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Benthic mapping of the Bluefields Bay fish sanctuary, Jamaica

Karen McIntyre

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Department of
Physical Geography and Ecosystem Science
Centre for Geographical Information Systems
Lund University
Sölvegatan 12
S-223 62 Lund
Sweden

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Department of Physical Geography and Ecosystems Science, Lund University

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Karen McIntyre
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Ulrik Mårtensson
Director of Studies, Department of Physical Geography and Ecosystems Sciences, Lund University

Kurt McLaren
Lecturer, Forest Ecology, Department of Life Sciences, University of the West Indies

Abstract

Nearshore marine ecosystems and resources serve numerous facets of our natural and human existence, and in order to effectively manage these coastal zones, knowledge of the spatial configuration of benthic habitats is important. In this regard, the Government of Jamaica is desirous of mapping the benthic features at all fish sanctuaries across Jamaica; however several habitat mapping methodologies exist, and as such, it was deemed necessary to test the practicality of applying two methods, namely optical and acoustic remote sensing. Consequently, benthic habitats at a pilot site, the Bluefields Bay fish sanctuary, were mapped using optical remote sensing, particularly pixel-based supervised classification of two available multispectral images (WorldView-2 and GeoEye-1), and by a sonar survey using a BioSonics DT-X Portable Echosounder and undertaking subsequent interpolation by means of indicator kriging in order to create continuous benthic surfaces. Image classification resulted in the mapping of three benthic classes, namely submerged vegetation, bare substrate and coral reef, with an overall map accuracy of 89.9% for WorldView-2 and 86.8% for GeoEye-1 imagery. These accuracies surpassed those of the acoustic classification method, which attained 76.6% accuracy for vegetation presence, and 53.5% for bottom substrate (silt, sand and coral reef/ hard bottom). Both approaches confirmed that the Bluefields Bay is dominated by submerged aquatic vegetation, with contrastingly smaller areas of sand and coral reef patches. The mapping exercise ultimately compared each method and although it was found that satellite image classification was perhaps the most cost-effective and well-suited for Jamaica given current available equipment and expertise, it is acknowledged that acoustic technology offers greater thematic detail required by a number of stakeholders and is capable of operating in turbid waters and cloud covered environments ill-suited for image classification. The choice in mapping approach, as well as the survey design and processing steps is not an easy task; however the results of this study certainly highlight some of the pros and cons of implementing optical and acoustic classification approaches in Jamaica.

Keywords: remote sensing, image classification, GIS, acoustic survey, benthic habitat mapping

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"Giving thanks always and for everything to God the Father in the name of our Lord Jesus Christ" (Ephesians 5:20)

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List of acronyms and abbreviations

A	AGGRA	Atlantic and Gulf Rapid Reef Assessment
	amsl	Above mean sea level
B	BBFFS	Bluefields Bay Fishermen's Friendly Society
	BBSFCA	Bluefields Bay Special Fisheries Conservation Area
	BSM	Bathymetric surface model
C	C	Celsius
	CARIBSAVE	CARIBSAVE Partnership
	CBD	Convention on Biological Diversity
	C-FISH	Caribbean Fish Sanctuary Partnership
D	DEM	Digital elevation model
	DSM	Digital surface model
E	E	East/ Easting
	EIA	Environmental Impact Assessment
	ESRI	Environmental Systems Research Institute
F	ft	Feet
G	GIS	Geographic information system/ science
	GNSS	Global Navigation Satellite System
	GOJ	Government of Jamaica
	GPS	Global Positioning System
H	HA	Hectares
	hr	Hour
I	IDW	Inverse distance weighted
	IK	Indicator kriging
	IPCC	Intergovernmental Panel on Climate Change
	IR	Infrared
	IUCN	International Union for Conservation of Nature
J	JAD 2001	Jamaica Grid 2001
K	KED	Kriging with external drift
	km	Kilometre
L	L8 OLI/TIRS	Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)
	LAT	Lowest Astronomical Tide
	LICJ	Land Information Council of Jamaica
M	m	Metre
	m^3/sec	Cubic metres per second
	ms	Milliseconds
	m/s	Metres per second
	ME	Mean error (prediction)
	MSE	Mean squared error (prediction)
	min	Minute (s)
	mm	Millimetre
	MMU	Minimum mapping unit
	MoAF	Ministry of Agriculture and Fisheries
	MPA	Marine protected area
	MSDR	Mean squared deviation ratio
N	N	North/ Northing
	NEPA	National Environment and Planning Agency
	NIR	Near infrared

	NMIA	Norman Manley International Airport
	NRCA	Natural Resources Conservation Act
	NSDMD	National Spatial Data Management Division
O	OK	Ordinary kriging
R	RMSE	Root mean squared error (prediction)
S	s	Second
	SAV	Submerged aquatic vegetation
	SFCA	Special Fisheries Conservation Area
T	TPS	Tidal Prediction Service
U	UK	Universal kriging
	UKHO	United Kingdom Hydrographic Office
V	VBTTM	Visual Bottom Typer ™
W	WGS	World Geodetic System
Y	yr	Year

Chapter 1. Introduction

1.1 Project background and context

1.1.1 Importance of marine habitats

Coastal and nearshore habitats such as mangroves, seagrasses, and coral reefs act as natural coastal infrastructure and collectively constitute approximately one-third of the coastline in the Caribbean (UNESCO, 1983). The offshore environments in Jamaica are comprised of sand, seagrass beds, rocky platforms, and coral reefs (Warner and Goodbody, 2005) and these habitats are all essential to maintaining the connectivity and functioning of coastal ecosystems. Seagrass beds stabilize sediments and act as contaminant filters; they also provide habitats and act as shelter, primary producers, and nurseries to juvenile fish species (Thorhaug, 1981; Creary, 1999; Green and Short, 2003). The rich and varied epibenthic flora and fauna that is supported by seagrass include sea urchins, sea cucumbers, conch (*Strombus* spp.), star fish (e.g. *Oreaster reticulatus*), coral and juvenile fish (Creary, 1999; Jones and Sefton, 2002; Warner and Goodbody, 2005). Coral reefs are sometimes referred to as the "rain forests of the sea" (Burke, et al., 2011) because they support diverse marine populations (UNESCO, 1983), approximating to 1 million associated species (Nellemann and Corcoran, 2006). Non-sessile fauna associated with reef structures in Jamaica include small fish, sea urchins, gastropods and crinoids (Warner and Goodbody, 2005). They contribute to the geomorphological attributes of coastal systems as well; they produce sand and function as protective barriers to incoming wave energy (UNESCO, 1983; UNEP/IUCN, 1988) for in excess of 150,000 km of shoreline globally (Burke, et al., 2011).

Small island states such as those in the Caribbean are described as being reef-dependent (Burke, et al., 2011) and this dependency can equally be extended to the complete nearshore ecosystem complex and its resources. Nearshore habitats are of recreational and cultural value and the goods and services provided by theses habitats are also particularly indispensable to tourism and fishing industries (UNEP/IUCN, 1988; Day, 2009; Waite, et al., 2011). As such, they contribute significantly to economies and employment within the region (Natural Resources Conservation Authority, Technical Support Services, Inc., 1996). For example, tourism accounts for approximately one-third of the labour force in the region (Schill, et al. 2011) - in 2011, this equated to approximately 28 million direct, indirect and induced jobs (World Travel and Tourism Council, 2012). Tourism also contributed to 25.6% of Jamaica's GDP in 2011, which was larger than the contribution from any other sector (World Travel and Tourism Council, 2012). The fishing industry similarly contributes to regional and national economies and provides a source of livelihood for coastal populations. On average, 5% of the Caribbean labour force was employed in the fisheries sector in 2008, with Jamaica having the highest national percentage of 15% (Masters, 2012). In Jamaica, the fisheries sector provides direct and indirect employment (e.g. fish vendors, boat builders, gear manufacturers, and ice suppliers) (Waite, et al., 2011) for approximately 200,000 persons (ECOST Project, 2007).

The provision of ecosystem services and 'markets' of coastal nearshore areas depend greatly on the healthy functioning of these ecosystems; nonetheless the coastal areas and nearshore waters across the world have been, and continue to be degraded and developed unsustainably. Nearshore communities are often impacted by various types of land-based pollution such as solid waste, sewage effluent and sediments (UNEP/IUCN, 1988; Nellemann and Corcoran, 2006; Ferwerda, et al., 2007), as well as developments on adjacent coastal lands and within nearshore habitats. Structures or activities that fall under "development" include coastal engineering works (Burke, et al., 2011) such as breakwaters or piers, dredging (UNEP/IUCN, 1988), sand mining and swimming area "manicuring". Improper boating, destructive fishing and overfishing negatively impact marine seagrass and coral communities as well (UNEP/IUCN, 1988); the latter two activities affecting more than 55% of the world's reefs (Burke, et al., 2011). Regionally, more than 75% of reefs throughout the Atlantic are threatened, and in Jamaica all are rated as threatened (Burke, et al., 2011). Coral reef deterioration is notable in Jamaica and algal overgrowth owing to overfishing of herbivorous fish species and increased nutrient levels is a major threat (Goreau, 1992) in addition to those already mentioned. Overfishing is considered detrimental to the fisheries sector in Jamaica (Aiken and Kong, 2000) and unfortunately, Jamaica is one the most overfished areas in the Caribbean, with the exception of offshore conch (Waite, et al., 2011; Aiken, 2014).

Global or regional occurring phenomena have the potential to cause widespread habitat degradation, compound local threats (Waite, et al., 2011) and reduce the resilience of ecosystems (Nellemann and Corcoran, 2006). Thermal stresses (coral bleaching), ocean acidification (Burke, et al., 2011), storm events, disease or mortalities that result in community changes (e.g. *Diadema antillarum* sea urchin mortality in the 1980s) (Liddell and Ohlhorst, 1986; UNEP/IUCN, 1988), geological coastal uplift or subsidence (Green and Short, 2003) are examples of such phenomena. A number of studies have also assessed the biodiversity impacts of climate change (Foody, 2008), one facet to these considerations being "coastal squeeze" (Day, 2009). Owing to the development of coastal land with permanent manmade barriers on the land side of the equation, as well as increased sediment loads and permanent structures previously mentioned existing within the nearshore zone, natural seaside reactions from climate change such as migration of seagrass beds, mangroves and associated fauna inland are restricted, thereby resulting in nearshore and coastal habitats competing for the little area that remains.

1.1.2 Conservation of marine resources

As defined by the Protected Areas Committee (2012), a protected area is a "clearly defined geographical area of land and or water that is dedicated to and managed for the long term conservation and sustainable use of its ecological systems, biodiversity and/or specific natural, cultural or aesthetic resources". Currently, protected areas in Jamaica may be grouped into 19 categories (Protected Areas Committee, 2012) and this can be distinguished between natural areas and built heritage, as well as national governance and international designations, each with a responsible authority and overarching legislation. Those protected areas of interest to this study are the natural marine areas which account for 15% of the Jamaica's archipelagic waters (Protected Areas Committee, 2012), and specifically the marine protected areas (MPAs) and marine parks declared under the Natural Resources Conservation Authority Act 1991 and the Beach Control Act 1956, as well as fish sanctuaries established under the Fishing Industry Act 1975 (Government of Jamaica, 1975) and for which the Fisheries Division, Ministry of Agriculture and Fisheries (MoAF) have jurisdiction. Within the past two years, the Fishing Industry (Special Fishery Conservation Area) Regulations 2012 was promulgated and this was used to declare 14 areas as Special Fishery Conservation Areas (Ministry of Agriculture and Fisheries, Government of Jamaica, 2011). A Special Fishery Conservation Area (SFCA) is analogous with "fish sanctuary" and although it is broadly understood that SFCAs, akin to fish sanctuaries, are no-fishing zones, specific terms and conditions for each area may be directed by the Minister to allow for specific fishing activities for conservation, management or educational purposes (Government of Jamaica, 2012).

Given the myriad of human, as well as natural activities with the potential to cause spatial and temporal changes within the nearshore environment, continuous change must be accepted as being inevitable (Ferwerda, et al., 2007) and often unpredictable. If these changes need to be identified, quantified and monitored, some baseline data must exist, whether obtained when the environment was in a pristine state prior to human interference or an accepted starting point that encompasses anthropogenic impacts (Olenin and Ducrotoy, 2006). Cogan, et al. (2009) discusses the role of marine habitat mapping in ecosystem-based management practices and suggest that the mapping and classification of habitats should be undertaken in the early phases of management planning, prior to biodiversity mapping and management. At the base of this, is the simple fact that the management of a natural area should be influenced by the natural ecological boundaries. This is recognised in the Draft Fisheries Policy where sound scientific research is accepted as a basis for the management of fisheries stocks (Fisheries Division, Ministry of Agriculture and Lands, 2008), and similarly by the Protected Areas Committee (2012) that acknowledged that an absence of comprehensive and representative data was an institutional gap. A scientific basis is required for planning by means of a sustainable ecosystem approach.

The development of management strategies for any protected area is an integrated process that assimilates aspects of the natural (ecological) and human (social, economic, cultural, political) environment (Day, 2009), both existing and projected. A spatial context underpins this multi-criteria process and this spatial structure facilitates the measurement of inevitable change, whether owing to direct influences on the marine benthos, or indirectly from outside sources over time in a quantitative manner. Key to the management of fish sanctuaries and the productivity of the fisheries sector in particular, is the association between key fish species and the spatial composition of the marine habitats, that is, the benthic landscape ecology and connectivity within habitats. A number of studies have explored connections between fish and other faunal populations and habitat structure parameters (Blanc, et al., 2001; Bostrom, et al., 2006; Friedlander, et al., 2007). Knowing the spatial extent of various habitats assists in understanding the ecology of the area and examining the "functional flows and movements through the landscape" (Forman, 1995). Quantifiable knowledge also lends itself to economic valuation (Waite, et al., 2011), instrumental in resource management and decision making processes. Not only does a spatial basis support further ecological modelling and ultimately inform management practices, but on the ground an important use is simply knowing the location of seafloor features.

1.1.3 Benthic habitat mapping

1.1.3.1 Nomenclature

Typically the "benthic" zone is the lowest region at the bottom of a water body that comprises the sediment surface and some sub-surface layers, whilst the "benthos" is specific to the organisms, both flora and fauna living in or on the seabed. The term "habitat" is often heard in conjunction with other scientific terms such as ecosystem, biotype and biome; however within a purely scientific context, a habitat may be considered a subset of the larger ecosystem and is lexically defined as "the place or type of site where an organism or population naturally occurs" (United Nations, 1992). The ambiguity of the term "habitat" lends itself to the understanding that as suggested by Diaz, et al. (2004), a benthic habitat is "more than substrate" and for the purpose of this study, it is the marine communities (benthos), in addition to the physical seabed features such as sediment or pavement that constitute a "benthic habitat". As defined by Brown et al. (2011), marine habitat mapping is "the use of spatially continuous environmental data sets to represent and predict biological patterns on the seafloor (in a continuous or discontinuous manner)".

Zonation of coastal and marine areas, as well as associated nomenclature, are often specific to the various scientific disciplines within which they are studied; for example coastal beach morphology (Komar, 1998), coral reef ecology (Levinton, 2001) and coastal management (Norrman, et al., 1997). The potential uses of this study stretch across more than one field of study and it is not the intention to focus on any single specialized inclination and semantics of terms used within each. As such, terminology used throughout this report is somewhat "fluid" in description, as opposed to exact in definition. A nearshore area, typically used in beach morphology descriptions, generally encompasses the area between the shoreline and area of wave breaking (Komar, 1998);

whilst utilising a more coral-focussed zonation, terms such as lagoon, bank/shelf and fore reef come into play (Figure 1). For the purposes of this study, descriptive terms such as "nearshore" or "lagoon" or "bank/shelf" may be interchanged to collectively describe the subtidal areas within the study area and does not include coastal features inland of the water's edge. Further, owing to the dynamic nature of waves and tides and transitions between high and low water levels; any reference made to the "coastline", "shoreline" or "intertidal zone" will be assumed to be a fuzzy land-water margin.

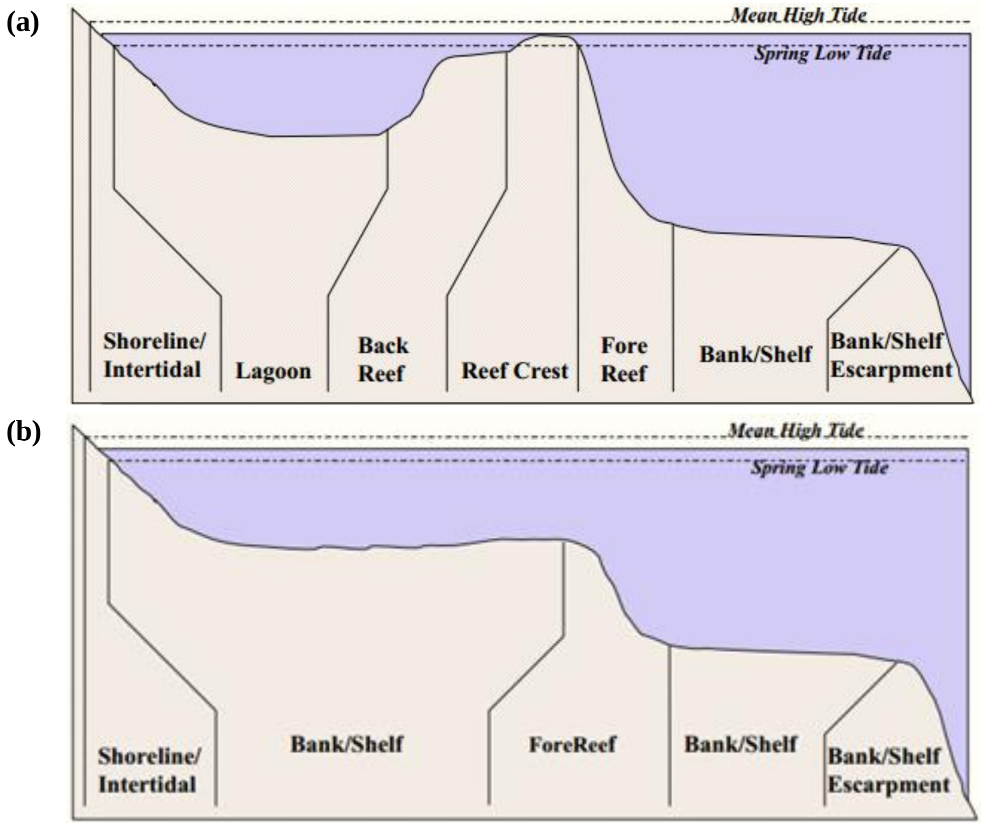


Figure 1. Cross-sectional view of typical coral reef geomorphological zones where: (a) an emergent reef crest is present and (b) emergent reef crest is absent (Kendall, et al., 2001).

1.1.3.2 Remote sensing techniques and geographic information systems

The science of remote sensing involves the acquisition of information without being in direct physical contact with the object under investigation; its applicability to distinguishing features is based on the fact that interactions with objects will differ. It is often automatically associated with the observation of the Earth's surface by means electromagnetic energy sensors fitted to satellites in space or airborne platforms, distinctly referring to optical remote sensing. However the science of remote sensing is not exclusively confined to this optical application; acoustic survey is another form of remote sensing.

Of the two main types of optical remote sensors, passive and active, the former type, and the focus of this study, uses a natural source of electromagnetic radiation, this typically being the Sun. Electromagnetic radiation is transmitted to the Earth's surface and the energy emitted and reflected from the surface is "sensed" and transformed into a digital image. Marine and underwater sensing comprises factors unique to its field; the use of measured signals at the sensor and recorded in images is not straightforward as there are added interactions within and above the water column that often introduce complications in marine benthic image classification (Figure 2). With increasing depths from the coastline, water column properties and the inability of sensor wavelengths to penetrate water (Roob, 2000; Foody, 2008; Baumstark, et al., 2013) often limit the application of image classification. In instances where optical sensing falls short, acoustic/ sonar technology can supersede optical image sensing as this technique is applicable irrespective of water quality and is capable of acquiring data in greater depth ranges (Roob, 2000; Foster, et al., 2011). Sonar technology involves the recording of acoustic signals (waveforms) reflected from seabed characteristics and the subsequent classification based on a library of acoustic signatures. Acoustic seabed classification (ASC) is also referred to as acoustic ground discrimination systems (AGDS).

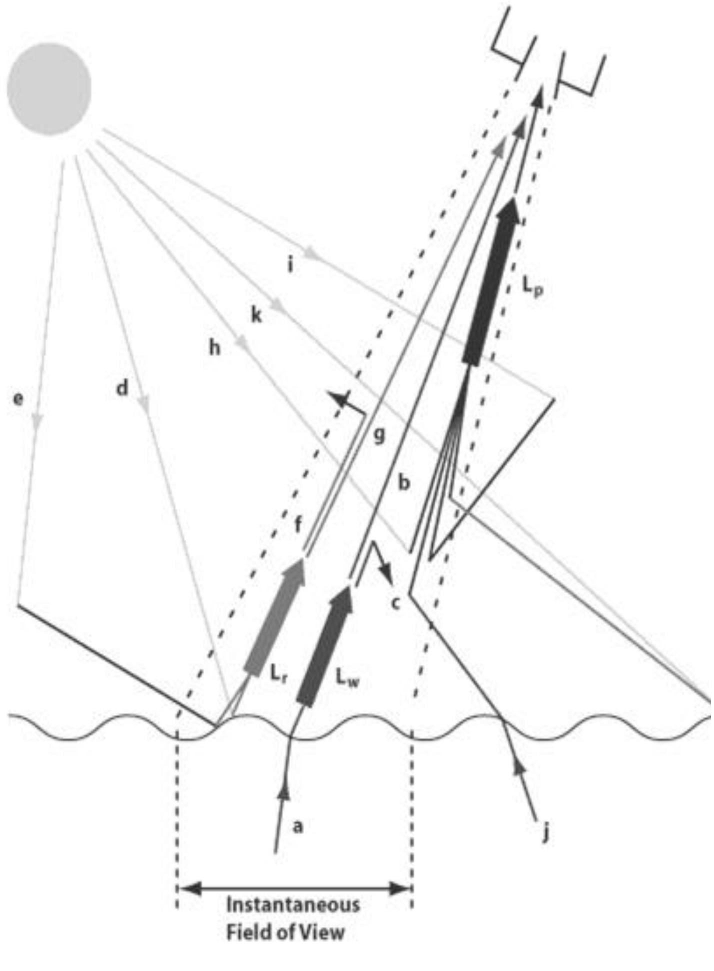


Figure 2. Schematic representation of ocean remote sensing: (a) water-leaving radiance; (b) attenuation of the water-leaving radiance; (c) scattering of the water-leaving radiance out of the sensor's field of view (FOV); (d) sun glint; (e) scattered light reflecting from the water surface; (f) scattering of reflected light out of the sensor's FOV; (g) reflected light attenuated towards the sensor; (h) scattered light from the sun which is directed toward the sensor; (i) light scattered by the atmosphere toward the sensor; (j) water-leaving radiance originating out of the sensor FOV, but scattered toward the sensor; and (k) surface reflection out of the sensor FOV scattered toward the sensor. Lw denotes the total water-leaving radiance; Lr, the radiance above the sea surface due to all surface reflection effects within the FOV; and Lp, atmospheric path radiance (Loisel, et al., 2013, adapted from Robinson, I. S., 1983. Satellite observations of ocean colour, *Philo. Trans. Royal Soc. of London, Series A*, 309, 338-347).

Remotely sensed products are often further modelled and/or combined with other spatial information in a geographic information system (GIS). It should be noted that although the coined acronym "GIS" is most commonly referenced to geographical information systems, it is not unique to this single description; geographic information science (Goodchild, 1992), geographic information studies (Longley, et al., 2005) and geospatial information studies are other examples. In the same vein that GIS may be described as a system or a science, this project embraces both concepts with an emphasis being on the shared "GI" (Longley, et al., 2005) representing "geographic information" or "geospatial information".

1.2 Justification and purpose

Nearshore marine ecosystems provide essential ecosystem services to diverse communities, yet Jamaica's coast and nearshore waters have been, and continue to be developed extensively. In recognition of the value and their contribution to the livelihoods of local communities, they were given priority for protection in an effort to promote and improve the management and sustainable use of coastal/nearshore marine resources to meet local and national needs. Consequently, some have been designated as SFCAs (fish sanctuaries), as well as marine parks and protected areas. However, a knowledge-gap exists that precludes the effective management of these sites. The current extent and state of habitats within designated SFCAs are currently unknown and local management organizations face severe limitations as there is a lack of resources and capacity to undertake the foundational research required to develop and guide scientifically-based management strategies. The Fisheries Division, MoAF, Government of Jamaica (GoJ) sought to fill this gap, and will map nearshore habitats at all designated fish sanctuaries across the island, and in doing so, build on the geospatial data inventory within the established boundaries. Additionally, the Caribbean Fish Sanctuary Partnership (C-FISH) Initiative was launched in November 2012 through the CARIBSAVE Partnership (CARIBSAVE) with the main goal of strengthening the management of fish sanctuaries.

Remote sensing is used extensively to map and assess the spatial characteristics of benthic habitats and the use of these technologies for mapping coastal and nearshore marine ecosystems has been convincingly demonstrated. This project aims to map the benthos of a pilot site, namely the Bluefields Bay SFCA (BBSFCA), using optical and acoustic remote sensing technologies and techniques. The mapping exercise will ultimately compare these mapping techniques to determine the feasibility, practicality and cost effectiveness of each approach when applied to the Jamaican (and possibly Caribbean) context, and will directly support the efforts of the Fisheries Division and C-FISH, as well as broadly contribute to coastal research in the region.

1.3 Research objectives

The aim of this research was to test marine habitat mapping technologies and techniques for use in Jamaica and the wider Caribbean. Specifically, the use of two primary mapping techniques for benthic mapping - optical and acoustic remote sensing technologies - were evaluated. Habitat maps for the Bluefields Bay fish sanctuary produced from this assessment will be used by the relevant stakeholders in support of various conservation and management initiatives.

The specific task-based objectives of this project were as follows:

Objective 1.	*Map and classify nearshore benthic features using acoustic/sonar survey data.*
Objective 2.	*Map and classify nearshore benthic features using remotely sensed images (Landsat 8, WorldView-2 and GeoEye-1).*
Objective 3.	*Assess and compare the accuracy of each mapping technique using an accuracy assessment with ground-truth data.*
Objective 4.	*Determine the most cost effective and efficacious mapping method that can be replicated at other sites across Jamaica and the Caribbean.*

Chapter 2. Study area

2.1 Location and boundary delineation

The research area of interest, the BBSFCA, or colloquially referred to as the Bluefields Bay fish sanctuary, is located in the western parish of Westmoreland, Jamaica, within one of two pilot sites for benthic habitat mapping proposed by the Fisheries Division (Figure 3). At present, 14 fish sanctuaries exist at nearshore sites across the island of Jamaica and at one offshore location (Government of Jamaica, 2012), and with an area of 13.82 km^2, the Bluefields Bay fish sanctuary is the second largest declared. The landward boundary has a general northwest to southeast orientation, extending 13.82 km along the coastline between the settlement of Paradise to the north and Belmont Point at its southernmost extent, with a seaward extent less than 2 km from the shore (Figure 3). As defined by the second schedule of the Fishing Industry (Special Fishery Conservation Area) Regulations 2012, the exact bounding limits are as follows:

Starting at Point A, a land-based mark at Belmont Point with geographical coordinates 18°09' 9.432" N and 78°01' 58.449" W, and shall proceed –

(a) from Point A, the boundary shall run in a straight line to Point B, a water-based mark at geographical coordinates 18° 11' 28.147" N and 78° 03' 40.638" W;

(b) from Point B, the boundary shall run in a straight line to Point C, a water-based mark at Paradise, with geographical coordinates 18° 12' 11.103" N and 78° 05' 12.93" W;

(c) from Point C, the boundary shall to Paradise Point, a land-based mark geographical coordinates 18° 12' 20.724" N and 78° 05' 13.944" W; and

(d) from Point C, the boundary shall follow the contours of the coastline back to the starting point.

2.2 Description

2.2.1 Coastal land-water margin

The southern extent of Jamaica is characterised by plains (Warner and Goodbody, 2005) and Bluefields Bay is located within the south-western coastal plain and wetlands coast region, defined as being one of the natural coastal regions in Jamaica (Norrman, et al., 1997). The underlying geology inland of the bay is the Gibraltar – Bonny Gate formation, with alluvium and other superficial deposits lining the coast (Mines and Geology Division, 1984). Alluvial sand and deposits of boulder and sand material is characteristic of the geology in the general area (Burrowes, 2013). Natural drainage features existing within the Bluefields Bay 135.6 km^2 watershed include Bluefields River, Bluehole, Sawmill River, Robins River, Sweet River and Waterwheel (Ebert, 2010).

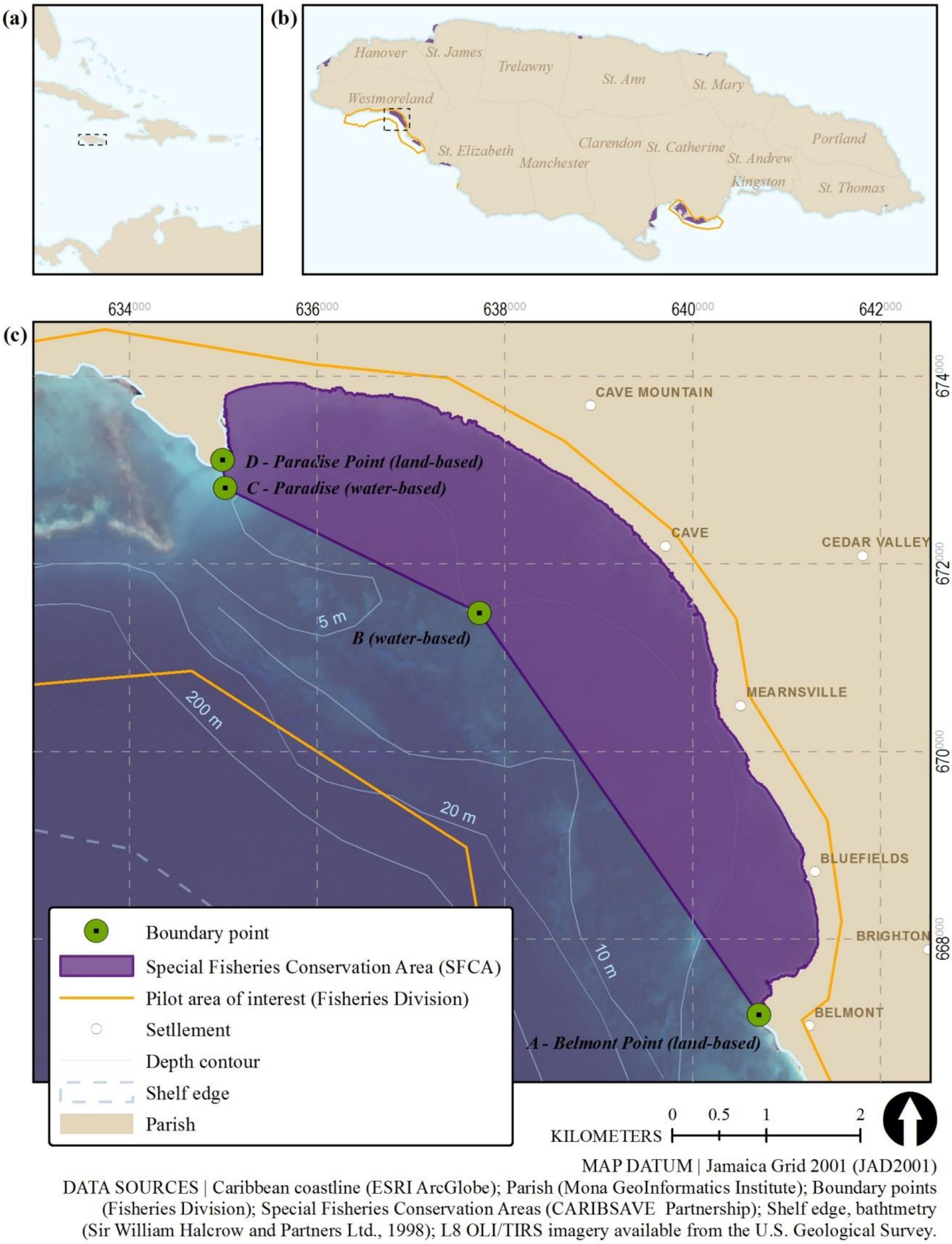


Figure 3. Bluefields Bay Special Fisheries Conservation Area (BBSFCA) boundary delineation, Bluefields Bay, Westmoreland, Jamaica (c), with the extent of this map shown as a dotted box in the map of Jamaica inset (b), along with the locations of all SFCAs across Jamaica. The location of Jamaica in the northern Caribbean region is denoted by a dotted box in inset (a).

A large percentage of the shoreline/ intertidal zone comprise mangrove stands (41.7%) (Plate 1a), followed by 35.5% sandy beach (Plate 1b) and the remaining 22.8% of shoreline consisting of naturally occurring limestone bedrock and cliffs or manmade structures including rip rap (Plate 1c), sea walls, and boulder/ rubble (Plate 1d) (Carroll, 2013). Mangroves and sandy beaches are predominant towards the northern section of the bay, with smaller sections occurring throughout the central and southern regions of the bay. Bedrock, limestone cliffs, sea walls, boulder rubble and rip rap are primarily found at the southern section of the bay (Carroll, 2013). Piers and jetties have been constructed within the bay, one example being those situated at the Bluefields Bay fishing beach and Bluefields Bay Bluefields Bay Fishermen's Friendly Society (BBFFS) office (Plate 1e). In addition to small fishing villages distributed along the shoreline, a public Blue Flag certified beach (Blue Flag, n.d.), namely Bluefields Beach Park is situated in the southern section of the bay and is used recreationally by locals and visitors. A number of accommodations including those owned by Bluefields Bay Villas, as well as residences are located along the coastline.

2.2.2 Land use and population

The combined population of the eight enumeration districts (EDs) that share a boundary with the Bluefields Bay coastline was 3,671 in 2011 (Statistical Institute of Jamaica, 2011) (Figure 4). Four of these EDs fall within the larger community of Bluefields, which was reported to have 1,121 households and a total population of 4,708 persons, based on a 2009 socioeconomic survey conducted by the Social Development Commission (Social Development Commission, 2014). Land use inland of the bay's intertidal zone is varied; the coastal towns of Belmont, Bluefields, Mearnsville and Cave have given rise to residential and commercial areas amidst a generally rural area. Within the past few decades, fields, inclusive of herbaceous crops, fallow and cultivated vegetables, as well as secondary forest have generally constituted the primary land use in the Bluefields area (Forestry Department, 1998) (Figure 4). In addition to subsistence farming, artisan fishing is another important livelihood in the coastal communities surrounding the bay (Garffer, 1992), which is a primary fishing ground within the country (ECOST Project, 2007). At present, there are 282 registered fishers and 89 vessels operating from the Belmont Beach landing site (Figure 4) (Reid, 2014).

(a) (b) (c) (d) (e)

Plate 1. Features along the BBSFCA coastline: (a) red mangrove (*Rhizophora mangle*) in the north, (b) sandy beaches, (c) rip rap abutting seaside property and sea wall towards southern section, (d) man-made boulder jetty structure in foreground with red mangrove (*Rhizophora mangle*) and (e) pier at Bluefields Bay fishing beach and Bluefields Bay Bluefields Bay Fishermen's Friendly Society (BBFFS) office (Photography credit: Karen McIntyre, 2013).

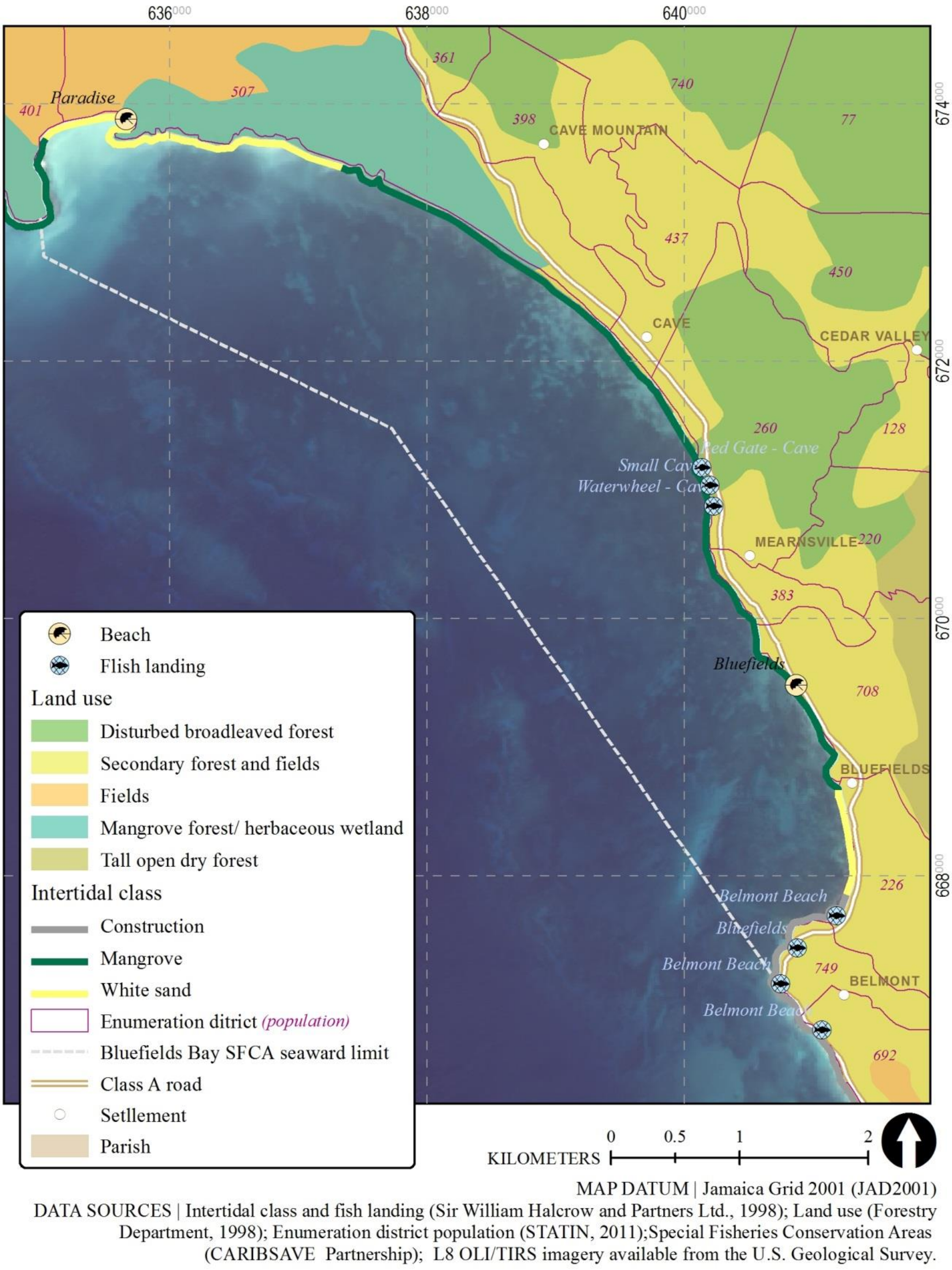


Figure 4. Socioeconomic and recreational characteristics of the Bluefields Bay, including land use, population distribution, beaches, hotels and intertidal classification.

2.2.3 Physiography and benthos of the subtidal nearshore area

Bluefields Bay experiences mixed semidiurnal tides, characteristic of the western Caribbean (Kjerfve, 1981). With relatively small annual tidal ranges of less than 1 m at Savanna-la-Mar and Black River (United Kingdom Hydrographic Office, 1980), Jamaica's south-western coast may generally be described as microtidal, based on classifications established by Davies (1964) in Hayes, et al. (n.d.) and Komar (1998). Wave and wind energy are typically the driving factors in such microtidal coastal regimes (Hayes, et al., n.d.). Owing to its western location, the bay is sheltered from the predominant easterly trade winds that affect the Caribbean, thereby resulting in a low-wave environment within the bay. Average nearshore wave heights of 0.35 m, primarily approaching from the south southeast are reported at the Bluefields Beach Park (Smith Warner International, 2000). Shore-parallel currents with average speeds of 7 cm s^{-1} and a net drift to the northwest of 2.5 cm s^{-1} have been recorded offshore Savanna-la-Mar, approximately 4 km west of Bluefields Bay; there are no known current measurements in the Bluefields Bay (Smith Warner International, 2000). An average surface salinity of 3.8% was measured within the bay (Carroll, 2013) and this is slightly greater than average salinities of ~ 3.6% for Jamaica (CARICOM Fisheries Resource Assessment and Management Program, 2000). Sea surface temperatures range annually between 24 and 27.5 °C (Goreau, 1959).

A "relatively shallow shelf up to 20 km wide" (Warner and Goodbody, 2005) is characteristic of Jamaica's south coast. At Bluefields Bay, the shelf edge is situated approximately 6 km from the coastline, and at its nearest, 3 km from the seaward edge of the BBSFCA. The study area for this project is primarily within the nearshore subtidal zone (below low water level). Emergent reefs are not evident at Bluefields Bay and according to zones described by Kendall, et al. (2001) (Figure 1), the extent of the sanctuary is situated within the bank/shelf region shoreward of the fore reef, where maximum depths of 10 m have been reported (Carroll, 2013). The seafloor of the BBSFCA may be described as seagrass and sand-dominated (Keegan, et al., 2003) with mud and boulder deposits also constituting the seafloor sediment to the south (Dryer, 2010; Thompson, 2013; Burgess, 2013; Bluefields Bay Fishermen's Friendly Society, n.d.). Spatial coverage of seagrass within the bay is believed to have changed over time; excavation surveys suggest that there was a well-developed high salinity seagrass habitat during Ostonian occupation during the 9th century and approximately 600 years later during the Meillacan period, the seagrass community was far less abundant with a more stagnant lower salinity environment (Keegan, et al., 2003). During the 1990s, seagrass coverage generally increased (Smith Warner International, 2000) and in recent years, temporal changes in the sand and seagrass distribution have been observed following severe weather such as Tropical Storm Nicole in October 2010, wherein seagrass meadows were buried by extensive sand movement in the bay (Thompson, 2013; McNaught, 2013).

Offshore reefs at Bluefields Bay have been classified as part of a coastal barrier reef complex (UNEP-WCMC, WorldFish Centre, WRI, TNC, 2010), as well as an intra-shelf barrier reef, described to be a fringing system of reefs along land separated by a lagoon (Maxam, et al., 2011). This fringing system is the dominant type of reef existing in Jamaica, although it has an intermittent distribution (Goreau, 1959; UNESCO, 1983; UNEP/IUCN, 1988; Warner and Goodbody, 2005). Owing to a greater proportion of sediment loaded rivers exiting along the south coast of Jamaica, coastal waters typically have higher levels of turbidity in the south, when compared to the island's northern coastal waters (Warner and Goodbody, 2005; Norrman, et al., 1997), perhaps causing the discontinuity of the fringing reef system along the south cost. Coral reefs are located towards the seaward limit of the BBSFCA, with an artificial reef structure consisting of 350 EcoReef modules erected in July 2011 at 18° 10' 18.4" N; 78° 02' 34.0" W (World Geodetic System (WGS) 1984 datum) at a depth of 7.92 m within the sanctuary (Rudolph, 2012). Other notable man-made features existing within the bay are 22 lobster "condominiums", which were placed across the bay between July 2010 and August 2011 (McNaught, 2013; Squire, 2013). The deployment of these simple box-like configurations of concrete blocks, are a part of the Lobster Casita Project and were placed in the sanctuary to encourage the proliferation of lobster populations (Jamaica Information Service, 2008).

2.2.4 Threats and conservation efforts

Up until the mid-20th century, Bluefields Bay was considered to be in "excellent environmental condition" (Bluefields Bay Fishermen's Friendly Society, n.d.) and capable of supporting local fishers. Owing to numerous factors, also recognisable at the national level, there has been an observed decline in catch. The reefs of Bluefields Bay have been described to have "very high" local threat levels (Waite, et al., 2011); likely threats include land-based sources of pollution and effluent, leading to increased nutrient levels in the coastal bay (Ebert, 2010; Bluefields Bay Fishermen's Friendly Society, n.d.). Along the south coast, there is an apparent disposition for reef fishing; in 1997, 82% of fish landings along the south coast by artisanal fishers were coral reef species, such as parrotfish, groupers, goatfish, mullets, and wrasses, whilst the remaining 28% comprised offshore and coastal pelagics and invertebrates (CARICOM Fisheries Resource Assessment and Management Program, 2000). This propensity perhaps assisted in the destruction of reef habitats in the vicinity of Bluefields Bay owing to overfishing on reefs and destructive fishing practices such as dynamiting in the latter half of the 1900s (Bluefields Bay Fishermen's Friendly Society, n.d.). Today, coral reef finfish and lobster remain target species of fishers operating from Belmont Beach (Reid, 2014). Additionally, natural disturbances have played a role in the destruction of reefs nationally (Ecosystems Management Branch, National Environment and Planning Agency, 2008), as well within the local Bluefields area (Bluefields Bay Fishermen's Friendly Society, n.d.).

Since being declared a fish sanctuary in March 2009, there has been an evident improvement in Bluefields Bay. As reported by the Bluefields Bay Fishermen's Friendly Society (n.d. a), a noticeable growth in fish and lobsters has been observed in the vicinity of the previously mentioned lobster "condominiums" and EcoReef structure. Similarly, from a survey undertaken in 2012, the Bluefields Bay Fishermen's Friendly Society reported that 67% of those interviewed observed improvements in the catch within the past six months (Bluefields Bay Fishermen's Friendly Society, n.d. b). In addition to the growth of fish populations, Thompson (2013) believes that healthier reef assemblages seen throughout the bay are due to the prohibition of traps and dynamites. Improvements within the BBSFCA may be attributed as well to the effective management and on-going monitoring undertaken by the various entities such as BBFFS, NEPA and the Fisheries Division. Such efforts are also supported by "voluntourism", termed by Jacks (2011), which is easily achieved in the Bluefields area owing to resort and real estate development in the area (Sir William Halcrow and Partners Ltd., 1998), as well as growing ecotourism efforts (Garffer, 1992) (National Environment and Planning Agency, n.d.). Such collective work indeed resulted in the founding of the BBFFS, the management authority of the BBSFCA in 2006.

2.3 Motivation for study area selection

One of the site selection criteria used for the establishment of SFCAs is the ecological characteristics of the site and specifically the existence of coastal and marine habitats such as seagrass meadows, coral reef and adjoining mangroves forest, crucial for the development of various ontogenic stages of marine fish (Ministry of Agriculture and Fisheries, Government of Jamaica, 2011). Coral reef, sand and seagrass are marine conservation targets, that is, "specific biological features that serve as the focus of conservation planning and management efforts", in Jamaica's National Ecological Gap Assessment Report (Anon., 2009). The BBSFCA is comprised of these three benthic habitat types (Carroll, 2013) and falls within one of the Fisheries Divisions pilot mapping sites (Figure 3). The area is also a primary fishing ground within the country (ECOST Project, 2007); the parish of Westmoreland accounted for the second largest proportion of fishers by parish or approximately 12.3% (2,250 fishers) of all registered fishers within the country, with the smallest parish on the island, Kingston, having the highest proportion or 18.9% (3,461 fishers) (Ministry of Agriculture and Fisheries, 2011). Further, in addition to its local and national environmental importance as a fish sanctuary, at the global level, Bluefields Bay is identified as a Habitat/Species Management Area (Category IV) under the International Union for Conservation of Nature (IUCN) Protected Areas Categories System (ProtectedPlant, 2014; United Nations Development Programme, n.d.) and is cited as a potential marine heritage site (since not confirmed by means of field survey) and a natural anchorage site (Sir William Halcrow and Partners Ltd., 1998). For these multiple reasons, BBSFCA was considered an ideal site for the study.

Chapter 3. Methods

3.1 Interviews and participatory approaches

Approaches taken to map the benthic environment of the BBSFCA and other similar coastal areas should ideally be guided by persons involved in the use, research, management and protection of these areas. For this reason, garnering information from stakeholders within the marine and coastal arena was regarded as a paramount component of the project. With the purpose of establishing useful habitat mapping requirements, such as minimum mapping unit (MMU) (threshold area that dictates whether a feature is mapped or not) and benthic classes, as well as identifying existing data and resources in Jamaica, a questionnaire (Appendix A) was administrated to a range of coastal stakeholders, including scientists, engineers and management bodies by means of email, as well as via telephone calls between August and December 2013 (Appendix B). In addition to this formal questionnaire, the perspectives and local knowledge of marine users from coastal communities along Bluefields Bay were captured by means of informal interviews during field surveys. Indeed, participatory methods have the additional benefit of acting as an important introductory liaison with the area and associated stakeholders.

3.2 Standards

3.2.1 Habitat classification scheme

The classification system developed by the National Oceanic and Atmospheric Administration (NOAA) for shallow-water (< 30 m) benthic habitats (Kendall, et al., 2001) has been applied across the Caribbean, for example in the U.S. Virgin Islands (Kendall, et al., 2004), Puerto Rico (Zitello, et al., 2009) and Jamaica (Haynes-Sutton, et al., 2010) (Carroll, 2013). This system classifies habitats according to a larger biogeographic zone within the nearshore area, then subsequently into a collapsible hierarchy with four major habitat groupings (Kendall, et al., 2001). An improvement was made to this 2001 system, such that classifications would no longer be biased to coral cover but would now encompass all biological assemblages as major cover types (Zitello, et al., 2009). The redeveloped system groups habitat classes into four ecosystem attributes, namely Geographic Zone, Geomorphological Structure, Biological Cover and Coral Cover (Figure 5). In order to satisfy the requirements of the Fisheries Division (Table 1), facilitate comparison amongst existing benthic data outputs in Jamaica and allow for additional ecological data to be appended in the future, the NOAA hierarchal shallow-water classification scheme described in (Zitello, et al., 2009) was chosen for use. It must be noted that although mangrove forests are important intertidal habitats, it is not considered a marine benthic habitat here.

Geographic Zone	Geomorphological Structure	Biological Cover
Land	*Coral Reef and Hard Bottom*	Major Cover
Salt Pond	Rock Outcrop	Algae
Shoreline Intertidal	Boulder	Live Coral
Lagoon	Aggregate Reef	Coralline Algae
Reef Flat	Individual Patch Reef	Mangrove
Back Reef	Aggregated Patch Reefs	Seagrass
Reef Crest	Spur and Groove	No Cover
Fore Reef	Pavement	Unknown
Bank/Shelf	Pavement with Sand Channels	Percent Major Cover
Escarpment	Reef Rubble	10% -<50%
Channel	Rhodoliths	50% -<90%
Dredged	Unknown	90% -100%
Unknown	*Unconsolidated Sediment*	Unknown
	Sand	**Coral Cover**
	Mud	Percent Coral Cover
	Sand with Scattered Coral & Rock	0% -<10%
	Unknown	10% -<50%
	Other Delineations	50% -<90%
	Land	90% -100%
	Artificial	Unknown
	Unknown	

Figure 5. NOAA shallow-water classification scheme, with four primary attributes grouped into boxes and associated hierarchical levels within each (Zitello, et al., 2009).

Table 1. Benthic classes recommended by the Fisheries Division for the classification of fish sanctuaries (Fisheries Division, Government of Jamaica, 2013).

Feature	Definition
Hard Coral	Areas of Interest (AOI) covered in greater than 1 m^2 patches by Acroporidae spp.
Rubble	Assemblages of skeletal rubble greater than 5 m^2 in area, which may be bonded by coralline algae.
Sparse seagrass	Extent to which any of the major seagrass species from the Hydrocharitaceae family are present in community of less than 50% cover. Green algae (Chlorophyta) may be associated with seagrass.
Dense seagrass	Extent to which any of the major seagrass species from the Hydrocharitaceae family are present in community of greater than 50% cover. Green algae (Chlorophyta) may be associated with seagrass.
Pavements	Hard ground covered by dense Gorgonian spp., other forms of soft corals with low to moderately high three-dimensional cover or macro-algae.
Sand	Small particles derived from coralline, rock fragments or other minerals sources, and range in size from 0.63 mm to 2 mm.
Mud	Submerged regions of thick deposits of soft, unconsolidated silty clay, which remains saturated with water.

3.2.2 National GIS data standards

The current accepted national coordinate system for Jamaica is the Jamaica Grid 2001 (JAD 2001); this was considered the working projection of the project, and to which all spatial data was referenced to. Available national guidelines useful to mapping, cartography and metadata were also applied as required throughout the project activities (Land Information Council of Jamaica, 2006; Geographic Information Systems (GIS) Cartographic Standards and Symbologies Technical Committee, 2010).

3.3 Field surveys and equipment

3.3.1 Sonar survey

3.3.1.1 Equipment and sampling logistics

A sonar survey was conducted within the BBSFCA between 26 July and 2 August 2013 using a factory calibrated BioSonics DT-X Portable Echosounder with split-beam transducer. The echosounder was set to have a pulse duration of 0.4 ms and sampling frequency of 206 kHz; all three available data channels (bathymetry, macro and fish) were enabled. The echosounder was coupled with a Garmin Global Positioning System (GPS) and both securely affixed to a 14' jon boat utilised throughout the survey, with the exception of one day when the BBFFS 21' Sea Cat was used (Plate 2). In order to ensure that the equipment remained mounted correctly and to prevent cavitation around the transducer, boat speed was maintained below 2.5 ms^{-1} (5 knots) and the survey was run during calm wave conditions, particularly at night and during morning hours. Weather throughout the duration of the sonar survey was fair; whenever calm conditions deteriorated or if rainfall was imminent, the survey was suspended. Tide data from the United Kingdom Hydrographic Office (UKHO) Tidal Prediction Service (TPS) predicted lowest predicted tide at 0.299 m and highest tide at 0.485 m above Chart Datum (Lowest Astronomical Tide, LAT) during the field survey time periods (Table 2).

Predefined transect lines spaced 50 m apart and perpendicular to the major axis of the shoreline were generated prior to the survey (Figure 6); this systematic placement enabled full coverage of the study area. Ideally, for model validation purposes, diagonal transects would have been run in addition to those represented in Figure 6; however owing to constraints in the field, this data collection was not possible. During the survey, transects were run as close as possible to the shoreline and extended seaward of the sanctuary boundary in anticipation of the interpolation process (to avoid extrapolation at the sanctuary boundary). Gaps in the survey data occurred in areas where the vessel was unable to survey (such as shallow waters less than 0.5 m), or where the data files were corrupted or where potentially erroneous data was recorded due to rough seas or questionable transducer alignment (this was noted in the field) (Figure 6).

(a) (b) (c)

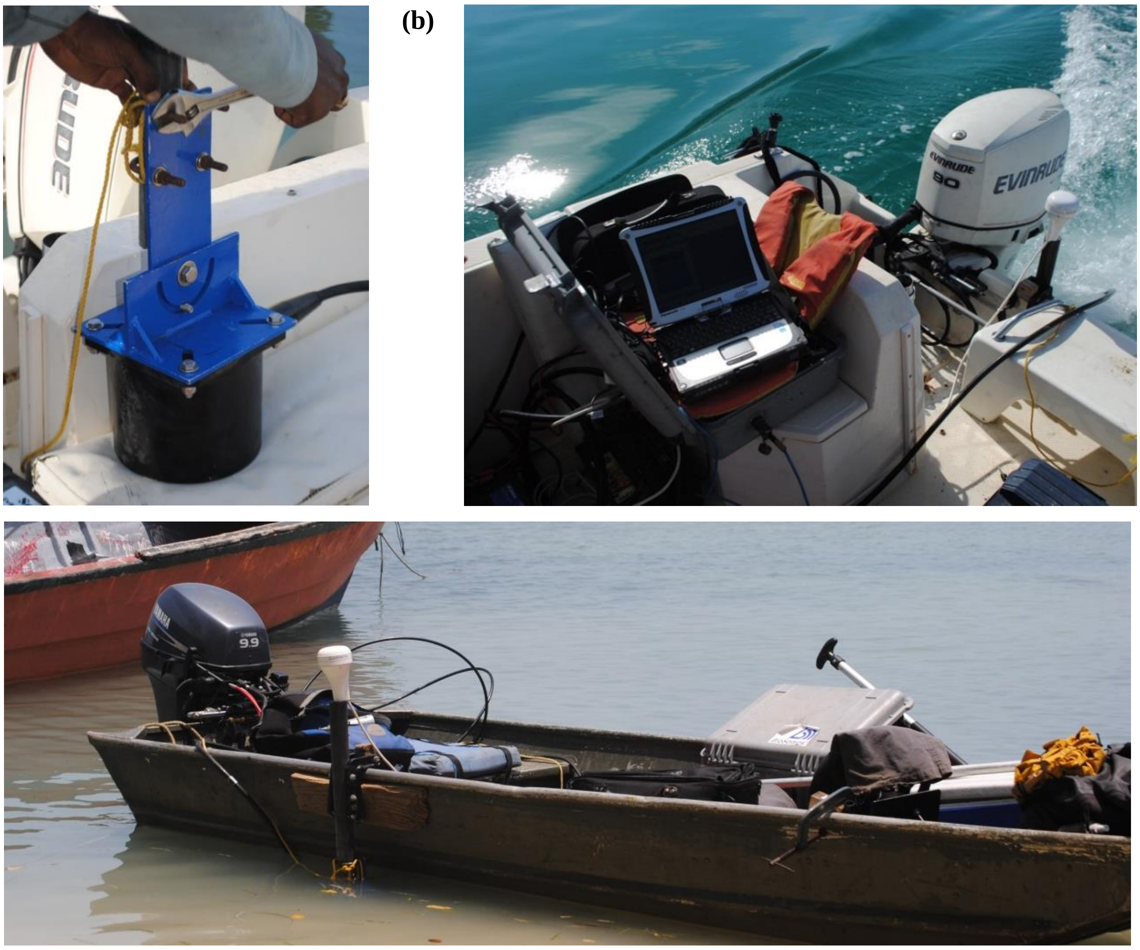


Plate 2. Arrangement of BioSonics DT-X Portable Echosounder (a), GPS antenna and linked laptop on the BBFFS 21’ Sea Cat[*] (b) and 14’ jon boat (c) (Photography credit: Karen McIntyre, 2013).

Table 2. Dates and times during which surveys were undertaken, along with highest tide (HT) and lowest tide (LT) modelled values obtained from the UKHO TPS Savanna-la-Mar port.

Day	Date	Survey times	Tidal range (m)
1	26 July 2013	12:30 – 6:40 PM	LT: 0.300, HT: 0.432
2	27 July 2013	10:00 AM – 1:00 PM	LT: 0.370, HT: 0.419
3	28 July 2013	7:00 AM – 12:30 PM	LT: 0.299, HT: 0.390
	28 July 2013 - 29 July 2013	6:40 PM – 4:00 AM	LT: 0.369, HT: 0.406
4	30 July 2013	8:20 AM – 5:10	LT: 0.300, HT: 0.430
5	1 August 2013 - 2 August 2013	7:50 PM – 8:10 AM	LT: 0.349, HT: 0.475
6	2 August 2013 – 3 August 2013	8:00 PM – 3:10 AM	LT: 0.341, HT: 0.485

[*] The photograph shows the echosounder mounted beside one of the two outboard engines on the Sea Cat; however it should be noted that this engine was not in operation during data collection.

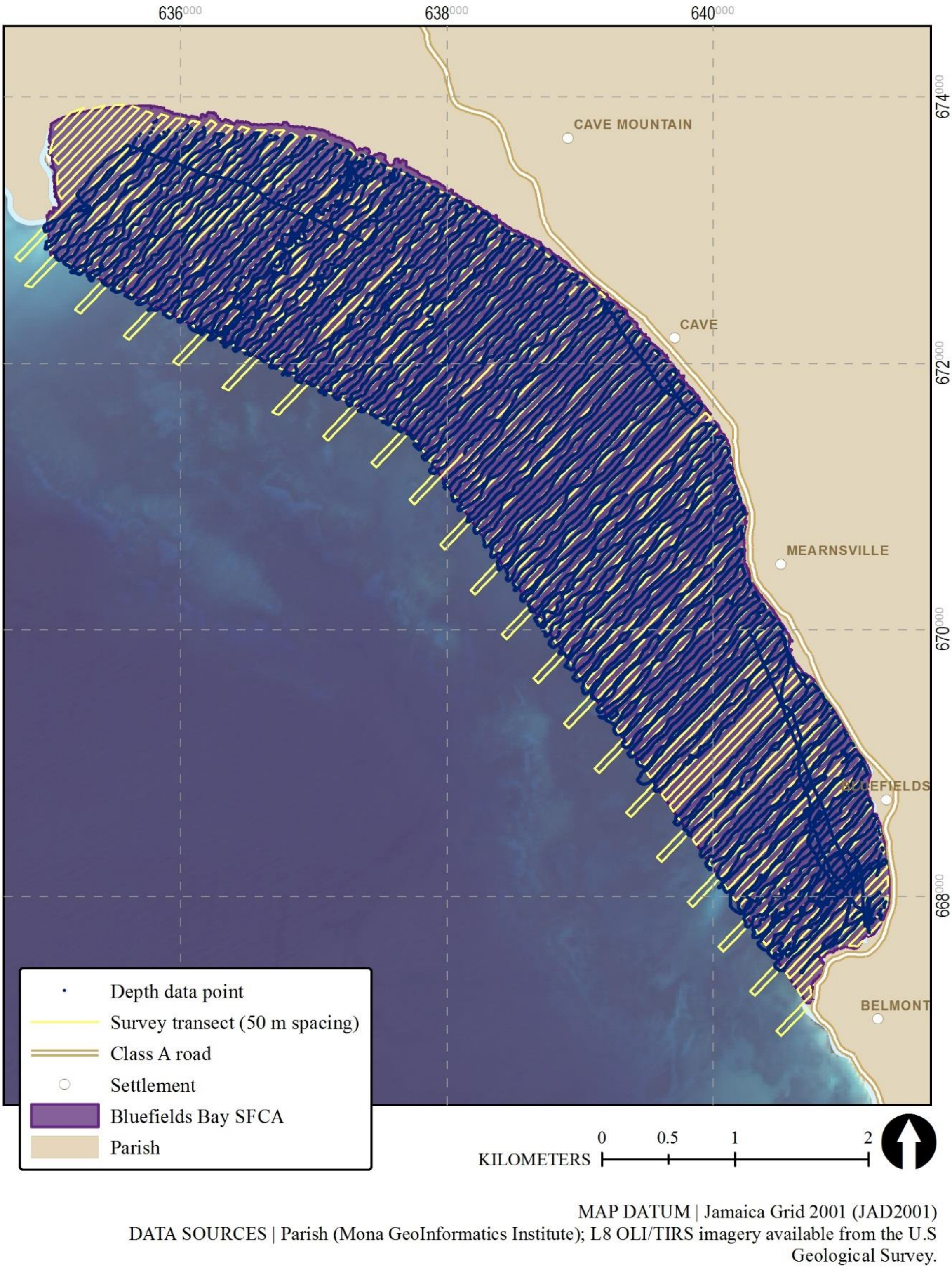


Figure 6. Sonar survey transects generated 50 m apart and data points plotted from sonar survey bathymetry output records.

3.3.1.2 *Sonar ground-truth library*

As part of the data collection process, a standard library of hydroacoustic signals specific to the BBSFCA, termed the "ground-truth" library was created for sand, mud/silt and coral. In June 2014, signals were recorded at 16 sites whilst simultaneously identifying the bottom type by means of grab samples. Non-intrusive methods of collecting ground truth data were preferred in the BBSFCA, however, grab sampling was deemed necessary in order to accurately distinguish between sand and other sediment types present in the BBSFCA (e.g. mud, silt).

3.3.2 Videography

3.3.2.1 *Image classification training*

A Seaviewer Underwater video camera and connected Garmin GPS was used to record georeferenced video of the seabed during the sonar survey. The georeferenced videos were used to provide in situ benthic information necessary for the identification of features during the sonar survey and classification training. Bottom types such as bare substrate, rubble and coral reef were determined visually from the georeferenced video files and were represented as points. Additional information such as estimated vegetation cover and species were also recorded, and was used as auxiliary information when applying benthic classification scheme (Kendall, et al., 2004).

3.3.2.2 *Accuracy assessment ground-truth data*

A stratified random sampling method was employed in order to generate in excess of 200 ground truth points across the bay on three different occasions in July 2013, March 2014 and June 2014. Each reference point description was collected by means of video camera drops, and supplemented by additional inspection of grab samples where possible. Recorded benthos descriptions included substrate type, estimated vegetation cover, species present and type of sediment and were subsequently categorised according to the Kendall, et al. (2004) hierarchy.

3.4 Study area boundary mapping

The BBSFCA boundary points defined by the (Government of Jamaica, 2012) were mapped as vector point and polyline features using the WGS 1984 latitude longitude coordinates indicated and subsequently projected to the JAD2001 system. The area of interest encompasses the marine environment within the fish sanctuary and excludes all land features. The images acquired for the purposes of the image classification project components, and in particular the near infrared (NIR) bands were utilised to detect land features and manually digitise the coastline of Bluefields Bay at a minimum scale of 1:3,000. The WorldView-2 image was preferentially used owing to its relatively high spatial resolution and collection date (Figure 19), and the remaining images (GeoEye-1 and L8 OLI/TIRS) were used in areas of cloud cover on the WorldView-2 image. The seaward limit and coastline polyline files were merged in order to create a detailed, up-to-date outer boundary for the BBSFCA; this was considered the working extent of the study.

3.5 Bathymetric modelling

The production of a bathymetric model for the BBSFCA was not an objective of this study; nonetheless a continuous representation of depth across the bay was needed for input in the water column correction procedure as part of the image pre-processing (section 3.7.2.2). Furthermore, since high density bottom data is a by-product of the BioSonics, Inc. processing software (Figure 7), it was used to create a bathymetric model. In order to generate a continuous raster model, interpolation, that is, the process of estimating the attribute value of unknown vector points within surrounding sampled data (Burrough and McDonnell, 1998) is applied. Geostatistical and deterministic methods are one subdivision of interpolation techniques; both take into the account the principle of spatial autocorrelation - the closer something is to a known point, the likelihood that it is more similar is higher than if further away (de By, et al., 2001). Geostatistics almost always refers to kriging (Babish, 2002), the term being credited to Daniel Krige (Oliver and Webster, 2014). Interpolation by means of a kriging technique typically involves the following steps: 1) dataset building and exploration; 2) semivariogram modelling and kriging; and 3) validation. The overall process is iterative; the final result is only accomplished subsequent to a series of data building and experimental modelling steps.

3.5.1 Dataset building and exploration

The batch processing functionality of BioSonics, Inc. processing software Visual Bottom Typer ™ (VBT^{TM}) was used to extract and process bottom depth data from the hydroacoustic data. The bottom typing method used was the B4 (Fractal Dimension and Cluster Analysis) and output reports averaged 20 pings per record. Output files from the VBT^{TM} were collated for each of the six days of field survey, mapped as vector points using the latitude and longitude coordinates (WGS 1984) provided in the report files and subsequently reprojected to JAD2001. Identical coordinate pairs were summarised and the mean depth reading calculated for these points. Data points were spaced 4 – 5 m along transects and more or less 50 m between transects. Depth measurements were corrected for the position of the sounder on the vessel (39 cm below water surface), as well as tide (Figure 7). Tide data was provided courtesy of the UKHO via its TPS. Tidal heights above Chart Datum (LAT) were received for the port closest to the study area, namely Savanna-la-Mar, located at 18.20°, -78.13° (WGS 1984) in 10-minute intervals.

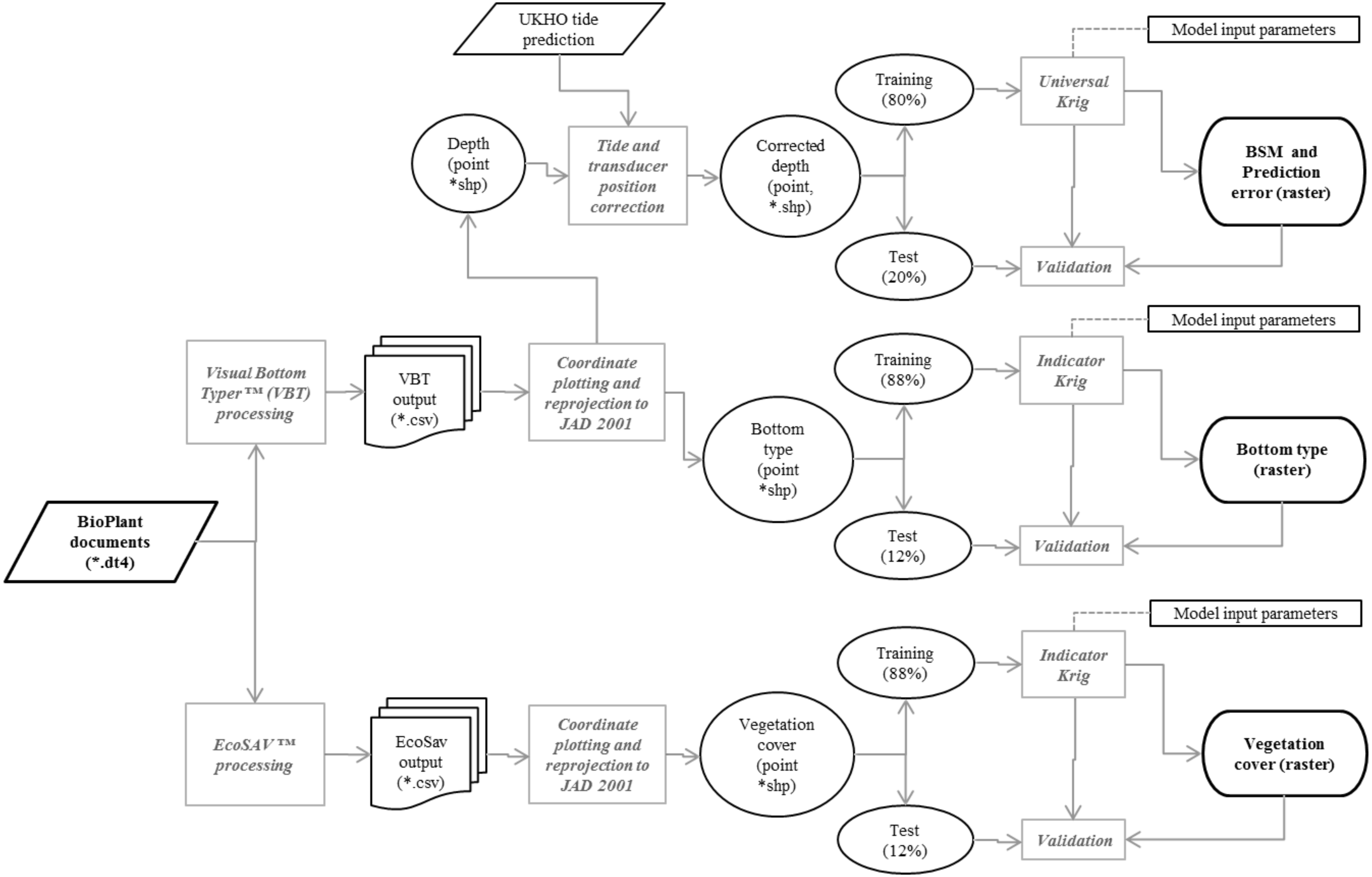


Figure 7. Flowchart showing main data processing and GIS modelling stages for acoustic data.

In order to avoid erroneous extrapolation, it was essential to explicitly demarcate the landward boundary of the BSM (Hell, 2009) and assign a depth reading in anticipation of the interpolation process. Mock coastline data points were created along the sanctuary coastline with a spacing of 5 m and assigned a depth reading of 0.1 m in order to represent the shoreline extent of the boundary. These coastline points were merged with VBT™ processed sonar data for the six days of field survey undertaken resulting in a combined total of 69,072 records; this represented the "working" dataset of depth points.

The suite of tools available in the ArcGIS ArcMap 10 software were used in order to carry out all data exploration and interpolation steps for the project (bathymetric, as well as submerged vegetation and bottom subgrade, sections 3.6.1.2 and 3.6.2.2). Prior to interpolation, the working dataset of depth points was examined in order to identify outliers, investigate the statistical properties and explore potential dataset trends and spatial autocorrelation. Systematic errors in measured data may also lead to erroneous models and as such it was imperative to detect and remove these errors (Hell, 2009). Semivariograms are typically used to identify outliers and potential erroneous data. Unfortunately, the respective ArcMap Semivariogram Cloud tool did not function with the full training dataset; histogram and voronoi maps however revealed that relatively shallow depths existed amongst areas of deeper depths close to the seaward study area boundary (Figure 8). A number of these instances corresponded with the occurrence of coral which was documented during the videography exercises, and as such were deemed accurate. Other potential errors of concern included erroneous deeper depths found close to the shoreline (Figure 9) and these were not found to be true representation of reality when they were compared with VBT™ echogram windows. Although these outliers were within the typical range of depths for the bay, they were inconsistent with neighbouring values and were considered as local outliers. Those points deemed inaccurate were removed from the working dataset, resulting in a total of 68,604 vector points for further exploration.

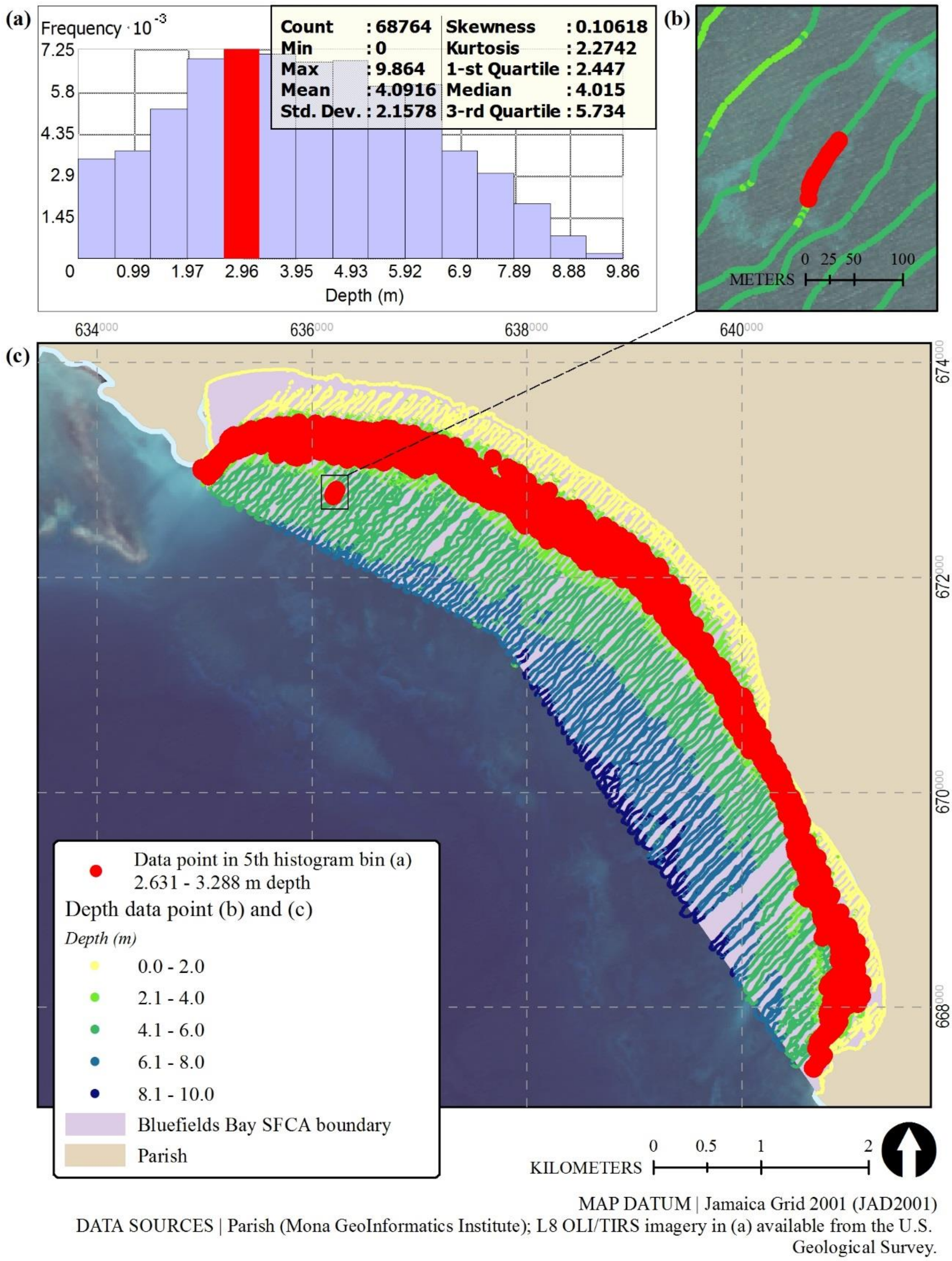


Figure 8. Graphical and spatial representation of untransformed acoustic depth data: (a) histogram and summary statistics for depth data, (b) larger scale map of area under investigation showing depth data points and (c) spatial distribution of all data points across BBSFCA. All points falling within the fifth histogram depth bin shown in red in (a) with depths between 2.631 and 3.288 m are highlighted in red in (b) and (c).

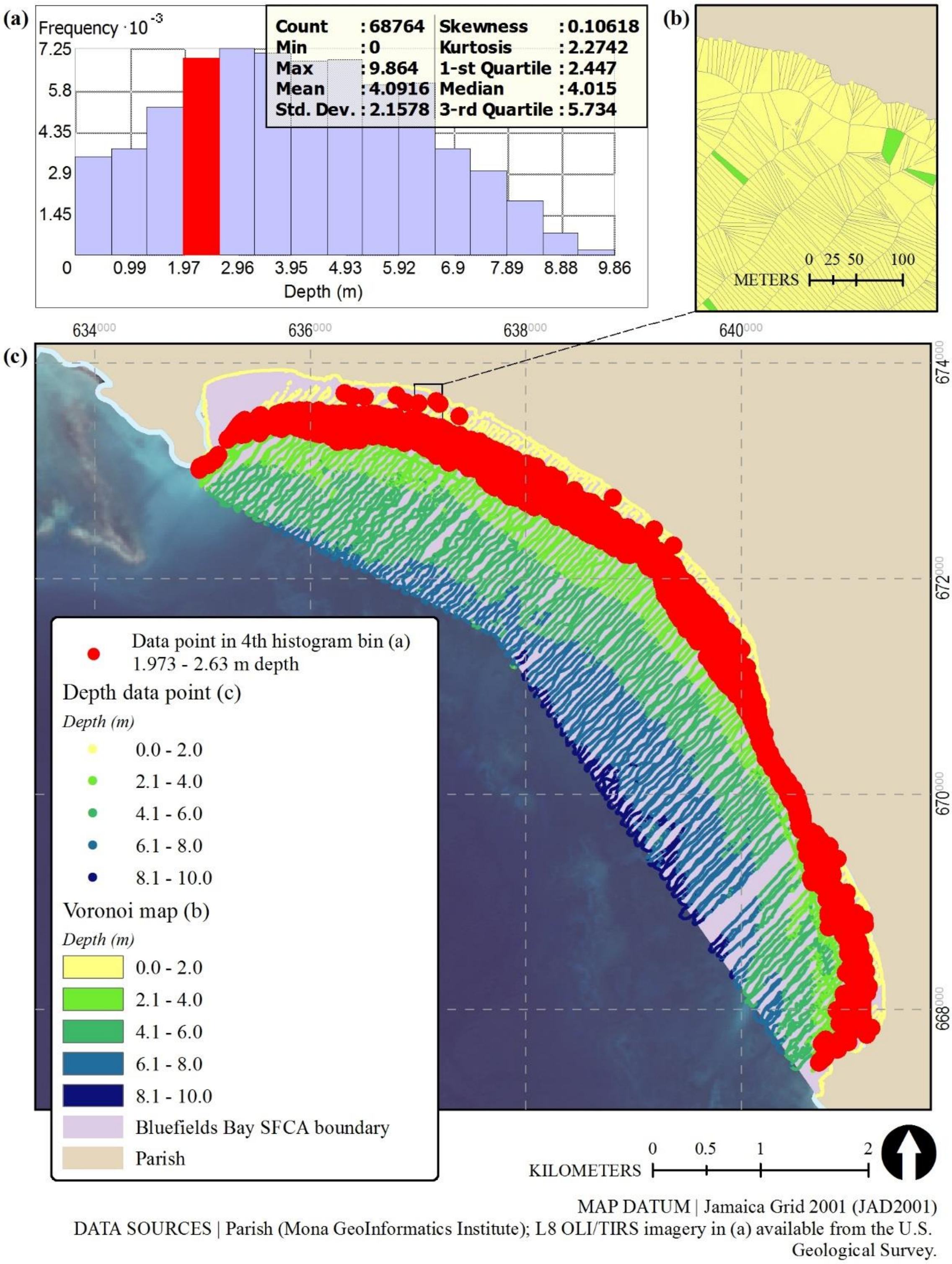
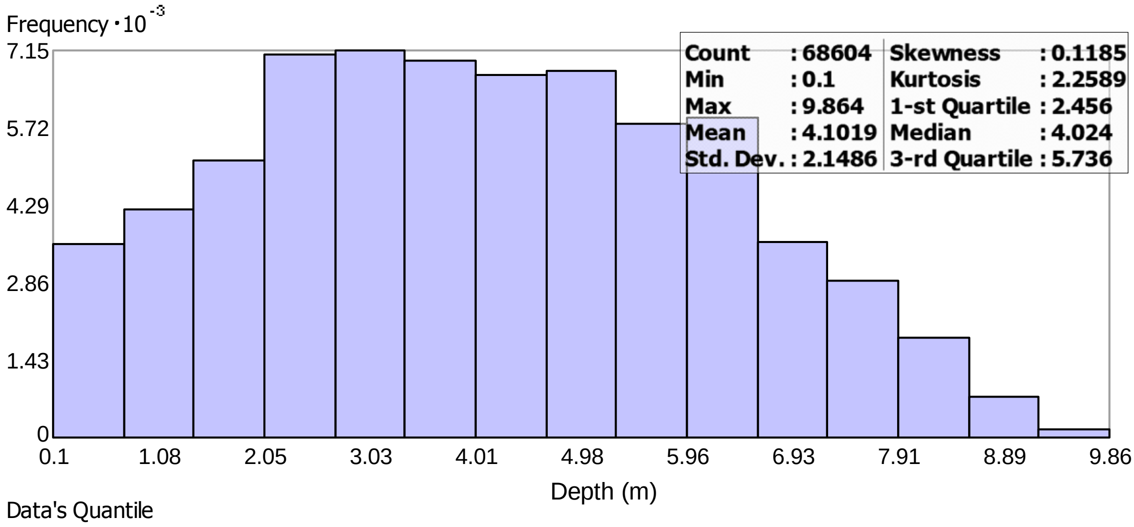


Figure 9. Graphical and spatial representation of untransformed acoustic depth data: (a) histogram and summary statistics for depth data, (b) larger scale voronoi map of area under investigation and (c) spatial distribution of all data points across BBSFCA. All points falling within the fourth histogram depth bin shown in red in (a) with depths between 1.973 and 2.63 are highlighted in red in (b) and (c).

The kriging method is based on variography, that is, the assessment of spatial variability and for which there is an assumption of normality. The frequency distribution of depths across the BBSFCA may be described as normal with a slight positive skew of 0.12 (Figure 10a). Although the median and mean are more or less comparable (4.02 and 4.10 respectively), the distribution was not perfectly symmetrical and the histogram shape was platykurtic with a kurtosis of 2.26. In addition to the normality suggested by the bell-shaped appearance of the histogram, the QQ plot showed that the majority of the data fits the normal line (Figure 10b) and thereby data transformation was not required.

(a)



(b)

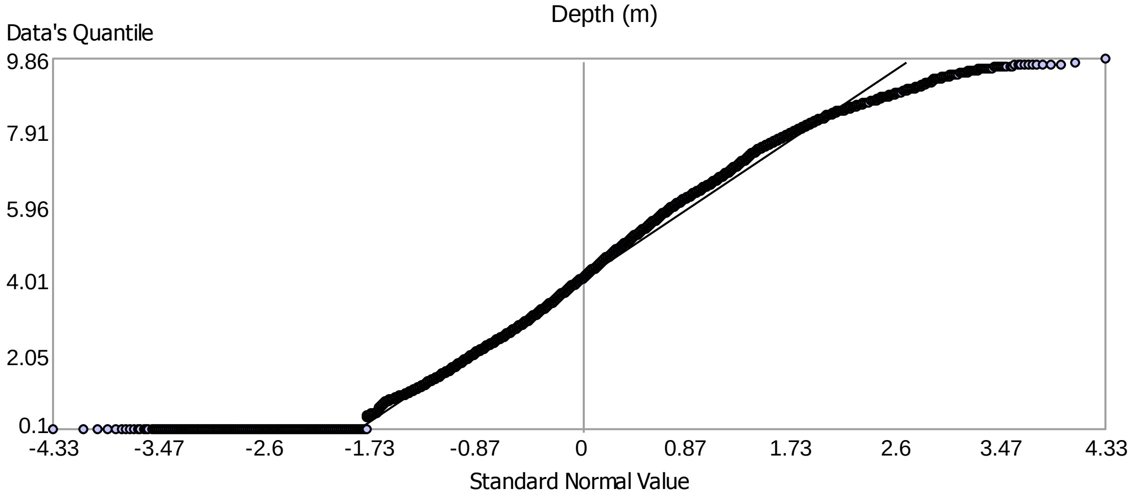


Figure 10. Plots for the final depth dataset (m) subsequent to changes made during data exploration steps: (a) histogram and (b) normal QQ plot.

Two types of trends or patterns may be identified in a dataset: a broader scale pattern or fixed 'global fit' (Babish, 2002), and secondly a local directional effect (anisotropy). The global trend may be described as "overriding" (Johnston, et al., 2001) and in the study area, water depth is likely a result of short range coastal geomorphology and underlying geology that affects all data points and which do not change over time. Trend analysis revealed an intrinsic trend of decreasing depths in a NE to SW direction, which may be modelled using a second or third order polynomial (Figure 11).

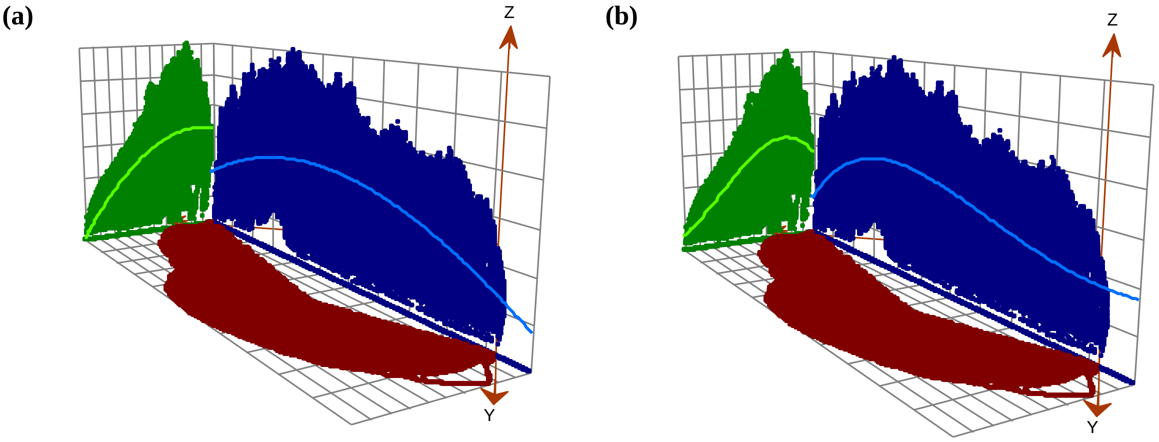


Figure 11. Trend analysis for the final depth dataset at a 225° angle showing a: (a) second order polynomial and (b) third order polynomial trend on projections. Projected data points in YZ plane shown in navy blue, in the ZX plane in green and XY plane in red. Trend lines in YZ plane depicted in blue, and in XZ plane in lime green.

The working dataset was randomly subsampled in order to generate training data for input to the interpolation (80%) and an independent test dataset to be used in model validation (20%). The smaller test dataset (500 data points) was used to generate semivariogram clouds (Figure 12), which revealed a NE-SW principal axis for anisotropy. This directional pattern was observed over a smaller distance than all directions, as expected by the spatial extent of data in the NE-SW direction and the narrow distance between the coast and seaward SSFCA boundary limit. Outliers were not readily identified from any of the semivariograms generated and those paired points close to the outer limits of the cloud were found to be accurate on further inspection. Given that no further erroneous data points were discovered, the working dataset of 68,604 points was considered final with a subsample of 54,883 points for the training and 13,721 data points for testing.

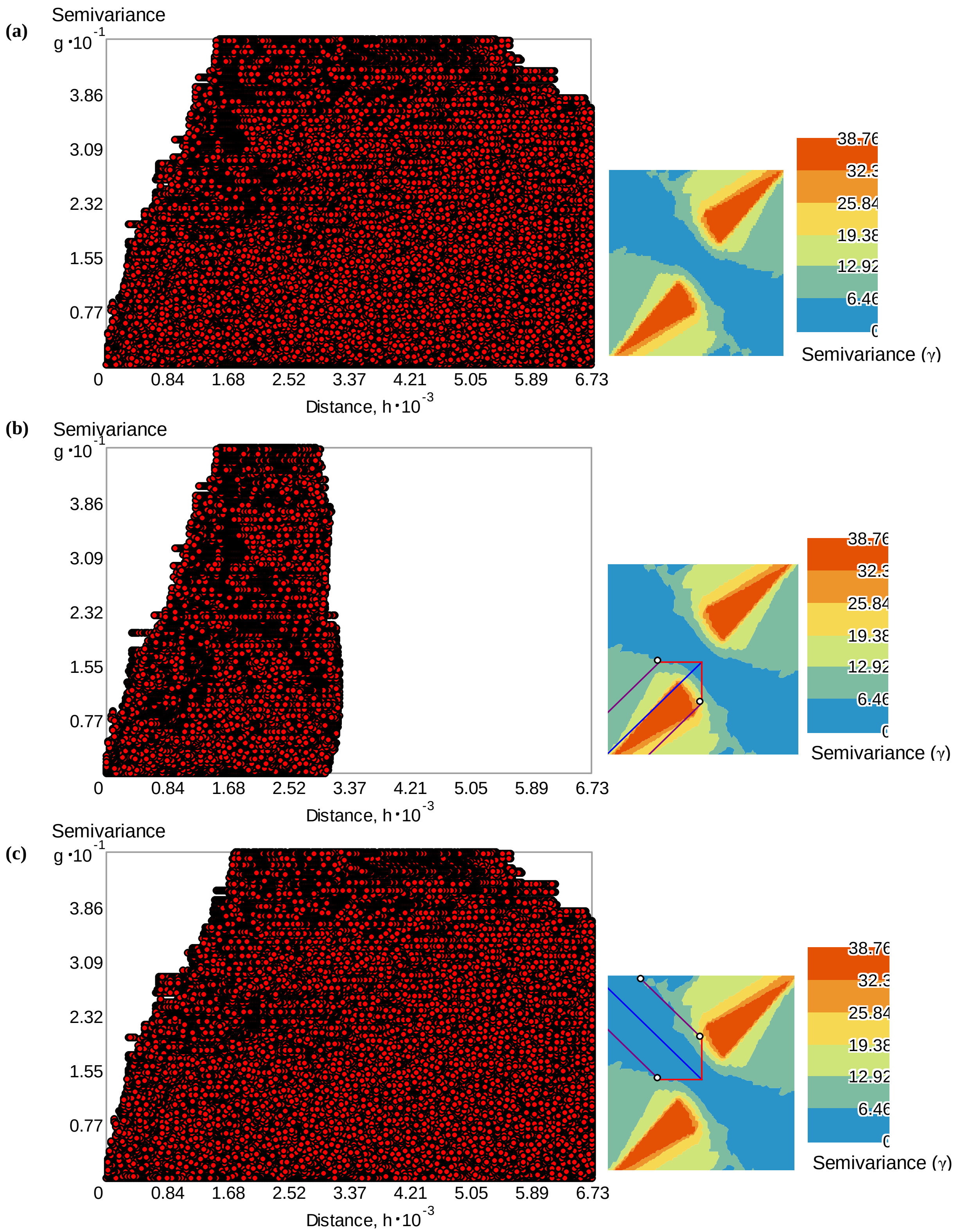


Figure 12. Semivariogram clouds and surface maps with angle direction (insets) generated using the test subsample of data points for: (a) all directions, (b) NE-SW direction (225° angle) and (c) NW-SW direction (315° angle).

3.5.2 Kriging

Numerous types of kriging exist, however universal kriging (UK) was employed owing to its approach of combining global trends (Oliver and Webster, 2014), such as those evidenced for BBSFCA, with local statistical variation. It is possible to overfit a global trend, and it is recommended that global surfaces be modelled as simply as possible since over fitting can result in negligible local variation in residuals to accurately explain model uncertainty (Johnston, et al., 2001). The NE-SW trend in BBSFCA appeared to be satisfactorily modelled by simple both second order and third order polynomial trends (Figure 11); however it was found that a constant, local exponential method with an exploratory trend surface of 1 best fit the general depth trend of the bay.

Unlike global trends which may be attributed to a known physical process or phenomenon, reasons for anisotropy are typically unknown or random and do not affect all data points. In order to examine the local, spatially related variation, an experimental semivariogram is plotted and this allows spatial autocorrelation between data points to be examined. The shape of the variogram may vary with direction; however the detrended dataset revealed to be isotropic and as such an omnidirectional was utilised (Figure 13b). The fit of various variogram model types were investigated within the first few distance lags (intervals), given that changes in the shape of the model near the origin of the graph have greatest influence on the prediction. The exponential form graphically fit with the empirical variogram and generated the best statistical cross-validation results when compared to other test variogram models.

It has been stated that variogram lag sizes should be in similar size to the sampling distance if a sampling grid was used (Johnston, et al., 2001; Oliver and Webster, 2014), which in this case was 50 m between transects and at minimum 4 m along transects. In an attempt to avoid any masking of short-range autocorrelation caused from local benthic features, a relatively small lag size of 10 m was chosen, with a total of 40 lags. Measurement error and spatial variation occurring at scales smaller than the sampling spacing result in nugget effects. Features less than 5 m in extent, such as coral heads or lobster condominiums do in fact exist and the mapping of these features was thought to be important. Owing to the dense sample data along transects and existence of co-located data records averaged prior to variogram modelling, it was reasonable to assume that the nugget effect seen may be attributed to local fluctuations in depth as well as measurement error, and was therefore modelled with a value of 0.0015. Other variogram parameters utilised included a range of 191.79 and partial sill of 0.11. Given the general NE-SW direction of the transect lines, a four-sector type search neighbourhood with 5 maximum and 2 minimum data points within each sector allowed for sample points to be included from neighbouring transect lines.

(a)

(b)

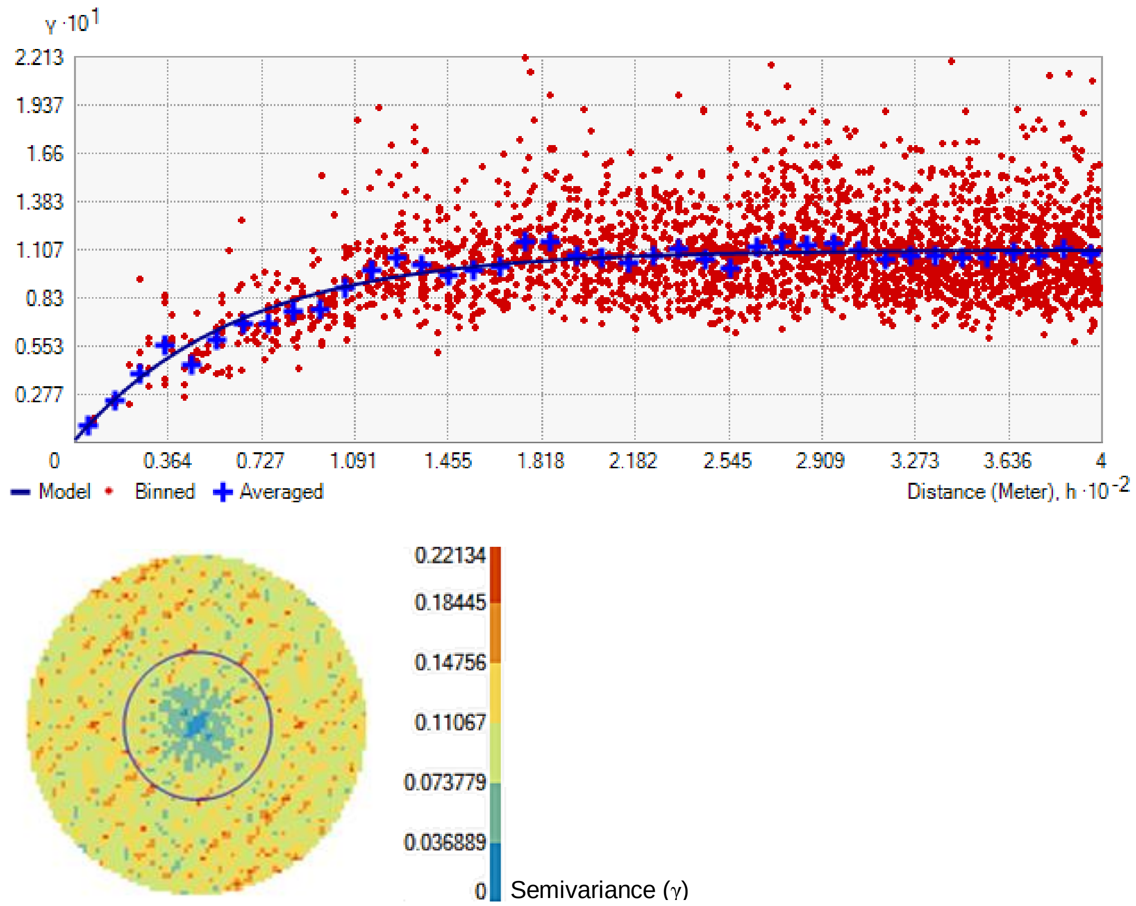


Figure 13. Exponential semivariogram model used to produce the BSM (a), and corresponding semivariogram map for the training data set (b).

3.5.3 Validation

Cross-validation predicts a value for a point momentarily removed from the dataset and compares the measured value with the predicted value (prediction error); this is repeated for all points within the training dataset. Graphical plots, together with statistical measures, and specifically mean prediction error (ME), mean squared error (MSE) and root mean squared error (RMSE) were used to assess the quality of the interpolated maps produced by the kriging methods. That model resulting in the smallest RMSE (Ly, et al., 2011), a RMSE standardised closest to 1 and a ME closest to 0 (Johnston, et al., 2001) may be used to identify the most accurate model. These diagnostic measures are comparable to some extent with those suggested by Oliver and Webster (2014), who state that ME should theoretically be zero and the MSE minimized. However Oliver and Webster (2014) further stated that these measures do not necessarily pinpoint the 'correct' krig model and recommended that the mean squared deviation ratio (MSDR) should be used as the indicator parameter, and that the MSDR value closest to 1 should be selected as the optimal model. The RMSE and the RMSE standardised that are generated are the square roots of the MSE and MSDR respectively. RMSE standardised is thought to be a good measure of model performance (Li and Heap, 2011) and this was used as the main measure for assessing model performance, as well as others. That kriging model resulting in the RMSE standardised closest to 1 from the cross-validation was deemed the optimal model for this study.

The resulting surface was referred to as a Bathymetric Surface Model (BSM), the oceanic equivalent to a Digital Surface Model (DSM), representing the topography of the seabed's surface, including the sea bottom, vegetation canopy and other manmade features that may be present on the seafloor. Such bathymetric representations are also referred to as Digital Bathymetric Models (DBMs) (Hell, 2011) and Digital Depth Models (DDMs) (Roob, 2000). In order for the resulting BSM to be combined with the satellite imagery data, the cell size chosen was identical to the spatial resolution of the imagery. The optimal kriging model was therefore exported to a raster GRID format with a spatial resolution of 2 m, and clipped to the BBSFCA boundary. Lastly, the cross-validation step described previously exclusively uses the input points (training dataset); as such it was deemed necessary to undertake validation of the final UK surface using the independent test dataset subsampled prior to interpolation in order to independently assess the performance of the interpolation.

3.6 Acoustic classification

3.6.1 Submerged vegetation

3.6.1.1 EcoSAV™ processing

The macro acoustic data collected from the field survey (section 3.3.1.1) was processed using the BioSonics, Inc. processing software EcoSAV™ in order to assess submerged aquatic vegetation (SAV). The echogram was used as a validating source, and processing parameters were defined to ensure that the most accurate vegetation reports were generated. Data for all six days was processed for every ten pings, and were then plotted as vector points in WGS1984 and subsequently reprojected to JAD2001. Duplicate points were removed and a total of 121,929 processed points with an average spacing of 2 - 3 m along transects. In order to obtain validation points from this across the bay, a random start transect was chosen and every tenth transect of data points, as well as transects perpendicular to the shoreline were selected for inclusion in the test subset of data points for model validation (representing 12% or 14,853 points) (Figure 14). The remaining 107,076 points comprised the training dataset for modelling (approximately 88% of all data points, Figure 7).

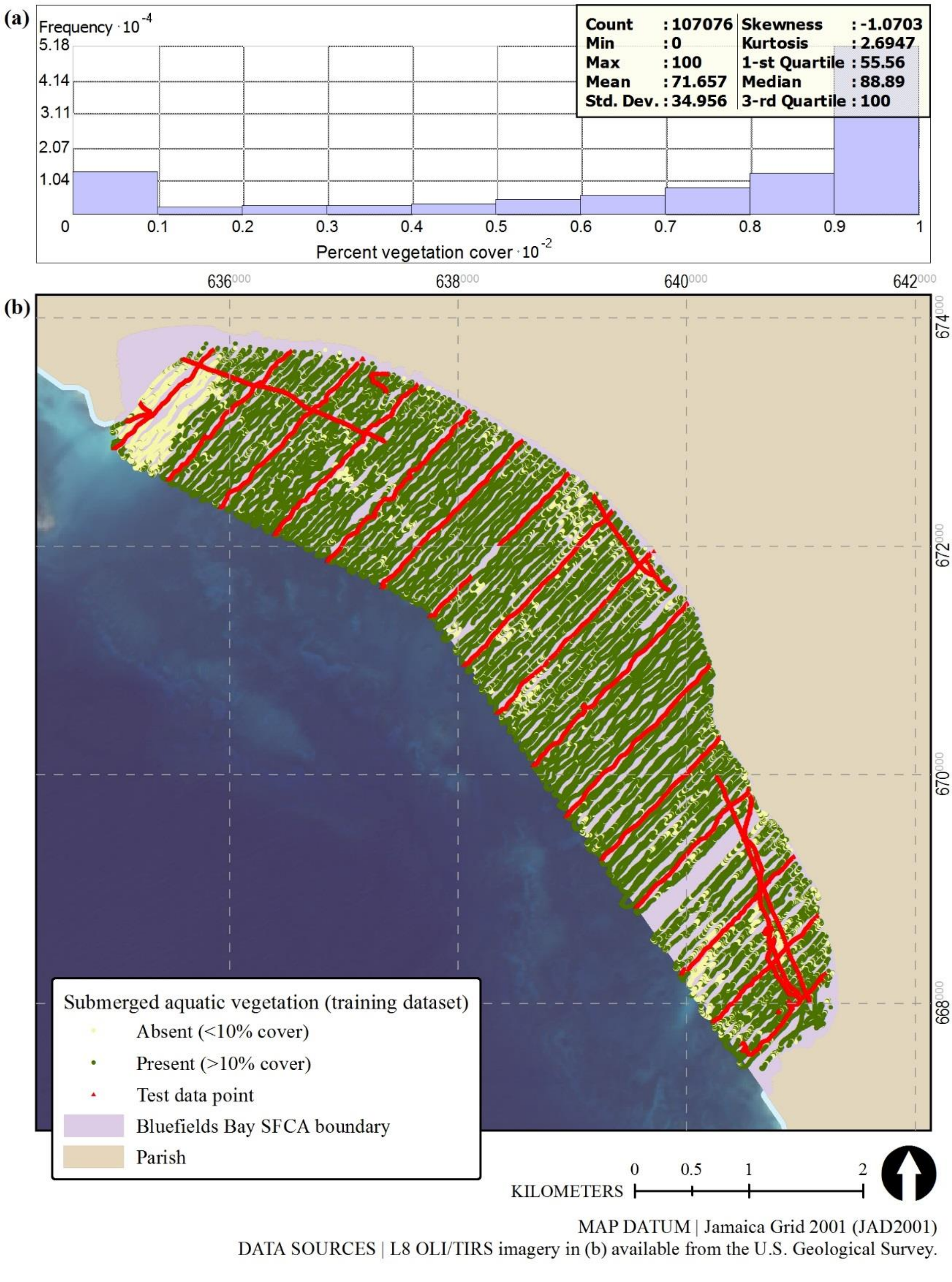


Figure 14. Graphical and spatial representation of EcoSAV™ training data points: (a) histogram and summary statistics for vegetation percent cover, (b) spatial distribution of training data points showing presence /absence across BBSFCA, as well as spatial distribution of test data points.

3.6.1.2 Interpolation

Given that various researchers successfully utilised IDW (Roob, 2000; Sabol and Johnston, 2001; U.S. NOAA Coastal Services Center, 2001; Cholwek, et al., n.d.) and various types of kriging (Valley, et al., 2005; Stevens, et al., 2008), IDW, as well as ordinary kriging (OK) and indicator kriging (IK) were tested on the SAV data output from EcoSAV™. Similar to Valley, et al. (2005), evaluation of prediction error parameters showed that OK and IK produced the more accurate models compared to IDW. IK, which is a binary form of OK, was favoured owing to its application to categorical data (Bierkens and Burrough, 1993) and the fact that binary values (0 or 1) are kriged, and not continuous variables (Babish, 2002). Although EcoSAV™ outputs a number of useful georeferenced vegetation features including plant height (cm) and areal coverage (%), the presence/ absence of SAV was selected as the classification output. Owing to the high variability of SAV temporally and spatially within the bay (Thompson, 2013; McNaught, 2013) and the unavoidable time lag between image and field data collection, this was the only output that was chosen. Indeed, vegetation presence data is fundamentally nominal in nature; it is not a continuous feature and may be regarded as patchy across a study area and may therefore be aptly represented in binary form.

The training dataset (107,076 points) was input to the IK model, and because a trend was not apparent during data exploration, trend removal was not necessary. In order to create a binary dataset, a threshold value of 9.99% was set; consequently, vegetation cover less than 10% was considered as bare substrate (and was assigned a binary value of 0) and those points having a percentage cover of 10% or more, were considered as vegetated (and were assigned a binary value of 1). The 9.99% threshold value was chosen so that the SAV classification corresponded with the NOAA habitat classification scheme that was used throughout this project (Figure 5). The processed data points were not normally distributed (Figure 14) and as such did not meet the normality requirement of variography and kriging; nonetheless, one benefit of IK is its ability to deal with skewed distributions (Babish, 2002) and this model produced optimal results and as such was chosen for interpolation of the SAV for the bay. Statistical cross-validation results were utilised to inform the selection of model parameters. This included the choice of an exponential variogram model type and since anisotropy was not evident in the experimental semivariogram plotted, an omnidirectional variogram was used (Figure 15). Short range change and thereby smaller lag sizes was considered particularly important in modelling SAV owing to a very small sampling distance along transects of 2-3 m for the EcoSAV™ processed data and the abrupt changes from vegetated to bare sediment. After testing various models, a lag size of 4 and 20 lags was found to be optimal. The empirical variogram had a nugget 0.009, range of 34.37 and sill of 0.06. Large differences were not observed when neighbourhood type and size were tested and it was concluded that an eight-sector search neighbourhood, with 89.48 m axes (no anisotropy present) were best suited for the modelling exercise.

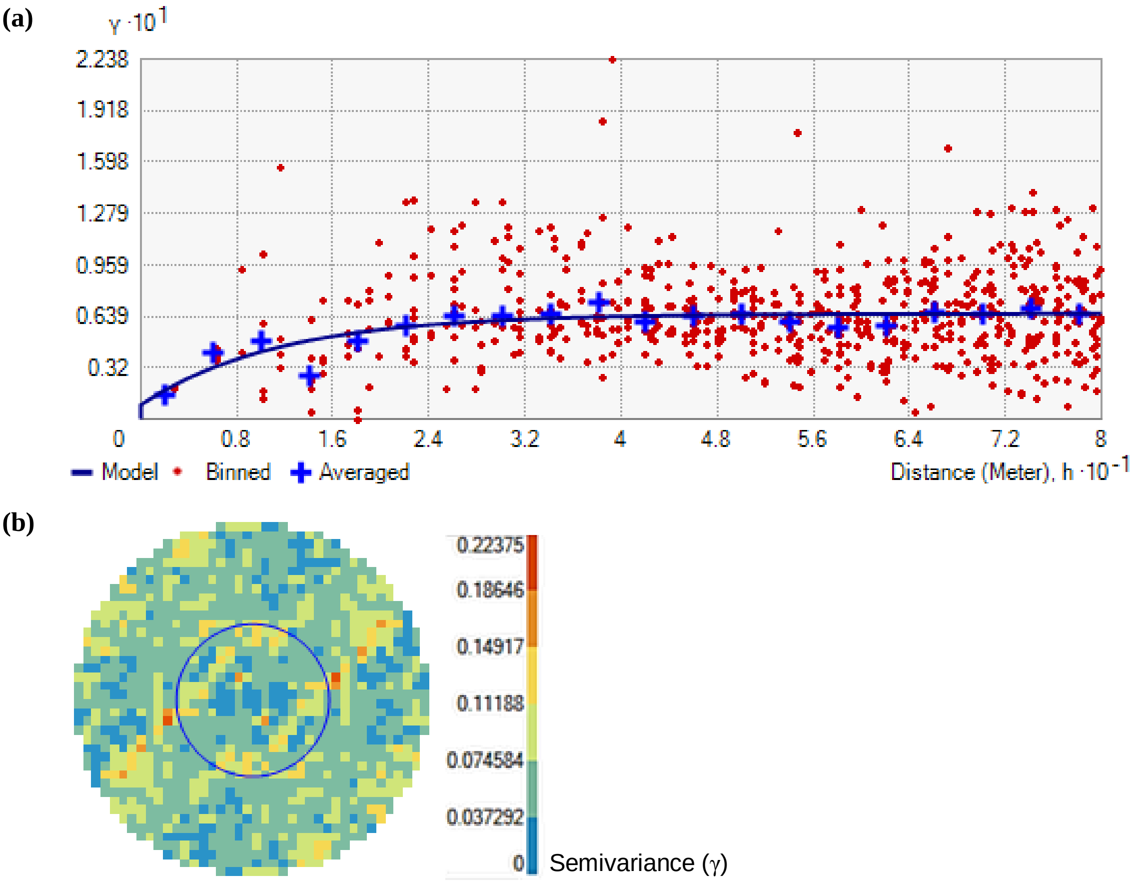


Figure 15. Exponential semivariogram model utilised for IK of SAV (a), and corresponding semivariogram map for the training data set (b).

Once the final model for SAV was obtained, a final validation exercise was undertaken using the test data subset (14,853 points) created prior to modelling. Furthermore, in order to delineate the resulting surface of vegetation occurrence probabilities into meaningful SAV presence and absence classes, a 50% threshold was employed. That is, areas in which vegetation occurrence with probabilities less than 50% were considered as bare, whilst those having probabilities greater than 50% were considered vegetated. One pixel or 4 m^2 was established as the MMU for the project, and was used to eliminate all areas that were less than this size.

3.6.2 Bottom classification

3.6.2.1 VBT™ processing

The BioSonics, Inc. processing software VBT™ B4 method (Fractal Dimension) was used to decode the field-collected acoustic data into bottom type (BioSonics, Inc., 2011). A ground-truth library was manually created for the study area; ground-truth data collected in the field were analysed and feature spaces (also referred to as acoustic classes) for three bottom types were distinguished, namely silt (type 1), sand (type 2) and coral/ hard bottom (type 3) (Figure 16). Using this library, all acoustic data was processed for every twenty pings and subsequently plotted and projected as vector points in JAD2001. Similar to the bathymetric data, the average along transect point spacing ranged from 4 and 5 m. Test and training datasets were created similar to the vegetation processed data from a total 66,092 plotted points (with collocated points removed). A total 58,034 points comprised the training dataset (88% of all data points), whilst 8,058 comprised the test dataset (12% of all data points) (Figure 17).

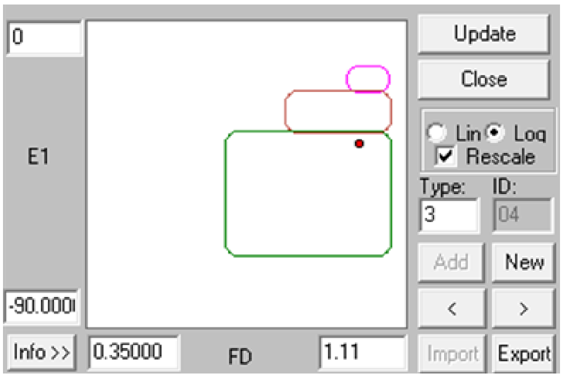


Figure 16. Feature spaces of ground truth data points for coral reef/ hard bottom (pink), sand (brown) and silt (green) using the B4 bottom typing method in VBT™.

3.6.2.2 Interpolation

Of the various interpolation methods evaluated in order to predict seabed composition in areas for which field survey tracts did not cover, kriging, specifically IK proved to be the most statistically-accurate model. Like SAV presence/ absence, bottom type is categorical in nature and as such the best suited interpolation technique available in ArcMap 10 was IK owing to the possibility of modelling binary values. IK was performed on the training subset of data (58,034 points) three times in order to arrive at the probability of occurrence for each bottom type (1-silt, 2- sand and 3-coral reef/ hard bottom). Trend removal was deemed unnecessary and a spherical omnidirectional variogram model was chosen for all three interpolations owing to the optimal statistical measures produced (Figure 18). A lag size of 5 and 12 lags and an eight-sector type search neighbourhood, with 90.02 m axes (no anisotropy present) were employed. Once all models were finalised, a final validation exercise was undertaken using the test data subset (8,058 points) in order to independently evaluate the performance of each IK model for bottom type. Similar to the IK for vegetation presence, the resulting bottom substrate surfaces were categorised using a 50% threshold for the probability of occurrence, whereby areas with probabilities greater than 50% were considered as having the respective bottom type present. The three data layers for bottom type created using the 50% probability threshold were subsequently combined using the ArcMap Raster Calculator to produce a single bottom substrate map output showing silt, sand and coral reef/ hard bottom distribution across the bay. Areas less than the $4m^2$ MMU were eliminated.

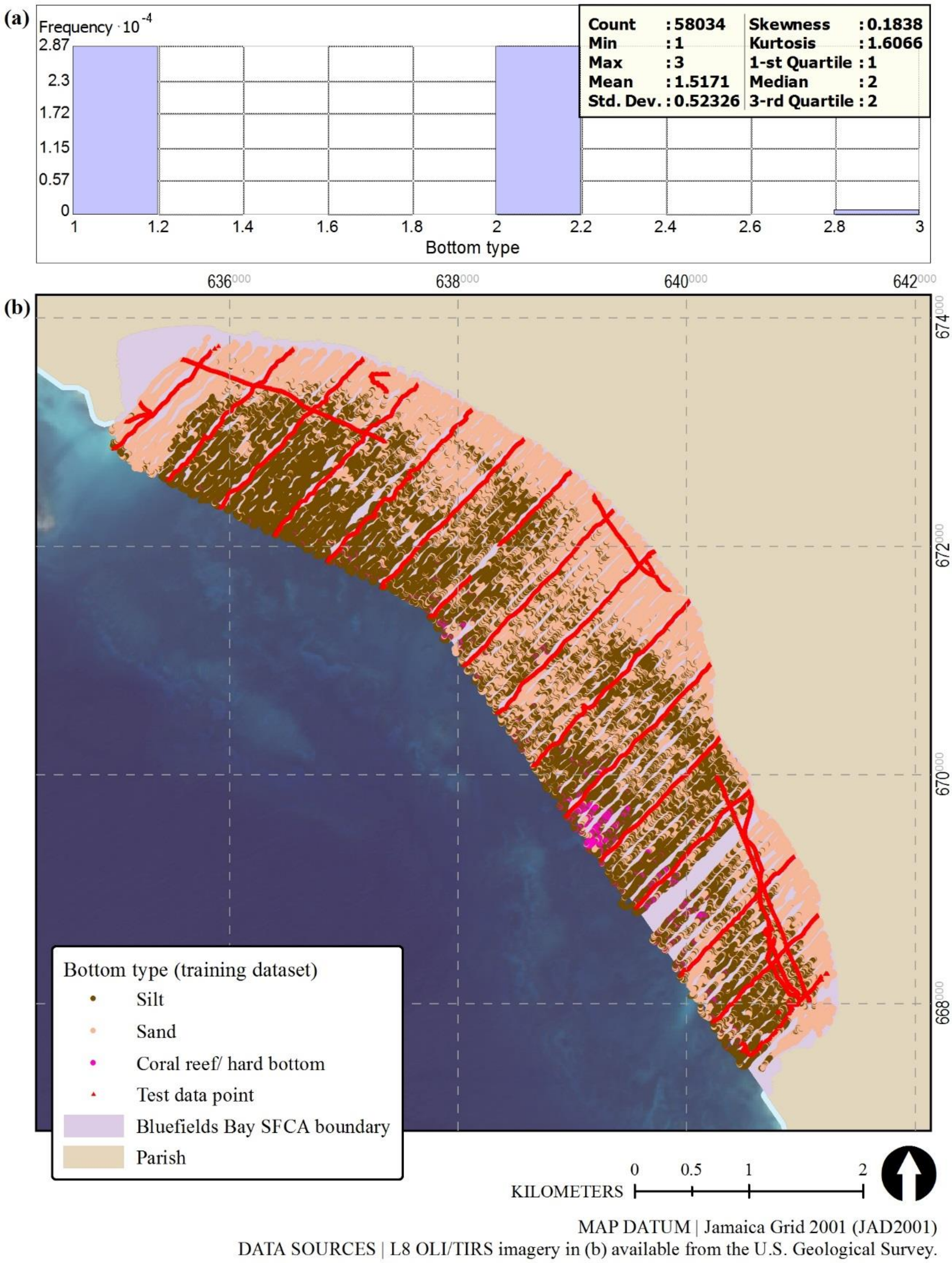


Figure 17. Graphical and spatial representation of VBT^{TM} training data points: (a) histogram and summary statistics for coral/ hard bottom (type 3), (b) spatial distribution of all training data points showing bottom type, as well as spatial distribution of test data points.

(a) Silt
Range: 35.83
Sill: 0.061
Nugget: 0.062

(b) Sand
Range: 37.71
Sill: 0.059
Nugget: 0.068

(c) Coral reef/ hard bottom
Range: 59.24
Sill: 0.002
Nugget: 0.005

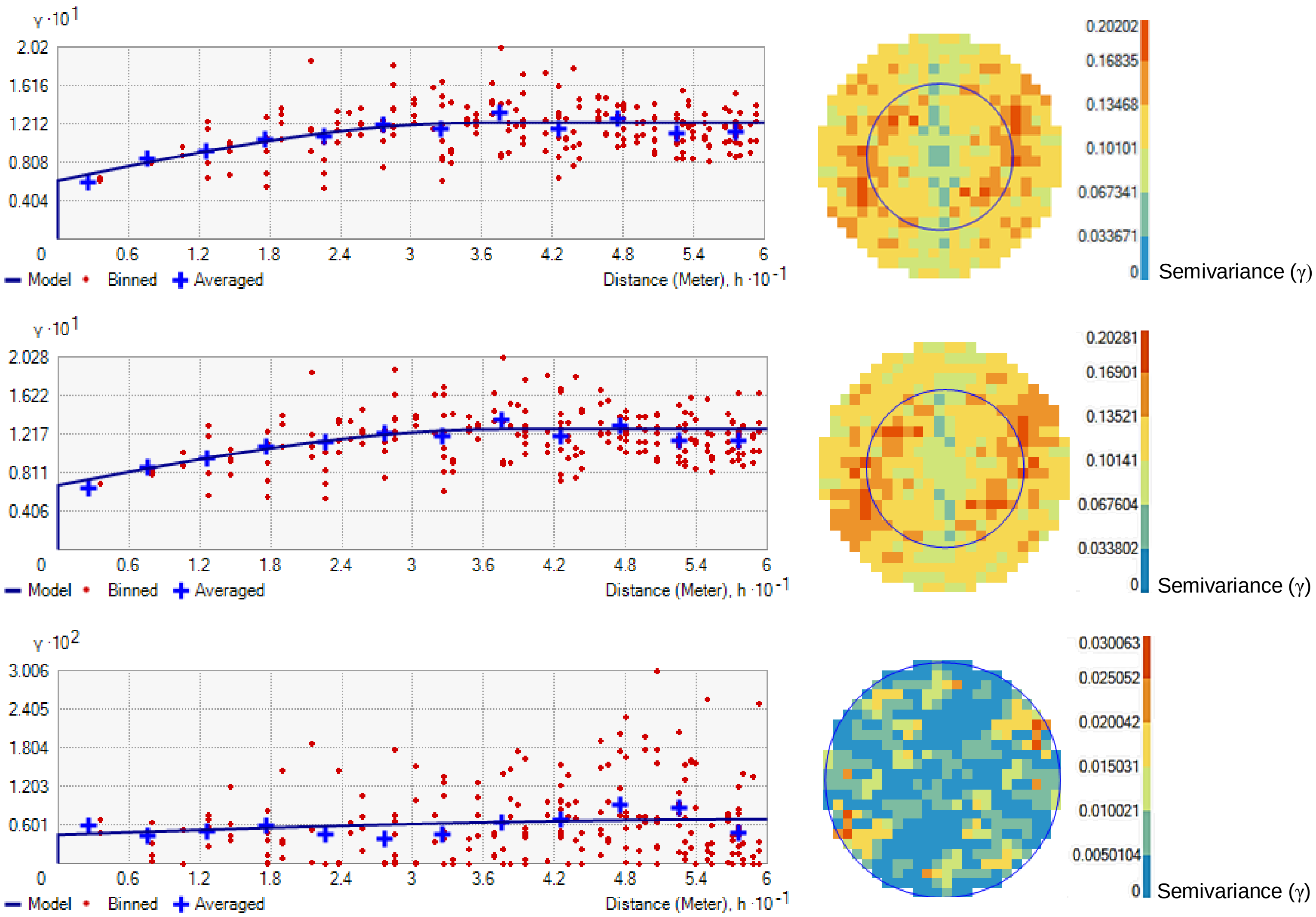


Figure 18. Spherical semivariogram model and associated parameters utilised for IK of bottom type training data and corresponding semivariogram map for: (a) silt, (b) sand and (c) coral reef/ hard bottom.

3.7 Satellite image classification

3.7.1 Image acquisition

Several studies have used remotely sensed images to map benthic features by means of image classification; however the accuracy of classified maps vary depending on the type of airborne and satellite imagery used (Green, et al., 2000; Fyfe, 2003; Phinn, et al., 2008). The aim of this study was to test the viability of various mapping methodologies and therefore efficacy of different types of remotely sensed images available at the time of the study were compared. Archived standard multispectral image products were acquired from the following satellite sensors: 1) GeoEye-1; 2) WorldView-2; and 3) Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) (L8 OLI/TIRS) (Figure 19, Appendix C). The L8 OLI/TIRS image (WRS Path 012, Row 048) was downloaded via the U.S. Geological Survey Earth Explorer web utility (http://earthexplorer.usgs.gov/), whilst WorldView-2 and GeoEye-1 images of the study area were donated by the DigitalGlobe Foundation (formerly GeoEye Foundation).

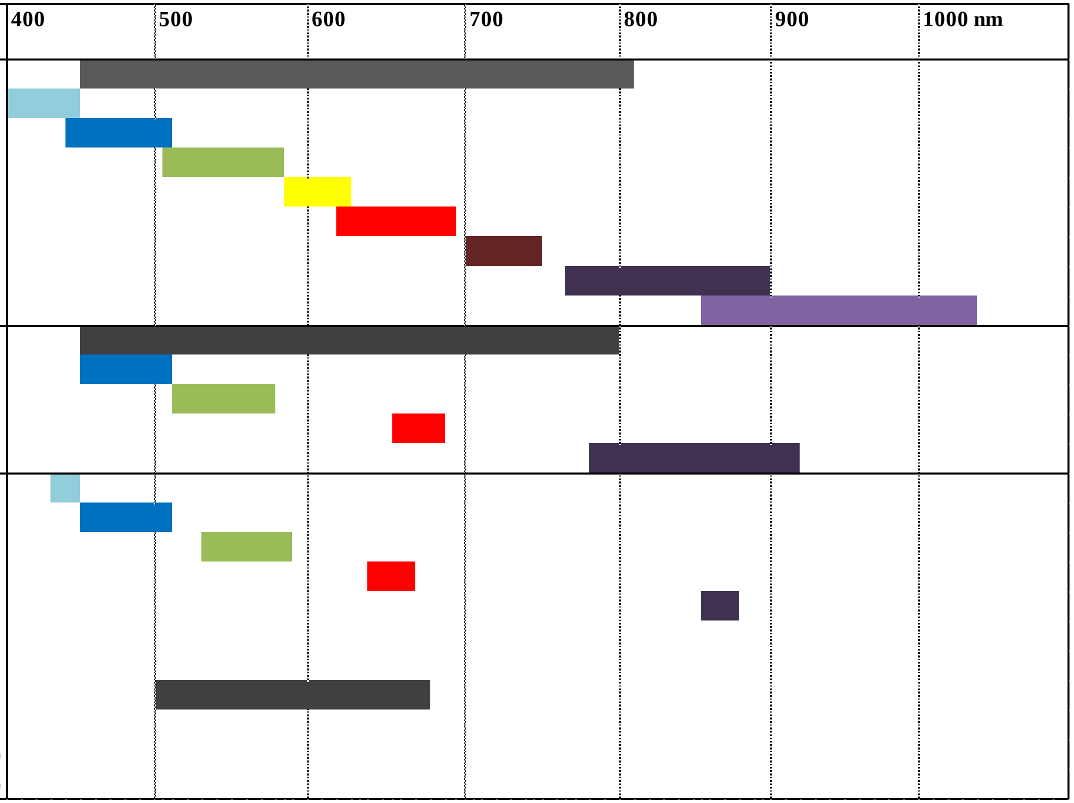
Processing undertaken by DigitalGlobe include radiometric, sensor, and geometric corrections, projection to a plane using map projection and datum and normalization for topographic relief with the use of a coarse DEM (DigitalGlobe, 2014). In the case of the Landsat image product, the Level 1 Product Generation System (LPGS) was applied by the provider and this included cubic convolution resampling, orientation of image north-up, projection to Universal Transverse Mercator (UTM) with WGS 1984 datum, and is available in the GeoTIFF file format (U.S. Geological Survey, 2014). Furthermore, the L8 OLI/TIRS image was processed to Standard Terrain Correction (L1T) using ground control points and DEMs developed by the U.S. Geological Survey (USGS) and NASA Global Land Surveys were used to correct for topographic distortions and improve radiometric and geometric accuracy.

3.7.2 Image enhancement and processing

3.7.2.1 Geometric correction and resampling

Downloaded images were reprojected from Universal Transverse Mercator (UTM) Zone 17N (WorldView-2 and GeoEye-1) and Zone 18N (L8 OLI/TIRS) to JAD2001 (Figure 20) and image to image georectification undertaken utilising a nationally-accepted dataset (IKONOS 2001 island images). The visible and infrared L8 OLI/TIRS image was pansharpened using the 15 m panchromatic band and subsequently resampled to ensure that the cell size of all L8 OLI/TIRS image bands was 2 m. WorldView-2 and GeoEye-1 images were not spatially enhanced and the spatial resolution of the visible bands was 2 m.

Satellite sensor	Collection date		Band	Spatial resolution (m)	Wavelength (nm)
WorldView-2	7-Apr-13		Panchromatic	0.5	447-808
		1	Coastal Blue	2.0	396-458
		2	Blue	2.0	442-515
		3	Green	2.0	506-586
		4	Yellow	2.0	584-632
		5	Red	2.0	624-694
		6	Red-Edge	2.0	699-749
		7	NIR1	2.0	765-901
		8	NIR2	2.0	856-1,043
GeoEye-1	3-Jan-12		Panchromatic	0.5	450-800
		1	Blue	2.0	450-510
		2	Green	2.0	510-580
		3	Red	2.0	655-690
		4	NIR	2.0	780-920
Landsat 8 (OLI/TIRS)	16-Apr-13	1	Coastal aerosol	30	430-450
		2	Blue	30	450-510
		3	Green	30	530-590
		4	Red	30	640-670
		5	Near IR	30	850-880
		6	SWIR 1 *	30	1,570-1,650
		7	SWIR 2 *	30	2,110-2,290
		8	Panchromatic	15	500-680
		9	Cirrus	30	1,360-1,380
		10	Thermal IR 1	100	10,600-11,190
		11	Thermal IR 2	100	11,500-12,510



** Wavelength ranges not depicted.*

Figure 19. Characteristics of WorldView-2, GeoEye-1 and Landsat 8 (OLI/TIRS) archived satellite imagery products acquired (DigitalGlobe, 2014) (U.S. Geological Survey, 2014).

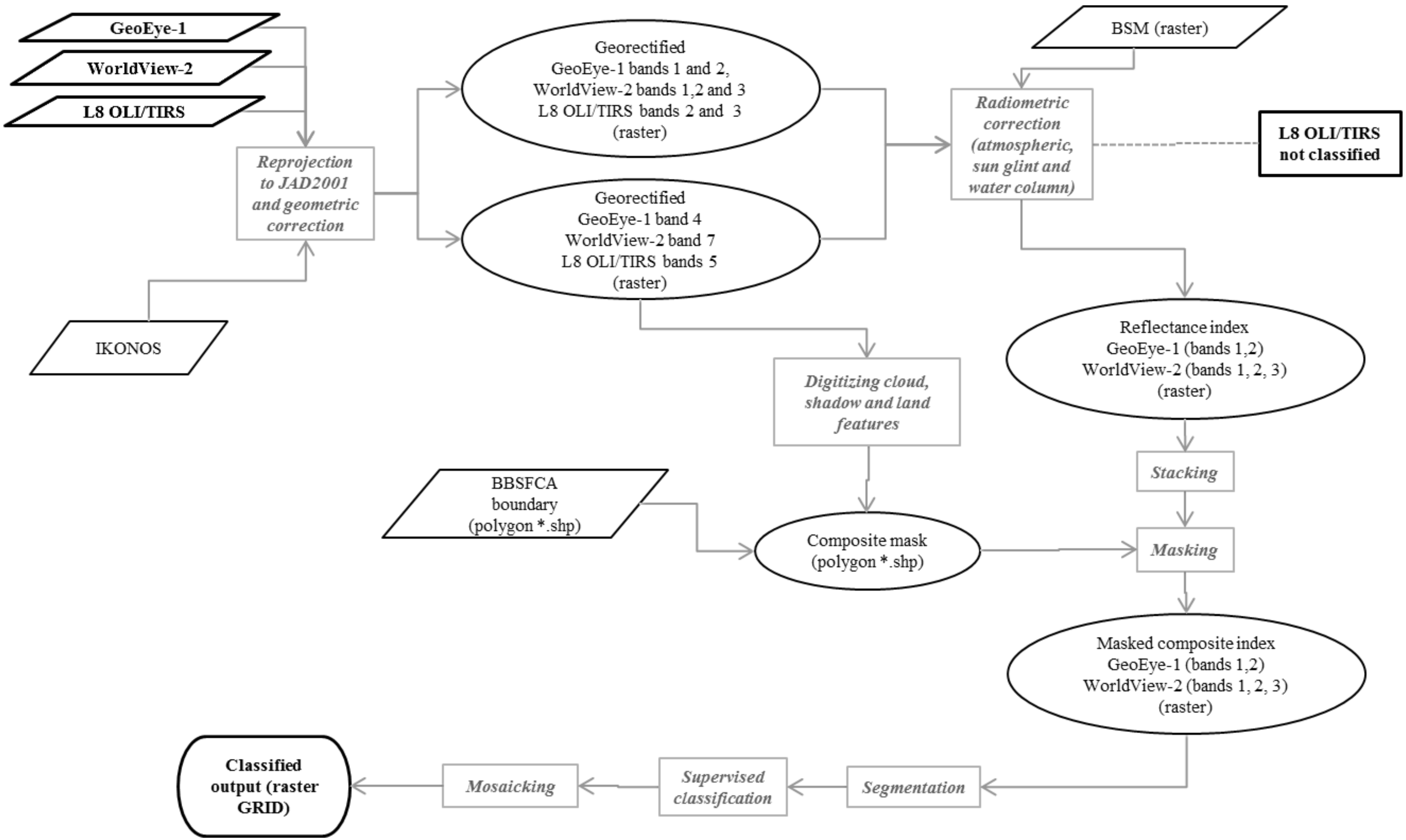


Figure 20. Flowchart showing key image correction and classification stages.

3.7.2.2 Imagery band selection

Spectral resolution, that is, the portion of the electromagnetic spectrum measured by the sensor and the image band groupings is important for remote sensing of marine environments. Water primarily reflects in the shorter visible part of the spectrum (blue and green wavelengths), and in the longer visible wavelengths (red wavelengths) and NIR energy is absorbed more than the shorter visible wavelengths. As such, the visible bands for all three imagery products were assessed in order to select bands with reasonable penetration of water, yet with differences in bottom reflectance. Similar to work undertaken by DigitalGlobe (2012), Florida Environmental Research Institute (2010), Sagawa, et al. (2010) and Green, et al. (2000), the blue and green bands in all three imagery products (respectively GeoEye-1 bands 1 and 2; WorldView-2 bands 2 and 3; and L8 OLI/TIRS bands 2 and 3), as well as the coastal blue (band 1) and coastal aerosol (band 1) bands available in WorldView-2 and L8 OLI/TIRS products respectively, were selected for use in the image classification exercise. Because of the high absorption and low reflection of the NIR and red portions of the electromagnetic spectrum of water, these bands were not used for image classification. The NIR bands were however used for coastline digitisation (section 3.4) and thresholding techniques (section 3.7.2.4).

3.7.2.3 Radiometric correction

ATMOSPHERIC CORRECTION

Although correction of atmospheric effects is an optional first step in the sun glint removal technique employed, it has to precede the water column correction method employed, and as such, it was the first pre-processing step undertaken. Several techniques such as FLAASH Module in ENVI (ENvironment for Visualizing Images) (Vahtmäe and Kutser, 2013) and ATCOR (Atmospheric Correction and Haze Reduction) implemented in ERDAS can be used to remove the effects of the atmosphere. The effect of path radiance was removed using the dark pixel subtraction method, also referred to as the histogram minimum method (developed by Chavez et al. 1977, cited in Green, et al. (2000)). It was applied to each image band by following this equation:

$$\boldsymbol{Atmosphercially\ corrected\ radiance = L_i - L_{si}} \qquad \textbf{Equation 1}$$

Where L_i is the measured radiance for a single image band *i;* and L_{si} is the average radiance observed over deep water for image band *i*.

SUN GLINT

On inspection of the acquired imagery, it was found that sun glint was abundant throughout each image product. Several sun glint removal methods were reviewed by Kay, et al. (2009) and a method suggested by Hedley, et al., (2005) was found to be applicable to shallow waters and for sub-surface use. Similar to Schill, et al. (2011) and Vahtmäe and Kutser (2013), the following steps outlined by Hedley, et al. (2005) were employed for each visible band:

Step 1: Sample areas in homogenous regions of deepwater where sun glint is present were demarcated and the minimum NIR value was ascertained (Min_{NIR}).

Step 2: A linear regression of visible band values (y-axis) against NIR values (x-axis) was performed for each band (i), and the slope for each line noted (b_i).

Step 3: Image bands were deglinted using Equation 2:

$$\boldsymbol{R_i' = R_i - b_i(R_{NIR} - Min_{NIR})} \qquad \textbf{Equation 2}$$

Where $R_i'$is the sun-glint corrected pixel value in band *I;* R_i is the pixel value in band i*;* $b_i$is the slope of the regression; R_{NIR} is the pixel NIR value; and Min_{NIR} is the ambient NIR level.

WATER COLUMN CORRECTION

Common amongst water column correction models researched (e.g. Lyzenga, 1978, 1981, Mishra, et al., 2006, Gilvear, et al., 2007; Sagawa, et al., 2010, Kanno, et al., 2011), is the recognition of Lyzenga's original water reflectance equation (Lyzenga, 1978):

$$\boldsymbol{L_i = L_{si} + \kappa_i r_{Bi} exp(-k_i f z)} \qquad \textbf{Equation 3}$$

Where L_i and L_{si} are similar to Equation 1; κ_i is a constant including solar irradiance, transmittance of the atmosphere and water surface, as well as the reduction of the radiance due to refraction at the water surface; r_{Bi} is the bottom reflectance; k_i is the effective attenuation coefficient of the water; f is a geometric factor which accounts for pathlength through water; and z is the water depth.

The model expressed in Equation 3 is applicable for areas over clear shallow water and does not take into account internal reflection at the water surface or the effects of scattering in the water (Lyzenga, 1978). Lyzenga (1978) addresses the neglect of scattering effects in the water at the surface by introducing a more general algorithm:

$$\boldsymbol{X_i = ln(L_i - L_{si})} \qquad \textbf{Equation 4}$$

Where $X_i$is the transformed radiance of a pixel in band *i*; and L_i and L_{si} are the same as in Equation 1.

Bottom reflectance is an exponential function of water depth and this thereby forms the basis of this equation, wherein when transformed using natural logarithms (ln), the relationship becomes approximately linear. The bottom reflectance (r_{Bi}) from Equation 3, that is the reflectance without the interference of the varying water column, is the parameter being sought; however, a number of the remaining input values are unknown. In order to determine the unkown parameters, the ratio of the effective attenuation coefficients of the water (k_i) (also included in Equation 3) is calculated from a linearized bi-plot of two selected band pairs (i and j) and a depth-invariant index generated and applied to the entire image.

Due to several limitations of the Lyzenga method, such as the unaccounted effects of internal reflection, the disregard for disparities in water quality and clarity (Sagawa, et al., 2010; Kanno, et al., 2011), and variations in bottom type and reflectance (Mishra, et al., 2006; Kanno, et al., 2011) several authors have attempted to extend or improve the method. The method proposed by Sagawa, et al. (2010) in which a reflectance index was created using Equation 5, was used (Equation 5):

$$\boldsymbol{Index_i} = \frac{(\boldsymbol{L_i} - \boldsymbol{L_{si}})}{\boldsymbol{exp}(-\boldsymbol{K_i g Z})} \qquad \textbf{Equation 5}$$

Where L_i and L_{si} are similar to Equation 1; K_i is the effective attentuation coeffiecnt of the water, similalr in Equation 3; g is a geometric factor which accounts for pathlength through water, similalr to f in Equation 3; and Z is the water depth , similalr in Equation 3.

The numerator, $(L_i - L_{si})$ is essentially the band radiance and at this stage in pre-processing, it is the radiance values that were corrected for atmospheric effects and sun glint. As mentioned previously, bottom reflectance is an exponential function of water depth; as such, in order to ascertain $K_i g$, radiance for each band (i) was plotted against depth and a regression curve obtained and from which the gradient was used to represent $K_i g$. The BSM created from the sonar bottom processing provided the requisite depth data and the reflectance index was calculated for each band and imagery product. The resulting reflectance index layers were stacked for each product, thereby producing 3-index stacked composite images for L8 OLI/TIRS (bands 1, 2 and 3) and WorldView-2 (bands 1, 2 and 3) and a 2-index stacked image for GeoEye-1 (bands 1 and 2).

3.7.2.4 Masking and thresholding

Cloud cover and cloud shadows were present in the WorldView-2 and GeoEye-1 images, therefore cloud masks were created for the radiometrically corrected images. The NIR bands for each imagery product and a thresholding technique were used to isolate the extent of cloud and land/ manmade features such as boats or piers present within the study area, similar to Mishra, et al. (2006), Florida Environmental Research Institute (2010) and Schill, et al. (2011). The blue bands were useful for highlighting the cloud shadows over water; in contrast, for land-based image classification the NIR bands are used in thresholding process (Martinuzzi, et al., 2006; Song, et al., 2014). Where the thresholding process failed, such as inaccurately identifying clouds in areas with high amounts of suspended sediment, subjective judgement was employed and regions of cloud, cloud shadow and land/ man made features were manually digitised; this also ensured the inclusion of mixed pixels. Masks for each feature of interest (cloud, cloud shadow and land/ manmade features) were compiled along with the BBSFCA boundary, and a polygon feature was generated to represent the final image masks for WorldView-2 and GeoEye-1 images. Each image by-product (reflectance indices) was clipped to the respective mask prior to classification. In addition, for comparison purposes, a composite mask combing both WorldView-2 and GeoEye-1 masks were used to clip the classification results. The L8 OLI/TIRS did not require masking, as clouds and cloud shadows were absent from the image within the study area extent; the respective index was clipped solely to the BBSFCA boundary polygon.

3.7.3 Classification

After visual assessments and numerous unsupervised and supervised classification trials, it was concluded that manual segmentation based on the characteristics inherent within each individual region, rather than a gridded structure or based purely on one characteristic such as depth was necessary. WorldView-2 and GeoEye-1 products were segmented into 30 and 59 segments respectively, and each segment buffered using a distance of 5 m to allow for a 10 m overlap between segments. Owing to the medium scale resolution of the L8 OLI/TIRS imagery, only the stacked reflectance indices for the larger scale WorldView-2 and GeoEye-1 products were segmented and subsequently classified.

A supervised, per-pixel maximum-likelihood classification was employed in ERDAS IMAGINE 9.1 in order to classify each WorldView-2 and GeoEye-1 segment into three benthic classes - submerged vegetation, bare substrate and coral reef. Although these classes do not correspond perfectly with the NOAA classification scheme (Figure 5), it was necessary to include bare substrate as a class and remove hard bottom from the coral reef grouping since it is impossible to differentiate bare hard bottom or pavement and unconsolidated sediment from optical image sources. Known benthic information from local experts and videography were used to identify features and training samples were created using the region growing tool within each individual segment. The signatures were evaluated using histogram plots and contingency matrices in order to ensure minimal overlap between signatures. In cases of high overlap, further segmentation was carried out in order to attain distinct signatures for benthic types within segments. Classified image segments were mosaicked and areas of overlap were blended in order to generate a single classified map of the study area. Pixel based classification often result in ‘salt and pepper’ effects (Lu and Weng, 2007) and in order to reduce this, classified images were clumped and the MMU of 4 m^2 was used to eliminate all classified areas that were less than this size. Finally, contextual editing, that is, “the application of common sense to habitat mapping” (Mumby, et al., 1997) was employed. A priori and on site knowledge of the area were used to identify the misclassified areas with similar spectra that were recoded; for example, circular patches surrounded by a ring of bare substrate classified as submerged vegetation were recoded as coral reef.

3.8 Accuracy assessment

Accuracy assessments of all final mapped outputs from the image classification (with and without contextual edits) and acoustic survey techniques were undertaken using referenced ground truth points collected in the field (section 3.3.2.2). Given the temporal variability of the BBSFCA seabed, care was taken to avoid using reference points on the edges of vegetation patches. Depending on the classification method employed, the areas that were removed using the cloud mask and the level of detail required (e.g. unconsolidated sediment type for acoustic bottom type classification), the number of accuracy assessment points varied for each assessment (Table 3). An error matrix was created for each classified output and statistics on classification accuracy were calculated; this included user's accuracy, producer's accuracy, overall accuracy and the kappa coefficient.

Table 3. Number of ground truth points collected for use in the accuracy assessment of image and acoustic classification mapped outputs.

Method/ Mapped output	No. of benthic classes	No. of ground truth points	
		By reference class	Total
Image classification - GeoEye-1 ***(clipped by GeoEye-1 cloud mask)***	3	Bare substrate =29 Submerged vegetation (SAV) = 82 Coral reef = 18	129
Image classification - WorldView-2 and GeoEye-1 ***(clipped by composite mask)***†	3	Bare substrate = 24 Submerged vegetation (SAV) = 68 Coral reef = 6	98
Acoustic classification - SAV	2	SAV absence (bare substrate) = 29 Submerged vegetation (SAV) = 82	111
Acoustic classification – Bottom type	3	Silt = 19 Sand = 16 Coral reef/ hard bottom = 23	58

3.9 Feasibility analysis

Required resources, including time/effort, software and hardware, and associated costs were collated in the form of a table in order for the feasibility of the various mapping methods and resulting accuracies to be evaluated. Labour costs for data manipulation and modelling were estimated using a rate of USD 30.00 per hour in order to be comparable to studies reviewed (Baumstark, et al., 2013); field survey, image acquisition, equipment and software costs (set up costs) were also assessed similar to Baumstark, et al. (2013) and Green, et al. (2000). In addition to time and cost considerations presented in the form of a table, other considerations such as technical competence necessary for carrying out each method, as well as stakeholder requirements, use of maps, and existing available resources were important considerations. Here, the results from the questionnaire survey (section 3.1) were particularly useful.

† Accuracy assessment points did not fall within the area masked by clouds and cloud shadow for the GeoEye-1 image and as a result, the points falling within the WorldView-2 image clipped by the respective WorldView-2 mask alone were the same as those for the composite masked images (WorldView-2 and GeoEye-1).

Chapter 4. Results

4.1 BBSFCA boundary

The BBSFCA mapped boundary totalled 13.82 km^2 in area, with a perimeter of 22.35 km, 8.53 km of which represented the seaward boundary of the sanctuary.

4.2 Bathymetry

Along the seaward edge of the BBSFCA boundary, the northern section of the bay is generally shallower than the southern half where maximum depths of 9.3 m occur (Figure 21). A general NE-SW progression of increasing depth towards the sanctuary's seaward limit is observed throughout the study area. Along the coast in proximity to the settlement of Mearnsville, the slope from the coastline to the 2 m contour is dramatically steeper than other areas along the bays shoreline. An apparent feature resembling a sandbank is located in the southern section of the bay (Figure 22). The BSM also appeared to model localised seabed features such as sand patches, shown to be slightly deeper than surrounding areas vegetated by seagrass and algal communities. Aggregated patch reefs within the back reef in proximity of the seaward SFCA boundary are revealed to have heights ranging between 2.5 and 3.5 m and situated in waters with a depth of 8 m. Patch reefs towards the centre of the boundary and in the northern section of the sanctuary are also identifiable by enclosed contour lines (Figure 21).

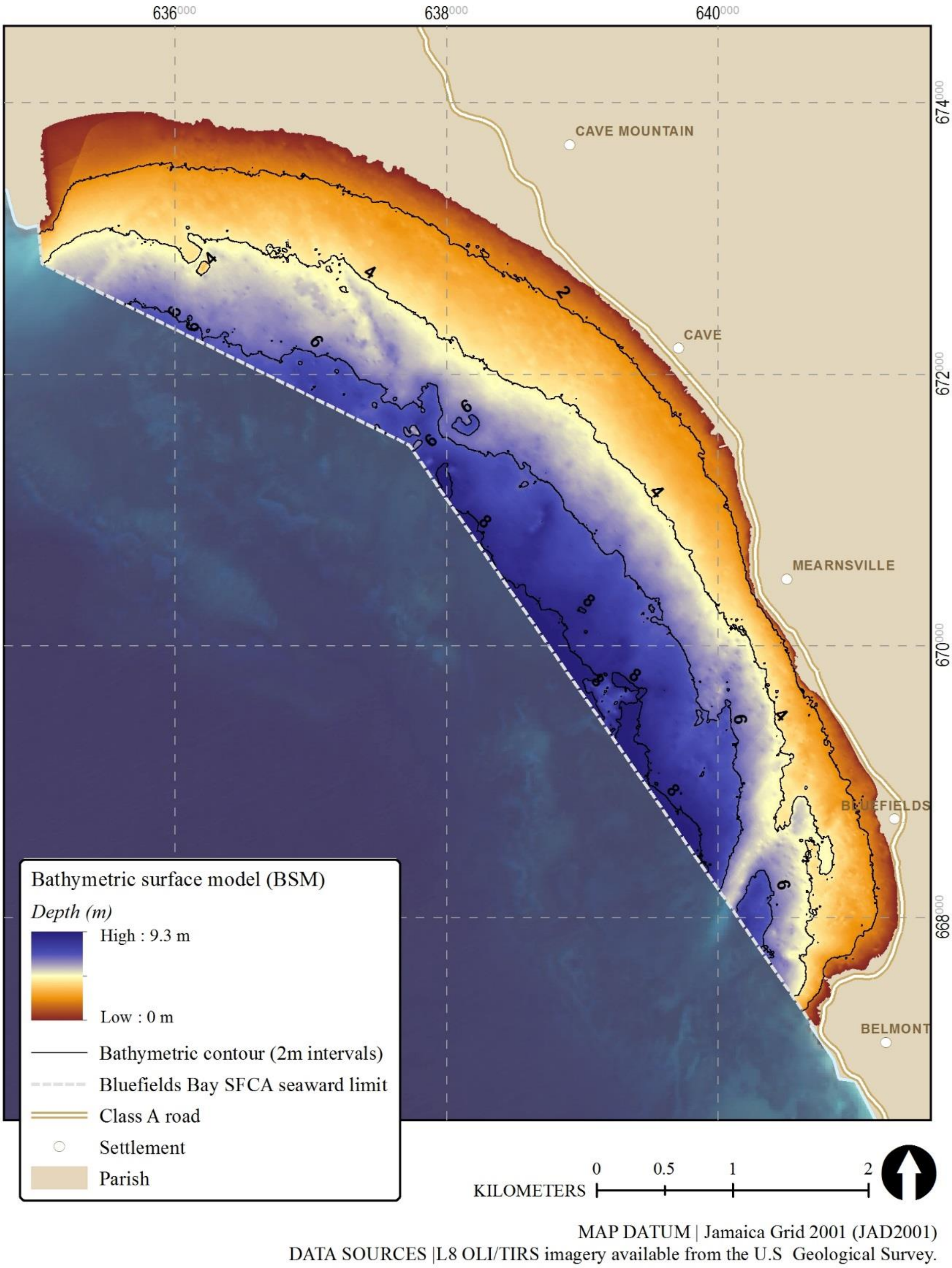
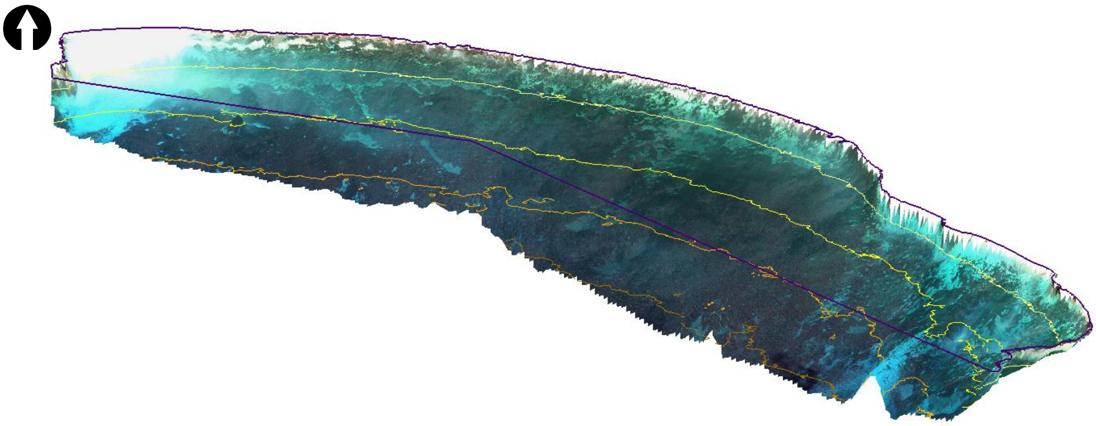
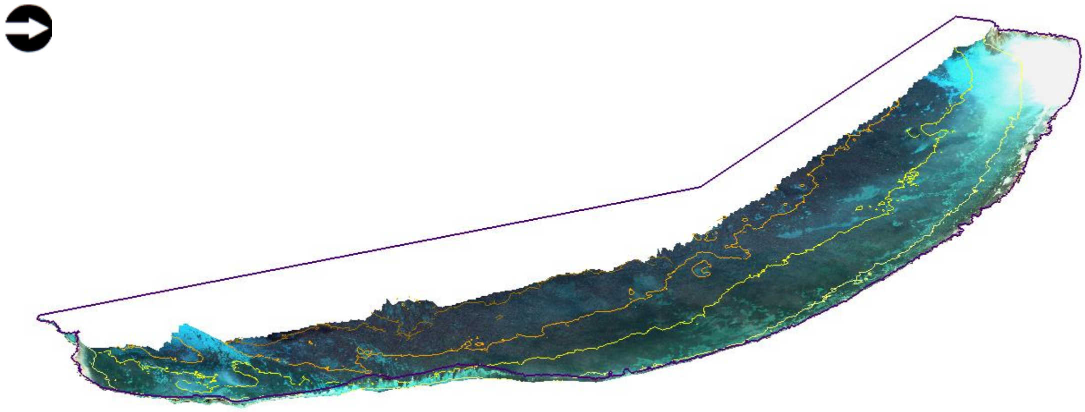


Figure 21. Bathymetric surface model of the BBSFCA with 2 m depth contours.

(a)



(b)



Depth contour (metres) 2 m 4 m 6 m 8 m

** Not drawn to scale; horizontal and vertical scales do not correspond.*

Figure 22. Vertically exaggerated 3D representations of the BBSFCA BSM, highlighting various benthic morphological features from two perspectives: (a) no rotation and (b) north rotated approximately 45°, facing east.

Although both training and test datasets have comparable mean depths, all minimum and maximum predicted depths were slightly under predicted (Table 4). Examination of graphical plots (Figure 23) reveal that significant scatter was not observed along the linear trend line and the predicted and measured depth values are highly correlated (R^2 = 0.9982).

Table 4. Statistical summary of measured and model predicted data for training and test datasets.‡

	Training		Test	
	Measured	**Predicted**	**Measured**	**Predicted**
Count	54,883	54,883	13,721	13,721
Minimum (m)	0.100	-0.007	0.100	0.049
Maximum (m)	9.864	9.760	9.729	9.688
Mean (m)	4.100	4.100	4.108	4.107
Standard deviation (m)	2.144	2.141	2.168	2.167

‡ All data points were used for validation, including those outside the BBSFCA boundary.

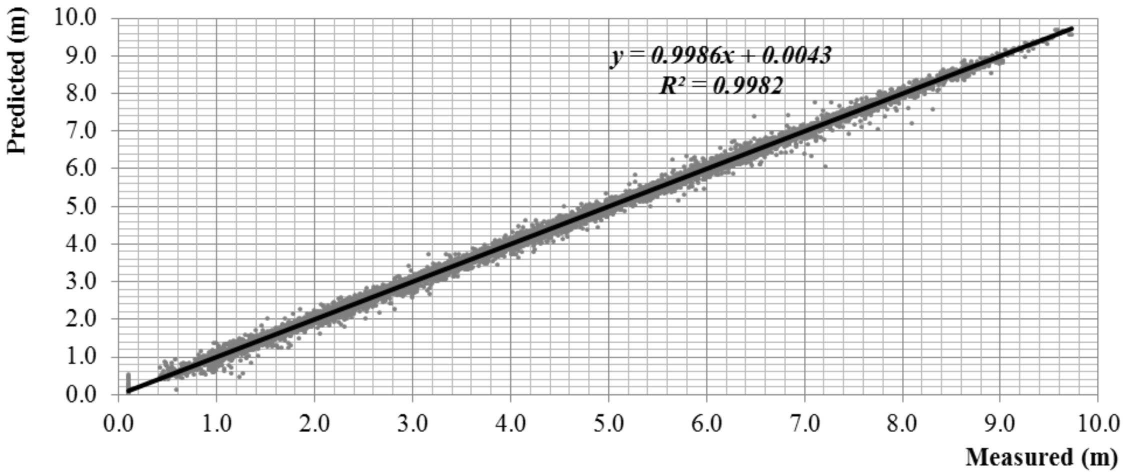


Figure 23. Scatter plot of predicted versus measured depth data values (m) using the independent validation results. Depth values plotted as circles and linear trendline represented by black line.

The BSM accepted as the optimal model had RMSE standardised values of 0.909 and 0.906 using the training and independent test datasets respectively (Table 5), all other test models resulted in lower RMSE standardised values after cross-validation (not presented here). The average difference between the measured and the predicted values (ME) using both the training and test datasets, were very close to zero and spatial trends in these errors were not evident within the study area (Figure 24). Standard errors of the BSM ranged from 0.0294 to 0.389 across the BBSFCA with lower values around input data points (Figure 25). The average standard errors were greater than the RMSE prediction errors by 0.0123 m and 0.0116 m for the training and test datasets respectively.

Table 5. Prediction errors for the final BSM using the training and test datasets as cross-validation and validation source datasets respectively.

	Training dataset	Test dataset
No. of points	54,883	13,721
ME (m)	0.0000224	-0.00128
RMSE (m)	0.0917	0.0914
ME standardised	0.000185	-0.0122
RMSE standardised	0.909	0.906
Average standard error (m)	0.104	0.103

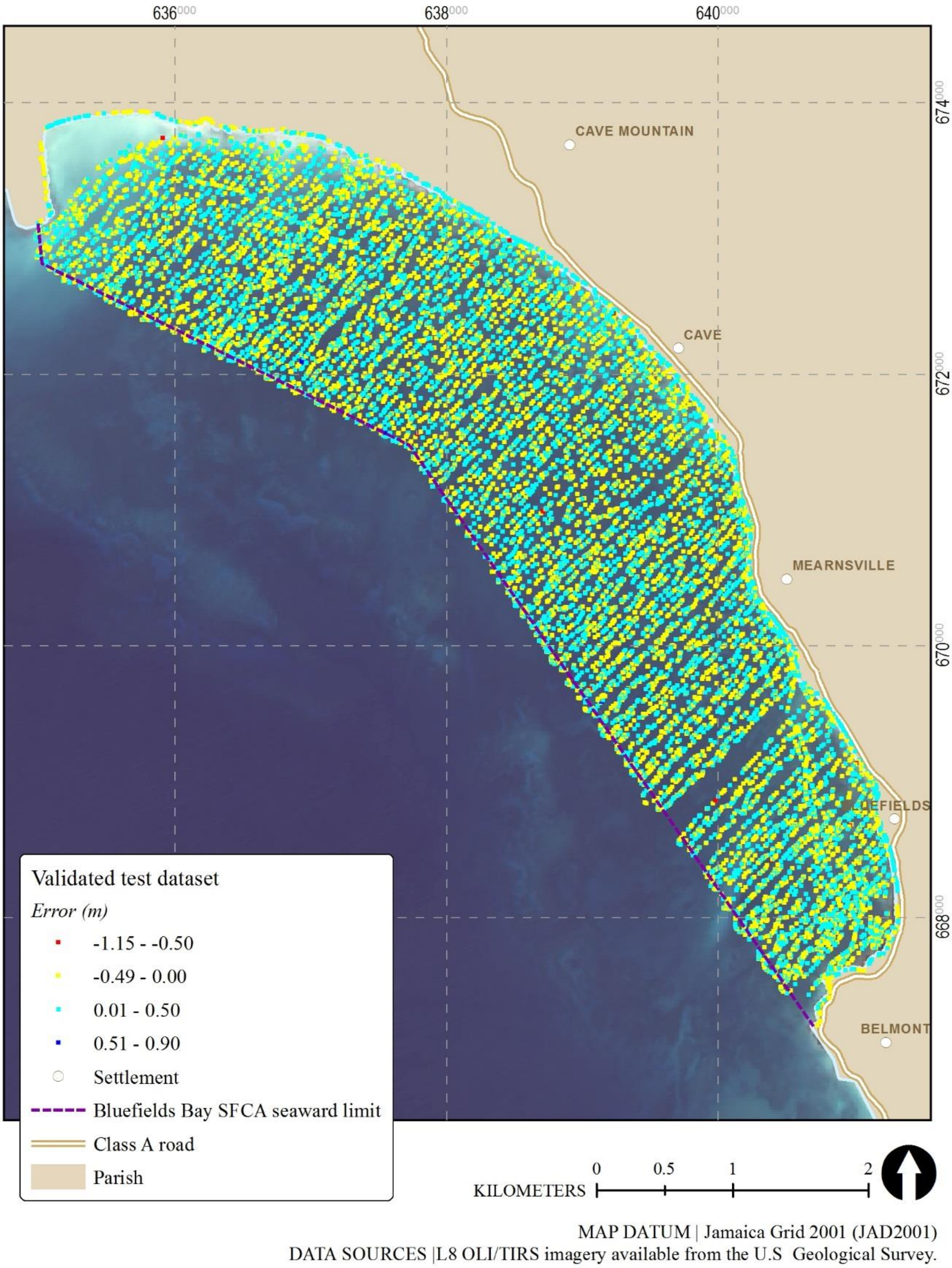


Figure 24. Error of BSM for the BBSFCA depicted by validated independent test data points.

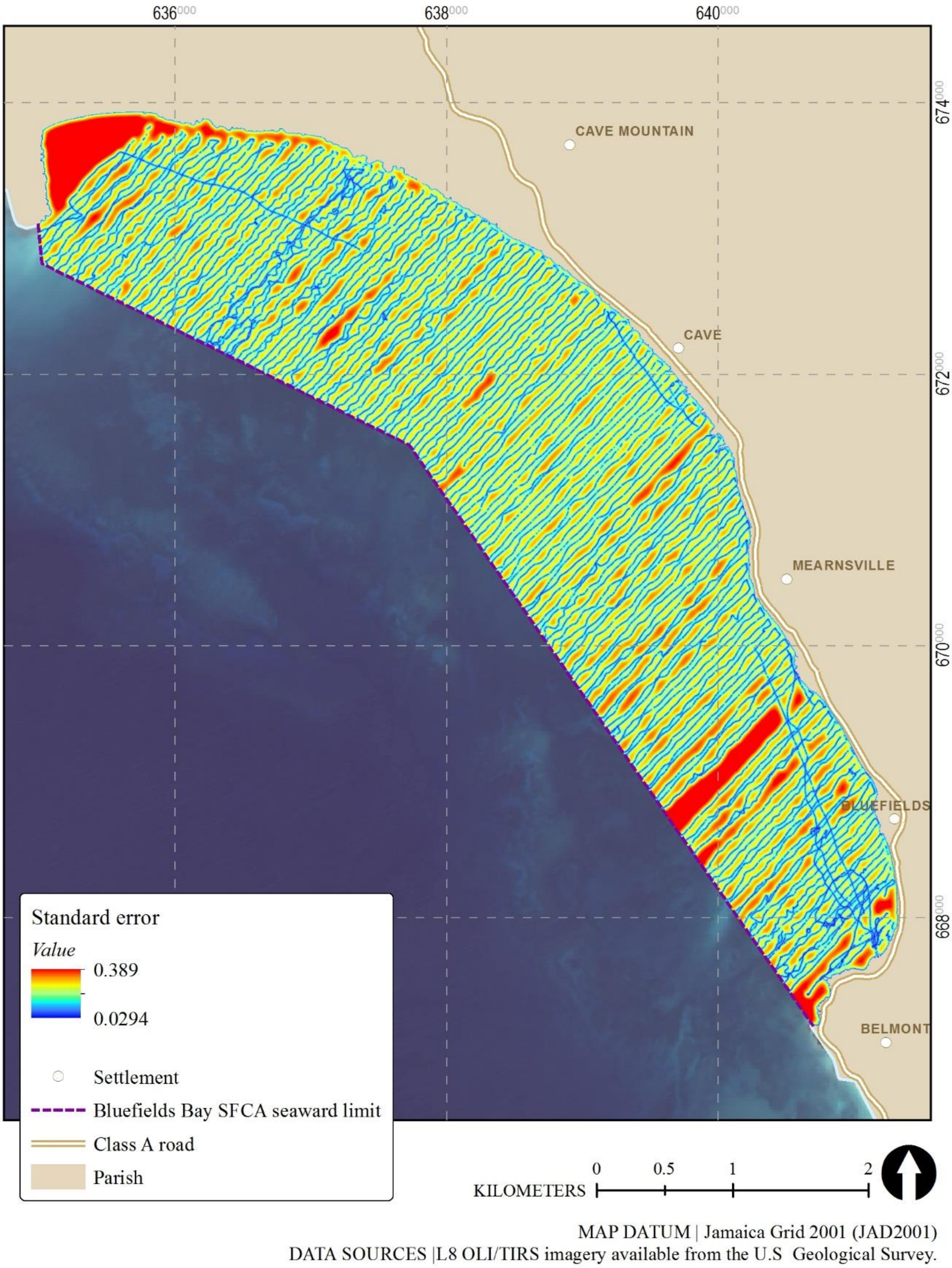


Figure 25. Standard error of final BSM for the BBSFCA.

4.3 Acoustic classification

4.3.1 Vegetation cover

The BBSFCA may be described as SAV-dominated with high probabilities of SAV occurring across the bay and fewer areas exhibiting less than 50% SAV probability occurrence and constituting bare substrate (Figure 26)[§]. Although model artefacts are evident in the northern section of the bay, this area contains the greatest homogenous expanse of bare substrate. Based on the final SAV IK model, and using 50% probability of occurrence as a cut-off for vegetated versus non-vegetated areas, 12.6 km^2 or 91.2% of the substrate within BBSFCA may be categorised as vegetated, whilst 1.2 km^2 was devoid of SAV (or 8.8% of the SFCA). Field evidence from this study suggest that a large proportion of the BBSFCA sea bottom inhabited by SAV is characterised by three seagrass species, namely *Thalassia testudinum* (turtle grass) (Plate 3a), *Syringodium filiforme* (manatee grass) and *Halodule wrightii* (shoal-grass) (Plate 3b) that are found in monospecific and mixed beds, as well as algal species including *Halimed*a spp. (Plate 3c) and *Penicillus* spp..

[§] The IK method outputs the percentage probability of vegetation occurring (and exceeding a cut-off value of 10% vegetation cover) and this must not be confused with the threshold of 50% model probability of occurrence used to designate an area vegetated or bare.

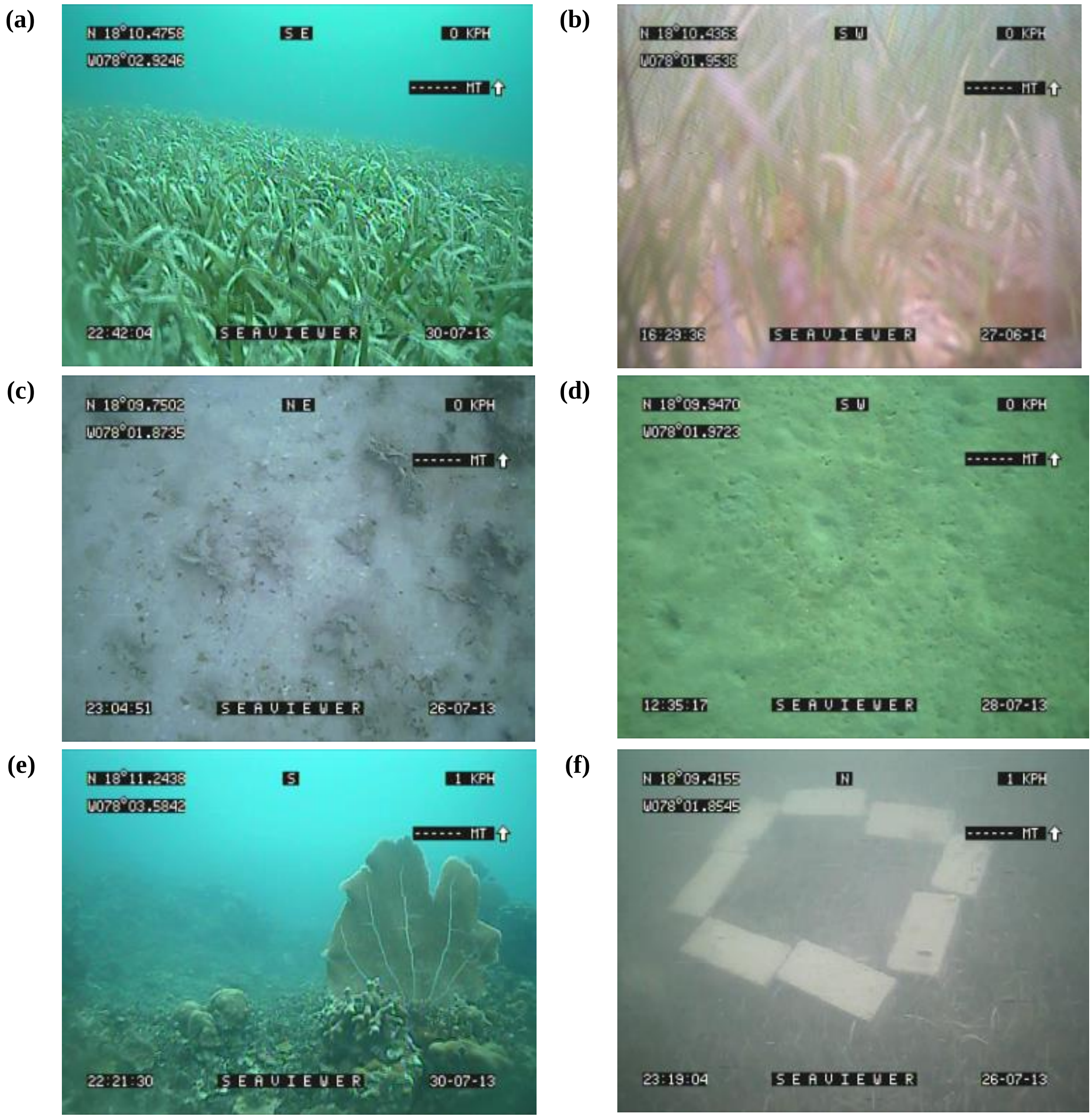


Plate 3. Oblique underwater images showing various benthic features with the BBSFCA: (a) seagrass bed dominated by *Thalassia testudinum*, (b) seagrass bed dominated by *Halodule wrightii*, (c) unconsolidated bare sediment with sparse algal cover, including *Halimeda* sp., (d) unconsolidated bare sediment, (e) reef assemblage including finger coral (*Porites* sp.) and sea fan (*Gorgonia* sp.) and (f) lobster condominium within *Thalassia* dominated seagrass bed (Videography credit: Karen McIntyre, 2013, 2014).

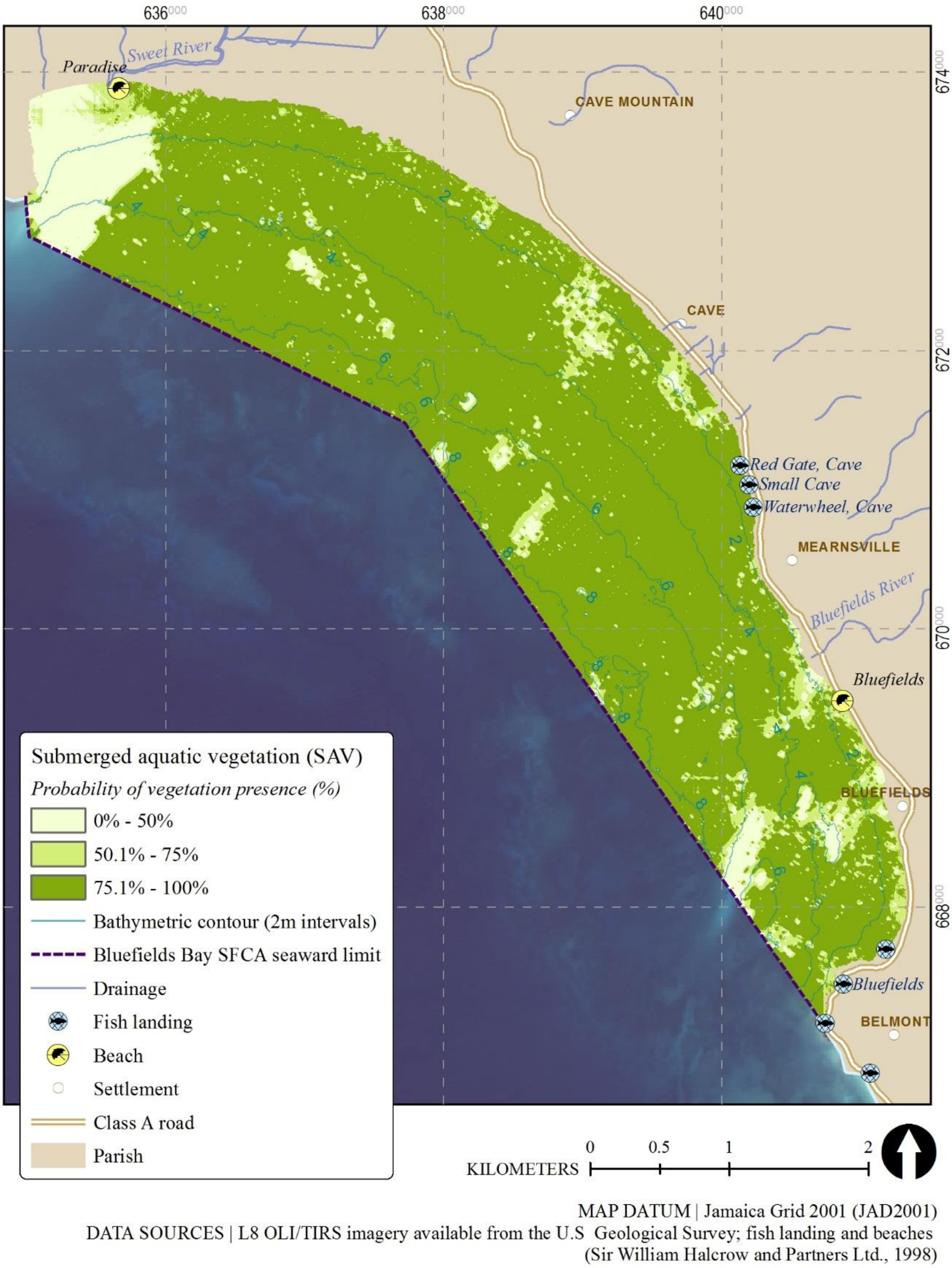


Figure 26. Probability of SAV presence across the BBSFCA.

RMSE for the training dataset was small (0.183) compared to other models tested and the ME was very close to zero (Table 6); these results assisted in the selection of the final IK model for SAV. The ME for the test dataset, although larger than the ME for the training dataset, is also close to zero. Areas of highest error occur over highly heterogeneous areas close to shore, small patches of non-vegetated areas within the bay, as well as in the last transect in the northern section of the bay, north of which only three survey transects occur. RMSE is also greater for the test dataset when compared to the training dataset. A RMSE standardised value of 1.199 was obtained from the cross-validation automatically undertaken with the model training data; this is further away from 1 than the RMSE calculated for the test dataset (1.105). Average standard error of the final IK model was 0.248 when the test dataset was used for validation; no apparent spatial pattern was observed when these points are plotted, however a greater number of lower than average standard errors were interspersed along those transect lines parallel to the shore and crossing the sonar survey transects (Figure 28). The final SAV IK shows that standard error along transects were lowest, and in areas for which transects were not possible, for example in shallow areas close to shore, standard error was highest (Figure 26). The average standard errors were less than the RMSE prediction errors for the training and test datasets by 0.03 and 0.02 respectively.

Table 6. Prediction errors for the SAV IK model using the training and test datasets as cross-validation and validation source datasets respectively.

	Training dataset	Test dataset
No. of points	107,076	14,853
SAV presence (Indicator = 1)	94,079	12,541
SAV absence (Indicator = 0)	12,997	2,312
ME	0.0000841	0.00357
RMSE	0.183	0.266
ME standardised	0.000102	0.0177
RMSE standardised	1.199	1.105
Average standard error	0.153	0.248

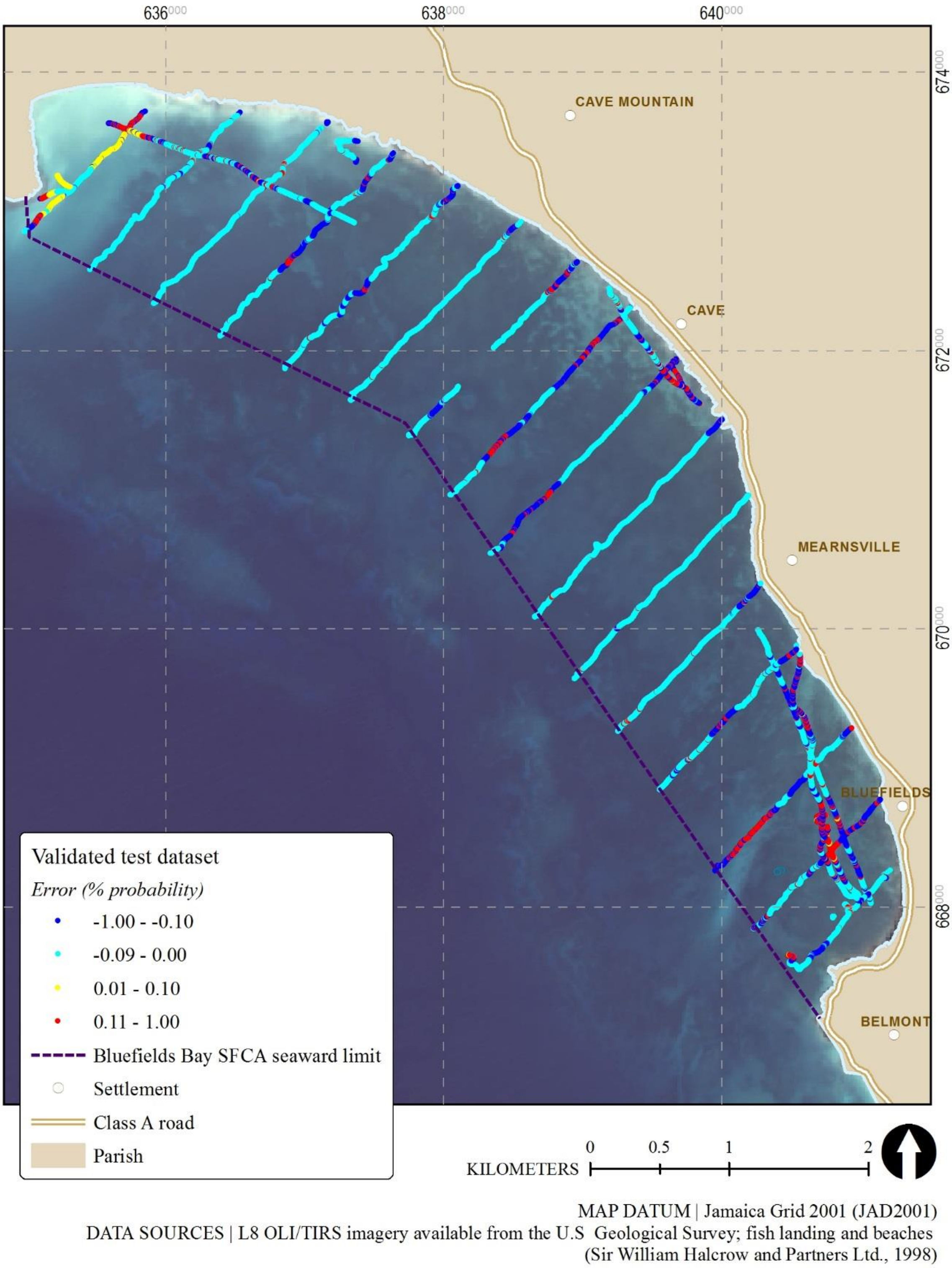


Figure 27. Error of indicator krig for SAV within BBSFCA, depicted by validated independent test data points.

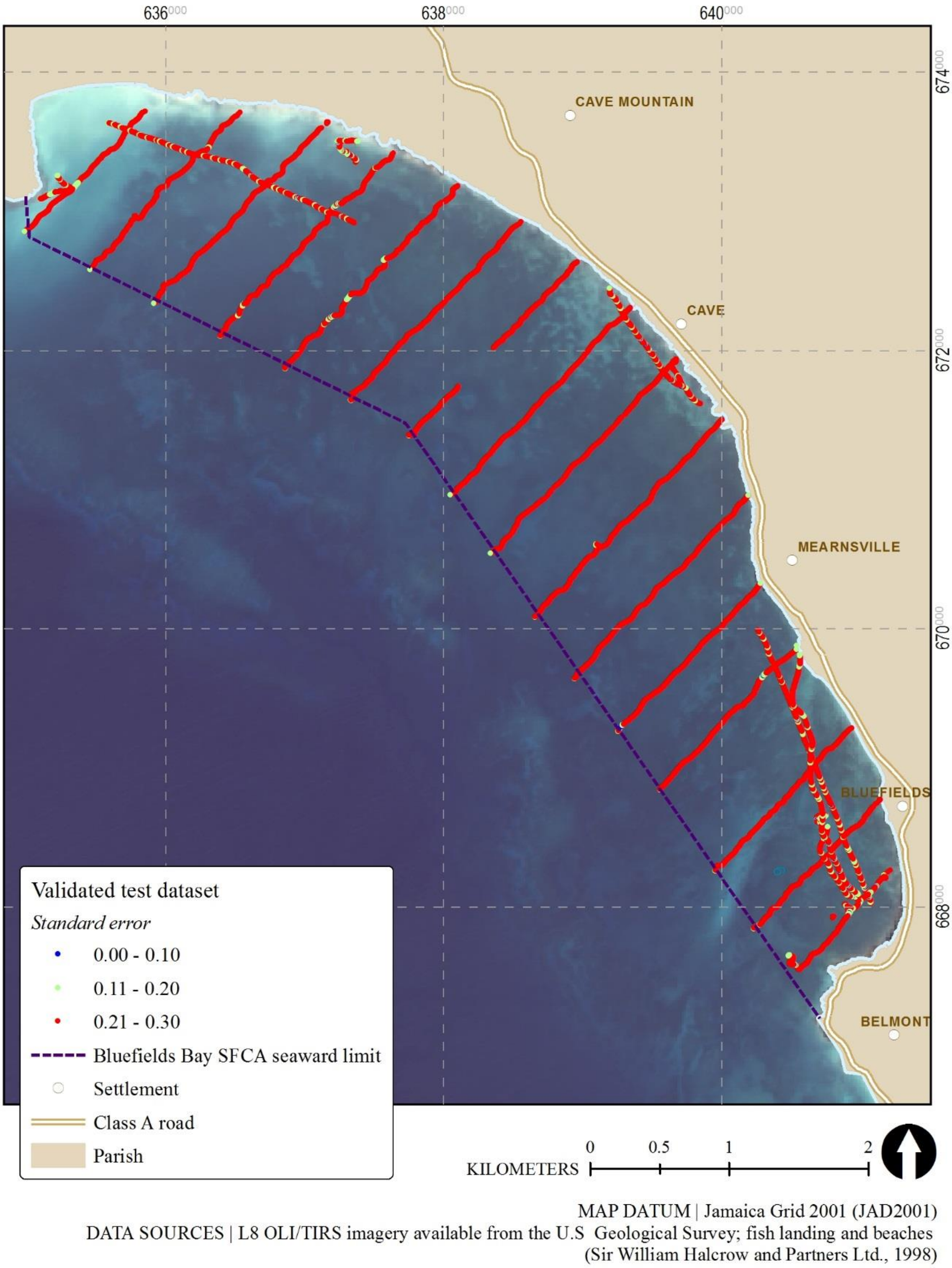


Figure 28. Standard error of indicator krig for SAV within BBSFCA, depicted by validated independent test data points.

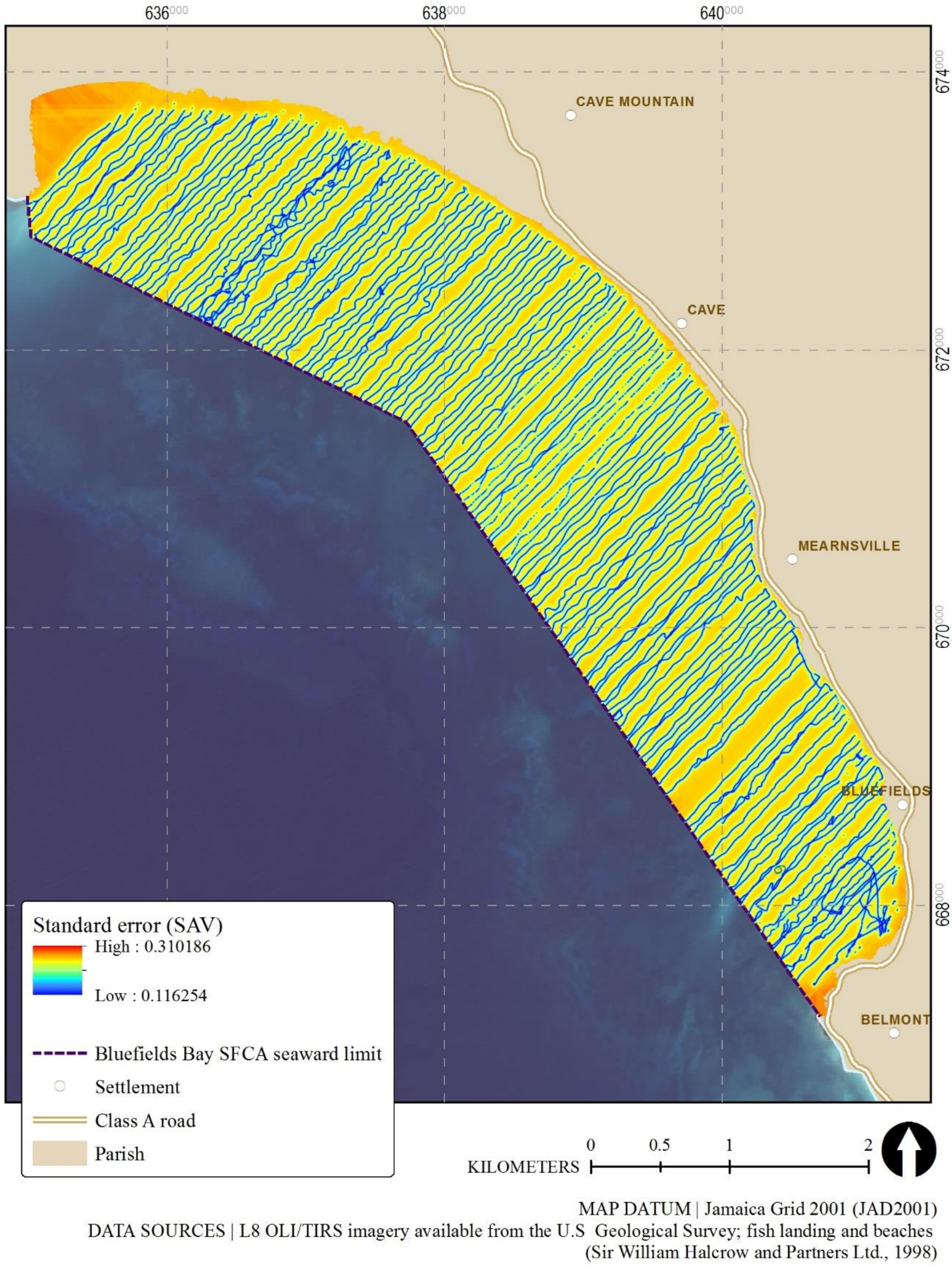


Figure 29. Standard error of final indicator krig for SAV within BBSFCA.

4.3.2 Bottom classification

The probability of silt occurrence is highest primarily close to shore and in select areas of deeper waters within the BBSFCA, whilst the opposite was seen for the occurrence of sand (Figure 33a and b). One distinct patch of coral reef was modelled in the southern half the bay by the IK for coral reef occurrence (>50% probability of coral reef/ hard bottom occurrence) (Figure 33c). When substrate occurrence was combined, it was evident that there were areas in which probabilities of <50% existed for all three substrates of interest, as well as areas having >50% probability of two or more substrate classes; these areas were deemed unclassifiable (Figure 30). Approximately equal areas of silt and sand are predicted (6.88 km^2 or 49.7% and 6.78 km^2 or 49.0% respectively), 0.05 km^2 or 0.3% coral reef/ hard bottom (Plate 3e) and 0.13 km^2 or 0.9% unclassified.

Of the three substrates modelled, ME, RMSE and average standard error were smallest for coral reef/ hard bottom substrate; however RMSE standardised values for silt and sand were closer to 1 (Table 7, Figure 32). Lower measures of standard error are evident in the shore-parallel transects and in a few areas across the bay (Figure 31). Similar to previous krigs created for this project, standard error of the models for each substrate are highest in the northern section of the bay, and other areas where transect data was not collected and data used in the modelling process.

Table 7. Prediction errors for the final indicator krig for bottom substrates using the test data points as validation source datasets.

	Silt	Sand	Coral reef/ hard bottom
No. of points	8,058	8,058	8,058
Presence (Indicator = 1)	4,643	3,369	46
Absence (Indicator = 0)	3,415	4,689	8,012
ME	-0.02060	0.01950	0.00115
RMSE	0.346	0.351	0.070
ME standardised	-0.0615	0.0574	0.0135
RMSE standardised	0.999	0.994	0.845
Average standard error	0.349	0.355	0.082

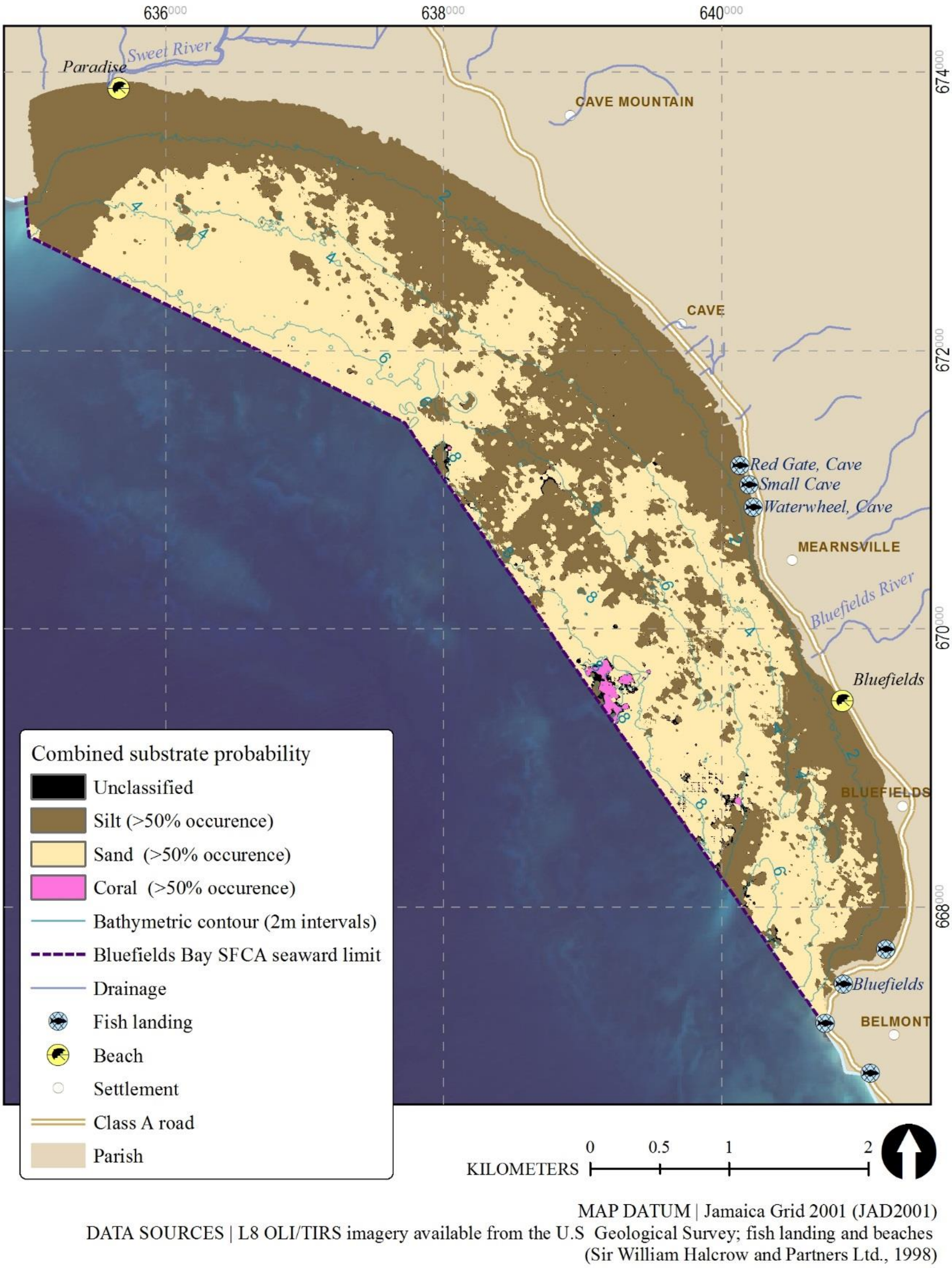


Figure 30. Combined probability of bottom substrates across the BBSFCA. Unclassified accounts for areas having <50% occurrence of silt, sand or coral, or areas having >50% probability of two or more substrate classes.

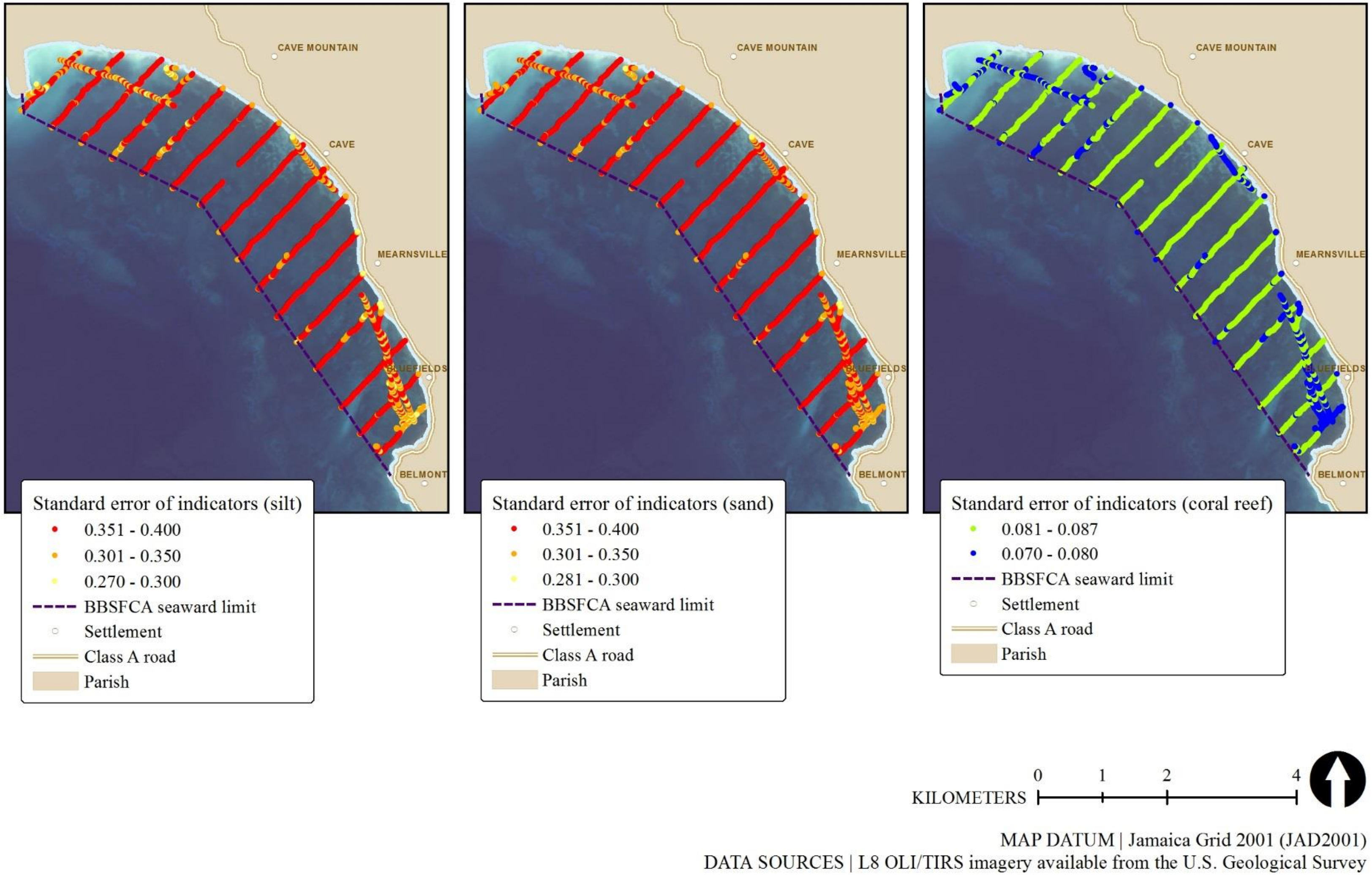


Figure 31. Standard error of validated independent test dataset for indicator krig of bottom substrates across the BBSFCA: (a) silt, (b) sand and (c) coral reef/ hard bottom.

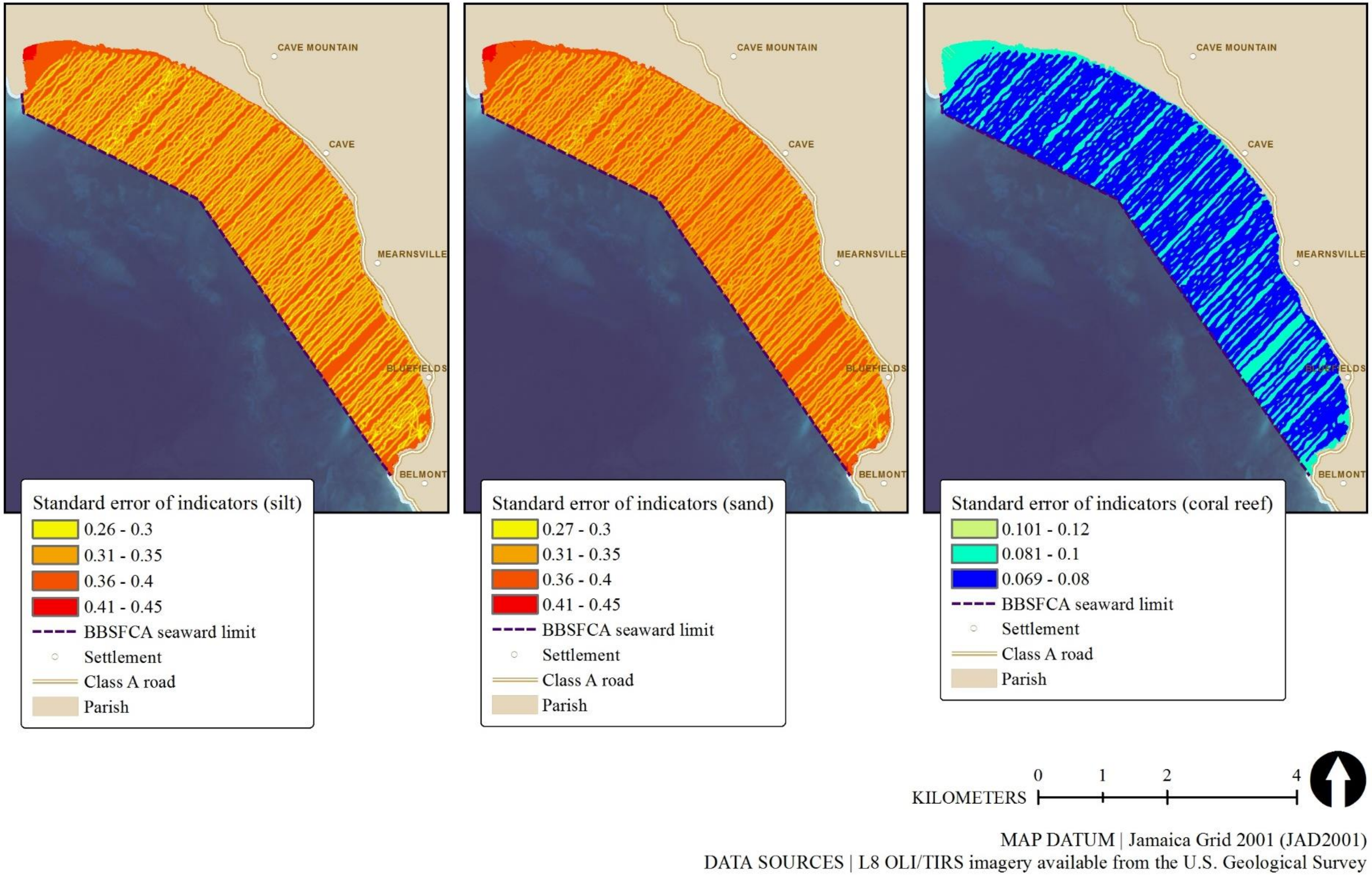


Figure 32. Standard error of indicator krig for bottom substrates across the BBSFCA: (a) silt, (b) sand and (c) coral reef/ hard bottom.

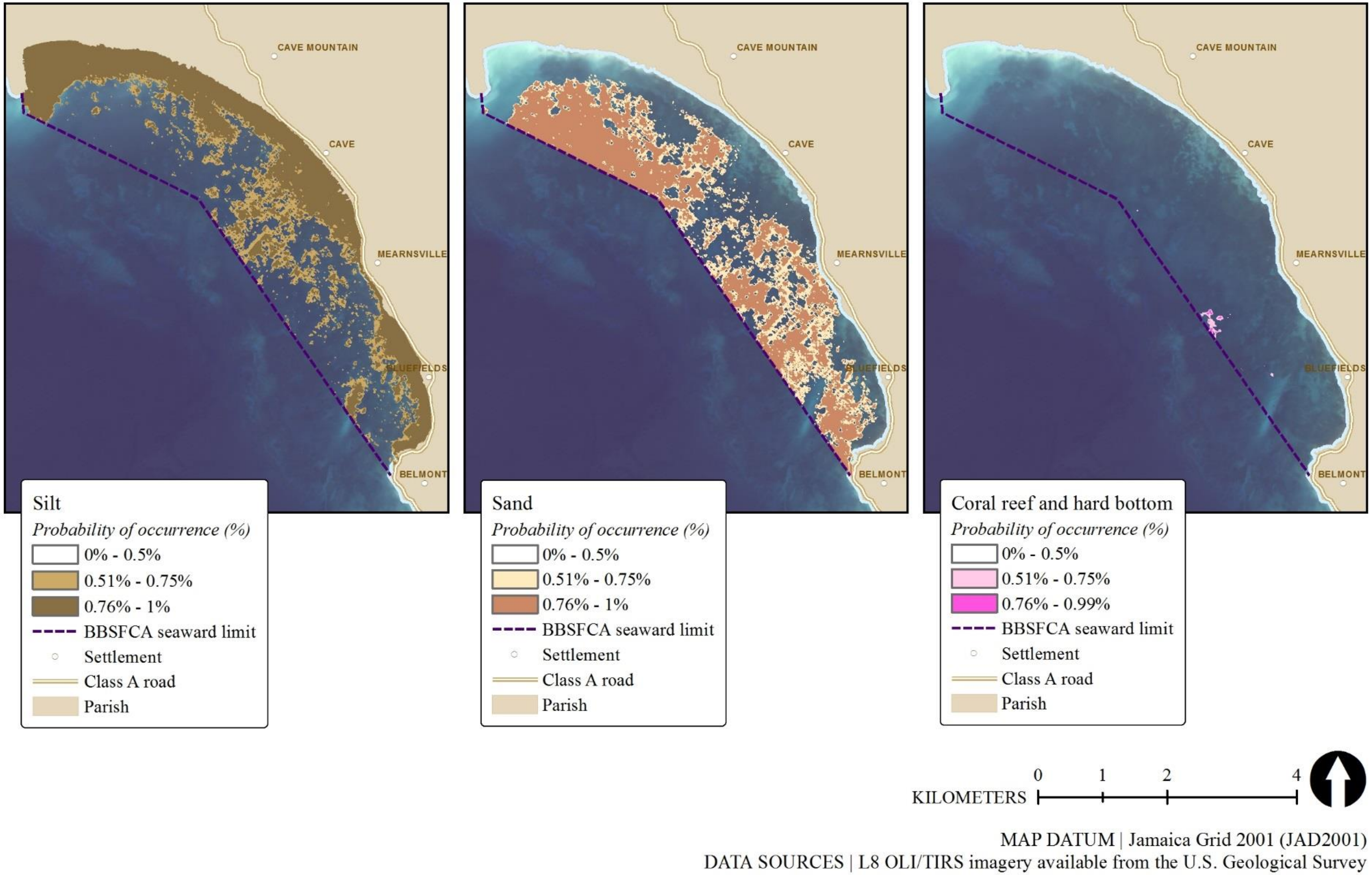


Figure 33. Probability of bottom substrates across the BBSFCA: (a) silt, (b) sand and (c) coral reef/ hard bottom.

4.4 Image classification

The mask for the WorldView-2 isolated areas for cloud and cloud shadow and collectively accounted for 2.89 km^2 (approximately 21% of study area); therefore only 10.93 km^2 of the BBSFCA was classified using the WorldView-2 image (Figure 34). On the other hand, less than one percent of the study area was masked owing to cloud shadow for the GeoEye-1 image; 13.75 km^2 remained for classification (Figure 35). Combining these, the composite mask accounted for a total of 2.91 km^2, resulting in only 10.91 km^2 of the classified study area for comparison purposes.

Although the resulting coverage of the classification without contextual coral reef edits is presented in Table 8, given that coral reef is a known benthic feature within the BBSFCA (Plate 3e), the image classification results with contextual edits for coral reef were presented (Table 9). Only 0.6% of the sanctuary was masked by cloud shadow in the GeoEye-1 image, therefore the resulting classification can perhaps give a representative estimation of the areal coverage of benthic classes within the bay (Table 9a). Areas classified as SAV totalled 10.79 km^2 (78.1%), whilst 2.75 km^2 (19.9%) accounted for bare substrate, and 0.20 km^2 (1.4%) comprising the coral reef class. When images are compared using areas clipped by the composite mask, SAV coverage is comparable (64.3% and 63.0% for the WorldView-2 and GeoEye-1 images respectively) and was the main benthic habitat within BBSFCA (Table 9b, Figure 34, Figure 35). Spatial coverage of the coral reef/ hard bottom habitat were similar between imagery products as well, with GeoEye-1 results exhibiting only 0.02 km^2 more coral coverage than WorldView-2 classification (Table 9b). Bare substrate accounts for 13.8% and 15.0% of the classified WorldView-2 and GeoEye-1 masked images (1.91 and 2.07 km^2 respectively). Differences in the spatial pattern of bare substrate were not significant; slightly larger bare patches were evident in the northern section of the BBSFCA whereas smaller patches were observed towards the southern section of the bay for the Worldiew-2 results (Figure 34, Figure 35).

Table 8. Spatial coverage of benthic classes computed from image classification of WorldView-2 and GeoEye-1 stacked reflectance indices without contextual edits for coral reef: (a) clipped by respective image masks and (b) clipped by composite mask.

(a)	**WorldView-2**		**GeoEye-1**	
	Area (m^2)	**Percentage**	**Area (m^2)**	**Percentage**
Bare substrate	1.93	14.0%	2.78	20.1%
Submerged vegetation	9.00	65.1%	10.96	79.3%
Unclassified (mask)	*2.89*	*20.9%*	*0.08*	*0.6%*
TOTAL:	**13.82**	**100.0%**	**13.82**	**100.0%**

(b)	**WorldView-2**		**GeoEye-1**	
	Area (m^2)	**Percentage**	**Area (m^2)**	**Percentage**
Bare substrate	1.93	13.9%	2.10	15.2%
Submerged vegetation	8.98	65.0%	8.81	63.7%
Unclassified (composite mask)	*2.91*	*21.1%*	*2.91*	*21.1%*
TOTAL:	**13.82**	**100.0%**	**13.82**	**100.0%**

Table 9. Spatial coverage of benthic classes computed from image classification of WorldView-2 and GeoEye-1 stacked reflectance indices with contextual edits for coral reef: (a) clipped by respective image masks and (b) clipped by composite mask.

(a)	**WorldView-2**		**GeoEye-1**	
	Area (m^2)	**Percentage**	**Area (m^2)**	**Percentage**
Bare substrate	1.91	13.8%	2.75	19.9%
Submerged vegetation	8.91	64.4%	10.79	78.1%
Coral reef/ hard bottom	0.11	0.8%	0.20	1.4%
Unclassified (mask)	*2.89*	*20.9%*	*0.08*	*0.6%*
TOTAL:	**13.82**	**100.0%**	**13.82**	**100.0%**

(b)	**WorldView-2**		**GeoEye-1**	
	Area (m^2)	**Percentage**	**Area (m^2)**	**Percentage**
Bare substrate	1.91	13.8%	2.07	15.0%
Submerged vegetation	8.89	64.3%	8.71	63.0%
Coral reef	0.11	0.8%	0.13	0.9%
Unclassified (composite mask)	*2.91*	*21.1%*	*2.91*	*21.1%*
TOTAL:	**13.82**	**100.0%**	**13.82**	**100.0%**

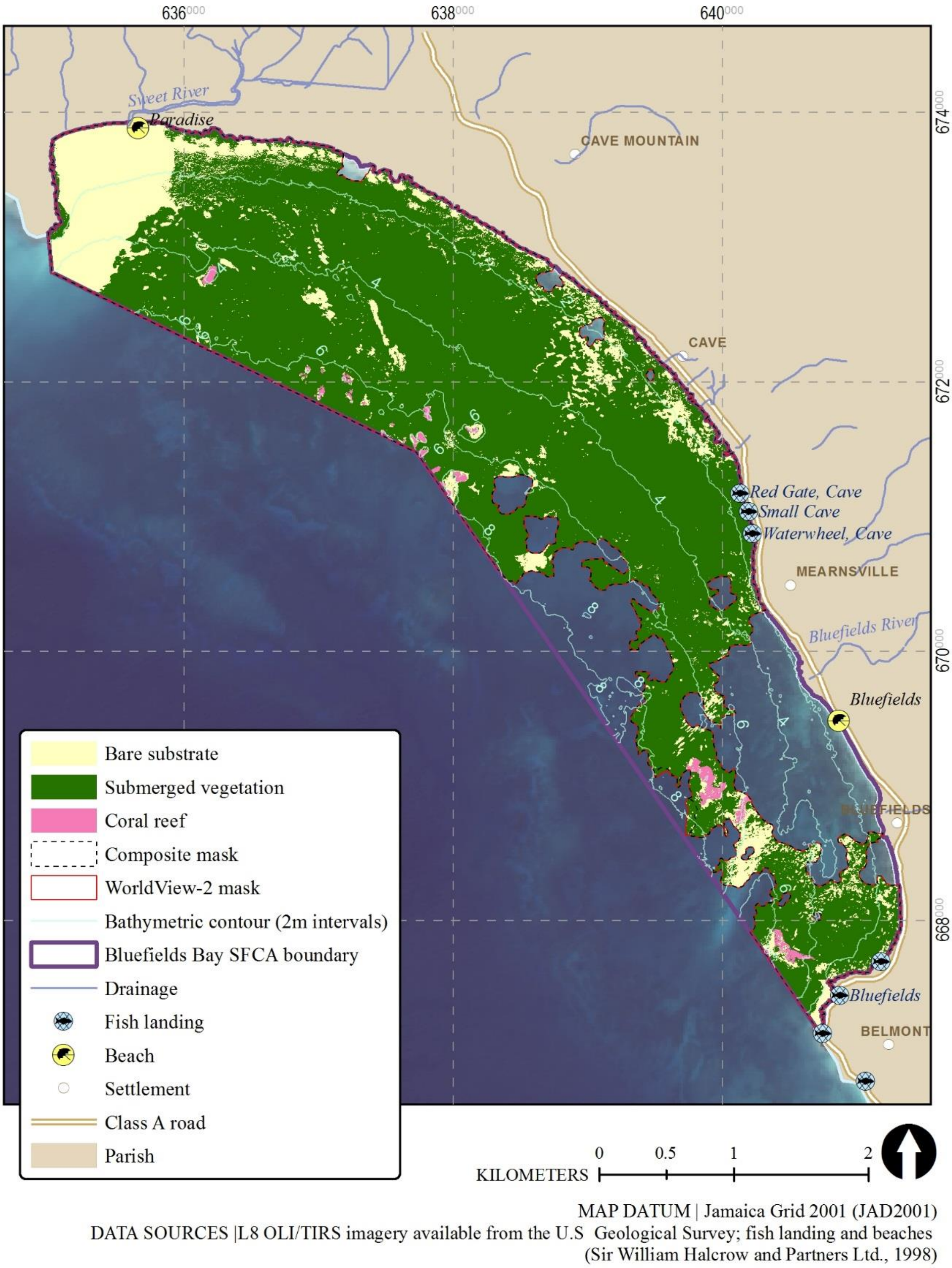


Figure 34. Image classification results utilising the composite Worldiew-2 reflectance index, showing areas of classed as unconsolidated sediment, submerged vegetation and coral reef within the BBSFCA.

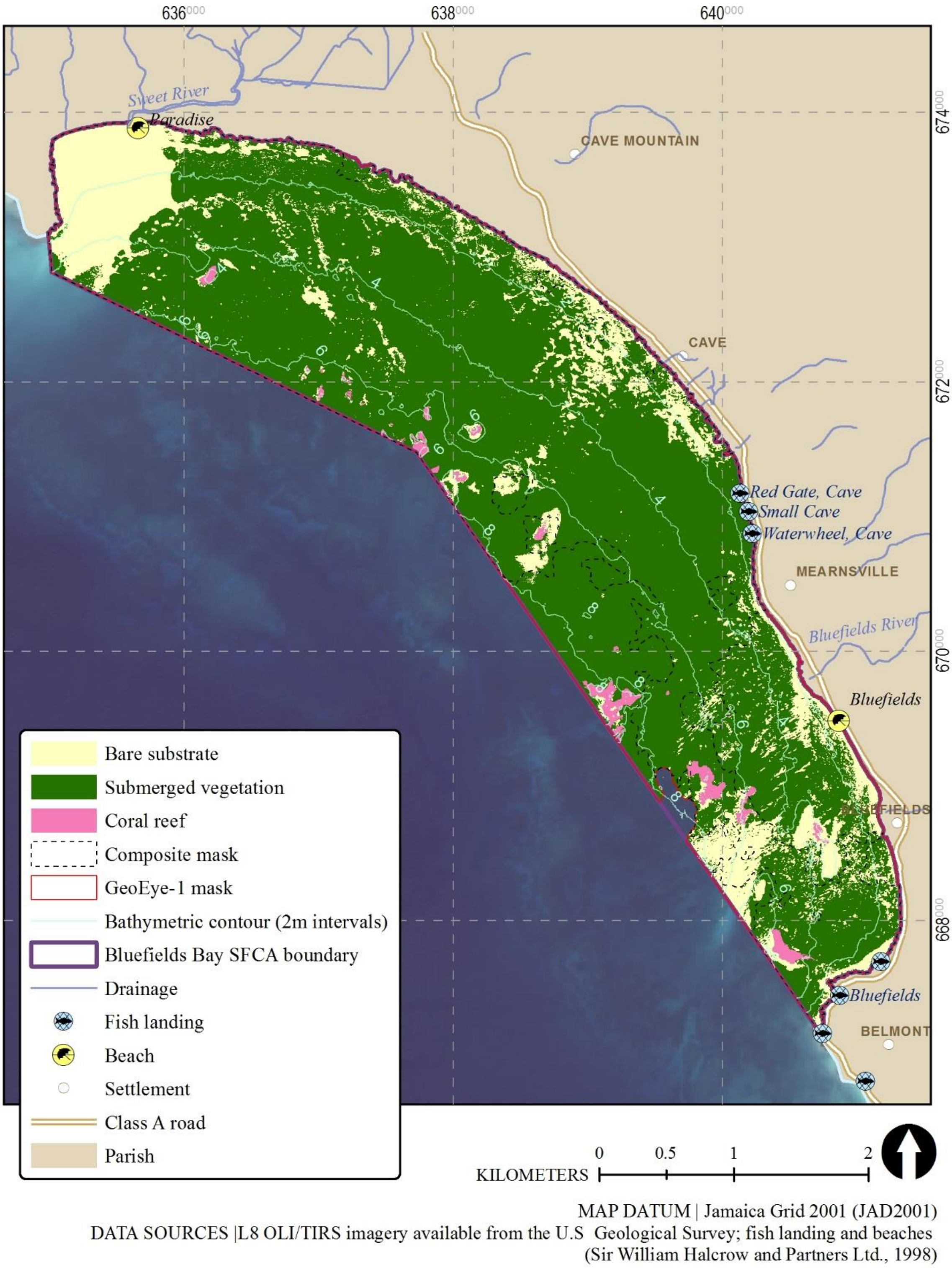


Figure 35. Image classification results utilising the composite GeoEye-1 reflectance index, showing areas of classed as unconsolidated sediment, submerged vegetation and coral reef within the BBSFCA.

4.5 Accuracy assessment

The accuracy assessment revealed that of all the classification outputs tested, image classification with contextual edits for coral reef produced the highest overall accuracies of 89.9% and 86.8%, with kappa statistics of 0.78 and 0.77 for Worldiew-2 and GeoEye-1 reflectance indices respectively, clipped to their respective masks (Table 10a). The GeoEye-1 reflectance index, when clipped to the composite mask also attained similar accuracy results of 86.7% overall accuracy and 0.73 kappa. These results surpass those of both image classification without contextual edits for coral reef, as expected owing to the relatedness of coral and vegetation signatures within the image and subsequent absence of the coral reef class. Accuracies for this benthic class (coral reef), as well as the kappa coefficients had values of 0 for the image classification outputs without contextual edits. Interestingly, the Worldiew-2 imagery attained a slightly higher overall classification accuracy (82.7%) than the GeoEye-1 image (72.9%) without contextual edits when clipped by the composite mask.

A reasonably high producer's accuracy of over 80% for bare and vegetated classes in the image classification outputs indicate that it was highly probable that a randomly chosen location in BBSFCA belonging to any of these classes was correctly mapped (Table 10). User's accuracy varied amongst these classes, with SAV having consistently higher user accuracy values than bare substrate. The SAV benthic class therefore outperformed unconsolidated sediment in terms of map classification accuracy, being correct when compared to field data.

Overall accuracies for the acoustics survey were slightly lower than satellite image classification with contextual edits (Table 11). Although the SAV prediction attained a reasonable overall accuracy of 76.7%, bottom substrate mapping was less accurate, having an overall accuracy of 53.5%; both kappa statistics were generally poor (0.3). SAV presence had reasonable high producer's and user's accuracies of 90.2% and 80.4%, however the kappa value was 0.25. Similar to the image classification with contextual edits, user's accuracy for coral reef/ hard bottom was 100.0% with a kappa coefficient of 1.00; however producer's accuracy was only 17.4% suggesting that is unlikely that a randomly chosen coral reef patch in BBSFCA was correctly mapped. Unlike sand, finer silty sediment appears to be mapped reasonably accurately, with 94.7% and 72.0% producer's and user's accuracy and a kappa value of 0.58.

Table 10. Calculated accuracies (%) and kappa coefficients from accuracy assessments of GeoEye-1 and Worldiew-2 reflectance indices classifications with contextual edits for coral reef: (a) clipped using respective image masks and (b) clipped using composite masks (P = producer's accuracy, U = user's accuracy, 0 = overall accuracy, K = kappa coefficient).[**]

(a)	GeoEye-1						Worldiew-2					
	Without contextual edits			With contextual edits for coral reef			Without contextual edits			With contextual edits for coral reef		
	P	U	K	P	U	K	P	U	K	P	U	K
Bare substrate	89.7%	63.4%	0.53	89.7%	65.0%	0.55	83.3%	71.4%	0.62	87.5%	75.0%	0.67
Submerged vegetation (SAV)	82.9%	77.3%	0.38	82.9%	95.8%	0.88	89.7%	87.1%	0.58	89.7%	95.3%	0.85
Coral reef	0.0%	0.0%	0.00	100.0%	100.0%	1.00	0.0%	0.0%	0.00	100.0%	100.0%	1.00
Overall accuracy (%)		*72.9*			*86.8*			*82.7*			*89.9*	
Overall K		*0.45*			*0.77*			*0.6*			*0.78*	

(b)	GeoEye-1						Worldiew-2					
	Without contextual edits			With contextual edits for coral reef			Without contextual edits			With contextual edits for coral reef		
	P	U	K	P	U	K	P	U	K	P	U	K
Bare substrate	87.5%	65.6%	0.54	87.5%	67.7%	0.57	83.3%	71.4%	0.62	87.5%	75.0%	0.67
Submerged vegetation (SAV)	85.3%	87.9%	0.60	85.3%	95.1%	0.84	89.7%	87.1%	0.58	89.7%	95.3%	0.85
Coral reef	0.0%	0.0%	0.00	100.0%	100.0%	1.00	0.0%	0.0%	0.00	100.0%	100.0%	1.00
Overall accuracy (%)		*80.6*			*86.7*			*82.7*			*89.9*	
Overall K		*0.57*			*0.73*			*0.6*			*0.78*	

[**] Recall accuracy assessment points did not fall within the area masked by clouds and cloud shadow for the GeoEye-1 image and as a result, the points falling within the WorldView-2 image clipped by the respective WorldView-2 mask alone were the same as those for the composite masked images (WorldView-2 and GeoEye-1). Accuracies for the Worldiew-2 image clipped using the respective image mask and the composite mask are therefore identical for this reason.

Table 11. Calculated accuracies (%) and kappa coefficients from accuracy assessments of the acoustic SAV and bottom substrate IK model (P = producer's accuracy, U = user's accuracy, 0 = overall accuracy, K = kappa coefficient).

		P	U	K	*Overall accuracy*	*Overall K*
SAV	**SAV absence**	37.9%	57.9%	0.43	*76.6%*	*0.32*
	SAV presence	90.2%	80.4%	0.25		
Bottom substrate	**Silt**	94.7%	72.0%	0.58	*53.5%*	*0.33*
	Sand	56.3%	32.1%	0.06		
	Coral reef/ hard bottom	17.4%	100.0%	1		
	Unclassified	0.0%	0.0%	0		

Chapter 5. Discussion

The main goal of this study was to investigate the applicability of acoustic and optical remote sensing techniques in mapping benthic features within the BBSFCA. The spatial patterns resulting from each mapping technique presented in Chapter 4 are discussed briefly first; however the emphasis in this section was placed more on evaluating the methods employed, resulting accuracies and feasibility of use.

5.1 Bottom features within BBSFCA

5.1.1 Bathymetric model

Given the general NE-SW trend from the coastline identified during the data exploration steps, the progression of increasing depth towards the sanctuary's seaward limit is expected throughout the study area. When compared to previous models (United Kingdom Hydrographic Office, 1980; Carroll, 2013), the maximum depth of 9.3 m and the overall bathymetric surface pattern resulting from this study are similar, with deepest depths occurring in the southern section of the bay (Figure 21). On the other hand, the BSM depicted here (Figure 21) appears to expose more localised morphological detail, revealing likely benthic features such as bare patches and patch reefs. The sandbank depicted in Figure 22 was also not pronounced in previous bathymetric models. The disparity in data collection dates for previous studies precludes direct comparisons as it relates to dynamic seabed features and in particular sand and seagrass beds, that are reported to change considerably over short time frames within the bay (Thompson, 2013; McNaught, 2013). However, given the scale of the admiralty charts produced by the United Kingdom Hydrographic Office (1980) (1:200,000), as well as the density of the depth soundings from the Carroll (2013) study, the BSM produced for the purposes of this study exposes finer scale patterns.

With regard to the bathymetric modelling process, the variable of interest (water depth) is considered a regionalised variable and numerous interpolation techniques have been employed to model this parameter and its land-based counterpart elevation. These techniques include IDW (Burroughes, 2001); spline (Hell, 2011); and kriging (Lloyd and Atkinson, 2006) (Vella and Ses, n.d.). A set of regionalised variables however is one realisation of random function, whose complex nature precludes the use of deterministic interpolation functions (Oliver and Webster, 2014). Though deterministic techniques have been used extensively to model depth (Hell, 2011), kriging is generally more favoured owing to its robust nature (Oliver and Webster, 2014). For this reason, kriging was the primary focus for interpolation of depth data within the study area and ultimately, the BSM was created using UK, one of the more complex forms of kriging. The specification of numerous parameters for UK may generate better model fits over OK if used correctly (Babish, 2002), however it also has the potential to reduce confidence in the resulting surface. Unlike OK, which assumes that there is no global trend existing within the dataset (Babish, 2002), the U.S. Environmental Protection Agency (2004) highlighted that UK is appliable where a global trend is present and consequently for this study, the implementation of the IK method was deemed appropriate given the observed NE-SW trend within BBSFCA (Figure 11).

Caruso and Quarta (1998) used two viewpoints to assess interpolation methods, namely prediction and characterization. Based solely on visual assessment, the BSM appeared to model the features known to exist within the bay fairly well. In fact, a number of trial models performed well and seemed "acceptable" in terms of characterisation. This is perhaps attributable to the dense sampling regime employed wherein larger datasets typically result in similar results for varying interpolation methods (Burrough and McDonnell, 1998). The average standard errors of the model were slightly greater than the RMSE prediction errors and the RMSE standardised values were slightly less than 1; therefore it can be concluded that there was a slight overestimation in the variability of predictions. Finally, the model for BBSFCA slightly under-predicted minimum and maximum predicted values; however the underestimation of larger values and overestimation of small values is an artefact of kriging (Babish, 2002).

5.1.2 Benthic classification

The sonar survey was conducted in July and August 2013, whilst the WorldView-2 image was taken in April 2013 and GeoEye-1 in January 2102. Given historical temporal changes in seagrass distribution within the bay (McNaught, 2013; Thompson, 2013), variation in vegetation cover is probable within these data collection time periods; unfortunately, such dynamics are not often integrated into benthic classifications (Anderson, et al., 2008) and are beyond the scope of this project. Vegetation cover was estimated from hydroacoustic data irrespective of bottom substrate; in contrast, the image classification approach classified coral reef/ hard bottom without any further separation of benthic classes found in the bay. Also, bare substrate classified from the images could either be unconsolidated sediment or hard bottom/pavement, whereas the acoustic method was used to separate the two. For these reasons, resulting quantities of benthic cover could not be compared directly, nor could the significance of any differences observed be tested statistically.

5.1.2.1 Submerged vegetation

The dominance of SAV throughout the BBSFCA is exhibited by both techniques, wherein 78.1% and 64.4% of vegetation surface resulted from the GeoEye-1 and WorldView-2 images respectively (clipped by respective masks) and 91.3% for acoustic classification (Figure 36). This is not unlike the recent habitat assessment conducted by Carroll (2013) which concluded that seagrass constituted 82.3% of the seabed environment. Carroll (2013) reported the presence of *Thalassia testudinum* and *Syringodium filiforme* within the bay and this project likewise revealed the presence of these seagrass species, in addition to another, namely *Halodule wrightii*. Though differences in data collection dates and mapping resolutions between this study and older accounts including Carroll (2013), Keegan et al. (2003), as well as the South Coast Sustainable Development Study (SCSDS) and the Coastal Atlas of Jamaica (Norrman, et al., 1997) (Figure 37) prohibits direct quantitative and qualitative comparisons, the general conclusion of a SAV-dominated bay is evident.

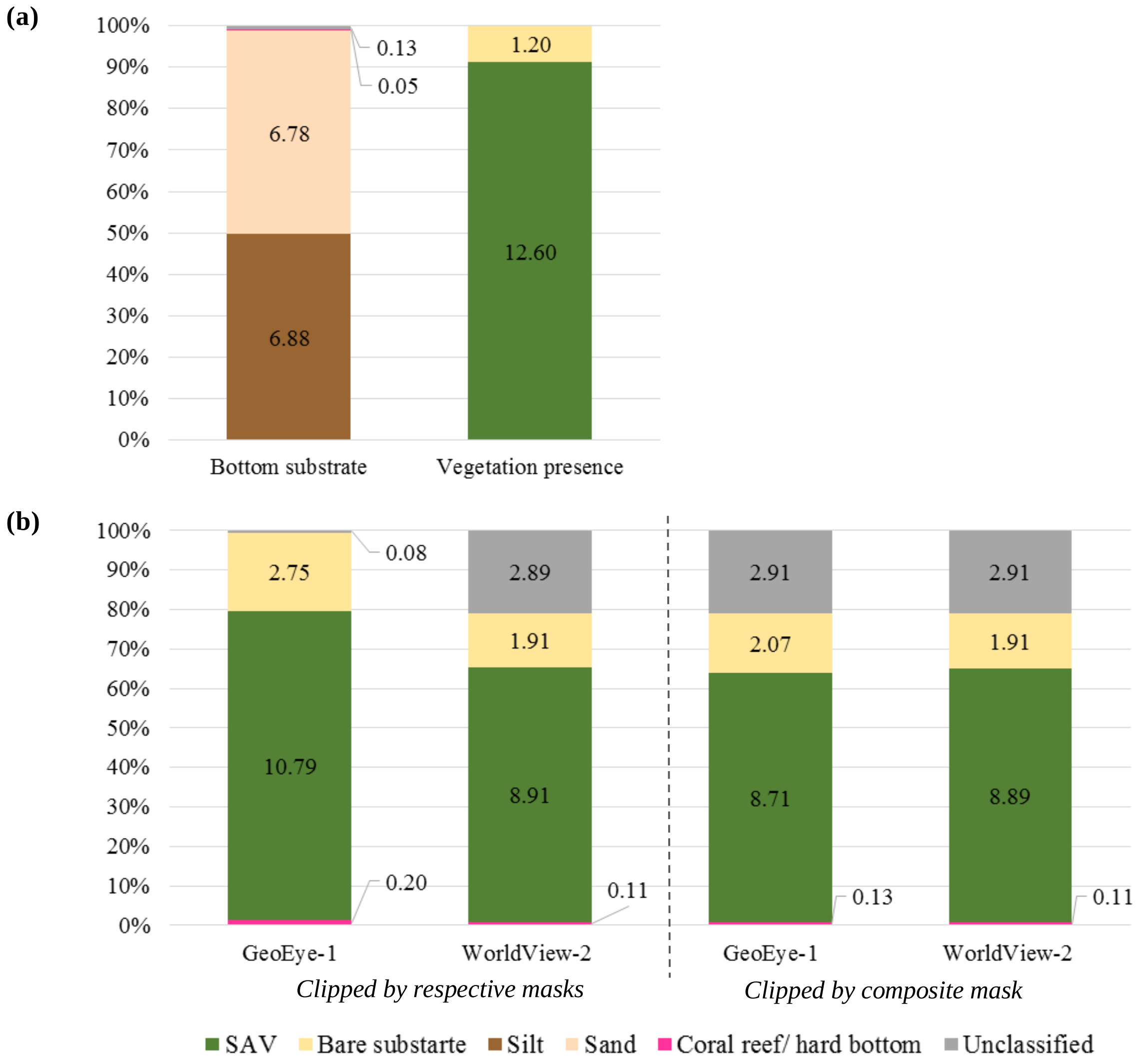


Figure 36. Relative coverage of benthic classes (km^2) resulting from: (a) acoustic survey and interpolation and (b) image classifications, clipped by respective masks and composite mask.

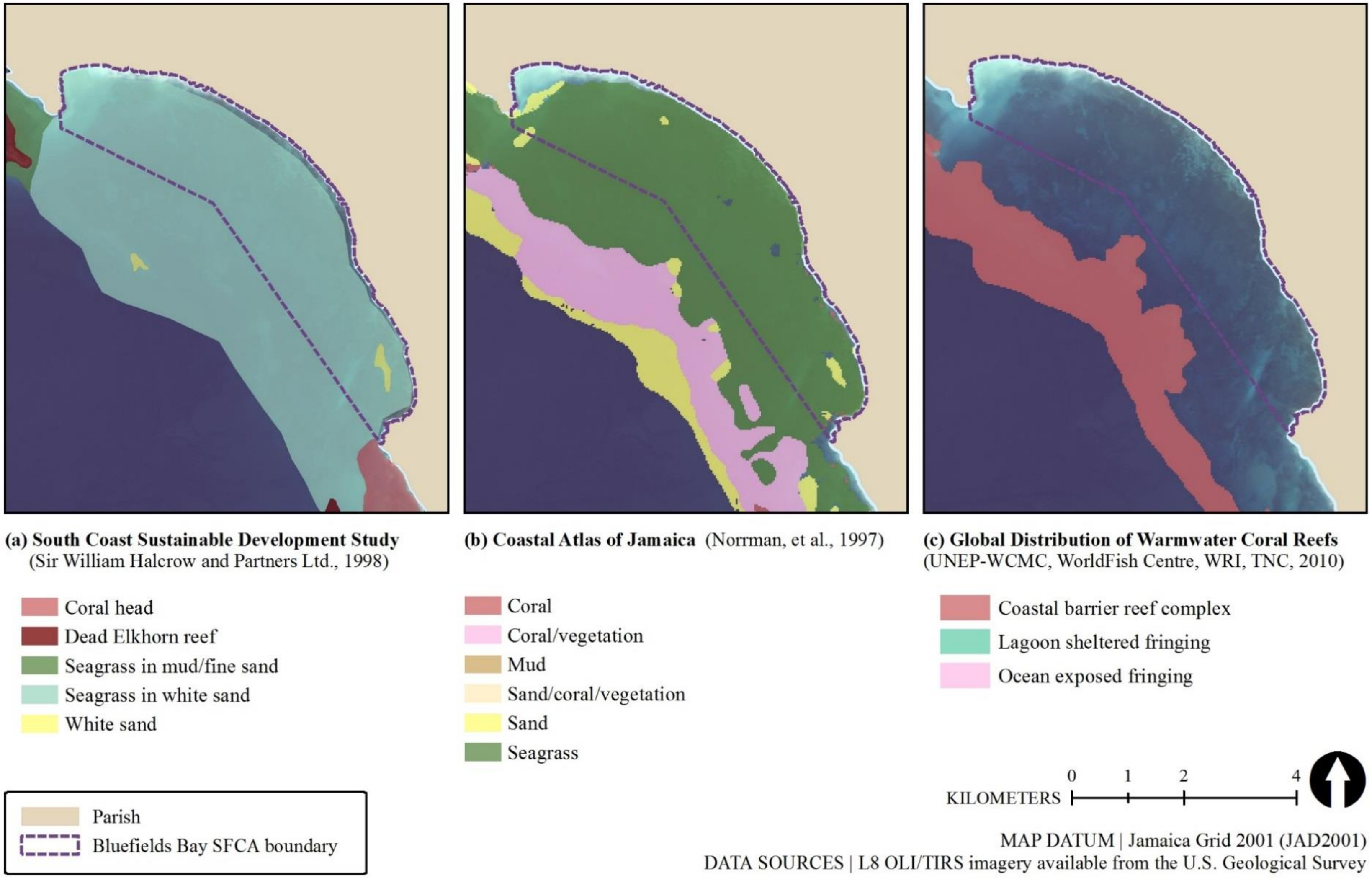


Figure 37. Existing benthic data for Bluefields Bay from the following sources: (a) Sir William Halcrow and Partners Ltd., 1998, (b) Norrman, et al., 1997 and (c) UNEP-WCMC, WorldFish Centre, WRI, TNC, 2010.

Establishing an acceptable mapping accuracy within the realms of habitat classification is problematic because benthic features are semi-continuous in nature, and as such achieving extremely high accuracies of 95% from benthic classification exercises is impractical (Mumby, et al. 1997). This is exemplified by the map accuracy requirements of 86.4% of interviewed stakeholders who required 70% and higher accuracies. These required accuracies were met by this study, wherein producer's and user's accuracy were 77% and higher for the SAV vegetation class and greater than 72% for overall classification accuracies in both the image and acoustic SAV classification results (Table 10, Table 11). These accuracies are also more or less comparable to accuracies reported for other studies that included SAV classification. For example Ludin, et al. (2011) achieved more than 70% accuracy using WorldView-2 imagery up to 5m depth depending on the water conditions; Mishra, et al. (2006) obtained 80.6% overall accuracy using QuickBird multispectral data, with the dense seagrass class having producers and users accuracies of 75.8% and 66.4% respectively; and for areas classified as continuous seagrass, Stevens, et al. (2008) reported acoustic classification accuracy of 76%. Lower accuracies from remote sensing classifications have also been reported, for example Wabnitz, et al. (2008) classified seagrass density from Landsat scenes with 46% overall accuracies (and high of 88%); Riegl, et al. (2005) obtained an overall accuracy of approximately 60% from an acoustic SAV survey differentiating sand, seagrass and algae, and for areas classified as patchy seagrass by Stevens, et al. (2008), acoustic classification accuracy was 42%. The SAV and overall accuracies for this study may be deemed "acceptable" based on stakeholder requirements and other studies; conversely, whilst the SAV class and overall kappa coefficient for the image classification with contextual edits were favourable (greater than 0.75), the kappa coefficients for the acoustic vegetation occurrence map were poor (< 0.4), suggesting that the SAV classification is only moderately better than a classification undertaken by chance.

The area classified as being devoid of vegetation were very small when compared with the area occupied by SAV for all techniques considered and these values are comparative to that achieved by Carroll (2003) wherein 11.8% was classed as sandy bottom, 4.0% sand or consolidated sediment with scattered coral/rock and 1.8% coral. The localised sediment patterns were more noticeable in the image classifications (Figure 34, Figure 35) when compared to the acoustic classification IK (Figure 26), where the patterns were far more generalised and the smaller bare patches were less numerous. Producer's and user's accuracies for the bare substrate class, as well as kappa coefficients were all greater for the image classification result (lowest accuracy and kappa were 63.4% and 0.53 respectively, Table 10) compared to those achieved for the acoustic SAV absence class (37.9% producer's, 57.9% user's and 0.43 kappa, Table 11). Nevertheless, the generalised vegetation pattern within BBSFCA is comparable amongst all mapped final outputs, with the largest areas of vegetation absence occurring towards the northern section of the bay and other bare areas smaller in size similarly noticeable across the bay.

5.1.2.2 *Bottom substrate*

Visual assessment of sediment grab samples at ground-truthing locations allowed for a coarse classification of bottom sediment into two groupings, namely silt and sand. Indeed, laboratory sieving and subsequent grain size analysis can be used to produce quantitative measures of grain size and thereby a more precise delineation between the two sediment groupings; unfortunately this was outside the scope of this project. Nonetheless, the rough classification of sediment type employed was considered sufficient for this study given the unavoidable subjectivity in defining the number of classes and restricted ability of the sonar to precisely discern between these. The two sediment classes used resulted in feature spaces with minimal overlap (Figure 16) and allowed for the distribution of sand and silt to be mapped across the sanctuary; such local-scale sediment mapping being absent prior to this study (Figure 37). Seasonal changes in the sediment regime in the Bluefields watershed are reflected in the bottom substrate makeup within the bay. Descriptive accounts of the study area reveal that owing to flood events, fine silty sediment has been observed in localities along the shoreline to the south of the bay, such as the Bluefields Bay fishing beach (Thompson, 2013), the Bluefields Beach Park (Bluefields Bay Fishermen's Friendly Society, n.d.) and the Bluefields River mouth (Dryer, 2010); this overlaps with the resulting silt distribution in the bay (Figure 33a). Interestingly, the sandbank feature identified from the bathymetric model described previously is also a noticeable linear formation in the resulting combined substrate map; however is modelled as silty sediment (Figure 30). Silt also constitutes the largest expanse of bare sediment in the northern BBSFCA.

Two distinct patches of coral reef (>50% probability) were predicted in the southern half of the bay for the acoustic interpolated surface (Figure 33c). Although clear distinctions between bottom substrate are not typically easy, for example owing to coral reef covered by a sediment layer or where they are interspersed with sand channels (Roob, 2000), VBT processing results did in fact identify more than two regions of coral reef/ hard bottom and were subsequently included to the IK model (Figure 17). Field knowledge, that was also used to contextually edit the image classification results, confirmed the presence of coral reef as individual coral heads, patch reef and aggregated patch reef, along with reef rubble at numerous locations across the bay and align well with morphological features revealed from the bathymetric model of the bay (Figure 34, Figure 35). Image classification results for GeoEye-1 show that coral reef/ hard bottom covered a total of 0.20 km^2 or 1.4% of the seafloor and that for WolrdView-2 indicate 0.11 km^2 or 0.8%. Although both these percentages take into account the unclassified areas owing to respective image masks, both coral reef cover estimates are greater than that predicted by the acoustic IK (0.05 km^2 or 0.3% (Figure 36). Similarly Carroll (2013) estimated that coral reefs covered 1.8% of the BBSFCA (not including scattered coral reef or rock in consolidate sediment), and this is also greater than the acoustic classification IK, further demonstrating the underestimation of coral reef areas by the acoustic IK model (with a 50% probability threshold). With regard to the coral reef class, producer's and user's accuracies of 100.0% for both image classifications with contextual edits, and 17.4% and 100.0% respectively for the acoustic bottom substrate classification output, with kappa coefficients of 1 for both methods (Table 10, Table 11) demonstrate the level of coral mapping precision using both methods. However, overall accuracies for the acoustic bottom substrate classification was only 53.5%, and this was generally lower than overall accuracies obtained in the literature reviewed (Gleason, 2009; Foster, et al., 2009; Diesing, et al., 2014) and accuracies deemed acceptable by the interviewed stakeholders.

5.2 Feasibility analysis

5.2.1 Considerations for benthic classification methods

Various benthic mapping methods exist and the choice of method is often influenced by the level of detail required, the extent of the study area, technical capacity and available resources (equipment, human, financial). In-situ sampling and assessments produce reliable species data, however the ability to apply such methods to large study extents is limited (Sabol, et al., 2009). Remote sensing, including both optical and acoustic approaches, has the ability to derive biodiversity data and associated indices at varying spatial and temporal scales (Foody, 2008).

5.2.1.1 Image classification techniques

Passive optical remote sensing is often employed for mapping features spanning large areas, such as MPAs, and the sensed data products, such as aerial photographs and satellite imagery, can generate moderate- to high- resolution digital images of such large areas (Walker, et al., 2008). Spatial, temporal and spectral resolution are important considerations when selecting images for benthic classification. Various researchers have successfully mapped benthic habitats using high spatial resolution products (< 10 m pixel size) from various sensors including IKONOS (Schill, et al., 2011; Baumstark, et al., 2013), QuickBird (Mishra, et al., 2006; Schill, et al., 2011) and the newly launched WorldView-2 (Florida Environmental Research Institute, 2010; DigitalGlobe, 2012; Vahtmäe and Kutser, 2013), as well medium spatial resolution products (10 – 100 m) such as Landsat (Roob, 2000; Andréfouët, et al., 2003; Wabnitz, et al., 2008; Pu, et al., 2012). Though spatial resolutions of airborne sensors are flexible depending on aircraft altitude (Green, et al., 2000), these sensors typically provide finer spatial resolution products than satellite sensors (Foody, 2008), and thereby have the capability to produce better results (Phinn, et al., 2008; Vahtmäe and Kutser, 2013) and allow for the assessment of small scale changes over time. The reason for this is that the spatial resolution of an image has an effect on the spectral mixing within each image pixel. A mixed pixel can result from various combinations of benthic features (Hochberg and Atkinson, 2003), preventing the accurate extraction of a single benthic feature that otherwise has a spectral signature different from the other features it is mixed with (Mishra, et al., 2006). Fine spatial resolutions reduce the amount of intermixing; for instance Andréfouët, et al. (2003) found that IKONOS-based classifications (4 m resolution) achieved 15-20% better overall accuracies when compared to Landsat (30 m resolution). However fine spatial resolutions are more costly (Lu and Weng, 2007) and require more storage space and processing power.

Unfortunately, even with a fine spatial resolution of 2 m for the GeoEye-1 and WorldView-2 multispectral images available for this study (Figure 19), there was confusion between SAV and coral reef spectral signatures, which necessitated the use of post classification contextual editing. Coral heads and benthic patches smaller than 2 m and the MMU (4 m^2) would perhaps not be mapped owing to the mixing of the spectra with the habitat surrounding these features. The misclassification of coral reef and SAV may also not be as a result of spectral mixing, because it possible that some of the coral reef found in the bay might be covered by algal communities which would result in a spectral appearance similar to SAV. Notwithstanding the drawbacks encountered with this study, features including coral reef assemblages have been mapped successfully at varying resolutions, such as 4 m IKONOS by Riegl and Purkis (2005) and at the larger 30 m spatial resolution of Landsat 7 ETM satellite images (Andréfouët, et al., 2001). Benefits of the medium resolution Landsat imagery that should be mentioned here are its cost efficiency and longest set of continuous imagery scenes (Cohen and Goward, 2004), which enables spatiotemporal analysis.

The resolution of the spectral bands can also improve optical remote sensing efforts; Vahtmäe and Kutser (2013) obtained a higher overall accuracy (77.5%) classifying Compact Airborne Spectrographic Imager (CASI) hyperspectral than utilising WorldView-2 (71.6%) multispectral images. Similarly, Green, et al. (2000) report that CASI enables classification of seagrass beds with 80-90% accuracies and satellite imagery typically with lower accuracies of about 60%. Generally, hyperspectral remotely sensed images provide greater information owing to a greater number (~100) of smaller ranged spectral bands (Ferwerda, et al., 2007). Although DigitalGlobe's newest 8-band sensor, the WorldView-2 satellite, is not considered to be truly hyperspectral, it nevertheless provides multispectral imagery with a relatively high number of bands with the added advantage of having the Red Edge band that is specific for coastal mapping (DigitalGlobe, 2012). Since its launch in 2009, a number of studies have used WorldView-2 image datasets to map seabed habitats (Florida Environmental Research Institute, 2010; Ludin, et al., 2011; DigitalGlobe, 2012) and the results of this study showed marginally greater accuracies for classifications using this sensor's products when compared to GeoEye-1 (Table 10). However, whilst SAV presence/ absence, density and biomass have been successfully undertaken by various authors (Pasqualini, et al., 2005; Mishra, et al., 2006; Wabnitz, et al., 2008), distinction between seagrass species (Green, et al., 2000) or between algal and seagrass habitats (Mumby, et al., 1997) is not easily achieved with image classification using multispectral imagery and hyperspectral data is promising for this utility (Fyfe, 2003; Phinn, et al., 2008; Pu, et al., 2012). Acoustic technologies also offer additional benefits, as additional substratum detail such as plant height and the possibility of differentiating between biological species is possible (BioSonics, Inc., n.d.).

As found in this study, the georectification of satellite images with large expanses of ocean/ coastal areas is not as straightforward as land-based imagery owing to a smaller number of well distributed points suitable to rectify the acquired imagery. The imagery acquired had sufficient land coverage to enable georectification using land-based control points; however other factors such sea surface disturbances (waves and sun glint) also often render affected sections of satellite images unusable. The problem of sun glint has been encountered in a number of studies (Goodman, et al., 2008; Bouali, et al., 2009; DigitalGlobe, 2012; Streher, et al., 2013) including this study; in fact Wicaksono (2012) found that on average, 64.3% of the differences classified within a benthic habitat was attributed to sun glint. Sun glint removal techniques have been successfully applied (Hochberg, et al., 2003; Hedley, et al., 2005; Goodman, et al., 2008; Bouali, et al., 2009; Kay, et al., 2009; DigitalGlobe, 2012; Streher, et al., 2013) and once the problem is corrected, the accuracy of benthic classifications has been shown to improve (Hochberg, et al., 2003). For this reason, sun glint removal was considered a necessary step in this study and the method suggested by Hedley et al. (2005) was found to be easily implemented.

Coastal areas are also subject to influences from land-based activities, such as suspended sediment load at river mouths and increased turbidity levels. Such areas are at times incorrectly confused with cloud cover by NIR masking techniques as turbid waters contribute to NIR backscatter (Nordkvist, et al., 2009); this was experienced throughout the thresholding process of this study and which ultimately necessitated supplementation with subjective judgement and manually digitisation of regions of cloud. Aerosols present in coastal areas from land-based sources may also have an effect on the signals received by sensors (Ferwerda, et al., 2007; Vahtmäe and Kutser, 2013). Together, these influences make radiometric corrections more difficult and if not undertaken, or applied incorrectly, classification results may be inaccurate (Vahtmäe and Kutser, 2013). In some cases, aerial or satellite-based mapping techniques are entirely not suitable owing turbidity (Kendall, et al., 2005) and in such waters, visual assessments are also rendered futile and acoustic sensing is perhaps the only applicable method of ascertaining bottom features. This is of special importance along the southern coast of Jamaica where coastal waters are known to have higher levels of turbidity than the island’s northern coastal waters (Norrman, et al., 1997; Warner and Goodbody, 2005).

The effects of varying water depth and water column (Mumby, et al., 1997; Mishra, et al., 2006) is another factor that was deemed crucial to address. In fact, Andréfouët, et al. (2003) invited reserachers to further assess the benefits of radiometric depth correction techniques in comparison to contextual editting in coastal reef zones or depth strata and this project examined the effectiveness of water column correction approches in Jamaican nearshore waters. Water column correction is capable of diminishing the effects of depth above bottom features and thereby ascribing the image radiance to the benthos and increasing the accuracy of benthic habitat classifications (Green, et al., 2000; Pu, et al., 2012; Baumstark, et al., 2013). The measurement of water depth and attenuation characteristics of the water column is essential to achieving in situ water column correction. In the absence of optical equipment capable of acquiring radiance measurements above and beneath the surface, and thereby estimating the attenuation characteristics of the water column related to depth in situ, models developed by various researchers were reviewed (Lyzenga, 1978; Lyzenga, 1981; Mishra, et al., 2006; Gilvear, et al., 2007; Sagawa, et al., 2010; Kanno, et al., 2011). The Lyzenga method generally takes into consideration the majority of the radiance recorded by an optical sensor and although it is the most common method used in reviewed literature (Mishra, et al., 2006; Gilvear, et al., 2007; Sagawa, et al., 2010; Kanno, et al., 2011), it requires the fulfilment of unrealistic statistical and physical assumptions. Despite the fact that the extended and alternative methods proposed by Sagawa, et al., (2010) and Kanno, et al. (2011) produce higher map accuracies than that resulting from the application of the original Lyzenga method, these proposed methods do not appear to be applied extensively by other authors, perhaps owing to the relative newness of these methods. This study opened an opportunity to test the Sagawa, et al. (2010) method and although this method was successfully implemented in this study, because of the well documented use and simplistic nature of the Lyzenga method (Lyzenga, 1978; Lyzenga, 1981; Green, et al., 2000; Kanno, et al., 2011), the Lyzenga method may also be considered for implementation in future projects in order to increase the likelihood and ease of reproducibility. Still, the Lyzenga method is restricted to waters deeper than 2 m since nonlinearity caused by internal reflection effects at the surface is not incorporated in this algorithm; therefore the utility of this model is restricted to areas where these effects are insignificant, such as waters that are not considered very shallow or having high reflectance (Lyzenga, 1978).

Image segmentation prior to classification (Pasqualini, et al., 2005) or post classification (Baumstark, et al., 2013) was not foreseen as a compulsory step given the implementation of water column correction techniques and shallow water depths not exceeding 10 m across the bay. However, although the water column correction applied to the imagery showed visual improvements[††], irregularities in reflectance indices not corrected by the Sagawa method necessitated the segmentation of the images prior to classification. This additional task was likely due to high turbidity levels within the study area and resulted in an increase in image processing time; this was also reported by Baumstark, et al. (2013). Although the segmentation process was undertaken prior to classification, the option

[††] Classifications were not undertaken for pre-corrected images, and thereby quantitative comparisons of pre- and post-corrected classification accuracies was not possible. However studies have showed improved accuracies from water column correction techniques (Mumby, et al., 1998).

exists for this to be executed after unsupervised image classification (Baumstark, et al., 2013), which has the benefit of reducing subjectivity.

Cloud cover is another major limitation throughout optical remote sensing efforts (Green, et al., 2000) as excess cloud cover may render acquired images useless. Detection and removal of cloud cover and associated cloud shadows may be accomplished by manual digitisation or by employing automatic thresholding methods (Dare, 2005; Huang, et al., 2010; Krezel and Paszkuta, 2011; Fisher, 2014). Thresholding techniques were tested for the study area in order to identify clouds, as well as white caps on the water's surface. However this method was not solely used owing to cloud-free areas being selected; on further inspection, it was found that these areas appeared to be affected by sun glint or were highly turbid. An algorithm suggested by Nordkvist, et al. (2009) has utility here, as it was developed to overcome the problem of turbid coastal waters being confused with cloud during the thresholding technique. In addition to creating a cloud and cloud shadow mask, a land mask was necessary in order to restrict the classification to marine features (Krezel and Paszkuta, 2011; Curran, 2011) and the NIR proved useful in this regard by highlighting land features (Mishra, et al., 2006). Islands were not observed within the bay and the boundary created for the BBSFCA essentially mirrored the resulting land mask.

The subjectivity of supervised classification and contextual edits may be eliminated by electing to train the images using a spectral library (Vahtmäe and Kutser, 2013); however additional resources in terms of equipment, software, expertise and time are required in order to employ this training method. Another alternate option is to use object-oriented classification such as in eCognition, a method involving the merging of like pixels into objects which are then classified. This classification has been demonstrated to surpass the classification capabilities of per pixel classification (Lu and Weng, 2007).

5.2.1.2 Acoustic survey, processing and interpolation techniques

The various drawbacks of implementing optical remote sensing highlight the attractiveness of acoustic technology and specifically its ability to sample the benthos regardless of water column effects and cloud cover and its relative ease of operation and processing (Foster, et al., 2009). Moreover, sonar has the ability to sense certain characteristics of benthic features, such as sediment type and vegetation height, which cannot be detected by imagery. However, similar to optical remote sensing wherein obtrusions such as cloud cover and turbidity result in discontinuous data inputs, expanses of unsurveyed seafloor interspaced between narrow footprints along survey transects is one disadvantage of single beam acoustic devices (Anderson, et al., 2008). Since data collection is restricted to sonar footprints (Bruckner, 2012), the efficacy of this type of sensing is dependent on sampling scale (Riegl and Purkis, 2005) and requires the application of interpolation techniques in order to produce a continuous mapped surface (U.S. NOAA Coastal Services Center, 2001). The process of interpolation may be limited by user capabilities and introduces a disadvantage of failing to capture fine-scale features in unsampled areas (Brown, et al., 2011). In this regard, multibeam systems are advantageous. Multibeam sonar functions on the same principle as single-beam units, however multibeam sonar simultaneously emits many acoustic pulses, obtaining continuous swaths of coverage rather than a single point beneath the vessel. Compared to single beam acoustics however, multibeam systems have higher costs, a need for greater data storage and more complex calibration and processing (Anderson, et al., 2008).

Regardless of the type of acoustics system, rapid changes in benthic cover, as well as positional inaccuracies contribute to acoustic signatures being potentially misclassified. Furthermore, although automated data processing allows for easy interpretation of acoustic data, the results may be erroneously refined by simply changing software settings. Owing to restrictions of this study, empirical test data was not collected in order to accurately estimate percentage plant cover and although only distinctions between SAV presence and absence were made, the effectiveness of the processing to accurately calculate plant cover could not be tested. User-defined parameters inputs to EcoSAV™ and VBT™ can affect the resulting point data used in the interpolation exercise; as such, a series of trial and error allowed for the selection of parameters that resulted in the generation of the most accurate data, which was subsequently used for final processing.

The hardest decision for interpolation is often the first, that is, which of the many existing methods should be implemented (Caruso and Quarta, 1998). A number of factors may be considered when selecting the type of interpolation to be performed on a dataset; the research objectives, type of data and relative importance of ease versus accuracy all come into play (Babish, 2002). Of interest to acoustic classification is the applicability of interpolation techniques on nominal/categorical data and specifically submerged vegetation cover and bottom substrate. A wide range of interpolators have been used to map percentage cover, plant height and biovolume of SAV data from point data, such as natural neighbour (Sabol, et al., 2009), nearest neighbour (Riegl, et al., 2005), minimum curvature method (Hoffman, et al., n.d.) and IDW (Roob, 2000; Sabol and Johnston, 2001; U.S. NOAA Coastal Services Center, 2001; Cholwek, et al., n.d.). Valley, et al. (2005) assessed three methods of interpolating biovolume, specifically IDW, spline and kriging; it was found that kriging resulted in the best modelled data, followed by IDW. Following this finding and the realisation that linear interpolators are not best suited for patchy features such as SAV, Stevens, et al. (2008) chose to apply kriging to their data. Likewise, various interpolation methods have been employed in order to predict seabed composition in areas for which field survey tracts did not cover; these include IDW (U.S. NOAA Coastal Services Center, 2001; Reid and Maravelias, 2001), IK (Bierkens and Burrough, 1993; Jerosch, et al., 2006), cokriging (Meilianda, et al., 2011; Diesing, et al., 2014), UK (Omran, 2012) and OK (Cholwek, et al., n.d.). As illustrated by these studies, one interpolation algorithm is not a one-size-fits-all method, that is, one particular interpolation technique is not suited for all environmental variables.

Li and Heap (2011) found that IK and ordinary IK were two of the least implemented (2 and 1 study respectively) interpolators in the environmental sciences field, both with a recommendation rate of 0%. Although IK was not a favourable interpolation method, IK consistently produced optimal results throughout this study when compared with IDW and other forms of kriging and was chosen for the interpolation of vegetation cover as well as bottom substrate owing to its ability to deal with skewed distributions (Babish, 2002) and its ability to interpolate categorical information as binary forms of data. Furthermore, a user-friendly tool for performing IK was available in the software being used for this study (ArcMap 10) and to allow for replication at other sites, the use of IK was justified here. As with all methods however, IK has its drawbacks, including the possibility of computational complications and the challenging nature of modelling accurate variograms for less frequently occurring categories (Hengl, 2007), such as coral reef in the case of this study. Here, other hybrid interpolators have proven to be more robust, e.g. kriging with external drift (KED) (Verfaillie, et al., 2006), the similar concept regression kriging (RK) (Hengl, et al., 2004; Hengl, et al., 2007), Bayesian Maximum Entropy (BME) (D'Or and Bogaert, 2004) and Markovchain algorithms (mentioned in Hengl (2007)). These techniques are certainly more complicated than other kriging forms and require more user interaction in perhaps less friendly computer environments (Hengl, et al., 2007). Computational demand and software restrictions also play an important role as a number of the mentioned hybrid interpolators require far more complex computational requirements (Hengl, 2007) and are not as readily available to the general environmental science community.

Not only is the interpolation method an important choice, but the selection of model parameters is a crucial step as changes to these can bring about varying results (Oliver and Webster, 2014). Ascertaining the best kriging model involves an often time consuming iterative process of trial and error and subjective judgement is used throughout (Babish, 2002), for example while fitting semivariograms with an appropriate model and specifying lag sizes and search neighbourhoods. Any model discrepancies resulting from these decisions are assessed by means of cross-validation and for all interpolations carried out for this project, optimal prediction error results were weighed more heavily than favourable visual assessments in ultimately selecting the final models. This facility to quantitatively test prediction capabilities is an obvious benefit of all kriging forms. It must be stressed however that the purpose of cross-validation is not to determine whether a model is accurate or not, although it does reveals where a model fails and suggests that it is perhaps not inaccurate (Babish, 2002). Similarly, although validation diagnostics assists to reveal properties of the model, it does not necessarily provide an absolute measure of accuracy as it may give misleading results depending on the spatial configuration of the independent test data points and those points input to the model. Test data in proximity to measured points may result in better validation results, than if these stations were placed far away from measured input points (Ly, et al., 2011). This was observed for the acoustic vegetation probability IK models, wherein the test dataset prediction errors were less favourable than those resulting from the use of the training datasets in the cross validation exercise (Table 6).

The chosen interpolation method does not solely affect the accuracy of the classified map; additional factors such as data diversity and variation, as well as sampling design come into play (U.S. NOAA Coastal Services Center, 2001; Li and Heap, 2011; MacCormack, et al., 2013). Interestingly Li and Heap (2011) state that the effect of various influences such as data density on model accuracy are inconsistent amongst studies reviewed. Whereas it is believed that higher density data points contribute to robust modelling (Foster-Smith and Sotheran, 2003) and minimise prediction errors (Ly, et al., 2011), Li and Heap (2011) suggest that data variation is also a major factor affecting any influence sampling density may have on interpolation results, where in instances of high data variation, sampling density should be increased in order to improve the interpolation. MacCormack, et al. (2013) found that the number of input points is more crucial compared to distribution for highly complex geological environments, whilst the opposite was found for simple geological settings. Generally, data quantity and distribution can be optimized for interpolation and as such can be used to inform data sampling regime (MacCormack, et al., 2013). A dense uniform grid extending across the entire study area is the preferred sampling design for any type of spatial interpolation (U.S. Environmental Protection Agency, 2004). In regard to this study, although smaller intervals such as 8 m (Sabol and Johnston, 2001), 10 m (Valley, et al., 2005) and 25 m (Stevens, et al., 2008; Foster, et al., 2011) would increase mapping details, limited time and resources necessitated a wider spacing of 50 m. A 50 m transect interval has been successfully implemented in other surveys (e.g. Clizia, et al., 2002; Stevens, et al., 2008; Sabol, et al., 2009; Hoffman, et al., n.d.), as well as wider spacings of 75 m (Foster, et al., 2009) and greater than 100 m (Anderson, et al., 2002; Cholwek, et al., n.d.).

Acoustic coverage across the entire study area was unattainable owing to the inability of the vessel and equipment to navigate very shallow waters of less than 0.5 m, such as in proximity to the coast and particularly to the north of the study area (Figure 6). Generally, in areas of increased transect spacing and where data points are deficient, modelled detail is reduced (Valley, et al., 2005) and in such areas, model artefacts become easily recognisable. Artefacts of the modelling process were observed throughout the interpolation model testing phase, and the character of the resulting interpolated surfaces reflected the sampling regime and model parameters chosen. Owing to the arrangement of dense data points along transects perpendicular to the shoreline, a predisposition exists for predicted surfaces to reflect this sampling pattern and a bias exists here where more accurate predictions result along transect interpolation, as shown by lower standard errors along transects than between them (Figure 29). This is one likely reason for scarcer localised vegetation patterns being exhibited by the acoustic IK for vegetation presence.

Finally, the choice of using a 50% probability as the threshold for the delineation of the SAV class and bottom substrates was highly subjective and affected the resulting acoustic classification maps. Indeed, any probability value could have been selected; however after examination of varying possibilities, 50% probability was believed to be a reasonable threshold. The resulting bottom substrate map is a combination of IK models for the three bottom types in question (silt, sand and coral). Although areas remained unclassified either because in these instances all bottom types had less than 50% probability of occurrence, or more than one bottom type was likely to occur there (> 50 %), this may be seen as advantageous in the sense that it shows ambiguous areas and offers a sense of reality (Zhang and Stuart, 2001).

5.2.2 Additional limitations and error propagation

Errors may be defined for every step of data collection, modelling and interpretation, and all contribute to the overall error budget of a study. Error propagation embraces sources of uncertainty throughout the modelling process and Burrough and McDonnell (1998) suggest that the quality of input data, the quality of the model and the way in which the data and model interact all influence the modelled results. Error sources and propagation should particularly be considered for example with the BSM, which was not only a final output, but also used as input to image classification. Similarly, although the iterative data processing and model testing undertaken for the kriging approaches assisted in reducing errors inherent in all final kriged outputs (bathymetry, vegetation and bottom substrate probability), interpolation was the penultimate step in acoustic classification methods and crucial data collection and processing steps led up to this and are equally as important.

Error can be measured against the real world such as in the case of accuracy assessments. However, although the creation of an error matrix and subsequent accuracy assessment is frequently used for evaluating classification outputs (Lu and Weng, 2007) resulting accuracies are dependent on the selection of reference data points, and specifically the number of points and sampling regime used to identify them. If a purely random sample is taken, the possibility to under sample rarer habitat classes or regions within the study area exists, and thus the inclination to undertake stratified random selection according to benthic class. The essence of stratified random selection is that each point within each benthic class has an equal chance of being selected and thus statistically, this type of sampling would produce the best sample. This also applies to interpolation validation, wherein a more representative division of training and test points is achievable if sampled based on classes rather than by purely random function or systematic selection. Here, kappa, which incorporates the influence of chance, and other measures such as the balanced error rate (BER) supersede the use of traditional accuracy assessment percentages. It must be noted that though useful, a quantitative measure of error/ accuracy does not pinpoint the numerous sources and types of error (spatial, positional and thematic) that may have occurred throughout the various stages, such as from classification, interpretation or even the accuracy assessment itself (Lu and Weng, 2007). The time lapse between data collection (imagery and acoustic) and ground-truthing exercises must be taken into account given the dynamic nature of the seabed within BBSFCA, and this may have given rise to errors in the accuracy assessment (Mumby, et al., 1997).

Spatially inconsistent scales across data collection and verification methods is a crucial consideration. All final interpolated surfaces, inclusive of the final BSM, vegetation and bottom substrate probability maps were exported as 2 m gridded rasters and this spatial model resolution, though chosen to be comparable amongst all project raster layers (including image classification) may introduce some ambiguity when defining any errors in the interpolated surface. In this regard the question of whether resulting inaccuracies are as a result of the model itself, owing to the spatial resolution or both may be posed (Goodchild, 2011). Acoustic ground-truth sites are essentially calibration sites used to train the classification process, similar to the use of training samples for supervised image classification. The positioning of acoustic pings are not exact and with regard to the ECOSAV™ vegetation processing, each cycle of ten pings covers varying distances. As such, although the spacing of output points averaged 2-3 m, this ranged from as small as 1.5 m to 20 m in some localities. The bathymetric data and bottom substrate processed data points however were spaced between 4 and 5 m on average along transects owing to the averaging of 20 pings. The spatial resolution of output rasters of 2 m is therefore smaller than some sampling distances occurring along field transects for the sonar survey and features smaller than 4 m, such as coral heads would perhaps not have been detailed owing to the averaging of returns in the acoustic survey output. Correspondingly, as discussed previously with regard to image classification, the spatial resolution of the image is the basic measure of scale; both the 2 m GeoEye-1 and WorldView-2 images mask any potential variation in vegetation coverage that may have been revealed using a 1 m^2 quadrant for example within the 4 m^2 area pixel. Despite the limitations discussed regarding data collection scales and the ultimate removal of areas smaller than the MMU of 4 m^2 from all mapped results, the resulting surfaces certainly revealed some local-scale bottom variations, such as coral reef structures and bare sediment patches. Furthermore, natural variations in spatial extent of habitats is inevitable and even though clear distinctions are mapped in final outputs, the intrinsic "fuzzy" nature of benthic habitats both horizontally as well as vertically, particularly at scales incapable of accurate mapping must not be forgotten.

Another factor considered by a number of researchers (Kendall, et al., 2005; Diesing, et al., 2014) which must be mentioned, is that the scale of the accuracy assessment may also be smaller than the MMU. This disparity was considered and in order to minimise this potential error, an effort was made to use points in homogenous areas and not along patch boundaries or highly diverse areas. Accuracy assessment results are also affected by the number of benthic groupings, wherein increased habitat complexity and number of benthic classes produce lower map accuracies (Andréfouët, et al., 2003; Pu, et al., 2012). Relating to the level of detail attained for both methods employed, the number of classes per mapped output did not exceed 3 classes. Such broad groupings lessen the potential for misclassification (Foster-Smith and Sotheran, 2003) and perhaps explains the relatively high accuracies of the acoustic SAV and image classification results (Table 10, Table 11).

Subjective judgement also played a major role in thematic accuracy. Although vegetation presence was based on the chosen NOAA classification scheme (Figure 5), accurately quantifying 10% vegetation cover from imagery was not straightforward and certainly subjective since exact areal coverage measures were not possible by means of a quadrant. This is unlike the characterization algorithm employed by EcoSAV^{TM} that summarises cyclic acoustic ping data to output a percentage cover numerical value. Generally, classification associated with sonar technology is far less subjective than that of supervised image classification and has been described as objective by Anderson, et al. (2002). It must be added that although accuracies improved with contextual edits, subjective interpretation was used during the contextual editing for coral reef areas and the potential bias introduced by this editing (Green, et al., 2000) must not be overlooked.

Finally, although accuracy assessments give an indication of error of the final output, they may be considered only as a first step in map assessment as stakeholder-involved critique is another form of assessment (Schill, et al., 2011). The final maps resulting from this project are yet to undergo stakeholder assessment and it is hoped that sharing of these mapped outputs will encourage map critique and assist in any needed map revisions. This local interaction is not only necessary at this stage, however throughout the project life cycle as collaboration ultimately improves the usefulness of mapped products.

5.2.3 Mapping requirements and use

The main goal of this study was to ascertain the feasibility of image and acoustic classification in a Jamaican context. In addition to the advantages and limitations of the methods discussed thus far, it is important to determine the reproducibility of these methods in other localities and settings. The study area in question, map user requirements and availability of resources, including budget, technical expertise, equipment, software and allotted time frames influence the choice of classification method.

5.2.3.1 Map applicability

Fundamental to any habitat mapping exercise, is the selection of a suitable classification scheme that will structure the study area into defined classes. Numerous marine benthic classification schemes have been developed worldwide (Kendall, et al., 2001; Madley, et al., 2002; Madden, et al., 2008); however a national standard for marine benthic classification does not exist in Jamaica. Of the 22 completed stakeholder questionnaires, 9 persons described data collection standards utilised at their organisation (e.g. Atlantic and Gulf Rapid Reef Assessment, AGGRA and Reef Check), national GIS standards stipulated by the Land Information Council of Jamaica (LICJ), or did not provide any description. One response (Kenny, 2013) also suggested the usefulness of employing the System for Classification of Habitats in Estuarine and Marine Environments (SCHEME), developed by the Florida Fish and Wildlife Conservation Commission, Florida Marine Research Institute (Madley, et al., 2002). Given the similarity between coastal ecosystems in Jamaica, the wider Caribbean and Florida, the tiered SCHEME system appears applicable to Jamaica. The importance of applicability and reproducibility of classification schemes cannot be disregarded and classifications should be able cross all boundaries that may be imposed owing to differences in equipment, methods, study suite, data of data collection, analysis, scale, targets and policies (Cogan, et al., 2009). Classification systems should also be structured in such a way to allow for comparison of mapping results from various sources, that is, provide a "common language" (Madley, et al., 2002) for habitat groupings at various levels of detail and allow for future additions. Whereas the SCHEME system was developed with previous systems in mind and may be applied to a number of these easily, it was recognised that a number of studies within the Caribbean had not applied this system; however that developed by the NOAA hierarchal classification system (Figure 5) and used in this study.

Thematic scale of the final mapped outputs from this study may be considered broad; however owing to the simple geographic setting of the study area, it was not possible to split the area further into geographic zones defined by NOAA; however such post classification zonation similar to Anderson, et al. (2002) can be undertaken in larger areas. Similarly, although the main focus for SAV output from the acoustic data was presence/ absence, it is possible to map SAV species and percentage cover, as well as additional sediment groupings with acoustic technologies; this would certainly fulfil the desires of stakeholders interviewed. In addition to the classes represented on the final mapped outputs of this project, other benthic features and characteristics that were thought to be useful by stakeholders were cobbles, boulders, gravel, rock outcrop, rubble, seagrass species, rugosity, sediment depth and health of biological cover. Indeed, these relate to the often varying user needs which exist, as evidenced by the results of the stakeholder questionnaires, in which applications to coastal zone management and planning, engineering works, impact assessments, hazards and vulnerability, ecological studies such as natural valuations, health assessments, change monitoring, habitat restoration and development for recreational activity were anticipated. The advantage of employing the NOAA system is that the hierarchal groupings consist of collapsible tiers and allow for the mapped products to be supplemented with further zonation and class detail as required by future applications.

Detail finer than 2 m, such as coral patches 1 m^2 in size as specified by Fisheries Division (Table 1) was unattainable utilising the acquired imagery and sonar survey transect data. The spatial resolution of the acquired GeoEye-1 and WorldView-2 visible bands is 2 m, whilst the smallest resolution of the sonar data was between 2 and 3 m along transects. In an attempt to retain the highest level of detail and allow for comparison amongst resulting classifications, a 2 m grid cell size and MMU of 4 m^2 (1 pixel) was accepted as the working spatial resolution for all raster data generated. Further, favourable resolutions for mapped outputs expressed by stakeholders varied from 1 x 1 m to 10 x 10 m and as such it is believed that the 2 x 2 m resolution of the mapped data was suitable within the Jamaican setting.

The resulting digital data products are primarily in the form of GIS vector and raster, both of which may be easily converted to tabular or Google KML and used in the creation of cartographic maps; all of which are formats specified as being useful to stakeholders. It should be noted that this study did not require a comprehensive database system, however if benthic mapping is to be undertaken at numerous sites across the island, consideration should be made for implementing a relational database. It should also be borne in mind that depending on the scale and level of detail required for a particular project, geometrical object types become dynamic; for instance, on a regional level, a point location for coral may be sufficient; however within locales of an MPA, the extent of coral coverage will be required for management purposes. In data modelling the semantics of scale may be related to the mapping extent, as well as the spatial resolution of the data and modelling (Goodchild, 2011). It is important to note that manipulating very detailed data of a large scale from a database for modelling and presentation with a smaller scale often involve generalization techniques which inevitably loses information and has the potential to give rise to erroneous results.

The mapped outputs of this study are representative of benthic habitats at the time of data collection and in a dynamic environment such as BBSFCA, the shelf life of such mapped information should be deliberated (Anderson, et al., 2008). The majority of questionnaire respondents required updates to benthic maps every 2 to 5 years (59.1%) and updates would also be required after natural disturbance or significant anthropogenic activity within the bay. Indeed the regularity at which mapping is required and the available resources will both influence survey design.

5.2.3.2 Associated costs

Recurring costs comprise the costs associated with the time taken to undertake all necessary processing steps, as well as data acquisition (images and field survey). Processing labour costs are more expensive for the acoustic classification method (USD \$276.43 per km^2) when compared to the satellite image classification (USD \$70.72 per km^2) and this is directly related to the time taken for each method, which is tripled for the acoustic method. Imagery costs vary depending on the provider, type of image, area required and collection method; costs for standard ortho-ready images (50/60 cm resolution) based on minimum area requirements range from USD $400.00 for archived GeoEye-1 imagery (25 km^2 scene, with minimum width of 3 km) to USD $3,800.00 for new collect (not older than 90 days) WorldView-2 images (100 km^2 scene, with minimum width of 5 km) (McDonald, 2014). Satellite image acquisition costs were comparable between this study and Baumstark, et al. (2013) (USD $16.00 for archived 4-band multispectral), however the total per km^2 labour costs for image classification estimated for this study (USD $70.72, Table 12) greatly exceed those of Baumstark, et al. (2013), who found that it cost USD $28.20 per km^2 to carry out satellite image processing. This may be attributable to differences in processing steps; inconsistent spatial properties encountered in this study post water column correction can lead to complications in the image processing steps (Baumstark, et al., 2013).

Set-up costs associated with software and equipment for the acoustic survey carried out for this project are greater than that for optical remote sensing (USD $52,000.00 and $12,000.00 respectively, Table 12); and similar to Green, et al., (2000), these costs comprise the largest portion of costs (90%). However, set-up cost is a one-time obligation that is perhaps more easily warranted if the mapping exercise is to be repeated. The total cost of the image classification method, inclusive of set-up costs, labour and data collection (new collect 100 km^2 WorldView-2 imagery scene, $3,800.00) was estimated to be USD $16,790.00, whilst the acoustic survey was USD $39,080.00 more costly (Table 12). A number of factors can greatly affect total cost estimates for benthic mapping exercises however. Firstly, increased image spectral and spatial resolution available with optical options such as aerial photography and hyperspectral imagery provide enhanced mapping capabilities and are both typically more costly. If fine-scale bottom features such as smaller sand and coral reef assemblages are requisite mapped outputs, increasing the sampling density of the acoustic survey may be necessitated, further increasing the cost of this method per mapping exercise. It should also be noted that only the equipment utilized in this study are presented in Table 12 and more affordable acoustic equipment and software specific to benthic mapping are available, for example the BioSonics, Inc. MX Aquatic Habitat Echosounder system costing USD $12,000 (Munday, 2015). Further, the cost of carrying out the bathymetric data collection and processing was not included in the image classification process as bathymetric data may be collected reasonably cheaper than using the sonar equipment and the method used for this study, and in some cases already exists.

Although the many benefits of undertaking an acoustic survey have been discussed, comparing the resulting accuracies, as well as the time and cost allocated to each method employed highlights some drawbacks of this method. Resulting from this study and vital to mapping technique applicability and cost, is the fact that image classification attained the higher classification accuracies and kappa statistics (Table 10 and Table 11) and are more affordable than acoustic surveys (Table 12); however benthic detail is compromised as acoustic surveys are capable of achieving a greater level of bottom feature characterisation. Cost effectiveness is particularly a major consideration in assessing mapping feasibility in Small Island Developing States (SIDS) as limited resources, in terms of financial support, expertise, equipment and software often restrict research activities (Schill, et al., 2011). Typically, measures required to improve map accuracy are reflected in increased costs; however a point is normally reached where increased effort does not reap further improvements (Mumby, et al., 1998). Not only should such a threshold be considered, but the ultimate use of the maps must be deliberated; that is, if improved accuracies or detail is not essential, then the increased effort and associated costs for instance of USD $180.00 to undertake radiometric corrections or USD $13.00 per km^2 for 8-band imagery versus 4-band imagery are perhaps not justified. This is similar to comparing aerial photograph interpretation and satellite imagery-based classification, wherein if medium-scale thematic resolution of reasonable accuracy is sufficient for user needs, then the lower associated costs of satellite sensing make it a more viable option than airborne sensing (Mumby, et al., 1999). When available cost and time are considered, there is often compromise between resolution (spatial and map detail) and coverage; whilst it is possible to attain the highest level of accuracy and map detail for a smaller setting, acquiring such comprehensive data on a much larger scale will be more expensive and time consuming.

Table 12. Times (hrs) and costs (USD) associated with benthic classification methods employed.

Method	Steps	Approx. time (hrs)	Recurring cost (USD)			Equipment and software (USD)
			Labour‡‡	Other	Per km^2§§	
Image	***Image acquisition***				Archived: $29.00 (WorldView-2), $16.00 (GeoEye-1); New collect: $38.00 (WorldView-2), $25.00 (GeoEye-1)***	ERDAS Imagine: $10,500.00; ArcGIS 10.2.2 for Desktop Basic: $1,500.00 †††
	Processing					
	Projection and geometric correction	1.5	$45.00		$3.21	
	Resolution merge and resampling	0.5	$15.00		$1.07	
	Band selection	0.25	$7.50		$0.54	
	Radiometric correction (atmospheric, sun glint and water column corrections) ‡‡‡	6	$180.00		$12.86	
	Masking and thresholding	1	$30.00		$2.14	
	Classification					
	Segmentation and supervised pixel-based §§§	20	$600.00		$42.86	
	Mosaicking	0.5	$15.00		$1.07	
	Contextual editing	3	$90.00		$6.43	
	Clump and eliminate	0.25	$7.50		$0.54	
	TOTAL:	**33**	**$990.00**		**$70.72**	
Sonar	***Sonar survey***	52	$1,560.00	Boat rental: $900.00 ****	$175.71	BioSonics DT-X Portable Echosounder, differential GPS, laptop and associated software: $52,000.00
	Vegetation presence					
	EcoSAV processing	9	$270.00		$19.29	
	Interpolation	3	$90.00		$6.43	
	Bottom classification					
	VBT processing	30	$900.00		$64.29	
	Interpolation	5	$150.00		$10.71	
	TOTAL:	**99**	**$2,970.00**		**$276.43**	

‡‡ Labour cost calculated based on USD $30/hour.
§§ Labour unit costs for field survey and processing steps based on 14 km^2 (BBSCFA study area).
*** Unit costs quoted are for standard ortho-ready (50/60 cm) images. Imagery not older than 90 days is considered new collect. Pricing courtesy of Mona GeoInformatics Institute (McDonald, 2014).
††† http://store.esri.com/esri/showdetl.cfm?SID=2&Product_ID=29&Category_ID=121 [Accessed 08 November 2014]
‡‡‡ Water column correction requires bathymetric data, time and cost for which is not included here.
§§§ Time estimated based on 30 segments.
**** Based on rental of boat for 150 USD/day, for 6 days.

5.2.3.3 Available resources

Cogan, et al. (2009) draws attention to technological factors that may limit the implementation of certain mapping methods. The development of software to carry out geostatistical tasks have enabled users to perform modelling techniques with ease; however some are described as “black boxes” since an interpolated surface may be created by an inexperienced user at the press of a button (Oliver and Webster, 2014). Software driven by menus such as the ArcMap Geostatistical Wizard run the necessary code “behind the scenes” (U.S. Environmental Protection Agency, 2004); whilst this may be considered a positive feature, a prior understanding of the theory should still be gained so that users may intervene by manipulating parameters during the interpolation process. ArcMap is also beneficial owing to display outputs and its ability to effortlessly overlay with other data; however the Semivariogram Cloud tool was incapable of handling the very large bathymetric dataset created for this study, and the software may be regarded as costly (Table 12). Of specific mention here are freeware such as GStat and R that afford users the ability to undertake geostatistical hybrid interpolation techniques with direct control over all aspects of the modelling process, without licensing and at no cost. There is the belief that R can meet all statistical needs and for this reason Hengl (2007) promotes its use. However, an expert level of statistical knowledge is required in order to effectively use the R package, and since visualisation is not recommendable in R, export to other GIS software is necessitated. Google Earth has become an everyday tool for persons worldwide, and its utility in the visualisation process and data sharing as Keyhole Markup Language (KML) is advantageous since it is available freely and a number of stakeholders desire data in this format.

As summarised by Hengl (2007), available user resources scarcely match the capabilities of some researchers and one program hardly encompasses all the required GIS and statistical functions. In the same regard, findings from the stakeholder questionnaire survey demonstrated that although GIS, underwater photography and scuba are common skills (greater than 60% of stakeholders), image classification and sonar processing skills were not (6 respondents or 27.3% and 2 respondents or 9.1% respectively). Access to equipment also shows a propensity to GIS use and marine surveys with 50% or more of respondents having access to GPS and GIS software, satellite imagery, boats, underwater camera and scuba gear, yet only 5 organisations (22.7%) had access to acoustic devices and 1 (4.5%) to remote sensing software. Recently, the Khaled bin Sultan Living Oceans Foundation (KSLOF), in partnership with The Nature Conservancy undertook the assessment of coral reef community structure at Pedro Bank using transects and recorded observations and/or photographic assessments to assess benthic cover (Bruckner, 2012). Although a pilot sidescan sonar survey was a part of this research mission (Quester Tangent, 2012), sonar is not a widespread technique used for the purpose of benthic mapping in Jamaica.

Chapter 6. Conclusions

Bluefields Bay is dominated by submerged seagrass and algal species, inhabiting varying types of substrates across the bay, such as finer silty substrate along the shoreline, sand found further offshore, as well as smaller areas of coral reef and hard bottom. The general benthic patterns within the BBSFCA were comparable amongst both optical and acoustic remote sensing classifications produced, yet image classification outperformed acoustic methods in terms of overall accuracy. The inability of optical remote sensing to classify sections of the bay owing to cloud presence and complications due to water column properties were obvious shortcomings of the image classification process however. Furthermore, this method was only applicable given the broad level of benthic detail necessary for this particular study, which is not always the case - more detailed information such as seagrass species and sediment groupings were found to be indispensable benthic parameters to a number of stakeholders. The benefits of acoustic surveys have been praised by numerous studies (Anderson, et al., 2002; Anderson, et al., 2008; Foster, et al., 2009; BioSonics, Inc., n.d.) and this was shown by the capability of attaining fine thematic groupings, in addition to its operation in turbid waters otherwise unsuitable for optical remote sensing. A major step in the acoustic classification process however, was the interpolation of processed data which gave rise to a number of additional considerations. The accuracy of a chosen interpolation algorithm was not viewed as a standalone factor in selecting a particular method and the software, expertise and intricacies of carrying out the necessary steps were major influences. Certain interpolators are often implemented more frequently than others simply owing to its availability in GIS software and ease of use (Lu and Wong, 2008). Availability of particular methods should not be seen as an instant benefit, as without an appreciation of how a model functions, the tools may be used incorrectly; expert input is vital to geostatistical modelling (Diesing, et al., 2014) and must not be overshadowed by friendly user interfaces.

The pros and cons of each method cannot be weighed without the consideration of user needs and available resources that may ultimately render a method ill-suited for a particular locality. Both mapping methodologies may theoretically be replicated at additional sites in Jamaica given that similar benthic features will likely be encountered and satellite imagery and expertise, as well as sonar technology exists locally (albeit only for a few organisations); the acoustic survey however was more costly and certainly requires greater financial resources than satellite image classification. So, the question remains as to which approach is better for benthic habitat mapping in Jamaica and possible the wider Caribbean. Based on the results of this study, the most cost effective and efficacious mapping method is satellite image classification. Nevertheless, similar to Diesing, et al. (2014), it must be reiterated that each method has associated limitations and benefits and the effective implementation will depend on a number of factors that must be weighed in order to select the most feasible mapping method for a particular site.

A consideration to be made as well, is combining techniques in order to overcome apparent method deficiencies and improve mapping products. It must also be added that technological advancements should not be a dominating factor and any chosen survey design should "remain science-based rather than technology-driven" (Cogan, et al., 2009). Irrespective of the mapping method chosen, maps are described as being "one truth and not the truth" (The Joint Nature Conservation Committee (JNCC), 2008); with any mapping exercise, careful attention must be given to the survey design in order for the methodologies and outputs to optimise accuracy and be of utmost use to interested groups.

It is hoped that the work undertaken for the purposes of this thesis will be of benefit to the efforts of the Fisheries Division in the mapping of benthic features at all designated fish sanctuaries across the island, as well as similar initiatives both locally and regionally. Not only will the results of the feasibility analysis be useful in the selection of a viable mapping approach, but the intricacies of each method discussed throughout may assist in designing the survey programme. The mapped data of the benthic mapping exercise will certainly augment spatial marine resource inventories, and hopefully be considered as inputs to further ecological studies and management deliberations.

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Appendices

Appendix A: Stakeholder questionnaire

M.Sc. THESIS | *Karen McIntyre, Masters in Geographical Information Systems (GIS), Lund University*

Benthic mapping of the Bluefields Bay, Jamaica – implications for establishing a viable mapping approach in the Caribbean

Stakeholder Questionnaire

Synopsis of Research

Remote sensing is used extensively to map and assess the spatial characteristics of benthic habitats and the utility of these technologies for mapping coastal and nearshore marine ecosystems has been convincingly demonstrated. The aim of this project is to map and classify the benthos of the Bluefields Bay fish sanctuary using several optical and acoustic remote sensing technologies and techniques, including remotely sensed images (Landsat, Worldview-2 and GeoEye-1), acoustics and underwater videography. As part of this mapping exercise, the various techniques will be compared in order to determine the feasibility, practicality and cost effectiveness of each approach when applied to the Jamaican (and possibly Caribbean) context.

Purpose of Stakeholder Questionnaire

Approaches taken to map the benthic environment of Bluefields Bay fish sanctuary and other similar coastal areas should be guided by persons involved in the use, research, management and protection of these areas. Although this research is primarily method-based, garnering information from stakeholders within the marine and coastal arena is regarded as a paramount component of the project. It is hoped that information relating to the purpose and use of benthic maps, end-user map requirements, level of resources along with existing data and knowledge at your organisation will be gleaned. In addition to this formal questionnaire, the perspectives and local knowledge of marine users from coastal communities along Bluefields Bay will be captured by means of informal interviews and focus group discussions at a later date.

Instructions

Please complete all items for which you have personal knowledge by answering in the grey shaded areas and checking the most suitable answers. There is also a section for "Additional comments" at the end of the questionnaire. Your collaboration is greatly appreciated and the receipt of your completed questionnaire by email (karenvironment@yahoo.com) at your earliest convenience is anticipated. Please do not hesitate to contact me via email if you have any queries.

Page **1** of **7**

Name:			
Organization:		**Email:**	
Position:		**Telephone:**	

Existing Data and Knowledge

1. Are you aware of any past, current or planned benthic mapping studies in Bluefields Bay? If so, please provide details regarding date, researcher, methods, outputs etc.

2. Is there any existing benthic information for the Bluefields Bay fish sanctuary? If so, please provide details regarding format, owner, accessibility etc.

3. Are you familiar with the Bluefields Bay fish sanctuary? If so: **3a. Which natural and man-made features exist on the seafloor of the sanctuary?**

3b. Do you believe the benthic habitats have changed in the past three (3) years? If so, how?

Purpose of Benthic Maps

4. Have you had access to benthic data for any coastal area (protected or unprotected), and if so, what was/is it used for?

5. In the future, what would be the potential uses of a benthic habitat map within your organisation?

6. Apart from your organisation, which other entity or individual do you believe would utilise benthic maps?

End-user Map Requirements

7. **Which data formats are most useful to your organisation? (please tick all that apply)**	
☐ Tabular data	
☐ GIS vector format	
☐ GIS raster format	
☐ Google KML	
☐ Static map images for reports	
☐ Large-format printed maps	
☐ Other. Please specify:	

8. What is the ideal benthic map classification for your purposes?

Please complete the below table with the following information:

- Name of benthic class
- Rank (1-very important, 2-fairly important, 3- slightly important)
- Brief description
- Required resolution (minimum mapping unit)

Class Name	Rank	Description	Resolution
Example: Dense Seagrass	*1*	*Dominated by seagrass from the genera Syringodium and Thalassia. Seagrass cover is > 70%. Green algae are likely to be present. The substratum is dominated by sand or mud.*	*5 x 5 m*

9. What is the minimum benthic map classification that can be utilised by your organisation?

Please complete the below table with the following information:

- Name of benthic class,
- Rank (1-very important, 2-fairly important, 3- slightly important)
- Brief description
- Required resolution (minimum mapping unit)

Class Name	Rank	Description	Resolution
Example: Sand	*2*	*Dominated by sand (over 90% cover). There is usually some sparse algae.*	*20 x 20 m*

10. What level of map classification accuracy is acceptable for your purposes?
☐ Very high accuracy (90 - 100%)
☐ High accuracy (70 - 90%)
☐ Medium accuracy (50 - 70%)
☐ Low accuracy (< 50%)

11. How frequently would you require benthic maps to be updated?	
☐ Monthly	
☐ Yearly	
☐ Every 2-5 years	
☐ More than every 5 years	
☐ Other. Please explain:	

12. Do standards for coastal, marine or GIS data exist that relate to collection methods, formatting, accuracy, content etc.?

Level of Resources

13. Which of the following does your organisation presently own, have access to, or will likely be in a position to acquire:	
☐ Boat	
☐ Global Positioning System (GPS) device	
☐ GIS software	
☐ Acoustic equipment and software	
☐ Satellite or aerial imagery	
☐ Remote sensing software	
☐ Underwater camera or video camera	
☐ Scuba diving equipment	
Other comments:	

14. Which skill sets currently exist at your organization:	
☐ GIS	
☐ Image classification	
☐ Sonar data acquisition and analysis	
☐ Underwater photography/ videography	
☐ Scuba diving	
Other comments:	

Additional Comments

Thank you for your collaboration. Please return the questionnaire by email to: karenvironment@yahoo.com

Appendix B: Stakeholder questionnaire participants

Appendix Table 1. List of participants who completed and returned questionnaire survey

	Organization	Administration	Interviewee
1	Bluefields Bay Fishermen's Friendly Society (BBFFS)	Telephone interview	Livingston Thompson
2	Bluefields Villas	Telephone interview	Houston Moncure
3	Caribbean Coastal Area Management (C-CAM)	Email	Donovan B. Hay
4	Caribbean Natural Resources Institute (CANARI)	Email	Terrence Phillips
5	CEAC Solutions Co. Ltd.	Email	Christopher Burgess
6	Centre for Marine Sciences, University of the West Indies (UWI)	Email	Marcia Creary Ford
7	Caribbean Fish Sanctuary Partnership Initiative (C-FISH)	Email	Michelle McNaught
8	CL Environmental Co. Ltd.	Email	Matthew Lee
9	Discovery Bay Marine Lab, UWI	Email	Dayne Buddo
10	Environmental Management Consultants Caribbean Ltd. (emc2)	Email and Telephone interview	Marc Rammelaere, Ravidya Burrowes
11	Environmental Solutions Limited (ESL)	Email	Kimberly Bryan
12	Environmental Foundation of Jamaica (EFJ)	Email	Karen McDonald Gayle
13	Fisheries Division, Ministry of Agriculture and Fisheries (MoAF)	In person interview	Junior Squire
14	Marine Geology Unit, UWI	Email	Shakira Khan
15	Montego Bay Marine Park Trust	Email	Hugh Shim
16	National Environment and Planning Agency (NEPA)	Email	Sean Green
17	Natural History Division (NHD), Institute of Jamaica (IOJ)	Email	Keron Campbell
18	Oracabessa Bay Foundation	Telephone interview	Inilek Wilmot
19	Planning Institute of Jamaica (PIOJ)	Email	Nadine Brown
20	Seascape Caribbean	Email	Andrew Ross
21	Smith Warner International Ltd.	Email	David A. Y. Smith
22	Urban Development Corporation (UDC)	Email	

Attempts were made to interview the following stakeholders; however either successful contact was not be made, or if contact was made, completed questionnaire not received:

- *ALLOAH Fisherman Cooperative*
- *Breds Treasure Beach Foundation*
- *EcoReef*
- *Jamaica Conservation and Development Trust (JCDT)*
- *Jamaica Environment Trust (JET)*
- *Jamaica National Heritage Trust (JNHT)*
- *Ministry of Water, Land, Environment and Climate Change (MWLECC)*
- *Negril Area Environmental Protection Trust (NEPT)*
- *Negril Coral Reef Preservation Association (NCRPS)*
- *Northern Jamaica Conservation Association (NJCA)*
- *Westmoreland Parish Council*
- *Port Royal Marine Laboratory & Biodiversity Centre, UWI*
- *Sandals Foundation*
- *The Nature Conservancy (TNC)*
- *Veterinary Division, MoAF*

Appendix C: Satellite image metadata

Appendix Table 2. WorldView-2 satellite image metadata

[Online] Available at: https://browse.digitalglobe.com/imagefinder/showBrowseMetadata?catalogId=1030010020450700 [Accessed 6 Feburary 2014].

Catalog ID	1030010020450700
Acq Date	Apr 7, 2013
Center Lat/Long	18.295°/-78.066°
Avg Off Nadir Angle	6°
Avg Target Azimuth	256°
Sensor	WV02
Band Info	Pan_MS1_MS2

Appendix Table 3. GeoEye-1 satellite image metadata

[Online] Available at: http://geofuse.geoeye.com/landing/image-details/Default.aspx?id=2012010315562781603031602297201201031556278160303160 2297_000 [Accessed 6 Feburary 2014].

Attribute	Value
Best of Ranking	6580
Cloud Cover Percentage	7
Collection Date	03-Jan-2012
Collection Month	1
Collection Year	2012
COLLECTION_DATE_DAY	3
Data Owner	GEOY
DOWNLINK_FACTORY_ID	ET
Full Metadata URL	http://geofuse.geoeye.com/landing/image-details/Default.aspx?id=20120103155627816030316022972012010315562781603031602297_000
Ground Sample Distance	0.44
Image Identifier	20120103155627816030316022972012010315562781603031602297_000
IMAGE_FILE_URL	http://geofuse.geoeye.com/static/browse/geoeye/ge1/2012/01/03/20120103155627816030316022297_0.jpg
Imagery Source	GEOEYE-1
Imagery Source Abbreviation	GE-1
IS_GEORECTIFIED	1
Is_Line_Rate_Enhanced	0
LAYER_FILE_URL	N/A
Line_Rate_MS	2500
Line_Rate_Pan	10000
LL_LAT	18.0996
LL_LON	-78.1447
LR_LAT	18.0993
LR_LON	-77.9815

Attribute	Value
OBJECTID	6480170
Order Identifier	2012010315562781603031602297 (1125081)
Product Information URL	http://www.geoeye.com/CorpSite/products/Default.aspx
Scene Identifier	2012010315562781603031602297_000
Sensor Azimuth Angle	250.28043
Sensor Elevation Angle	70.956764
Sensor Mode	PAN/MSI
SHAPE	Shape Type: esriGeometryPolygon WKID: 4326
SHAPE.STArea()	278444940.17594
SHAPE.STLength()	66861.2578240599
SHAPE_Area	0.0237777341718836
SHAPE_Length	0.618349628375529
Spatial Reference System	EPSG:4326
SQKM	278
STEREOMATE_STRIP_ID	N/A
Strip Identifier	2012010315562781603031602297
Sun Azimuth Angle	153.56877
Sun Elevation Angle	44.512035
UL_LAT	18.2473
UL_LON	-78.1397
UR_LAT	18.2465
UR_LON	-77.9796
WORLD_FILE_URL	http://geofuse.geoeye.com/static/browse/geoeye/ge1/2012/01/03/2012010315562781603031602297_0.jgw

Appendix Table 4: Landsat 8 satellite image metadata

[Online] Available at: http://earthexplorer.usgs.gov/metadata/4923/LC80120482013106LGN01/ [Accessed 6 Feburary 2014].

Data Set Attribute	Attribute Value
Landsat Scene Identifier	LC80120482013106LGN01
WRS Path	012
WRS Row	048
Target WRS Path	012
Target WRS Row	048
Nadir Off Nadir	NADIR
Full or Partial Scene	FULL
Data Category	NOMINAL
Roll Angle	-.001
Station Identifier	LGN
Day/Night	DAY
Data Type Level 1	L1T
Sensor Identifier	OLI_TIRS
Date Acquired	16-APR-13
Start Time	16-APR-13 03.35.26.9736770 PM
Stop Time	16-APR-13 03.35.56.7696980 PM

Data Set Attribute	Attribute Value
Image Quality	9
Scene Cloud Cover	6.95
Sun Elevation	65.88749737
Sun Azimuth	103.50098079
Geometric RMSE Model X	7.274
Geometric RMSE Model Y	5.57
Browse Exists	Yes
Center Latitude	17°20'39.95"N
Center Longitude	77°48'35.57"W
NW Corner Lat	18°19'55.74"N
NW Corner Long	78°30'21.85"W
NE Corner Lat	17°58'00.84"N
NE Corner Long	76°44'54.31"W
SE Corner Lat	16°20'46.61"N
SE Corner Long	77°07'24.35"W
SW Corner Lat	16°42'49.21"N
SW Corner Long	78°51'55.22"W
Center Latitude dec	17.34443
Center Longitude dec	-77.80988
NW Corner Lat dec	18.33215
NW Corner Long dec	-78.50607
NE Corner Lat dec	17.9669
NE Corner Long dec	-76.74842
SE Corner Lat dec	16.34628
SE Corner Long dec	-77.12343
SW Corner Lat dec	16.71367
SW Corner Long dec	-78.86534

Department of Physical Geography and Ecosystem Science

Master Thesis in Geographical Information Science (LUMA-GIS)

1. *Anthony Lawther:* The application of GIS-based binary logistic regression for slope failure susceptibility mapping in the Western Grampian Mountains, Scotland. (2008).
2. *Rickard Hansen:* Daily mobility in Grenoble Metropolitan Region, France. Applied GIS methods in time geographical research. (2008).
3. *Emil Bayramov:* Environmental monitoring of bio-restoration activities using GIS and Remote Sensing. (2009).
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