin, E., Tenkanen, H., & Toivonen, T. (2015). Prospects and challenges for social media data in conservation science. *Frontiers in Environmental Science, 3*, 1-6.

Figueroa-Alfaro, R. W., & Tang, Z. (2017). Evaluating the aesthetic value of cultural ecosystem services by mapping geo-tagged photographs from social media data on Panoramio and Flickr. *Journal of Environmental Planning and Management, 60*, 266-281.

Ghermandi, A., & Sinclair, M. (2019). Passive crowdsourcing of social media in environmental research: A systematic map. *Global Environmental Change, 55*, 36-47.

Goodchild, M. F. (2007). Citizens as sensors: The world of volunteered geography. *GeoJournal, 69*, 211-221.

Goodchild, M. F. (2013). The quality of big (geo)data. *Dialogues in Human Geography, 3*, 280-284.

Goodchild, M. F., & Li, L. (2012). Assuring the quality of volunteered geographic information. *Spatial Statistics, 1*, 110-120.

Kahila-Tani, M., Kytta, M., & Geertman, S. (2019). Does mapping improve public participation? Exploring the pros and cons of using public participation GIS in urban planning practices. *Landscape and Urban Planning, 186*, 45-55.

Kenter, J. O., O'Brien, L., Hockley, N., Ravenscroft, N., Fazey, I., Irvine, K. N., Reed, M. S., Christie, M., Brady, E., Bryce, R., Church, A., Cooper, N., Davies, A., Evely, A., Everard, M., Fish, R., Fisher, J. A., Jobstvogt, N., Molley, C., Orchard-Webb, J., Ranger, S., Ryan, M., Watson, V., & Williams, S. (2015). What are shared and social values of ecosystems? *Ecological Economics, 111*, 86-99.

Klain, S. C., & Chan, K. M. A. (2012). Navigating coastal values: Participatory mapping of ecosystem services for spatial planning. *Ecological Economics, 82*, 104-113.

Levin, N., Lechner, A. M., & Brown, G. (2017). An evaluation of crowdsourced information for assessing the visitation and perceived importance of protected areas. *Applied Geography, 79*, 115-126.

Li, L., Goodchild, M. F., & Xu, B. (2013). Spatial, temporal, and socioeconomic patterns in the use of Twitter and Flickr. *Cartography and Geographic Information Science, 40*, 61-77.

Lomborg, S., & Bechmann, A. (2014). Using APIs for data collection on social media. *The Information Society, 30*, 256-265.

Lowery, D. R., & Morse, W. C. (2013). A qualitative method for collecting spatial data on important places for recreation, livelihoods, and ecological meanings: Integrating focus groups with public participation geographic information systems. *Society and Natural Resources, 26*, 1422-1437.

Martínez Pastur, G., Peri, P. L., Lencinas, M. V., García-Llorente, M., & Martín-López, B. (2016). Spatial patterns of cultural ecosystem services provision in Southern Patagonia. *Landscape Ecology, 31*, 383-399.

McLain, R., Poe, M., Biedenweg, K., Cerveny, L., Besser, D., & Blahna, D. (2013). Making sense of human ecology mapping: An overview of approaches to integrating socio-spatial data into environmental planning. *Human Ecology, 41*, 651-665.

Moore, S. A., Brown, G., Kobryn, H., & Strickland-Munro, J. (2017). Identifying conflict potential in a coastal and marine environment using participatory mapping. *Journal of Environmental Management, 197*, 706-718.

Moran, E. F. (2010). *Environmental social science: Human-environment interactions and sustainability*. West Sussex, UK: John Wiley & Sons.

Muñoz, L., Hausner, V. H., Runge, C., Brown, G., & Daigle, R. (2020). Using crowdsourced spatial data from Flickr vs. PPGIS for understanding nature's contribution to people in Southern Norway. *People and Nature*, 1-13.

Munro, J., Kobryn, H., Palmer, D., Bayley, S., & Moore, S. A. (2019). Charting the coast: Spatial planning for tourism using public participation GIS. *Current Issues in Tourism, 22*, 486-504.

Neuman, W. L. (2011). *Social research methods: Qualitative and quantitative approaches* (7th ed.). Essex, UK: Pearson.

Oteros-Rozas, E., Martín-López, B., Fagerholm, N., Bieling, C., & Plieninger, T. (2018). Using social media photos to explore the relation between cultural ecosystem services and landscape features across five European sites. *Ecological Indicators, 94*, 74-86.

Pocewicz, A., Nielsen-Pincus, M., Brown, G., & Schnitzer, R. (2012). An evaluation of internet versus paper-based methods for public participation geographic information systems (PPGIS). *Transactions in GIS, 16*, 39-53.

Ramirez-Gomez, S. O. I., Brown, G., Verweij, P. A., & Boot, R. (2016). Participatory mapping to identify indigenous community use zones: Implications for conservation planning in southern Suriname. *Journal for Nature Conservation, 29*, 69-78.

Ramirez-Gomez, S. O. I., Brown, G., & Fat, A. T. S. (2013). Participatory mapping with indigenous communities for conservation: Challenges and lessons from Suriname. *The Electronic Journal of Information Systems in Developing Countries, 58*, 1-22.

Retka, J., Jepson, P., Ladle, R. J., Malhado, A. C. M., Vieira, F. A. S., Normande, I. C., Souza, C. N., Bragagndo, C., & Correia, R. A. (2019). Assessing cultural ecosystem services of a large marine protected area through social media photographs. *Ocean and Coastal Management, 176*, 40-48.

Richards, D. R., & Friess, D. A. (2015). A rapid indicator of cultural ecosystem service usage at a fine spatial scale: Content analysis of social media photographs. *Ecological Indicators, 53*, 187-195.

Richards, D. R., & Tunçer, B. (2018). Using image recognition to automate assessment of cultural ecosystem services from social media photographs. *Ecosystem Services, 31*, 318-325.

Senaratne, H., Mobasheri, A., Ali, A. L., Capineri, C., & Haklay, M. (2017). A review of volunteered geographic information quality assessment methods. *International Journal of Geographical Information Science, 31*, 139-167.

Sieber, R. (2006). Public participation geographic information systems: A literature review and framework. *Annals of the Association of American Geographers, 96*, 491-507.

Strickland-Munro, J., Kobryn, H., Brown, G., & Moore, S. A. (2016a). Marine spatial planning for the future: Using public participation GIS (PPGIS) to inform the human dimension for large marine parks. *Marine Policy, 73*, 15-26.

Strickland-Munro, J., Kobryn, H., Brown, G., Pearce, J., & Moore, S. (2016b). Human values and aspirations for coastal waters of the Kimberley: Social values and management preferences using Public Participation GIS. Technical Report. Kimberley Marine Research Program Node of the Western Australian Marine Science Institution. https://www.wamsi.org.au/sites/wamsi.org.au/files/files/WAMSI_Project_2_1_2_Technical_Report_2_final_April_2016.pdf

Tadaki, M., Sinner, J., & Chan, K. M. A. (2017). Making sense of environmental values: A typology of concepts. *Ecology and Society, 22*, 7.

Tang, Z., & Liu, T. (2016). Evaluating internet-based public participation GIS (PPGIS) and volunteered geographic information (VGI) in environmental planning and management. *Journal of Environmental Planning and Management, 59*, 1073-1090.

Tenerelli, P., Demšar, U., & Luque, S. (2016). Crowdsourcing indicators for cultural ecosystem services: A geographically weighted approach for mountain landscapes. *Ecological Indicators, 64*, 237-248.

Toivonen, T., Heikinheimo, V., Fink, C., Hausmann, A., Hiippala, T., Järv, O., Tenkanen, H., & Di Minin, E. (2019). Social media data for conservation science: A methodological overview. *Biological Conservation, 233*, 298-315.

van Riper, C. J., Kyle, G. T., Sutton, S. G., Barnes, M., & Sherrouse, B. C. (2012). Mapping outdoor recreationists' perceived social values for ecosystem services at Hinchinbrook Island National Park, Australia. *Applied Geography, 35*, 164-173.

van Zanten, B. T., Van Berkel, D. B., Meentemeyer, R. K., Smith, J. W., Tieskens, K. F., & Verburg, P. H. (2016). Continental-scale quantification of landscape values using social media data. *Proceedings of the National Academy of Sciences, 113*, 12974-12979.

Vihervaara, P., Kumpula, T., Tanskanen, A., & Burkhard, B. (2010). Ecosystem services: A tool for sustainable management of human–environment systems. Case study Finnish Forest Lapland. *Ecological Complexity, 7*, 410-420.

Wood, S. A., Guerry, A. D., Silver, J. M., & Lacayo, M. (2013). Using social media to quantify nature-based tourism and recreation. *Scientific Reports, 3*, 1-7.

Yoshimura, N., & Hiura, T. (2017). Demand and supply of cultural ecosystem services: Use of geotagged photos to map the aesthetic value of landscapes in Hokkaido. *Ecosystem Services, 24*, 68-78.

Zook, M., Barocas, S., Boyd, D., Crawford, K., Keller, E., Gangadharan, S. P., Goodman, A., Hollander, R., Koenig, B. A., Metcalf, J., Narayana, A., Nelson, A., & Pasquale, F. (2017). Ten simple rules for responsible big data research. *PLoS Computational Biology, 13*, 1-10.

Appendix B. Ruleset for classifying geotagged Flickr photographs

Table B.1. Detailed ruleset for classifying social value types captured by geotagged Flickr photographs that refer to the natural environment or natural resources, examples and description for each vale type, as well as the exclusion criteria.

Social value types	Examples	Description
Direct use, non-consumptive		
Scenic/aesthetic	*Landscapes*	Wide view over the landscape that does not focus on a specific feature
Photographs that depict landscapes or attractive scenery	*Scenic*	Attractive scenery or environments (e.g. gorges, waterfalls, flood plains, tidal flats, caves, islands, beaches, ocean, river)
	Aerial view	Aerial view over the landscape (e.g. taken from a plane)
	Sunrise or sunset	Presence of a sunrise or sunset
	Moon or stars	Presence of moon or stars either during the day or at night
	Natural processes	Natural processes (e.g. lightning, fires, rain, rainbows)
Aboriginal culture/heritage	*Rock art*	Aboriginal rock art
Photographs that depict Aboriginal culture or heritage	*Painting or artwork*	Traditional Aboriginal painting (e.g. dot painting) or artwork
	Aboriginal history	Artefacts or objects (e.g. in a museum, Derby Prison Tree) or buildings that represent Aboriginal history
European culture/heritage	*World war two*	World war two artefacts (e.g. plane wrecks)
Photographs that depict European culture or heritage	*Exploration*	European exploration or pastoralism
	European history	Artefacts or objects (e.g. in a museum) that represent European history in Australia
Learning/research	*Learning*	People engaged in educational activities or signage that educates people
Photographs that depict people engaging in research or educational activities, with research equipment or photographs without people but showing research equipment	*Research*	People engaged in research activities with research equipment (e.g. clipboards) and research equipment without people
	Specimens	Live or preserved specimens
	Art centre	Art presented in a centre or studio
	Museums	Artefacts or objects presented in a museum
Spiritual	*Religious buildings*	Religious buildings (e.g. church)
Photographs that depict religious or spiritual places	*Spiritual places*	Spiritual places (e.g. gravestones, cemeteries, memorials)
Recreation	*Off-road vehicles*	Presence of cars, quad bikes, motorcycles or scooters in the natural environment (e.g. on the beach) or driving down dirt tracks, and tire marks indicating the presence of an off-road vehicle
Photographs that depict people with or without recreational equipment and recreational equipment without people or people in social settings	*Boats*	Presence of recreational boats, jet skis, yachts, sailing boats or kayaks
	Camping	Presence of camping gear, including cars with caravans and campervans that are parked in campgrounds or in the natural environment in the photograph
	Hiking or bushwalking	People hiking or bushwalking (e.g. walking through the bush wearing backpacks)
	Sunbathing or swimming	People wearing swimming gear (e.g. bathers, boardies) or sitting on towels wearing swimming gear in or near water (e.g. ocean, waterfall)

Table B.1. Continued.

Social value types	*Examples*	Description
Recreation continued	*Cycling*	Presence of cycling gear (e.g. bicycle)
	Riding	Presence of animals (e.g. horses, camels) with riding gear
	Diving or snorkeling	Presence of diving or snorkelling gear or photographs taken underwater
	Social	Social activities (e.g. bonfires, picnics) in the natural environment
	Surfing, kite surfing or wind surfing	Presence of boards (e.g. surfboards, boogie boards, paddleboards) or kites used for surfing
Direct use, consumptive		
Fishing (recreational) Photographs that depict fishing equipment or people engaged in fishing	*Fishing*	Presence of fishing equipment (e.g. fishing rods, crab pots) or people engaged in fishing for fish and other marine life (e.g. crabs, cockles, oysters) in the photograph
Economic (non-tourism) Photographs that depict natural resources used by humans and infrastructure that transports these resources	*Oil/gas*	Oil/gas infrastructure
	Mining/minerals	Mining infrastructure or mining minerals (e.g. salt, iron ore)
	Pastoralism	Agriculture/crop production or livestock (e.g. cows, sheep, goats)
	Aquaculture	Aquaculture infrastructure (e.g. aquaculture tubs or pools)
	Commercial vessels	Commercial vessels (e.g. tugboats, transport vessels, bulk carriers)
	Trucks or road trains	Trucks or road trains
	Trains or train tracks	Trains or train tracks
Nature-based tourism Photographs that depict iconic tourism destinations and tourism activities	*Tourism infrastructure*	Infrastructure developed for tourism opportunities (e.g. boardwalks, jetties, picnic benches, lookouts)
	Accommodation	Accommodation (e.g. homestead, cabins, glamping, lodges, campgrounds)
	Cruise ships	Cruise ships or expedition cruises
	Camel riding	Camels with riding gear with or without people
	Dinosaur footprints	Dinosaur footprints in the rocks or people looking for the footprints
	Gorges, caves or waterfalls	Gorges, caves or waterfalls
	Signage	Signage (e.g. information points, signs for national parks)
	Statues or sculptures	Statues or sculptures
	Wildlife observation	Animals freely observed (e.g. bird watching), through tours (e.g. whales, dolphins) or in wilderness parks
	Fixed wing or helicopter	People inside or photograph taken inside a fixed wing or helicopter (photographs taken from an aerial view not included)
	Tours	Vehicles used for tours (e.g. buses, boats) and buildings that provide tours (e.g. visitor centres)
Indirect use		
Nature appreciation Photographs that depict nature	*Plants*	Plants primarily depicted
	Animals	Animals primarily depicted
	Habitats	Habitats (e.g. reefs, mangroves) primarily depicted

Table B.1. Continued.

Social value types	Example	Description
Exclusion criteria		
Photographs that were unidentifiable, or did not refer to the natural environment or natural resources excluded from further analyses	*Urban environment*	Urban environments (e.g. residential houses, airport, streets with shops) primarily depicted
	Industrial environment	Industrial environments (e.g. industrial infrastructure, machinery) primarily depicted
	Wrong geotag	Photographs wrongly geotagged within the study area confirmed using geographic coordinates
	Food	Food or drinks
	Cars	Cars not in the natural environment (e.g. in a carpark)
	Building	Buildings that do not have spiritual or historical significance (e.g. general store, deli, bakery, roadhouses)
	Road signs	Road signs (e.g. highways, speed limits)
	Inside	Inside of buildings, planes, or vehicles
	Advertisements	Advertisements (e.g. billboards) primarily depicted
	Fireworks	Fireworks
	Restaurants	People sitting in restaurants (not including photographs taken from restaurants but depicting the natural environment)
	Selfies	Selfies or groups of people where the background does not depict the environment
	Personal	Personal items or objects of everyday life (e.g. colouring in books, children's drawings not presented in an art centre or exhibition)
	Pets	Animals domesticated as pets (e.g. dogs, cats) not in the natural environment (e.g. backyards)
	Clothing	Clothing (e.g. shoes, shops)
	Videos	Geotagged videos not included regardless of content

Appendix C. Correlation matrices of socio-ecological driver variables

Table C.1. Correlation matrix for all socio-ecological drivers. Ocean mask used for geological features, major roads, minor roads and tracks, roadhouses and waterbodies as the distance surface from these variables were unlikely to be important to the marine environments of the study area. Correlations > 0.8 and < -0.8 are indicated in red, and variables excluded from the model are indicated in bold.

Variables	**1**	2	3	4	5	**6**	7	8	9	10	**11**	12	13	14	15	16	17
1 Distance from aircraft facilities	1																
2 Distance from coastal access	0.99	1															
3 Distance inland	-0.29	-0.26	1														
4 Distance seawards	0.81	0.82	-0.29	1													
5 Distance from geological features	-0.31	-0.28	0.79	-0.31	1												
6 Distance from human settlements	0.98	0.98	-0.30	0.84	-0.32	1											
7 Indigenous protected areas	-0.16	-0.14	0.36	-0.17	0.36	-0.15	1										
8 Distance from major roads	-0.23	-0.19	0.58	-0.26	0.62	-0.22	0.55	1									
9 Marine protected areas	-0.07	-0.05	-0.14	0.06	-0.15	-0.08	-0.09	-0.13	1								
10 Distance from minor roads and tracks	-0.27	-0.24	0.65	-0.29	0.79	-0.27	0.58	0.74	-0.14	1							
11 Distance from roadhouses	-0.28	-0.24	0.69	-0.30	0.73	-0.28	0.58	0.96	-0.14	0.83	1						
12 Coastal geomorphology	-0.18	-0.17	0.05	-0.20	0.19	-0.18	0.18	0.24	0.02	0.28	0.27	1					
13 Terrestrial protected areas	-0.13	-0.11	0.29	-0.13	0.28	-0.13	0.20	0.44	-0.06	0.36	0.45	0.14	1				
14 Distance from major towns	0.65	0.66	-0.23	0.64	-0.25	0.72	-0.08	-0.07	-0.06	-0.19	-0.14	-0.12	-0.05	1			
15 Vegetation diversity	-0.11	-0.10	0.10	-0.12	0.22	-0.11	0.11	0.24	-0.03	0.23	0.27	0.34	0.09	-0.08	1		
16 Distance from waterbodies	-0.30	-0.27	0.76	-0.32	0.95	-0.31	0.42	0.68	-0.15	0.86	0.77	0.22	0.33	-0.24	0.22	1	
17 Distance from waterfalls	0.58	0.58	-0.19	0.60	-0.19	0.55	-0.21	-0.29	-0.03	-0.27	-0.33	-0.21	-0.16	0.01	-0.11	-0.21	1
18 Topographic rugosity	0.00	0.00	-0.02	0.00	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01

Table C.2. Correlation matrix for only terrestrial socio-ecological drivers using an ocean mask. Correlations > 0.8 and < -0.8 are indicated in red, and variables excluded from the model are indicated in bold.

Variables	**1**	2	3	4	**5**	6	7	8	**9**	10	11	12	13	14	15
1 Distance from aircraft facilities	1														
2 Distance from coastal access	0.81	1													
3 Distance inland	-0.17	-0.06	1												
4 Distance from geological features	0.08	0.06	0.13	1											
5 Distance from human settlements	0.89	0.85	-0.12	-0.04	1										
6 Indigenous protected areas	0.14	0.17	-0.09	-0.23	0.30	1									
7 Distance from major roads	0.56	0.58	-0.16	-0.23	0.65	0.30	1								
8 Distance from minor roads and tracks	0.56	0.48	-0.21	0.16	0.49	0.35	0.28	1							
9 Distance from roadhouses	0.53	0.53	-0.16	-0.29	0.63	0.34	0.93	0.34	1						
10 Coastal geomorphology	0.18	0.09	-0.50	-0.14	0.16	0.04	0.15	0.21	0.19	1					
11 Terrestrial protected areas	-0.06	0.03	0.01	-0.13	0.00	0.04	0.26	0.08	0.28	0.01	1				
12 Distance from major towns	0.54	0.60	-0.14	-0.19	0.64	0.27	0.98	0.24	0.88	0.12	0.24	1			
13 Vegetation diversity	0.13	0.07	-0.26	-0.06	0.11	-0.06	0.07	0.02	0.09	0.38	-0.02	0.05	1		
14 Distance from waterbodies	0.26	0.15	-0.01	0.74	0.16	-0.08	-0.04	0.41	-0.10	-0.05	-0.02	-0.01	-0.06	1	
15 Distance from waterfalls	-0.32	-0.37	0.13	0.29	-0.41	-0.35	-0.57	-0.38	-0.81	-0.18	-0.23	-0.47	-0.07	0.14	1
16 Topographic rugosity	0.00	0.01	-0.01	-0.01	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	-0.02

Appendix D. Kernel density maps

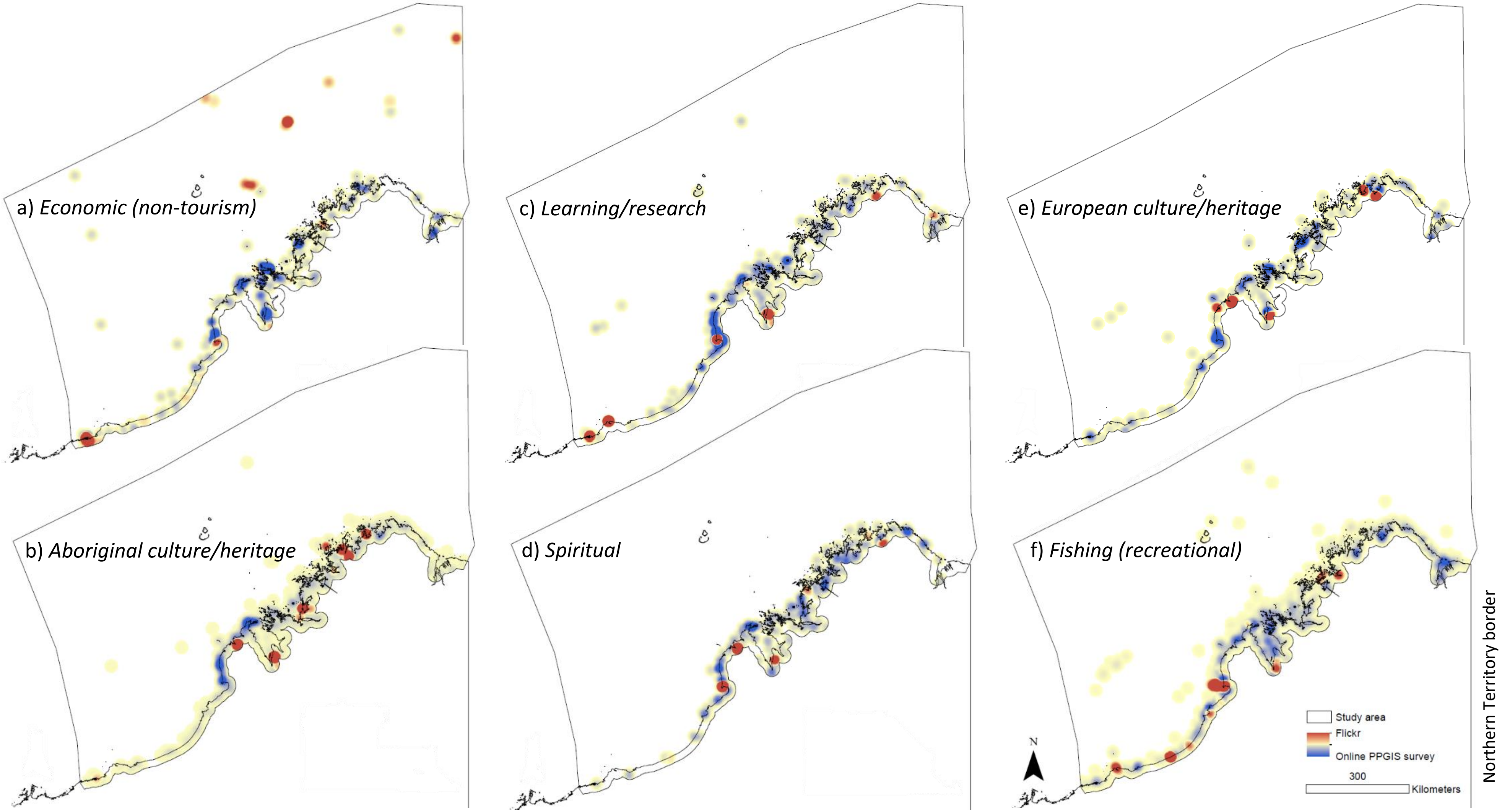


Figure D.1. Kernel density maps depicting the relative hotspots of value types between Flickr and the online PPGIS survey for a) *economic (non-tourism)*, b) *Aboriginal culture/heritage*, c) *learning/research*, d) *spiritual*, e) *European culture/heritage*, and f) *fishing (recreational)*. Red areas indicate where Flickr was more commonly mapped compared to the online PPGIS survey, blue areas indicate where the online PPGIS survey was more commonly mapped compared to Flickr, and yellow indicates areas that were similarly mapped between the two methods. The darker the colour, the greater the difference.

Appendix E. Maxent predictive maps

Economic (non-tourism)

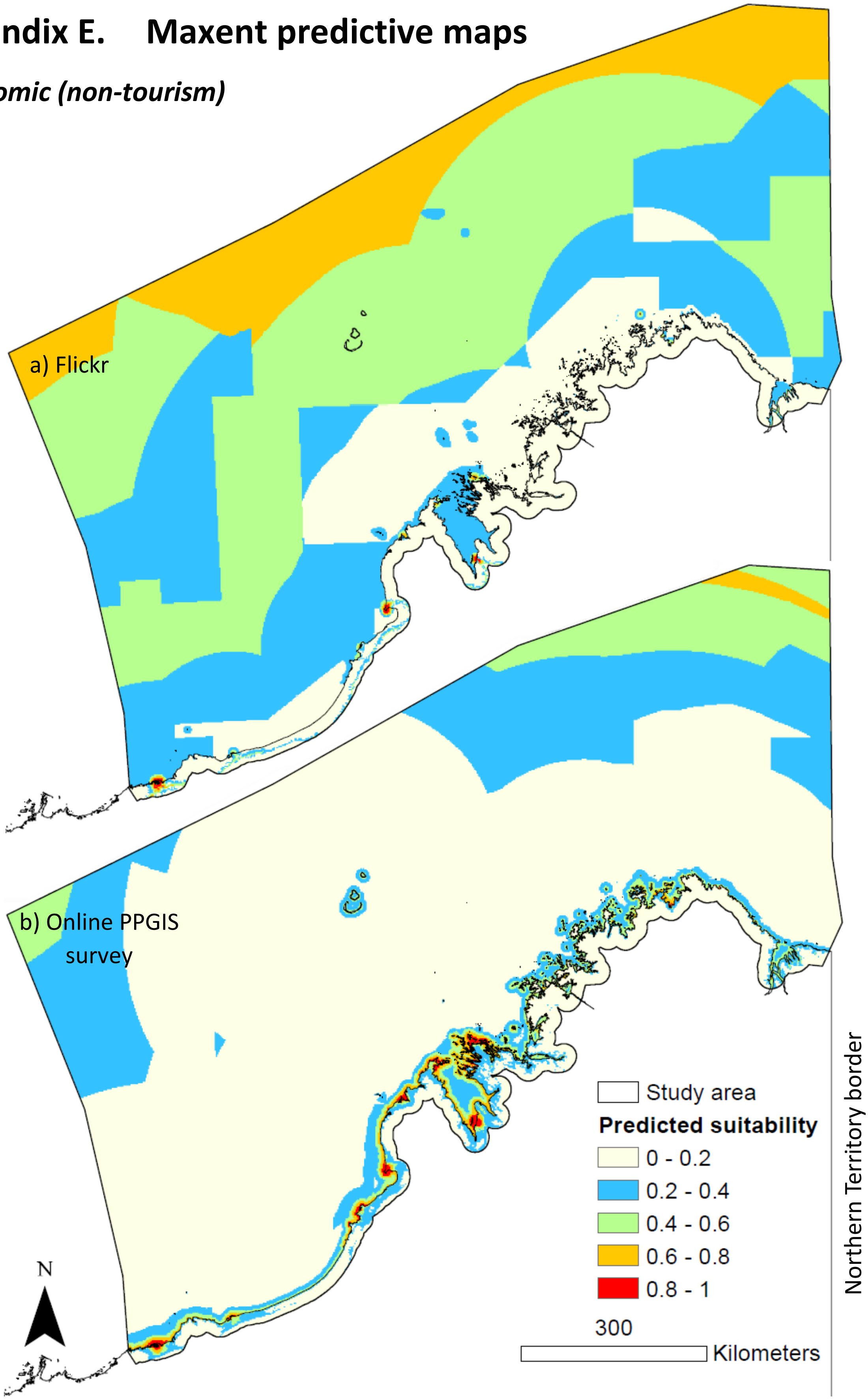


Figure E.1. Areas predicted suitable by Maxent models for occurrence points for the value type *economic (non-tourism)* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

Aboriginal culture/heritage

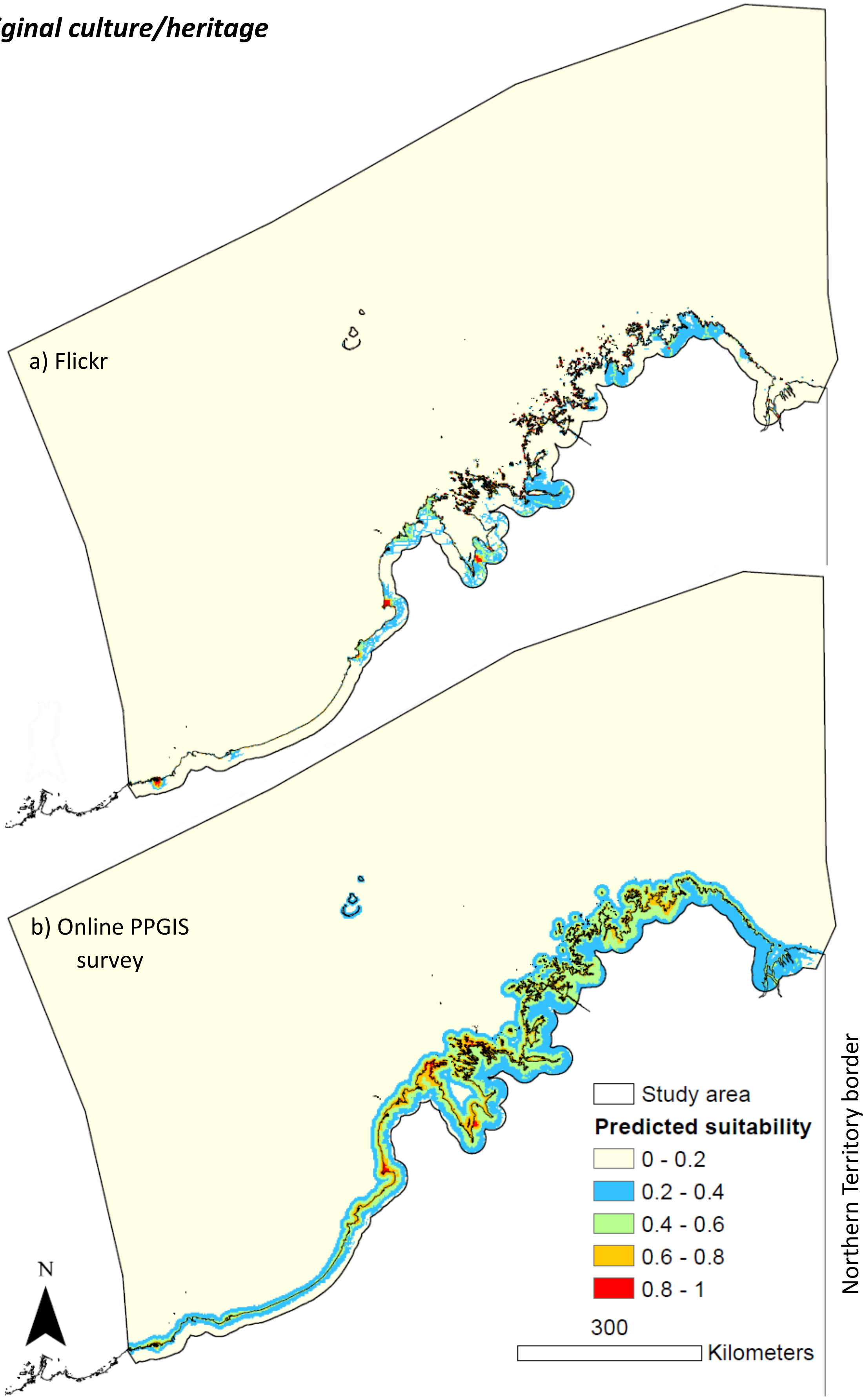


Figure E.2. Areas predicted suitable by Maxent models for occurrence points for the value type *Aboriginal culture/heritage* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

Learning/research

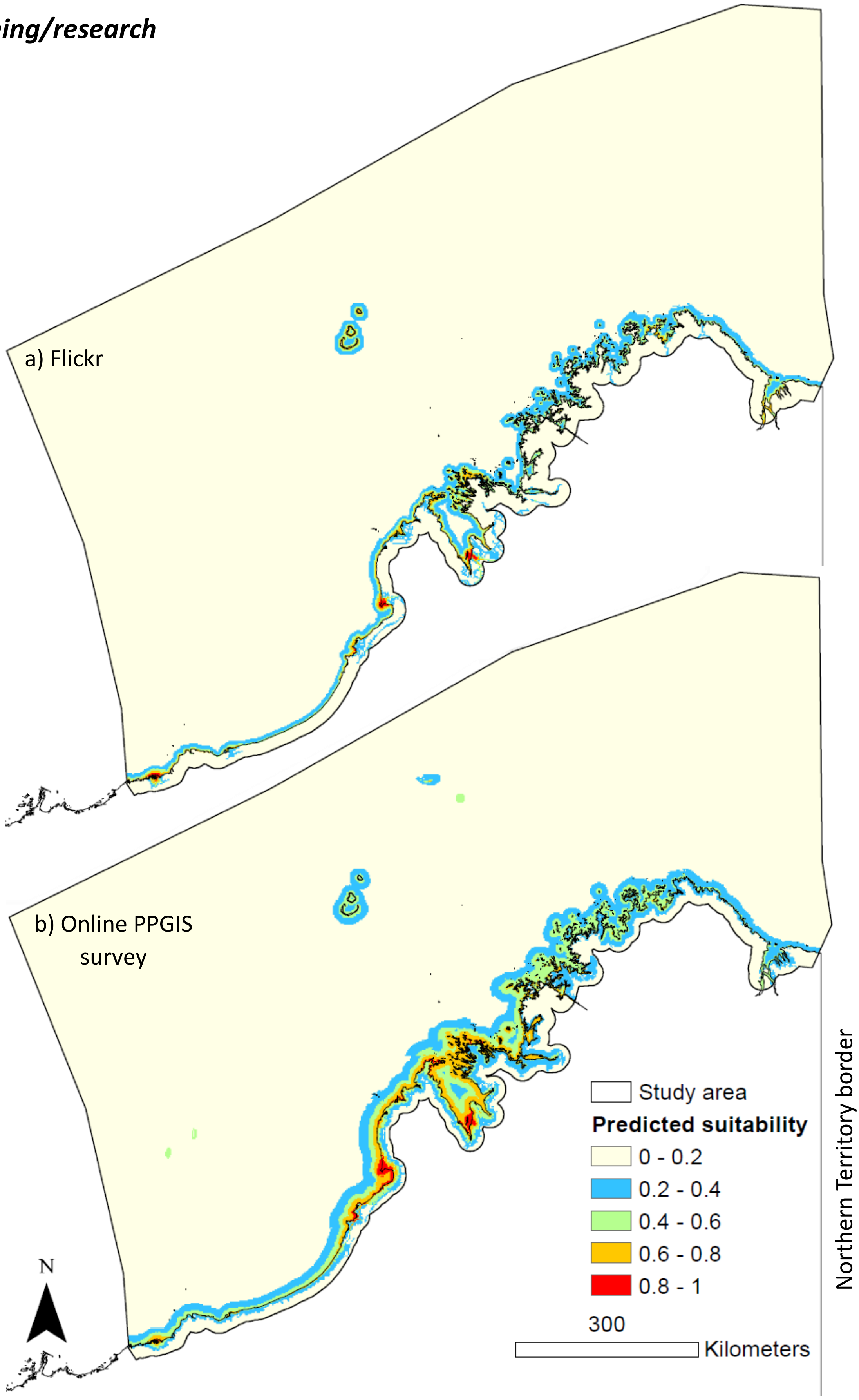


Figure E.3. Areas predicted suitable by Maxent models for occurrence points for the value type *learning/research* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

Spiritual

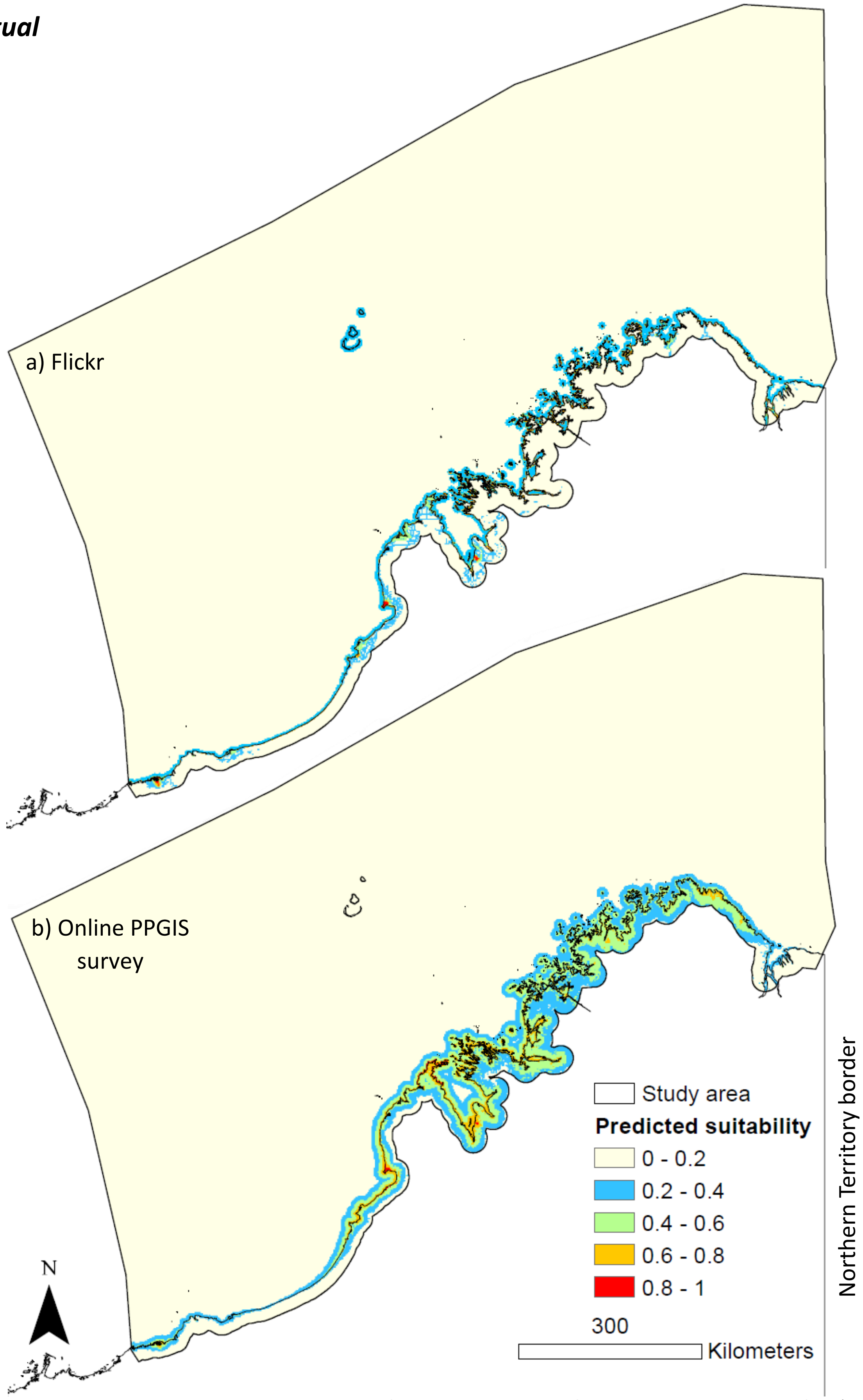


Figure E.4. Areas predicted suitable by Maxent models for occurrence points for the value type *spiritual* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

European culture/heritage

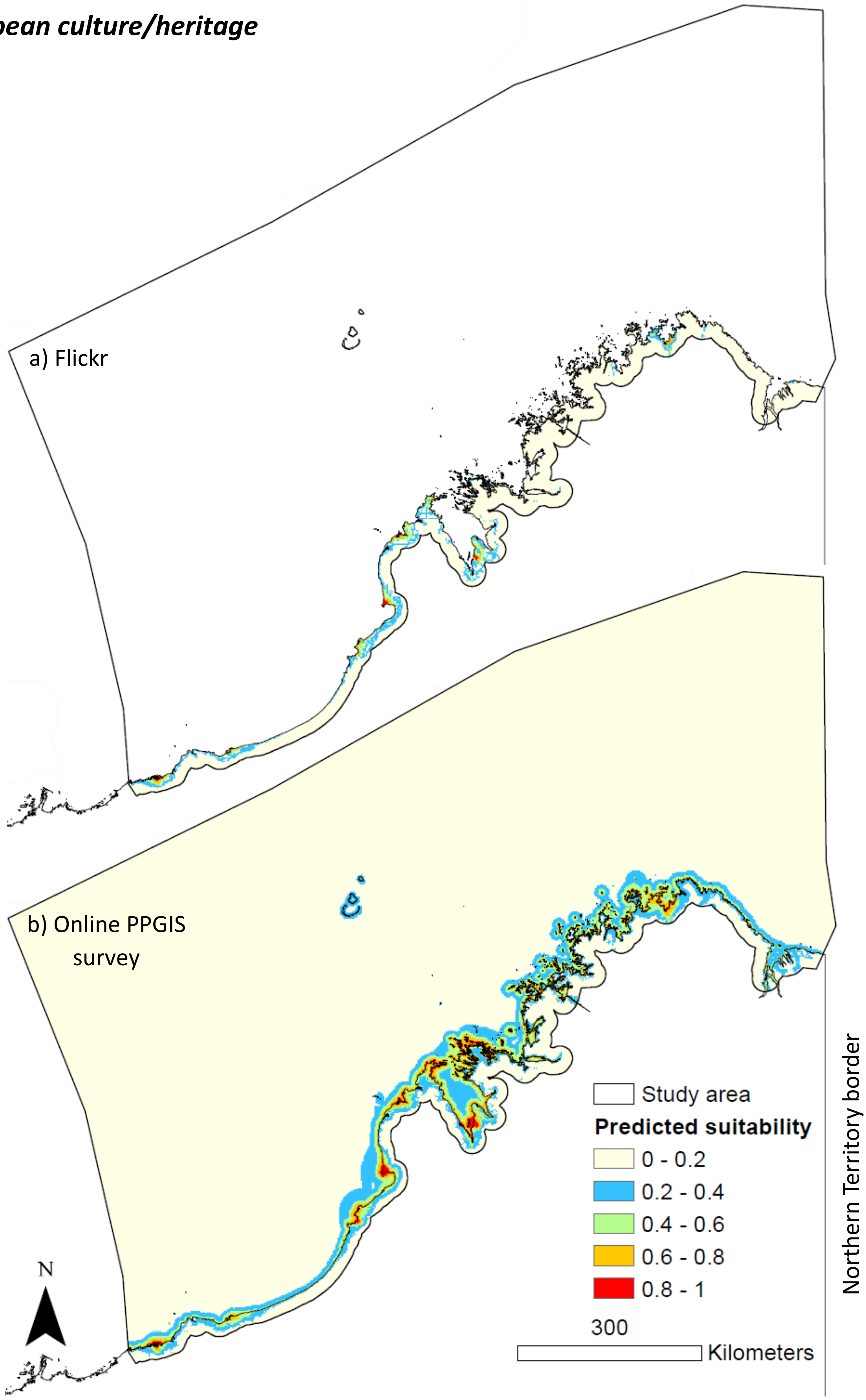


Figure E.5. Areas predicted suitable by Maxent models for occurrence points for the value type *European culture/heritage* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1). White for the marine part of the study area indicates no value points occurred in the marine environment for Flickr.

Fishing (recreational)

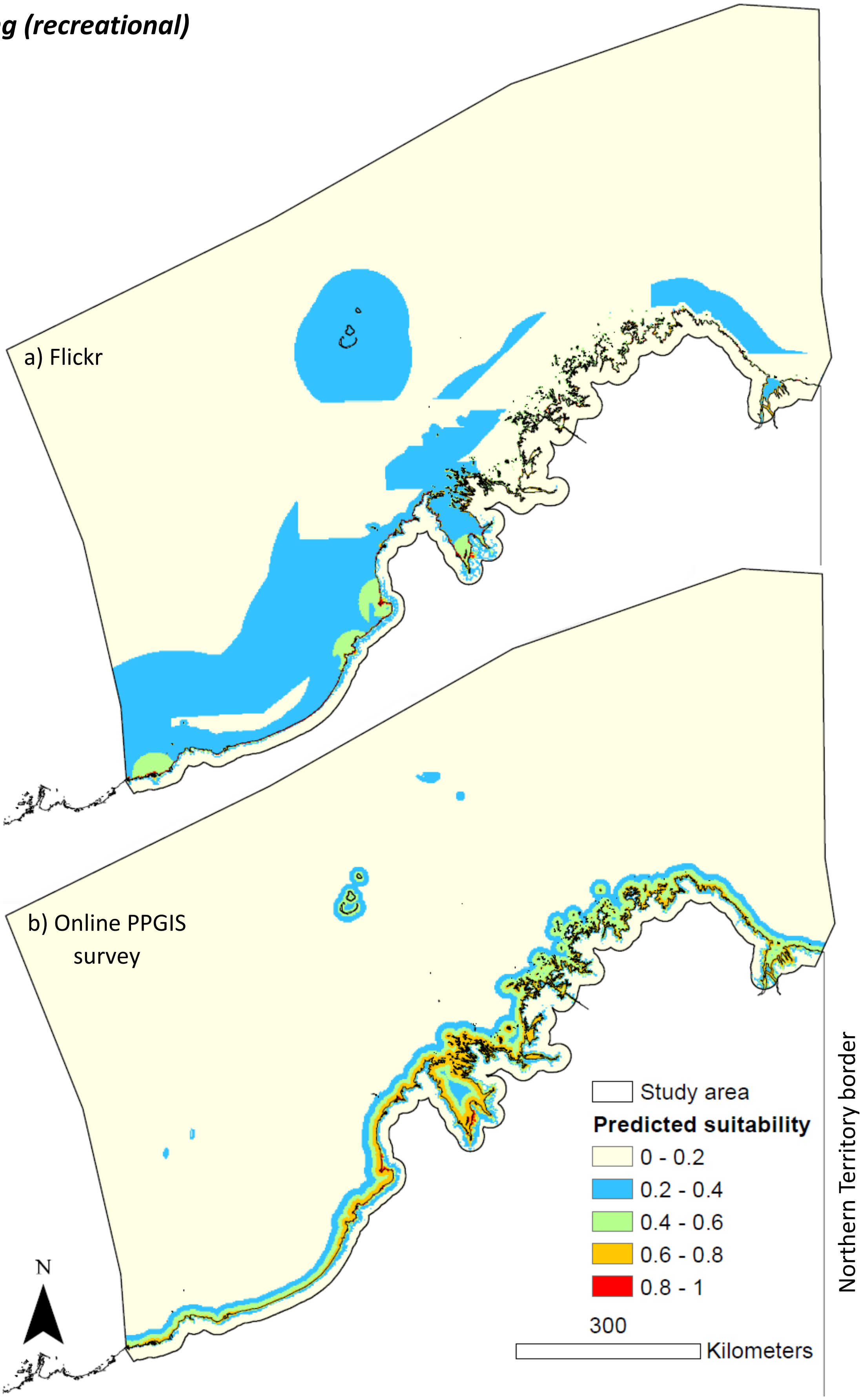
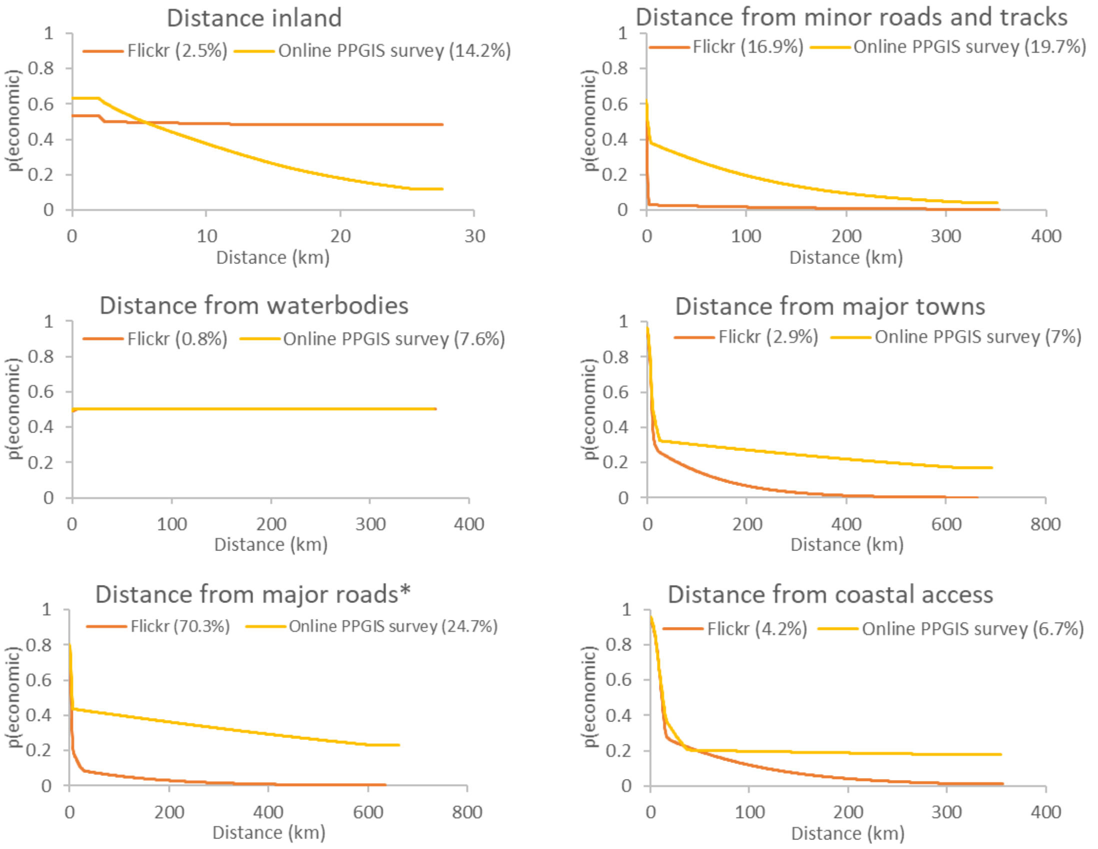


Figure E.6. Areas predicted suitable by Maxent models for occurrence points for the value type *fishing (recreational)* for a) Flickr and b) the online PPGIS survey, where 0 = no suitability and 1 = perfect suitability. Light yellow and blue indicate areas of no to low predicted suitability (0–0.4), green and orange indicate areas of moderate suitability (0.4–0.8), and red indicates areas of high suitability (0.8-1).

Appendix F. Maxent response curves

a) Response curves of *economic (non-tourism)* for terrestrial models



b) Response curves of *economic (non-tourism)* for marine models

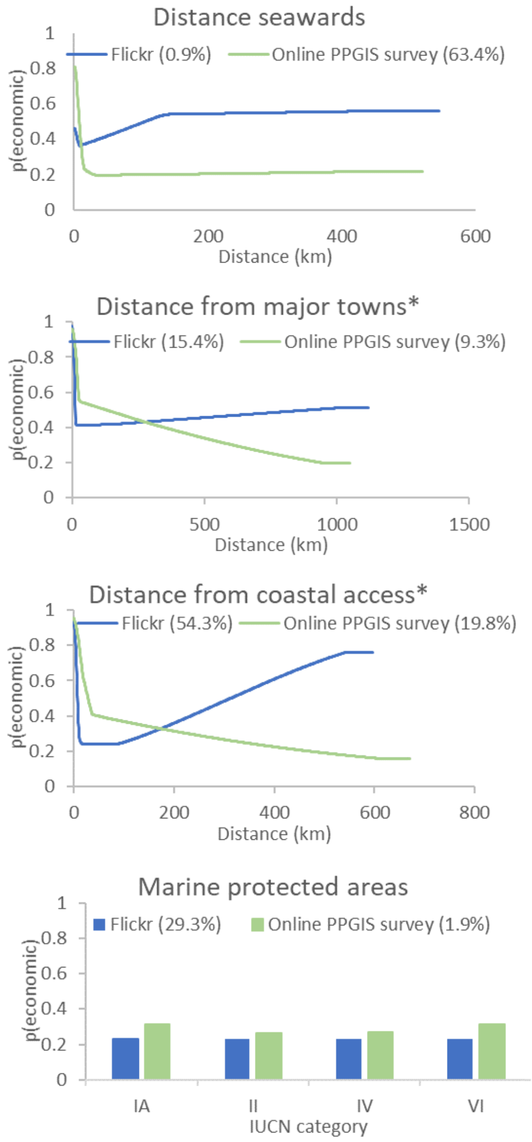


Figure F.1. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *economic (non-tourism)* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above average in importance for both Flickr and the online PPGIS survey.

a) Response curves of *Aboriginal culture/heritage* for terrestrial models

b) Response curves of *Aboriginal culture/heritage* for marine models

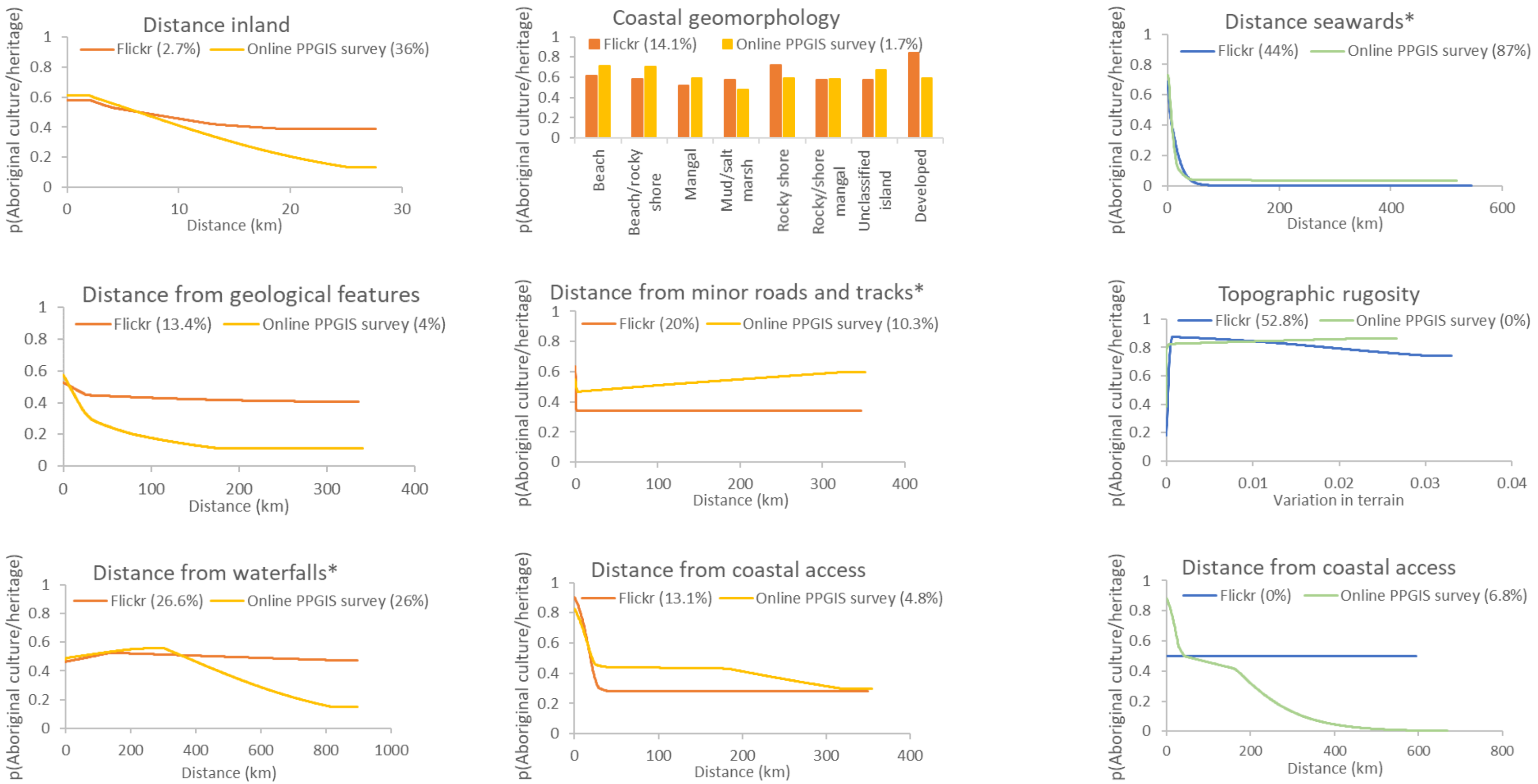
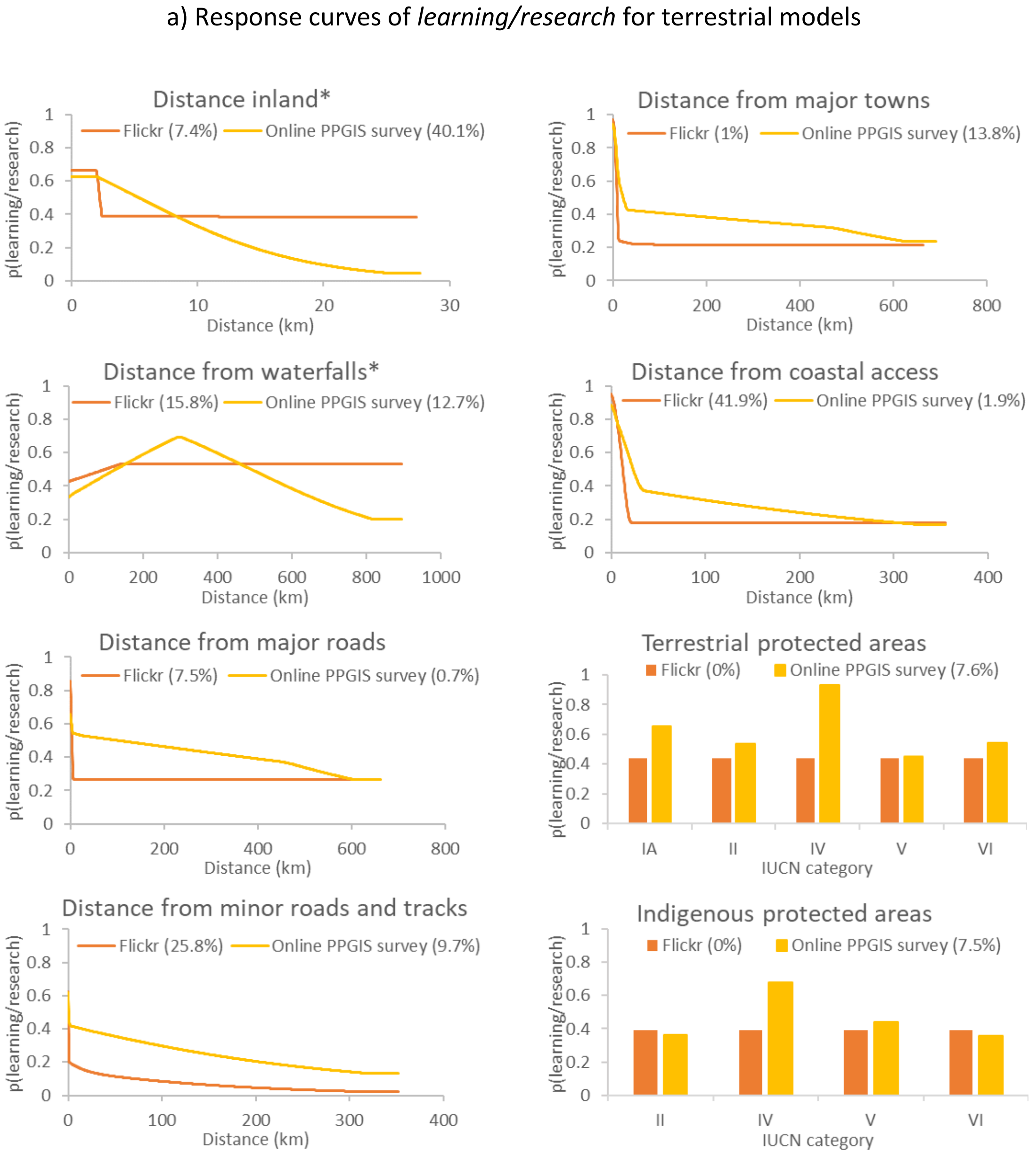


Figure F.2. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *Aboriginal culture/heritage* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above average in importance for both Flickr and the online PPGIS survey.



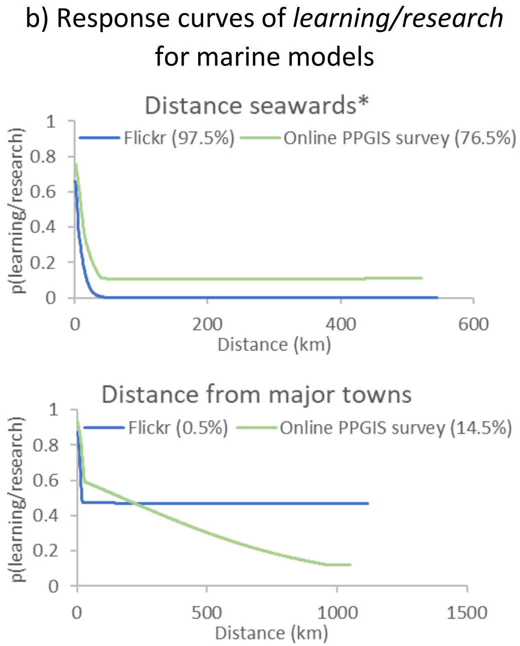


Figure F.3. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *learning/research* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above average in importance for both Flickr and the online PPGIS survey.

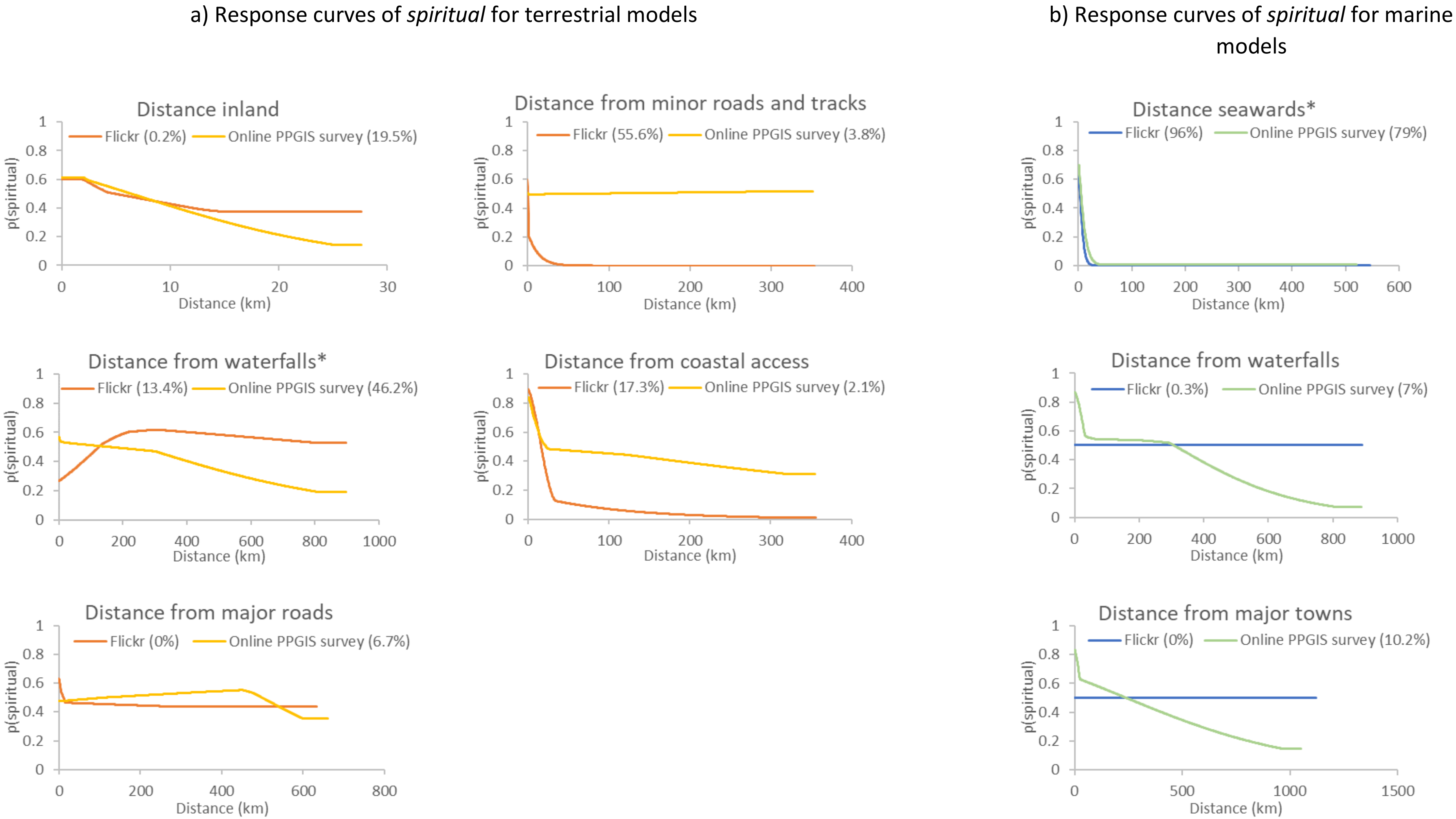


Figure F.4. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *spiritual* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above average in importance for both Flickr and the online PPGIS survey.

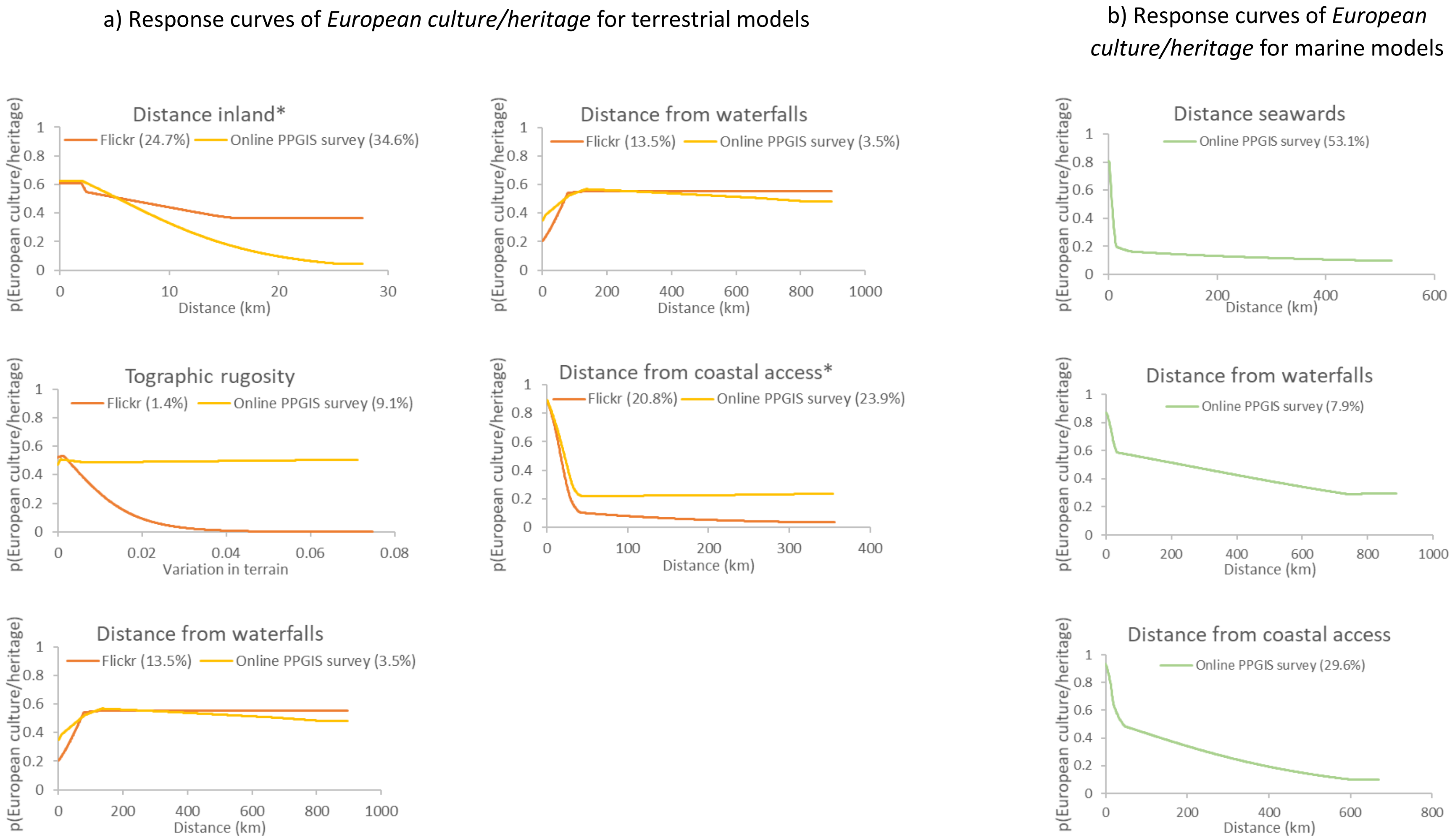


Figure F.5. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *European culture/heritage* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. There are no response curves for Flickr for marine models as no value points occurred within the marine environment. Variables with * were above average in importance for both Flickr and the online PPGIS survey.

a) Response curves of *fishing (recreational)* for terrestrial models

b) Response curves of *fishing (recreational)* for marine models

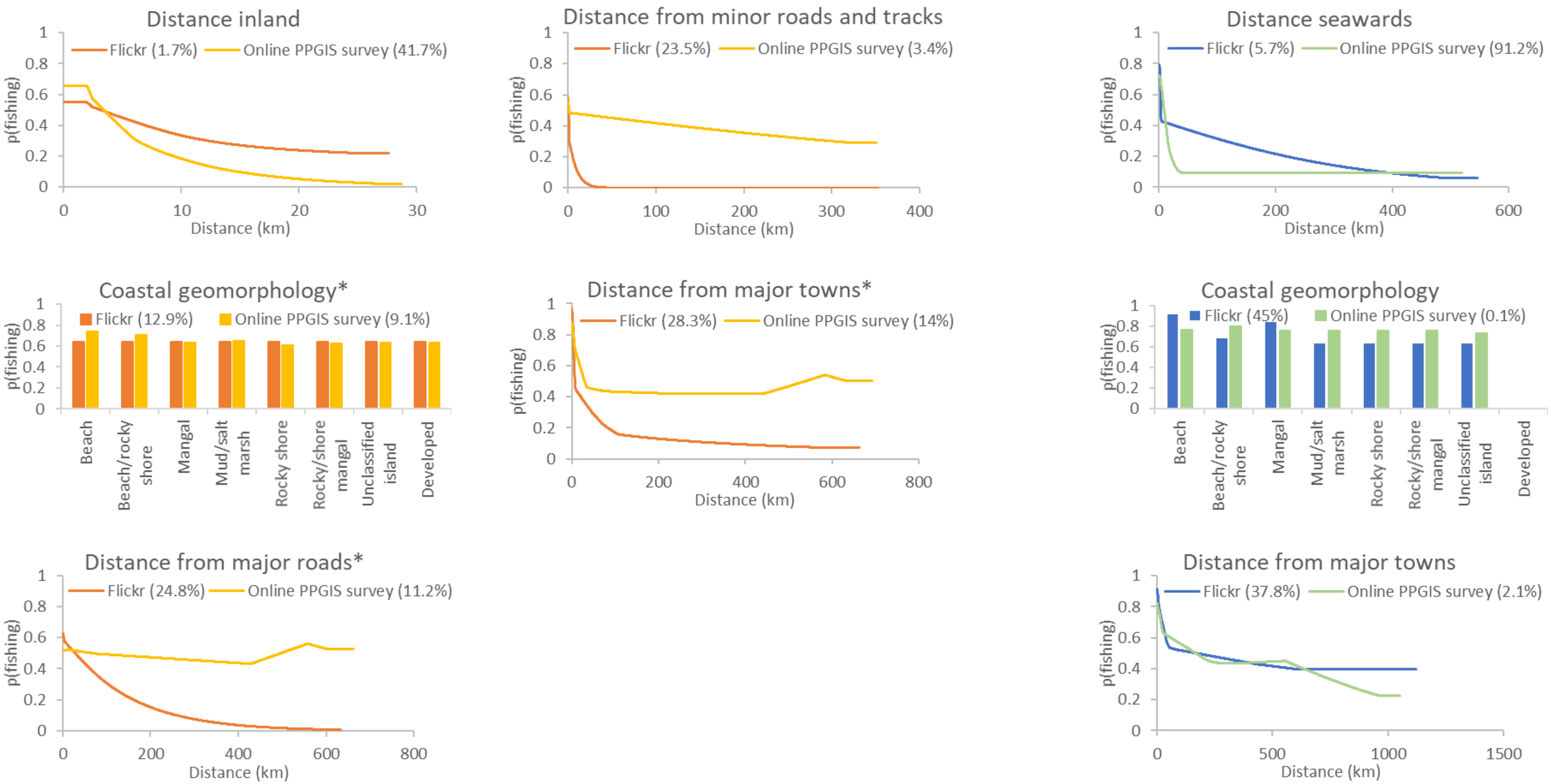


Figure F.6. Univariate response curves from Maxent models showing the relationship between socio-ecological drivers with above average importance (>6.7%) and predicted probability of the value type *fishing (recreational)* a) modelled for the terrestrial environment and b) modelled for the marine environment. Response curves illustrate the association between important variables, with the percent importance provided in brackets, for Flickr or the online PPGIS survey, and counterpart. Variables with * were above average in importance for both Flickr and the online PPGIS survey.