UNIVERSITY OF SOUTHAMPTON

FACULTY OF NATURAL AND ENVIRONMENTAL SCIENCES

Ocean and Earth Science
National Oceanography Centre, Southampton

Marine Landscape Mapping in Submarine Canyons

by

Khaira Ismail

Thesis for the degree of Doctor of Philosophy

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ABSTRACT

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As the largest portion of the Earth's surface, the deep-sea contains various ecosystems and harbours among the highest biodiversity on the planet. Complex deep-sea environments such as submarine canyons are some of the true ecosystem hotspots harbouring extensive species diversity owing to their high terrain variability. However, their complexity and limited accessibility has left many unanswered questions concerning their spatial structure and ecology. Recently, there has been an increasing amount of interest to understand the ecosystem function of this challenging environment, which has led to the development of technology to enable accessibility for research and exploration. Along with this, evidence of anthropogenic impacts has been uncovered, and this calls for more effective management in this complex type of deep-sea environment. Although there is a growing awareness for conservation in the deep-sea, scientific knowledge to underpin these strategies is still inadequate. Often what is known to the scientific community is not properly conveyed to policy makers. Hence, implementation of marine spatial management is not always successful.

This thesis provides a scientific framework to underpin ecosystem-based management. It examines the seabed spatial structure in submarine canyons by 1) developing a mapping procedure to represent the spatial structure using commonly available data types for seabed studies, 2) proposing an approach to quantify the structural variability as an indicator for biodiversity to aid decision-making in prioritising conservation areas and 3) evaluating the spatial structure information transfer across different spatial scales and data types.

As a result, a novel technique that is objective, automated and statistically robust is developed to map marine landscapes, which are geomorphologically and ecologically meaningful. The marine landscape map is found to be the best representation of environmental characteristics in submarine canyons. Based on this finding, marine landscape configuration and composition is quantified as a proxy for habitat heterogeneity and potentially an indicator of

biodiversity. Additionally, the method is transferred to a high-resolution dataset for marine landscape mapping at a local scale, in order to evaluate the evolution of spatial characteristics across data scales. This study reveals that a link between regional and local scale spatial structure can be identified and mapped, and that information from one scale can be transferred to the other. Additionally, regional scale marine landscape maps provide first-level structural information that is suitable and sufficient to facilitate marine spatial management for large heterogeneous areas such as submarine canyons.

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DECLARATION OF AUTHORSHIP

I, *Khaira Ismail* declare that the thesis entitled *Marine Landscape Mapping in Submarine Canyons* and the work presented in it are my own and have been generated by me as the result of my own original research.

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. Parts of this work have been published as:

   Ismail, K., Huvenne, V.A.I., Masson, D.G., 2015. Objective automated classification technique for marine landscape mapping in submarine canyons. Marine Geology 362, 17-32.

Signed:..

Date: 30 December 2015 ....

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I would like to express my special thank you to Dr. ir. Veerle Huvenne, whose selfless time were sometimes all that kept me going, though she might not know this, you have been an irreplaceable supervisor. Thank you for guiding me in my research and for allowing me to grow as a research scientist. I would also like to thank my supervisors Dr. Doug Masson, Prof. Paul Tyler and my panel chair Dr. Lisa McNeil for brilliant advice, suggestions, comments and guidance during my Ph.D. Thanks are extended to the whole CODEMAP team, especially Dr. Tim Le Bas, Dr. Claudio Lo Iacono (@my personal psychologist) and Dr. Katleen Robert, without your help and encouragement this Ph.D. would have been impossible to complete. Dr. Azhar Hussin, whose fieldtrips first opened my eyes to the wonders of the ocean and research, and for daring me to take my first plunge into the ocean, and now I'm only going deeper.

As mentioned throughout this thesis, thank you for the team that has collected the deep-sea datasets that are the main essence of this whole Ph.D. I would like to acknowledge the crew, and scientific parties of the RRS Charles Darwin cruises 157 and 179, Pelagia 219, RSS Discovery 297, RRS James Cook 035, 036. Funding for the cruises was provided by MAREMAP (NERC), HERMES (EU FP6 integrated project), HERMIONE (EU FP7 project), and CODEMAP (ERC Starting Grant no 258482). Funding for this Ph.D. was provided by the CIMB Foundation (CIMB Regional Scholarship 2011/2012) and CODEMAP (ERC Starting Grant no 258482) project.

On a more personal note: to the love of my life, Ismail Nurut and Jamaliah Arshad your love, support, and guidance are what I held on to as my pillar of strength. My beloved sisters, Kautsar, Nashrah, Zikra, Azza and Hijreen, and the whole Hj Ismail clan, thank you for keeping Adik sane all this while. To my dearest housemates Zatil and Ira, you are the rainbow to my heart after every rainy day. Lynn and Asmah, it's not the amount of time that counts but the memorable path that we had walked together. My best friends for life, Azyani, Erfa and Has, you stick to my heart like barnacles onto rocks. Arina, Sarah, Anas, Ali, Eric, Maria, and Ming, thank you for reminding me how to laugh especially towards the end of my Ph.D. when the sound of the keyboard seems to echoes louder than my laughter. Thank you all for being a great support system and for never letting me doubt myself. To Ryan Gosling at some point you were my research motivation and the rest is history (but not with me).

Dedication

Yang kail panjang sejengkal

Lautan dalam tetap diduga

Yang ombak terus berungkal

Ayahanda Bonda pesisirannya

~Adik

Chapter 1: Introduction

"Or [the state of a disbeliever] is like the darkness in a vast deep sea, overwhelmed with waves topped by waves, topped by dark clouds, (layers of) darkness upon darkness: if a man stretches out his hand, he can hardly see it! And he for whom HE has not appointed light, for him there is no light"

24:40

1.1 Research context

1.1.1 Background

The deep sea covers 63.6% of our biosphere (Hüneke and Mulder, 2011) and provides various ecosystems that harbour millions of known and unknown species (Ramirez-Llodra et al., 2010). Like Earth's landmasses, the deep seafloor contains canyons, mountain ranges and other formations. Being the largest portion of the Earth's surface, their role is non-negligible. Yet, this challenging environment is still underexplored and much of its ecological processes are poorly understood. The reasons for this are varied, and include, besides inaccessibility, difficulties in defining and quantifying seabed properties and the lack of a well-developed scientific framework that incorporates the uniqueness of these environments.

Although research in the deep sea is still limited and hampered by time and money, the effort to understand the deep-sea environment is increasing (Danovaro et al., 2014). At the same time, awareness for deep-sea conservation is growing and management plans are increasingly being developed, even beyond national waters (Barbier et al., 2014). This is in parallel with the increase of human activities affecting the deep sea, such as fisheries, hydrocarbon exploration and more recently deep-sea mining. These anthropogenic activities are moving into depths beyond 1500 m, interrupting the equilibrium of the deep benthic ecosystem.

Ecosystem-based management represents effective and much needed approaches to conservation and management for marine systems (De Young et al., 2008). Ecosystem-based management is defined as an integrated approach to management that considers the entire ecosystem, including humans, in order to maintain an ecosystem in a healthy, productive and resilient condition so it can provide the services humans want and need (McLeod and Leslie, 2009). However, the scientific knowledge base to underpin these strategies is much lacking. To facilitate ecosystem-based management, ecosystem processes in the deep-sea must be synthesized, interpreted and communicated across an extended community of scientists, policy makers and stakeholders. One of the first steps to establish a successful ecosystem-based management should be to characterise the seabed habitat features in the ecosystem, which effectively corresponds to marine habitat mapping (Cogan et al., 2009). Habitat mapping is a powerful tool to support modelling and management of marine ecosystems. It has now becoming a standard activity in surveys of both national waters (e.g. Australia's National Representative System of Marine Protected Areas (NRSMPA)) and international areas of interest (e.g. UNESCO Global Open Oceans and Deep Seabed (GOODS) Biogeographic Classification). The general approach is to construct marine habitat maps, followed by evaluation of biodiversity and development of management procedures (Figure 1.1).

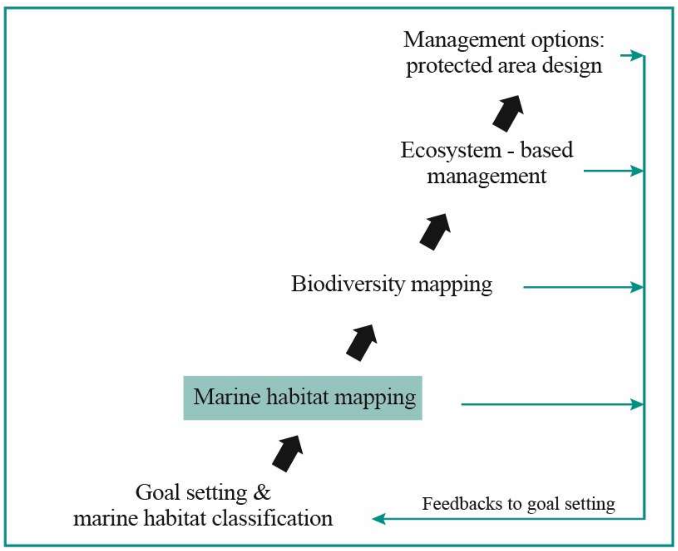


Figure 1.1: The role of marine habitat mapping to support ecosystem-based management. Adapted from Cogan et al. (2009).

Biodiversity refers to the variation of life forms in an ecosystem, and this is surprisingly high the in deep-sea (Ramirez-Llodra et al., 2010). Niche Theory (Chase and Leibold, 2003) states that spatial variability in environmental conditions is the main driver behind marine biodiversity especially in structurally complex environments. Ecosystems that contain true three-dimensional and highly variable terrains such as submarine canyons are able to create true ecosystem hotspots, harbouring extensive species diversity (Tyler et al., 2009). Despite this, spatial heterogeneity is seldom quantified as an indicator of biodiversity.

Looking from an ecosystem perspective, quantification of spatial structure becomes meaningless without incorporation of biological components. Biological investigations are generally carried out at a fine or local scale, while management plans are often taken at much broader scale. Due to this, relating biological information to regional patterns has always been a challenge (Ellis and Schneider, 2008). However, a broad spectrum of data with different extent and resolution are now available with the emergence of new technologies. Such data will aid in finding ways to relate information from metre-scale seabed observations to kilometre-scale regional maps.

The thesis aims to promote a marine landscape mapping approach to facilitate ecosystem-based management by developing an objective automated technique to map **marine landscape in complex deep-sea environments** (with the focus in submarine canyons) in a **statistically robust way at broad and medium scale** and to propose a **measure for marine landscape heterogeneity** to evaluate its potential as a **proxy for biodiversity at broad scale**.

The issues are summarised into three main objectives:

1. To establish marine landscapes as a basis for submarine canyon mapping. Developing a marine landscape mapping technique that is objective and automated, and acts as a harmonised approach to map and interpret seafloor natural zones in submarine canyons.

2. The marine landscapes will be the representation of terrain variability in submarine canyons. Therefore they are to be quantified through a spatial heterogeneity measure for submarine canyons and as an indicator for biodiversity.

3. To evaluate the information transfer across different types of data, extent and resolution to assess the spatial scale relationship from fine to broad scale.

1.1.2 Marine habitat mapping

According to the International Council for the Exploration of the Seas (ICES 2006), marine habitats are defined as "*particular environments distinguished by their abiotic characteristics and associated biological assemblages operating at particular but dynamic spatial and temporal scales in a recognisable geographical area"*. It is clearly stated here that there are two components in delineating a habitat: abiotic characteristics and biotic assemblages. Abiotic characteristics are the non-living factors that can affect the ecosystem such as geomorphic features, substrate type, hydrodynamic properties and their spatial structure. Biotic assemblages are the species and the living organisms that inhabit a particular area.

The natural world has often been viewed as a hierarchal structured system. To underpin the ecosystem-based management plans it is fitting to use natural regions to represent the seabed. Most existing habitat mapping approaches classify a marine ecosystem following a pre-defined hierarchal system composed of abiotic and biotic components. Among the well-known classification schemes are the European Nature Information System (EUNIS), United States

Coastal and Marine Ecological Classification Standard (CMECS) and the more recent UNESCO Global Open Oceans and Deep Seabed (GOODS).

Apart from the mainstream classification systems mentioned above, a number of additional existing classification systems have been applied to the deep sea using different characteristics to represent the distribution of abiotic and biotic characteristics of the seafloor. Classification systems are often limited to regions of the globe such as Europe, UK, Canada, USA, Australia etc. This is only logical, because the momentum for the establishment of marine spatial planning is driven by national and regional initiatives. Some of the examples of classification applied to the deep sea for management purposes are shown in Table 1.1.

Common characteristics used to create divisions within the hierarchical schemes include depth, geomorphology, substrate type and biology. Mutual problems that can be found in these classification schemes include that they often are an incomplete representation of the deep-sea realm and do not always relate well to what can be mapped with current technologies (especially acoustics). For instance EUNIS, the system used to classify habitats within Europe, although well developed and fit for purpose in shallow waters, contains a fundamental flaw in classifying the deep sea. At the initial level in the classification, i.e. at the broad scale, the deep sea is divided based on depth. In a complex deep-sea environment, this can cause conflict of interest especially when designing a framework for marine spatial planning, since ecological diversity can vary within a heterogeneous terrain in addition to depth. Moreover geomorphic entities within highly heterogeneous ecosystem (e.g. submarine canyons) may extend across several depth ranges.

Table 1.1: Example of classifications that is applicable to the deep sea

<table>
<tr><th>Classification</th><th>Levels/Hierarchies</th><th>Descriptions</th></tr>
<tr><td>Greene et al., 1999</td><td>
<table>
<tr><th>System</th><th>Subsystem</th><th>Class</th><th>Subclass</th><th>Modifiers</th></tr>
<tr><td>Mega:
Submarine canyons</td><td>Meso :
Define by depth
Head <100m
Upper 100-300m
Middle 300-500m
Lower >500m</td><td>Meso and macro:
Based on seafloor morphology
Vertical wall
Terrace
Channel
Pinnacle</td><td>Macro and micro:
Substratum type
Slope angle</td><td>*additional descriptions based on bottom morphology, deposition, texture or physical, chemical, biological or anthropogenic processes</td></tr>
</table>
</td><td>1. Classification is divided based on geomorphological features.

2. Habitats are divided according to feature sizes e.g.: mega- kilometres to 10s of kilometres or larger, meso- tens of metres to a kilometer, macro- one to ten meters, micro centimetres in size or smaller.

3. Potentially, for management purposes at Class level submarine canyons will be divided based on features, however substratum type and slope angle which usually affects biological properties will not be included to describe the habitats.</td></tr>
<tr><td>Allee et al., 2000</td><td>
<table>
<tr><th>Level 6</th><th>Level 7</th><th>Level 8</th><th>Level 9</th><th>Level 10</th><th>Level 11</th></tr>
<tr><td>Depth:
Shallow <200m
Medium 200-1000m
Deep >1000m</td><td>Regional wave/ wind energy:
Exposed
Protected</td><td>Hydrogeomorphic features:

Continental

Non-continental</td><td>Hydrodynamic features:
Supratidal
Intertidal
Subtidal</td><td>Photic/ Aphotic</td><td>Topography: e.g. Cliff, reef flat, ledge, terrace</td></tr>
</table>
</td><td>1. Consist of 13 levels altogether, each level represents different characteristic to describe habitats (shown here are levels related to submarine canyons classification i.e. Level 6-Level 11).

2. Using this classification, a submarine canyon system is identified as a hydrogeomorphic feature (level 8). Further division in submarine canyons is based on local hydrodynamics, exposure to sunlight and topography.</td></tr>
<tr><td>Roff and Taylor, 2000</td><td>
<table>
<tr><th>Level 1</th><th>Level 2</th><th>Level 3</th><th>Level 4</th><th>Level 5</th></tr>
<tr><td>Geographic / temperature</td><td>Pelagic/benthic</td><td>Depth/light:
Bathyal 200 -2000m
Abyssal >200m</td><td>Substrate type:
Mud/silt
Gravel/sand</td><td>Exposure/slope:
Low slope
High slope</td></tr>
</table>
</td><td>1. Introduces classification based solely on abiotic dataset and uses biological data at later stage only for validation (i.e. marine landscape)

2. At Level 5 submarine canyons will be divided based on depth, substrate and slopes.</td></tr>
</table>

<table>
<tr>
<td>Butler et al., 2001</td>
<td>
<table>
<tr><th>Level 1</th><th>Level 2</th><th>Level 3</th><th>Level 4</th><th>Level 5</th><th>Level 6</th><th>Level 7</th></tr>
<tr><td>Province: ~1000km extent</td><td>a) biome
b) sub-biome
c) mesoscale unit</td><td>Geomorphological unit ~100km extent</td><td>Primary biotopes ~ 10km</td><td>Secondary biotopes</td><td>Biological biotopes</td><td>Micro-communities</td></tr>
</table>
</td>
<td>1.A bioregionalisation approach at national level

2. The unit is divided based on size; for instance, geomorphological units are typically about 100km in extent.

3. Submarine canyons are identified at Level 3, divided further at Level 4 & 5 based on features about 10s of km in extent (e.g. Level 4: soft sediments between reef and Level 5: fine sediments)</td>
</tr>
<tr>
<td>EUNIS; Davies et al., 2004</td>
<td>
<table>
<tr><th>Level 1</th><th>Level 2</th><th>Level 3</th><th>Level 4</th><th>Level 5</th></tr>
<tr><td>A: Marine</td><td>A6: Deep sea bed</td><td>A6.8 Deep-sea trenches and canyons, channels, slope failures and slumps on the continental slope</td><td>A6.8.1 Canyons, channels, slope failures and slumps on the continental slope</td><td>A6.8.11 Active downslope channels Inactive downslope channels A6.8.12 Inactive downslope channels
A6.813 Alongslope channels
A6.814 Turbidites and fans</td></tr>
</table>
</td>
<td>1. The deep seabed is divided based on chemical conditions, if none, habitats are categorized based on seabed relief/features.

2. However, no further geomorphological features or substratum types are included to classify habitats within submarine canyons

3. Lack of spatial structural information especially for submarine canyons that contain high terrain variation</td>
</tr>
<tr>
<td>UNESCO GOODS; Vierros and Commision, 2009</td>
<td>
<table>
<tr><th>Zones</th><th>Characters</th><th>Provinces</th></tr>
<tr><td>Pelagic</td><td>Water masses & currents</td><td></td></tr>
<tr><td>Benthic</td><td>Depth zones
Bathyal 300-3500m
Abyssal 3500-6500m
Hadal >6500m
Hydrothermal vents</td><td>Water masses</td></tr>
</table>
</td>
<td>1. First classification system covering the entire oceans beyond national jurisdiction

2. A global attempt to comprehensively classify the open ocean and deep seafloor into distinct biogeographic regions

3. Biogeographic classification classifies specific ocean regions using environmental features and it aims to find homogeneous regions with respect to habitat and associated biological communities</td>
</tr>
</table>

Howell, 2010

Level 1	Level 2	Level 3	Level 4
Biogeography: Arctic Atlantic Bioherms	Depth: Upper slope 200-750m Upper bathyal 750-1100m Mid bathyal 1100-1800m Lower bathyal 1800-2700m Abyssal 2700-5000m	Substratum: Mud Sand Mixed Coarse Hard	Biology: 40 benthic megafaunal assemblages

1. The first attempt to design a classification that represents biological diversity for deep sea MPA (Marine Protected area) network

2. The classification is driven by biological relevance and used a bottom up approach. It was developed for a small area in NE Atlantic but is applicable to the whole deep sea and critically the high seas.

2. Classification omits the geomorphological surrogates, and abiotic component is based on depth and substratum type

CMECS; Federal geographic data committee, 2012

Biogeographic setting	Aquatic setting	Water column component	Geoform component	Substrate component	Biotic component
Realm Province Ecoregion	System Subsystem Tidal zone	Layer Salinity Temperature Hydroform Biogeochemical feature	Tectonic Physiographic Level 1 Geoform Level 2 Geoform	Origin Class Subclass Group Subgroup	Setting Class Subclass Group Community

1. The first national standard for classifying coastal and marine ecosystems in the United States

2. The classification gives a representation based on different 'components'.

3. Maps produced are versatile and can be based on each component, therefore the end product can be very flexible and descriptive of most abiotic properties

Parry et al., 2015

Environment	Biological zone	Substratum	Broad community	Biological assemblages
Marine	Biogeographic region and vertical zone	Rock Mud Sand Coarse sediment Mixed sediment Biogenic sediment	occupy a certain niche and fulfill a certain functional roll e.g. deep sponge aggregation	linked to one 'parent' broad community e.g. *Pheronema carpentreri* field

1. A new deep sea section for marine habitat classification of Britain and Ireland that is proposed to be included as part of upcoming revision of the EUNIS classification

2. A system designed to achieve a representation of biological diversity within a deep-sea MPA (Marine Protected Area) network

In order to achieve harmonised mapping and integrated deep-sea research efforts globally, there is a growing need for statistically robust and repeatable mapping techniques. Existing marine habitat mapping methods do not always fulfill this requirement as they are often based on expert judgment and subjective decisions. At regional and medium scales, mapping is mostly done through manual delineation, algorithm assisted digitising or a combination of those. These approaches used for mapping are still time-consuming and labour extensive. With the rapid development of seabed acoustic surveying techniques and increasing environmental data in recent years, an objective, automated and repeatable technique is much needed to handle the volume of information efficiently. Indisputably, the fundamental concept behind hierarchical classification is useful. However, the subjective approach taken to delineate the natural zones on the seabed hinders the quantification of seabed properties.

Marine landscape mapping is an approach of habitat mapping that was introduced by Roff and Taylor (2000) and will be adopted in this thesis. Each delineated natural zone will be referred to as a marine landscape. Roff and Taylor (2000) first introduced the concept adapting it from landscape ecology. They applied the hierarchal abiotic classification based on easily available abiotic datasets such as bathymetry, slope, bed stress and seabed substrata to produce marine landscape maps.

Marine landscape is defined as "***an environment distinguished by its abiotic characteristics with a potential to provide colonisation ground for specific biological assemblages***". Marine landscape mapping hence is defined as broad scale classification based solely on abiotic factors to distinguish natural seabed zones that can support particular biological assemblages.

The concept was trialed in a shallow marine environment by Verfaille et al. (2009). The work was applied to the Belgian part of the North Sea (BPNS) to divide the area into ecologically relevant zones using an objective statistical method. The advantage of the BPNS as a trial area to attempt a harmonized approach of habitat mapping is the various abiotic datasets available and a large dataset of macrobenthic samples to be used as ecological validation. The protocol proposes six steps to classify the area into ecologically relevant marine zones; 1) principal component analysis (PCA) for data reduction and to avoid multicolinearity of the abiotic attributes, 2) hierarchal cluster analysis was applied onto the resulting principal components (from PCA) to group the pixels with abiotic data on a statistical basis, 3) K-means partitioning using the result from the hierarchal clustering as starting points to cluster the pixels in groups in which the distance to its center is minimal, 4) number of clusters is determined using the Calinski-Harabasz criterion, an F-statistic multivariate analysis of variance and classified pixels from the cluster analysis, 5) split-run procedure as a measure to validate the clustering analysis based on its internal properties 6) indicator species analysis of the clusters to evaluate whether the obtained clusters represent ecologically relevant marine zones. The outcome (Figure 1.2) reflects the natural spatial variability in the area and showed clear relationship between its abiotic attributes and occurrence of macrobenthic species. Overall evaluation of the protocol as an objective approach can be summarized as follows; 1) it allows possibility to use all available abiotic variables as input for PCA as it eliminates data redundancy 2) no necessity to classify continuous abiotic variables into predefined clusters 3) and the optimal number of clusters is statistically determined. However, the possible risk if the protocol were to be applied over a large area and datasets, obtained based on different techniques and accuracies, is that it may create unpredictable error propagation. Nevertheless, the protocol creates opportunities towards a harmonised habitat mapping approach with caution on primary data origin, qualities and accuracy. Following the success of the objective protocol in the BPNS, shallow marine environment to delineate ecologically relevant marine zones on the seabed based on geophysical characteristics, it motivated the development of a similar procedure with added values for the deep-sea environment.

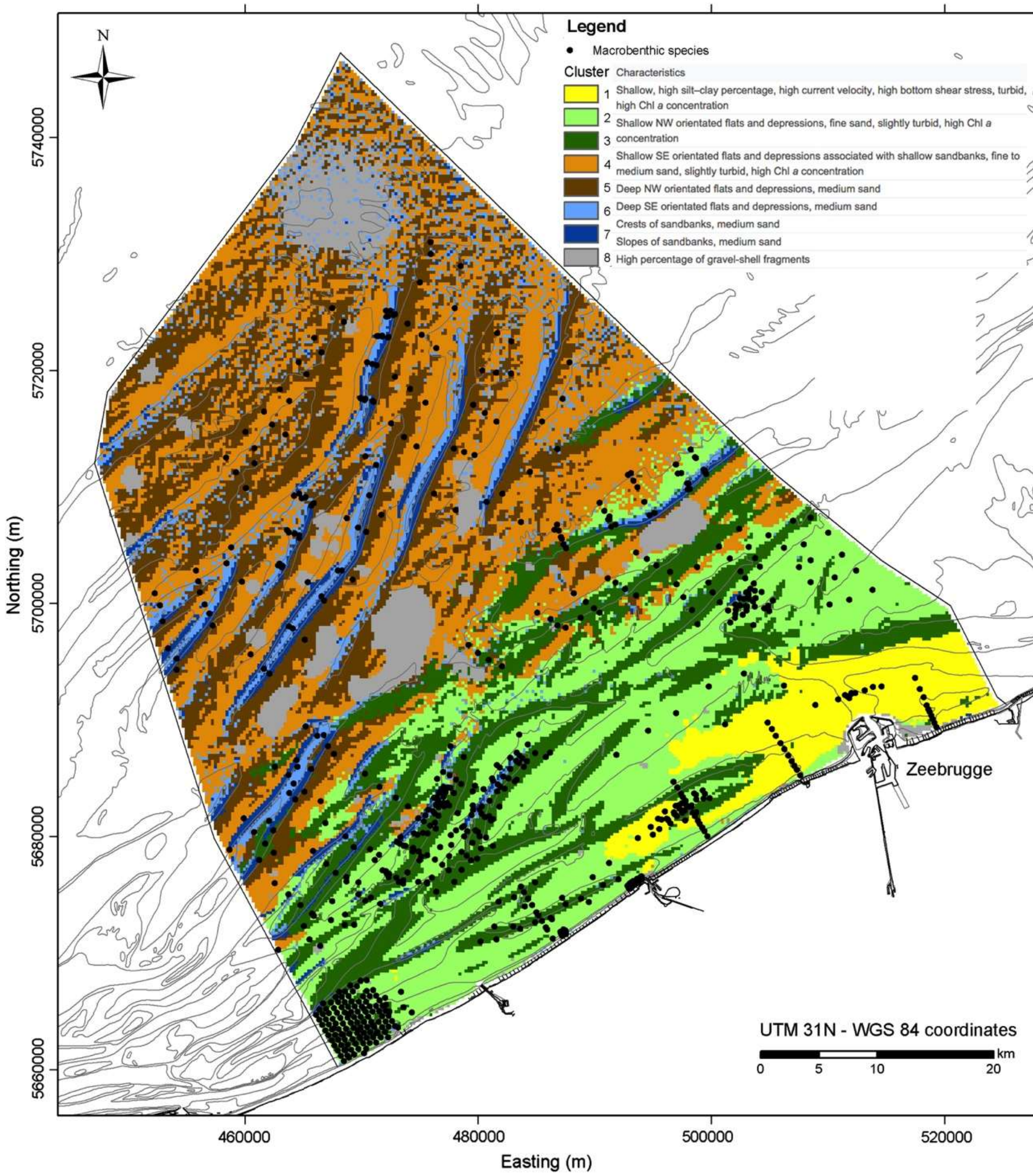


Figure 1.2: The Belgian part of the North Sea was classified into 8 clusters or zones by using the objective protocol proposed by Verfaille et al. (2009). Interpretation of each cluster is shown in the legend above. Each cluster is described according to the characteristics of the original abiotic variables. (Source: Verfaille et al., 2009).

1.1.3 Spatial structure and biodiversity

Biodiversity has often been considered as an indicator for ecosystem functioning and status. Studies have shown that a higher biodiversity supports increased efficiency and higher rates of ecosystem processes (Danovaro et al., 2008). However, assessment of biodiversity in the deep sea is difficult to accomplish owing to limited sample coverage. Due to this, a surrogate to act as an indicator for biodiversity in complex deep-sea environments is a more realistic approach.

According to Stability–Time hypothesis (Sanders, 1969), high species richness in the deep-sea environment is attributed to the apparent stability of the environment by allowing time for specialisation. However, rather than its stability, spatial variability in environmental condition has shown to be the main driver behind marine biodiversity (i.e. Niche Theory) (Chase and Leibold, 2003), especially in structurally complex environments (Henry et al., 2010) as they provide a larger number of niches. Based on these fundamentals, spatial heterogeneity of environmental conditions in a terrain is proposed as an indicator of biodiversity in structurally complex deep-sea environments.

The niche concept has been defined in many ways throughout the history of ecology (Schoener, 1989, 2009; Chase & Leibold, 2003) and was often depicted descriptively through observing associations between organisms and habitats. The first qualitative description of the interaction made by Grinnell (1917) and Elton (1927) describing the roles and requirements of species in communities. According to the concept, a niche is defined as a multidimensional hypervolume that includes a whole range of conditions forming a stable population that can be successfully maintained.

Quantitatively, when the niche space is set to its optimal conditions under which a species can live and replace itself, it is termed as the ‘fundamental niche’, as opposed to ‘realized niche’ that takes into account biotic interactions such as predation and competition. Here, niche in the marine landscape context refers solely to fundamental niche under an ideal condition in structurally complex deep-sea environment. The challenge then is to derive an approach to quantify the spatial structure with regard to the relationship between biodiversity and spatial heterogeneity in complex deep-sea environments.

Evaluating ecosystem function using spatial pattern metrics is a well-developed approach in landscape ecology (Turner, 1989). Most terrestrial conservation and management activities view the landscape perspective as an essential way to manage resources (Uuemaa et al., 2013). However, the landscape approach in the marine realm is still lacking (Wedding et al., 2011). Although there are a number of studies in shallow waters that extend the usage of terrestrial spatial pattern metrics to characterize and quantify marine structural features, there is only one metric that is specifically developed in the context of the marine environment and was used to quantify atoll structure (Andréfouët et al., 2001; Andréfouët et al., 2003). With regard to the deep-sea environment, the relationship between biodiversity and spatial pattern was studied at a local scale and shows that an association exists between biological distribution and spatial seabed characteristics (Robert et al., 2014a). Although the ultimate aim for the deep-sea research community would be to develop a unique spatial pattern metric for the marine realm, adaptation from the terrestrial environment can open new opportunities to explore and understand the relationship between spatial pattern and ecological processes.

1.1.4 Spatial information across scale

A long-standing issue in seafloor mapping is the scaling relationship, which combines the concept of grain and extent (Turner, 2001). Grain refers to the data resolution and extent is the area encompassed in the study. Biological information is usually limited to fine or local scale in contradiction with management decisions that are made at much broader scale. Often broad scale maps used for management purposes are doubted to give a good portrayal of the structural information in local scale surveys.

Acoustic surveys are also affected by scale issues. There is a trade-off between data resolution and survey extent. The question remains how to relate the information obtained from two different scales. As technology advances, many new tools are capable of acquiring high-resolution data to give better insight in the deep sea. Generally, these types of data are obtained over smaller coverage areas but in more detail. For instance Autonomous Underwater Vehicles (AUV) with the ability to survey close to seabed are capable of acquiring sidescan sonar and bathymetric data that can be processed to the finest resolution of 0.05 m x 0.05 m pixel but the coverage extent is approximately around 7 km x 1.5 km at around 6 hours (Wynn et al., 2014). In comparison, ship-borne multibeam bathymetry at water depth of approximately 3000 m or more, may get a coverage of approximately 100 km^2 but with pixels of 100 m x 100 m.

There are different types of structural features that can be mapped at different scales from different acoustic systems (Figure 1.3). In this study, the availability of data from ship-borne multibeam bathymetry and nested acoustic surveys using multibeam echosounders mounted on ROVs (Remotely Operated Vehicles), provides the opportunity to study the structural variation across fine and broad scale data. Intrinsic spatial characteristics of the terrain will be used to define scale relationships.

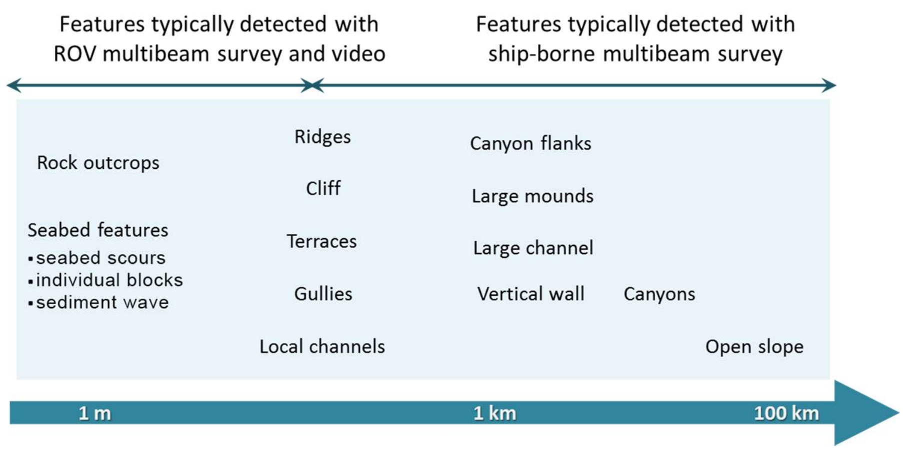


Figure 1.3: Some of the typical seafloor features that can be mapped by ship borne and ROV multibeam bathymetry.

1.2 Research details

1.2.1 Submarine canyon

In the last decade, submarine canyons have been a major interest for research communities with the growth of new sampling and surveying technologies (Huvenne and Davies, 2014). Their deep V- or U-shaped valleys cut across continental margins of the world's oceans, making them important geological features (Harris & Whiteway, 2011). Improved and well-developed equipment such as Autonomous Underwater Vehicles (AUV) and Remotely Operated Vehicles (ROV) allows access to the dramatic scenes of submarine canyons (Karson et al., 2015). Regardless of their unique structural characteristics, many questions about their spatial structure and ecosystem processes still remain. According to Niche Theory (Chase and Leibold, 2003), spatial variability in species distributions and the resulting biodiversity are ruled by spatial variation in environmental conditions, which makes submarine canyons the fitting complex deep-sea environment to fulfil the study objectives.

Submarine canyons are the main pathways that connect the shallow waters to the deep sea. They transport sediments (Puig et al., 2014) and organic matter as a source of nutrients to the deep sea (Amaro et al., 2010). However, also human litter and pollutants are brought along to the deep depositional system via this pathway (Schlining et al., 2013). Owing to their high terrain variability, steep topography, unique hydrodynamic regime and increased nutrient content contributing towards increased food availability, submarine canyons are often considered potential hotspots of biodiversity (Tyler et al., 2009; De Leo et al., 2010). Studies have shown that submarine canyons are complex habitats with specific hydrographic and sedimentological characteristics to intensify mixing and amplify currents (Turchetto et al., 2007) that influence faunal community structure and biodiversity (Schlacher et al., 2010).

Extensive datasets for submarine canyon systems have been collected by the National Oceanography Centre, Southampton. The data used for this study cover the Setubal/Lisbon and Cascais Canyons offshore Portugal, and Whittard Canyon in the Bay of Biscay. These data were collected in the framework of the EU FP6/7 IP HERMES and HERMIONE, and the NERC MAREMAP programme, a follow-on from NERC's OCEAN2025 programme. They were analysed in those projects for habitat mapping using traditional visual interpretation. Structured, repeatable and automated habitat mapping was still lacking, which became one of the main motivations for the ERC CODEMAP project of which this thesis is part.

1.2.2 Technique and technology

In general habitat mapping techniques can be divided into two kinds of approach: top-down and bottom-up. A top-down approach delineates map units (habitats/landscape types/terrains) by splitting broad, full-coverage abiotic data (often from acoustic surveys) based on abiotic similarity, following the assumption that environmental attributes can predict biological patterns. Incorporation of biotic data (ground-truth data) only takes place to evaluate the validity of the abiotic characterised regions. Marine landscape mapping is one of the important examples of a top-down approach. In contrast, a bottom-up approach first establishes significant relationships between biological communities and environmental characteristics, and then uses both biotic and abiotic data to predict ecologically relevant regions. This approach starts with point coverage information that can then be interpolated to a full coverage map (Robert et al., 2014b). Between the two, top-down is often the more popular approach for regional mapping efforts (Brown et al., 2011), as abiotic information is more widely available than detailed biological information especially in deep-sea environments.

Abiotic data for the submarine canyons studied in this thesis are primarily derived from acoustic signals (Figure 1.4). They are the best way to investigate the seabed efficiently and accurately. Seabed imaging revolutionized in the 1940s with the first system reported to survey the seabed being relatively high-frequency echosounders that yielded the first sidescan sonar sonographs (Fish and Carr, 1990). The most rapid developments in acoustic electronics were reported during 1970s and 1980s (Kenny et al., 2003). From then onwards, many recent developments have enhanced the ability to map the seabed, making deep-sea exploration more tangible (Wynn et al., 2014).

Acoustic mapping systems can be roughly divided into three categories: single beam echosounders, multibeam echosounders and sidescan sonars. Single beam echosounders are widely used for navigational purposes on most vessels. They transmit a single acoustic signal at a time close to the vessel's nadir. The first return from the seabed corresponds to the point closest to the vessel. The usage is limited because they only provide information directly below the survey vessel. Due to this limitation, multibeam echosounders were designed, which are more fitting for mapping purposes.

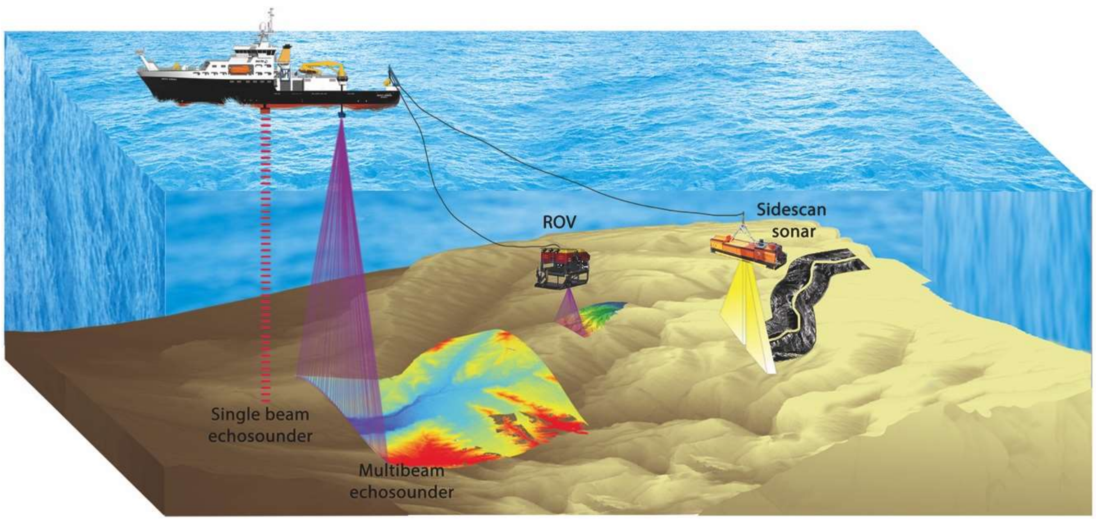


Figure 1.4: Illustration of the common acoustic systems used during seabed surveys. ROVs can be equipped with video, camera and a multibeam system. This thesis uses acoustic data acquired from ship-borne and ROV-mounted multibeam bathymetry and sidescan sonar system.

Multibeam bathymetry

Multibeam echosounders are the successors of the single beam echosounders. They transmit a fan-shaped acoustic signal across the vessel's track and record in several strips perpendicular to this direction (Figure 1.5). They record the depth in the cross-sections of the transmitted signals and record strip, creating the beams that cover a wide swath from underneath the ship to either side of the vessel's track. Each beam acquires a bathymetry measurement and additionally backscatter strength can also be derived (Brown and Blondel, 2009). Various technical (e.g. Lurton, 2002) and applied publications (Gardner et al., 2003; Roberts et.al, 2005; Wilson, 2006; Costa et al., 2009) have documented the principles of a multibeam system. The important factors to be considered when using multibeam bathymetry data in the deep sea are data density and spatial resolution as they decrease with depth. Wider beam widths and longer pulse length are required for deep-sea surveys to overcome losses in the water column and provide sufficient acoustic energy for a detectable return at greater depths. Water depth, beam angle and topographical features will affect multibeam acoustic footprint, for instance a bathymetric feature whose lateral dimensions are less than the acoustic footprint size will not be resolved into the data. Multibeam systems are often optimised for operation according to these factors especially depth of survey area by utilising different frequencies to achieve desirable bottom detection. However, multibeam data are often surveyed from surface vessels and have a limitation in the spatial resolution as it decreases with depth. This is a major drawback for data acquisition in the deep sea. Nevertheless, the advancement of survey vehicles, such as ROVs and AUVs permits multibeam surveys to be carried out closer to the seabed hence giving higher resolution data. But at the same time, the data extent will be reduced in comparison to ship-borne multibeam bathymetry.

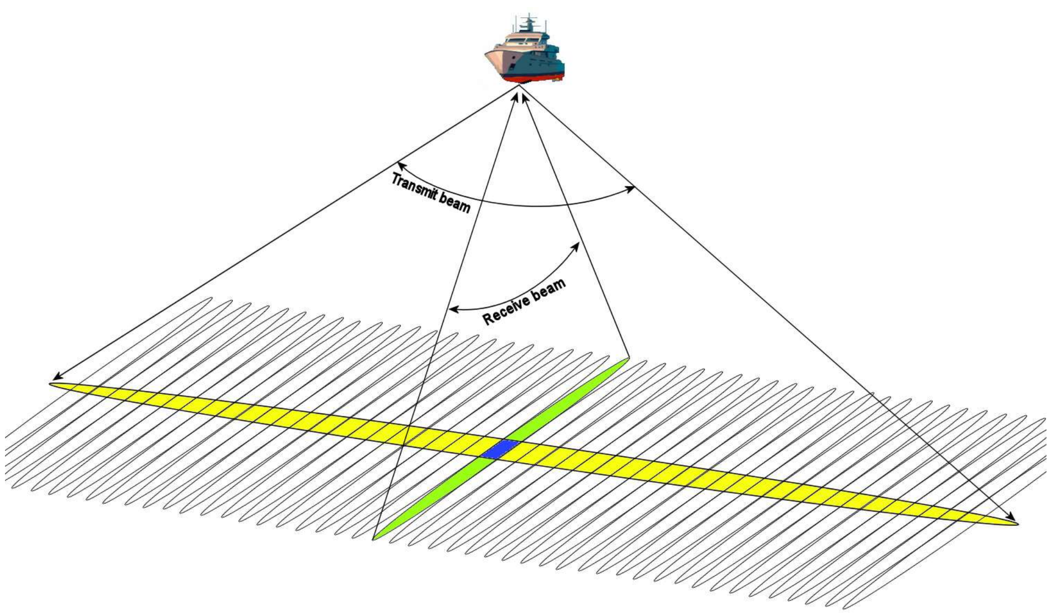


Figure 1.5: Visualisation of a multibeam echosounder sending out an array of sound pulses in a fan shape, then the beams bounce off the seabed and returns depths from underneath to the ship where the echoes are recorded. (Source: AML Oceanographic)

The availability of multibeam technology has been a great tool and a significant development for habitat mapping. Their value for seabed studies has widely been regarded as the standard baseline for benthic habitat studies. They now create the most widely surveyed and commonly available data type for seabed studies. The common practice for multibeam data is to be readily transformed into digital terrain models, which may be visualised into two or three dimensions and incorporated in Geographic Information Systems (GIS), to provide spatial context for habitat mapping. The decrease of data density with depth has important consequences in habitat mapping since the same level of detail cannot be obtained at all depths especially in a highly heterogeneous terrain such as submarine canyon. Inevitably, data gridding is another major issue when dealing with multibeam bathymetry processing for deep-sea areas. The effects of data gridding were artificially reproduced by Wilson (2006) on data from Galway Bay (shallow water area) to simulate the changes in detail one might expect to resolve in deeper waters (Figure 1.6). Most multibeam processing software has incorporated gridding algorithms that take into account the geometry of the sonar system to ensure optimisation of multibeam data representation.

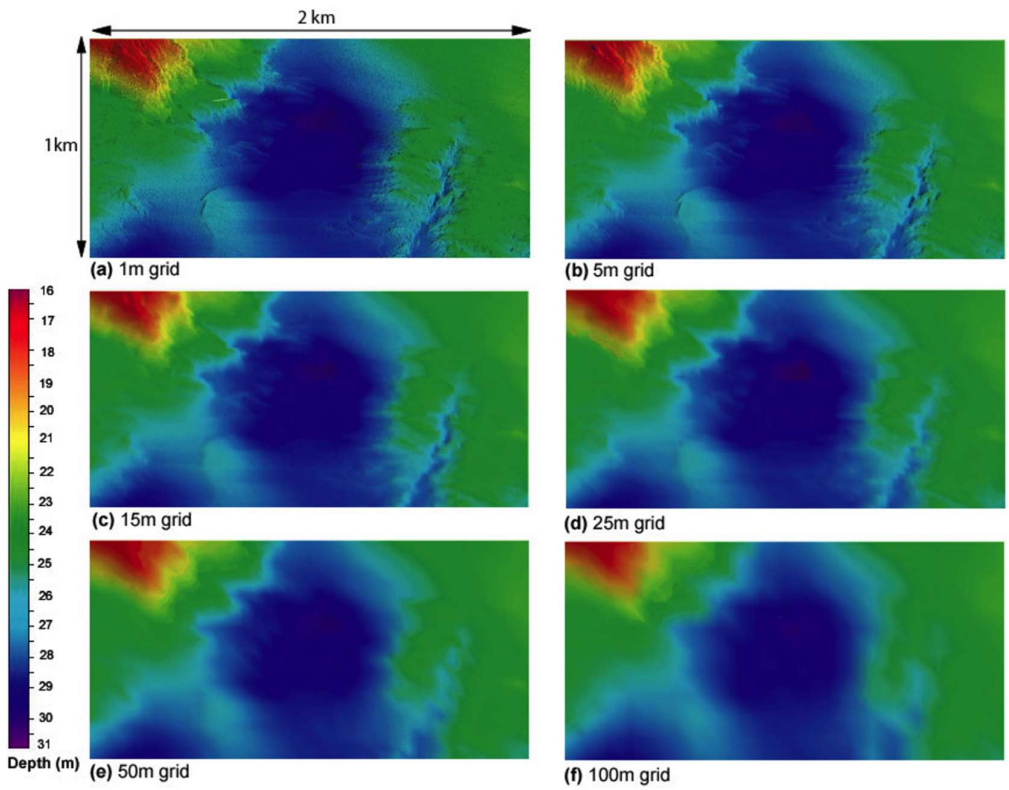


Figure 1.6: Illustration of the effect of data gridding reproduced on shallow water data at six different grid sizes to simulate the type of detail one might expect to resolve in deeper waters. Features appear on the smaller grid size disappears at larger grid size. This is worth noting especially when matching with direct observation data such as video data. Features that are attainable in video may be smoothed in large grid bathymetric data. (Source: Wilson, 2006)

Sidescan sonar imagery

Sidescan sonar is an acoustic survey system either towed on a cable or built into an AUV produces high-resolution imagery of the seabed. Sidescan sonars repeatedly emit a pulse and record the intensity of the backscattered signal over time. The transmitted beams form the shape of a fan that sweeps the seafloor under and on either side of the towed sonar equipment. These beams are narrow along-track to obtain a high-resolution image while across-track they are wide to cover as much range as possible. The components of the acoustic signal and scattering are shown in Figure 1.7. The slant range is the distance between the sonar to a point on the seabed and the ground range is the distance between this point on the seabed to the point immediately below the sonar known as nadir. The angle of incidence is the angle between the line of sight to the sea bottom and the sea floor itself. The incidence angle of the incoming acoustic wave is the most important in sonar backscattering, as it will determine how the sound will scatter. The acoustic waves are scattered around the reflection angle and only a portion will be scattered back toward the sonar and is used in sidescan sonar, hence the backscatter.

The receiver records the relative strength of this backscatter from the seafloor. The backscatter is influenced by three factors: local geometry of ensonification, roughness of the seafloor and intrinsic properties of the seafloor (Blondel, 2009) (Figure 1.8). For instance hard (rocky) seafloor will absorb very little signal and return most of it to the receiver while muddy seafloor will absorb most of the signal. Most sidescan sonar systems cannot provide depth information, however with the right algorithm and techniques, sidescan sonar imagery can provide information on sediment texture, topography and seabed features. The sidescan sonar data is commonly presented as greyscale sonar imagery which is often then interpreted visually by experts (Blondel, 2009) or by using advanced techniques such as textural analysis (Huvenne et al., 2002) or quantitatively to enable direct extraction of seabed properties such as mean backscatter intensity (Collier and Brown, 2005), grain size and sediment sorting.

Sidescan sonar imagery, like any data, is rarely devoid of anomalies and artefacts. They can be easily mistaken for real features, as they are often difficult to interpret or remedy. It is important to identify these artefacts, anomalies and noise. Here, three artefacts that are recognised are near-nadir distortion, shadows and exaggerated features at the edge of the processed sonar imagery. The nadir is a known area for having very poor data quality due to the vertical angle of incidence. For the same reason, feature exaggeration occurs at the edge of the sidescan sonar data in the survey area where the towed sidescan was almost vertical to the flank of the canyons. A shadow is an area that is less ensonified than the surrounding region caused by the acoustic signal being blocked by an acoustically opaque object.

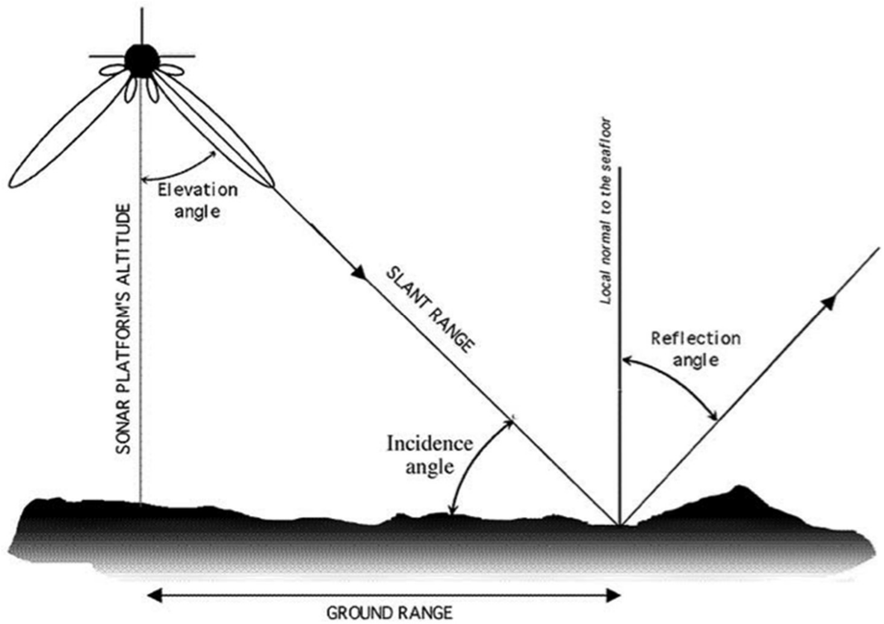


Figure 1.7: Components of an echo event on the seafloor (Source: Blondel, 2009)

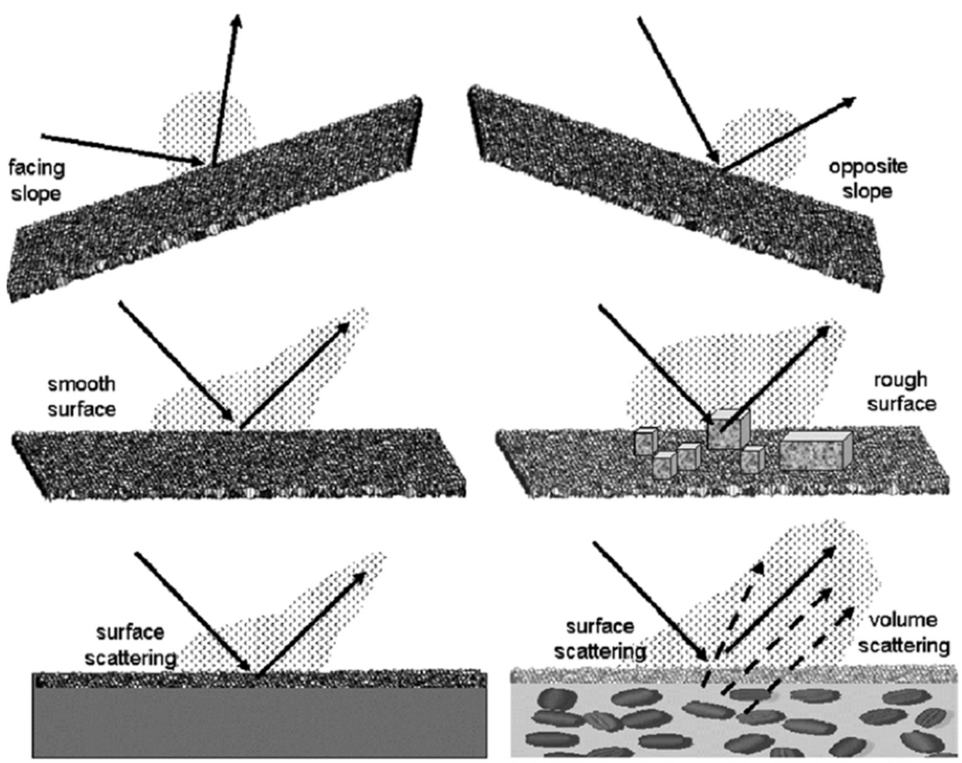


Figure 1.8: Backscattering is affected by three factors with decreasing order of importance: 1) geometry of the sensor-target system (local angle of incidence of the sonar beam, local slope), 2) physical characteristic of the surface (roughness of the seafloor at scales comparable with sonar's wavelength) and 3) intrinsic nature of the surface (e.g., rocks vs. sediments) (Source: Blondel, 2009)

Bathymetric terrain analysis

Derivatives from the bathymetric grid are one of the important sets of data used in the analysis for the thesis. These terrain variables are derived from multibeam bathymetry data. They are used as part of the abiotic variables throughout this thesis. The derivation is performed on the multibeam bathymetry represented in a pixel grid. Based on a study by Wilson (Wilson et al., 2007), terrain variables can be grouped into four categories: slope, orientation, relative position of features and terrain variability (Figure 1.9).

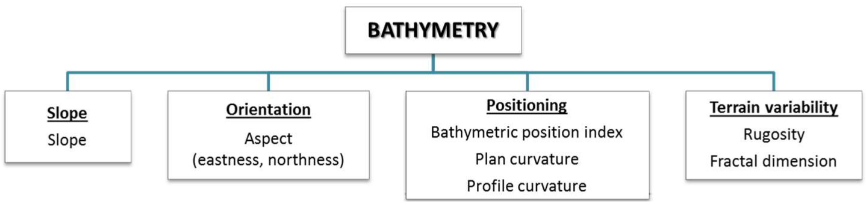


Figure 1.9: Derivatives from bathymetry data can be divided in to four types of secondary layers; slope, orientation, positioning and terrain variability. Modified from Wilson et al. (2007).

Slope is a key variable in landscape ecology. It is one of the common indices adopted from landscape analysis and widely used in the marine realm. Slope represents the maximum rate of change in value from a cell to its neighbour. The lower the slope value the flatter the terrain. Slope is calculated in Landserf v2.3 using Evans et al. (1979) method using the following equation:

$$slope \quad \arctan(\sqrt{\left[\frac{\partial Z}{\partial x}\right]^2 + \left[\frac{\partial Z}{\partial y}\right]^2}$$

where Z is the bathymetry depth and x and y are the coordinates

Slope is one of the most widely used terrain variable used in studies related to seabed mapping. There are many other slope algorithms readily available in GIS and related software to calculate slope from bathymetric data. The effect of using different slope calculation was examined extensively in terrestrial studies (e.g. Dunn and Hickey, 1998; Hickey, 2000; García Rodríguez and Giménez Suárez, 2010; Gao et al, 2012;). However, there is a only small volume of literature that focuses on DTM uncertainty and the computation and use of terrain variables in marine context. The most thorough investigation on this was made by Dolan and Lucieer (2014) by 1) quantifying the effect of error in bathymetric data on slope derivatives, 2) examining the effect of different algorithms used to calculate slope and 3) effects of bathymetric data grid resolution and slope computation analysis window. According to their investigation they suggest that using Landserf's multiple scale analysis is beneficial for bathymetric data as this can tailor the length scale/ window sizes for the analysis to a particular type of environment containing different sizes of features. For instance, in submarine canyons where you have small gullies and broad features such as the canyon floor (area near the thalweg), by computing multiple scale analysis, it retains full detail of bathymetric surface through the minimum windows analysis (i.e. 3 x 3 window size) and bigger windows for broader features. They conclude that although there is no one analysis that can be pointed out as the best method for seabed mapping or marine geomorphology, they recommende suitable algorithms to calculate slope based on the purpose of the analysis and quality and resolution of bathymetric data.

Aspect is a derivative from multibeam bathymetry and commonly available from most GIS application (e.g. ArcGIS, Erdas IMAGINE). It identifies downslope direction of the maximum rate of change value in from each pixel to its neighbours. It is closely linked to slope and can be simply thought of as the direction of slope. The output value is expressed in degrees clockwise from north. The aspect is calculated in Landserf v2.3 as follows:

$$aspect = \arctan(\frac{\partial Z}{\partial y} / \frac{\partial Z}{\partial x})$$

where Z is the bathymetry depth and x and y are the coordinates

As this derivation is typically measured in degrees, different values may be oriented in the same direction (e.g. 1^{o} and 359^{o}). To avoid confusion in statistical calculation, aspect is split into two components: eastness and northness (Hirzel et al., 2002; Wilson et al., 2007).

$$eastness = \sin(aspect) \qquad northness = \cos(aspect)$$

Aspect is one of the most common and widely used first order derivatives of DTMs. Its usage is well known in the terrestrial context as a significant factor in generating differences in ecosystem characteristics (Bale and Charley, 1994; Bale et al, 1998). For instance, the direction of the hydrological and sunlight exposure of mountains (i.e. the aspect) effects the distribution patterns of vegetation (Hartung and Lloyd, 1969; Ganuza and Almendros, 2003), and local variation in temperature and precipitation regulates decomposition rates of soil organic matter (Chen et al., 1997; Lisiki and Westman, 1997; Casanova et al., 2000). In a marine context, aspect is a valuable variable for shallow water, where it provides information regarding the exposure to dominant swell or where sunlight is able to reach the seabed (Lucieer et al., 2013). However, in the deep-sea environment, aspect is more relevant to be associated with local and regional currents (Gage and Taylor, 1992) rather than sunlight exposure due to the limited presence of sunlight (Schrope, 2007). However its usage is still limited in marine habitat related studies. This is partly because of the lack of oceanography and circulation patterns data, which with such information only then makes the aspect a significant variable (Wilson, 2007). The issue is further discussed in Chapter 2 and 4.

The *Bathymetric position index* (BPI), the algorithm is adapted from topographic position index, TPI), is commonly used to categorise topographic position in terrestrial environment (Weiss, 2001) and has been applied to a number of benthic habitat studies (Iampietro et al., 2004; Lundblad et al., 2006; Wilson et al., 2007). The BPI compares the elevation of each pixel to the mean elevation of neighbouring pixels. The algorithm calculates the difference between cell elevation value and the average elevation within a circular neighbourhood within a certain radius (known as scale factor). Other options of neighbourhood type to calculate BPI are available in the toolbox and are described in detail by Jenness et al. (2010). Positive BPI values represent locations that are higher than their average surrounding while negative values indicate otherwise. Since BPI is innately scale dependent, a large scale factor is useful for delineating large scale seabed features in comparison to a small scale factor. BPI in this thesis is calculated in ArcGIS 10.2 using the Land Facet Corridor Designer extension (Jenness et al., 2011). The BPI algorithm for a circular neighbourhood is as follows;

$$BPI(scalefactor) = int\left(\left(bathy — focalmean(bathy, circle, rad)\right) + 0.5\right)$$

where *scalefactor* = radius of circular neighbourhood in pixel unit; *bathy* = raster bathymetry grid and *rad* = radius of circular neighborhood (pixel)

The BPI is described in detail by Lunblad et al. (2006) and demonstrated the ability of broad and fine scale BPI to capture different component of overall terrain variations (Figure 1.10).

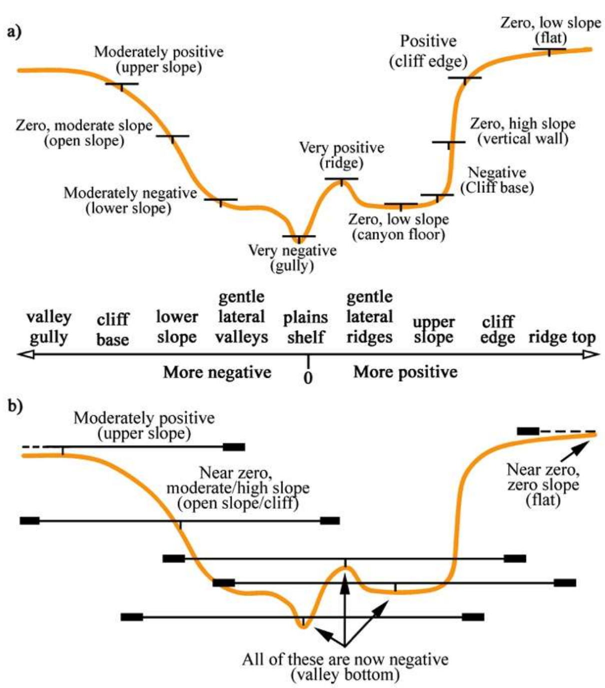


Figure 1.10: A description of the resulting bathymetric position index values derived from bathymetry data, based on topographic position index by Weiss (2001). a) fine scale and b) broad scale BPI values (image is adapted from Weiss, 2001).

Curvature is a second spatial derivative of multibeam bathymetry explaining concavity and convexity of the surface. The values, similarly with slope, depend upon the line or plane along which calculation are made. There are multitudes of ways to define curvature of a surface as mentioned in literature (Schmidt et al., 2003) that has been widely applied for terrain analysis in terrestrial (Porres de la Haza and Pardo Pascual, 2002; Yu et al., 2015) and marine realm (Wilson et al., 2007; Hasan et al., 2014). It is also one of the most commonly available terrain analyses in GIS software (Hengl and Reuter, 2009). Plan and profile curvature are both represent the rate of change in slope at that point in a horizontal and vertical plane, respectively. Negative value indicates a concave shape, positive is convex and zero if there is no sloping. According to Wilson et al., (2007), based on her analysis plan curvature are beneficial in highlighting ridges and channels while profile curvature are useful to pick out breaks in the slope possibly may be of significance for feature boundaries. The profile and plan curvature in this study are derived as follows using Landserf v2.3 (Wood, 2009);

$$profc = \frac{-200\ (ad^2 + be^2 + cde)}{(e^2 + d^2)(1 + e^2 + d^2)^{1.5}} \qquad planc = \frac{200\ (bd^2 + ae^2 - cde)}{(e^2 + d^2)^{1.5}}$$

where *a*, *b*, *c*, *d* and *e* are the coefficients of the DTM surface and the curvature terms are multiplied by 100 to express them as per cent gradient per unit length

The DTM surface can be locally approximated by the bi-variate quadratic funcion (Evans, 1980):

$$Z = aX^2 + bY^2 + cXY + dX + eY + f$$

where Z is the bathymetry depth, and X and Y are the horizontal coordinates

Rugosity or seafloor roughness calculates the ruggedness of the seafloor, especially in the terms of how convoluted and complex a surface is. Jenness (2004) developed a method to calculate rugosity, which is essentially a ratio of a surface area to the planar area, across the neighbourhood of the central pixel. The algorithm is made available via DEM Surface Tools as an extension for ArcGIS 10.2 and was used to derive the following parameter in this study as follows;

$$Rugosity\ = \frac{surface\ area\ of\ 3\ x\ 3\ neighbourhood}{planar\ area\ of\ 3\ x\ 3\ neighbourhood}$$

Values nearing 1 indicates a smooth surface while a higher ratio is more rugged.

Fractal dimension is a measure of the surface complexity or changes over an area. It has been used to study the terrain variation on the continental slope with relevance for benthic habitat and fauna distribution (Wilson, 2007), habitat structure and biodiversity on rocky shores (Commito and Rusignuolo, 2000; Kostylev et al., 2005) and tropical coral reef structures (Basillais, 1997). Here, fractal dimension is calculated in Landserf v2.3 (Wood, 2005). There are various ways of calculating fractal dimension, Landserf uses the 'Variogram method' (e.g. Mark and Aronson, 1984) to produce a raster map of fractal dimension values indicating the surface complexity over space. The variogram is calculated as:

$$\gamma(h) = \frac{1}{2n(h)} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(z_i - z_j\right)^2$$

where h is the lag between measured cells, n is the number of pairs considered and z bathymetry depth.

Landserf calculates the fractal dimension within a moving window around each cells across the raster to gain an indication of surface roughness changes over the entire multibeam bathymetry raster. The outcome raster will be a range of fractal dimension values ranging from 2.0 indicating smooth, scale invariant behaviour and a theoretical maximum of 3.0 indicating space filling rough surface.

Ratio of real to synthetic sidescan sonar imagery is a derivation from real and synthetic sidescan sonar imagery (Figure 1.11); the latter is produced from multibeam bathymetry. Synthetic sidescan imagery is created similar to the sidescan sonar imagery by simulating the flight of the sonar through the bathymetry along the sonar vehicle track (LeBas and Mason, 1997; Ismail, 2010). In comparison to the real sidescan sonar imagery, synthetic imagery created is entirely dependent on topographical attributes and slope reflection and assumes the lithological variations and terrain roughness to be constant. Based on this property, calculating the ratio of backscatter between real and synthetic sidescan sonar imagery depicts the lithological attributes and cancels out the effect of slope on the backscatter.

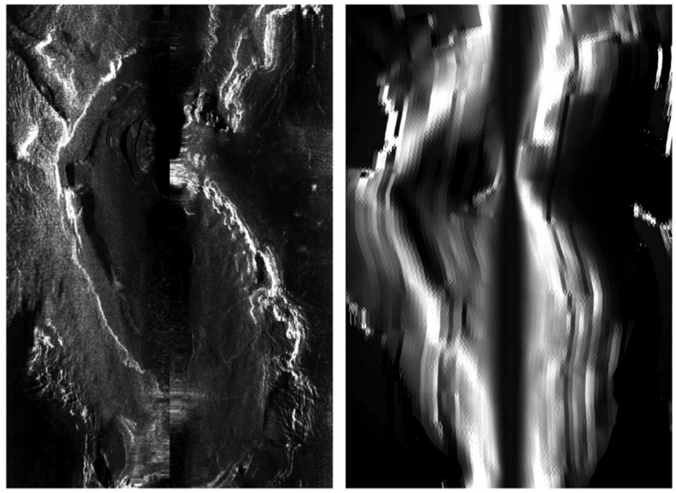


Figure 1.11: On the left is a section of real sidescan sonar imagery acquired through sonar survey in a submarine canyon. Meanwhile, image on the right is a synthetic sonar imagery produced by simulating the flight of the sonar onto multibeam bathymetry data of the same area. Synthetic imagery contains topographical and slope attributes without any lithological effect in comparison to real sidescan sonar imagery. Topographical features can be clearly seen and matching between the two images.

Object based image analysis

Object based image analysis (OBIA) is a pattern recognition technique that has been widely used in remote sensing to segments and classify images based on meaningful objects regardless of its pixel. The concept of image segmentation has long existed, but is more common in industrial image processing such as medical image processing and was not used extensively in geospatial applications (Blaschke et al., 2004). The strength of OBIA is that it examines pixels in context of the environment that they occur in rather than in isolation. OBIA builds up an image iteratively, recognizing groups of pixels as objects. It uses the colour, shape, texture and size of objects as well as their context such as pixel location and relationships to other objects to draw conclusions and inferences regarding classification rules (Lucieer et al., 2013). The use of this technique in marine habitat mapping is still at its infancy, some of the studies that has adopted the image segmentation technique are Lucieer (2007) to characterise rocky reef habitat and Lucieer and Lamarche (2011) to map deep water substrates. These studies have shown that OBIA is the way forward for marine habitat mapping and there are endless opportunities to be explored and contribute towards the development of automated and quantifiable marine habitat mapping. In this study, the use of OBIA is trialled onto sidescan imagery since they have much higher resolution than multibeam bathymetry data and therefore has the more identifiable seafloor features. By using OBIA, these features potentially can be retained in the marine landscape procedure to produce the marine landscape map. Further investigation of the OBIA usage is reported in Chapter 3.

1.2.3 Rationale and objectives

The thesis is built on the fundamental goal to bridge the gap between science community and policy makers. Additionally, the methodology uses the most common data type obtained for seafloor related studies and aims to optimise its usage. The objective is addressed as follows:

Objective 1: Technique development

A simple and straightforward but statistically robust marine landscape mapping method is developed for bathymetric grid data that is usually available from initial seabed surveys. The aim is to promote the use of the marine landscape approach as a way to represent spatial information in complex deep-sea areas. The proposed technique is a step forward to aid existing deep-sea classification schemes. The technique developed is objective, automated and statistically robust, time and labour efficient and suitable for broad regional scale mapping.

Chapter 2 is dedicated to the development of an objective automated marine landscape mapping technique using multivariate statistical analysis. The method was tested in the Cascais and Lisbon–Setúbal Canyons. This chapter follows the publication

> Ismail, K., Huvenne, V.A.I., Masson, D.G., 2015. Objective automated classification technique for marine landscape mapping in submarine canyons. Marine Geology 362, 17-32.

A way of translating sediment point sample data to provide a full coverage substrate distribution map is discussed in **Chapter 3**. A semi-automated methodology, based on Object-Based Image Analysis (OBIA), to produce a substrate distribution map is discussed in Chapter 3, together with its effect towards the marine landscape delineation.

Objective 2: Quantifying spatial structure

Based on Niche Theory, spatial variability in environmental conditions is the main driver behind marine biodiversity. With this fundamental concept, marine landscape heterogeneity is proposed as a proxy for biodiversity. The quantification of spatial heterogeneity is carried out on a marine landscape map produced using the technique developed. The index used for marine landscape quantification is extended from landscape ecology. The detail of the quantification is discussed comprehensively as part of **Chapter 3**. This chapter is aimed for publication in an international peer-reviewed journal,

> Ismail, K., Robert, K., Huvenne, V.A.I., 2015. Quantification of marine landscape heterogeneity in submarine canyons. *To be submitted*

Objective 3: Spatial information across scale

Pixel size and extent are the primary scaling factors affecting heterogeneity. The technique used for broad scale mapping (~100 km^2) is put to trial for transferability in medium scale (~1 km^2) surveys. The method developed in Chapter 2 and 3 for broad scale mapping is applied to the high-resolution multibeam bathymetry acquired using ROV. The issue on scaling relationship here is addressed in **Chapter 4** and is in preparation to be submitted to an international peer-reviewed journal,

> Ismail, K., Robert, K., Huvenne, V.A.I., 2015. Application of marine landscape mapping to high-resolution data. *To be submitted*

Chapter 5 provides a synopsis describing the key findings in relation to the thesis aims and objectives. Recommendations are made about issues raised during the study, followed by suggestions for future directions relating to marine habitat mapping to support the scientific framework in ecosystem-based management for submarine canyons. The chapter finishes with a summary of this research.

Chapter 2: Objective Automated Classification Technique for Marine Landscape Mapping in Submarine Canyons

2.1 Abstract

This study proposes a fully automated and objective technique to map marine landscapes in submarine canyons. The method is suitable for broad and regional scale mapping derived from sonar data and uses multivariate statistical analysis. The method is divided into two main parts: the terrain analysis and the multivariate statistical analysis. The first part aims to optimise the sonar data and comprises three steps 1) data resampling 2) determination of length scale and 3) multiple scale analysis. The second part covers the actual marine landscape classification and consists of 1) principal component analysis (PCA) 2) K-means clustering and 3) cluster determination. In addition, a confidence map is presented based on clusters membership derived from clusters distance in attribute space.

The technique was applied in the Lisbon-Setubal and Cascais Canyons offshore Portugal. The area was classified into 6 marine landscapes that represent the geomorphological features present in submarine canyons. The main findings from the study are 1) transferability of a tool from geomorphometric analysis – Estimation of Scale Parameter (ESP) - to detect length scale of potential patterns in bathymetric grids; 2) multiple scale terrain analysis allows an appropriate discrimination of local and broad scale geomorphic features in marine landscape mapping; 3) the method does not only delineates geomorphic seafloor features but also points out properties that might influence biodiversity in a complex terrain.

2.2 Introduction

Over the past decade, the ongoing effort to develop an efficient and reliable method to map and study benthic habitats in various environments has promoted the advancement of classification techniques in the habitat mapping community (Brown et al., 2011). Benthic habitats are physically distinct areas of seafloor that are associated with particular communities of plants and/or animals. Of those two components that structure a benthic habitat - the physical environment and the species community - it is often the detailed species information that is lacking during seafloor characterisation. General geophysical mapping is therefore commonly used as the basis for benthic habitat mapping. Advances in sonar technology now permit seafloor imaging with high resolution and wide coverage using a wide variety of instruments and systems of different frequency and resolution (Hayes and Gough, 2009; Hansen et al., 2011; Nakanishi and Hashimoto, 2011; Paull et al., 2013; Harris et al., 2014; Wynn et al., 2014). These data can be used to depict various seafloor geomorphic features and interpreted to provide potential habitats represented on a marine landscape map.

"Marine landscape" is a concept introduced originally by Roff and Taylor (2000), who developed a classification based on enduring geophysical features that reflect changes in biological communities composition. They emphasized the importance of identifying and conserving representative spaces or landscapes rather than preserving individual species. They produced a classification using geophysical features to identify representative and distinctive benthic habitats supporting different communities, which works as an ecological framework for marine conservation.

Based on this fundamental concept, the marine landscape in this study is defined as an environment distinguished by its abiotic characteristics with a potential to provide colonization ground for specific biological assemblages. This approach has been applied successfully in the marine realm, specifically in shallow water environments (Al-Hamdani et al., 2007; de Grosbois et al., 2008; Verfaillie et al., 2009; Kotilainen and Kaskela, 2011). On a global scale a similar approach is being used to segment the ocean floor based on its geomorphological features as done by Harris et al. (2014).

Although the aim of the studies mentioned above is similar, i.e. to classify the seabed in relation to its biological associations, either for managerial purposes or to predict biological occurrences, each study offers a different methodology. The methods vary from the conventional approach of manual digitising over algorithm-assisted digitising to fully automated techniques, or use combinations thereof. Unfortunately, most methods developed so far always still a have subjective aspect in several stages of the methodology e.g. the parameters to use, the number of classes, the scale. The ideal methodology should offer a robust statistical way to make these choices in an objective way. Moreover at this day and age, with the current state of the art in acoustic technology, large volumes of data are becoming available, therefore a time- and labour-savvy approach is preferable. A robust approach that is objective, repeatable and can speed up the delineation of marine landscapes from acoustic survey data is much needed especially when these data are now easier to obtain compared to a decade ago.

2.2.1 Scope and aims

Therefore, taking the above arguments into account, the aim of this study is to develop a fully automated marine landscape mapping technique that is robust, objective and repeatable, based on remotely sensed acoustic survey data, using multivariate statistical analysis. The method is developed in submarine canyons because of their complex characteristics defined by their spatial structure that contains true three-dimensional morphology and terrain variability often supporting increased biodiversity. However, submarine canyons are difficult to quantify as they often overwhelms conventional mapping techniques. This aim will be addressed through the following objectives:

1. Evaluate and compare the effect of a single scale vs. multiple scale approach

2. Test the transferability of a method used in Object Based Image Analysis (OBIA) to detect the scale that best represents real-world objects in multibeam bathymetry data.

3. Evaluate the advantages of the proposed method in comparison to manual delineation for marine landscape mapping.

2.3 Materials and methods

2.3.1 Study area

Submarine canyons are important geological features incised in most continental margins of the world’s oceans (Harris and Whiteway, 2011). They serve as conduits for the transport of large amounts of sediment and organic matter from continental shelves to the deep abyssal plains (Hickey et al., 1986; Puig and Palanques, 1998; Monaco et al., 1999). The deep and complex topography, strong currents and occurrence of high turbidity promotes a high variability of substrates and terrain, affecting the habitat heterogeneity and making submarine canyons a potential hotspot for biodiversity (Vetter and Dayton, 1998; Mortensen and Buhl-Mortensen, 2005; Tyler et al., 2009). Considerable interest in benthic habitats associated with submarine canyons (Tyler et al., 2009; Huvenne et al., 2012; Currie and Sorokin, 2014; De Leo et al., 2014), especially in vertical and overhanging terrains that occur at the heads of shelf-incising canyons, has been generated (Yoklavich et al., 2000; Brodeur, 2001; Huvenne et al., 2011; Johnson et al., 2013). Such terrains hold biologically diverse communities, but are especially difficult to map.

The Cascais and Setúbal-Lisbon Canyons that form the basis for this study, cut the western Portuguese continental margin between 38° and 38° 30'N (Figure 2.1). Cascais Canyon begins at a water depth of 175 m at the shelf edge of the Portuguese margin. It is not connected directly to a river system but its head is situated 27 km southwest of the Tagus river mouth. It is the shortest canyon on the Central Portuguese continental margin. Although the average gradient of the whole axis is only about 3°, its slope gradients typically exceed 10°, making it the steepest canyon (Lastras et al., 2009) in the region. The upper Cascais Canyon first trends south-southwest then changes direction further down, to a westward and later north-westward trend.

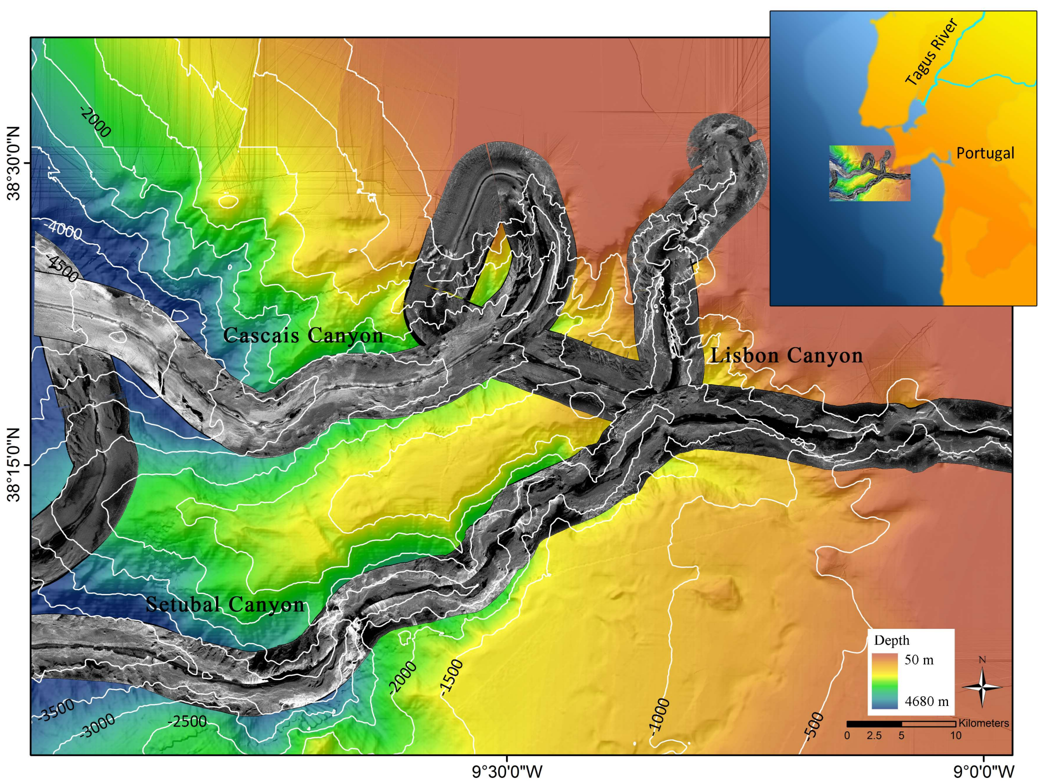


Figure 2.1: Bathymetry map of Lisbon–Setúbal and Cascais Canyons offshore Portugal, overlain by TOBI sidescan sonar imagery coverage. Contour interval is 500 m. The inset map shows the location of the study area relative to the location of Portugal.

The Lisbon Canyon head is situated 13 km southwest from the Tagus river mouth and 5 km west of the nearest coastline at approximately 120 m water depth. It incises 28 km into the shelf with a total length of 37.5 km (Lastras et al., 2009). The canyon trends north-south towards the middle course of Setúbal Canyon and is almost perpendicular to the Setúbal branch at 2010 m water depth, where these canyons join.

The Setúbal Canyon is east-west oriented and the canyon head is located at approximately 90 m water depth, situated at about 20 km south-southwest of the Sado river mouth and 6 km west of the nearest coastline in Setúbal Bay. The branch cuts 41 km into the continental shelf (Arzola et al., 2008). Setúbal Canyon is among the submarine canyons that extend across the continental shelf and approach the coast. This type of canyon is known to intercept organic-matter-rich sediments; these cause organic rich material to be supplied downslope. For example, Gage et al. (1995) reported finding sea grass at a water depth of 3400 m in the middle canyon.

2.3.2 Data

Data and samples used in this study were collected during 5 different cruises in the area. Multibeam bathymetry data were compiled from RRS Charles Darwin cruises 157 (May/June 2004) and 179 (April/May 2006) and from ancillary data kindly provided by IFREMER (French Research Institute for Exploration of the Sea). The data were integrated during the HERMES project (Hotspot Ecosystem Research on the Margins of European Seas) (http://www.eu-hermes.net). The multibeam bathymetry was processed using SwathEd and results in an image with pixel size of 100 m.

30 kHz TOBI (Towed Ocean Bottom Instrument) sidescan sonar imagery was collected during three cruises in 2003, 2005 and 2006: RV Pelagia 219, RSS Discovery 297 and RSS Charles Darwin 179. The sidescan sonar imagery, also published in Lastras et al. (2009) was pre-processed using the PRISM (v4.0) (Le Bas and Hühnerbach, 1998) and Erdas Imagine (v8.5) software suites to produce imagery with improved geographical registration (Ismail, 2011). TOBI is towed at an altitude of approximately 400 m above the seafloor at about 2 knots, producing 6 km wide swath images with a horizontal resolution of 6 m (Le Bas et al., 1995).

The grids of multibeam bathymetry and sidescan sonar imagery used here had a different resolution of 100 m and 6m, respectively. Data have to have equal pixel size to carry out the multivariate statistical analysis. Therefore, the data was resampled to a common cell size of 25 m resolution. This is thought as a good compromise to keep the sidescan sonar detail, without over-interpolating the multibeam-derived datasets.

2.3.3 Research strategy

The technique to map the marine landscape in submarine canyons developed here, is divided into two parts: the terrain analysis and the multivariate statistical analysis. The first part focuses on optimising the usage of the acoustic dataset while the second part addresses the classification of the data into distinct physical areas and is partly based on the work of (Verfaillie et al., 2009) in shallow waters. Both parts comprise 3 steps each, a simplified illustration of the research strategy is presented in Figure 2.2.

The software used for each step in the first and second part is listed as follows; the first part: 1) data were resampled in ArcMap 10.0 using bilinear algorithms, 2) determination of length scale for multiple scale analysis using the Estimation Scale Parameter tool in Ecognition Developer v8.9, 3) production of terrain indices using multiple scale analysis in Landserf v2.3 (Wood, 2005), whilst RStudio v0.98.484 was used in the second part of the method to carry out 1) principal component analysis (PCA), 2) K-means clustering and 3) cluster determination using within group sum of squares.

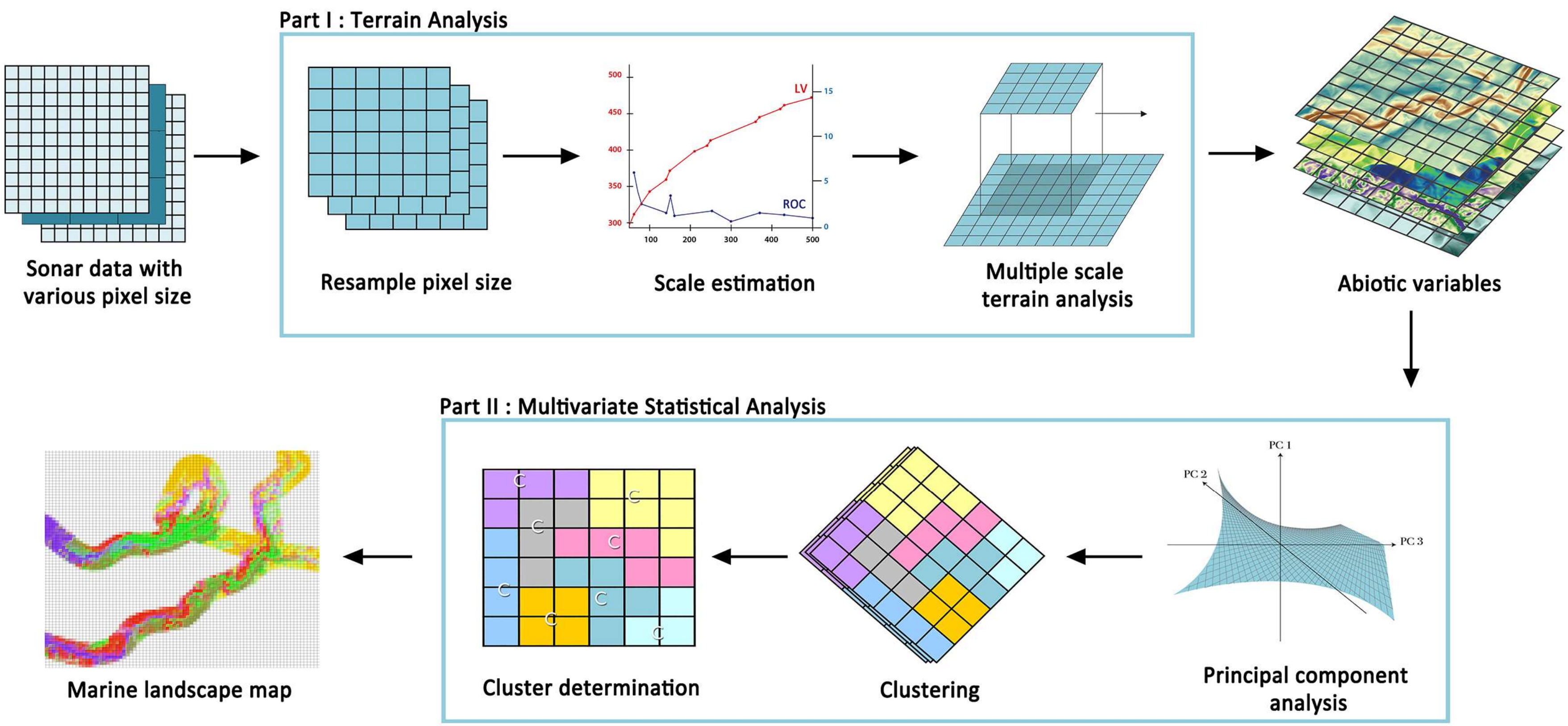


Figure 2.2: A simplified flowchart of the automated and objective techniques used to produce marine landscape maps for submarine canyons. The method consists of two parts; terrain analysis and multivariate statistical analysis.

2.3.3.1 Single scale vs. multiple scale terrain analysis

Multiple scale analysis refers to the incorporation of terrain indices produced at different scales to optimise the detection of details and features in bathymetric surfaces for marine landscape characterisation. Two length scales are used to represent local features and broad features, both of which are valued for habitat characterisation. The length scales represent n x n analysis window sizes to calculate terrain indices, where n is any odd integer value (Wilson, 2007). Due to computational limitation and processing time for a large area, multiple scale terrain analysis only manages to be tried out with two scales. As suggested by Dolan and Lucieer (2014), using terrain indices obtained from multiple scale analysis in comparison to other approaches allows retaining the full detail of the bathymetric surface, while at the same time keeping the computation time reasonable. However, in their studies the length scales for the analysis were predetermined and therefore subjective.

An automated and objective procedure to select length scales for multiple scale analysis is proposed here and is adapted from a technique used for image segmentation in geomorphometry (Dragut et al., 2010). The Estimation Scale Parameter (ESP) tool is used for fast estimation of scale parameters for a multiresolution segmentation in Object Based Image Analysis (OBIA). The tool is based on the fundamental concept of the relationship between spatial structures of images and the size of objects in the real world. Hence both methods – multiple scale terrain analysis and segmentation – try to emulate real-world units by aggregating cells. The tool calculates the local variability or Local Variance (LV) in the segment or window, for increasing segment/window sizes. However, for multiple scale analysis, the LV graph does not show an obvious threshold for suitable scale, therefore the rate of change of local variance (ROC-LV) graph is used instead, as suggested by Dragut et al. (2010). ROC-LV measures the amount of change in LV from one scale level to another. Steps in the ROC-LV graph indicate the scale at which groups of real-world objects are more appropriately imaged.

Based on a study by Wilson (2007), multiple scale analysis has proven to be beneficial to delineate terrain features at particular scales and facilitate habitat mapping work. However, due to computational limitation, only one additional scale is included for the terrain analysis in this study. The scale size is determined as an equivalent of the scale parameter obtained using the ESP tool. Since the Scale Parameter (SP) value has no unit, the segments produced using the SP in Ecognition are exported in ArcGIS as polygons (feature class). The mean value of the area of the segments (i.e.: polygons) is calculated and by using the calculation below, the additional window size for the terrain analyses (i.e.. slope, curvature etc. calculations) is determined (see also Appendix A):

$$\begin{matrix} window\ size\ for \\ multiple\ scale \\ terrain\ analysis \\ (pixel) \end{matrix} = \frac{\sqrt{mean\ area\ of\ segments(m2)}}{\begin{matrix} multibeam\ bathymetry \\ pixel\ size\ (m/pixel) \end{matrix}} X \begin{matrix} minimum\ window \\ size\ for\ analysis \\ along\ one\ side\ (pixel) \end{matrix}$$

Once the appropriate length scales are determined through the ROC-LV graph, terrain variables are calculated at those scales using Landserf v2.3. The resulting layers are then exported to R and are subjected to the multivariate statistical analysis. Comparison between marine landscape maps created using single scale and multiple scale terrain indices is carried out to evaluate the significance of this step. A total of 18 abiotic terrain variables (Table 2.1) are used in the final multivariate statistical analysis. They include the multibeam bathymetry data and the TOBI sidescan sonar imagery, and their derivatives

Table 2.1: List of abiotic variables included in the principal component analysis. Ticked boxes indicate the available scale for the variables.

Abiotic Variable	***Descriptions***	***Length scale***	
		Fine	***Broad***
Digital terrain model (DTM) of bathymetry	Obtained from multibeam bathymetry survey. Represent depths of the ocean floor.	☑	
Slope	First derivative of DTM. Represents the maximum rate of change in value from a cell to its neighbour	☑	☑
Aspect	First derivatives of DTM.		
Eastness= sin(aspect)	Describes the orientation of slope. Indices for eastness	☑	☑
Northness= cos(aspect)	and northness provide continuous measure (-1 to +1)	☑	☑
Bathymetric position index (BPI)	Measures the elevation of each cell compared to the mean elevation of neighboring cells (Weiss 2001)	☑	☑
Fractal dimension	A derivative from DTM. Indicates the spatial variation in roughness	☑	☑
Plan curvature	A second derivative of DTM. Provides the rate of change of aspect	☑	☑
Profile curvature	A second derivative of DTM. Provides the rate of change of gradient	☑	☑
Rugosity	A measure of small scale variations of the surface area across the neighbourhood of the central pixel (Jenness 2004)	☑	
Sidescan sonar imagery backscatter intensity	Obtained from TOBI. Sonar images are acquired by emitting continuous sonar pulses while moving, this returns with the image of the seafloor.	☑	
Ratio of sidescan sonar to synthetic imagery	Synthetic sidescan sonar imagery was produced by simulating the TOBI vehicle movement over the canyon bathymetry, and represents the sidescan backscatter components produced by the sloping terrain (Ismail 2011). Ratio represents the lithological attribute of the imagery.	☑	

2.3.3.2 Principal component analysis

One of the most difficult tasks when automating a seabed classification technique is to ensure objectivity when selecting the variables that will form its basis. A commonly used method to condense a highly collinear dataset prior to clustering is Principal Component Analysis (PCA) (Kabacoff, 2013). The abiotic variables in this study are highly collinear because they are derived from only two primary sources (i.e., multibeam bathymetry and sidescan sonar imagery). PCA is used to compute a set of new and linearly independent variables that are known as Principal Components (PC). Prior to PCA, all variables are standardised to have zero-mean and unit-variance in order to give them an equal weight in the PCA. The first PCs account for most of the variance in the original data, and can be chosen to form a smaller set of variables. The remaining variance, represented by the last PCs, is the error portion of the dataset.

A decision criterion based on the eigenvalues of the underlying correlation matrix is often used to determine how many PCs are to be retained in the analysis (Kabacoff, 2013). Following the Kaiser–Harris criterion, the analysis is limited to those PCs that have eigenvalues larger than 1, because they explain more variance than is contained in an original variable

2.3.3.3 Clustering

The PCs resulting from the PCA are then used as attributes for clustering. The K-means algorithm is often used for data partitioning, also in the marine environment (Legendre et al., 2002; Verfaillie et al., 2009; Amiri-Simkooei et al., 2011; Ahmed and Demsar, 2013). K-means is an iterative procedure that starts with a random allocation of class centres. All data points are given the class of the closest class centre, calculated using the Euclidian distance in the N-dimensional space of the retained PCs (Hartigan and Wong, 1979). Once the clusters are formed, the class centres are updated to the location of the average for each cluster. Re-allocation of the centres proceeds by iteration until a stable solution is reached where the location of the centres no longer moves.

2.3.3.4 Cluster determination and confidence

An important step in achieving objectivity in automated classification is to determine the optimal number of clusters. There are many criteria that have been used to decide on the correct number of clusters for K-means partitioning (Dunn, 1973; Caliński and Harabasz, 1974; Davies and Bouldin, 1979). However the large dataset of this study hinders the use of these statistical procedures in R due to the computational limit. Out of the many trialled, the method that is applicable for such huge data is using the within group sum of squares plot. The plot shows the within group sum of squares against number of clusters from the K-means clustering solution (ranging from 2 to 15) and the change in gradient in the plot is used to determine the optimal number of clusters from the K-means solutions (Kabacoff, 2013).

Once the final clustering through K-means solution is achieved, a separate map of cluster membership is produced to show cluster dominance at each location. The membership value can be expressed as follows

$$\mu_{ik} = \frac{1}{(d_{ik}^2)} \times \frac{1}{\sum_{k=1}^{n} \frac{1}{(d_{ik}^2)}}$$

where μ_{ik} is the membership value of the *i*th data point to cluster *k*, d_{ik} is the distance between data point *i* and cluster center *k* in attribute space and n is number of clusters. The above expression is modified from an expression used for fuzzy k-means classification for soil survey data (Burrough et al., 1997). The original expression was also used and reviewed in a study by Lucieer and Lucieer (2009) for seafloor sediment classification. Membership values are assigned to each cluster so that all values for each pixel sum to 1. Using this characteristic, clustering uncertainty can be quantified using the confusion index, CI

$$\mathrm{CI} = \frac{\mu_{(max-1)_i}}{\mu_{max_i}}$$

where μ_{max_i} is the membership value of the cluster with maximum μ_{ik} at location i and $\mu_{(max-1)_i}$ is the second largest membership value at the same i location. If the value of CI nears 0, then only one cluster k dominates the location and it has a low confusion (high maximum membership value of cluster k), however if the value of CI is nearing 1 there is high confusion between two or more clusters at location i.

2.3.4 Qualitative assessment

Expert visual interpretation based on sidescan sonar imagery from previous work in 2005 was used to evaluate the performance of the automated technique. The interpretation is independent from any input from the automated marine landscape map. Visual comparison was made between expert interpretations for Setúbal Canyon and the automated marine landscape map produced by overlaying both in ArcMap 10.0.

2.4 Results

2.4.1 Terrain analysis: ROC-LV graph

The ESP yields the ROC-LV graph as shown in Figure 2.3. According to Dragut (2010), the ROC-LV plot enhances the discrimination of the threshold at which the appropriate scale for real-world object representation is reached compared to an LV graph. The threshold is defined as the first break in the ROC-LV graph after the initial continuous and abrupt decay, and may appear as step or small peak. In this case, it appears as a step in the ROC-LV curve. The next level after 25 m (initial pixel) that is recognised as the appropriate scale that represents real-world objects is a SP of 225. Meaningful objects refer to real world objects such as gullies, the canyon thalweg and other geomorphological features that can be found in submarine canyons. The variation in slope and bathymetric position index using different length scales is shown in Figure 2.4. The local scale (25 m) picks out fine-scale variability in the canyon such as gullies or small branches, whereas the broader scale (SP = 225; features of 16.5m, i.e. requesting window sizes of 49 x 49 pixels - see Appendix A) shows the overall pattern of the whole canyon system, highlighting major features and smoothing out details present in the local scale analysis.

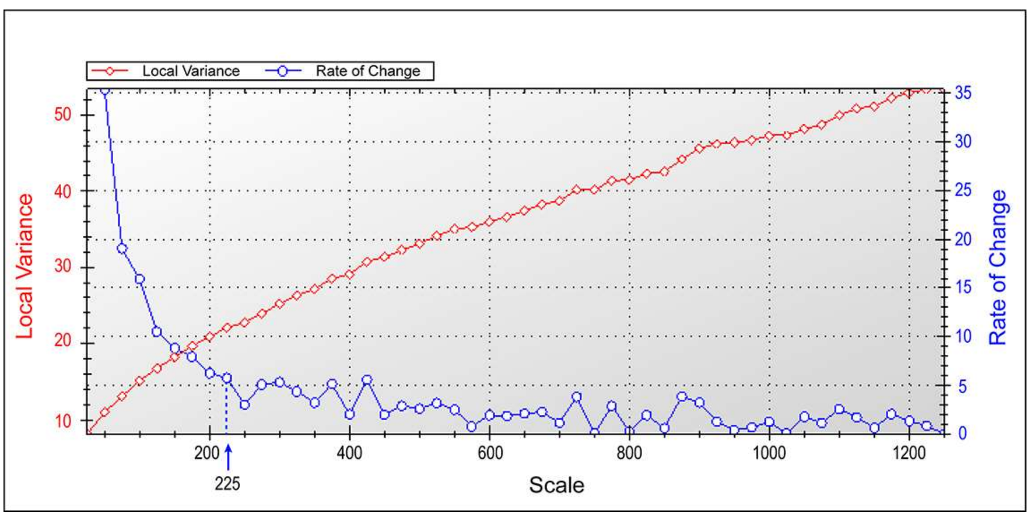


Figure 2.3: ROC-LV graph obtained using the ESP tool to determine the most appropriate analysis window size for multiple scale terrain analysis. Blue arrow indicates the threshold at which the analysis window size best represents real-world objects. Dragut et al. (2010) defined the threshold as the first break in ROC-LV curve after continuous and abrupt decay.

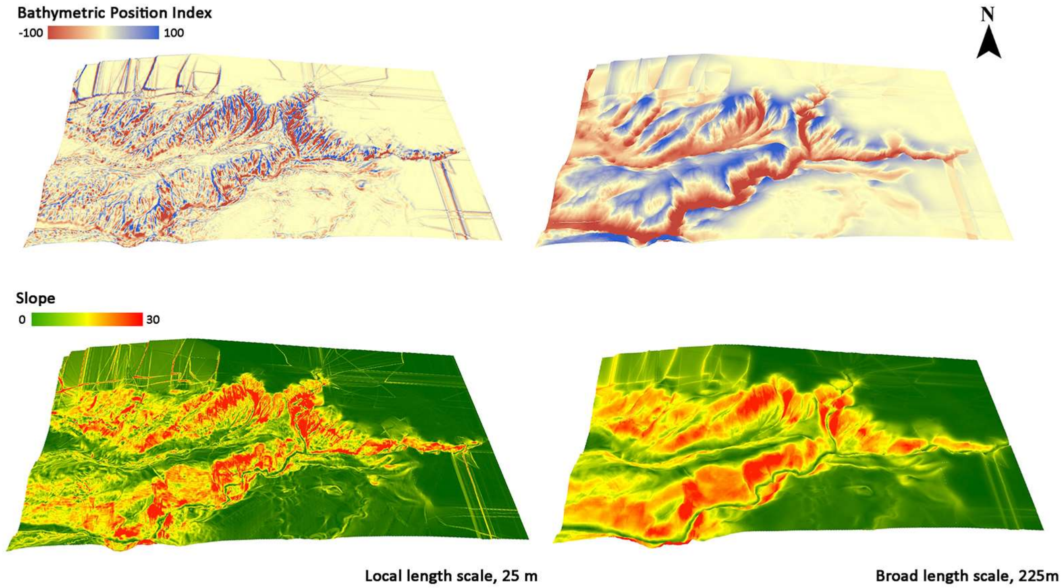


Figure 2.4: 3D views of the Portuguese Canyons from south. The figure shows variations of bathymetric position index analysis (top) and slope analysis (bottom) resulting from using two different length scales. The local length scale and broad length scale. Note the different features delineated at the different analysis scales. Results from local length scale contained detail features but noisier whereas broader length scale shows the gross canyon morphology.

2.4.2 Multivariate statistical analysis

2.4.2.1 PCA

The principal component analysis is conducted using the 18 abiotic variables listed in Table 2.1. Retaining only those PCs with eigenvalues larger than one, the PCA results in seven PCs, explaining 78% of the total variance. The rotated component matrix (Table 2.2) shows the factor loads that explain the correlations between the rotated PCs and the original variables. The main variables that drive the PCA are bathymetric position index (BPI), slope and northness (Figure 2.5).

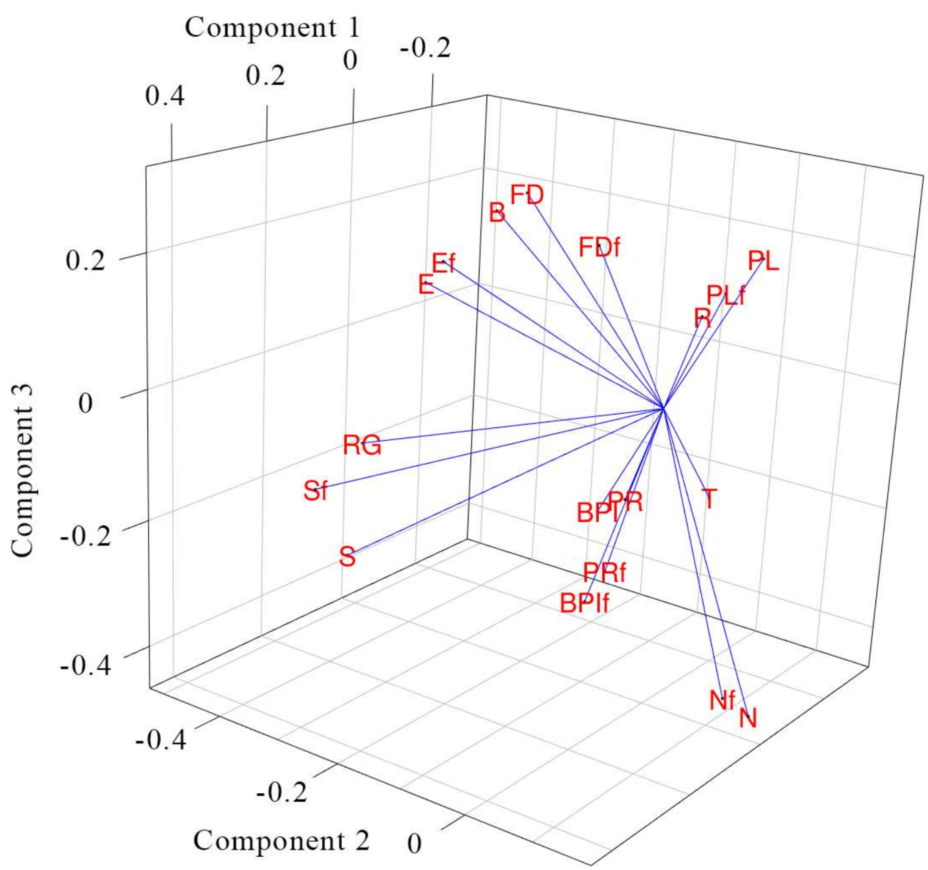


Figure 2.5: 3D representation of the first three principal components and coefficients of each variable. The plot illustrates which variables are driving the PCs. The longest arrow in the plot represents the most prominent abiotic variable in the principal components. The distances between arrows describe their correlation, the closer the arrows, the more correlated they are.

Table 2.2: Component matrix showing correlation between rotated PCs and the original variables. Highest factor loads in each PC are highlighted in bold. A 3D representation for the first three principal components is illustrated in Figure 2.5 with each variable plotted in abbreviation.

Abiotic Variables	*PC1*	*PC2*	*PC3*	*PC4*	*PC5*	*PC6*	*PC7*
Bathymetry (B)	0.2576	-0.1159	0.3103	0.2140	-0.1298	0.2465	-0.0423
Bathymetric position index broad (BPI)	**0.4394**	0.1544	0.0142	0.0268	-0.1071	0.2407	-0.2126
Bathymetric position index fine (BPIf)	0.4036	0.1249	-0.1295	-0.0777	0.1791	-0.2815	0.2215
Northness 225 (N)	-0.0479	0.1407	**-0.4570**	0.2537	-0.4265	-0.0165	0.0851
Northness (Ns)	-0.0436	0.1015	-0.4402	0.2692	**-0.4538**	-0.0402	0.1055
Fractal dimension 225 (Fd)	0.0802	-0.1813	0.2934	0.5053	-0.0154	-0.2200	0.0507
Fractal dimension (Fdf)	0.1150	-0.0489	0.2515	**0.4934**	-0.0843	-0.2849	0.0112
Plan curvature 225 (PL)	-0.3397	-0.0353	0.1511	0.0739	-0.0011	-0.1184	-0.0033
Plan curvature (PLf)	-0.2532	-0.0476	0.1102	0.0534	-0.1564	0.3108	-0.3650
Profile curvature 225 (PR)	0.4106	0.1735	0.0268	0.0118	-0.0645	0.1577	-0.2578
Profile curvature (PRf)	0.3523	0.1213	-0.1047	-0.0651	0.1485	-0.2263	0.1186
Ratio (R)	-0.0908	0.0002	0.1187	-0.0431	0.0149	0.1965	**0.7205**
Rugosity (RG)	0.0704	-0.4444	-0.1567	0.2245	0.1883	0.0108	0.0208
Eastness 225 (E)	0.1273	-0.3059	0.1436	-0.3623	-0.4339	-0.1911	0.0023
Eastness (Ef)	0.0926	-0.3014	0.1696	-0.3201	-0.4505	-0.2685	0.0296
Slope 225 (S)	0.1191	-0.4309	-0.3260	-0.0703	0.0979	0.2034	-0.0631
Slope (Ss)	0.0871	**-0.5155**	-0.2498	0.0845	0.1544	0.1058	0.0124
TOBI backscatter intensity (T)	-0.1474	0.0050	-0.1772	-0.0329	0.1826	**-0.5329**	-0.3803
Eigenvalues	3.4889	2.6542	2.3138	1.8017	1.4611	1.2085	1.1530

2.4.2.2 Clustering

A total of 2,316,746 pixels with seven PC variables were subjected to K-means clustering, in a cascade from two to fifteen clusters. The plot of within groups sum of squares against number of clusters is shown in Figure 2.6, and indicates a distinct increase at six clusters. This change in slope suggests that a six cluster solution may be a good fit for the data. Hence, final clustering is carried out using the K-means algorithm with six clusters.

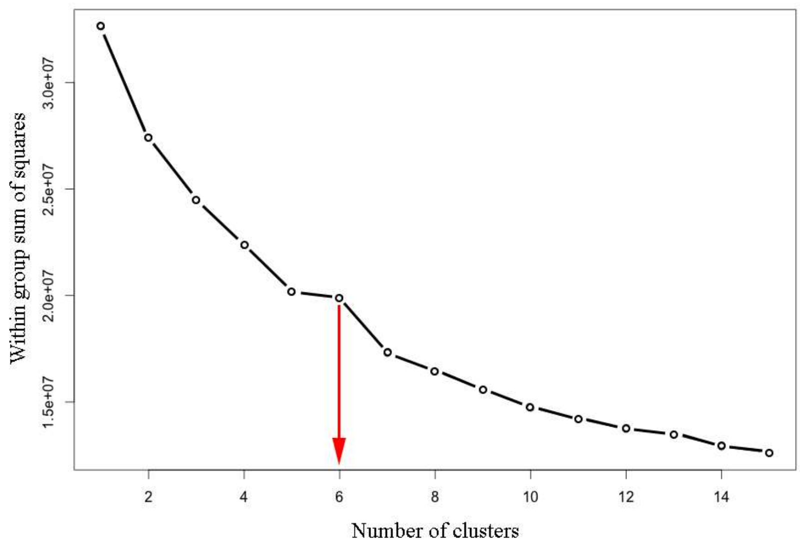


Figure 2.6: Plot of number of clusters against within sum of squares. The bend (change in slope) marked in red and projected towards the x-axis indicates the optimum number of cluster is 6.

2.4.2.3 Membership value and confusion index

The concept of membership values originates from the technique of fuzzy classification, where it is used to show continuous spatial variation by creating overlapping classes (Lucieer and Lucieer, 2009). Through this, using the Euclidean distances of data points towards cluster centres from the K-means partitioning, the same calculations were used to show classification uncertainty (Figure 2.7). High membership value means only one cluster is dominant for the data point; meaning at that location there is a high certainty of classification.

Based on the membership value for each cluster, a confusion index is produced (Figure 2.7). The confusion index map has very narrow transition zones between clusters, with high confusion values only at the cluster boundaries. If spatial correlation in membership values was weak, broad zones of high confusion index values would be observed, but they are not seen in confusion index map. The density plot of confusion index values indicates a positively skewed distribution, with a high percentage of data points with confusion value approaching zero. A low value in confusion index (approaching zero) indicates a less conflicting classification.

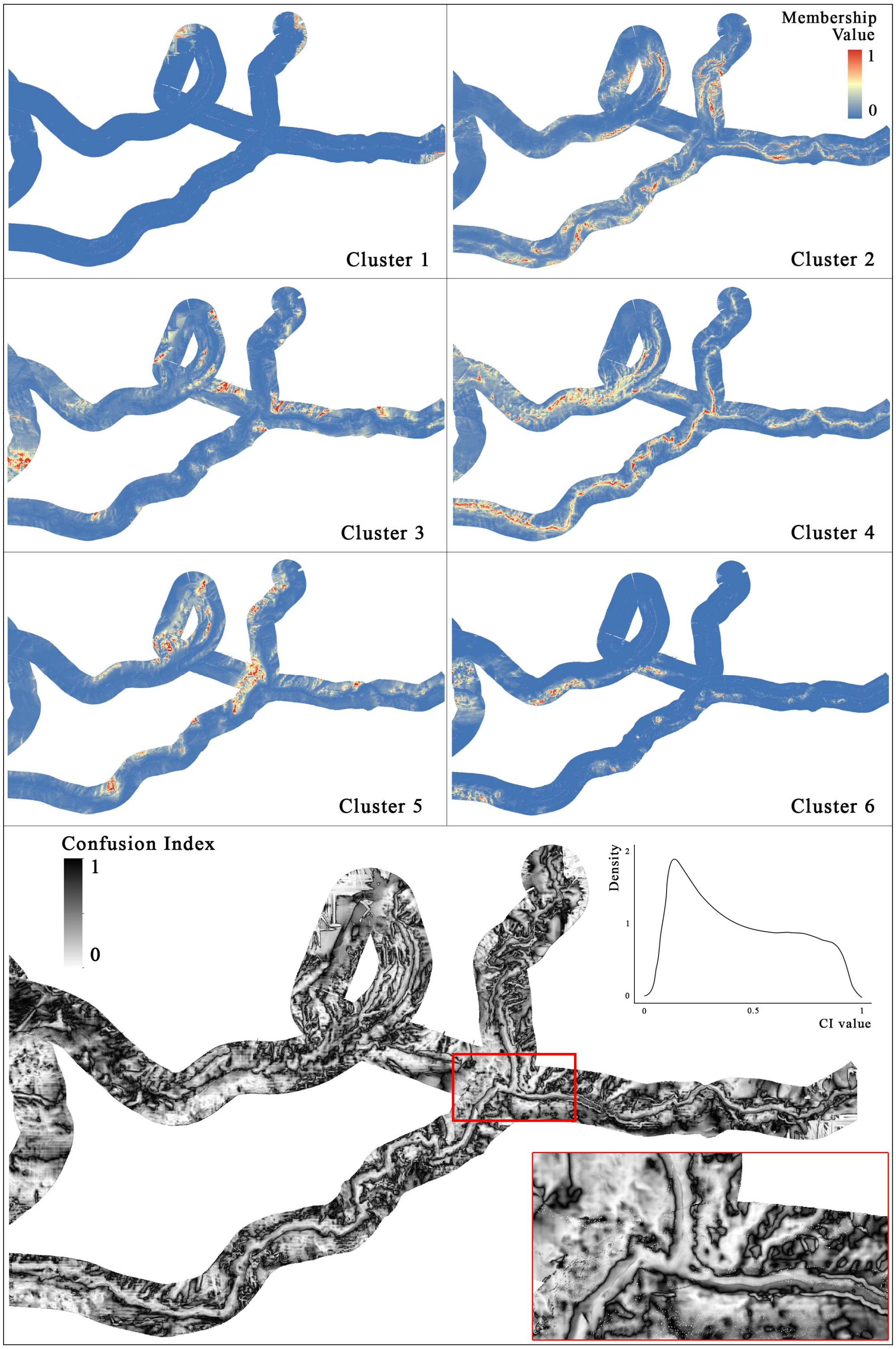


Figure 2.7: Upper maps: membership value of K-means partitioning for each cluster ranging from 0.0–1.0, where 1.0 indicates the highest membership value. The bottom map is a confusion index map. It shows a quantification of clustering uncertainty ranging from 0.0 to 1.0, with 1.0 being the most uncertain. A zoomed area in red box shows the uncertain area as black and approaching white is much certain area. Inset plot is a density plot of confusion index value for the attributes. Narrow highly confused zones (black) in the confusion index map and a positive skewed density plot indicates a low conflicting clustering with good separation amongst the clusters.

2.4.3 Marine landscape map

The result of the six cluster solution is presented in Figure 2.8 and Table 2.3. The six cluster solution represents the final marine landscape map produced for this area. The interpretation of each cluster is based on the boxplots of the original abiotic variables against the clusters (Figure 2.9a & 2.9b). Through these boxplots, characteristics of each cluster can be obtained based on the correlation with the original variables. Seventeen out of 18 abiotic variables show an obvious contribution to the classification.

For instance, rugosity, which represents the ruggedness of the terrain, shows a clear difference between the clusters. Cluster 2, interpreted as canyon wall, has the highest slope value and a wide range of distribution of rugosity. As canyon walls often consist of outcropping bedrock with the tendency to be covered by biological communities, such high value of rugosity is expected. Its wide range of distribution is also explainable, because canyon walls have the most varied surface ruggedness. They can consist of just bare rocks, or be covered with sediments or fauna. Similarly, based on the boxplot (Figure 2.9a), the BPI for Cluster 2 has the biggest range although the mean value is zero. Such a characteristic is observed because the Cluster 2 morphology is narrow and steep; therefore the value can change significantly from one neighbouring cell to another.

The rest of the clusters are also interpreted based on criteria seen in the boxplots and the final interpretation is shown in Table 2.3. Each cluster has its own prominent variable that best shows its characteristics. Cluster 1 is mainly driven by the bathymetry and fractal dimensional variable, Cluster 2 is influenced by rugosity and slope, Cluster 4 has the lowest BPI, whilst Clusters 3, 5 and 6 are dominated by the aspect variables.

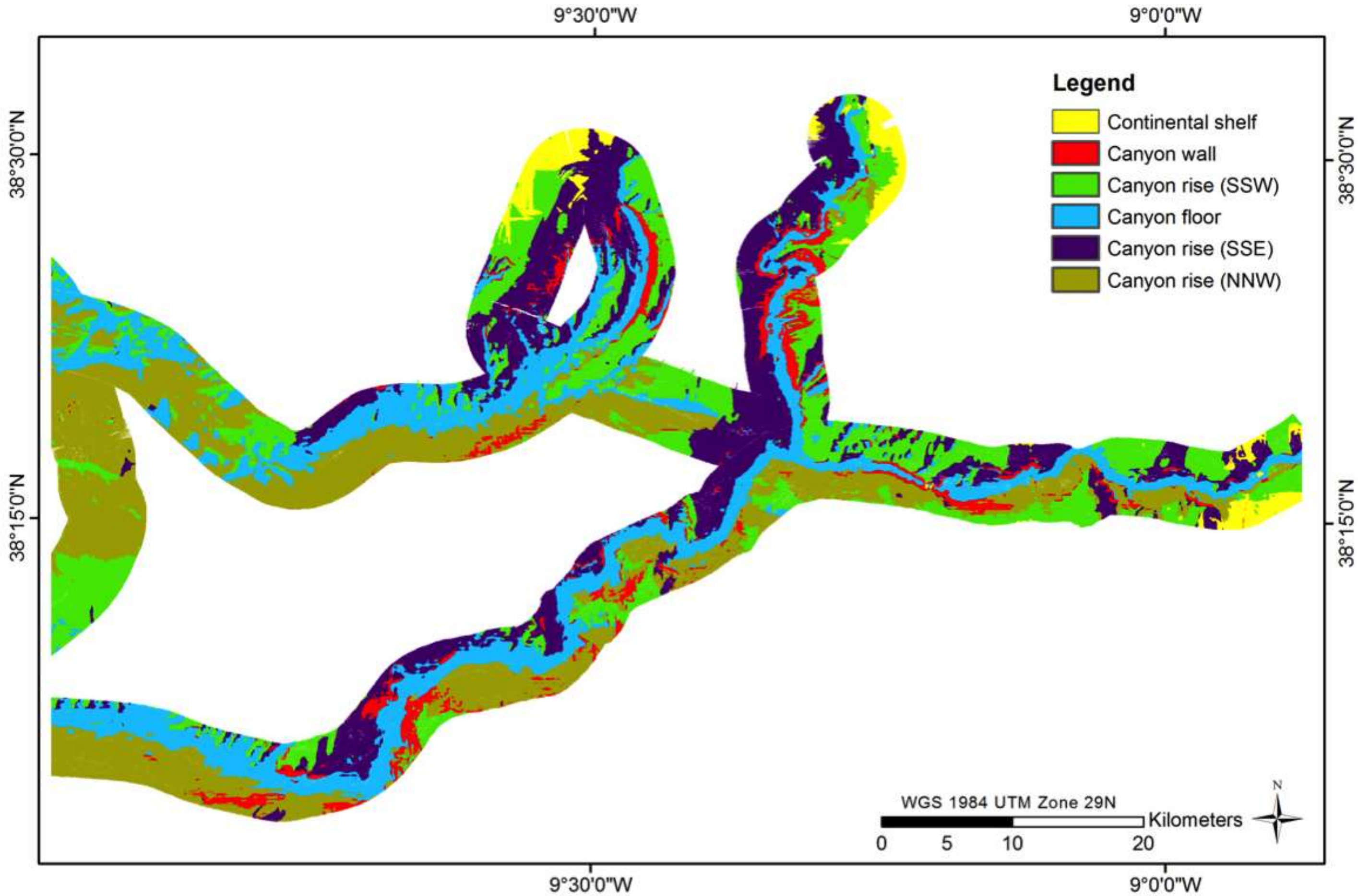
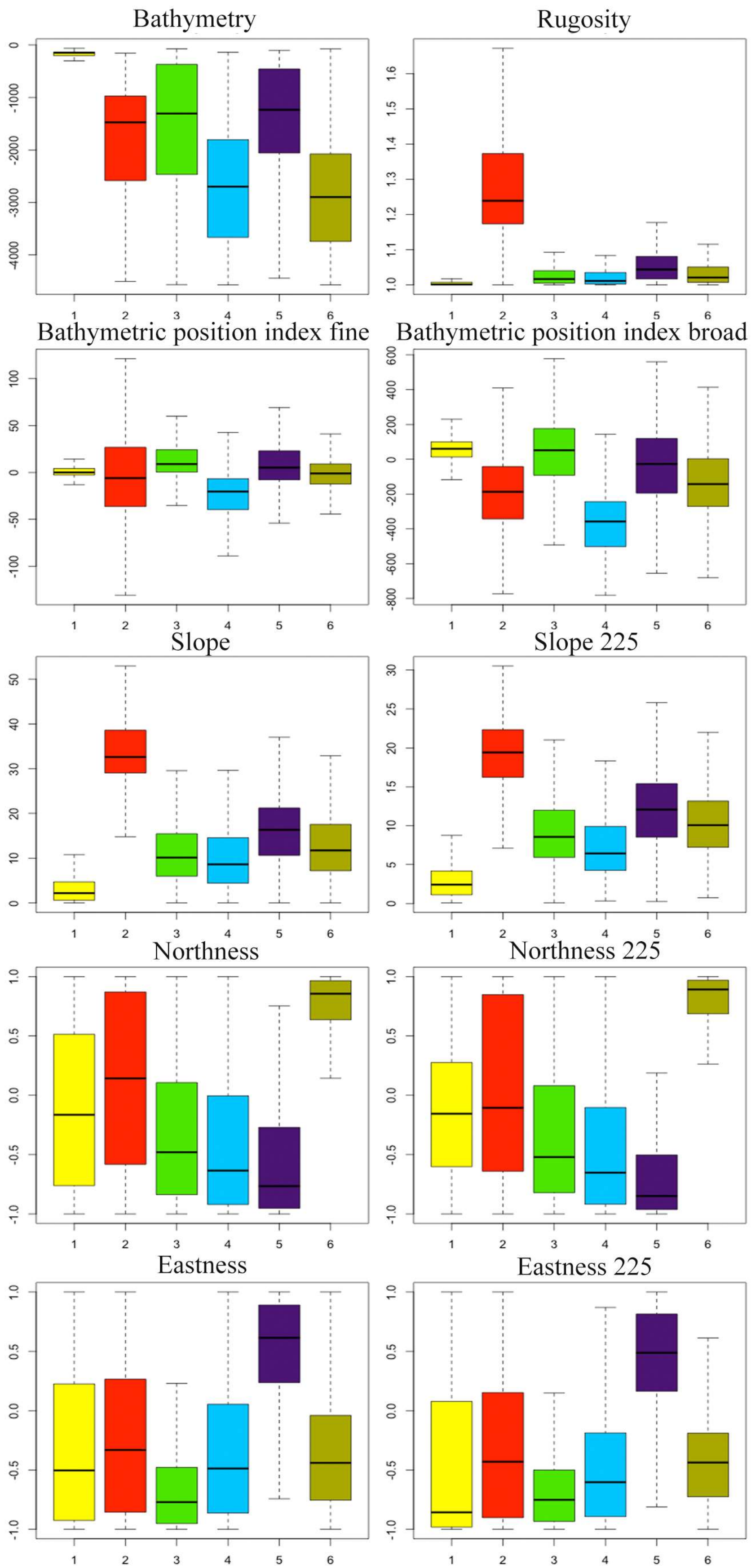


Figure 2.8: Interpretation map showing Portuguese Canyon with 6 clusters solution using the fully automated technique summarised in Figure 2.2. Characteristics and interpretation for each cluster are described in Table 2.3. Important geomorphological features of the canyon are clearly visible from the classification; Cluster 1 being the shallowest and flat is the continental shelf, Cluster 2 as wall or cliff with highest ruggedness, Cluster 3, 5 and 6 are the flanks with different orientation and Cluster 4 with depression features is the channel floor.


Bathymetry
Rugosity
Bathymetric position index fine
Bathymetric position index broad
Slope
Slope 225
Northness
Northness 225
Eastness
Eastness 225
1
2
3
4
5
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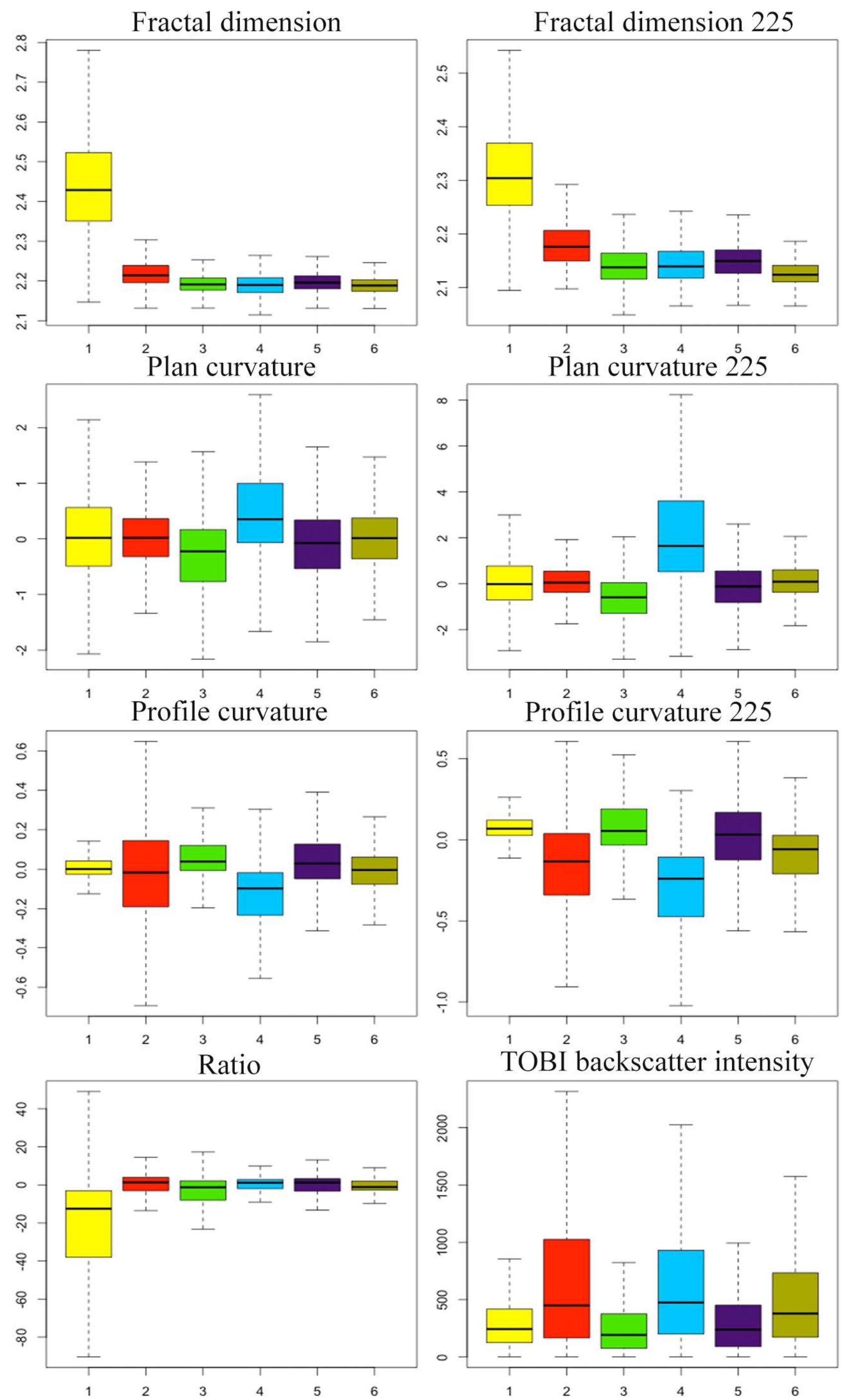


Figure 2.9a & b: Boxplot of clusters against original abiotic variables. Description of each abiotic variable is given in Table 2.1. In the boxplot, the middle line is the mean, the lower and the upper box boundaries are the first and third quartiles. The whiskers are the maximum and minimum observed values that are not statistical outliers.

Table 2.3: The characteristic of the 6 clusters and their interpretation based on the boxplot in Figure 2.9.

Clusters	***Characteristics***	***Interpretation***
1	Shallowest, most homogeneous, flat, planar and linear surface	Continental shelf/slope
2	Most rugged and heterogeneous surface with steepest slope	Canyon wall or cliff (including cliff edge)
3	Mid depth SSW oriented canyon slope with linear surface	Canyon slope/rise (facing SSW)
4	Planar to depression, slight sidewardly and upwardly concave and diverge surface, valleys, channel-like features	Canyon floor
5	SSE oriented canyon slope	Canyon slope/rise (facing SSE)
6	NNW oriented canyon slope	Canyon slope/rise (facing NNW)

2.4.4 Single scale vs. multiple scale terrain analysis

An alternative marine landscape map was produced using only local scale terrain indices to evaluate the effect of using multiple scale analysis on the classification result (Figure 2.10). The map produced was classified into 12 clusters. The main difference observed is that the clusters are more patchy and incoherent in the marine landscape map produced using single scale analysis. The map corresponds less well to features that can be seen in sidescan sonar imagery. Zoomed figures were made at three locations (Area A, B, C) to highlight the differences between using single scale and multiple scales into the multivariate statistical analysis (Figure 2.10). For example in Area A, the thalweg that appears in the sidescan sonar imagery was not delineated in the single scale marine landscape map. However, in the marine landscape map produced using multiple scale analysis, thalweg is classified as a separate cluster (Cluster 4), distinguishing it from a canyon slope (Cluster 3). In Area B, the clusters from the single scale map can be seen as patchy and incoherent as mentioned above. Of the 10 clusters, one cluster (Cluster 3) is identified as a product of over-classification from Cluster 11 because they consistently appear next to each other and Cluster 3 almost forms an outline to Cluster 11. Meanwhile, Cluster 1 is identified as noise that has been picked out from TOBI sidescan sonar imagery. Area C shows an example of clusters that result from over-classification and noise.

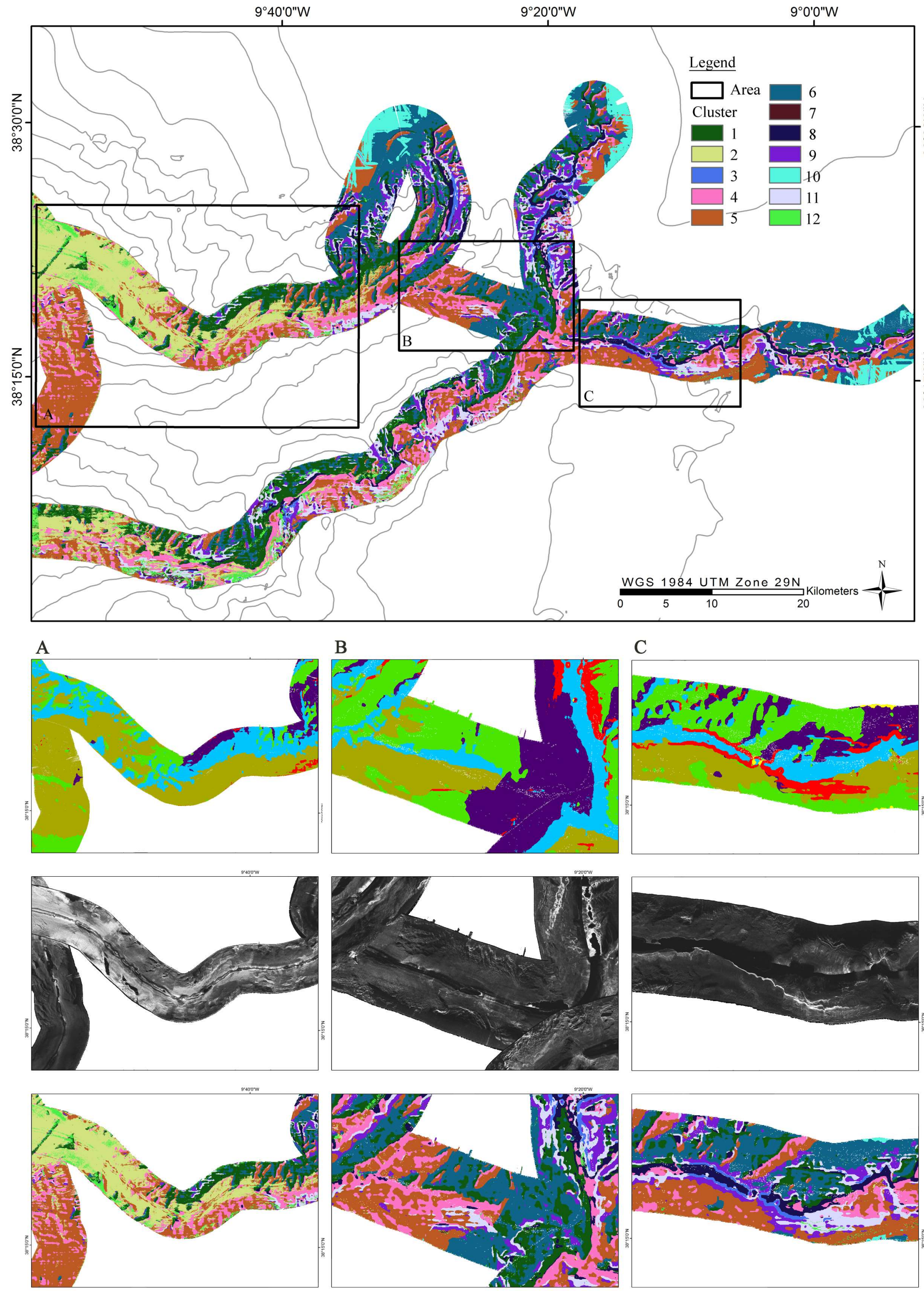


Figure 2.10: Marine landscape map produced using automated marine landscape classification with single scale in contrast to map in Figure 2.8. The three selected areas A, B and C are compared to sidescan sonar imagery and marine landscape maps produced using multiple scale terrain analysis. The close-ups are shown in the nine smaller maps. First row: marine landscape map using multiple scale, second row: sidescan sonar imagery and third row: marine landscape map using single scale. The marine landscape map produced using single scale exhibit patchy and incoherent classes. There are products of over-classification since having fine details introduces noise and causes over-analysis.

2.4.5 Qualitative assessment

A visual interpretation (Figure 2.11) was carried out for Setúbal Canyon based on the sidescan sonar imagery collected in 2005 (hence only covering Setúbal Canyon). General comparison of the marine landscape map produced by the automated technique and the manual delineations shows that most clusters from the automated technique coincide with the features delineated manually by the expert. Misclassifications of features occur occasionally and mostly are within the navigational error. The navigational adjustment may have contributed towards a number of misclassifications between the two maps. The sidescan sonar map used for this study was navigationally corrected by correlation with the bathymetry (Ismail, 2011), which was not the case for the data used for expert interpretation. There are many features that can be identified visually by the human eye. These features can be very small and overwhelm the algorithm in the automated technique. However, often the algorithm will naturally group these features together into the same cluster. The automated approach is observed to be more consistent in picking out features and identifying homogeneity within features. The most obvious features that can be seen to coincide successfully between the two maps are the thalweg and canyon wall. However in manual delineation the thalweg seems narrower than in the automated marine landscape map. This is because the expert tends to follow the axis of the thalweg closely and has difficulty deciding class boundaries. In particular, the area of transition between two features/clusters is often left unidentified in manual delineation, whereas the map from the automated technique gives an complete coverage.

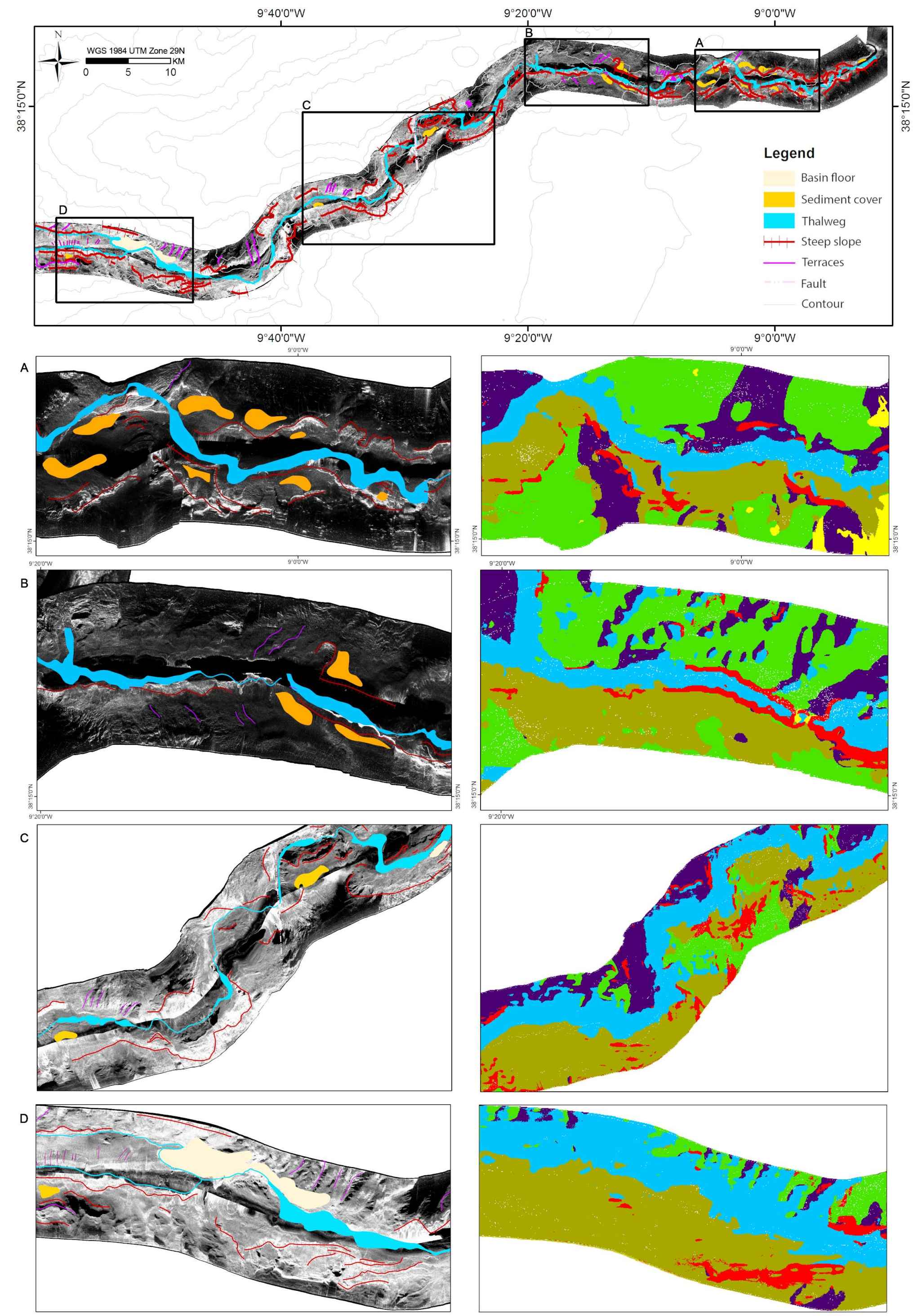


Figure 2.11: An expert visual interpretation of Setúbal Canyon from sidescan sonar imagery collected in 2005 used for visual comparison with automated marine landscape map. A, B, C, and D are zoomed figures of the visual interpretation map from sidescan sonar imagery (left) in the selected area (outline in black) compared to automated marine landscape map (right). Refer to Figure 2.8 for symbol legends in the automated marine landscape map. The expert interpretation in this area lacked contiguity and coverage, although manual delineation allows individual features to be picked out there is always a possibility of it being missed due to human error. In comparison, the automated technique produced a more consistent map but often too generalized (i.e.: small features are often grouped together).

2.5 Discussion

2.5.1 Multiple scale terrain analysis

The ESP tool technique was adopted from segmentation in object based image analysis (Dragut et al., 2010). It was used for fast estimation of the optimum length scales in an automated way. This tool gives an advantage over manual estimation, as it reduces the time spent on trial and error selection of the appropriate scale that best represents real-world objects in multibeam bathymetry data. It also provides an objective answer to the scale question. The ROC-LV graph indicates that at SP = 225 it recognises patterns that are suitable to represent a real-world object.

The incorporation of terrain indices produced from local and broad scales allows an appropriate discrimination between features of different ecological relevance. For instance, in a single scale approach using only the local length scale, terrain indices may have similar slope values on the side of small geomorphic features such as gullies compared to slopes on the main canyon wall. However, if broad scale terrain indices were to be used on their own, slopes over small features will effectively disappear since the analysis scale will be too large to capture the finer features available from the multibeam bathymetry data. Therefore, by including local and broad length scale terrain indices together, both fine scale and broad scale features are retained and stand out as distinct properties of the seabed which contribute as indicators of potential benthic habitats.

Additional to this, with the incorporation of broad length scale terrain indices, it is observed that the noise, compared to the local, single scale map was reduced, subsequently increasing the feature to noise ratio. Through this step, the automated technique is performed on meaningful objects that represent both fine and broad scale features that can be found in real-world canyons.

Apart from this, using multiple scale terrain analysis appears to reduce excessive clustering that result in meaningless clusters being delineated in the map. Since multivariate statistical analysis is affected by pixel size, having only single local scale terrain indices causes over-analysis, which contributes to clustering of artefacts into the classification. It became oversensitive towards slight changes in characteristics between pixels causing similar features to be clustered into separate clusters. However, by using multiple scale terrain indices, the multivariate statistical analysis operates on meaningful objects related to real features rather than just the pixel representation of the acoustic data.

2.5.2 Abiotic variables

One of the difficulties in maintaining objectivity in automated mapping is to justify the abiotic variables that are incorporated into the analysis without compromising the objectivity of the whole method. It is important to ensure that the method is as objective as possible with minimum input from the user. Every abiotic variable included will affect the automated classification, therefore all abiotic variables should contain relevant information about the canyon. Parameters yielded by the GIS software must be considered with care, and not simply included by default. For example, hillshade is an available variable that can be generated easily through GIS software. It can be a good abiotic variable if the purpose is, for example, to evaluate correlation between the seabed and a (residual, unidirectional) current. However, if there is no evidence of such an interaction taking place, it would give a false result because the azimuth used for hillshading would be arbitrary, rather than representing an actual characteristic of the terrain. Therefore, in this case, hillshade is not included as an abiotic variable. Instead, directionality of the terrain and any potential interaction with oceanographic effects is simulated by the inclusion of aspect properties that are divided into northness and eastness to provide continuous variables (Hirzel et al., 2002; Wilson et al., 2007). Hence each abiotic variable included is relevant and has a useful input regarding the canyon and will contribute to the automated classification. In addition, by using PCA, there is no problem if more than one abiotic variable gives a similar input or representation of the canyon (i.e., if there is collinearity). The more abiotic variables with useful information are incorporated as input, the more potential habitats can be classified (Verfaillie et al., 2009). Once all the abiotic variables have been gathered, there are no subjective selections to be made. Instead they are subjected to PCA, which overcomes the problem that most conventional classification methods encounter, the selecting of abiotic variables (Al-Hamdani and Reker, 2007). Also the selection of the relevant PCs (with eigenvalue >1) and the optimal number of clusters (based on the within group sum of squares) is fully objective.

2.5.3 Marine landscape map

The resulting map for the Cascais and Setúbal-Lisbon Canyons has a total of 6 clusters that represent the marine landscapes of the area (Figure 2.8). Each of these clusters is interpreted based on the correlation of the clusters with the original abiotic variables. The marine landscape map is largely based on the geomorphological features present in the multibeam bathymetry data, and hence corresponds to the first levels of typical hierarchical habitat classification systems (Davies et al., 2004), that are based on broad-scale geomorphological divisions of the marine realm. TOBI sidescan sonar data that potentially represents sediment distribution did not yield much contribution into the classification. The rotated component matrix (Table 2.2) shows that TOBI sidescan sonar imagery only starts playing a role in PC6. In addition, based on the boxplot distributions (Figure 2.9b), when correlated with TOBI data the 6 clusters are more or less congregated around similar values. A derivative from TOBI sidescan sonar, the ratio of TOBI to synthetic TOBI imagery (Ismail, 2011), did not contribute to the automated classification either. It has the highest load in PC7, which only explains 0.06% of the total variance. However, when visually compared to the TOBI sidescan sonar, the marine landscapes classified here can easily be related to the TOBI sidescan sonar features. It is already known that sedimentological distributions in canyons are strongly controlled by the geomorphological properties of the terrain (Arzola et al., 2008). This explains the correlation between the marine landscape map and TOBI sidescan imagery when compared visually.

Geomorphology is also recognised as a major control on biological communities and diversity in submarine canyons (Kenchington et al., 2013). Therefore, the marine landscape map can be useful to identify areas with ecological relevance. Although the ultimate goal of habitat mapping is to identify ecologically relevant habitats that support different biological communities, this is not the case for marine landscape. The purpose of a marine landscape map is to identify areas that can give an indication about the biological community, but not to predict the biology. Therefore, the map produced in this study only acts as a proxy to aid biological predictions and focus future surveys. This is especially beneficial as an alternative when biological data are limited since it uses only abiotic variables to produce the marine landscape map.

Based on the marine landscape map produced from this study, three out of the six clusters are influenced by the aspect variable. Aspect is represented in continuous values by northness and eastness. Northness takes values close to 1 if the aspect is northward, -1 if southward and close to zero if aspect is either east or west. Eastness behaves similarly, except that values close to 1 show east-facing slope and -1 west-facing slope. However, is aspect an important feature to define marine landscape in submarine canyons? Naturally, aspect is a valuable variable for shallow water, where it provides information regarding the exposure to dominant swell or where sunlight is able to reach the seabed (Lucieer et al., 2013). However this is not the case for the deep sea environment, where it is known that light only penetrates approximately to no more than 1000 m (with significant light only penetrating to about 200 m) (Schrope, 2007). Nevertheless, slope orientation in the deep sea may still be meaningful if interaction between the current regime and differently orientated slope surfaces creates variable habitats.

Organisms inhabiting the deep sea environment are known to be subjected to the regulating disturbance related to upper water-column processes (Gage and Tyler, 1992), which makes it possible to predict faunal response in homogeneous deep sea habitats, and identify the controlling factors that affect the presence of organisms. However, in a more complex and complicated environment this is not as straightforward. This is particularly true in submarine canyons, where the different regulating processes, heterogeneous environmental conditions and ecological functions are far from understood. Ongoing research in submarine canyons has shown that due to the terrain heterogeneity, the biological communities in submarine canyons vary compared to the adjacent continental slope (Soetaert et al., 1991; Grémare et al., 2002); even twin branches within the same canyon may exhibit a large difference in their community composition (Bianchelli et al., 2008) and flanks of the same branch can exhibit different biological coverage due to differences in substrate cover as a result of the orientation of the canyon with regard to the overall oceanographic regime in the area (Van Rooij et al., 2010; De Mol et al., 2011). This shows that submarine canyons are dynamic and varied from one another, which leads to a conclusion that no variables should be overlooked or neglected without solid reason. Amongst the potential factors that can be related to aspect, the current regime is the most prominent. It will affect the sediment, organic matter and food source pathways into submarine canyons. Although the community structures are influenced by food supply and food availability, which are strongly related to upper water column processes, in canyon communities, variability caused by habitat heterogeneity and water depth differences can easily override the effect of upper water column processes (Ramalho et al., 2014). Unfortunately, the lack of detailed current information in most submarine canyons hinders the process of evaluating the influence of aspect towards the community structure. The marine landscape map produced here indicates the potential influence of the aspect variable. The next step now is to evaluate this against the community composition.

2.5.4 Qualitative assessment

A qualitative assessment was made based on visual comparison with sidescan sonar imagery expert interpretation. The comparison between the marine landscape map and visual interpretation of the sidescan sonar imagery supports that the automated method yields a useful and meaningful marine landscape map. Manual delineation in this study lacked in contiguity whereas the automated map provides a better coverage for a continuous classification. Other manual interpretations may have the same coverage as automated classification but they will be more time consuming to produce. The advantage of expert interpretation is the ability to pick out individual features in sidescan sonar that often overwhelm the automated method. Since the automated method is restricted to its pixel size for the ability to detect geomorphic features, it produces a more generalized map in comparison. On the other hand, with manual delineation there are still a percentage of features that are overlooked due to human error. Classification and boundaries between classes are more consistent throughout the whole automated process and this will be a useful contribution for further habitat quantification at later stages.

2.6 Conclusion

This study offers another step forward towards a better marine landscape mapping technique that stands out for being a fully automated approach. The philosophy behind this study is to ensure the methodology is objective and suitable for broad and regional scale mapping based on seafloor geomorphic features that can be identified from different types of sonar data. Such information is often included as one of the attributes for actual habitat classification in one of the nested levels of hierarchal habitat mapping schemes. Additionally, the method utilizes bathymetric grid data that are the most common type of data obtained for most seafloor related studies. Therefore many habitat mappers will find this method useful, time and labour efficient. This method could also be advantageous to monitor seafloor changes through time. Dynamics of the marine environment changes seafloor conditions, however, the objective approach allows monitoring an area over a period of time with more confidence without bias from expert interpretations. Mapping marine landscape provides a surrogacy for biodiversity and prospectively this method will contribute to design our marine environmental management measures.

The following list summarises the conclusions from this study: 1) The ESP method that was designed to detect characteristic scales in geomorphometric analysis for OBIA is transferable, and can be used to detect potential patterns in bathymetric grids. The comparison between single scale and multiple scale maps convincingly revealed the delineation of seafloor features associated with patterns of real-world submarine canyons geomorphic features. 2) It is shown that using multiple scale terrain analysis, appropriate discrimination between features of different ecological relevance is achieved regardless of fine or broad scale features. Incorporation of both local and broad length scale terrain indices enables a production of marine landscape map that contains fine and detailed canyon features without compromising the prominent and large scale geomorphic features. 3) Potentially this methodology is thought to be a useful guideline for complex deep sea habitat mapping because it does not only delineates seafloor geomorphic features for potential habitat but also points to properties that might influence biodiversity in a complex terrain as pointed out in the discussion on the importance of aspect as a driving parameter in submarine canyon marine landscape delineation.

Chapter 3: Quantifying Marine Landscape Heterogeneity in Submarine Canyons

3.1 Abstract

Spatial variability in environmental conditions has been attributed as the main driver behind marine biodiversity in structurally complex environments. Despite this, spatial heterogeneity, reflecting terrain organisation of environmental conditions, is seldom quantified in the marine environment especially at regional scale. In contrast, quantification of spatial patterns has been widely applied to characterise structural features of terrestrial landscapes and has demonstrated a great utility in landscape ecology and spatial planning. To address this problem we use landscape ecology indices and objective automated marine landscape mapping techniques to evaluate the typical landscape ecology approach by quantifying marine landscape heterogeneity as proxy for biodiversity in submarine canyons. Submarine canyons enhance marine landscape diversity at regional scales and provide unique habitat settings for diverse and abundant faunal assemblages. The deep and complex topography, strong currents and occurrence of high turbidity affect the habitat heterogeneity potentially making canyons a hotspot for biological activity, with high faunal diversity.

Multibeam bathymetry and sidescan sonar imagery is used to generate a marine landscape map for Whittard Canyon using objective automated classification and object-based image analysis (OBIA). The resulting marine landscape map is characterised by seven clusters, of which five clusters were found to be ecologically relevant using species indicator analysis (INDVAL). The area was divided into three strata to quantify marine landscape heterogeneity using the entropy-based contagion index. Differences in the contagion index were highly significant between branches and lower canyon. The two main canyon branches were not significantly different from each other. Differences in contagion across the three strata can help to determine areas suitable for Marine Protected Area establishment.

3.2 Introduction

As a result of its inaccessibility, our knowledge of biodiversity in the deep sea is limited and its ecological processes are poorly understood. However, with an increasing number of human activities affecting this fragile ecosystem, the need to understand the deep-sea environment is crucial. There has been a major increase in the awareness for this issue. Conservation policies such as the OSPAR Convention or the EU Habitats and Marine Strategy Framework Directives have initiated serious effort to designate deep-water Special Areas of Conservation (SACs) and Marine Protected Areas (MPAs). Globally this issue has also been addressed, through a call for formal governance structures to create a network of deep-sea reserves that maintain and restore biodiversity (Barbier et al., 2014; Van Dover et al., 2014). A practical perspective is urgently needed to support the decision making by stakeholders while at the same time representing the functional diversity in marine ecosystems. This can only be achieved through the creation of adequate maps, illustrating the spatial distribution of the marine landscapes and/or habitats in the area under consideration. In this context, it is important to create a tool that will assist the creation of such maps. We propose that the maps should encompass the following components: 1) information on terrain and substrate; 2) a representation of the environment; 3) a measure of the environment variability and 4) groundtruthing information to support the ecological interpretation.

In this context, we focus on one of the most complex terrains that can be found in the deep sea, a submarine canyon system. Submarine canyons are naturally heterogeneous, composed of habitats that vary in size, shape and spatial arrangement across the marine landscape. This spatial variability of habitats within the marine landscape potentially exerts a strong influence on biodiversity. Submarine canyons are important geological features found along most continental margins with at least 9000 large canyons known worldwide (Harris et al., 2014). Generally, canyons consist of valleys with steep-sided walls, either V- or U-shaped in cross section, and many show tributary systems in plan view (Lastras et al., 2009). They play a major role as a conduit between shallow and deep depositional systems, transporting sediment (Hickey et al., 1986; Monaco et al., 1999; Puig et al., 2014), organic matter (Martín et al., 2006; Garcia et al., 2007; Waterson and Canuel, 2008) and pollutants (Buscail and Germain, 1997; Richter et al., 2009). As a result of their complex topography, they also affect the hydrodynamic regime though intensified mixing and amplification of currents (Martín et al., 2007; Turchetto et al., 2007) which contributes to the support of diverse potential habitats (Mortensen and Buhl-Mortensen, 2005; Albaina and Irigoien, 2007; Morais et al., 2007; Schlacher et al., 2007; Tyler et al., 2009). This has recently generated a wide interest in submarine canyon studies (Yoklavich et al., 2000; Brodeur, 2001; Tyler et al., 2009; Currie and Sorokin, 2014; De Leo et al., 2014; Huvenne and

Davies, 2014). However, the complexity of the terrain greatly complicates mapping of this marine habitat.

For spatial management purposes, high quality full coverage maps of abiotic variables are invaluable in understanding and predicting marine habitats. In the deep sea, where biological data are often scarce, substrate and geomorphology are the best surrogate available to predict potential benthic communities (Schlacher et al., 2007; Schlacher et al., 2010). In submarine canyons, although seafloor geomorphic properties are among the main drivers controlling community structure (Ramalho et al., 2014), substrate also plays an important role affecting the distribution of biological communities (Van Rooij et al., 2010; De Mol et al., 2011; Morris et al., 2013; Robert et al., 2014b). However, most substrate information is interpolated from widely distributed sediment sampling points and video transect interpretation using inadequate interpolation techniques. As such, a robust technique is required to produce a full-coverage substrate map using commonly available acoustic data and limited point data substrate information.

Environmental representation of the seabed has been used for some time in marine spatial planning in both shallow and deep-water areas. However, in comparison to deep-sea areas, marine spatial planning in shallow waters is more developed and extensive methods have been developed to improve the understanding of the spatial ecology of the seafloor (Brown et al., 2011). Ferrier and Guisan (2006) identified three general spatial modelling strategies and Brown et al. (2011) categorised benthic habitat mapping studies based on these strategies. Among the three strategies, the one that adopts a delineation of natural environmental patterns using abiotic information remained the most popular approach. In the deep sea, this is also most favourable because of the common lack of biotic information for broad spatial mapping. On this basis, an automated objective marine landscape mapping methodology for submarine canyons was developed (Ismail et al., 2015). However the method was tested only on a single canyon mainly using bathymetric data and resulted in a marine landscape map strongly influenced by geomorphology. In this study, the robustness and transferability of the approach is tested by applying it to a different canyon system. In addition, the method is expanded through the incorporation of substrate information into the methodology. Finally, the result is used to quantify habitat heterogeneity as a surrogate for the submarine canyon's biodiversity.

Biodiversity is a key element in understanding the marine ecosystem and has been considered as the main indicator of ecosystem status and function (Danovaro et al., 2008). However, assessing biodiversity in the deep sea is a well-known challenge for deep-sea ecologists (Brandt et al., 2014). The effort to evaluate biodiversity is currently limited to extreme extrapolations of minimal data from traditional sampling schemes and video surveys. Those are often time consuming and expensive to obtain. Here, we propose a way to present a marine ecosystem at a broad scale for marine spatial planning that uses spatial heterogeneity of the marine landscape as a proxy for biodiversity. Studies have shown that spatial variability in environmental conditions is the main driver of biodiversity, especially in structurally complex environments (Chase and Leibold, 2003; Harborne et al., 2006; Henry et al., 2010). This approach is well developed in the terrestrial environment (Dale and Fortin, 2014; Sauder and Rachlow, 2014) and most of the concepts and techniques are developed for the terrestrial environment. Over the past 30 years, these approaches were extended into the marine realm but were generally limited to coastal and shallow waters (Wedding et al., 2011) and are even more scarce in deep-sea environment (Robert et al., 2014a).

The main aim of this study is to propose a procedure to delineate ecologically relevant marine landscapes in addition to a spatial heterogeneity measure that acts as an indicator of biodiversity in submarine canyons. The aim will be addressed through the following objectives:

1. Propose a method to map substrate distribution in submarine canyons using object based image analysis (OBIA) on sidescan sonar imagery.

2. Test the transferability and applicability of an objective automated marine landscape mapping technique previously developed in a suite of canyons offshore Portugal (Ismail et al., 2015).

3. Propose a way to quantify the spatial heterogeneity of a marine landscape using landscape ecology indices.

4. Groundtruth the ecological relevance of the mapped marine landscapes using video transects interpretation.

3.3 Materials and methods

3.3.1 Study area

Whittard Canyon is a large dendritic submarine canyon located on the Celtic Margin, southwest of the UK and Ireland (Figure 3.1). The prominent Western and Eastern branches begin at approximately 200 m and meet at about 3600 m water depth, leading to the Whittard Channel which opens up onto Porcupine Abyssal Plain (Duineveld et al., 2001; Zaragosi et al., 2006; Hunter et al., 2013). It is reported that the present-day canyon activity for sediment transport is relatively low for a submarine canyon (Zaragosi et al., 2000; Toucanne et al., 2008). Canyon processes are governed by small-scale slope failures, turbidity currents and internal waves and tides with current strengths that are sufficient to transport fine sediment (Reid and Hamilton, 1990). In terms of biodiversity, submarine canyons have been proposed as a suitable habitat to harbour cold-water corals and filter feeding animals owing to their heterogeneous seabed, canyon morphology and complex hydrographic patterns (Mortensen and Buhl-Mortensen, 2005; Orejas et al., 2009; Schlacher et al., 2010; Edinger et al., 2011; Gori et al., 2013). This is consistent with the observation from video footage that the vertical walls of the Whittard Canyon are rich in diversity with large colonies of cold-water corals and clams (Huvenne et al., 2011; Johnson et al., 2013; Morris et al., 2013; Robert et al., 2014b).

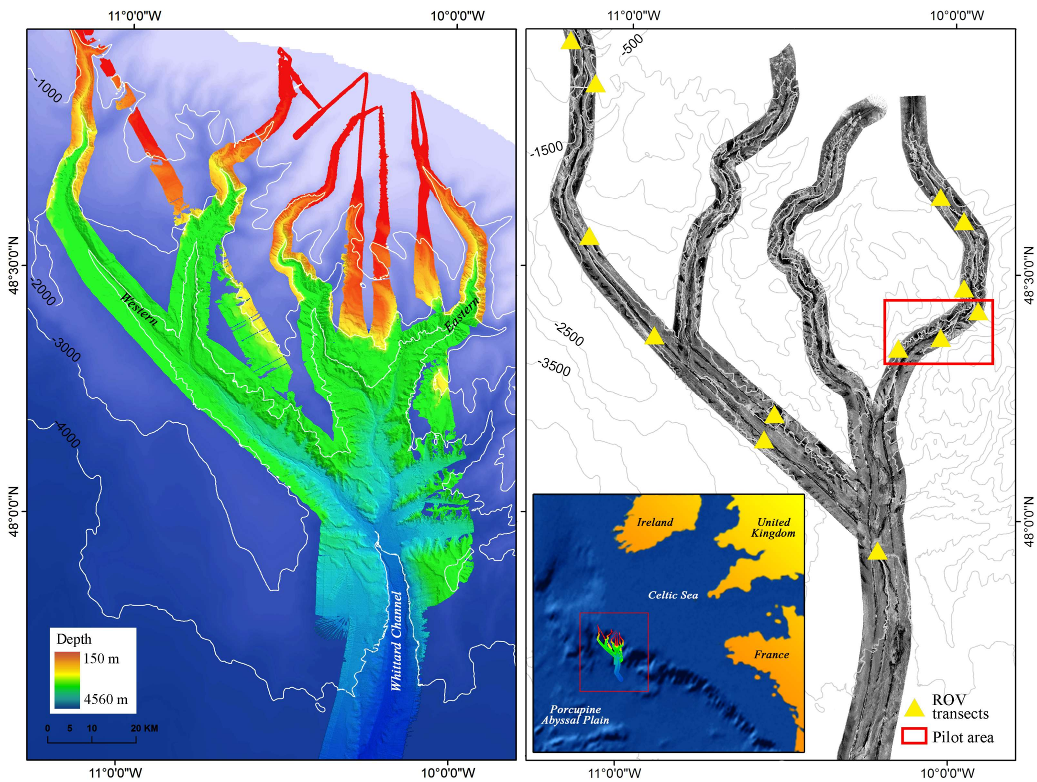


Figure 3.1: Bathymetry map of Whittard Canyon on the left and TOBI sidescan sonar imagery coverage on the right. Contour interval is 1000 m. The inset map shows the location of the study area relative to the location of Celtic Sea. Red box indicates the pilot area for sensitivity test and yellow triangle are location of ROV transects.

3.3.2 Data

The acoustic data for the study area were acquired during the 2009 RRS James Cook cruise 035, using a shipboard EM120 multibeam system and the 30 kHz TOBI (Towed Ocean Bottom Instrument) sidescan sonar. The multibeam bathymetry data were processed using CARIS HIPS & SIPS software to 50 m pixel size. Terrain indices derived from the multibeam bathymetry data are slope, aspect (split into continuous measures of eastness and northness), curvatures (plan and profile), bathymetric position index and rugosity. We used the software packages ArcGIS 10.2 and Landserf v2.3 for these calculations. The sidescan sonar imagery was pre-processed using the NOC in-house PRISM software v4.0 (Le Bas and Hühnerbach, 1998), Erdas Imagine 2014 and

ArcGIS 10.2 to produce imagery with improved geographical registration (Ismail, 2011). TOBI was towed at an altitude of approximately 400 m above the seafloor at about 2.5 knots. It produces images with ~6 km wide swath and horizontal resolution of 3 m.

A total of 10 video transects were collected during 2009 RRS James Cook cruise 036, plus 3 additional transects from 2007 RRS James Cook cruise 010, using the ISIS ROV (Remotely Operated Vehicle). The dives were carried out in the Eastern and Western branches of the canyon at depths varying from 600 to 4000 m. Based on video analysis by Robert et al. (2014 b), transects were analysed in 50 m sections for substratum type and divided into soft, hard and mixed sediments. In addition, identification of all epibenthic megafauna > 1cm into morphologically distinct taxa was also carried out during the video analysis.

3.3.3 Research strategy

The proposed procedure to map deep-sea habitat for marine spatial planning purposes is divided into four components: 1) information on seafloor geomorphology and substrate 2) an objective method to produce a marine landscape map 3) a quantification technique to measure marine landscape heterogeneity and 4) biotic information as groundtruthing for ecologically-relevant marine landscapes.

A technique to map marine landscapes in complex deep-sea environments has been proposed, but so far was only tested in one submarine canyon (Ismail et al., 2015). The study used multibeam bathymetry and derivatives as the abiotic variables to produce the marine landscape map, resulting in it being greatly influenced by geomorphology. To test the robustness of the technique, the same method is applied here with additional variables derived from sidescan sonar imagery. The derivation is a surrogate for substrate distribution in the submarine canyon. Derivatives from multibeam bathymetry, on the other hand, will provide the terrain information. The whole approach is illustrated in Figure 3.2. Procedure and software used for each component are outlined in the following sections.

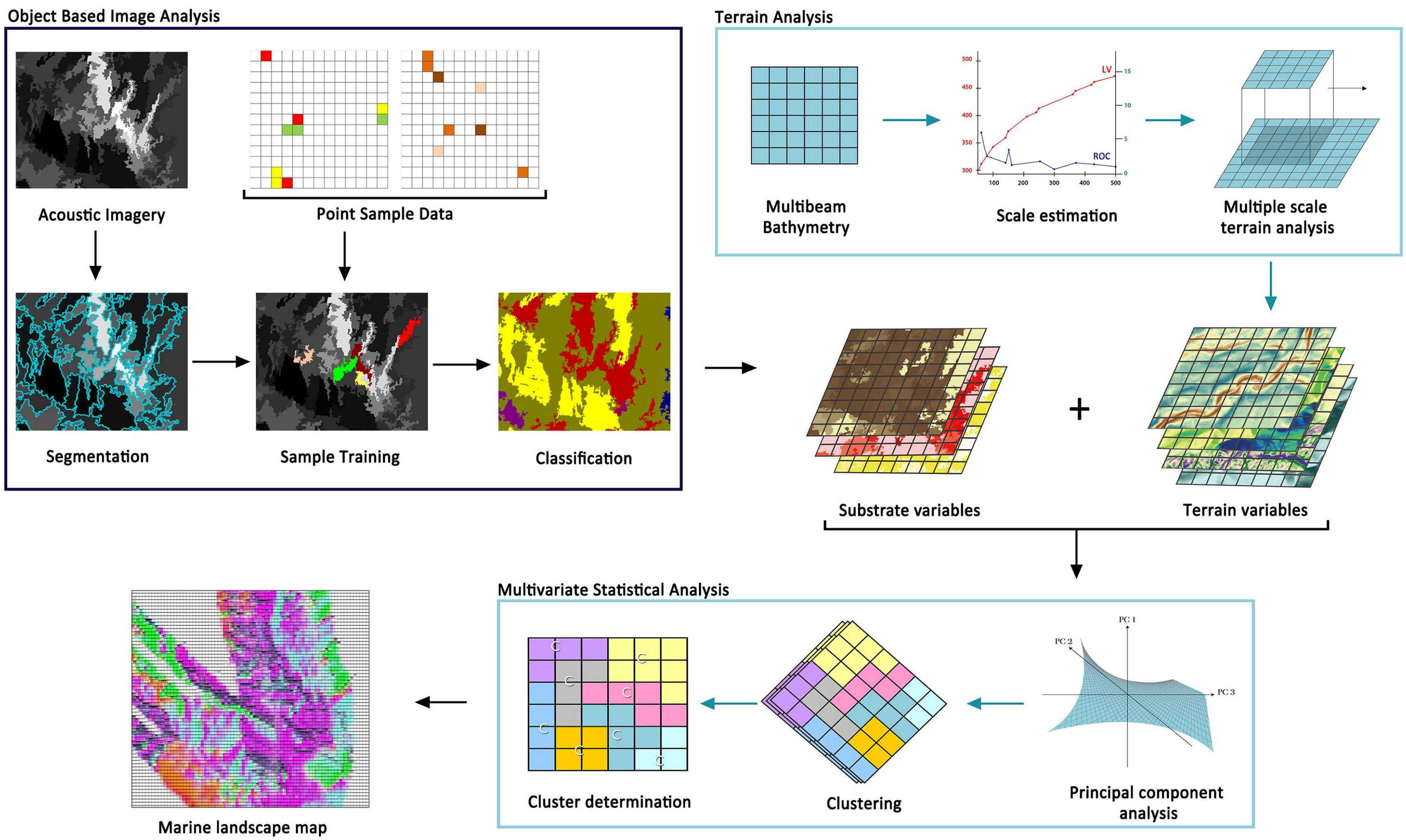


Figure 3.2: A simplified flow chart of the mapping procedure for marine landscape mapping in submarine canyons. The flow chart is divided into three parts; i) object based image analysis to produce substrate map, ii) terrain analyses for multibeam bathymetry to produce terrain variables and iii) multivariate statistical analysis to produce the marine landscape map for Whittard Canyon.

3.3.3.1 Substrate distribution

Substrate type and habitat heterogeneity are among the factors that influence the distribution, abundance and composition of benthic organism in submarine canyons (Cunha et al., 2011; Hunter et al., 2013; Morris et al., 2013; Kenchington et al., 2014; Ramalho et al., 2014). Geomorphic features, producing high terrain variability and forcing local current patterns, are among the key drivers that control the sediment distribution in submarine canyons. However, lack of sediment samples and limited video survey coverage usually hinders the production of high quality sedimentological maps in submarine canyons. Acoustic amplitude data such as sidescan sonar imagery and multibeam backscatter can, however, compensate for the lack of sample data, and can be a powerful tool in the production of full coverage substrate distribution maps. Experts use these data to assist in substrate interpretation, which is often done manually; this tends to limit the coverage and quantitative means of interpreted sediment distribution maps. However in recent years, several automated image analysis techniques and algorithms have become available to quantify acoustic textures and support seafloor classification (Huvenne et al., 2002; Lucieer and Lamarche, 2011; Brown et al., 2012; Lucieer et al., 2013). Here, a method is proposed using the acoustic responses in sidescan sonar imagery as a proxy for substrate distribution, combined with object based image analysis (OBIA) in eCognition Developer v8.9.

OBIA (Blaschke, 2010) is a technique that recognises meaningful patterns in an image regardless of its pixel size. It involves two steps: segmentation and classification. Segmentation commonly refers to the process of subdividing entities into smaller partitions. However in eCognition, the operation is not limited to subdivision, but includes merging and reshaping objects to specific criteria. Various segmentation techniques are made available in eCognition and are divided into two basic principles: 1) cutting larger images into smaller objects known as top-down strategy and 2) merging smaller pieces to get something bigger, which is a bottom-up strategy. A segmentation technique that was demonstrated to be a reliable tool to analyse seafloor backscatter images in eCognition, and that therefore will be used in this study, is multiresolution segmentation, based on a region-growing principle (Lucieer, 2007, 2008; Lucieer and Lamarche, 2011; Lucieer et al., 2013). The process merges the pixels in backscatter imagery into potentially a real-world features, and the segments are known as image objects. In detail, multiresolution segmentation is a bottom up region-merging technique starting with single-pixel objects, while subsequently smaller image objects are merged into larger ones. The algorithm minimises the average heterogeneity and maximizes the homogeneity of each image object. Region growing will stop once a segment reaches a considerable object size defined by a scale parameter. This scale parameter (SP) is a unitless term used in the software and it controls the maximum allowed size and heterogeneity in an image object. The size of the SP can be determined automatically (and objectively) using the ESP (Estimation of Scale Parameter) tool developed by Dragut et al. (2010). However, the SP is governed by a shape and spectral criterion, which together define the homogeneity threshold of an image object. Both shape and spectral criteria are pre-defined by the user, based on a trial and error approach. The shape criterion is defined by a relative weighting between smoothness and compactness of an image object. It relates to the ratio of the perimeter length to the number of pixels forming the image object. The selection for shape criterion ranges from 0 to 0.9, with 0 allowing a more elongated and smoothed image object while 0.9 results in compact and spherical image objects. Meanwhile, the spectral criterion is based on the colour homogeneity within an image object. The value for the spectral criterion is defined between 0 and 1, with 0 meaning the region merging is not influenced by the spectral variation of the imagery (Darwish et al., 2003).

Image objects are then classified into substrate categories using supervised classification on a range of characteristics or features calculated for each object (e.g. area, perimeter, image texture etc.). For the classification, the eCognition Nearest Neighbour algorithm was trained using samples from the 50 m interpreted video transects, with 9 out of 13 transects used for training and 4 held back for later cross validation. We used two types of training samples: substrate samples and artefact samples. The substrate samples are derived from ROV video interpretation and comprise ‘rock’, ‘sediments’, and ‘mixed substrates’. Meanwhile, the artefact samples are recognisable and unavoidable artefacts that typically appear in sidescan sonar imagery. These artefacts are caused by the limitations of the equipment operating in a complex terrain. They are grouped into ‘nadir’, ‘edge’ and “shadow’. Nadir zones are areas directly below the sidescan sonar, where the sound has a vertical angle of incidence. These areas are often of limited use due to the high level of noise in the backscatter signal and the geometry of the acoustic beam pattern. Due to the complex terrain and the fact that sidescan sonar was towed near to the bottom of the canyon, the steep flanks of the canyon caused the angle of incidence to be near perpendicular in some locations, which may cause exaggeration of features, giving rise to the 'edge' artefacts. Shadows are a common occurrence in sidescan sonar data due to the acoustic signal being blocked by acoustically opaque objects, which causes the area behind them to be less ensonified.

Classifications were made based on acoustic characteristics of the sidescan sonar objects, using the nearest neighbour feature space optimisation function (Laliberte et al., 2012). The function finds the best combination of features that produces the largest average minimum distance (separation distance) between the samples of different classes. The acoustic features included into the algorithm are mean brightness, standard deviation, GLCM (Haralick grey level co-occurrence matrix) correlation, GLCM entropy, GLCM contrast, GLCM homogeneity and GLCM mean. Once classification is achieved, cross validation using inter-rater agreement was carried out between the resulting substrate map and the remaining four video transects to evaluate the correlation.

The substrate map produced is in categorical form and before subjecting it to any statistical analysis the map needs to be converted into a continuous variable. Membership functions are used to convert distinct classes into membership degrees between 0 and 1, indicating the membership of each pixel to each substrate class. The underlying concept is based on fuzzy c-means (FCM) algorithms (Bezdek, 1981). The membership value represents a degree of belonging of each segment to the class centroid. These values are the ones used as continuous variables for further marine landscape classification.

3.3.3.2 Sensitivity Test

The scale parameters for segmentation and length scale in the terrain analysis, calculated using the ESP tool, were subjected to a sensitivity test. The test compares the use of different length scales to generate the substrate distribution map and terrain analysis. It was carried out on a pilot area (Figure 3.1) and consisted of three steps: 1) production of a substrate distribution map at each scale parameter of 150, 250 and 370, using OBIA and supervised classification based on samples from two ROV video transects 2) accuracy assessment on these substrate distribution maps against the third video transect in the area 3) production of marine landscape maps using substrate distribution maps and terrain variables calculated at each scale parameter of 150, 250 and 370. The final substrate distribution map for the full dataset were also test for accuracy using Kappa coefficient measure and BER. The accuracy assessment includes:

Kappa coefficient measure

Cohen's Kappa coefficient measure was first introduced by Cohen (1960), and the algorithm is now generally known as unweighted Kappa. It provides a numerical rating of the magnitude of agreement between two observers. The calculation is based on the difference between observed agreements compared to the expected agreement. Observed agreement is how much agreement is actually present between two observers and expected agreement is how much agreement would be expected to be present by chance alone. Data layout for Kappa coefficient agreement matrix is shown as follows:

Results	Observer 1		
Observer 2	*Yes*	*No*	*Total*
Yes	*a*	*b*	m_1
No	*c*	*d*	m_o
Total	n_1	n_o	n

a and *d* represent the number of times two observers agree while *b* and *c* represent the number of times the two observers disagree. If *b* and *c* are zero, there are no disagreements, and observed agreement (p_o) is 1 or 100%. While zero *a* and *d* indicates no agreements and the observed agreement (p_o) would be 0.

The calculation of expected agreement (p_e) and kappa coefficient, K measure is as follows:

$$\text{Expected agreement}, p_e = [({}^{n_1}/_{n})({}^{m_1}/_{n})] + [({}^{n_0}/_{n})({}^{m_0}/_{n})]$$

$$\text{Kappa coefficient, K} = \frac{(p_o - p_e)}{(1 - p_e)}$$

where p_o is the observed agreement and p_e is the expected agreement. K measure of this difference is standardised to a scale of -1 to 1, where 1 is perfect agreement 0 is exactly what would be expected by chance and negative values indicate agreement less than chance.

Here, the two observers are the substrate interpreted from video transects and the substrate information from the substrate map. Observed agreement simply reflects when the map agrees with the video interpretation on the same type of substrate at every 50 m section of video transect. For the substrate map, the highest average substrate present within the 50 m section is used as the substrate type at the intersection points with the video transect.

Balanced error rate

Additionally, due to unbalanced class frequencies in the training data (i.e. most observations are sediment), the performance for each substrate distribution map is evaluated via balanced error rate (BER). BER was first suggested by Luts et al. (2010) to effectively give rarer classes a higher weighting by incorporating class misclassifications into accuracy assessment. The method has also been applied successfully to evaluate predictive models in seabed mapping (Stephens and Diesing, 2014; Diesing and Stephens, 2015). The criterion calculates the misclassified classes based on the Kappa coefficient agreement matrix as follows:

$$Balanced\ error\ rate, BER = \frac{{}^{b}/_{m_1} + {}^{c}/_{m_0}}{2}$$

where, *b* and *c* represent the number of times the two observers in disagreement and m_1 and m_0 are the total element in a categories. Here, BER represents the average of the proportion of wrong classifications in each class, the element refers to groundtruthed classified pixels and the categories are the substrate classes (i.e. sediments, rocks and mixed).

Statistical significance measure

Further examination to assess the classification accuracy is by evaluating the statistical significance of the differences in Kappa coefficient measure and balanced error rate among the three maps segmented at different SP. The evaluation was first proposed by McKenzie et al. (1996), to compare Kappa derived from related samples statistically using a resampling techniques. The method was then applied in remote sensing studies to support conventional accuracy assessment result (i.e. confusion matrix, Kappa coefficient measure) with a statistical confidence limit (Foody, 2004). Further implementation can be found on more recent studies and applied specifically for classification accuracy test in benthic substrate predictive models (Diesing et al., 2014; Stephens and Diesing, 2014; Diesing and Stephens, 2015).

Here, the test is to determine if one level of agreement (for Kappa) or disagreement (for BER) is significantly different from another. The p-values of the significance test for both statistic is generated via Monte Carlo type resampling. The significance of the difference between statistics is calculated as follows: 1) Using 1000 permutations (*n*) of the groundtruth data, statistics (i.e. Kappa and BER) for each map were recalculated on each permutation, 2) if the difference of the statistics from the permuted data equalled or exceeded the original difference, it is then counted towards a value (*c*), 3) at the end of the permutation, p-values is yielded using the following equation:

$$proption\ of\ differences = {}^{c+1}/_{n+1}$$

where the statistics difference is only significant if the returned value is less than 0.05. According to McKenzie et al. (1996) and Foody (2004), a thousand permutations are adequate for significance testing at 5 percent level of significance.

3.3.3.3 Marine landscape map

For the marine landscape mapping in Whittard Canyon, the technique used is an extension of the objective automated method that was developed in the Portuguese Canyons (Ismail et al., 2015). By applying this method here, its robustness for use in different submarine canyons is tested. The method is divided into two parts: the terrain analysis and the multivariate statistical analysis (Figure 3.2). It uses abiotic variables (Table 3.1) derived from acoustic data to delineate marine landscapes. In the first part, multiple scale terrain analysis approaches (Dolan and Lucieer, 2014) were used to calculate slope and aspect using Landserf v2.3 at two length scales equivalent to scale parameter obtained from the ESP tool and verified through the sensitivity test. The approach has been demonstrated to retain local and broad scale features from multibeam bathymetry (Ismail et al., 2015). However, curvatures were calculated only for the broad scale as fine scale analysis returned with pseudo surface variation as a result of the poorer bathymetry data quality compared to the data used in Ismail et al. (2015). Fine scale analysis with a 3 x 3 window picked out artefacts (noise) in the bathymetric data as features, which would have introduced false information into the multivariate statistical analysis. Bathymetric position index was derived using the Land Facet Corridor Designer extension for ArcGIS 10.2 (Jenness et al., 2011) at fine and broad scale, while rugosity was calculated at fine scale using DEM Surface Tool (Jenness, 2004) in ArcGIS 10.2. Apart from multibeam derivatives, the continuous substrate maps (from Section 3.3.3.1) were included and subjected to the multivariate statistical analysis to produce the overall marine landscape map for Whittard Canyon. Multivariate statistical analysis comprised of three analyses; 1) principal component analysis (PCA) for data reduction by computing linearly independent variables known as principal components (PC) 2) K-means for clustering of PCs using the most minimal iteration and 3) optimal number of classes are determined using within sum of squares plot.

Table 3.1: List of abiotic variables included in the principal component analysis. Ticked boxes indicate the available scale for the variables.

Abiotic Variable	*Descriptions*	*Length scale* *Fine*	 *Broad*
Digital terrain model (DTM) of bathymetry	Obtained from multibeam bathymetry survey. Represent depths of the ocean floor.	☑	
Slope	First derivatives of DTM. Represents the maximum rate of change in value from a cell to its neighbour	☑	☑
Aspect Eastness= sin(aspect) Northness= cos(aspect)	First derivatives of DTM. Describes the orientation of slope. Indices for eastness and northness provide continuous measure (-1 to +1)	 ☑ ☑	 ☑ ☑
Bathymetric position index (BPI)	Measures the elevation of each cells compares to the mean elevation of neighboring cells (Weiss 2001)	☑	☑
Plan curvature	A second derivative of DTM. Provide the rate of change of aspect		☑
Profile curvature	A second derivative of DTM. Provide the rate of change of gradient		☑
Rugosity	A measure of small scale variations of the surface area across the neighbourhood of the central pixel (Jenness 2004)	☑	
Sidescan sonar imagery	Obtained from Towed Ocean Bottom Instrument (TOBI). Sonar images are acquired by emitting continuous sonar pulses while moving, this return with the image of the seafloor.	☑	
Substrate Membership (Rock, Sediment, Mixed, Artefact)	Synthesised substrate map into quantitative layers by giving membership value in feature space to each pixels for each substrate class.	☑	

3.3.3.4 Marine landscape spatial heterogeneity quantification

The spatial heterogeneity hypothesis is one of the basics in ecology (Simpson, 1949; MacArthur, 1967). It assumes that structurally complex habitats may provide a wider range of niches and hence allow for diverse ways of exploiting environmental resources, thus increases species diversity. The response of organisms to heterogeneity in a landscape has been observed in terrestrial (Tews et al., 2004) and aquatic systems (Robert et al., 2014a; Parnell, 2015) including submarine canyons (Schlacher et al., 2010). Most terrestrial studies show positive relationships between heterogeneous landscape and biodiversity; however most studies are biased towards vertebrates and habitats under anthropogenic influence (Tews et al., 2004).

According to a review by Wedding (2011), application of spatial pattern metrics in the marine science literature between 1980 and 2011 was limited to only 17 studies that quantified spatial patterns using 2-dimensional patch-mosaic models (i.e. benthic habitat maps). Most studies followed terrestrial-based studies or modified metrics from terrestrial studies, and only one truly unique metric was developed for a marine landscape ecology study in a Pacific atoll (Andréfouët et al., 2001; Andréfouët et al., 2003). In a more recent study by Robert et al. (2014a), such application was extended in deep-sea settings where landscape metrics were used to characterize the spatial pattern of substratum types. Li and Reynolds (1995) give a general guideline for the quantification of heterogeneity in terrestrial ecology and suggest that heterogeneity should be defined based on two components: the system property of interest and its complexity or variability. In this study, the system property refers to the occurrence of the marine landscapes; complexity refers to qualitative descriptors of this property. Here, the heterogeneity is defined as the spatial variability of marine landscapes measured without reference to any functional effect (adapted from Li and Reynolds (1995)).

Heterogeneity in categorical maps can be defined as complexity in the number of patch types, proportion, patch shape and contrast between neighbouring patches. To address these aspects of heterogeneity, landscape ecologists have developed statistical tools to quantify spatial patterns in mapped surfaces. The contagion index is one such type of landscape index that is used to quantify heterogeneity in categorical maps (Li and Reynolds, 1993; Li and Reynolds, 1995). A robust landscape index to quantify heterogeneity should measure two components: composition and configuration (Li and Reynolds, 1993; Parresol and Edwards, 2014). Both components are adapted using definitions from landscape ecology to be used in this study. Composition refers to the total number of marine landscapes and their proportions in each area, whereas configuration refers to the spatial pattern of patches in the landscape.

Two scenarios were considered to quantify the spatial heterogeneity of the marine landscapes in the study area. The first is to divide the study area equally into a number of zones, each covering approximately 200 000 km^2. This approach is taken to simulate examples for decision-making in conservation zones if given a specific area to decide upon. The second approach is by dividing the area based on the morphology of the canyon, the branches and its outflow channel. In this case three zones are recognised - the Western and Eastern branch and Whittard Channel. The cut-off point between branches and the channel is based on the canyon cross-section profile where the valley shape changes from a V-shaped to a U-shaped profile.

The entropy-based contagion index, extended from landscape ecology and used to quantify spatial heterogeneity of the zones in the Whittard Canyon is expressed as follows:

$$\Gamma = \sum_{i=1}^{n}\sum_{j=1}^{n} p_i \frac{N_{ij}}{\sum_{j=1}^{n} N_{ij}} \ln\left(p_i \frac{N_{ij}}{\sum_{j=1}^{n} N_{ij}}\right)$$

where p_i is proportion of marine landscape type i and n is the total number of marine landscape types in the area (each zone), N_{ij} is the number of adjacencies between pixels of marine landscape i and j. Note that a higher contagion corresponds to a lower heterogeneity and vice versa. The proportion of each marine landscape type and the adjacency matrices for each zone were computed in FRAGSTATS based on a 50 m image resolution.

Hypothesis testing using one way analysis of variance (ANOVA)

Analysis of variance (ANOVA) was developed by Fisher (1925) and is widely used to determine whether there is a significant difference between the mean values of the different categories. In this case, to answer the question if the contagion means of the study zones are different, a simple one-way analysis of variance (ANOVA) was performed. ANOVA compares differences of means among groups by looking at variation in the data. Specifically it compares the amount of variation among groups with the amount of variation within groups. ANOVA is used to calculate a test statistic or the F-ratio with which the probability (the P-value) is obtained. The probability refers to the probability of obtaining the observed data assuming the null hypothesis. As null hypothesis we assume that the means of all groups are equal. A significant P-value, taken here as P statistically significant at 0.001 level ($P<0.001$), suggests that at least one zone mean is significantly different from the others. ANOVA calculates the variation in dataset into two parts as follows:

$$\text{among group variance} = \frac{\sum_{i=1}^{k} n_i(\bar{x}_i - \bar{x})^2}{k-1},$$

measures the variation of the *k* group means about the overall mean, where $(\bar{x}_i - \bar{x})^2$ is the square difference between each group mean to the overall group mean, *k* is the number of groups and k-1 is the degrees of freedom

$$\text{within group variance} = \frac{\sum_{i=1}^{k}\sum_{j=1}^{n_i}\left(x_{ij} - \bar{x}_i\right)^2}{\sum_{i=1}^{k}(n_i - k)}$$

measures the variation of the *n* sample about *k* group means, where $\left(x_{ij} - \bar{x}_i\right)^2$ is the sample standard deviation from the *i*th group, n_i is the sample size taken from group *i* and *k* is the number of groups with $(n_i - k)$ is the degrees of freedom

The F ratio is then calculated for the hypothesis testing by dividing among group variance by the within group variance. If the average difference among group is similar to that within groups, the F ratio will come to about 1. As the average difference among groups becomes greater than that within groups, the F ratio becomes larger than 1. The P-value is obtained by testing it against the F-distribution of a random variable with the degree of freedom associated with the among and within group variance. Larger F ratio will give smaller P-values which indicates greater difference of variance, and less chance that the null hypothesis is correct.

Based on the above equations, Parresol and Edwards (2014) constructed the simple one-way ANOVA for the entropy index using mean and variance for the statistical estimate Γ of the contagion of a landscape:

$$\text{among group variance} = \frac{\sum_{i=1}^{t}\left(\Gamma_i - \hat{\Gamma}\right)}{t-1} \quad , \quad \hat{\Gamma} = \frac{\sum_{i=1}^{t} T_i \Gamma_i}{\sum_{i=1}^{t} T_i}$$

$$\text{within group variance} = \frac{\sum_{i=1}^{t} T_i var(\hat{\Gamma}_i)}{\sum_{i=1}^{t} T_i}$$

$$\mathrm{F} = \frac{among\ group\ variance}{within\ group\ variance} \text{ with } t-1, \Sigma T_i - t \text{ degrees of freedom}$$

where zones are equivalent to groups and patches to samples, Γ_i =contagion value of the *i*th zone, t=number of zone and T_i=number of patches for the *i*th zone.

Tukey's test

While ANOVA is used to test whether there is significant difference between groups in the data, it does not however tell which groups differ. In the event the ANOVA indicates that there is a significant difference among groups, Tukey's test or post-hoc analysis (Tukey, 1949) can be used to find the means that are significantly different from each other. Tukey's test compares all possible group means in pairs and is based on a studentised range distribution (q) to find groups that differ significantly. Here, the Tukey's test value (q) between two zones (i and j) is calculated as follows (Parresol & Edwards, 2014):

$$q_{ij} = \frac{\Gamma_i - \Gamma_j}{\sqrt{\text{mean squared error}}}$$

where Γ_i and Γ_i is contagion for ith zone and jth zone with i being the larger of the two contagions compared. The test value (q_{ij}) is then compared to a q value (q_{critical}) obtained from the studentised range distribution. If the q_{ij} value is larger than the $q_{critical}$, the two zones are significantly different.

Biological characteristics

Due to the limited number of biological samples, relationships with biological characteristics were only investigated for the second approach where the study area is divided into three zones based on canyon morphology. Biological characteristics based on epibenthic megafauna counts from the video transect interpretation were calculated for the Eastern and Western branch and Whittard Channel to evaluate the relevance of the contagion index as a biodiversity indicator. The biological characteristics are abundance, richness and Simpson's reciprocal index (diversity index). Abundance and richness represent the number of individuals present and number of different kinds of organisms present in a sample, respectively. Simpson's reciprocal index, from Simpson's Index (Simpson, 1949), is a diversity measure that takes into account both richness and abundance, meaning that a community dominated by one or two species, is considered to be less diverse than one in which several different species have a similar abundance. The biological characteristics were used instead of specific species assemblages to evaluate the ecological relevance due to high turnover in species assemblages in Whittard Canyon (Robert et al., 2014b).

3.3.3.5 Ecologically relevant marine landscapes

A species indicator analysis or INDVAL, as suggested by Dufrêsne and Legendre (1997), was performed to evaluate the ecological relevance of the marine landscape map obtained. This method identifies indicator species for each marine landscape (cluster). Potentially, should the marine landscape be ecologically relevant, indicator species will be identified, whereas if no indicator species can be identified the cluster lacks ecological significance. The index is calculated in the R package labdsv and defined as follows:

$$\text{INDVAL}_{ij} = A_{ij} \times B_{ij} \times 100$$

$$A_{ij} = \text{N}individuals_{ij} / \text{N}individuals_{j}$$

$$B_{ij} = \text{N}sites_{ij} / \text{N}sites_{j}$$

where INDVAL is the indicator value of species *i* in site cluster *j*, and site is the interpreted 50 m section of video transect. A_{ij} is the mean abundance of species *i* in the sites of marine landscape *j*, compared to all groups in the study. B_{ij} is the relative frequency of occurrence of species *i* in the sites of marine landscape *j*. Final multiplication by 100 produces percentages. In addition to the INDVAL statistical approach, species were grouped into their feeding type to evaluate the overall distribution of biota in relation to marine landscapes in the submarine canyon, based on the 50 m video transect sections.

3.4 Results

3.4.1 Substrate map

Sensitivity Test for ESP Tool

The ESP tool used to determine the appropriate scale parameter for segmentation in OBIA yielded the rate of change in local variance (ROC-LV) graph (Figure 3.3). The pattern observed in the graph reveals the transition from pixels to the smallest characteristic objects in the scene of interest. This transition is shown as a step or small peak in the ROC-LV plot. Based on Figure 3.3, at scale parameter 150, 250 and 370 meaningful objects emerge. Segmentation was therefore carried out at 150, 250 and 370. Part of the segmented sidescan sonar image is shown in Figure 3.3.

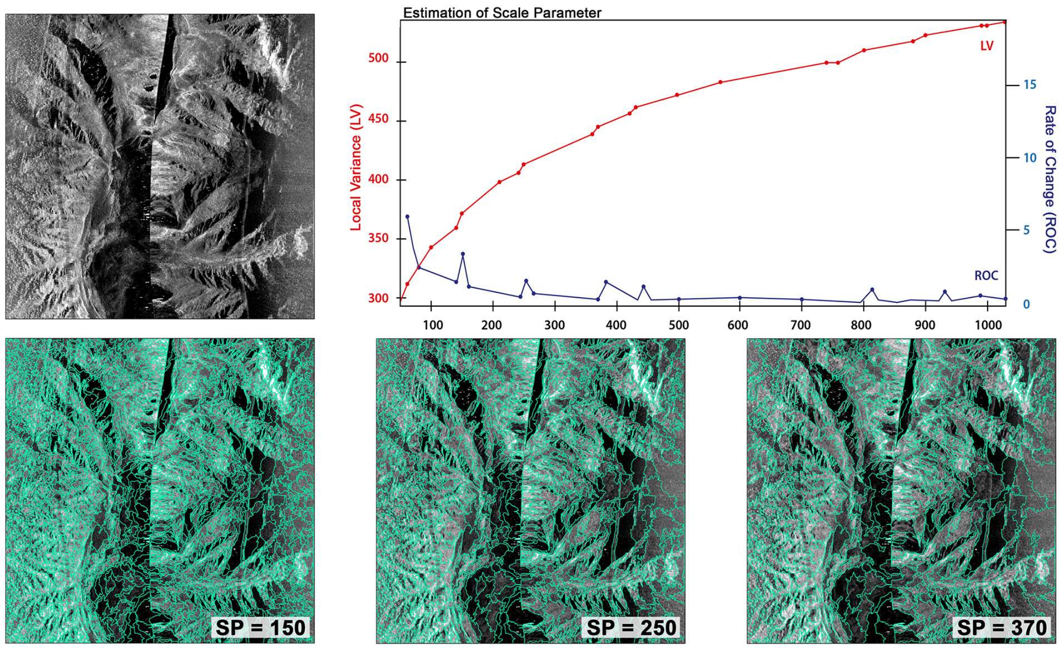


Figure 3.3: ROC-LV (Rate of change – local variance) graph obtained using the ESP Tool to determine the most appropriate segmentation size for object based image analysis. Peaks in ROC plot (blue) indicate the threshold at which the analysis window size best represents the real-world objects. Dragut et al. (2010) defined the threshold as the first break in ROC-LV curve after continuous and abrupt decay. Segmentation results for a part of TOBI sidescan sonar image are shown for scale parameter (SP) at levels 150, 250 and 370.

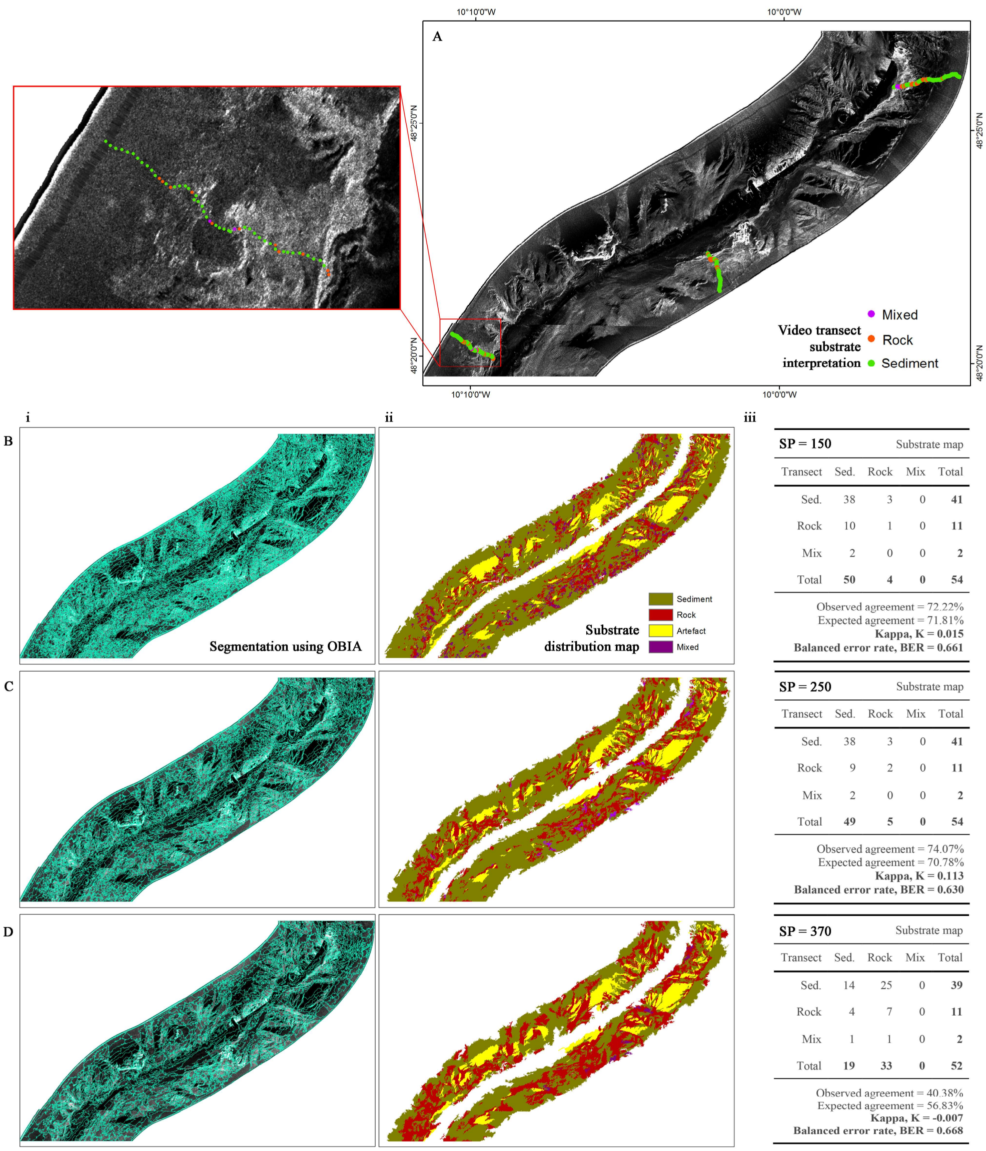
Once the pilot area was segmented using a SP of 150, 250 and 370, substrate distribution maps were produced based on the segmentation. Results for each segmentation and its substrate distribution are shown in Figure 3.4. Based on the Kappa statistic, the observed agreement is reasonable between the video transect and substrate distribution map for Sediment. Substrate class Rock is highest for misclassification except in map SP 370 and Mixed substrate was not classified correctly on any of the maps. The highest agreement was achieved in the image segmented with SP 250, followed by SP 150 and the lowest agreement, at 40.38%, belongs to the segmentation with SP 370. Lowest agreement in map SP 370 is a result of the over-estimation of the Rock class versus the Sediment class. However, the Kappa values are low for all three outcomes. Relatively among the three segmentations, SP 250 has the highest Kappa value although according to interpretation of Kappa statistics, a value between 0.01 – 0.20 is still considered to be a poor agreement (Viera, 2005). SP 370 with the lowest value is interpreted to have no chance of agreement. Balanced error rate is in agreement with the Kappa statistic result, with SP 250 map has the lowest misclassification and SP 370 map being the highest. However, due to rare class substrate Mixed that imbalanced the class frequencies in the training data, contributes to the small range of BER between the three maps. BER for map SP 150, SP 250 and SP 370 are 0.661, 0.630 and 0.668, respectively. Although, absolute comparison between maps indicate small margin of differences in Kappa and BER values, however at 5% level of significance, the differences are weak and insignificant from one another. Monte Carlo permutation (McKenzie et al., 1996; Foody, 2004) used to compare the statistical difference does not yield a supportive evidence towards the selection of scale parameter.

Substrate distribution maps along with terrain analyses calculated at length scales equivalent to SP 150, 250 and 370 (refer appendix 1) were subjected to multivariate statistical analysis to create marine landscape maps for the pilot study area. Results for the marine landscapes, together with PCA results, plots of optimal number of clusters and boxplots of clusters against original abiotic variables for each segmentation at SP 150, 250 and 370 are laid out in Figure 3.5 – 3.7.

Segmentation at SP level 150 resulted in 11 clusters, at SP of 250 returned 6 clusters and at level 370 gave 5 clusters. PCA results for all marine landscapes came with broad-scale BPI as the main contributing abiotic variable, followed by Eastness for marine landscape of SP 250 and 370 but not for SP 150, while fine-scale BPI is the next in order. Based on the plot for the optimal number of clusters, the change in slope to determine the number is distinct in both marine landscapes for segmentation at SP level of 250 and 370, however for SP 150 the knick-point is less obvious.

Based on visual assessment the outcome of the marine landscape map for SP 150 is patchy and noisier in comparison to SP 250 and SP 370. The cluster characteristics overlap with each other and have too many outliers based on the boxplots between clusters and the original abiotic variables. SP of 370 has fewer clusters and the clusters are simplified. The boxplots are aggregated around similar values for most clusters against the original abiotic variables.

Based on the results of this sensitivity test, it was decided to carry out the full Whittard Canyon marine landscape classification using the broad scale equivalent to an SP of 250. The SP 150 produced a result that was too noisy, while with SP 370 potentially information was lost, especially in terms of substrate mapping (as illustrated by the negative Kappa value).



SP = 150

Transect	Sed.	Rock	Mix	Total
Sed.	38	3	0	**41**
Rock	10	1	0	**11**
Mix	2	0	0	**2**
Total	**50**	**4**	**0**	**54**

Substrate map
Observed agreement = 72.22%
Expected agreement = 71.81%
Kappa, K = 0.015
Balanced error rate, BER = 0.661

SP = 250

Transect	Sed.	Rock	Mix	Total
Sed.	38	3	0	**41**
Rock	9	2	0	**11**
Mix	2	0	0	**2**
Total	**49**	**5**	**0**	**54**

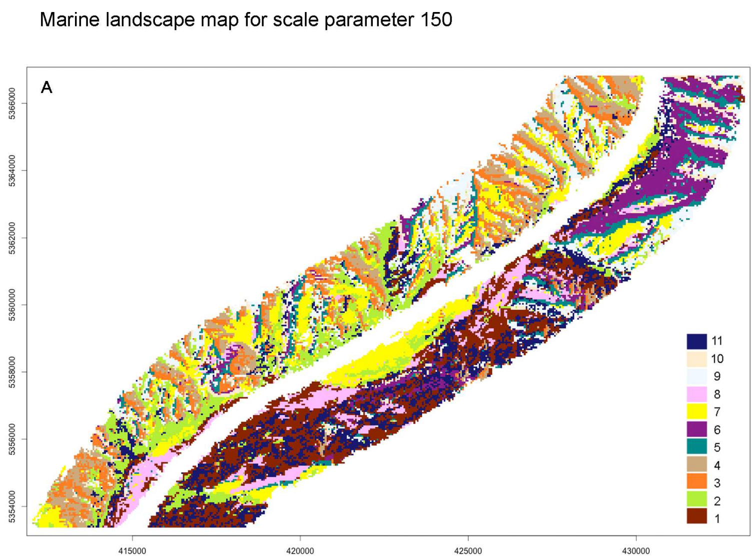
Substrate map
Observed agreement = 74.07%
Expected agreement = 70.78%
Kappa, K = 0.113
Balanced error rate, BER = 0.630

SP = 370

Transect	Sed.	Rock	Mix	Total
Sed.	14	25	0	**39**
Rock	4	7	0	**11**
Mix	1	1	0	**2**
Total	**19**	**33**	**0**	**52**

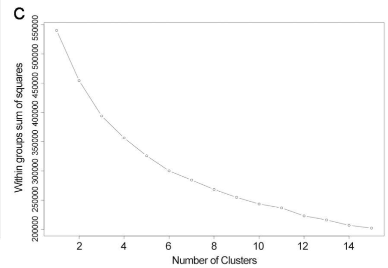
Substrate map
Observed agreement = 40.38%
Expected agreement = 56.83%
Kappa, K = -0.007
Balanced error rate, BER = 0.668

Figure 3.4: **A**) TOBI imagery of the pilot area for the sensitivity test, with three video transects: two were used for sample training to create the substrate distribution maps and one transect (in red box) is used for the Kappa statistic test. **Row B – D**: results for analysis on segmentation using SP B) 150, C) 250 and D) 370. **Column i**) segmentation results on pilot area TOBI imagery, **ii**) substrate distribution map generated using OBIA and supervised classification **iii**) Kappa statistic test result between substrate distribution map and video transect.



B

Abiotic variables	PC1	PC2	PC3	PC4	PC5	PC6
Bathymetry	0.2820	0.1047	-0.1121	-0.1715	-0.1640	0.0516
Bathymetric position index fine	0.3407	**-0.3935**	0.0195	0.1619	0.0007	-0.0061
Bathymetric position index broad	**0.3887**	-0.3719	0.0090	0.1167	0.0060	-0.0064
Eastness	0.1271	0.2528	0.1923	0.3744	0.4818	0.0177
Eastness 150	0.1393	0.2711	0.1840	0.3746	0.4656	0.0151
Mixed	-0.1175	-0.0507	-0.2196	0.1727	0.0351	**-0.6208**
Artefact	0.1147	0.0036	0.4039	**-0.3834**	0.0883	-0.2405
Northness	-0.1290	-0.2383	-0.2917	-0.2821	**0.5023**	0.0912
Northness 150	-0.1374	-0.2478	-0.2961	-0.2853	0.4829	0.0906
Plan curvature 150	-0.3003	0.3050	0.0078	-0.1274	-0.0272	0.0137
Profile curvatire 150	0.3031	-0.3093	0.0308	0.0829	-0.0127	0.0036
Rock	-0.0494	0.0331	-0.3037	0.2769	-0.1387	0.5900
Rugosity	0.2607	0.2775	-0.2239	-0.1386	0.0468	-0.0414
Sediment	0.0157	-0.0076	0.2453	-0.1409	0.0511	0.3969
Slope	0.3786	0.2921	-0.2746	-0.1666	0.0133	-0.0334
Slope 150	0.3715	0.2913	-0.2786	-0.1655	0.0105	-0.0276
TOBI	-0.1455	-0.0272	**-0.4188**	0.3442	-0.0664	-0.1659
Eigenvalues	3.2046	2.7046	2.3820	2.1140	1.5288	1.4484



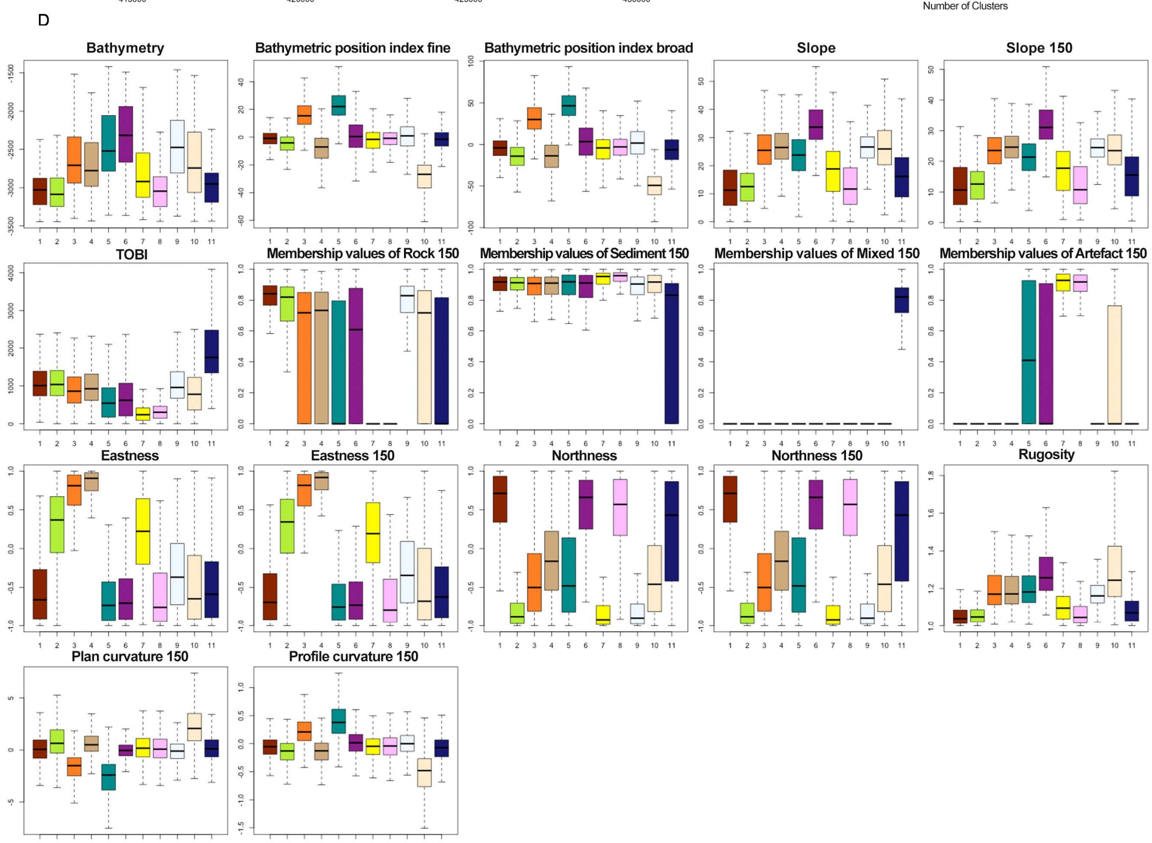
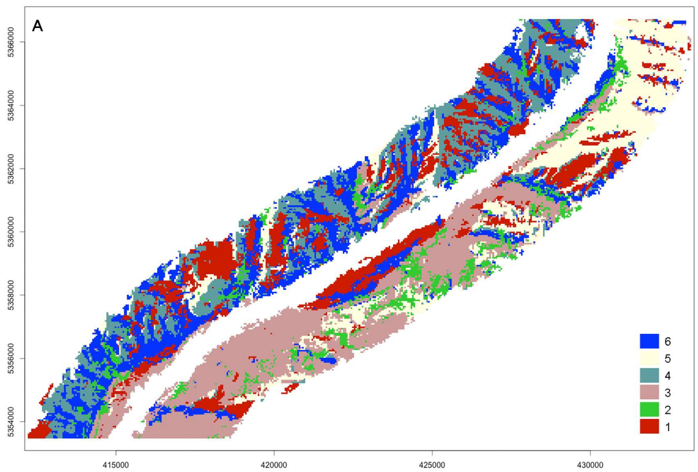


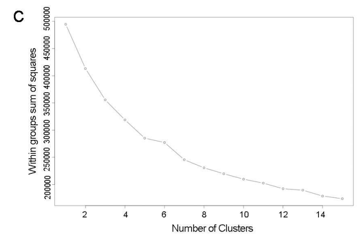
Figure 3.5: **A**) Marine landscape map produced using substrate distribution map along with terrain analysis calculated at length scale equivalent to SP 150 **B**) Component matrix showing correlation between rotated principal components and the original variables (highest factor loads in each PC are highlighted in bold) **C**) Plot of number of clusters against within sum of squares, change of slope indicates the optimum number of clusters for the marine landscape map **D**) boxplots of clusters against the original abiotic variables

Marine landscape map for scale parameter 250



B

Abiotic variables	PC1	PC2	PC3	PC4	PC5	PC6
Bathymetry	0.2963	0.0113	-0.1176	-0.1836	0.0186	0.1940
Bathymetric position index fine	0.2818	-0.3262	0.1081	0.2811	-0.0357	-0.0066
Bathymetric position index broad	**0.3895**	-0.3216	0.0871	0.1912	-0.0198	-0.0114
Eastness	0.1151	0.3590	0.1040	0.3141	0.0664	-0.4800
Eastness250	0.1319	**0.3851**	0.0870	0.3111	0.0610	-0.4502
Mixed	-0.1134	-0.0632	-0.2122	0.1113	**-0.6009**	-0.1080
Artefact	0.1543	0.0442	**0.3919**	**-0.3968**	-0.2485	-0.1466
Northness	-0.1165	-0.3500	-0.2096	-0.2267	0.1706	**-0.4919**
Northness 250	-0.1310	-0.3697	-0.2115	-0.2313	0.1618	-0.4555
Plan curvature 250	-0.3010	0.2750	-0.0528	-0.2168	0.0205	0.0409
Profile curvatire 250	0.3102	-0.2780	0.1063	0.1547	-0.0033	0.0120
Rock	-0.1101	-0.0168	-0.3558	0.3433	0.3942	0.1925
Rugosity	0.2657	0.1881	-0.2976	-0.1540	0.0344	-0.0401
Sediment	0.0011	0.0052	0.2251	-0.0623	0.5603	0.0733
Slope	0.3841	0.1704	-0.3444	-0.1873	0.0186	-0.0004
Slope 250	0.3706	0.1644	-0.3504	-0.1896	0.0208	0.0039
TOBI	-0.1691	-0.0552	-0.3741	0.3052	-0.2000	0.0243
Eigenvalues	3.3306	2.5763	2.3611	2.0072	1.4686	1.4461



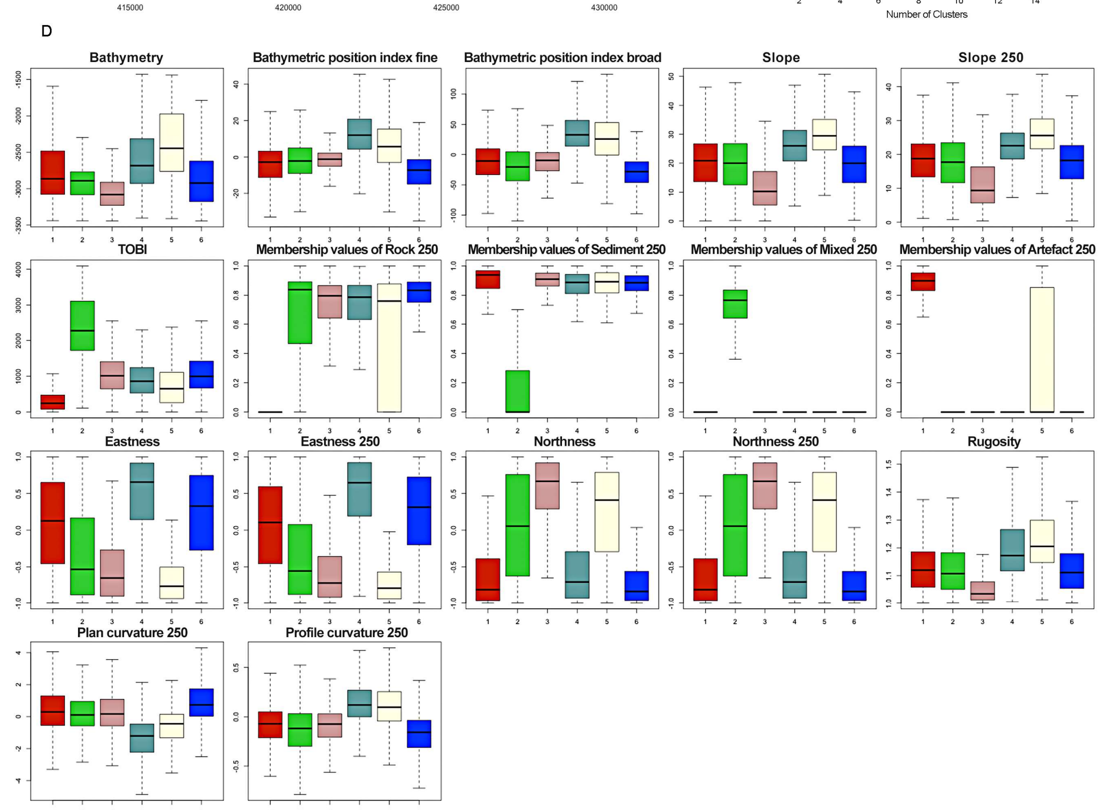
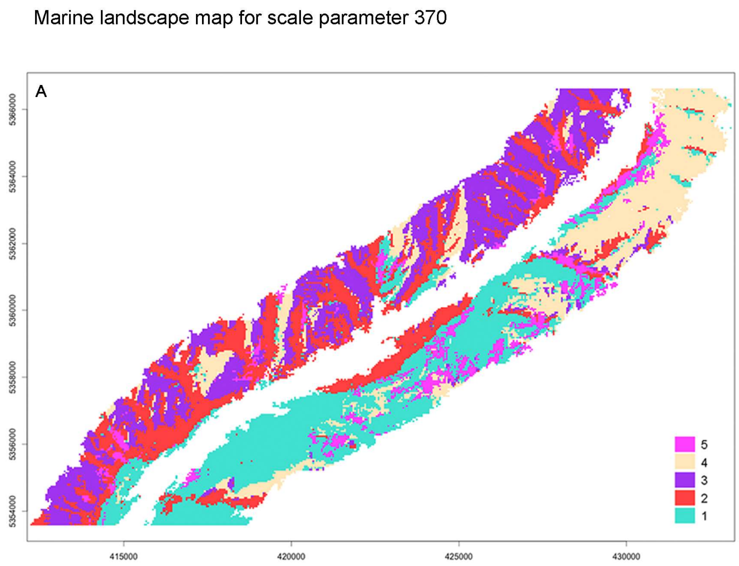
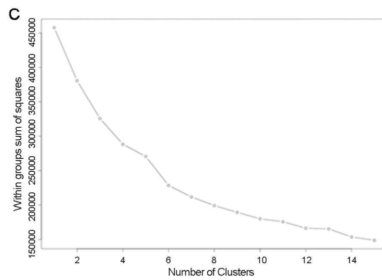


Figure 3.6: **A**) Marine landscape map produced using substrate distribution map along with terrain analysis calculated at length scale equivalent to SP 250 **B**) Component matrix showing correlation between rotated principal components and the original variables (highest factor loads in each PC are highlighted in bold) **C**) Plot of number of clusters against within sum of squares, change of slope indicates the optimum number of clusters for the marine landscape map **D**) boxplots of clusters against the original abiotic variables.



B

Abiotic variables	PC1	PC2	PC3	PC4	PC5	PC6
Bathymetry	0.3041	0.0582	0.1106	-0.1363	0.0053	0.2329
Bathymetric position index fine	0.2380	0.2445	-0.1296	0.3338	-0.1630	-0.0571
Bathymetric position index broad	**0.3918**	0.2699	-0.1194	0.2296	-0.0746	-0.0278
Eastness	0.1101	-0.4092	-0.0039	0.2521	0.0542	**-0.4880**
Eastness 370	0.1299	**-0.4391**	0.0262	0.2472	0.0593	-0.4387
Mixed	-0.1322	0.0882	0.2936	-0.0244	-0.5362	-0.1367
Artefact	0.1678	-0.0643	**-0.3755**	**-0.4414**	-0.2142	-0.1857
Northness	-0.1096	0.4048	0.0939	-0.1560	0.2933	-0.4580
Northness 370	-0.1291	0.4350	0.0923	-0.1585	0.2708	-0.4066
Plan curvature 370	-0.2956	-0.2283	0.0603	-0.2599	0.0833	0.0749
Profile curvatire 370	0.3165	0.2357	-0.1378	0.1903	-0.0756	-0.0099
Rock	-0.1380	0.0574	0.3503	0.4066	0.2386	0.1930
Rugosity	0.2640	-0.1060	0.3186	-0.1747	0.1336	-0.0205
Sediment	0.0341	-0.0511	-0.2390	0.1310	**0.5622**	0.1919
Slope	0.3816	-0.0663	0.3626	-0.1993	0.0946	0.0220
Slope 250	0.3633	-0.0535	0.3697	-0.2014	0.0893	0.0259
TOBI	-0.1978	0.0822	0.3732	0.2253	-0.2197	-0.0391
Eigenvalues	3.4437	2.5405	2.3152	1.9073	1.5508	1.3691



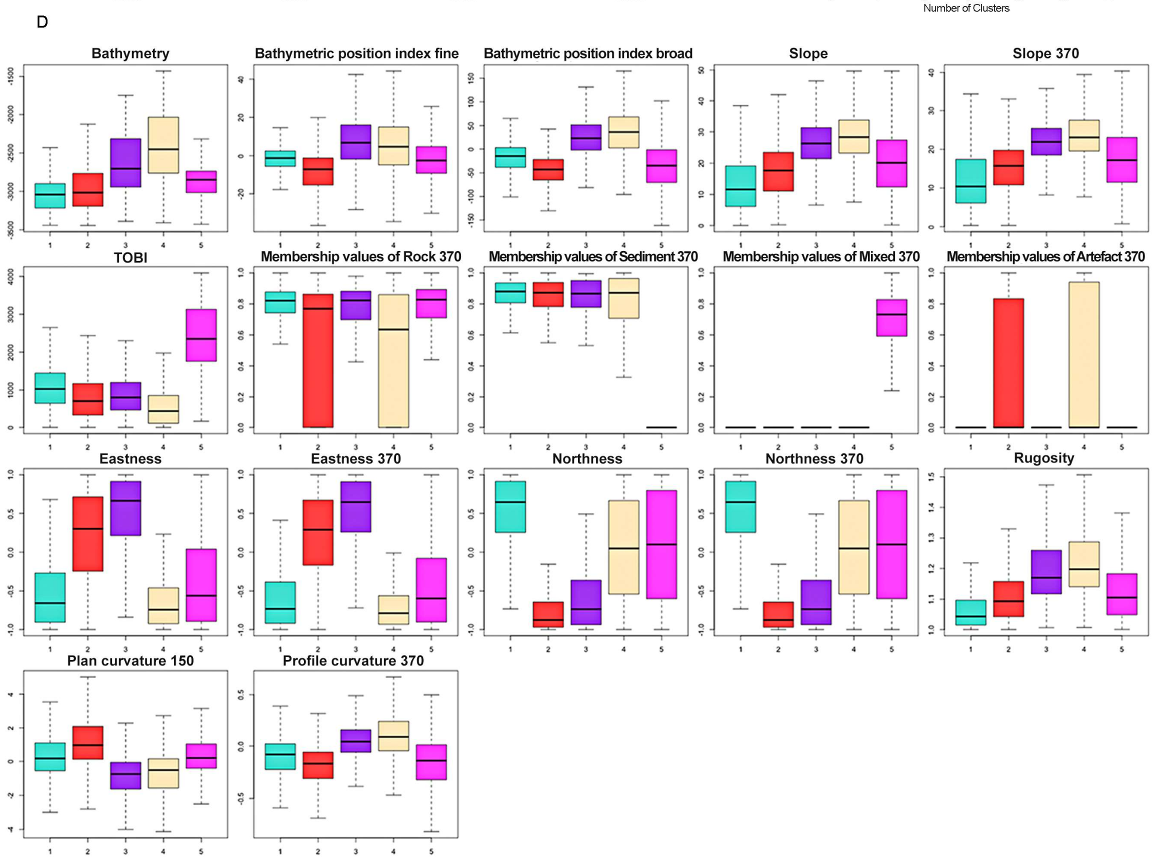


Figure 3.7**A**) Marine landscape map produced using substrate distribution map along with terrain analysis calculated at length scale equivalent to SP 370 **B**) Component matrix showing correlation between rotated principal components and the original variables (highest factor loads in each PC are highlighted in bold) **C**) Plot of number of clusters against within sum of squares, change of slope indicates the optimum number of clusters for the marine landscape map **D**) boxplots of clusters against the original abiotic variables.

Object Based Image Analysis

Classification for the substrate map was carried out using the nearest neighbour algorithm in the feature space optimisation tool available in eCognition (Laliberte et al., 2012). The algorithm established the best combination of descriptors for the separation and classification of training classes. The four features that best separate the classes identified by the algorithm are the mean brightness, standard deviation, and the Haralick grey level co-occurrence matrix (GLCM) correlation and entropy. The brightness and standard deviation are measures of image intensity and textural properties, respectively, providing a proxy for seafloor hardness and softness (Le Gonidec et al., 2003; Lucieer et al., 2013). These are good parameters for separatation of sediment and rocky substrate. The Haralick GLCM (Haralick et al., 1973) is a method to quantify image texture (Hall-Beyer, 2007); here both GLCM correlation and entropy measure a different characteristic of the sidescan sonar image. GLCM correlation deals with the linear dependency of grey levels on the neighbouring pixel within an image object, whilst GLCM entropy is part of an orderliness measure, it calculates the "chaotic-ness" of image objects within the image.

The classified objects for the substrate map are shown in relation to training objects in a 2D feature space plot (Figure 3.8). The class with the lowest variance (i.e. clustered most tightly) are shadows (artefact) from low grazing angles (yellow dots on Figure 3.8). The class has the most obvious separation from the rest of the classes in having the lowest backscatter value (brightness and standard deviation). While rock and sediments are fairly clearly separated from each other in the feature space, mixed substrate is more scattered. Based on TOBI backscatter intensity values alone (Figure 3.9), the mean brightness for rock, sediment and mixed substrates aggregated at about the same values. However, with incorporation of the other features from the OBIA analysis, the classes are well separated and give a fair agreement when correlated with video interpretation. The agreement percentage came to 52% using inter-rater agreement out of a total 195 points from four video transects. The classification represents the substrate composition of the study area. Apart from the classification of substrate, the procedure manages to separate noise at the sidescan sonar nadir and low grazing angles. Such types of noise are common for the kind of data (i.e. Sidescan sonar imagery, acoustic backscatter images) (Marsh and Brown, 2009) and often add complexity to automated interpretation of sidescan sonar imagery.

Class memberships

The substrate map produced from the OBIA technique is in categorical form, which is not suitable for further multivariate statistical analysis. Therefore, the substrate map is converted into four maps, one for each class, in which each pixel is given a relative value representing its membership within the class (Figure 3.9). Each image object has a membership value for each class ranging from 0 to 1. The values are relative measures of the distance in feature space between the object and the respective class centre. Zero indicates that the image object is furthest in feature space from the class centre in question, hence belonging to a different class altogether. The final substrate information included into the overall objective automated marine landscape mapping technique is based on the four membership maps representing the relative measure of class membership for rock, sediment, mixed substrate and TOBI artefacts. The membership distribution curves for rock, sediment and mixed substrate are skewed to the right, while in comparison the artefact class has a bimodal distribution. Positively-skewed distribution of sediment, mixed and rock membership clusters are caused by the high membership value for the second and third member. Thus the degree of belonging of an image object to a cluster is relatively high for all clusters and possibly may introduce confusion in multivariate statistical analysis (e.g assigning classes in k-means algorithm).

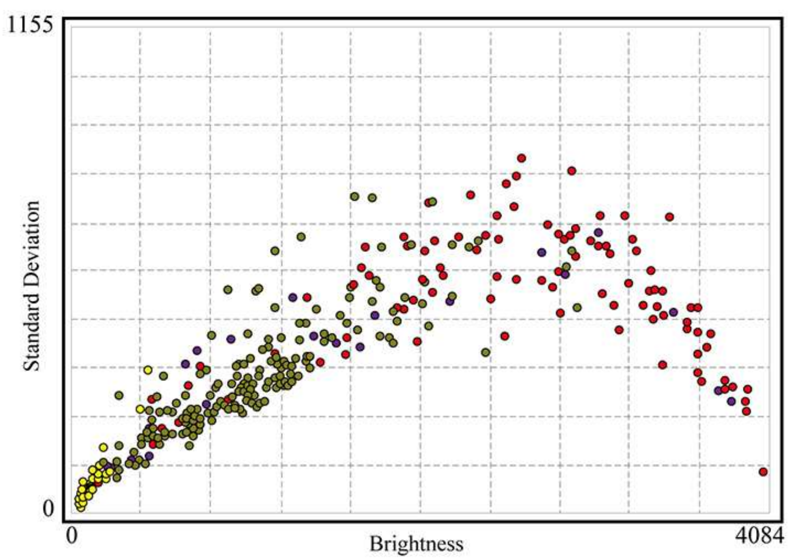
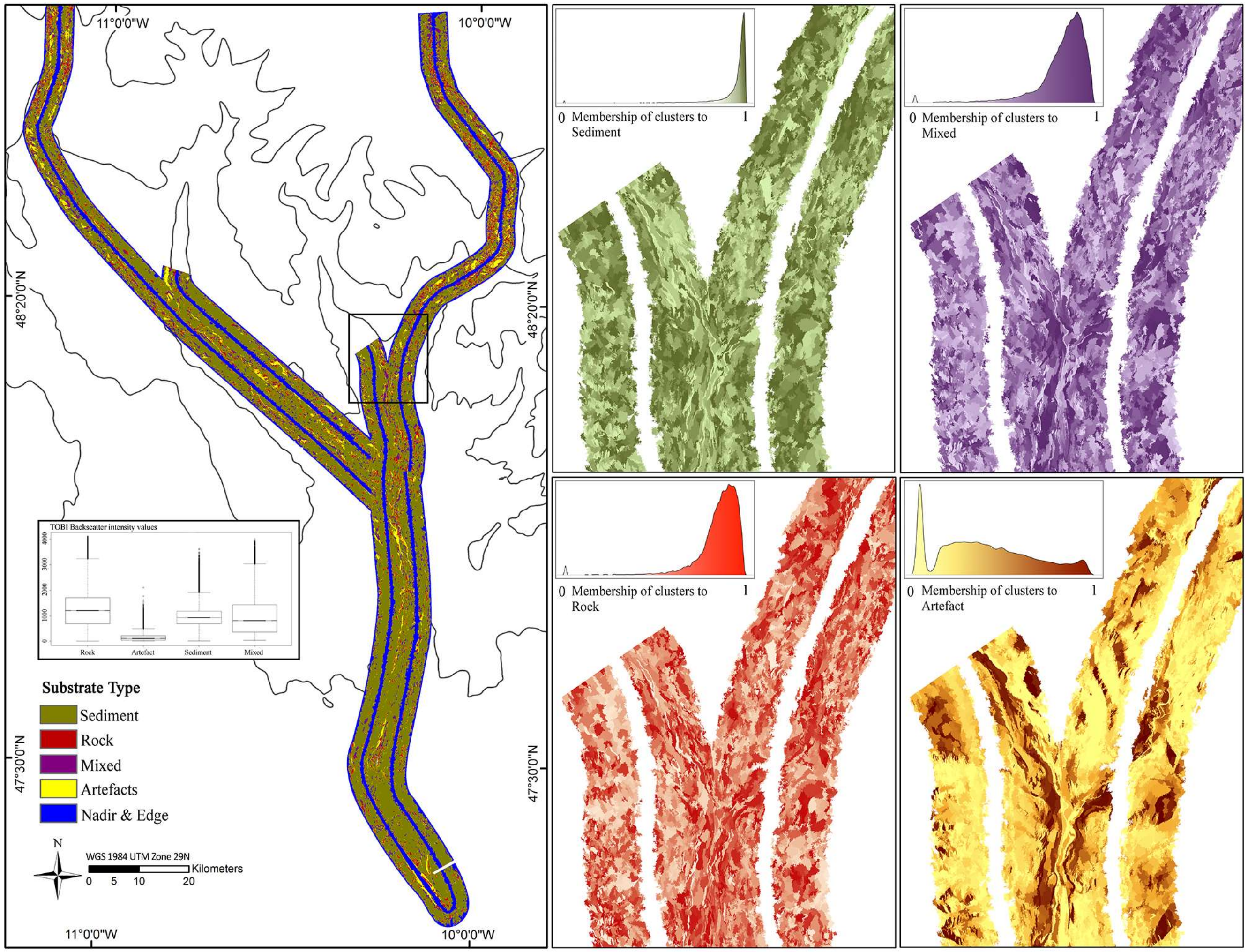


Figure 3.8: Feature space diagram of object backscatter brightness vs backscatter standard deviation for the four substrate classes. This plot shows the standard deviation of the objects by the brightness intensity for the training samples of all the four classes. The coloured circles are training samples for: red = rock, green = sediments, purple = mixed, yellow = artefacts.



	Substrate map			
Transect	Sed.	Rock	Mix	Total
Sed.	80	59	0	**139**
Rock	28	21	0	**49**
Mix	5	1	1	**7**
Total	**113**	**81**	**1**	**195**

Observed agreement = 52.31%
Expected agreement = 51.76%
Kappa, K = 0.011
Balanced error rate, BER = 0.617

Figure 3.9: Final classification map (left) produced using multi-level segmentation at scale parameter of 250. The map produced here is referred to as substrate map, inset is the boxplot of the 4 classes against TOBI backscatter intensity values (note that the boxplot is based on individual pixel intensity values, and not on the mean brightness of segments from OBIA segmentation). Area in the box is a close up shown on the right for all classes in their continuous variable form. Inset in each close-up maps are the data distribution for each classes, which are skewed to the right except for class Artefact. Accompanying the figure is the contingency table with Kappa and BER value for the substrate map.

3.4.2 Marine landscape map

The final outcome of the mapping procedure resulted in an optimum solution of seven clusters (Figure 3.11). Overall, the controlling factors that drive the PCA solutions are slope, membership value of mixed and rocky substrate, bathymetric position index and aspect (eastness), in order of their influence (Table 3.2). The marine landscape map of Whittard Canyon is presented in Figure 3.11. These clusters are interpreted based on boxplots of the original abiotic variables against the marine landscapes (Figure 3.12 a&b). For instance, Cluster 1 is interpreted as vertical and steep-sided canyon wall that has the steepest, most rugged terrain and has a high membership value of rock and the highest TOBI backscatter intensity. Cluster 2 is influenced by the slope orientation, has the highest mixed substrate and sediment membership, with steep slopes and positive bpi, and is interpreted as southwest facing terraces and ridges. Cluster 3, mostly in the deeper area and with a flat (slope) and smooth (rugosity) surface, represents the flat seabed in the Whittard Channel. Cluster 4 and Cluster 6 likewise are marine landscapes that are affected by aspect (eastness and northness) and similarly they are driven by bathymetry position index of which both are flanks in a different direction. Cluster 5 is mainly defined by bathymetric position index and profile curvature, and is interpreted as canyon floor. Cluster 7 contains TOBI artefacts.

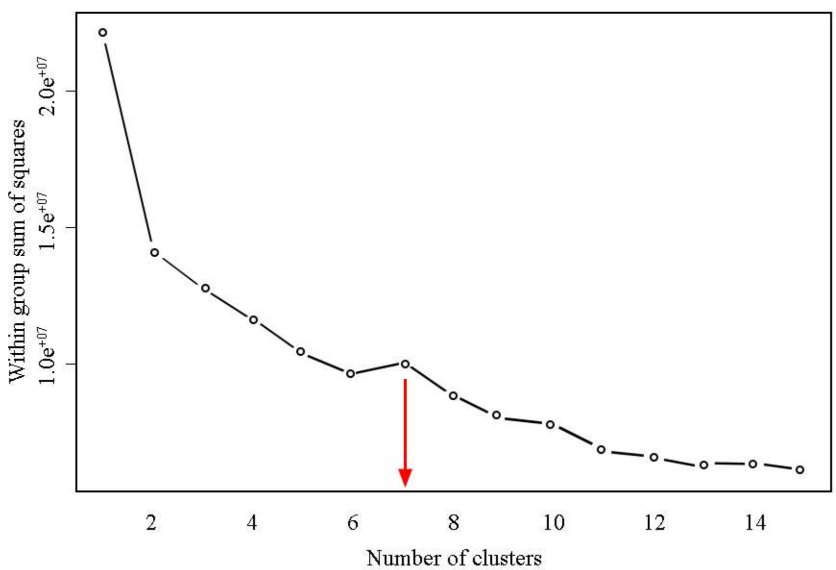


Figure 3.10: Plot of number of clusters against within sum of squares to determined the optimal number of clusters. The plot indicates a distinct increase at seven clusters solution (marked in red).

Table 3.2: Component matrix showing correlation between rotated PCs and the original variables. Highest factor loads in each PC are highlighted in bold.

Abiotic Variables	*PC1*	*PC2*	*PC3*	*PC4*	*PC5*	*PC6*
Bathymetry	-0.26292	0.024547	-0.25578	-0.09527	0.034132	0.019562
Bathymetric position index fine	0.252933	0.284695	**-0.3617**	-0.06944	-0.28378	0.136341
Bathymetric position index broad	0.352171	0.233958	-0.21767	-0.0018	-0.22348	0.163672
Eastness	0.043384	0.031379	-0.12494	0.52734	0.308338	0.324822
Eastness 250	0.034846	0.044669	-0.16724	**0.55755**	0.25919	0.272241
Northness	-0.03913	-0.00221	-0.14641	0.443306	-0.14972	**-0.4965**
Northness 250	-0.05632	-0.00153	-0.1422	0.305622	-0.25537	-0.58167
Membership values of artefact	0.106427	0.189487	-0.27885	-0.20124	**0.50226**	-0.26822
Membership values of mixed	0.146688	-0.5088	-0.28541	-0.06100	0.007468	0.02117
Membership values of rock	0.062606	**-0.5259**	-0.22499	-0.01954	-0.06134	0.070735
Membership values of sediment	0.227536	-0.45126	-0.23787	-0.06743	0.010781	-0.01046
Plan curvature	-0.05709	-0.13340	0.204385	0.021735	0.218404	-0.05375
Profile curvature	0.134882	0.200078	-0.29916	-0.05185	-0.2846	0.120512
Rugosity	-0.39211	0.01022	-0.1915	-0.04755	-0.02156	0.117142
Slope	-0.4715	0.020743	-0.27024	-0.05624	-0.03994	0.093801
Slope 250	**-0.4754**	0.014265	-0.27828	-0.05887	-0.03006	0.060436
TOBI	-0.15184	-0.16461	0.293714	0.214547	-0.48024	0.26208

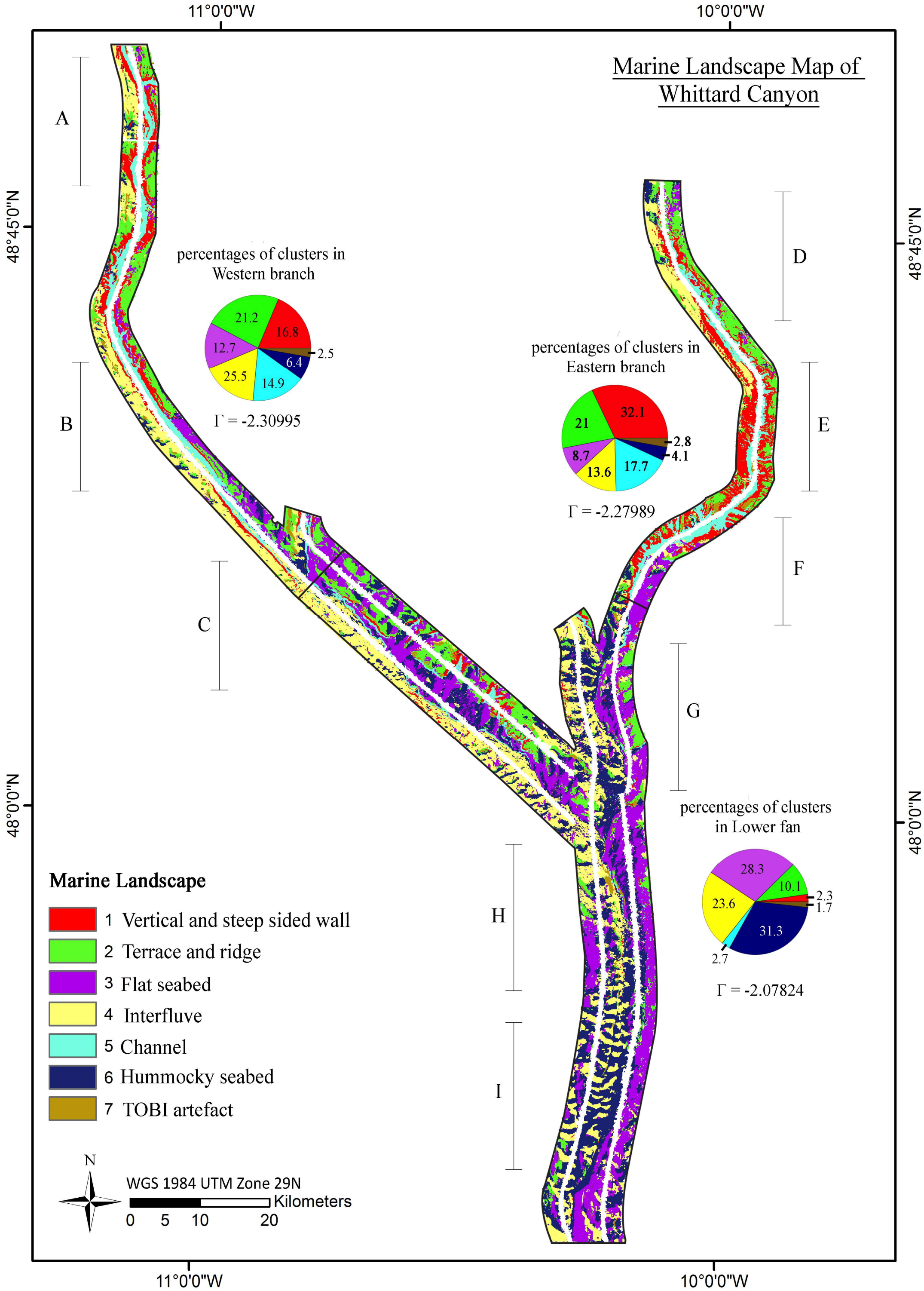
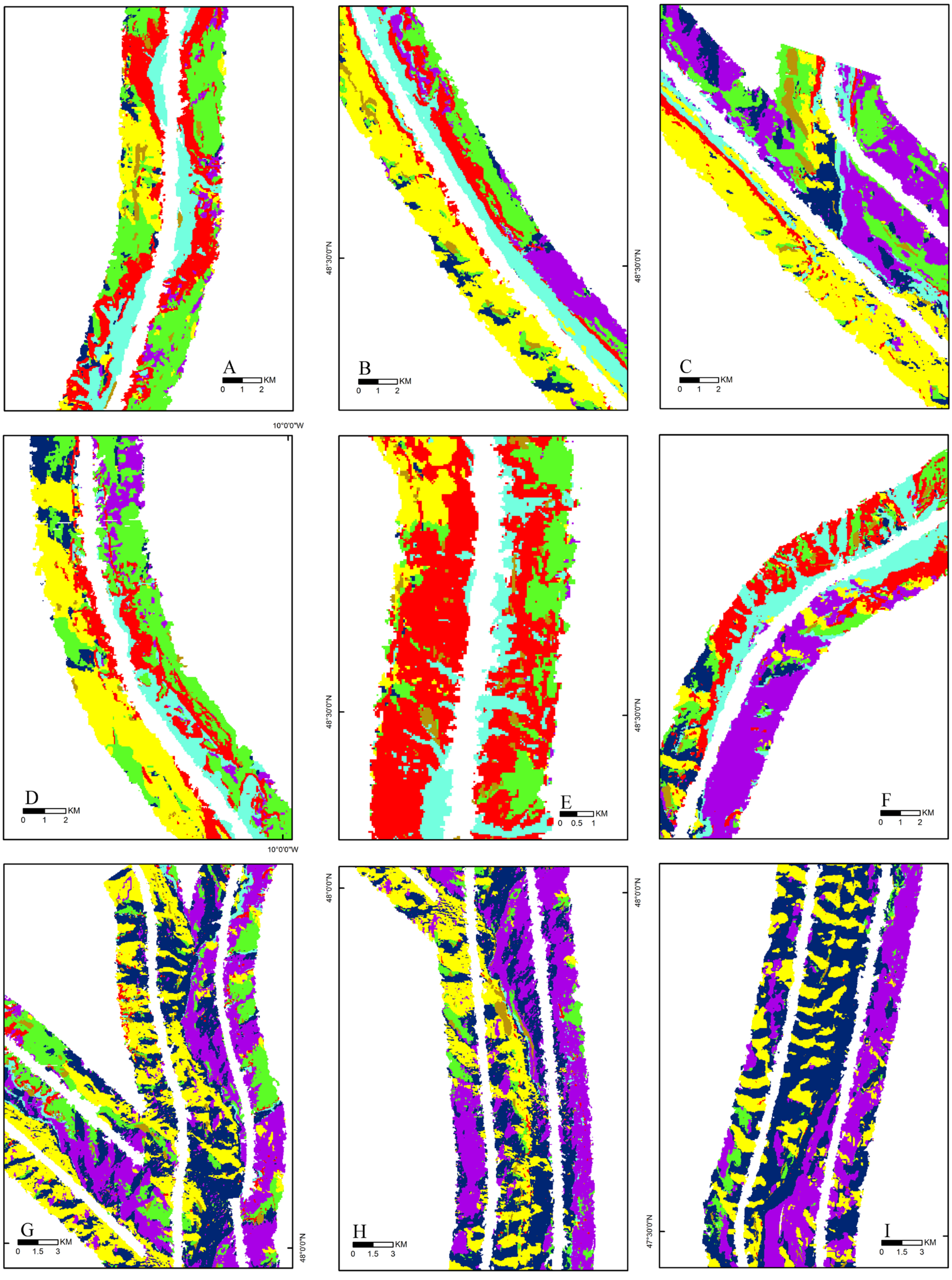
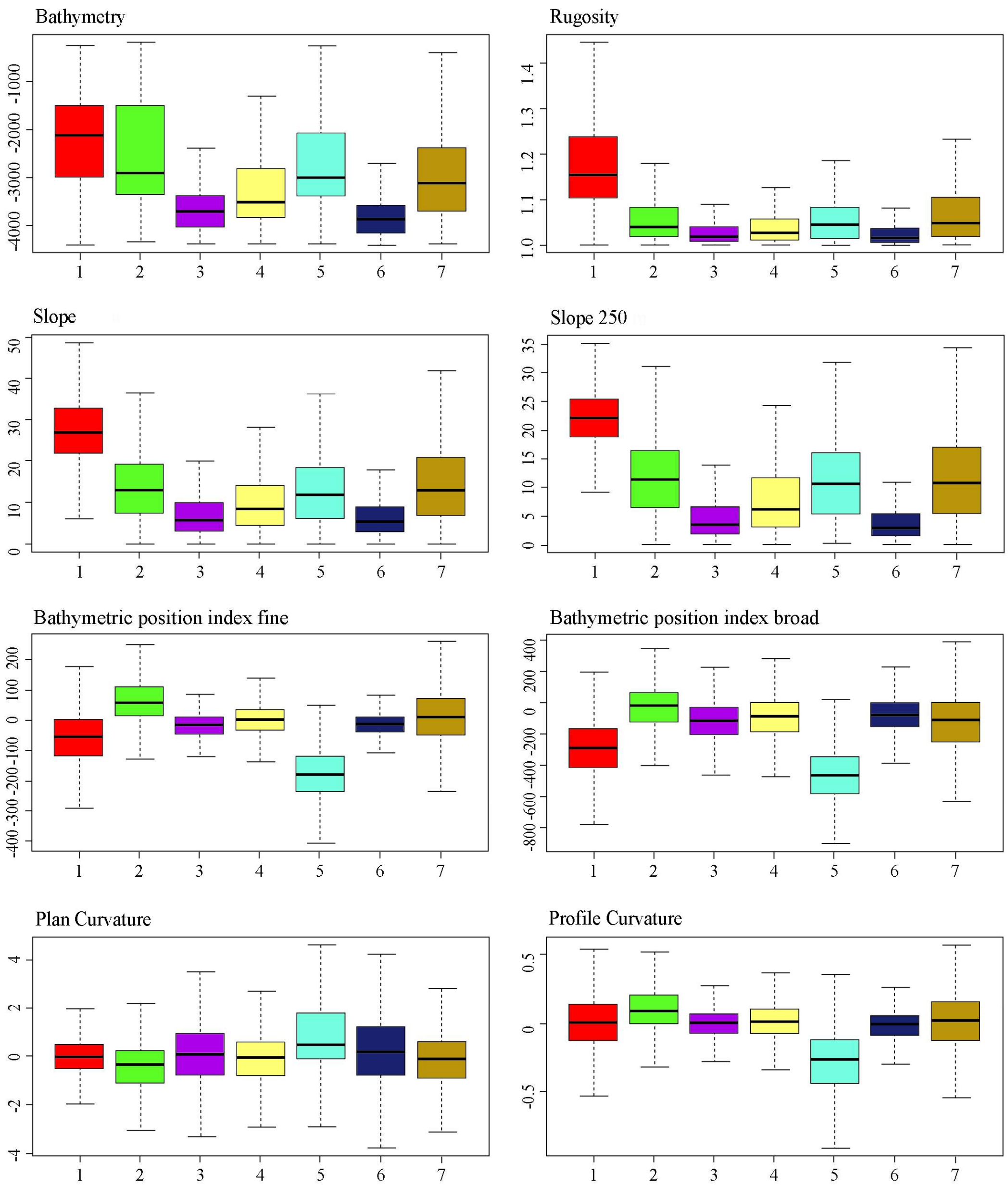


Figure 3.11a & b: a) Whittard Canyon with 7 marine landscapes identified using the objective automated classification technique. b) Close-up of the classification is shown for section A – I. The surveyed Whittard canyon area also is divided into 3 areas (outlined in black): western, eastern branches and Whittard Channel for marine landscape heterogeneity evaluation (second scenario). Each pie chart displays the proportion of marine landscape and the marine landscape measures resulted in three separate entropy-based contagion value (Γ) representing each area respectively.



b) Close-up of the marine landscape map is shown for section A – I.


Bathymetry
-4000 -3000 -2000 -1000
Rugosity
1.0 1.1 1.2 1.3 1.4
Slope
0 10 20 30 40 50
Slope 250
0 5 10 15 20 25 30 35
Bathymetric position index fine
-400 -300 -200 -100 0 100 200
Bathymetric position index broad
-800 -600 -400 -200 0 200 400
Plan Curvature
-4 -2 0 2 4
Profile Curvature
-0.5 0 0.5
1 2 3 4 5 6 7

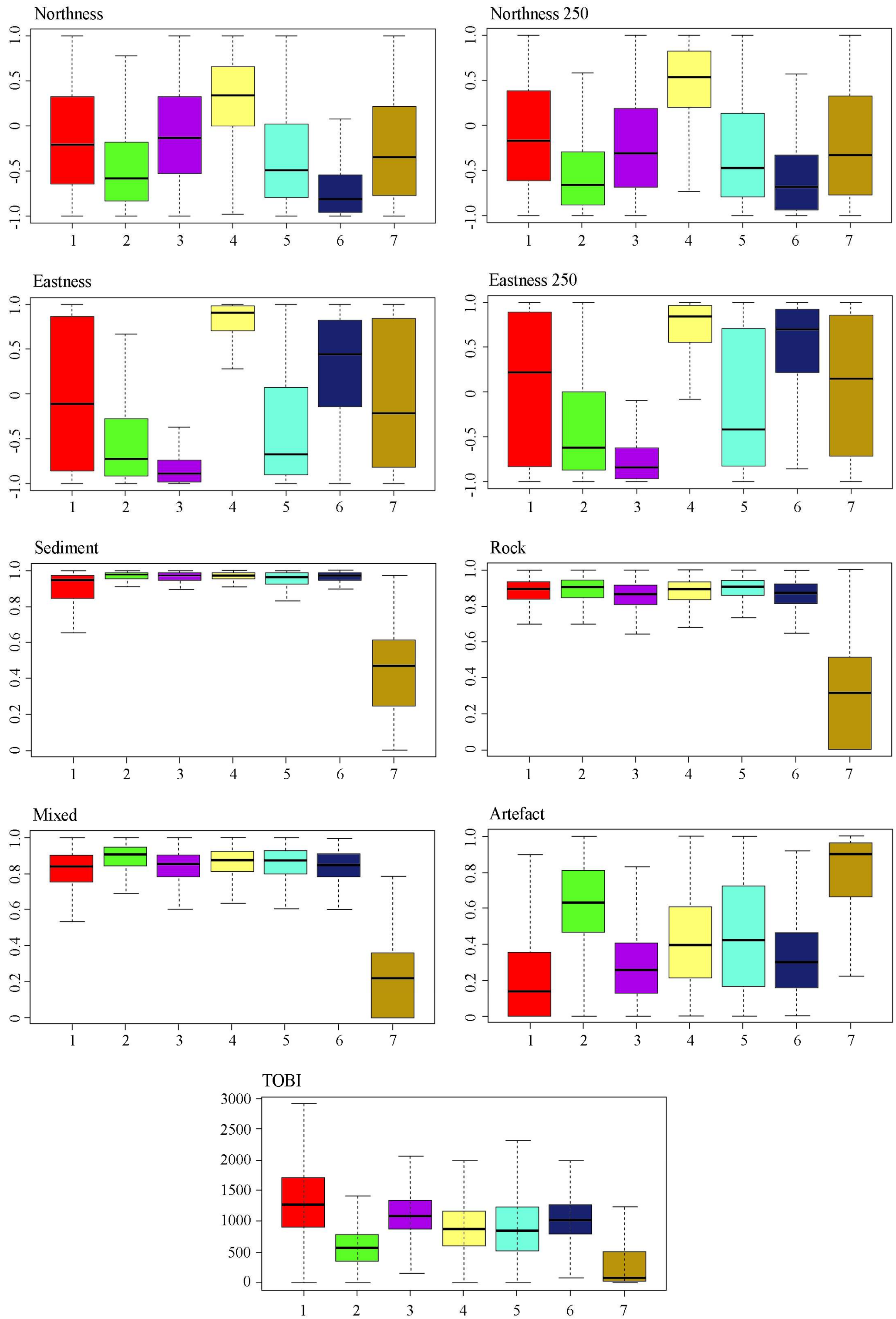


Figure 3.12a & b: Boxplot of clusters against original abiotic variables. Description of each abiotic variable is given in Table 3.1. In the boxplot, the middle line is the mean, the lower and the upper box boundaries are the first and third quartile. The whiskers are the maximum and minimum observed values that are not statistical outliers.

3.4.3 Quantification of marine landscape heterogeneity

The adjacency matrix is a tally of pixel adjacencies for each pairwise combination of marine landscapes computed using Fragstats. Exampled here is the adjacency matrix for Eastern branch (Table 3.3). The adjacency matrix, together with the proportion of each marine landscape, was used to calculate contagion values and their variance for each zone.

Table 3.4 lists the contagion values, their variances, the number of patches, the result of the ANOVA and Tukey's multiple comparison procedure for each zone for the first scenario. The contagion values range from -1.5 to -2.3, with the largest contagion value for the East 5 zone (Figure 3.13), and smaller contagion values for East 1 and West 4. Higher contagion values indicate less heterogeneous areas and vice versa. The ANOVA yielded significant variation among the zones with $p < 0.001$. A post hoc Tukey test showed that the zones have five groups differing significantly at $\alpha = 0.05$. The first group consists of East 1, West 2, West 3 and West 4, and the second group is East 3 and West 1, whereas East 2, East 4 and East 5 are significantly different from all zones.

Results for the second scenario where the study area is divided based on the canyon morphology are shown in Table 3.5. Whittard Channel has a significantly larger contagion than both branches, indicating a lower heterogeneity. The eastern and western branches were not significantly different from each other based on post hoc Tukey's test at $\alpha = 0.05$.

Biological characteristics calculated from video analysis of the 50 m transects showed positive relationships with the contagion index (Figure 3.14). Both branches are high in abundance and richness in comparison to the Whittard Channel, which corresponds to a low contagion index for both branches and a higher index for the Whittard Channel. Simpson's reciprocal index however showed a slightly different relationship, with the western branch having a higher diversity while the eastern branch and Whittard Channel had similar values. Interestingly, contagion indices of zones in the Western branch (i.e.: West 1, 2 and 3) from the first approach give positive correspondence with the Simpson's reciprocal index. On average, the three zones in Western branch have lower contagion values in compare to the zones in Eastern branch (i.e.: East 1, 2 and 3).

Table 3.3: Adjacency matrix for eastern branch computed using FRAGSTAT ecological software.

Marine Landscape	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1- Vertical Wall	**16942**	739	1680	303	346	89	725
2- Terraces & Ridges	739	**62682**	1205	575	487	479	3364
3- Flat Seabed	1680	1205	**93746**	2106	891	974	7117
4- Interfluves	303	575	2106	**39396**	972	139	982
5- Channel	346	487	891	972	**78836**	669	7061
6- Hummocky Seabed	89	479	974	139	669	**9766**	2218
7- TOBI Artefact	725	3364	7117	982	7061	2218	**143334**

Table 3.4: Entropy-based contagion values (Γ), variances (var(Γ)), ANOVA F-test, and Tukey's test on the zones of equal area corresponding to the Whittard Canyon marine landscape map

Zones	**Γ (*)**	**var(Γ)**	**T**	**ANOVA**
East 1	-2.30605(a)	0.001059	1487	F=225.14
East 2	-1.98767(b)	0.001414	1429	P<0.001
East 3	-2.16722(c)	0.000742	2564	
East 4	-1.97760(d)	0.000605	3230	
East 5	-1.58883(e)	0.000986	1609	
West 1	-2.16655(c)	0.001390	1235	
West 2	-2.21413(a)	0.001545	1078	
West 3	-2.21431(a)	0.000807	2218	
West 4	-2.31924(a)	0.000706	2554	

*Tukey's test, values followed by the same letter are not significantly different using α=0.05

Table 3.5: Entropy-based contagion values (Γ), variances (var(Γ)), ANOVA F-test, and Tukey's test on the three areas corresponding to the Whittard Canyon marine landscape map.

Zones	**Γ(*)**	**var(Γ)**	**T**	**ANOVA**
Western branch	-2.30995[a]	0.000526	3076	F=73.33
Eastern branch	-2.27989[a]	0.000554	3130	P<0.001
Whittard Channel	-2.07824[b]	0.000177	11073	

*Tukey's test, values followed by the same letter are not significantly different using α=0.05

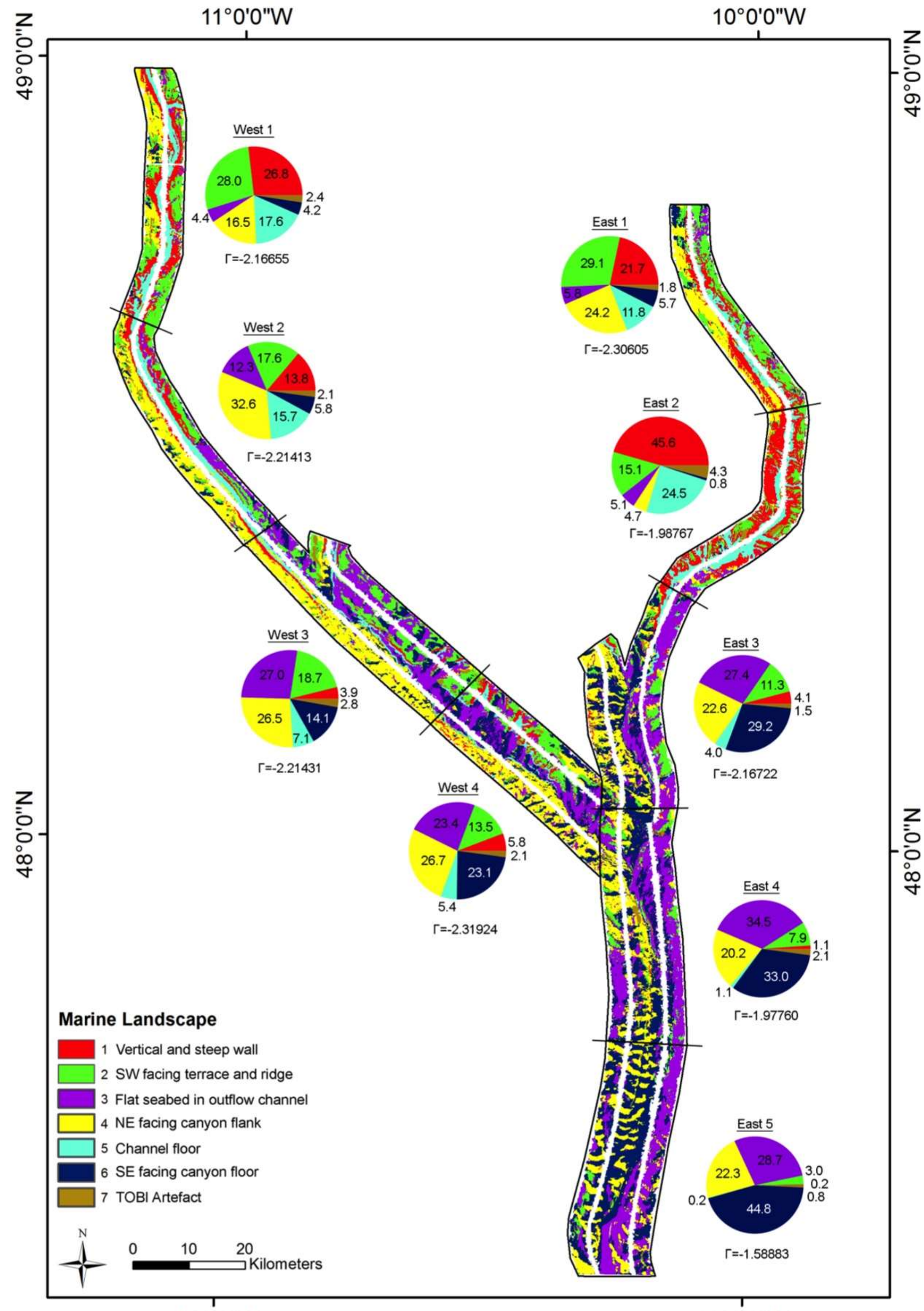


Figure 3.13 : Whittard Canyon with 7 marine landscapes identified using the objective automated classification technique. The surveyed Whittard canyon area is divided into 9 equal zones, namely East 1, East 2, East3, East4, East 5, West 1, West 2, West3 and West 4. Each pie chart displays the proportion of marine landscape and the marine landscape measures resulted in three separate entropy-based contagion value (Γ) representing each area respectively.

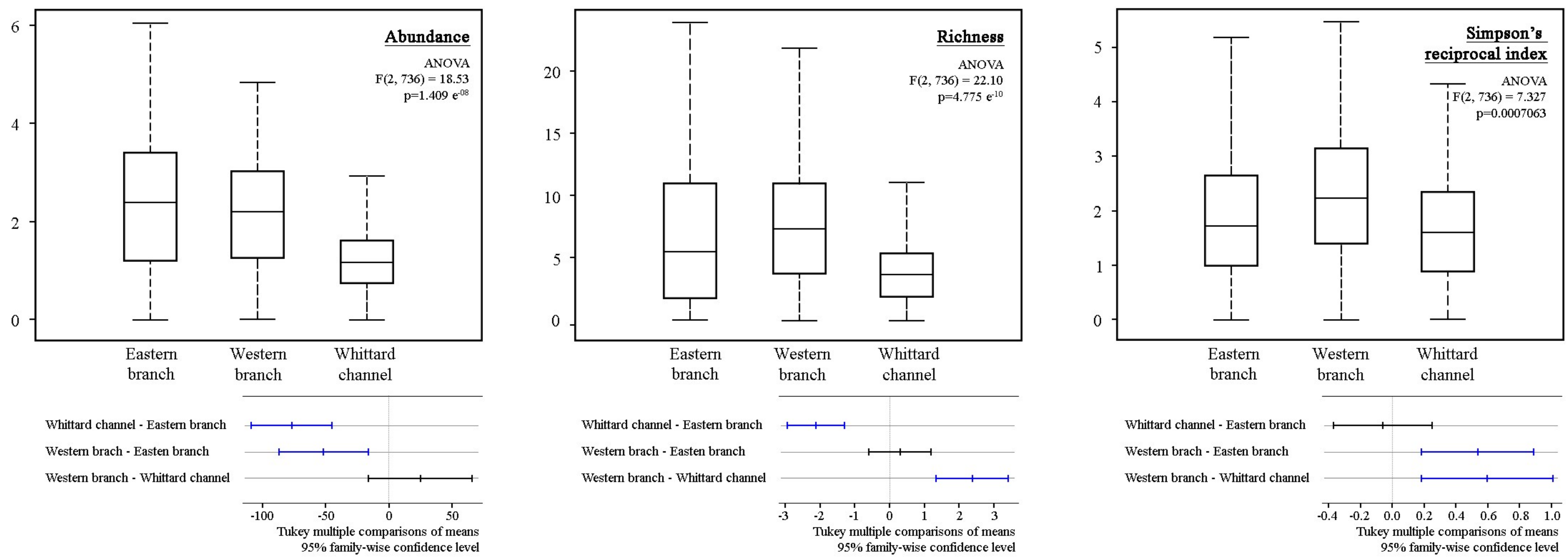


Figure 3.14: Boxplot of abundance, richness and Simpson's reciprocal index calculated from video analysis of 50 m transect against the three strata in Whittard Canyon - Eastern branch, Western branch and Whittard Channel. Tukey's multiple comparison test are shown on the plot below each boxplot, blue indicates significant difference between a pair where the mean difference does not cross the zero value.

3.4.4 Ecologically relevant marine landscape

Out of 183 species identified from 13 video transects divided in 50 m samples, the INDVAL procedure identified 25 species as having a significant indicator value at the 5% level of significance. The result showed that for each cluster, except for Cluster 5, significant indicator species could be found. Species with indicator values higher than 5 % (Table 3.6) are *Acanella* sp., *Distichoptilum* sp and *Anthomastus* sp2 for Cluster 1, *Hyalonema apertum* and *Pentametrocrinus* sp. for Cluster 2 and *Benthothuria* for Cluster 6. Cluster 3 and Cluster 4 do have indicator species, but with low values. Cluster 7 that is interpreted as TOBI artefacts has several indicator species, however it is not considered as a real type of marine landscape.

Species grouped together based on their feeding type are plotted against each marine landscape (Figure 3.15). Steep wall (Cluster 1) has the highest species count with approximately 60% filter feeders followed by 25% of deposit feeders. In comparison, Cluster 3 and Cluster 6, a flat seabed and flank in the lower canyon, have lower species counts and are mostly dominated by deposits feeders. Fair species count is found on terraces, ridges and flanks with approximately a similar split between deposit and suspension filters. Areas interpreted as canyon floor on the other hand have a higher filter feeding species. All marine landscapes have a low amount of carnivorous feeding species.

Table 3.6: Significant indicator species analysis for each marine landscape, which is represented here as clusters. Cluster 1 = vertical and steep wall, Cluster 2 = SW facing terrace and ridge, Cluster 3 = flat seabed in Whittard Channel, Cluster 4 = NE facing canyon flank, Cluster 5 = channel floor, Cluster 6 = SE facing canyon flank and Cluster 7 = TOBI artefact. INDVAL values > 10% are marked in bold.

Species	***Feeding Type***	***Cluster***	***p****	***INDVAL***
Anthomastus sp2	Suspension/Filter	1	0.027	9.28%
Benthothuria	Deposit	6	0.022	**12.45%**
Brisingida sp2	Suspension/Filter	7	0.001	**27.78%**
Cerianthids	Suspension/Filter	7	0.017	**19.80%**
Pentametrocrinus	Suspension/Filter	2	0.025	**12.18%**
Hyalonema apertum	Suspension/Filter	2	0.001	**32.56%**
Acanella	Suspension/Filter	1	0.03	**16.82%**
Distichoptilum	Suspension/Filter	1	0.025	**12.90%**

p*statistically significant at the 0.05 level

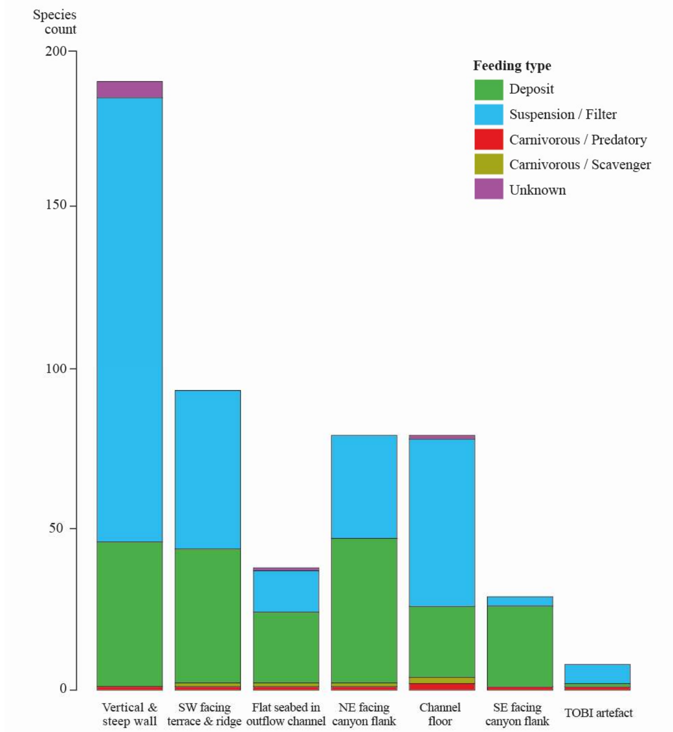


Figure 3.15: Barplot of species count against marine landscapes grouped based on feeding type. Data is from video transects analysed in 50 m sections.

3.5 Discussion

3.5.1 Sensitivity test

The sensitivity test was carried out to demonstrate the implications of scale parameter selection on the production of marine landscape maps. A first level qualitative evaluation of the results showed the substrate distribution pattern corresponded to the image object sizes based on the segmentation. At SP 150 the image objects are smaller in comparison to the SP 250 and SP 370. Substrate maps are classified based on the image objects, therefore smaller image objects lead to the ability to sample detailed features as seen on the substrate distribution maps of SP 150 and 250, while generalisation of seabed features occurs greatly at SP 370.

Based on the quantitative results, the substrate distribution maps of SP 150 and 250 share similar Kappa values and small range of BER. Due to the limited number of video transects in the pilot area, the Mixed class does not appear often along the video transect. The supervised classification results miss this class completely along the track of the video transect. This limitation caused the Kappa value to be significantly low which indicates no to slight agreement. However very low

Kappa values may not necessarily reflect low rates of overall agreement. The observed agreement for both SP 150 and SP 250 are 72.22% and 74.07 % respectively. SP 370 has the lowest overall agreement and corresponds with a very low Kappa value interpreted as no chance of agreement.

Marine landscapes produced for all the three scale parameters as observed in Figure 3.5, 3.6 and 3.7, have broad-scale BPI as the main contributing abiotic variable. Number of clusters increases as the SP decreases. However at SP 150 the delineations does not represent unique characteristics for each cluster. Overlapping characteristics can be observed qualitatively on the marine landscape map and quantitatively in the boxplots of clusters against abiotic variables. For instance, cluster 1 and 8 appear adjacent throughout the marine landscape map and they have similar characteristics based on the boxplots. The within sum of square plot used to determine the optimal number of clusters is least stable for SP150 and required more iteration in compare to SP 250 and SP 370. Based on these results and observations on the implications of scale parameter size towards the marine landscape mapping technique, the OBIA segmentation for the entire Whittard Canyon was applied at SP 250 and terrain analysis was carried out at a window size equivalent to SP 250.

3.5.2 Performance of substrate variables

The first level qualitative result of the substrate map gives a fair percentage of agreement with the substrate interpretation from video analysis. The method has the potential to produce a substrate map for deep-sea environments using limited data available from deep-sea surveys. However, once it is synthesised into four separate quantitative layers, the distribution curves for the classes are strongly skewed to the right. Such behaviour may contribute to highly confused pixels during multivariate statistical analysis. Nevertheless, the contribution for each substrate class towards the marine landscape map can be seen from Table 3.2 and Figure 3.12b. Their contribution is highest for mixed and rock observed in PC 2 and artefact in PC 5. Based on the marine landscape map, amongst all four substrate classes, the most distinctive delineation is the TOBI artefacts (shadows from low grazing angles). It has the lowest variance for training samples (Figure 3.5) and is best separated from all the other substrate classes. Worth noting that the second highest load in PC 5 is TOBI backscatter intensity; it corresponds well with the final marine landscape map, where the artefact membership shares the lowest TOBI backscatter intensity. In comparison to marine landscape mapping without the substrate variables (Ismail et al., 2015), TOBI backscatter intensity contributes less in delineating marine landscapes. Therefore, the substrate variables display significant advantage to extract meaningful information from TOBI imagery and potentially for its kind of data. The most widespread of all the substrate classes is sediment, but it does not have a significant contribution in marine landscape delineation.

3.5.3 Quantification of marine landscape heterogeneity

According to Parresol and Edwards (2014), the contagion value is bounded by -2ln(n) to 0, where n is the number of type of patches, in this case the number of marine landscapes. All three strata of the submarine canyon have seven types of marine landscapes, meaning the minimum contagion is about -3.9. For both scenarios, zones with the highest contagion value, which indicates lowest heterogeneity, are Whittard Channel, East 4 and East 5. These zones occur in the same area that is the lower part of the canyon (canyon mouth). Contagion index is sensitive to both composition and configuration. Based on the behaviour of the contagion index, aggregated landscapes will have the highest values, followed by uniform landscapes and lowest contagion values will be found in randomly arranged landscapes. The reason behind this is that random landscapes have little spatial autocorrelation whereas uniform and aggregated landscapes have increasing spatial autocorrelation. The contagion index has the ability to distinguish between spatial configurations and it decreases with increases of patch categories.

To understand the differences in contagion across the zones, we examined their marine landscape composition and configuration. The pie charts illustrating the proportion of each marine landscape in the zones (Figure 3.11 & 3.13) show that minor components are present in each zone.

For the first scenario, all seven marine landscapes appear in each zone, the difference is the proportional make-up of their marine landscape. Zones with higher contagion index among the nine zones are East 2, East 4 and East 5, their values are all >-2.0. They have more minor components which result in increasing their contagion values. All three zones have four marine landscapes that cover less than 8%. For the second scenario, the western branch has 2.5% of TOBI Artefact, the eastern branch has 4.1% of southeast facing canyon flank and 2.8 % of the TOBI Artefact and the Whittard channel has three marine landscape that range from 1% to 3%. These minor components have the effect of lowering the contagion index. The existence of TOBI Artefact contributes towards the lowering of the contagion value, but since it exists at approximately the same value for all the three areas, the effect of TOBI Artefact does not create a bias to any of the areas. Compositionally, the western and eastern branch have a similar proportional make-up, but in different marine landscape. For example, 25% of the western branch consists of NE facing canyon flanks while 32% of the eastern branch is steep wall. However, in overall composition the western and eastern branches are more similar to each other than to the Whittard Channel.

3.5.3.1 Relationship between contagion index and biological characteristic

Contagion is a type of landscape index that subsumes richness, evenness and spatial pattern, and therefore it is analogous to a diversity index (Parresol and Edwards, 2014). The entropy-based contagion index proposed by Parresol and Edwards (2014) exhibits the ability to quantify the spatial configuration and composition. Based on limited studies using landscape indices in shallow waters, composition and spatial arrangement of benthic structure explained a large and significant proportion of the variation in density and number of species in shallow waters (Pittman et al., 2004). Hence, spatial configuration seems a strong predictor for density and species richness. Such correlations were exhibited not only in various terrestrial environments such as forest bird species (Andren, 1994; McGarigal and McComb, 1995), some butterflies (Baz and Garcia-Boyero, 1995; Tscharntke and Kruess, 1999), mangrove (Pittman et al., 2004) but also in deep submarine canyons (McClain and Barry, 2010) where some species show a preference especially for patchy habitat structure. Low contagion index indicates high spatial configuration and composition, which is proposed to be able to indicate a high biodiversity.

Based on the result of both scenarios investigated here, the areas in the branches mostly have lower contagion values, indicating more heterogeneous areas. Zone East 1 contains the location of the vertical wall colonised by Lopehelia pertusa observed during the JC 36 cruise. This is also the area predicted to hold potential for a high abundance, species richness and diversity (Robert et al, 2014b). However, West 4 is the zone with the highest heterogeneity based on its contagion value. Without any biological grountruthing data, little could be done to verify the relationship. Based on limited quantitative results from the available transects, Simpson's reciprocal index corresponds with the zones in the western branch for having average contagion indices and higher Simpson's reciprocal index. The observations proved that the entropy-based contagion index has potential to effectively provide information with regard to biodiversity by quantifying the composition and configuration between marine landscapes. Additionally, one contributing element that could be beneficial to be considered when developing an index to quantify marine landscape heterogeneity is to include intrinsic characteristic of the marine landscape as part of the measure. For instance, two areas that contain the same number of marine landscapes of different kinds could have the same entropy-based contagion index but one may have a higher biodiversity than the other based on its own characteristics.

Looking at the relationship of the contagion value to the biological characteristics, both western and eastern branch share the same magnitude of contagion index and based on the Tukey test they are not significantly different in comparison to the Whittard Channel. This corresponds with the findings by Robert et al. (2014b), that the eastern and western branch harboured similar numbers of species although abundance is found to be slightly higher in the eastern branch. The difference in abundance can in part be explained by a sampling transect across a vertical coral wall in eastern branch mapped by Huvenne et al. (2011) that contributed to a higher abundance.

Although the relationship between biological characteristics and landscape indices seems positive, no final conclusion could be drawn here as a result of the limited biological data. Diversities found in the video transects are not necessarily a good estimate for each zone since video transects were not randomly placed. It also depends on the area of which substrate and habitat type can be found along transects. Additionally, a few considerations should be taken into account when implementing landscape indices as a measure. The metrics may vary significantly between marine landscapes maps, depending on map classification and mapping accuracy used. Furthermore, since the proportion of marine landscape effects the landscape indices, it is important that the partition of the area evaluated is justified and fit for purpose. In this case, the two scenarios put forward could be examples for future marine conservation efforts in submarine canyons or complex deep sea alike.

3.5.4 Ecological relevance

The concept of marine landscape mapping used in the methodology is a top-down approach, meaning that the classification is based on the natural variability present in abiotic datasets. Biological information is used at the end of the process to validate the marine landscape's potential of being a habitat. Should a marine landscape be ecologically relevant it will potentially be populated by specific biota. As such, the marine landscapes delineated through the methodology are supposedly a good proxy for biological predictions. However, the purpose of a marine landscape map is not to predict biological assemblages, a more fitting approach for this purpose is predictive modelling.

The ecological validation for this study was based on an indicator species analysis, finding significant indicator species for the delineated marine landscapes. Based on the results, six of the marine landscapes have indicator species while only channel floor (Cluster 5) has no significant biological association. Channel floor is the closest area to the axial point of a submarine canyon (thalweg) and has characteristics that are less suitable to harbour benthic species. It is often disturbed by frequent sediment flushing from the continental shelf, is high in suspended sediments and mobile substrates that hinder the benthos. Cluster 7, interpreted as sonar artefacts rather than a real marine landscape, also appears to have indicator species associated with it. *Brisingida* sp2, *Umbellula* sp2 and cerianthids, are suspension/filter feeders that are often associated with irregular and highly sloping terrains. Most of the preferred areas for these species often end up being in the shadow caused by the irregular terrain morphology and low grazing angles from sonar surveys. Although Cluster 7 is not a real marine landscape, the associated biological assemblages are explicable even if they are caused by the limitation of the sonar survey system.

As the final map is a broad-scale classification of a regional area, most of the structures and features that can be associated with biological assemblages are greatly generalised. In addition, the lack of biological data hinders the detailed characterisation of each marine landscape. A more comprehensive approach to finding the relationship between marine landscapes and their associated biological assemblages can be made by grouping together species based on their feeding type (Figure 3.9). For instance, the highest species count is for steep wall (Cluster 1), which are mostly dominated by suspension/filter feeders such as *Brisingid* sp., *Crinoid* sp. and *Anthomastus* sp2. In comparison, Cluster 3 and Cluster 6 occur mostly in the lower canyon, have lower species counts and are mostly dominated by deposits feeders. This corresponds well with the result from the indicator species analysis where *Benthothuria sp.* is found as the significant indicator species for Cluster 6, although no species are found to be significant for Cluster 3.

As such, the marine landscape map is a good proxy for a broad-scale biological understanding of the submarine canyon. However, the marine landscape map is not a substitute for actual benthic observations, or for predictive habitat maps. The aim of the marine landscape map is to give an indication of the potential habitat characteristics derived solely from abiotic datasets, and is a valuable biological information alternative in areas where biological data are scarce or absent.

3.6 Conclusion

This paper used bathymetry and sidescan sonar data from a complex deep-sea environment (Whittard Canyon) to provide a statistically robust marine landscape map that formed the basis for the development of a new measure for marine landscape heterogeneity. The method creates interesting opportunities for large scale habitat mapping especially for use in marine spatial planning, environmental protection and management of marine areas. Quantification of marine landscape heterogeneity is of value for stakeholders and policy makers and can be used to determine critical areas for conservation in order to prioritise conservation efforts and selection of marine protected areas.

The following conclusions are drawn: 1) object based image analysis of sidescan sonar imagery generates a four-class substrate map from the geomorphologically diverse Whittard Canyon. The methodology used to synthesise the imagery data is potentially a way forward to produce a substrate map from a complex deep-sea environment where sedimentological samples are scarce and limited. The substrate variables allow more meaningful information to be extracted from sidescan sonar imagery and other acoustic backscatter images. 2) The objective automated marine landscape mapping technique developed for a different submarine canyon was successfully applied to the Whittard Canyon and delineates geomorphologically and ecologically relevant marine landscapes. Therefore, the methodology used is not limited for local usage but is robust for different canyon settings. 3) Landscape indices are appropriate to be used as heterogeneity measures, and our results advocate a wider use of such approach in marine studies. The attempt in this study to use the contagion index to comparatively evaluate the marine landscape heterogeneity between different areas in submarine canyons is a success. 4) The marine landscapes mapped out in Whittard Canyon are ecologically relevant based on the correlation between interpreted video transects and the marine landscape map produced using the objective automated technique. Marine landscapes show a great potential for biological prediction, but are not however a substitute for actual observations or for a predictive habitat map. The methodology is time and labour-saving, using full coverage acoustic data that can be synthesised into useful abiotic variables.

Chapter 4: Application of Marine Landscape Mapping to High Resolution Data

4.1 Abstract

A thorough understanding of the structural variations across scale is much lacking in habitat mapping. Often broad scale maps used to represent terrain variation are criticised for their lack of detail. Taking advantage of the availability of three high-resolution datasets nested within a ship-borne acoustic survey in Whittard Canyon, the relationship between habitat maps of different scales is investigated. To address this issue, high-resolution data were subjected to the marine landscape mapping technique that was developed for regional scale data. The information transfer of structural variation and its context across different data scales was investigated by comparing the resulting fine marine landscape map to i) the broad scale marine landscape map from the same area, ii) video interpreted substrate type from transects overlapping the area and iii) species assemblage community analysis along the video transects. Two set-ups were made to test the effect of aspect as environmental property at local scale marine landscape classification and quantification. The two set-ups of the high-resolution data were classified with and without aspect as abiotic variable. The entropy-based contagion index was used to quantify marine landscape heterogeneity for both set-ups as a proxy for local scale habitat heterogeneity and biodiversity.

When classified separately, the fine-scale marine landscape maps for the three high-resolution datasets resulted in 6 clusters for each area. Across-scale comparison between fine and broad scale marine landscape maps shows that pertinent structural features were transferred successfully. The fine-scale marine landscape maps are ecologically relevant and provide more context for ecological analyses. When classified together in one segmentation exercise, the two set-ups (with and without aspect) both resulted in a 5 cluster solution. Quantification of marine landscape heterogeneity at local scale provides insights on the effects of classification, abiotic variables and the limitations of using the entropy-based contagion index as proxy for habitat heterogeneity.

4.2 Introduction

Landscape mapping is a concept that is based on the identification of geophysical attributes of the terrain that could reflect biological communities. The concept relies largely on spatial analysis and is often implemented in terrestrial environments (Rosa-Freitas et al., 2007; Svoray et al., 2007). With the advancement of underwater surveying tools, such analysis is now also applicable to the marine environment, making use of acoustic remotely sensed data. The concept has been adapted for the marine realm to map shallow water environments (Al-Hamdani et al., 2007; Connor et al., 2006; Verfaillie et al., 2009) and deep-sea environments (Ismail et al., 2015). Such broad-scale approach for mapping exhibits potential, especially in spatial management and conservation in deep-sea environment.

In general, the aims of marine management, among others, are to maintain a healthy and productive marine ecosystem, which is a combination of abiotic and biotic factors. These management decisions are often built based on information from broad scale maps, in contrast to biological investigations that are generally carried out at a fine or local scale. In habitat mapping, it has been a long-standing problem to relate biological and spatial feature information acquired from these different scales of data (Gustafson, 1998). Not only in terms of relationship between ecology and spatial features, but also in general, there are few studies relating fine and broad scale spatial features. Acoustic surveys by themselves are also affected by scale and the trade-off between map resolution and extent depends on the distance of the surveying instrument from the seabed (Blondel, 2009). Opportunely, with increasing availability of well-positioned underwater survey vehicles such as Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs), observations can be made to understand the translation of spatial information (i.e. terrain, substrate, slope angles etc.) through different survey scales. We intend to weigh the relevance of using broad scale maps to convey spatial arrangement at local scale surveys. Here, we attempt to demonstrate how the terrain features are related between sub-metre-scale seabed observations (video), over metre-scale high-resolution maps (ROV/AUV surveys) to 10s of metre resolution regional maps (ship-borne surveys).

Spatial variability in species distribution is ruled by spatial variation in environmental conditions, as explained by the Niche Theory (Chase and Leibold, 2003). A spatial variation indicator is defined by aggregating a landscape structural attribute over a spatial extent. Some examples of structural attributes are the number of different land cover types, the proportion of each cover type, the shape of patches, and the spatial arrangement and connectivity of patches (Li and Reynolds, 1995). The entropy-based contagion index, a landscape metric, was proposed to quantify marine landscape heterogeneity based on broad scale marine landscape maps in submarine canyons (Chapter 3). The index is defined based on the marine landscape composition and configuration. Most studies in landscape ecology show that the results of spatial analysis depend highly on the mapping classification and pixel size (Uuemaa et al., 2013). We will demonstrate the effect of mapping classification towards the index by altering the environmental attributes incorporated in the marine landscape mapping.

Based on the above issues, the aim of the study is to assess the spatial scale relationships of marine landscape mapping performed on maps with different pixel resolution and extent. The aim is addressed following these objectives:

1. To test the transferability and applicability of objective seafloor classification methods developed for broad scale marine landscape mapping, onto high-resolution fine scale data

2. To compare the classification and interpretation of data from different spatial scales, going from video interpreted data, over high resolution bathymetry, to broad scale maps

3. To evaluate the performance of a landscape index (entropy-based contagion index) to quantify marine landscape heterogeneity for fine scale marine landscape maps

4. To demonstrate the effect on the landscape index when using different mapping classifications

4.3 Materials and methods

4.3.1 Study area and data

During the 2009 James Cook cruises 35 and 36 to Whittard Canyon (Bay of Biscay, NE Atlantic), fine resolution (1 m) bathymetry data were collected using a Simrad SM2000 multibeam echosounder mounted on the ROV Isis. The fine resolution data were acquired in three different areas at different depths; two areas in the western branch and one on the eastern branch of the canyon (Figure 4.1). The three dives are referred to here as Dive 108 and 109 in the western branch at 600 - 1000 m and 1000 – 1800 m, respectively, and Dive 120 in the eastern branch at 1600 – 2400 m depth. Along with the fine resolution bathymetry, a lower resolution bathymetry for wider canyon coverage was acquired at 50 m resolution using the RRS JC EM120 shipboard multibeam system. Both bathymetry datasets were processed (using the Caraibes and Caris software packages, respectively) and projected to WGS 1984 UTM Zone 29 N. Fine resolution bathymetry was resampled to 3 m resolution in ArcGIS 10.2 using bilinear algorithm prior to analysis to average out the three sets of bathymetry data that were processed at different pixel sizes and match them with TOBI sidescan sonar imagery resolution.

An objective and automated method for marine landscape mapping was developed for regional mapping in a set of Portuguese canyons (Ismail et al., 2015) and tested further in Whittard Canyon (Chapter 3). In both areas, the technique successfully delineates geomorphologically and ecologically relevant marine landscapes. In this study, the objective automated technique will be tested at a finer resolution, with a slight modification due to limited data. The limitation is explained further in the discussion. The technique will be applied on the multibeam bathymetry acquired from the three ROV dives.

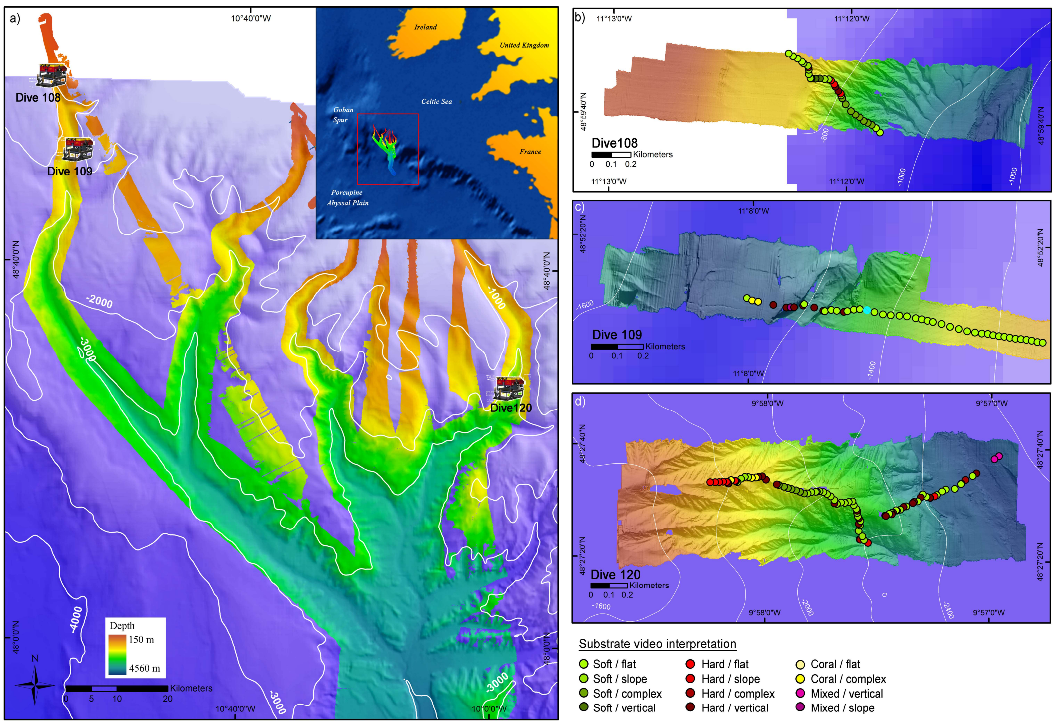


Figure 4.1: a) Bathymetric map of Whittard Canyon (50 m pixel resolution) acquired using the RRS James Cook EM120 multibeam system. Location of the three ROV surveys (Dive 108, 108 and 120) is indicated. Inset shows the location of Whittard Canyon. b-d) High resolution bathymetry data collected using the Simrad SM2000 multibeam echosounder mounted on ROV Isis. Dotted lines overlaid on the high-resolution bathymetry are the video transects with the colour representing the substrate type interpreted via video analysis.

The data were analysed for slope, aspect (divided into eastness and northness), bathymetric position index (BPI), rugosity, plan and profile curvature (Wilson et al., 2007). Slope, aspect and curvatures were calculated using Landserf v2.3 (Wood, 2005) at two scale lengths representing fine and broad scale terrain features. The length scales were not determined using ESP method as used in Chapter 3 for broad scale mapping. The reason being, that there was no exclusive sidescan image acquired with the same extent of the ROV multibeam bathymetry surveys. This limits the use of the ESP tool to delineate features in multibeam bathymetry. The broad scale analysis window size was then determined by measuring the average width of medium sized features (i.e.: gullies). The calculated average came to approximately 250 m. For the terrain analysis to identify broader features the window size has to be smaller than 250 m, thus by using 45 m (9 x 9 pixel), such features could be identify in approximately four analysis windows. BPI was computed using Land Facet Corridor Designer (Jenness et al., 2010) and rugosity using DEM surface tools (Jenness, 2004), both in ArcGIS 10.2. Broad scale bathymetry however was not analysed in this study, only the final regional marine landscape map produced in Chapter 3 was used for comparison purposes.

30 kHz TOBI (Towed Ocean Bottom Instrument) (Le Bas et al., 1995) sidescan sonar imagery was acquired during the same cruise for the whole canyon. The data were processed with the NOC in-house software PRISM (Le Bas and Hühnerbach, 1998) to maps with 3 m pixel resolution. Where the data overlaps with the high-resolution bathymetry, TOBI information is included into the analysis as it can be used as a proxy for sediment hardness (Iacono et al., 2008; Micallef et al., 2012). Additionally, substrate information derived from TOBI sidescan sonar imagery (as described in Chapter 3, Figure 3.5) is included into the mapping technique. The information is divided into four layers referred to in this study as Rock, Sediment, Mixed Substrate and Artefact.

Three ROV video transects crossing the survey areas of Dive 108, 109 and 120 were collected using colour camera on the ROV Isis. The video transects were analysed in 20 m sections to match up higher resolution bathymetric data. They were analysed for substratum type (divided into soft, hard, mixed and coral covered), slope angle (annotated as vertical, complex, sloping or flat) and all megabenthic invertebrates larger than 1 cm were identified to morphospecies. The video analysis interpretations for substrate, slope angle and megabenthic identification were made based on the paper by Robert et al. (2014b). The video transects were georeferenced using the ROV's ultra-short baseline navigation system. All video ROV analysis and interpretation was part of the Robert (2014c) PhD work.

4.3.2 Research strategy

4.3.2.1 Marine landscape mapping

The objective automated marine landscape technique is divided into two components: the production of variables and the multivariate statistical analysis. The first component consists of the production of substrate variables from sidescan sonar imagery using object based image analysis and production of terrain variables derived from multibeam bathymetry data using multiple scale terrain analysis. The substrate variables derived from the TOBI sidescan sonar imagery are explained in Chapter 3 (section 3.3.3.1), and the multiple terrain analysis is discussed in Chapter 2. Both substrate and terrain variables are then compiled and subjected to multivariate statistical analysis comprised of three steps: the variables are subjected to principal component analysis (PCA) for data reduction, the resulting principal components are then clustered using K-means with the optimal number of classes determined using a within sum of squares plot. A comprehensive explanation of the multivariate statistical analysis, together with flowcharts illustrating the process can be found in Chapters 2 and 3. The adaptation of the method for the high-resolution ROV data is illustrated in Figure 4.2.

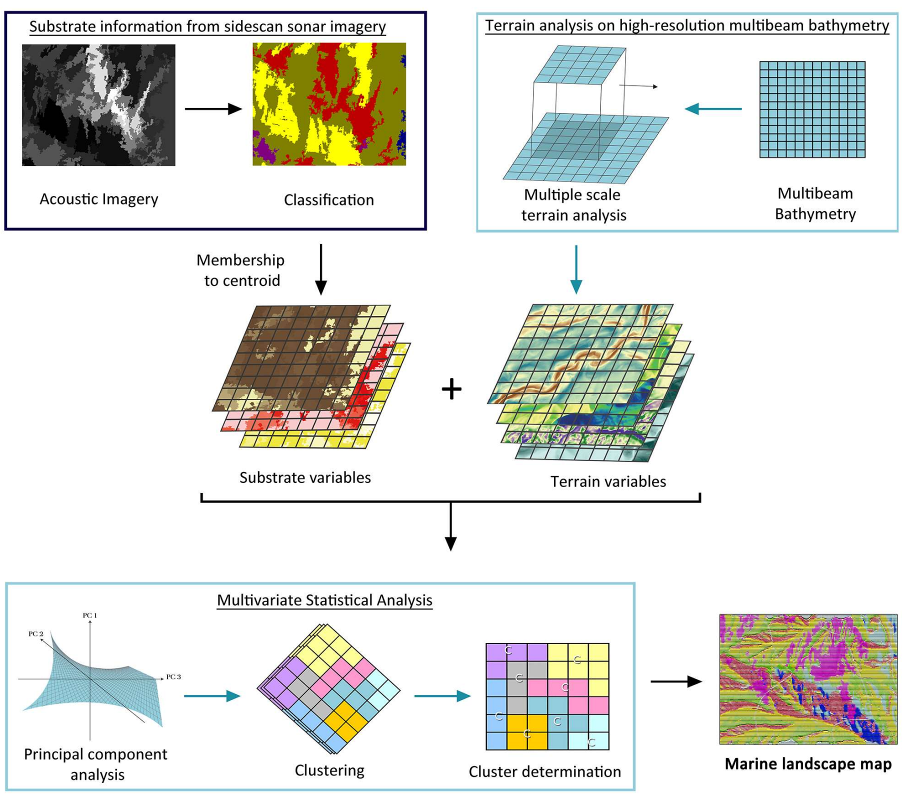


Figure 4.2: A simplified flow chart of the mapping procedure for marine landscape mapping, modified from canyon-wide classification as discussed in Chapter 3.

4.3.2.2 Information through different scales

Visual comparison will be made between broad and fine scale marine landscape maps to observe the spatial patterns. Additionally, to observe the spatial information conveyed through different scales, the fine scale marine landscape is tabulated as follows:

Fine vs. broad scale marine landscape map

The fine scale maps produced in this study will be compared to the broad scale marine landscape map produced for Whittard Canyon in Chapter 3. The assessment is limited to Dive 109 and 120 because the broad marine landscape map is not available for the area of Dive 108. Visual comparison is made and cross-tabulation of areas between fine and broad marine landscape maps were carried out using the Tabulate Area tool in ArcGIS 10.2.

Fine scale marine landscape map vs. substrate type video interpretation

Substrate type interpretation from video along the 20 m subsections of the ROV transects is compared to the fine scale marine landscape maps. At each point on the transects, a 10 m buffer was constructed and the highest percentage marine landscape cover within this buffer will represent the local classification.

Fine scale marine landscape map vs. species assemblages community analysis

A brief community analysis was carried out to describe the species assemblages observed and how they varied along the ROV transects (Robert, 2014c). A Bray-Curtis dissimilarity matrix based on the log+1 transformed abundance matrix was created, based on the species counts in the 20 m subsections. Group-average hierarchical clustering was carried out and a SIMPER analysis was conducted on groups showing 40% similarity or more to determine which species tended to occur within the same areas. The statistical software PRIMER was used for community analyses (Clarke and Gorley, 2006).

4.3.2.3 Marine landscape heterogeneity quantification

Landscape heterogeneity is often quantified based on the spatial composition and configuration of the landscape types, using the entropy contagion index (Parresol and Edwards, 2014). This approach was successfully applied to the regional marine landscape map of Whittard Canyon, as demonstrated in Chapter 3. However, in this set-up the index is not applicable to compare the three areas because they are isolated surveys and were classified separately. Extensive literature in the terrestrial environment has demonstrated that the entropy contagion index can only be used in comparative studies when the areas to be compared are classified with the same classification system. Therefore, and also to demonstrate how abiotic variables influence the marine landscape heterogeneity and its metrics, two further set-ups were made to compare the marine landscape heterogeneity quantification. First, the three dives were subjected to the marine landscape classification technique as a single system, with all abiotic variables included, while a second classification was made without aspect (eastness and northness) properties included. For both marine landscape maps, entropy-based contagion indices were calculated as proposed for the canyon-wide classification (Chapter 3).

Aspect was excluded for the second set-up because it has been a debatable variable for deep-sea classification (Ismail et al., 2015). Aspect has always been useful in the ecological study of terrestrial vegetation especially when associated with sun exposure (Bonham, 2013). In shallow marine environments, aspect has been demonstrated to be beneficial to provide information regarding the exposure to dominant swell or similarly to sun exposure (Lucieer et al., 2013). However, in the deep sea the contribution is still unknown, although potentially it could provide information on potential interaction with current properties or sediment dynamics.

4.4 Results

4.4.1 Marine landscape interpretation

The marine landscape maps constructed for each area resulted in 6 clusters representing the marine landscapes. Rotated component matrix showing the factor loads explaining the correlations between rotated PCs and the original variables for each dives is shown in Table 4.1, 4.2 and 4.3. Optimal number of cluster determined using within sum of squares plot for each dives is shown in Figure 4.3, 4.5 and 4.7. Along with each marine landscape map, boxplots for each original abiotic variable against the marine landscapes are shown in Figure 4.4 for Dive 108, Figure 4.6 for Dive 109 and Figure 4.8 for Dive 120. The boxplots determine the characteristics of the clusters and lead to the interpretation of the marine landscapes as follows:

Dive 108

Based on the PCA result, the driving variables defining the classification are BPI, slope and northness. Cluster 1 is interpreted as gully floor having the lowest BPI for both length scales. Cluster 2 and 3 are both flat seabed but are further divided based on the aspect variable. Cluster 4 is gully ridge with highest BPI and high rugosity. Cluster 5 and 6 are geomorphologically similar and are both interpreted as a slightly sloping seabed, however they are separated by different aspect (eastness).

Table 4.1: Component matrix showing correlation between rotated PCs and the original variables for Dive 108. Highest factor loads in each PC are highlighted in bold.

Abiotic variables	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Bathymetry	-0.145	-0.021	-0.323	-0.025	0.2873	-0.026	0.3293
Bathymetric position index fine	**-0.399**	-0.283	0.0918	0.0392	-0.022	0.0278	0.0104
Bathymetric position index broad	-0.345	-0.202	0.0052	-0.009	0.0477	-0.068	0.1143
Eastness	0.049	-0.221	**-0.483**	0.0705	0.2867	0.0663	0.0755
Eastness 45 m	0.0668	-0.246	-0.475	0.0591	0.2884	0.0655	0.0596
Northness	0.0976	-0.135	-0.258	0.3923	**-0.472**	-0.064	-0.105
Northness 45 m	0.0947	-0.139	-0.263	**0.4042**	-0.452	-0.063	-0.081
Plan curvature	0.2576	0.193	-0.099	-0.047	0.1003	**-0.542**	0.03
Plan curvature 45 m	0.3354	0.2415	-0.104	-0.047	0.0928	-0.463	0.0062
Profile curvature	-0.268	-0.217	0.0871	0.0315	0.0024	-0.465	-0.094
Profile curvature 45 m	-0.316	-0.251	0.0771	0.0187	0.0337	-0.496	-0.042
Slope	0.2806	**-0.293**	0.2886	0.2413	0.2189	0.0129	0.0275
Slope 45 m	0.2689	-0.291	0.2672	0.247	0.2197	0.0144	0.05
Rugosity	0.2647	-0.27	0.2651	0.1972	0.1748	0.0016	-0.038
Artefact	-0.15	0.2636	0.1477	0.3067	-0.027	-0.047	0.2798
Mixed	-0.145	0.2424	0.0174	0.323	0.2439	0.0164	-0.248
Rock	0.0293	0.0466	0.1027	0.1422	-0.167	-0.034	**0.8258**
Sediment	-0.169	0.2737	-0.032	0.3999	0.2279	0.0471	-0.114
TOBI backscatter intensity	0.1746	-0.279	-0.01	-0.36	-0.189	-0.011	0.0276
Eigenvalues	3.4555	3.2463	2.4808	2.3092	1.4823	1.2705	1.0204

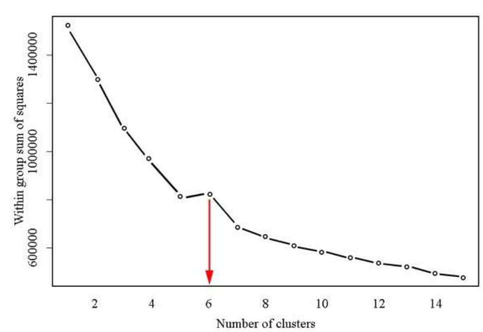


Figure 4.3: Plot of number of clusters against within sum of squares. The bend (change in slope) marked in red and projected towards the x-axis indicates the optimum number of cluster is 6.

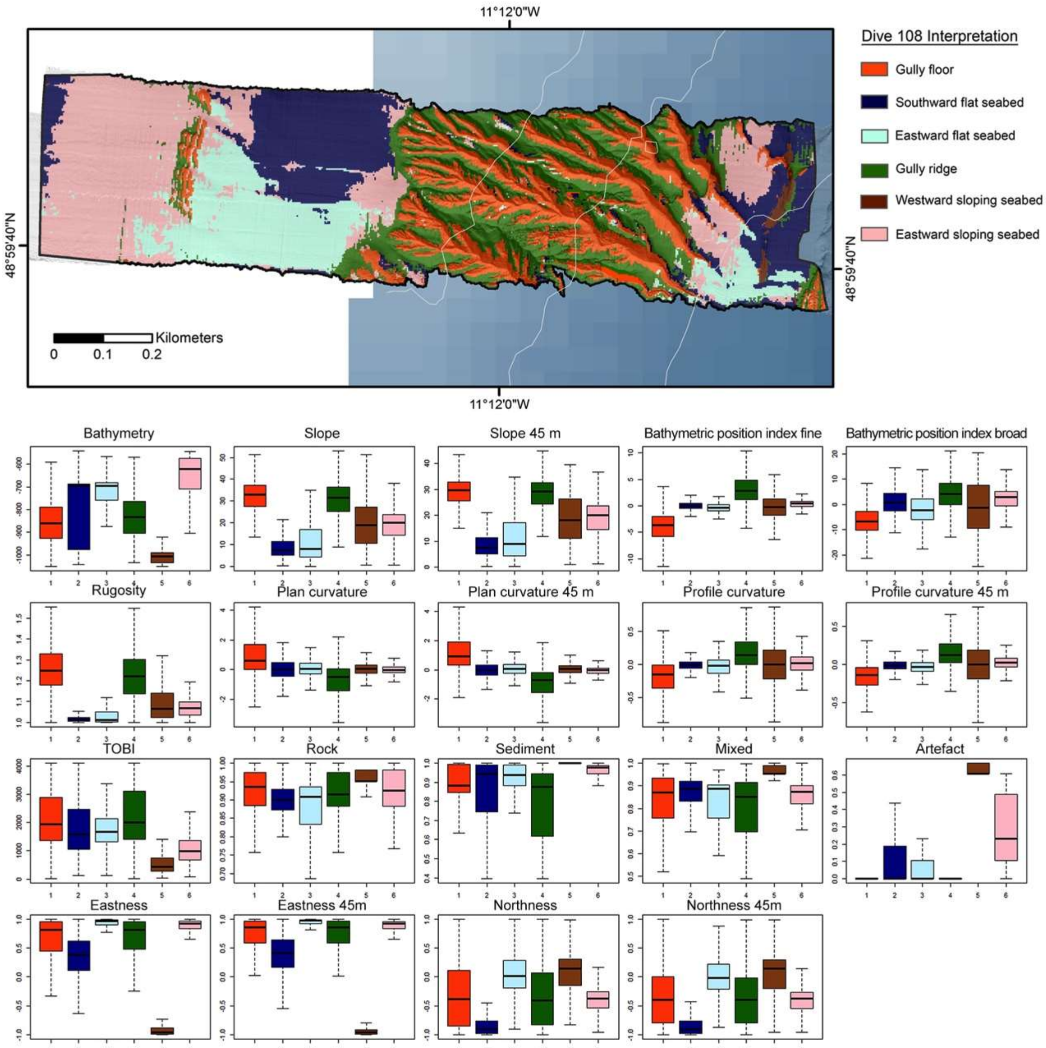


Figure 4.4: Fine scale marine landscape map for Dive 108 with boxplots of clusters against the original abiotic variables used for interpretation.

Dive 109

The variables controlling the PCs are northness (aspect), sediment (substrate), artefact (substrate) and BPI at fine scale. Although northness is the most influential variable, it does not contribute much in characterising the clusters. Cluster 1 is defined by having the lowest BPI and highest curvature. It is interpreted as cliff base with moderate sloping angles. Cluster 2 is small cliffs having the highest rugosity and slope. Cluster 3 and 5 are the canyon flanks and they differ in terms of the sedimentary cover. Cluster 4 is flat seabed in the deepest part of the dive. The characteristic that stands out for Cluster 6 is eastness and it is interpreted as eastward sloping seabed.

Table 4.2: Component matrix showing correlation between rotated PCs and the original variables for Dive 109. Highest factor loads in each PC are highlighted in bold.

Abiotic variables	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Bathymetry	0.298	-0.013	-0.004	0.2687	-0.063	-0.266	0.1292
Bathymetric position index fine	0.1328	-0.123	**-0.44**	-0.034	-0.18	-0.052	0.3246
Bathymetric position index broad	0.1479	-0.146	-0.341	0.0088	-0.224	-0.259	0.4613
Eastness	-0.356	-0.207	-0.047	-0.29	-0.078	-0.284	-0.165
Eastness 45 m	-0.359	-0.209	-0.057	-0.298	-0.073	-0.302	-0.151
Northness	0.3915	-0.085	0.1333	0.024	-0.031	-0.32	-0.294
Northness 45 m	**0.4087**	-0.094	0.1448	0.03	-0.036	-0.301	-0.266
Plan curvature	-0.058	0.0335	0.3199	0.0304	**-0.633**	0.0252	0.1902
Plan curvature 45 m	-0.091	0.0447	0.3731	0.0281	-0.564	0.1159	-0.055
Profile curvature	0.0723	-0.07	-0.36	-0.014	-0.22	0.3013	**-0.547**
Profile curvature 45 m	0.1175	-0.108	**-0.441**	0.006	-0.339	0.193	-0.227
Slope	0.2363	-0.336	0.1607	-0.344	0.0444	0.1194	0.0597
Slope 45 m	0.2491	-0.331	0.1664	-0.321	0.0442	0.0892	0.0356
Rugosity	0.1643	-0.225	0.0994	-0.378	0.0508	0.3025	0.1776
Artefact	-0.242	-0.363	-0.022	0.1032	-0.023	-0.237	0.0037
Mixed	-0.033	-0.321	0.044	0.3085	0.0564	**0.3175**	0.0981
Rock	0.0875	-0.286	0.0932	**0.3914**	0.0253	0.0414	-0.121
Sediment	-0.187	**-0.364**	0.0401	0.2408	0.0861	0.2261	0.0656
TOBI backscatter intensity	0.1321	0.3446	-0.064	-0.263	-0.027	0.1704	0.0615
Eigenvalues	3.6937	3.3907	2.7341	1.9214	1.3561	1.1866	1.0312

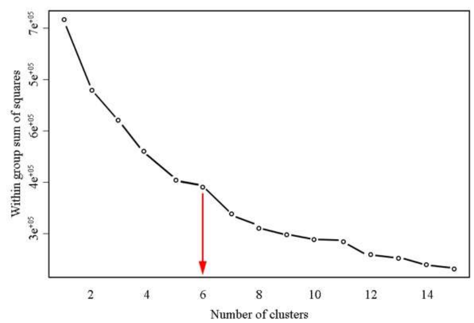


Figure 4.5: Plot of number of clusters against within sum of squares. The bend (change in slope) marked in red and projected towards the x-axis indicates the optimum number of cluster is 6.

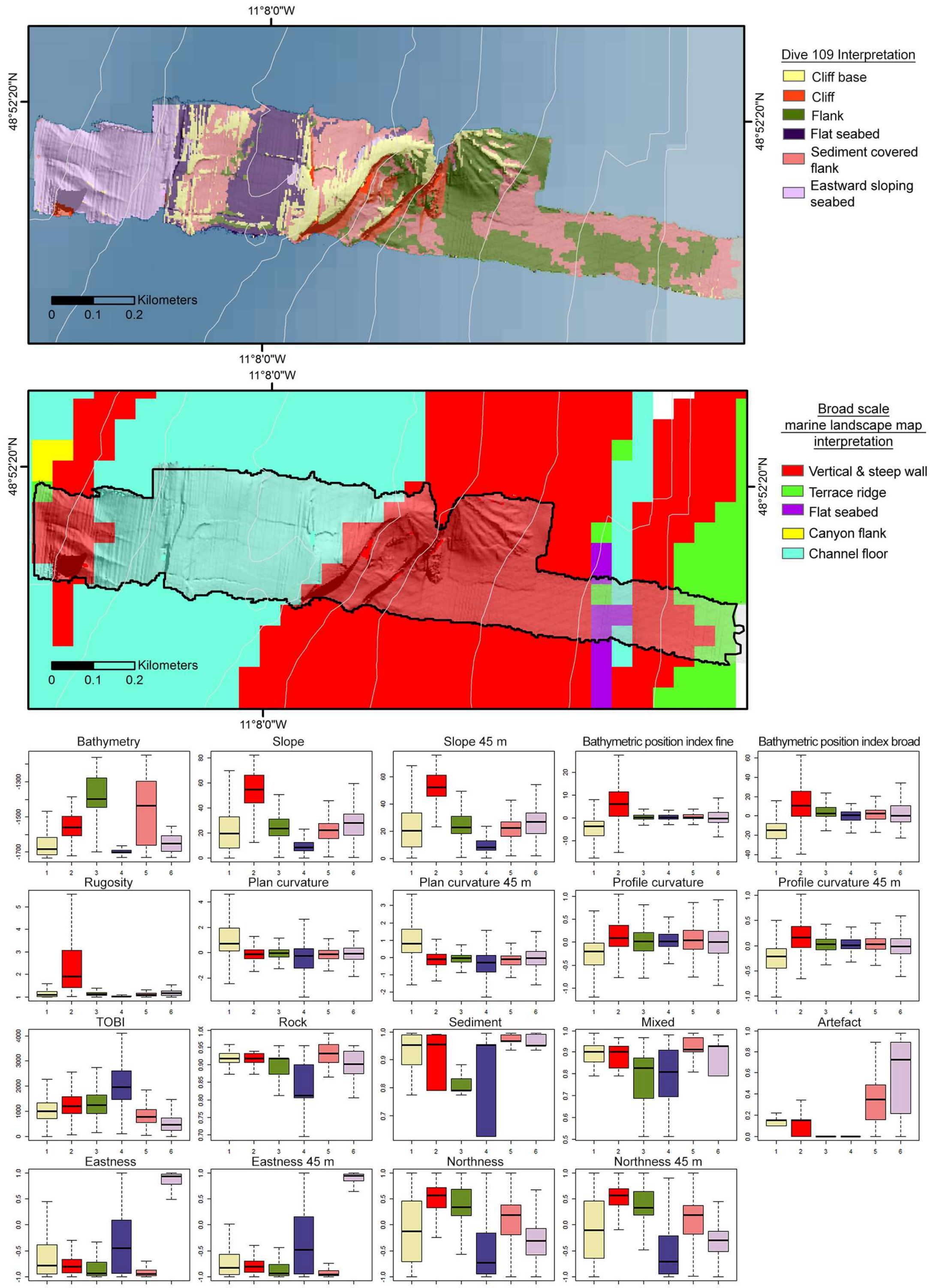


Figure 4.6: Fine and broad scale marine landscape map for Dive 109 with boxplots of clusters against the original abiotic variables used for fine scale marine landscape interpretation.

Dive 120

Based on the PCA result for Dive 120, the PCs are driven by slope, BPI and eastness (aspect). Cluster 1 is interpreted as southward gully wall, defined based on high rugosity, slope and low northness. Cluster 2 is platform having a moderate rugosity and slope. Cluster 3 and 5 both are flat seabed but they differ in direction of south and east, respectively. Cluster 4 is north facing ridge, it has high BPI and moderate slope. Cluster 6 is the northward facing flank with the lowest BPI and profile curvature.

Table 4.3: Component matrix showing correlation between rotated PCs and the original variables for Dive 120. Highest factor loads in each PC are highlighted in bold.

Abiotic variables	PC1	PC2	PC3	PC4	PC5	PC6
Bathymetry	-0.274	0.012	0.0793	-0.051	0.0415	-0.101
Bathymetric position index fine	-0.078	**-0.474**	0.0153	-0.006	-0.014	-0.057
Bathymetric position index broad	-0.069	-0.434	0.0000	-0.008	-0.02	-0.07
Eastness	-0.148	0.0241	-0.2799	-0.18	**-0.594**	0.0059
Eastness 45 m	-0.161	0.0289	-0.2874	-0.186	-0.581	-0.002
Northness	-0.109	0.0089	-0.2053	**-0.582**	0.3203	0.0089
Northness 45 m	-0.112	0.0124	-0.2072	-0.581	0.318	0.0061
Plan curvature	0.041	0.3242	-0.0260	0.0082	0.01	**-0.591**
Plan curvature 45 m	0.0548	0.4072	-0.0171	0.0133	0.0112	-0.495
Profile curvature	-0.053	-0.351	0.0306	0.0057	0.0066	-0.401
Profile curvature 45 m	-0.076	-0.405	0.0332	0.0025	0.0043	-0.462
Slope	-0.306	0.0793	**0.4608**	-0.132	-0.067	0.018
Slope 45 m	-0.313	0.0775	0.4345	-0.13	-0.088	0.0198
Rugosity	-0.212	0.066	0.4547	-0.126	-0.082	0.0426
Artefact	0.3871	-0.046	0.1087	-0.061	0.0106	0.0416
Mixed	**0.3917**	-0.051	0.1645	-0.208	-0.116	-0.005
Rock	0.2466	-0.03	0.1729	-0.241	-0.177	-0.065
Sediment	0.3028	-0.043	0.2124	-0.263	-0.179	-0.053
TOBI backscatter intensity	-0.369	0.0468	-0.1508	0.1735	0.0793	0.0039
Eigenvalues	4.4733	3.5364	2.1532	1.9209	1.7539	1.1608

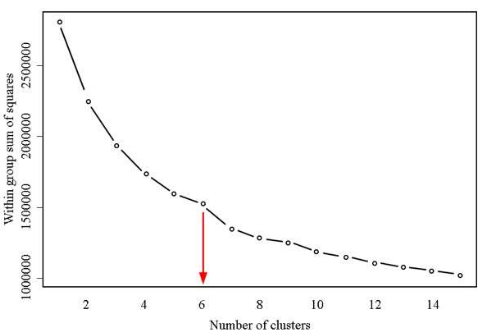


Figure 4.7: Plot of number of clusters against within sum of squares. The bend (change in slope) marked in red and projected towards the x-axis indicates the optimum number of cluster is 6.

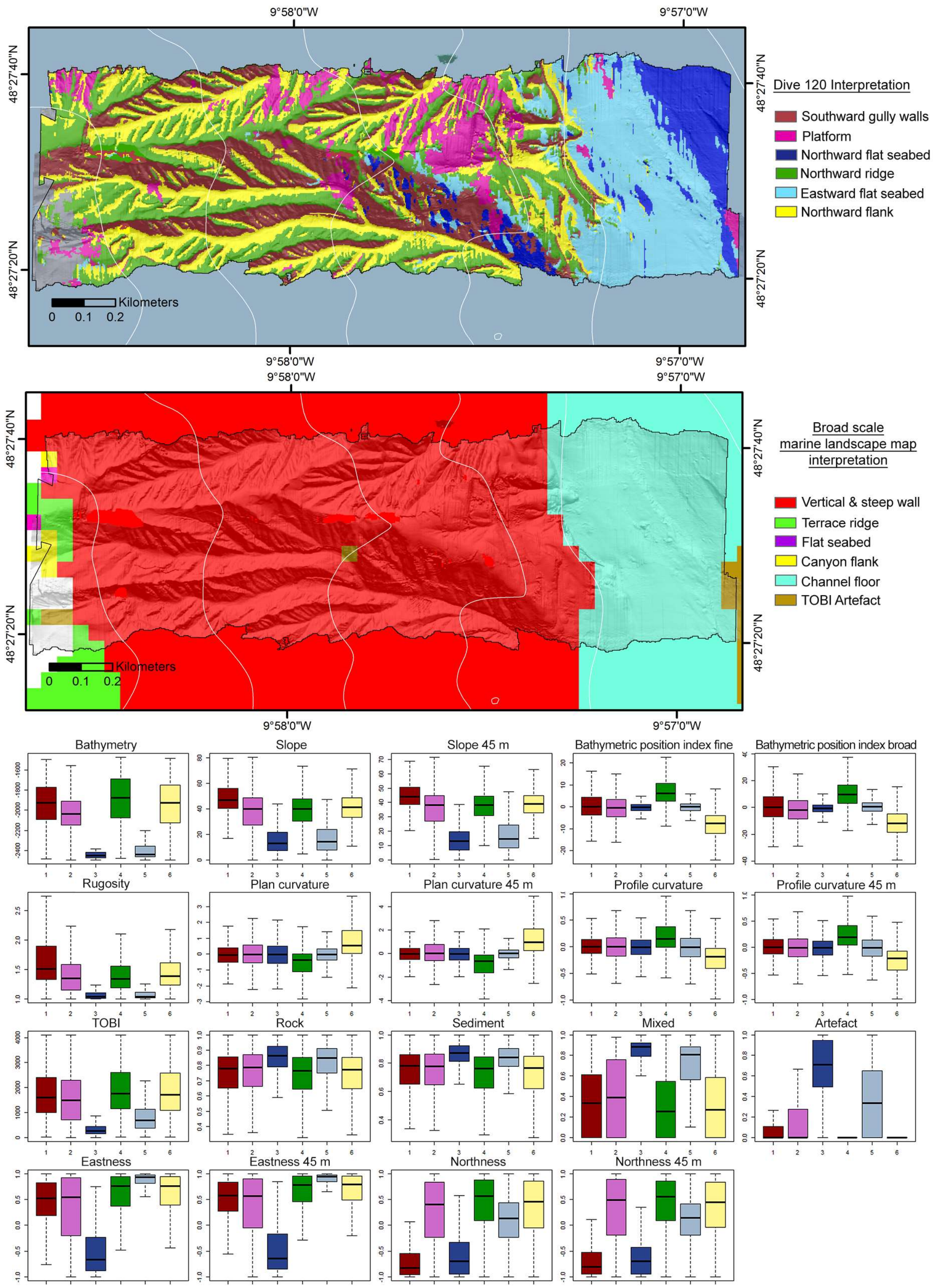


Figure 4.8: Fine and broad scale marine landscape map for Dive 120 with boxplots of clusters against the original abiotic variables used for fine scale marine landscape interpretation.

4.4.2 Spatial information across scale

To understand the information gain and loss across scales, comparisons were made between the fine scale marine landscape maps and (1) the broad scale marine landscape map, (2) video interpreted substrate types and (3) community analysis for species assemblages. Comparisons are limited to Dive 109 and 120, due to data limitations in the Dive 108 area.

Fine vs. broad scale marine landscape map

Visual comparisons between the two maps are shown in Figure 4.6 for Dive 109 and Figure 4.8 for Dive 120, while a cross-tabulation of pixel classifications is shown in Table 4.4. The results for both dives show that the boundary between the flat seabed of the channel floor and the canyon slopes can be picked up in the two maps. The boundary is prominent enough to be delineated in the broad marine landscape map and is retained in fine scale marine landscape map. High percentages of flank and gully walls coincide with vertical and steep walls in the broad scale marine landscape map. Flat seabed in both dives occurs mostly in the channel floor of the broad scale classification. For Dive 120, broad scale channel floor coincides with fine scale flat seabed and occurs less than 1% elsewhere. A small percentage (<5%) of fine scale flat seabed occurs in vertical & steep wall landscape of the broad scale maps.

Table 4.4: Cross-tabulation of pixel classifications for the fine and broad scale marine landscape interpretation for a) Dive 109 and b) Dive 120, value in parentheses are in percentages and crosshatched cells indicate no intersection. Coloured rows are based on representation colours in broad scale marine landscape map (Figure 4.4 and 4.5).

a) Marine landscape Dive 109 (broad/fine)	Cliff base	Cliff	Flank	Flat seabed	Sediment covered flank	Eastward sloping seabed
Vertical & steep wall	6062 (6.7)	3858 (4.3)	19288 (21.3)		12124 (13.4)	6613 (7.3)
Terrace & ridge			551 (0.6)		2204 (2.4)	551 (0.6)
Flat seabed			1653 (1.8)			
Channel floor	6062 (6.7)	1102 (1.2)	1653 (1.8)	9919 (11.0)	8817 (9.8)	9919 (11.0)

b) Marine landscape Dive 120 (broad/fine)	South-ward gully walls	Platform	North-ward flat seabed	North-ward ridge	Eastward flat seabed	North-ward flank
Vertical & steep wall	37118 (18.2)	16538 (8.1)	2940 (1.4)	44468 (21.8)	6983 (3.4)	40058 (19.6)
Terrace & ridge	1103 (0.5)			1838 (0.9)		735 (0.4)
Canyon flank	735 (0.4)					368 (0.2)
Channel floor	368 (0.2)	368 (0.2)	13598 (6.7)	368 (0.2)	33076 (16.2)	1838 (0.9)
TOBI Artefact	368 (0.2)	1470 (0.7)				

Fine scale marine landscape map vs. substrate type video interpretation

Substrate types from video interpretation are categorised in four general groups: hard, soft and mixed substrate and coral covered seabed. The four groups are further divided by sloping angle - vertical, sloping, complex and flat. Table 4.5 shows the results for the cross-tabulated intersection between the fine scale marine landscapes and video interpreted substrate types.

For Dive 108 (Table 4.5a), from the six marine landscapes, gully flank and gully floor would naturally be expected to intersect with hard substrate as identified through video interpretation. Based on the cross-table, 19 out of 31 transect points ended up in the gully flank landscape, which is approximately 58%. Out of the 19, four points coincide with hard substrate and the remaining 15 are soft substrates. Marine landscapes that are interpreted as flat seabed and gully floor are mostly covered with sediments, which coincide with the substrate interpretation of soft substrate.

Dive 109 (Table 4.5b) contained 45 transects points in total, which were interpreted into three types of substrate. Both cliff and cliff base mainly contain hard substrate areas in the video interpretations. Sediment covered platform also had the same substrate type video interpretation in about 18% of the cases while the remaining 82 % intersects with soft substrates and flat areas. Flat seabed represented two types of substrate interpretation - coral rubble and soft sediments both with a flat sloping angle.

Dive 120 (Table 4.5c) with 92 points has the longest video transect. There is more variation in the video interpreted substrate type. The gully walls coincide with hard, coral covered and soft substrate in the video interpretation. Northward flank has three points that are interpreted as hard substrate and one point that coincides with soft substrate. Platform has only one point coinciding with the soft substrate video interpretation. Almost 40% of the video transect coincides with the

the area interpreted as gully flank in the fine marine landscape map. The intersection spreads between soft, hard and coral-covered substrates at different sloping angles. Northward ridge coincides with soft substrate with slopes at approximately 60% of the total intersecting points in its class. Northward and eastward flat seabed has ten points coinciding with hard substrate, two with mixed substrates and ten with soft substrates.

Table 4.5: Summary table for video interpreted substrate type against fine scale marine landscape map for a) Dive 108, b) Dive 109 and c) Dive 120. Coloured rows are in accordance to substrate type: red for hard substrate, purple for mixed substrate, yellow for coral covered and green for soft substrate.

a) Substrate interpretation for D108	Gully floor	South-ward flat seabed	East-ward flat seabed	Gully ridge	West-ward sloping seabed	East-ward sloping seabed
Hard vertical	1			1		
Hard complex				3		
Soft vertical				4		
Soft slope	4			3		1
Soft flat		5				
Soft complex	1			8		

b) Substrate interpretation for D109	Cliff base	Cliff	Flank	Flat seabed	Sediment covered platform	Eastward sloping seabed
Hard vertical	2	2			3	
Coral rubble flat				2		
Soft flat		1	20	1	13	

c) Substrate interpretation for D120	South-ward gully walls	Platform	North-ward flat seabed	North-ward ridge	East-ward flat seabed	North-ward flank
Hard vertical	4		2	4	5	1
Hard complex	1			7	2	1
Hard flat					1	1
Hard slope				1		
Mixed flat			2			
Live coral flat	2			1		
Live coral complex				1		
Soft slope	11	1	1	12	4	
Soft flat	2		1	4	5	1
Soft complex	5			5		

in the video interpretation. Northward flank has three points that are interpreted as hard substrate and one point that coincides with soft substrate. Platform has only one point with the area interpreted as gully flank in the fine marine landscape map. The intersection spreads between soft, hard and coral-covered substrates at different sloping angles. Northward ridge coincides with soft substrate with slopes at approximately 60% of the total intersecting points in its class. Northward and eastward flat seabed has ten points coinciding with hard substrate, two with mixed substrates and ten with soft substrates.

Table 4.5: Summary table for video interpreted substrate type against fine scale marine landscape map for a) Dive 108, b) Dive 109 and c) Dive 120. Coloured rows are in accordance to substrate type: red for hard substrate, purple for mixed substrate, yellow for coral covered and green for soft substrate.

a) Substrate interpretation for D108	Gully floor	South-ward flat seabed	East-ward flat seabed	Gully ridge	West-ward sloping seabed	East-ward sloping seabed
Hard vertical	1			1		
Hard complex				3		
Soft vertical				4		
Soft slope	4			3		1
Soft flat		5				
Soft complex	1			8		

b) Substrate interpretation for D109	Cliff base	Cliff	Flank	Flat seabed	Sediment covered platform	Eastward sloping seabed
Hard vertical	2	2			3	
Coral rubble flat				2		
Soft flat		1	20	1	13	

c) Substrate interpretation for D120	South-ward gully walls	Platform	North-ward flat seabed	North-ward ridge	East-ward flat seabed	North-ward flank
Hard vertical	4		2	4	5	1
Hard complex	1			7	2	1
Hard flat					1	1
Hard slope				1		
Mixed flat			2			
Live coral flat	2			1		
Live coral complex				1		
Soft slope	11	1	1	12	4	

a) Community Analysis for Dive 108	Gully floor	South-ward flat seabed	East-ward flat seabed	Gully ridge	West-ward sloping seabed	East-ward sloping seabed
Echinoidea sp2, Asteroidae sp12, Anthoptilum		1		4		
Cerianthids, Paguridae spp	9	1		11		
Anthozoa sp1, Benthogone rosea		5				1

b) Community Analysis for Dive 109	Cliff base	Cliff	Flank	Flat seabed	Sediment covered flank	East-ward sloping seabed
Solenosmilia variabilis, Anthomastus sp2, Freyella elegans, *Anthomastus sp1, Anachalypsicrinus*	1				1	
Lophelia pertusa, Solenosmilia variabilis, Freyella elegans, Primnoa	2	2				
Pentametrocrinus, Echinoidea sp2, *Echinus,* cerianthids*, Actinoscyphia,* Asteroidae sp9, Freyastera, *Anthomastus sp2*			12		11	
Echinoidea sp2, Asteroidae sp12, Anthoptilum			2			
Cerianthids, Paguridae spp	5	3	11	9	10	

c) Community Analysis for Dive 120	South -ward gully walls	Plat-form	North-ward flat seabed	North-ward ridge	East-ward flat seabed	North-ward flank
Solenosmilia variabilis, Anthomastus sp2, Freyella elegans, *Anthomastus sp1, Anachalypsicrinus*	8		3	8	4	5
Anachalypsicrinus , Cnidaria sp10					1	
Pentametrocrinus, Echinoidea sp2, *Echinus,* Cerianthids*, Actinoscyphia,* Asteroidae sp9, Freyastera, *Anthomastus sp2*	3			13		1
Acanella, Cerianthids, *Anthomastus sp1, Pentametrocrinus*	3	1	1	14		
Distichoptilum, Cerianthids	8		1	5	6	
Cerianthids, Paguridae spp	8	1	14	6	13	3

4.4.3 Marine landscape heterogeneity quantification

Figure 4.9 shows the result when all abiotic variables are treated as one system and subjected to the marine landscape classification, rather than analysing every dive area separately. Figure 4.10 shows the fine scale marine landscape map without incorporating aspect (eastness and northness) at both length scale. Both marine landscapes are classified into 5 clusters. The PCA for classification with aspect is driven by mixed (substrate), BPI and aspect (eastness and northness). Classification without aspect is driven by mixed (substrates), BPI of both scales and rugosity.

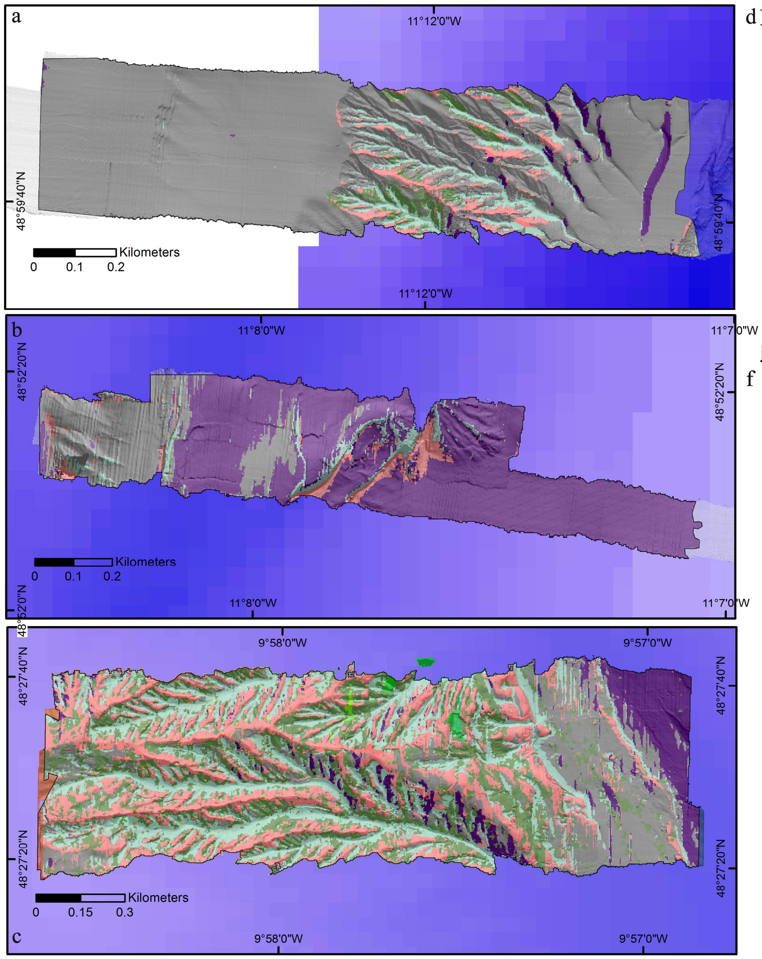
Table 4.7 shows the contagion values, their variances and ANOVA for the marine landscape maps produced for the two sets of classification with and without aspect variables. The entropy-based contagion index (Parresol and Edwards, 2014) is used as a metric to quantify marine landscape heterogeneity (Chapter 3). Lower contagion values indicate a more heterogeneous area with patchy structures that have the potential to harbour more diverse biological communities. However, in this case the contagion values of the three dives cannot be compared to the absolute values of biodiversity for the three areas, because they are located at very different depths, which are deemed to be a stronger influence on biodiversity than habitat heterogeneity.

Contagion is bound by -2ln(n) and 0 where n is the number of marine landscapes, meaning that the minimum contagion is -3.21, being the most heterogeneous terrain. Results show that without aspect variable, the contagion values have a slightly bigger range from -0.8 to -2.1, while with the aspect variable included, the contagion values range from -1.0 to -2.2. But overall, both marine landscape maps give relatively similar results. Both classifications return a highly significant ANOVA with P<0.001 and the three dives are significantly different based on Tukey's test. In both results, Dive 120 is the most heterogeneous while Dive 108 is the least. However the difference between Dive 108 and Dive 109 is more obvious in the classification without aspect, where the contagion values differ by 0.4.

Table 4.7: Entropy-based contagion values, variances, ANOVA F-test and Tukey's test for the three dives. The table is divided into two; the left represents the classification with aspect variable included and the right represents the classification without the aspect (eastness and northness) variable.

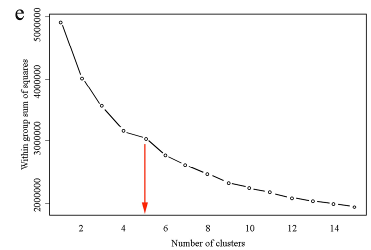
Classification with aspect variable				**Dive**	Classification without aspect variable			
Γ(*)	var(Γ)	**T**	ANOVA		Γ(*)	var(Γ)	**T**	ANOVA
-1.0464^{a}	0.003011	668	F=956.82	Dive 108	-0.8055^{a}	0.002996	714	F=945.60
-1.2005^{b}	0.004288	477	P<0.001	Dive 109	-1.4845^{b}	0.002110	858	P<0.001
-2.2837^{c}	0.000208	4296		Dive 120	-2.1839^{c}	0.000263	4821	

*Tukey's test, values followed by different letter are significantly different using α=0.05



d

Abiotic variables	PC1	PC2	PC3	PC4	PC5	PC6	PC7
Bathymetry	-0.135	0.0466	0.2563	-0.069	0.0655	**0.6377**	-0.064
Bathymetric position index fine	0.0389	**0.4828**	-0.013	-0.01	-0.013	-0.006	0.0644
Bathymetric position index broad	0.0298	0.4279	-0.014	0.0024	-0.029	0.0039	0.0928
Eastness	0.1535	-0.011	0.3912	-0.096	-0.559	-0.057	0.0029
Eastness 45 m	0.1652	-0.012	**0.3925**	-0.094	**-0.549**	-0.057	0.0053
Northness	0.1643	-0.007	-0.357	**0.4462**	-0.306	0.2254	-0.015
Northness 45 m	0.172	-0.01	-0.364	0.4421	-0.302	0.2098	-0.011
Plan curvature	-0.018	-0.325	0.0214	0.0176	0.0011	0.0764	**0.5969**
Plan curvature 45 m	-0.024	-0.411	0.0208	0.0061	0.0092	0.0663	0.5026
Profile curvature	0.0274	0.3534	-0.011	-0.023	0.0112	0.0133	0.3997
Profile curvature 45 m	0.041	0.4194	-0.007	-0.023	0.0106	0.0425	0.4551
Slope	0.3509	-0.044	-0.247	-0.391	-0.02	0.1112	-0.014
Slope 45 m	0.3545	-0.042	-0.243	-0.368	-0.03	0.0971	-0.016
Rugosity	0.2688	-0.038	-0.247	-0.413	-0.013	0.0776	-0.008
Artefact	-0.279	-0.001	-0.244	-0.111	-0.205	-0.398	0.0511
Mixed	**-0.408**	0.0221	-0.117	-0.146	-0.144	0.1606	-0.011
Rock	-0.31	0.0171	-0.07	-0.166	-0.132	0.3776	-0.035
Sediment	-0.351	0.02	-0.142	-0.21	-0.228	0.2094	-0.02
TOBI backscatter intensity	0.2897	0.0022	0.2929	0.1288	0.25	0.2855	-0.046
Eigenvalues	4.1543	3.3909	2.2338	1.7697	1.655	1.3911	1.1918



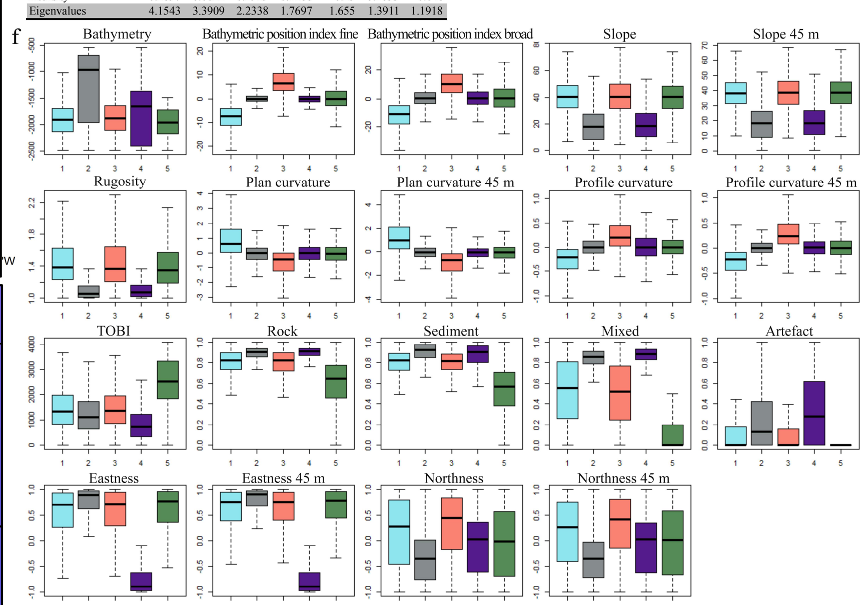
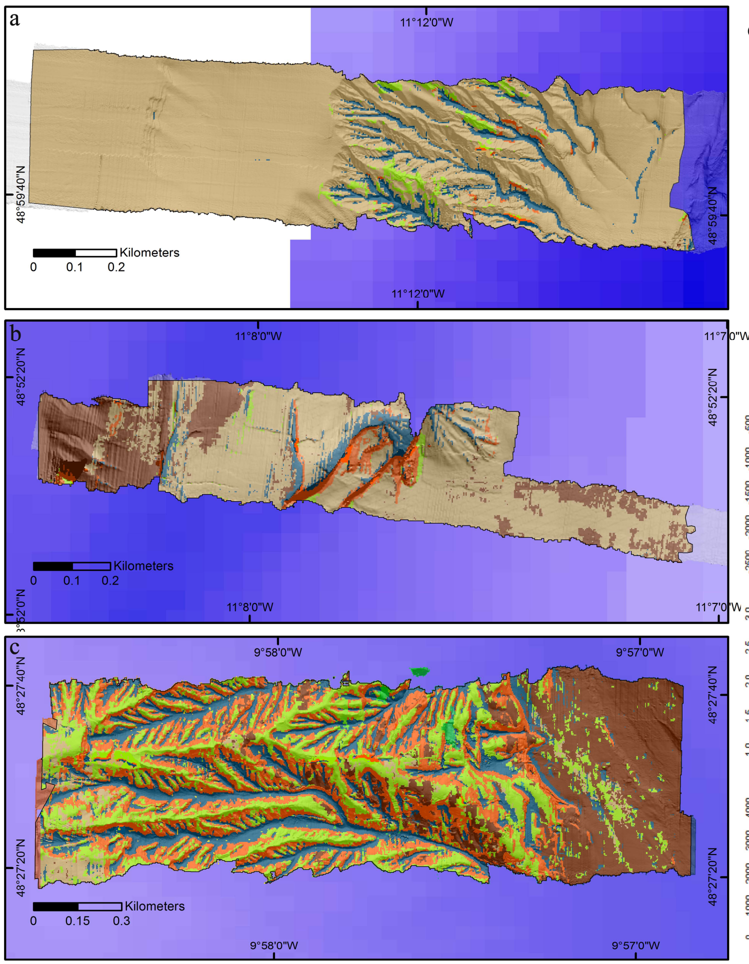
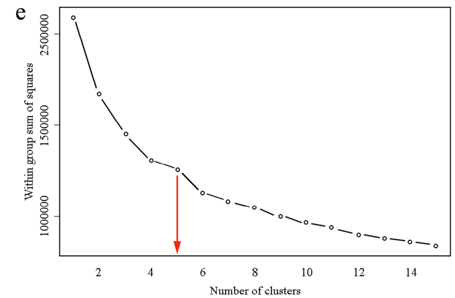


Figure 4.9: (a-c) Fine scale marine landscape maps for Dive 108, 109 and 120 when classified as a single system. (d) Component matrix showing correlation between rotated PCs and the original variables. (e) Plot of number of clusters against sum of squares to determine optimal number of clusters. (f) Boxplots of clusters against original abiotic variables were used to characterise the marine landscapes.



d

Abiotic variables	PC1	PC2	PC3	PC4	PC5
Bathymetry	-0.135	0.0508	-0.214	**0.6679**	-0.056
Bathymetric position index fine	0.0525	**0.4815**	0.0205	-0.007	0.0645
Bathymetric position index broad	0.0392	0.4272	0.0169	-0.005	0.0935
Plan curvature	-0.028	-0.324	-0.032	0.0602	**0.5985**
Plan curvature 45 m	-0.035	-0.41	-0.026	0.0577	0.5036
Profile curvature	0.0391	0.3523	0.02	0.0164	0.3992
Profile curvature 45 m	0.0547	0.4179	0.0149	0.0416	0.4554
Slope	0.3731	-0.057	0.4194	0.1858	-0.015
Slope 45 m	0.3746	-0.054	0.406	0.1646	-0.017
Rugosity	0.292	-0.048	**0.4347**	0.1677	-0.01
Artefact	-0.293	0.0075	0.3402	-0.377	0.0438
Mixed	**-0.424**	0.0347	0.2085	0.1754	-0.009
Rock	-0.326	0.0271	0.1662	0.3864	-0.029
Sediment	-0.372	0.0317	0.2858	0.2305	-0.017
TOBI backscatter intensity	0.3094	-0.007	-0.391	0.2829	-0.042
Eigenvalues	3.8882	3.3923	2.1485	1.8457	1.1929



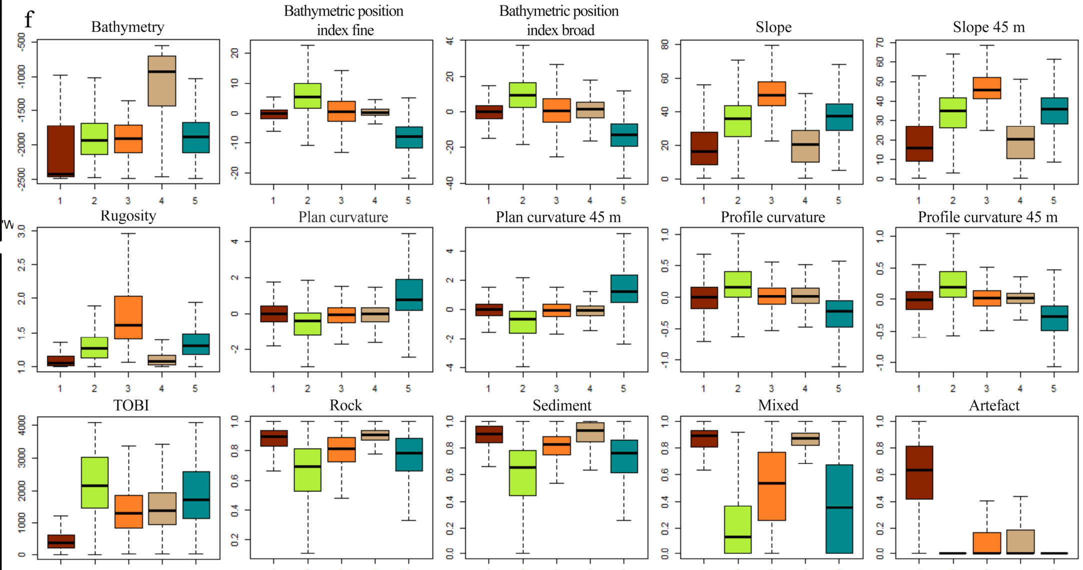


Figure 4.10: (a-c) Fine scale marine landscape maps for Dive 108, 109 and 120 when classified as a single system without aspect variables (eastness and northness). (d) Component matrix showing correlation between rotated PCs and the original variables. (e) Plot of number of clusters against sum of squares to determine optimal number of clusters. (f) Boxplots of clusters against original abiotic variables were used to characterise the marine landscapes.

4.5 Discussion

This study provides a means to compare the evolution of spatial characteristics through different data scales by incorporating different data types at various resolutions. The types of data used in the study are the ones most commonly acquired in deep-sea surveys. Based on the successful marine landscape maps produced for the three dives, it can be concluded that the objective automated seabed classification method designed for regional scale data is also applicable to fine scale data. It is easily transferable and requires a short time to apply. The delineated marine landscapes are interpretable and represent the geomorphology and substrate variation across the ROV surveyed areas. However due to data limitation, some modifications were made for the lack of seabed sonar images in the fine scale marine landscape mapping. The method used to detect potential patterns in bathymetric grids is not applicable here. The two length scales for the multiple scale terrain analysis are based on the finest scale it could run on (9 m) and on an approximation of broad features that can be observed from the bathymetry grids (45 m).

Fine to broad scale comparison

Across-scale comparison shows that the most pertinent terrain characteristics are mapped out at both scales. High-resolution data provide a way to further map detailed geomorphological features and terrain variation. Information at fine scale shows that the most influential abiotic variables delineating the marine landscapes are BPI, slope and aspect. Most of the clusters are characterised by these properties. However this is not always the case. For instance in broad scale classification the driving factor for PCA is BPI, profile curvature and slope for the Portuguese Canyons (Ismail et al., 2015) and for Whittard Canyon it is slope, substrate properties (mixed and rock) and BPI (Chapter 3). Although the features delineated in the high-resolution maps are much more detailed, large features can be related to the broad scale (regional) marine landscape map. In terms of conservation and spatial marine management for a large heterogeneous area such as a submarine canyon, the broad scale map is suitable and sufficient to show the first level of structural variation in which is parallel to how the existing hierarchical classification systems work.

Ecologically relevant marine landscape

The fine marine landscape map is more advantageous to identify geomorphological features that are often not comprehensible from video analysis. Video interpretations used in most ecological studies are often limited to substrate type and local slope angle to describe terrain properties. From our finding, fine scale marine landscape maps could provide more context to the ecological observations than what can be obtained from the narrow video transect. As observed in Table 4.6, although no communities are exclusively associated to one type of marine landscape, they show higher occurrence in some of the marine landscapes. For instance, cerianthids, Paguridae spp that occur in the three dives occurred mostly on seabed covered with soft sediment and relatively flat areas such as gully floor (Dive 108), flank (Dive 109) and flat seabed (of different direction) (Dive 120) . Species that are associated with small vertical walls, *Solenosmilia variabilis* and *Lophelia pertusa,* can be found to coincide more commonly with marine landscapes such as cliff and cliff base (Table 4.6b) and gully walls (Table 4.6c). As recommended in the new proposed classification for deep-sea habitats for Britain and Ireland (Parry et al., 2015), at one of the hierarchal levels (level 4) a broad community is thought to occupy a certain niche and fulfil a certain functional role. This niche could span over several depth zones and substratum types. Instead of using substratum type as the only environmental description, marine landscapes can provide a better environmental representation for ecological means. Furthermore, it is a way forward to study the relationship between geomorphology and biology and to overcome the issue of false homogeneity (failing to differentiate similar features that support different biological distribution) (Williams et al., 2009)

Fine scale geomorphological information is crucial to better understand structures, dynamics and changes that will affect ecological composition, usually observed at a finer scale. However, for a vast heterogeneous area like a submarine canyon, meaningful ecological changes can only be observed if there are sufficient changes in spatial features. Hence it is crucial to carry out the fine scale seafloor mapping at the right grain and extent for the system under study. Based on the community analysis, at too fine a scale there are too many sections of the video transects without any organisms, while at large scale (>50m section length) rare assemblages start to disappear causing difficulties to separate species assemblages (Robert, 2014c). Therefore to have spatial environmental information surveyed at 1 m resolution is probably more detail than needed to evaluate the effect of spatial variation on ecological composition, but using only ship-based bathymetry will not be sufficient to pick up necessary details. The ideal approach to gain optimally from high-resolution data may be to have bigger survey coverage than what was tested here, with slightly coarser pixel size, rather than going for the finest pixel with smaller extent (i.e. to operate the acoustic system further from the seabed).

Additionally, ecological variations are greatly affected by depth. Geomorphology may be less influenced by depth, but biological communities are greatly affected by this, among others. Therefore to really study the relationship between ecology and spatial variations at different scales, replicate surveys should be carried out at a constant depth. Due to the limitation in extent of ROV coverage vs. depth variation, no further analysis could be carried out to evaluate the ecological relevance of the calculated contagion index as proxy for biodiversity. Due to the depth differences in the three ROV surveys, it would be invalid to draw conclusions from these three dives in terms of ecological properties (abundances, diversity etc.) compared to the contagion index.

However, this study offers a way forward to aid in designing nested acoustic surveys (Lark, 2011). Such surveys will provide a link to relate information from metre-scale seabed observations (video) to kilometre-scale regional maps (ship-borne surveys), and at the same time are beneficial for ecological studies. Preferably, to obtain optimal information from a high quality survey, ROV surveys should aim for sufficient coverage and replicate surveys at constant depth if data are to be use for ecological evaluation. Too fine a resolution without enough coverage will limit the usage of such powerful tool. However, more detailed geomorphological information may be necessary for sediment dynamics studies in submarine canyons. Therefore it is important to design a survey based on the information needed. Although geomorphological and sedimentological features can be delineated through this practice, the dive extent limits the insight in the relationship between ecology (communities, biodiversity) and spatial variations. Potentially, a fine scale marine landscape mapping could be trialled at a pixel scale of 5-10 m with more coverage (extent).

The aspect variable

The aspect properties were suggested to be potentially beneficial if associated with hydrographic regime (Ismail et al., 2015). In another environment, cold-water coral reefs, it was found that hydrographic gradients are more important in broad scale assembly (Henry et al., 2013). In contrast, for local scale food supply and fauna interaction are more influential. Geomorphologically, aspect properties defined the marine landscape more prominently when the three dives were classified individually. The situation is different for the classification as one system, based on the boxplots in Figure 4.9: only cluster 5 is explained by aspect. The two set-ups show that it is important to carefully consider the input variables, since selection of abiotic variables will alter the quantification of marine landscape heterogeneity. However, the overall pattern (highest heterogeneity for Dive120, lowest for Dive108) stayed the same, with or without the aspect variable. Hence advice to support conservation decisions would probably be the same in both cases.

The fact that the surveys were carried out at different depths impeded the ability to validate the use of the contagion index to quantify marine landscape heterogeneity as a biodiversity indicator. Nevertheless, entropy contagion indices were calculated by treating the dives as one system. It provides an important information especially if such measure is to be used for repeat surveys. For instance if a repeat survey were made, to apply the landscape metrics, the same cluster centres from previous classification should be used to ensure the same classification were carried out for both data.

4.6 Conclusion

This study provides the opportunity to understand the information transfers across different type of data, extent and resolution. It also draws additional attention to the need for optimal survey design to study ecological and spatial relationships in the deep sea. The study demonstrates the following: 1) objective automated marine landscape mapping developed for kilometre-scale regional maps is applicable and transferable to high-resolution data. The marine landscapes delineated from the high-resolution data are interpretable and relevant to display terrain and substrate variation across the surveyed areas. 2) Fine scale marine landscape maps provide more context for ecological studies in comparison to terrain information from video interpretation 3) In order to study the effect of geomorphological and sedimentological variation on ecology, high resolution surveys using ROV/AUV should aim for the optimal balance between extent and detail. The outcome is in agreement with the finding by Robert (2014c) that states a resolution of 20-50 m is adequate to capture trends in biological distribution and changes in ecological community are observed to be irrelevant at scales less than 5 m in Whittard Canyon. Therefore, structural variations at 5 m pixel could potentially be more practical to study relationship between ecology and marine landscape for fine marine landscape map. However this is only true for ecological studies and not necessarily for other purposes such as sediment dynamics that can be heavily influenced by fine geomorphological features. Such study is still limited in submarine canyons. 4) Aspect is a potential environmental variable acting as proxy for current regime interaction with different slope orientations, and may also provide an insight on possible sediment depositional areas. Until first-hand information can be obtained on hydrography and sediment transport properties at local scale, aspect is still relevant to be included in habitat mapping and providing such information. 5) Each abiotic variable included affects the classification, as demonstrated by altering the aspect properties. Therefore it is important to ensure objectivity throughout the procedure. Accordingly, quantification of marine landscape heterogeneity as a biodiversity indicator is not validated in this study due to the lack of fine-scale surveys at a constant depth.

Chapter 5: Synthesis

The main aim of this study was to develop an objective automated technique to map marine landscapes in complex deep-sea environments with a focus on submarine canyons. The aim is formulated to facilitate the implementation of ecosystem-based management by providing a scientific context of spatial pattern information through marine landscape maps. The study examined the potential analyses and approaches to optimise the usage of commonly available data in deep-sea seafloor surveys and the ability of a marine landscape approach to support marine habitat mapping in highly heterogeneous areas.

5.1 Scientific contributions

This thesis provides three novel contributions in habitat mapping especially for deep-sea environments: 1) it developed an objective automated marine landscape mapping technique to underpin marine habitat mapping, 2) quantified spatial structure of marine landscape as a proxy of habitat heterogeneity measure and 3) it demonstrated the potential of marine landscape as a mapping unit for habitat mapping

1) **Development of an objective, automated and statistically robust marine landscape mapping technique for broad scale mapping in submarine canyons**

The exact mapping procedure and its continued development is illustrated in each chapter. Research contributions towards the technique development are outlined in Figure 5.1. Each chapter in the thesis provides improvement to the developments of the technique following the findings:

Evaluation of the potential of multiple scale terrain analysis as a way to the incorporate broad and fine scale features in broad scale mapping

The approach was first demonstrated on the continental slope, where a habitat suitability model performs better in cross validation for ecological relevance when multiple scales are included in comparison to single scale (Wilson et al, 2007). This result became the motivation to incorporate multiple scale terrain analysis as part of the marine landscape mapping technique. Since submarine canyons contain high terrain variability and the geomorphic features vary in size, multiple scale terrain analysis would allow the variability in the environmental features to be captured. Broad scale mapping often smoothed out fine features and on the other hand fine single scale analysis caused artefact patchiness and incoherent classifications that introduced noise especially for regional mapping. The study carried out here supported that multiple scale terrain analysis is beneficial to delineate ecologically relevant marine landscapes in highly heterogeneous areas. The approach managed to retain the fine and broad characteristics of the terrain and capture the variability in terrain features.

Transferability of the Estimation of Scale Parameter (ESP) tool of Object Based Image Analysis of sidescan sonar images to detect potential features in bathymetric grids

While multibeam echosounders are designed to measure seafloor depth, sidescan sonar produces acoustic images of the seabed. Sidescan sonar imagery is a powerful tool for seafloor mapping with its ability to provide near-photographic high-resolution images. Based on the merit and the availability of sidescan sonar images overlapping the multibeam bathymetry, Estimation of Scale Parameter (ESP) is adapted into the mapping procedure to segment the potential real-world submarine canyon geomorphic features and give an estimate of the mean length size of the features. This is used as a way to estimate the broader length scales to be used in multiple scale terrain analysis for bathymetric grid data. The approach is an automated way to estimate feature sizes present and allows objectivity throughout the mapping techniques.

Extracting substrate information from sidescan sonar and video interpretation using Object Based Image Analysis

Developments in acoustic survey techniques have revolutionised the way to image and map the seabed environment. This includes the availability of acoustic amplitude data such as sidescan sonar imagery and multibeam backscatter data. Traditional methods of interpretation for such data rely on experienced interpretation of grey scale images by eye. Semi-automated methods have been proposed in the literature to overcome the subjectivity of the manual interpretation. Here, a method that is widely used to classify satellite images, especially in the terrestrial environment, has demonstrated its potential to map substrate distribution in submarine canyons. Object Based Image Analysis (OBIA) recognises meaningful patterns in an image regardless of pixel size and involves two steps: segmentation and classification. Segmentation subdivides the image into potential real-world features or objects. Classification then assigns to these objects an interpretation using a supervised classification algorithm, based on substrate information from point data of video transects. The substrate distribution map was also included as part of the abiotic variables and was subjected to the marine landscape mapping procedure. It is potentially a way forward to extract substrate information from acoustic amplitude data in a complex deep-sea environment where sedimentological samples are often scarce and limited. The approach is more automated and allows increased meaningful information to be extracted from acoustic amplitude data.

Applicability of method to a different canyon system, different survey scale

The final marine landscape procedure that was developed for the Portuguese Canyons was subsequently trialled in a different system, the Whittard Canyon. The method performed successfully on both canyons and delineated marine landscapes that are ecologically and geomorphologically relevant. Not only was it trialled on ship-borne multibeam bathymetry of different pixel size (25 m for the Portuguese Canyons and 50 m for Whittard Canyon), transferability was also achieved for high-resolution data (ROV surveyed multibeam bathymetry) of 3 m pixel resolution.

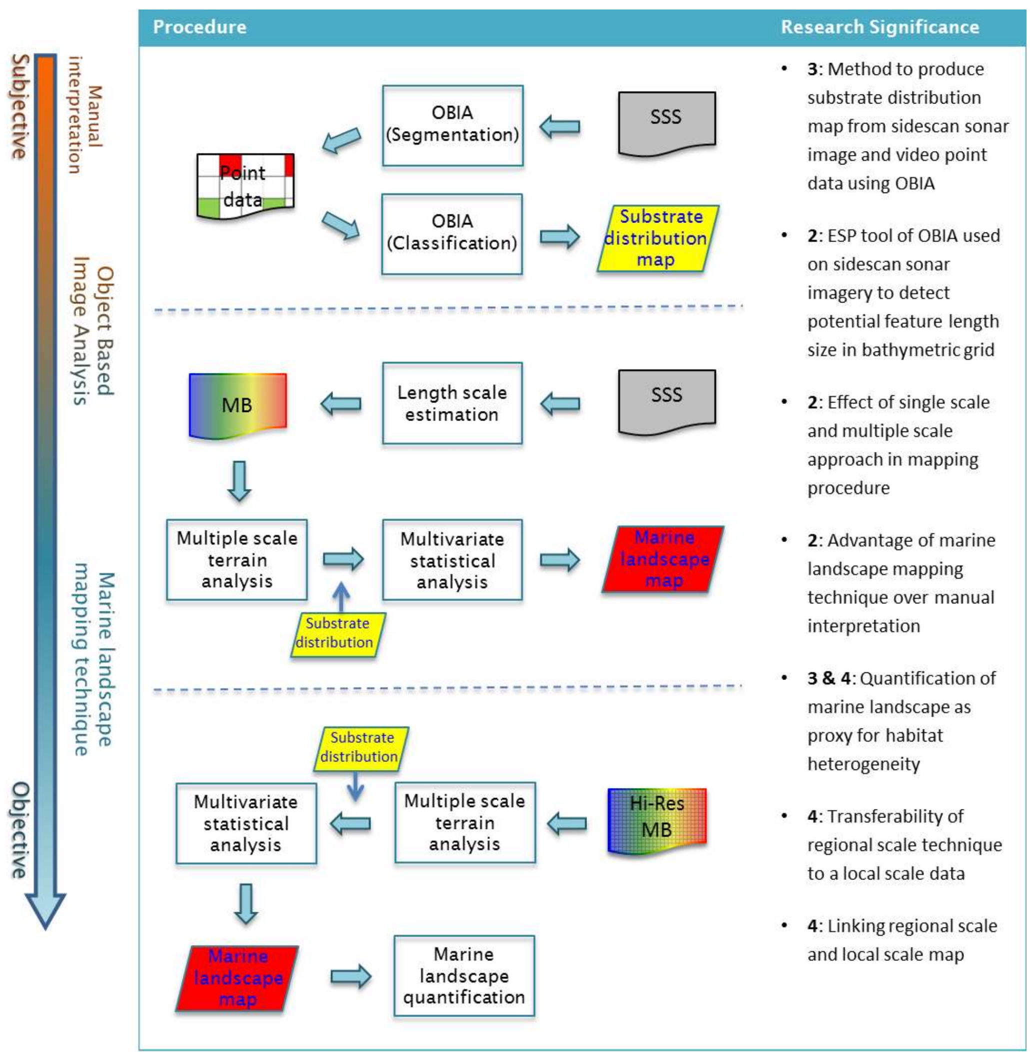


Figure 5.1: Research contribution towards the development of the marine landscape mapping technique. Bold numbers are chapters corresponding to the findings. Arrows on the left show the objectivity measures of the analysis incorporated in the marine landscape techniques.

2) **Promoting the use of marine landscape as a mapping unit**

The marine landscapes delineated are based on the *natural variability* present in environmental parameters. In this thesis, the only abiotic information available are the geomorphology and substrate type, and therefore the natural zones delineated are heavily based on the geomorphology. However the technique is not limited to these data types, other data types can also be incorporated (e.g. oceanographic parameters, outputs from current modelling etc.). The application of the marine landscape technique on the abiotic variables throughout the study shows that the marine landscape has a potential correlation with biological distributions and is *ecologically meaningful*. This is demonstrated in Whittard Canyon for both broad and fine scale marine landscape maps. Additionally, the canyon-wide broad scale marine landscape classification has demonstrated its ability to represent prominent local scale terrain variability. It shows the *first level structural variation*, which is parallel to most existing hierarchal classification systems for deep-sea habitat mapping. Potentially, it may be a way forward to provide scientific input for ecosystem-based management in submarine canyons. This also suggests that broad scale marine landscape maps are beneficial to represent environmental conditions in highly heterogeneous areas for ecological observation. Apart from that, also fine-scale marine landscape maps have demonstrated their capacity to *provide more context* than direct video interpretations of the terrain variation. They also show a potential link with species communities, which is in sync with the newly proposed approach to classify deep-sea marine habitat in Britain and Ireland for management purposes (Parry et al., 2015).

3) **Quantification of marine landscape structure as a proxy for habitat heterogeneity and potentially biodiversity**

Taking advantage of the link between high terrain variability and increased biodiversity as supported by Niche Theory, to quantify terrain variation is potentially the best proxy to select and locate high biodiversity areas. Continuing the use of the marine landscape as a mapping unit, quantification of its spatial structure is proposed here as a habitat heterogeneity measure. The landscape metric chosen (entropy-based contagion) was extended from a landscape metric widely used in the terrestrial environment to quantify spatial patterns by measuring composition and configuration of patches. The patches in this study are the marine landscapes. The *quantification of marine landscape structure* shows a great potential as a measure for habitat heterogeneity. It was carried out in Whittard Canyon, for both the broad and fine marine landscape maps. The quantification was examined for its relationship with biological observations and analysis from video transects. From the limited survey video transects, the marine landscape quantification using the entropy-based contagion index shows positive results between the measure and the biological characteristics. It is of value for scientists to present to stakeholders and policy makers prioritisation of areas when determining critical zones for conservation. Such approach could possibly be a way to improve the efficacy of selecting and allocating target areas for conservation.

5.2 Future directions

Translating the marine landscape maps for inclusion in deep-sea habitat classification system

There is an urgent need for effective management and conservation for deep-sea environments especially in areas with potentially high ecological value. Although there is a rising awareness towards implementing an effective deep-sea management such as ecosystem-based management, the lack of scientific context and understanding in the approach could hamper the effort. It is important to find the most fitting environmental representation to devise a successful deep-sea spatial management. As such a way forward is to incorporate the use of marine landscapes in an existing hierarchal deep-sea classification. Added studies of the relationship between marine landscape and biological distribution will also improve the understanding of environmental parameters on biota.

Development of an exclusive marine landscape metric for complex deep-sea environments that incorporates its unique characteristics

Although the quantification of marine landscape structure has shown great potential as a proxy for habitat heterogeneity using the contagion-index, there are many other landscape indices that are available in landscape ecology that could benefit spatial pattern quantification in deep-sea environment. However, ideally a new exclusive metric for complex deep-sea environments should be developed to include its typical characteristics into the measure. The metric used in this study only measures the spatial pattern composition and configuration among marine landscape regardless the characteristics within, which is crucially an important factor affecting the spatial distribution of organisms in the marine realm. Additionally, the marine landscape metric for complex deep-sea environments should incorporate its 3-dimensional terrain characteristics as part of the components in the measure.

5.3 Conclusion

The study proposed an objective and automated marine landscape mapping technique for submarine canyons by incorporating acoustic data that is usually available from initial deep-sea seabed surveys. The method is simple, straightforward, statistically robust and repeatable. The resulting marine landscape maps represent the spatial variation of the terrain in submarine canyons and show a strong potential as a bridge to communicate across the extended community of scientists, policy makers and stakeholders to support ecosystem-based management in submarine canyons. Not only does it represent the structural properties of the environment, it also demonstrates a convincing relationship with biological distributions in submarine canyons. However, there are various other processes affecting the complex environment-species relationships, and this study does not intend to limit but rather to contribute as a way to further understand this relationship. Looking at spatial variation as a marine landscape rather than an entity of a single abiotic factor (i.e. substratum type or depth), could potentially be a way forward to understand the complex interaction between abiotic and biotic variables that make up a habitat.

Highly heterogeneous areas such as submarine canyons provide a means to understand the relationship between terrain variations and biodiversity. Quantification using spatial pattern metrics as practiced in terrestrial and shallow water environments offers a great potential for ecological research and environmental management. With ongoing developments of equipment and technologies available to study the complex deep-sea environment, it is about time to find a way to quantify these structural properties as a way to evaluate the conservation values to support deep-sea spatial management. In this study we manage to provide the insight on spatial pattern information across scale using marine landscape as representation and quantify them as habitat heterogeneity and demonstrate its relationship with biological distribution in an ecological context. In order to work towards a successful implementation of ecosystem-based management in submarine canyons, it is the task of scientists to ensure that crucial scientific information is translated correctly to stakeholders and policy makers who will be responsible for making decisions about our deep-sea environment that are currently threatened with anthropogenic activities.

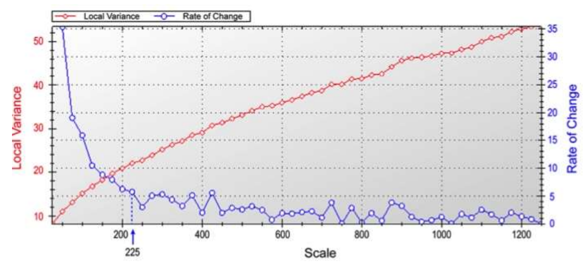
Appendices

Appendix A

<u>Using Estimation of Scale Parameter (ESP) Tool on sidescan sonar imagery to detect feature size in bathymetric grid</u>

1. ESP tool plots values of local variance and rate of change against scale level. A sudden decrease in ROC indicates meaningful scale parameters. SP has no unit.

2. SP value is used to segment the sidescan sonar in eCognition developer (v8.9). The segments are exported to ArcGIS as polygons (feature class)



3. In ArcGIS (v10.2), Calculate Areas (Spatial statistic tools / Utilities) toolbox is used to determine the mean area of polygons.

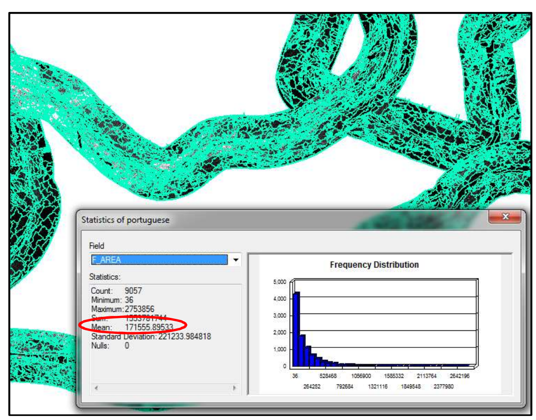
4. To obtain window size (for broad scale features) for multiple scale terrain analysis in Landserf (v2.3), the following calculation was used:

$$\begin{matrix} window\ size\ for \\ multiple\ scale \\ terrain\ analysis \\ (pixel) \end{matrix} = \frac{\sqrt{mean\ area\ of\ segments}}{\begin{matrix} multibeam\ bathymetry \\ pixel\ size \end{matrix}} X \begin{matrix} minimum\ window \\ size\ for\ analysis \\ along\ one\ side \end{matrix}$$

For example,

The mean area for Portuguese Canyons sidescan image segments of 225 SP is 171555 m^2, minimum window size for analysis is 3 (along one side), and multibeam bathymetry pixel size is 25, therefore;

$$\frac{\sqrt{171555}}{25} X3 = 49\ pixel$$



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