Object Based Image Analysis for the Automated Mapping of Rocky-Reef Habitats

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Abstract

This research attempts to address problems involved with the mapping of remote rocky reefs. Object-Based Image Analysis (OBIA), through Definiens Developer software, of visible-band, high-resolution remote-sensed (aerial) imagery is used to partition and classify the reef regions using a combination of segmentation techniques and spectral as well as context based rules. The derived ruleset partitions imagery into features (vector polygons) that may be used with Geographic Information Systems (GIS), and describes four broad but distinct habitat classes. Production of maps from such output are at a meaningful scale, acting as a baseline for generating a refined habitat classification using the Joint Nature Conservation Committee's approved marine classification system – the Marine Nature Conservation Review BioMar hierarchy. While further work is needed to refine the results, this baseline is of utility to ecologists and managers, for monitoring and further ecological studies of rocky reefs.

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Chapter 1

Introduction

The marine environment incorporates some of the most diverse and least well understood regions in all of the Earth's biomes, and is fast becoming a focal point for political and public environmental concerns. There is renewed interest in the current status and protection of these environments (for example, with the recent introduction of the UK Marine and Coastal Access Bill), a consequence of which is the requirement of important work toward establishing ecological baselines for our shores, evaluating location of Marine Protected Areas (MPAs), and subsequent monitoring. In the current research we explore the use of Object Based Image Anaysis (OBIA) for the classification of habitat types using an established classification scheme.

The structure of the rest of this work is as follows; we first introduce the region of interest, and explain its character and value. Following introduction, we explore the biotic and abiotic factors that determine habitat regions on rocky shores, and how these have been used to identify, classify and lend protection to ecologically important regions. Remote Sensing, the technological foundations to this work, is described in the context of environmental management, succeeded by introduction of the approach used – OBIA – and how it has been

previously applied. The methods used are described, for both the (main) OBIA portion of the work as well as that of a field survey conducted as part of this exploratory research. We analyse the different techniques attempted during the classification and inspect the final rule-set. The research is concluded with a discussion of how it may be applicable to management of marine and coastal environments, the consequences of its use and a critical evaluation of the limitations and weaknesses, and potential for improvement and extension.

We begin then, with an introduction to the region of interest...

1.1 *Les Îles d'la Manche*

Les Îles d'la Manche (or Channel Islands), situated near the French coast in the English Channel, consist of several large islands bordered by small rocky outcrops, it is these outcrops that form the area of interest for the current research.

Above, the islands are referred to by their local (historic) name, and this is by no means a mistake; the Islands make up the most Southerly part of Britain, more contained by France than any English speaking neighbour, and Jèrriais (a Norman-French derivative) is Jersey's native language – now relatively unused. The remainder of the current research will make no apologies for referring to study areas by their French, Jèrriais or English nicknames; readers should not be surprised by interchange between the formal and colloquial names, particularly when reference is made to datasets (for text-encoding reasons, if not for ease of use).

1.1.1 Jersey

Before introduction of the rocky reefs ('rocky reefs' being defined after Diesing et al. (2009), and hereon simply referred to as 'reefs'), it would be wise for the reader to be familiar with the islands themselves, and become acquainted with one in particular; Jersey. The island of

Jersey is the largest and furthest south of all five islands (whose approximate 46 square miles of area equals that of all the other islands together), around which the reefs of interest are situated (Beechey-Newman 1957). Physically, Jersey is a low plateau that dips toward the south, the geology of which presents large granite beds to the north-west. The island and surrounding reefs were once part of 'Armorica' – the ancient region of what is now France – connected by the now submerged sediment, consisting of slope deposits and wind-blown loess (Renouf & Andrews 1996).

1.2 The Reefs

The reefs around Jersey form the basis of this research. *Les Minquiers* (Jèrriais: '*Les Mîntchiers*', English: 'The Minkies') to the South, form the largest of our 3 sites. *Les Écréhous* (Jèrriais: '*L's Êcrèhos*') in the North-East has the largest settlement (the only other consisting of one building and a helipad on the Minkies), and is accompanied by *Les Dirouilles* to the West. *Les Pierres de Lecq* (Jèrrias: '*Les Pièrres Dé Lé*', English: 'The Paternostas') – to the far West – while geographically part of the same reef, shall be referred to exclusively for the current research (figure 1.1). Below, we further acquaint ourselves with the reefs, focusing on the Écréhous for which there is most available literature, and whose past and present is most anthropogenically active.

1.2.1 Geography & Geology

All three of the reefs that form our areas of interest (AOI) are visible from the island of Jersey, which gives some impression of their proximity (though on a clear day it is also possible to see the coastline of Normandy). The reefs to the North of Jersey lie approximately 6 miles (9.5 kilometers) away, with the *Écréhous* only 8 miles (11 kilometers) from France (Renouf

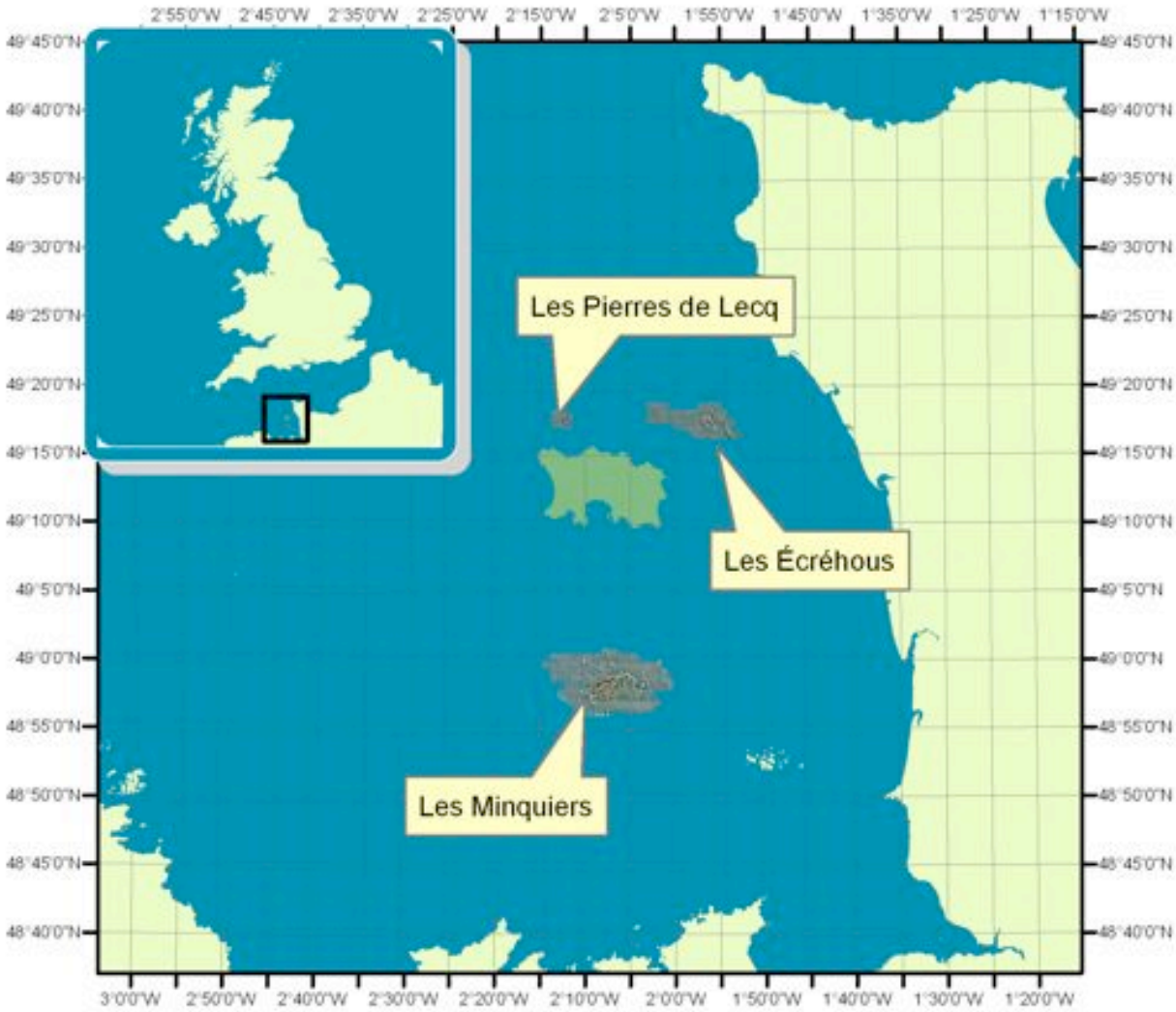


Figure 1.1: Locations of the three reefs around the island of Jersey.

& Andrews 1996). The Minkies to the South are ∼13 miles (21.5 kilometers) offshore, whose nearest neighbour are the French *Îles Chausey* (∼11 miles, 17.5 kilometers).

Though previous work exists, the geology of the reefs are best described by MJ Andrews in Renouf & Andrews (1996). In the chapter, the main rock types and formation of the Écréhous are established (see below), as is the geographic history. The reefs are formed from the same landmass as the main islands; indeed, until 5000 BC all of the archipelago were part

of what is now France, the sea level being such that the stretch of land between the islands was exposed, and forested (Renouf & Andrews 1996). All three of our areas of interest are geologically similar, though the North areas of the Minkies consist of a darker Diorite rock type than the Écréhous (MJ Andrews, 2009 *pers. comms.*).

The majority of rock consists of pink muscovite-granodiorite – a type of granite with foliated with micaceous minerals (MJ Andrews, 2009 *pers. comms.*). There are essential lineaments predominantly from East-North-East—West-South-West and West-North-WestW—East-South-East with other important lineaments also aligned to North-North-West—South-South-East and North-North-East—South-South-West. Other major features of the rock-beds include 'structural grain' (Renouf & Andrews 1996) which can be identified in the aerial images as areas of very fragmented rock (see figure 1.2, compare with overlay figure 1.3).

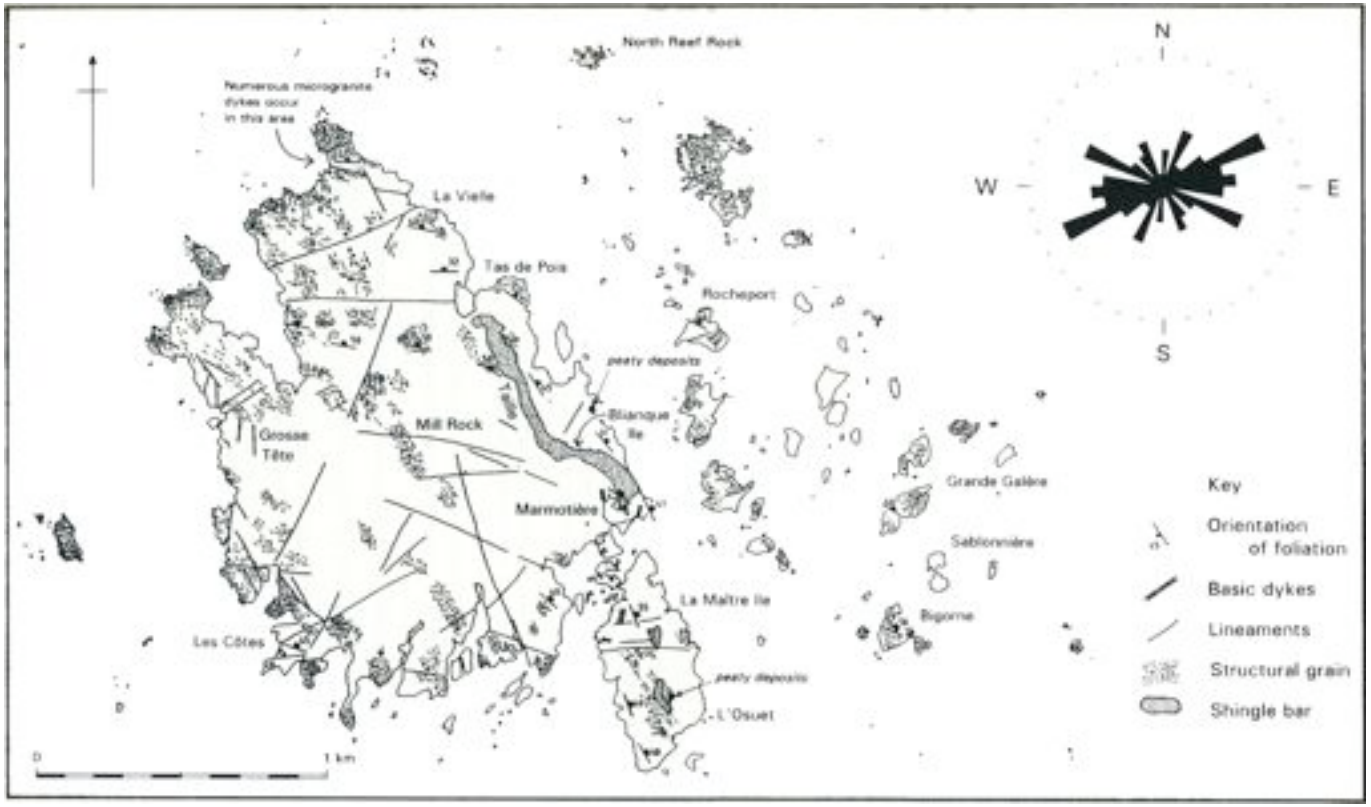


Figure 1.2: A photogeological interpretation of the Écréhous, with rose diagram showing direction of lineaments (Renouf & Andrews 1996).

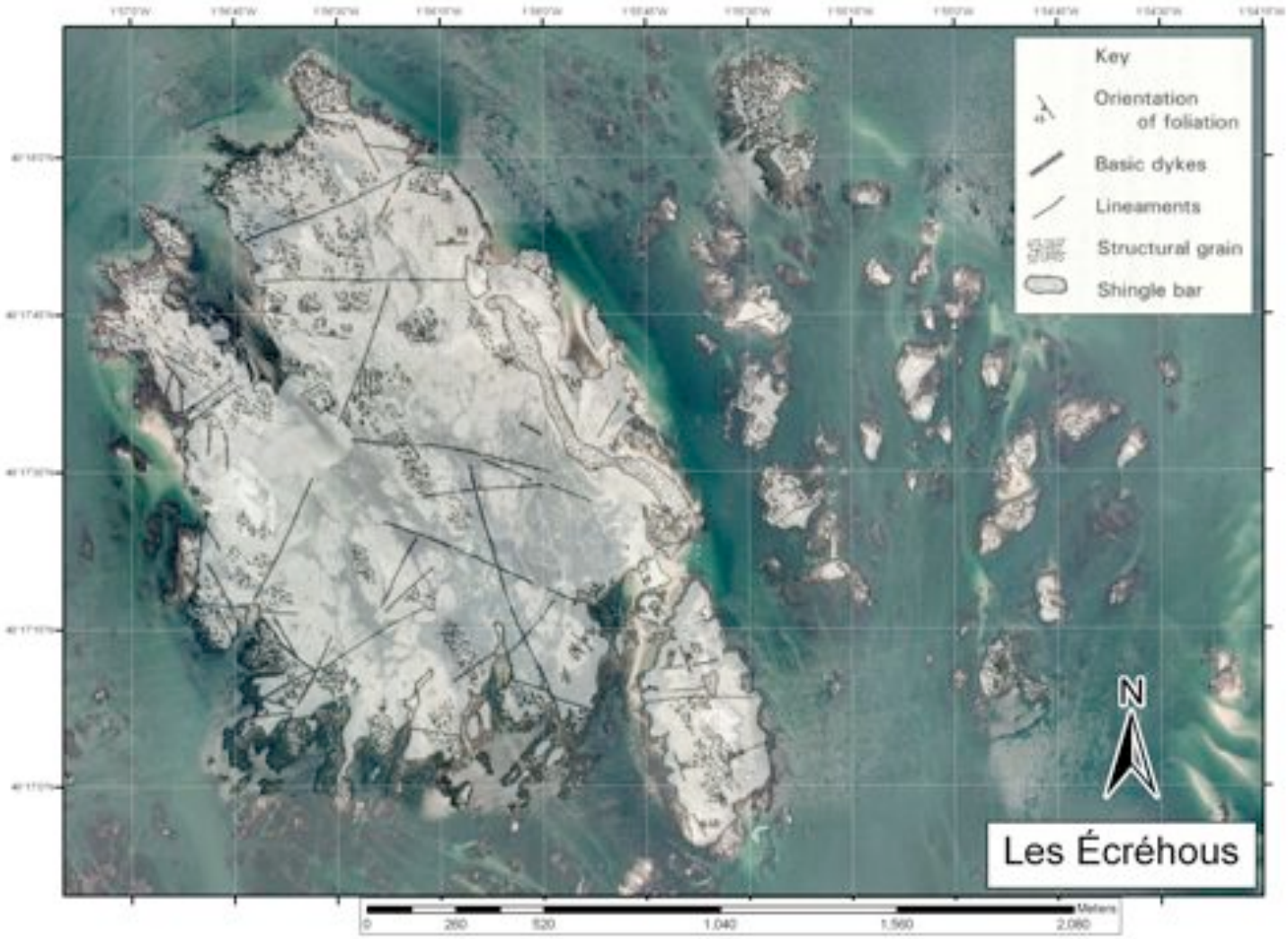


Figure 1.3: Main reef at the Écréhous, overlayed with geology from Renouf & Andrews (1996) (see figure 1.2).

1.2.2 Biology & Marine Environment

Rocky-reefs are known to be rich in biodiversity (Taylor 1998), and the three reefs in our study area (Figure 1.1) also have several abiotic factors which further elevate their value. Firstly, the tidal range of the area can exceed 12 metres, and constitutes one of the largest tidal ranges in the world (Rodwell 1996). The land area of Jersey increases from 117 km^2 at high tide to 163 km^2 at low tide; the land area of the reefs increases similarly, with a total area of over 155 km^2 exposed at low tide. This presents a huge area of myriad intertidal habitats, making these reefs valuable to many different fauna and flora (Bossy 1996).

The reefs are fed by clean, well oxygenated water, positioned in Le Golfe Normano-Breton; their location bordering both the cold and warm temperate marine biogeographical regions. These factors, together with the large tidal range, differing wave energy conditions and variety of substrata provide for an unusual assemblage of species, including species at the limits of their distribution; the combination of these features makes these sites rare and thus important locations for conservation and research (Freeman 2000, 2005*b*,*c*,*a*, Bossy 1996).

In and around the reefs, large teleost fish stocks are supported, particularly the european sea bass (*Dicentrarchus labrax*) and mackerel species (*Scromber* spp., *Trachurus* spp.) owing to the abundance of food species and high tidal stream rate (figure 1.4). There is an abundance of bivalves (*Pecten maximus*, *Venus verrucosa*), the gastropod *Buccinum undatum*, various edible crustaceans (*Cancer pagurus*, *Maja squinado*, *Homarus gammarus*) and the local 'delicacy', the Ormer (*Haliotis tuberculata*) (Bossy 1996). The high productivity of the areas has, in the past, caused conflict with the French – the outcome of one such dispute (after the French proposed the use of the Écréhous for tidal power) resulting in the eventual designation of ownership to Jersey by the courts of Hague, in 1953 (Beechey-Newman 1957). The abundance of edible organisms, combined with viable access here naturally lead to increased anthropogenic activity, and associated disturbance and pollution.

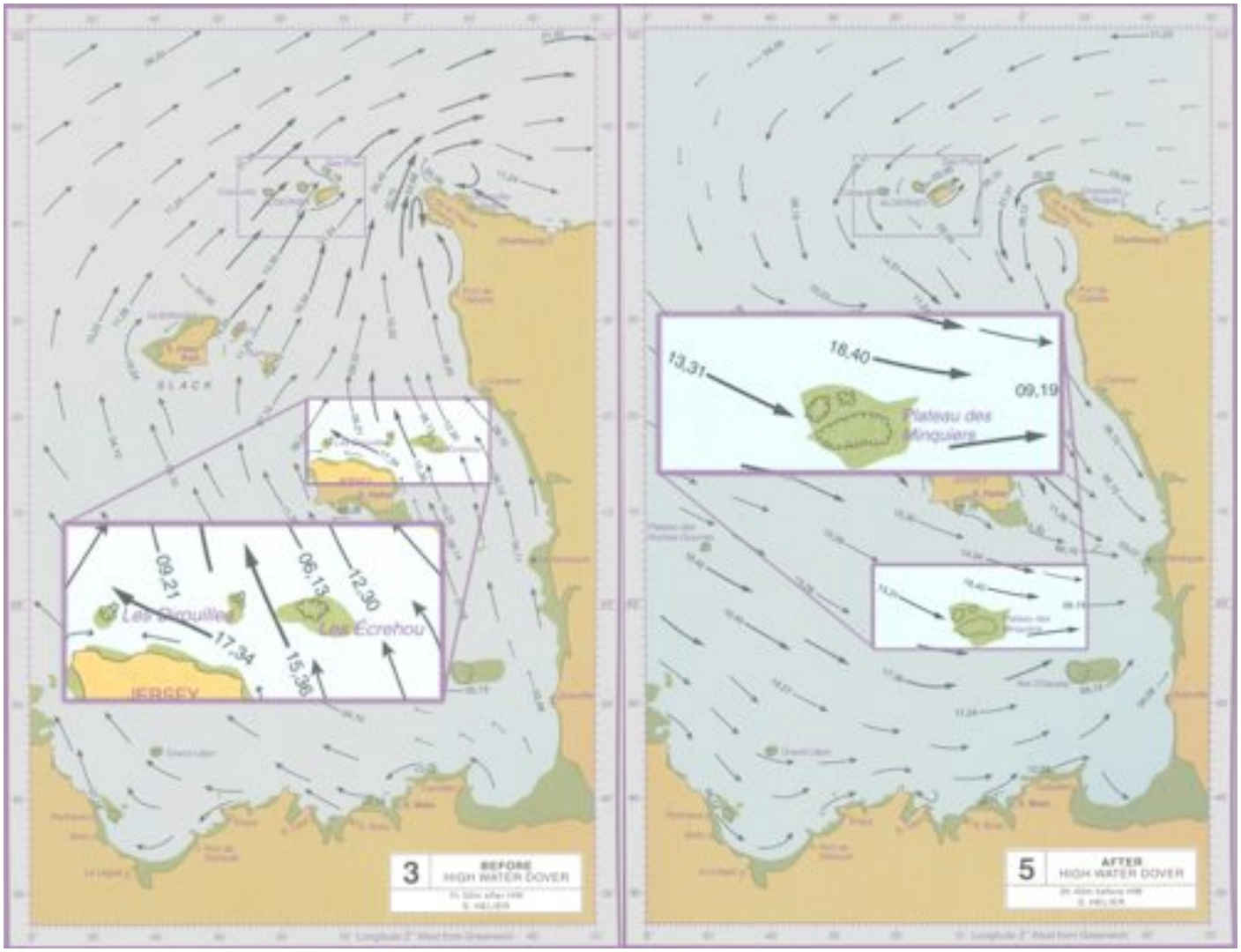


Figure 1.4: The tidal stream around the Channel Islands. Note the high rate around the reefs (zoomed); classed as 'Very Strong' by the JNCC's habitat-classification scheme (see section 2.1.2). Adapted from The United Kingdom Hydrographic Office (UKHO) (2008).

There are several notable species that can be found in and around the sites. At least seven Cetacean species have been noted, including: *Tursiops truncatus*, *Delphinus delphis*, *Lagenorhynchus albirostris*, *Grampus griseus*, *Stenella coeruleoalba*, *Phocoena phocoena* and *Globicephala melas*, all of which are protected under the Conservation of Wildlife (Jersey) Law, 2000. Additionally, *Acipenser sturio* – an IUCN listed ('Critically Endangered') species as well as an IUCN listed 'Vulnerable species' – *Cetorhinus maximus* may be found within the geographic area of the reefs. Less mobile species such as *Actinia equina* and *H. tuberculata* are also present – the latter of which is considered to be at its northern limit-of-range (Freeman 2005*b*,*c*,*a*).

1.2.3 Ramsar Designation

The Channel Islands themselves host several endemic species, in part due to their isolation, large range of habitats and mild climate. Their geographic location, in the English Channel, complements these factors and lends opportunity for migrating birds and in 2000, the South-East coast of Jersey was designated a Ramsar wetland site of international importance (ID 1043) (Ramsar 2009). This site (for which an ecological baseline is currently being established by Plymouth Marine Laboratory (PML)) provides for a large number of Brent Geese (*Branta bernicla*, as well as the more rare visitor ssp. *B. bernicla bernicla* and *B. bernicla hrota* (Young et al. 2008)), for example, during their over-winter migration from the Arctic to Northern Europe. The South-East coast supports extensive beds of *Zostera* spp. (seagrass) (Jackson et al. 2006), which are both an important food source for the geese as well as being highly productive primary producers, sediment stabilisers, and nutrient cyclers (Waycott et al. 2009).

In 2005, the 3 reefs were also given the Ramsar designation – Les Écréhous & Les Dirouilles, ID 1455; Les Minquiers, ID 1456 and the Paternosters, ID 1457 (Ramsar 2005,

2009). The reefs consist of similar vegetation and geology to the South-East Ramsar site, and support many common marine avian species, providing breeding grounds for Eurasian Oystercatchers (*Haematopus ostralegus*), Rock Pipits (*Anthus petrosus* and recorded migrant visits of ssp. *A. petrosus littoralis*), Common Terns (*Sterna hirundo*), European Shags (*Phalacrocorax aristotelis* – whose breeding status is currently poor), Great Cormorants (*Phalacrocorax carbo*), Lesser Black-backed Gulls (*Larus fuscus*) and Herring Gull (*Larus argentatus*, also showing recently declined breeding), among others (Young et al. 2008). The status afforded by the Ramsar designation brings focus to the reefs, and such status has in the past been shown to improve social concern and government expenditure on such areas (Gardner et al. 2009). It is in part because of this designation that mapping is of interest to the Government of Jersey.

1.3 Aims of the Research

Having now become acquainted with the region of interest, and aware of the importance of and protection given to the reefs, we establish the exact aims of the current research, before continuing to explore the related literature.

The current research aims to:

1. Establish the main biotopes located in the intertidal zone of the reefs, with regard to the chosen habitat classification system.
2. Be able to extract habitat classes from visible-spectrum aerial photography.
3. Explore Object-Based algorithms in order to determine the most appropriate manner in which to extract habitat classes from the available data.
4. Produce useful, usable habitat class maps.

Chapter 2

Background

With respect to the aims of this research, above, this chapter will explore the available literature and establish the state-of-the-art with regards to OBIA. We begin by becoming acquainted with relevant biology of the marine environment, with particular regard to rocky shores. Recent and relevant habitat classification systems are explored, and the classification system to be used in the current research is described. Remote Sensing (RS) is introduced, with an emphasis on RS for environmental study/monitoring, and applications of OBIA are discussed as well a brief comparison to more traditional classification techniques.

2.1 Marine Environment

The marine environment is of crucial importance in biogeochemical cycles, and essential for the functioning of current life on Earth. As well as being the first environment in which life evolved, it acts as a carbon dioxide sink (Siegenthaler & Sarmiento 1993), directly affects meteorological systems and feeds billions of people — the average consumption of fish and crustaceans, 2003–2005 was 16.4 kg/year (world-wide, *per capita*) (FAO 2006). It is an

incredibly complex environment with many interacting biotic and abiotic factors, temporal changes and vast spaces; the focus of this research, however, is on the rocky shores, whose intertidal zones are diverse both taxonomically and in terms of habitat types.

2.1.1 Rocky Shores

Rocky shores present myriad habitats, within which a range of intertidal and sublittoral organisms may colonise – they are rich in biodiversity (Taylor 1998). Acting within these habitats are a great range of key biotic and abiotic variables; of particular relevance are wave energy (sometimes referred to as 'exposure' though this may be confused with other variables relating to vegetative cover) and tidal emersion time, which principally affects organism distribution according to desiccation tolerance. These two abiotic variables offer interacting clines along which communities with differing species (particularly sessile) compositions may exist. It has long been recognised that these crucial factors affect the expected broad pattern of community type for a given area of the shore, with biotic interactions (predation, resource competition etc.) operating at finer scales (Little & Kitching 1996).

Ballantine (1961), defined a scale upon which organism distribution could be related to one particular abiotic factor of the local environment – that of exposure (wave energy). Realising the ambiguity and incomparability of some terminology used by researchers, Ballantine developed the exposure scale based on standard biological (community) trends seen across the range of wave-action affected sites. Though the definition of Ballantine's scale is tautological in nature – in that it uses community structure to define exposure that affects community structure – it provides for comparative analysis, forming a constant around which other variable parameters (such as salinity) can be further investigated. The Ballantine scale identifies negative (compelled to shelter) or positively (tolerant of high-energy) correlated occurrence of species. For example, *Pelvetia canaliculata* is negatively correlated with wave-energy –

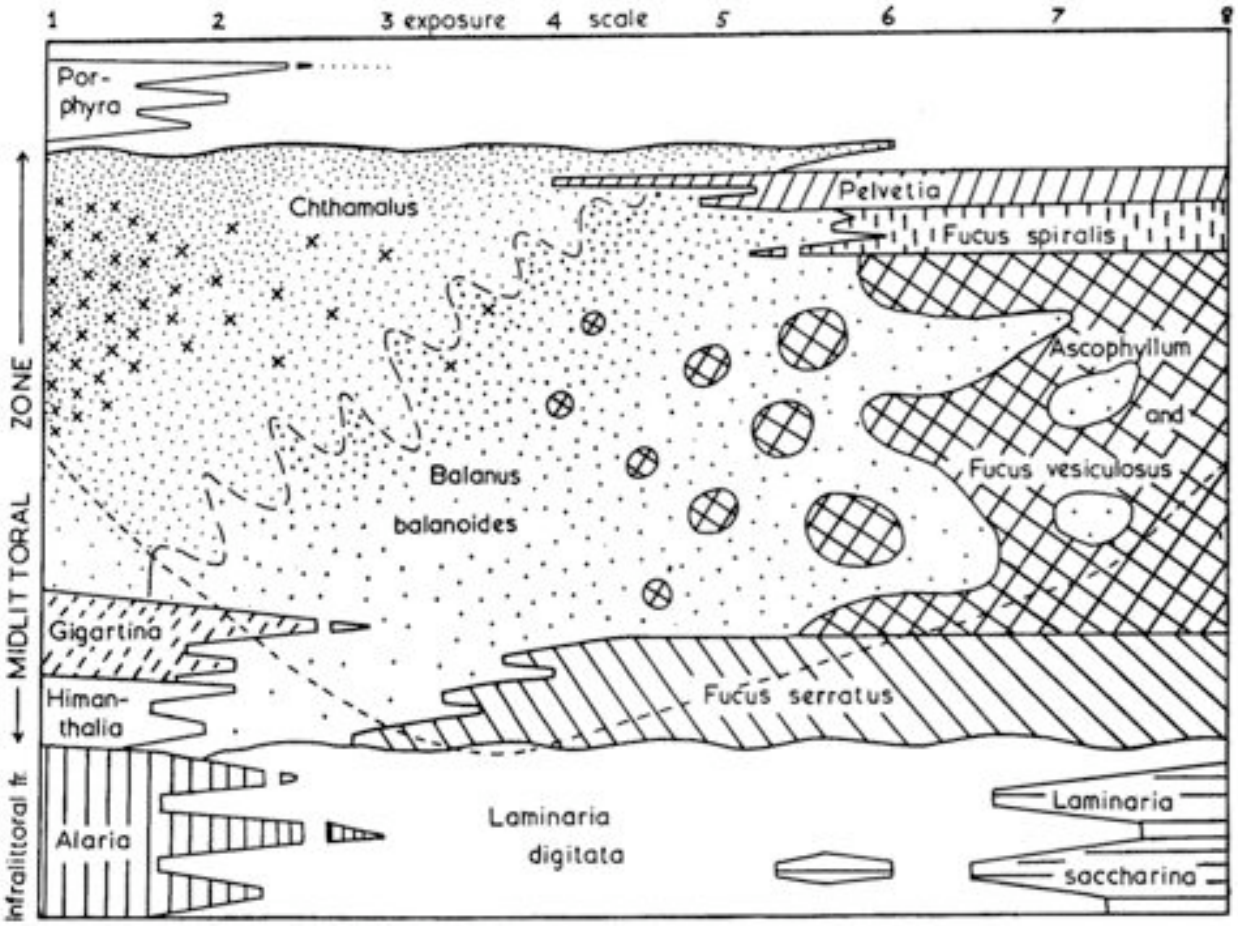


Figure 2.1: Ballantine's exposure (wave energy) scale from 1 (*extremely exposed*) to 8 (*extremely sheltered*) (Ballantine 1961).

it is absent from sites of high-exposure, while *Alaria esculenta*, which occurs sub-tidally, is positively correlated with high wave energy environments (figure 2.1). Current literature consistently reasserts the importance of wave exposure, and the way it affects many other abiotic factors that influence community structure (see for example Wernberg & Connell (2008), Gaylord (1999)).

While Ballantine (1961) exploits the community 'zone' patterns to form the (qualitative) biological scale of exposure, McQuaid & Branch (1985) present a quantitative analysis of different exposures, and relate this to the trophic structure of the community. McQuaid &

Branch found that there was a strong relationship between wave exposure and trophic structure, affecting the biomass of the important species in the community (but not species richness). They find that on sheltered shores, macroalgae form the largest component of biomass, and thus the community is a net producer (exporter) of energy, derived from macroalgal primary production, while on exposed shores where filter-feeders form the largest component of biomass, the system is a net consumer of energy. It should be noted that 'exposed' and 'sheltered' in the study areas of McQuaid & Branch would be rated 'extremely exposed' and 'exposed', respectively, by European standards.

The clines described above, and their causal factors, form identifiable zonation patterns on the shore (Little & Kitching 1996). The community zones around the British isles typically conform to Ballantine's descriptions, however, in any such attempt to rigidly define natural systems will result in some discrepancy, and Ballantine concedes this in his paper. The macroalgal zonation patterns certainly experience variance when moving from the waters of the United Kingdom to the shores of the Channel Islands. Trowbridge & Farnham (2004) identify variance in the littoral communities around Jersey, showing that *Codium* species' distribution across the tidal gradient differs from that of sites studied around the UK, nearby Guernsey and the French coast. Explanation may be due to Jersey's geographic location lying in the centre of the *Codium* species' distributional range. Trowbridge & Farnham's study shows that while generalisations are useful, field-surveys are a necessary requirement for classifications in environments where great variability exists.

One other aspect that helps describe habitats of rocky shores (and indeed other aquatic environments) is the sediment type. For this purpose, Wentworth describes several aggregate classes, with particle sizes ranging from $\frac{1}{2048}$ mm diameter (clay) through to $\geq$ 2048 mm (boulders); see table 2.1. This abiotic factor is crucial to many organisms – while some faunal members require interstitial spaces in which to breed, others (e.g. the Polychaetea and

Oligochaeta) require fine sediment with which to construct or bore their particular habitat. Flora, too, are affected by the sediment type and increased movement of sediment affects settling (or recruitment) of algal species (Schiel et al. 2006).

Table 2.1: The Wentworth scale of sediment particle sizes (Wentworth 1922).

Particle size (mm)	Class	Subclass
> 256	Boulder	
$64 - 256$	Cobble	
$4 - 64$	Pebble	
$2 - 4$	Granules	
$1 - 2$	Sand	Very Coarse
$\frac{1}{2} - 1$		Coarse
$\frac{1}{4} - \frac{1}{2}$		Medium
$\frac{1}{8} - \frac{1}{4}$		Fine
$\frac{1}{16} - \frac{1}{8}$		Very Fine
$\frac{1}{4} - \frac{1}{2}$		Medium
$\frac{1}{256} - \frac{1}{16}$	Silt	
$< \frac{1}{256}$	Clay	

It is through identifying such factors and providing robust scales upon which we may predict the likelihood of particular species assemblages, as well as through rigorous field surveys, that we may begin to accurately classify, better understand and hence better manage such environments.

2.1.2 Habitat Classification, Reserves & Management

Classification and mapping of habitats has long been practiced to aid management and conservation. Terrestrial systems have benefitted from such endeavours for decades, with mathematical strategies (Margules et al. 1988) and underlying principles (Pressey et al. 1993) being identified to aid reserve selection. Marine environments present difficulties for habitat mapping due to their variable nature, large coverage and harsh conditions, and thus effective

selection for management and protection has been somewhat slower and more problematic.

Parameters

Much work is currently being done in the field to establish parameters and procedures for selecting reserves (Kelleher 1996), including a recent report for the Countryside Council for Wales which aims to identify Highly Protected Marine Reserves (HPMRs) (Roberts et al. 2008).

With the collapse of marine capture fisheries world-wide, the consequence of industrial and indeed, smaller scale fisheries practices (Pauly 1998), the establishment of marine reserves, and management thereafter, is ever more important as part of a toolkit to protect fisheries and more importantly, the marine food web upon which they depend (Roberts et al. 2005).

Gladstone (2002) suggest the use of indicator species in the rocky intertidal zones for the selection of marine reserves, following successful terrestrial methods. Gladstone assessed the use of molluscs and macroalgae for this purpose, and concluded that indicator mollusc species may provide valuable insight into total species, though concede that this approach is not without limitations due to the spatio-temporal variability of marine environments. These findings are in agreement with Ward et al. (1999), who posit the use of fish and invertebrate species assemblages as surrogates for biodiversity indices when selecting reserves that constitute ~ 10 % of an area, while habitat selection is preferable when able to reserve ≥ 40 % of an area.

Roff & Taylor (2000) argue that delineation and mapping of habitats in the marine environment are crucial to managing these areas. By mapping and classifying habitats, resources can better be focused where they are needed. Roff & Taylor considers a geophysical classification scheme, arguing that marine ecosystems are crucially connected to physical parameters and influenced across a range of spatial-temporal scales. Using geophysical parameters allows

for classification in a 'top-down' manner, rather than a species-centric 'bottom-up' classification. The 'top-down' approach requires knowledge of the correlations between species and physical parameters, but removes the need for direct surveying of organisms – part of the benefit of remotely sensed data, and the only *practical* way to map and classify the marine habitat. Using geophysical parameters for classification also makes the classification hierarchy reusable, allowing interpretation of classification at the lowest (community and species levels) to be applied by means of more localised parameters.

Management of marine areas, then, can only be achieved through careful consideration of ecological and socio-economic parameters of a given site. Combining knowledge of habitat types with 'human-use' parameters allows for effective decision-making with regards to where and to what extent management areas should extend. Roberts et al. (2003) evaluate criteria for selection of marine management areas, adopting a more biology-centric approach than other management criteria. Roberts et al. (2003) posit that in order to ensure the effective choice of management areas, it is the underlying biology that is crucial to selection; with increased biodiversity or biological value comes greater returns in the long-term, providing dividends to fisheries and other human activities through careful protection of the sources. In agreement with Roff & Taylor's classification parameters, Roberts et al. recognise that whether it is species or habitat that are focused on for protection, it is important to cover all biogeographic regions; representation of all habitat types is essential.

Heterogeneity of a management area, therefore, is highly desirable: increased number of habitats of a given area supports a greater diversity of invertebrate species, for example. Benedetti-Cecchi et al. (2003) identify spatial heterogeneity as an important factor for management of Marine Protected Areas (MPAs), noting that there may be lower conservation value in designating an area of low heterogeneity for protection; they show that 2 unprotected areas incorporating more varied habitat types encompass assemblages found in a spatially

close (but variably distant) MPA.

There is an express need to know what habitat types exist; either as a direct measure of biodiversity, for consideration in a wider zonation system (e.g. Ortiz-Lozano et al. (2009)) or simply as a baseline for further studies.

In general, the literature uses several key parameters upon which classifications are based:

1. Exposure (Wave Energy)
2. Tidal amplitude and bottom slope
3. Nutrients stratification
4. Light
5. Water masses (as a function of temperature and salinity signatures)
6. Temperature
7. Salinity
8. Sediment type

Classification

At national and international scales, classification systems have been developed to aid governmental policy and land management. The European Environment Agency have conducted extensive work to produce the EUNIS (European Union Nature Information System) habitat classification system, which covers both terrestrial and marine systems[1]. This system is compatible with several national-scale classification systems such as UK BAP (Biodiversity Action Plan), OSPAR (Oslo-Paris Convention for the Protection of the Marine Environment of the North East Atlantic[2]), the *Council Directive 92/43/EEC* (1992), and the JNCC's Marine Habitat Classification system (Connor et al. 2004).

[1] `http://eunis.eea.europa.eu/habitats.jsp`
[2] `http://www.ospar.org/`

Mumby & Harborne (1999) introduce a standardised hierarchical scheme for mapping of coastal reefs in the Caribbean. They describe means to ensure confusion is reduced when interpreting results from remote-sensed class maps, for example by using coarse descriptive resolution for classes where there is uncertainty (for example, where depth may not be certain). They also use a combination of geophysical (abiotic) features coupled with biotic features to classify regions, so for example "low relief spur and groove + branching corals" is used to elevate the flexibility and ability to interpret community type from resulting maps. Mumby & Harborne also state the importance of using class labels that correlate well to the end-users' interpretation of them – where ambiguity exists, or where technical detail is too high, a compromise should be found.

Howes (2001) presents the 'Biophysical Shore-Zone Mapping System' used in British Columbia and the Pacific North-West. The use of 'bio-bands' (distinguishable component communities, or biotopes) in the shore-zone is made to establish shore units (see definition, below), which can then be sub-divided into components depending on their physical characteristics.

> *"a change in one or more components (form or texture) or in the process(es) operating in the shore zone"*
>
> – Definition of a shore unit (Howes 2001)

The classification system that we will use in this research will be the Joint Nature Conservation Committee (JNCC) approved system as defined by Connor et al. (2004) (henceforth referred to as the Marine Nature Conservation Review (MNCR) BioMar system). This system, refined from earlier projects, is structured to enable detailed classification in a scientifically sound, ecologically grounded manner, whilst being clear and sufficiently broad

enough that it can be used by the layman (Connor et al. 2004). The classification specification explicitly states that the system should be used in conjunction with GIS technologies in order to be useful, and hence is highly appropriate for this task. Furthermore, although the Channel Islands are not technically part of Britain (and hence does not fall under the JNCC's 'jurisdiction'), this classification is followed by Jersey's Environment Department as it is 'best practice'.

The MNCR BioMar classification is hierarchical and hence can be used at different levels (Table 2.2). The 5 broad habitat types are as follows: littoral rock, littoral sediment, infralittoral rock, circalittoral rock and sublittoral sediment. Further classification follows up the 6 levels, and becomes more well defined; this classification is recorded in a coded way. Factors involved in the classification follow other published parameters for marine classification (e.g. Roff & Taylor (2000)) and include salinity, wave exposure, tidal currents, zone (i.e. supralittoral to lower circalittoral) and substratum, as well as the species assemblage in the habitat space (Connor et al. 2004).

The MNCR BioMar classification uses definitions of wave exposure (table 2.3), sediment type (after Wentworth (1922)), zonation (figure 2.2), salinity and both vegetative and macroinvertebrate species composition. In Methods (chapter 3), following, this classification system will be used both in the field survey and during classification. Though the classification system makes use of many biotic and abiotic factors, the current research is only able (at present) to use these in a limited fashion, due to the feasible descriptive resolution that can be achieved in the scope of the current study.

Table 2.2: MNCR BioMar Marine Classification Hierarchy

Level	Classification	Class Count
Level 0	Environment (marine)	1
Level 1	Broad habitat types	5
Level 2	Main habitats	24
Level 3	Biotope complexes	75
Levels 4 & 5	Biotopes and sub-biotopes	370

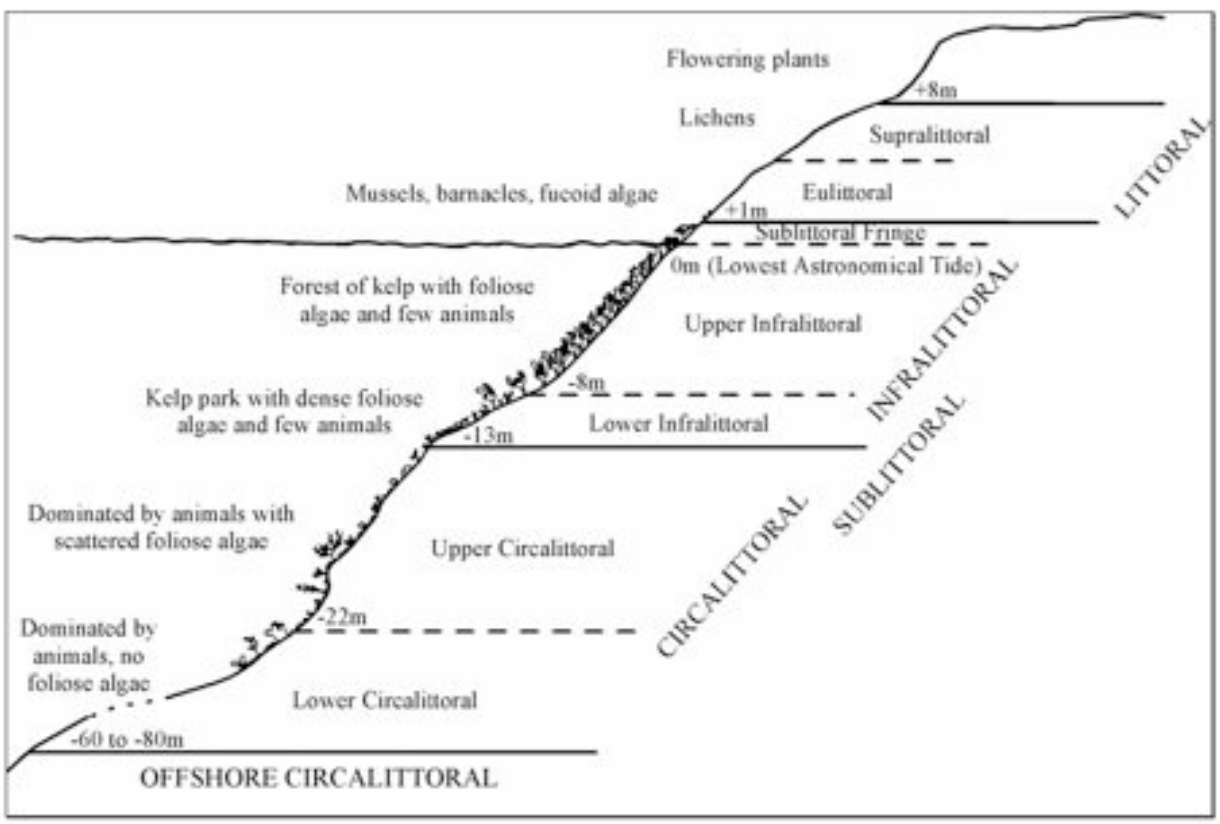


Figure 2.2: Shore profile, showing littoral zones (Connor et al. 2004).

Table 2.3: Wave exposure definition (Connor et al. 2004).

Wave Exposure	Description
Extremely exposed	This category is for the few open coastlines which face into prevailing wind and receive oceanic swell without any offshore breaks (such as islands or shallows) for several thousand km and where deep water is close to the shore (50 m depth contour within about 300 m, e.g. Rockall).
Very exposed	These are open coasts which face into prevailing winds and receive oceanic swell without any offshore breaks (such as islands or shallows) for several hundred km but where deep water is not close (>300 m) to the shore. They can be adjacent to extremely exposed sites but face away from prevailing winds (here swell and wave action will refract towards these shores) or where, although facing away from prevailing winds, strong winds and swell often occur (for instance, the east coast of Fair Isle).
Exposed	At these sites, prevailing wind is onshore although there is a degree of shelter because of extensive shallow areas offshore, offshore obstructions, a restricted ($< 90°$) window to open water. These sites will not generally be exposed to strong or regular swell. This can also include open coasts facing away from prevailing winds but where strong winds with a long fetch are frequent.
Moderately exposed	These sites generally include open coasts facing away from prevailing winds and without a long fetch but where strong winds can be frequent.
Sheltered	At these sites, there is a restricted fetch and/or open water window. Coasts can face prevailing winds but with a short fetch (say <20 km) or extensive shallow areas offshore or may face away from prevailing winds.
Very sheltered	These sites are unlikely to have a fetch greater than 20 km (the exception being through a narrow ($< 30°$)) open water window, they face away from prevailing winds or have obstructions, such as reefs, offshore.
Extremely sheltered	These sites are fully enclosed with fetch no greater than about 3 km.
Ultra sheltered	Sites with fetch of a few tens or at most 100s of metres.

2.2 Remote Sensing

The field of Remote Sensing (RS) is rapidly expanding in use and application. RS provides datasets from satellite or aerial-borne sensors, which, after some processing can be applied to various fields of research. RS technologies were initially created for military use, however, they have since been invaluable for urban planning (e.g. Masser (2001)), disaster detection (Tralli et al. 2005) and management (Montoya 2002) and environmental sciences.

2.2.1 RS for Conservation of the Environment

RS for environmental studies has been in practice since the 1960s (Low & Clancy 1967), and methods borrowed from RS for agriculture (Myers & Allen 1968) have been successfully applied to conservative environmental practices. Recently, much research is being carried out to extend the use of these technologies in the field of environment and ecology (see Kerr & Ostrovsky (2003), Turner et al. (2003) for reviews). Particular attention is given to land-cover, and changes therein (Anderson et al. 1976, Pfaff 1999, Mucher et al. 2000), for land-use planning management and detection of illegal logging (Asner et al. 2002, Bocco et al. 2001). RS and GIS are also highly beneficial to wildlife management – for habitat mapping (Viña et al. 2008), for example, and tracking of larger animals (Ropert-Coudert & Wilson 2005).

Though use of RS and GIS has long been prescribed for use in study of aquatic environments (Maher 1987), recently, it is ever-more increasingly in use, for benthos mapping, coastal and aquaculture management, and for detecting changes such as algal blooms (Kapetsky & Aguilar-Manjarrez 2002, Urbański & Szymelfenig 2003, Lobitz et al. 2000).

2.2.2 Aerial Photography for Marine Environments

While much of modern remote sensing uses multispectral satellite imagery for analysis, the field is not limited to this higher bandwidth imagery. Classically, visible-light only aerial photography was used, and indeed is still particularly useful with historic data where satellite imagery is unavailable. Photographic data may be available only in black and white, and this is typical of historic imagery. Ekebom & Erkkilä (2003) use black and white aerial photographs for broad habitat mapping in a manual way, and give insight into the positive and negative properties of different types of imagery for marine mapping. They also conclude that shallow marine habitats can be identified using aerial photographs to some extent, though even with colour images turbidity will reduce this capacity significantly. Where photographs are in the RGB band, more useful analysis can be achieved, using the separate bands to better distinguish vegetation for example.

Cuevas-Jiménez et al. (2002) showed that the use of RGB colour aerial photographs could be used to successfully distinguish corals and seagrass beds in the Gulf of Mexico. They combined the use of two <0.5 km^2 aerial photographs with underwater photography. The distinction was made in water of a consistent 4 m depth, on a clear day in clear waters, and allowed the researchers to identify different types of coral and seagrass, though there was an overlap of spectral signatures from the different benthic communities. Cuevas-Jiménez et al. stress the importance of the limitations of their study, pointing out that favourable conditions, consistent depth and selective use of photographs made classification easier than it would be with mixed-quality data.

Table 2.4: Factors affecting reliability of image processing for benthic cartography (from Pasqualini et al. (1997)).

Factors	Scale of reliability St Florent reef formation (2)	Urbino lagoon (3)	Mouth of the Fium'Alto (1)	Cap Corse (4)
Survey site				
Topography: slope	Slight and even (3)	Slight and even (3)	Slight and even (3)	Strong and uneven (0)
Bathymetric range	0 to 10 m (2)	0 to 10 m (2)	0 to 20 m (1)	0 to 20 m (1)
Water turbidity: visualization of assemblages and bottom types	100% of the depth range studied (3)	Less of 50% of the depth range studied (0)	100% of the depth range studied (3)	100% of the depth range studied (3)
Nature of assemblages and bottom types	Different (2)	Different (2)	Very different (3)	Similar (1)
Aerial photography				
Quality	Very good (3)	Very good (3)	Very good (3)	Very good (3)
Surface effects: specular reflexion, wave plane	No surface effect (3)	No surface effect (3)	No surface effect (3)	No surface effect (3)
Scanning				
Pixel size	Pixel $\leqslant$ 2 m (3)	Pixel $\leqslant$ 2 m (3)	2 m < Pixel $\leqslant$ 5 m (2)	2 m < Pixel $\leqslant$ 5 m (2)
Geometrical rectification				
Reference points: number	Number $\geqslant$ 20 (1.5)	Number $\geqslant$ 20 (1.5)	Number $\geqslant$ 20 (1.5)	Number $\geqslant$ 20 (1.5)
distribution	In 3 directions (1)	In 4 directions (1.5)	In 2 directions (0.5)	In 3 directions (1)
Referentiel scale/Image scale	Referentiel > image (3)	Referentiel = image (2)	Referentiel = image (2)	Referentiel = image (2)
Field data				
Area covered by field data/study site area	Area $\geqslant$ 10% of the study site area (3)	5% > Area $\geqslant$ 1% of the study site area (1)	Area < 1% of the study site area (0)	Area < 1% of the study site area (0)
Classification				
Number of polygons by assemblages and bottom types	Number > 30 (3)	Number > 30 (3)	Number > 30 (3)	Number > 30 (3)
Percentages (%)	92	76	76	62

Pasqualini et al. (1997) describe a procedure for ensuring accuracy of benthic mapping by aerial photography. They posit that due to the variability in the water layer above the benthos – of depth, surface roughness, turbidity etc. – that there needs to be defined procedures for coping with these differences. While the terms used are somewhat subjective (e.g. 'Good Quality'), Pasqualini et al. identify parameters (table 2.4) for consideration and a point scale upon which reliability can rated when using aerial photography for benthic cartography.

2.2.3 Hyper-spectral Data for Benthic Mapping

There has been much research into mapping of diverse and sensitive marine environments, particularly of coral reefs and seagrass beds (*Zostera* spp.) which are both highly productive and highly sensitive systems (Waycott et al. 2009). As these systems are in decline, research into monitoring them is now more crucial, and more abundant (e.g. Baden et al. (2003), Urbański et al. (2009), de Vel & Bour (1990), Mumby et al. (1997), Pasqualini et al. (2001)).

Side-scan sonar – an acoustic system – has been effectively used to map seagrass beds (for example Pasqualini et al. (1998, 2000)). It is widely used for bathymetric and benthic sediments and assemblages (Brown et al. 2002, Cochrane & Lafferty 2002, Freitas et al. 2003). Cochrane & Lafferty (2002) confirm use of Grey-Level Co-occurence Matrices (GLCM) (after Haralick et al. (1973)) for better distinction of different bottom types from the resulting sonograms. Side-scan sonar imaging is currently being used to assess the conservation value of Serpulid reefs in the Scottish Loch Creran, a Special Area for Conservation (SAC) (Moore et al. 2009). The current author and the research group at Glamorgan University are also undertaking investigations into the use of this imagery with OBIA techniques to establish position and size of such reefs.

In recognition of the need to identify and begin classification of the marine environment (particularly with the incorporation of the EU Habitats Directive into UK law), Diesing et al.

(2009) carried out research into identifying rocky reefs in the English channel. They used 2 echo-sounding methods along with underwater video transects to establish parameters of a broad stretch of the channel south of the Isle of Wight, recording the bathymetry, seabed character, benthic structures and point-sampled biotopes. From this information they mapped three EUNIS habitat types – high-energy circalittoral rock, circalittoral coarse sediment and deep circalittoral coarse sediment, and identify parameters for finding rocky reefs elsewhere. They note that stable, cobble-based sediments are similar in faunal species assemblage to that of exposed rock, and hence can be classified as solid (rock) habitats.

In Collin et al. (2008), the SHOALS (Scanning Hydrographic Operational Airborne Lidar Survey) system is introduced as a means by which the benthic environment can be mapped. SHOALS uses 2 signals to interrogate aquatic environments, employing near infra-red (NIR) which is absorbed by water, and the visible green band which is highly penetrative in water. The return times of these two signals can be used to establish benthic depth, the green response used to determine benthic substrate and objects, and the other waveforms produced by the radiative interaction are useful to establish land-masses and the water-air interface. SHOALS depth data is affected by turbidity, and benthic response affected by depth due to the conical spread of the laser.

SHOALS data is readily available for most of the North American coast, and has been successfully used in benthic cartography. Cochran-Marquez (2005) classified aerial imagery of the Hawaiian island of Molokai into 14 different substrates that describe the reef morphology, using SHOALS data and SCUBA-dived transects. While SHOALS uses a non-imaging approach, depth (bathymetry) can also be established by imaging techniques – that is by pixel value – with the log-transformed return signal having a negative correlation with depth (i.e. the 'darker' the pixels, the deeper the water) (Gao 2009). These techniques were pioneered by Polcyn et al. (1970) and Lyzenga (1978), and use two spectral bands with a correlated

difference coefficient with changing depth between them. The techniques have limitations, and require a known depth on which to calibrate the equation. Techniques from Lyzenga (1978) and Stumpf et al. (2003) can also be used to linearise the spectral response of a given substrate/assemblage through varying depth (equation 2.1). Linearisation of spectral response through the water column. $_i$ refers to the spectral bands (e.g. R, G and B), while $L_{i\infty}$ is the response of deep water for that band. Holden & LeDrew (2001) urges caution with this assumption of logarithmic attenuation of the signal, however, and shows that this is not reliable for short wavelengths.

$$X_i = \ln\left(L_i - L_{i\infty}\right) \tag{2.1}$$

A further limitation of the above, and other aspects of aquatic remote sensing is the effect of sea-surface roughness. The signal sent (or light detected) by the remote sense equipment (whether it be hyper-spectral satellite or black and white aerial photography) is subject to scatter from the sea-surface, should it be rough due to wind etc. Much research exists to reduce the effects of this scatter, and have been described for example by Hochberg et al. (2003). Such methods utilise the NIR band which is wholly absorbed from the water body, and thus exhibits no reflectance, which can then be used to calibrate reflectance in the visible light bands.

2.2.4 Object-Based Image Analysis for Classification with Definiens

The most recent methods of classification for both terrestrial and marine applications use not only the pixel values (spectral response) of the target sites, but also the *context* in which the pixel, or rather clusters of like-pixels, resides. This, the Object-Based paradigm of image analysis (OBIA) and subsequent classification (OB-classification), uses pixel values along

with some parameters for separation (such as weighting given to size and colour or shape) to create distinct objects ('image primitives') which can then be analysed in a similar way to classic RS methods (see section 2.2.5, below). For the most part, OBIA methods are carried out using Definiens software, and this has been established as the industry standard at the time of writing. Meinel & Neubert (2002) compare the segmentation algorithm used by Definiens (known as *e*Cognition in its earlier form) with that of other commercial and open-source software packages and find it produces the best results, alongside 'InfoPACK'. Leduc & Lavigne (2007) confirm that feature extraction (of boats) with Definiens is highly accurate, though it may take longer to set up initially (as it requires rulesets to be constructed by the user). They note that due to the manner in which Definiens is instructed to perform its classification, the accuracy of Definiens is wholly determined by the users ability to use the software.

In terms of applicability, pixel-based analyses are out-moded for modern high-resolution datasets. Blaschke et al. (2000) note that use of pixel-based analysis for high-resolution imagery produces rather unnatural classifications with what is known as the 'salt-and-pepper' effect, whereby small, isolated 1-pixel classes occur in amongst other larger groups of different 1 (or more) pixel objects – the result being a rather confusing and non-intuitive class map. The advantage of using objects over pixels for analysis at high-resolutions, then, are that the resulting classification is inherently more 'natural'. While there may be a small group of pixels of class A that are within one object that is classified as B, and thus could be argued to be incorrect, this is dependent on the descriptive resolution of the classification to be used; as discussed above, hierarchical classifications – which are analogous to the way in which humans naturally describe things, with reference to scale – allow for this, and OBIA can handle such instances through application of refined scale (see below).

Blaschke et al. (2001) and Benz et al. (2004) introduce OBIA procedures for GIS appli-

cations, describing how they differ from pixel-based processing. Benz et al. describe how one important aspect of OB-classification removes the burden on domain experts (such as foresters, marine biologists, urban planners etc.) to know the operational characteristics of the RS technology; instead they are able to concentrate on the objects in their field of expertise (e.g. trees, maritime environments, buildings etc.), and apply rules to the objects of interest – 'domain-limitation'. The rules applied to the objects create a spatial, semantic network where each object can access information about its surrounding objects, and each iteration of rule application further enhances this.

Blaschke et al. and Benz et al. explain the benefit of using scale as a means to understand and interpret an image; using successively closer scales can provide valuable context information, for example information about a single tree is enhanced when knowledge of its surrounds are combined: is it part of a forest, or is it part of an urban green-space? Using scale in the OBIA paradigm has a close mapping to real world hierarchies of structure, and is strongly applicable in the field of ecology – Wiens (1989) discusses the relative affects that scale imposes on studies of ecological systems, and the precautions that must be taken when evaluating studies that are limited by scale. Blaschke et al. notes that at increasingly fine resolutions the boundaries between seemingly distinct patches ('landscape elements') become more gradient-like.

Almeida et al. (2007) uses OBIA techniques in GIS to make urban population estimates. They used 3 levels of scale – block/street, vegetation/builtup areas and finally the urban objects (trees, grass, building, soil etc.). The type of building or settlement was then established using various parameters ('features'), for example the domain containing 'Favelas' (squatter settlements) could be limited in part by areas that do not contain swimming pools. These building/settlement classes would be used in future to estimate population size and distribution.

Jiang et al. (2008) also describe methods for building extraction, but introduce a mechanism for differentiating trees and houses from a 'tall' class, derived using a Digital Surface Model. Not having an available NIR band to compute the Normalized Difference Vegetation Index (NDVI), they used the red and green bands to produce their own 'NDVI', which the current research also makes use of (hereafter referred to as 'NDVI after Jiang et al.' or simply 'NDVI' – equation 2.2).

$$NDVI = \frac{(G - R)}{(G + R)} \tag{2.2}$$

Bock et al. (2005) use the OBIA approach to mapping various habitat types across Europe, using the hierarchical EUNIS classification system with Quickbird and Landsat ETM+ data. Bock et al. use fuzzy membership functions to distinguish between main classes, then apply Nearest-Neighbour classification for classes that have a large overlap in feature space – i.e. where rules are too complex to be manually created, the classification is trained using sample objects (figure 2.3). Bock et al. find a high accuracy of classification for many terrestrial habitats, but discovers difficulty with accurately classifying some marine habitats, citing issues with segmentation at the coastline. They also report that land cover types with objects of variable size and shape, or poorly defined boundaries, return a less accurate classification. Older datasets are posited for use with new OB-classification, as Bock et al. find a high transferability of the algorithm across datasets – the importance of this possibility is stated with regard to long-term conservation monitoring.

In Sims & Mesev (2007), assessment is made of the use of ancillary data, such as digital line graph, to enhance feature extraction. Sims & Mesev find that using these extra data increase the accuracy of classification, for both manual (user) and automatic classification. Pringle et al. (2009) compares pixel and OB-methods for the detection of changes in habitat of *Hoplocephalus bungaroides*. They report on the problems of pixel based methods

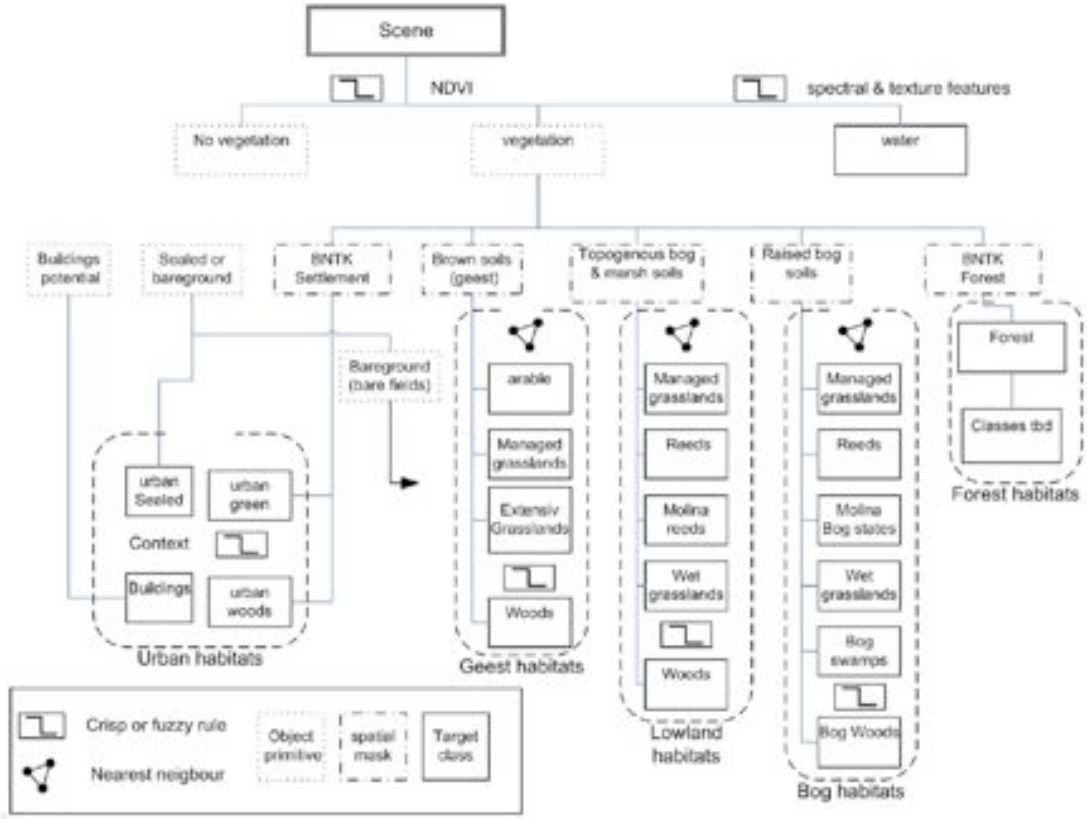


Figure 2.3: Procedural diagram for classification of terrain using the EUNIS classification system, in an Object-Oriented manner. From Bock et al. (2005).

excluding a hierarchical classification, and find that OB-methods produced more accurate classifications than pixel-based classifications, and also produced better results for images of lower resolution.

Mathieu et al. (2007) use OBIA methods to extract and distinguish vegetation communities, using IKONOS data. They compare this method with the traditional manner of manual classification from inspection of aerial photography. Mathieu et al. concludes that OBIA methods may not provide as detailed a classification as by manual procedures with aerials, but identify it as an efficient way to classify ecologically significant classes in a much shorter timeframe.

Benfield et al. (2007) applies OBIA techniques to the marine environment, and uses two datasets (and two different resolutions) – Landsat ETM+ and QuickBird imagery – to compare the classification methods maximum likelihood classifier, contextual editing and use of Definiens (*e*Cognition). Benfield et al. identifies that use of context sensitive classification for marine habitats is particularly useful due to the strong correlation of marine habitats with the particular environmental gradients (see section 2.1.1). This poses benefits over traditional pixel-based methods that cannot take advantage of context.

Andréfouët et al. (2000) shows that the use of probabilistic methods of classification derive more 'natural' boundaries, using fuzzy logic to state to what degree an object (or pixel) belongs to a given class. This 'fuzziness' allows interpretation of thematic maps to better correlate to real-world transitions in environmental gradients, for example, where an object may be mostly in one class but tending toward another. The use of fuzzy membership (where something is a a member of a class to a greater or lesser extent) can be leveraged to create decision rules, and combined with the contextual information made available by OBIA methods, powerful classification algorithms can be described.

2.2.5 Classification Background

Here, a brief overview of classic RS methods of classification, with an introduction into the methods and steps used in OBIA classification.

Unsupervised Classification

Aside from manual classification, where a user draws around areas with vector tools to define class areas, unsupervised classification is the most basic method available. Classification in an unsupervised manner takes parameters of each pixel and assigns clusters of like-pixels to a unique class. Pixels whose parameter values lie in more than one of the clusters' parameter

domains will be assigned to a class according to how close they are to each cluster group. The user is left to use knowledge of the image or ground-truth data to determine what each of the resulting classes represents.

This method, while semi-automated, does not use the object-oriented paradigm. Only pixel values are used to determine their closeness ('distance') to a given class, and their context is ignored.

Supervised Classification

Supervised classification, like unsupervised classification, borrows from pixel-based classification, using pixel values to define the classes. The difference with supervised classification is that the software is 'trained' to attribute certain pixels to certain classes based on their values; this is achieved by the user informing the software of some example pixels that lie within each class of interest – supervising, as the name suggests.

2.2.6 Object-Based Classification

The use of image objects over pixels is fundamental to object-oriented classification. While each pixel could be considered an 1×1 object in itself, this rather misses the power of segmenting the image into larger (discrete) objects. Segmentation – which uses a 'fractal net evolution approach' – is performed on the image according to fitting-functions of the relatedness of groups of pixels (Blaschke et al. 2001, Baatz & Schäpe 2000). Definiens achieves this in various ways, but crucially the algorithms take combinations of scale, shape, colour and compactness as their parameters, where values of shape and colour are inversely related to each other and compactness describes the linearity of pixel groups – both these scales (i.e. the range from colour to shape dominated and non-compact to compact) are defined between the values 0 and 1. Scale is a unit-less parameter that determines allowed heterogeneity of

an object (Navulur 2006, Definiens 2008).

Post-segmentation, the image is divided into small chunks, or objects; known as object primitives, as they are simply based on the algorithm's parameters for segmentation and do no necessarily relate immediately to real life. These object primitives contain similar pixels (according to the above parameters), enclosed by other objects that have significantly dissimilar pixels within them. These objects form the basis of our classification technique. Because each object is enclosed by other objects which are dissimilar, but have a relationship to each other (see Tobler (1970) for the 'first law of geography' relating to proximity of real-world objects), rules can be defined that use the context of one object to place it in a class, as well as the pixel-based parameters of unsupervised classification (though these now relate to an object's mean pixel values rather than an individual pixel's values).

Chapter 3

Methods

3.1 Study Site

The area of study comprises 172 km^2, located to the north and south of Jersey, in the Channel Islands. The 3 main reefs, the Paternostas, Les Écréhous and Les Minquiers are located at co-ordinates (2°12'37.69"W, 49°17'31.19"N), (1°56'6.35"W, 49°17'30.662"N) and 2°7'35.654"W, 48°58'16.75"N) respectively (WGS84).

3.2 Data

3.2.1 Acquisition

Imagery and photographc meta-data were obtained from the States of Jersey Environment Department. The images were captured by Fugro-BKS Limited, on the 16th and 17th April, 2003 between the hours of 13:06–14:59 and 14:12–15:36 (local time), from an average height of 1086 m and 1342 m respectively. Only images acquired on the 17th cover our AOI.

The photography was flown using a film camera (Leica RC30) and exposed onto Agfa

```
False Easting: 40000.000000000000000000
False Northing: 70000.000000000000000000
Central Meridian: -2.134999999999999800
Scale Factor: 0.999999900000000050
Latitude Of Origin: 49.225000000000001000

Name: GCS_ETRF_1989
Angular Unit: Degree (0.017453292519943299)
Prime Meridian: Greenwich (0.000000000000000000)
Datum: D_ETRF_1989
  Spheroid: WGS_1984
    Semimajor Axis: 6378137.000000000000000000
    Semiminor Axis: 6356752.314245179300000000
    Inverse Flattening: 298.257223563000030000
```

Figure 3.1: The Jersey Transverse Mercator Projection

X100 colour aerial film. The film was converted to digital format using a ZI Photoscan TD high resolution roll feed geometric scanner. After the images were orthorectified they were dodged (to even hot spots and vignetting effect) using Zeiss Image Station Raster Utilities software and then colour balanced to remove radiometric variations using INPHO OrthoVista software. There was no IR capability with the imagery.

After data acquisition, some further processing was made before the imagery was used in the Definiens Developer software. A script was run over the data, using Python and the ESRI ArcMap Python Library (`arcgisscripting`) to project the imagery into the Jersey Transverse Mercator grid (figure 3.1), supplied with the imagery. The imagery was then loaded into ESRI ArcMap 9.3 along with shapefiles of the surrounding territories (Great Britain, Jersey, Guernsey, France; acquired from maplibrary.org[1]) to establish context. Several image tiles were chosen containing representative contents of the entire dataset, in order

[1] `http://maplibrary.org`

to familiarise the user with anticipated land cover types and common features.

Predicted tide data was acquired from the Proudman Oceanographic Laboratory (POL) for the relevant dates, from the station in Jersey at St. Helier, and the station in Sark at Maseline Pier.

Geological thematic layers were created from scans of Renouf & Andrews (1996).

3.2.2 Meta-data Use

The available Meta-data described the height, X Y coordinates and time at which the photographs were taken. This data was used in various ways – initially, the X Y Coordinates were loaded into ArcMap with the imagery to establish the times at which each image tile was acquired. This procedure allowed for estimates to be made of tidal state, after interpolation from tidal data acquired from POL. Data from the two stations, St. Helier (Jersey) and Maseline Pier (Sark) were plotted (to the nearest 30 minutes) and the resulting graph used used to estimate the water height range over the photographs (figure 3.2).

Some error was introduced through using predicted tide data, plotting it to the nearest 30 minutes and also assuming linear tidal movement. From the graph in figure 3.2 the tidal range of the imagery was determined to be between approximately 1 and 2 meters above chart datum, with the introduced error not deemed to be significant, as the images range across time and therefore some error pre-exists. With knowledge of the lunar cycle (from the University of Texas McDonald Observatory[2]), it was established that the imagery was acquired during a spring tide, thus for all intents and purposes the images provide a reasonable exposure of the intertidal zone, excepting the lowest $\sim$ 1 to 2 m.

[2] `http://stardate.org`

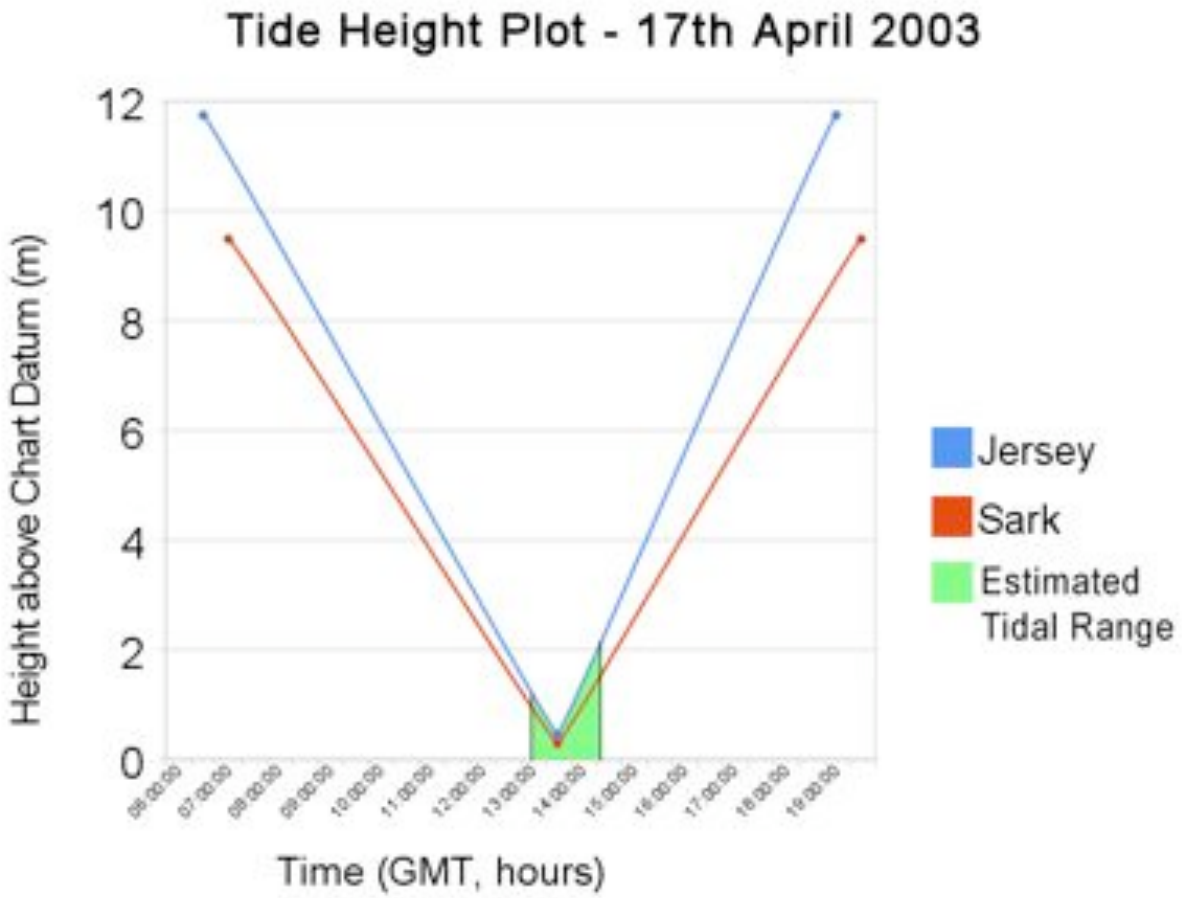


Figure 3.2: Tide plot taken from the two closest stations. The estimated tidal range has been drawn in green, based on the timestamps of the photographs. Note the photo-capture period has been corrected to GMT.

3.3 Ground Truthing

In order to verify and further refine the classification derived in section 3.4, it was necessary to carry out ground-truthing (field surveys). This serves as a calibratory tool for the further development of the algorithm, to quantify accuracy, and for the determination of exact species assemblage structure for these particular environments (as Trowbridge & Farnham (2004) confirms).

3.3.1 Methods

Methods were taken after Bunker et al. (2001), visiting the site and establishing the major biotopes by recording GPS co-ordinates along with a photograph, loading these points into a GIS (ArcMap 9.3) and transcribing the biotope data to the MNCR BioMar shortcodes thereafter. The survey methods described by Bunker et al. were used only in part, due to the automated manner in which the current research intends to establish classification, and the target descriptive resolution desired. Further, to work out what each biotope is on the aerial photographs precisely, by hand, would be to bias the author's development of the algorithm such that it tends toward perfection, rather than producing a testable algorithm that can be applied to establish major biotopes elsewhere.

Survey

The field survey to the Écréhous was made on the 7th of August, 2009, departing from the fisheries offices at La Collette, Jersey at 0915 (BST). Arrival to the reef was at 1100, at GPS co-ordinate N 49°17'26.4", W 01°53'43.1" (WGS84). The tide was high on the reef at approximately 0811 am (BST), at $\sim$ 10.08 m above chart datum (estimates based on St. Helier predictions, figure 3.3).

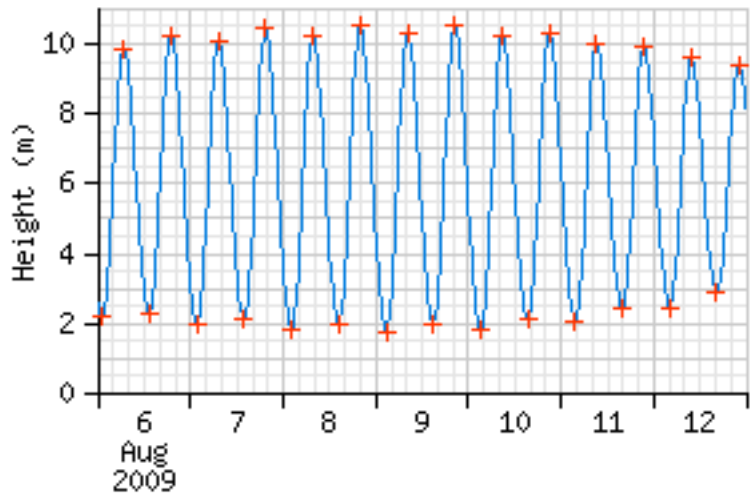


Figure 3.3: Tidal plot estimate for the St. Helier, Jersey (6–12th August, 2009). Source: http://www.pol.ac.uk

Equipment

The following items were used in the survey:

1. GPS Unit – Garmin eTrex
2. Compass
3. Canon 40D DSLR with Canon EF-S 18-55 mm IS + hama UV filter
4. 1 m rule
5. Safety equipment including: Mobile phones, radio, rope, med kit.

Biotopes

The reef was walked from the landing point, up the main shingle bar in a North-Westerly direction. Biotopes were assessed and recorded as they became apparent, and as the tide permitted (figure 3.4). This form of survey is known as 'purposive' or 'judgmental' sampling, whereby the samples are selected purposefully as they are determined to be representative

– as discussed in McCoy (2005), this is a permissible and valid field method as the survey team included a domain expert (a marine biologist) who is the end-user of any classification maps produced.

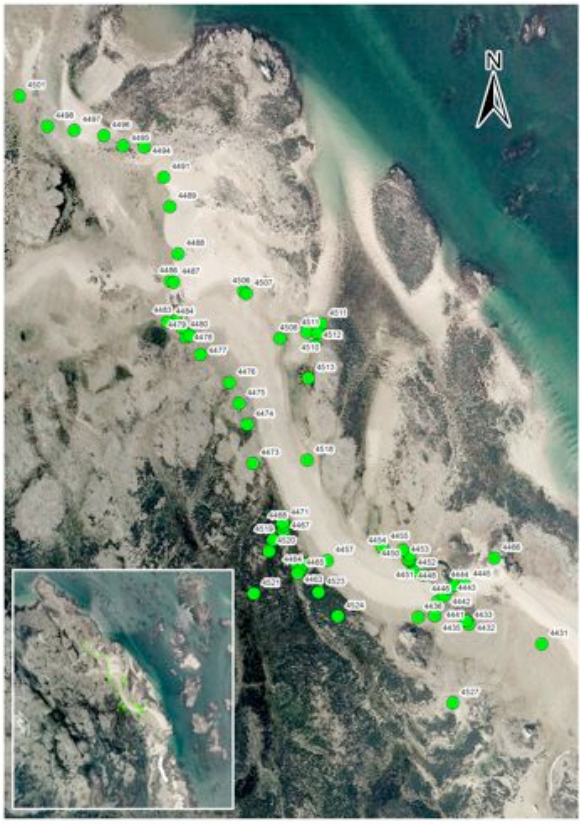


Figure 3.4: Samples at the Écréhous – photo ID numbers shown.

Transect

A transect was carried out across the reef from a supralittoral area down to the sea to establish zonation (figure 3.5). The transect line was recorded with the GPS and the track is show in figure 3.6. A meter rule was placed and a photograph was taken, along with a GPS reading.

Figure 3.5: Zonation across the reef at the Écréhous

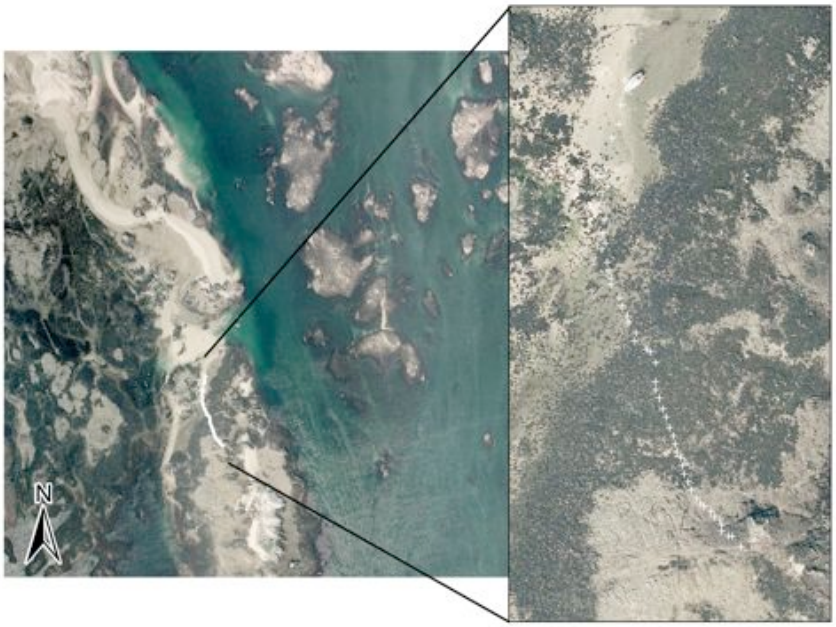


Figure 3.6: Transect at the Écréhous

3.3.2 Issues

Data from the GPS unit is subject to a degree of error, and this is typically up to 10 m. During the survey, the GPS unit was reporting an accuracy of $\sim$ 7 m, and hence the data points acquired may not be accurate. This is particularly important when considering the upper littoral area of the shore, where the zones progress rapidly – the readings for the GPS can be misleading, indeed, with reference to figure 3.6, it is clear that the starting point in the South is not on the rock plateau where the transect actually begun.

3.3.3 Results

After the GPS waypoints were loaded onto the GIS, each photograph was assessed and given an MNCR BioMar classification shortcode. Due to the descriptive resolution of the imagery – namely that of flora and immobile fauna only – MNCR BioMar codes were used that excluded faunal species (excepting *Semibalanus*/*Chthamalus* and *Patella* spp.), i.e. where a shortcode existed that could be determined on site by identification of fauna only, the code used was the lowest hierarchical tier above this that excluded faunal species. The main biotopes potentially identifiable from the aerial photography are described in figure 3.7.

3.3.4 Observations

Some observations were made that may affect the results of the classification ruleset.

Bird Nesting and Guano Deposits

As discussed in section 1.2.3, Les Écréhous is a designated Ramsar wetlands site of international importance – i.e. it is of importance to birds. During the survey, several groups of Common Terns (*Sterna hirundo*) were encountered, fiercely guarding both their feeding

(a) **LR.LLR.F.Pel** – *Pelvetia canaliculata* on sheltered littoral fringe rock

Figure 3.7: Potentially identifiable biotopes

grounds (where the survey team attempted to sample!) and the rock peaks they had chosen for their nesting sites; the sites yet to be free of this year's fledgelings. It was noted that due to the guano deposits on the rocks, the reflectance of these rocks was altered – a feature known to be of use for distinguishing bird nesting sites (Schwaller et al. 1984). These sightings are encouraging as the reef has previously suffered abandonment, probably due to human activity and a strong algal bloom thought to disrupt the bird feeding patterns, causing significant reductions in bird population levels[3].

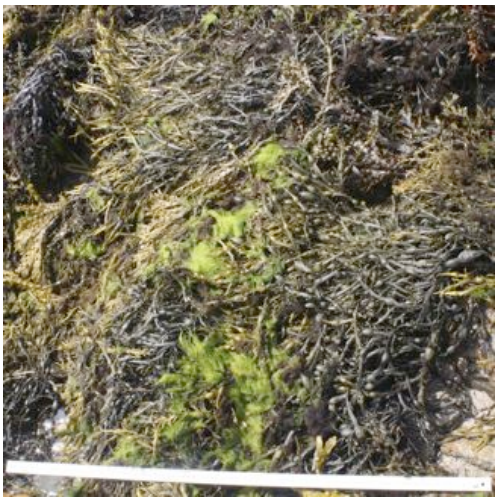
Algal Variation

One algal species whose identity was not immediately apparent when surveying demonstrates some of the problems that may be encountered when carrying out the classification. This particular specimen (figure 3.8) had a strong green colouration compared to its neighbours, perhaps due to natural variation and hybridisation that occurs among algal species (Coyer et al. 2002). This phenotypical morphing may affect what species groups can be distinguished

[3] `http://www.societe-jersiaise.org/ornithology/2007-breeding-season-autumn-2007.html`

(b) **LR.FLR.Lic.YG** – Yellow and grey lichens on supralittoral rock

(c) **LR.FLR.Eph.Ent** – *Enteromorpha* spp. on freshwater-influenced and/or unstable upper eulittoral rock



(d) **LR.LLR.F.Asc.X** – *Ascophyllum nodosum* on full salinity mid eulittoral mixed substrata

(e) **LS.LSa.MoSa** – Mobile littoral sand

Figure 3.7: Potentially identifiable biotopes

(f) **LS.LCS** – Littoral shingle

(g) **LR.FLR.Rkp.FK.Sar** – *Sargassum muticum* in eulittoral rockpools

(h) **LR.FLR.Lic.Ver.B** – *Verrucaria maura* and sparse barnacles on exposed littoral fringe rock

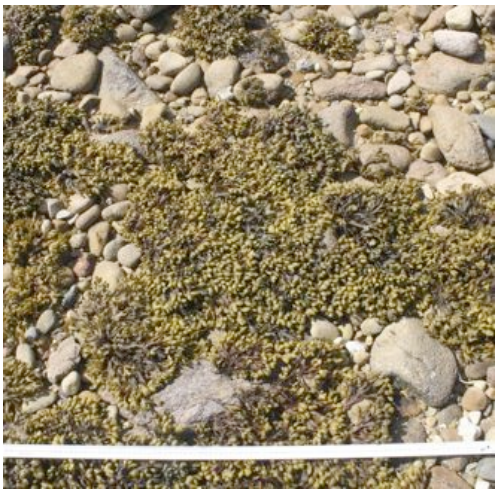
(i) **LR.FLR.Lic.Ver.Ver** – *Verrucaria maura* on very exposed to very sheltered upper littoral fringe rock

Figure 3.7: Potentially identifiable biotopes

(j) **LR.FLR.Rkp.G** – Green seaweeds (*Enteromorpha* spp. and *Cladophora* spp.) in shallow upper shore rockpools

(k) **LR.HLR.MusB.Sem** – *Semibalanus balanoides* on exposed to moderately exposed or vertical sheltered eulittoral rock

(l) **LR.LLR.F.Fves.X** – *Fucus vesiculosus* on mid eulittoral mixed substrata



(m) **LR.LLR.F.Fspi.X** – *Fucus spiralis* on full salinity upper eulittoral mixed substrata

Figure 3.7: Potentially identifiable biotopes

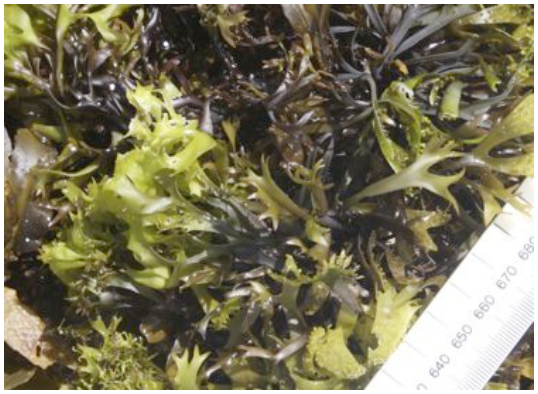


Figure 3.8: Unidentified fucoid (*Mastocarpus* spp.?), with strong green colouration.

from aerial images, as the resolution is likely to be too low (despite its 'high-resolution' status) for this sort of determination. This is where context from zonation and topography should play a key role in classification of this sort.

3.4 Classification Automation

The majority of work in this research has involved homing in on the best approach for classification of the rocky reefs, given limited data. As described in chapter 2, there are many well established ways of classifying land and habitats from imagery, however, the exact parameters of our research are somewhat under-explored.

Peculiar to this research is the limited band width of the imagery available, namely that of the visible light. Typically, Remote Sensing methods utilise at least the Red, Green, Blue and Very-Near Infra-Red (R, G, B, VNIR respectively), and maximally have hyper-spectral ranges extending into the microwave frequencies. The imagery made available for this research is limited to only the RGB bands and hence much 'quick' domain-limiting analysis (such as the masking of water bodies using the VNIR band) is not applicable. Below we examine the

methods attempted to extract meaningful classes from the imagery.

3.4.1 Segmentation

Initially, attempts were made to segment the full resolution images – which contain 100 million pixels – at small scales. Trials were carried out to establish the performance of Definiens Developer on the available computer systems, to ascertain the feasibility of classifying all image tiles at full resolution.

Methods were chosen after Benfield et al. (2007), who describe parameters to locate extended reaches of sea, and pick out compact areas of reef. Segmentation was performed at a very large scale (2000) creating 'Level 000', and a smaller scale (900) creating 'Level 001', to extract broadly similar areas; Benfield et al. used scale parameters of 1000 and 450 with 0.6 m/pixel resolution imager in this instance. Scales of 2000 and 900 were chosen as the available imagery has a resolution of 0.1 m/pixel, and these scales were found to provide good segmentation of smaller potential objects in the image such as the rock beds in a similar way to Benfield et al.. Parameters for shape and colour were set to 0.2 and 0.8, compactness set to 0.6; after Benfield et al. – the compactness weighted high to define compact areas of rocky reef. This segmentation, taking approximately 40 minutes resulted in well defined broad-cover objects at Level 000 (Figure 3.9), and a further 35 minutes to produce less useful objects at Level 001. Segmentation was also performed weighting the RGB layers differently in an attempt to expose the most optimal segmentation, however, the results were not significantly different at this scale.

Due to the time constraints of the work, and the performance of segmentation at this resolution, it was decided to reduce the effective resolution of the images to that of QuickBird data (0.6 m/pixel) as these data are well established in their use for classifying habitats (e.g. Pringle et al. (2009), Benfield et al. (2007),Bock et al. (2005)) and thus can provide reliable

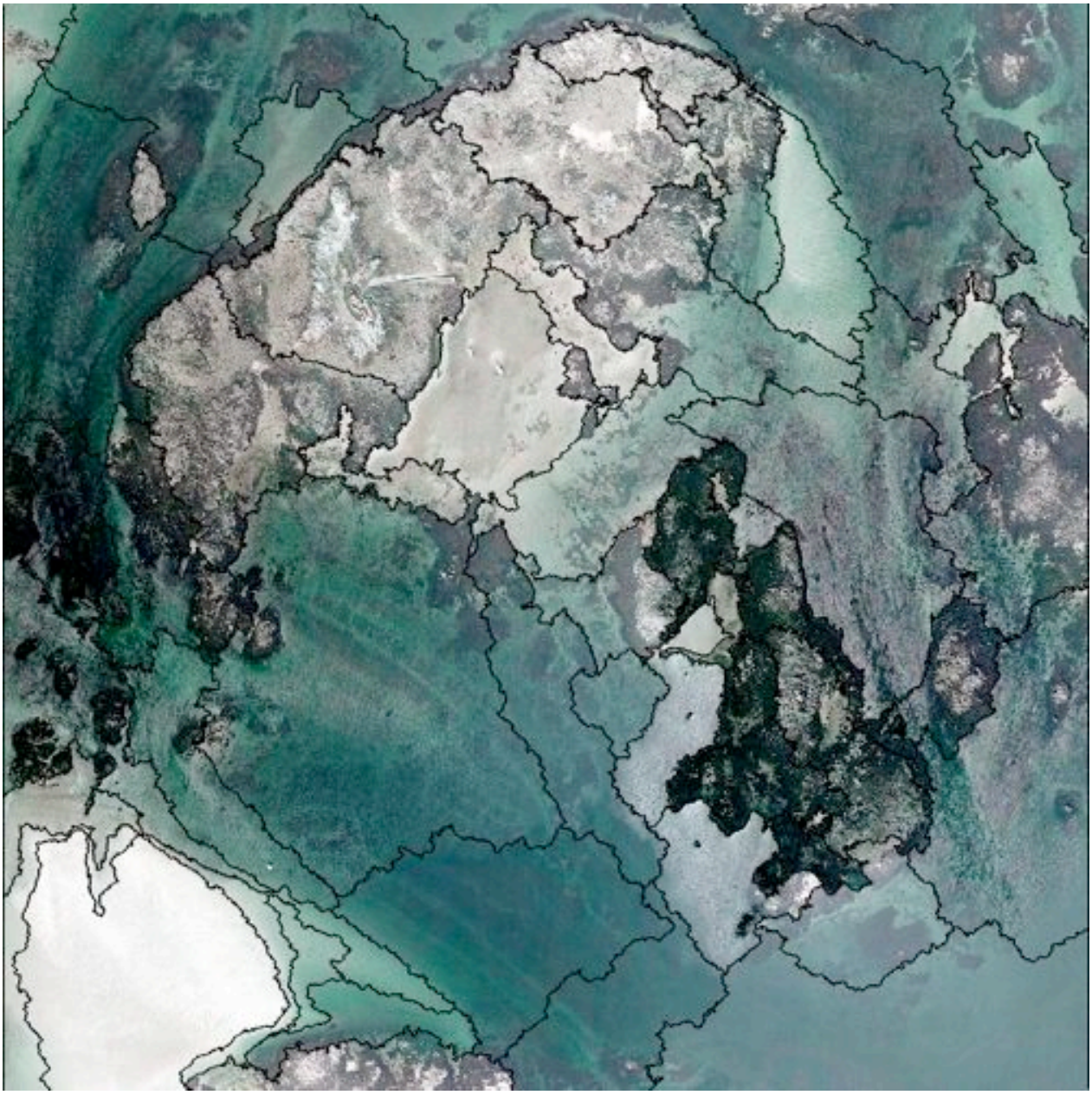


Figure 3.9: Showing a 2000-scale segmentation of the training image (10 cm per pixel resolution)

habitat maps at broader scales. This allows faster segmentation, and broader classifications to be made effectively which could then be exported as thematic maps and over-layed onto the original high-resolution images for refined classification of areas of high interest (such as the rocky habitats) in future.

3.4.2 Hierarchical Classification

The first step in classification is to reduce the image domain to find a region of interest (ROI). This domain-limiting (top-down) approach closely maps to real-life hierarchical classification schemes, and the top-down manner of classification has been posited as best-practice (see for example Roff & Taylor (2000), Mumby & Harborne (1999), Connor et al. (2004)). With this approach in mind, a prototype image breakdown was constructed by inspection of the initial segmentation, and the real-life habitat classes contained within (figure 3.10). This is not an attempt to mimic a true hierarchical tree – there are portions at a 'higher' level of segmentation (i.e. broader scale) that will contain areas that need to be sub-segmented and reclassified.

3.4.3 Multi-Resolution Segmentation and Domain Limiting

NDVI after Jiang et al. (2008)

While techniques exist to assist with the desired initial split into three broad classes ('Sea Dominated', 'Vegetation Dominated' and 'Mineral Dominated'), many of these methods require the use of the NIR band, which allows for both masking of the sea by (near) zero-return values, and extraction of vegetation by very high return values, the NIR band was not available for the current research. As a substitute, the method described by Jiang et al. (2008) is employed, using equation 2.2 (see section 2.2.4). Using 3 fuzzy membership value ranges,

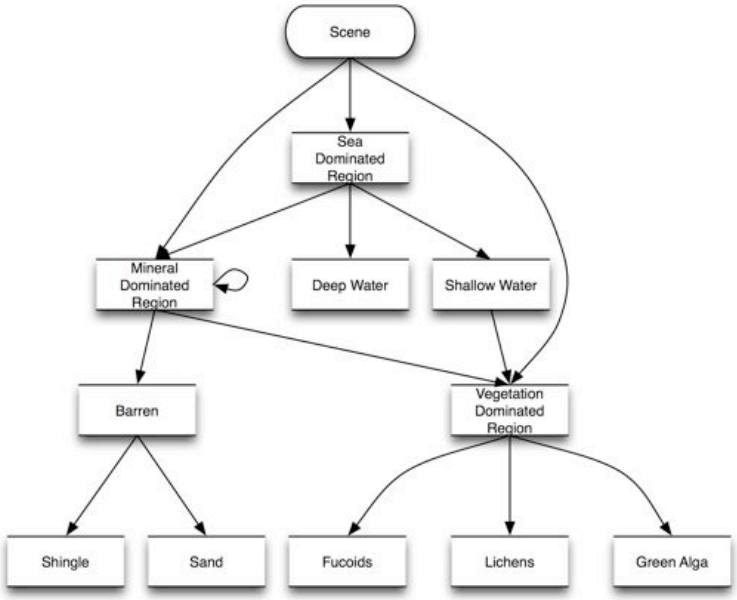


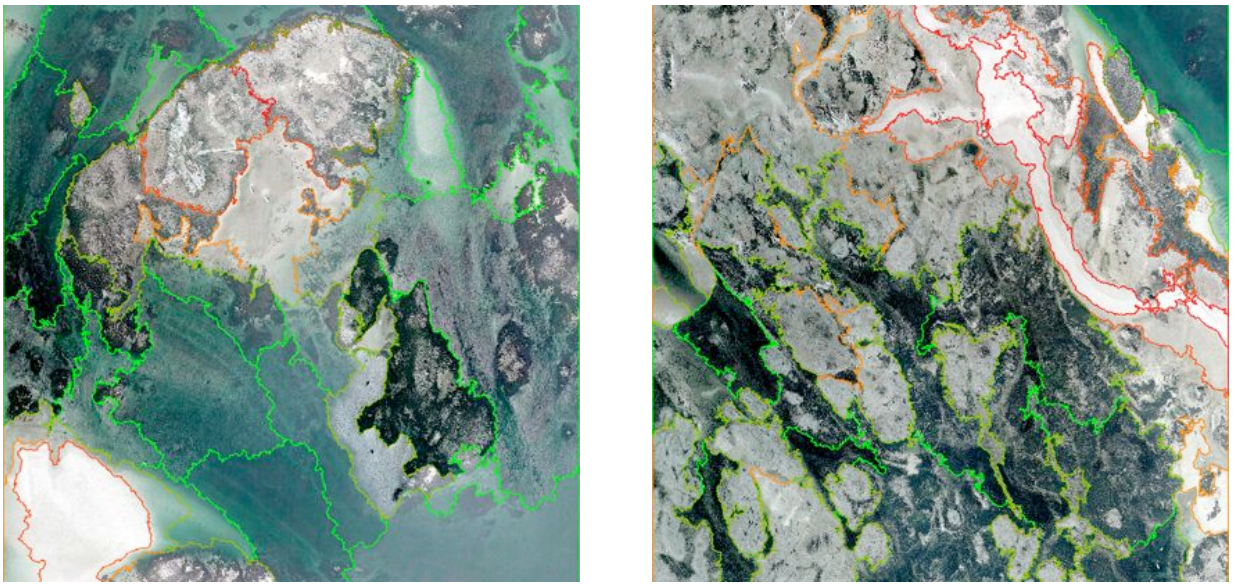
Figure 3.10: Top-down prototype of image breakdown.

the imagery is classified into objects that lie in the low, mid or upper NDVI range (where NDVI refers to Jiang et al.'s substitute). Table 3.1 shows how the 3 ranges correspond to areas of the image, also see figure 3.11 showing two test images (one from the Écréhous and one from the Minkies) with object classification outlines displayed.

A note on nomenclature: Throughout the creation of the ruleset, conformation to the following convention was attempted – `^Class` denotes a non-final, non-strict hierarchical class; `_class` denotes a temporary working class; `Class` denotes a final classification class.

Table 3.1: NDVI after Jiang et al. (2008), final fuzzy ranges used to broadly split the imagery, and how the image regions fit into these classes

NDVI Range	Lower limit	Membership curve	Upper limit	Image relationship
High	0.05		0.7	This range incorporates homogenous areas of sea, sea with small rocky outcrops, sea with submerged vegetation and areas of mixed algae.
Medium	-0.02		0.06	Here, rockbeds and sandy areas are represented, typically with some brown and green algae. This range also includes patches of sea that are subject to a large glint effect.
Low	-0.4		-0.01	Rockbeds and sandbanks/shingle bars, with emersion tolerant fucoids, lichens and barnacle communities.



(a) Les Minquiers (b) Les Écréhous

Figure 3.11: 1 km^2 tiles, with the NDVI ranges applied. (Green = High, Orange = Intermediate, Red = Low)

Vegetation Extraction by Domain Limitation

After the initial broad split, the vegetation was extracted. Due to the way in which the ranges of NDVI divided the imagery, particular forms of vegetation occurred in the different divisions.

Typically, lower-eulittoral fucoids would occur in the `^Low NDVI` regions which also contain broad expanses of sea. In order to separate these out further, 3 classes were created: `Sea`, `^Lower-Eulittoral Fucoids` and `^Upper Infralittoral Fucoids`, based on two properties of the objects – `Brightness` and `Mean Canny Edge (Red band)` level. The `Brightness` feature is calculated using the RGB bands; while `Sea` regions cover a broad range of `Brightness`, the fucoid classes typically tend toward the lower limits. `Mean Canny Edge (Red band)` is an edge-extraction algorithm (Canny 1986) which, for this process, used the red band of the image (as the red frequencies are well-absorbed by water bodies) – regions

of `^Low NDVI` that have a high mean value for their Canny Edge layer will typically contain small areas of rock-surface (for vegetated areas) or glint (on the sea). The combination of this and the `Brightness` values allows for separation, though some confusion remains for areas of sea that exhibit a high degree of glint (see section 4.2 for comments on how to overcome this).

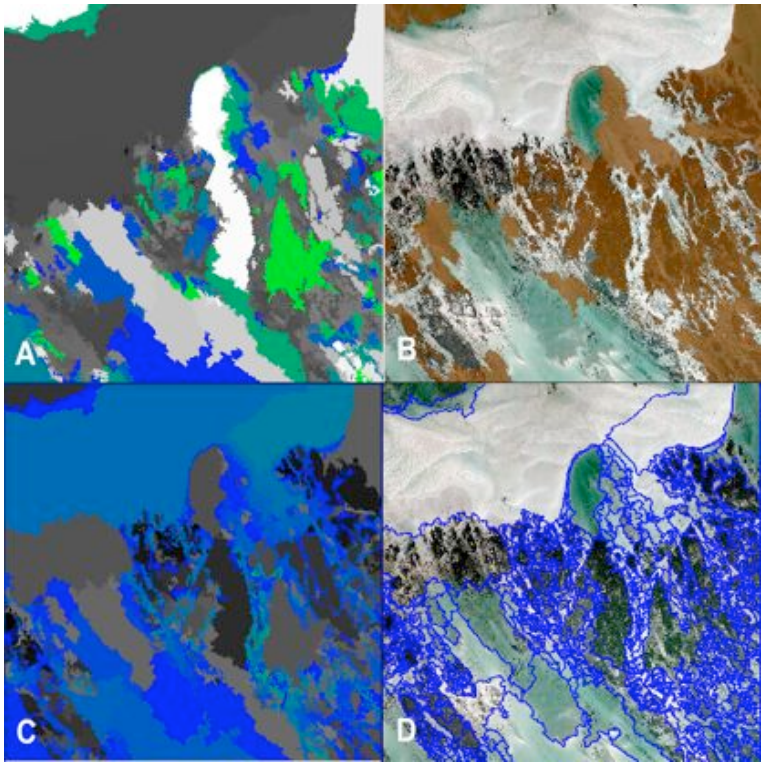


Figure 3.12: Establishing thresholds for parameters that identify small objects dominated by algae. `A` highlights objects with relevant NDVI, the blue through green objects are 'in range'. `B` shows a classifictaion during refinement; objects coloured brown should all be macroalgae – there are mismatches. `C`'s blue objects are in the desired range for Brightness. `D` is the original image with segmented objects outlined in blue.

Similarly, the `^Mid NDVI` regions contained some patches of algae. While not as substantial as those in the `^Low NDVI` regions, they are significant enough to warrant separation. This was achieved by identifying regions of `^Mid NDVI` that had a relatively high Standard Deviation (SD); as this region is typically bright, a higher SD would mean that the region

contains darker parts – algal patches. These regions were classified using an intermediate class called `^Vegetated Eulittoral`.

Once broad beds of vegetation had been classified, and regions including patches, these regions were further segmented with parameters: Shape = 0.1, Colour = 0.9, Compactness = 0.6, Scale = 75, producing distinct objects at `Level 001`. The NDVI was then recomputed for these objects and used in combination with brightness to identify the newly created objects. The range values were established by means of hard thresholds, rather than fuzzy membership (figure 3.12).

3.4.4 Quad-Tree, Region-Growing

An object-based approach used in cell biology to extract the stained nucleus of a cell, for example, is to use quad-tree segmentation with region-growing (Definiens 2008). A fast segmentation using a quad-tree algorithm is performed, then the brightest region of the image (which will always occur in the nucleus, for this type of imagery) is identified and this 'parent' object (known as the Parent Process Object (PPO)) used to find all adjacent objects which are within a limited range of brightness compared to the parent. This action is

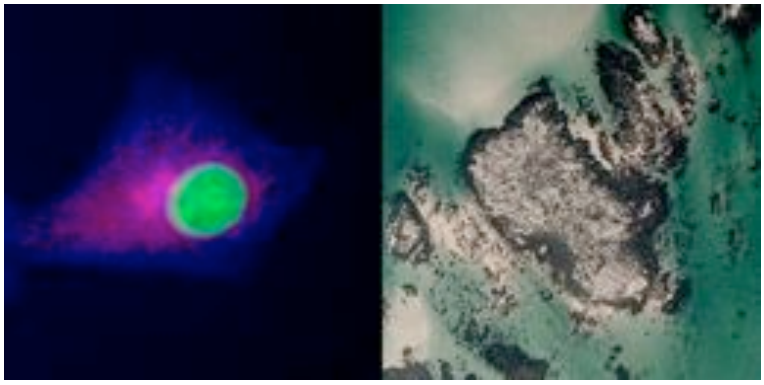


Figure 3.13: A typical cell image, for which the PPO-region growing technique is useful, and likeness to protruding rock peaks.

Figure 3.14: A seagrass meadow at Les Écréhous, mixed with *S. muticum* (photo – N. Jouault, Société Jersiaise)

performed iteratively on all adjacent objects which do fit the criteria, treating each of them as the new PPO for evaluation of those surrounding.

Because of the apparent similarities between a protruding, vegetated rock peak and bright cell nucleus surrounded by less distinct organelles and cell membrane (figure 3.13), it was posited that this algorithmic paradigm may be applicable. Though parallels can be drawn, the colouration of the cell lends itself to this sort of analysis, however, it is more difficult to find such a distinguishing feature of the rock peaks, without the use of NIR. Direct transferral of this technique proved inappropriate due to this reduced distinction with many parent objects being identified in the first instance. However, while iterative region-merging runs classified the entire image as one class (a consequence of the shallow gradient of feature values across the image), a single region-growing run proved adequate to classify most of the rock peaks after a quad-tree segmentation with a scale factor of 45.

Quad-tree segmentation was further utilised to identify infralittoral regions that are potentially vegetated. These regions, that may contain crucial resources such as seagrass meadows (figure 3.14), are critical for many organisms (see section 2.2.3), and the methods used to locate them were relatively simple in comparison to other classes in the imagery. Regions

identified as `^High NDVI` (with large areas of sea) or `^Intermediate NDVI` (containing sea with small rock peaks) that had not been classified as fucoids, but had been identified as `^Vegetated Eulittoral` at `Level 000` were segmented at `Level 001` using the quad-tree algorithm (scale 45), producing over a million small objects. These objects were then assigned a class of `_submerged` if they were sufficiently dark (values less than 90) and had a value over 40 in the red band (in order to distinguish shallow submerged vegetation from deep water, where near-zero values occur in the red band). The resulting objects were tidied up by merging and removing any very small objects (area less than 150 pixels), and the remaining objects grown over the candidate objects to envelop small enclosed regions.

3.4.5 Context

Identification of enclosed regions is a useful algorithm that was taken advantage of in the ruleset. This method demonstrates one way in which context can be used to infer the nature of the objects. For example, given a net-like array of `Fucoid Bed` objects, any objects entirely enclosed by these objects will translate to either peaks of rock protruding out from them, or rockpools recessed within them – the difference identified by colour or NDVI. Another area in which this form of enclosure context can be applied is to objects that have a parent of `Sea` or `^Vegetated Eulittoral` at Level 0, but no classification at Level 1, but around which there exists a ring of `_submerged` objects. Typically, the classification from the peak identification (above) identifies at least one small object within this ring, and so a rule can be constructed which uses the unclassified objects within the ring as candidates, and reclassifies them as `^Rock Peak` if they are in contact with a `^Rock Peak` object. The resulting objects are merged, and the process looped until there are no further modifications (the process is guaranteed to terminate, since we only modify objects enclosed by the `_submerged`).

3.4.6 Nearest Neighbour Approach

One initial approach tested was the nearest-neighbour techniques that use samples from the desired class to classify other objects which have similar values for given features. The approach is useful for quickly classifying all objects in one image tile, though the user has to select their samples carefully, and there is a tendency to keep selecting more and more samples until all the objects expected to be classified *are* classified. This proves problematic when transferring the algorithm to another test tile, as the exact type of objects in the image may differ. Nearest-neighbour techniques were used to separate out objects that had overlapping feature spaces; where possible, however, separation of the domain in which they occur was attempted.

The procedure was applied to the `^Rock Peak` regions, which incorporate barren rock, the lichen bands – the dark band of *Varrucosa maura* that encircles fully emersed rock, and the yellow and grey lichens (*Xanthoria* spp. agg.) that inhabit the emersed rock in the upper spray zone, barnacle-dominated rock, sand, shingle and certain areas of fucoids on rock. The fucoids had previously extracted due to their low NDVI value, a result of their sparsity or position on the shore – some are subject to long periods of emersion and tend to be lighter brown (after drying) and contain less mixed-in green algae (such as *Enteromorpha* species which occur in the rockpools and mid-eulittoral zone). Samples were manually chosen to represent these classes, after multiresolution segmentation with a scale of 75, and these samples were iteratively refined, manually.

3.4.7 Multi-tile Classification

Due to software license restriction, the output classifications from individual tiles cannot be stitched in Definiens to create an entire thematic layer. While they can be exported to

individual 1 km^2 tiles, and imported into GIS software such as ArcMap for example, and processed after, it is desirable to classify across the entire image set. This is particularly true when context is a factor – image edges have an effect on features such as whether or not an object is enclosed by another class, for example. The procedure described for segmentation and classification, above, was therefore tested on mosaiced versions of the imagery.

Processing of the imagery was done by creating an ArcMap-Python script to batch-resample the imagery to 0.6 m / pixel. This was performed with the resampling algorithm option set to 'BILINEAR', as it averages the surrounding pixels in a consistent manner, keeping the resulting values within the original bounds. It also smoothes the data, maintaining the gradient of values typical of RGB imagery. This process also converted the filetype from ECW to IMG, and thus rendered the output readable in ERDAS Imagine 9.0, which was then used to mosaic the imagery into ∼9-tile squares using the Mosaic Tool utility. Larger mosaics, while desirable, proved too large for the memory requirements of Definiens on the computer system available. The mosaics were then processed in the same way as the 1 km^2 down-sampled (0.6 m) tiles.

Ruleset Summary

Above, the core techniques used to create the ruleset are discussed. Using the approaches described, a final ruleset was formed and tested using the multi-tile mosaic. In the following section this ruleset is explained and examined.

Chapter 4

Results and Analysis

The ultimate outcome of this research is a robust ruleset (algorithm) that can be used to quickly classify large areas of imagery accurately, reliably and at ecologically meaningful descriptive resolutions. Much of the time involved in the work was involved in experimental trials of the methods described above (section 3.4), with refinements of both the parameters used for specific rules, and refinements in the exact manner in which to approach the extraction of different classes in the imagery. In this chapter, we examine the final rulesets produced, and analyse their use in the context of marine habitat classification. We also inspect the final classifications produced by the rulesets (see plates I and II), and assess their utility to ecologists.

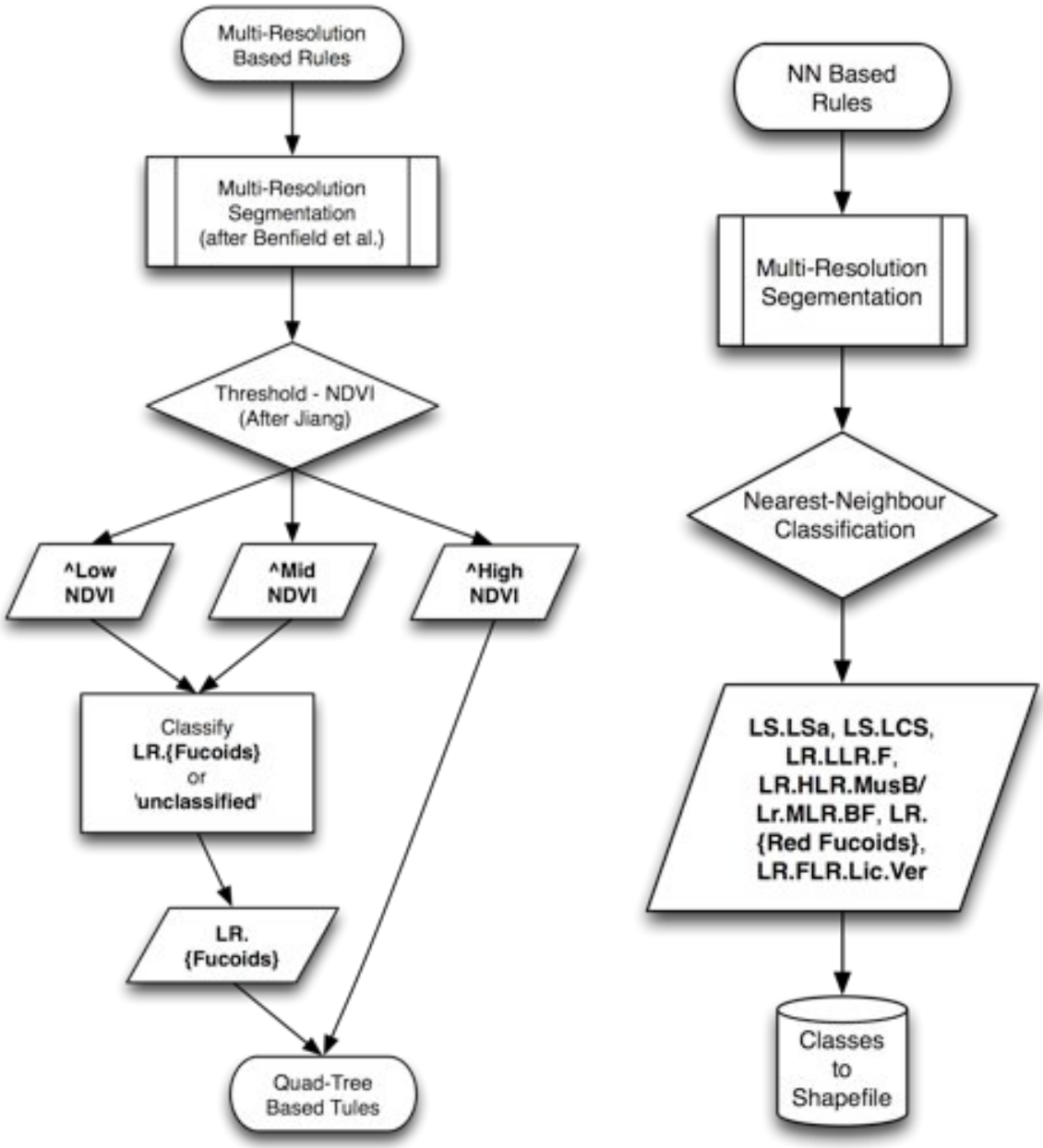
4.1 Rulesets

The final product of the research exist as rulesets that can be applied to RGB-only imagery of temperate rocky-shore marine environments, to a broad descriptive resolution described by the classes in table 4.1. It should be noted that the research established static values for

Table 4.1: Classes used in the classification, and their rôle in the ruleset, as final or working classes

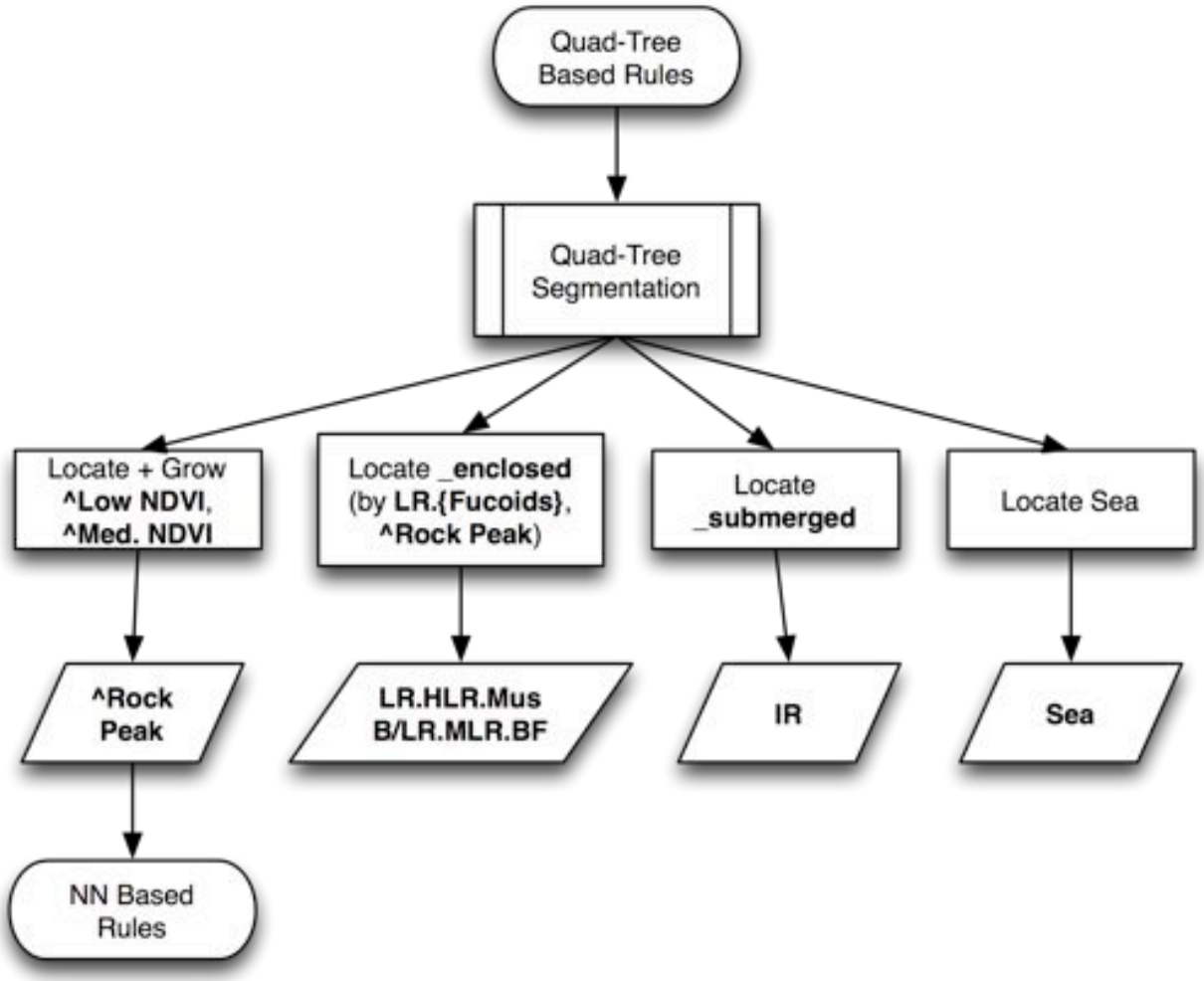
Classname	Rôle	Description
`_bright`	Working class	Identification of peaks (bright areas, low NDVI)
`_dark`	Working class	Identification of fucoids on `^Rock Peak`
`_find_peaks`	Working class	Quad-tree segmentation class, originally for identification of peaks (but reused)
`_submerged`	Working class	Identification of `IR (?)`
`_enclosed`	Working class	Context rules of enclosure, temporary classification.
`^Low NDWI/NDVI`	Higher-tier class	Areas of very bright land – some red algae & lichens
`^Intermediate NDWI/NDVI`	Higher-tier class	Areas of rock and algae or rock peaks in sea
`^High NDWI/NDVI`	Higher-tier class	Sea dominated or greener algae
`^Vegetated Eulittoral`	Higher-tier class	Used for fucoid extraction from `^Intermediate NDWI/NDVI`
`^Mid-Lower Eulittoral Fucoids`	Higher-tier class	Used for fucoid extraction from `^High NDWI/NDVI`
`^Upper Infralittoral Fucoids`	Higher-tier class	Used for fucoid extraction from `^High NDWI/NDVI`
`^Variable Supra/High Eulittoral`	Higher-tier class	Used for vegetation extraction from `^Low NDWI/NDVI`
`^Rock Peak`	Higher-tier class	Broad class for any areas of extruding rock, not heavily vegetated
`Sea`	Final class	Any areas dominated by water not otherwise classified
`IR (?)`	Final class	Potentially vegetated infralittoral areas.
`LR.{HLR.{FR,FT},MLR.{MusF,BF}, LLR.F,FLR.Rkp}`	Final class	Fucoids (also referred to as the class `Fucoid Bed`)
`LR.HLR.MusB, LR.MLR.BF`	Final class	Barnacle dominated rock areas
`LR.LLR.F.{Pel,Fspi}`	Final class	High-Eulittoral Fucoids
`LS.LCS.Sh`	Final class	Shingle
`LS.LSa.MoSa`	Final class	Sand
`LR.FLR.Lic.Ver`	Final class	*Verrucosa maura*
`LR {Red?}`	Final class	Algae identified as potentially containing mobile red species

certain parameters within the rulesets, and hence the resulting classification is susceptible to differences in imagery. That is not to say that the rulesets could not be used on any other dataset other than that described in the current research, only that edits would be required to either the desired dataset, or to the parameters of the algorithms, before reliable use of them can be made.



(a) Multi-resolution segmentation dominated subprocess (b) Nearest-neighbour dominated subprocess

Figure 4.1: Process flow diagrams



(c) Quad-tree segmentation dominated subprocess

Figure 4.1: Process flow diagrams

4.1.1 Multi-Resolution Segmentation with Domain Limitation

With reference to figure 4.1(a), the multi-resolution segmentation dominated subprocess is relatively simple. This form of segmentation produces well defined objects when appropriate segmentation parameters are used; the results of parameters used in the current research confirm the work of Benfield et al. (2007), extracting relatively discrete reef objects. The resulting objects can, through careful process construction, be manipulated and classified effectively. Particularly for the extraction of specific classes, this, combined with the domain-limiting approach (as described in section 3.4.3, regarding vegetation extraction) produces promising results. The classification for `Fucoid Beds` (MNCR BioMar code level 3 – **LR.HLR.FR**, **LR.HLR.FT**, **LR.MLR.MusF**, **LR.MLR.BF**, **HR.LLR.F** and some of level 2 **LR.FLR**) was trained on a single 1 km^2 image from the Écréhous and tested on a 7×5 km mosaic of the Minkies. The resulting classification (plate VI), while misclassifying small areas performed well, though the number of classes in this image are fewer than those in other regions. Such regions where there are more distinguishable classes, but where these classes have similar features upon which the algorithm is constructed, errors can occur. Plate V shows a comparison (with transparent class polygons) of the somewhat erroneous classification (on the right), and the training area, where the classification is much more accurate. This was the result of one rule which used the result of a merge on the intermediate class `_find_peak` – in the training image this was effective due to the small number of these remaining objects, however in the tile shown in plate V, objects of this class were dominant (and hence the merge produced large, broad objects), and the result is clearly incorrect. This highlights the importance of training and testing the ruleset on imagery that is typical of the entire dataset, and also reinforces the assertion of Leduc & Lavigne (2007) that the classification result really is very much a reflection on the user's competence and rigorousness.

This method also relates closely to the hierarchical (top-down) approach which many

classification systems follow, and is most meaningful to human interpreters given different levels of scale – scale being an important factor for consideration in ecological analysis (Wiens 1989). It is also a recommended approach – Blaschke et al. (2001) describe the use of multi-scale delineation of imagery, how it may produce hierarchical classification models, and extol and reaffirm the virtues of this approach cited in earlier literature. Ehlers et al. (2003), too, use hierarchical methods in semi-automated analysis of biotype mapping to drill-down from broad classes (such as 'tall vegetation') toward more refined classes (e.g. 'coniferous forest').

While the ruleset produced only classified at a broad level, this use of scale should be harnessed to further refine the classification. Ideally the polygons produced from this classification would be used with the high-resolution (0.1 m/pixel) imagery, and within-class differentiation performed (e.g. `Fucoid Bed` would be sub-classed into those MNCR BioMar codes listed above). It was a limitation of the software license that prevented scaled-analysis becoming part of the ruleset here, however, the original images could be processed outside of Definiens to clip out the desired areas (e.g. with ERDAS Imagine), and these then used to produce the refined ruleset.

4.1.2 Quad-Tree, Region Growing

The quad-tree based subprocess, depicted by the flow-chart in figure 4.1(c), was somewhat more complex, and involved much more manipulation of objects than the multi-resolution subprocess. The 'seek, grow and merge' approach that much of this part of the ruleset follows is highly flexible – because it deals with small objects that are highly homogenous, it is well suited to seeking out objects with a known spectral response, as exemplified by the stained cell nucleus example described in section 3.4.4 (e.g. the brightest pixel, etc.). However, for very heterogenous images, like those that form the basis of this research, the objects that result from the segmentation tend to be only 1 or 2 pixels square, in many instances – reducing the

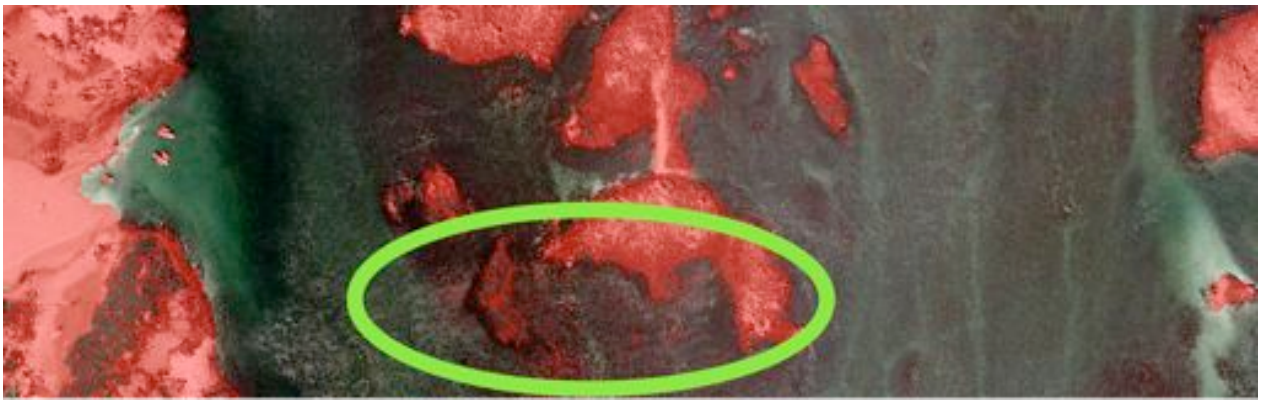


Figure 4.2: The 'salt-and-pepper' effect, ringed in green, as a result of small objects from quad-tree segmentation

advantages object-based methods add, to something more analogous to pixel-based analysis – something of a step backward (figure 4.2). Despite this, it did prove useful, and the effects of 'pixelation' (salt-and-pepper effect) from small objects was reduced by using rules that examine distance to other objects and area of these objects after merging with others of the same class. This method, therefore, should be considered carefully before use; however its increased speed (compared with multi-resolution segmentation) is an asset.

4.1.3 Context in Classification

While the results of this research relied heavily on image-only evaluation, the author concedes that for the re-use of the product ruleset to be of use, it must be adapted to make better use of context. In the initial literature review, much was made of marine zonation patterns, and how these are affected by abiotic clines such as wave exposure and salinity. Unfortunately, only a limited amount of the information gathered about the reefs in this study was incorporated into the classification itself; and this in an *a priori* fashion. A good example of one easily performed enhancement to the classification would be by use of an 'exposure' dataset – perhaps as a raster image, based on tidal stream rate (averaged or interpolated from the

admiralty charts exemplified by figure 1.4). This form of ancillary data, if the resolution is high enough, would be of great use for quickly honing the exact species assemblage for a given area of classified fucoid bed, for example. This sort of ancillary data has been shown to increase accuracy of results in land classification of roads (Sims & Mesev 2007), and while they used a rather specific and well defined dataset, it supports the provision of such data for refined classification in OBIA practices. Certainly, with topographic and bathymetric data for the region, making predictions about the zonation based on these data combined with the aerial imagery, and subsequent affirmations of the predictions through field survey, the resulting ruleset of the current research would be much improved.

One instance where the use of context was successfully applied within the ruleset was for differentiating between dark patches occurring on the rock peaks. In some instances these had been misclassified as `IR (?)` (Infralittoral – likely to be vegetated), but could also be *V. maura* bands, high-eulittoral fucoids such as *F. spiralis* or simply shadows. Proximity to a super-object that had been classified as `High NDVI` was used as a comparator, and the resulting object classifications were more robust, reverting these objects to a higher-tier class (`^Rock Peak`) for later re-analysis. This method was also applied after nearest-neighbour classification to re-classify areas of *V. maura* that were particularly close to sea objects (zonation patterns suggest that this would be unlikely). As discussed above, the salt-and-pepper effect – induced by small-object segmentation – was reduced by use of context, reverting classifications of objects that were enclosed by a more dominant class, as well as through distance and size constraints.

4.1.4 Use of Nearest Neighbour

In figure VII – an early test – which uses the tile originally estimated to contain most classes, the classification is predominantly performed using nearest-neighbour samples, and it appears

particularly good. Refinements would be necessary within the classes shown, as they do not strictly conform to the MNCR BioMar classification scheme, but this level of classification provides a useful point from which further refined analysis can be performed. However, even at this broad level, there are objects that are misclassified – as this tile is the training tile for this particular ruleset, these inaccuracies present concerns for replication.

4.1.5 Nearest Neighbour versus Hierarchical Approaches

Though there is apparent overlap of much of the feature space of objects produced by small-scale segmentation, the method of working hierarchically down and identifying broad, vague biotopes (which may initially not appear useful to ecologists), the domain in which these smaller objects can actually be classified is limited, and thus accuracy is improved. This concurs with Bock et al. (2005), whose rulesets demonstrate the use of fuzzy rules/thresholds to limit the domain, and then use nearest-neighbour methods to separate out the final classes if there is significant overlap. The initial domain limitation is very important because nearest-neighbour methods cannot easily account of context without some higher-tier classification with which to refer. In fact, they may well produce many confused results if either the wrong features are selected for comparison, or poor samples are chosen (perhaps due to uncommon classes residing in training images, or the reverse being true). Plate III shows the broad classes (semi-transparent to expose the underlying imagery), and two nearest-neighbour classifications using sample objects from the rock peak shown. The first trial is acceptable, though areas of shingle are misplaced; the second trial uses more classes, and some split classes in order to limit large fuzzy-membership curves being produced for a single class that has a variable feature space (for example using two classes for sand, one that contains detritus – this being significantly darker). The second trial appears to be more accurate though there are significant errors for objects classified as `LR.FLR.Lic.Ver`, even

after correction through context based rules. In terms of reliability, as asserted by Mumby & Harborne (1999), where there is uncertainty it is perhaps more appropriate to reduce the classification to a higher tier until a sufficiently robust classification ruleset is produced.

4.1.6 Consequences of the Results

As stated in Blaschke et al. (2001), the scale, data resolution and number of classes produced are strongly affecting factors of how the classifications are used. The dataset in the current research was down-sampled and hence the descriptive resolution must also undergo reduction. Certainly, with improved resolution, differentiation between certain crucial feature-space values (such as standard deviation of RGB bands) improves, and finer classifications can be made both for the current object scale, and through further segmentation, within.

It is recognised that automated classification may not provide the highest possible descriptive resolution from the given imagery – indeed, the author experienced much frustration in being able to identify distinct areas of the imagery by eye that were not easily translated into the ruleset. However, the ability to quickly reproduce the classifications without human interaction, over larger spatial scales, and over an extended temporal scale makes this form of classification valuable as an ecological baseline (for a given scale). This argument is supported by the work of Mathieu et al. (2007).

With regards to misclassifications of sand (**LS.LSa**), shingle (**LS.LCS**) and areas of littoral rock (**LR**), there is weight to the argument that the final classifications should be left broad. Diesing et al. (2009) establish that stable cobbles support similar faunal communities to exposed rock, while highly mobile sand beds support very different communities to stable sand and beds of larger particle size. This disparity of species-level makeup means that it would be dangerous to give hard classifications where there is uncertainty – again, an assertation made by Mumby & Harborne (1999).

4.2 Refinements

The work that has been produced, while establishing a useful baseline, can be much improved upon. There are some simple refinements that can (and should) be incorporated, and issues for which the author has yet to come up with a satisfactory resolution, as analysed below.

4.2.1 Glint

Glint is a problem for remote sensing of water bodies, and though there are methods to overcome this (Hochberg et al. 2003), they are largely unavailable in this research due to the lack of NIR band data (which, if present, would also aid the partitioning of land from sea). The occurrence of glint on the sea surface was a major factor of misclassification in initial trial algorithms. Initial trials involved nearest-neighbour sampling to attempt to distinguish sea-glint from rock beds that had algae patches. Due to the similarities in many features of the objects at lower resolution (such as standard deviation and mean of the bands and texture; see figure 4.3 – an early experiment), even nearest-neighbour samples performed poorly for classification of these areas. Despite the differences in the two samples shown in 4.3, the objects at the 'edge' of the classifications (i.e. that differed significantly from the samples, but remain part of the intended class) would not necessarily fall under the membership rules imposed by the nearest-neighbour sampling, and hence produce misclassifications. The confusion between glint and the rocky beds may have been further exacerbated by the nature of the geology; Renouf & Andrews (1996) informs us that much of the rock on the reefs is subject to 'variable strike and foliation' – the random nature of the grain on the rock resembles the random glint pattern on the sea surface. While glint has some lineation from the wind direction, it is not substantial enough at the used resolution to present a comparative feature.

A workaround was established, however, using the image meta-data; but this has not yet

been incorporated into the ruleset. The glint typically occurs to the South-West (centered approximately 450 m South and 450 m West) of the photographic nadir, due to the position of the sun during the flight. Note that a single 1 km^2 image tile consists of parts of several single photographs, and so the glint occurs in different areas of each image tile. The provided meta-data has the photographic nadir recorded, and by loading this data into ESRI ArcMap and running the field calculator, it was possible to create new points around which glint was expected to be centered (see plate IV). Though a crude calculation, this information can be used as a thematic layer within Definiens to guide the classification as to how likely the object is to contain glint, and thus perform more accurate classification split of mineral beds versus sea with glint.

4.2.2 Conditional Rules

Due to the number of classes to distinguish in marine imagery, some techniques that are very useful for extracting particular classes often fail for regions where these classes do not exist. As an example, the domain-limiting fucoid classification ruleset performs well for areas dominated by sediment and rockbed, but poorly where the dominant class in the image is open water, and particularly deep water. It is this sort of scenario where conditional rules may serve well as a constraint – for example, the entire image could be given a mean 'sea' rating, and the fucoid ruleset bypassed if this is high. Instead, a different ruleset would fire that achieves high accuracy at detecting the infralittoral fucoids.

4.2.3 Transferral across datasets

The ruleset defined using the methods described above are intended to be re-useable. For this to be feasible, modifications would need to be made to either imagery or the values of

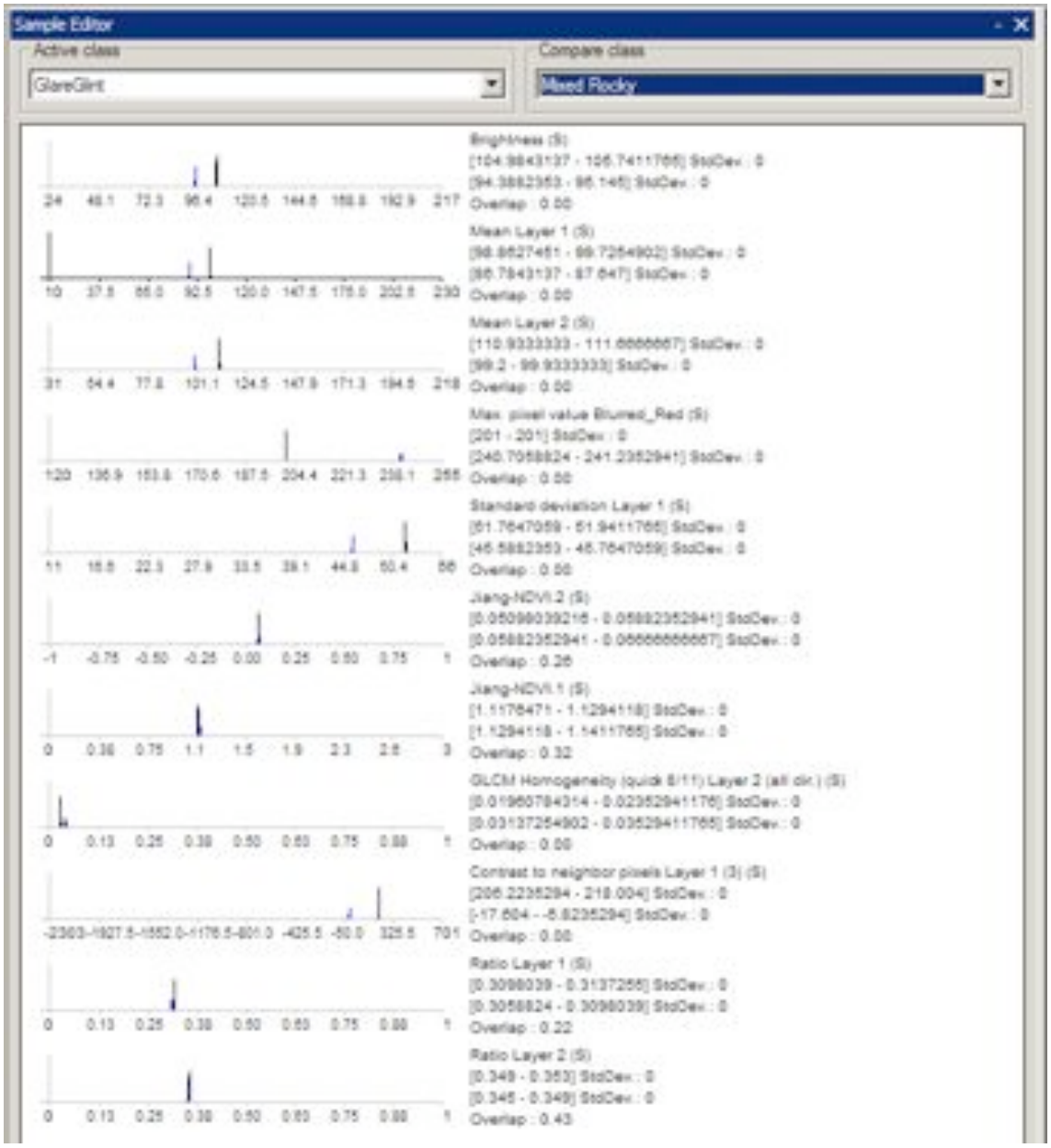


Figure 4.3: Sample comparison of `Mixed Rocky` and `Glint` – two intermediate classes.

certain parameters within the ruleset. In the introduction to section 4.1, it is stated that the ruleset is limited due to the static values for certain parameters; the consequence of this is that running the ruleset over imagery that differs according to these values will result in different (and perhaps unexpected or unreliable) classifications.

The ruleset was tested on one tile of imagery from the Gower peninsula, South Wales. It was able to successfully classify the rock regions at the higher-level class `^Rock Peak`, and the sea, however refined classes were not reliably produced and most of the sea was classified as `IR (?)` in the final part of the classification. This may be due to the imagery being somewhat darker, and again, is a result of using fixed values for thresholds and other parameter values in the ruleset.

4.2.4 Cascading Errors

While the use of context is clearly a powerful advantage of OBIA, it may incur costs for rulesets that are not well tested. In situations where objects are reclassified by their relationship to neighbour objects may be problematic where such neighbour objects have been misclassified themselves. As a simple (and somewhat contrived) example, imagine a looped region-growing rule, using a seed class (call it class A) that is expected to only be in regions entirely entirely enclosed by another (class B) and grows into class C; for some reason this class A object has occurred in an open part region of class C, not enclosed by class B – then this loop will envelop the entire connected region of class C objects. Of course there are checks and tests that can be used to prevent this, but their use is noteworthy if the rulesets are to be used on many and varied datasets.

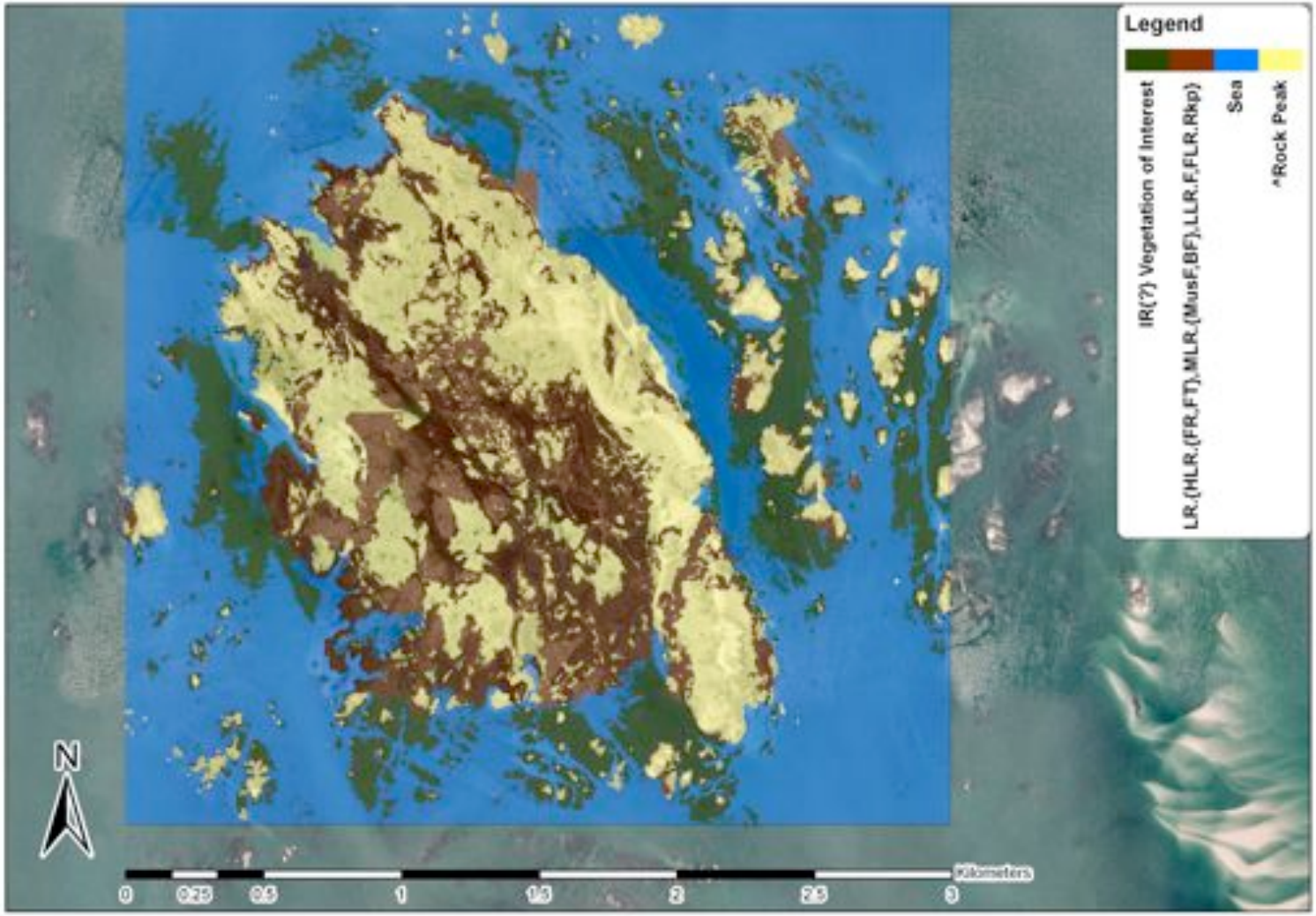


Plate I: Final classification output of Les Écréhous, without run of nearest-neighbour subprocess.

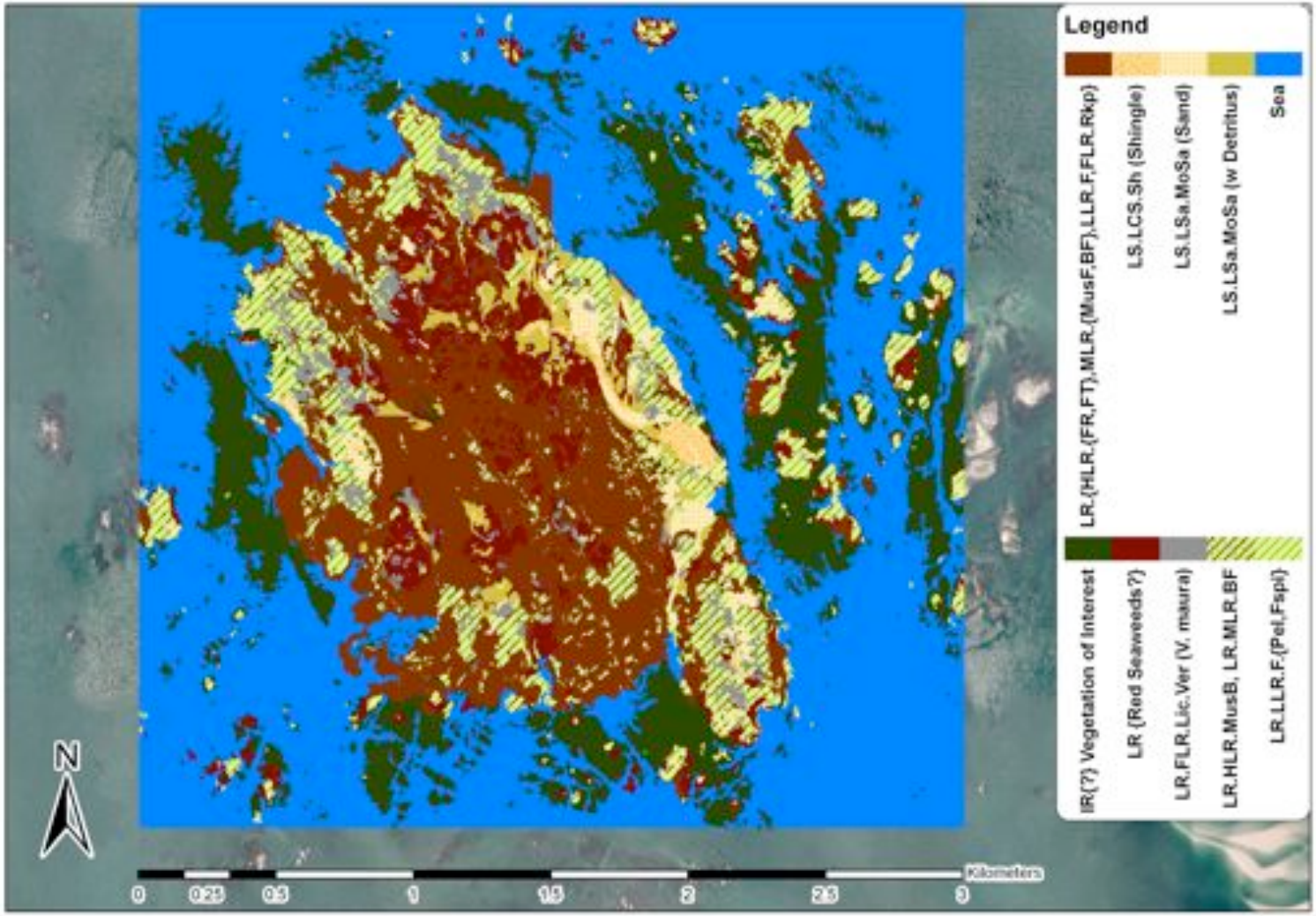


Plate II: Final – full – classification output of Les Écréhous

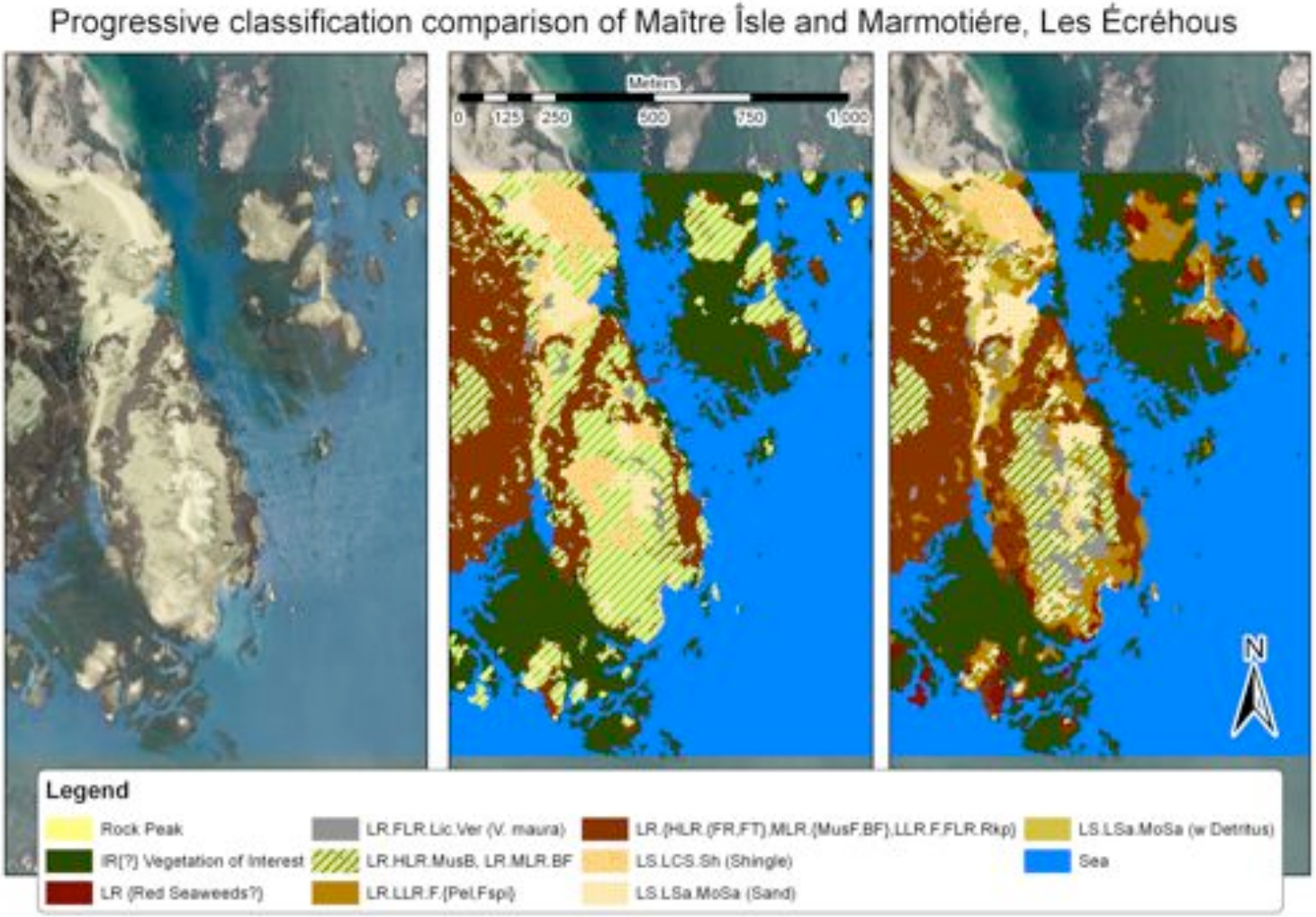


Plate III: Comparative classifications across Les Écréhous, without nearest-neighbour, and 2 attempts with nearest-neighbour using different samples and classes

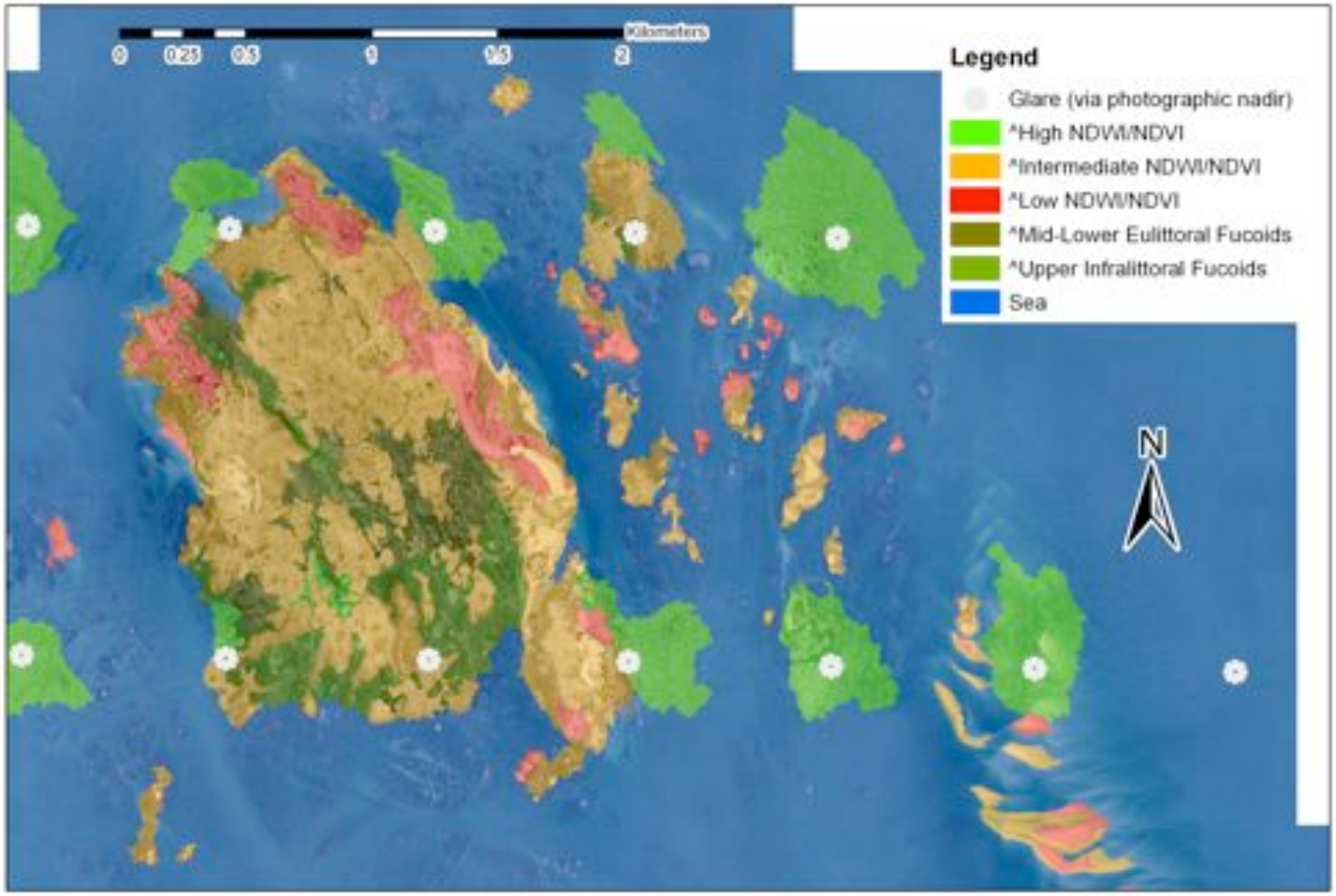


Plate IV: Full `Level 000` classification of the Écréhous mosaic
Note the '`^Low NDVI`' areas tend to coincide with the calculated glare/glint points centres

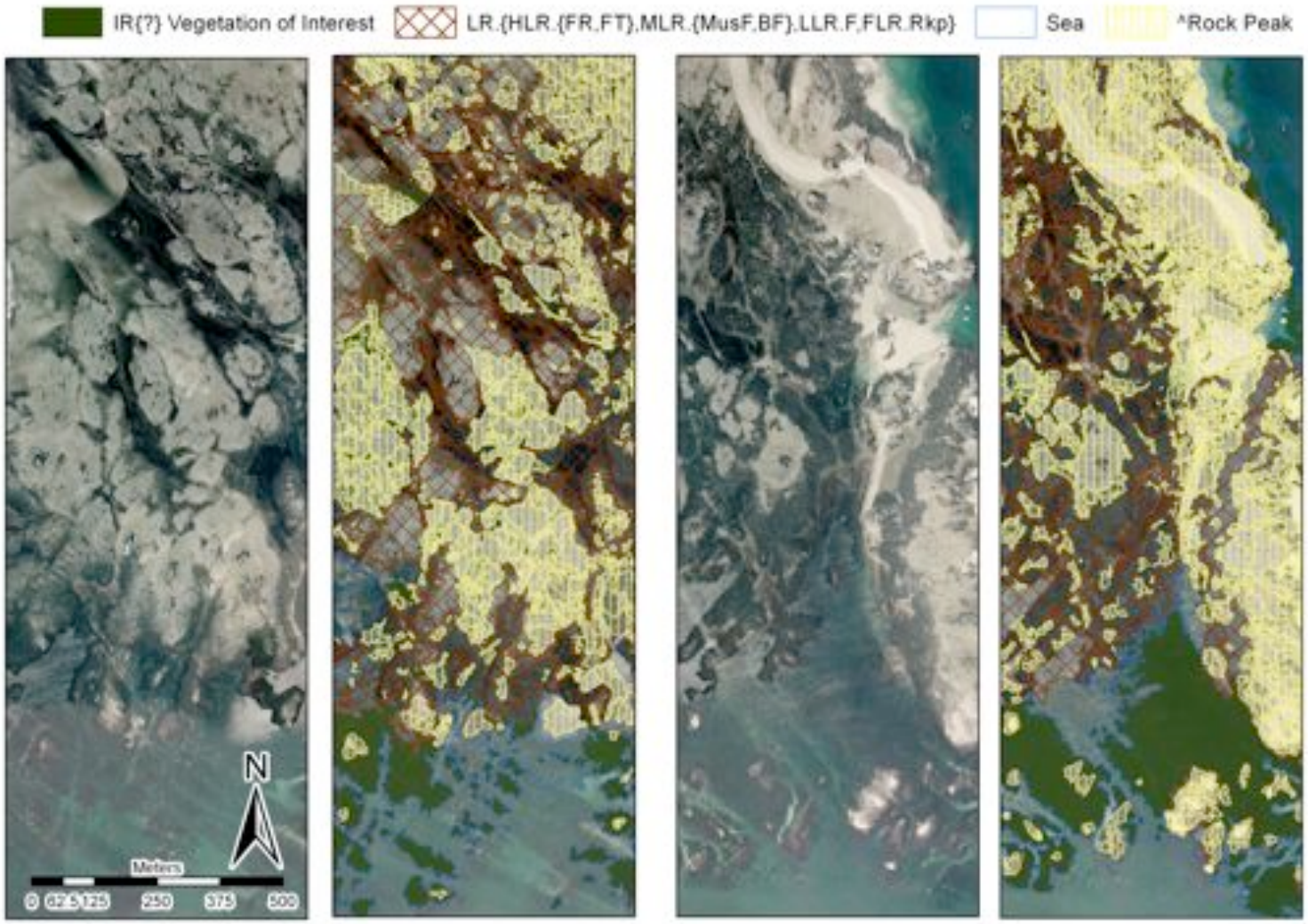


Plate V: Fucoid classification run on a non-training region of the Écréhous

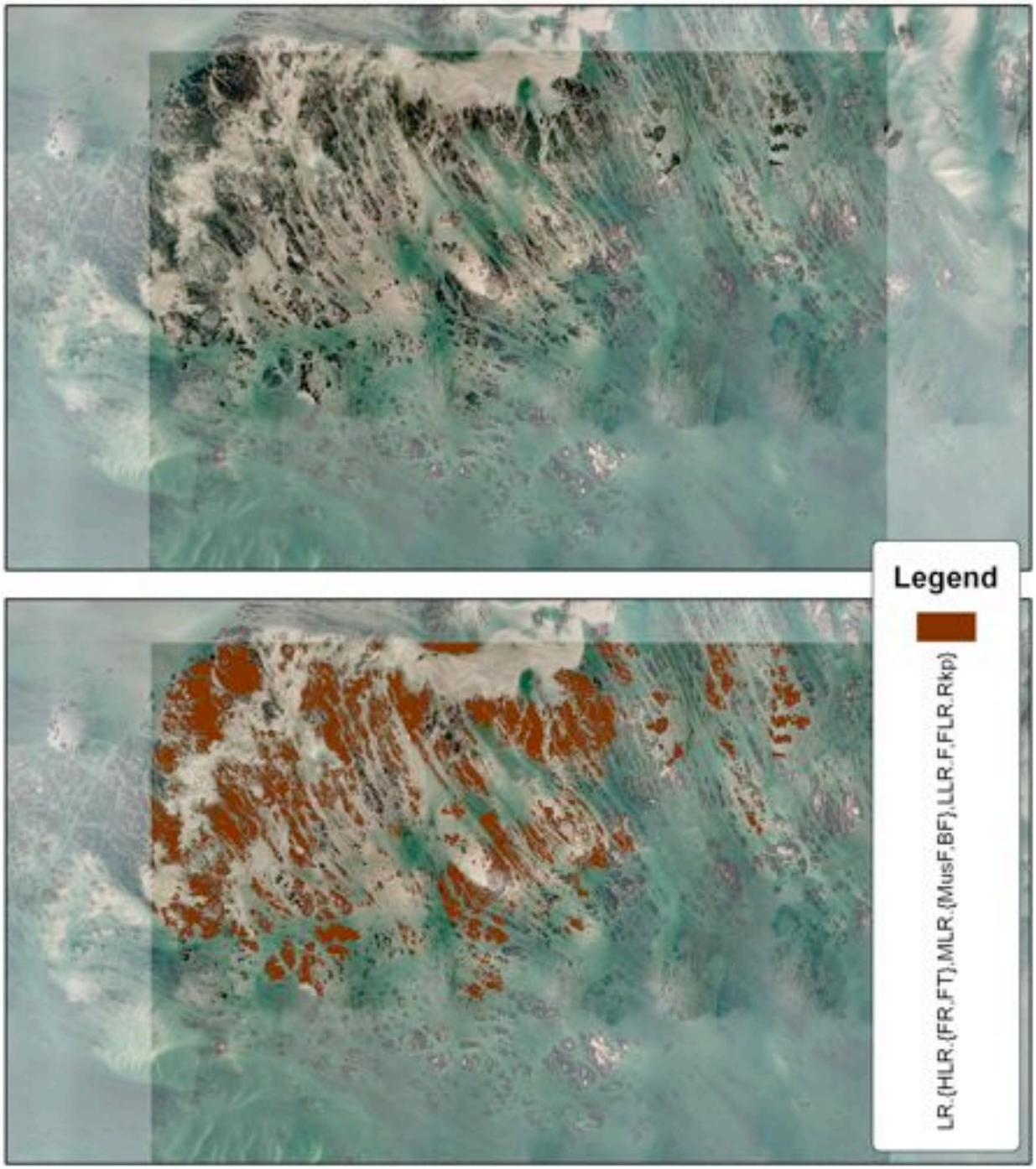


Plate VI: Fucoid classification run on part of the Minkies, trained on the Écréhous

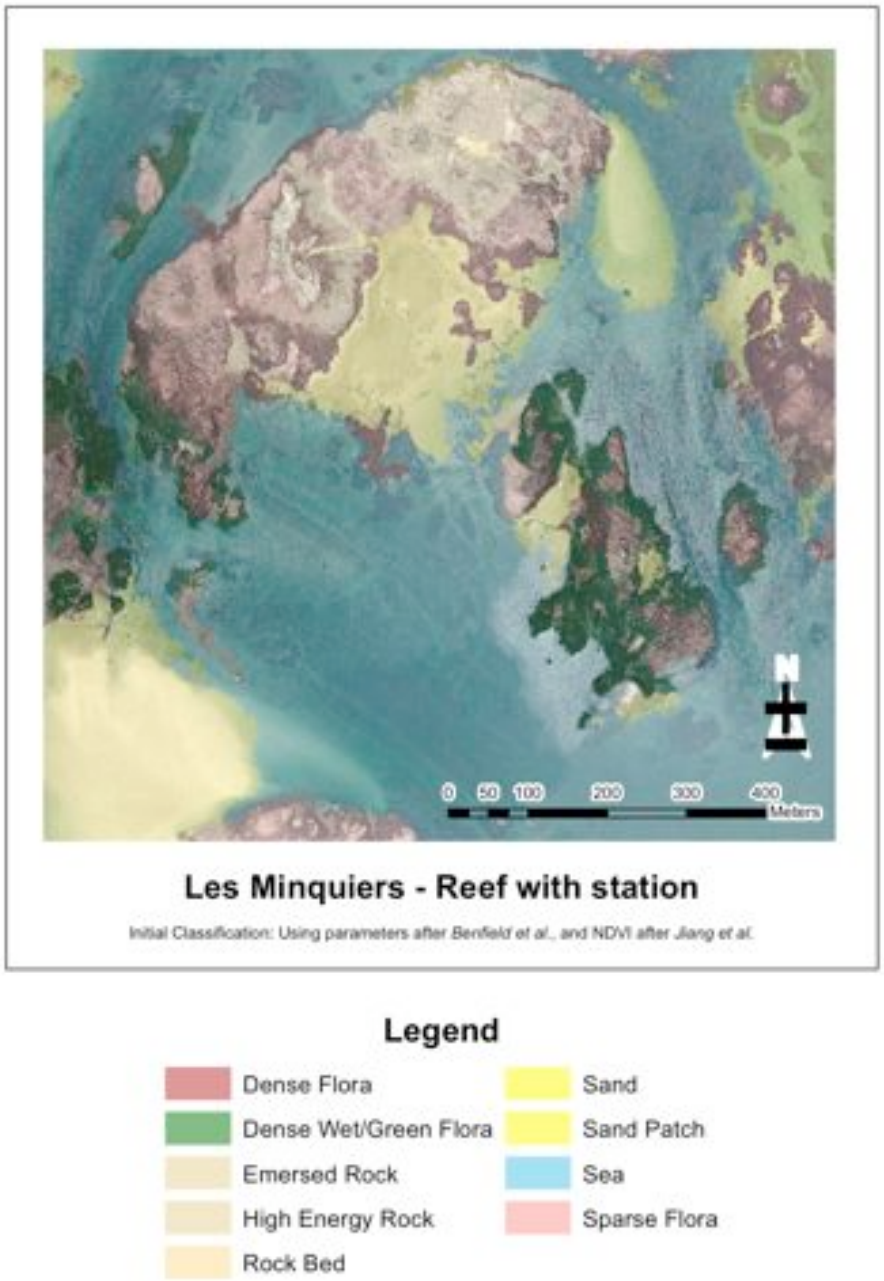


Plate VII: Classification result predominantly using Nearest Neighbour techniques having split the image with a threshold based on NDVI

Chapter 5

Discussion and Conclusions

5.1 Use – for Ecologists and Management

One of the main aims of this research is to produce usable habitat class maps. The results, while not as detailed as the research had initially set out to achieve are still of use, however.

In terms of management of remote areas like the reefs of the current research, and indeed any landscape for which there needs to be some element of planning, there is a need to begin compartmentalising and defining the main regions of the overall landscape (Blaschke 2006). This simplification of a complex system (i.e. the ecosystem) into a more simplified and 'labelled' form allows us to understand such a system at differing levels, dependent on the scale of this level (Wiens 1989). Thus, the step that the current research makes toward providing a simplification (partitioning, classification) of the complex landscape of a rocky reef, is valuable; it provides a baseline for both understanding of "what's there?" and for the further, refined-scale analysis of the now apparent, simplified compartments.

In terms of creation of habitat maps, particularly for the marine environment, there is much work to be done. There is valuable work by researchers such as Roff et al. (2003), Jordan

et al. (2005), Diesing et al. (2009) to establish the theory behind how such environments should be classified, and the application of this theory to find or map areas of potential ecological value. The current research hopes to add a facet to this toolkit, as a step toward the ultimate goal of full knowledge and subsequent understanding of our marine habitats, and this knowledge is ever-more valuable as threats to these ecosystems emerge and amass. Prior knowledge and quantification of the such habitats will prove important for ameliorating these threats, and by digitising this knowledge through application of RS, OBIA and GIS, we are better able to process and manipulate it.

The ability to reuse the generated ruleset for future image analysis is of great importance. There is necessity for constant re-evaluation of highly dynamic environments, such as that of the intertidal zone of rocky shores, particularly where important, sensitive species (such as *Zostera* spp.) occur, which require monitoring (Waycott et al. 2009). It is through the development of these once-created, oft-used semi-automated methods that the relative cost of such monitoring will be reduced – in man-hours devoted to ground surveying, and the inherently associated monetary costs, even if this involves some form of manual input to the classification process (Mathieu et al. 2007).

5.2 Comments on Feasibility and Recommendations

While the results of this research did produce ecologically meaningful classifications, the author was left with a sense of dissatisfaction at the descriptive resolution of the classification and robustness of the rulesets. While theoretically, there are myriad methods to improve the ruleset to tease out the misclassifications and home in on high-resolution classes (such as the exact nature of the fucoid beds), by far the most useful of these methods is through technological upscaling. Through simple upgrade of software and increase of RAM, the

author estimates that trials of improvements would be far more successful as out-of-memory errors would be reduced, and the latest patches to Definiens would prevent several crashes that regularly occurred. The speed increase in these trials would also go some way to increase the rate and efficiency of ruleset development. The author therefore recommends that any work using Definiens is not performed on minimum-specification hardware, in order to take full advantage of the powerful workflow that Definiens permits, and to spare the sanity of future researchers.

Further to this, and as a result of reduced capacity for processing, the author's use of smaller image tiles contributed to errors in classification. Much accuracy is lost where edge of image objects would benefit from the context given by their absent neighbours. The effects of this can be seen in the results, above (section 4), where fucoid beds at the edge of tiles have hard, straight lines defining an edge where their should be a gentle curve – the result of its remainder in the adjacent tile being of too small a scale to affect the initial split by NDVI, for example, and thus exclusion from the fucoid detection algorithm occurs. This of course can be refined by subsequent parsing of the image for hard lines (easy to detect, and unlikely to occur in a marine environment), for out-of-place objects (such as dark patch on a rock peak that cannot be attributed to shadow) and so forth, but again, the processing power and time limitations of the current research did not permit for this.

However, the use of Definiens comes highly recommended, in literature (Leduc & Lavigne 2007, Meinel & Neubert 2002, Pringle et al. 2009), and by the current author. As with much technology, the initial expenditure in terms of resources (time, cost etc.) seems to outweigh the alternative, more traditional methods; the gains in speed and reusability once the technology is acquired pays dividends, however, and this too is well recognised (Mathieu et al. 2007).

5.3 Further Work and Points of Interest

While there is much still to be done to refine the current research, the author has identified directions in which it could progress. Below, a short discussion of these directions.

5.3.1 Topography from Zonation

In the current research, topographic data was unavailable. Much more effort went into refining the algorithm to establish zonation patterns than would have been necessary if this information was available as it is possible to use the topography and knowledge of MHWS / MLWS heights to produce a thematic map from which the classification can be limited. It is possible, therefore, to reverse engineer this process, so that given the zonation, one can determine the MHWS / MLWS heights from the classification. Providing the algorithm produces reliable results, this may present possibilities for topographic extrapolation.

5.3.2 Tidal Stream from Fucoid Beds

As a point of interest to the author, the 'mean direction of sub-objects' feature was applied at Level 000. Where fucoid beds are present, this feature results in mean direction equivalent to that of the main flow of the tidal stream (see figure 1.4). It is thought that there may be application of this feature, in combination with some assessment of 'strength' of direction (perhaps by standard deviation), to extrapolate strength and main direction of tidal stream flows, for example, where limited data exist. If location of certain species assemblages can be inferred from abiotic factors, then it follows that certain abiotic factors can be inferred from species assemblages – much in the same way that the scale developed by Ballantine (1961) has its own somewhat 'circular' logic. This may be useful for identifying changes in current over time, though the author concedes that this is perhaps a moot point given more reliable

sensory technologies already tailored to this task.

5.3.3 Automation

While manual classification and mapping of habitats is highly accurate, vast areas of (inaccessible) land are not feasible to map once, let alone regularly for monitoring purposes. The use of an automated algorithm for this purpose, as this research demonstrates, is highly feasible – despite the inherently lower descriptive resolution when compared to manual classification by field survey. An appropriate extension of the automation of classification would be to automate change detection between consecutive years. This sort of analysis is currently used to monitor changes in forestry, peatlands and other land ecosystems (Coppin et al. 2004, Dissanska et al. 2009) and while application to a marine environment may not be as effective due to the variable nature of the environment (and difficulty in getting 'matched' imagery that arises from this variability), there is scope for it to be of major benefit to researchers. This is particularly true for study of sensitive sessile communities, such as seagrass beds, which are currently under threat (Waycott et al. 2009) and may prove invaluable with improved robustness of the algorithm under different atmospheric and sea-state conditions.

5.3.4 Crowdsourcing

Further improvements could be made by 'out-sourcing' aspects of automated classification checks and ground-truthing. At the time of writing, web-based GIS and indeed mass-participation GIS projects are becoming widespread (Miller 2006, Goodchild 2007) and the computer literate members of the public are familiar with online maps. The vast number of users on the Internet can be mined for information, and various projects exist in order to make use of human input for automated research purposes (von Ahn et al. 2008, von Ahn

& Dabbish 2004) without burdening the user – known as crowdsourcing. Frameworks and Application Programmer Interfaces (APIs) also exist to allow mapping facilities like Google Maps, Bing Maps, Open Street Map etc. available to developers to do with what they please. (Albors et al. 2008)

One such project, GeoDjango[1], builds on the development of an extensible web framework (Django[2]) by addition of spatial-database interoperability and manipulation. A GeoDjango application, when combined with sister projects that aim to solve development of user-oriented websites (such as Pinax[3]) could be harnessed as a means to sanity-check automated classifications that are subject to uncertainty (such as that of a marine environment). For example, users could be presented with a polygon and the image used to produce it and asked to classify it out of 3 possible classes. Assuming no malicious users, the 'best-guess' could be derived by statistical analysis and any rogue classifications (after 10 users' answers, say) could be reported to researchers. An incentive to complete this task would of course be required, but studies have shown this to be possible (von Ahn et al. 2006, von Ahn 2006).

This could be supplemented by allowing users to ground-truth data for themselves and submit it to the webservice, which could later be used for refinement or verification of the algorithm. Such as system would have been a tremendous boon to the author of the current research as access to the area of interest was particularly difficult, and had not time have been a limiting factor, this system would most certainly have found itself under development!

[1] `http://geodjango.org`
[2] `http://djangoproject.org`
[3] `http://pinaxproject.org`

5.4 Conclusion

The current research assessed and refined techniques for classifying marine rocky-shore environments in a semi-automated manner using object-based image analysis using Definiens Developer software. The result of the research is a set of methods that can be applied to visible-spectrum, high-resolution aerial imagery in order to extract habitat classes of these environments. The nature of the extracted classes constitute a level of scale that is useful as a baseline upon which managers and ecologists can build. While the research did not produce the refined habitat classes the author had intended, the methods described show that this is certainly possible, and with greater time and resources this could be easily achieved. The research also shows that although the use of extended data is desirable, it is possible to extract features from maritime landscapes with limited data — the visible band of the electromagnetic spectrum provides adequately to distinguish many distinct 'shore units' and their associated biotopes.

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