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**Quantitative comparison of benthic habitat maps
derived from Multibeam Echosounder backscatter
data**

A thesis submitted in fulfilment
of the requirements for the degree of

Doctor of Philosophy
in
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by
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ABSTRACT

In the last decade, following the growing concern for the conservation of marine ecosystems, a wide range of approaches has been developed to achieve the identification, classification and mapping of seabed types and of benthic habitats. These approaches, commonly grouped under the denominations of Benthic Habitat Mapping or Acoustic Seabed Classification, exploit the latest scientific and engineering advancements for the exploration of the bottom of the ocean, particularly in underwater acoustics. Among all acoustic seabed-mapping systems available for this purpose, a growing interest has recently developed for Multibeam Echosounders (MBES). This interest is mainly the result of the multiplicity of these systems' outputs (that is, bathymetry, backscatter mosaic, angular response and water-column data), which allows for multiple approaches to seabed or habitat classification and mapping.

While this diversity of mapping approaches and this multiplicity of MBES data products contribute to an increasing quality of the charting of the marine environment, they also unfortunately delay the future standardization of mapping methods, which is required for their effective integration in marine environment management strategies. As a preliminary step towards such standardization, there is a need for generalized efforts of comparison of systems, data products, and mapping approaches, in order to assess the most effective ones given mapping objectives and environment conditions. The main goal of this thesis is to contribute to this effort through the development and implementation of tools and methods for the comparison of categorical seabed or habitat maps, with a specific focus on maps obtained from up-to-date methodologies of classification of MBES backscatter data.

This goal is attained through the achievement of specific objectives treated sequentially. First, the need for comparison is justified through a

review of the diversity characterizing the fields of Benthic Habitat Mapping and Acoustic Seabed Classification, and of their use of MBES data products. Then, a case study is presented that compares the data products from a Kongsberg EM3000 MBES to the output map of an Acoustic Ground Discrimination Software based on data from a Single-beam Echosounder and to a Sidescan Sonar mosaic, in order to illustrate how map comparison measures could contribute to the comparison of these systems. Next, a number of measures for map-to-map comparison, inspired from the literature in land remote sensing, are presented, along with methodologies for their implementation in comparison of maps described with different legends. The benefit of these measures and methodologies is demonstrated through their application to maps obtained from the acoustic datasets presented previously. Finally, a more typical implementation of these measures is presented as a case study in which the development of two up-to-date classification methodologies of MBES backscatter data is complemented by the quantitative comparison of their output maps.

In the process of developing and illustrating the use of methods for the assessment of map-to-map similarity, this thesis also presents methodologies for the processing and classification of backscatter data from MBES. In particular, the potential of the combined use of the spatial and angular information of these data for seabed classification is explored through the development of an original segmentation methodology that sequentially divides and aggregates segments defined from a MBES backscatter mosaic on the basis of their angular response content.

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I would have liked to start this part of my thesis by the usual statement that “there are many people and organisations to thank for their support”. However, the untimely passing of one’s main supervisor in the middle of one’s Ph.D. research is not a usual event so I ask my reader to forgive me for being more emotional than the norm to begin with.

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TABLE OF ACRONYMS

2D:	Two-Dimensional
AGDS:	Acoustic Ground Discrimination System(s)
AMI:	Average of Mutual Information
ARA:	Angular Range Analysis
ASC:	Acoustic Seabed Classification
AVG:	Angle Varying Gain
BHM:	Benthic Habitat Mapping
BS:	Backscattering Strength
CUBE:	Combined Uncertainty and Bathymetry Estimator
DGPS:	Differential Global Positioning System
DoC:	Department of Conservation of New Zealand
FFT:	Fast Fourier Transform
GIS:	Geographic Information System(s)
GPS:	Global Positioning System
ICES:	International Council for the Exploration of the Sea
KS:	Kolmogorov-Smirnov
MBES:	Multibeam Echosounder(s)
MESH:	Mapping European Seabed Habitats
NIWA:	National Institute of Water and Atmospheric Research
PCA:	Principal Components Analysis
SBES:	Single-beam Echosounder(s)
SB-AGDS:	Single-beam echosounders based Acoustic Ground Discrimination System(s)
SCUBA:	Self Contained Underwater Breathing Apparatus
SSS:	Sidescan Sonar(s)
TS:	Target strength
TVG:	Time Variable Gain
UTM:	Universal Transverse Mercator
WGS:	World Geodetic System
XTF:	eXtended Triton Format

CHAPTER 1

INTRODUCTION

1.1 Benthic Habitat Mapping: rationale and definition

The past ten years have witnessed significant advancement of the tools for the identification, classification and mapping of marine habitats (Brown *et al.*, 2011). This advance has arisen principally from the growing need for ecosystem-based management of the marine resource (Cogan *et al.*, 2009), which is viewed as a necessary and urgent shift in management policies to counter the considerable decline of the marine environment that has resulted from the dramatic increase of marine anthropogenic activities in the last decades (Murawski, 2007; Halpern *et al.*, 2008).

Habitat is an ambiguous ecological concept that can be understood either as the place where a given organism or population is found, the set of environmental conditions that characterize this place, or the biological community that inhabits this place (Begon *et al.*, 1996; Hall *et al.*, 1997; Mitchell, 2005). This ambiguity is especially significant in marine sciences, where it results in marine habitats (or specifically *benthic habitats*, which constrains this concept to the bottom of the ocean) being defined differently depending on the study objectives or scale, and on the technologies used for their identification, classification or mapping (Diaz *et al.*, 2004; Brown *et al.*, 2011). As a result, Benthic Habitat Mapping (BHM) does not designate a specific scientific method, but rather an ensemble of diverse approaches concerned with identifying, or predicting the physical and/or biological aspect of the seabed on large scales.

1.2 Seabed type and acoustic technology

The measurable variables of the marine environment that influence the distribution of benthic organisms, and can therefore be used to discriminate between benthic habitats, are numerous and diverse. They include, but are not limited to, depth, water temperature, sediment type or substrate complexity, salinity, oxygen saturation and bed stress induced by tide action or wave exposure (McArthur *et al.*, 2010). In particular, sediment type and substrate complexity (often measured by sediment grain-size, or identified as seabed type), as highly variable parameters over small scales, have a major influence in structuring local benthic communities (Gray, 1974; Snelgrove and Butman, 1994). They are therefore the principal focus of BHM efforts in the nearshore and on the continental shelf (Brown *et al.*, 2011).

Acoustic seabed-mapping systems are currently the most advanced technologies for the remote identification and mapping of seabed type over large areas (Kenny *et al.*, 2003). These systems are made possible by the physics of sound interaction with solid interfaces, which translate in a large influence of the substrate characteristics, such as roughness and material density, on the level and shape of the acoustic echoes reflected from the seabed (Urlick, 1983; Lurton, 2002). Acoustic seabed-mapping systems record these echoes in a digital format as *reflectivity* or *backscatter* data, named after the physical processes of sound interaction with the sea bottom at the origin of these echoes.

1.3 Acoustic Seabed Classification

The extraction of information about seabed substrate from backscatter data is not a simple task (Lurton, 2002). A first major obstacle is the influence on the signal by many other factors related to the acoustic system itself (*e.g.* beamwidth, frequency, pulse length, resolution), the conditions of acquisition (*e.g.* range, angle of insonification, vessel movements) and the environment (*e.g.* absorption and sound velocity gradient in the water column, subsurface stratification). More importantly, the natural variety and high heterogeneity of the bottom of the ocean

typically results in an ambiguity of the information that can be extracted from the signal, and hinders its interpretation.

As a result of this fundamental difficulty, a wide variety of acoustic systems, data processing methodologies, and classification algorithms have been suggested to allow the identification and mapping of seabed types, and by extension, of benthic habitats (ICES, 2007). These research efforts constitute the science of Acoustic Seabed Classification (ASC).

1.4 Multibeam Echosounders

Acoustic seabed-mapping systems typically used in ASC, and by extension in BHM, can be broadly categorised into three types: Single-Beam Echosounders (SBES), Sidescan Sonars (SSS), and Multibeam Echosounders (MBES). Traditionally, the characteristics of the study site (*i.e.* expected depth and substrate-type) and the objectives of the mapping study (*i.e.* coverage, resolution, costs) have dictated the most appropriate system for classification (Kenny *et al.*, 2003). However, the continuous development of the MBES technology, combined with recent improvements in positioning, motion sensing, data storage, and computer processing speed, have resulted in MBES beginning to supersede SBES and SSS in most modern ASC efforts (Brown *et al.*, 2011).

This preference for the MBES technology over SSS and SBES is mainly due to its capabilities to provide both bathymetry (water depth) data with a better coverage and resolution than SBES (Mayer, 2006), and backscatter data of a similar coverage and resolution as SSS (Le Bas and Huvenne, 2009). In addition, these two data types and their combination present a formidable potential for complex automatic/statistical approaches that are not within the capabilities of traditional SBES and SSS systems (ICES, 2007). The growing affordability and availability of MBES systems, the diversity and potential of their data products, and their suitability to the application of varied automatic/statistical processing approaches, have resulted in a wide number of new ASC and BHM approaches having been

developed these past few years based on these systems alone (Brown and Blondel, 2009), or in combination with other data types (Brown *et al.*, 2011).

1.5 The need for standardization

The variety of approaches to ASC and BHM, driven by the use of MBES systems over the past few years, is contributing to significant advances in the quality of the maps being created. However, this diversity presents the main disadvantage of delaying a future standardization of methods that is much required in order to effectively play a role in the development of ecosystem-based management (Anderson *et al.*, 2008).

A preliminary step towards this standardization would be the ability to systematically compare different approaches in order to assess their respective merits. To achieve this would require:

- (i) regular reviews of the current state of the fields of BHM and ASC;
- (ii) the development and use of methods for the quantitative estimation of success of a given seabed (or habitat) map against ground-truth data, in order to allow the indirect comparison of approaches applied on different datasets acquired at different sites;
- (iii) an increase of the number of comparative studies applying different approaches on a common site, or on a common dataset, and;
- (iv) the development and use of methods for the quantitative comparison between seabed (or habitat) maps of a same site, in order to allow a more direct comparison of approaches.

The scientific community is well aware of this need for comparison of approaches: review efforts are relatively frequent (*e.g.* Kenny *et al.*, 2003, ICES, 2007; Brown *et al.*, 2011), methods for the estimation of map success are being

developed and applied (*e.g.* Rooper and Zimmermann, 2007; Lucieer, 2008; Walker *et al.*, 2008), and their results occasionally used for comparison (*e.g.* Brown and Collier, 2008), and different approaches are regularly implemented to a common site or common datasets for the purpose of comparison (*viz.* Hamilton *et al.*, 1999; Hewitt *et al.*, 2004; Brown *et al.*, 2005; Hutin *et al.*, 2005; Shumchenia and King, 2010). There is, however, a lack of tools and methodologies for a more systematic quantitative comparison between overlapping benthic habitat maps.

1.6 Objectives of the study

The overall goal of this study is to develop and implement new tools to allow the quantitative comparison of benthic habitat or seabed maps, with a specific focus on maps derived from up-to-date approaches based on MBES systems. This aim is to be met by achieving the following objectives:

- (1) to review the current state of the fields of BHM and ASC, and principally their use of MBES data products;
- (2) to collect MBES data for a number of shallow-water sites, where SBES and SSS data were previously acquired and used for seabed mapping;
- (3) to develop new methods for the processing of MBES backscatter data, so as to fully exploit their potential for discrimination between seabed types;
- (4) to develop and implement new methods for the quantitative comparison of habitat or seabed maps, and finally;
- (5) to implement these methods to compare maps derived from various approaches using MBES, SSS or SBES systems in order to compare their respective seabed- or habitat-type discrimination potential.

1.7 Structure of the study

In order to achieve the objectives listed above, the study was carried out in four main phases, leading to four core chapters (2 to 5)

Chapter 2

Benthic Habitat Mapping, Acoustic Seabed Classification, and Multibeam Echosounders: a General Background

Chapter two develops a general background for the study by reviewing the diversity characterizing the fields of BHM and ASC. Therefore, it relates to objective (1) of the thesis. In this review, the various origins of this diversity are explored, including: the ambiguity in habitat terminology, the multiplicity of views and approaches to classification or mapping, the array of processing and classification algorithms that have been developed over the past decades, the range of technologies available and their respective data features for classification. As a main source of diversity, an emphasis is put on describing the MBES technology, with its multiple data products and classification approaches.

Chapter 3

The issue: a case study comparison of MBES data products with that of SBES and SSS

Chapter three presents a simple methodology for extracting the main data features from a MBES (mosaic, but also bathymetry and its derivative, seafloor slope), and its application to two sites previously surveyed with SBES and SSS systems for the visual comparison of their data products. This chapter therefore relates to objectives (2) and (3) of the thesis. The MBES system used in this study is a Kongsberg EM3000 operating at 300 kHz. The sites are located in the Tamaki Strait, Hauraki Gulf, New Zealand. The similarities and differences between the MBES, SSS and SBES outputs are identified, and a number of hypotheses for the origin of the differences are suggested. Conclusions are drawn about the potential of MBES for habitat mapping in comparison to the more traditional SBES and SSS systems. This case study illustrates the need for tools for the quantitative

comparison of seabed or habitat maps. This chapter was peer-reviewed and published as an article in the Journal of Coastal Research (Schimel *et al.*, 2010a).

Chapter 4

The solution: tools for the quantitative comparison of categorical maps

Chapter four introduces several methods and metrics for the quantitative comparison of overlapping, hard, categorical seabed maps, irrespective of the differences in classification schemes. These methods and metrics are inspired from the literature in terrestrial remote sensing. The benefits and limitations of these methods and metrics are explored through their application to the overlapping MBES-SBES-SSS dataset acquired over the Te Matuku Marine Reserve, Hauraki Gulf, New Zealand, which was presented in the previous chapter. This chapter, therefore, relates to objectives (4) and (5) of the thesis. This chapter was peer-reviewed and published as an article in the ICES Journal of Marine Science (Schimel *et al.*, 2010b).

Chapter 5

The application: comparing complex ASC approaches that combine MBES mosaic and angular-response data

Chapter five illustrates the benefit of the metrics developed in the previous chapter by quantifying the similarity between complex ASC approaches based on MBES data. One of these approaches is an original and up-to-date segmentation methodology that combines the angular response content from MBES backscatter data with a traditional MBES backscatter mosaic, for an optimal use of the backscatter dataset in both the mosaic and angular space. The combination of mosaic and angular-response, which are commonly used separately in traditional ASC approaches, can be viewed as a step towards a complete, integrated exploitation of the potential of MBES backscatter data for habitat/seabed delineation. Hence, this chapter relates to objectives (3) and (5) of the thesis.

Exploiting the backscatter data processing capabilities of the *Geocoder* software, developed at the Center for Coastal and Ocean Mapping (CCOM, University of New Hampshire, NH, USA), the methodologies presented in this chapter are applied to a Kongsberg EM3000 MBES backscatter dataset acquired over the Tapuae Marine Reserve, North Taranaki, New Zealand. The map similarity metrics are used to quantify the success of the original methodology in comparison to a similar approach developed at CCOM, and to traditional segmentations of the MBES backscatter mosaic. The backscatter data processing methodology was developed in collaboration with CCOM research staff, and the chapter was formatted for submission in a peer-reviewed scientific journal.

Chapter 6

Summary and Conclusion

Chapter six concludes the thesis by summarising the major findings from the research, and outlining how they met the individual objectives made in this introduction.

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CHAPTER 2

BENTHIC HABITAT MAPPING, ACOUSTIC SEABED CLASSIFICATION, AND MULTIBEAM ECHOSOUNDERS: A GENERAL BACKGROUND

2.1 Introduction

Marine environments worldwide are experiencing an accelerating decline as a direct result of anthropogenic activities, particularly fishing pressure, habitat fragmentation and pollution (Jackson *et al.*, 2001; Halpern *et al.*, 2008). This impact on the marine biodiversity and the concern over the future of the fishing resource have raised the awareness of a need for a management approach of the marine environment that is primarily concerned with maintaining ecosystems in a healthy condition (Pikitch *et al.*, 2004; Halpern *et al.*, 2008). However, this objective requires considerable advances in the knowledge of the processes underlying marine ecosystems and in charting of both the biological and physical parameters of the marine environment (Murawski, 2007; Cogan *et al.*, 2009). The main obstacles to these advancements are the inherent complexity of these systems and the difficulty to access, observe and map the seabed.

These challenges are not new. In particular, the difficulty of accessing and observing the bottom of the ocean is a major obstacle in scientific fields concerned with studying its topography, geology or biology. Fortunately, the past decades have witnessed continuous improvements of the techniques for accessing the seabed physically (SCUBA-diving, manned submarines) and remotely (dropping of instruments from a static vessel, towed sledges, remotely operated or autonomous vehicles), as well as of the instruments for sampling or observing the seabed and of the tools for the remote measurement or prediction of some of its physical parameters. The emergence and development of these technologies has

resulted in a tremendous improvement of our capabilities to characterise and map the marine physical environment at various resolutions, accuracies, and scales. In particular, the large-scale and high-resolution mapping of underwater topography, seabed geology, and geomorphology have benefited from the development and recent evolution of acoustic seabed-mapping technologies (Lurton, 2002; Mayer, 2006).

The sciences of marine biology and ecology have also greatly benefited from the evolution of some of these technologies (Rumohr, 1995). In the last decade, driven by the rising concern for marine ecosystems, efforts have multiplied to exploit these technologies to map the biological component of the marine environment (Brown *et al.*, 2011). This objective faces two inherent obstacles:

- (i) What do we mean by mapping the biological component of the marine environment?
- (ii) How can this be done using tools designed for mapping its physical component?

This issue of the complex relationship between biological organisms and their environment is at the heart of a cornerstone concept of ecology: “habitat”.

“Habitat” is an extremely ambiguous notion (Hall *et al.*, 1997). Intuitively, it is understood as “the environment where organisms are found” (Begon *et al.*, 1996). However, in practice it has multiple facets as it is commonly used by the scientific community to designate many different aspects of the ecosystem, including the spatial distribution of a given species of interest, a set of relatively homogeneous environmental conditions with no mention of the associated biology, a community of organisms, and various combinations of the above (Mitchell, 2005). Additionally and specifically to the marine environment, a coupling between biology and seabed sediment has often been assumed, which has resulted in a popular, but criticised understanding of the term benthic “habitat” as an equivalent for seabed substrate-type (Diaz *et al.*, 2004).

As a result of this complexity of defining a benthic “habitat”, of the diversity of the scientific backgrounds of the stakeholders involved in this issue, and of the multiplicity of technologies available to explore the marine environment, there has been no agreement on a standard procedure to map the biological aspect of the marine environment to date. Rather, a large variety of approaches have been developed and continue to be developed to perform this task, which is commonly identified by the umbrella terminology of *Benthic Habitat Mapping* (BHM) (Brown *et al.*, 2011).

BHM is closely related to another marine science termed *Acoustic Seabed Classification* (ASC), which is concerned with the characterisation, identification and mapping of the seabed (without necessarily an interest in the relevance to biological organisms, that is, as a “habitat”) using acoustic seabed-mapping systems. Among all the acoustic technologies available for ASC (and by extension, for BHM), a strong interest has developed in multibeam echosounders (MBES) over the past few years. MBES are acoustic remote-sensing systems that record underwater topography (*bathymetry*) data with high resolution, accuracy and coverage, as well as echo-strength (*backscatter*) data from the seabed or the water-column. The continuous technological improvements of MBES systems, their increasing affordability, and the diversity of their data products have resulted in a wide integration of these data in most recent developments of BHM and ASC.

This chapter summarizes the diversity of the fields of BHM and ASC with a particular focus on the use of MBES systems. First, the diversity characterising BHM is explored through a review of the complexity of the notion of “habitat” and of the diversity of technologies available for its “mapping”. Then, the field of ASC, from which most of current BHM approaches are derived and where the use of MBES originates, is reviewed. This will be followed by a review of the acoustic seabed-mapping systems most commonly used as sources of data for ASC and BHM with a special emphasis on MBES systems, their data products, and their varied uses. Finally, the likely near-future development of both the MBES technology and the field of BHM are presented and the growing need for comparison of mapping approaches is discussed.

2.2 “Benthic habitat mapping”: a background

2.2.1 “Habitat”: an ambiguous ecological concept

To date, there is no universally accepted, standard use for the term “habitat” (Hall *et al.*, 1997; Mitchell, 2005). Yet, the basic idea behind the term is very intuitive: it designates, for a given organism, the environment where this organism is generally found. This simple notion is well illustrated by the formal definition in dictionaries (viz. Oxford, 1989):

Habitat: the natural home or environment of an animal, plant, or other organism,

or ecological glossaries (viz. Begon *et al.*, 1996):

Habitat: place where a microorganism, plant or animal lives.

Confusion develops when this definition is put to practical use. In practice, “habitat” tends to apply to a group of individuals of the same species, or *population*, rather than a single organism. A significant initial ambiguity is then apparent: is habitat the actual locality where the population is found, or the type of environment that characterises this locality (Mitchell, 2005)? Under the first view, a population’s habitat is equivalent to its spatial distribution. Under the second view, it is equivalent to the concept of *Hutchinson’s fundamental niche*, commonly defined as (Begon *et al.*, 1996):

the n-dimensional hypervolume of environmental conditions within which the organisms can maintain a viable population.

The major difference between the two views is that the physical, measurable parameters of the environment that characterise the place where a given population is found (the niche) are often not sufficient to predict the distribution of this population (the locality) because this distribution is often limited by biological factors such as competition, predation, food supply, or disease

(Mitchell, 2005). The practical use of the locality-view of “habitat” is best illustrated in species spatial distribution models, the output of which is commonly termed “habitat suitability maps” (Guisan and Thuiller, 2005), while the niche-view of “habitat” is central to animal-environment relationship analysis which allows predicting the consequences of potential human and natural environmental impacts on species’ populations.

The difference between these two views is particularly important when extending the concept of “habitat” from the species/population level to the community level. *Communities* are groups of organisms from different species that are found in the same place. Community patterns are an important focus of ecological research as they provide some simplifying structure of the geographic organisation of the biological realm that allows for ecosystem classification and management (Ferrier and Guisan, 2006). For the same reason as before, if “habitat” is limited to describing the physical environment, then its mapping will not allow prediction of community patterns. To resolve this ambiguity, the term *biotope* is often used to describe the ensemble consisting of a concept of “habitat” that is considered purely physical (niche view) and the community that inhabits it (Olenin and Ducrotoy, 2006). However, this terminology is not standard. What’s more, the term “habitat” and the above notion of biotope are frequently confused, which leads to yet two other common understandings of the term “habitat” as (1) the association of the *abiotic* (physical) and *biotic* (biological) components of the ecosystem, or even as (2) the community itself (Dauvin *et al.*, 2008).

Many pleas for consistency in “habitat” terminology have been made, both in general ecology (viz. Whittaker *et al.*, 1973; Hall *et al.*, 1997; Mitchell, 2005), and marine ecology (viz. Olenin and Ducrotoy, 2006; Dauvin *et al.*, 2008; Costello, 2009). Modifiers (*e.g. physical, natural or potential* habitats) or new terms (*e.g. ecotopes, ecosystems, landscapes*) are often suggested to attempt resolving the “habitat” ambiguity, but just like “biotope”, they invariably lead to more confusion after they are inappropriately used in subsequent scientific literature (Dauvin *et al.*, 2008).

2.2.2 “Benthic habitats”: seabed substrate or more?

In the benthic realm, the common parameters of the physical environment that will affect the potential colonisation by organisms can be separated into characteristics of the seabed (such as sediment-type, mobility, complexity, roughness, compaction, or rate of sedimentation) and characteristics of the body of water immediately above the seabed (such as temperature, salinity, oxygen concentration, light availability, and water movement) (McArthur *et al.*, 2010).

Among these physical parameters, sediment-type (commonly identified by grain-size) has often shown a strong association with species distribution or community patterns. Differences in species and community distributions are naturally observed between soft and hard substrate-types (*e.g.* Beaman and Harris, 2007; Barrie *et al.*, 2011), and between mobile and non-mobile hard substrata (Shears *et al.*, 2004), but differences have also often been reported between various types of soft sediments (Sanders, 1958; Gray, 1974; Thrush *et al.*, 2003; Anderson, 2008).

These observations lead to an impression that marine ecosystems display an animal-sediment coupling, which is in fact inaccurate (Snelgrove and Butman, 1994). Indeed, sediment-type is an important factor in the distribution of organisms, but different communities can be found in any given substrate environment (Zajac *et al.*, 2000; Newell *et al.*, 2001; Brown *et al.*, 2002; Shears *et al.*, 2004) and a given community can be found in different substrate environments (Kostylev *et al.*, 2001; Freitas *et al.*, 2003). Finally, community patterns are sometimes more clearly associated with other environmental factors than substrate such as salinity, temperature, or wave exposure, particularly at larger scales (Zacharias and Roff, 2001; Post *et al.*, 2006).

Despite the evidence of their misleading character, observations of animal-sediment correlation have driven the development of a number of classification schemes that emphasize the importance of the geological and geophysical structure of the seabed in defining habitat types (*e.g.* Greene *et al.*, 1995; Greene *et al.*, 1999; Roff and Taylor, 2000). This emphasis was mainly a response to the

urgent need for habitat classification schemes for fisheries management (Roff and Taylor, 2000) combined with the fact that underwater geology and topography are often the only parameters of the seabed that can be identified and mapped over large areas using acoustic technologies (Lurton, 2002).

The absence of a universal definition for “habitat”, the importance of seabed- type in the distribution of some organisms, the early geologically-centred classification schemes, and the ubiquity of tools and procedures for seabed-geology mapping all combined to make the seabed geology a main factor in studies concerned with mapping benthic habitats, probably beyond its actual importance (Diaz *et al.*, 2004). Early habitat mapping studies based themselves on the traditional geology-mapping procedures of their time to produce maps of “habitats” described as the combination of a type of seabed and its associated community (*e.g.* Kostylev *et al.*, 2001; Brown *et al.*, 2002), or even sometimes, the type of seabed only (*e.g.* Anderson *et al.*, 2002; Ellingsen *et al.*, 2002). This latter over-simplification has repeatedly been criticised (Diaz *et al.*, 2004; Brown *et al.*, 2011) and is now mainly discontinued (except from rare cases, *e.g.* Whitmire *et al.*, 2007; Freitas *et al.*, 2008). The most common view of benthic “habitat” nowadays is somehow equivalent to “biotope” defined previously as the combination of the physical environment and its associated community type (Brown *et al.*, 2011). In practice however, seabed-type is often the main, if not the only, physical variable used in this combination (Kostylev, *in press*).

2.2.3 “Benthic habitat mapping”: lack of a universal definition

Benthic Habitat Mapping (BHM) can be basically understood as the process of determining the spatial distribution of the variable “benthic habitat” and representing it as a map. However, since “benthic habitat” is an ambiguous and multifaceted concept for which no standard definition is universally accepted, one can expect as much of its “mapping” (Diaz *et al.*, 2004; Brown *et al.*, 2011). For example, Brown *et al.* (2011) quoted the following definition for “marine habitat mapping” from the European programme Mapping European Seabed Habitats (MESH):

Plotting the distribution and extent of habitats to create a map with coverage of the seabed showing distinct boundaries separating adjacent habitats,

only to quickly point out the limitation of this definition as excluding the approaches that avoid imposing discrete boundaries of “habitats”. As a result, the authors proposed an alternative definition of “marine habitat mapping” as:

The use of spatially continuous environmental data sets to represent and predict biological patterns on the seafloor (in a continuous or discontinuous manner).

However, even such a broad definition can be questioned as it excludes the large-scale studies that can only represent the physical properties of the seafloor (*i.e.* “abiotic” habitat mapping in Brown *et al.*, 2011), the studies based on spatially discontinuous environmental data sets such as those produced by some acoustic systems (*e.g.* Freitas *et al.*, 2003), or even earlier ecological studies – now mostly discontinued – that were not using environmental data sets at all (*e.g.* Souissi *et al.*, 2001). This illustrates that the absence of a consistent, universal definition for “benthic (or marine) habitat mapping” is mainly due to the diversity of objectives and means that characterises the existing approaches. Until a standardisation of objectives and methods is established, “benthic habitat mapping” will remain an umbrella expression designating the ensemble of these various approaches, which therefore justifies the use of its acronym “BHM”.

2.2.4 *In situ* and *ex situ* technologies

Most of the diversity of BHM approaches stems from the variety and limitations of technologies available to explore the marine environment. These technologies can be grouped in two types.

A first type of technologies, often qualified as “*in situ*” (Brown *et al.*, 2011) or “ground-truth” techniques (Anderson *et al.*, 2008), includes:

- (i) tools and methods for sampling the seabed or marine organisms (grabs, dredge, core, trawl) for later laboratory analysis and identification, and;
- (ii) optical technologies operated at a distance from the seabed or marine organisms close enough to overcome water turbidity (up to a few meters) and allow photographing or filming.

These technologies can be operated at discrete locations (point sampling) or in transects, but are inherently limited to characterising the seabed geology or biology on a small, local scale, such that charting the seafloor on a large-scale using solely these techniques would be prohibitively expensive and time-consuming. A comprehensive review of these *in situ* technologies and their *in situ* data products can be found in Brown and Coggan (2007).

All other technologies that do not directly sample the seabed or observe it from a short distance can be considered a second type of *ex situ* technologies[†]. They are often qualified as “seabed-mapping” or “remote-sensing” techniques (Kenny *et al.*, 2003; Anderson *et al.*, 2008) and their data products described as “environmental predictors” (Ferrier and Guisan, 2006) or “environmental data

[†] Contrary to *in situ*, *ex situ* is not a common terminology in the fields concerned with mapping the seabed or benthic habitats. It is suggested here because the terms mentioned in the next sentence that are more commonly used to designate this second type of technology tend to restrict the range of technologies that can be considered.

layers” (Brown *et al.*, 2011). This diversity of terminology reflects the variety of tools that composes this second category, which includes:

- (i) satellite and airborne remote-sensing systems (radar imagery, aerial photography, lidar, *etc.*);
- (ii) acoustic remote-sensing systems (seabed-mapping or water-column-imaging systems);
- (iii) modelling tools based on ocean and atmosphere physics (models of temperature, salinity, bed stress due to waves and tide action, *etc.*), and;
- (iv) other various large-scale datasets (maps of seabed geology, bathymetry from nautical charts, latitude, GIS-derived layers such as distance from the coast, *etc.*).

2.2.5 *In situ* and *ex situ* data integration (or not)

Most BHM approaches consist of the integration of *in situ* and *ex situ* datasets (Brown *et al.*, 2011). This choice stems from the complementary aspect of the two data types. *In situ* data usually perfectly measure or describe the “benthic habitat” variable to be “mapped” (*e.g.* seabed and community types can be assessed from underwater video footage, species count can be obtained from benthic sampling, *etc.*), but are too sparse in coverage to be relied solely upon. In contrast, *ex situ* data usually do not measure exactly the variable of interest and are at best a proxy of it (*e.g.* depth, latitude, acoustic backscatter image, *etc.*), but are usually acquired on a large scale with dense coverage and in a practical amount of time (Brown *et al.*, 2011).

It is worth noting that there are approaches in which “habitat maps” are obtained from the classification of one or several *ex situ* datasets without integration of *in situ* data (that is, the “abiotic surrogates strategy” in Brown *et al.*, 2011), or approaches that are based solely on the spatial extrapolation of *in situ* datasets

without integration of *ex situ* data (for example some community spatial modelling approaches, such as Souissi *et al.*, 2001). However, only the approaches implementing integration of the two types of data will be considered here. It can be argued that the maps produced by *ex situ* only approaches are of limited ecological use as they do not contain any information on marine biology (Brown *et al.*, 2011) and that the maps produced by *in situ* only approaches are becoming increasingly rare with the growing availability of environmental *ex situ* data sets.

The problem of integration of *in situ* and *ex situ* data can be approached from the “bottom-up” or “top-down”. *Bottom-up* designates a focus that is put on the *in situ* data. Under this view, the mapping issue is that of the extrapolation of *in situ* data to a large scale, for which integration of *ex situ* data (often called “predictors” in this view) can provide some help. Bottom-up BHM approaches are mainly applied in marine ecology, where they consist in the determination or modelling of the spatial distribution of a “habitat” variable obtained from *in situ* data: for example a count of organisms (Guisan and Thuiller, 2005), the presence/absence of a given population (Galparsoro *et al.*, 2009), or a type of community (Ferrier and Guisan, 2006).

Conversely, *top-down* designates a focus that is put on the *ex situ* data. Under this alternative view, the mapping issue is that of arranging *ex situ* data into a small number of significantly different regions, for which integrating *in situ* data (often called “ground-truth” in this view) can provide some help. Top-down BHM approaches typically consist in the realisation of a categorical map of a region of interest based on the spatial variations of *ex situ* data, which are assumed to be representative of “habitat” variations. This type of approaches characterises the field of Acoustic Seabed Classification.

2.3 Acoustic Seabed Classification

2.3.1 Definition and scope

Relatively recently, a comprehensive review of acoustic seabed-mapping systems and their use for seabed geology or habitat mapping was made under the auspice of the International Council for the Exploration of the Sea (ICES, 2007). The ensemble of these mapping approaches was considered to constitute a science, termed Acoustic Seabed Classification (ASC), which was defined as (ICES, 2007):

The organization of bottom types into discrete units based on a characteristic acoustic response,

even though ASC is also concerned in practice with the biological aspect of those bottom types, that is, as “habitats” (Anderson, 2007).

This definition appropriately conveys the top-down character of ASC approaches to BHM. They are focused on *ex situ* data, and specifically on backscatter data provided by acoustic seabed-mapping systems (Kloser, 2007). ASC approaches are not concerned with other *ex situ* data such as those obtained from satellite imagery, aerial photography, or oceanographic models, regardless of their habitat-discriminative power. Moreover, all ASC approaches implement a process of categorisation of a region into seabed or habitat types, hence the term “classification” (Simard and Stepnowski, 2007). Finally, this focus on *ex situ* data implies that *in situ* data are only considered for verification purposes (hence the common use of the term “ground-truth” for *in situ* data) or as a support to the classification of acoustic data (Brown and Coggan, 2007).

The focus of ASC on backscatter data from acoustic seabed-mapping systems stems from the important, and still not completely realized, potential of underwater acoustics for the study of marine geology.

2.3.2 Underwater acoustics for seabed mapping

Acoustic seabed-mapping systems are one of the many developments of *sonar* technology, which was originally designed for military applications after the end of the first World War (Urick, 1983), and which has now evolved into a wide range of military, recreational, commercial and scientific marine applications (Lurton, 2002). In particular, acoustic seabed-mapping systems are the main contributors to modern advances in hydrography and marine geosciences (Mayer, 2006). Prior to the rising interest in marine habitats, specific methodologies had been developed for processing the data from these systems to allow three interconnected applications in marine geosciences: *seabed characterisation*, *identification*, and *mapping*.

Seabed characterisation denotes the attempt at solving the acoustical oceanography Holy Grail “inverse problem” that consists of the determination, from the acoustic data, of the physical characteristics of the seabed at the origin of the echo (Lurton, 2002). These attempts are based on an understanding and modelling of the physics of interaction of sound with interfaces and volumes, which cause the acoustic signal reverberated from the interface to be dependent on characteristics of the structure of this interface, including, but not limited to, its surficial roughness, impedance, and subsurface layering (Urick, 1983). Many seabed characterisation methodologies have been designed based on extensive compilations of field measurements (*e.g.* Hamilton, 1980) and varied theoretical models of sound interaction with the seabed (*e.g.* Jackson *et al.*, 1986; APL, 1994; Guillon and Lurton, 2001).

The objective of a universal and efficient characterisation methodology has not been attained yet (Berron, 2008). The main obstacles are the extreme complexity and variety of natural seabed environments, which translate in various physical processes of influence on the signal, themselves controlled by a very high number of interdependent seabed parameters (Holliday, 2007). This natural complexity makes the inverse problem extremely difficult to solve without strong assumptions or restrictions to specific conditions. In practice, the problem is made

even more convoluted by other unaccounted or oversimplified parameters of the environment that influence the recorded signal, such as absorption and sound-velocity effects in the water-column, seabed slope or presence of biological organisms (Berron, 2008). Finally, commercial sonar systems often come without the information necessary to completely remove the built-in corrections that are usually applied to the acoustic signal (Lamarche *et al.*, 2011). Despite these major obstacles, a few methodologies have been developed to characterise the seabed from data recorded by standard commercial acoustic seabed-mapping systems, with some success (Canepa and Berron, 2006; Fonseca and Mayer, 2007). More generally, these difficulties have driven the development of empirical or heuristic approaches to achieve the more practical applications of seabed identification and mapping (Lurton, 2002).

Seabed identification denotes the attempt to determine the type of seafloor within a “restricted classification [...] using a maximum of around ten classes (*e.g.* rock, boulders and pebbles, gravel, coarse sand, fine sand, silty sand, silt and vegetal cover)” depending on the study application (Lurton, 2002). Rather than seeking to extract physical characteristics of the seabed from the acoustic signal, seabed-identification approaches rely solely on the variety of influences of these characteristics on the signal to allow discrimination between significantly different types of seafloor. Typically, seabed-identification approaches consist of processing the data in order to extract empirical features of posited seafloor-type discriminative power, and comparing the variation of these features with ground-truth data to assess their success (*e.g.* Lamarche *et al.*, 2011). A main interest of this pragmatic approach over seabed characterisation is that the lack of a restraining physical framework implies that other forms of empirical information on seabed-type than that contained in the acoustic signal amplitude can be used. For example, a particularly rich source of information for seabed identification can be found in the textures of acoustic images of the seafloor (Blondel *et al.*, 1998) or bathymetry maps (Cutter *et al.*, 2003).

Seabed mapping is the complementary process to seabed characterisation or identification that consists in determining the spatial extent of the seabed characteristics or seabed-type classes over a given region of interest.

2.3.3 From seabed to habitat mapping

Since the seabed geology and geomorphology are important components of marine habitats, acoustic seabed-mapping systems were naturally occasionally used for biological applications all throughout the development history of these tools for marine geosciences (*e.g.* Able *et al.*, 1987). However, it is only in the late 1990s, with the rising concern for marine ecosystems, that the number of these efforts significantly increased and methodologies for seabed identification, characterisation and mapping using acoustic systems were adapted for the identification and mapping of marine habitats (*e.g.* Greenstreet *et al.*, 1997; Collins and McConnaughey, 1998; McRea Jr. *et al.*, 1999).

The authors of these early habitat-mapping studies were concerned by the possibility that the geological information provided by acoustic systems might not successfully predict biological patterns. Therefore, these studies often consisted of separate biological and geological analyses (*e.g.* standard geological seabed mapping in parallel to an analysis of the distribution patterns of organisms found in sediment samples) complemented by a comparison of these results (*e.g.* Kostylev *et al.*, 2001; Brown *et al.*, 2002; Freitas *et al.*, 2003). The comparisons showed various degrees of correlation, but were globally positive enough for the authors to support the use of acoustic seabed-mapping systems for habitat mapping. Based on these early results, many subsequent studies stopped short of testing the animal-sediment relationship before associating biological and geological information. A recurrent study structure emerged consisting of classifying data from acoustic seabed-mapping systems into a number of categories to be identified by both geological and biological *in situ* data (Kostylev, *in press*).

Notably, other studies attempted in parallel to use acoustic systems and ASC techniques to directly identify and map the distribution of some specific marine species of potential influence on acoustic data. These studies were concerned for example with the characterisation of shells through physical models (Stanton, 2000), the identification of conspicuous organisms such as underwater vegetation

(Preston *et al.*, 2006; Noel *et al.*, 2008) or biogenic reef structures (Roberts *et al.*, 2005; Collier and Humber, 2007), or the prediction of the spatial distribution of some species of molluscs through a one-to-one association with an identifiable seabed type (*e.g.* scallops with gravel lag deposits in Kostylev *et al.*, 2003). These studies confirmed the potential of acoustic seabed-mapping systems and processing approaches for purely biological or ecological applications.

2.3.4 Diversity of ASC approaches

Since the acoustic signal does not actually determine the seabed substrate (let alone the associated biology), but only provides proxy information to categorise its type, the central problems in all ASC approaches are that of accessing, processing and exploiting this information. This is the origin of the great variety of approaches that can be found in the ASC literature, which is basically distributed around two axes:

- (i) the general classification approach; that is supervised or unsupervised, manual or automatic, and the choice of classification algorithm, and
- (ii) the acoustic data features used for classification; dependent on the type of acoustic seabed-mapping system being used, generally categorised as acoustic ground discrimination systems based on single-beam echosounders (SBES), sidescan sonars (SSS) or multibeam echosounders (MBES), as well as on the methodology used to process these systems' data and obtain these data features.

2.3.5 ASC general approaches and classification algorithms

While the focus of ASC is clearly on acoustic data, the top-down classification of one or several acoustic data features into a limited number of categories has traditionally been performed under two different approaches to the integration of *in situ* data: supervised or unsupervised (Simard and Stepnowski, 2007).

In the supervised approach, *in situ* data are integrated before the classification in order to guide the classification process, while in the unsupervised approach, *in situ* data are integrated after the classification for the sole purpose of identifying the resulting classes. It is important to note that both approaches make the *a priori* assumption that the data feature(s) selected for classification are able to discriminate between seafloor types. This assumption is only verified *a posteriori* by comparing the resulting classification to additional *in situ* data, set aside for this purpose. Since another distinction commonly made between methods is that of manual or automatic classification, there are in total four general approaches to ASC.

A manual supervised classification involves a subjective discrimination between seafloor types from the acoustic data by a human operator with the help of ground-truth data. This approach requires the acoustic data to be in a format that the human brain can process – usually an image – and the operator to present some experience of the task. All classification techniques were of this type prior to the advent of computers, but they are now often shunned in favour of more automatic techniques, which involve less subjectivity (Anderson *et al.*, 2008). However, the efficiency of the human brain in image classification is such that these approaches are still common, especially when one is more interested in the quality of the resulting classification than the design of a repeatable procedure (*e.g.* Ehrhold *et al.*, 2006; Collier and Humber, 2007).

A manual unsupervised classification denotes a similar process, in which an operator is responsible for the classification of acoustic data, but without the assistance of ground-truth data. Such a procedure is rarely implemented as a

mapping approach of choice since it presents as much subjectivity as the supervised method, but with a lower chance of success given the additional constraint. Its main use is as a test to assess if a classification based on acoustic data alone actually relate to the ground-truth data (*e.g.* Hewitt *et al.*, 2004; Ehrhold *et al.*, 2006).

An *automatic supervised classification* denotes the methodologies that implement the following sequence: (1) identify a scheme of seabed/habitat types from the ground-truth data, (2) train a classification algorithm on the acoustic features of each seabed/habitat type, and (3) apply the trained algorithm to the rest of the data. Supervised ASC approaches are often more successful than their unsupervised counterparts (Hutin *et al.*, 2005). Methods for automatic supervised classification include maximum likelihood estimators (Augustin *et al.*, 1997; Foster-Smith *et al.*, 2004), artificial neural networks (Müller and Eagles, 2007) and Bayes decision rules (Canepa and Pace, 2000).

An *automatic unsupervised classification* basically consists in using an automatic algorithm to classify the acoustic feature(s) into a number of categories without the assistance of ground-truth data. In this case, ground-truth data are only used after classification, to help identify the categories. In these approaches, the number of categories is established either by a human operator prior to the classification or by the algorithm itself, for more objectivity. The sole human input in this approach is the labelling of categories with ground-truth data, but it is a minor concern in terms of subjectivity since it occurs after the classification is done. The ASC community is much in favour of this type of approach for its repeatability (Anderson *et al.*, 2008). A wide range of classification algorithms has been implemented in automatic unsupervised approaches including k-means clustering (Fonseca and Calder, 2007; Blondel and Gómez Sichi, 2009), Bayes decision rule (Simons and Snellen, 2009), complex clustering processes (Preston, 2009), and self-organising artificial neural networks (Marsh and Brown, 2009).

2.3.6 Bottom-up approaches

In the top-down supervised approaches described above, *in situ* data are used to guide the acoustic classification process under an *a priori* assumption that the data feature(s) selected for classification are able to discriminate between seabed/habitat types. A bottom-up approach is a very similar process albeit for one fundamental difference: the capability of the data features to discriminate between habitat/seabed types is established rather than assumed.

The central methodological difference between a traditional top-down supervised ASC approach and a bottom-up approach is therefore that the latter starts with a statistical analysis to assess the relationship between *in situ* and *ex situ* data. Statistical methods such as discriminant analysis (Hutin *et al.*, 2005), redundancy analysis (Hewitt *et al.*, 2004), decision trees (Ierodiconou *et al.*, 2007; Rooper and Zimmermann, 2007) and various multivariate statistical techniques (Brown and Collier, 2008; Shumchenia and King, 2010) have been implemented with success. These statistical analyses usually result in a function of prediction of the *in situ* variable of interest based on *ex situ* data, which can then be extended to locations where *in situ* data are absent in order to achieve the classification.

These relatively recent bottom-up approaches to BHM and ASC present two main advantages over the traditional top-down ASC approaches. First, they circumvent the usual implicit assumptions that acoustic patterns correspond to seabed-type patterns and that seabed-type patterns correspond to biological patterns (Kostylev, *in press*). Second, since the link between *in situ* data and *ex situ* data is tested rather than assumed, these methods can handle and test a wide range of different *ex situ* data types and are expected to provide better results in these conditions. For example, current bottom-up approaches are often implemented on data features extracted from bathymetry datasets in addition to backscatter datasets (Ierodiconou *et al.*, 2007; Shumchenia and King, 2010).

2.4 Acoustic seabed-mapping systems and data features for classification

Acoustic seabed-mapping systems for ASC and BHM are generally categorised as either acoustic ground discrimination systems based on single-beam echosounders (SBES), sidescan sonars (SSS) or multibeam echosounders (MBES, Kenny *et al.*, 2003). In reality, there are other types of swath bathymetric systems commonly used that blur the difference between SSS and MBES (*e.g.* bathymetric SSS systems), or do not fit the “multibeam” terminology (*e.g.* hull-mounted bathymetric interferometers, which do not implement a beam-forming algorithm). Nevertheless, this categorisation is useful since mapping approaches can be widely different depending on the capability of the systems to record bathymetry or not. Therefore and despite the imperfection of these terminologies, the “SSS” category usually implies NON-bathymetric seabed-imaging sidescan sonars, while the “MBES” category usually implies all types of bathymetric seabed-imaging systems, including bathymetric sidescan sonars and hull-mounted bathymetric interferometers.

2.4.1 Sidescan sonars

First designed in the late 1950s, sidescan sonars (SSS) were the first acoustic seabed-mapping systems allowing underwater geological identification (Stride, 1992). SSS are acoustic systems towed close to the seafloor that transmit sound pulses on both its sides within single beams that are wide in the across-track plane, but narrow in the along-track direction, so as to “sweep” the seabed in a narrow across-track stripe (Lurton, 2002). The sound pulses are then backscattered from the interface at increasingly low incident angles as they propagate, and the backscattered signal is recorded as a single trace on each side. Traces are stacked as the SSS system is towed, thus effectively “scanning” the seabed on both sides. The stacked traces resemble acoustic “images” of the seafloor of excellent resolution (down to 5cm for most recent systems), in which variations in intensity reveal the variations in hardness or micro-roughness of the seabed features, and projected acoustic shadows reveal the general seabed geomorphology. The part of these images corresponding to the water-column is

then removed, and the images can finally be projected onto a georeferenced surface to form the final seabed image that is commonly called an SSS *mosaic*.

SSS mosaics are the main sources of data for manual ASC approaches relying on interpretation by experienced geophysicists (Ehrhold *et al.*, 2006). With the advent of digital processing, automatic methodologies were designed to extract features from SSS data that could be used for classification. These data features can be grouped in two main categories:

- (i) data features characterising the image textures, the classification of which can be seen as an attempt to imitate or even outperform human image recognition (*e.g.* Blondel *et al.*, 1998; Huvenne *et al.*, 2002), and;
- (ii) data features characterising the signal itself; for example statistical moments within neighbourhood of pixels (Preston *et al.*, 2004; Brown and Collier, 2008), spectral features obtained from Fourier analysis (Pace and Gao, 1988), or wavelet transform (Atallah *et al.*, 2002).

In addition to seabed/habitat classification, SSS are also occasionally used in some characterisation studies that attempt to relate statistics describing the grey-level of the mosaic with sediment grain-size (Collier and Brown, 2005).

The main shortcoming of traditional SSS systems is that they cannot resolve the angle of arrival of the backscatter signal and therefore cannot measure bathymetry. Traditional SSS mosaics are formed by assuming a flat bottom, which causes inaccuracy in the location of features. Additionally, even though SSS systems operate mostly at low-incidence angles where angular variations are not critical, the lack of bathymetry measurement implies that the dependence of backscatter intensity with angle of incidence cannot be properly compensated. These two issues, along with the ubiquity of acoustic shadows on the images, result in the seabed aspect on traditional SSS mosaics being strongly dependent on the position of the system at the time of acquisition, which is a main obstacle to the repeatability of classification results. The ability of more modern SSS systems to measure bathymetry through interferometric processing significantly reduces

those limitations and allows similar processing approaches to that of MBES systems.

2.4.2 Single-beam echosounders

The single-beam echosounder (SBES) technology is the simplest, oldest (in use since the 1920s) and still most common form of technology for measuring water depth (Urlick, 1983; Lurton, 2002). SBES systems achieve this purpose by transmitting sound pulses within one large beam, directed vertically downwards from the ship, and timing their return. The use of these systems for seabed identification and mapping started in the 1980s with the development of methodologies to exploit the dependence of the echo shape in SBES signal with seabed hardness and roughness (Pace and Ceen, 1982; Burns *et al.*, 1985; Chivers *et al.*, 1990).

The two main features that can be extracted from SBES acoustic data for seabed classification are the energy in the tail of the main echo and the energy of the first of the multiple echoes (Chivers *et al.*, 1990). Many commercial systems implement classification approaches based solely on these two data features, as the first is characteristic of seabed roughness and the second is characteristic of seabed hardness (Michaels, 2007). A different system, QTC View, operates by extracting a large number of data features from the main echo only and then selects the most appropriate features for classification through a Principal Component Analysis (Hamilton *et al.*, 1999).

These commercial SBES-based approaches to seabed identification and mapping have often been termed Acoustic Ground Discrimination Systems (AGDS) (ICES, 2007), or more recently SB-AGDS to avoid confusion with similar commercial systems based on MBES or SSS that have been developed since (Brown *et al.*, 2011).

The major advantage of AGDS based on SBES is their turnkey, automatic approach to seabed mapping. Both supervised and unsupervised approaches are

possible, but the unsupervised version is often preferred as it allows exploiting fully the objectivity of these methods. Their major shortcoming is an extremely low resolution, which is inherent to the SBES technology on which they are based, and a characteristic inability to produce a spatially continuous output unless completed by some spatial interpolation. These defaults have resulted in mixed success depending on the complexity of the seabed environment to be mapped (Freitas *et al.*, 2003; Hewitt *et al.*, 2004; Hutin *et al.*, 2005). Despite their limitations, these systems remain popular as an inexpensive and highly objective approach to seabed/habitat identification and mapping (Freitas *et al.*, 2008; 2011).

2.4.3 Multibeam echosounders

Multibeam echosounders (MBES) are acoustic systems typically mounted close to the surface, on a ship hull, which transmit and receive a wide across-track fan of multiple, individually small beams directed at the seabed below the ship, so as to insonify and record data from a large corridor of seabed centred on the ship's track (Lurton, 2002). The multiple beams are obtained from an electronic processing known as "beamforming", which involves either Fast Fourier Transform (FFT) or increasingly, phase-shifting and summing of the signals received by the individual transducers composing the receiving array. Detection of the bottom within each beam is usually obtained through analysis of the peak amplitude for central beams and through interferometry for outer beams. Bathymetric sidescan sonars or hull-mounted interferometers rely solely on this interferometric approach to achieve the same purpose as MBES without the formation of multiple beams.

MBES were designed in the late 1970s for the acquisition of multiple simultaneous depth measurements allowing the production of high-resolution bathymetric maps (Mayer, 2006). A complementary capability of recording backscatter data from the seafloor was developed in the late 1980s (De Moustier, 1986). After decades of continuous improvements in MBES technology, data storage, data processing capabilities, vessel motion measurement and positioning, the bathymetry and backscatter data outputs produced by modern MBES have

now reached unprecedented resolution and accuracy (Mayer, 2006). Most recent MBES systems have the additional capability to record backscatter data from the water column, which has already shown a high potential for the detection and mapping of seabed vegetation (Kruss *et al.*, 2008; McGonigle *et al.*, 2011). The diversity of these data outputs implies a high number of potential different data features for multiple approaches to BHM or ASC.

2.4.3.1 Bathymetry

Water depth is a data type of minimal use to studies concerned with seabed geology, in comparison to backscatter data. However, it is a major feature for habitat mapping, as it is an excellent proxy for all physical variables of the body of water immediately above the seabed (light availability, temperature, or oxygen concentration) and as such, is of major importance in the distribution of organisms. Therefore, bathymetry is a data type that is rarely used in ASC approaches for seabed mapping, but is a fundamental input in BHM.

A second main interest of the bathymetric datasets produced by MBES systems is their high resolution, which allows the production of a number of data features describing the local spatial variations of water depth, akin to slope or roughness. In a pioneer study using Fourier histogram textures, Cutter *et al.* (2003) explored the potential of these local variations in MBES bathymetry for top-down, unsupervised ASC classification. More recently, a number of studies have used MBES datasets to derive bathymetric equivalents to indices describing the local topography that are commonly used in terrestrial ecology, including Topographic Position Index (Iampietro *et al.*, 2005), Roughness (Ierodiaconou *et al.*, 2007), Rugosity (Wilson *et al.*, 2007), and Terrain Ruggedness Index (Marsh and Brown, 2009). These indices, grouped under the term “morphometrics” (Brown *et al.*, 2011), have so far been mainly used in spatial distribution modelling of individual species (Galparsoro *et al.*, 2009) or in bottom-up ASC approaches as alternatives or complements to backscatter features (Rattray *et al.*, 2009).

It is important to note that these morphometrics cannot entirely replace backscatter data for the characterisation and identification of geology, as they are limited to the resolution of the bathymetric dataset from which they are computed. In comparison, the variations in backscatter data are usually characteristic of geology and geomorphology variations that are much smaller than the resolution of bathymetry or even backscatter datasets. By covering a different scale range, morphometrics and backscatter data features are therefore complementary.

2.4.3.2 Mosaic

Since MBES backscatter data are recorded within a wide across-track swathe, they can be processed into an acoustic image of the seabed in a similar way as the SSS traditional mosaic output. However, the differences between the MBES and SSS technologies result in a number of differences between the two types of images (Le Bas and Huvenne, 2009).

First, MBES images display much less acoustic shadowing than their SSS counterparts, as MBES are not towed close to the seafloor like SSS, but mounted near the water surface. The absence of acoustic shadows in MBES images implies that they lack most of the textures that facilitate seafloor identification on SSS images, but also results in MBES images presenting an aspect that does not depend as much on the system's position at time of acquisition. Second, MBES raw images typically display a strong along-track banding resulting from the variation of backscatter strength with incident angle, which is much more marked than on SSS images since MBES record data from a wider range of incident angles, typically from 0° at nadir to more than 60° for outer beams. Last, the differences between the two systems in terms of data acquisition approach (SSS low-incidence “sweeping” compared to MBES beam-forming) and altitude above the seabed result in MBES images typically presenting a coarser resolution than SSS images.

As a result of these differences, SSS mosaics have long been preferred over their MBES counterpart for seabed imaging. However, recent improvements in MBES

image resolution and processing techniques to compensate for the banding effect have resulted in MBES imagery improving to the point where their quality is approaching that of SSS imagery, albeit for the absence of shadows. This improvement, combined with the possibility to exploit bathymetry and the ease of using a system hull-mounted rather than towed have contributed to the growing use of MBES systems for backscatter image classification in place of SSS mosaics.

The similarity with SSS mosaic means that most features extracted from SSS data for classification can also be extracted from MBES backscatter images, including amplitude statistics (Marsh and Brown, 2009), indices from grey-level co-occurrence matrices (Blondel and Gómez Sichi, 2009), and features describing the signal power spectrum (Preston, 2009).

2.4.3.3 Angular response

Ironically, the same variation of backscatter strength with incident angle that is responsible for the undesirable banding effect on MBES imagery is the second major advantage of MBES backscatter data. In effect, this variation, commonly known as *angular response*, has long been known to be dependent on seabed type and therefore to present a great potential for seabed identification (Urlick, 1983). Most research efforts relating to seabed characterisation using commercial sonar systems were actually concentrated on the MBES system through the comparison of the recorded angular response to theoretical models (de Moustier and Alexandrou, 1991; Michalopoulou *et al.*, 1994; Hellequin *et al.*, 2003; Canepa and Berron, 2006; Fonseca and Mayer, 2007).

Backscatter angular response is the source of many data features for seabed identification and mapping, including various empirical parameters describing the shape of the response (Beyer *et al.*, 2007; Parnum *et al.*, 2007; Marsh and Brown, 2009), and solutions to a geoacoustic model fitted to the response (Fonseca *et al.*, 2009; Lamarche *et al.*, 2011).

2.5 Summary, perspectives and conclusion

2.5.1 The need for comparison

This review described the wide diversity of existing approaches to classify a given region of the bottom of the ocean into discrete seabed or habitat types, from acoustic (and/or other) datasets. It showed that the origins of this variety are multiple, but mainly include: the absence of a clear, universal definition for a benthic “habitat”, the wide range of technologies available to access the seabed, the difficulties to relate acoustic data to seabed characteristics, the development of computer capabilities for automatic and objective data processing, and the growing availability of MBES systems and their multiple data products.

In parallel to this expanding diversity, there have been clear efforts made by the BHM and ASC scientific community to try to constrain these developments in order to evolve towards a much-needed future standardisation. These efforts have been expressed through:

- (i) the publication of concerns about the limitations of current terminologies and methods (Diaz *et al.*, 2004; Kostylev, *in press*);
- (ii) regular reviews of, and attempts at classifying, the diversity of technologies and approaches (Kenny *et al.*, 2003; ICES, 2007; Brown *et al.*, 2011), and;
- (iii) increasingly frequent applications of different approaches to a common site (sometimes using a common dataset) for the purpose of comparing their respective success and limitations (Hamilton *et al.*, 1999; Hewitt *et al.*, 2004; Brown *et al.*, 2005; Hutin *et al.*, 2005; Brown and Blondel, 2009; Shumchenia and King, 2010).

This last type of effort is the expression of a necessity to identify the most efficient approaches to ASC and BHM, given specific mapping objectives and

types of environment. These comparative studies rely on the development of standard methods and measures for the assessment of the success of a map against ground-truth data and of map similarity. However, while a number of measures of map success are available and are being increasingly used in individual and comparative BHM or ASC studies (e.g. Rooper and Zimmermann, 2007; Lucieer, 2008; Walker *et al.*, 2008), there is a lack of measures of map similarity and particularly of measures that can be applied even in the case of a mismatch between the legends of the maps to be compared.

2.5.2 Perspectives of evolution

The latest developments in BHM and ASC show a clear evolution towards more objective and complex approaches, while highlighting the limitations of traditional top-down approaches to reliably explain biological patterns. Increasingly, mapping methods cross over between ecology (mostly bottom-up views) and geology (mostly top-down views), which should result in the development of hybrid methods that exploit acoustic data in an increasingly efficient manner to characterise marine habitats without *a priori* assumptions on animal-sediment relationship. Such hybrid methods would most likely implement a combined use of multiple *ex situ* data types, which would support the use of systems capable of providing several of them and encourage the research for new data sources of potential habitat discriminative power.

The MBES technology itself is still evolving. New systems include an ever-increasing number of beams and coverage, which translates to bathymetry data that are both denser and of better quality. The resolution of MBES backscatter data keeps improving and methodologies for processing them into a higher quality acoustic image are becoming commonplace in commercial software. It is also expected that the new capability of MBES for water-column imaging will provide new features to characterise the vegetation cover, which should revolutionise the characterisation of hard-substrate habitats, which are mainly categorised by this parameter (Shears *et al.*, 2004). Finally, the MBES transducer technology is evolving towards the use of wider bandwidths, which will add a frequency

dimension to the analysis of the angular response and should yield new features for seabed discrimination. Given the evolution of BHM and ASC approaches towards a more general use of multiple datasets, it can be confidently predicted that MBES systems will remain the main data-providing technologies for the future developments of BHM and ASC.

2.5.3 Conclusion

After this short review of the diversity characterising the fields of BHM and ASC, the next chapters of this thesis will focus on the need for tools to achieve map comparison and on the need for integrating the multiple data products of MBES systems, as identified in the previous sections. These chapters will implement a number of BHM and ASC case studies, introduce and test methods for the assessment of map similarity withstanding potential mismatch in legends, and develop methodologies for extracting, processing and combining MBES data products for the purpose of classification.

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CHAPTER 3

THE ISSUE:

A CASE STUDY COMPARISON OF MBES DATA PRODUCTS WITH THAT OF SBES AND SSS.

3.1 Preface

This chapter was peer-reviewed and published as an article in the *Journal of Coastal Research* in 2010. It is reprinted here with only minor edition of acronyms, figure and table numbers and format, and references in order to match the thesis format. Since this chapter was written to stand alone as a published article, it contains minor repetitions of reasoning previously found in this thesis and objectives that may differ from those of the thesis.

I, Alexandre Carmelo Gregory Schimel, assume responsibilities for fieldwork, laboratory and data analysis, development of methods, and writing, unless specified within the text. The work was undertaken with the supervision and editing input of Professor Terry Healy and Dr. Peter McComb, and the significant involvement of Dirk Immenga for the mobilisation and use of the acoustic systems.

The recommended format for the purpose of citation is:

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3.2 Abstract

A methodology for automatically processing the data files from an EM3000 multibeam echosounder (Kongsberg Maritime AS, 300 kHz) is presented. Written in Matlab, it includes data extraction, bathymetry processing, computation of seafloor local slope, and a simple correction of the backscatter along-track banding effect. The success of the latter is dependent on operational restrictions, which are also detailed. This processing is applied to a dataset acquired in 2007 in the Tamaki Strait, New Zealand. The resulting maps are compared with a habitat classification obtained with the acoustic ground-discrimination software QTC View linked to a 200-kHz single-beam echosounder and to the imagery from a 100-kHz sidescan sonar survey, both performed in 2002. The multibeam backscatter map was found to be very similar to the sidescan imagery, quite correlated to the QTC View map on one site but mainly uncorrelated on another site. Hypotheses to explain these results are formulated and discussed. The maps and the comparison to prior surveys are used to draw conclusions on the quality of the code for further research on multibeam-based benthic habitat mapping.

Additional index words: MBES, SBES, SSS, AGDS, reflectivity, backscatter, seafloor slope, XTF, Te Matuku marine reserve.

3.3 Introduction

The decline of worldwide marine environments has recently raised an awareness of the importance of the “sustainable management” of marine ecosystems (Jackson *et al.*, 2001; Pauly *et al.*, 2002). This, consecutively, triggered an increase in research efforts for mapping, classifying, and understanding seafloor habitats (see, *e.g.*, Ministry of Fisheries and Department of Conservation, 2008, for the latest seafloor habitat classification effort in New Zealand). A number of different acoustical mapping systems are often used in ecological studies to characterize the physical parameters of the benthic habitats of interest. The most widely used are the single-beam echosounder (SBES), coupled to an acoustic ground discrimination system or (AGDS), such as RoxAnn or QTC View, and the sidescan sonar (SSS), but particular attention has been given recently to the multibeam echosounders (MBES) because of their ability to provide full-coverage maps of precise bathymetry and coregistered, quantitative backscatter (Anderson *et al.*, 2008; Kenny *et al.*, 2003). A range of methods making use of MBES bathymetry and/or backscatter mapping has already been designed and implemented to help with ecological mapping of the seafloor at various scales: Human interpretation and classification of bathymetry and backscatter images aided with ground-truthing (Kostylev *et al.*, 2001; Roberts *et al.*, 2005), automated classification of multibeam bathymetry maps (Cutter *et al.*, 2003) or backscatter data (Brown and Blondel, 2009) and new “bottom-up” approaches to relate acoustic data and ground-truth (Rooper and Zimmermann, 2007).

The University of Waikato, Department of Earth and Ocean Sciences, owns a Kongsberg Maritime EM3000 multibeam echosounder for its various research projects in the coastal zone that require precise bathymetry data and recently expressed interest in using this system for Benthic Habitat Mapping (BHM). As a preliminary step, it was desirable to estimate its potential in comparison with its more traditional counterparts in this field: the AGDS and the SSS technologies. Documented comparison studies among classifications from different AGDS or between AGDS and SSS are common (Foster-Smith *et al.*, 2004; Hamilton *et al.*,

1999), but studies that include MBES in the comparative process have been, so far, either limited to theoretical performance (Kenny *et al.*, 2003; Le Bas and Huvenne, 2009) or used proprietary software (Preston *et al.*, 2003). The existence of prior BHM studies near the University of Waikato in the Tamaki Strait (Hauraki Gulf, New Zealand) realized with QTC View and a 100-kHz SSS provided the opportunity for an experimental comparative study of our MBES output with these systems to assess its potential for future habitat mapping surveys (Figure 3.1).

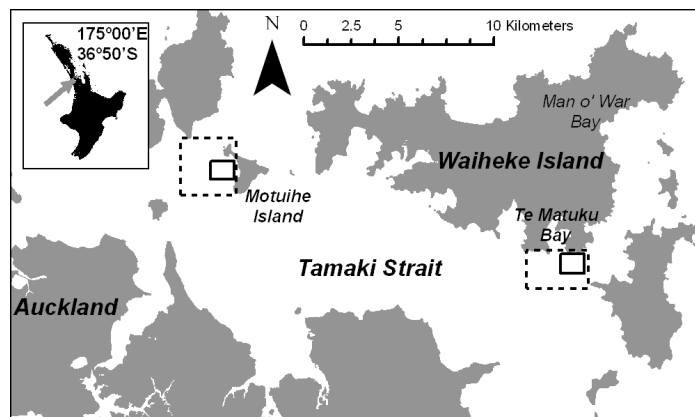


Figure 3.1. Site location in the Tamaki Strait, New Zealand. The dashed squares represent the extent of the QTC View survey sites (and also sidescan sonar survey for the Te Matuku site), and the solid squares represent the extent of the multibeam survey sites.

At the beginning of this research, the University of Waikato was using the Triton Imaging Inc. software suite for multibeam bathymetry data acquisition (ISIS) in the XTF file format (eXtended Triton Format) (Triton Imaging Inc., 2006) and processing (BathyPro). Although ISIS could record backscatter data along with bathymetry in the XTF files, the software suite did not have the capability to extract and process this data type further. In addition, no other software was found to have both the capability of MBES backscatter processing and the support of EM3000 data in the XTF format. Because the complete replacement of the current acquisition procedure was out of question, it was decided to design Matlab codes to read the XTF files, extract the backscatter data, and realize the necessary corrections following techniques described in detail in the scientific literature. In this article, the current status of the processing code is presented. It includes backscatter data extraction and a simple correction of the backscatter along-track

banding effect. The success of this simple correction depends on operational restrictions that are also detailed. The code also includes extraction and correction of bathymetry data followed by computation of seabed slope because the precise coregistration of this data type with backscatter is a requisite for further complex backscatter correction.

An EM3000 MBES survey was conducted in August 2007 in the Tamaki Strait on the same sites previously surveyed for habitat mapping for the comparison study and to provide a pool of multibeam data for the development of the processing code. Accordingly, the objectives of this article are (1) to present the simple MBES data processing methodology, to assess its success with the results on the Tamaki Strait datasets, and to identify further potential improvements; and (2) to evaluate the potential of the resulting MBES maps for BHM by comparing with the maps from previous QTC View and SSS surveys.

3.4 Background

In 1996, the Unitec Institute of Technology (Auckland, New Zealand) performed a series of dives outside the Te Matuku bay, south of Waiheke Island, a site proposed for a marine reserve (Figure 3.1). The area was found to be predominantly covered in fine, silty mud with extensive bioturbation in some areas, occasional patches of shell debris or beds of Horse Mussel (*Atrina zelandica*), and rocky outcrops around headlands and islands (The Royal Forest and Bird Protection Society of New Zealand Inc., 1998).

In 2002, the National Institute of Water and Atmospheric Research (NIWA) realized habitat maps of several sites in the Hauraki Gulf using the AGDS QTC View and underwater video footage for ground-truthing (Morrison *et al.*, 2003). This work was commissioned by the Department of Conservation (DoC) to provide an overview of the types of benthic habitats in the area that would assist the potential placement of marine reserves. One of these sites was the area described previously, outside Te Matuku bay, and another one was located west of Motuihe Island at the western end of the Tamaki Strait (Figure 3.1). QTC View is

an AGDS by Quester Tangent Corporation, which performs a cluster analysis of the three principal components from a Principal Component Analysis run on 166 features extracted from the bottom echoes within the signal of an SBES to deliver a classification of seafloor types (Hamilton *et al.*, 1999; Preston *et al.*, 2004a). This system is widely used in conjunction with a ground-truthing survey for the mapping of benthic habitats (Anderson *et al.*, 2002; Ellingsen *et al.*, 2002; Freitas *et al.*, 2003). In the Hauraki Gulf survey, QTC View was linked to a Simrad EA501P SBES working at an operating frequency of 200 kHz, with a ping rate of 5 Hz and a fixed beam width of 7° (Morrison *et al.*, 2001; Morrison *et al.*, 2003) and was run in unsupervised mode (Preston *et al.*, 2004a). QTC View delivered a class type for each stack of 5 pings, resulting in a typical along-track resolution of 6 m, whereas the typical across-track resolution was equal to the distance between vessel tracks, approximately 120 m. A nearest-neighbour interpolation algorithm allowed extending the classification results to completely cover the entire area. A targeted video-camera survey followed the acoustic mapping to ground-truth the resulting map (Morrison *et al.*, 2003). The Motuihe site displayed high acoustic and habitat variability, namely, soft to hard mud, sand, coarse sand, heavy dead shells, cobbles and screw shells (*Maoricolpus rosea*) (Figure 3.2). Abundant and diverse epifauna was also reported. On the contrary, the Te Matuku site was characterized by poor acoustical and habitat variability; identified habitats ranged from very soft mud to mud with some shells (Figure 3.2).

The same year, the University of Waikato obtained an SSS imagery of the Te Matuku site using a Klein 595 SSS working at an operating frequency of 100 kHz. This work was also commissioned by the Department of Conservation to help with identifying the types of habitats within the proposed marine reserve boundaries. The surveyed area coincided with the extent of the QTC View survey. The imagery was created with a resolution of 1 m. No ground-truthing survey followed this mapping.

The Te Matuku Marine Reserve was established in 2005, covering a total of 690 ha, including the intertidal Te Matuku Bay, and extending into the deeper water of the Waiheke Channel approximately to the boundaries of the QTC View and

sidescan surveys coverage (Department of Conservation, 2005). The maximum depth of the reserve is 25 m.

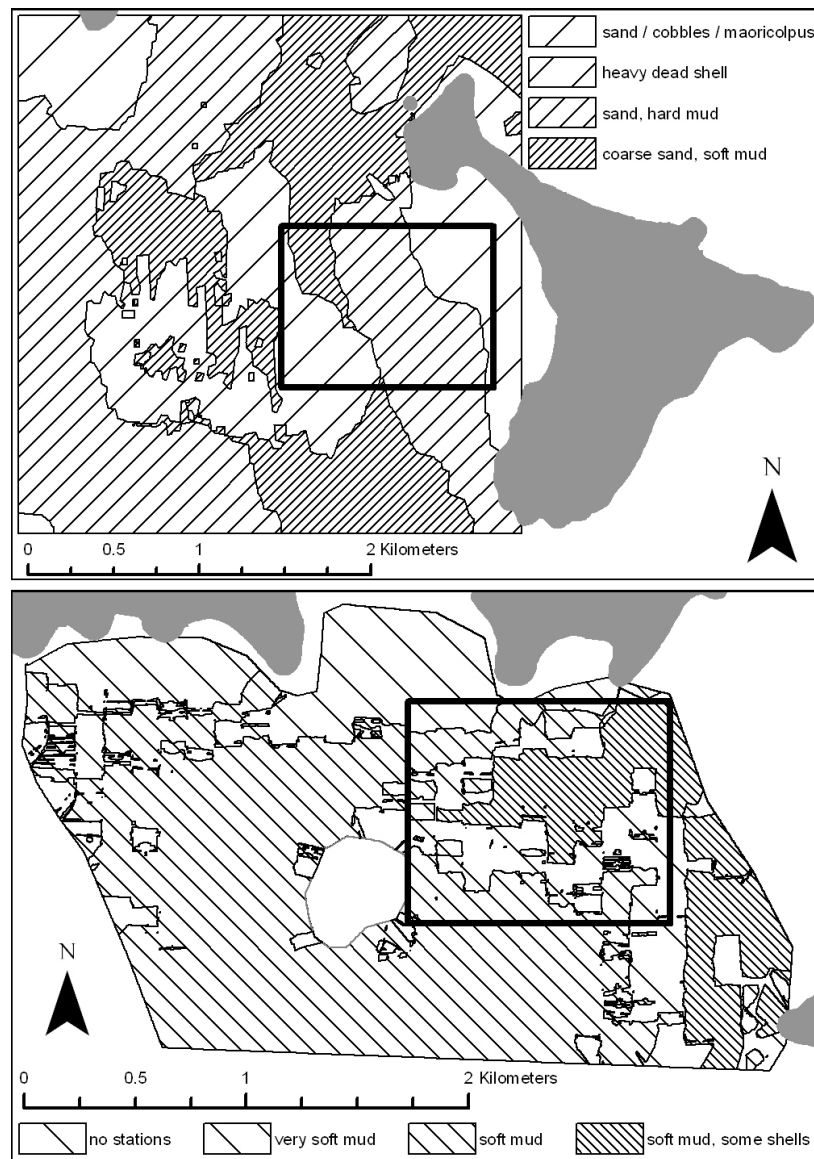


Figure 3.2. QTC View classifications of the Motuihe (up) and Te Matuku (down) sites from Morrison *et al.* (2003). Legends indicate results of the ground-truthing survey. The solid squares are the extents of the multibeam surveys.

3.5 Methods

3.5.1 Multibeam Survey Sites

The multibeam survey was carried out on the Motuihe and Te Matuku sites on the 14th, 21st, and 22nd of August 2007. At each site, a rectangular area of approximately 1 km² was mapped, with “100% coverage” ensured by running survey lines so that outer beams of two consecutive lines were slightly overlapping. At the Motuihe site, the multibeam area was located in the centre-eastern part of the QTC View area, outside Waihaorangatahi Bay (Figure 3.2). At the Te Matuku site, the multibeam area was located in the northeastern corner of the QTC View area, outside Otakawhe Bay (Figure 3.2). The choice of the Motuihe and Te Matuku sites for the MBES survey among the other areas previously surveyed with QTC View arose from the QTC View survey conclusions that these two areas present fundamentally different habitat and acoustical response variability; such a wide range of bottom variability would allow testing of the robustness of a future automated processing of the multibeam data. Although smaller than the original QTC View sites, both multibeam survey sites boundaries were defined so that they covered sufficient occurrences of all habitats identified on the full QTC View sites as well as the full depth range of the area. In the following reporting, the names Motuihe and Te Matuku describe both the multibeam survey sites and the QTC View survey sites, although their respective extents are different.

3.5.2 Equipment and Data Information

The EM3000 MBES was operated from the research vessel *Tai Rangahau* at a cruising speed of approximately 5 knots. A TSS Meridian Attitude and Heading Reference System (MAHRS) motion sensor ensured the measurement of vessel attitude and a Trimble MS750 GPS, computing a Differential Global Positioning System (DGPS) solution, ensured the measurement of vessel position. The EM3000 hardware was computing the ray-bending solutions from a sound-velocity profile acquired at the beginning of each day of survey by an Applied Microsystems Ltd SVPlus.

The EM3000 typically transmits a pure tone pulse of 300 kHz and 150 μ s long within a swath of 130° (across-track) *per* 1.5° (along-track), at a ping rate varying with water depth. On receive, the signal is sampled at a rate of 15 kHz, and 127 beams are formed using the Fast Fourier Transform (FFT) algorithm. The receiving beam width in the across-track plane varied with the beam steering angle from 1.5° at normal incidence up to 3.0° at $\pm 60^\circ$ (Kongsberg Maritime AS, 2001). The average ping rate for the Hauraki Gulf surveys was around 9 Hz, which produced an average density of soundings on both sites of approximately 12 *per* square meter.

The data were acquired with Triton Imaging Inc. ISIS software and recorded in XTF files. The tide level, measured by a tide gauge in Auckland, was provided by Ports of Auckland and compensated for the difference in tidal phase and amplitude between Auckland and the survey sites. The compensation was based on cotidal factors and time differences provided by Ports of Auckland for the Motuihe site and on tide range and delay information for Man o' War Bay (in the Waiheke channel, northeastern part of Tamaki strait, see Figure 3.1) from the New Zealand Nautical Almanac 2007–08 for the Te Matuku site (Land Information New Zealand, 2007).

The XTF files recorded during this survey contain data in various formats: *Depth* and *Seabed Image* datagrams, following Kongsberg Maritime format terminology (Kongsberg Maritime AS, 2006), and *XTFAttitudeData* and *XTFPingHeader* datagrams, following Triton Imaging Inc. format terminology (Triton Imaging Inc., 2006). The *Depth* data packets contain, for each ping and each of the 127 beams, a single sounding position and a single *Reflectivity* value. The bathymetry processing described below made use of the soundings position in Cartesian coordinates (*across-track distance* / *along-track distance* / *depth*, with reference to the sonar-head depth and the GPS antenna horizontal location). The *Reflectivity* value is in decibels at a half-decibel precision and is an average value of the signal amplitude recorded in the *Seabed Image* data packets after the Time Variable Gain (TVG) law has been taken out (Hammerstad, 2000), therefore, allegedly representing the *Target strength (TS)*, *i.e.*, the ratio in decibels of the intensities of

the backscattered and incident signal (Lurton, 2002). The *Reflectivity* processing described below made use of this single value per beam. Vessel heading and position were respectively extracted from the *XTFAttitudeData* and *XTFPingHeader* data packets. Ping bathymetry, ping reflectivity, vessel heading, and vessel position values are time-tagged in their respective data packets.

3.5.3 Bathymetry Processing

The bathymetry processing was similar to the classical sequence performed by any commercial multibeam data processing software displaying bathymetry data onto a georeferenced map. Processing of the data from the ancillary sensors (heading and GPS position) included filtering out the outliers, interpolating the data to match the pings time, correcting for navigation latency computed from a prior calibration (or *patch*) test, converting the WGS84 GPS coordinates to a suitable map projection (Universal Transverse Mercator or New Zealand Transverse Mercator 2000) and correcting the heading for grid convergence. Processing of bathymetry data included correcting the sounding positions for the sonar head angular offsets computed from a prior calibration test, correcting the sounding altitude values for the sonar head depth and the tide referenced to a desired datum, applying heading and vessel position to the sounding horizontal position values, and gridding the resulting Easting/Northing coordinates at a 1-m resolution. Lastly, an interpolation algorithm was run on the resulting digital terrain model (Easting/Northing/Depth) to give a value to the few isolated empty grid cells located in between runlines with insufficient overlapping. Note that this methodology did not include a recomputation of the ray-bending solution after the angular offsets correction. This step will be included in further refinements of the processing code.

A map of local seafloor slope was then obtained using a local plane-fitting algorithm applied sequentially to each cell from the gridded bathymetry. Because the number of neighbouring cells to include in the algorithm controls the scale of the resulting slope, this parameter (henceforth, referred to as the *slope scale parameter*) was left to the user. Practically, the neighbouring cells used in the

algorithm were those situated at a Manhattan distance from the centre cell that was smaller than the input parameter. With a small parameter value, only the few closest cells were used, and the map displayed the very local roughness (down to a minimum of 1-m resolution). With a larger parameter value, further cells were used, and the map displayed the global terrain slope trend.

3.5.4 Reflectivity Processing

The interaction of an acoustic signal with the seabed is a complex physical phenomenon controlled by numerous parameters depending on the signal characteristics (frequency, pulse length, source level, beam pattern, *etc.*), the geometry of the signal–seafloor interaction (angle of incidence, surface of insonification, *etc.*), and the seafloor geoacoustic properties (roughness, impedance, heterogeneity, *etc.*). Ideally, one would want to compensate for the two first types (respectively, radiometric and geometric corrections) so that the residual signal variations are only representative of changes in seafloor composition. The knowledge of the signal parameters at time of acquisition usually allows simple and efficient radiometric corrections, but the geometric corrections are more complex, especially the compensation of the variation with angle of incidence, because the effects to compensate are dependent on seafloor type.

The variation of the returned acoustic signal with angle of incidence (the angle between the incident sound wave and the perpendicular to the seafloor) is due to different physical processes involved at different angles: specular reflection at low incident angles (at nadir for a flat seafloor), microroughness backscattering at high incident angles (toward outer beams for a flat seafloor), and a mix of these two processes, as well as backscattering by volume heterogeneities, at intermediate angles (Lurton, 2002; Urick, 1983). (Note: for convenience and according to the common usage, the terms *backscatter* and *reflectivity* are used in this article, independently of the actual physical processes involved, to describe the intensity of the returned signal). Inherently, different seafloor types and orders of roughness will induce different backscatter variation with incident angle (often

termed *angular response*). Some methodologies actually attempt to discriminate among seafloor types and degrees of roughness from the varying angular response in the multibeam data (Fonseca and Mayer, 2007; Hughes Clarke, 1994). For common seafloor conditions, the angular response displays a global decrease with increasing angle of incidence, which appears on raw multibeam backscatter maps as a strong along-track banding.

Because it is dependent on seabed characteristics, the compensation of this along-track banding effect with theory-based techniques would require the prior knowledge of the seafloor geoacoustic properties, which are usually unknown (and are often the expected end-product of multibeam backscatter processing). Instead, an empirical compensation is classically used. Assuming the seafloor type and roughness are constant along the entire swath and for a given number of consecutive pings, an average angular response can be computed from each stack of pings. Within each stack, and for each incident angle, this average value can then be subtracted from the original data, and the value of a reference angle (from the same stack) introduced in its place. Because this process is applied independently to each stack of pings, it takes into account the variation of seafloor types and roughness along the data file. This approach cancels the quantitative character of the angular response but is successful in removing the along-track banding effect and, therefore, improves dramatically the backscatter mapping. This methodology has been widely used and has increased in complexity over the years (Beaudoin *et al.*, 2002; Beyer *et al.*, 2007; de Moustier and Matsumoto, 1993; Parnum *et al.*, 2006; Preston *et al.*, 2004b).

In this article, a simplified version of radiometric and geometric corrections and empirical compensation was implemented. The main reason for the simplification is the early stage of development of the processing code. This methodology has a unique step that consists of the subtraction of the average raw backscatter value (*i.e.*, the *Reflectivity* value) for each beam within a full runline (Figure 3.3). Such approach relies on the assumption that the seafloor swathe profile remains constant during a runline to provide satisfying results. Under this assumption, each beam in the runline corresponds to a constant depth and a constant angle of incidence on the seafloor so that the subtraction described above realizes the

compensation for the varying surface of insonification, the correction for beam patterns, and an “empirical compensation for incident angle” (as described previously, but using the full runline as the stack of pings and without the addition of a reference value) altogether. Because of the absence of correction for source level and the absence of introduction of a reference value, the backscatter levels resulting from this procedure are not quantitative, but this is not a requirement for further image classification. Because the average backscatter strength for each runline and each beam remains null, it results in creating “positive decibels” values that help remind that the map is not quantitative (Figure 3.3). After this correction, the backscatter data were gridded at a 1-m resolution and interpolated in the same way as bathymetry.

The constant swathe-profile assumption can be approximately achieved in areas of limited roughness (*i.e.*, soft sediment), in the absence of strong vessel roll movements (*i.e.*, mainly sheltered zones), and by acquiring runlines both short (to ensure the depth variation induced by the tide remains negligible) and as parallel as possible to the site isobaths. These operational restrictions were approximately met in the current study.

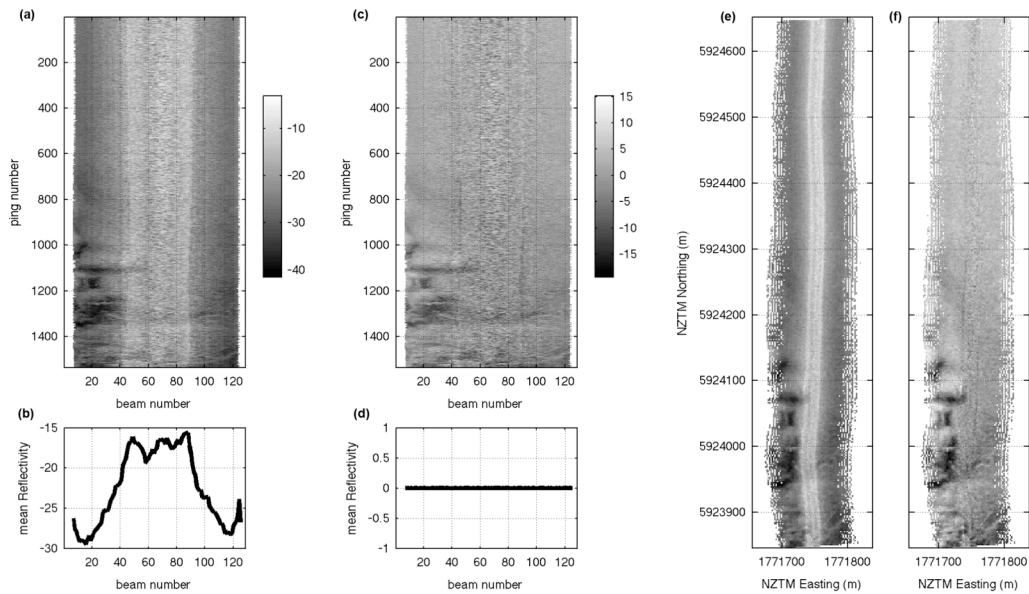


Figure 3.3. Illustration of the along-track banding effect and the results of the correction applied. Data displayed are from the westernmost runline of the Motuihe site. (a) The raw backscatter data, in decibels, are directly extracted from the file and arranged in a ping number *per* beam number array. The mean reflectivity *per* beam is then (b) computed, and extracted from the original data to obtain (c, d) the corrected data. There is no further addition of a reference average level, so that the corrected data have a zero mean reflectivity and can take positive values (see legend for part c). After georeferencing and gridding, the improvement appears clearly between (e) the raw and (f) corrected data.

3.5.5 Comparison with QTC View

Unlike the results from the QTC View survey, the multibeam backscatter mapping presented in this work is not classified. As a consequence, the comparison between the two different kinds of data, QTC View habitats and multibeam backscatter, is not straightforward. However, the QTC View classification is realized on the basis of SBES reflectivity data (actually, on the shape of the signal amplitude), which depend on the same physical processes that control MBES reflectivity near nadir (specular reflection), and the habitats subsequently identified have been mainly defined in terms of substrate grain size, which is one of the main factors of influence on the MBES signal. As a result, it can be relevant to compare the boundaries of the QTC View survey habitats and the multibeam backscatter main variations. Also, because bathymetry and local seafloor slope are

important physical parameters in the distribution of habitats, it is interesting to include these two other multibeam datasets in the comparison process. The following comparative approach is more focused on the systems' capability of mapping a given area into habitats than on their ability to characterize the seafloor from the signal they record. In this context, the limited resolution of the AGDS system is a drawback that must be taken into account in the comparison. As a result, the interpolated QTC View maps were used for comparison with MBES rather than the original ping-footprint map.

3.6 Results

3.6.1 MBES Data Processing

Figures 3.4 and 3.5 present the maps resulting from the processing described above and applied, respectively, to the data on the Motuihe and Te Matuku sites. The maps displayed are gridded bathymetry, seafloor slope at small and large scale, raw backscatter image and cleaned backscatter image.

A shift in bathymetry of up to 0.3 m can be observed between some contiguous east–west runlines on the southern part of the Te Matuku site (Figure 3.5a). This part of the site was surveyed with runlines acquired on the first day of survey, interlaced with runlines acquired on the second day, actually 19 hours later. The difference in the average tide level used for correction for these two types of runlines was 1.5 m. Because of the bad quality of the tide data for this site (which used tide compensation factors for a location in the channel some 6 km from the study site), it is very likely that incorrect tide compensation is responsible for the artefact. This is further supported by the observation that no other important artefact was observed between overlapping runlines on the bathymetry maps of both the Motuihe site (which was surveyed in only one day and which used precise compensation factors for tide correction) and the rest of the Te Matuku site (Figures 3.4a and 3.5a).

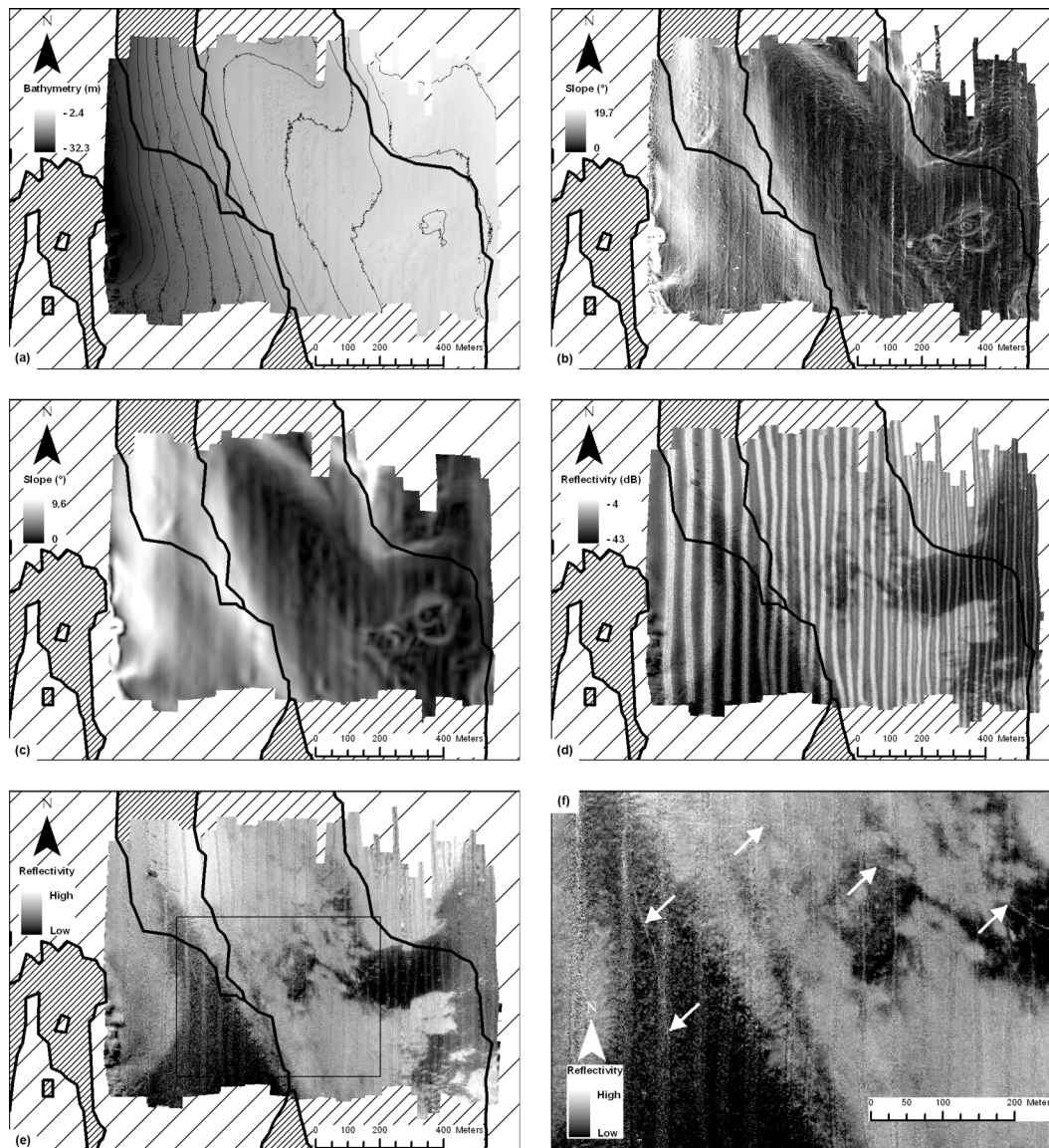


Figure 3.4. Results of the processing applied to the MBES Motuihe dataset. The boundaries of the QTC View classification are overlaid on the MBES data in thick solid lines to allow for comparison (except in part f). Outside the MBES data, the QTC View classification is displayed (following the legend in Figure 3.2). (a) Bathymetry, overlaid with 2-m contours (in thin solid lines). (b) Seabed slope map obtained with slope scale parameter of 2 m. (c) Seabed slope map obtained with slope scale parameter of 15 m. (d) Raw reflectivity in decibels. (e) Reflectivity after correction. (f) Detail of the reflectivity after correction (indicated on the previous panel as a thin, solid square) to illustrate the visual enhancement resulting from the processing. The correction allows the observation of continuous lines on the seafloor, a few hundred meters long (indicated by arrows).

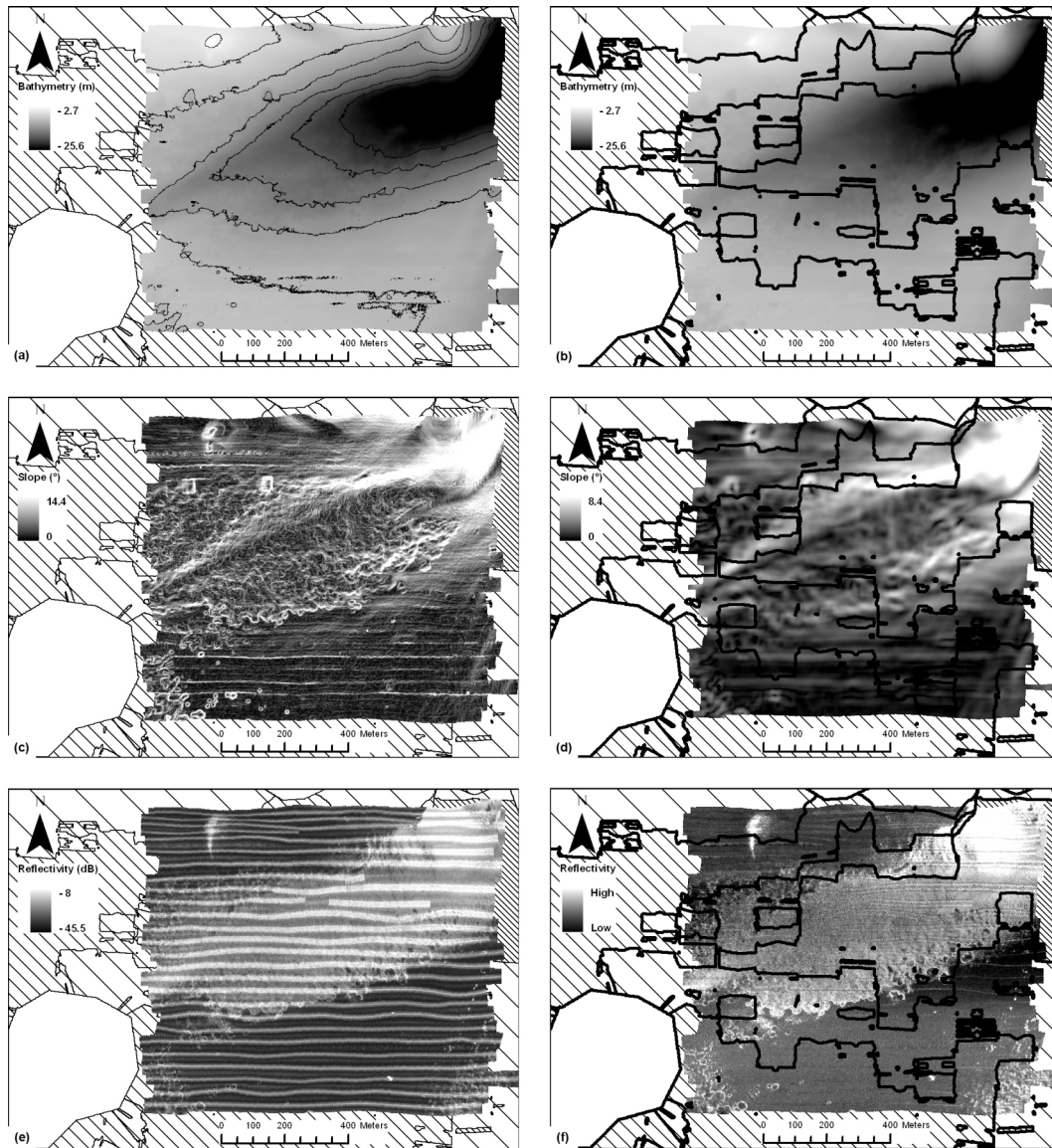


Figure 3.5. Results of the processing applied to the MBES Te Matuku dataset. The boundaries of the QTC View classification are overlaid on the MBES data in thick, solid lines on the panels on the right to allow for comparison but are absent from the panels on the left because their complexity would affect the reading of the MBES map. Outside the MBES data, the QTC View classification is displayed (following the legend in Figure 3.2). (a) Bathymetry, overlaid with 2-m contours (in thin solid lines). (b) Bathymetry overlaid with boundaries of the QTC View classification). (c) Seabed slope map obtained with slope scale parameter of 2 m. (d) Seabed slope map obtained with slope scale parameter of 15 m. (e) Raw reflectivity in decibels. (f) Reflectivity after correction.

Both large-scale trends in seafloor slope and small-scale roughness features are easily identifiable on the seafloor slope maps produced with a small slope scale parameter value (Figures 3.4b and 3.5c). They clearly display features, such as bedforms, individual boulders, or reefs, which present a roughness scale of at least 1m. They also display important errors at the boundaries between runlines, which cumulate bad soundings, lack of data, and interpolation errors (and the tide-related bathymetry artefacts identified on the Te Matuku site). In comparison, the processing using a larger slope scale parameter acts as a low-pass filter: It decreases the errors at the boundaries between runlines and enhances the large-scale slope trends, but it also tends to remove the small-scale features from the map (Figures 3.4c and 3.5d).

Comparison between original and cleaned backscatter images shows that processing yields significant improvement in image quality and visual analysis possibilities (Figures 3.4d and 3.4e for Motuihe; Figures 3.5e and 3.5f for Te Matuku). Although compensated for its higher reflectivity, the centre of the swathe in each runline remains partly visible on the cleaned backscatter image. This is due to both the important variance of backscatter strength when controlled by specular reflection in the near-nadir area and the approximation used for the empirical compensation of angular variation. It confirms that the simple method used for processing the backscatter data has a purpose of global visual enhancement only and that no quantitative analysis can be performed. The cleaned backscatter maps are very similar to the imagery that can be provided by an SSS. Patches of different acoustic return now have clear boundaries and should allow easier comparison with the other systems and easier manual or automatic classification. The identification of some bottom marks—probably trawling marks—on the Motuihe cleaned backscatter map while absent from the bathymetry map is another example of the important improvement obtained through the image-enhancement processing (Figure 3.4f).

3.6.2 Dataset Comparisons

The high acoustical variability at the Motuihe site is confirmed by the multibeam backscatter mapping (Figure 3.4d): The original reflectivity values (before angular dependence correction) range from -43 dB to -4 dB. After the correction, the site presents patches of different backscatter strength that are not directly related to depth or slope (*i.e.*, patches of similar backscatter values do not have a constant slope or bathymetry value), but whose patterns and boundaries correspond globally to important changes in seafloor slope (Figures 3.4b and 3.4c). This can be expected, as the slope, through roughness, is a parameter of main influence on backscatter and because, as stated before, distinct sediment facies can display distinct patterns of roughness and reflectivity. In the southwestern corner of the site, bathymetry, slope, and backscatter maps display a seafloor feature of complex roughness, probably a reef (particularly visible on Figures 3.4b and 3.4e). The QTC View habitats on the Motuihe site seem mostly correlated with local depth and not at all with MBES backscatter or seafloor slope. Especially, the habitats found in the shallow and intermediate depths, respectively, “sand/cobbles/*maoricolpus*” and “sand, hard mud” do not correlate with the variability of the multibeam backscatter in this area. Even the boundary between these two habitats cannot be related to a significant change in multibeam backscatter. The boundary between the QTC View “sand, hard mud” and “heavy dead shells” habitats (centre-south of the multibeam site extent) is more or less consistent with a change in multibeam backscatter level, but the habitats in the deep channel “heavy dead shells” and “coarse sand, soft mud” are not related to constant patches of similar backscatter level. Lastly, the rough feature identified in the southwestern corner of the site on MBES maps does not appear as a QTC View habitat distinct from its surroundings.

The MBES backscatter map for the Te Matuku site (Figure 3.5e) also displays an important acoustical variability (-45.5 dB to -8 dB) despite the observation from the QTC View survey that the single-beam acoustical variability of this area is low. On the multibeam backscatter map, an extended patch of high reflectivity is present across the site of dominant low reflectivity (Figure 3.5f). This reflectivity contrast makes the boundaries of this patch well defined although very rugged. By

comparing the multibeam reflectivity, bathymetry, and slope maps, it is clear that this patch is correlated to the deep waters of the channel entrance, the boundaries of which are defined by the areas of important slope. It also seems in accordance with the QTC View “soft mud, some shells” habitat (Figure 3.2). Apart from this specific area, multibeam backscatter seems unrelated to the local depth, whereas it is clearly the case for the QTC View classification. This correlation was identified in the subsequent classification ground-truthing as a trend toward softer mud as waters get shallower (Figure 3.2).

Figure 3.6 presents a detail of the sidescan image resulting from the 2002 SSS survey. The sidescan image and the multibeam backscatter map (Figure 3.5f) are very similar. The high-reflectivity zone identified on the Te Matuku multibeam backscatter map is present on the sidescan imagery as well. In addition to that patch, local features presenting high reflectivity (probably reefs) in the northwestern part or in the southern part are clearly visible on both images.

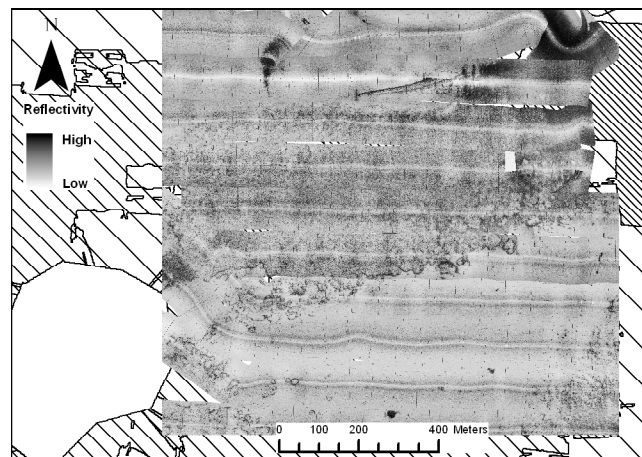


Figure 3.6. Detail of the 2002 sidescan imagery of the Te Matuku site, reduced to the boundaries of the MBES survey. Note that the colour scale is inverted from the previous multibeam reflectivity maps: Dark tones represent high reflectivity and light tones represent low reflectivity. Outside the sidescan imagery, the QTC View classification is displayed (following the legend in Figure 3.2).

3.7 Discussion

3.7.1 MBES Data Processing

From the visual analysis of the bathymetry and reflectivity maps for both the Motuihe and Te Matuku sites, it can be concluded that the processing quality is relatively good. The main artefacts identified on the bathymetry and seafloor maps could have been avoided with better tide data and better survey planning to ensure complete overlapping. In particular, the good quality of the cleaned backscatter map demonstrates the constant swath profile assumption used for processing was approximately valid in the current study. This shows how a simple backscatter-processing methodology, fast to implement and with no need of specific processing software, can effectively tackle the issue of multibeam backscatter along-track banding compensation, under certain operational restrictions. It would be interesting to actually estimate the limit conditions of this assumption that would result in the failure of the methodology (*i.e.*, an order of seafloor roughness, vessel movement, failure to follow isobaths, and tide range within a runline), but this would require additional test datasets. More likely, our methodology will be refined in further developments to accommodate a wider range of seafloor and survey conditions. The possible improvements are numerous. First, recomputing the ray-bending solution after correction of the angular offsets and using the multibeam sounding processing algorithm CUBE (Combined Uncertainty and Bathymetry Estimator) (Calder and Mayer, 2003), instead of a simple gridding, would allow obtaining more precise bathymetry and slope maps. From the latter, the angle of incidence could be measured and used for angular-response analysis or improved empirical compensation. Then, the correction for source levels, beam patterns, and the true area of insonification would allow keeping the results quantitative. Lastly, applying this methodology to the reflectivity data contained in the *Seabed Image* data packets, which are approximately 10 times denser than the data contained in the *Depth* packets (Kongsberg Maritime AS, 2006), would dramatically improve the maps resolution. Despite this important room for processing improvement, the quality of the datasets from the current methodology was found to be good enough to allow running image-based classification schemes during subsequent work.

3.7.2 Comparison with QTC View and SSS

The main importance of the difference between the respective MBES and QTC View resolutions was discussed previously and was illustrated on both sites. On the Te Matuku site, the QTC View classification is described in “blocky” habitat patterns (Figure 3.2), which is an artefact classically produced by the nearest-neighbour interpolation that was required to compensate for the low resolution of the original data (Reid, 2007). On the Motuihe site, the identification of a feature in the south-western part of all MBES datasets, while absent from the QTC View classification, is a good example of a habitat quite distinct from its surroundings and of potential high influence on the area ecology, but whose limited size and position in between two vessel tracks made it invisible to an SBES-based AGDS mapping.

Clear differences were found between the QTC View classification and the MBES reflectivity mapping on the Motuihe site whereas these two datasets were quite similar on the Te Matuku site. Such inconsistency reminds that the similarity study is limited because the first data type is resulting from a complex classification process while the analysis conducted on the second one was a simple visual observation. In addition, the QTC View classification in this study was obtained from the processing of unknown features extracted from the shape of the bottom echo resulting from the specular reflection of a 200 kHz signal on the seafloor, whereas the MBES reflectivity map displayed an average amplitude of the bottom echo resulting from the specular reflection and the surface backscattering of a 300 kHz signal on the seafloor. These slight differences in the physical nature of the information conveyed by the two signals are such that a perfect correspondence of the results from the two systems could not have been expected. On the contrary, the systems difference was illustrated in the correlation of QTC View with depth while this was not the case for the MBES reflectivity. This correlation, whether it is due to actual habitat change with depth or an artefact from the classification process, has been reported in other studies (Anderson *et al.*, 2002; Legendre, 2003). Another example can be found in the difference between MBES and SBES reflectivity variability identified on the Te Matuku site. The ground-truthing survey performed after the QTC View survey

indicated the area was covered in a rather homogenous soft-sediment habitat, thus backing up the observation of a low variability of the SBES reflectivity (Morrison *et al.*, 2003). However, the extensive bioturbation and presence of shell fragments observed during the 1996 dives in parts of the site (The Royal Forest and Bird Protection Society of New Zealand Inc., 1998) are features reported in the underwater acoustics literature to be of potentially high influence on backscattering of high-frequency acoustic signals (Pouliquen and Lyons, 2002; Stanton, 2000). This suggests that these features could have been of low influence on the SBES signal and, to the contrary, of high influence on the MBES signal, resulting in the difference observed in the two systems' reflectivity variability.

This hypothesis could also explain why the results of the comparison were so different from one site to another: The habitats of the Te Matuku site could have lead to different SBES and MBES responses, whereas the habitats of the Motuihe site could have lead to similar ones. Another potential explanation for the sites difference is the 5-years interval between the QTC View and MBES surveys: The possibility of a change through time in seafloor characteristics on one site, and not on the other, cannot be discarded. Lastly, it is possible that the scale at which the seafloor types change is larger on the Te Matuku site than the Motuihe site, resulting in the low-resolution QTC View classification succeeding at matching the high-resolution MBES for the first site but failing to do so for the second site. Further research, particularly in completing the MBES mapping with ecological data and classification would help validate or invalidate some of these hypotheses.

The MBES backscatter map displayed a higher similarity with SSS imagery than QTC View habitats, despite the more important difference in respective signal frequency (300 kHz for the MBES, 200 kHz for QTC View, and 100 kHz for the SSS). The agreement between MBES and SSS mapping arises from the similarity of the systems' operational characteristics: Both systems are designed to map the seafloor with high resolution and to record mainly the effect of surface backscattering at high-incident angles. Because of this similarity, MBES is increasingly being advocated as a possible substitute for SSS in the mapping of seafloor reflectivity with the choice between the two systems depending on a

trade-off between the need for bathymetry acquisition (which favours MBES) or higher reflectivity resolution (which favours SSS) (Le Bas and Huvenne, 2009).

3.8 Conclusions

A methodology to exploit the data from a Kongsberg Maritime EM3000 MBES was presented in detail, including bathymetry, seafloor slope, and backscatter processing. Because of its early stage of development, this methodology was rather simple compared with other existing commercial software (*e.g.*, SonarScope [Augustin and Lurton, 2005], Geocoder [Fonseca and Mayer, 2007] or QTC Multiview [Preston, 2009]) and required some operational conditions for the approximations to be valid. However, under these conditions, it proved successful in attaining the objectives in data quality required for running further basic classification schemes. The artefacts identified on bathymetry and slope maps were found to be unrelated to the processing itself, whereas the backscatter maps can only be improved with further methodology refinement. These refinements will be implemented in the near future unless a change in acquisition procedure occurs or a commercial software update proves to support our data format.

The maps from the Tamaki Strait were then used for an experimental comparison with a QTC View and a SSS survey, both realized 5 years prior. Although the difference in the maps' resolution and data type (classification against imagery) implies a necessary caution in the conclusions drawn from a visual comparison of the datasets, it was found that MBES reflectivity presented a very close (and expected) agreement with SSS imagery, an approximately good correlation with QTC View on one site, and a rather poor one on the other site. Hypotheses to explain this difference between sites were formulated and discussed. A subsequent classification of the SSS and MBES datasets, their ground-truthing, and a more quantitative comparison scheme would allow an objective confirmation of the trends identified in this work and validate or invalidate the hypotheses suggested. In the present case study, these trends suggest that MBES backscatter provide different seafloor information than traditional AGDS

classifications and similar information as SSS imagery, thus confirming the potential of MBES as a complement to AGDS technology and as a substitute of SSS for BHM.

Because of the difference in the instruments used for the 2002 and 2007 surveys and the simplicity of the analysis conducted (*i.e.*, visual comparison), this preliminary work does not pretend to provide a meaningful conclusion on potential changes within the surveyed area following its establishment as a Marine Reserve in 2005. Geoacoustical properties of the seafloor sediments are the main contributors to echosounders signals, so that the three systems allow conclusions to be drawn about the sediment distribution, not benthic biomass or distribution. However, the animal–sediment relationship and the contribution of biogenic structures (*e.g.*, bioturbation and dead shells, as discussed previously) to the contrast in water–seabed acoustical impedance can be, in some cases, of sufficient influence to allow acoustical surveys to be helpful for mapping benthic communities. This would require an important survey resolution, quantitative data analysis, and extensive biological data acquisition. Because these requisites are absent from this work, the observed apparent absence of change in seafloor acoustical properties cannot provide conclusions on the possible change in benthic biomass or distribution in the Te Matuku marine reserve.

3.9 Acknowledgements

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CHAPTER 4

THE SOLUTION:

TOOLS FOR THE QUANTITATIVE COMPARISON OF CATEGORICAL MAPS

4.1 Preface

This chapter was peer-reviewed and published as an article in the ICES Journal of Marine Science in 2010. It is reprinted here with only minor edition of acronyms, figure and table numbers and format, and references in order to match the thesis format. Since this chapter was written to stand alone as a published article, it contains minor repetitions of reasoning previously found in this thesis and statement of objectives that may differ from those of the thesis. The previous chapter is cited as Schimel *et al.*, (2010) in the text.

I, Alexandre Carmelo Gregory Schimel, assume responsibilities for fieldwork, laboratory and data analysis, development of methods, and writing, unless specified within the text. The work was undertaken with the supervision and editing input of Professor Terry Healy and Dr. David Johnson, and the significant involvement of Dirk Immenga for the mobilisation and use of the acoustic systems. This chapter also benefited from the review and comments of two anonymous reviewers and of the editing staff of the ICES Journal of Marine Science.

The recommended format for the purpose of citation is:

Schimel, A. C. G., Healy, T. R., Johnson, D. and Immenga, D. 2010. Quantitative experimental comparison of single-beam, sidescan and multibeam benthic habitat maps. ICES Journal of Marine Science 67: 1766–1779.

4.2 Abstract

Map comparison is a relatively uncommon practice in the field of acoustic seabed classification to date, contrary to the field of land remote sensing, where it has been developed extensively over recent decades. The aim here is to illustrate the benefits of map comparison in the underwater realm with a case study of three maps independently describing the seabed habitats of the Te Matuku Marine Reserve (Hauraki Gulf, New Zealand). The maps are obtained from a QTC View classification of a single-beam echosounder (SBES) dataset, manual segmentation of a sidescan sonar (SSS) mosaic, and automatic classification of a backscatter dataset from a multibeam echosounder (MBES). The maps are compared using pixel-to-pixel similarity measures derived from the literature in land remote sensing. All measures agree in presenting the MBES and SSS maps as the most similar, and the SBES and SSS maps as the least similar. The results are discussed with reference to the potential of MBES backscatter as an alternative to SSS mosaic for imagery segmentation, and to the potential of joint SBES–SSS survey for improved habitat mapping. Other applications of map-similarity measures in the field of acoustic classification of the seabed are suggested.

Keywords: accuracy, average of mutual information (AMI), contingency matrix, Cramér's V , Goodman–Kruskal's lambda, kappa statistic, Theil's uncertainty coefficient

4.3 Introduction

In the past ten years, the human-induced worldwide decline of marine environments has raised awareness of the urgent need to improve the management of marine living resources and triggered an increase in research efforts to understand, classify, and protect ocean habitats (Jackson *et al.*, 2001; Pauly *et al.*, 2002; Pikitch *et al.*, 2004). The mapping of benthic habitats is typically achieved on the basis of direct biological or geological observations combined with data from remote-sensing acoustic systems (Diaz *et al.*, 2004), a practice known as acoustic seabed classification (ASC; Anderson *et al.*, 2008).

Direct observations are obtained from *in situ* techniques such as photography, video, sampling, coring, or SCUBA diving (Brown and Coggan, 2007). The remote-sensing acoustic systems typically used are single-beam echosounder (SBES), sidescan sonar (SSS), and multibeam echosounder (MBES; Kenny *et al.*, 2003; Michaels, 2007). *In situ* technologies allow the efficient localized description of the seabed but have limited coverage, whereas remote-sensing technologies allow excellent coverage but their output is ambiguous in terms of habitat description. A combination of both approaches allows counter-balancing for the respective flaws of each type and allows cost-effective surveying (Diaz *et al.*, 2004). However, the wide range of approaches to combine *in situ* data and acoustic data into a map testifies to the lack of agreement on a single, optimal habitat-mapping technique.

Numerous and varied acoustic features can be used for classification. Examples of SBES features include the energy of the first and second bottom echoes (Heald and Pace, 1996; Siwabessy *et al.*, 2000), or parameters describing the spectrum, envelope, or amplitude of the first echo (Anderson *et al.*, 2002; Ellingsen *et al.*, 2002; Preston *et al.*, 2004a). Examples of features derived from MBES or SSS backscatter imagery include statistical moments within a neighbourhood of samples (Preston *et al.*, 2004a; Brown and Collier, 2008), spectral features from Fourier or wavelet transform analysis (Pace and Gao, 1988; Atallah *et al.*, 2002),

or indices from grey-level co-occurrence matrices (Huvenne *et al.*, 2002; Blondel and Gómez Sichi, 2009). Examples of features derived from MBES bathymetry include seabed roughness (Ierodiconou *et al.*, 2007), topographic position index (Iampietro *et al.*, 2005), or local Fourier histogram texture features (Cutter *et al.*, 2003). Examples of features derived from MBES-backscatter angular response include empirical parameters describing the response shape (Hughes Clarke, 1994; Beyer *et al.*, 2007), or solutions to an inverted geo-acoustic model fitted to the response curve (Fonseca *et al.*, 2009).

Also, there is a wide range of classification algorithms available. The traditional interpretative approach, in which experts are responsible for manually segmenting an acoustic image, is still often used because of its reliability (Kostylev *et al.*, 2001, Roberts *et al.*, 2005; Ehrhold *et al.*, 2006; Collier and Humber, 2007; Prada *et al.*, 2008), but advances in computer processing capabilities now allow the use of various automated approaches (Simard and Stepnowski, 2007). Examples of automated algorithms used in recent literature include *k*-means clustering (Legendre *et al.*, 2002; Blondel and Gómez Sichi, 2009), decision tree (Ierodiconou *et al.*, 2007), discriminant analysis (Hutin *et al.*, 2005), Bayes decision rule (Simons and Snellen, 2009), and neural networks (Marsh and Brown, 2009).

Finally, the design of a given classification methodology is subjective. Different results can be obtained if acoustic data are classified with the help of *in situ* data (supervised approach) or without (unsupervised approach; Simard and Stepnowski, 2007). Other important considerations include the number of categories to work with, whether to run the classification on individual features or coherent localized groups of features (object-orientated analysis; Lucieer, 2008), or whether to run a “hard” or fuzzy classification (Lucieer and Lucieer, 2009).

The increasing number of acoustic systems, data-processing techniques, classification schemes, and methodologies to link acoustic and *in situ* data, some of which are described above, implies a growing need for comparison. Ultimately, comparative studies could lead to the identification of the most appropriate systems (or combinations of systems) and methodologies for given survey

objectives and conditions. With this purpose, a number of studies offer a comparison of the theoretical performances of different acoustic-mapping systems (Hamilton *et al.*, 1999; Kenny *et al.*, 2003; Le Bas and Huvenne, 2009). However, such a system-orientated approach ignores the variable results that can be obtained from different processing or classification methodologies.

The conventional approach for comparing different processing or classification methodologies is to produce a case-study map for each, estimate their respective accuracy in reference to a ground-truth dataset, and compare the two estimates. The techniques for estimating the accuracy of a thematic map have their origin in the field of land remote sensing (Congalton, 1991; Foody, 2002, 2008), and their use is gaining momentum in ASC (Foster-Smith and Sotheran, 2003; Brown *et al.*, 2005; Brown and Collier, 2008; Lucieer, 2008; Walker *et al.*, 2008). Obtaining an estimate of map accuracy is now relatively straightforward, but comparing two estimates is difficult because it requires the calculation of their respective variances, and this is highly dependent on the size and design of the ground-truth dataset (Stehman and Czaplewski, 1998; Foody, 2009). This is an important issue in ASC, where seabed ground-truthing presents specific challenges including access difficulty, poor visibility, acoustic/ground-truth data-scale difference, position precision, and habitat subjective description (Brown and Coggan, 2007).

A second approach to comparing different processing or classification methodologies is the direct comparison of one map with another, without referring to an *in situ* dataset as ground truth. Such map-to-map comparison benefits from decades of development in diverse fields involving land mapping (Boots and Csillag, 2006). Techniques for the comparison of land maps include measures derived from pixel-to-pixel comparison (Foody, 2006), features identification and analysis (Dungan, 2006), pattern-based techniques (White, 2006), or fuzzy-logic-based measures that take into account possible vagueness in pixel location or legend category (Hagen-Zanker, 2006). In contrast to land remote sensing, map-to-map comparison is still relatively uncommon in ASC to date, with the notable exception of the works by Foster-Smith *et al.* (2004) and Brown *et al.* (2005).

The main advantage of direct map-to-map comparison is that it allows one to circumvent the complications posed in the first approach by its requirement for a properly designed ground-truth survey (Stehman, 2006). However, the reciprocal drawback is that in the absence of evaluation of map accuracy, the observation of map similarity or dissimilarity is ambiguous. For example, the observation that two given maps A and B differ importantly could be the result of A being accurate and B not, or B being accurate and A not, or both A and B being inaccurate, or both A and B being equally accurate, but happening to depict different ground characteristics. As a result, map-to-map comparison is generally limited to specific study objectives where the accuracy ambiguity is lifted or made irrelevant. Examples of objectives for map-to-map comparison include the basic characterization of the degree of similarity between different mapping algorithms, the detection of changes over time, or the validation of a map produced under the assumption that it is compared with a map that actually represents the ground truth (Foody, 2007).

Here we aim to illustrate the potential benefit of map-to-map comparison in ASC for comparing seabed maps produced by different acoustic systems or classification methodologies. As a case study, three maps were created to represent the result of independent, typical benthic habitat-mapping efforts at the same site. They were obtained from SBES, SSS, and MBES datasets, which were acquired at a different time with different resolution and coverage, classified in unsupervised mode using the usual algorithms for each acoustic system, and ground-truthed using different *in situ* surveys. The small size of the ground-truth surveys precluded reliable estimation of map accuracy, but not a direct map-to-map comparison. A number of measures derived from the literature in land remote sensing and selected for their suitability to this study context were applied to estimate map similarity. The similarity results were then examined, the benefits and limits of the selected approach discussed, and other potential applications of map-similarity measures in ASC suggested.

4.4 Material and methods

The study site was the Te Matuku Marine Reserve, located south of Waiheke Island in the Hauraki Gulf in New Zealand ($\sim 36^{\circ}51'S$ $175^{\circ}08'E$; Figure 4.1a). The 690 ha reserve was established in 2005 to cover the Te Matuku Bay estuary and its subtidal extension in the sheltered Tamaki Strait. The study focuses on the subtidal part of the reserve, which accounts for ~ 550 ha, including flats off the bay headlands and the entrance of the Waiheke Channel to a depth of 25 m. Early surveys recognized the area as typical of inner Hauraki Gulf sheltered shores: the dominant seabed substratum is fine, silty mud, with extensive bioturbation in places, occasional patches of horse mussel (*Atrina zelandica*) shell debris, and rocky outcrops around headlands and Passage Rock Island (The Royal Forest and Bird Protection Society, 1998).

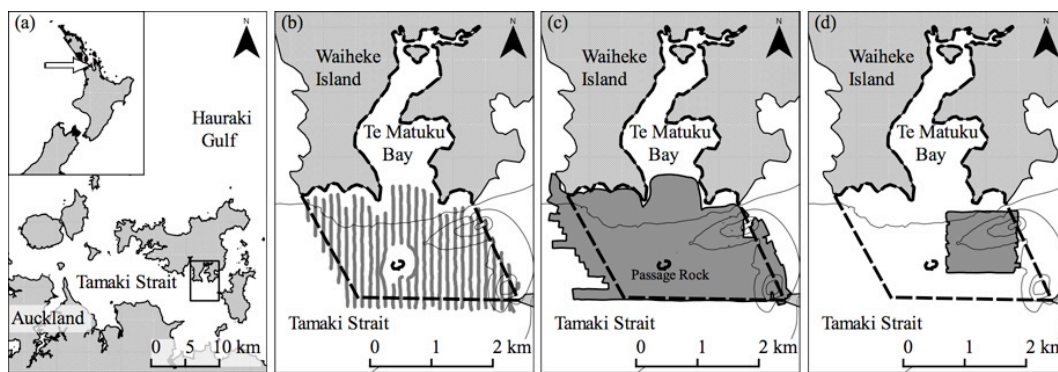


Figure 4.1. (a) Location of the study site in the Tamaki Strait, Hauraki Gulf, New Zealand ($36^{\circ}51'S$ $175^{\circ}08'E$). (b) Coverage of the SBES survey (north–south continuous lines), after Morrison *et al.* (2003). (c) Coverage of the SSS survey (dark area). (d) Coverage of the MBES survey (dark area). All panels except the left one also display the extent of the Te Matuku Marine Reserve (dashed contour) and the 5, 10, 15, and 20 m isobaths.

4.4.1 SBES classification

In 2002, New Zealand's National Institute of Water and Atmospheric Research (NIWA) conducted a habitat survey of the proposed area for the Te Matuku Marine Reserve, as part of a wider programme of habitat identification in the Hauraki Gulf. The habitat mapping was performed with a Simrad EA501P single-beam echosounder, the signal of which was processed and classified with Quester Tangent software QTC View Series 4 and QTC IMPACT (Morrison *et al.*, 2003). The SBES used in the survey had an operating frequency of 200 kHz, a ping rate of 5 Hz and a fixed beamwidth of 7° (Morrison *et al.*, 2001). The acoustic dataset covered the entire subtidal part of the marine reserve (Figure 4.1b), with a total of 30 lines acquired in a north or south direction at a speed of $\sim 3 \text{ m s}^{-1}$, separated by 120 m on average (Morrison *et al.*, 2003). The QTC software analysed the SBES signal in stacks of consecutive pings in order to minimize signal variability (Preston *et al.*, 2004a). This process resulted in the generation of one ping-stack every 6 m on average along the lines (Morrison *et al.*, 2003). Accordingly, the original dataset for classification had an average spatial resolution of $120 \text{ m} \times 6 \text{ m}$.

The QTC software first extracted 166 features from the ping stacks, then applied a principal components analysis (PCA) to identify the three principal components, which are termed Q-values. The Q-values were then clustered using a semi-automatic algorithm, in which the user was responsible for the decision of whether there should be further splitting of the clusters with the help of statistical diagnostics. When the final set of clusters was decided, the Q-values were compared with the centroid of each of them, resulting in a category being assigned to each ping-stack along with a confidence value between 0 and 100% (Preston *et al.*, 2004a, 2004b). This process of classification resulted in an optimal number of four categories (Morrison *et al.*, 2003). An interpolation algorithm was then applied to the ping-stack classification to obtain a thematic map covering the entire site (Morrison *et al.*, 2003). However, the resulting map displayed a general unrealistic “blocky” aspect (Morrison *et al.*, 2003; Schimel *et al.*, 2010). This effect is found frequently when using traditional interpolation algorithms for categorical data on point-based datasets with both an imbalance between along-

and across-track resolution and a high point-to-point variability (Foster-Smith and Sotheran, 2003; Reid, 2007).

In this case, the ping-stack classification was interpolated again using an alternative algorithm designed for categorical data and based on an inverse distance calculation, with the aim of obtaining a map with a more realistic aspect. The inverse distance calculation was expected to create a spatial averaging effect to filter out the rapid variations in the original data, and the specific design for categorical data ensured that no artificial categories were created in the process (Reid, 2007).

With any point x , the algorithm would associate the category for which the sum of the inverse distances between x and the points belonging to the set to be interpolated, classified in this category and located within a given threshold distance from x , is maximized over all categories. The resulting category is

$$c(x) = \arg \max_{k \in [1, n]} \sum_{y \in Y_{k,D,x}} \frac{1}{d(x, y)}, \quad (4.1)$$

where Y is the entire dataset of points to be interpolated, n the total number of categories in which Y is partitioned, $Y_{k,D,x}$ the subset of Y consisting of the elements classified in category k and located within the threshold distance D from x , and d is a distance function. In practice, the QTC ping-stack classification dataset Y was limited to the elements y that scored more than 80% confidence during the classification process, the interpolation was run on a grid of points x set up at a resolution of 1 m, the Euclidian distance was used for d , the threshold distance D was set to 100 m, and the final results were limited to the convex hull of the QTC ping-stack classification data set Y , in order to remove unnecessary extrapolation.

The interpolated map was ground-truthed with a video and sediment-sampling survey of 12 stations arranged in a stratified design: three stations were selected within patches of “pure” category for each of the four categories (Morrison *et al.*,

2003). At each station, underwater video footage was acquired and a sediment sample obtained with a Smith–McIntyre grab sampler. Primary substratum type, secondary cover, and conspicuous epifauna were described from video footage and sediment sample observation, and grain-size distribution was derived from the analysis of samples using a GALAI (CIS-100) laser particle sizer (Morrison *et al.*, 2003). In order to complete this original ground-truthing effort, the sediment grain-size analysis was carried on further in this study with the computation of the volume percentage of clay, silt, sand, and gravel-size particles (>2 mm), as well as the mean grain-size and sorting of the <2 mm fraction. All 12 stations were used for category identification; none were conserved for map-accuracy estimation.

4.4.2 SSS classification

In 2002, the University of Waikato’s Department of Earth and Ocean Sciences conducted an SSS survey of the proposed site for the Te Matuku Marine Reserve using a Klein 595 sidescan sonar for data acquisition and Triton Imaging Inc. ISIS software suite for data processing (Figure 4.1c). SSS imagery was obtained from mosaicking the 100 kHz data at a resolution of 0.2 m using the assumption of a flat seabed. As the poor quality of the data precluded efficient data conditioning for modern image-analysis techniques to be applied, the mosaic was segmented manually. Segmentation was performed with the digitizing tools of GIS software on the basis of a visual assessment of areas of homogeneous tone and texture. Five categories were identified. The map was then rasterized at a resolution of 1 m.

In 2005, New Zealand’s Department of Conservation performed a sediment-sampling survey of the marine reserve. The survey consisted of 146 stations arranged in a simple random design over the entire reserve, including its intertidal part. Sediment samples were collected at each station using a small rectangular dredge described in Grace and Whitten (1974), then analysed for grain-size distribution using a Malvern laser particle sizer (K. Sivaguru, pers. comm.). For each sample, the volume percentage of clay, silt, sand, and gravel (>2 mm), and the mean grain size and sorting of the <2 mm fraction, were calculated. Only 69

of the 146 stations were located within the area covered by the SSS imagery and were used for ground-truthing the SSS map. All 69 stations were used for category identification; none were conserved for map-accuracy estimation.

4.4.3 MBES classification

In 2007, an MBES survey was conducted over a rectangular area of ~100 ha in the Waiheke Channel part of the Te Matuku Marine Reserve (Figure 4.1d). The specific purpose of the survey was to acquire an MBES dataset for development of a processing methodology and for the preliminary comparison of its results with the SBES and SSS classifications (Schimel *et al.*, 2010). Accordingly, the survey was not performed on the entire subtidal part of the marine reserve, as were the previous surveys, but only on an area large enough to cover occurrences of each category from the previous classifications, as well as the full depth range of the area.

The survey was conducted with a Kongsberg EM3000 multibeam echosounder (300 kHz), planned so that outer beams from two consecutive runlines were slightly overlapping to ensure 100% coverage. The backscatter data were processed to remove the along-track banding effect and gridded at a resolution of 1 m (Schimel *et al.*, 2010). A 10 m × 10 m two-dimensional median filter was then applied to the imagery to remove the high-frequency noise typically present in MBES backscatter data recorded near the nadir. Observation of the filtered image histogram revealed three main concentrations of pixels at respectively high, medium, and low backscatter levels. The filtered image was classified using a *k*-means clustering algorithm, with the number of categories *k* accordingly set to three.

The map produced by this semi-automatic classification was ground-truthed using footage from a drop-video-camera survey carried out in 2008 and comprising 24 stations arranged in a systematic design over the area covered by the MBES. The video camera was fitted on a frame lowered to the seabed, and the vessel was allowed to drift during the length of footage recording on each site. Such drifting

minimized the error in the frame position, assumed to be identical to the vessel position, measured with DGPS, and ensured that the habitat observed was representative of its surroundings. Map categories were described on the basis of visual assessment of the video footage. In addition, four of the stations were sampled and observed by a SCUBA diver. The samples were analysed for sediment grain-size distribution with a Malvern laser particle sizer. All 24 stations were used for category identification; none were conserved for map-accuracy estimation.

4.4.4 Map-comparison measures

As outlined above, a wide range of approaches developed for the comparison of land maps can be used directly in ASC, depending on study context and objectives. The objective of the current study is to estimate the overall similarity of three overlapping maps with identical resolution of 1 m but different legends and different coverage, and for which no samples are available for map-accuracy assessment. In this context, a map-to-map comparison approach can be implemented using similarity measures obtained from the count of pixels shared by the maps, which is usually presented in the form of a contingency matrix (Table 4.1).

Table 4.1. Contingency matrix for two maps A and B comprising respectively m and n categories. c_{ij} designates the number of pixels that fall conjointly in category A_i in map A and B_j in map B. The numbers c_{+j} and c_{i+} , respectively, designate the sum of the elements in column j and the sum of elements in row i . N is the total number of pixels shared by the two maps.

Map A categories	Map B categories					Total rows
	B_1	...	B_j	...	B_n	
A_1	c_{11}	...	c_{1j}	...	c_{1n}	c_{1+}
...	...	...	...	...	...	...
A_i	c_{i1}	...	c_{ij}	...	c_{in}	c_{i+}
...	...	...	...	...	...	...
A_m	c_{m1}	...	c_{mj}	...	c_{mn}	c_{m+}
Total columns	c_{+1}	...	c_{+j}	...	c_{+n}	N

Diverse measures expressing different aspects of map similarity can be computed from the contingency matrix. Here, several measures were selected and applied with the objective of providing an overview of the range of existing measures and of the diverse aspects of map similarity that can be estimated. Following a review by Rees (2008), the measures of categorical agreement A (overall accuracy), Cohen's κ , and Foody's κ^* and the measures of categorical association Theil's U , Cramér's V , and Goodman–Kruskal's λ were selected.

Historically, the first map-similarity measures used in land remote sensing were metrics originally designed for estimating the accuracy of a map produced against a reference ground-truth dataset. Therefore, they require the two maps to be described with the same legend. In reference to the terminology in Table 4.1, this implies that m and n must be equal, that A_i and B_i must be the same for each row/column i , that the elements on the diagonal represent the count of pixels where the classifications agree, and that the off-diagonal elements represent classification disagreements.

In this specific case, the overall accuracy A is the straightforward proportion of pixels where the two classifications agree. Accordingly, it takes values between 0, indicating no agreement, and 1, indicating complete agreement:

$$A = \frac{1}{N} \sum_{i=1}^n c_{ii}. \quad (4.2)$$

Cohen's κ is a popular measure of agreement that uses the off-diagonal elements to estimate chance agreement and to compensate A accordingly (Cohen, 1960, Congalton, 1991; Monserud and Leemans, 1992; Couto, 2003):

$$\kappa = \frac{A - \frac{1}{N^2} \sum_{i=1}^n c_{i+} c_{+i}}{1 - \frac{1}{N^2} \sum_{i=1}^n c_{i+} c_{+i}}. \quad (4.3)$$

The estimation of chance agreement in κ has often been criticized, and various alternatives have been suggested (Brennan and Prediger, 1981; Ma and Redmond, 1995). In particular, the estimation of chance agreement assuming that the marginal distributions are not specified *a priori* is considered more suitable in the context of geographical mapping (Foody, 1992; Stehman, 1999). Modifying κ accordingly, this measure becomes

$$\kappa^* = \frac{A - 1/n}{1 - 1/n}. \quad (4.4)$$

As κ and κ^* are re-scaled versions of A that take into account chance agreement, they systematically take lower values than A . They take a value of 0 if map agreement is equivalent to that expected by chance, a negative values if map agreement is less than would be expected by chance, and a maximum value of 1 in the case of complete agreement.

The requirement that the two maps to be compared must have the same legend to allow using A , κ , or κ^* is an obstacle in many studies where the legends differ in the number of categories and/or category labels. Using A , κ , or κ^* in this context implies aggregating and re-labelling some categories until a common legend is obtained, which is often done subjectively (Foster-Smith *et al.*, 2001; Giri *et al.*,

2005; McCallum *et al.*, 2006). A better approach is to use alternative measures that can be computed regardless of a possible legend mismatch, *i.e.* from a “not necessarily square” contingency matrix (Boots and Csillag, 2006; Foody, 2006).

Finn (1993), drawing from information theory, suggested a map-similarity measure with this characteristic. If map uncertainty is considered to be the information content of a map, then an estimation of map similarity can be obtained through computing the average mutual information (*AMI*), which measures the reduction in one map’s uncertainty when the other map is known (Theil, 1972; Finn, 1993; Couto, 2003; Foody, 2006; Rees, 2008):

$$AMI = H(A) + H(B) - H(A,B) , \quad (4.5)$$

where $H(A)$ and $H(B)$ describe the respective entropy (uncertainty) of the two maps, and $H(A,B)$ describes their joint entropy. With a constant term of 1 and in Hartley units, they are respectively

$$H(A) = - \sum_{i=1}^m \frac{c_{i+}}{N} \log \left(\frac{c_{i+}}{N} \right), \quad (4.6)$$

$$H(B) = - \sum_{j=1}^n \frac{c_{+j}}{N} \log \left(\frac{c_{+j}}{N} \right), \quad (4.7)$$

and

$$H(A,B) = - \sum_{i=1}^m \sum_{j=1}^n \frac{c_{ij}}{N} \log \left(\frac{c_{ij}}{N} \right). \quad (4.8)$$

Theil’s uncertainty coefficient U is a normalized and symmetric estimate of mutual information based on *AMI* that originated in the field of categorical statistics, where the above concepts apply equally (Theil, 1972). It is written (Press *et al.*, 1992) as

$$U = \frac{2 \times AMI}{H(A) + H(B)} . \quad (4.9)$$

More recently, Rees (2008) suggested two other pixel-to-pixel comparison measures drawn from the field of categorical statistics, which can also be computed from the contingency matrix without the requirement of identical legends: Cramér's V and Goodman–Kruskal's λ .

Cramér's V is a normalized version of Pearson's χ^2 statistic (Cramér, 1946; Rees, 2008):

$$V = \sqrt{\frac{\chi^2}{N(\min(m, n) - 1)}}, \quad (4.10)$$

and Pearson's χ^2 is

$$\chi^2 = \sum_{i=1}^m \sum_{j=1}^n \frac{(c_{ij} - c_{i+}c_{+j}/N)^2}{c_{i+}c_{+j}/N}. \quad (4.11)$$

Goodman–Kruskal's λ is a measure of the proportional reduction in error in one map obtained from knowledge of the other map (Goodman and Kruskal, 1954; Rees, 2008). In its symmetrical version, it is

$$\lambda = \frac{\sum_{i=1}^m \max_j(c_{ij}) + \sum_{j=1}^n \max_i(c_{ij}) - \max_j(c_{+j}) - \max_i(c_{i+})}{2N - \max_j(c_{+j}) - \max_i(c_{i+})}. \quad (4.12)$$

U , V , and λ are normalized; they take values between 0, indicating no association, and 1, indicating complete association.

4.4.5 Map-comparison methodology

In this study, the three maps to be compared had different legends because they were ground-truthed independently. The measures of association U , V , and λ were therefore adapted while the measures of agreement, A , κ , and κ^* , were not, unless the map legends were modified. A methodology was developed to automate the decision process for legend modification and allow the use of the three measures of agreement in this study.

Consider two maps A and B having the same number of categories m but different or unknown category labels. One could assess the similarity between A and B by computing a measure of agreement for all possible category bijections between A and B and keeping only one of the resulting values, intuitively the largest one. This process is equivalent to forming all of the $m!$ possibilities of category permutations in one map.

If A and B have different numbers of categories m and n such that $n > m$, one could still apply the permutation process described above after having formed all the possibilities of aggregating categories from B so that only m categories remained. This category-aggregation process is equivalent to identifying all the possibilities to partition a set of n elements into m non-empty subsets, as given by the Stirling numbers of the second type (Abramowitz and Stegun, 1964):

$$S(n, m) = \frac{1}{m!} \sum_{k=0}^m (-1)^{m-k} \frac{m!}{k!(m-k)!} k^n. \quad (4.13)$$

Accordingly, the total number of values that can be taken by a measure of agreement between two maps A and B having a different number of categories m and n after the aggregation/permutation process is $m!S(n, m)$. The main advantage of this process is that it allows the popular measures of categorical agreement to be used for maps with different legends in an automated manner. A second advantage is that it provides an optimal solution for the comparison of the legends, which is the aggregation/permutation possibility that maximizes the map-similarity measure. This information allows verification that the computed

measure is actually an estimate of map agreement rather than the product of a chance association of completely different categories.

In the present study, the SBES, SSS, and MBES maps were compared using the measures of categorical agreement and the measures of categorical association described above. As the three maps were created at a common resolution of 1 m, each pair of maps led to a straightforward contingency matrix. The measures of association U , V , and λ were computed directly from the contingency matrices, and the measures of agreement A , κ , and κ^* were computed after the application of the automatic aggregation/permutation process. At the end of the process, only the maximum value of each measure and the corresponding solution in legend agreement were reported.

This comparison methodology had its limitations. First, the difference in map size (Figure 4.1) could have an influence on the results. As the MBES map was smaller than the other two, the MBES–SBES and the MBES–SSS comparisons were limited to the size of the MBES map, whereas the SBES–SSS comparison was limited to the area shared by the two maps, *i.e.* almost the entire study site. This difference may artificially lessen the level of agreement or association of the latter comparison. Second, the level of agreement generally increases as categories are aggregated (Giri *et al.*, 2005; Foody, 2007), implying that comparisons between maps described with fewer categories may artificially show better agreement or association than other comparisons.

In order to assess the influence of map size and the number of categories in this study, the three maps were compared a second time after being limited to the pixels shared by the three maps, *i.e.* approximately the MBES area, and after the maps were all reduced to a same number of categories by subjective aggregation. This process was termed map reduction.

4.5 Results and discussion

4.5.1 Map results and analysis

Figure 4.2a shows the SBES ping-stack dataset classified by the QTC software into four classes, labelled A, B, C, and D, and Figure 4.2b the result of interpolation of the dataset using the categorical inverse distance algorithm. Both figures also show the locations of the ground-truth stations. Table 4.2 lists the results of the ground-truthing survey.

The video footage and visual assessment of the sediment samples confirmed the dominance of mud as a primary substratum on the entire study site. In contrast, grain-size analysis revealed that sediment samples contained mainly sand-size particles. Despite this discrepancy, both video footage and grain-size analysis agreed that classes A and B proved similar in demonstrating the softer sediment at the site, that class C had a slightly coarser sediment, and that class D was defined mainly by its notable cover of shells and shell fragments.

The origin of this discrepancy was not determined, but the upper layer of the seabed at the site might be stratified so that the samples, which were mostly of subsurface sediment, would naturally yield a different result from the video footage, which only allowed assessment of the composition of the surface sediment (M. Morrison, pers. comm.). Another hypothesis is that the organic content in the samples, which is high at the site, was not entirely degraded during the analysis, and might have bound silt-size grains into coarser particles.

Earlier studies using the QTC software reported cases of correlation between QTC classification and water depth (Anderson *et al.*, 2002; Hewitt *et al.*, 2004). A similar correlation was found on this site by Schimel *et al.* (2010), who observed that the distribution of class A corresponded to shallow water and those of classes C and D to deeper water. Classes C and D were identified as distinctive habitats from the ground-truthing survey, but classes A and B were identified as similar. This suggests that depth, or another environment factor correlated with it but not measured in the ground-truth survey, might have contributed to separating A and B during the classification process.

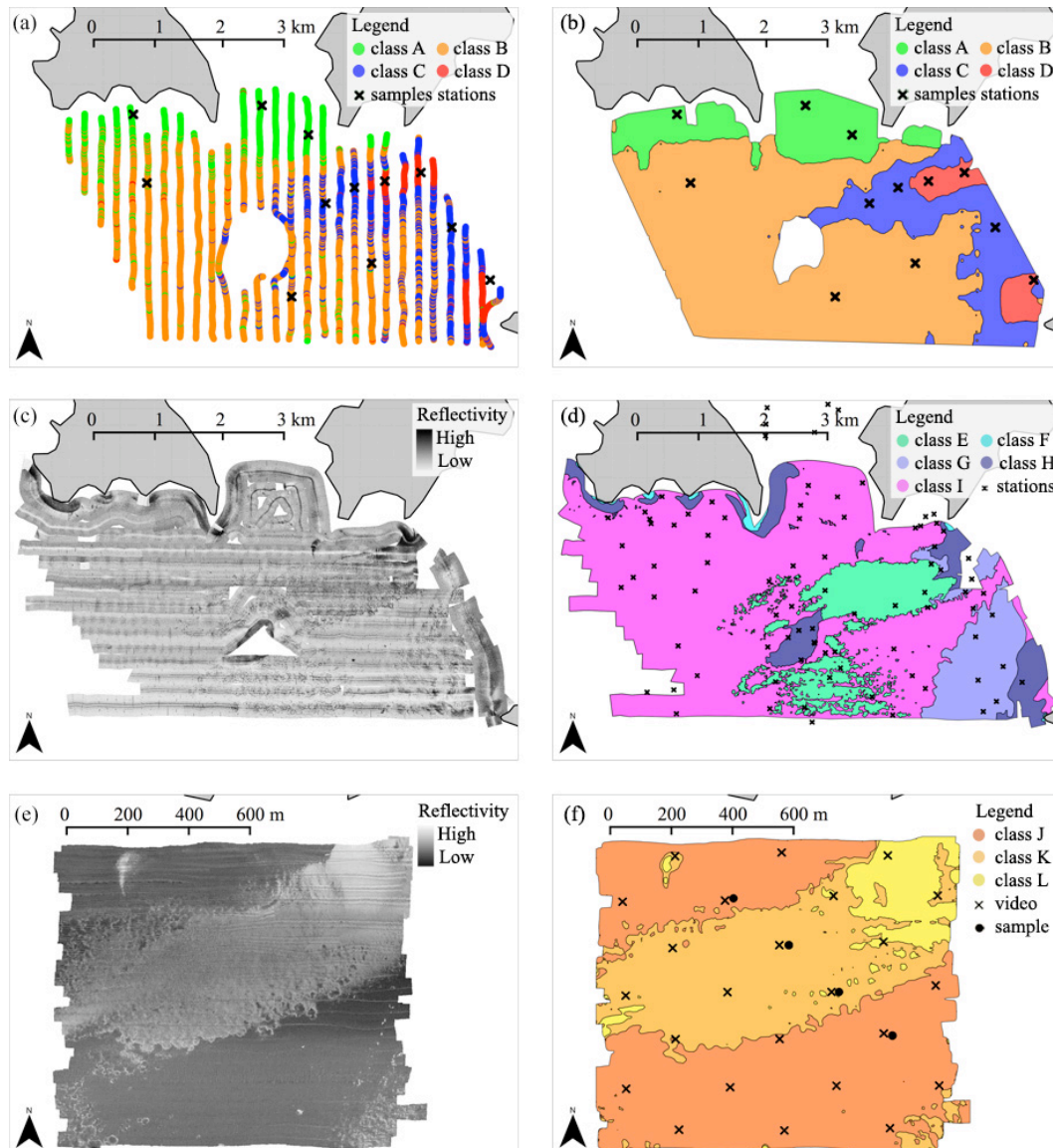


Figure 4.2. (a) SBES ping-stack classification by QTC View/Impact (after Morrison *et al.*, 2003). (b) Map resulting from the application of the interpolation algorithm to the SBES classification. Both panels also display the location of the ground-truth stations for the SBES map. (c) SSS mosaic. (d) Map resulting from manual classification of the SSS mosaic and location of the sampling stations from the 2005 survey. (e) MBES imagery. (f) Map resulting from the automatic classification of the MBES imagery and location of the ground-truth stations from the 2008 survey. The location of the data displayed in the two last panels is indicated in Figure 4.1.

Table 4.2. Results of the ground-truth survey of the SBES classification. The four QTC classes are described on the basis of observation of the video footage and of the content of the grab-samples (Morrison *et al.*, 2003). The grain-size analysis results are averaged for the three ground-truthing sites falling in each class. The analysis results include the mean grain size and sorting of the <2 mm content (both in phi scale), and the percentage content in volume of clay, silt, sand, and gravel-size (>2 mm) particles.

Class	Video observation	Sample observation
A	Mud and sloped burrows. Cushion stars.	Very soft mud. Shell fragments underneath the surface.
B	Mud and sloped burrows.	Soft to very soft mud. Few shell fragments on surface.
C	Sandy mud. Dead shells.	Soft grey clay. Shell fragments.
D	Poor visibility. Heavy sand and shell in places. Hard mud in others.	Soft mud. Many shell fragments on surface and beneath.
% content in volume		
Statistics of the <2 mm content		
Mean (phi)	Sorting (phi)	
A	3.13 (very fine sand)	0.1 22.9 75.4 1.6
B	3.30 (very fine sand)	0.3 32.8 64.7 2.2
C	1.41 (medium sand)	0.2 12.1 83.0 4.7
D	0.24 (coarse sand)	0.1 2.7 72.1 25.1

Figure 4.2c shows the SSS imagery and Figure 4.2d the thematic map resulting from manual classification, and the locations of the 2005 sediment samples used for ground-truthing. From the SSS imagery, the operator identified five classes labelled E, F, G, H, and I, for which tone and texture appeared clearly different from each other. Figure 4.3 depicts the results of the grain-size analysis for each class. There was a notable variation in the ground surface occupied by each SSS class. A smooth-textured low-reflectivity background covered most of the mosaic (class I), but it was replaced in places by a rougher texture type with greater reflectivity, mainly in a large patch in the centre east of the mosaic and in intermittent, smaller patches in the centre and the south (class E). The extension of rocky headlands and islands on the seabed showed great reflectivity and could be separated into two different texture types (classes F and H), both of which, but particularly class F, were rare. A last texture type presenting a pattern alternating high and low reflectivity marks was identified mainly in the eastern part of the site (class G).

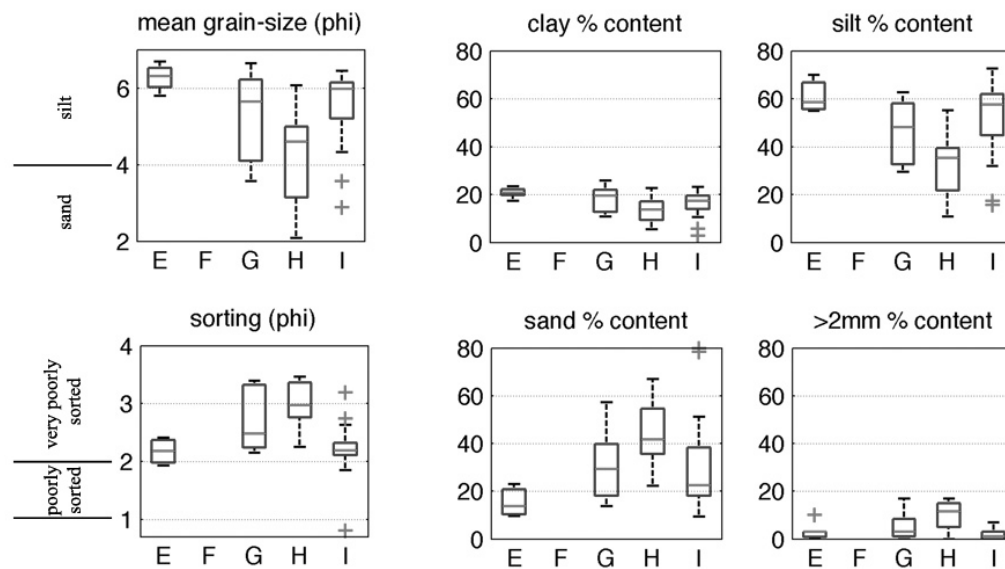


Figure 4.3. Boxplots describing the content of the 2005 samples within each SSS acoustic class. Measures displayed are the mean grain size and sorting of the <2 mm content (both in phi scale), and the percentage content in volume of clay, silt, sand, and gravel- size (>2 mm) particles.

As the SSS ground-truthing sampling scheme was devised randomly, the high variability in SSS class surface resulted in a great variability in the number of samples available for each class. In all, 43 were located within the largest class (I), whereas no samples were located within the smallest class (F). Respectively 9, 9, and 8 samples were located within classes E, G, and H. The acoustic classification and the grain-size analysis matched poorly, with a substantial variation of grain-size results in classes G, H, and I, and similar grain-size results between all classes (Figure 4.3). Classes E and I, which showed radically different tone and texture and were therefore particularly distinguishable from each other on the acoustic imagery, proved to be particularly similar in sediment content, *i.e.* a medium to fine silt poorly to very poorly sorted. They both had a negligible fraction of gravel-size (>2 mm) and clay-size particles. The main difference was that I had a higher sand content than E. Class G was quite similar but with a less sorted, less silty, and sandier content, and its gravel-size fraction was more in evidence. Finally, class H was also similar, but increasing the trend from G into less sorted and larger grain sizes. It is the only class for which the mean volume content was greater for sand than for silt. Accordingly, the classes were further labelled as E (mainly fine silt, poorly sorted), F (no stations), G (sandy silt, very-poorly sorted), H (silty sand, very poorly sorted), I (mainly medium silt, with sand occurrence).

Similar difficulties in relating grain-size results and sidescan classification have been observed in other studies on soft-sediment areas with even less homogeneous surficial sediment distribution than in the present case (Zajac *et al.* 2000; Brown *et al.*, 2002). An important variation of tone and texture in the sidescan imagery that cannot be linked clearly to sediment grain size suggests a contribution of other environmental factors, possibly related to seabed roughness. This hypothesis implies that the *in situ* technique selected for ground-truthing the SSS map may not be suitable for all classes.

Figure 4.2e depicts the MBES reflectivity map after partial correction of the along-track banding effect (Schimel *et al.*, 2010), and Figure 4.2f the thematic map resulting from the semi-automatic classification of this reflectivity map, and the location of the ground-truth stations. The clustering algorithm was set to split

the dataset into three classes labelled J, K, and L. The algorithm attributed class J to the low-reflective, smooth-textured background of the reflectivity map, class K to the medium-reflective, rough-textured features, which were mainly in a band crossing the area from its central west to northeast, and class L to the high-reflective features dominating the northeast corner of the map.

The 2008 video survey confirmed the quasi-homogeneous sediment distribution of the zone, as observed in the previous ground-truth surveys. All videos showed areas completely covered in soft mud, with a variable cover of burrows and shells or shell fragments. This general observation was confirmed by analysis of the four sediment samples, which yielded a similar content primarily dominated by clay-size particles bound into medium-silt-size particles by organic matter. The only notable variation between samples was the size of the >2 mm fraction, which was entirely made up of shell fragments, in all cases. Compilation of video observations for each MBES map class suggested that the cover of either shells or shell fragments was the principal difference between classes. Shell fragments were almost absent in class J, but quite frequent though dispersed in class K. Shell cover was, in contrast, very important in class L. Accordingly, the classes were further labelled as J (medium silt), K (medium silt and sparse shell fragments), and L (medium silt, shells and shell fragments).

This video-survey analysis supported the previous analysis of the SSS map. In the context of a seabed with a highly homogeneous, very soft sediment type, it is likely that some variations in the SSS or MBS imageries were controlled by environmental factors other than grain size. The density and distribution of burrows and shell fragments, which were reported in earlier studies and confirmed in the 2008 video survey, were possible contributors through their influence on sediment-surface hardness and roughness (Stanton, 2000; Pouliquen and Lyons, 2002). However, traditional ground-truthing techniques such as grab samples or qualitative observation of video footage do not allow their density to be measured precisely, and so confirming their influence.

Here, every sample from each ground-truthing survey was used for class identification. No additional samples were available for measuring map accuracy.

The uncertainty on the suitability of the selected ground-truthing techniques for some classes implies that even if more samples had been available, accuracy estimation may have been flawed. In the current state of the ground-truth surveys, it is therefore impossible to quantify the quality of the three maps. Moreover, each dataset could have been classified using different approaches in order to achieve better map quality, *e.g.* using supervised approaches or producing a different number of classes, but quantifying this quality through the computation of map accuracy would have remained impossible.

4.5.2 Map-comparison results and analysis

Figure 4.4a shows an overlap of the SBES and SSS maps, and Table 4.3 is the associated contingency matrix. The comparison of the SBES and SSS maps using the measures of agreement required a single step of aggregation of two classes of the SSS map. Figure 4.4b shows an overlap of the SBES and MBES maps, and Table 4.4 is the associated contingency matrix. Comparison of the SBES and MBES maps required a single step of aggregation of two classes of the SBES map. Figure 4.4c is an overlap of the SSS and MBES maps, and Table 4.5 is the associated contingency matrix. Comparison of the SSS and MBES maps also required a single aggregation step of two classes of the SSS map, because SSS class F did not overlap with the MBES map and had, therefore, to be removed from the computations. Table 4.6 lists the scores obtained for each measure of agreement and association from the contingency matrices.

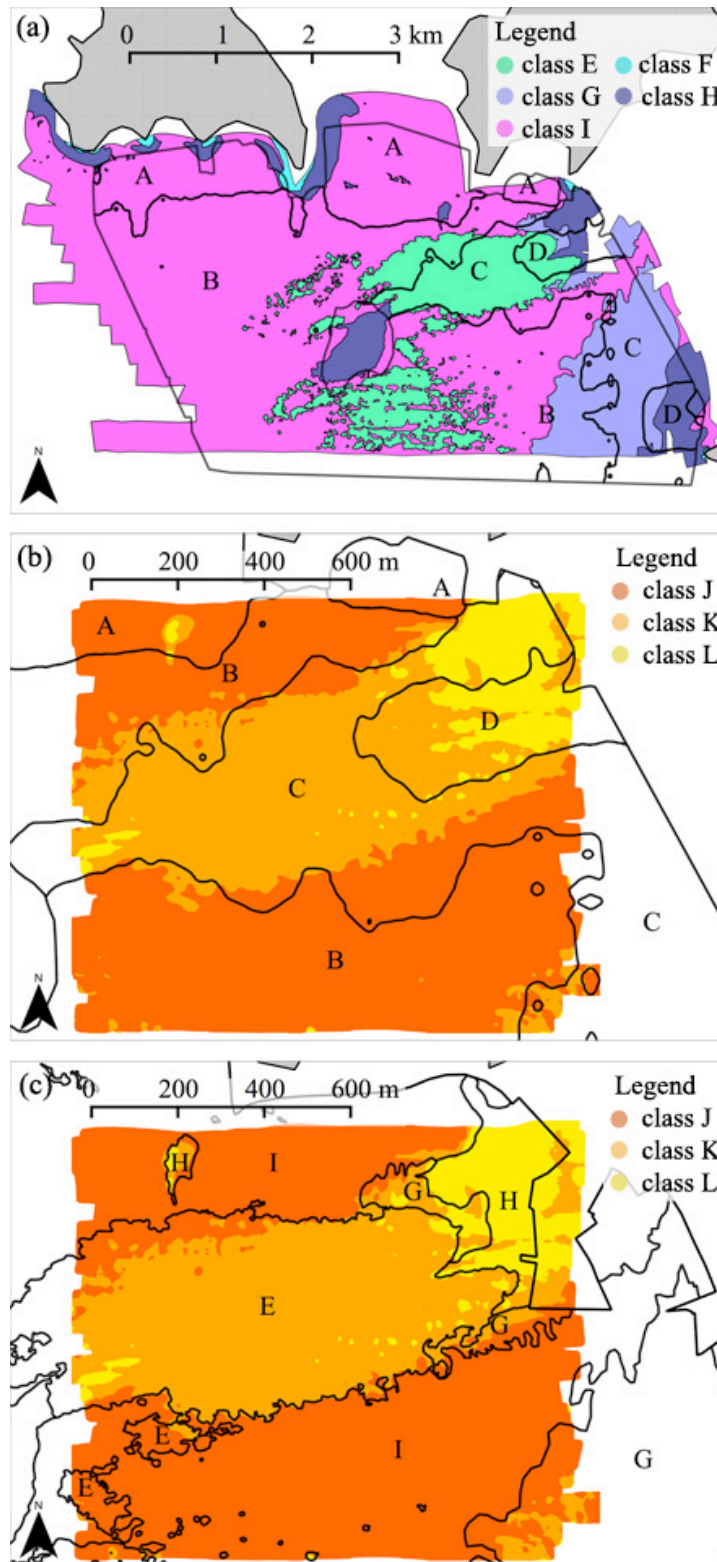


Figure 4.4. SBES map overlaid on (a) the SSS map and (b) the MBES map, and (c) the SSS map overlaid on the MBES map. In (a) and (b) the SBES segments of importance are labelled with their class, and in (c) the SSS segments of importance are so labelled. In (a) the SSS map classes are given in the legend, and in (b) and (c) the MBES map classes are also given.

Table 4.3. Contingency matrix of the SBES and SSS maps.

SBES map class	SSS map class					Total
	E	F	G	H	I	
A	0	2 401	0	37 081	690 920	730 402
B	423 370	136	189 776	11 823	2 230 261	2 855 366
C	255 631	353	291 193	85 643	109 186	742 006
D	53 079	0	44 445	86 069	2 355	185 948
Total	732 080	2 890	525 414	220 616	3 032 722	4 513 722

Table 4.4. Contingency matrix of the SBES and MBES maps.

MBES map class	SBES map class				Total
	A	B	C	D	
J	51 216	482 693	100 527	0	634 436
K	2 920	52 185	263 330	59 000	377 435
L	1 248	1 724	49 126	41 389	93 487
Total	55 384	536 602	412 983	100 389	1 105 358

Table 4.5. Contingency matrix of the MBES and SSS maps. Note that the F class column is empty because this SSS class does not overlap the MBES map.

MBES map class	SSS map class					Total
	E	F	G	H	I	
J	71 420	0	44 249	2 397	514 254	632 320
K	315 018	0	32 826	10 937	8 763	367 544
L	11 171	0	8 359	56 981	1 288	77 799
Total	397 609	0	85 434	70 315	524 305	1 077 663

Table 4.6. Measures of association and measures of agreement obtained from the contingency matrices (Tables 4.3, 4.4, and 4.5). For the measures of agreement, the automatic permutation/ aggregation procedure was applied and only the maximum values were reported.

Compared maps and contingency matrices	Measures of association			Measures of agreement		
	V	λ	U	$\max A$	$\max \kappa$	$\max \kappa^*$
SBES/SSS (Table 4.3)	0.417	0.141	0.247	0.672 ^a	0.307 ^b	0.563 ^a
SBES/MBES (Table 4.4)	0.545	0.462	0.325	0.759 ^c	0.567 ^c	0.638 ^c
MBES/SSS (Table 4.5)	0.768	0.661	0.497	0.863 ^d	0.746 ^d	0.795 ^d

^a: A~F, B~E+I, C~G, D~H

^b: A~F, B~I, C~E+G, D~H

^c: J~A+B, K~C, L~D

^d: J~G+I, K~E, L~H

Each measure in this study provided an assessment of global map similarity in a different manner, so yielded a different range of scores (Table 4.6). Some measures independently estimated different aspects of map similarity. U , for example, measured the amount of information shared by two maps, often showing the lowest scores, whereas A , which measured the overall accuracy of one map in reference to the other, had the highest scores. Other measures were related. For example, κ and κ^* systematically scored lower than A because they are only re-scaled versions of A to take into account chance agreement. In addition, κ scored systematically lower than κ^* because its estimate of chance agreement was less conservative. Despite these differences in score range, all measures were consistent in indicating the SSS and MBES maps as the most similar, and the SBES and SSS maps as the least similar (Table 4.6).

The next step was that of testing the influence of map size and number of classes on the measures. As the MBES map had the fewest classes in the study, the other two maps were reduced to match that number. Using the ground-truth survey results to identify similar classes, classes A and B were aggregated in the SBES

map, and classes G and H in the SSS map. After limiting all three maps to their common area, the resulting reduced MBES, SBES, and SSS maps were described by three classes each: J, K, and L for the MBES map, A+B, C, and D for the SBES map, and E, G+H, and I for the SSS map. Tables 4.7, 4.8 and 4.9 list the contingency matrices for comparing these reduced maps, and Table 4.10 lists the scores obtained by the measures of categorical association and agreement on these matrices. As all the reduced maps had the same number of classes, computation of the measures of agreement did not require further class aggregation, but still required all possibilities of class permutation.

Table 4.7. Contingency matrix of the reduced SBES and SSS maps.

Reduced SBES map class	Reduced SSS map class			Total
	E	G+H	I	
A+B	103 546	43 727	444 701	591 974
C	240 984	82 492	79 134	402 610
D	53 079	28 622	0	81 701
Total	397 609	154 841	523 835	1 076 285

Table 4.8. Contingency matrix of the reduced SBES and MBES maps.

Reduced MBES map class	Reduced SBES map class			Total
	A+B	C	D	
J	533 909	98 294	0	632 203
K	55 098	257 312	54 484	366 894
L	2 967	47 004	27 217	77 188
Total	591 974	402 610	81 701	1 076 285

Table 4.9. Contingency matrix of the reduced MBES and SSS maps.

Reduced MBES map class	Reduced SSS map class			Total
	E	G+H	I	
J	71 420	46 646	514 137	632 203
K	315 018	43 247	8 629	366 894
L	11 171	64 948	1 069	77 188
Total	397 609	154 841	523 835	1 076 285

Table 4.10. Measures of association and measures of agreement obtained from the contingency matrices (Tables 4.7, 4.8, and 4.9). The percentage increase or decrease of the measures in comparison to their original value in Table 4.6 is indicated in parenthesis. For the measures of agreement, the automatic permutation procedure was applied, and only the maximum values are reported.

Compared maps and contingency matrices	Measures of association			Measures of agreement		
	V	λ	U	$\max A$	$\max \kappa$	$\max \kappa^*$
SBES/SSS (Table 4.7)	0.423	0.378	0.212	0.664 ^e	0.423 ^e	0.496 ^e
	(+1%)	(+168%)	(-14%)	(-1%)	(+38%)	(-12%)
SBES/MBES (Table 4.8)	0.524	0.495	0.344	0.760 ^f	0.560 ^f	0.641 ^f
	(-4%)	(+7%)	(+6%)	(~0%)	(-1%)	(~0%)
MBES/SSS (Table 4.9)	0.675	0.634	0.478	0.831 ^g	0.707 ^g	0.746 ^g
	(-12%)	(-4%)	(-4%)	(-4%)	(-5%)	(-6%)

^e: A+B~I, C~E, D~G+H

^f: J~A+B, K~C, L~D

^g: J~I, K~E, L~G+H

As the MBES/SBES and MBES/SSS map comparisons were already limited to the small MBES area and included automatic class aggregation to match the lowest number of classes, the map reduction was expected to have an influence only on the SBES/SSS map comparison. This was not observed (Table 4.10). Only λ and κ indicated that the SBES/SSS map similarity increased notably following the map reduction. The other measures only indicated a very small increase or even a decrease. The reduction actually had a clearer effect on the MBES/SSS map comparison, because all measures indicated that the map similarity decreased as a result. For the MBES/SBES map comparison, the reduction showed no influence on the measures of agreement, but mixed influence on the measures of association, where λ and U both increased and V decreased. Despite these modifications in the scores, the initial observation that the MBES and SSS maps were the most similar and that the SBES and SSS maps were the least similar remained valid after the reduction.

The very good agreement in location and extent between the SSS classes E and I and the MBES classes K and J (Figure 4.4c, Table 4.5) probably contributed to the high similarity scores attained in comparing these two maps. The decrease in similarity observed after map reduction can probably be linked to the forced aggregation of SSS classes G and H, whereas they were previously better associated with separate MBES classes, respectively J and L (see Table 4.5 and legend agreement solution in Table 4.6).

The general confusion between SBES classes B and C and SSS classes E and G probably contributed to the low similarity scores found in comparing these two maps. The scattered SSS E segments in the south of the study site were associated with SBES class B, whereas the main SSS E segment in the centre was associated with SBES class C, which in turn was found too in the southeast in a zone dominated by SSS class G (Figure 4.4a). This confusion is also apparent in the detail of the optimal solutions resulting from the aggregation/permutation procedure (Table 4.6): SSS class E appeared better associated with SBES class B for computing the overall accuracy A and κ^* , but better associated with SBES class C for computing κ .

In this study, the three maps were obtained independently and showed various differences or similarities in technology (frequency, bandwidth, beam patterns, sonar depth, operating angular sector, *etc.*), signal processing (calibration, acquisition gains, post-survey processing, *etc.*), survey design (spatial coverage and resolution), and classification methodology (features to classify, classification algorithm, and analysis design). Therefore, the observed MBES/SSS similarity and SBES/SSS dissimilarity cannot be linked to a single varying parameter, but is rather the result of the combined effects of several parameters with unknown contributions.

The main potential origins for the MBES/SSS map similarity and SBES/SSS map dissimilarity are the map resolution and coverage. The MBES and SSS maps relied on high-resolution, full-coverage acoustic imageries, whereas the SBES map relied on a dataset with such a lower resolution that it required interpolation to be compared with the other maps. The interpolation means that most of the content of the SBES map is predicted rather than measured, and that one should remain critical of its results (Foster-Smith and Sotheran, 2003). A second potential explanation is the systems' respective operating angular sectors (Michaels, 2007). The SSS operated from very low to mid-range grazing angles, in the 1–40° range under the assumption of a flat seabed. The MBES operated from low to very-high grazing angles, in the 25–90° range. The SBES operated at very-high grazing angles only, in the 86–90° range. As the contributions of both surface roughness and volume heterogeneity backscattering processes vary considerably with grazing angle (Lurton, 2002), particularly the former in the 70–90° range, perhaps some spatial changes in seabed characteristics are detectable in a signal recorded at certain angles, but invisible at other angles. Therefore, the separation of the SBES and SSS operating angle sectors could lead to different aspects of the seabed being measured, and the partial overlap of MBES and SSS angle sectors may increase the chance that these two systems measure the same seabed variations. A third possible explanation is the choice of the features used for classification. Both MBES and SSS maps were obtained from classification of the amplitude of their respective signals, which translated into image tone and texture. In comparison, the SBES map was obtained from classification of three

unknown Q-values, which can be any of the 166 features the QTC software extracted from the SBES signal cumulative amplitude, amplitude quantiles and histogram, power spectrum, and wavelet packet transform (Preston *et al.*, 2004a). This difference in number and nature of features implies that the resulting SBES map could be based on different seabed characteristics from those of the MBES and SSS maps (Simard and Stepnowski, 2007).

Similar hypotheses can be formulated to explain the greater similarity of SBES with MBES than with SSS. For instance, it is less likely that SBES and MBES measured different seabed characteristics because their operating angular sectors overlap. In addition, the SBES and MBES maps were obtained from a similar automatic clustering-classification algorithm, whereas the SSS map was obtained from subjective interpretation. The first approach is insensitive to the spatial distribution of the features, but the second implies some degree of spatial analysis as a result of the capabilities of the human brain for object and texture recognition (Russ, 2007).

4.6 Conclusions

Three benthic habitat maps covering the same site were created from different acoustic datasets, but the size and design of the ground-truth surveys rendered estimation of their accuracy impossible. However, direct map-to-map comparison was possible and performed. Several techniques for map-to-map comparison exist, but in this case, a set of measures for a map pixel-to-pixel comparison originating from the fields of statistics and land remote sensing was used. This approach did not allow any conclusions to be drawn on the accuracy of individual maps, but it did permit estimates to be made of how much the different systems/processing methodologies led to similar results which were, in summary, that the MBES and SSS maps were essentially similar, whereas the SSS and SBES maps were not similar.

The basis for classification of SSS and MBES was their imagery, which appeared to be similar (Schimel *et al.*, 2010). The similarity measured between their

respective segmentations confirms this and supports the argument that MBES imagery, even at a lesser resolution, is a viable alternative to SSS imagery to segmentation.

The hypothesis that a SBES map could be representative of different seabed characteristics from those appearing on SSS maps has been suggested in previous comparative studies, which advised that the two systems should be run in tandem so that the output map can benefit from such a multisystem approach (Foster-Smith *et al.*, 2004; Brown *et al.*, 2005; Anderson *et al.*, 2008). The low similarity measured here between the SBES and SSS maps supports this argument. However, it remains unclear whether most of the dissimilarity observed is created by potential SBES map artefacts resulting from its lower resolution or by genuinely different mapped seabed characteristics.

Estimating the respective accuracy of the SBES and SSS maps could have helped clarify this ambiguity. All this shows that, despite the benefits, a map-to-map comparison approach cannot replace the value of a well-designed ground-truth survey accompanying all acoustic mapping effort and hence allowing estimation of map accuracy and its variance (Foody, 2002, 2009; Anderson *et al.*, 2008). As far as possible, the map-accuracy comparison and map-to-map comparison approaches should be performed together in analyses of overlapping maps.

It is important to note that this study was limited to a specific quasi-homogeneous soft-sediment coastal environment, a specific resolution, and specific segmentation methodologies, so its conclusions must be viewed in this context. Only repetition of such multisystem experimental comparative studies in different environments would help extend the range of the conclusions.

A wide range of comparative studies in seabed mapping would benefit from the measures presented here, or from other map-comparison tools used in the field of land remote sensing. In contrast with this study, particular focus could be on reducing the variability in the origin of the maps in order to target the similarity study.

For example, comparing maps obtained from:

- (i) a unique system's output classified with various segmentation methodologies would specifically address the similarity between methodologies;
- (ii) different datasets, but classified using a unique segmentation methodology, would specifically estimate the complementarity of different datasets;
- (iii) a unique system and methodology, but acquired at different times, would facilitate monitoring the changes at a given site over time;
- (iv) a unique system, segmentation methodology, and survey, but classified with different legends in supervised mode, would specifically address the issue of similarity between different classification schemes.

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CHAPTER 5

THE APPLICATION:

COMPARING COMPLEX ASC APPROACHES THAT COMBINE MBES MOSAIC AND ANGULAR-RESPONSE DATA

5.1 Preface

This chapter was submitted as a manuscript to the Estuarine, Coastal and Shelf Science journal for publication. It is titled “Unsupervised acoustic seabed classification combining angular and spatial information from multibeam backscatter data” and is authored by Alexandre C. G. Schimel, Yuri Rzhanov, Luciano Fonseca, Larry Mayer, Terry R. Healy and Dirk Immenga. At present (13 November 2011), the submitted manuscript is being reviewed. It is reprinted here with only minor edition of acronyms, figure and table numbers and format, and references in order to match the thesis format. Since this chapter was written to stand alone as a published article, it contains minor repetitions of reasoning previously found in this thesis and statement of objectives that may differ from those of the thesis. The previous chapters are cited as Schimel *et al.*, (2010a) and Schimel *et al.*, (2010b) in the text.

I, Alexandre Carmelo Gregory Schimel, assume responsibilities for fieldwork, laboratory and data analysis, development of methods, and writing, unless specified within the text. In particular, the methods developed previously and independently by Dr. Yuri Rzhanov, Dr. Luciano Fonseca and Professor Larry Mayer of the Center for Coastal and Ocean Mapping (University of New Hampshire, USA) are referenced whenever necessary (Rzhanov *et al.*, 2011). The work was undertaken with the supervision and editing input of Professor Terry Healy, Dr. Willem de Lange and Dr. David Johnson, and the significant involvement of Dirk Immenga for the mobilisation and use of the acoustic systems.

5.2 Abstract

Multibeam Echosounders are increasingly used for benthic habitat mapping, primarily as a result of the multiplicity of their outputs: bathymetry, backscatter mosaic, angular response and water-column data. While many classification methodologies have been proposed based on either one of these data types, there have been comparatively few attempts to combine them, and particularly to combine backscatter mosaic and angular response. In this paper, two methodologies are presented that perform this promising combination. Both methodologies make use of the processing capabilities of the Geocoder software developed at the Center for Coastal and Ocean Mapping (University of New Hampshire, USA), and are applied to a Kongsberg-Simrad EM3000 Multibeam Echosounder backscatter dataset acquired over the Tapuae Marine Reserve, located in North Taranaki, New Zealand. The two methodologies are two different approaches to the grouping of segments from a fine segmentation of a backscatter mosaic on the basis of their angular response content. The first methodology is a labelling approach recently described in the literature that is investigated here for discussion and validation of its results. The second methodology is an aggregating approach, presented for the first time, which seeks to exploit the more recent capabilities of Geocoder in extraction of the full angular response distribution from the MBES backscatter data. The two methodologies are compared to the ground-truth data and to each other, using measures of map-to-map similarity. Their differences and similarities and their respective advantages, shortcomings and successes in this particular application are discussed.

5.3 Introduction

Backscatter data from multibeam echosounders (MBES) are now routinely used in attempts at remotely characterizing, identifying or mapping seafloor geology. This research was initiated in the late 1980s (De Moustier, 1986), and has undergone a continuous development following advances in MBES technology and computer processing capabilities (De Moustier and Alexandrou, 1991; Augustin *et al.*, 1996; Hughes Clarke *et al.*, 1996; Mayer, 2006). One particular research area, stimulated by the growing need for benthic habitat mapping, is acoustic seabed classification, that is the development of techniques that automatically construct a map of homogeneous seafloor-types from acoustic data (Kenny, 2003; ICES, 2007; Parnum, 2007; Brown and Blondel, 2009).

Acoustic classification techniques based on MBES backscatter data can be broadly separated into two groups, implementing two opposite approaches to the dependence of backscatter strength with grazing-angle at the seafloor (*angular response*). A first group of methodologies are based on the analysis of the angular response, exploiting the fact that its level and shape vary widely between different seafloor-types (*e.g.* Hughes Clarke *et al.*, 1997; Parnum, 2007; Fonseca *et al.*, 2009). In contrast, a second group of methodologies rely on the compensation of the angular response, in order to exploit the remaining spatial variations in the compensated data, which are indicative of local changes in seafloor-type (*e.g.* Preston 2009, Marsh and Brown 2009, McGonigle *et al.*, 2009).

These two approaches exploit respectively the angular information and the spatial information about seafloor type within an MBES backscatter dataset (Parnum, 2007). They are equally good descriptors of the seafloor-type variations (Hughes Clarke *et al.*, 1996), are very possibly complementary (Fonseca *et al.*, 2009), and lead to similarly good results (Brown and Blondel, 2009). It is therefore expected that a combined approach exploiting both spatial and angular information would lead to even better results (Hughes Clarke *et al.*, 1996). Historically, the potential of such a combination has been explored in two methodologies implementing a supervised classification of the angular information of an MBES dataset into

classes having been manually pre-defined from its spatial information (Augustin *et al.*, 1997; Canepa and Pace, 2000).

More recently, Rzhanov *et al.* (2011) suggested a new methodology that realizes an unsupervised segmentation of an MBES backscatter dataset by exploiting both its spatial and angular information. Through this combined approach, the methodology seeks to identify areas on the seafloor that present the same angular response throughout. A region of seafloor that presents the same angular response throughout is said to have a *spatially consistent* angular response, and is termed an *acoustic theme* (Fonseca *et al.*, 2009).

The aim of this article is threefold: First, to validate the themes-construction methodology proposed by Rzhanov *et al.* (2011) through its application to a complete MBES dataset and the comparison of its results with ground-truth; Second, to introduce an alternative approach to the construction of acoustic themes, which was developed in an attempt to exploit a more detailed form of angular-response data; And third, to compare the two approaches.

In the first part of this paper, the MBES and ground-truth datasets are presented. The backscatter data are then processed to allow the exploitation of their angular and spatial information, namely: reduction to backscattering strength, angular compensation, formation of a mosaic, and mosaic segmentation. The themes-construction methodology proposed by Rzhanov *et al.* (2011) is then summarized and directly applied to the dataset. The same process is followed for the alternative methodology. Next, the thematic maps resulting from both methodologies are presented, qualitatively analyzed, and quantitatively compared to each other, and to the ground-truth dataset. The results are summarized and discussed, and further methodology developments are suggested.

5.4 MBES and ground-truth dataset

5.4.1 Study site: The Tapuae marine reserve

The study site is the Tapuae Marine Reserve, located west of the city of New Plymouth, in North Taranaki, New Zealand (approximate location $39^{\circ}4'S$ $174^{\circ}0'E$, Figure 5.1). The seafloor of the marine reserve is in 0 to 40 meters water depth. It is known to comprise large sandy areas interspersed with a range of rocky regions, mostly cobble and boulder platforms of variable complexity, which occasionally support kelp forests (Ngā Motu Marine Reserve Society Inc., 2004).

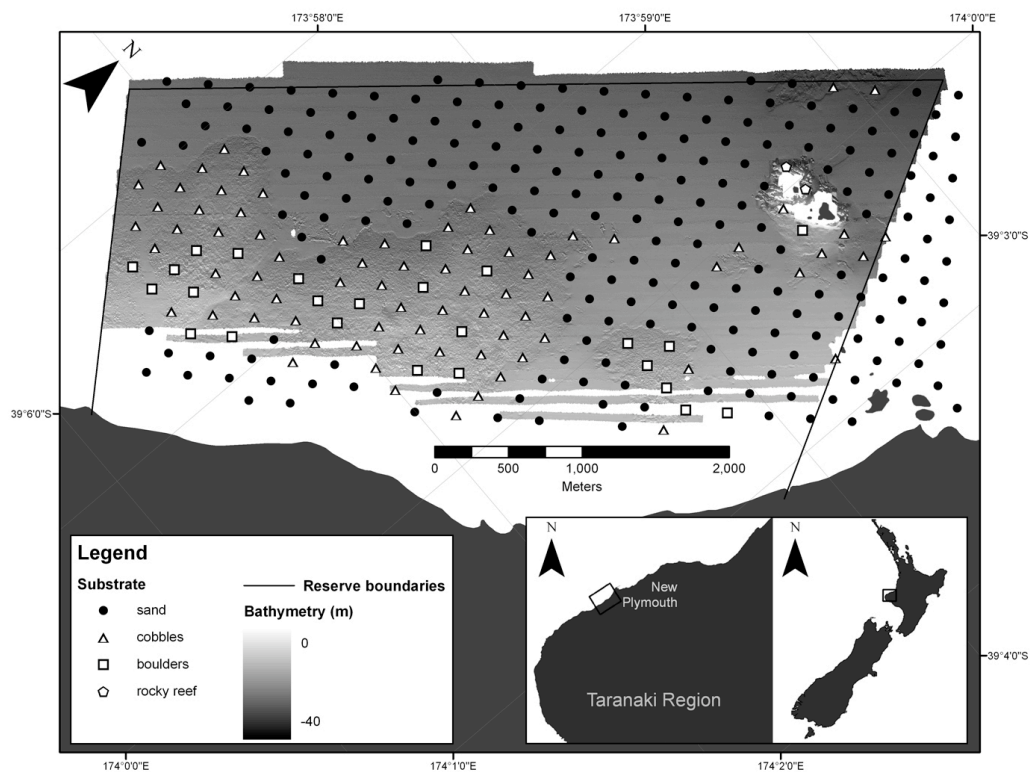


Figure 5.1. Location of the study site, bathymetry grid, and ground-truth dataset. Survey site is the Tapuae Marine Reserve, located in the Taranaki region, in New Zealand North Island ($39^{\circ}4'S$ $174^{\circ}0'E$). The sun-illuminated bathymetry grid is displayed here in a grey scale coded by depth. The 2004 video survey was composed of 318 stations, which were assigned one of four substrate-type categories (“Sand”, “Cobble field”, “Boulder field”, or “Rocky reef”). The ground-truth dataset is defined as the 248 stations that overlapped the MBES dataset.

5.4.2 Multibeam survey

The Tapuae Marine Reserve was surveyed with a Kongsberg-Simrad EM3000 MBES in February 2008 as part of a habitat mapping effort supported by the Department of Conservation of New Zealand.

The EM3000 has an operating frequency of 300 kHz (Kongsberg Maritime AS, 2005). It emits short 150 μ s pulses at a high ping-rate dependent on water depth, approximately 12 Hz in average in this study, within a 120° across-track by 1.5° along-track swath. At reception, the signals received by the individual transducers composing the array are sampled at 15 kHz, and 127 beams are formed using a Fast Fourier Transform beam-forming algorithm. The across-track width of the reception beams ranges from 1.5° for central beams to an estimated 3.0° for outer beams.

In this survey, the EM3000 was pole-mounted on the University of Waikato research vessel *RV Tai Rangahau*. The EM3000 software performed real-time ray tracing correction using a water-column sound-velocity profile acquired at the beginning of each survey day with an Applied Microsystems Ltd SVPlus profiler, and real-time electronic pitch stabilization using measurements from a TSS MAHRS motion sensor. A Trimble MS750 Differential GPS setup provided vessel position. Tide elevation was obtained from a tidal gauge located at nearby Port Taranaki. MBES and ancillary data were recorded in individual files described in the eXtended Triton Format (*.xtf) using Triton Imaging Inc. ISIS acquisition software (Triton Imaging Inc., 2006). The files were subsequently converted to the Kongsberg “EM Series” datagram format (*.all) using a converter developed at University of Waikato (Kongsberg Maritime AS, 2009).

5.4.3 Bathymetry processing

A bathymetry grid was produced from the MBES data files using a Matlab program developed at University of Waikato, an earlier version of which is described in Schimel *et al.* (2010a). The processing included compensation for the transducer's setup angles and GPS latency, ray-tracing, filtering of the vessel position and heading, correction for tide elevation, compensation of sensor heave and then of residual roll and heave artefacts in the data (following Crawford (2003)), geo-coding in the appropriate Universal Transverse Mercator (UTM) projection including compensation for grid convergence, and gridding of soundings at a 1m resolution using a weighted average with weights based on both soundings quality factors (Kongsberg Maritime AS, 2009) and distance to nadir. The resulting bathymetry grid is shown in Figure 5.1.

5.4.4 Ground-truth dataset

In order to assess the quality of the methodologies presented in this study, the results from a video survey of the Tapuae Marine Reserve, performed and analyzed by the Department of Conservation of New Zealand in 2004, were used as ground-truth (Ngā Motu Marine Reserve Society Inc., 2004). The survey comprised 318 stations arranged systematically over the entire marine reserve. 248 of these stations were covered by the 2008 MBES survey and composed the ground-truth dataset (Figure 5.1).

In the original analysis, each station was assigned a decimal score describing the complexity of the substrate observed on the video footage, ranging from 1 for uniform soft-sediment to 4 for complex reef structures with ledges and crevasses (Mead and McComb, 2002; Ngā Motu Marine Reserve Society Inc., 2004). In the present study, this score was used to assign to each station one of four substrate-type categories from the coastal marine classification scheme established by the Ministry of Fisheries and the Department of Conservation of New Zealand (Ministry of Fisheries and Department of Conservation, 2008). Table 5.1 describes the scheme used and its relation to the complexity score.

Table 5.1. Definition of the ground-truth classification scheme, based on the score describing the complexity of the substrate observed on the video footage.

Complexity score (Ngā Motu Marine Reserve Society Inc., 2004)	Substrate-type classification category (Ministry of Fisheries and Department of Conservation, 2008)
[1 : 1.5 [	Sand
[1.5 : 2.5 [	Cobble field
[2.5 : 3.5 [	Boulder field
[3.5 : 4]	Rocky reef

5.5 Backscatter data processing

The MBES backscatter data was originally in the so-called *snippets* format, as recorded in Kongsberg “Seabed Image” datagrams (Kongsberg Maritime AS, 2009). Snippets are short time-series of signal samples recorded in each beam around the sample estimated to be at the exact range at which the beam pointing-vector intersected the seafloor, according to the bottom-detection algorithm. These data were processed using the Geocoder software, research version 5.02, developed at the Center for Coastal and Ocean Mapping, University of New Hampshire, USA (Fonseca and Calder, 2005).

5.5.1 Reduction to backscattering strength

The level of the signal sample found at range R in beam N , $EL_N(R)$, can be expressed using the sonar equation (Lurton, 2002; Augustin and Lurton, 2005):

$$EL_N(R) = SL + DT(\theta) - 2TL(R) + BS(\beta) + 10\log(S[R, \beta]) + DR_N(\theta) + PG(R) \quad (5.1)$$

where SL is the source level, DT is the directivity loss from transmission beam pattern, TL is the transmission loss, BS is the backscattering strength, S is the backscattering surface, DR_N is the directivity loss from the receive beam pattern

for beam N , and PG is the hardware receive processing gain. Most of these terms are dependent on a number of parameters – not all of them are being indicated in equation (5.1) – including the angle at sonar transducer θ and the grazing angle at seafloor β .

In order to allow the exploitation of the angular information in the backscatter data, the recorded echo level in equation (5.1) must be reduced to the backscattering strength term BS.

First, the transmission loss TL and the processing gain PG were removed using information provided by the manufacturer (Hammerstad, 2000; Fonseca and Calder, 2005). Then, the local seafloor slope at the horizontal location of each sample was estimated from the bathymetry grid created previously. This information was used to calculate the grazing angle at seafloor β , and the instantaneous backscattering surface S (Fonseca and Calder, 2005). The surface S was compensated, while the grazing angle β was conserved for the formation of the angular response BS(β).

Ideally, the remaining terms in equation (5.1) should be compensated using test tank calibration measurements. For the MBES system used in this study however, there was no information for DR_N , and only generic measurements were available from the EM3000 manufacturer for the source level SL and the directivity loss in transmission DT (Hammerstad, 2005). Geocoder includes these generic measurements but their suitability for this study was doubtful since they were not representative of the specific system that recorded the data, nor did they take into account a probable hardware wear or drift with time (Lamarche *et al.*, 2011). In the absence of reliable tank calibration measurements, a tentative alternative procedure is to estimate these terms through a field calibration.

The field calibration procedure in Geocoder consists of measuring an estimate of the cumulative contribution of SL, DT and DR_N (also termed *experimental beam-pattern*) as the difference between the measured and expected average backscatter level as a function of the angle at sonar transducer θ . The measurement is performed over a site of known sediment-type, and after a prior compensation for

TL, PG and S (Fonseca *et al.*, 2006). The modified effective density fluid model implemented in Geocoder provides the expected backscatter level for the site's mean grain-size (Fonseca *et al.*, 2002; Fonseca and Mayer 2007). The use of a calibration site presenting a coarse grain-size ensures a limited influence of the other model parameters, when their values are unknown.

For this study, such an experimental beam-pattern was obtained from data acquired over a coarse-sand area located off Tairua beach, in the Coromandel, New Zealand (approximately 36°59.0'S 175°52.7'E), which has been extensively studied and sampled (Green *et al.*, 2004; Trembanis *et al.*, 2004, Stark, 2010). Its application to the Tapuae dataset completed the reduction of the recorded signal level to an estimation of BS.

5.5.2 Angular compensation and mosaicking

In order to allow the exploitation of the spatial information in the backscatter data, the angular dependence must be compensated, and the resulting adjusted backscatter level must be processed into a mosaic. The compensation of the angular response is not as straightforward as the other terms compensated previously because it is dependent on seafloor-type, which is a piece of information that is unknown *a priori* (Hughes Clarke *et al.*, 2008).

Most modern MBES backscatter-data mosaicking approaches now implement some form of statistical compensation of the angular response. A statistical compensation consists of subtracting from each sample with a given grazing-angle the average level of a subset of samples with the same angle, and then adding the average level computed at a reference angle. The existing approaches generally differ in the definition of the subset. Suggested subsets include the entire dataset (Lamarche *et al.*, 2011), the runline containing the sample to correct (Schimel *et al.*, 2010a), all samples recorded at the same range or depth (Mitchell and Hughes Clarke, 1994; Preston, 2009), or a local, spatially interpolated set of samples (Parnum, 2007).

In the statistical compensation implemented in Geocoder (*AVG correction*), the subset used for the correction of any given sample consists of a stack of consecutive pings centred around this sample (Fonseca and Calder, 2005). For this study, the default AVG correction was applied (merging port and starboard samples in the ping stacks, a correction termed *flat AVG*, see Huff *et al.* (2009)), using the default ping-stack size (300 pings), and the default reference level (average BS level between 30 and 60 degrees within the same stacks).

Following the application of this angular correction, a backscatter image of the study site was obtained from the mosaicking of the compensated data at a resolution of 1 meter in the UTM projection, zone 59 South (Figure 5.2). The mosaicking procedure in Geocoder includes a feathering algorithm to accommodate for the overlap of consecutive acquisition lines (Rzhanov *et al.*, 2003; Fonseca and Calder, 2005).

Figure 5.2 shows that the compensation removed most of the angular variations in the dataset (*i.e.* the horizontal banding effect in Figure 5.2a), but that visual artefacts remain around the sharp transitions between the high- and low-reflectivity regions of the mosaic. Since those two regions present two very different angular response profiles, the average computed from ping-stacks that cover both regions are not representative of either of them, hence the artefacts (Hughes Clarke *et al.*, 2008). The use of a smaller ping-stack size in the AVG correction, or better, the manual adaptation of its settings to suit visible local changes in mosaic tone and texture, could allow reducing the number and intensity of these artefacts. However, this mosaic was intentionally left unaltered to allow testing of the performance of the segmentation methodologies on an automatically generated, artefact-ridden mosaic.

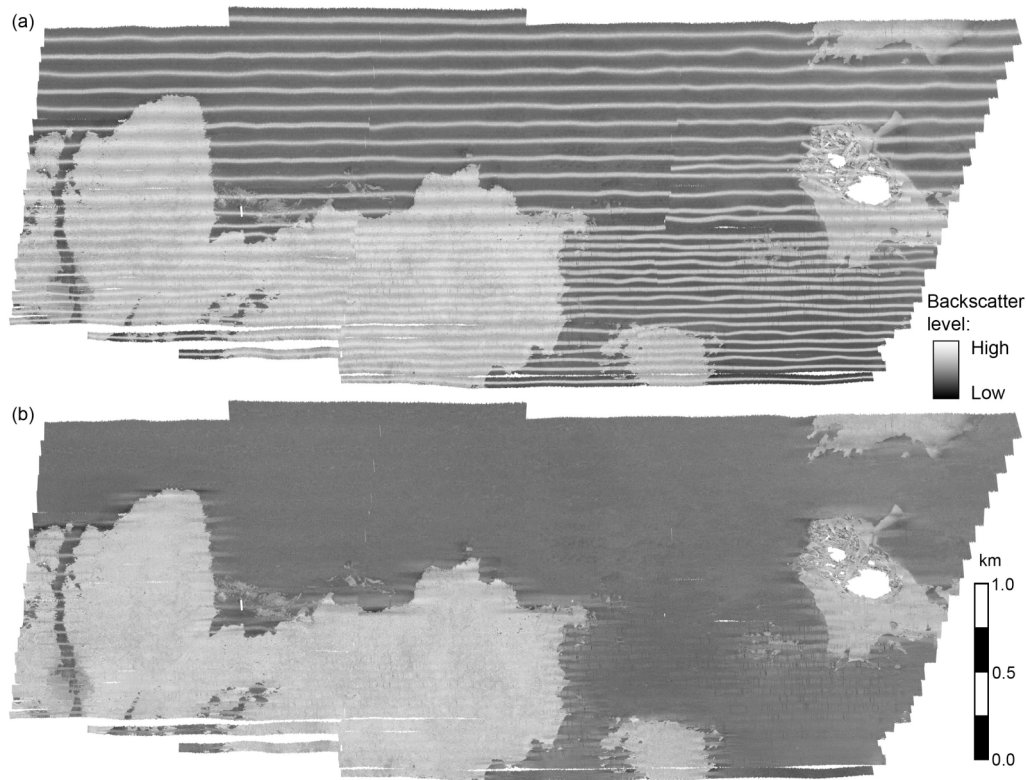


Figure 5.2. Mosaic of the study site (a) before and (b) after compensation of the angular response. Dark tone indicates low reflectivity, and light tone indicates high reflectivity.

5.5.3 Mosaic segmentation

The backscatter mosaic was then segmented at several levels of detail using a colour-quantization algorithm that progressively aggregates segments based on their grey-level similarity (Rzhanov *et al.*, 2011). The algorithm started with the individual pixels taken as the initial segments, and ended when the entire mosaic has become a single segment. Outputting the segmentation at various levels of this algorithm produced a set of thirteen maps with increasingly larger segments. Thus, in this processing scheme, a given segment at a given segmentation level is exactly coinciding with one or several segments from the previous levels. Figure 5.3 presents the maps at the second, third, sixth and seventh levels, respectively noted S_2 , S_3 , S_6 and S_7 , which were used in subsequent processing.

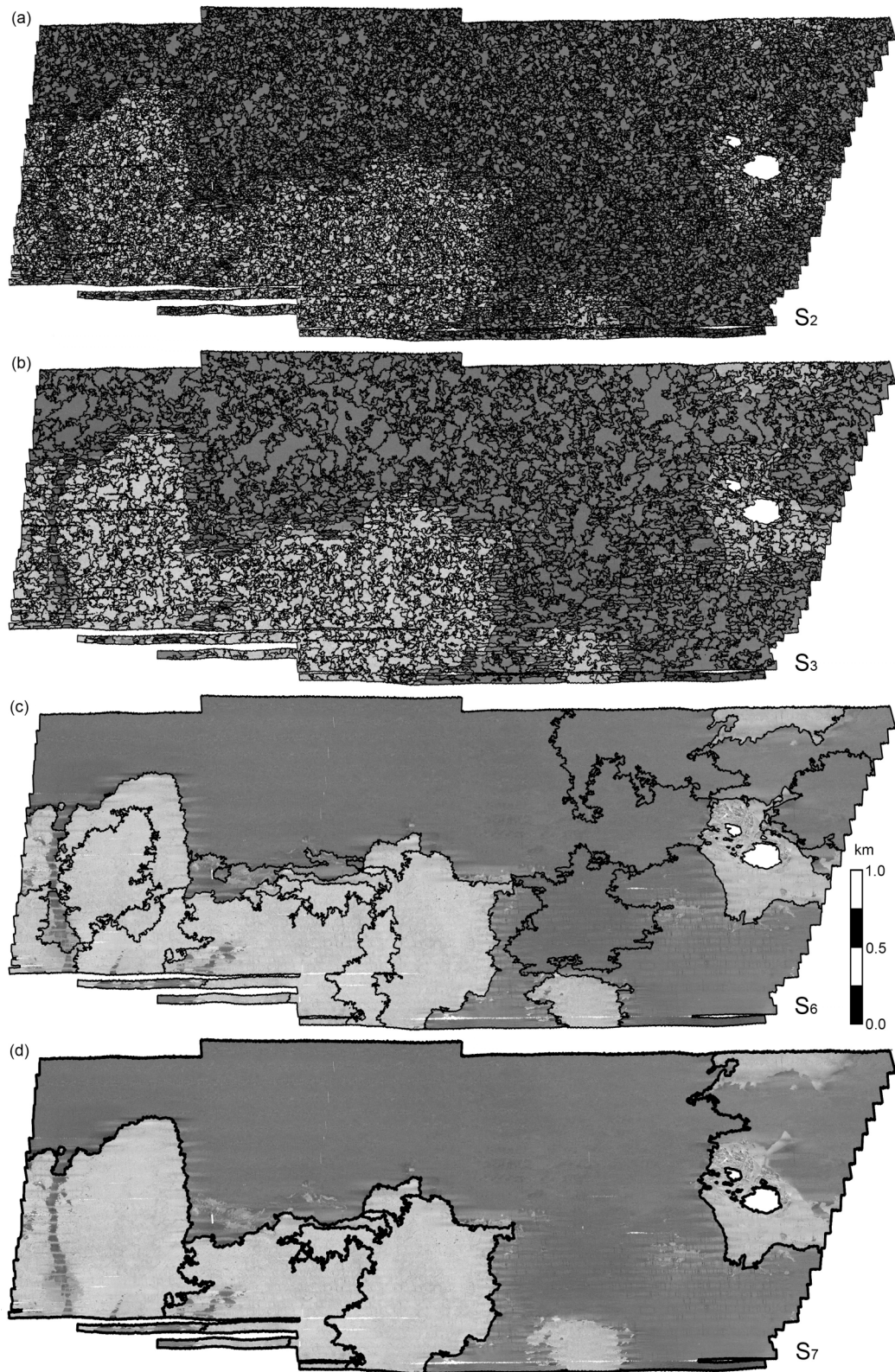


Figure 5.3. Mosaic segmented at several levels of detail. (a) S_2 is composed of 14,158 segments. (b) S_3 is composed of 2,805 segments. (c) S_6 is composed of 24 segments. (d) S_7 is composed of 7 segments. The boundaries of individual segments are displayed in black over the backscatter mosaic.

5.6 Construction of acoustic themes: a labelling approach

5.6.1 Methodology

Recent versions of Geocoder offer the capability to extract the average angular-response curve in MBES backscatter data from any arbitrary region of seafloor (Fonseca *et al.*, 2009). Using this capability, Rzhанov *et al.* (2011) suggested a labelling approach to the construction of acoustic themes based on the processing of two segmentations of a standard mosaic, and the angular-response content of their segments. The next paragraphs summarize this methodology. For more information, refer to Rzhанov *et al.* (2011).

As an initial step, a catalogue of labels representing “ideal” angular-response curves is defined (*base functions*). These curves are derived from the fitting of the Geocoder modified effective density fluid model to the average angular-response curves extracted from the relatively large segments composing a coarse segmentation of the mosaic. The fitting is performed automatically with the *Angular Range Analysis* (ARA) constrained iterative fitting algorithm, which operates on a small number of parameters describing the curves rather than the curves themselves (Fonseca and Mayer, 2007).

After definition of the catalogue, each of the relatively small segments composing a fine segmentation of the mosaic is assigned one of the base functions. This labelling is obtained from a combinatorial optimization algorithm operating on two cost terms that respectively describe (1) the distance, in amplitude, between the segments’ average curve and each of the base functions (*data*), and (2) a penalty for labelling neighbouring segments with different base-functions (*smoothness*). The relative weight of these two cost terms in the algorithm is manually adjusted (Rzhанov *et al.*, 2011).

5.6.2 Application to the study site

In the methodology described above, the choice of the coarse segmentation defines the number and types of base functions for the subsequent labelling process. An ideal coarse segmentation should therefore contain a small number of segments, and each of them should cover a uniform region of the mosaic. In practice however, these two conditions are usually conflicting and a compromise must be found.

In the present study, S_7 was composed of an appropriately small number of segments (7), but all except one of them covered non-uniform regions of the mosaic (Figure 5.3d). More importantly, none of them covered a uniform low-reflectivity region of the mosaic (Figure 5.3d). Segmentation S_6 was composed of an impractically high number of segments (24) and many of them covered heterogeneous regions of the mosaic, but the entire apparent range of facies present in the mosaic was covered by at least one uniform segment (Figure 5.3c). S_6 was therefore chosen as the coarse segmentation for the definition of the catalogue of base functions, with the expectation that the labelling algorithm would favour the more representative base functions and discard those originating from heterogeneous segments.

S_6 was imported in Geocoder and the average angular response curves were extracted for its 24 segments. The ARA algorithm was then applied to these curves to produce a catalogue of 24 base functions, sequentially noted BF_0 to BF_{23} (Figure 5.4).

Modelled curves obtained from the ARA inversion are used as the base functions instead of the average data curves in order to extract the characteristic curve from the dominant mosaic facies in segments that cover several of them (Rzhanov *et al.*, 2011). Figure 5.4 shows the limitation of this approach in the Tapuae dataset, as some segments visibly covered a unique facies but the modelled curve did not fit the data (*e.g.* Figure 5.4g), while some segments visibly covered multiple facies but the modelled curve did fit the data (*e.g.* Figure 5.4h). Two hypotheses that could explain this behaviour on this particular dataset are: (1) a possible lack

of validity of the geoacoustic model used in the ARA algorithm, and/or (2) a possible lack of quality in the field calibration. The first hypothesis is supported by the fact that the model implemented in Geocoder is limited to soft-sediment (Fonseca *et al.*, 2002; Fonseca and Mayer, 2007), while the Tapuae site includes many occurrences of hard substrate (cobbles and boulders, Figure 5.1). The second hypothesis is supported by the observation that, despite the previous fact, a relatively good fit was apparent between data and the geoacoustic model for some segments that cover hard-substrate regions of the study site (*e.g.* Figures 5.4d and 5.4f).

Despite the above, the catalogue of base functions was kept unaltered. S_3 was then used as the fine segmentation for the labelling algorithm. It was imported in Geocoder and the average angular-response curves were extracted from its 2,805 segments. Finally, the combinatorial optimization algorithm was applied to the curves from these 2,805 segments to label each of them with one of the 24 base functions.

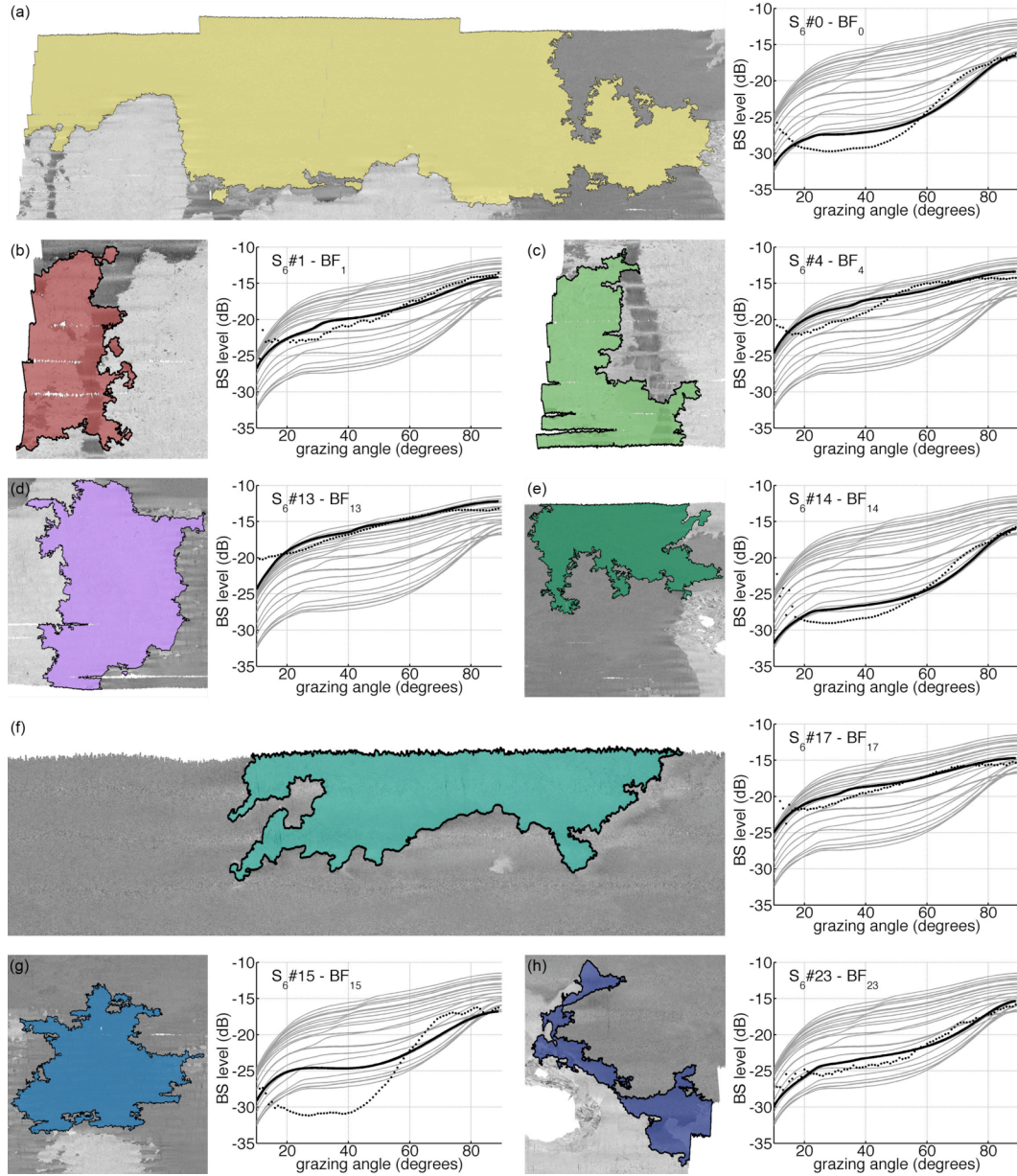


Figure 5.4. Some base functions defined from segments from the coarse segmentation S_6 . The base functions illustrated are (a) BF_0 , (b) BF_1 , (c) BF_4 , (d) BF_{13} , (e) BF_{14} , (f) BF_{17} , (g) BF_{15} and (h) BF_{23} . For each, the left panel shows the original greyscale backscatter mosaic shining through the coloured segment of interest, and the right panel shows the average angular response data extracted from the segment (dots), the model curve fitted on these data, i.e. the base function (bold line), and the 23 other base functions in the background for reference (light lines).

5.7 Construction of acoustic themes: an aggregating approach

5.7.1 Methodology

The version of Geocoder used in this research (v5.02) also offers the capability to extract the angular-response data in the form of tabulated frequencies of samples within 0.5 dB bins in the BS space and 1° bins in the grazing-angle space. These two-dimensional (2D) histograms represent estimations of the probability distribution of BS, for each individual grazing-angle bin. Figures 5.5 and 5.6 show examples of this data format.

An alternative methodology of construction of acoustic themes was developed in order to exploit this format, which has shown a more important potential for the characterization of seafloor-type than the more usual, simple average curve (Lyons and Abraham, 1999; Le Gonidec *et al.*, 2003; Parnum, 2007).

The suggested methodology implements a non-parametric approach to the analysis of the 2D histograms, in order to remain insensitive to a possible lack of quality in the field calibration step. Two measures were designed to estimate empirically (1) the *modality* of a 2D histogram, and (2) the *similarity* between two 2D histograms. The use of the modality measure allows the identification of the segments that potentially present a spatially inconsistent angular response, and should therefore be divided into smaller segments, while the use of the similarity measure allows the identification of pairs of neighbouring segments that potentially present the same angular response and should therefore be aggregated.

5.7.1.1 The modality measure

Several candidate theoretical distributions have been suggested for BS, including the Rayleigh, Rice, Gamma, and K distributions (Lyons and Abraham, 1999; Lurton, 2002; Parnum, 2007). Despite the lack of certainty about the most appropriate one, all these distributions share the characteristic of being unimodal. In effect, the experimental distribution of BS for a single, homogeneous seafloor-type is very often observed to be unimodal at all grazing angles (Le Gonidec *et al.*, 2003). An area covering two or several distinct seafloor-types that present distinct angular responses is therefore expected to display a bi- or multi-modal angular response.

This observation suggests that a measure of the modality of an angular response can be used as an indicator of its spatial consistency. A few studies have explored this approach for the identification of areas composed of more than one substrate-type, through the detection of abnormal sample statistics that characterize multimodality, such as a very high standard deviation (Mitchell, 1996; Canepa and Pace, 2000) or a very high difference between the mean and the mode (Le Gonidec *et al.*, 2003).

Here, the direct estimation of the modality of the distribution is suggested, through the use of Hartigan's DIP statistic. The DIP statistic measures the modality of a sample as the maximum difference between its empirical distribution, and the unimodal distribution that minimizes this maximum difference (Hartigan and Hartigan, 1985). This measure is traditionally used in a statistical test based on the null hypothesis that the sample follows a uniform distribution. For the present application, the measure is better targeted at low grazing-angles where the distribution of BS typically presents a low dispersion for a single seafloor-type, but a high variability between different seafloor-types.

The suggested modality measure M is computed as follows and is illustrated in Figure 5.5. First, the angular bins in the histogram are stacked over grazing-angle intervals of 3° in order to increase the sample size for the calculation of the statistic, and therefore its precision. The DIP statistic is then calculated for each

stack under 45° . Next, the p-value associated with the DIP statistical test is obtained from a table of quantiles (Maechler, 2010). Finally, the measure M is calculated as the average p-value over all stacks, weighted by the number of samples in each stack. M is normalized, tends towards 0 for a 2D histogram presenting a strong bi- or multi-modal profile under 45° , and tends towards 1 for a histogram presenting a strong unimodal profile under 45° (Figure 5.5).

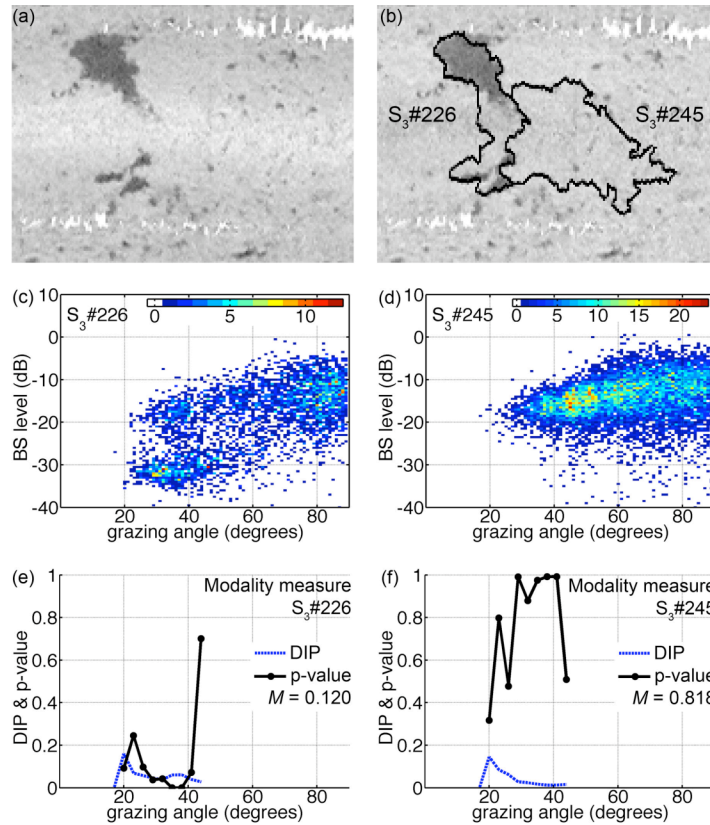


Figure 5.5. Computation of the modality measure M for the 2D histograms of S_3 segments $S_3\#226$ and $S_3\#245$. (a) displays an extract of the mosaic before compensation of the angular response and (b) shows the boundaries of the segments overlaid on the mosaic after compensation. (c,d) The 2D histograms are extracted from the data within both segments using Geocoder. The angular histograms under 45° are then stacked over 3° bins, from which the DIP statistic and its associated p-value are computed. M is finally calculated as the mean weighted p-value. (e) The low value ($M=0.120$) in the first example indicates the strong multimodality, i.e. the probable spatial inconsistency, of the angular response of $S_3\#226$. (f) The high value ($M=0.818$) in the second example indicates the strong unimodality, i.e. the probable spatial consistency, of the angular response of $S_3\#245$.

5.7.1.2 The similarity measure

An analogous measure was designed to evaluate the degree of similarity between two 2D histograms, based on the calculation of the two-sample Kolmogorov-Smirnov (KS) statistic. The KS statistic estimates the likeliness that the two samples are drawn from the same distribution, as the maximum distance between their respective empirical distribution functions (Fisz, 1963).

The suggested similarity measure S is computed as follows and illustrated in Figure 5.6. First, the angular bins in the histogram are stacked over grazing-angle intervals of 3° in order to increase the sample size for the calculation of the statistic, and therefore its precision. The KS statistic is then calculated for each corresponding pair of stacks over the entire angular range. Finally, the measure is calculated as the average KS statistic over all stacks, weighted by the stacks' joint sample size. S is normalized, equal to 0 for two perfectly identical histograms, and equal to 1 for two completely different histograms, or two histograms with no angle bins in common (Figure 5.6).

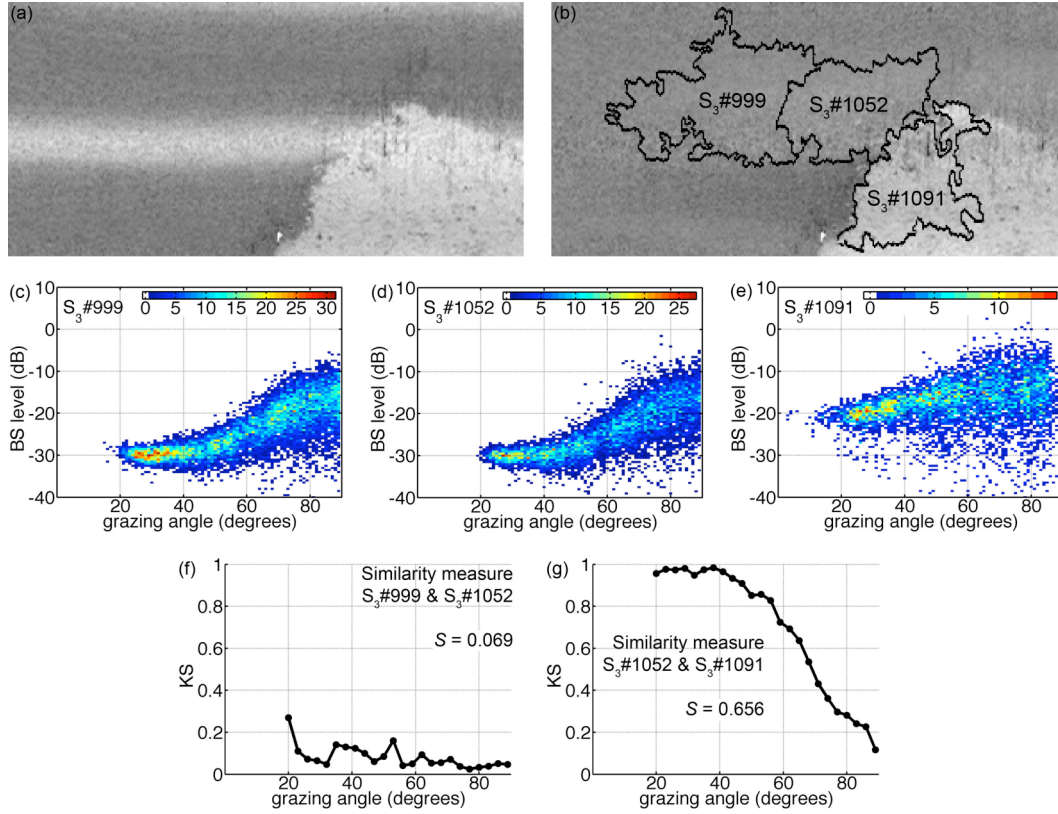


Figure 5.6. Computation of the similarity measure S between the 2D histograms of segments $S_3\#999$ and $S_3\#1052$, and between the 2D histograms of segments $S_3\#1052$ and $S_3\#1091$. (a) displays an extract of the mosaic before compensation of the angular response and (b) shows the boundaries of the segments overlaid on the mosaic after compensation. (c,d,e) The 2D histograms are extracted from the data within the three segments using Geocoder, and then stacked over 3° bins. The KS statistic is computed for all pairs of stacks where data are available in both histograms being compared, and S is calculated as the mean weighted KS statistic. (f) The low value ($S=0.069$) in the first example indicates the strong similarity between the 2D histograms of $S_3\#999$ and $S_3\#1052$. (g) The high value ($S=0.656$) in the second example indicates the weak similarity between the 2D histograms of $S_3\#1052$ and $S_3\#1091$. Note in this second example that the measured KS statistic decreases with grazing angle, as a result of the increasing similarity between the two 2D histograms.

5.7.2 Application to the study site

Ideally, a dividing/aggregating approach based on the two measures M and S should be implemented within the same software that mosaics the data, segments the mosaic and extracts the 2D histograms, in order to allow a recursive improvement of an original segmentation of the mosaic towards increasingly larger themes presenting a consistent angular response. At the present stage however, this approach could only be implemented outside of Geocoder. Accordingly, a suboptimal, non-recursive methodology was designed, based on the prior extraction of the 2D histograms from the segments composing S_2 and S_3 (Figures 5.3a and 5.3b), and on the sequential use of measures M and S .

In a first step, the modality measure M was computed for the 2D histograms from each of the 2,805 segments in S_3 . 36 segments presented a value under an empirical threshold of $M=0.5$, and were therefore considered as possibly presenting a spatially inconsistent angular response. These segments were then replaced by the corresponding, underlying segments from S_2 , resulting in a new, composite segmentation (S_3') made up of 2,912 segments. All segments in S_3' were assumed to present a spatially consistent angular response.

In a second step, the similarity measure S was computed for each pair of neighbouring segments in S_3' . Neighbouring segments were here empirically defined as segments separated by less than 10 meters. An iterative aggregating algorithm was then applied that would; (1) find the pair of neighbouring segments whose histograms showed the highest similarity, (2) merge them into a single segment, (3) compute the histogram of this new segment as the sum of the original pair of histograms, and (4) compute a new similarity measure for the new segment with each of its new neighbouring segments. This algorithm was stopped when no pair of neighbouring segments could be found to display similar 2D histograms, using an empirical threshold of $S=0.5$.

The major advantage of this approach is that it does not require the prior definition of labels, and is therefore completely unsupervised. Its major fault is that it presents the risk of aggregating completely different seafloor-profiles,

provided that they slowly transition into one another, and that the initial segmentation is detailed enough over this transition for the differences in angular response from one segment to the other to be too small to be noticeable in the similarity test. This fault might be overcome if the consistency of growing segments was checked – for example using the modality test, as in the ideal recursive methodology mentioned earlier – but such a check was not implemented in the present suboptimal methodology.

5.8 Results

Figure 5.7 presents the thematic maps resulting from both methodologies.

The thematic map resulting from the labelling approach is composed of 13 categories (BF_0 , BF_1 , BF_4 , BF_5 , BF_9 , BF_{11} , BF_{15} , BF_{16} , BF_{17} , BF_{18} , BF_{21} , BF_{22} and BF_{23}) that were retained by the combinatorial optimization algorithm among the 24 base functions that comprised the original catalogue (Figure 5.7a). Almost all segments within the low-reflectivity background of the mosaic were labelled with BF_0 (in yellow, Figure 5.4a). Most of the segments that covered high-reflectivity regions of the mosaic were labelled with BF_1 , BF_4 or BF_{23} (respectively in red, green and blue and on Figures 5.4b, 5.4c and 5.4h). BF_4 was selected for a large block of segments on the main high-reflectivity region in the southern part of the site. BF_1 was selected for several medium-sized blocks of segments throughout the entire mosaic, including two individual high-reflectivity areas in the northern part of the site. BF_{23} was selected for a large number of small blocks of segments all through the site, but particularly at the zones of transition between high- and low-reflectivity regions of the mosaic. The nine other base functions were rarely used, but in all cases for small segments also located in those zones of transition.

The thematic map resulting from the aggregating algorithm is composed of 36 segments (Figure 5.7b). By design, the algorithm prevented two regions more than 10 meters apart to be joined as a single segment. This resulted in the isolation of a large number of small segments whose angular response was probably deemed different to that of the segments that immediately surround them. Despite this multitude, the map is actually composed of five main segments: one covering the

low-reflectivity background of the mosaic, and four covering the main large high-reflectivity regions of the mosaic.

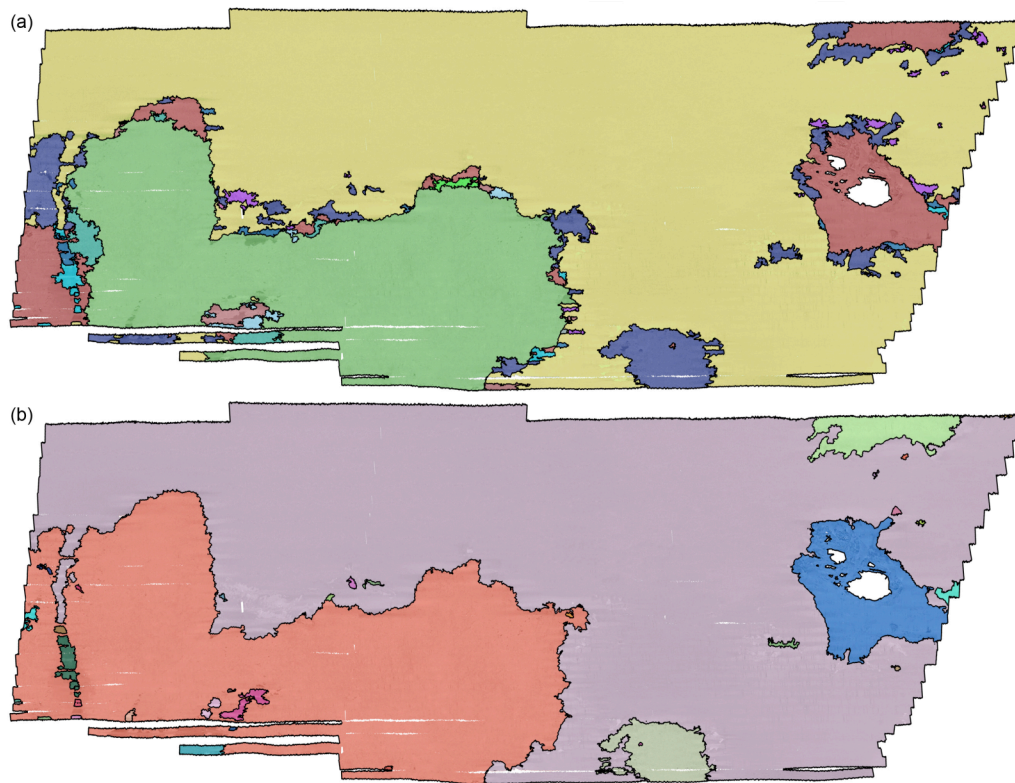


Figure 5.7. (a) Thematic map resulting from the labelling algorithm and (b) thematic map resulting from the aggregating algorithm. Both maps show the original greyscale backscatter mosaic shining through the coloured categories/segments. The colour scheme used in the first map is the same as the one used for depicting individual base functions in Figure 5.4. In this map, the boundaries between neighbouring segments that were labelled identically are not shown. The colour scheme used in the second map is defined randomly, and is therefore not related to the colour scheme used in the previous map.

5.9 Analysis and discussion

5.9.1 Map comparison

The two thematic maps appear very similar and visually correlate well with the general distribution of low- and high-reflectivity regions on the mosaic (Figure 5.2b). Their main difference is their aspect at the zones of transition between these regions. In these zones, the map resulting from the labelling methodology presents a fragmented aspect that appears at times to be correlated with mosaic artefacts (Figure 5.7a), whereas the map resulting from the aggregating methodology presents a coarser aspect that appears to overlook a number of small, genuine features of the seafloor (Figure 5.7b).

The fragmented aspect in the first map can be seen as the consequence of several combined factors. First, the smoothness penalty term in the optimization algorithm is proportional to the difference between the base-functions used to label neighbouring segments (Rzhanov *et al.*, 2011). In this context, a segment located at a sharp transition between two very different seafloor-types may be less penalized if labelled with an intermediate base-function than with one of the two used on each side of the transition. Second, these zones of transition are also where mosaic artefacts are concentrated. The segments located in these zones are therefore more likely to cover a mix of different seafloor-types, and to present uncharacteristic average angular-response curves. Third, as observed previously, the catalogue in this study contains many intermediate base-functions that were defined from segments covering a mix of seafloor types.

The coarse aspect in the second map might be a demonstration of the risk of over-aggregation that was mentioned previously in the description of the aggregating methodology.

The general level of similarity between the two thematic maps was quantified using Theil's U (Schimel *et al.*, 2010b). Theil's U is a measure originally designed to estimate the level of association between two categorical variables as the amount of information they share (Theil, 1972). In the fields of land and

seafloor mapping, it is used as a measure of success of a map against ground-truth, or as a measure of similarity between two maps, which presents the significant advantage to be applicable even when the two variables to be compared are not described with the same classification scheme (Foody, 2006). Theil's U is directly computed from the contingency matrix resulting from the cross-tabulation of the two variables, in the present case, of the pixels in the two thematic maps. Theil's U is a normalized measure, and the higher its score, the larger amount of shared information, that is, the higher the correlation between the two maps. Using equation (9) in Schimel *et al.* (2010b), its computation for the two thematic maps resulted in a high value of $U=0.7202$.

5.9.2 Comparison to video ground-truth

The two thematic maps were then compared to the video ground-truth to quantitatively assess their respective success in separating the regions of different seafloor types. The category (in the first map) and the segment number (in the second map) of the closest pixel to the location of the video stations were cross-tabulated with the corresponding substrate-type into contingency matrices (Tables 5.2 and 5.3), from which Theil's U was computed.

Table 5.2. Contingency matrices for the thematic map from the labelling approach, obtained from cross-tabulation of the map categories with the ground-truth categories.

Labelling map categories	Ground-truth categories				Total
	Sand	Cobbles	Boulder	Rocky reef	
BF₀	153	5	0	0	158
BF₁	0	9	2	2	13
BF₄	1	45	13	0	59
BF₅	0	0	1	0	1
BF₉	0	2	0	0	2
BF₁₇	0	1	1	0	2
BF₂₁	0	1	0	0	1
BF₂₃	3	5	4	0	12
Total	157	68	21	2	248

Table 5.3. Contingency matrices for the thematic map from the aggregating approach, obtained from cross-tabulation of the map segments with the ground-truth categories.

Aggregating map categories	Ground-truth categories				Total
	Sand	Cobbles	Boulders	Rocky reef	
1	152	6	0	0	158
2	2	53	16	0	71
6	0	0	1	0	1
18	0	1	0	0	1
21	0	2	0	0	2
22	3	6	1	2	12
25	0	0	3	0	3
Total	157	68	21	2	248

The computation resulted in similar results, with the aggregating approach yielding a slightly higher score ($U=0.5974$) than the labelling approach ($U=0.5725$). For comparison, the same procedure was applied for the mosaic segmentations S_2 , S_3 , S_6 , and S_7 , which respectively scored 0.2786, 0.2806, 0.3655 and 0.4166.

In order to provide a more familiar estimation of success, the overall accuracy A was also computed from the matrices. The computation of this measure, however, requires the map and the ground-truth to be described with the same labels, which is not the case in this study. The “Cobbles”, “Boulders” and “Reef” columns in the matrices were collapsed into a single “Hard-substrate” column, and an automatic aggregation/permutation procedure developed in a previous article (Schimel *et al.*, 2010b) was applied to the segments/categories (the matrices’ rows) to collapse them into the combination that maximizes A .

This procedure also yielded similar results for the two thematic maps, with the labelling approach showing this time a slightly higher score ($A=96.4\%$) than the aggregating approach ($A=95.6\%$). It is important to note, however, that these accuracy scores are not characteristic of the original matrices – and therefore of the original maps – but of their collapsed versions. The procedure used here typically results in an artificial inflation of the accuracy scores as a consequence of the very small size of the contingency matrix after collapse (Foody, 2007), and the specific design of the automatic aggregation/permutation procedure for the maximization of A (Schimel *et al.*, 2010b).

A probable uncertainty in the position of the video stations or the unreported drift of the camera during footage may have an impact on the scores calculated above. In order to test for the influence of these factors and to provide an interval of confidence for these scores, the methodology was repeated after it was modified to consider a circular buffer around each station. In a first test, a contingency matrix was obtained from the cross-tabulation of the most recurrent label/segment within the buffer with the substrate-type (*modular test*). In a second test, a matrix was formed that reported only the cases where the most recurrent label/segment was actually the only one present within the buffer (*singular test*). These two tests

were run for both maps, repeated for several buffer radius sizes, and A and Theil's U were calculated from each matrix. Figure 5.8 presents the results.

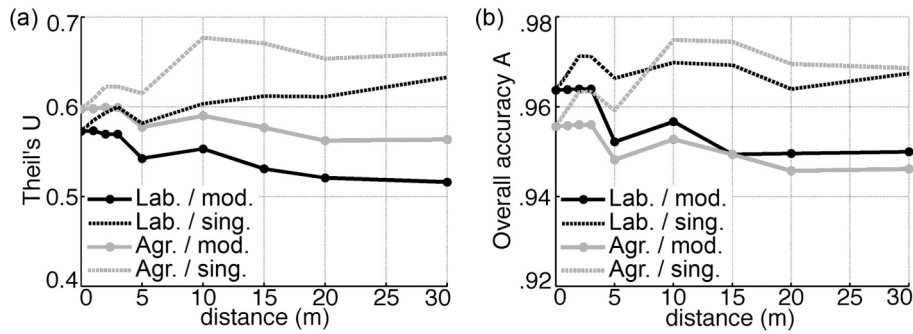


Figure 5.8. Evolution of (a) Theil's U and (b) the Overall Accuracy A with buffer radius, for the thematic maps resulting from the labelling (dark lines) and aggregating methodologies (grey lines), and calculated in the modular test (dotted, solid lines) and the singular test (dashed lines).

The scores showed a decrease with buffer size in the modular test, and an increase in the singular test. Both effects are expressions of the influence of classification error and video station location uncertainty at the zones of transition from a seafloor-type into another. The singular test limited the cross-tabulation to the cases where the map was homogeneous around the stations, and therefore discarded most of the uncertain stations at the zones of transitions, which resulted in an increase of the map/ground-truth correlation. By contrast, the modular test retained all stations in the cross-tabulation while giving more weight to these uncertain stations, which resulted in a decrease of the scores.

The important overlap of the score ranges from the two methodologies as shown in Figure 5.8 supports the argument of the equivalence of the two thematic maps in this study.

5.10 Conclusion

The two methodologies presented and applied in this paper seek to automatically segment an MBES dataset by exploiting sequentially its spatial information and its angular information. In both methodologies, the dataset first undergoes an “over-segmentation” based on its spatial information, and then a “coalescence” based on its angular information.

The over-segmentation part is common to both approaches and consists in angular compensation, mosaicking, and a very fine segmentation of the mosaic in its uniform facies. The two techniques then differ on the coalescence part. The labelling approach is based on the similarity of the segments’ average angular-response curves to a set of automatically predefined ideal curves, while the aggregating approach is based on the similarity between the 2D histograms from neighbouring segments.

The visual and quantitative analysis of the results showed that the two techniques yield similar thematic maps, and that both maps are equally successful in their comparison with ground-truth. This dual success supports the proposition that future MBES-backscatter-based classification techniques should tend towards the exploitation of both the spatial and angular information of the dataset, as was suggested by Hughes Clarke *et al.* (1996) in the early days of MBES-based seafloor classification.

Despite their success in the present study, the two methodologies implemented here presented a few limitations that had visible consequences on the two thematic maps. The analysis of these consequences suggests that the labelling approach in its present state might be more suited to sites dominated by soft sediment and presenting gradual changes from one seafloor-type to the other, while the aggregating approach in its present state would be more suited to sites presenting sharp transitions between soft- and hard-substrate areas. However, only the application of these methodologies to other MBES datasets could confirm these suppositions. In the meantime, the reported limitations will guide future methodology improvements. An important breakthrough would be to use the

spatial and angular information more intricately, rather than sequentially as in the present study.

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CHAPTER 6

SUMMARY AND CONCLUSIONS

6.1 Introduction

In the past decade, a need for the conservation of marine ecosystems has arisen and grown, leading to the development of many different methods for Benthic Habitat Mapping (BHM). These methods are closely related to – and sometimes indistinguishable from – the methods concerned with the classification of the seafloor into different seabed types using data from acoustic seabed-mapping systems, which compose the science of Acoustic Seabed Classification (ASC). Of all existing acoustic systems available for BHM and ASC, the main interest has been on Multibeam Echosounders (MBES), primarily as a result of the multiplicity of their outputs (*i.e.* bathymetry, backscatter mosaic, angular response and water-column data), which allow for multiple approaches to seabed/habitat classification and mapping.

This diversity of BHM and ASC approaches – augmented by the variety of MBES data products and processing methodologies – is at the origin of a research need for comparison of acoustic systems, data and classification approaches. Such comparisons necessitate the development of tools for quantitative assessment of seabed/habitat map similarity. The overall goal of this thesis was to develop and implement such tools, with a specific focus on maps derived from up-to-date approaches based on MBES backscatter data. This aim was to be met by achieving five separate objectives. These objectives and their achievement are detailed in the following sections.

6.2 Objective (1): literature review

Objective (1) was defined as:

(1) to review the current state of the fields of BHM and ASC, and principally their use of MBES data products.

The important growth of BHM and ASC this past decade has been accompanied by occasional reviews of the diversity of technologies and approaches implemented in these fields. The purpose of this objective was to complete this series of reviews in order to illustrate this diversity, the need for comparative approaches, and the lack of map comparison measures and methods. This objective was achieved through the literature review carried out in chapter 2, which was echoed in the introduction to chapter 4.

6.3 Objective (2): Data collection

Objective (2) was defined as:

(2) to collect MBES data for a number of shallow-water sites, where SBES and SSS data were previously acquired and used for seabed mapping.

Although this thesis was focused on the development of general tools and methods rather than on the study of a particular area, a number of overlapping habitat/seabed maps were required to test these tools. This objective of MBES data acquisition was therefore a necessary preliminary objective, which was achieved through the acquisition of three MBES datasets in New Zealand. The sites surveyed were:

- (i) an area located West of Motuihe Island in the Hauraki Gulf, which had been previously surveyed with a SBES (chapter 3 and 4);

(ii) a portion of the Te Matuku Marine Reserve located in the Hauraki Gulf, which was previously surveyed with a SBES and a SSS (chapter 3 and 4), and;

(iii) the totality of the surface of the Tapuae Marine Reserve, located in the North Taranaki region (chapter 5).

6.4 Objective (3): MBES backscatter data processing

Objective (3) was defined as:

(3) to develop new methods for the processing of MBES backscatter data, so as to fully exploit their potential for discrimination between seabed types.

Again, this objective was secondary to the development of tools for map comparison, but it was necessary to the testing of map comparison measures. Map comparison tools and methods had to be experimented on up-to-date approaches to habitat or seabed classification and mapping. Given the growing use of MBES data products in ASC and BHM, it was therefore necessary to develop methods to process MBES backscatter data into maps. This objective was achieved through the development of two different methodologies.

First, a simple processing methodology of the full range of MBES data products was developed in chapter 3 for the purpose of basic comparison with SBES and SSS data products, and was completed by a simple classification methodology presented in chapter 4.

Then, a second, more complex, up-to-date processing methodology of MBES backscatter data alone was developed in chapter 5. This complex methodology was designed to automatically segment a MBES backscatter dataset using both the spatial information (backscatter mosaic) and the angular information (angular response). This segmentation is obtained through an original sequential procedure

of division and joining of segments of the backscatter mosaic on the basis of the homogeneity and similarity of their angular response. This method is one of the rare efforts that have been made to combine these two formats of MBES backscatter data.

6.5 Objective (4): Methods for map comparison

Objective (4) was defined as:

(4) to develop and implement new methods for the quantitative comparison of habitat or seabed maps.

This was the main objective of the thesis. Its need was illustrated in chapter 3 and 5, but the tools were developed and tested in chapter 4. The objective was achieved through the presentation of a set of several measures of similarity for the quantitative comparison of categorical maps, adapted to ASC and BHM from the literature in terrestrial remote sensing, and through the development of a new methodology for allowing the application of the most popular of these measures (the measures of agreement) to maps described with different classification schemes.

The similarities and differences between these measures and the success of this methodology were assessed through their application to several SBES, SSS and MBES datasets. Their results allowed additional conclusions to be derived from the typical BHM case study that was made in the previous chapter (chapter 3) as an illustration of the need for comparison.

In conclusion to this application, it was emphasized that the map similarity measures are not intended to inform on map success, and therefore do not replace the need for an extensive ground-truth survey, nor the evaluation of map success rate, but rather complete these methods. It was also suggested that the main interest of map similarity measures lies in the comparison of studies in which the

variability in the origin of the maps is reduced, in order to target more specifically the similarity analysis. For example, comparing maps obtained from:

- (i) a unique system's output classified with various segmentation methodologies would specifically address the similarity between methodologies;
- (ii) different datasets, but classified using a unique segmentation methodology, would specifically estimate the complementarity of datasets;
- (iii) a unique system and methodology, but acquired at different times, would facilitate monitoring the changes at a given site over time;
- (iv) a unique system, segmentation methodology, and survey, but classified with different legends in supervised mode, would specifically address the issue of similarity between classification schemes.

6.6 Objective (5): Method implementations

Objective (5) was defined as:

(5) to implement these methods to compare maps derived from various approaches using MBES, SSS or SBES systems in order to compare their respective seabed- or habitat-type discrimination potential.

This objective entailed the implementation of the measures and methods that were developed as an achievement of the previous objective. One initial implementation was realized in the same chapter in which those tools were presented. A second, more realistic implementation was illustrated in the final chapter, which consisted in an application of the type (i), as outlined in the previous section. Two comparable ASC approaches based on MBES backscatter data were applied to a common dataset and required a direct comparison of the resulting maps, in order to complete the comparison of their success rates and

assess their general similarity, or absence thereof. This implementation allowed additional conclusions to be drawn regarding the relative successes of the two approaches.

6.7 Concluding remarks

The fields of BHM and ASC are still in their infancy and much progress can be expected from the combination of the variety of scientific disciplines concerned with the production of seabed and benthic habitat maps. Although it is still too early to discuss and agree on standard mapping procedures, it is probably time to discuss and agree on standard methods for the comparison of approaches and to encourage the attempts to merge the most efficient of them. Through the proposition and testing of new tools and methods for the assessment of map similarity, and through the development of methodologies to combine MBES backscatter mosaic and angular response, the research in this thesis contributed to these general efforts.

