TOWARDS A COST-EFFICIENT & STANDARDISED MONITORING PROTOCOL FOR SUBTIDAL REEF FISH IN THE AGULHAS ECOREGION OF SOUTH AFRICA

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Abstract

Under the growing demand for marine fish resources, and the apparent and expected impacts of global climate change, there is a need to conduct long-term monitoring (LTM) to ensure effective management of resources and conservation of biodiversity. However LTM programmes often suffer from design deficiencies and fail to achieve their objectives. These deficiencies stem from the fact that insufficient consideration is afforded to the design phase, with programmes selecting methods that are not suitable to address the objectives, or are not cost-efficient, compromising the sustainability of the LTM. To facilitate the establishment of LTM programmes along the southern coast of South Africa, background research needed to be conducted to identify which methods were most appropriate for LTM of reef fish.

This study presents a detailed field-based assessment of the suitability and cost-efficiency of monitoring methods for long-term monitoring of reef fish in the Agulhas Ecoregion of South Africa. The approach adopted to identify the method, or suite of methods most suited for LTM, involved (i) the selection of methods considered suitable for LTM, (ii) the individual assessment and optimisation of method performance, and (iii) the comparative assessment of the fish community sampled by the different methods. The most suited method(s) were then identified as those that provide the most comprehensive assessment of the fish community and had the highest cost-efficiency.

The research was conducted between January 2008 and 2011 in the Tsitsikamma and Table Mountain National Park (TNP and TMNP, respectively) marine protected areas (MPAs) within the Agulhas Ecoregion. The methods selected included fish traps (FT), controlled angling (CA), underwater visual census (UVC), remote underwater video (RUV), baited RUV (BRUV) and remotely operated vehicles (ROV).

The individual assessment and optimisation was conducted with the FT, UVC, RUV and BRUV methods. The assessment of the FT method aimed to identify the optimal soak time, and whether or not the size of the funnel entrance to the trap affected the catch. The results identified that larger funnel entrances caught more fish and soak times of 80

minutes produced the highest catches per unit effort. However the data were highly variable and the method detected few of the species typical of the region. Fish traps were also associated with high levels of mortality of fish post-release. The assessment of UVC strip transect method involved directly comparing the precision of data collected by researchers and volunteers using a novel double-observer technique (paired-transects). The results showed considerable error in both the volunteers and researchers data, however the researchers produced significantly higher precision data, compared to the volunteers. The distinction between researchers and volunteers was not evident in the data for the dominant species of fish. For all observers, the abundance of a species in the sample had a significant influence on its detectability, with locally scarce or rare species poorly detected. UVC was able to sample the majority of species typical of reefs in the region, however it appeared plagued by observer and detectability biases. The assessments of RUV and BRUV were conducted simultaneously which enabled the assessment of the effect of bait on the observed fish community. In addition the optimal deployment time for both methods to maximise species richness and abundance was determined. The results showed that BRUV, and to a lesser degree RUV, were able to effectively survey the reef fish community for the region with a 50 minute and 35 minute deployment time, respectively. Baited remote underwater video was especially good at detecting the invertebrate and generalist carnivores, and cartilaginous species. On the other hand, RUV was more effective at surveying the microinvertebrate carnivores. Remote underwater video was characterised by higher data variability, compared to BRUV, and was ultimately considered a less cost-efficient monitoring method.

Comparative methods assessments were conducted during two field experiments with the FT, UVC and BRUV methods in the TMNP MPA, and the FT, CA, UVC, RUV, BRUV and ROV methods compared in the TNP MPA. The objectives of the comparison were to investigate differences in the fish communities observed with the different methods, and to determine the power of the data to detect an annual 10 % growth in the fish populations over a period of five years. The results from the method comparison were in turn used to conduct the cost-benefit analysis to determine the efficiency of the different

methods at achieving monitoring objectives requiring population data from multiple trophic and functional groups with the community, and from species of fisheries importance.

The results indicated that FT, CA and ROV were ineffective at monitoring the reef fish community, although CA appeared to provide valuable data for the dominant fisheries species. Both CA and FT required minimal initial investment however, the variability in the data translated into high annual monitoring costs, as the required sampling effort was great. The ROV required the highest initial investment and was identified as the least cost-efficient method. Underwater visual census was able to adequately survey the bony fish within the community, however it did not detect the cartilaginous species. Underwater visual census required a large initial investment and was not cost-efficient, as a many samples were required to account for the variability in the data. Remote underwater video provided a comprehensive assessment of the reef fish community, however it too was associated with high levels of variability in the data, compared to BRUV, reducing its cost-efficiency.

BRUV provided the most comprehensive assessment of the reef fish community and was associated with the highest cost-efficiency to address the community and fisheries species monitoring objectives. During the course of this research stereo-BRUV has gained considerable support as an effective reef fish monitoring method. Although not tested during this research, stereo-BRUV is preferred to BRUV as it provides accurate data on the size of fish. However, the initial investment of stereo-BRUV is over three times that required for the BRUV. Although it is recommended that a baited video technique be used for LTM in the Agulhas Ecoregion, the choice between BRUV and stereo-BRUV will depend on the specific objectives of the programme and the available budget at the implementing agency.

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Dr Albrecht Götz, my primary supervisor deserves a special mention. Ali provided guidance on the concept and experimental design for the research within this thesis, and I am very grateful for all the time and understanding that he has shown me during the course of my PhD. I would also like to thank my second supervisor Prof Alan Hodgson. Although this thesis was outside of the normal research that Alan conducts, he was willing to supervise me and I am grateful for this and for the time he spent reviewing this thesis.

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One should always be drunk. That's all that matters;
that's our one imperative need. So as not to feel Time's
horrible burden one which breaks your shoulders and bows
you down, you must get drunk without cease.

But with what?
With wine, poetry, or virtue
as you choose.
But get drunk.

And if, at some time, on steps of a palace,
in the green grass of a ditch,
in the bleak solitude of your room,
you are waking and the drunkenness has already abated,
ask the wind, the wave, the stars, the clock,
all that which flees,
all that which groans,
all that which rolls,
all that which sings,
all that which speaks,
ask them, what time it is;
and the wind, the wave, the stars, the birds, and the clock,
they will all reply:
"It is time to get drunk!
So that you may not be the martyred slaves of Time,
get drunk, get drunk,
and never pause for rest!
With wine, poetry, or virtue,
as you choose!"

Charles Baudelaire

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Chapter 1

General Introduction: Towards a standardised protocol for monitoring subtidal reef fish

1.1 Role of long-term monitoring programmes

Most marine ecosystems are impacted by anthropogenic disturbance (Halpern et al. 2008; Sink et al. 2012), and rocky reefs on continental shelves and coastal environments are under particular threat. These threats include over-exploitation of fish resources, habitat loss from indiscriminate fishing techniques and inappropriate coastal development, and pollution (Halpern et al. 2008; Sink et al. 2011, 2012). In addition, climate change is expected to strongly influence the distribution and abundance patterns of fish and invertebrate species occupying rocky reefs (Fields et al. 1993; Hughes et al. 2003), and the synergistic effects of exploitation and climate change are expected to exacerbate the rate of change in these ecosystems (Harley et al. 2006; Johnson et al. 2011). For the effective conservation of reef ecosystems and management of resources, monitoring is required to fully understand the current and predicted future effects of anthropogenic disturbance and climate change (Pikitch et al. 2004).

The contribution of long-term monitoring (LTM) to the improvement of knowledge and understanding of ecosystems is recognised by ecologists and managers (Ward and Jacoby 1992; Vos et al. 2000; Yoccoz et al. 2001; Caughlan and Oakley 2001; Lindenmayer and Likens 2009), and monitoring is considered essential for the effective management and conservation of ecosystems and threatened species (Vos et al. 2000; Caughlan and Oakley 2001; Yoccoz et al. 2001). Furthermore, measuring the response of ecosystems to climate change, anthropogenic disturbance, management interventions or experimental manipulation is best achieved though monitoring (Yoccoz et al. 2001; Lindenmayer and Likens 2009).

However, monitoring programmes often suffer from design deficiencies (Ward and Jacoby 1992; Vos et al. 2000; Yoccoz et al. 2001). These deficiencies stem from the fact that insufficient time and thought are allocated to identifying why the programme is necessary, what the programme should monitor, and how monitoring should be conducted to achieve the programme objectives (Yoccoz et al. 2001). The apparent lack

of explicit objectives and *a priori* hypotheses of many programmes has added to the perception that monitoring is a management activity and is unrelated to scientific research (Yoccoz et al. 2001; Lindenmayer and Likens 2009). Yet, well thought out and appropriately executed monitoring programmes can address scientific objectives, as well as test and develop ecological theories, and in this way aid the understanding of the factors that control the abundance and distribution of species (Yoccoz et al. 2001; Lindenmayer and Likens 2009; Langlois et al. 2011).

The focus of this general introduction is to briefly present information on why monitoring of reef fish is important, where monitoring can play a role for resource management and conservation of biodiversity, and what information should be collected to address the monitoring objectives. Using selected scenarios provided as motivation for monitoring, information on how monitoring can and should be conducted will be briefly presented. The selection of suitable methods for monitoring reef fish is the focus of this research thesis, and the information presented in the introduction will provide the rationale behind this research. To conclude the general introduction the overarching aim of the thesis will be presented, together with the approach implemented to achieve this aim.

1.1.1 Why is monitoring important?

1.1.1.1 Resource management

Worldwide fisheries are collapsing following decades of over-exploitation and indiscriminate fishing techniques that result in habitat destruction (Jackson et al. 2001; Worm et al. 2006; Halpern et al. 2008; Norse et al. 2012). Marine habitats in South Africa, and around the world, are under increasing pressure to provide services and resources to support recreational and industrial activities, meet food requirements, and create employment opportunities for the ever expanding human populations (Halpern et al. 2008; Sink et al. 2012). Fishing is considered a primary driver of degradation in the marine environment, particularly in the nearshore regions (Roberts et al. 2002; Halpern et al. 2008; Sink et al. 2012).

South Africa's commercial and recreational hook and line fishing sector (line-fishery) is largely responsible for the depletion of many vulnerable endemic reef species (DAFF 2010). In 2000 a state of emergency was declared to protect the marine line-fish stocks along the South African coast, as legislation had proved inadequate to restrict fishing pressure to sustainable levels (Mann 2000). Despite cuts in commercial fishing effort, and the creation of numerous marine protected areas (MPAs), the latest status report indicates that most reef associated fish species are still considered collapsed or over-exploited (DAFF 2010). Furthermore, stock assessments for many additional species considered to be threatened have never been completed. Alarmingly, this was identified in the 2000 fisheries status report (Mann 2000) and as yet little progress has been made to address this knowledge gap. For effective management of fisheries resources, sound information on the population characteristics is required. In addition, fisheries management interventions are often viewed as contentious by different stakeholders, and population statistics derived from LTM can provide much needed support for these interventions.

1.1.1.2 Global change

Superimposed on direct anthropogenic impacts are the effects of natural drivers such as changes in ocean water temperature, chemistry and current systems caused by increasing levels of atmospheric carbon dioxide fuelling global climate change (Fields et al. 1993; Hughes et al. 2003; Harley et al. 2006; Cheung et al. 2012). The impact of climate change on the marine environment is expected to result in changes to: (i) ecosystem functioning (Holbrook et al. 1997; Johnson et al. 2011), and (ii) species distributions (Fields et al. 1993; Holbrook et al. 1997; Johnson et al. 2011; Wernberg et al. 2011; Cheung et al. 2012) with the outcome being the tropicalisation of temperate environments as global sea water temperature rises and tropical species extend their distributions into the higher latitudes (Cheung et al. 2012). In addition, fishing pressure and habitat degradation have already placed marine ecosystems under severe stress

(Halpern et al. 2008), reducing the resilience of these ecosystems to cope with climate change (Harley et al. 2006; Johnson et al. 2011; Wernberg et al. 2011).

To understand how climate change will influence the structure and functioning of marine ecosystems, the effects of direct anthropogenic disturbance (i.e. fishing) and the effects of climate change need to be measured separately. No-take MPAs are essentially large-scale ecological experiments that exclude direct human impacts (Hughes et al. 2005). Research within these no-take MPAs allows scientists to measure the effect of climate change on marine ecosystems without the confounding effects of anthropogenic disturbance (Bohnsack et al. 2004). At the same time, by using management measures as experimental manipulations, scientists can monitor the direct and indirect effect of fisheries on ecosystem structure and functioning.

1.1.1.3 Ecosystem Based Management

With the shift away from managing marine ecosystems based on single or multiple species of fisheries importance, towards ecosystem based management (EBM) practices, there is increasing demand for monitoring techniques for reef species from a variety of trophic and functional groups (Pikitch et al. 2004; Johnson et al. 2012; Langlois et al. 2012b). Furthermore, monitoring programmes not only need to provide relevant information on the diversity and appropriate population parameters of selected species of fish, but also detailed information on the other biotic components that make up the community and the habitat on which the community is built (Johnson et al. 2012).

With EBM, resource and biodiversity trends, established through monitoring determine what levels of precaution are acceptable (Pikitch et al. 2004). In data-poor situations a blanket precautionary approach is advised, but with increasing knowledge on the structure and functioning of the ecosystems and target species, the blanket can be tailored to suite socio-economic needs and ensure maintenance and resilience of the ecosystem that supports the target species. Long-term monitoring is thus essential for effective EBM as it increases the certainty around decision making (Pikitch et al. 2004).

Marine protected areas are key tools for EBM and, as with other fisheries management interventions, are often viewed with scepticism and contention by stakeholders who are affected by the MPAs. Monitoring that demonstrates the value of MPAs will thus not only improve the science base for MPA management (Sink et al. 2012), but also improve the public's understanding of the importance of MPAs.

1.1.1.4 Additional monitoring objectives

Spatially and temporally comprehensive LTM is required for macroecological studies that address questions relating to the patterns and processes that structure reef fish assemblages and drive distribution patterns in biodiversity and abundance (Fisher et al. 2010; Dambach and Rodder 2011). Monitoring is also used to measure the rate of change or recovery of populations prior to, and following impacts such as coastal development and natural or anthropogenic disasters (Underwood 1992).

1.1.2 What should be monitored?

Whether monitoring programmes are designed to address management related objectives, scientific related objectives, or both, selecting what to monitor is critical (Vos et al. 2000; Caughlan and Oakley 2001; Yoccoz et al. 2001; Lindenmayer and Likens 2009). Clues for the choice of what to monitor will be given in the objectives of the programme (Lindenmayer and Likens 2009), and the more specific the scientific or management questions, the simpler the choice of target populations. It is important to bear in mind that additional information on the abiotic and biotic components of the environment where the target species or assemblages occur will be relevant and required to efficiently address most monitoring objectives.

Monitoring programmes need to provide statistically robust and cost-effective data that meet clearly defined and ecologically relevant monitoring objectives (Caughlan and Oakley 2001). However, financial constraints limit the scale and scope of what a programme can achieve (Vos et al. 2000; Caughlan and Oakley 2001). Hence, the

selection process of what to monitor must also consider the cost implications of these choices.

Typically, monitoring programmes aim to monitor either an individual target species, or group of species with similar functional or trophic traits (i.e. for monitoring species of fisheries importance), the entire community (i.e. for monitoring patterns in biodiversity), or multiple species representing different functional or biological traits (i.e. for monitoring ecosystem level effects of fisheries). It is unrealistic to assume that any cost-efficient sampling design will be able to provide sufficient data to analyse trends in population size and structure for every component of the community. However, within different trophic or functional groups, certain species will be detected on sufficient occasions to allow detailed analysis of their spatial and temporal patterns in abundance. Numerous authors have explored what features make a species a good indicator (Ward and Jacoby 1992; Babcock et al. 2005; Goodsell et al. 2009). Aspects considered to be favourable include: (i) detectability, (ii) a rapid and unambiguous response to multiple drivers of change, (iii) a wide distribution, including areas that are not expected to be affected by the driver of change, (iv) qualifying as an important component of the ecosystem, and (v) information from previous studies (Ward and Jacoby 1992).

Monitoring biological diversity requires the selection of suitable indices, such as the Shannon-Weaver and Simpson indices (Yoccoz et al. 2001). More advanced indices include additional weighting criteria that take into account the status (IUCN red listing) or rarity of a species (Yoccoz et al. 2001). Multivariate dispersion is another approach to measure beta diversity (Anderson et al. 2006). The advantage of multivariate dispersion over other diversity indices is that any ecologically meaningful dissimilarity measure can be used to calculate the dispersion, and it can also be used to test for statistical differences in beta diversity between areas and treatments (Anderson et al. 2006).

As the selection of what to monitor is directed by the objectives of the programme, identification of targets should be conducted during the formulation of the explicit objectives (Yoccoz et al. 2001). Combining detailed abundance modelling of individual

species, considered indicators of community health or representatives of functional traits, with community indices, that investigates broader patterns in the entire community, will provide sufficient data to meet any general monitoring objective. By doing so, the design will incorporate sufficient effort to enable effective monitoring of the different indicators and ensure that the programme delivers meaningful results on the patterns in community structure.

1.1.3 How should the monitoring be conducted?

The question of how to monitor can be broken down into the experimental design and the method selection process. The design and methods selected will ultimately determine the confidence (or statistical power) with which ecological changes can be detected and related to specific causes (Vos et al. 2000).

1.1.3.1 Experimental design

Experimental design makes reference to the process of selecting representative study areas to account for spatial variation, the temporal sampling resolution to account for seasonality, and the design of the sampling approach (Yoccoz et al. 2001). In the design of the sampling approach it is recommended that each study area is stratified on the permanent features of the habitat (i.e. reef type, reef profile and depth), as well as the management treatments (i.e. spatially differential exploitation/protection), and that within a strata, sampling is randomised as this will maximise possibilities for future *ceteris paribus* comparisons (Vos et al. 2000; Murray et al. 2001; Yoccoz et al. 2001). Additionally, stratification over seasons will be important where relevant to the objectives of the programme.

1.1.3.2 Monitoring methods

There are numerous methods that can be employed to survey reef fish populations and there are criteria that can be used to reduce the available options to only those that are suitable for the objectives of a monitoring programme.

Fisheries-dependent monitoring relies on catch, effort and catch per unit effort (CPUE) data obtained from fisheries landings (Murphy and Jenkins 2010). While fisheries-dependent data can provide valuable information specific to fisheries trends outside MPAs, it can't be used in MPAs, and is biased by the selectivity of the fishing gear, the targeting of specific species, and the size and catch restrictions for the different species (Murphy and Jenkins 2010; Harvey et al. 2012; Langlois et al. 2012b). Following this, for most monitoring objectives, fisheries-dependent approaches are not suitable. Fisheries-independent monitoring relies on data collected specifically to address management or scientific objectives, and is not associated with the same biases inherent in fisheries-dependent data (Murphy and Jenkins 2010). Therefore, fisheries-independent data provide a sounder statistical basis from which to measure changes in fish community structure and abundance distribution patterns (Murphy and Jenkins 2010).

Although fisheries-independent methods aim to be non-destructive, certain extractive methods (i.e. those that require the fish to be captured and brought to the surface), such as trawl surveys, are associated with high levels of mortality and cause considerable damage to the habitats from which the samples are collected (Murphy and Jenkins 2010). Although trawl surveys can provided valuable data (Cappo et al. 2004), the method is restricted to low profile habitats to avoid snagging, while the destructive nature of the method limits its applicability to broader ecological studies (Murphy and Jenkins 2010). Other extractive methods include controlled angling (standardised hook and line fishing) and fish traps (Murphy and Jenkins 2010). Both methods have been widely applied in fisheries-independent monitoring programmes throughout the world (Sheaves 1992, 1993; Willis et al. 2000; Thrush et al. 2002; Travers et al. 2006; Götz et al. 2007; Bennett et al. 2009; Harvey et al. 2012; Langlois et al. 2012b), and are typically associated with lower levels of mortality than trawling. However, the extractive nature of the methods does place the fish under stress, with barotrauma in ray-finned fish often resulting in high rates of mortality (Götz et al. 2007, Wilke et al. in press).

In situ methods (i.e. methods where the fish are observed in their natural habitats and are not extracted) offer a less invasive alternative to the traditional extractive methods

described earlier. *In situ* methods can be grouped as underwater visual census (UVC) techniques (i.e. strip transects, line transects, point counts or rapid visual techniques) and underwater video techniques (i.e. diver operated video transects, remote underwater video (RUV), baited remote underwater video (BRUV), stereo-RUV or stereo-BRUV, and remotely operated vehicles (ROV)) (Murphy and Jenkins 2010). As these *in situ* methods minimize the negative effects of sampling on the fish and their habitat, they are suitable for use in MPAs. In addition most *in situ* methods provide further information relating to the habitat in which the surveys were conducted.

1.1.3.3 Biases and cost-efficiency

Abundance estimates from all monitoring methods are characterised by biases that influence the accuracy and precision of the data. These biases originate from various sources which can be coarsely grouped into: (i) biases attributed to detection error, and (ii) biases attributed to spatial variation and survey error (Yoccoz et al. 2001; Elphick 2008). Biases in monitoring data linked to spatial variation in target populations and survey error typically result from inappropriate site selection, and sampling strategies that produce unrepresentative data for the sites (Yoccoz et al. 2001). Detection error can arise from inappropriate survey design (i.e. samples collected from habitats where the target species does not occur), detection mistakes (i.e. present individuals missed), and erroneous counts (i.e. misidentification of species, and incorrect counting of groups of individuals) (Elphick 2008). Numerous assessments of reef fish monitoring methods have highlighted inconsistent detectability of different species between different methods (Willis et al. 2000; Cappo et al. 2004; Watson et al. 2005, 2010; Götz et al. 2007; Harvey et al. 2007, 2012; Bennett et al. 2009; Colton and Swearer 2010; Langlois et al. 2010; Pelletier et al. 2011). Similarly, variations in the way a method is employed by an observer, the relative skill and experience of an observer, the experimental design, and the ecosystem where the monitoring takes place will influence the precision and accuracy of the data (Lincoln-Smith 1988; Thompson and Mapstone 1997, 2002;

Kulbicki 1998; Edgar et al. 2004; Götz et al. 2007; Harvey et al. 2007; Bennett et al. 2009; Ward-Paige et al. 2010; Bozec et al. 2011).

Potential solutions to both sources of bias described above include the application of multiple monitoring methods to account for variation in detectability (e.g. Watson et al. 2005; Colton and Swearer 2010), and increased spatial and temporal resolution of the sampling. However, LTM is costly to maintain and many programmes cannot feasibly do this.

Marine research is expensive and long-term programmes require sustainable funding, and personnel time, over decades before the data begin to have true value (Vos et al. 2000; Molloy et al. 2010). Consequently, financial constraints and long-term feasibility are important considerations when selecting how, when and what to monitor to meet specified research objectives (Langlois et al. 2010; Murphy and Jenkins et al. 2010). To know what the relative costs of different methods are, and to measure the trade-off between cost and improved knowledge, systematic cost-benefit analyses are required that provide general guidelines on which approach is best suited to answer a type of question (Elphick 2008). What is evident from past work is that local environmental conditions (e.g. habitat structure and temperature), and biological characteristics (e.g. community structure and biogeography) influence the quality of data collected by a method (Willis et al. 2000; Harvey et al. 2007; Colton and Swearer 2010; Pelletier et al. 2011). It is therefore important to assess how the different methods perform under local conditions, and not assume that global experience will dictate which method will provide the most comprehensive assessment of the local fish community.

Very rarely do different monitoring programmes employ the same method to collect data. This reduces the ability to compare trends over large spatial scales as different methods and approaches to using the methods, produce results that are not directly comparable and can lead to erroneous inferences. Global climate change and the impacts of fisheries occur over large spatial and temporal scales, and often multiple research institutes and management agencies will be involved in monitoring. To enable

regional scale assessments of community change, monitoring protocols and methods need to be standardised. There is thus a need to develop standardised monitoring protocols to enable effective regional scale and long-term assessments of reef fish communities.

1.2 Aim

The overarching aim of this thesis is to identify the most suitable and cost-efficient method, or suite of methods, for LTM of the subtidal reef fish populations in the warm-temperate Agulhas Ecoregion of South Africa.

1.2.1 Approach

The first step in achieving this aim was to identify methods deemed suitable for monitoring the subtidal reef ecosystems in the Agulhas Ecoregion. As there is no general methods section in this thesis, this process will be briefly described here.

As stated above, there are numerous methods that can be used for collecting population information on reef fish. To narrow down the options, this study focussed only on fisheries-independent and non-destructive methods. Fisheries-independent monitoring methods were considered as they meet both scientific and management monitoring objectives, and are more widely applicable to general monitoring objectives. To enable the research to be conducted in MPAs and for the future application of the selected monitoring methods in MPAs, only non-destructive methods were considered. Fish communities in no-take MPAs are considered to be more representative of natural conditions, as diversity and abundance of predatory fish, targeted through fisheries, are higher in the protected areas (Bennett and Attwood 1991; Watson et al. 2007). Thus the decision to conduct the research in established MPAs allowed for a more comprehensive assessment of the selected monitoring methods. Although it is accepted that in most cases fish communities in established no-take MPAs will not be truly reflective of their historical baselines, they offer the closest proxy to what the natural community should look like. As such, MPAs can be considered baselines for natural variability and provide benchmarks for comparisons with exploited areas. MPAs are therefore crucial components in LTM programmes.

Six methods were identified:

1. Fish traps (FT)
2. Controlled angling (CA)
3. Underwater visual census (UVC) strip transects
4. Remote underwater video (RUV)
5. Baited remote underwater video (BRUV)
6. Remotely operated vehicle (ROV)

These methods cover a broad spectrum of traditional and innovative techniques from the logistically simple and relatively cheap extractive methods (e.g. FT and CA) to the technologically advanced and complex underwater video methods (e.g. ROV).

Following the selection of the methods, the approach adopted to achieve the overarching aim was based on three steps:

1. General assessment and optimisation of the selected methods
    a. Aim: Assess the ability of the selected methods to monitor the reef fish communities and identify and test methodological adaptations that optimise method performance
2. Comparative assessment of the selected methods
    a. Aim: Compare the ability of the optimised methods to detect the fish species typical of the subtidal reef habitats in the Agulhas Ecoregion
3. Cost-benefit analysis of the selected methods
    a. Aim: Identify the method or combination of methods that are the most cost-efficient at surveying the reef fish community to best address standard monitoring objectives

Not all six methods were included in the general assessment and optimisation step of the research. Previous assessments of CA within the Agulhas Ecoregion meant that the optimisation was not necessary, and the method was only used during the comparative method assessment. Similarly, financial and logistical constraints limited the use of the ROV to the comparative method assessment. Although size information of the fish sampled was collected by certain methods (i.e. FT, CA and UVC), it was not available from all methods and as a result only abundance data are presented in this thesis. It is recognised that size information is crucial for most fisheries monitoring objectives, and

for this reason the ability of a method to measure the size of fish was scored favourably in the cost-benefit analysis presented in Chapter 6.

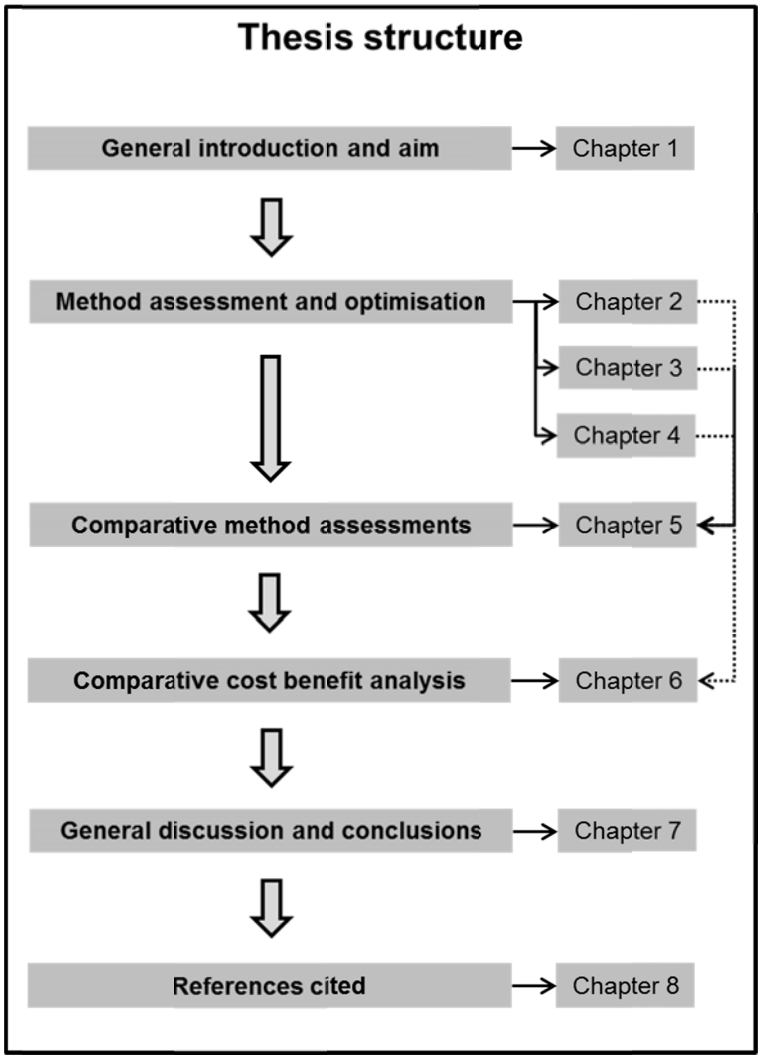

Figure 1.1: Layout of the thesis, showing the association between the different chapters with the steps adopted to achieve the overarching aim of the research. The dotted lines indicate where outputs from chapters were synthesised in a destination chapter.

The layout of the thesis follows steps one to three described above (Fig. 1.1). Each research chapter (Chapters 3-6) is written up as a stand-alone manuscript with

introduction, methods, results and discussion. Where methods are duplicated between chapters the information is only provided in the chapter where the method first appears, with all subsequent information making reference to the original chapter. In addition, the references cited in the chapters have been merged into a single bibliography located at the end of the thesis. Where appendices are mentioned in a chapter they follow directly after that chapter.

Chapter 2

Assessment of observer bias and detection probability in underwater visual census of reef fish measured with independent double-observers

2.1 Introduction

Underwater visual census (UVC) is widely used to assess the status of fish populations in relation to climate change, resource exploitation and management actions (Edgar et al. 1997; Jackson et al. 2001; McClanahan et al. 2007; Ward-Paige et al. 2010). However, it is generally accepted that this method is plagued by biases from multiple sources. With UVC strip transects, bias can originate from transect length (Kulbicki et al. 2010), width (Cheal and Thompson 1997), and the swimming speed of the observer (Lincoln-Smith 1988). Observer related bias is typically large, as individual observers differ in their ability to accurately estimate distance underwater (Thresher and Gunn 1986; Harvey et al. 2004), correctly identify species (Thompson and Mapstone 1997) and estimate the size of individuals (Edgar et al. 2004). Observer experience also influences the precision of data collected with UVC (Thompson and Mapstone 1997; Williams et al. 2006). Furthermore, environmental characteristics such as water clarity (MacNeil et al. 2008a, b) and habitat complexity (Edgar and Barrett 1999) often affect the confidence around population estimates, while species abundance, size, appearance and behaviour alter their detectability (Kulbicki 1998; Willis 2001; Edgar et al. 2004; MacNeil et al. 2008a, b; Bozec et al. 2011).

Many of the biases are difficult to separate, and as a result UVC data reflects a complex mix of errors from the method, observer, habitat, and community, on top of the natural population variability that is of interest. This makes mitigation difficult and the conclusions from studies investigating biases in UVC usually state that most biases can’t be avoided, and stress the importance of measuring all potential covariates and standardising observer training to aid the interpretation of the observed data (Thompson and Mapstone 1997; Edgar et al. 2004). However, this predicament is not restricted to UVC, and comparative method assessments have demonstrated that UVC still holds many advantages over alternative non-destructive monitoring methods (Stobart et al. 2007; Colton and Swearer 2010).

UVC is one of the most suitable methods for non-destructive population assessments of subtidal reef fish (Edgar et al. 2004; Barrett et al. 2007; Kulbicki et al. 2007; MacNeil et al. 2008a, b; Bozec et al. 2011). The data resulting from UVC surveys are in turn analysed to explain spatial and temporal trends in the species composition (Anderson and Millar 2004; Kulbicki et al. 2007), abundance (Buxton and Smale 1989; Ward-Paige et al. 2011), and population structure (Buxton and Smale 1989; Barrett et al. 2007; Kulbicki et al. 2007), relating to fisheries exploitation (Jennings and Polunin 1997; McClanahan and Arthur 2001) and effectiveness of management actions (Edgar and Barrett 1999; Garcia-Charton and Perez-Ruzafa 1999; Russ et al. 2005; Edgar and Stuart-Smith 2009).

Underwater visual census surveys can be conducted following a number of different protocols. Examples of these include: (i) strip transects – where a diver swims along a line and estimates the number of target species within a half cylinder (Bennett et al. 2009), (ii) point counts – where a stationary diver estimates the abundance of target species within a 360^{o} half sphere around a point (Buxton and Smale 1989), (iii) timed transects – where a diver swims within a broad area and records the number of species encountered during a fixed time interval (Edgar et al. 2004), and (iv) rapid visual techniques –where the encounter sequence of species is used to rank each species (Edgar et al. 2004). Each approach has its benefits and biases, while their suitability will depend on the specific objectives of the research programme and the study location. For example, strip transects outperform point counts in temperate waters of South Africa (Bennett et al. 2009), however results from the broader literature are equivocal (see Thresher and Gunn 1986; Watson and Quinn 1997) with point counts often preferred in tropical waters.

Subtidal long-term monitoring (LTM) programmes are used to document the effect of climate change (Dayton et al. 1998), historical exploitation (Jackson et al. 2001) and the effectiveness of management actions (Suchanek 1994; Edgar et al. 1997; Hughes et al. 2005) on fisheries recovery and conservation. Often these programmes involve working in marine protected areas (MPAs) and have to rely on non-destructive sampling

methods to measure population parameters. There are a number of non-destructive monitoring methods including UVC, remote underwater video (RUV), baited RUV (BRUC), fish traps (FT) and controlled angling (CA), however, only UVC, RUV and BRUV are non-extractive, making them better suited for working in MPAs (Murphy and Jenkins 2010). The BRUV method has gained popularity since its first use in the late 1990s, however the method is relatively new and is still establishing its niche within the broader research community. Consequently, most LTM studies rely on one or other form of UVC (Edgar and Barrett 1999; Micheli et al. 2004; Barrett et al. 2007; Kulbicki et al. 2007; Tetreault and Ambrose 2007; Edgar and Stuart-Smith 2009; McClanahan et al. 2009).

For LTM programmes to be successful they need to show thorough and rigorous planning, be spatially and temporally comprehensive, and function over time scales suitable to examine population and community level processes (Underwood 1992; Ward and Jacoby 1992; Garcia-Charton and Perez-Ruzafa 1999; Vos et al. 2000; Yoccoz et al. 2001; Thompson and Mapstone 2002). However, the cost of establishing LTM programmes limit the ability to collect adequate data (Vos et al. 2000; Caughlan and Oakley 2001; Yoccoz et al. 2001). A solution is to use volunteer SCUBA divers to collect the data as the potential workforce is larger, the cost is reduced, and stakeholder participation is facilitated (Halusky et al. 1994; Darwall and Dulvy 1996; Greenwood 2003; Pattengill-Semmens and Semmens 2003; Edgar and Stuart-Smith 2009; Leapold et al. 2009; Ward-Paige et al. 2011). This not only contributes to the longevity of the programme, but also has the ability to improve the public's perception of contentious management decisions. Nonetheless, the involvement of "non-experts" to conduct the surveys has the potential to introduce new, and exacerbate existing biases associated with data from UVC surveys (Mumby et al. 1995).

Accurate interpretation of trends in reef fish populations relies on data with low noise to signal ratio (Thompson and Mapstone 2002). A number of studies have validated data collected by volunteers through comparison with data collected by experienced researchers, concluding that the data is of a similar quality (Mumby et al. 1995; Darwall

and Dulvy 1996; Edgar and Stuart-Smith 2009). However, this conclusion is based on the assumptions that (i) the data collected by the researchers are always accurate and (ii) that small-scale spatial and temporal variability had no effect on the fish community in the space or time between researcher and volunteer surveys (Darwall and Dulvy 1996; Edgar and Stuart-Smith 2009). This is unlikely to be the case as observer bias is evident in comparisons between data collected by different researchers (Thompson and Mapstone 1997). Furthermore, rapid changes in the observable fish community, driven by interactions with observers, or opportunistic feeding, have been reported to significantly influence estimates of fish populations over short time scales (McClanahan et al. 2007).

Recent adaptations to the traditional UVC methods have begun to alleviate some of the underlying biases. For example, in New Caledonia researchers have adapted land based distance sampling procedures to subtidal reef environments (Kulbicki 1998; Kulbicki et al. 2010; Bozec et al. 2011). In this approach the perpendicular distance from the transect to an observed fish is recorded, allowing the detection probability to be estimated from the frequency distributions of the distance estimates (Bozec et al. 2011). The results suggest that the approach is favourable as it accounts for inconsistent detection probabilities between species. However, the method is not free from its own set of biases as difficulties in estimating perpendicular distance of a fish from the transect line underwater will influence the precision of the method (Harvey et al. 2004). In addition, the assumptions of distance sampling require that all fish on the transect line are detected and no fish enter or leave the survey area during the count (Kulbicki and Sarramegna 1999; Riddle et al. 2010). As many species of fish are either attracted to, or avoid SCUBA divers (Kulbicki 1998), it's unlikely that this assumption will be met.

Following a similar line of thought, MacNeil et al. (2008a, b) proposed the application of capture-mark-recapture (CMR) models to determine species specific detection probabilities. Here the authors conducted repeated single observer surveys of fixed strip transects within a 20 minute sampling window to estimate species specific detection probabilities using closed population CMR models. Again, the results are promising and

have led to additional insights into species characteristics that influence their detectability, such as body size and schooling behaviour (MacNeil et al. 2008a, b). There are areas of concern with their approach as they make the assumption that by repeatedly sampling the same transect the population is closed, which is unlikely to be the case as observed fish communities change rapidly with disturbance and foraging activity (McClanahan et al. 2007). Although it is possible to apply CMR models to this data, the detection probability estimates are model dependant and relatively imprecise (Nichols et al. 2000).

In his review of field survey methods in applied ecology, Elphick (2008) noted that significant improvements in field methods are those that account for detection errors, include distance sampling and employ multiple-observer approaches. Most UVC surveys involve two divers, either with both conducting different surveys on either side of the transect line (as per Kulbicki, 1998), or where only one diver conducts the survey and the other serves as a buddy (as per Bennett et al. 2009). To date no studies have used two divers conducting independent surveys along the same transect at the same time to estimate the effect of observer bias on detection probability of fish.

In the terrestrial environment, double-observer methods have been applied to estimate visibility bias, observer bias and detection probabilities (Cook and Jacobson 1979; Graham and Bell 1989; Nichols et al. 2000). Two approaches have been specified, the dependant-double-observer (DDO) approach (Cook and Jacobson 1979; Graham and Bell 1989) and the independent-double-observer (IDO) approach (Jenkins and Manly 2008). The DDO approach relies on limited and specific communication between a primary and secondary observer. In this situation the observers make independent observations, however, the primary observer informs the secondary observer of each sighting incidence, and the secondary observer records whether or not it was seen by only the primary observer or both observers. Similarly, sightings recorded only by the secondary observer are also recorded (Graham and Bell 1989). The DDO approach allows joint detection probabilities for both observers to be calculated (Forcey et al. 2006). In the IDO approach, both observers act as primary observers conducting

independent surveys of the same sample at the same time (Jenkins and Manly 2008). By recording the location of each unique sighting the detection probabilities can be modelled with the closed population CMR models, which accommodate the effect of distance and additional covariates that may introduce heterogeneity into the data (Jenkins and Manly 2008).

In a comparison of the two approaches, Forcey et al. (2006) advocated the use of the DDO as it was associated with higher species specific detection probabilities. Conversely, Nichols et al. (2000) recommended the investigation into the IDO approach, as the data could be used with the entire suite of closed population CMR models. Both double-observer methods rely on the researcher being able to distinguish if a unique individual was seen by one observer or by both observers. Communication underwater is complicated and time consuming, and as a result the DDO technique is not suitable. Similarly, it is very difficult to record where and when unique individuals were seen during a transect, as fish move quickly in and out of the survey area, and it is difficult to record geographical reference points for post-hoc comparisons, complicating the application of the IDO. However, using the IDO method and only considering the summed observations recorded along a transect, the species composition, and abundance per species can be directly compared. These data can then be used to assess species detection probabilities and construct dissimilarity indices allowing for fine-scale patterns in the biases associated with the traditional UVC technique to be isolated and described.

2.1.1 Aim

The aim of this study was to develop and test an independent double-observer approach to traditional UVC line transects that would allow direct comparison of data collected by two observers. The method was then employed to measure the influence of observer type (researcher or volunteer), habitat characteristics and fish community structure, on the detection probability and count dissimilarity when looking at the entire fish community and individually for the dominant fish species.

2.2 Materials and methods

2.2.1 Study areas

Two MPAs within the warm temperate Agulhas Ecoregion of South Africa (Cape Point to Mbashe River) were targeted (Fig. 2.1a). The Ecoregion is characterised by high levels of endemism, with the majority of the endemic and commercially important sea-bream (Sparidae) species occurring in the region (Branch et al. 2010). Furthermore, the diversity and abundance of important fisheries target species are higher within well-established MPAs (Bennett and Attwood 1991; Babcock et al. 1999; Watson et al. 2007). Thus, the study areas were assumed to represent the best possible proxy for natural reef fish populations and allowed for a more focused assessment of the observers ability to survey the reef fish community typical to the Agulhas Ecoregion. To allow for volunteers and researchers to take part in the survey the dive sites within the MPAs needed to be easily accessible to both observer groups. With this in mind the selected MPAs represent a balance between accessibility to divers (MPA remoteness) and protection status of fish communities (MPA size).

The Table Mountain National Park (TMNP) MPA straddles the Cape Peninsula to the south of Cape Town, with the False Bay section lying at the western boundary of the Agulhas Ecoregion (Fig. 2.1a). Cape Town is home to a large and active recreational SCUBA diving community. The park management has been in the process of establishing a volunteer monitoring programme, providing this study access to a diverse pool of volunteers as well as researchers (Bernard and Götz 2012). The survey was conducted in the Castle Rock no-take MPA and the adjacent Caravan reef (Fig. 2.1b). Castle Rock is one of the preferred dive sites in Cape Town, and is also an old and established (since 1979) no-take MPA. As such, it represents a stable and diverse biological community, ideal to assess the ability of the divers to collect the required data. Caravan reef lies to the north of the Castle Rock no-take MPA, and is an

extension of the reef complex within the Castle Rock MPA with easy access for SCUBA divers through the Millers Point slipway (Fig 2.1c).

The Tsitsikamma National Park (TNP) MPA lies in the centre of the Agulhas Ecoregion (Fig. 2.1a). It is the oldest (1964), and one of the largest, no-take MPAs in Africa. Subtidal communities within the park are free from direct anthropogenic disturbance and provide one of the best examples of pre-exploitation inshore ecosystems available today. The Rheeders Reef complex lies to the east of Storms River mouth in the centre of the TNP MPA (Fig. 2.1d). It is a large, diverse, reef complex (Fig. 2.1e), and has an on-going LTM programme in place. As such it is accessible to researchers and accompanying volunteers to participate in surveys and, considering the ecological status, is an ideal location to test the ability of divers to conduct subtidal monitoring surveys.

2.2.2 Habitat mapping

To standardize the sampling procedure both study areas, Castle Rock and Rheeders Reef, were bathymetrically mapped with GPS linked echo-sounder and side-scan sonar. Additional bathymetric data was obtained for Castle Rock from the South Africa Council for Geoscience, and for Rheeders Reef from data collected by Bennett (2007).

The Latitude, longitude and depth data were interpolated to create a three dimensional bathymetric contour map using the geographic information systems (GIS) analysis package ArcMap (version 9.2). Interpolation of the data to a raster file was conducted using tension-splines with the spatial analyst package, following the recommendations of Götz (2005). Raster files are made up from a layer of cells with a specified size covering a specific area, with interpolation predicting the values of the cells from a limited number of data points. Using a dataset the interpolation method predicts the values of missing cells based on the characteristics of the eight surrounding cells. Splines incorporate a mathematical formula that uses the input data points to create a smooth surface that aims to minimise the surface curvature of the output raster. When

the tension-spline method is used, the output bathymetry raster is less smooth, however it reflects closely the character of the modelled data, more so than what is produced using the alternate regularized-spline method (ESERI, 1996). Following this, a surface analysis was conducted to generate a slope map. For raster files, the slope is defined as the maximum rate of change in elevation over each cell and its eight neighbours. Spatial analyst uses an input bathymetry raster to create a slope raster containing the slope at each cell. In this instance, the lower the slope value the flatter the terrain. For example, a slope angle of 45 degrees equates to equal change in vertical height over horizontal distance. When expressed as a percentage the slope of this angle is 100 percent, while this percentage approaches infinity as the slope gets closer to vertical (90^{o}) (ESERI, 1996).

For this study, the output cell size for the interpolation raster was set to 5 m^2. The slope raster produced was characterised by very high angles close to 90^{o}, ranging between 86.23 and 89.99^{o}. To predict the reef profile the slope raster cells were classified using a five level geometric interval method. The geometric classification scheme predicts class breaks that have a geometrical series. The classification scheme uses an algorithm to create geometric intervals by minimizing the square sum of elements per class. In doing so, each class range has a similar number of values and the change between intervals is fairly consistent (ESERI, 2006). This approach works very well with continuous data and it produces a comprehensive surface or bathymetric map (ESERI, 2006). Of the five levels selected, only three were represented in the data, and they were classified according to their slope values as (i) sand (very low profile bathymetry), (ii) low profile reef bathymetry and (iii) high profile reef bathymetry (Fig. 2.1c, e). Where side-scan sonar data was available the reef habitat was isolated and displayed on the habitat maps.

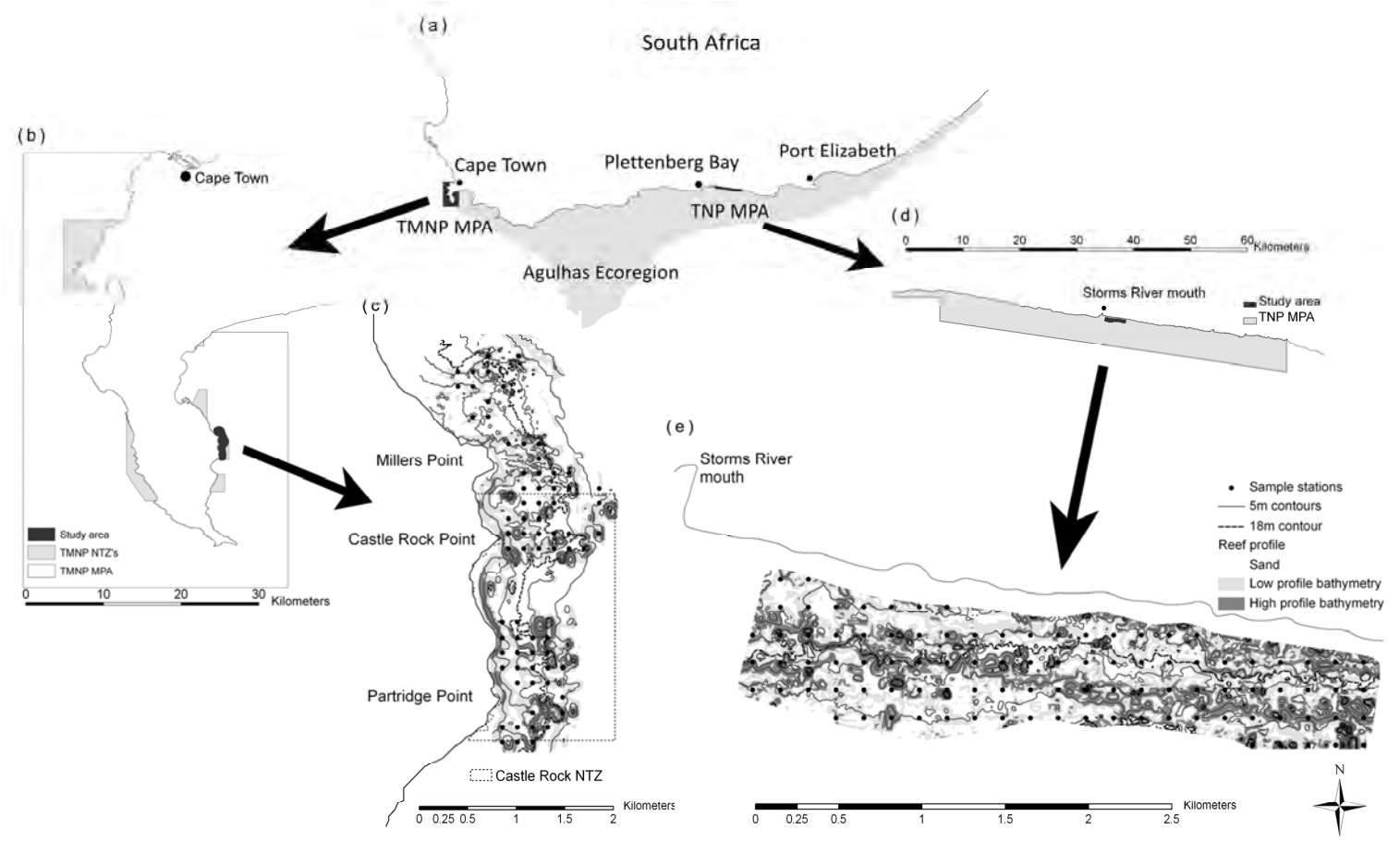

Figure 2.1: Map of South Africa identifying the Agulhas Ecoregion (a), together with the location of the Table Mountain National Park (TMNP) marine protected area (MPA) with no-take zones (NTZs) (b) and the Tsitsikamma National Park (TNP) MPA (d). Detailed bathymetric maps of the Castle Rock (c) and Rheeders Reef (e) study areas and positions of potential sample stations are included.

2.2.3 Sampling strategy

The study areas were then subdivided into 150x150 m grid-cells. Bennett (2007) promoted the use of the 150x150 m grid-cell size in subtidal reef surveys (5-30 m depth), as it avoids pseudo-replication and autocorrelation by taking into account transect length, GPS error and boat swing on the anchor. Each grid-cell was classified according to depth (Shallow < 18 m, Deep = 18-30 m) and reef profile (High and Low), and the centre point of each grid-cell was the target point for a potential sample. The grid-cells were selected following a stratified random approach with even sample allocation between strata (depth and profile) and only cells with greater than 50 % reef coverage were considered for selection. This approach produced four classes of sampling cells, representing shallow/low profile (1), shallow/high profile (2), deep/low profile (3) and deep/high profile (4) bathymetry in the study area. During each sampling trip the grid-cells from within each class were randomly selected, with even sample allocation between classes. The sampling procedure was further randomised by the sequence with which the classes were targeted. The approach described above follows the protocol described by Götz (2005) and Bennett (2007).

2.2.4 Underwater visual census method

The double-observer method employed during this study is based on the IDO approaches employed to investigate observer bias and calculate detection probabilities in terrestrial surveys of birds and mammals, and boat based surveys of marine mammals (Alldredge et al. 2006; Forcey et al. 2006; Smith et al. 2006; Jenkins and Manly 2008). With the formal IDO approach, the position of each observation must be mapped during the course of the transect so that observations that were common to both observers can be matched (Riddle et al. 2010). UVC transects can be complicated as the density of fish is often very high and they move rapidly thought the survey area. As such it was felt that the formal IDO approach would be too time consuming and complicated for inexperienced volunteers and a simplified method that provided only

total abundance of individuals per species per observer per transect was employed (referred to as paired-transects from this point forward).

The UVC method employed was an adaptation of the approach of Bennett et al. (2009). In this approach, all fish seen within a quarter-sphere, with a 3 m radius directed forward and to the sides of the observer, are identified and counted. Only fish entering from the front and sides are recorded. For the paired-transects, two divers would initially lay a 50 m transect line along the reef in a randomly selected direction. They would then position themselves as close together as possible on either side of the line and simultaneously swim back along the line performing fish counts. Observers had to maintain a swimming speed of approximately 6 m per minute, and every effort had to be made not to stagger their positions relative to each other. The output from the paired-transect consisted of two independent species and species abundance lists from the same sample. This allowed for direct assessment of the precision of the count data by calculating sample dissimilarity scores. To assess the change in precision with increasing experience, the observers were required to conduct multiple paired-transect dives, with the repeat dive number being a proxy for experience level. Divers would not communicate any information during the paired-transect, however they were allowed to discuss and compare their results afterwards to aid in the learning process. Because of difficulties related to specific divers being available at certain times and certain buddy pairs only wanting to dive together, no constraints were placed on whom the observers dived with, so long as they were from the same observer group (researchers or volunteers). When observers with different levels of experience dived together, the experience level was taken to be that of the observer with the least number of paired-transect dives.

For the data analysis the following assumptions had to be made:

1. observations by paired observers were taken as being independent (i.e. there was no communication and assistance between the observers),

2. all fish within the survey area were assumed to be equally visible to both observers (i.e. not obscured by the other observer or by high profile reef),
3. all and only fish within the bounds of the survey area were counted, and
4. all fish seen were correctly identified.

The validity of these assumptions will be reviewed in detail in the discussion section of this chapter.

2.2.5 Observer selection and training

The observers that participated in this study consisted of researchers who had considerable experience (between four and 20 years) conducting subtidal fish community surveys in the Agulhas Ecoregion, and newly trained, inexperienced volunteers. Although inexperienced in marine research, all volunteers had appropriate recreational SCUBA diving certificates and ranged in diving experience from one to 30 years. The volunteers were trained as part of a pilot study to test the feasibility of a volunteer monitoring programme for the TMNP MPA (Bernard and Götz 2011). All volunteers attended a standardised two day training course where they were taught how to identify all the target fish species in the area and how to perform the UVC method.

Before and after the training course the volunteer's identification skills were assessed with photo tests. The observers were shown slides of a random selection of target fish species covering various life stages and were required to identify each species. In addition, identification and counting skills were assessed after the training course with a video test. The video test consisted of a series of short clips recorded in the TMNP and TNP MPAs, with the observers being required to identify and count all target fish species. The researchers that participated in this study were also tested as described above, but without attending the training course. Analysis of the test results was performed using paired Student t-tests and non-parametric Mann-Whiney U tests in the R (version 2.13.0) environment for statistical analysis (R Development Core Team 2011).

In addition to the classroom tests, the ability of the volunteers to estimate distance underwater was investigated. As only the volunteers attended the training courses, the researchers' ability to estimate distance underwater was not tested. The test involved observers in full SCUBA gear swimming down a strip transect in a pool while estimating the distances of 15 conspicuous buoys from the transect line. The buoys were suspended between 0.1 and 1.5 m in the water column, and were placed at random distances between 0.5 and four meters on either side of a transect line. Two versions of the test were employed with separate groups of volunteers. The first version was based on the traditional single observer UVC method with one observer swimming down a transect line and estimating the perpendicular distances to the buoys. The second variation was based on the paired-transect adaptation to the UVC method, with a pair of observers swimming down the transect line with each observer independently estimating the distances to the buoys. The accuracy of the estimates were measured against the actual distances, and expressed as a percentage deviance, centred on zero (i.e. zero = 100% accuracy). The statistical analysis of the test results was conducted with paired Student t-tests and non-parametric Mann-Whiney U tests in the R environment (version 2.13.0, R Development Core Team 2011).

2.2.6 Paired-transect similarity/dissimilarity calculation

To estimate the precision of the count data collected during a paired-transect a species detection probability measure, the Jaccard Coefficient (*JC*), and two measurements of sample dissimilarity, namely CY dissimilarity (*CYd*) (Cao et al. 1997) and binomial deviance dissimilarity (*BDd*) (Anderson and Millar 2004), were selected.

The double-count method employed by Graham and Bell (1989) to address problems of visibility bias in aerial surveys was the basis for selecting the *JC*. Graham and Bell (1989) used a CMR procedure based on the Lincoln-Peterson estimator, where the product of count 1 and count 2 is divided by the number of re-sampled individuals between counts 1 and 2. Graham and Bell (1979) used the dependant-observer technique which involved two observers working in tandem, simultaneously counting the

same population with controlled communication allowed. This produced three sets of observation data; groups of animals seen by observer-one only, groups seen by observer-two only, and groups seen by both observers. Here a group of animals is defined as one or more individuals seen within close proximity. To calculate the probability P of one observer recording a group, the following equation was used:

$$P = \frac{B(S_1+S_2+B)}{(S_1+B)(S_2+B)} \qquad \text{(equ. 2.1)}$$

, where groups recorded only by observer-1 are labelled S_1, by observer-2 S_2, and by both observers B. Equation 2.1 provides a sighting probability of a group by one or the other observer, however, it does not provide a measure of the probability of both observers recording a group. Adapting equation 2.1, the probability of both observers recording a group can be expressed simply as,

$$JC = \frac{B}{S_1+S_2+B} \qquad \text{(equ. 2.2)}$$

, which is equivalent to estimating the *JC*, and is useful for detecting major differences in species composition between samples. *JC* ranges between zero and one, with one indicating 100 % similarity. When *JC* = 1, both S_1 and S_2 will be equal to zero as all groups would have been seen by both observers (*B*).

CY dissimilarity was developed by Cao et al (1997) in an attempt to overcome bias in weighting, originating from variation in species density, associated with traditional dissimilarity-similarity measure, such as the Bray-Curtis measure and the Canberra metric. *CYd* is a distance measure ranging from zero to infinity, with identical samples equal to zero, and is expressed as:

$$CYd = \frac{1}{N_l}\sum\left(\frac{(X_{ijl}+X_{kjl})\log_{10}\left(\frac{X_{ijl}+X_{kjl}}{2}\right)-X_{ijl}\log_{10}X_{kjl}-X_{kjl}\log_{10}X_{ijl}}{X_{ijl}+X_{kjl}}\right) \qquad \text{(equ. 2.3)}$$

, where X_{ijl} and X_{kjl} are the number of individuals from species j, recorded by observer i and observer k during simultaneous paired-transect l, while N_l is the total number of species observed during simultaneous paired-transect l. The nominator section calculates the dissimilarity between the two observers, and the denominator section is used to remove the effects of absolute species abundance. To account for zeros in the count data, 0.1 is added to all X_{ijl} and X_{kjl} values. According to Cao et al. (1997) this step avoids mathematical paradox and enables the measure to respond to all significant variation sensitively and weight them with minimum bias. To account for variability in species richness, $\frac{1}{N_l}$ is used to produce an average dissimilarity measure independent of the total number of species.

The second approach was developed by Anderson and Millar (2004) and is based on likelihood theory, which is considered an advantage over the method of Cao *et* al. (1997). The approach uses the summed binomial deviance as a measure of ecological dissimilarity between the pairs of count data, and is expressed as:

$$BDd = \sum_{k=1}^{p} \frac{1}{n_{kl}} \left\{ y_{1kl} \log\left(\frac{y_{1kl}}{n_{kl}}\right) + y_{2kl} \log\left(\frac{y_{2kl}}{n_{kl}}\right) - (y_{1kl} + y_{2kl}) \log\frac{1}{2} \right\} \qquad \text{(equ. 2.4)}$$

In this instance, y_{1kl} and y_{2kl} are the counts for species k by observer-1 and observer-2, respectively, during simultaneous paired-transect l, and n_{kl} is the sum of y_{1kl} and y_{2kl}. Following this, the null hypothesis is that there is no difference in species composition and abundance between counts of observer-1 and observer-2 (Anderson and Millar 2004). To remove the effect of different scales of abundance per species, a scale-invariant measure is included by dividing species specific binomial deviance by n_{kl}, before summing the deviances for all species from paired-transect l. As with *CYd*, *BDd* is a distance measure ranging from 0 to infinity, with identical samples equal to zero.

BDd and *CYd* both calculate a dissimilarity measure by taking into account the species specific differences in abundance, however, critical differences exist in the way the

measures handle variation between samples regarding species. While *BDd* and *CYd* both standardise the dissimilarity between two samples at the species abundance level, *BDd* does not take into account variability in the total number of species seen. As a result, the estimated dissimilarity increases with species richness. On the other hand, *CYd* calculates an average species dissimilarity between two samples as the sum of the species specific dissimilarity is divided by the total number of species recorded in the two counts.

2.2.6.1 Comparison of selected dissimilarity measures

An exploratory analysis was conducted to determine the sensitivity of *CYd* and *BDd* to variations in species richness, abundance and percentage difference in species richness data.

Considering a consistent density with a 50% difference in abundance per species between two samples, and without weighting *CYd* by species richness, both measures increase proportionally with increasing species richness. Dividing *CYd* by the total number of species in both samples, results in a monotonic value over varying levels of species richness. With respect to weighting scores according to varying abundance of species, both measures responded similarly to proportional changes in total species abundance, although *CYd* produces higher scores. Under constant species richness and proportional differences between samples, the measures follow a logarithmic curve, with samples dominated by rare species scoring lower (i.e. higher similarity) than samples dominated by abundant species (n>30), with more or less identical relative differences between samples (Fig. 2.2a). Under the above conditions, changes in the number of species causes no change in the *CYd* score but decreases the *BDd* with decreasing number of species. The introduction of rare species (n<8 individuals) into a sample dominated by abundant species results in the dissimilarity dropping, relative to the average group size, even though the proportional difference between samples stays the same (Fig. 2.2b). Finally, both measures show large increases in dissimilarity when a species is only present in one sample. In contrast to the similarity in response,

described above, *CYd* and *BDd* handle zero counts differently with *CYd* showing a continuous increase in dissimilarity with increasing group size while *BDd* plateaus at approximately 50 individuals, with major increases in group size resulting in only slight increases in dissimilarity (Fig. 2.2c).

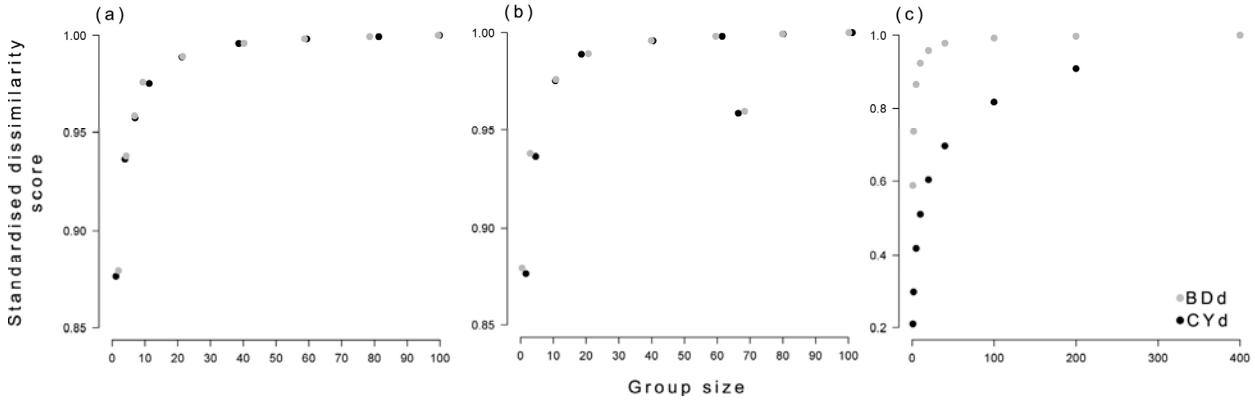

Figure 2.2: Response of *CYd* and *BDd* to changes in average group size (a), the occurrence of rare species in a sample dominated by abundant species (b), and species present in only one sample (i.e. one zero count) under increasing group size (c). Dissimilarity scores are standardised by the maximum value obtained, and group size is the average number of individuals per species. In all the plots, seven species were used to calculate the dissimilarity scores. In plots "a" and "b" there was 50 % difference between the two samples used to calculate each score. In plot "b", three rare species were introduced into a sample, illustrated by the outlying point.

From an ecological perspective, when monitoring a community that is dominated by resident species, the *BDd* scores will be less biased by schooling species that are rarely seen (considering its response to zero counts, Fig. 2.2c). However for the purpose of this study, the increased sensitivity to changes in abundances shown by *CYd* is preferable as it is better suited to measure observer bias. In addition, by removing the additive effect of increased species richness on the score, *CYd* is able to directly assess the effect of increased species richness on the ability of observers to conduct visual surveys. Following this, *BDd* was not used during the analysis below.

Table 2.1: Description of the covariates included in the full generalised linear models

Name	Description	Levels
Observer type	Measure of the background experience of the different observers	Researcher Volunteer
Experience level	Minimum number of replicate paired-transects conducted by the observers within a pair	1-12
Location	Study area	Castle Rock or Rheeders Reef
Profile	Reef bathymetry	High or Low
Species richness	Total number of species recorded during a paired-transect	1-17
Average species abundance	The total number of fish recorded divided by the species richness per paired-transect	1-47
Abundance	The abundance of an individual species per paired-transect	1-125

To ease understanding of the results, use of the acronyms will be limited, and the *JC* and *CYd* measures will be referred to as species detection probability, paired-transect dissimilarity, respectively. It is important to understand that with paired-transect dissimilarity, taking into account the number of species recorded along the transect only removes the mathematical effect of adding the species specific dissimilarities to the overall transect dissimilarity, and enables investigation into trends between observer error and community diversity.

2.2.7 Data analysis

The data were analysed at the community level, as well as the species level. The community level analysed the species detection probability and paired-transect dissimilarity measures, as described above. The species level analysis focussed on the detection probability for the dominant species recorded along a paired-transect. The analysis at the community level is a similar approach to that employed by Edgar and

Stuart-Smith (2009) who selected a sample similarity measure, Bray-Curtis, to make comparisons between data collected by volunteers and researchers.

2.2.7.1 Generalised linear models

Generalised linear models (GLMs) were used to assess the effect of study area (*Location*), community (*Species richness* and *Average species abundance*), habitat (reef *Profile*) and observer (*Observer type* and *Experience level*) related covariates on species detection probability and paired-transect dissimilarity measures (Table 2.1). Modelling a response variable against a large number of predictor variables (covariates) leads to statistical over fitting (Venables and Ripley 2002). Due to the large number of potential covariates in this dataset, only those thought to directly influence the precision of paired-transect data were included in the models. This excluded the covariates of depth, temperature and bottom type. All three parameters are known to influence fish diversity and abundance (Anderson and Millar 2004; Bennett et al. 2009), however their direct influence on paired-transect precision was assumed to be negligible. Furthermore, the influence of variability in the community structure on paired-transect precision was catered for by including community measures such as species richness and species abundance.

Prior to the GLM analysis, detailed exploratory analysis was conducted following the approach of Zuur et al. (2010). Where possible, outliers in the response variable were retained in the model, they were however checked for calculation and transcription errors. If it was not possible to correct outliers resulting from transcription errors, they were omitted from the dataset. Where colinearity was identified between covariates, the covariates with the highest variance inflation factor (VIF) were sequentially removed from the model until all the VIFs were less than the threshold of three (Zuur et al. 2010). Colinearity is defined as the presence of correlation between covariates, and it is problematic as it confuses statistical analysis (Zuur et al. 2010). This resulted in the removal of *Location* from all the analyses, as it was correlated with Species richness.

GLMs represent a mathematical extension of linear models allowing for non-normal response distributions to be modelled through transformation to linearity (Venables and Ripley, 2002). GLMs are based on assumed relationships between the mean of a response variable and a combination of linear predictors (Guisan et al. 2002). By accommodating several families of probability distributions, GLMs lend themselves to the analysis of ecological data that are typified by non-normal error structures (Guisan et al. 2002). A GLM is defined as:

$$g(E[y]) = \beta_0 + \sum_k \beta_k x_k \qquad \text{(equ. 2.5)}$$

, where $g(\cdot)$ is the link function = the assumed relationship between the response and predictor variables, and $E[y]$ is the expected value of the response variable y. The right-hand side of the equation is the linear predictor, where the intercept, β_0, is combined with the sum of the predictor variable (x_k), and the regression coefficients (β_k).

GLMs were fitted using the MASS package (Venables and Ripley 2002) in the R environment (version 2.13.0, R Development Core Team 2011). Where data were in the form of proportions and presence/absence, the models were fitted with binomial distributions with a logit link:

$$Y_i \sim B(\pi_i, n_i) \qquad \text{(equ. 2.5)}$$

$$E(Y_i) = \pi_i \times n_i \quad and \quad var(Y_i) = n_i \times \pi_i \times (1 - \pi_i) \qquad \text{(equ. 2.6)}$$

, where the expected response, $E(Y_i)$, is assumed to be binomially distributed with a probability of π_i and n_i independent trials. For presence/absence data $n_i = 1$, while for proportional data n_i is the total number of trials. The expected mean and variance for Y_i are then given by $\pi_i \times n_i$ and $n_i \times \pi_i \times (1 - \pi_i)$, respectively. The full model was then equivalent to:

$$logit(\pi) =$$

$$\alpha + \beta_1(Observer\ type) + \beta_2(Experience\ level) + \beta_3(Profile) + \beta_4(Species\ richness) + \beta_5(Average\ species\ abundance) \quad \text{(equ. 2.7)}$$

, where the predictor function consists of a combination of covariates used to explain the variability in the response variable. The Gaussian distribution with identity link was used to fit the remaining data:

$$Y_i \sim N(\mu_i, \sigma^2) \quad \text{(equ. 2.8)}$$

$$E(Y_i) = \mu_i \quad and \quad var(Y_i) = \sigma^2 \quad \text{(equ. 2.9)}$$

, where the response variable Y_i is assumed to be normally distributed with mean μ_i and variance σ^2 (Zuur et al. 2009). The full model was then equivalent to:

$$E(Y) =$$
$$\alpha + \beta_1(Observer\ type) + \beta_2(Experience\ level) + \beta_3(Profile) + \beta_4(Species\ richness) + \beta_4(Average\ species\ abundance) + \varepsilon \quad \text{(equ. 2.10)}$$

, where the predictor function consists of a combination of covariates used to explain the variability in the response variable, and ε is the error term (Zuur et al. 2009). Model selection was conducted by fitting a full model, i.e. one containing all the relevant covariates, and comparing the Akaike Information Criterion (AIC) score for all possible model combinations (Logan 2010; Barto 2011). All models were then ranked according to the difference in AIC (Δ AIC) from the model with the lowest AIC value. For models with a Δ AIC < 2, the significance of the model parameters was explored further to determine their contribution to the model (Bolker et al. 2008 supplementary data; Logan 2010). The approach aims to select a set of models with the lowest AIC scores with the final model representing the most parsimonious balance between model fit and simplicity.

2.2.7.2 Graphical representation

All data were visualised with trellis plots from the lattice and latticeExtra packages in R (Sarkar 2008). Trellis plots are able to draw a replicate plot for subsets of data corresponding to different levels of a categorical variable or corresponding to the selected intervals of a numeric variable and are ideal to illustrate the effect of factorial and continuous covariates on a response variable (Becker and Cleveland 1996).

2.3 Results

2.3.1 Observer training and assessment

Sixty-one volunteers were tested prior to and after training. The ability to identify species improved significantly ($t=18.5$, $p<0.001$) between the first (50.8 ± 14.0 %) and second (79.9 ± 14.5 %) tests. Although 13 % lower than that obtained by the researchers (93.5 ± 3.8 %), there was no significant difference ($W=188.5$, $p>0.05$) between the marks obtained by the volunteers following training and the researchers. However, there was considerably greater variability in the volunteers results (coefficient of variation= CV = SD/mean = 0.18) compared to researchers (CV = 0.04).

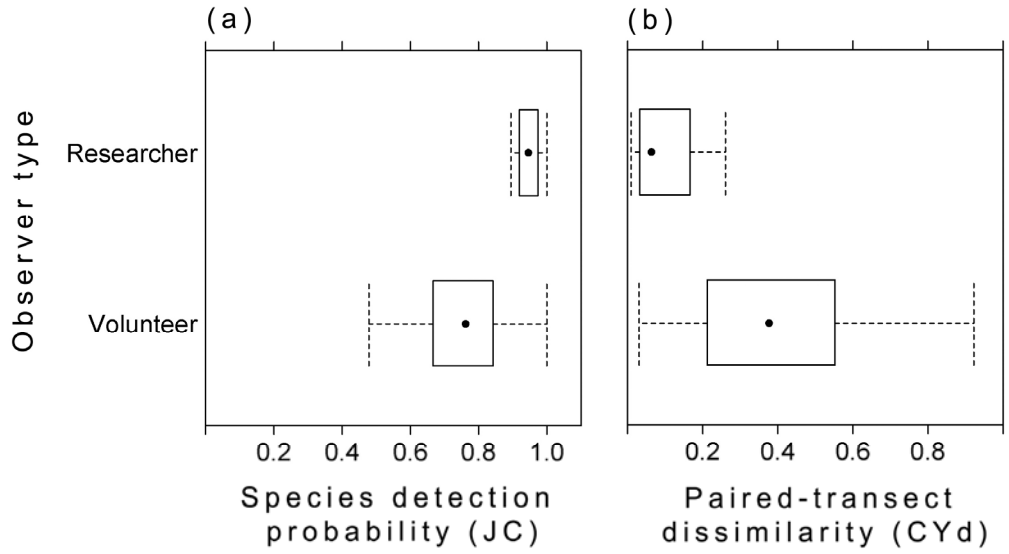

Figure 2.3: Results from the video test performed by the volunteers and researchers illustrating the difference in species detection probability (a) and paired-transect dissimilarity (b). The error bars show the standard deviation.

Although the number of researchers tested was low relative to the number of volunteers tested, the low levels of variability in the researchers data suggests that the restricted sample size did not bias the interpretation. The difference in sample size is not abnormal, as studies that use researchers to collect data typically rely on a small group of trained observers (Bennett et al. 2009), while studies that use volunteers rely on much larger groups of observers to collect the data (Edgar and Stuart-Smith 2009).

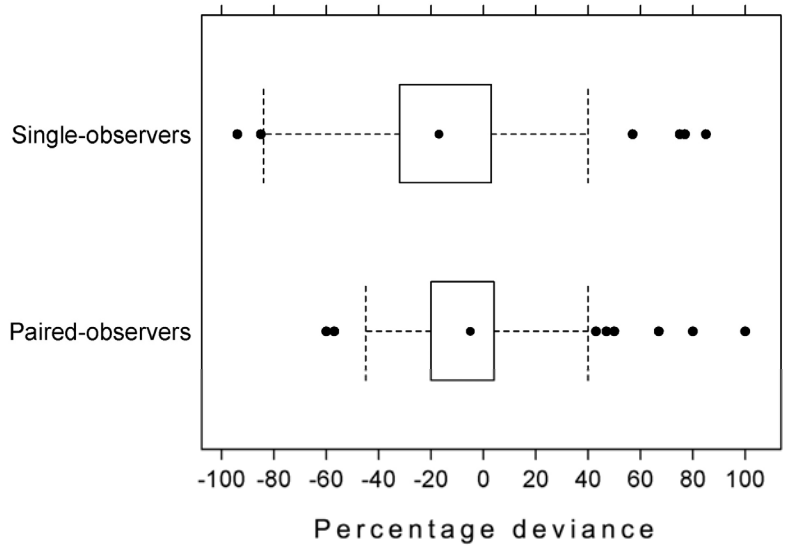

Figure 2.4: Results from the underwater distances estimates, showing the percentage deviation from the correct distance (centred on zero) for the single-observer and paired-observer underwater visual census techniques.

The community data recorded by each observer type during the video test was converted to species detection probabilities and the paired-transect dissimilarity measures by comparing the results from the tests to the actual fish community present in the video footage. Results from the video test indicated that the researchers were significantly better than the volunteers at identifying the species present in the video (*JC*: Volunteer = 0.76 ± 0.13, Researcher = 0.95 ± 0.04; W=25, p<0.01), as well as

counting the individuals of a species (*CYd*: Volunteer = 0.40 ± 0.24, Researcher = 0.10 ± 0.11; W=252, p<0.01) (Fig. 2.3).

Table 2.2: Summary of the sampling effort using paired-transects, with the distribution of the samples between the levels of the factorial covariates used in the generalised linear models.

Name	Levels	n
Observer type	Researcher	38
	Volunteer	65
Experience level	1	20
	2	12
	3	9
	4	10
	5	8
	6	7
	7	5
	8	6
	9	6
	10	7
	11	7
	12	6
Location	Castle Rock	71
	Rheeders Reef	32
Profile	Low profile	38
	High profile	65

The ability to accurately estimate distance underwater was assessed by testing 32 volunteers, with 16 individuals per UVC method type, namely single- or paired-observer approaches (435 distance estimates). The accuracy of the underwater distance estimates conducted in the pool was highly variable (Fig. 2.4). Both, the single- and paired-observer methods underestimated distance underwater, however the error was significantly higher (W=26130, p<0.001) for the single- (-14.1 ± 26.4 %) compared to the paired-observer (-3.6 ± 25.7 %) method.

Considering that the test was conducted in a controlled environment this result is of particular concern. However, as the test was carried out on novice observers it is expected that their ability to estimate distance underwater would improve with experience. The significant effect of the UVC method on distance estimate accuracy likely reflects the skill of the different observers in performing the different tests, and less so a direct method related effect. Importantly this result suggests that the paired-transect method should not reduce the accuracy of distance estimates underwater.

Table 2.3: List of all fish species recorded during the paired-transects surveys at the Castle Rock and Rheeders Reef study areas.

Class	Family	Scientific name	Common name	N[a]	Mean[b]	SD[b]	Min	Max
Osteichthyes	Sparidae	*Chrysoblephus laticeps*	Roman	85.44	7.57	6.76	1	40
	Cheilodactylidae	*Chirodactylus brachydactylus*	Twotone fingerfin	71.84	6.68	6.94	1	33
	Sparidae	*Pachymetopon blochii*	Hottentot	64.08	9.73	10.30	1	50
	Cheilodactylidae	*Cheilodactylus fasciatus*	Redfingers	56.31	2.34	1.56	1	13
	Sparidae	*Boopsoidea inornata*	Fransmadam	53.40	19.07	20.73	1	100
	Sparidae	*Spondyliosoma emarginatum*	Steentjie	36.89	12.63	21.17	1	125
	Sparidae	*Pachymetopon aeneum*	Blue hottentot	32.04	9.15	8.06	1	34
	Cheilodactylidae	*Cheilodactylus pixi*	Barred fingerfin	31.07	3.13	3.10	1	16
	Sparidae	*Gymnocrotaphus curvidens*	Janbruin	24.27	2.24	2.01	1	9
	Oplegnathidae	*Oplegnathus conwayi*	Cape knifejaw	21.36	3.18	3.34	1	21
	Sparidae	*Diplodus capensis*	Blacktail	17.48	2.56	2.06	1	11
	Sparidae	*Petrus rupestris*	Red steenbras	13.59	1.64	1.15	1	5
	Sparidae	*Sarpa salpa*	Strepie	11.65	73.42	97.53	1	310
	Parascorpididae	*Parascorpis typus*	Jutjaw	9.71	1.20	0.42	1	2
	Sparidae	*Diplodus hottentotus*	Zebra	9.71	2.15	1.38	1	8
	Sparidae	*Chrysoblephus gibbiceps*	Red stumpnose	6.80	1.93	1.17	1	4
	Sparidae	*Rhabdosargus holubi*	Cape stumpnose	6.80	1.64	0.75	1	3
	Cheilodactylidae	*Chirodactylus grandis*	Bank steenbras	3.88	1.00	0.00	1	1
	Sparidae	*Chrysoblephus cristiceps*	Dageraad	3.88	1.75	1.50	1	4
	Serranidae	*Acanthistius sebastoides*	Koester	2.91	1.00	0.00	1	1
	Ariidae	*Galeichthys feliceps*	White seacatfish	1.94	1.00	–	1	1
	Carangidae	*Trachurus trachurus*	Maasbanker	0.97	175.00	–	–	–
	Coracinidae	*Dichistius capensis*	Galjoen	0.97	1.00	–	–	–
	Haemulidae	*Pomadasys olivaceum*	Piggy	0.97	2.00	–	–	–
	Sparidae	*Argyrozona argyrozona*	Carpenter	0.97	2.00	–	–	–
	Sparidae	*Lithognathus mormyrus*	Sand steenbras	0.97	1.50	–	–	–
	Sparidae	*Pterogymnus laniarius*	Panga	0.97	24.00	–	–	–
	Congiopodidae	*Congiopodus spinifer*	Spinenose horsefish	0.97	1.00	–	–	–
Condrichthyes	Scyliorhinidae	*Haploblepharus edwardsii*	Puffadder shyshark	10.68	1.14	0.32	1	2
	Scyliorhinidae	*Poroderma africanum*	Striped catshark	3.88	1.00	0.00	1	1
	Carcharhinidae	*Triakis megalopteris*	Spotted gullyshark	1.94	1.00	–	1	1
	Hexanchidae	*Notorynchus cepedianus*	Spotted sevengill cowshark	0.97	2.00	–	–	–

[a] Species sorted by the % of the total number of paired-transects where they were present (N)

[b] The mean and SD are calculated from only the paired-transects where the species was present

3.1.1 Paired-transect sampling effort and data description

A total of 103 paired-transects was conducted, 71 in the TMNP MPA and 32 in the TNP MPA. Of these, 65 were conducted by a group of 28 volunteers and 38 were conducted by a group of seven researchers (Table 2.2). Twelve repeat dives (representing *Experience levels*) were conducted by each *Observer type* with at least three replicates per *Experience level* (Table 2.2). Of the 28 volunteers, only eight conducted more than six paired-transects, reflecting a drop-out rate of > 71 %. As a result, the volunteer data is unbalanced with higher replication at the lower experience levels (Table 2.2). The distribution of samples between the *Profile* levels was skewed, with most paired-transects conducted on high profile reef (n = 65) compared to low profile reef (n = 38).

Thirty species of fish were recorded during the survey with the seabreams (*Sparidae*) contributing 50 %. Of these 30 species, only eight were observed on more than 30 paired-transects, accounting for 73 % of the 608 observations (Table 2.3). On average (±SD), the *Species richness* for each paired-transect was 5.9 (± 3.2) species, with a minimum of one and a maximum of 17 species. The data collected by the researchers had a higher *Species richness* per paired-transect (7.3 ± 3.1) compared to that of the volunteers (5.1 ± 2.9). This difference in *Species richness* reflects the greater sampling effort by researchers at Rheeders Reef, and by volunteers at Castle Rock, and highlights the covariation between *Species richness* and *Location*, as *Species richness* at the Rheeders Reef study area was considerably higher (8.6 ± 3.1) compared to the Castle Rock study area (4.7 ± 2.4), while there was no notable difference between researchers and volunteers at each study area (Rheeders reef: 8.3 ± 3.2 and 9.5 ± 2.7, respectively; Castle Rock: 5.7 ± 2.1 and 4.5 ± 2.4 respectively). The total number of fish recorded on each transect ranged from 1 to 473 individuals, with an average of 47.1 (± 71.2). The *Average species abundance* ranged from single individuals to large schools (n = 310), with an average abundance of 7.8 (±7.8) individuals.species^{-1}. The *Average species abundance* was higher for volunteers (9.1 ± 9.2) than the researchers (5.6 ± 3.8).

Table 2.4: Summary of the fit and parameter estimates from the most parsimonious binomial and Gaussian generalised linear models fitted to the species detection probability (*JC*) and paired-transect dissimilarity data (*CYd*), respectively.

	Species detection probability (JC)				Paired-transect dissimilarity (CYd)			
	Estimate[1]	SE	z value[2]		Estimate	SE	z value	
Volunteers	0.311	0.171	1.819	.	0.343	0.049	7.039	***
Researchers	0.343	0.185	1.855	.	-0.088	0.043	-2.072	*
Experience level	—	—	—		-0.009	0.005	-1.801	.
High profile	—	—	—					
Species richness	—	—	—		0.015	0.007	2.166	*
Average species abundance	0.042	0.013	3.353	***	-0.006	0.003	-2.180	*
Null deviance	119.58 on 102 DF				3.33 on 101 DF			
Residual deviance	105.35 on 100 DF				2.91 on 97 DF			

1: Estimate = log(Odds ratio)

2: Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

2.3.2 Analysis at the community level

2.3.2.1 Species detection probability (JC)

Species detection probability averaged (± SD) 0.69 (± 0.22), with the volunteers having a slightly lower species detection probability score (0.68 ± 0.24, range: 0 – 1), compared to the researchers (0.72 ± 0.18, range: 0.22 – 1). As the detection probability is a proportion, the data were modelled with a binomial GLM with the logit link, and weighted by *Species richness*. During the exploratory analysis, none of the covariates were found to greatly inflate the model variance (VIF > 3), indicating that colinearity was not a problem. The model selection process showed that *Experience level*, *Profile* and *Species richness* had little influence on the observed variability in the species detection probability. These covariates were omitted from the most parsimonious model:

$$logit(JC) = \beta_0 + \beta_1(Observer) + \beta_2(Average\ species\ abundance) + \varepsilon$$

, which was able to explain 12.0 % of the observed variability in the data (Table 2.4). The likelihood ratio tests using the step-wise regression showed that the effect of

Observer type was marginally not significant ($X^2 = 3.46$, $p = 0.06$), with researchers having a higher probability (0.71 ± 0.03) of detecting all species along a transect than volunteers (0.66 ± 0.07) (Fig. 2.5a). The effect of *Average species abundance* was significant ($X^2 = 13.56$, $p<0.001$), with increasing abundance increasing the probability that all species would be detected (Odds ratio ± SE = 0.042 ± 0.01) (Fig. 2.5b).

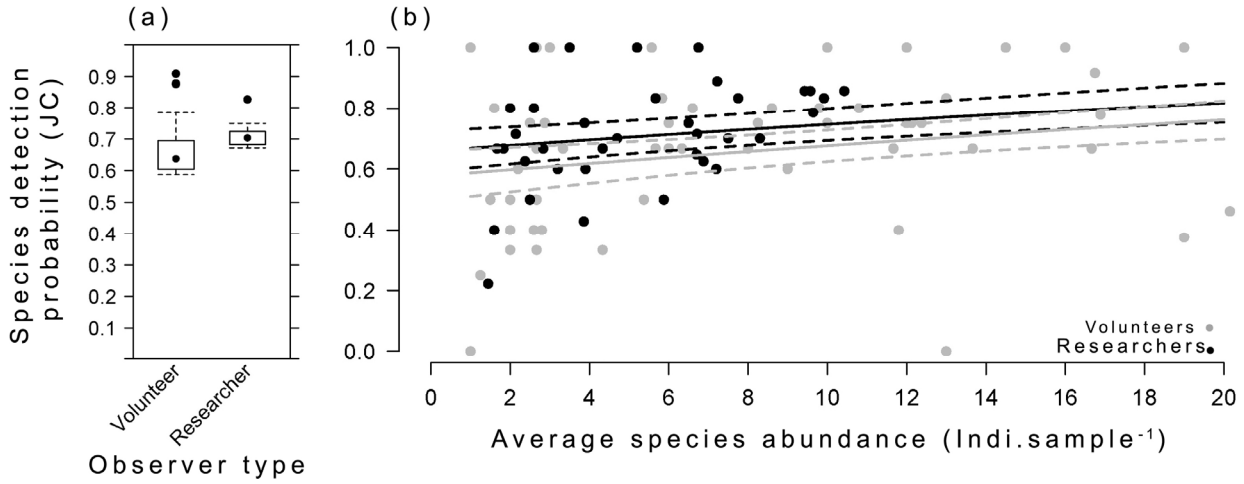

Figure 2.5: Predicted species detection probability (*JC*) showing the effect of *Observer type* (a), together with the effect of *Average species abundance* on *JC* (b). The data points in plot "b" are the observed data, while the trend lines were predicted from the generalised linear models (± 95 % confidence intervals).

2.3.2.2 Paired-transect dissimilarity (CYd)

The paired-transect dissimilarity averaged (± SD) 0.32 ± 0.23, with the researchers having lower dissimilarity scores (0.28 ± 0.15, range: 0.01 – 0.62), compared to the volunteers (0.35 ± 0.27, range: 0 – 1.8). The paired-transect dissimilarity data were modelled using a GLM fitted with the Gaussian family and an identity link. One influential outlier was identified and dropped from the analysis. The outlier was from a paired-transect conducted by volunteers with only one species recorded at a high abundance (13 individuals) by one of the observers. As the analysis above indicated

that detection probability increased with species abundance it was felt that this data point was a transcription error by the volunteer. There was no indication of colinearity amongst the covariates. The model selection process identified that *Profile* did not explain any of the variability in the *CYd* data and it was omitted from the most parsimonious model. The most parsimonious model:

$$CYd = \beta_0 + \beta_1(Observer\ type) + \beta_2(Experience\ level) + \beta_3(Species\ count) + \beta_4(Average\ species\ abundance) + \varepsilon$$

, was able to explain 12.4 % of the observed variability in the paired-transect dissimilarity data (Table 2.4). The likelihood ratio test identified that the effect of *Observer type* was significant ($X^2 = 4.42$, $p<0.05$), with the predicted dissimilarity scores greater for volunteers (0.33 ± 0.06) compared to researchers (0.28 ± 0.06) (Fig. 2.6a). Although the covariate *Experience level* was included in the most parsimonious model, its negative effect (Odds ratio ± SE = -0.009 ± -0.005) on paired-transect dissimilarity was negligible ($X^2 = 3.36$, $p = 0.07$).

Species richness had a significant effect on paired-transect dissimilarity ($X^2 = 4.82$, $p<0.05$), with increasing species richness resulting in higher paired-transect dissimilarity (Odds ratio ± SE = 0.015 ± 0.007) (Fig. 2.6b). An opposite pattern for *Average species abundance* was predicted, with higher abundances resulting in significantly ($X^2 = 4.88$, $p<0.05$) lower paired-transect dissimilarity scores (Odds ratio ± SE = -0.006 ± 0.003) (Fig. 2.6c).

Errors in species detection and counting were evident in the data collected by both researchers and volunteers. However, there appears to be sufficient information to suggest that researchers collect data of a better quality to volunteers. The effect of *Observer type* was strongest for the paired-transect dissimilarity (*CYd*) that is based on the difference between observed abundances. On the other hand the effect of *Observer type* was weak for the species detection probability (*JC*) that is based on the presence or absence of species from a paired-transect. This suggests that accurately counting

the fish is a bigger bias in volunteer UVC data than accurately detecting the different species. *Average species abundance* appears to play a significant role in the precision of paired-transect data. The negative effect of *Average species abundance* on paired-transect dissimilarity may indicate that rare species have a strong influence on the quality of UVC data collected by both *Observer types*.

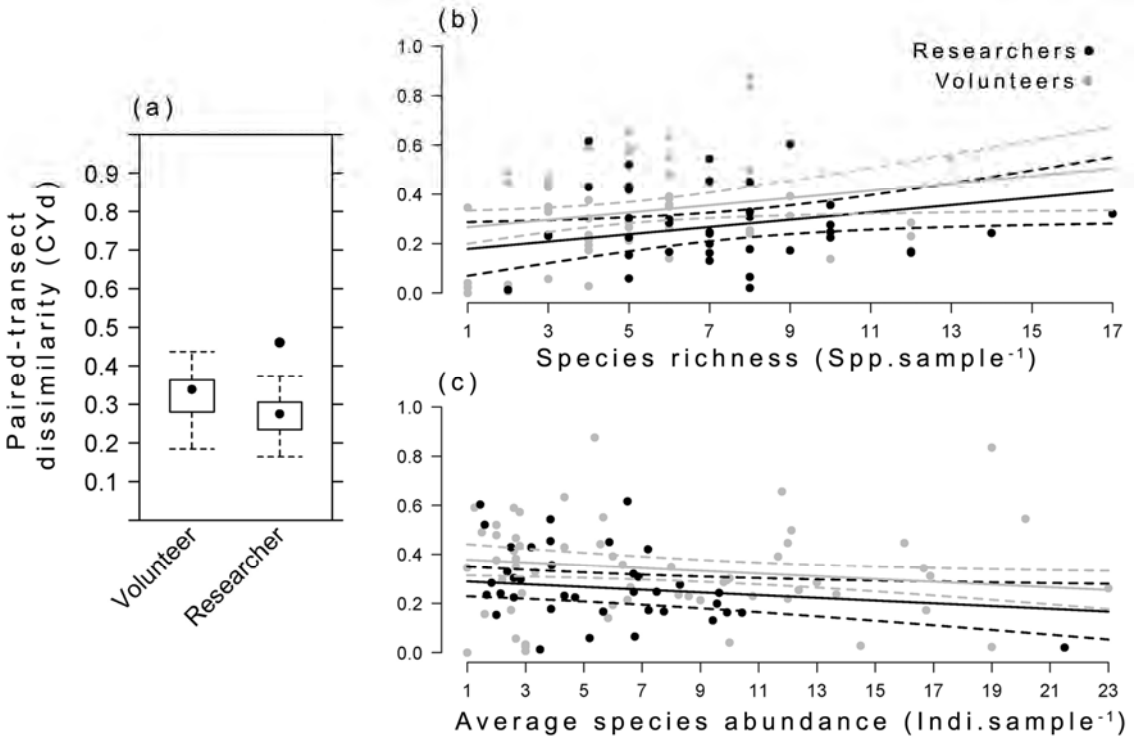

Figure 2.6: Predicted paired transect dissimilarity (*CYd*) showing the effect of *Observer type* (a), together with the effect of *Species richness* (b) and *Average species abundance* (c) on *CYd*. The data points in plot "b" and "c" are the observed data, while the trend lines were predicted from the generalised linear models (± 95 % confidence intervals).

2.3.3 Influence of species on detection probability

To investigate the detection probabilities associated with the dominant species observed during this study, binomial GLMs were run on the binary presence/absence to estimate the probability that both observers would record a species if present within the paired-transect survey area. Only species that were observed on more than 30 paired-transects were included in the analysis (see Table 2.3). The subset included five species of sparid, namely roman *Chrysoblephus laticeps*, hottentot *Pachymetopon blochii*, fransmadam *Boopsoidea inornata*, steentjie *Spondyliosoma emarginatum*, and blue hottentot *Pachymetopon aeneum*, and three species of fingerfin, namely twotone fingerfin *Chirodactylus brachydactylus*, redfingers *Cheilodactylus fasciatus* and barred fingerfin *Cheilodactylus pixi*.

The additional environmental covariates included in the model were, *Observer type*, *Profile* and *Average species abundance*. The covariate *Observer type* was included as it allowed the reassessment of the observer effect without the potentially negative effect of rare species detection probability and count dissimilarity. On the other hand, *Average species abundance* further investigated the effect of scarcity on the paired-transect detection probability and count dissimilarity. *Profile* was included due to its potential influence on the ability of both *Observer types* to see a fish within the survey area. The full model was standardised for all the species, with the exception of blue hottentot where *Profile* was excluded as the species was only recorded on high profile reef.

2.3.3.1 Roman

The model selection process resulted in *Observer* and *Profile* being dropped from the most parsimonious model:

$$Detection\ probability_{roman} = \beta_0 + \beta_1(Abundance) + \varepsilon.$$

Abundance was able to explain 68.5 % of the observed variability in the probability that both observers would detect roman if present within the survey area (Table 2.5).

Table 2.5: Summary of the fit and parameter estimates from the most parsimonious binomial generalised linear models fitted to the binary presence/absence data for the eight dominant species recorded during the paired-transect surveys.

	Roman				Hottentot				Twotone fingerfin				Barred fingerfin			
	Estimate[1]	SE	t value[2]		Estimate	SE	t value		Estimate	SE	t value		Estimate	SE	t value	
Intercept	-5.210	2.102	-2.479	*	-0.474	1.022	-0.464		-0.579	0.508	-1.141		-0.615	0.550	-1.119	
Observer: Researcher	—	—	—		—	—	—		—	—	—		—	—	—	
Profile: High	—	—	—		—	—	—		—	—	—		—	—	—	
Abundance	3.183	1.112	2.863	**	0.901	0.493	1.826	▪	0.451	0.153	2.948	**	0.237	0.127	1.873	▪
Null deviance	60.695 on 100 DF				37.145 on 77 DF				92.751 on 84 DF				47.804 on 34 DF			
Residual deviance	19.110 on 99 DF				21.714 on 76 DF				71.101 on 83 DF				42.739 on 33 DF			

	Steentjie				Fransmadam				Redfingers				Blue hottentot			
	Estimate	SE	t value		Estimate	SE	t value		Estimate	SE	t value		Estimate	SE	t value	
Intercept	-3.563	1.395	-2.553	*	-3.885	2.070	-1.877	▪	-2.169	0.661	-3.280	**	-3.325	1.681	-1.978	*
Observer: Researcher	1.687	1.069	1.577		2.095	1.443	1.452		1.026	0.591	1.736	▪	3.753	1.614	2.326	*
Profile: High	—	—	—		—	—	—		—	—	—		—	—	—	
Abundance	0.721	0.316	2.281	*	1.535	0.971	1.581		0.692	0.217	3.193	**	0.498	0.275	1.809	▪
Null deviance	51.796 on 39 DF				47.121 on 59 DF				92.149 on 66 DF				34.575 on 33 DF			
Residual deviance	24.340 on 37 DF				13.446 on 57 DF				68.616 on 64 DF				11.44 on 31 DF			

1: Estimate = log(Odds ratio)

2: Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

The likelihood ratio test showed the effect of abundance to be highly significant (X^2 = 41.56, p<0.001), with increasing abundance resulting in a rapid increase in detection probability (Odds ratio ± SE = 3.2 ± 1.1) (Fig. 2.7a). For examples, at an abundance of one individual in the transect area the detection probability (± SE) for roman was 12 % (± 11), while at an abundance of five individuals the detection probability was 100 % (Table 2.6).

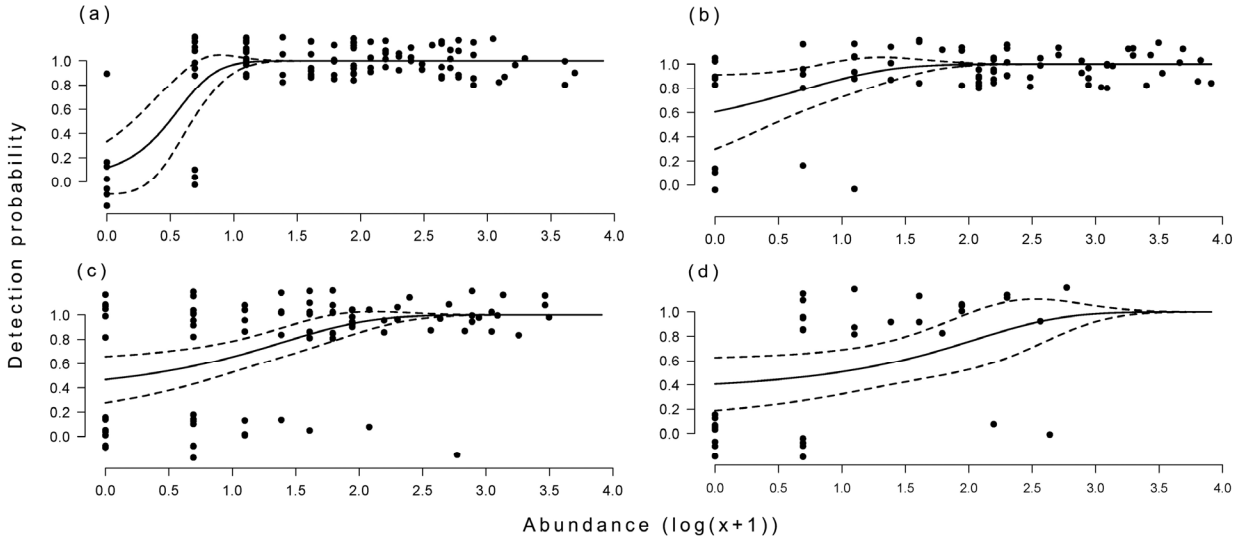

Figure 2.7: Probability (± 95 % confidence intervals) of both observers detecting roman (a), hottentot (b), twotone fingerfin (c), or barred fingerfin (d) during a paired-transect, with increasing abundance per species. The x-axis was log transformed to aid graphic presentation and the data points have been jittered to reveal overlapping data.

2.3.3.2 Hottentot

The model selection process resulted in *Observer* and *Profile* being dropped from the most parsimonious model:

$$Detection\ probability_{hottentot} = \beta_0 + \beta_1(Abundance) + \varepsilon.$$

Abundance was able to explain 41.6 % of the observed variability in the hottentot detection probability (Table 2.5). The likelihood ratio test showed the effect of abundance to be highly significant (X^2 = 15.43, p<0.001), with higher probability that both observers would detect the species when hottentot were more abundant within the transect area (Odds ratio ± SE = 0.90 ± 0.49) (Fig. 2.7b). Compared to roman, hottentot had a higher detection probability for one individual (61 ± 16 %) (Table 2.6).

2.3.3.3 Twotone fingerfin

As above, the model selection process discarded both *Profile* and *Observer* from the most parsimonious model for twotone fingerfin:

$$Detection\ probability_{twotone\ fingerfin} = \beta_0 + \beta_1(Abundance) + \varepsilon.$$

The abundance of twotone fingerfin within the transect area explained 23.3 % of the variability in the detection probability (Table 2.5), with higher abundances associated with significantly (X^2 = 21.65, p<0.001) higher detection probabilities (Odds ratio ± SE = 0.45 ± 0.15) (Fig. 2.7c).

2.3.3.4 Barred fingerfin

The model selection process singled out *Abundance* as the only covariate to influence the detection probability for barred fingerfin. The most parsimonious model:

$$Detection\ probability_{barred\ fingerfin} = \beta_0 + \beta_1(Abundance) + \varepsilon$$

, was able to explain 10.6 % of the variability in the detection probability of barred fingerfin (Table 2.5). As with the previous analyses, the likelihood ratio test identified a significant effect of *Abundance* (X^2 = 5.06, p<0.05), with detection probability greater when the abundance of barred fingerfin within the transect area was high (Odds ratio ± SE = 0.24 ± 0.13). Barred fingerfin had the lowest detection probability of all the tested species (Table 2.6), requiring an abundance of 20 individuals per paired-transect to be 98 % (± 3) sure that both observers would detect the species.

Table 2.6: Predicted detection probabilities (± SE) with increasing abundance for the eight dominant species of fish recorded during the paired-transect surveys. Where observer type was included in the most parsimonious generalised linear models, the detection probability is given for researchers and volunteers.

		Abundance (Indi.sample^{-1})			
Species	Observer type	1	5	10	20
Roman	Both	0.12 (0.11)	1	1	1
Hottentot	Both	0.61 (0.16)	0.98 (0.03)	1	1
Twotone fingerfin	Both	0.47 (0.1)	0.84 (0.06)	0.98 (0.02)	1
Barred fingerfin	Both	0.41 (0.11)	0.64 (0.1)	0.85 (0.12)	0.98 (0.03)
Steentjie	Researchers	0.24 (0.15)	0.85 (0.12)	1 (0.01)	1
	Volunteers	0.06 (0.06)	0.51 (0.24)	0.97 (0.05)	1
Fransmadam	Researchers	0.44 (0.39)	1 (0.01)	1	1
	Volunteers	0.09 (0.1)	0.98 (0.07)	1	1
Redfingers	Researchers	0.39 (0.12)	0.91 (0.06)	1 (0.01)	1
	Volunteers	0.19 (0.08)	0.78 (0.12)	0.99 (0.01)	1
Blue hottentot	Researchers	0.72 (0.25)	0.95 (0.06)	1 (0.01)	1
	Volunteers	0.06 (0.08)	0.3 (0.24)	0.84 (0.26)	1 (0.01)

2.3.3.5 Steentjie

The model selection process resulted in Profile being dropped from the most parsimonious model:

$$Detection\ probability_{steentjie} = \beta_0 + \beta_1(Abundance) + \beta_2(Observer\ type) + \varepsilon$$

Together, *Abundance* and *Observer type* were able to explain 53.0 % of the observed variability in the probability that both observers would detect steentjies if present within the survey area (Table 2.5). The likelihood ratio test identified that the effect of *Abundance* was highly significant ($X^2 = 26.17$, $p<0.001$), with higher abundance associated with higher detection probabilities (Odds ratio ± SE = 0.72 ± 0.32) (Fig. 2.8a). The effect of *Observer type* was marginally not significant ($X^2 = 3.81$, $p = 0.09$), with researchers showing better detection probabilities compared to volunteers (Fig. 2.8a), particularity at low abundance levels (Table 2.6).

2.3.3.6 Fransmadam

The most parsimonious model for fransmadam included the covariates *Abundance* and *Observer type*:

$$Detection\ probability_{fransmadam} = \beta_0 + \beta_1(Abundance) + \beta_2(Observer\ type) + \varepsilon$$

Together, *Abundance* and *Observer type* were able to explain 71.5 % of the variability in the probability that both observers would detect fransmadam if present within the survey area (Table 2.5). The likelihood ratio test identified that the effect of *Abundance* was highly significant (X^2 = 29.21, p<0.001), with higher abundance associated with higher detection probabilities (Odds ratio ± SE = 2.09 ± 1.44) (Fig. 2.8b). The effect of *Observer type* was not significant (X^2 = 2.30, p >0.1) (Fig. 2.8b).

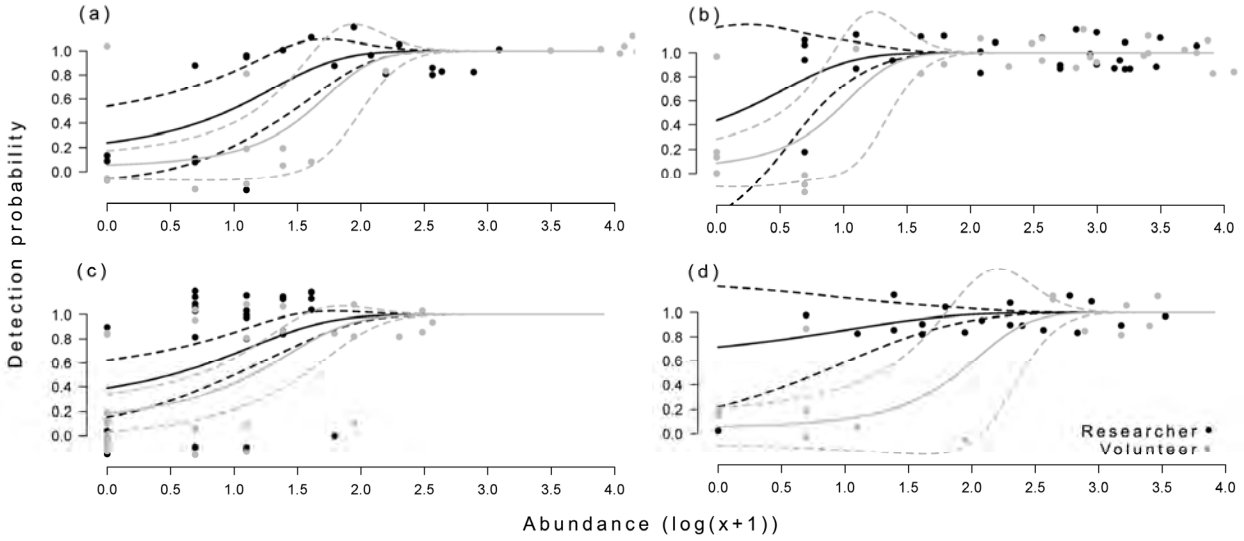

Figure 2.8: Probability (± 95 % confidence intervals) of both researchers (black dots and lines) and both volunteers (grey dots and lines) detecting steentjie (a), fransmadam (b), redfingers(c) or blue hottentot (d) during a paired-transect, with increasing abundance per species. The x-axis was log transformed to aid graphic presentation, and the data points have been jittered to reveal overlapping data.

2.3.3.7 Redfingers

The most parsimonious model for redfingers included the covariates *Abundance* and *Observer type*:

$$Detection\ probability_{redfingers} = \beta_0 + \beta_1(Abundance) + \beta_2(Observer\ type) + \varepsilon$$

Together, *Abundance* and *Observer type* were able to explain 25.5 % of the variability in the probability that both observers would detect redfingers if present within the survey area (Table 2.5). The effect of *Abundance* was significant ($X^2 = 20.83$, $p<0.001$), with higher abundance associated with higher detection probabilities (Odds ratio ± SE = 0.69 ± 0.22) (Fig. 2.8c). The effect of *Observer type* was marginally not significant ($X^2 = 3.07$, $p = 0.08$), with the both researchers predicted to have a higher probability of detecting redfingers if present within the survey area compared to volunteers (Fig. 2.8c).

2.3.3.8 Blue hottentot

No blue hottentot were recorded on low prolife reef so *Profile* was not included in the full model prior to the selection process. The model selection process identified that the full model to be the most parsimonious model:

$$Detection\ probability_{blue\ hottentot} = \beta_0 + \beta_1 + \beta_1(Abundance) + \beta_2(Observer\ type) + \varepsilon$$

The selected model was able to explain 66.9 % of the observed variability in the probability that both observers would detect blue hottentot if present within the survey area (Table 2.5). The likelihood ratio test identified that the effect of abundance was highly significant ($X^2 = 15.62$, $p<0.001$), with the probability of both observers detecting blue hottentot lower when the species was scarce within the survey area (Odds ratio ± SE = 0.50 ± 0.27) (Fig. 2.8d). The effect of *Observer type* was significant ($X^2 = 7.62$, $p<0.01$), with researchers associated with higher detection probabilities compared to volunteers (Fig. 2.8d). For examples, at an abundance of one individual per paired-

transect, researches had a 72 % (± 25) probability of detecting blue hottentot, compared to volunteers who had a 6 % (± 3) detection probability (Table 2.6).

2.4 Discussion

2.4.1 Validity of assumptions

The first important question is whether or not the theoretical assumptions made at the beginning of this chapter held under practical application.

It is believed that the first assumption, being that of independent observation, was true. Although there is no way to confirm this, the observers were all informed that the validity of the research relied on them not assisting each other underwater. To this end all the observers accepted this and agreed to participate.

The main area of concern in this study revolved around the second assumption that all fish within the survey area were equally visible to both observers. This relied not only on the observers maintaining their positions relative to each other, but also on the possibility that the structure of the reef did not hide fish from, or reveal fish to, only one of the observers due to the slightly different angle of view of each observer in a pair. The potential effect of habitat was measured by taking into consideration reef profile during the analysis of detection probabilities and observation dissimilarity. The results from the GLMs indicated no significant effect of reef profile on the species detection probability, paired-transect dissimilarity or species specific detection probabilities. This suggests that if there was an effect of profile it was negligible compared to the overriding effects of the *Observer type* and abundance.

Unlike the effect of habitat, there was no way to infer if one observer obstructed the view of the other. The UVC line transect approach applied in this study, only considered fish in front of and to the sides of the observer. The posterior limit of the survey region was perpendicular to the line of sight and, as a result, if the observers maintained their parallel positioning, their presence should not have obscured the other divers view. During the observer training, pool sessions were used to teach the divers how to perform a paired-transect, and although initial abilities differed, all divers were capable

of maintaining their relative positions and buoyancy while swimming side by side down a dummy transect line. Similarly, Darwall and Dulvy (1996) found no difference in the precision of data collected by individual divers and groups of divers. As the paired-transect was simultaneous, fish moving into and out of the survey area should not have affected the divers differently, if the divers were estimating the bounds of the survey area correctly.

The third assumption, being that of all and only fish within the survey area were counted, then becomes relevant. It is important to understand that this assumption is one that is globally applied to all UVC methods and, not just the paired-transect approach. Failure to meet this assumption should not detract from the paired-transect approach specifically, but rather from the UVC method as such. Knowing which fish to count relies on the ability to estimate distance underwater. The analysis of the underwater distance estimates raised two important points. First, the paired-transect approach had little to no effect on an observers ability to estimate the distance of a buoy from the transect line, even though they were not positioned directly above the transect line. Second, inexperienced volunteers showed a high degree of variability in their ability to estimate distance underwater, while the change in variability with increasing distance was inconsistent between observers. A similar result was found by Harvey et al. (2004), where experienced and inexperienced research divers failed to estimate distance underwater accurately. As Edgar et al. (2004) point out, biases that are not systematic, be it through space, time, method or observer, have the ability to create misleading conclusions. The bias introduced through inconsistent distance estimates is an area of concern because it is impossible, or at least very difficult, to correct for. Consequently, training should focus on teaching the required skills to standardise and reduce this error between observers. Although no researchers were tested in the pool it was assumed that their abilities would be at least equal to that of the volunteers.

The final assumption was that all fish seen were identified correctly. The identification tests performed during the observer training suggested that the identification accuracy was relatively high, but there was considerably greater variability in the ability of

different volunteers to accurately identify the target fish species compared to researchers. During the paired-transect data exploration clear identification errors were seen in the dataset. Interestingly, this was evident for both the volunteers and researchers, where similar looking species were observed at similar and relatively high abundances in the different samples making up the pair. It is assumed that this assumption did not hold under practical application, and that measures need to be put in place to ensure accuracy of identification. As the inability to correctly identify the species is an observer bias, and the fact that the assumption was not met, does not detract from the comparison of the data collected by the volunteers and researchers. It just needs to be kept in mind that the observed differences in count data could either stem from lack of accuracy in identification, or lack of precision in counting.

In summary, it is believed that the assumptions made for the paired-transect UVC surveys were met, and any instances where they failed to be met can be ascribed to observer biases that are similar in the traditional single observer UVC technique.

2.4.2 Observer effects

The data from the paired-transect identified a clear effect of *Observer type* on the accuracy and precision of species detection probability and paired-transect dissimilarity. Although significant differences were detected the scale of the differences were marginal, particularly for the species detection probability. This was supported in the analysis of the dominant species, where *Observer type* had limited significant influence on the probability that both observers would detect a species if present. However, it is believed that the evidence presented indicates that special care should be taken when involving volunteers in UVC surveys.

This contrasts with the conclusions of past studies that have looked into the reliability of using data collected by volunteers (Mumby et al. 1995; Darwall and Dulvy 1996; Edgar and Stuart-Smith 2009). For example, Edgar and Stuart-Smith (2009) compared data collected by volunteers and researchers at the community level by calculating the Bray-

Curtis similarity indices between transects performed by volunteers and researchers within the same region at a similar time. They found that variation between individual divers within the different observer groups contributed little to the overall variation between transects. Darwall and Dulvy (1996) arrived at similar conclusions, in that once volunteers had gained experience, the data were of a similar precision to that produced by researchers.

A number of factors could have contributed to these contradictory results. Firstly, the approach by Edgar and Stuart-Smith (2009) did not take into account instantaneous variation in the fish community, resulting from foraging behaviour or the response of the fish to the presence of the diver. Instantaneous variation in fish communities, defined as "stochastic processes such as movements and the difficulty of detecting small, fast-moving and cryptic species", has been identified a large source of variability in UCV data (McClanahan et al. 2007). It is possible that instantaneous variation in the fish community would increase dissimilarity between separate samples, no matter how close in space or time, and blur the potential effects of observer type. On the other hand, the approach of Darwall and Dulvy (1996) used a solitary research diver as a control to assess the quality of volunteer data, however they provided no measure of the precision of the data collected by their solitary control diver. The results from this study showed that there was a large amount of variability in the data from both the volunteers and the researchers, with certain pairs of researchers consistently producing data with a paired-transect similarity lower than the average for the volunteers. This suggests that it may be inappropriate to assume that all researchers produce data that can be considered to be a baseline.

An alternative explanation for the poorer performance of the volunteers could be that the training carried out during this study was considerably shorter than what has been used in other studies (see Darwall and Dulvy 1996). However, Frontier Tanzania (Darwall and Dulvy 1996) programme is conducted in subtropical and tropical environments, which harbour considerably higher diversities of fish species, many of which are small, cryptic and hard to accurately identify. Considering that this study was

conducted in temperate waters with lower fish diversity and that small cryptic species were not targeted, it is believed that the duration of the training course was adequate.

On the other hand, reef life survey selects only the best volunteers to collect data for the programme (Edgar and Stuart-Smith 2009). By controlling the quality of observers participating in the programme, the effects of *Observer type* are negated. During this study, all volunteers who passed the tests and attended the pool training sessions were used to collect data in the field. Consequently no quality controls were implemented with respect to the volunteers' field capabilities. This reflected in the results, with certain volunteers consistently associated with samples that had high dissimilarity and low species detection scores. In this regard, the paired-transect method can be useful for detecting observers unable to collect data of a sufficient accuracy and precision.

2.4.3 The effect of community parameters on paired-transect similarity

Three community level parameters were included in the analysis of the paired-transect data: species richness, species abundance and species type. All three of these parameters were identified as having an effect on the detection probability and paired-transect dissimilarity.

An increase in the number of species along transects resulted in a decrease in the probability that both observers would record all the species. This trend was echoed in the paired-transect dissimilarity data, with paired-transects that had a higher number of species typically having a higher dissimilarity. Lincoln-Smith (1988) and Thompson and Mapstone (1997) observed a similar relationship, where increasing species richness resulted in lower levels of precision in the data. As mentioned in the results section, 24 of the 32 species recorded during this study were present on less than 29 % of the paired-transects. This suggests that the vast majority of the species observed were rare, and agrees with the general understanding of ecological communities (Cunningham and Lindenmayer 2005). It logically follows that samples with higher species richness would include more rare species than samples with lower species

richness. This suggests a negative effect of these rare species on the ability to accurately survey subtidal reef fish communities.

Rare species are broadly classified as those that are scarce in the places where they occur, even though their distribution may be widespread and their occurrence common (Cunningham and Lindenmayer 2005). Increasing species abundance was identified as having a positive effect on the probability that both observers would detect a species and on the similarity of the count data. At the community level this effect is closely linked to the variations in species richness. Following the logic from the previous paragraph, if samples with higher species richness contain more rare species, the average abundance per species will be lower compared to a sample with lower species richness that contains fewer rare species. When looking only at the dominant species, the effect of rarity or localised scarcity on the probability of the species being detected was again clear, with the detection probability lower for all species when they were scarce in the survey area. At an abundance of more than ten individuals the detection probability was close to 100 % for both the volunteers and researchers, whereas the detection probability varied between six and 19 % for the volunteers and 24 and 72 % for the researchers when only one individual of a species was present in a transect. This is in agreement with Thompson and Mapstone (1997) and Kulbicki (1998) who found that detection probability increased with the number of fish in the survey area.

There was considerable species specific variation in the detection probability and in the similarity of the count data suggesting that factors other than abundance may have contributed to this pattern. Detection probability has been shown to increase with the size and behaviour of the fish (Kulbicki 1998; Bozec et al. 2011). In our study, roman had one of the highest detection probabilities despite its moderate abundance. Roman is a large, dominant and conspicuous fish that is indifferent to the presence of divers. In this instance it is likely that these characteristics enhanced the detectability of the fish. On the other hand, for the smaller, drab steentjie and blue hottentot, which were abundant in the paired-transect data, a low detection probability was found. It is

possible, however, that much of this error was an artefact of misidentification, as the two species are similar in size, behaviour and colouration.

The reduced detection probability for rare species will have implications for research investigating the change in fish community structure following disturbance, and comparing fish populations inside and outside of protected areas (MacNeil et al. 2008b). In these instances, as populations of different species grow, the detection probability will increase, confounding assessments on the rate and scale of recovery. McClanahan et al. (2007) identified that the coefficient of variation (the standard deviation divided by the mean, see McArdle et al. 1990) was generally, but not exclusively, greater for rare species than for abundant ones and, that instantaneous variation is more pronounced for population estimates of rare species. The results presented here indicate that the ability to estimate differences is further compromised because the detection probability of the species will be lower in the area where it is less abundant. Often long-term monitoring programmes aim to document population recovery of fisheries species and in this instance alternative methods that inherently target fisheries species, such as controlled angling (Götz et al. 2008) or BRUV (Willis et al. 2000), may be better suited. However, these methods are less efficient at monitoring entire reef communities compared to UVC (Götz et al. 2008; Colton and Swearer 2010), and as such approaches that allow for inclusion of detection probability into abundance estimates from UVC need to be advocated.

2.4.4 Role of double-observer UVC surveys to account for detection probability

Accounting for detection probability is essential for accurate estimation of population abundance (Elphick 2008; Jenkins and Manly 2008; Riddle et al. 2010). Detectability is comprised of several facets, as the fish needs to be present in the transect area during the survey, the fish needs to be available for detection (i.e. it's not taking refuge in a crevice) and given that the fish is present and available, it needs to be detected (Riddle et al. 2010). Methods to estimate detection probability include distance sampling (Kulbicki et al. 2010) and repeated-counts (MacNeil et al. 2008a, b), both of which have

received limited use for UVC of reef fish communities. Although these methods offer a means to account for detection probability in UVC, they both come with weaknesses that will influence the precision of the probability estimates (see Introduction for details).

The double-observer method is an alternative approach which offers a number of advantages over distance sampling and repeated-counts. Firstly, the need to estimate distance underwater is reduced as the observer only needs to estimate the boundary of the survey area. There is no need to capture and mark individuals so that they can be tracked over multiple visits to a sample site, and as the two surveys of the transect area are instantaneous there is no need to return to the sample site. Similarly, as the double-observer method is instantaneous the assumptions that the sample population is closed are met. However, as with all methods, the double-observer approach has weaknesses as the location of each observation along a transect needs to be mapped to enable the matching of observations that are common to both observers (Riddle et al. 2010).

As discussed in the introduction and methods within this chapter, two double-observer approaches have been specified, the DDO (Cook and Jacobson 1979; Graham and Bell 1989) and the IDO (Jenkins and Manly 2008) methods. While the DDO method requires communication between the observers, IDO requires mapping of the location fish sighting, both of which are not suited for UVC of fish communities.

An alternative approach that has received limited application is the unreconciled double-observer method (Riddle et al. 2010). The method is basically an independent double-observer method that does not require matching observations or any communication between observers (Riddle et al. 2010), and is equivalent to the paired-transect method used in this study. The data are analysed with hierarchical models developed for repeated counts of a sample through time (Riddle et al. 2010; Fiske and Chandler 2011). By using a two stage hierarchical model, based on a Poisson or negative binomial distribution, both state process that determine abundance or species occurrence at a site, and the detection probability can be accommodated in the abundance estimates (Riddle et al. 2010; Fiske and Chandler 2011). This was not

attempted during this study, due to the failure of assumption four, that all species were correctly identified, as this would have led to misleading results. However, by installing mechanism that ensure correct identification of species, this approach may alleviate some of the underlying biases that reduce the diagnostic power of UVC data.

2.4.5 Conclusions

One of the benefits of volunteer programmes is the increased manpower that they afford. However, the results from this study suggest that most volunteers produce data that is of a lower quality than that provided by experienced researchers. In this study certain species were easier to survey than others suggesting that volunteer programmes can improve data quality if they focus on a subset of the community that is less prone to observer bias. Although important information may be lost by not looking at the community as a whole, conspicuous indicator species that are easy to identify and count will increase the power of the data and the ability to infer trends in the long term. Similarly, variation between different observers was very high, with certain volunteers consistently producing better data than certain researchers. Volunteer monitoring programmes that only consider the data produced by the best volunteers (e.g. Edgar and Stuart-Smith 2009) will mitigate some of the observer biases identified in this study, while still raising stakeholder awareness through public participation.

Species abundance was found to have a strong influence on detection probability. Although other factors such as size, behaviour and crypticity may have influenced the data, the ability of the observers to detect species that were scarce in the transect area was poor. The results from this study suggest that it may be feasible to use the unreconciled double-observer method (Riddle et al. 2010), with experienced volunteers or researchers, to correct for detection errors in abundance estimates of subtidal fish populations. In additional the method has wide applicability as a training and quality control tool for monitoring programme using both researchers and volunteers.

Chapter 3

Assessment of remote underwater video to conduct subtidal reef surveys in the Agulhas Ecoregion of South Africa

3.1 Introduction

Baited remote underwater video (BRUV) was originally tested as an alternative non-destructive sampling method to bottom long-line (Ellis and DeMartini 1995) and demersal trawls (Priede and Merrett 1996). Over the last decade the BRUV method has gained considerable support, with research investigating the effects of fishing and protection on ecosystems and species (Babcock et al. 1999; Willis et al. 2003; Cappo et al. 2007; Malcolm et al. 2007; Watson et al. 2007, 2009; McLean et al. 2011; Goetze et al. 2011; Langlois et al. 2012a) and the effect of environmental conditions on fish distribution patterns (Brooks et al. 2011; Langlois et al. 2011a; Moore et al. 2011; Cheung et al. 2012; Birt et al. 2012). At the same time BRUV has undergone further development (Willis and Babcock 2000; Harvey et al. 2002, 2007; Watson et al. 2005, 2010; Stobart et al. 2007; Langlois et al. 2010) and has been rigorously tested against traditional fish monitoring methods such as angling, underwater visual census (UCV), traps and trawls (Willis et al. 2000; Cappo et al. 2004; Watson et al. 2005; Colton and Swearer 2010; Pelletier et al. 2011; Harvey et al. 2012; Langlois et al. 2012b).

Since the initial research the BRUV method has advanced and become more standardised in its application. Baited remote underwater video systems come in a number of different configurations. The camera system can either be fully enclosed in a camera housing making it independent from the research platform and enabling greater sampling effort (Ellis and DeMartini 1995; Harvey and Shortis 1996), or it can be dependent on a live feed to the surface restricting the sampling effort to one station at a time, but ensuring that the camera lands correctly and the video is recorded (Willis and Babcock 2000). The camera configuration varies, with either a simple mono-camera allowing for basic recording of fish communities (Willis and Babcock 2000), or a stereo-camera configuration that allows for the size of fish to be measured (see Harvey and Shortis 1996). Lastly, the camera can be mounted facing downwards providing a small but consistent area of view (Willis and Babcock 2000), or horizontally, providing a larger but inconsistent area of view (Cappo et al. 2004). Apart from these differences between

BRUV systems, all studies using BRUV function along the general principle of estimating abundance through attracting fish into the frame of view of a video camera using bait. The only difference between the BRUV method and the unbaited remote underwater video (RUV) method is that the bait and the bait arm that hold the bait are not attached to the structure.

Baited remote underwater video and RUV deployment times vary between different studies, ranging from 15 minutes (Watson et al. 2005) to 90 minutes (Brooks et al. 2011), however most recent publications recommend the use of a 60 minute deployment time (Watson et al. 2009; Colton and Swearer 2010; Langlois et al. 2010). Estimating the abundance of fish from the video footage is typically done with the MaxN measure of abundance (Ellis and DeMartini 1995; Willis and Babcock 2000; Cappo et al. 2006). MaxN is the maximum number of individuals for a selected species visible at one time (i.e. in one frame) over the duration of the video (Cappo et al. 2003). This measure is considered a conservative measure of abundance, for two main reasons. Firstly, when two different individuals from the same species move into the cameras frame of view at different times the MaxN is recorded as one and not two (Cappo et al. 2004). Secondly, it is possible that more fish can be attracted to the bait that can fit into the cameras frame of view, and in this instance the MaxN will be considerably lower than the actual abundance (Willis and Babcock 2000). Both limitations will result in lower sensitivity to detect differences between high and low density areas (Willis and Babcock 2000; Cappo et al. 2004).

The core strengths of BRUV over other methods lie in (i) its ability to survey components of the fish community typically missed by other methods (e.g. underwater visual census [UVC]), including sharks and large piscivorous fish (Willis et al. 2000; Cappo et al. 2004; Brooks et al. 2011), (ii) increased diagnostic power from the reduced levels of variability between samples (Watson et al. 2005; Harvey et al. 2007; Stobart et al. 2007; Langlois et al. 2010), and (iii) when the system is set up with stereo-cameras it

is able to provide accurate measures of fish length (Harvey and Shortis 1996; Harvey et al. 2004; Watson et al. 2009). The data collected by the BRUV is not biased by the presence of an observer in the water that can alter the behaviour of the fish (Cappo et al. 2006). Although observer bias can enter the data during the analysis, the video is available for reanalysis if erroneous data are detected (Cappo et al. 2006). Furthermore the BRUV is both a non-destructive and non-extractive sampling tool and is thus ideally suited to monitor protected fish populations inside marine reserves (Willis et al. 2000; Cappo et al. 2006). This suggests that the BRUV method may provide a standardised approach for conducting comprehensive surveys of demersal fish communities, and that it is suitable for long term monitoring programmes (Langlois et al. 2010).

As with most survey methods the BRUV is also characterised by a number of biases. Results from past studies are equivocal regarding the ability of BRUV to survey the cryptic, and non-carnivorous reef species. Harvey et al. (2007) found that BRUV produced similar abundance estimates for herbivorous and omnivorous species when compared to the RUV method. On the other hand, Colton and Swearer (2010) indicated that BRUV was unable to survey herbivorous and cryptic fish species as efficiently as UVC, and recommended that studies restricted to one method use UVC. A similar result was found by Stobart et al. (2007). The post-sampling analysis of the video footage is extremely time-consuming has been identified as a weakness in the method (Colton and Swearer 2010). Count data from BRUV samples are difficult to standardize as the area of attraction is difficult to quantify (Cappo et al. 2006). Firstly, there is no defined approach to calculate how far the bait plume will travel in shallow coastal environments (Cappo et al. 2004; Stobart et al. 2007), while the dynamic environment created through wave surge and changing currents leads to variability in the size and direction that the plume will disperse (Stobart et al. 2007). Added to this are variable species specific responses that will alter the area of attraction within the plume (Bailey and Priede 2002; Colton and Swearer 2010). As a result, most studies only provide a relative abundance measure. While a unit of measure can be the duration of deployment (Willis et al. 2003; Watson et al. 2007), this too is dependent on plume dispersion, species specific

responses and water clarity (Cappo et al. 2004). Although many subtidal fish monitoring methods can only provide relative abundance, the ability to standardize a relative abundance into an absolute density allows more accurate comparisons between methods and estimates of population size, the latter of which is critical for effective management of exploited populations. The apparent inadequacies in BRUVs ability to survey the entire fish community is an area of concern and it has been suggested that a combination of methods are required if a study aims to assess the biodiversity of a fish assemblage (Watson et al. 2005; Colton and Swearer 2010).

The RUV method provides a discrete picture of the distribution of fish within the camera's frame of view, free from biases arising from altered fish behaviour in the presence of bait, or difficulties evaluating the sampled area. It is therefore an appealing monitoring option, as it is one of the closest examples of an unbiased survey method. Very few studies have conducted RUV surveys of fish communities, and most examples involve experimental method comparisons (Francour et al. 1999; Watson et al. 2005, Harvey et al. 2007; Pelletier et al. 2012). Data collected with RUV are subject to high spatial and temporal variability as changes in abundance, resulting from oceanographic or habitat variability, are not dampened by the attraction effect of the bait (Watson et al. 2005). As a result, RUV requires a considerably higher sampling effort to produce data with comparable statistical power to BRUV (Watson et al. 2005, Harvey et al. 2007). However it has been shown that RUV and UVC produce comparable data for the dominant and conspicuous components of the fish community (Francour et al. 1999). As such, RUV is recommended as a good approach to study natural behaviour of fish (Watson et al. 2005).

To date no research has been conducted in South Africa with either the BRUV or RUV methods. Although numerous international methodological studies have investigated the pros and cons of BRUV, and to a lesser degree the RUV, many questions still remain regarding the optimal application of the methods, their ability to effectively survey

different components of the fish community, and the extent of biases associated with the methods. It was therefore felt necessary to conduct a methodological evaluation to optimize method performance and evaluate variability in species specific responses to the attraction of bait.

3.1.1 Study Aim

The aim of this study was to conduct a comparative field experiment to assess the feasibility of using RUV and BRUV to survey the subtidal reef fish communities in the Agulhas Ecoregion of South Africa.

3.1.1.1 Study objectives

As the methods had not been used in South Africa prior to this study it was necessary that the objectives addressed methodological development as well as an assessment of the fish community sampled. To this end the objectives of the research were to:

1. Calculate the optimal deployment time for both RUV and BRUV method.
2. Investigate the effect of bait on the composition and abundance of the observed fish communities,
3. Determine the sensitivity of the RUV and BRUV methods to detect habitat related patterns in species abundance, and
4. Investigate the effect of bait on the levels of variability and statistical power of the data for the dominant species recorded.

3.2 Materials and methods

3.2.1 Study site

The research was conducted in the Tsitsikamma National Park (TNP) Marine Protected Area (MPA). See Chapter 2, section 2.2.1 (Fig. 2.1a, d, e) for relevant details on the study area.

3.2.2 Site stratification

To account for variability in the fish community associated with habitat, the study site was stratified according to depth and reef profile. Stratification on the permanent features of an environment allows collection of representative samples when the study site is not homogenous, which improves the overall precision of the sampling effort (Murray et al. 2001). The exact details of the site mapping and stratification procedure can be found in Chapter 2, sections 2.2.2 and 2.2.3.

3.2.3 Sampling strategy

The sampling strategy was based on the stratified-random approach described in Chapter 2, section 2.2.3, and will not be discussed in detail here.

To meet the aims of this study a repeated measures experimental design was employed, whereby at each sampling station both RUV and BRUV samples were collected. At all stations the RUV samples were collected prior to the BRUV sample so as not to bias the RUV sample by attracting fish into the area by the bait plume. A ten minute break between deployments on a site allow the fish community to settle. Each video was 60 minutes (min) in duration. A total of 28 stations was sampled, with seven replicates per bathymetric class. The effect of seasonal variation in oceanographic

conditions was taken into account by conducting the study over a number of sampling seasons (June 2008-February 2010).

Figure 3.1: Drawing of the tripod used to hold the remote video camera for the remote underwater video (RUV) and baited RUV stations. The bait-arm, holding the PVC bait container is attached. The cable and rope, which clip to the top of the tripod are not shown here.

3.2.4 RUVS

3.2.4.1 Setup

There are two principal configurations for horizontal remote video methods. The first involves a single camera mounted on a frame pointing forwards (as per Ellis and DeMartini 1995), while the second consists of paired cameras allowing stereo vision (as per Harvey and Shortis 1996), with the only difference being that the stereo camera allows for very accurate estimation of fish size and easy calculation of the visible area.

As this study was not concerned with measuring the size of fish, the single horizontal configuration was selected. The remote camera setup consisted of a custom made, weighted (20 kg), stainless steel tripod, with the camera facing forwards (horizontal) and positioned approximately one meter off the bottom (Fig. 3.1). The tripod had a wide leg spread radius that maximised the probability that the camera system would land upright and balance even in the roughest terrain. The tripod was tethered to the boat by a rope fitted with a bungee cord to lessen the impact of the structure upon landing on the reef, and absorb the pull of the rope on the tripod in high surge conditions. The tripod was fitted with a standard definition remote video camera with a live feed to the surface via a cable (150 m). The camera lens has a focal length of 35 mm, equivalent to a 54.4^{o} horizontal angle of view. The videos were recorded using a surface control box linked to a digital video recorder with a display screen allowing for real time viewing and ensuring the tripod was correctly orientated before starting to record. For the baited samples the tripod was fitted with a one-meter bait-arm holding a perforated PVC container designed to contain one kilogram of crushed sardine *Sardinops sagax* in the field of view of the camera.

3.2.4.2 Deployment

Deployments were conducted off a 5.5 m semi-rigid inflatable, with a minimum of three crew members. During all deployments the boat was on anchor, and as a result only one sampling station (RUV and BRUV pair) could be conducted at a time. As this study used a tethered live-feed setup, the method excluded the option of simultaneous deployments that can be conducted if the video recording system is fully enclosed in a housing. The benefit of the latter approach is that it increases the potential number of samples per unit effort, however, the researchers have little idea of what was recorded until the sampling station is over or the videos are played back in the laboratory. The benefit of the tethered approach was that the researcher was in control of the proper functioning of the setup, eliminating the potential for dud samples that could occur

through electrical malfunction, the camera sitting in a hole, the tripod falling over, or the site being on sand.

3.2.5 Data analysis

3.2.5.1 Video analysis

The videos were analysed by means of the video editing software Adobe Premiere (version CS4). This allowed for frame by frame playback and adjustment of the colours to account for murky conditions, when needed. During the review of each video all species were counted and their maximum abundance determined using the MaxN approach. In this instance MaxN is the maximum number of a species in any one frame in the video (Cappo et al. 2003; Priede et al. 1994). MaxN is the standard measure adopted in the analysis by all remote video techniques (Cappo et al. 2006), as it avoids the potential of recounting the same fish swimming in and out of the camera field of view. It is accepted that MaxN is an underestimate of the potential maximum number of fish around the video camera, as it is likely that not all individuals will be in the cameras field of view at once (Cappo et al. 2006).

To determine the optimal deployment time the videos were analysed in sequential five-minute sections (repeated measures) to describe species accumulation. Once optimal deployment times for the RUV and BRUV setup were calculated, the videos were analysed as a single sample. For consistency, only one observer was used to analyse the video footage.

3.2.5.2 Covariates

Water clarity at each station was determined by calculating the relative change in size of individual roman *Chrysoblephus laticeps* from the bait container (1m from the camera) to the point where their identification features no longer become visible. Secchi depth and water turbidity are alternative approaches, however both methods don't always reflect the actual water clarity on the reef, due to strong thermoclines separating water

layers with different clarity characteristics (Götz 2005). The relative change in size thus produced a standardised and unbiased estimate of actual water clarity in the video. To calculate this the height and length of individuals were measured once, while actively feeding at the bait container (L_{bc}), and then again, when the same individual was swimming at the extent of visibility (L_{ve}). The equation was expressed as:

$$Vis\ (m) = \frac{L_{bc}}{L_{ve}} + 1 \qquad \text{(equ. 3.1)}$$

To account for the position of the bait container, one meter was added to the visibility estimate. This estimate is not considered to be 100 % accurate due to the fact that size estimation using single video camera is less accurate then using stereo-video (Harvey and Shortis 1996). However, it is felt that the measure is better than what one would get from measuring secchi-depth from the surface or water turbidity, as thermoclines are often associated with distinct changes in water clarity, limiting the applicability to generalize surface measures to bottom conditions. Roman were selected because of their abundance within the survey area, striking colour patterns and their aggressive behaviour around the bait container. This increased the likelihood of seeing an individual feeding at the bait and at the visibility extent.

With the visibility estimate it was then possible to calculate the horizontal area (equ. 3.2) visible in each video. To do this the total radians in view (calculated by dividing the horizontal angle of view (H_θ) of the video camera by 360^o) was multiplied by the area of visible extent.

$$H_a(m^2) = \frac{H_\theta}{360} * \pi(Vis)^2 \qquad \text{(equ. 3.2)}$$

It is acknowledged that the bait plume would have attracted and concentrated certain species from further downstream and in the vicinity of the bait container. As a result for the comparison of methods the data was kept in count form for both RUV and BRUV,

while area was used as an offset in the regression analysis. This accounted for variability in the visible area resulting from fluctuations in underwater visibility.

The area of reef in view (visible reef) was calculated by analysing the % cover of reef in the video footage using Vidana (Version 1.0.1be) (Hedley 2003). This covariate was included as it was thought that a higher % of visible reef would result in greater diversity of cryptic species and a lower diversity of demersal species being seen (and *visa versa*). In this respect any effect of visible reef on the observed abundance of fish can be considered as a methodological bias.

Water temperature (average temperature recorded during the deployment) was recorded using a Hobo temperature logger attached to the tripod. Depth was measured off an echo sounder mounted on the boat. Reef profile was inferred from the bathymetric maps (Fig. 2.1e, Chapter 2) and confirmed from the video footage.

3.2.5.3 Optimal deployment time

Linear mixed effect (LME) models are a useful way to model repeated measures data because, through their flexible covariance structure, they allow for non-consistent correlation among observations and/or unbalanced data (Lindstrom and Bates 1990). Lindstrom and Bates (1990) described repeated measures data, as that obtained through repeated observations on a number of individuals under differing experimental conditions. Here, the individuals are assumed to be a random sample from the population of interest. As a result repeated measures models will incorporate an underlying functional relationship linking the observations between individuals and one or more of the predictor variables (Lindstrom and Bates 1990). Non-linear mixed effects models (NLME) extend the capabilities of traditional LME and standard fixed effects non-linear models to handle data defined by an expectation function that is non-linear in its parameters, while at the same time incorporating a flexible covariance structure required to handle repeated measures data (Lindstrom and Bates 1990). An example of this type of data is non-linear growth curve data, which is in turn similar to that observed

in species accumulation curves. As a result the NLME model is an appropriate method to analyse species accumulation during a video. The general NLME model is defined as:

$$y_{ij} = f(\emptyset_i, x_{ij}) + e_{ij}, \qquad \text{(equ. 3.3)}$$

where y_{ij} is the j^{th} response on the i^{th} individual, x_{ij} is the predictor variable for the j^{th} response on the i^{th} individual. The non-linear function of the predictor variable together with the parameter vector $\emptyset_i$ (length of r) are defined by f. The noise parameter is denoted by e_{ij}, which is assumed to follow a normal distribution. In this model the predictor variable is not restricted in anyway. The parameter variable varies between individuals and is incorporated into the model by defining $\emptyset_i$ as:

$$\emptyset_i = A_i\beta + B_i b_i\,,\ b_i \sim N(0, \sigma^2 D), \qquad \text{(equ. 3.4)}$$

where β is the p-vector for the fixed population parameters, b_i is a q-vector of random effects associated with the i^{th} individual. The matrices A_i and B_i are the design matrices of size *r* x *p* and *r* x *q* for the fixed and random effects respectively. The covariance matrix is identified by $\sigma^2 D$.

To be able to accurately predict an optimal deployment time for the RUV and BRUV methods, the NLME model was fitted with a two parameter logistic-ogive (or sigmoid curve) function typically used to model maturity of fish (Weyl and Booth 1998). This allowed determination of the average 50 % and 95 % saturation levels for species accumulation from all the samples. In other words it provided the average time at which species accumulation and species at MaxN accumulation was at 50 % and 95 % of the predicted average over all samples. The two-parameter logistic-ogive function was defined as:

$$P = \frac{1}{1+exp\left(-\frac{T-T_{50}}{\delta}\right)} \quad and \quad P = \frac{1}{1+exp\left(-ln19\frac{(T-T_{50})}{(T_{95}-T_{50})}\right)}, \qquad \text{(equ. 3.5)}$$

where P is the probability of 50 % saturated at time T (T_{50}), T_{95} is the probability of being 95 % saturated at time T, and δ is the inverse rate of saturation. The second logistic model can be generalized to have 2-parameters, the standard T_{50}, and T_X (the probability of being X saturated), to:

$$P = \frac{1}{1+exp\left(-ln\left(\frac{X}{1-X}\right)\frac{(T-T_{50})}{(T_X-T_{50})}\right)}. \quad \text{(equ. 3.6)}$$

For the purpose of this study optimal video deployment time was defined as the point at which 95 % of the species recorded had reached their MaxN. This corresponds to ln(19) when you solve for *X* in equ. 3.6, i.e. $\ln(0.95/1-0.95)$.

The NLME analysis was conducted using the NLME package (Pinheiro et al. 2011) in the R (version 2.13.0) environment for statistical analysis (R Development Core Team 2011).

3.2.5.4 Comparison of methods

Assessment at the community level

For this study generalized linear mixed effects models (GLMMs) were used to estimate the effect of bait on the fish community sampled using BRUV and RUV methods. Of particular interest was the potential variation in response by the different components of the fish community to the presences of bait. The community components were classified by grouping species according to (1) *Fisheries importance*, and (2) their *Class* and *Trophic guild* (Table 3.1).

Table 3.1: Description of the different levels used to sort the observed species by Fisheries importance and Trophic guild.

Community grouping parameters			
Name	Levels	Description	Codes
Class	Osteichthyes	Bony fish	Bony
	Condrichthyes	Cartilaginous fish	Cart
	Agnatha	Jawless fish	Jawless
Fisheries importance	non-target	Species that are not captured using line fishing or spearing techniques	Non-target
	by-catch	Non-target species that are captured but typically released	By-catch
	tertiary	Non-target species that are captured and kept	Tertiary
	secondary	Target species that are less desirabe than those of primary importance	Secondary
	primary	Target species that if captured are kept	Primary
Trophic guild	herbivore	Diet restricted to plant material	Herb
	omnivore	Mixed diet of plant and animal material	Omni
	microinvertebrate carnivore	Diet restricted to benthic and pelagic micro-invertebrates	micIC
	invertebrate carnivore	Diet restricted to benthic and pelagic invertebrates	IC
	generalist carnivore	Diet consisting of fish and invertebrate prey	GC
	piscivore	Diet restricted to fish	Pisc

GLMMs are an extension of the traditional generalised linear model (GLMs) that allow for correlation between observations. In this way they are suited to handle non-normal dependant data, typical of repeated measures studies (Bolker et al. 2008; Zuur et al. 2009). As the analysis dealt with count data the model was fitted with a Poisson distribution. The random effects included in the model were station and species. At each station a pair of RUV and BRUV samples were collected in sequence, while the species observed and the abundances that they were observed at were dependant on the environmental conditions and oceanographic conditions at that station. In other words, the species present and their abundances are only meaningful when the sampling station is taken into account (Pinheiro and Bates 2000). Because of this, species was

nested within station. As the species specific response to the effect of bait was of interest, the interaction was modelled as a random effect with the intercept suppressed. In this regard, the effect of bait at a station, and on the species present at a station can be considered a treatment with two levels (unbaited = RUV and baited = BRUV).

To account for variable survey areas resulting from changing water clarity between stations, survey area was used as an offset in the GLMM model. Zuur et al. (2009) promoted the offset option over the more typical alternatives of converting the response to a density, or including area as an explanatory variable. Working with densities, it is possible that the fitted values would become negative, while using area as an explanatory variable, results in modelling a functional relationship between area and the response variable (Zuur et al. 2009). In the GLMMs, the expected mean MaxN (μ) is:

$$\log(\mu) = X\beta + Z\gamma + log(area) \qquad \text{(equ. 3.7)}$$

where X is a matrix of covariates, β is a vector of the fixed effects covariates, Z is a matrix of the random effect covariates, γ is a vector of random effects parameters and $area$ is the horizontal field of view per station and is treated as an offset (Baum and Blanchard 2010). GLMMs were fitted using the lme4 package (Bates and Sarkar 2011) in the R (version 2.13.0) environment for statistical analysis (R Development Core Team 2011). This package employs the Laplace approximation of the likelihood for the parameter estimates.

While GLMMs are considered as one of the best tool for analysing non-normal data with random effects, they are challenging to use. In a review of past research conducted with GLMMs, Bolker et al. (2008) found that 58 % of these used the tool inappropriately in some way. In order to ensure accurate application of the analysis tools, the frameworks provided by Bolker et al. (2008), and in the supplementary information) and Zuur et al. (2009) were employed. Model selection was conducted using an Akaike Information Criterion (AIC) based approach, by sequentially removing parameters from the full model and selecting the model with the lowest AIC score (Logan 2010). If the data were

over dispersed with respect to the model, the quasi-AIC (QAIC) approach was used (Bolker et al. 2008). The advantage of the QAIC over the AIC is that it takes into account the over dispersion scale parameter of the full model. Modelling a response variable against a large number of predictor variables leads to statistical over fitting (Venables and Ripley 2002). Due to the large number of potential predictor variables in this dataset, only those that varied between the RUV and BRUV samples at each station were considered. This excluded the covariates of *Depth*, *Temperature*, *Profile*, and *Bottom*. Thus, only *Method*, *Visible reef*, and *Fisheries importance* or *Trophic guilds* were included in the full model.

Species level analysis

The effect of bait was further analysed separately for the dominant species. The structure of the GLMM was based on that described above, but excluded the random effect of species and included the fixed effect of Temperature. Of the dominant species (e.g. those observed in > 15 samples) six were selected. These included a common and scarce primary fisheries target (roman and red steenbras *Petrus rupestris*, respectively), a group of microinvertebrate carnivores (fingerfins *Cheilodactylidae*), a common small generalist carnivore (steentjie *Spondyliosoma emarginatum*), a large cartilaginous generalist carnivore (smooth-hound *Mustelus mustelus*) and a group of cryptic cartilaginous generalist carnivores (catsharks *Scyliorhinidae*).

The final step in the analysis was to estimate the power of the data. This was achieved by first modelling the variability in the RUV and BRUV MaxN data for each species independently using logistic regression, and then performing a power analysis to estimate the required sample size to detect a predefined population change. Exploratory analysis revealed non-linearity between the response variable (MaxN) and the continuous predictor variables for all species. As a result Poisson generalized additive models (GAMs) were implemented.

A GAM is a semi-parametric extension of the generalized linear model (GLM) where the linear predictor incorporates smoothing functions of the covariates (Wood 2006), and relies on the assumption that the functions are additive and the components are smooth (Guisan et al. 2002). GAMs are particularly useful when dealing with non-linear and non-monotonic relationships between the response and the predictor variables, and as a result offer benefits beyond those of GLMs when constructing ecological models (Guisan et al. 2002). A GAM is expressed as:

$$g(E[y]) = X_i^* \theta^* + \sum_j f_j(x_{ij}), \qquad \text{(equ. 3.8)}$$

where $g(\cdot)$ is the link function = the assumed relationship between the response and predictor variables, and $E[y]$ is the expected value of the response variable y. X_i is the *i*th row of X^* containing parametric model components, with the parameter vector θ***** and f_j are the smoothing functions of covariates x_j (Marra and Wood 2011). The level to which the covariates are smoothed is indicated by the estimated degrees of freedom (EDF) associated with the smoothing function. Here, low EDF correspond to lower levels of smoothing, in turn increasing the flexibility of the function obtained. When all smoothing functions have one EDF the GAM is equivalent to a GLM (Clarke et al. 2003).

GAMs were fitted using the package mgvc (version 1.7-6; Wood 2011) in the R environment (R Development Core Team 2011). Models were run on the Poisson family with the log link. Model diagnostics and basis dimension selection were conducted following the method of Wood (2011). Smoothness selection criterion was based on restricted maximum likelihood (REML). For all the GAM models, the discrete covariates were included as parametric coefficients, while the continuous variables were fitted with a tensor product smooth with the thin plate regression spline basis-penalty. Tensor product smooths are scale invariant and allow flexibility in different directions.

The statistical power of the analyses on the effect of bait was calculated following the approach of Willis et al. (2003). The approach is designed for assessing an analysis of

count data fitted on the Poisson distribution. Although the Poisson model assumes equality of the mean and the variance, count data are typically overdispersed, with the variance (σ^2) equalling the sum of the mean and an overdispersion parameter estimate ($\sigma^2 = \phi\mu$). The overdispersion parameter (ϕ) is calculated by dividing the model deviance by the residual degrees of freedom, and is also known as the residual deviance. Incorporating the overdispersion parameter, the ratio of two specified means (k) can be used to estimate the upper bound (β) on the probability of a type II error, taken as the probability of having a standard-normal quantile (Z_β),

$$Z_\beta = \frac{log(k)}{\sqrt{\left(\frac{\phi\ k+1}{n\mu_1\ k}\right)}} - Z_{\alpha/2}, \qquad \text{(equ. 3.9)}$$

where n is the sample size, and α is the type I error rate of the test, here equalling 0.05 and resulting in a $Z_{\alpha/2}$ of 1.96. μ_1 is the lower of the two means, which ensures that $log(k)$ is always positive (Willis et al. 2003).

From this equation the required number of samples to achieve a stipulated effect size (k) with a desired power (Z_β) can be estimated by making n the subject of the equation. In this study power analysis was used to determine the optimal number of samples required (Willis et al. 2003) to detect an effect size two. This could reflect a doubling or halving of the target population, and is thought to be a biologically meaningful effect criterion considering the levels of natural variability in fish populations (Edgar and Barrett 1999; Willis et al. 2003). Where applicable the variability in the count data between the RUV and BRUV for the different species was further investigated using the Coefficient of Variation (CV) (McArdle et al. 1990). The CV can be used as an indiscriminate method to compare levels of variation around a mean. The CV is calculated by dividing the standard deviation (SD) of the set of population estimates by the mean (McArdle et al. 1990).

3.2.5.5 Graphical representation

All data were visualised with trellis plots from the lattice and latticeExtra packages in R (Sarkar 2008).

3.3 Results

3.3.1 Environmental characteristics

A total of 27 stations was completed over three sampling trips to the TNP MPA, from February 2008 to February 2009. Visibility was typical for the region, averaging 3.6 (± 1.5) m, equating to an average horizontal survey area of 9.7 (± 7.5) m^2. The maximum area surveyed was 27.2 m², while the minimum area was 0.6 m² (Table 3.2). The visible reef in the video footage ranged from 0-90 %, with a mean of 40.5 (± 21.9) %. The water depths surveyed ranged from 10 to 33 m, with an average of 19.0 (± 5.6) m. Water temperature showed considerable variation (min = 11.4, max = 21.5 °C), with a mean of 17.2 (± 3.3) °C.

Table 3.2: Summary of the continuous covariates measured during the survey, together with the number of replicates for each factorial covariate.

Continuous covariates				
Name	mean	SD	min	max
Visibility (m)	3.8	1.5	1.0	6.5
Area (m²)	9.8	7.5	0.6	27.2
Visible reef (%)	40.5	21.8	0	90.0
Depth (m)	19.0	5.6	10.0	33.0
Temperature (°C)	17.2	3.3	11.4	21.5

Factorial covariates			
Name	Levels	Codes	n samples
Method	*BRUV*	Baited	27
	RUV	Unbaited	27
Bottom	*Patch reef*	Patch reef	6
	Bedrock	Rock	21
Profile	*Lowprofile*	Low	12
	High profile	High	15

3.3.2 Optimal deployment time

The comparison of rate of species accumulation with increasing deployment time showed that there was no significant difference between RUV and BRUV at the 50 % (Table 3.3, F = 2.17, p>0.1) and the 95 % saturation levels (F = 2.74, p>0.05). Remote underwater video reached the 95 % saturation time (± SE) at 20.7 (± 3.1) minutes, while BRUV required 28.6 (± 4.8) minutes to reach the same saturation level. Importantly, BRUV recorded higher numbers of species (mean ± SE) at both the 50 % (6.6 ± 0.6 species) and 95 % (10.5 ± 0.7) saturation levels when compared to the RUV (50 %: 5.9 ± 0.8, 95 %: 7.5 ± 0.9) (Fig. 3.2a).

Table 3: Results from the non-linear mixed effects analysis on the remote underwater video (RUV) and baited RUV (BRUV) data comparing the average time (± SE) at which species accumulation, and species at MaxN accumulation were at the 50 % and 95 % saturation levels. The observed number of species for the predicted times has been provided. The significance levels for the comparison of the optimal deployment time between RUV and BRUV have been provided.

	RUV				BRUV				Comparison of time		
	Time		*Number of species*		*Time*		*Number of species*				
	Mean	*SE*	*Mean*	*SE*	*Mean*	*SE*	*Mean*	*SE*	*F-test*	*p-value*	
Species accumulation: Entire community											
50%	8.00	0.99	5.90	0.82	9.52	1.39	6.62	0.65	2.17	0.142	
95%	20.69	3.14	7.49	0.91	28.64	4.81	10.54	0.70	2.74	0.099	.
Species at Max-N accumulation: Entire community											
50%	14.08	0.91	4.41	0.58	21.22	2.21	6.41	0.57	1.13	0.287	
95%	34.77	2.90	7.84	0.99	48.00	4.15	11.03	0.73	10.16	0.002	**
Species at Max-N accumulation: Bony fish											
50%	13.07	1.61	4.33	0.59	19.23	2.30	4.89	0.54	0.90	0.343	
95%	31.77	3.25	6.96	0.81	43.85	4.70	8.27	0.65	6.62	0.010	**
Species at Max-N accumulation: Cartilaginous fish											
50%	23.85	3.61	0.85	0.20	27.39	4.38	1.42	0.23	0.38	0.537	
95%	33.19	5.29	1.18	0.22	43.62	6.36	2.35	0.23	2.69	0.102	

Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "."<0.1

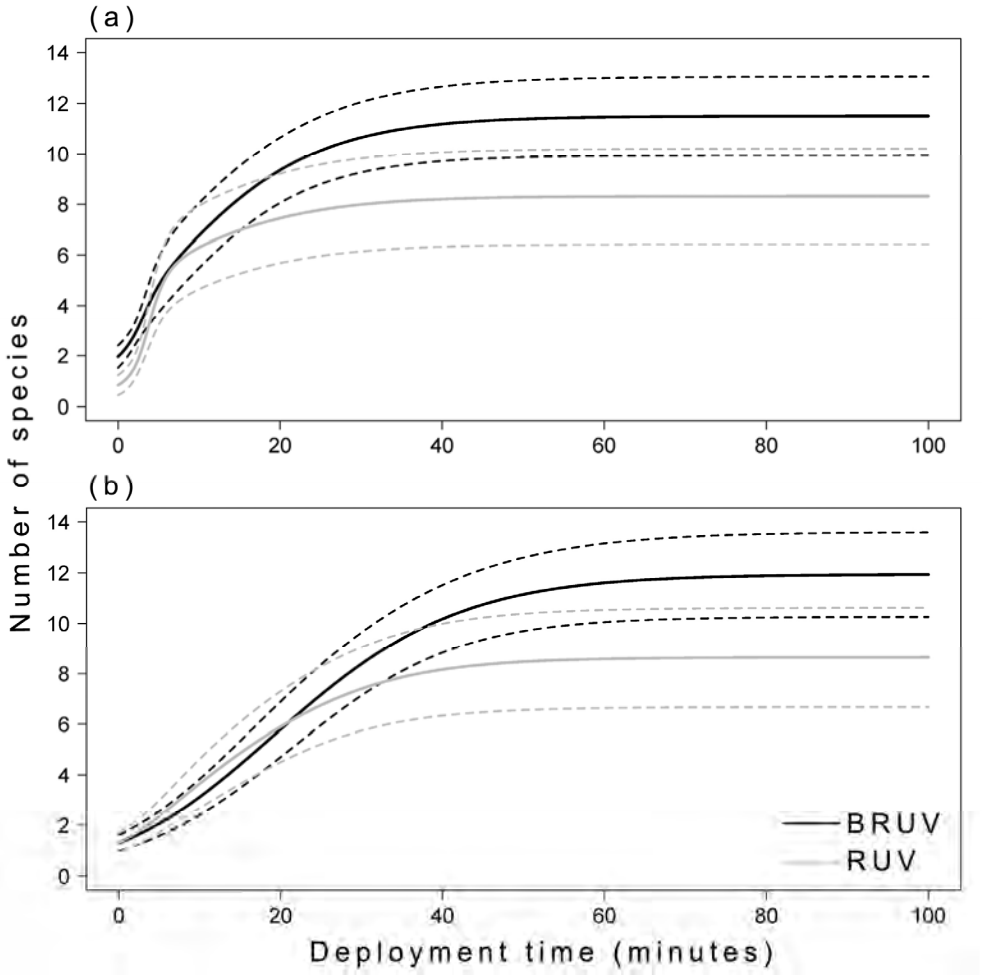

Figure 3.2: Predicted results from the non-linear mixed effects models, showing the accumulation of species (a) and species at Max-N for the entire community (b) plotted against video duration for the remote underwater video (RUV) and the baited RUV (BRUV). The dashed lines indicate the 95 % confidence interval.

The comparison of the rate of species at MaxN accumulation for the entire community identified a significant difference in the time taken for RUV (34.8 ± 2.9 min) and BRUV (48.0 ± 4.2 min) to reach the 95 % saturation level ($F = 10.16$, $p<0.01$). Although it is predicted that RUV requires a significantly shorter deployment time, BRUV records considerably more species within its optimal deployment time (RUV = 7.8 ± 1.0; BRUV

= 11.0 ± 0.7) (Fig. 3.2b). This suggests that the logistical benefits of using RUV may be outweighed by its inability to sample the entire community present. There was no significant difference in the time taken to reach the 50 % saturation level (Table 3.3). Removing the cartilaginous species from the analysis resulted in a slight decrease in the time taken for both RUV (31.8 ± 3.3 min) and BRUV (43.9 ± 4.7 min) to reach the 95 % saturation levels (Table 3.3). As with the above analysis the optimal deployment time for RUV was significantly shorter than that of BRUV ($F = 6.62$, $p<0.01$), however the difference in the number species was less than what was observed for the whole fish community, with RUV recording 7.0 (± 0.8) species and BRUV recording 8.3 (± 0.7) species at their respective optimal deployment times. As expected, following the above results, RUV sampled very few cartilaginous species (1.2 ± 0.2 species) in comparison BRUV (2.4 ± 0.2 species) at their respective optimal deployment times (95 %: RUV = 33.2 ± 5.3 min; BRUV = 43.6 ± 6.4 min). Although there was a difference in the optimal deployment times, the high levels of variability in the accumulation of cartilaginous species, together with the low numbers of cartilaginous species recorded blurred any clear distinction between the RUV and BRUV methods.

3.3.3 Effect of bait

3.3.3.1 Community level analysis

To total of 53 species of fish were recorded, of which 38 were bony fish, 15 were cartilaginous fish, while one species of jawless fish was recorded. Baited remote underwater video recorded 92 % of the observed species (49), while RUV only recorded 66 % of the observed species (35). From the species of bony fish, 26 were common to both the RUV and BRUV methods, while ten were unique to BRUV and two were unique to RUV. Of the 15 cartilaginous species recorded, eight were unique to BRUV, two were unique to RUV, while only five of the species were recorded by both methods. Species that were recorded by only one of the methods were rare within the survey area, occurring in less than 7 of the 28 samples and at MaxN abundances of less than two.

Table 3.4: List of all fish species recorded using the remote underwater video (RUV) and baited RUV (BRUV) methods. Species are sorted by class and according to the number of stations where they were present (Total N). For information on the classification of species into the different fisheries and trophic groups see Appendix 3.1.

Species information				Total	RUV						BRUV				
Class	Family	Common name	*Scientific name*	N	n	mean	SD	min	max	n	mean	SD	min	max
Osteichthyes	Sparidae	Roman	*Chrysoblephus laticeps*	25	24	2.92	2.32	1	10	23	6.00	3.72	1	13
Osteichthyes	Sparidae	Steentjie	*Spondyliosoma emarginatum*	24	18	7.56	9.08	1	30	24	30.29	21.14	3	80
Osteichthyes	Sparidae	Fransmadam	*Boopsoidea inornata*	23	18	6.17	4.48	1	25	22	8.91	6.73	1	26
Osteichthyes	Sparidae	Blue hottentot	*Pachymetopon aeneum*	22	18	3.17	2.96	1	10	19	6.05	4.29	1	18
Osteichthyes	Cheilodactylidae	Twotone fingerfin	*Chirodactylus brachydactylus*	20	20	2.40	1.35	1	5	10	1.50	0.85	1	3
Osteichthyes	Sparidae	Blacktail	*Diplodus capensis*	17	14	2.43	2.14	1	9	16	4.75	4.02	1	15
Osteichthyes	Sparidae	Red steenbras	*Petrus rupestris*	17	13	1.08	0.28	1	2	16	1.50	0.52	1	2
Osteichthyes	Sparidae	Janbruin	*Gymnocrotaphus curvidens*	12	11	1.27	0.47	1	2	5	1.40	0.89	1	3
Osteichthyes	Sparidae	Dageraad	*Chrysoblephus cristiceps*	11	9	2.00	1.41	1	5	8	2.63	1.19	1	4
Osteichthyes	Sparidae	Cape stumpnose	*Rhabdosargus holubi*	10	7	1.29	0.49	1	2	9	1.78	1.30	1	5
Osteichthyes	Sparidae	Panga	*Pterogymnus laniarius*	9	4	1.50	0.58	1	2	9	4.44	3.94	1	10
Osteichthyes	Sparidae	Zebra	*Diplodus hottentotus*	9	8	1.00	0.00	1	1	4	1.25	0.50	1	2
Osteichthyes	Cheilodactylidae	Barred fingerfin	*Cheilodactylus pixi*	8	8	1.25	0.46	1	2	1	1.00	NA	NA	NA
Osteichthyes	Oplegnathidae	Cape knifejaw	*Oplegnathus conwayi*	8	8	1.63	0.92	1	3	3	1.00	0.00	1	1
Osteichthyes	Carangidae	Maasbanker	*Trachurus trachurus*	8	3	43.67	50.90	1	100	6	20.00	25.40	1	70
Osteichthyes	Sparidae	Strepie	*Sarpa salpa*	8	5	84.60	71.45	3	200	8	44.13	49.14	2	150
Osteichthyes	Sparidae	Bronze bream	*Pachymetopon grande*	7	—	—	—	—	—	7	1.29	0.49	1	2
Osteichthyes	Serranidae	Koester	*Acanthistius sebastoides*	7	5	1.00	0.00	1	1	3	1.33	0.58	1	2
Osteichthyes	Cheilodactylidae	Redfingers	*Cheilodactylus fasciatus*	7	7	1.14	0.38	1	2	3	1.00	0.00	1	1
Osteichthyes	Sparidae	Sand steenbras	*Lithognathus mormyrus*	7	3	1	0	1	1	7	1.57	1.51	1	5
Osteichthyes	Sparidae	Red stumpnose	*Chrysoblephus gibbiceps*	6	4	1.25	0.5	1	2	5	1.00	0.00	1	1
Osteichthyes	Sparidae	White stumpnose	*Rhabdosargus globiceps*	6	—	—	—	—	—	6	1.67	1.21	1	4
Osteichthyes	Sparidae	Carpenter	*Argyrozona argyrozona*	5	—	—	—	—	—	5	2.20	1.10	1	3
Osteichthyes	Sparidae	Red tjor-tjor	*Pagellus bellottii natalensis*	5	2	8.00	NA	6	10	5	6.20	6.26	1	14
Osteichthyes	Tetraodontidae	Evileye blaasop	*Amblyrhynchotes honckenii*	4	—	—	—	—	—	4	1.25	0.50	1	2
Osteichthyes	Ariidae	White seacatfish	*Galeichthys feliceps*	4	2	1.00	NA	1	1	2	1.00	NA	1	1
Osteichthyes	Carangidae	Giant yellowtail	*Seriola lalandi*	3	—	—	—	—	—	3	1.00	0.00	1	1

Table 3.4 continued

Species information				Total	RUV						BRUV				
Class	Family	Common name	*Scientific name*	N	n	mean	SD	min	max	n	mean	SD	min	max
Osteichthyes	Parascorpididae	Jutjaw	*Parascorpis typus*	3	3	1	0	1	1	—	—	—	—	—
Osteichthyes	Haemulidae	Piggy	*Pomadasys olivaceum*	3	1	20.00	NA	NA	NA	3	34.00	57.16	1	100
Osteichthyes	Sparidae	Santer	*Cheimerius nufar*	3	1	1	NA	NA	NA	2	1.50	NA	1	2
Osteichthyes	Chaetodontidae	Doublesash butterflyfish	*Chaetodon marleyi*	2	—	—	—	—	—	2	1.00	NA	1	1
Osteichthyes	Scombridae	Chub mackerel	*Scomber japonicus*	1	—	—	—	—	—	1	1.00	NA	NA	NA
Osteichthyes	Sciaenidae	Geelbek	*Atractoscion aequidens*	1	1	10	NA	NA	NA	1	2.00	NA	NA	NA
Osteichthyes	Gobiesocidae	Rocksucker	*Chorisochismus dentex*	1	—	—	—	—	—	1	1.00	NA	NA	NA
Osteichthyes	Sparidae	White musselcracker	*Sparodon durbanensis*	1	1	2.00	NA	NA	NA	—	—	—	—	—
Osteichthyes	Serranidae	Yellowbelly rockcod	*Epinephelus marginatus*	1	—	—	—	—	—	1	1.00	NA	NA	NA
Osteichthyes	Sparidae	Sparid spp.	*Sparidae spp.*	1	—	—	—	—	—	1	2.00	NA	NA	NA
Condrichthyes	Carcharhinidae	Smooth-hound	*Mustelus mustelus*	19	6	1.00	0.00	1	1	18	2.06	1.59	1	5
Condrichthyes	Scyliorhinidae	Striped catshark	*Poroderma africanum*	16	7	1.00	0.00	1	1	15	1.80	1.15	1	4
Condrichthyes	Scyliorhinidae	Puffadder shyshark	*Haploblepharus edwardsii*	9	1	1.00	NA	NA	NA	9	1.22	0.44	1	2
Condrichthyes	Myliobatidae	Eagleray	*Myliobatis aqulia*	8	4	1.00	0.00	1	1	4	1.50	1.00	1	3
Condrichthyes	Carcharhinidae	Copper shark	*Carcharhinus brachyurus*	6	1	1.00	NA	NA	NA	6	1.00	0.00	1	1
Condrichthyes	Hexanchidae	Spotted sevengill cowshark	*Notorynchus cepedianus*	4	—	—	—	—	—	4	1.25	0.50	1	2
Condrichthyes	Dasyatidae	Diamond ray	*Gymnura natalensis*	3	—	—	—	—	—	3	1.00	0.00	1	1
Condrichthyes	Carcharhinidae	Requiem shark spp.	*Carcharhinidae spp.*	3	—	—	—	—	—	3	1.00	0.00	1	1
Condrichthyes	Scyliorhinidae	Catshark spp.	*Scyliorhinidae spp.*	2	—	—	—	—	—	2	1.00	NA	1	1
Condrichthyes	Rhinobatidae	Lesser guitarfish	*Rhinobatos annnulatus*	2	—	—	—	—	—	2	1.50	NA	1	2
Condrichthyes	Dasyatidae	Shorttail stingray	*Dasyatis brevicaudata*	2	—	—	—	—	—	2	1.00	NA	1	1
Condrichthyes	Carcharhinidae	Spotted gullyshark	*Triakis megalopteris*	2	—	—	—	—	—	2	1.00	NA	1	1
Condrichthyes	Myliobatidae	Duckbill ray	*Pteromylaeus bovinus*	1	—	—	—	—	—	1	1.00	NA	NA	NA
Condrichthyes	Dasyatidae	Stingray spp.	*Dasyatidae spp.*	1	1	1.00	NA	NA	NA	—	—	—	—	—
Condrichthyes	Sphyrnidae	Hammerhead spp.	*Sphyrna spp.*	1	1	1.00	NA	NA	NA	—	—	—	—	—
Agnatha	Myxinidae	Six-gill hagfish	*Eptatretus hexatrema*	1	—	—	—	—	—	1	1.00	NA	NA	NA

The sparid family was the best represented of the bony fish, with a total of 21 of the 25 species reported to occur in the region being present in the videos. The majority of the sparids were recorded by both methods (17), with the BRUV and RUV methods recording three and one unique species, respectively (Table 3.4).

The species accumulation curve showed BRUV to sample considerably more species than RUV (Fig. 3.3a). There was little difference in the rate of species accumulation within each method (Fig. 3.3b), with BRUV requiring 20 samples, and RUV requiring 21 samples to record 95 % of the species observed by each respective method. Importantly, only eight BRUV samples were required to observe the total number of species recorded by RUV (Fig. 3.3b).

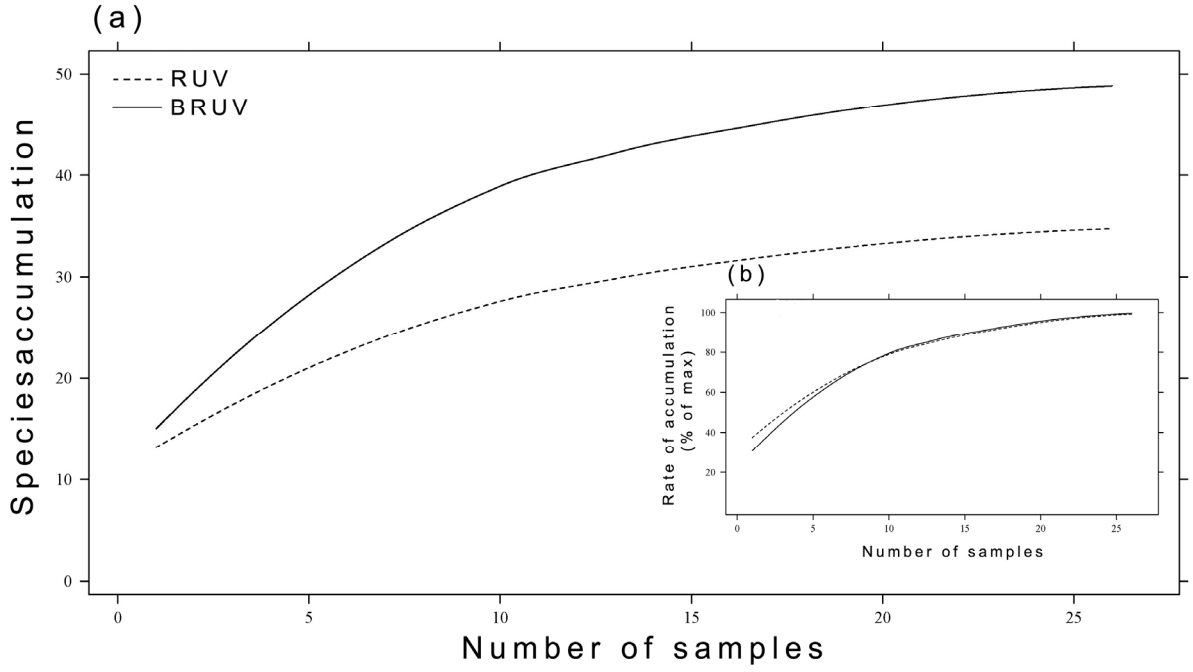

Figure 3.3: Species accumulation curves (a) for the remote underwater video (RUV) and baited RUV (BRUV) methods based on 33 repeated random sequences of station order. The insert (b) shows the relative rate of species accumulation for each method.

The response to the presence of bait by species that were recorded using both methods was typically consistent, however the direction and size of the response varied between species. For example, the three species of fingerfin recorded, were consistently seen at higher abundances in the RUV samples, while the majority of the cartilaginous species were recorded more often and at higher abundances in the BRUV samples (Table 3.4). The sparid family showed a variable response, with most species showing a positive response to the presence of bait (e.g. roman and steentjies), however the larger species recorded, such as dageraad *Chrysoblephus cristiceps* and red steenbras showed little to no response to the presence of bait. On the other hand, the janbruin *Gymnocrotaphus curvidens* was seen more often in the RUV samples.

3.3.3.2 The effect of bait on the abundance of fisheries groupings

The initial analysis looked at all species recorded during the study. However, the categories containing schooling species (massbanker *Trachurus trachurus*, piggy *Pomdasys olivaceum* and strepie *Sarpa salpa*) were associated with extremely high standard error (SE) estimates (>100 times the coefficient estimate), reflecting extreme variability in abundance. The high SE estimates are indicative of a poorly fitting model (Bolker et al. 2008) and as a result the schooling species were excluded from the analysis. Harvey et al. (2007) found a similar negative effect of schooling species dominating sample variance and blurring underlying patterns during their analysis.

The number of species recorded per *Fisheries grouping* varied, with species of tertiary importance being best represented (13 species), followed by the primary (12), by-catch (11) and secondary (9) *Fisheries groupings*. Only six species were represented in the non-target grouping, while only one species collected for aquarium trade (doublesash butterflyfish *Chaetodon marleyi*) was recorded. Because of this, the aquarium trade species was added to the tertiary *Fisheries grouping* (See Appendix 3.1 for grouping details).

The full model included an offset, log *Area*, the main effects of *Method*, *Fisheries grouping*, and *Visible reef*, and the interaction effects between *Method* and *Fisheries grouping*, and *Method* and *Visible reef*. The Poisson GLMM for these data is given by the following:

$$MaxN_{ij} \sim Poisson(\mu_{ij}) \Rightarrow E(MaxN_{ij}) \sim \mu_{ij}$$

$$\eta_{is} = offset\left(log(Area_{ij})\right) + \beta_1(Method_{ij}) + \beta_2(Fisheries\ grouping_{ij}) + \beta_3(Visible\ reef_{ij}) + \beta_4(Method_{ij}{:}\,Fisheries\ grouping_{ij}) + \beta_5(Method_{ij}{:}\,Visible\ reef_{ij}) + \alpha_{ij}$$

$$\alpha_{ij} \sim N(0, \sigma_\alpha^2)$$

$$log(\mu_{ij}) = \eta_{ij}$$

The first line states that the MaxN for species i at station j, $MaxN_{ij}$, is Poisson distributed with a mean of μ_{ij}. The second equation is the linear predictor and is typical of a normal GLM (see Chapter 2, section 2.2.7.1 for details on the GLM structure), with the addition of an offset, $log(Area_{ij})$, that accounts for the difference in survey area between stations, and a random intercept, α_{ij}, that allows for a different intercept for each station and each species nested within each station. The random intercept is assumed to be normally distributed with a mean of 0 and a variance of σ_α^2. The structure and description of the GLMM equation was based on information provided by Zuur et al. (2009).

The original random effect structure, a random intercept and slope together with species nested in station (i.e. 0+*Method*|station/species) was selected as the best fit for the model following assessment using the AIC procedure (Bolker et al. 2008). The model selection process identified that the full model, described above, was the most parsimonious model. The model deviance was 1337 on 722 residual degrees of

freedom, equivalent to an over-dispersion estimate (residual deviance) of 1.85. This suggests that the model was slightly over-dispersed, however, the analysis of the Pearson residuals showed no significant effect (X^2 = 241.15, p >0.5) indicating that the Poisson model was suitable to analyse the variability in the data (Bolker et al. 2008).

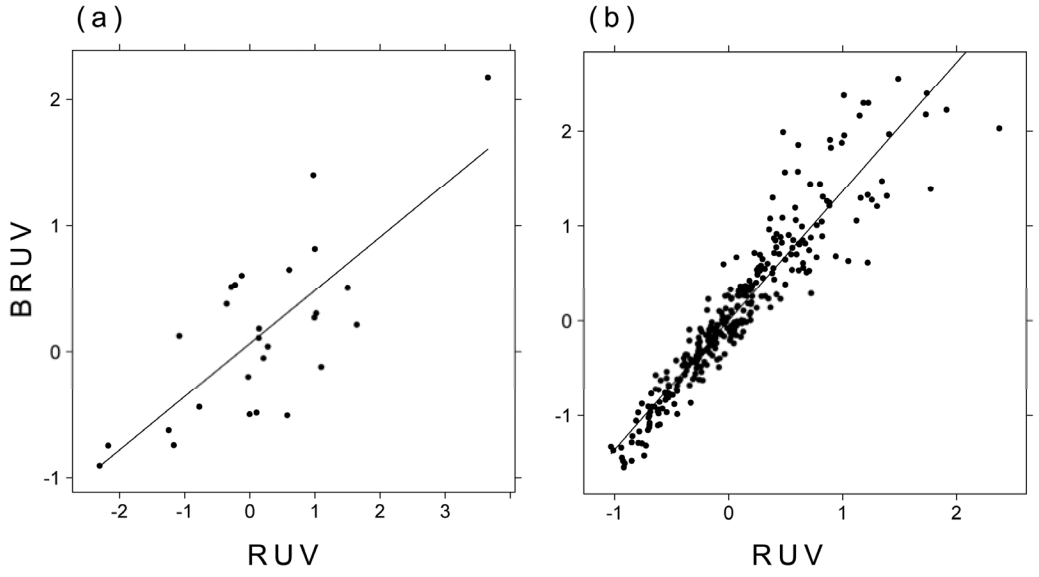

Figure 3.4: Results from the generalized linear mixed effects model investigating the effects of bait on the abundance of species grouped by *Fisheries importance*. The plots show the correlation between the remote underwater video (RUV) and baited RUV (BRUV) data with the random effects of station (a) and species nested within station (b).

Detailed output from the GLMM analysis is provided in Appendix 3.2. The results showed that *Method* was able to explain 68 % of the variation in MaxN for the random effect of station (Fig. 3.4a), and 80 % of the variation in MaxN between RUV and BRUV for the random effect of species nested within station (Fig. 3.4b). The model identified a significant main effects of *Method* (df = 8, X^2 = 16.54, p<0.001), *Fisheries grouping* (df = 11, X^2 = 81.32, p<0.001) and *Visible reef* (df = 8, X^2 = 53.16, p<0.001) on the MaxN data.

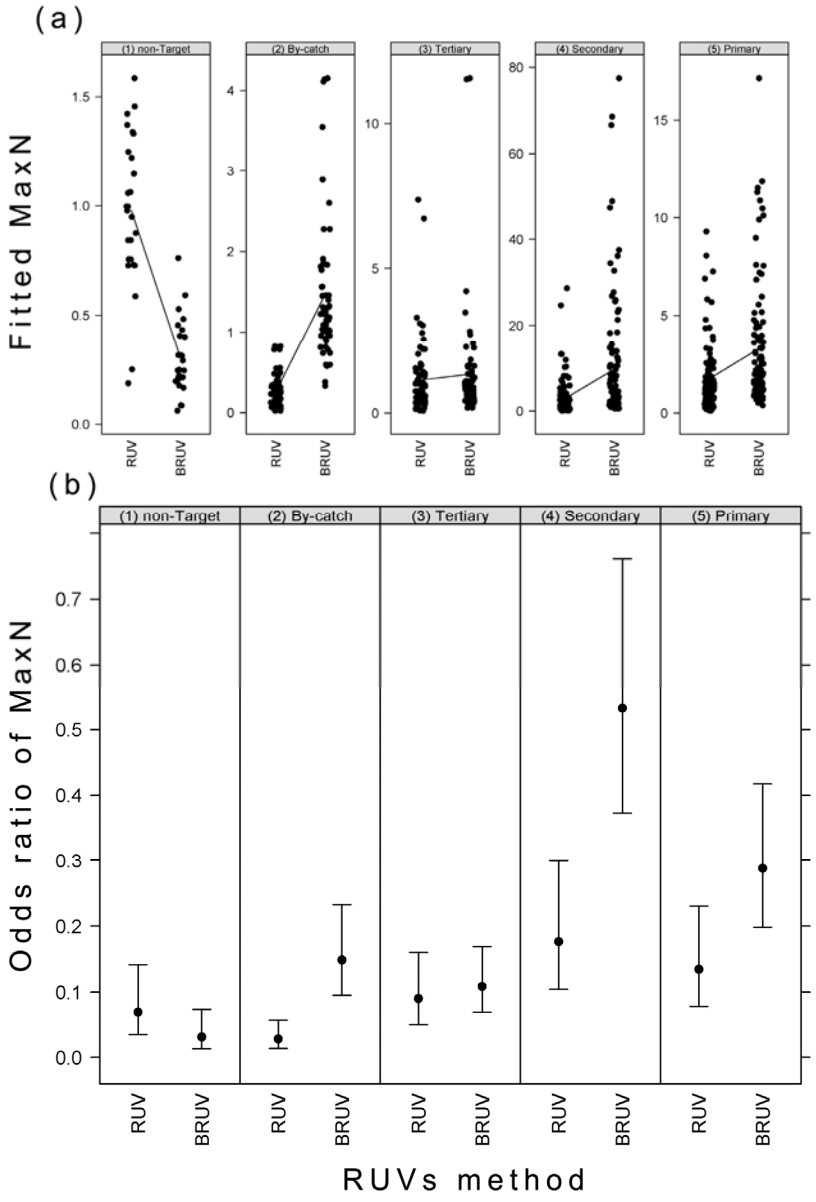

Figure 3.5: Interpretation of the results from the generalized linear mixed effects model showing the response of different *Fisheries* groupings to the effect of bait. Plot 'a' shows the distribution of the fitted data, with response lines between medians. Plot 'b' shows the difference between odd ratios of MaxN for the remote underwater video (RUV) and baited RUV (BRUV) methods, together with the 95 % confidence intervals. Visible reef was set to the average (40.5 %).

The regression estimates showed that the interaction effects between *Method* and *Fisheries importance* were significantly different from zero (Appendix 3.2). To determine if there was a significant difference between the average MaxN from RUV and BRUV for each level of *Fisheries importance*, the confidence intervals (CI) around the predicted odd ratios were calculated with *Visible reef* set to the observed average (40.5 %). The results showed clear separation between the MaxN of the BRUV and RUV methods for the secondary (BRUV: Odds ratio (OR) = 0.7 ± 0.2, fitted MaxN = 9.7 ± 14.4; RUV: OR = 0.2 ± 0.3, MaxN = 2.9 ± 4.3), and by-catch species (BRUV: OR = 0.2 ± 0.2, MaxN = 1.5 ± 0.9, RUV: OR = 0.04 ± 0.4, MaxN = 0.3 ± 0.2) (Fig. 3.5a, b). The separation between the CI for the primary species was marginally non-significant, with BRUV predicted to have a higher MaxN (OR = 0.4 ± 0.2, MaxN = 3.3 ± 3.1) than RUV (OR = 0.2 ± 0.3, MaxN =1.7 ± 1.7). Similarly, there was no clear separation between predicted MaxN for BRUV (OR = 0.2 ± 0.2, MaxN = 1.3 ± 1.9) and RUV (OR = 0.1 ± 0.3, MaxN = 1.1 ± 1.3) when only the tertiary species were considered (Fig. 3.5a, b).

Only with the non-target species did RUV produced higher odds ratios and MaxN estimates (OR = 0.1 ± 0.4, MaxN = 1.0 ± 0.3) than BRUV (OR = 0.04 ± 0.5, MaxN = 0.3 ± 0.2). However, this difference appeared not to be significant (Fig. 3.5a, b), when the *Visible Reef* was set at the average (40.5 %).

The significant interaction effect between *Visible reef* and *Method* indicated that *Visible reef* had a positive effect on MaxN for RUV and a negative effect for BRUV (Appendix 3.2). This suggests that increasing visible reef in the cameras field of view may have an inconsistent effect on the different *Fisheries groupings*. For example, when the odds ratios were predicted with *Visible reef* set at 90 % cover, there was no significant difference in predicted MaxN between the BRUV and RUV at most of the *Fisheries grouping* levels, except for the non-target species where the predicted MaxN for the RUV method (OR = 0.70 ± 0.51) was significantly greater than that predicted for the BRUV data (OR = 0.28 ± 0.53). Alternatively, with *Visible reef* set at 10 % cover, there was no difference between the predicted MaxN for the non-target species, while the

BRUV had significantly higher predicted MaxN for each of the other *Fisheries groupings*.

3.3.3.3 The effect of trophic guild on abundance

For this analysis the species were grouped according to their class (bony or cartilaginous) and trophic guild (Table 3.1). Distinguishing between bony and cartilaginous species before grouping the different species by *Trophic guild* removed the possibility of generating biologically implausible levels (i.e. cartilaginous herbivores), as certain trophic groups were exclusive to the different classes (Grueber et al. 2011). Exploratory analysis of the data (Zuur et al. 2010; Grueber et al. 2011) revealed that the low number of observations for both the bony and cartilaginous piscivorous species (Table 3.4) added undesirable uncertainty to the model. Grueber et al. (2011) promoted the 10:1 rule of thumb, for subject to predictor ratios in multiple regressions. As a result the piscivorous species were added to the generalist macro-carnivore group for the analysis. After the removal of the schooling species from the analysis, only one zooplanktivore was represented and it was grouped with the microinvertebrate carnivores. Only one jawless fish was recorded and it was grouped with the other cartilaginous species. This resulted in six *Trophic guilds* represented in the data. The generalist carnivore group was the most specious trophic guild with 15 species of bony fish and 11 species of cartilaginous fish. A total of 11 species was represented within the invertebrate carnivore group with six bony fish species and five cartilaginous species (either dasyatidae or myliobatidae species). The remaining trophic guilds, omnivores and microinvertebrate carnivores, were only represented by bony fish species, with five and six species respectively. The Poisson GLMM for these data is given by the following:

$$MaxN_{sij} \sim Poisson(\mu_{sij}) \Rightarrow E(MaxN_{sij}) \sim \mu_{sij}$$

$$\eta_{is} = offset\left(log\left(Area_{sij}\right)\right) + \beta_1\left(Method_{sij}\right) + \beta_2\left(Trophic\ guild_{sij}\right) + \beta_3\left(Visible\ reef_{sij}\right) + \beta_4\left(Method_{sij}{:}Trophic\ guild_{sij}\right) + \beta_5\left(Method_{sij}{:}Visible\ reef_{sij}\right) + \alpha_{ij}$$

$$\alpha_{ij} \sim N(0, \sigma_\alpha^2)$$

$$log\left(\mu_{sij}\right) = \eta_{sij}$$

The general structure of the above GLMM is identical to the one described for the previous analysis, however in this instance the species were grouped by *Trophic guild* rather than *Fisheries importance*.

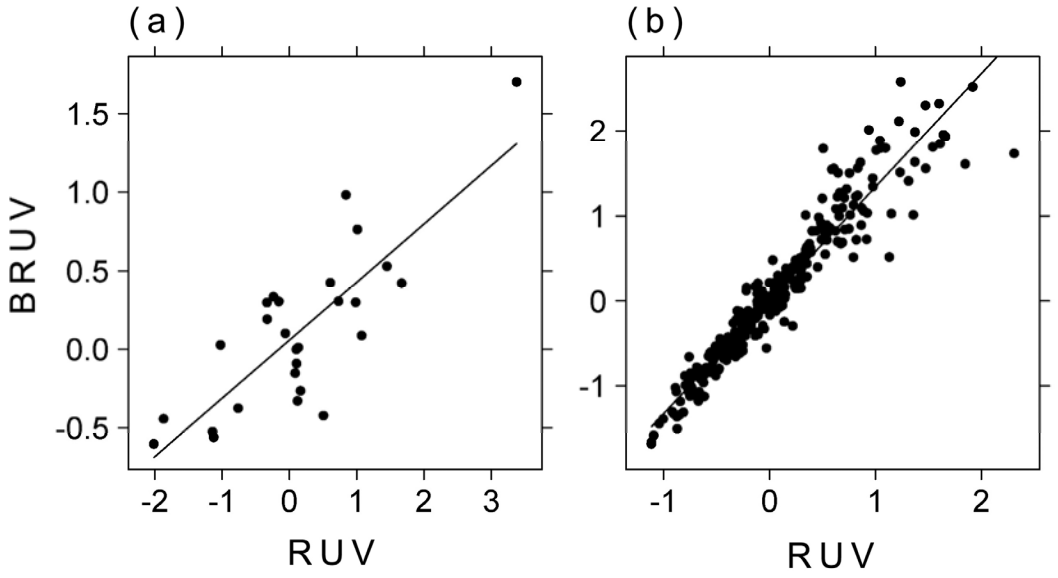

Figure 3.6: Results from the generalized linear mixed effects model investigating the effects of bait on the abundance of species grouped by *Trophic guild*. The plots show the correlation between the remote underwater video (RUV) and baited RUV (BRUV) data with the random effects of station (a) and species nested within station (b).

The full model was identified as the most parsimonious model. The model deviance was 1340 on 720 residual degrees of freedom, equivalent to an over-dispersion estimate (residual deviance) of 1.86. This suggests that the model was slightly over-dispersed, however, the analysis of the Pearson residuals showed no significant effect (X^2 = 237.48, p >0.5) indicating that the Poisson model was suitable to analyse the variability in the data (Bolker et al. 2008). The random effects showed a strong correlation between RUV and BRUV MaxN data, with 71.6 % of the variability explained by station (Fig. 3.6a), and 83.7 % of the variability in the data explained by species nested in station (Fig. 3.6b).

As this analysis was based on the same dataset as the previous analysis the significant effects of *Method* and *Visible reef* are the same as described above. In a similar vein, the interaction effect between *Method* and *Visible reef* produced the same results (see Appendix 3.2 for more details). Of interest was the effect of *Trophic guild* which was found to significantly (df = 12, X^2 = 79.51, p<0.001) explain the observed variability in MaxN. In addition the regression coefficients showed significant effects for the interaction between *Trophic guild* and *Method* (Appendix 3.2). With visible reef set to the observed average (40.5 %), analysis of the CI around the odds ratios of MaxN showed clear separation between BRUV and RUV for the cartilaginous-generalist carnivore group (BRUV: OR = 0.2 ± 0.2, MaxN = 1.4 ± 0.9; RUV: OR = 0.04 ± 0.4, MaxN = 0.2 ± 0.2) (Fig. 3.7a, b).

Similarly, the effect of bait on the bony-invertebrate carnivore group was significant with the average MaxN highly inflated in the BRUV data (OR = 0.4 ± 0.2, MaxN = 12.6 ± 17.1), compared to the RUV data (OR = 0.2 ± 0.3, MaxN = 3.0 ± 4.7). Although there was considerable difference between the estimates from the BRUV and RUV for the bony-generalist carnivore group (BRUV: OR = 0.4 ± 0.2, MaxN = 3.8 ± 4.3; RUV: OR = 0.2 ± 0.3, MaxN = 2.0 ± 2.3), the CIs overlapped (Fig. 3.7b) suggesting that there was no clear effect of bait on MaxN for this group.

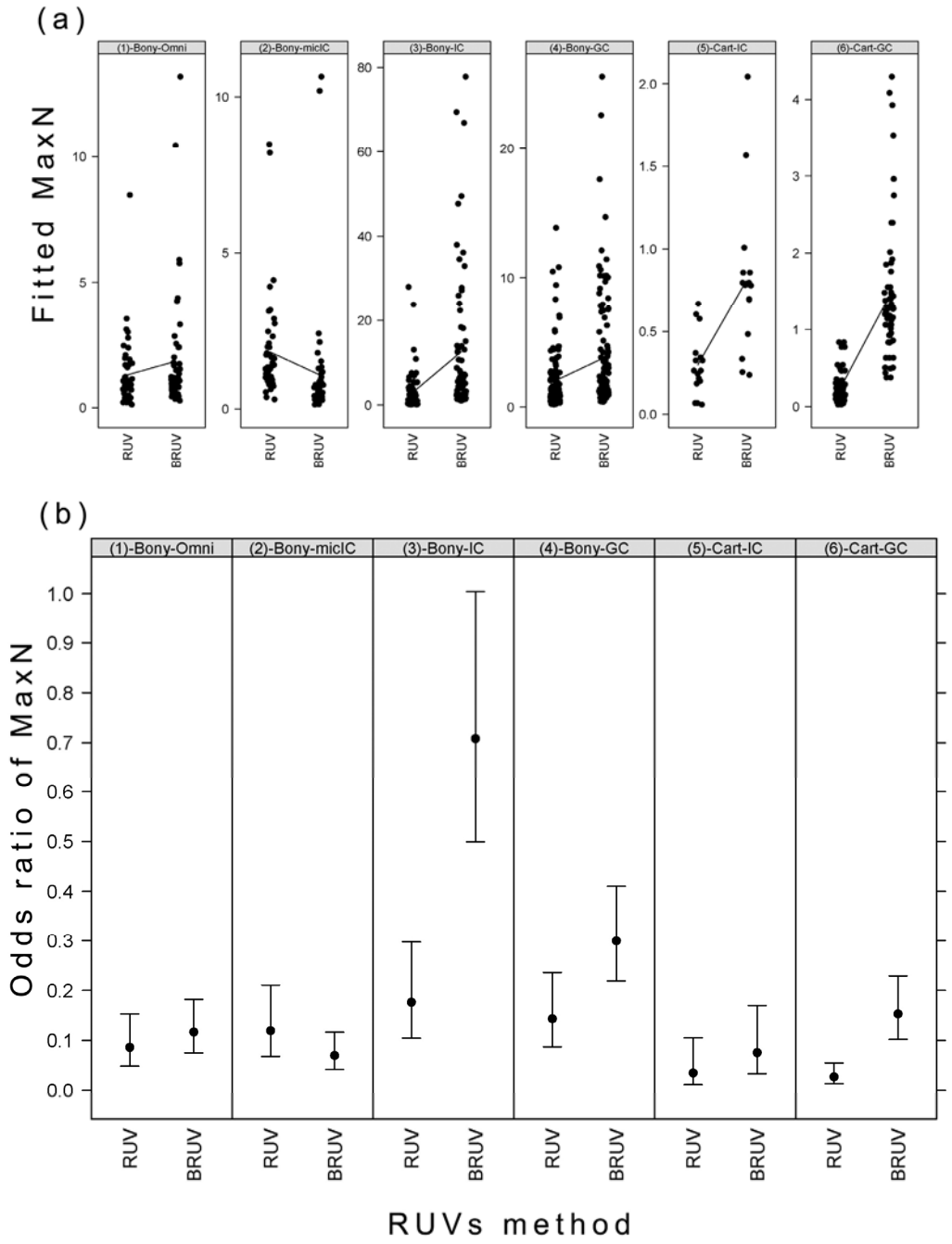

Figure 3.7: Interpretation of the results from the generalized linear mixed effects model showing the response of different *Trophic guilds* to the effect of bait. Plot 'a' shows the distribution of the fitted data, with response lines between medians. Plot 'b' shows the difference between odd ratios of MaxN for the remote underwater video (RUV) and the baited RUV (BRUV) methods, together with the 95 % confidence intervals. Visible reef was set to the average (40.54 %). Descriptions for the *Trophic guild* levels are given in Table 3.1.

There was little difference between the RUV and BRUV predicted odds ratios for the bony-omnivores (RUV: 0.1 ± 0.3; BRUV: 0.2 ± 0.2), bony-microinvertebrate carnivores (RUV: 0.2 ± 0.3; BRUV: 0.1 ± 0.3), and the cartilaginous-invertebrate carnivores (RUV: 0.05 ± 0.6; BRUV: 0.1 ± 0.4), indicating that the effect of bait was not significant for these groups of species (Fig. 3.7b). In all the above cases BRUV predicted higher count data than RUV. Only for the bony-microinvertebrate carnivore group, did RUV predict higher MaxN (1.8 ± 1.6), compared to BRUV (1.1 ± 2.1), although this pattern appeared not to be significant.

3.3.3.4 Species level analysis

The full GLMMs were run with three main effects, namely *Method*, *Visible reef* and *Temperature* and the interaction effect between *Method* and *Visible reef*. The general Poisson GLMM for these data is given by the following:

$$MaxN_j \sim Poisson(\mu_j) \Rightarrow E(MaxN_j) \sim \mu_j$$

$$\eta_j = offset\left(log(Area_j)\right) + \beta_1(Method_j) + \beta_2(Temperature_j) + \beta_3(Visible\ reef_j) + \beta_4(Method_j{:}Visible\ reef_j) + \alpha_j$$

$$\alpha_j \sim N(0, \sigma_\alpha^2)$$

$$log(\mu_j) = \eta_j$$

The first line states that the MaxN for station *j*, $MaxN_j$, is Poisson distributed with a mean of μ_j. The second equation is the linear predictor and is typical of a normal GLM. The original random effect structure, a random intercept and slope of station (i.e. 0+*Method*|station) was selected as the best fit for the model following assessment using the AIC procedure (Bolker et al. 2008).

Table 3.5: Results from the generalized linear mixed effects models conducted on the dominant species investigating the effect of bait and environmental characteristics on the observed MaxN data. For each species information on the model fit is provided, together with the model summary from the most parsimonious models providing the log odds ratio (OR) and significance levels for the regression estimates.

	Roman				Steentjie				Fingerfins			
	RDF[1]	Deviance	AIC	ΔAIC[2]	RDF	Deviance	AIC	ΔAIC	RDF	Deviance	AIC	ΔAIC
Full model	41	82.14	100.10		37	153.90	175.90		59	78.67	100.70	
Most parsimonious model	45	84.40	94.40	-5.74	43	161.20	171.20	-4.69	65	83.86	93.86	-6.84
Residual deviance	1.88				3.75				1.29			
	log(OR) ± SE	Z-value[3]			log(OR) ± SE	Z-value			log(OR) ± SE	Z-value		
Intercept (RUV)	-0.92 (0.19)	-4.87 ***			-0.95 (0.36)	-2.61 **			-1.45 (0.20)	-7.33 ***		
BRUV	0.70 (0.15)	4.60 ***			2.37 (0.31)	7.69 ***			-1.22 (0.26)	-4.61 ***		
	Red steenbras				Smooth-hound				Catsharks			
	RDF	Deviance	AIC	ΔAIC	RDF	Deviance	AIC	ΔAIC	RDF	Deviance	AIC	ΔAIC
Full model	23	24.46	46.46		27	36.81	51.00		47	60.45	74.45	
Most parsimonious model	29	28.51	38.51	-7.95	33	47.09	46.55	-4.45	49	60.73	70.73	-3.72
Residual deviance	0.98				1.43				1.24			
	log(OR) ± SE	Z-value			log(OR) ± SE	Z-value			log(OR) ± SE	Z-value		
Intercept (RUV)	-2.26 (0.30)	-7.50 ***			-3.13 (0.42)	-7.52 ***			-3.23 (0.47)	-6.87 ***		
BRUV	0.55 (0.35)	1.58			1.77 (0.45)	3.94 ***			1.69 (0.42)	4.04 ***		

1: RDF = Residual degrees of freedom

2: ΔAIC = The change in AIC between the full and most parsimonious model

3: Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

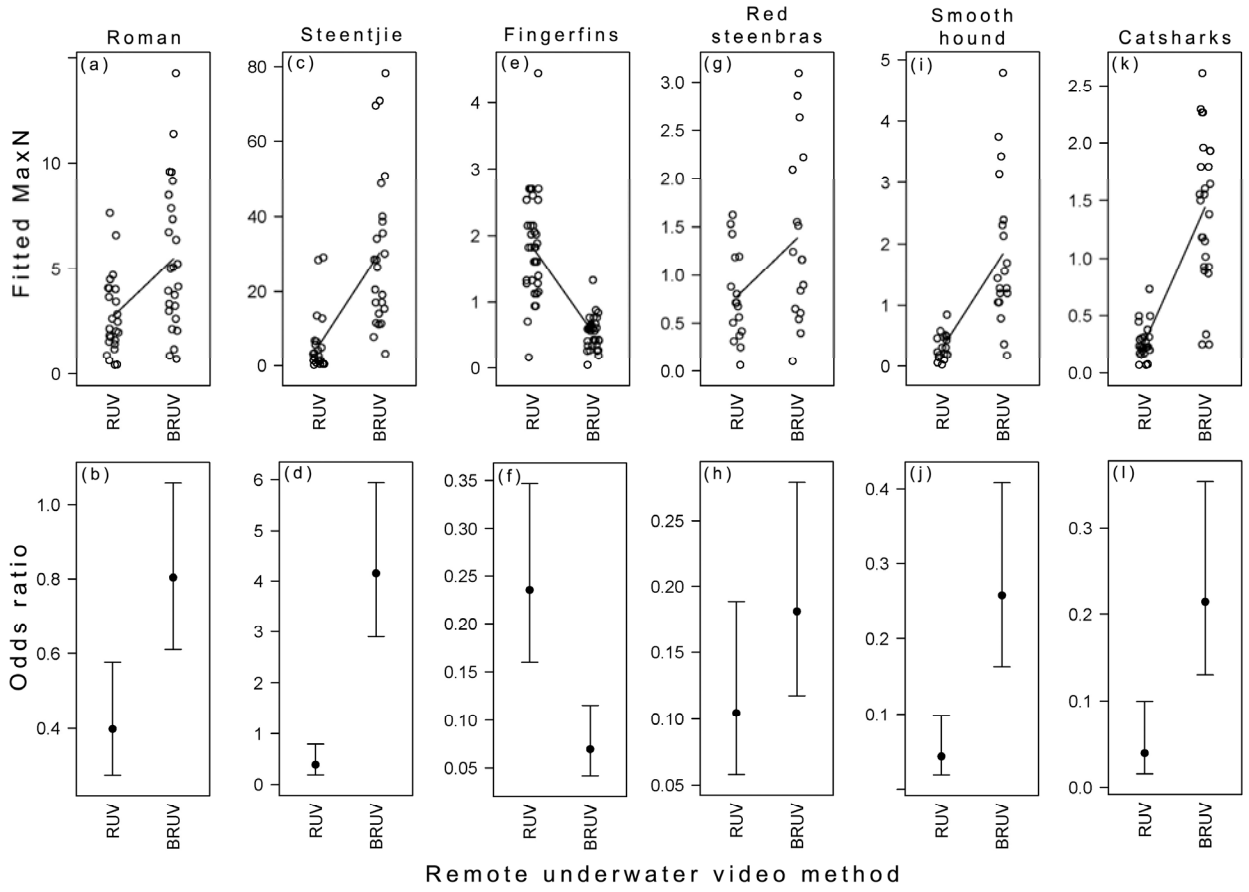

Figure 3.8: Interpretation of the results from the generalized linear mixed effects model showing the response of dominant species to the effect of bait. The upper row of plots show the distribution of the fitted data, with response lines between medians. The lower row of plots show the difference between odd ratios of Max-N for the remote underwater video (RUV) and the baited RUV (BRUV) methods, together with the 95 % confidence intervals.

The model selection process for the fixed effects resulted in only *Method* (RUV or BRUV) being retained in the most parsimonious model for all species (Table 3.5). Although the residual deviances of the GLMMs were high for some of the species, in particular the steentjie (3.75), none showed a significant effect on the Pearson residuals ($p>0.1$ in all cases), suggesting that a Poisson distribution was suitable to explain the data.

The presence of bait had a positive effect on the intercept (i.e. increased the MaxN) for all the species except the fingerfins, where the presence of bait had a negative effect on the intercept (Table 3.5, Fig. 3.8). The scale of the bait effect was significantly different from zero for all species except red steenbras, which was typically scarce in both the RUV and BRUV samples (Table 3.5, Fig. 3.8). This was reaffirmed in the comparison of the CI around the odds ratios for the effect of bait on MaxN with only red steenbras showing no significant separation (Fig. 3.8g, h).

There was, however, considerable variability in the effect size (e.g. the change in MaxN from the RUV to the BRUV) with MaxN (± SE) for roman (RUV = 2.7 ± 1.8; BRUV = 5.5 ± 3.5) and red steenbras (RUV = 0.7 ± 0.5; BRUV = 1.4 ± 0.9) showing an approximate doubling. In contrast steentjies (RUV = 5.6 ± 7.9; BRUV = 30.5 ± 20.7), smooth-hound (RUV = 0.3 ± 1.8; BRUV = 1.8 ± 1.2) and catsharks (RUV = 0.3 ± 0.2; BRUV = 1.4 ± 0.6) showed a five-fold increase in MaxN. The negative effect of bait on the MaxN of fingerfins (RUV = 1.8 ± 0.8; BRUV = 0.5 ± 0.2) resulted in a three-fold decrease in abundance between the RUV and BRUV samples.

3.3.4 Data variability and power analysis

The results from the analysis of the bait effect on observed abundance at the species level suggested that BRUV was characterised by lower levels of viability than RUV. In order to independently investigate the potential effect of variability on the power of the data to detect changes through time, separate GAMs were run on the RUV and BRUV data for the six species analysed above. GAMs were selected over GLMs as the relationships between the response variable and the continuous predictor variables (i.e*. Temperature*, *Depth and Visible reef*) were non-linear (Zuur et al. 2009). Subsequent to the GAM analysis, the sample size to detect an effect size of two was calculated using the predicted mean and dispersion parameter (Phi) from the Poisson GAMs.

The full Poisson GAM for each species was standardised as:

$$MaxN_i \sim Poisson(\mu_i) \Rightarrow E(MaxN_i) \sim \mu_i$$

$$\eta_i = \alpha + offset\big(log(Area_i)\big) + factor_1(Bottom_i) + factor_2(Profile_i) + f_1(Temperature_i) + f_2(Depth_i) + f_3(Visible\ reef_i) + \varepsilon_i$$

$$\varepsilon_i \sim N(0, \sigma^2)$$

$$log(\mu_i) = \eta_i$$

The underlying structure of the Poisson model is the same as that described for the GLMMs, with the offset, $log(Area_i)$, differentiating between the areas surveyed for each of the samples, i. The factorial covariates, $factor_1(Bottom_i)$ and $factor_2(Profile_i)$, were included as parametric coefficients, while tensor product smooths with the thin plate regression spline basis-penalties were applied to the continuous covariates ($f_1(Temperature_i)$, $f_2(Depth_i)$, and $f_3(Visible\ reef_i)$).

Model selection was conducted with the likelihood based method of restricted maximum likelihood (REML), whereby the inclusion or exclusion of covariates was decided by looking at changes in the REML scores. In addition to this, Null Space Penalization was employed, whereby covariates were effectively dropped from the model if the smoothing parameters tended towards infinity (Wood, 2006). The results are described per species and for the RUV and BRUV methods in the section below.

Table 3.6: Results from the likelihood ratio test runs on the Poisson generalized additive models investigating patterns and causes of spatial variability of the dominant fish species. Included are the results from the power analysis on the predicted mean and the number of samples required to detect a doubling or halving of the populations (k=2).

	Roman				Steentjie				Fingerfin family			
	RUV		*BRUV*		*RUV*		*BRUV*		*RUV*		*BRUV*	
	df/ edf[2]	*Chi.sq*[3]	*df/ edf*	*Chi.sq*	*df/ edf*	*Chi.sq*	*df/ edf*	*Chi.sq*	*df/ edf*	*Chi.sq*	*df/ edf*	*Chi.sq*
Bottom	1	7.31 **	1	14.19 ***	—	—	1	138 ***	—	—	—	—
Profile	—	—	—	—	—	—	—	—	1	7.78 **	1	7.32 **
te(Visible reef)	1.29	6.54 *	—	—	1.89	40.20 ***	1.76	15.85 ***	0.93	12.68 ***	—	—
te(Depth)	0.81	1.86	2.88	15.85 **	1	20.76 ***	—	—	0.90	8.89 **	—	—
te(Temperature)	—	—	—	—	3.709	48.52 ***	2.93	215.76 ***	2.80	25.64 ***	1.64	4.38
Model deviance	35.69		36.04		77.07		217.43		26.65		14.66	
Phi (ϕ)[1]	1.56		1.63		12.84		11.26		1.31		0.63	
Predicted mean	2.59		5.11		4.08		27.19		2.44		0.70	
Required n	15		8		78		11		14		22	
	Red steenbras				Smooth-hound				Catshark family			
Bottom	—	—	—	—	—	—	—	—	—	—	—	—
Profile	—	—	—	—	—	—	1	11.08 ***	1	1.42	1	6.22 *
te(Visible reef)	—	—	—	—	—	—	—	—	—	—	—	—
te(Depth)	1.22	5.03 .	0.74	2.71 .	1.46	2.74	—	—	—	—	—	—
te(Temperature)	—	—	—	—	—	—	1.22	6.94 *	2.14	3.05	2.79	18.96 ***
Model deviance	19.88		22.88		11.76		24.37		18.60		34.87	
Phi (ϕ)	0.84		0.94		0.50		1.07		0.81		1.57	
Predicted mean	0.50		0.88		0.19		1.27		0.30		1.48	
Required n	41		27		64		21		68		26	

1: Phi = overdispersion parameter

2: df/edf = degrees of freedom for the parametric coefficients and estimated degrees of freedom for the tensor product smooth terms [te(covariate)]

3: Chi-squared, significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

Roman

The most parsimonious model for the RUV data was able to explain 42.5 % of the observed variability in roman MaxN, and included significant effects for the parametric coefficient of *Bottom* ($X^2 = 7.31$, $p<0.01$) and the smooth term for *Visible reef* ($X^2 = 6.54$, $p<0.05$). *Depth* was included in the most parsimonious model, however its effect was not significant ($X^2 = 1.86$, $p>0.1$) (Table 3.6). Average (± SE) MaxN for roman was significantly higher on solid reef (3.0 ± 1.8) compared to patch reef (1.2 ± 1.0). MaxN was predicted to peak when the video frame had 40-50 % reef cover (Fig. 3.9a).

The most parsimonious model for the BRUV data was able to explain 55.8 % of the null deviance in roman MaxN, and included the significant parametric effect of *Bottom* ($X^2 = 14.9$, $p<0.001$), together with the significant smooth term for *Depth* ($X^2 = 15.85$, $p<0.01$) (Table 3.6). MaxN for roman was found to be significantly higher on solid reef (5.9 ± 4.1) compared to patch reef (2.3 ± 1.9). Roman count data was found to increase significantly with depth over the investigated depth range.

Results from the power analysis indicated that to observe a doubling or halving of the roman population, with a statistical power of 0.8 at a significance level of 0.05, 15 samples were required for the RUV method, while only eight were required for the BRUV method (Table 3.6).

Steentjie

The most parsimonious model for the RUV data explained 57.1 % of the null deviance in steentjie MaxN, and included significant smooth terms for *Depth* ($X^2 = 20.76$, $p<0.001$), *Temperature* ($X^2 = 48.5$, $p<0.001$), and *Visible reef* ($X^2 = 40.20$, $p<0.001$) (Table 3.6). MaxN was predicted to correlate positively with increasing *Depth* and *Temperature*. The effect of *Visible reef* indicated that MaxN was expected to be highest when the video had equal coverage of the reef and water column (Fig. 3.9b).

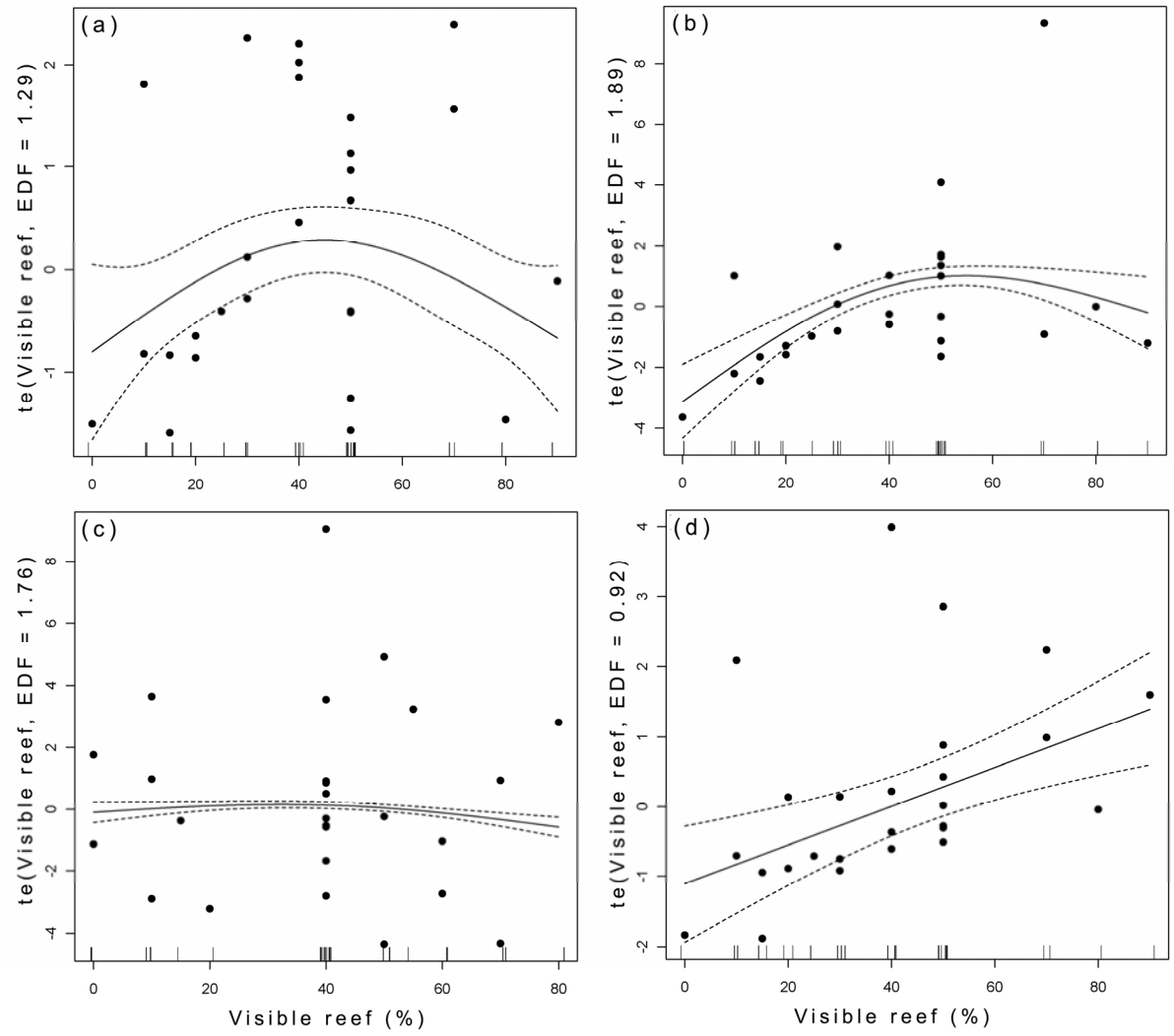

Figure 3.9: Log odds ratio for the effect of *Visible reef* on MaxN of roman (a), steentjie (b), and fingerfins (d) sampled with the remote underwater video (RUV), and steentjie (c) sampled with the baited RUV. The solid line represents the log odds ratio, and the dotted line the 95 % confidence intervals. te = tensor product smooth, EDF = estimated degrees of freedom

The most parsimonious model for the BRUV data was able to explain 61.1 % of the null deviance in steentjie MaxN. The analysis of the BRUV data indicated that solid rock was associated with significantly higher average MaxN of steentjies (30.8 ± 24.9) compared to patch reef (15.2 ± 13.2). A slight, but significant, negative effect of *Visible reef* (X^2 =

15.85, p<0.001) (Fig 3.9c), together with a significant positive effect of *Temperature* (X^2 = 215.76, p<0.001) was evident in the BRUV steentjie data.

There was considerable difference in the number of samples to detect an effect size of two with the BRUV requiring 11 samples and the RUV requiring 78 samples. This can be linked to the very large residual deviance associated with the RUV analysis (RUV phi = 12.8) combined with a low predicted mean MaxN, (4.1 Indi) (Table 3.6). The high residual deviance suggests that an alternative distribution, such as the negative binomial, should have been used to model the steentjie data from the RUV samples. This was attempted, however the negative binomial model appeared to underestimate the variance in the data which would have biased the comparison for the power analysis between the methods. As such, it was decided to retain the Poisson model.

Fingerfin group

The most parsimonious model for the RUV data explained 70.5 % of the null deviance in the count data for the fingerfin group. Fingerfins were significantly (X^2 = 7.78, p<0.01) more abundant on high profile reef (3.7 ± 2.7) compared to low profile reef (0.9 ± 1.0). Fingerfin MaxN increased significantly with increasing *Visible reef* (X^2 = 12.68, p<0.001) (Fig. 3.9d), *Depth* (X^2 = 8.89, p<0.01), and *Temperature* (X^2 = 25.64, p<0.001) (Table 5).

The most parsimonious model for the BRUV method was able to explain 50.9 % of the null deviance, and included the significant parametric effect of *Profile* (X^2 = 7.32, p<0.01). The selected model also included the smoothing term for *Temperature*, although the effect was not significant (X^2 = 4.38, p>0.1). As with the RUV data, high profile reef was characterized by significantly higher MaxN (1.1 ± 0.8) compared to the low profile reef (0.3 ± 0.8).

The results from the power analysis indicated that RUV required 14 samples to be able to detect an effect size of two, while BRUV required 22 samples. This appears to be the exception to the norm, and confirms the observed negative effect of bait on fingerfins.

Red steenbras

The most parsimonious models for the red steenbras data from the RUV and BRUV were very similar (Table 3.6), with only the smoothing term for *Depth* included. The RUV model explained 24.4 % of the null deviance, while the BRUV model explained 13.6 % of the observed variability in MaxN. In both instances *Depth* was found to increase the predicted counts, but not significantly (RUV: $X^2 = 5.03$, $p = 0.058$; BRUV: $X^2 = 2.71$, $p = 0.091$).

Due to the high deviance in the count data, together with a low predicted mean, for both BRUV and RUV the required sample size was large, with 27 and 41 samples required, respectively (Table 3.6). Again, the BRUV method requires considerably lower sampling effort compared to the RUV method.

Smooth-hound

The most parsimonious model for the RUV data was able to explain 31.7 % of the null deviance in smooth-hound MaxN, with only the non-significant smoothing term for *Depth* included in the model ($X^2 = 2.74$, $p>0.2$). The most parsimonious model for the BRUV method explained 45 % of the null deviance in smooth-hound MaxN, with the significant parametric effect of reef *Profile* ($X^2 = 11.08$, $p<0.001$), and the significant smoothing term for *Temperature* ($X^2 = 6.94$, $p< 0.05$). Smooth-hound sharks showed an opposite trend to the bony fish examined with significantly higher MaxN recorded on low profile reef (2.2 ± 1.8) compared to high profile reef (0.5 ± 0.4). The effect of *Temperature* on smooth-hound MaxN was positive.

The power analysis estimated that the minimum number of samples to detect an effect size of two for the BRUV was 21, while 65 samples were needed when sampling with RUV.

Catshark group

The most parsimonious model for the RUV data explained 30.2 % of the null deviance in catshark MaxN, and included the non-significant parametric effect of *Bottom* (X^2 = 1.42, p>0.1), and the non-significant smoothing term for *Temperature* (X^2 = 3.05, p>0.1) (Table 3.6). Although the effect of *Bottom* was not found to be significant the patch reef habitat was characterized by lower average MaxN (0.2 ± 0.2) compared to that of the solid reef habitat (0.3 ± 0.2).

The most parsimonious model for the BRUV MaxN data was able to explain 43.3 % of the null deviance, and included the significant parametric effect of *Bottom* (X^2 = 6.22, p<0.05), together with the significant smoothing term for *Temperature* (X^2 =18.96, p<0.001) (Table 3.6). The MaxN of catsharks was significantly higher on solid reef (1.6 ± 1.1) compared to patch reef (1.0 ± 1.2).

The power analysis produced results similar to those seen from the smooth-hound shark analysis, with 26 samples and 68 samples required by BRUV and RUV (Table 3.6), respectively, to detect an effect size of two with a power of 80 % and at an alpha level of 0.05.

3.4 Discussion

3.4.1 The effect of bait on the optimal deployment time

Numerous deployment times have been selected for past studies that have collected data with RUV and BRUV. For example, Watson et al. (2005) selected deployment times of 15 min, Babcock et al. (1999), Willis and Babcock (2000), Willis et al. (2000, 2003), and Malcolm et al. (2007) deployed their BRUV cameras for 30 minutes, while Harvey et al. (2007), Watson et al. (2007, 2009) and Colton and Swearer (2010) selected 60 min deployment times. This study selected a 60 min deployment time, however the analysis of the accumulation of species from BRUV indicated that only 29 min was required to detect 95 % of the species observed, while 48 min were required to detect 95 % of the species at their maximum abundance. This agrees with past investigations into optimal deployment time of BRUV systems that identified a minimum of 35 min (Stobart et al. 2007) and 36 min (Watson et al. 2007) to detect the majority of the species, while longer deployments of up to 60 min deployments were recommended to comprehensively survey the fish community (Watson et al. 2007). The results from the analysis of RUV indicated that at least 21 min and 35 min were required to record 95 % of the species and 95 % of the species at their maximum abundance, respectively. No past studies have calculated the optimal deployment time for RUV, and the results suggest that considerably shorter deployment times can be used for RUV compared to BRUV.

The agreement between the results from this study and past work adds to the global method development for sampling temperate rocky reef fish communities by means of RUV and BRUV, and promotes the use of 35 minute and 50 minute deployment times, respectively.

3.4.2 The effect of bait on the observed fish community structure

Past research on Rheeders Reef reported 30 species recorded during UVC strip transects and point counts (Bennett 2007; Bennett et al. 2009). The remote video methods sampled 53 species, of which 48 were identified down to species level, 36 % greater than that recorded with both UVC techniques. The BRUV method observed 46 of the 48 recorded species while only 34 species were observed in the RUV footage demonstrating the superiority of the baited video technique. In South Africa, sparid fish show a high degree of endemism (Branch et al. 2010), with 19 endemic species reported from the vicinity of the TNP MPA. The results from this study show that both BRUV (15 species) and RUV (12 species) sample the same endemic species as efficiently as UVC (13 species) (Bennett 2007). The sharks, skates and rays sampled by the remote video techniques accounted for most of the observed difference in species richness compared to the UVC. Bennett (2007) reported only two cartilaginous species with UVC, while RUV recorded seven, and BRUV recorded 13 cartilaginous species. Colton and Swearer (2010) report similar results, with elasmobranchs accounting for the higher taxonomic distinctness in BRUV compared to UVC samples. While these results show strong support for BRUV compared to UVC for monitoring reef fish in the Agulhas Ecoregion, the comparison may not be completely justified as variation in environmental variables between surveys may have influenced the species observed. A more direct answer to this question is presented in the results from two comparative method assessments found in Chapter 5.

Only one other study has directly compared the ability of BRUV and RUV to sample different trophic components of the demersal fish community. While Harvey et al. (2007) identified that bait had little effect on the observed abundance of herbivorous and omnivorous fish species, they identified a significant positive effect on the count data for piscivores, generalist carnivores, microinvertebrate carnivores and invertebrate carnivores sampled in temperate waters. The results from this study are generally in

agreement, with counts from all but one of the trophic guilds being higher when sampled with bait.

The BRUV method was originally developed to survey fisheries target species that were under-sampled by methods that did not rely on the attraction of bait (Babcock et al. 1999; Willis and Babcock 2000). The results from this study demonstrate that the BRUV method is able to sample species considered as primary and secondary fisheries targets in the temperate regions of South Africa at higher abundances than the RUV method. Interestingly, much of the observed effect with the primary fisheries species was attributed to the dominant roman, while the scarcer species such as red steenbras, dageraad and red stumpnose, showed only a slight response to the presence of bait. However, the BRUV was able to survey both the red steenbras and dageraad more effectively (lower SD relative to the mean – CV) indicating that it was a superior method to the RUV for surveying these important fisheries species. Red steenbras has been listed as threatened in South Africa, while dageraad is considered to be vulnerable (Sink et al. 2012), and as such the BRUV method is a suitable non-destructive method to monitor the relative abundance of these species.

The exception to the typically positive response to bait was with the microinvertebrate carnivore group that showed a 39 % drop in abundance when bait was present. A similar, but less distinct trend was evident in the non-target species from the analysis of species grouped by fisheries importance. This was mostly attributed to the fingerfins that were three times more abundant in the absence of bait. Harvey et al. (2007) found that temperate microinvertebrate species were significantly better sampled by BRUV than RUV, while there was no significant difference in the abundance estimates for the algae/invertebrate feeders or the true herbivores. These contrasting results may reflect differences in the structure and behaviour of the fish communities and oceanographic conditions. Although Harvey et al. (2007) did not report the average visibility observed during their study, they were able to identify fish up to seven meters away from the camera, suggesting that it was generally greater than the four-meter average recorded in this study. Harvey et al. (2007) found that many of the herbivorous and omnivorous

species could be seen in the background of the BRUV footage, and it is likely that the better visibility aided identification. In this study the density of fish, particularly steentjies, around the bait container often obscured the view of the background, while the poor visibility eliminated the possibility of observing and correctly identifying species present, but not attracted to the bait. This effect was likely compounded by avoidance behaviour by the non-carnivorous species, such as the fingerfins, cape knifejaw *Oplegnathus conwayi*, zebra *Diplodus hottentotus* and janbruin *Gymnocrotaphus curvidens*, in response to the high level of activity of predators at the bait container.

In comparison to UVC, RUV appears to be a reliable method at obtaining an unbiased abundance estimates for the dominant and conspicuous reef fish species (Francour et al. 1999). Compared to past data collected in the TNP MPA by UCV (Bennett 2007) the RUV method appears to under-sample the dominant microinvertebrate carnivore species, the twotone fingerfin *Chirodactylus brachydactylus* and barred fingerfin *Cheilodactylus pixi*, which are better surveyed by UVC. Simultaneously, RUV appears better at surveying the scarcer redfingers *Cheilodactylus fasciatus*, cape knifejaw, and janbruin. Considering that RUV typically surveyed less than 10 m^2 it is unrealistic to expect that the method should produce similar count data as UVC expressed over 100 m^2. When the survey areas are standardised the results show considerably lower counts from UVC than RUV. For example, steentjie is 100 times more abundant, red steenbras 33 times and roman, cape knifejaw, and janbruin are ten times more abundant in RUV data compared to UVC data. A combination of factors, including an underestimate of the survey area in RUV, and a combination of avoidance and attraction to divers during UVC, may have contributed to this disparity.

It is well documented that a number of factors contribute to inaccuracies in UVC count data (Edgar et al. 2004), however the consistently higher abundance in RUV data suggests that other factors were at play. Water visibility during dive surveys in the TNP MPA is typically in the region of four meters (ATF Bernard *pers. obs*.) and as a result

the visibility calculations from this study (mean = 3.85 m) appear realistic. Alternatively, it is possible that MaxN is not a suitable measure of abundance for RUV data, overestimating the number of fish in the visible area, and restricting the ability to calculate density.

One of the strengths of the BRUV over the RUV method is its ability to sample the cartilaginous components of the fish community (Cappo et al. 2004; Brooks et al. 2011). This was clearly demonstrated by the five-fold increase in abundance of cartilaginous generalist carnivores when bait was included as an attractant. Very few methods have a similar ability to sample shallow subtidal rocky reef shark populations. Controlled angling (CA) has been employed to survey the fish communities in the TNP (Bennett 2007) and the Goukamma MPAs (Götz 2005), but in both instances insufficient sharks were captured to warrant independent assessments of their populations. Most catsharks occurring on temperate rocky reefs in South Africa are endemic to the region (Branch et al. 2010), and recent reports suggest that there have been declines in the abundance of striped catsharks, *Poroderma africanum* (Sink et al. 2012). Considering this, there is a need to monitor future changes in this species' population and BRUV may offer an ideal, non-destructive sampling tool.

Consistently higher abundance is a convenient characteristic of data for analysis as it is associated with proportionally smaller variation around the mean (Thompson and Mapstone 1997), while at the same time it is less likely to be zero-inflated (Cunningham and Lindenmayer 2005). For trends in data to be significant, the variability around the mean needs to be low, i.e. have a low noise to signal ratio (Vos et al. 2000). Consequently, methods that consistently sample species at high abundances would improve diagnostic capability in long-term monitoring. As such, the higher counts per species recorded with BRUV compared directly to RUV, and indirectly to UVC and CA, suggest that it is a preferable tool for long-term monitoring.

The reduced variability around a mean described above was clearly evident in the power analysis for the individual species which favoured BRUV for all species except

the fingerfins. Considering the specific species analysed during this study, a BRUV survey would require 27 samples to detect a doubling or halving of the populations while a RUV survey would require 78 samples to collect sufficient data with a similar diagnostic power. Bennett et al. (2009), employing the same power analysis procedure, found that to efficiently sample the roman population with UVC or CA a minimum of 15 and 12 samples were required to detect a doubling or halving of the population, respectively. The results from this study suggest that RUV would require the same number of samples as UVC (n = 15) while BRUV was most efficient, requiring only eight samples to efficiently sample the roman population.

The extensive post-sampling analysis time has been identified as a weakness of BRUV (Cappo et al. 2003; Colton and Swearer 2010). In this study, BRUV samples required 5.7 (± 2.3) hours to extract the MaxN data. This equates to 7.0 hours to complete one station with the 50 minute optimal deployment time and 30 minutes to move between stations, deploy and retrieve the camera system. On the other hand, the RUV method required considerably shorter post-sampling analysis time with data extraction taking on average 2.4 (± 1.3) hours, with a complete sampling time of 3.5 hours. Extrapolating this sampling time by the number of samples required to detect a doubling or halving of the roman population, the total sampling effort required was 56.1 and 52.1 hours for BRUV and RUV, respectively. This suggests that RUV may in fact be a more time efficient tool to survey common and conspicuous fish species. As a core function of biological monitoring is to collect accurate and precise data, intensive post-sampling time should not be considered as a weakness, especially if higher diagnostic power is the end result. Furthermore, sea-time is considerably more expensive, and dependant on suitable weather conditions, than laboratory time. Thus, the consistently high diagnostic power from fewer samples for multiple species achieved by BRUV overrides the cost of greater overall sampling effort.

The response to bait was non-systematic between the different trophic guilds, with a much larger effect evident with the invertebrate carnivores compared to the generalist carnivores. Again, this pattern was also represented in the analysis of the species grouped by fisheries importance. Similarly, the analysis at species level illustrated the scale of the response from a twofold to a fivefold increase in abundance, while the response was not always positive with a threefold decrease seen with the fingerfins. This highlights a non-systematic effect of bait on the observed fish community, with certain groups of species responding more rapidly and from further away than others. From a sampling perspective, the variable speed of response can be accounted for by selecting the optimal deployment time, however, the distance that a fish is willing to move in search of food can't be controlled and complicates the calculation of absolute density as the survey area will not be consistent within a set plume area for different species. If BRUV data are to be standardised the area of attraction should be considered at the species level, while the change in abundance between BRUV and RUV samples (i.e. the effect size measured in this study) may provide sufficient information to infer the area of attraction. However, further effort needs to be invested to determine an ecologically realistic measure of abundance from which density can be estimated for RUV data.

Both remote video methods are prone to biases that will reduce their sensitivity to detect long-term changes in fish communities. With BRUV this is because the MaxN is a conservative estimate of abundance (Willis and Babcock 2000; Cappo et al. 2004), while for RUV it is because the natural variability is not dampened by the attraction of bait. An indirect approach to measure the sensitivity of a method to detect changes in species abundance is to use known patterns of spatial variation of species abundance, either related to habitat type (structurally complex vs. structurally simple reef) or management status (protected vs. exploited). In this regard BRUV appeared considerably more sensitive than RUV to detect spatial variability associated with habitat type, which is known to influence the abundance of different fish species in the Agulhas Ecoregion of South Africa (Götz et al. 2008). Watson et al. (2005) and Harvey

et al. (2007) found similar results when comparing the efficiency of baited and unbaited video techniques at detecting differences between various subtidal habitats.

Cappo et al. (2004) noted that variability in water visibility had a dramatic effect on BRUV performance. The effect was not directly assessed in this study, however it is noted that low visibility will reduce the sensitivity of data collected by both remote video methods. For the BRUV low visibility will increase the chance of saturating the field of view, while for the RUV the visible area will shrink thereby reducing abundance estimates and increasing the chance of zero counts. In structurally complex habitats the percentage cover of reef in the frame of view of the remote camera system will vary between samples. This study indicates that the amount of reef in the video footage affects the community composition and abundance of specific species seen when sampling with RUV and to a lesser degree with BRUV. This methodological bias has an ability to introduce undesirable uncertainty into the data and should be accounted for during the data analysis, particularly when using RUV.

3.4.3 Conclusions

The BRUV appears to be a promising method to survey subtidal reef fish communities along the South African coastline. It offers an effective, fishery independent tool to monitor species that were previously ignored. Although stereo-BRUV was not employed in this study, the additional benefits of this approach are well documented (Watson et al. 2005, 2010; Langlois et al. 2010, 2012b; Harvey et al. 2012). Stereo-BRUV provides a standard method to survey fish throughout their depth distribution and provides accurate length estimates to investigate stock status. The RUV approach is very appealing as it is the closest one can get to a non-invasive method, but the required number of samples to obtain data with a high statistical power is unfeasible for long-term monitoring programmes. Consequently, the benefits gained by sampling the fish community under natural conditions (i.e. with RUV) do not outweigh those obtained by

altering the community through the presence of bait, while the efficiency of BRUV at surveying a broader range of species makes it the preferred remote video method. However, in combination, the two methods offer a highly effective monitoring suite that will outcompete all other subtidal monitoring techniques, including UVC and CA.

3.5 Appendices

3.5.1 Appendix 3.1: Species classification criteria

Class	Family	Scientific name	Common name	Fisheries importance	Trophic guild
Osteichthyes	Ariidae	*Galeichthys feliceps*	White seacatfish	Tertiary	Generalist carnivore
	Carangidae	*Seriola lalandi*	Giant yellowtail	Primary	Piscivore
		Trachurus trachurus	Maasbanker	Tertiary	Zooplanktivore
	Chaetodontidae	*Chaetodon marleyi*	Doublesash butterflyfish	Aquarium	Microinvertebrate carnivore
	Cheilodactylidae	*Cheilodactylus fasciatus*	Redfingers	non-Target	Microinvertebrate carnivore
		Cheilodactylus pixi	Barred fingerfin	non-Target	Microinvertebrate carnivore
		Chirodactylus brachydactylus	Twotone fingerfin	Tertiary	Microinvertebrate carnivore
	Gobiesocidae	*Chorisochismus dentex*	Rocksucker	non-Target	Microinvertebrate carnivore
	Haemulidae	*Pomadasys olivaceum*	Piggy	Tertiary	Invertebrate carnivore
	Oplegnathidae	*Oplegnathus conwayi*	Cape knifejaw	Secondary	Omnivore
	Parascorpididae	*Parascorpis typus*	Jutjaw	non-Target	Zooplanktivore
	Sciaenidae	*Atractoscion aequidens*	Geelbek	Primary	Piscivore
	Scombridae	*Scomber japonicus*	Chub mackerel	Tertiary	Zooplanktivore
	Serranidae	*Acanthistius sebastoides*	Koester	non-Target	Generalist carnivore
		Epinephelus marginatus	Yellowbelly rockcod	Primary	Generalist carnivore
	Sparidae	*Argyrozona argyrozona*	Carpenter	Primary	Generalist carnivore
		Boopsoidea inornata	Fransmadam	Secondary	Generalist carnivore
		Cheimerius nufar	Santer	Primary	Generalist carnivore
		Chrysoblephus cristiceps	Dageraad	Primary	Generalist carnivore
		Chrysoblephus gibbiceps	Red stumpnose	Primary	Generalist carnivore
		Chrysoblephus laticeps	Roman	Primary	Generalist carnivore
		Diplodus capensis	Blacktail	Secondary	Omnivore
		Diplodus hottentotus	Zebra	Secondary	Omnivore
		Gymnocrotaphus curvidens	Janbruin	Secondary	Omnivore
		Lithognathus mormyrus	Sand steenbras	Tertiary	Invertebrate carnivore
		Pachymetopon aeneum	Blue hottentot	Primary	Invertebrate carnivore
		Pachymetopon blochii	Hottentot	Primary	Generalist carnivore
		Pachymetopon grande	Bronze bream	Secondary	Omnivore
		Pagellus bellottii natalensis	Red tjor-tjor	Tertiary	Microinvertebrate carnivore
		Petrus rupestris	Red steenbras	Primary	Generalist carnivore
		Pterogymnus laniarius	Panga	Secondary	Generalist carnivore
		Rhabdosargus globiceps	White stumpnose	Primary	Invertebrate carnivore
		Rhabdosargus holubi	Cape stumpnose	Tertiary	Invertebrate carnivore
		Sarpa salpa	Strepie	Tertiary	Herbivore
		Sparodon durbanensis	White musselcracker	Primary	Invertebrate carnivore
		Spondyliosoma emarginatum	Steentjie	Secondary	Invertebrate carnivore
	Tetraodontidae	*Amblyrhynchotes honckenii*	Evileye blaasop	By-catch	Generalist carnivore
Condrichthyes	Carcharhinidae	*Carcharhinus brachyurus*	Copper shark	Tertiary	Piscivore
		Mustelus mustelus	Smooth-hound	By-catch	Generalist carnivore
		Carcharhinidae spp.	Requiem shark spp.	Tertiary	Generalist carnivore
		Triakis megalopteris	Spotted gullyshark	By-catch	Generalist carnivore
	Dasyatidae	*Dasyatis brevicaudata*	Shorttail stingray	Tertiary	Invertebrate carnivore
		Gymnura natalensis	Diamond ray	By-catch	Invertebrate carnivore
		Dasytidae spp.	Stingray spp.	By-catch	Invertebrate carnivore
	Hexanchidae	*Notorynchus cepedianus*	Spotted sevengill cowshark	Tertiary	Generalist carnivore
	Myliobatidae	*Myliobatis aqulia*	Eagleray	Tertiary	Invertebrate carnivore
		Pteromylaeus bovinus	Duckbill ray	Tertiary	Generalist carnivore
	Rhinobatidae	*Rhinobatos annnulatus*	Lesser guitarfish	By-catch	Invertebrate carnivore
	Scyliorhinidae	*Scyliorhinidae spp.*	Catshark spp.	By-catch	Generalist carnivore
		Haploblepharus edwardsii	Puffadder shyshark	By-catch	Generalist carnivore
		Haploblepharus pictus	Dark shyshark	By-catch	Generalist carnivore
		Poroderma africanum	Striped catshark	By-catch	Generalist carnivore
		Poroderma pantherinum	Leopard catshark	By-catch	Generalist carnivore
	Sphyrnidae	*Sphyrna spp.*	Hammerhead	By-catch	Generalist carnivore
Agnatha	Myxinidae	*Eptatretus hexatrema*	Six-gill hagfish	By-catch	Generalist carnivore

3.5.2 Appendix 3.2: Summary tables from the community level GLMMs

3.5.2.1 Effect of bait on the abundance of species grouped by Fisheries importance.

Summary of model fit

	DF	Deviance	Residual DF	AIC
Full/ most parsimonious model	18	1337	722	1373

Summary of random effects

Groups	Name	Variance	Std.Dev.	Corr
Species:Sample	Method: RUV	0.64	0.80	
	Method: BRUV	1.08	1.04	0.84
Sample	Method: RUV	1.35	1.16	
	Method: BRUV	0.31	0.56	0.72

Number of obs: 740, groups: Species:Sample, 370; Sample, 27

Summary of fixed effects

Fixed effects	*log(Odds ratio)*	*SE*	*Z-value*	
Intercept (RUV: (1) Non-target)	-4.02	0.47	-8.62	***
BRUV: (1) Non-target	0.14	0.58	0.24	
RUV: (2) By-catch	-0.92	0.38	-2.40	*
RUV: (3) Tertiary	0.26	0.30	0.86	
RUV: (4) Secondary	0.93	0.28	3.35	***
RUV: (5) Primary	0.66	0.28	2.32	*
RUV: Visible reef	0.04	0.01	5.56	***
BRUV: (2) By-catch	2.51	0.53	4.70	***
BRUV: (3) Tertiary	1.01	0.48	2.10	*
BRUV: (4) Secondary	1.93	0.45	4.26	***
BRUV: (5) Primary	1.58	0.46	3.46	***
BRUV: Visible reef	-0.02	0.01	-2.98	**

Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

3.5.2.2 Effects of bait on the abundance of species grouped according to their Trophic guild.

Summary of model fit

	DF	Deviance	Residual DF	AIC
Full model/ most parsimonious model	20	1311	720	1351.00

Summary of random effects

Groups	Name	Variance	Std.Dev.	Corr
Species:Sample	Method: RUV	0.61	0.78	
	Method: BRUV	1.08	1.04	0.80
Sample	Method: RUV	1.56	1.25	
	Method: BRUV	0.51	0.72	0.68

Number of obs: 740, groups: Species:Sample, 370; Sample, 27

Summary of fixed effects

Fixed effects	log(Odds ratio)	SE	Z-value	
Intercept (RUV: (1) Bony-Omnivore)	-3.60	0.40	-8.91	***
BRUV: (1) Bony-Omnivore	1.26	0.40	3.13	**
RUV: (2) Bony-MicroInvertebrate carnivore	0.33	0.24	1.37	
RUV: (3) Bony-Invertebrate carnivore	0.72	0.22	3.26	**
RUV: (4) Bony-Generalist carnivore	0.51	0.21	2.48	*
RUV: (5) Cartilaginous-Invertebrate carnivore	-0.90	0.54	-1.66	.
RUV: (6) Cartilaginous-Generalist carnivore	-1.16	0.33	-3.46	***
RUV: Visible reef	0.04	0.01	5.18	***
BRUV: (2) Bony-MicroInvertebrate carnivore	-0.84	0.29	-2.86	**
BRUV: (3) Bony-Invertebrate carnivore	1.08	0.23	4.70	***
BRUV: (4) Bony-Generalist carnivore	0.43	0.22	1.91	.
BRUV: (5) Cartilaginous-Invertebrate carnivore	0.47	0.62	0.76	
BRUV: (6) Cartilaginous-Generalist carnivore	1.43	0.35	4.03	***
BRUV: Visible reef	-0.02	0.01	-3.23	**

Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

Chapter 4

Assessment of fish traps to monitor reef fish in the Agulhas Ecoregion of South Africa

4.1 Introduction

Long-term monitoring (LTM) programmes are a prerequisite for the conservation and effective management of reef ecosystems and commercially important fish and invertebrate species (Suchanek 1994; Vos et al. 2000; Yoccoz et al. 2001). However, LTM is a costly endeavour, and to be effective it requires the financial commitment of management institutions (Vos et al. 2000). Data collection represents a substantial part of the cumulative costs of a LTM programme. However, there is a degree of flexibility in this cost, as it will depend on the method selected, the effectiveness of the method and the sampling approach chosen (Vos et al. 2000). An obvious area to reduce cost would be to optimise the method performance and calculate the intensity of sampling required to ensure the precision of the data meets a minimum statistical power (Ward and Jacoby 1992; Vos et al. 2000; Yoccoz et al. 2001). First though, this requires selection of a suitable method or suite of methods.

Ideally the objectives of the monitoring programme should suggest which methods are suitable. However, within a group of chosen methods, the cost of collecting data will influence the selected method. A number of different sampling methods have been employed to monitor the reef fish communities within marine protected areas (MPAs) around the world. These include underwater visual census (UVC) transects (Edgar and Barrett 1999; Bennett et al. 2009; Edgar et al. 2009) or point-counts (Götz et al. 2007), diver operated video transects (Langlois et al. 2010), remote underwater video (RUV) (Francour et al. 1999; Watson et al. 2009), baited RUV (BRUV) (Willis et al. 2003; Langlois et al. 2011; McLean et al. 2011), controlled angling (CA) (Götz et al. 2007), and fish-trapping (FT) (Locham et al. 2010). Of these methods CA and fish-trapping have the lowest financial costs to establish the research capabilities and require little specialised training to conduct the surveys, compared to UVC and BRUV (Sheaves 1995; Bennett et al. 2009). In addition, with the former, the laboratory time is minimal compared to that required to analyse video footage collected during BRUV surveys (Colton and Swearer 2010). Both, CA and FT allow (i) accurate measurements of the

fish length, (ii) collection of genetic samples, and (iii) tagging of fish if required (Sheaves 1993; Recksiek et al. 1991). While, the size of fish can be estimated using both UVC and stereo-RUV stations, the size data collected by divers underwater is imprecise (Harvey et al. 2002). In addition, the number of measurements at each station for RUVs is limited to the maximum number of each species seen in one frame during the video (Watson et al. 2009). Average fish length is highly sensitive to fishing pressure, as the largest fish are typically removed first, leaving only the smaller ones behind (Boehlert 1996; Birkeland and Dayton 2005). However, lack of precision or insufficient data will reduce the confidence around the mean and make detection of fishery effects difficult. Both CA and FT can provide precise measurements, and are considered suitable for fisheries monitoring. However, two recent publications (Langlois et al. 2012b; Harvey et al. 2012) have demonstrated that stereo-BRUV can produce equivalent, if not better, data for species of fisheries importance, compared to CA and FT.

Table 4.1: Comparison of past results showing the relative contribution (%) of roman, fransmadam and steentjie to the total sampled community using controlled angling (CA) and underwater visual census (UVC) in the Agulhas Ecoregion of South Africa.

			CA		UVC	
Family	Common name	Scientific name	Gotz et al. (2007)	Bennett et al. (2009)	Gotz (2005)	Bennett et al. (2009)
Sparid	roman	*Chrysoblephus laticeps*	50.6	68.1	6.7	9.3
Sparid	fransmadam	*Boopsoidea inornata*	21.6	13.3	33.5	20.9
Sparid	steentjie	*Spondyliosoma emarginatum*	5.8	6.1	27.8	9.6

Controlled angling is considered suitable for monitoring the reef fish communities within MPAs in the Agulhas Ecoregion of South Africa (Götz et al. 2007; Bennett et al. 2009). Although the method is very efficient at sampling the dominant large sparid, roman *Chrysoblephus laticeps*, it is highly selective and sampled very few of the other species. Underwater visual census surveys from the same areas have shown this dominance of roman in CA data to be disproportionate to its relative abundance within the community,

as smaller sparids, such as fransmadam *Boopsoidea inornata* and steentjie *Spondyliosoma emarginatum* are more abundant (Götz 2007; Bennett et al. 2009) (Table 4.1).

The high abundances of roman in the CA data can be attributed to the dominance of the species over the other smaller or scarcer species (Götz et al. 2007). Furthermore, this pattern is compounded by the necessity to standardise methods, which meant that in Bennett et al. (2009), CA was restricted to one hook size (size = 4/0 = large) and bait type (sardine *Sardinops sagax*), which reduced the catchability of smaller fish or those that are more readily caught on other bait types. If the objective of a programme was to monitor the populations of roman then CA would be a highly effective method, however if the programme wished to infer more broader community level changes an alternate method would have to be selected.

Fish trapping is a very common fishing method on shallow reefs, particularity in the rural artisanal fisheries around the world (Rechsiek et al. 1991; Hawkins et al. 2007; Locham et al. 2010). While there is a considerable amount of literature looking into the dynamics of trap fisheries (Recksiek et al. 1991; Fogarty and Addison 1997), particularly in the Antilles (Munro et al. 1971; Munro 1974; Miller and Hunte 1987; Gobert 1998; Robichaud et al. 2000), very few studies have applied traps as a fisheries independent monitoring tool. Past fisheries independent research with FT have investigated distribution patterns of fish between habitats within estuaries (Sheaves 1992, 1993), as well as the effects of habitat, spatial and temporal variability on the nearshore fish communities (Thrush et al. 2002; Travers et al. 2006; Locham et al. 2010).

Although baiting of traps is rare in the artisanal trap fisheries (Munro et al. 1971; Recksiek et al. 1991), most of the studies using traps as a fisheries independent tool for community monitoring use bait to attract fish as it reduces the required soak time (Sheaves 1992; Travers et al. 2006). The soak time, referring to the time that the trap is left submerged in the water, for trap fisheries varies between 24 hours to a fortnight. For these extended deployments it has been shown that bait only attracts fish for the first

two days and after that the catch drops due to mortality or escapement (Munro et al. 1971; Munro 1974). In the examples from the fisheries independent studies with baited traps, soak time ranged from short, 20-minute deployments (Thrush et al. 2002) to long, two-day deployments (Sheaves 1992). Fish traps are highly unselective (Hawkins et al. 2007) and as a result species diversity within the catch can be high. However, Robichaud *et al*. (2000) found that the presence of piscivores in and around unbaited traps reduced the abundance of lower trophic guild species in the traps. With the baited traps these piscivores and generalist carnivores are expected to be more abundant (Sheaves 1992; Travers et al. 2006). As a result, bait may reduce the species richness from FT samples.

Although it is likely that unbaited traps would record higher species richness, the variability in the data would be high due to spatial and temporal variation in the population, together with behavioural interactions within the fish community. Conversely, the baited traps target the carnivorous and piscivorous portion of the community and attract these fish to the traps, thereby increasing the chance of capture and dampening the effect of spatial variability in the populations.

A number of studies have investigated the effect of design on the performance of FT. Fish traps come in a number of shapes and sizes but the underlying principle is the same, with metal or wooden frames covered by wire mesh or netting and with one or more funnel shaped entrances. Most often the traps are rectangular in shape (Thrush et al. 2002; Travers et al. 2006), however, alternate designs based on the original artisanal fisheries traps are also used (Sheaves 1992). The shape and size of the FT does appear to influence the number of species and the abundance of fish captured. For example, Collins (1990) found that chevron shaped traps performed better than rectangular or square shaped traps, but the comparison may have been confounded as the traps were of different sizes. Trap size has been found to increase the catch of fish (Sheaves 1995) and invertebrates (Boutillier and Sloan 1987). As a result the increased catch in the chevron traps may be an artefact of their larger size. Sheaves (1995) found that larger Antillean (or Z-shaped) traps were better for sampling only certain species,

and recommended the use of smaller traps because of practical advantages. The number of entrances to a trap was not found to have a significant effect on the catch of prawns (Boutillier and Sloan 1987), while the funnel size determined the maximum size of fish that could enter the trap. Kennelly (1989) determined that maximum catch-per-unit-effort (CPUE) for spanner crabs was reached within 60 minutes. Similarly, Collins (1990) and Sheaves (1995) recommended soak times of one to two hour and two hours, respectively, to survey subtidal and estuarine fish communities.

No literature could be found on the application of FT to conduct fisheries independent surveys in South Africa. Currently there is research being conducted on the deep reef pinnacles on the Agulhas Bank by the Department of Agriculture, Forestry and Fisheries (DAFF, Dr S Kerwath *pers. com.*). On the offshore reefs (30-100 m depth), the researchers faced a similar problem to that encountered on the nearshore reefs (10-30 m depth), with one species, namely carpenter *Argyrozona argyrozona*, dominating the catch during CA surveys. To overcome this, FT were employed to sample a wider range of fish species, and at greater depths than what is safe for UVC.

4.1.1 Study Aim

The aim of this study was to assess the feasibility of using FT to sample the nearshore reef fish community in the Agulhas Ecoregion of South Africa.

4.1.2 Study objectives

The objectives of the research included:

1. Calculate optimal soak times
2. Compare the effect of different entrance diameters on catch
3. Compare the effect of entrance diameter on the size of captured fish, and
4. Investigate patterns of variability in the data through power analysis

4.2 Materials and methods

4.2.1 Study site

The research was conducted in the Tsitsikamma National Park (TNP) MPA. See Chapter 2, section 2.2.1 (Fig. 2.1a, d, e) for the relevant details on the study area.

4.2.2 Site stratification

The sampling area was stratified according to reef depth and profile as per Chapter 2, sections 2.2.2 and 2.2.3.

4.2.3 Fish traps

4.2.3.1 Setup

The fish traps used during this study consisted of a rectangular galvanised steel frame (100x50x50 cm) wrapped in fine mesh chicken-wire (mesh diameter = 1-1.5 cm) (Fig. 4.1). The one end consisted of an inward pointing funnel made from the same chicken-wire, and the opposite end was a trap-door allowing for easy retrieval of the fish and bait from the trap (Fig. 4.1). Two funnel designs were used during the study, differing only in the diameter of the entrance to the trap. The large entrance (Trap A) had a diameter of 15 cm, while the small entrance (Trap B) had a diameter of 10 cm. Both funnel types started with a radius of 40 cm and were 25 cm long. The frame was supported by crossbeams in the middle of the trap, and the intersection was the attachment point for the bait container (Fig. 4.1). The bait container was a perforated PVC canister designed to hold one kilogram of crushed sardine. Four traps were used in the study, two replicates per trap design.

Figure 4.1: The fish trap used during the study. The locations of the entrance, bait container and trap door are indicated. The typical catch is evident, consisting of striped catsharks *Poroderma africanum* and steentjies *Spondyliosoma emarginatum*.

4.2.3.2 Deployment and processing

Fish traps were deployed off a small semi-rigid inflatable power-boat (5.5 m). The position of a trap was marked by a surface buoy tethered to the trap with a sinking rope. As the trap was independent of the boat, multiple deployments could be conducted simultaneously thereby maximising the number of deployments per sampling day.

The traps were retrieved after a predefined soak time and the fish were removed from the FT and placed in a seawater filled holding container for processing. Each individual was identified to species level and the fork length measured to the nearest millimetre. Prior to release, the condition of the fish were recorded to estimate the impact of the extractive monitoring technique on the fish. The fish were classified as damaged (those showing noticeable scale loss or fin tearing), and not damaged (those showing no signs of external physical damage). Mortalities were classed as those fish that floated on the

surface following release. It is likely that this is an under estimate of mortality as damage and stress incurred during capture may have weakened the fish and made them more vulnerable to infection or predation after release.

4.2.4 Sampling strategy

Sample site selection was based on the stratified random scheme described in Chapter 2, section 2.2.2 and 2.2.3. Each FT was deployed at a selected station for a predetermined soak time. The soak times ranged from 30 minutes to three hours. The predetermined soak times were selected according to a stratified (by trap design and sequential 30min time increments) random approach. This ensured an even distribution of deployments between trap designs and over the three hour soak time.

4.2.5 Data analysis

4.2.5.1 Environmental covariates

Water temperature (average temperature recorded during the deployment) was recorded using a submersible temperature logger (HOBO Temperature Logger - Onset Computer Cooperation) attached to each fish trap. Deployment depth was recorded off the echo sounder mounted on the boat. Bottom type and reef profile were inferred from the bathymetric maps (see Chapter 2, Fig. 2.1e).

4.2.5.2 Optimal soak time

The *Optimal soak* time was determined by predicting the time at which the catch per unit effort for species (species CPUE) and for total number of fish (CPUE) peaked. To aid interpretation of the species CPUE and CPUE results, the effect of *Soak time* on the number of species and the total number of fish captured was also modelled (Table 4.2).

A detailed exploratory analysis was conducted prior to the data analysis, following the approach of Zuur et al. (2010). See Chapter 2, section 2.1.9.1 for more information. The

exploratory analysis revealed that the response variables (Table 4.2), showed strong non-linear variation with *Soak time*, *Temperature* and *Depth*. As a result the data analysis was conducted with Poisson generalised additive models (GAMs). See Chapter 3, section 3.2.5.4 for the detailed description of the GAM.

Table 4.2: Description of the response variables used for the calculation of the optimal soak time, together with the factorial and continuous covariates considered for inclusion in the generalised additive models.

Name	Description	Levels
Response variables		
number of species	The number of species caught per sample	
species CPUE	The number of species caught per hour	
total catch	The number of fish caught per sample	
CPUE	The number of fish caught per hour	
Factorial covariates		
Bottom	Substratum type	Rock/ Sand
Profile	Reef profile, referring to the structural complexity of the reef	High/ Low
Continuous covariates		
Soak time	Duration that the FT is deployed	
Temperature	Water temperature	
Depth	Water depth	

For all GAMs, the discrete covariates (*Bottom* and *Profile*) were included as parametric coefficients, while the continuous variables (*Soak time*, *Temperature* and *Depth*) were fitted with a tensor product smooth with the thin plate regression spline basis-penalty (Wood 2011).

Optimal *Soak time*s were estimated as the peak in response variables. Estimated regression coefficients will vary under different model specifications. As a result replicate coefficient vectors (n = 1000) were estimated via posterior simulation, and for each replicate the time at which the peak in the response variable was obtained (Wood 2011). The optimal *Soak time* was then given as the mean ± 95 % confidence intervals (CI) of these peaks.

4.2.5.3 Species abundance and size

Incorporating the optimal *Soak time* calculated above, the average catch (number of species and individuals) was predicted with the coefficients from the Poisson GAM analysis. Comparisons between the catch were facilitated by comparing the approximate CI, calculated from the model predictions (μ ± 1.96 x SE).

To calculate the effect of *Trap design* on the length of the captured fish, the data were split according to species, with only species that were recorded in more than three replicate samples for both *Trap designs* included in the analysis. The lengths were then compared between Trap A and Trap B with non-parametric Mann-Whiney U-tests. Due to the few samples for certain species the non-parametric tests were preferred to parametric statistical methods.

4.2.5.4 Data variability and power analysis

The statistical power of the data collected by the trapping method was calculated following the approach of Willis et al. (2003) and described in detail in Chapter 3 (section 3.2.5.4).

Where necessary, the variability in the count data was further investigated using the Coefficient of Variation (CV; McArdle et al. 1990). See Chapter 3, section 3.2.5.4 for more details.

4.2.5.5 Graphical representation

All data were visualised with trellis plots from the lattice and latticeExtra packages in R (Sarkar 2008).

4.3 Results

4.3.1 Environmental characteristics

A total of 135 fish trap samples was collected (Table 4.3) between June 2008 and June 2009, on three separate sampling trips (winter 2008 and 2009, and summer 2009) to the TNP MPA. The majority of the samples were collected on reef, reflecting the dominance of the hard substratum within the survey area (see Chapter 2, Fig. 2.1e). The distribution of samples between high and low profile reef was more or less even for both Trap A and Trap B (Table 4.3).

Table 4.3: Description of the sampling effort and the distribution of the samples between the different factorial covariates.

		Trap A	Trap B
Total deployments		69	66
Bottom	Rock	60	54
	Sand	9	12
Profile	High	32	37
	Low	37	29

Soak time ranged between half an hour and three hours for both trap designs (Table 4.4). The average *Soak time* was 1.5 hours for both designs, resulting from a balanced distribution of samples along the continuous time period. Water temperature was slightly cooler than what is typically observed for the region, averaging (± SD) 13.6 (± 2.6) °C and 13.7 (± 2.6) °C during the deployments of Trap A and Trap B, respectively. For both trap designs the samples were collected from depths between 6.5 m and 35.0 m, with an average depth of 20.2 (± 7.6) m and 21.0 (± 8.3) m for Trap A and Trap B, respectively (Table 4.4).

Table 4.4: Summary of the continuous covariates measured during the trap deployments. *Soak time*s and deployment depths were stratified to ensure a balanced experimental design.

		mean	SD	min	max
Soak time (hours)	Trap A	1.52	0.77	0.33	3.00
	Trap B	1.51	0.77	0.35	3.00
Temperature (°C)	Trap A	13.58	2.57	10.00	17.80
	Trap B	13.68	2.45	10.00	17.00
Depth (m)	Trap A	20.21	7.64	6.50	34.00
	Trap B	21.00	8.30	7.00	35.00

4.3.2 Fish community sampled

The data from the FT was highly variable (CV of total catch = 1.5), with a one third (n = 45) of the stations capturing no fish, and 73 % of the stations capturing two or fewer fish. A total of 22 species of fish was captured in the FT, with 16 bony fish species and six cartilaginous fish species (Table 4.5). Of the 22 species recorded, 19 were captured using Trap A and 15 were captured using Trap B. The catch was dominated by the sea breams, Sparidae, accounting for 10 of the 16 species of bony fish captured. The catshark family, Scyliorhinidae, was the dominant group of sharks, accounting for four of the six species recorded. The steentjie was the most often captured species, followed by the striped catshark *Poroderma africanum*, roman and fransmadam (Table 4.5)

Fish traps failed to capture any of the dominant reef associated microinvertebrate carnivores, such as the fingerfins Cheilodactylidae and the cape knifejaw *Oplegnathus conwayi*.

Table 4.5: List of all species captured providing the number of samples where the species was recorded (n), together with the average abundance when captured for the fish traps with the large funnel entrance (Trap A) and with the small funnel entrance (Trap B). Data are sorted by Class and by the number of observations.

Species information				Trap A					Trap B				
Class	*Family*	*Common name*	*Scientific name*	*n*	*mean*	*sd*	*min*	*max*	*n*	*mean*	*sd*	*min*	*max*
Bony	Sparid	Steentjie	*Spondyliosoma emarginatum*	23	8.13	9.89	1	42	28	4.57	4.68	1	16
Bony	Sparid	Roman	*Chrysoblephus laticeps*	13	1.54	0.78	1	3	15	1.80	0.86	1	4
Bony	Sparid	Fransmadam	*Boopsoidea inornata*	12	2.25	2.01	1	7	13	1.54	0.66	1	3
Bony	Catfish	White seacatfish	*Galeichthys feliceps*	13	2.69	2.66	1	10	6	1.33	0.52	1	2
Bony	Sparid	Red tjor-tjor	*Pagellus bellottii natalensis*	10	2.30	1.77	1	6	3	1.33	0.58	1	2
Bony	Sparid	Blue hottentot	*Pachymetopon aeneum*	3	1.67	0.58	1	2	8	1.88	1.73	1	6
Bony	Sparid	White stumpnose	*Rhabdosargus globiceps*	4	2.50	1.29	1	4	4	1.50	0.58	1	2
Bony	Rockcod	Koester	*Acanthistius sebastoides*	2	1.00	0.00	1	1	1	1.00	NA	NA	NA
Bony	Sparid	Sand steenbras	*Lithognathus mormyrus*	2	1.00	0.00	1	1	1	1.00	NA	NA	NA
Bony	Sparid	Carpenter	*Argyrozona argyrozona*	2	1.00	0.00	1	1	—	—	—	—	—
Bony	Kingfish	Maasbanker	*Trachurus trachurus*	2	9.50	9.19	3	16	—	—	—	—	—
Bony	Sparid	Panga	*Pterogymnus laniarius*	2	1.50	0.71	1	2	—	—	—	—	—
Bony	Kob	Geelbek	*Atractoscion aequidens*	—	—	—	—	—	1	1.00	NA	NA	NA
Bony	Grunter	Piggy	*Pomadasys olivaceum*	—	—	—	—	—	1	3.00	NA	NA	NA
Bony	Sparid	Strepie	*Sarpa salpa*	1	1.00	NA	NA	NA	—	—	—	—	—
Bony	Rockcod	Yellowbelly rockcod	*Epinephelus marginatus*	—	—	—	—	—	1	1.00	NA	NA	NA
Cartilaginous	Catshark	Striped catshark	*Poroderma africanum*	13	2.46	1.45	1	5	16	2.06	1.95	1	8
Cartilaginous	Catshark	Puffadder shyshark	*Haploblepharus edwardsii*	7	1.57	0.79	1	3	4	1.50	1.00	1	3
Cartilaginous	Catshark	Leopard catshark	*Poroderma pantherinum*	1	1.00	NA	NA	NA	2	1.00	0.00	1.00	1.00
Cartilaginous	Requiem shark	Smooth-hound	*Mustelus mustelus*	3	1.33	0.58	1	2	—	—	—	—	—
Cartilaginous	Catshark	Dark shyshark	*Haploblepharus pictus*	1	2.00	NA	NA	NA	—	—	—	—	—
Cartilaginous	Requiem shark	Soupfin shark	*Galeorhinus galeus*	1	1.00	NA	NA	NA	—	—	—	—	—

4.3.3 Comparison of trap design and calculation of optimal *Soak time*

The covariates considered for inclusion in the GAM were *Trap design*, *Bottom*, *Profile*, *Temperature*, *Depth*, *Soak time*. Analysis of covariance showed a strong correlation between *Bottom* and *Profile*, and as a result *Bottom* was dropped from the analysis. Furthermore, the stations conducted on sand were typically associated with zero counts in the data. As the aim of the study was to assess the ability of the method to survey reef fish populations, the sand samples were considered as false samples and omitted from the analysis.

To enable the GAM to compare the effect of *Soak time* on the catch for the different *Trap designs*, the interaction between *Soak time* and *Trap design* was fitted using the "by" call in the mgcv package in R (Wood et al. 2011). This allowed prediction of the smoothing coefficients for the different *Trap designs* and calculation of independent optimal soak times. The full model was identical for each response variable considered and was described by:

$$\log(Y) = \alpha + factor_1(Trap\ design) + factor_2(Profile) + f_1(Soak\ time) \times Trap\ design + f_2(Temperature) + f_3(Depth) + \varepsilon \quad \text{(equ. 4.1)}$$

Here, Y, is the response variable being (i) the number of species, (ii) the species CPUE, (iii) the total catch, and (iv) the CPUE. During the model selection process *Profile* was identified as playing only a minor role in describing the variability observed in the fish trap data (p>0.3 in all cases), and as a result this covariate was dropped from the most parsimonious models for all the response variables described above.

4.3.3.1 Number of Species

The total number of species captured in a FT ranged from zero to eight species for Trap A and zero to five species for Trap B. The average number of species captured was 1.9 ± 1.7 and 1.8 ± 1.7 for Trap A ad Trap B, respectively.

The most parsimonious model was able to explain 26.6 % of the observed variability in the data (see Appendix 4.1, GAM 1, for detailed output from the GAM analysis). The model included the non-significant parametric effect of *Trap design* ($X^2 = 0.19$, $p<0.6$), with Trap A predicted to record marginally more species than Trap B (Fig. 4.2). The effect of *Soak time* on the number of species captured was not significant for Trap B (edf = 0.79, $X^2 = 3.62$, $p<0.06$), with the smoothing parameter showing a relatively linear increase in the number of species captured with increasing *Soak time* (Fig. 4.3a). *Soak time* had a significant effect on the number of species captured using Trap A (edf = 3.57, $X^2 = 12.16$, $p<0.05$) (Fig. 4.2), with the number of species captured peaking at 2.5 hours and predicted to drop at longer trap deployments (Table 4.6; Fig. 4.3b).

Table 4.6: Predicted optimal *Soak time*s (hours) for Trap A and Trap B to capture the maximum number of species, the maximum species CPUE, the maximum total catch and the maximum CPUE. The 95 % confidence intervals (CI) around the predicted times are given.

	Trap A			Trap B		
	Soak time	*2.5 % CI*	*97.5 % CI*	*SoakTime*	*2.5 % CI*	*97.5 % CI*
Max # of species	2.51	1.21	3.00	2.93	2.29	3.00
Max species CPUE	1.20	0.82	3.00	0.42	0.40	0.40
Max total catch	1.65	1.26	3.00	3.00	3.00	3.00
Max CPUE	1.28	1.20	1.38	0.56	0.40	3.00

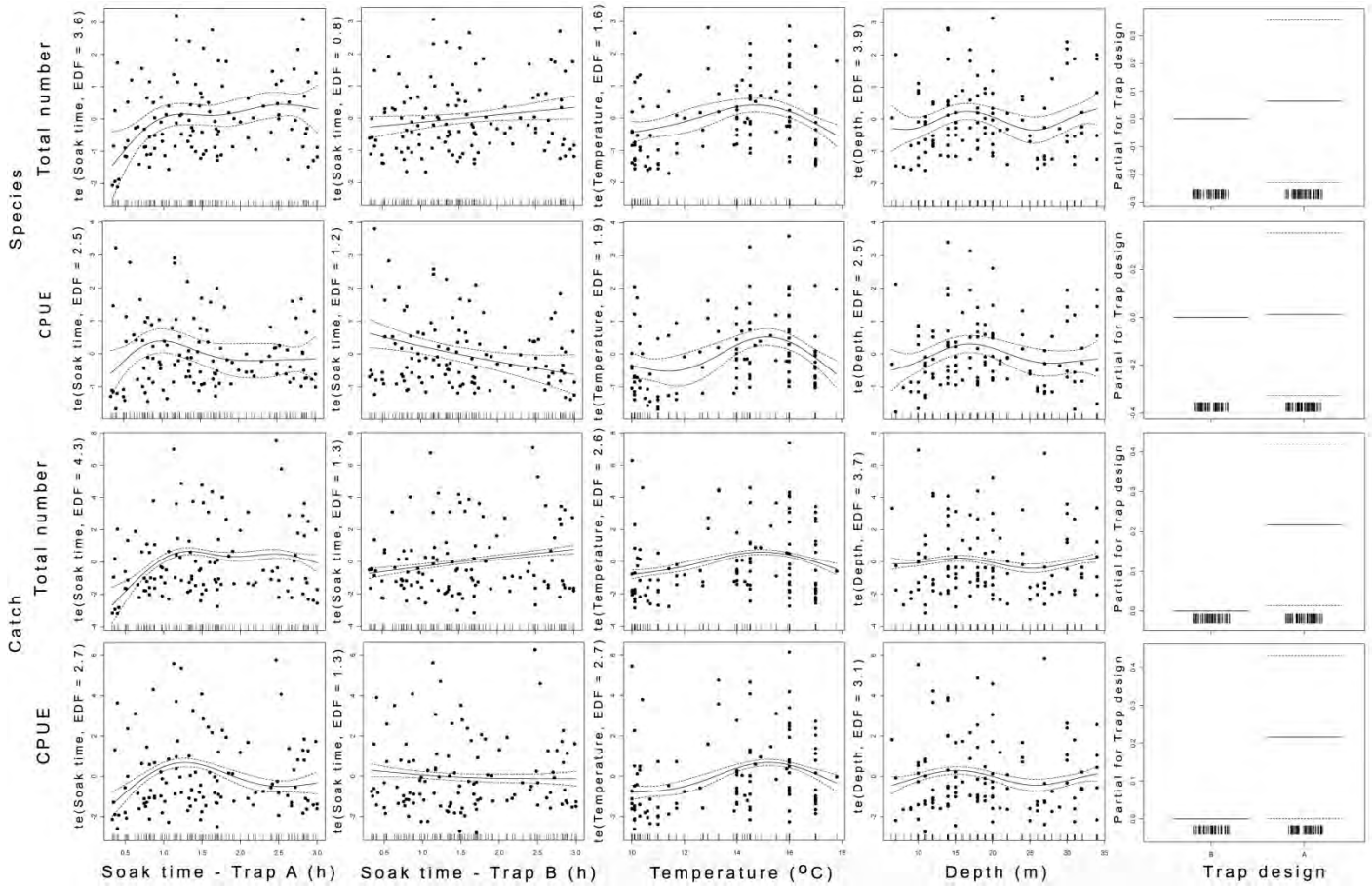

Figure 4.2: Results from the four generalised additive models (rows) illustrating the effect of *Trap design, Soak time*, *Temperature*, and *Depth* on number of species, species CPUE, total catch, and CPUE. The y-axis represents the regression estimate (log(odds ratio)) as a function of variation in the continuous covariate along the x-axis. The solid line represents the smoothed fit of the log odds ratio, and the dotted lines are the approximate 95 % confidence intervals.

The effect of *Temperature* on the number of species captured was highly significant (edf = 1.61, X^2 = 12.79, p<0.01), with traps deployed at temperatures less than 15 ^oC expected to record fewer species than those deployed at temperatures ranging between 15 – 18 ^oC (Fig. 4.2). The effect of *Depth* was marginally non-significant (edf = 3.94, X^2 = 9.96, p<0.1), with the regression estimates fluctuating around zero (Fig. 4.2).

Posterior simulation (n = 1000) predicted the optimal *Soak time* to maximise the number of species captured for Trap A and Trap B to be 2.5 hours and 2.9 hours, respectively (Table 4.6). The confidence intervals for the optimal *Soak time* for Trap A were very wide with the 2.5 % and 97.5 % values predicted at 1.2 hours and 3.0 hours. On the other hand the more or less linear trend in the number of species recorded for Trap B (Fig. 4.3a) resulted in narrow confidence intervals of 2.3 to 3.0 hours (Table 4.6). At the optimal *Soak time* the predicted number of species captured in the two traps designs were similar, with Trap A likely to capture (mean ± SE) 3.6 ±1.0 species, and Trap B, 3.0 (± 0.8) species (Table 4.7).

4.3.3.2 Species CPUE

Species CPUE averaged 1.4 (± 1.4) species.hour^{-1} for Trap A, and 1.5 (± 1.9) species.hour^{-1} for Trap B. The maximum species CPUE was 10.0 for Trap B and 6.9 for Trap A. The most parsimonious model was able to explain 34.4 % of the observed variability in the data, and there was no significant difference in the fit between the full and most parsimonious models (p>0.3) (see Appendix 4.1, GAM 2 for detailed output from the GAM analysis).

There was no significant difference in the species CPUE between Trap A and Trap B (X^2 = 0.01, p>0.9) (Fig. 4.2). The smooth terms showed a significant effect of *Soak time* on the species CPUE for Trap B (edf = 1.15, z = 6.11, p<0.05), with increasing *Soak time* associated with lower species CPUE (Fig. 4.3b). The optimal *Soak time* for species CPUE from Trap B was predicted to be 0.4 hours.

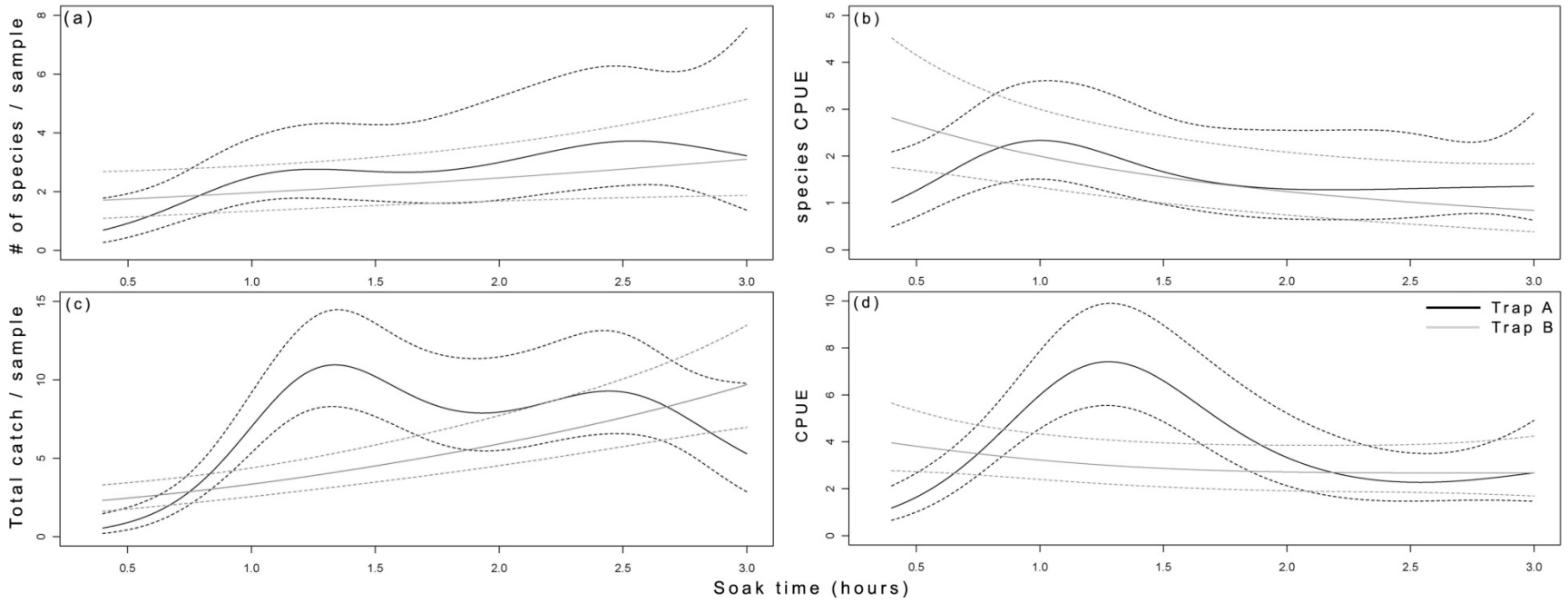

Figure 4.3: The predicted effect of *Soak time* against the number of species captured (a), the species CPUE (b), the total catch (c) and the CPUE (d) for the two trap funnel designs (Trap A = black lines; Trap B = grey lines). The solid lines are the predicted means, and the dotted lines are the 95 % confidence intervals.

The effect of *Soak time* was not significant for Trap A (edf = 2.46, X^2 = 5.71, p>0.1) (Fig. 4.2), with the optimal *Soak time* predicted at 1.2 hours, suggesting that the initial rate of species accumulation in the trap was sufficient to warrant longer deployment times (Fig. 4.3b).

At the optimal *Soak times* the predicted species CPUE (mean ± SE) was higher for Trap B (2.8 ± 0.5 species.hour^{-1}) than that predicted for Trap A (2.1 ± 0.5 species.hour^{-1}) (Table 4.7).

The effect of *Temperature* on the species CPUE was highly significant (edf = 1.87, X^2 = 16.21, p<0.001). The model predicted a similar effect of *Temperature* to that seen in the analysis on number of species, with water temperatures of 15 – 16 °C associated with highest species CPUE (Fig. 4.2). The influence of *Depth* on the species CPUE was not significant (edf = 2.53, X^2 = 7.84, p<0.1), however, there appeared to be some evidence that the species CPUE was higher in the mid-range depths of 15 – 20 m.

4.3.3.3 Total catch

Total catch ranged from 0 to 27 individuals, with an average catch of 5.7 (± 6.8) for Trap A and 4.4 (± 5.5) for Trap B. The most parsimonious model was able to explain 34.2 % of the observed variability in the catch data, while there was no significant difference between the fit of the full and most parsimonious models (p>0.2) (see Appendix 4.1, GAM 3, for detailed output from the GAM analysis).

Trap design had a significant effect on the total catch (X^2 = 4.57, p<0.05) (Fig. 4.2), with the regression estimates for Trap A having a significant positive effect on the model intercept (z = 2.14, p<0.05). The smooth terms for *Soak time* were significant for Trap A (edf = 4.31, X^2 = 52.18, p<0.001) and Trap B (edf = 1.28, X^2 = 45.5, p<0.001) (Fig. 4.2). A relatively linear increase in catch was predicted with increasing *Soak time* for Trap B (Fig. 4.3c), with the predicted maximum total catch occurring at a *Soak time* of 3.0 hours (Table 4.6). The total catch from Trap A was predicted to peak at a *Soak time* of 1.5 hours, and remain relatively constant from there on (Fig. 4.3c). The predicted total catch

at the optimal deployment time was on average (± SE) 9.7 (± 1.4) individuals and 9.5 (± 1.6) individuals for Trap A and Trap B, respectively (Table 4.7).

Significant effects of *Temperature* (edf = 2.56, X^2 = 90.54, p<0.001) and *Depth* (edf = 3.67, X^2 = 19.05, p<0.01) were identified, with the total catch peaking at water temperatures of approximately 15 °C, and at depths between 10 – 20 m (Fig. 4.2).

4.3.3.4 CPUE (total catch)

The CPUE for total catch ranged between 0 and 21.1 fish.hour^{-1}for Trap A and 0 and 17.5 fish.hour^{-1} for Trap B. The average CPUE was 3.9 (± 4.9) and 3.3 (± 4.0) fish.hour^{-1} for Trap A and Trap B, respectively. There was no significant difference in the fit between the full and most parsimonious models, with both models able to explain 33.8 % of the observed variability in the CPUE (see Appendix 4.1, GAM 4, for detailed output from the GAM analysis).

Table 4.7: Predicted number of species, species CPUE, total catch and CPUE of fish at the estimated optimal *Soak time*s (see Table 4.6) for Trap A and Trap B.

	Trap A		Trap B	
	Mean	*SE*	*Mean*	*SE*
Max # of species	3.62	0.96	2.98	0.75
Max species CPUE	2.14	0.51	2.76	0.66
Max total catch	8.52	1.34	8.68	1.55
Max CPUE	7.27	1.06	3.65	0.60

Trap design had a significant influence on CPUE (X^2 = 4.01, p<0.05), with the regression coefficients for Trap A having a significant positive effect on the model intercept (z = 2.00, p<0.05) (Fig. 4.2). The effect of *Soak time* on CPUE for Trap B was marginally not significant (edf = 1.30, X^2 = 4.55, p<0.1), with the CPUE decreasing with increased *Soak time* (Fig. 4.3d). Peak CPUE for Trap B was predicted to be at a *Soak*

time of 0.6 hours (Table 4.6). The effect of *Soak time* on the CPUE of Trap A was significant (edf = 2.70, X^2 = 46.09, p<0.001) (Fig. 4.2), with CPUE peaking at 1.3 hours (Fig. 4.3d). At their respective optimal *Soak times* the predicted CPUE (± SE) was 7.2 (± 1.1) fish.hour^{-1}for Trap A, and 3.7 (± 0.6) fish.hour^{-1} for Trap B (Table 4.7).

The trends in *Temperature* and *Depth* described in the previous three analyses were again evident, with a significant effect of *Temperature* (edf = 2.68, X^2 = 72.94, p<0.001) predicting peak overall CPUE at approximately 15 °C, while the FT conducted in shallower water (10 – 20 m) had a significantly higher overall CPUE (edf = 3.12, X^2 = 19.74, p<0.01) than those deployed in deeper water (21 – 30 m) (Fig. 4.2).

4.3.4 Effect of trap design on the size of captured fish

To compare the size of the fish caught by the two *Trap designs* non-parametric Mann-Whitney U-tests were performed on the length measurements for all species that were captured on more than three occasions by each trap (Table 4.8).

The largest fish caught in the FT was a 1030 mm smooth-hound shark *Mustelus mustelus* captured in Trap A. The largest bony fish captured was a 610 mm geelbek *Atractoscion aequidens* caught in Trap B. The smallest fish captured was a 67.5 mm maasbanker *Trachurus trachurus* caught in Trap A. For most of the dominant species captured there was considerable similarity in the mean fork length between those caught in Trap A and those caught in Trap B (Fig. 4.4). Only with the striped catshark, was the difference in fork length significant (W = 273, p<0.01), with the individuals captured in Trap B significantly bigger (759.3 ± 106.6 mm) than those captured in Trap A (667.3 ± 133.4 mm). As Trap A had the larger funnel diameter, this results is counter intuitive, but could be caused by the larger specimens being more willing to squeeze through a narrow opening, whereas the smaller individuals were more cautious (Fig. 4.4). For roman, white stumpnose *Rhabdosargus globiceps*, and blue hottentot *Pachymetopon aeneum*, the individuals captured in Trap A were considerably larger than those caught in Trap B*,* however, the results were marginally not significant

(roman: W = 349, p<0.1; white stumpnose: W = 47, p<0.1; blue hottentot: W = 53, p<0.1) (Table 4.8, Fig. 4.4). For the remainder of the species compared, namely puffadder shyshark *Haploblepharus edwardsii*, white seacatfish *Galeichthys feliceps*, fransmadam, steentjie, and red tjor-tjor *Pagellus bellottii natalensis*, there was very little difference in the mean fork length of individuals captured using Trap A and Trap B (Table 4.8, Fig. 4.4).

Table 4.8: Comparison of the length data for all the species captured using Trap A and Trap B. Data are sorted by Class and by the number of fish caught.

Species information		Trap A					Trap B				
Class	*Species*	*n*	*mean*	*sd*	*min*	*max*	*n*	*mean*	*sd*	*min*	*max*
Bony	Steentjie	187	179.98	30.22	159.57	250	128	177.80	23.27	161	196
Bony	Fransmadam	27	177.60	34.07	170.08	246	20	189.18	23.05	180	198
Bony	Roman	20	284.83	79.50	258.15	392	27	235.68	38.80	205	266
Bony	White seacatfish	35	249.31	25.02	233	342	8	259.25	39.42	253	265
Bony	Red tjor-tjor	23	174.29	9.13	163.6	201	4	161.00	20.66	158	164
Bony	Blue hottentot	5	173.00	21.64	166.33	205	15	159.44	10.77	155	165
Bony	Maasbanker	19	79.74	1.52	67.5	91	—	—	—	—	—
Bony	White stumpnose	10	192.65	16.38	185.5	215	6	174.25	10.84	173	176
Bony	Koester	2	249.50	36.06	249.5	275	1	199.00	NA	NA	NA
Bony	Panga	3	219.00	60.81	214.5	262	—	—	—	—	—
Bony	Piggy	—	—	—	—	—	3	176.00	13.01	162	188
Bony	Sand steenbras	2	205.00	2.83	205	207	1	167.00	NA	NA	NA
Bony	Carpenter	2	182.50	14.85	182.5	193	—	—	—	—	—
Bony	Geelbek	—	—	—	—	—	1	610.00	NA	NA	NA
Bony	Strepie	1	137.00	NA	NA	NA	—	—	—	—	—
Bony	Yellowbelly rockcod	—	—	—	—	—	1	325.00	NA	NA	NA
Cartilaginous	Striped catshark	32	677.19	131.77	733.08	970	33	768.74	106.38	738	803
Cartilaginous	Puffadder shyshark	11	443.57	10.29	446	455	6	443.00	73.64	434	451
Cartilaginous	Smooth-hound	4	853.33	112.40	903.33	1030	—	—	—	—	—
Cartilaginous	Leopard catshark	1	540.00	NA	NA	NA	2	645.00	63.64	645	645
Cartilaginous	Dark shyshark	2	530.00	NA	410	650	—	—	—	—	—
Cartilaginous	Soupfin shark	1	500.00	NA	NA	NA	—	—	—	—	—

The majority of the bony fish captured were below the size at 50 % sexual maturity (van der Elst 1988; Mann 2000), with the exception of roman where the average fork length recorded was larger than the size at 50 % maturity (± 180 mm). A similar pattern was evident for the red tjor-tjor, where all individuals captured were larger than their size at 50 % maturity (120-130 mm). The dominant sharks captured were typically large

relative to their size at 50 % maturity, with the average size of captured striped catshark, and puffadder shyshark similar to the size at 50 % maturity (van der Elst 1988) (Table 4.8, Fig. 4.4).

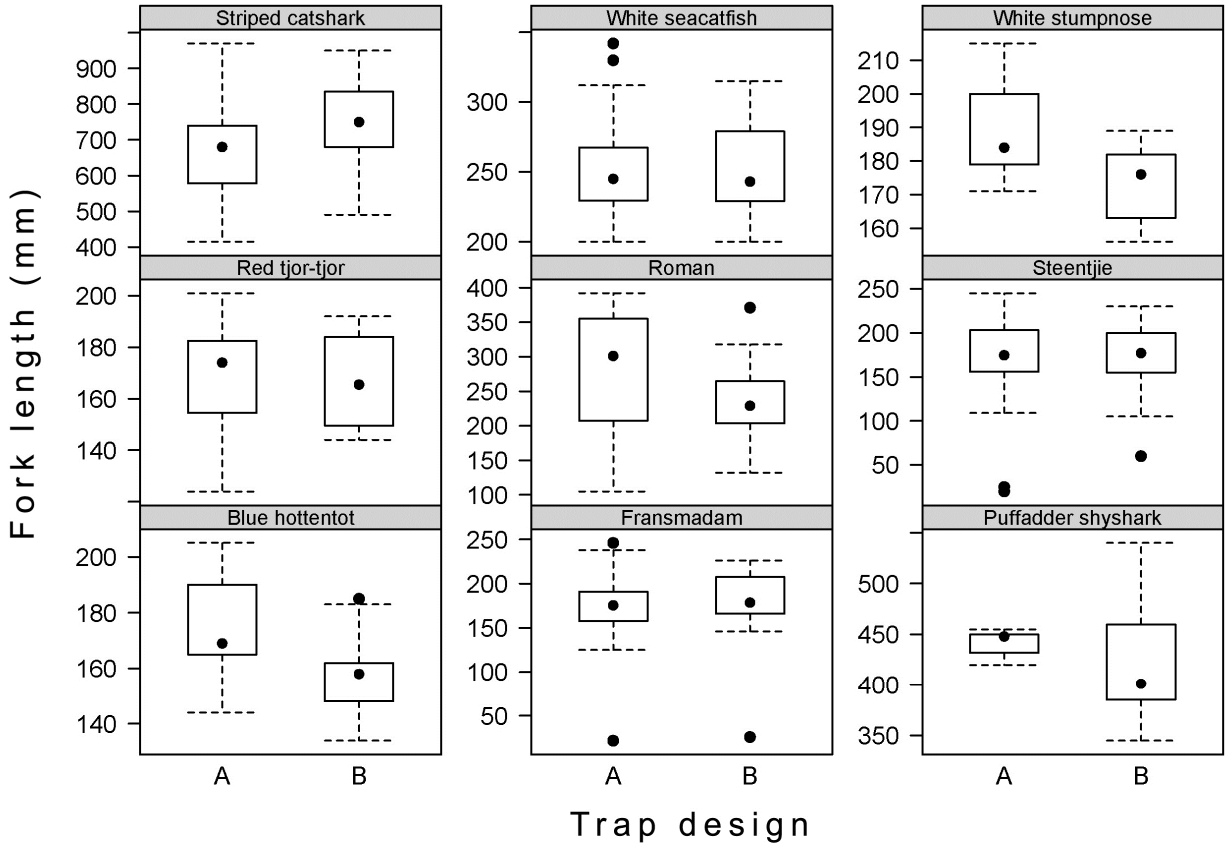

Figure 4.4: Box and whisker plots comparing the fork length measurements for the dominant species of fish sampled using the different trap funnel designs. Whiskers show the standard deviations.

4.3.5 Data variability and power

To calculate the power of the fish trap data, Poisson GAMs were fitted to the count data for the dominant species of fish recorded in the survey area. The species of fish

included steentjie, striped catshark, roman and fransmadam. Due to the low rate of capture for striped catshark, roman and fransmadam the data from both Trap A and Trap B were pooled (n = 135), however, as with the previous GAM analysis, only samples collected on rocky substratum were included.

To model the spatial variability in the data the covariates *Temperature*, *Depth* and *Profile* were included in the full model. To take into account the different *Soak times* of each trap deployment, the log of *Soak time* was used as an offset in the GAMs as recommended by Zuur et al. (2009). The full model for each species was described as:

$$\log(Y) = \alpha + log(Soak\ time) + factor_1(Profile) + f_1(Temperature) + f_2(Depth) + \varepsilon \quad \text{(equ. 3.2)}$$

Here, Y, is the separate catch data for each of the different species used in this analysis.

4.3.5.1 Steentjie

During the model selection process *Profile* was identified as playing no role in explaining the observed variability in the catch data for steentjie ($z = -1.26$, $p>0.2$), and was dropped from the most parsimonious model. The most parsimonious model was able to explain 36.7 % of the observed variability in the data. The effect of *Temperature* (edf = 2.72, $X^2 = 72.57$, $p<0.001$) and *Depth* (edf = 4.69, $X^2 = 52.16$, $p<0.001$) were highly significant in explaining the catch characteristic for steentjie (Table 4.9). Catch was predicted to be higher at water temperatures greater than 14 °C (Fig. 4.5a), and at water depths between 10 – 20 m (Fig. 4.5b).

Table 4.9: The effect of selected covariates on the observed variability, together with the results from the power analysis of catch data, for the dominant species recorded in fish traps.

	Steentjie			Striped catshark		
	df/edf	*Chi-sq*	*Sig level*	*df/edf*	*Chi-sq*	*Sig level*
Profile	—	—	—	1	3.441	.
te(Temperature)	2.72	72.57	***	0.89	5.96	*
te(Depth)	4.69	52.16	***	3.56	23.85	***
Model deviance		575.45			122.78	
Phi (ϕ) [1]		5.50			1.15	
Predicted mean		2.73			0.53	
Required n		50			54	
	Roman			Fransmadam		
	df/edf	*Chi-sq*	*Sig level*	*df/edf*	*Chi-sq*	*Sig level*
Profile	—	—	—	1	7.11	**
te(Temperature)	1.72	21.70	**	2.81	14.68	**
te(Depth)	3.74	11.19	*	—	—	—
Model deviance		112.18			122.93	
Phi (ϕ) [1]		1.05			1.14	
Predicted mean		0.42			0.40	
Required n		63			70	

1: Phi = overdispersion parameter

2: df/edf = degrees of freedom for the parametric coefficients and estimated degrees of freedom for the tensor product smooth terms [te(covariate)]

3: Chi-squared, significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

Within the survey area, the model predicted an abundance (± SE) for steentjie of 2.7 (± 0.4) individuals per trap deployment (Table 4.9), although the data was somewhat overdispersed (Phi = 5.5) reflecting the high variability in the catch data from the FT. The results from the power analysis indicated that to detect a doubling or halving of the steentjie population a minimum of 50 trap deployments is required (Table 4.9).

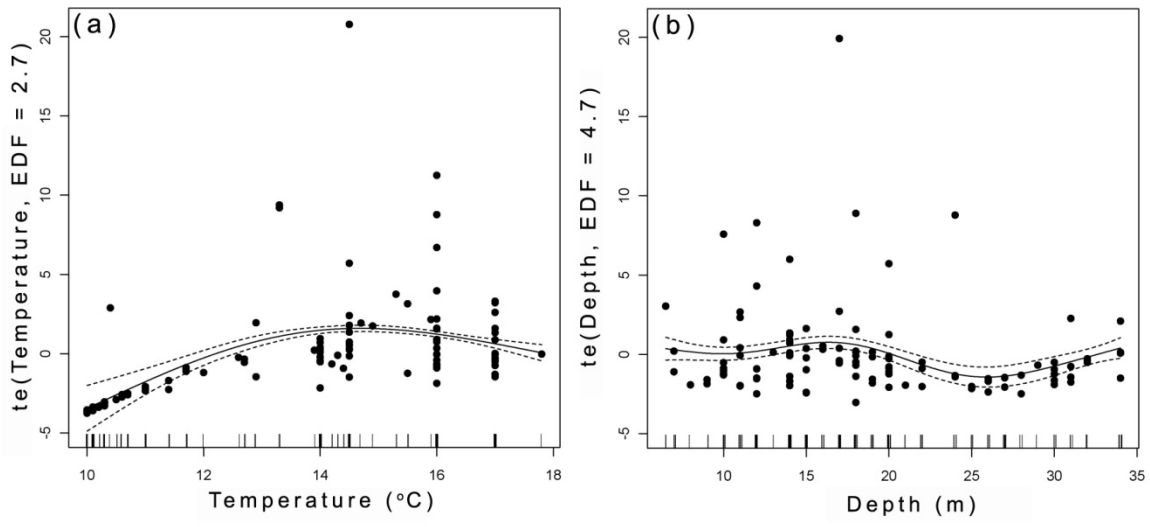

Figure 4.5: Results from the generalised additive model showing the effect of *Temperature* (a) and *Depth* (b) on the regression estimates for catch of steentjie using fish traps.

4.3.5.2 Striped catshark

During the model selection process for the striped catshark, the full model was identified as the most parsimonious model. The model was able to explain 23.6 % of the observed variability in the catch data. The effect of *Profile* was marginally not significant (df = 1, X^2 = 3.44, p<0.07), with the regression estimates for high profile reef having a positive effect on the model intercept (z = 1.86, p<0.07) (Table 4.9). The model predicted a significant positive influence of *Temperature* on catch (edf = 0.89, X^2 = 5.96, p<0.05). *Depth* had a significant influence on the catch (edf = 3.56, X^2 = 23.85, p<0.001), with shallow samples (< 15 m depth) more likely to contain fewer striped catsharks than samples collected between 15 and 35 m depth (Fig. 4.6).

The model predicted a mean catch of 0.5 (± 0.2) striped catshark per trapping station, and the power analysis indicated that a minimum of 54 trapping stations is required to detect a doubling or halving of the striped catshark population (Table 4.9).

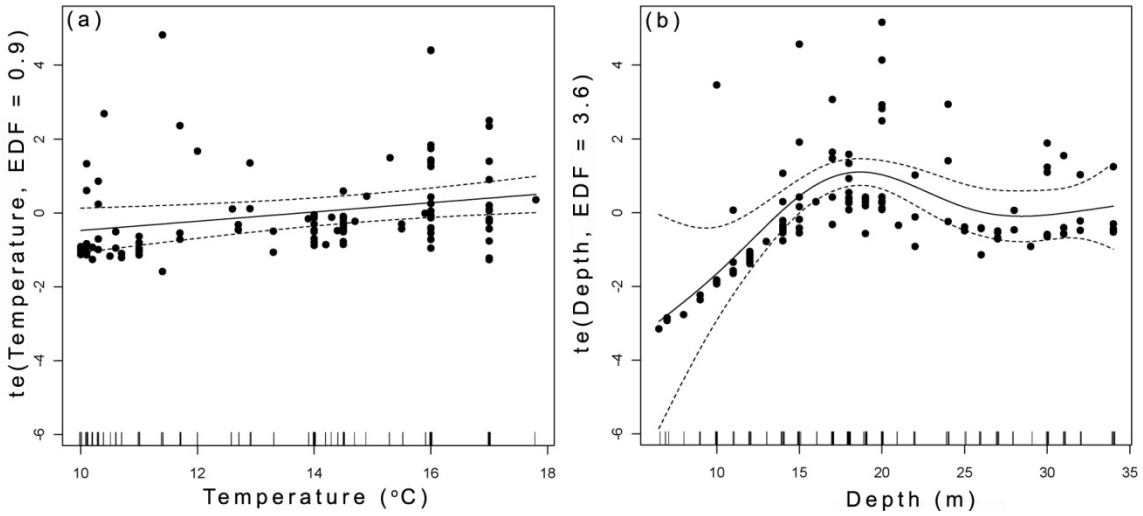

Figure 4.6: Results from the generalised additive model showing the effect of *Temperature* (a) and *Depth* (b) on the regression estimates for catch of striped catsharks using fish traps.

4.3.5.3 Roman

During the model selection process, *Profile* was identified as playing little role in describing the variability in the catch data ($z = 0.54$, $p>0.5$), and as a result was dropped from the most parsimonious model. The best fit-model was able to explain 28.9 % of the observed variability in the catch data. The effect of *Temperature* was highly significant (edf = 1.72, $X^2= 21.70$, $p<0.01$), with catch of roman peaking at *Temperatures* between 14 and 16 °C (Fig. 4.7a). The effect of *Depth*, although significant (edf = 3.74, $X^2 = 11.19$, $p<0.05$), was variable, with the regression estimates fluctuating around zero (Fig. 4.7b).

The model predicted a capture rate of 0.4 (± 0.2) roman per fish trap, and the power analysis indicated that a minimum of 63 fish trap samples is required to be able to detect a doubling or halving of the roman population (Table 4.9).

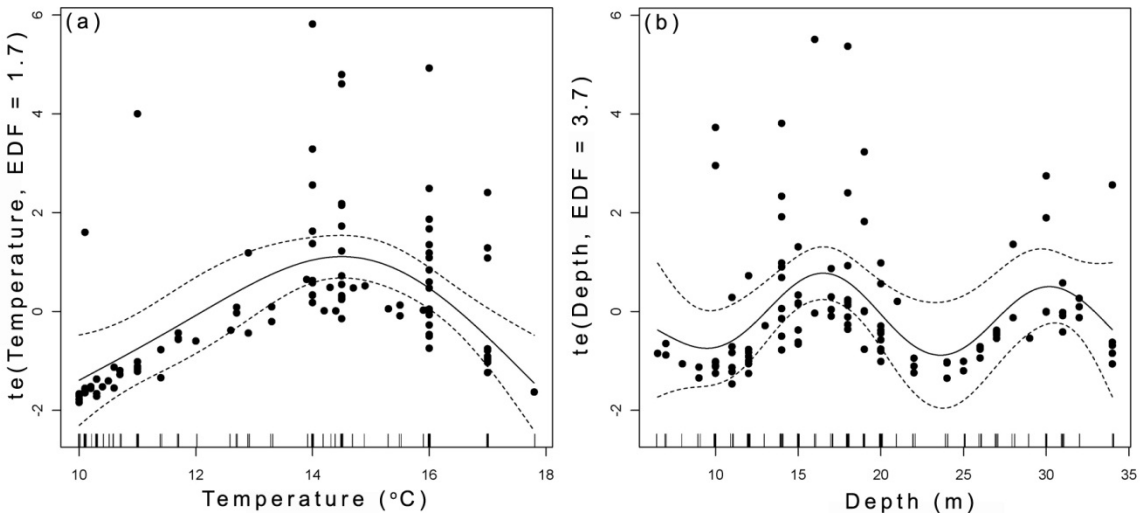

Figure 4.7: Results from the generalised additive model showing the effect of *Temperature* (a) and *Depth* (b) on the regression estimates for catch of roman using fish traps.

4.3.5.4 Fransmadam

During the model selection process *Depth* was identified as playing little role in explaining the observed variability in the catch data for fransmadam ($X^2 = 0.0$, $p>0.6$), and as a result it was dropped from the most parsimonious model. The most parsimonious model was able to explain 31.6 % of the observed variability in the catch data. *Profile* had a highly significant effect on the probability of capture (df =1, $X^2 = 7.11$, $p<0.01$) (Table 4.9), with the regression estimates showing a significant positive effect of high profile reef on the model intercept ($z = 2.67$, $p<0.01$). *Temperature* had a significant effect on the catch of fransmadam (edf = 2.81, $X^2 = 14.68$, $p<0.01$), with the smooth terms indicating that the probability of capture is low at temperatures less than 12 °C (Fig. 4.8).

The model predicted an average catch of 0.4 (± 0.1) fransmadam per trap deployment, and the power analysis indicated that a minimum of 70 trapping station is required to be able to detect a doubling or halving of the fransmadam population using the fish trap method.

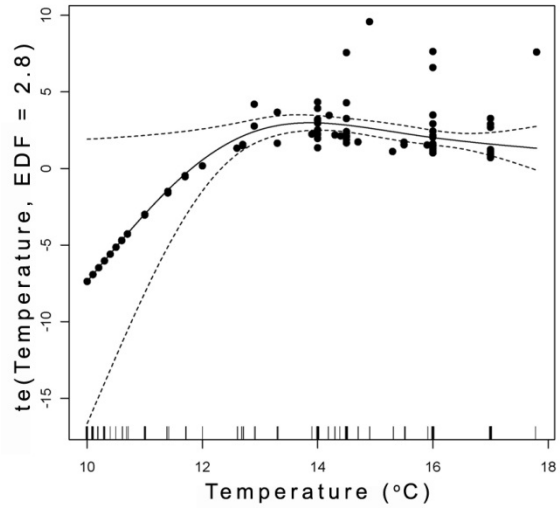

Figure 4.8: Results from the generalised additive model showing the effect of temperature on the regression estimates for catch of fransmadam using fish traps.

4.4 Discussion

In comparing the catch from the two trap designs the fundamental questions were (i) what effect does the entrance size have on the catch and (ii) how does the catch change with increasing soak time.

The size of the entrance had little influence on the number of species caught during each trap deployment, however, the larger entrances captured seven unique species in comparison to the three unique species captured by the small entrance, indicating a possible improvement in the diversity of the catch with the larger entrance. The unique species from both traps were rare (≤ 2 observations), and it is thus possible that the difference in total number of species captured, may be more a result of the high overall variability in the capture of fish rather than a true improvement in trap design.

The size of the entrance to the trap played a significant role in the number of fish caught, with the larger entrance catching more fish. This is to be expected as the larger the entrance the greater the proportion of the community that can theoretically enter the trap. The average size of the fish caught was similar for the majority of the dominant species, while the maximum size for each species was typically greater with the larger entrance. This suggests that although more fish were likely to get trapped by the large entrance trap, the change in entrance size had no noticeable effect on the average length distribution of the dominant species, even though a wider size spectrum was captured. It is possible that the difference in entrance size tested during this research was too small to clearly affect the size distribution of the fish captured. The traps used in this study were small (100 x 50 x 50 cm) with the narrow entrance of the conical funnel 10 cm in diameter for the small trap, and 15 cm in diameter for the large trap. In an effort to reduce the possibility of escapement, the maximum entrance size was restricted to ⅓ of the height of the square side of the trap (i.e. 15/50 cm). There were no guidelines available to select the shape and size of the funnel, so the criteria employed

here aimed to ensure that the entrance into the trap was not too large, or too close to the bait container, thereby blocking the entrance.

Escapement has been identified as a major factor influencing the total catch of fish using FT (Munro 1974; Sheaves 1995), while it has been shown that the relationship between capture and escapement within a trap is density dependant (Munro 1974; Gobart 1998). This density dependant escapement is clearly illustrated in the pattern of catch with soak time for the large entrance trap (Trap A) in figure 5 (a, c), as total catch saturated between 1 and 1.5 hours. On the other hand, the total catch using the smaller entrance appeared not to saturate, with a more or less linear increase in the number of fish caught with increasing soak time. It is possible that the smaller entrance restricted escapement, thereby allowing catch to increase with soak time, however this benefit was shadowed by the lower numbers of fish entering the trap. Although *in situ* observations are not available to confirm this, it is likely that the larger entrance increased the probability of fish entering the trap, while at the same time, it was more sensitive to density dependant escapement once the trap had saturated.

Analysis of the species CPUE, CPUE and total catch suggested that a soak time of less than 1.5 hours has the highest likelihood of maximising catch. Catch per unit effort is considered a more suitable measure of efficiency than total catch and as such a soak time of 1.3 hours (80 minutes) is advocated. This agrees with past studies that found catch to be the highest following soak times of between one to two hours (Collins 1990; Sheaves 1995). This is a relatively short deployment time, compared to what other authors have used (Sheaves 1992), and it allows for high number of deployments to be conducted per day. During this study, four traps were able to fit onto the small research vessel (5.5 m length). Allowing for 15 minutes between trap deployments, and a sit time of 30 minutes following the deployment of the last trap and the retrieval of the fist trap, 16 to 20 stations could be sampled during a six hour day at sea. The results from the power analysis suggested that to survey the dominant fish (steentjie) and shark (striped catshark), a minimum of 54 samples are required. This equates to three to four full days of work to conduct the surveys.

For the roman population the power analysis indicated that a minimum of 63 samples is required to be able to detect a doubling or halving of the population. Bennett *et al* (2009) found that 12 and 15 samples collected with CA and UVC strip transects, respectively, were adequate to survey the roman population in the TNP MPA for the detection of the same effect size. For the CA, the samples could be collected in two sea-going days with a team of four anglers, while a minimum of three sea-going days would be required to collect sufficient UVC samples with a team of two dive pairs conducting five dives per day. In this study, four days or 63 fish trap samples were required to detect a doubling or halving of the roman population. Out of the three methods (CA, UVC, and FT), FT appears to be the least efficient for sampling the roman population. However, the strength of the FT method is less in its ability to survey the large bodied dominant roman population, and more in its ability to survey the smaller abundant opportunistic scavengers, such as steentjie, and the cryptic catshark populations. Both the striped catshark and the steentjies are poorly sampled using the CA method (see Table 4.1) and, although the UVC strip transect method collects sufficient data to survey the steentjie population, the catsharks are typically under represented. This suggests that FT are one of the few methods that can collect sufficient data to survey the catshark population.

Past studies on the performance of FT have identified mortality in the traps as an additional factor contributing to the saturation of catch with increasing soak time (Munro 1974). The extended soak times preferred in the trap fisheries (up to 14 days), increase the probability that fish will die within the trap. The maximum deployment time from this study was three hours thereby limiting the possibility of fish mortality while the trap was fishing. There was, however, one case where a roman died while in the trap, but this was due to predation by octopus. Predation of spiny rock lobsters by octopus has been identified as a problem for the commercial trap fishery in South Australia (Brock et al. 2006), and efforts have been made to exclude the octopus from the traps. Of the 135 trap deployments made during this study, octopus were present in approximately 10 % of the samples. In instances when octopus were in the traps, fish were typically absent.

During baited video deployments (see Chapter 3) octopus would often feed at the bait container with the result that the fish would disperse until the octopus had left the bait container. This suggests that fish may be scared off when octopus are in a FT and this may have contributed to the lower catches.

While mortality within the traps was rare, damage incurred during trapping resulted in a large number of mortalities post-release. The main type of damage was barotrauma and physical damage to the fish. Barotrauma is inevitable with all extractive fishing techniques (Booth and Buxton 1997). Götz *et al*. (2007) found that 98 % of all roman captured showed some signs of barotrauma, although through deflating of the swim bladder, together with careful handling, the chance of post-release mortality was reduced. The physical damage observed during this study mostly constituted scale loss, and only affected the bony fish. Overall, 16 % of all bony fish captured were damaged, with the worst effected species being the small sparids such as blue hottentot, fransmadam and red tjor-tjor, with close on 50 % of all individuals showing signs of damage. Of the dominant species steentjies, showed the lowest levels of damage with 13 % of all individuals captured showing scale loss, and only 3 % of the fish released had to be classified as mortalities. Blue hottentot, fransmadam, red tjor-tjor, and roman showed mortality rates of between 13 and 15 %, while the all the individuals that died post-release showed signs of both, barotrauma and physical damage. A similar pattern was noted by Götz *et al*. (2007), where mortalities of roman captured with CA were highest when gut hooking occurred together with barotrauma.

If FT are to be effective as a non-destructive sampling tool, the high levels of damage and mortalities recorded during this experiment need to be mitigated. The physical damage appeared to result from the fish rubbing against the abrasive wire mesh that covered the traps. Wire mesh is typically used to cover FT, however, a softer netting may be more suitable if the traps are to be truly non-destructive for captured fish. As the netting would need to be thicker than the wire mesh (to avoid ripping on the reef), the trap will appear more solid, and fish may be less willing to enter to feed on the bait. Robichaud et al. (1999) found that the visibility of the trap had no effect on the total

catch, suggesting that thicker netting may not negatively affect the trap performance. As the fish trap data from this study showed such a high degree of variability, it is recommended that the effect of netting on the catch be tested prior to use of FT as a monitoring tool.

One of the perceived benefits of FT, mentioned in the introduction, was that there is potential to catch more fish and obtain a greater number of accurate length measurements in comparison to what is achievable with CA, UVC or RUV methods. The size of fish within a given area is a highly sensitive measure of fishing pressure (Boehlert 1996), and as a result, methods that provide researchers with a high number of precise size estimates are preferred in programmes that aim to monitor the impact of fishing activity and related management measures. The results from this study showed that the average abundance of roman was 0.42 individuals per sample, which is considerably lower than the average obtained from CA (6.9 individuals), UCV (15.6 individuals) (see Götz et al. 2007; Bennett et al. 2009), RUV (2.6 individuals) and BRUV (5.1 individuals) (see Chapter 3). This suggests that for fish trap data to be of value it would rely on its ability to survey the smaller fish species. Although steentjies were the most abundant species recorded with FT (2.7 individuals), BRUV stations typically observe the species at ten times this abundance (27.2 individuals), while the same pattern is true for fransmadam (see Chapter 3). This suggests that the benefits alluded to in the introduction are not realised, and that FT provide a relatively poor sampling tool, at least for the bony fish community.

Alternatively, FT appear to be one of the most efficient methods when it comes to surveying the catshark species. Catsharks are the dominant species of shark that reside on the temperate reefs along the South African south coast (Branch et al. 2010). Although they are not of fisheries importance, their abundance suggests that they are important components of the reef community. BRUV is the only other method that records catsharks at sufficient densities, but it is often difficult to correctly identify the different species as they are seen in the background, against which they are very well camouflaged (ATF Bernard *pers. obs.*). Furthermore, obtaining accurate size estimates

using stereo-BRUV would be limited due to the catsharks eel-like swimming motion, reducing the chance of seeing the body fully extended, thus complicating length estimation.

The high level of variability observed in the data is an area of concern. For both trap designs the CV was greater than one (standard deviation was larger than the mean), highlighting the low precision of the data. For data to be of value it needs to have high diagnostic power. Although noise is preferred to bias (Vos et al. 2000), too much noise limits the ability to identify underlying trends in the data. Although FT appeared to be highly sensitive to variation in temperature, the inability of the traps to capture fish, suggests that methodological errors contributed to a large proportion of the observed variability. There are a number of alternate trap designs that might improve the performance of FT. Rectangular traps are logistically simple to use and store on the small work vessels. However, simple adaptations to their design may result in drastic improvements in the catch and reduce methodological errors. The Z-shaped trap, or Antillean trap, may be one such design as it draws fish towards the funnels increasing the chance of fish entering the trap (Sheaves 1995). Alternatively, fish retention devices can be easily installed at the entrance to restrict escapement. Carlile et al. (1997) found that fish retention devices significantly increased the catch of Pacific cod, but reduced the by-catch of Pacific halibut indicating that care needs to be taken when employing the fish retention devices on traps to monitor the fish community. To improve the value of FT as a monitoring tool, it is recommended that further research be conducted looking into alternate trap shapes as well as the effect of fish retention devices on the catchability of different species.

4.4.1 Summary and conclusions

Past research suggested that FT are non-selective, efficient and low-cost monitoring tools that can be deployed in a wide variety of habitats under variable conditions (Sheaves, 92; Thrush et al. 2002; Travers et al. 2006). Their ability to catch a wide

variety of species together with the low cost of constructing the traps and collecting the data make FT an appealing option for LTM programmes.

The results from this study contrast with past results, highlighting many weaknesses of the fish trap method. There is a huge amount of variability in the data, which is attributed to low catch rates, and inconsistency in the presence of the dominant species. Furthermore, species richness was low with only 22 species captured, and only two of the species recorded at densities adequate to be monitored with some statistical power. This indicates that FT are not likely to be suitable to monitor the reef fish communities in the Agulhas Ecoregion of South Africa alone. However, a review of many papers that compare different methods identify that no one method is able to monitor the entire reef fish community, and that studies aiming to monitor changes at the community level should use multiple methods. In this regard, FT may be a useful addition for researchers aiming to collect population data on the catshark species that occur in the Agulhas Ecoregion.

Some recommendations can be made relating to the experimental approach and method optimisation. For example, the larger trap entrance in combination with short soak times resulted in the highest catch rate. The benefit of the short deployment time is that the sampling effort at each station is reduced, in turn increasing the possible number of deployments that can be conducted within a given time period.

As a non-destructive monitoring tool, the trapping method performed poorly, as high numbers of damaged fish and mortalities were recorded. Certain changes to the trap design are recommended, and these included replacing the wire mesh cover with a softer netting to reduce damage to the bony fish. Positioning the entrance of the trap closer to the reef may also reduce the by-catch of bony fish while having little effect on the catch of catsharks. The rectangular shaped traps employed in this study were logistically satisfactory, as four traps could be stored securely on a small, 5.5m vessel. It is felt, however, that certain design modifications could help improve the catch rates of the traps. The traps used in artisanal fisheries, such as the Z-shaped Antillean traps,

have undergone design modification over centuries and the current forms would only be used if they caught sufficient fish. If FT are to be employed as a monitoring tool, it is recommended that the Z-shaped traps with a netting covering be piloted, to determine whether or not they improve the catch, reduce the numbers of zeros in the data and the damage caused to the bony fish species.

4.5 Appendices

4.5.1 Appendix I: GAM analysis on the species and count data

GAM 1: The effect of Soak time and Trap design on the number of species caught

Likelihood ratio test (Saturated model vs Best-fit model)

	UBRE	Resid. Df	Resid. Dev	Deviance explained	P(>|Chi|)
Saturated model	0.47	101.09	141.66	26.60%	
Best-fit model	0.45	102.08	141.68	26.60%	0.881

Model summary

Parametric coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.48	0.11	4.43	0.000	***
Trap A	0.06	0.15	0.43	0.666	

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value	
te(Soak time): Trap B	0.79	0.95	3.62	0.053	.
te(Soak time): Trap A	3.57	4.22	12.16	0.019	*
te(Temperature)	1.61	1.88	12.79	0.001	**
te(Depth)	3.94	5.04	9.96	0.078	.

Approximate hypothesis tests related to GAM fit

Parametric Terms:

	df	Chi.sq	p-value
Trap	1.00	0.19	0.666

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value	
te(Soak time): Trap B	0.79	0.95	3.62	0.053	.
te(Soak time): Trap A	3.57	4.22	12.16	0.019	*
te(Temperature)	1.61	1.88	12.79	0.001	**
te(Depth)	3.94	5.04	9.96	0.078	.

Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

GAM 2: The effect of Soak time and Trap design on the species CPUE

Likelihood ratio test (Saturated model vs Best-fit model)

	UBRE	Resid. Df	Resid. Dev	Deviance explained	P(>|Chi|)
Saturated model	0.24	102.68	118.67	34.10%	
Best-fit model	0.23	103.99	120.00	33.40%	0.332

Model summary
Parametric coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.19	0.13	1.45	0.147
Trap A	0.01	0.17	0.08	0.940

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value
te(Soak time): Trap B	1.15	1.43	6.11	0.025 *
te(Soak time): Trap A	2.46	3.13	5.72	0.137
te(Temperature)	1.87	1.98	16.21	0.000 ***
te(Depth)	2.53	3.36	7.84	0.065 .

Approximate hypothesis tests related to GAM fit
Parametric Terms:

	df	Chi.sq	p-value
Trap	1.00	0.01	0.940

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value
te(Soak time): Trap B	1.15	1.43	6.11	0.025 *
te(Soak time): Trap A	2.46	3.13	5.72	0.137
te(Temperature)	1.87	1.98	16.21	0.000 ***
te(Depth)	2.53	3.36	7.84	0.065 .

Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

GAM 3: The effect of Soak time and Trap design on the total catch

Likelihood ratio test (Saturated model vs Best-fit model)

	UBRE	Resid. Df	Resid. Dev	Deviance explained	P(>|Chi|)
Saturated model	4.61	98.14	501.67	30.40%	
Best-fit model	0.00	99.18	502.99	0.00%	0.260

Model summary

Parametric coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	0.00	0.00	0.00	0.000 ***
Trap A	0.00	0.00	0.00	0.000 ***

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value
te(Soak time): Trap B	0.00	0.00	0.00	0.000 ***
te(Soak time): Trap A	0.00	0.00	0.00	0.000 ***
te(Temperature)	0.00	0.00	0.00	0.000 ***
te(Depth)	0.00	0.00	0.00	0.000 ***

Approximate hypothesis tests related to GAM fit

Parametric Terms:

	df	Chi.sq	p-value
Trap	1.00	36.41	0.000 *

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value
te(Soak time): Trap B	1.48	1.79	50.70	0.000 ***
te(Soak time): Trap A	3.24	3.98	22.10	0.000 ***
te(Temperature)	2.61	2.88	116.65	0.000 ***
te(Depth)	5.05	5.69	47.28	0.000 **

Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

GAM 4: The effect of Soak time and Trap design on the CPUE

Likelihood ratio test (Saturated model vs Best-fit model)

	UBRE	Resid. Df	Resid. Dev	Deviance explained	P(>|Chi|)
Saturated model	2.39	100.23	357.58	33.80%	
Best-fit model	2.37	101.20	357.57	33.80%	0.500

Model summary

Parametric coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)	
(Intercept)	0.93	0.09	10.76	0.000	***
Trap A	0.22	0.11	2.00	0.045	*

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value	
te(Soak time): Trap B	1.30	1.80	4.55	0.086	.
te(Soak time): Trap A	2.70	2.91	46.09	0.000	***
te(Temperature)	2.68	2.94	72.94	0.000	***
te(Depth)	3.12	4.01	19.74	0.001	***

Approximate hypothesis tests related to GAM fit

Parametric Terms:

	df	Chi.sq	p-value	
Trap	1.00	4.01	0.045	*

Approximate significance of smooth terms:

	edf	Ref.df	Chi.sq	p-value	
te(Soak time): Trap B	1.30	1.80	4.55	0.086	.
te(Soak time): Trap A	2.70	2.91	46.09	0.000	***
te(Temperature)	2.68	2.94	72.94	0.000	***
te(Depth)	3.12	4.01	19.74	0.001	**

Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

Chapter 5

Comparative assessment of subtidal reef fish monitoring techniques for the Agulhas Ecoregion of South Africa

5.1 Introduction

Effective fisheries and ecosystem based management (EBM) are founded on sound knowledge of the structure of exploited fish populations and the processes that drive ecosystem resilience (Pikitch et al. 2004). In data-poor situations a blanket precautionary approach is advisable, but with increasing knowledge the blanket can be tailored to suit socio-economic needs and ensure maintenance and resilience of the ecosystem that supports the target species (Pikitch et al. 2004). Well-designed long-term monitoring programmes can provide the required knowledge, and are thus essential for effective EBM as it increases the certainty around decision making (Vos et al 2000; Murphy and Jenkins 2010).

Many monitoring programmes highlight design deficiencies with insufficient thought placed on 'what', 'why' and 'how' to monitor (Yoccoz et al. 2001). The question "How should we monitor?" encompasses both method selection and experimental design, but it is the process of method selection that is of interest for this chapter. Assessing fish abundance is fundamental to most marine ecological monitoring programmes and there are many methods to select between. However, 'method-papers' (i.e. reports on research optimising method performance and comparing different methods) show that each method surveys a specific component of the fish community more effectively than others, and that no single method is suitable to effectively survey the entire fish community (Willis et al. 2000; Cappo et al. 2004; Watson et al. 2005, 2010; Harvey et al. 2007, 2012; Bennett et al. 2009; Colton and Swearer 2010; Langlois et al. 2010; Pelletier et al. 2011). In addition, subtle changes to the way a method is applied by an observer, the experimental design, and the ecosystem in which it is applied have important ramifications for how the method performs (Lincoln Smith 1988; Kulbicki 1998; Edgar et al. 2004; Götz et al. 2007; Harvey et al. 2007; Bennett et al. 2009; Ward-Paige et al. 2010; Bozec et al. 2011).

For example, observer swimming speed (Lincoln-Smith 1988) and experience (Edgar and Stuart-Smith 2009) impact the accuracy and precision of count data from underwater visual census (UVC) line transects. Line transects appear better suited to survey temperate reef fish assemblages (Bennett et al. 2009), while point counts (described in Chapter 2) are better suited to survey tropical reef fish assemblages

(Watson and Quinn 1997). In a similar fashion, appearance (cryptic vs. conspicuous), behaviour (shy vs. inquisitive) and size (large vs. small) influence the abundance estimates of fish from UVC (Bozec et al. 2011). Controlled angling (CA) produces more precise estimates of relative abundance and size than UVC for the comparable fish species (Willis et al. 2000; Bennett et al. 2009), however, CA is highly selective and therefore not suitable for monitoring the entire fish assemblage (Bennett et al. 2009). As with UVC, the CA method can be tweaked to improve the catch composition (hook size and bait type) and capture mortality (hook type) (Götz et al. 2007). Baited remote underwater video (BRUV) produces similarly precise data to CA (Willis et al. 2000), but is less selective and therefore more suitable to investigate reef fish assemblages (Harvey et al. 2007). Also, BRUV is much more effective than fish traps (FT) at surveying reef fish assemblages (Harvey et al. 2012). However, in comparison to UVC, BRUV has been shown to underestimate species richness (Colton and Swearer 2010). Again, tweaking the BRUV method influences the quality of data collected, with species richness and abundance increasing with longer deployment times (Watson et al. 2005). Similarly, using bait to attract fish to the camera drastically improves the precision of abundance estimates (Harvey et al. 2007). Different video monitoring techniques also alter the quantity and quality of data collected. For example, stereo-BRUV incorporates all the benefits of BRUV but enables highly accurate length measurements of the counted fish (Harvey and Shortis 1996). Stereo diver operated video (stereo-DOV) is a video based adaption to the traditional UVC transect technique, but produces less biased count data, survey area estimates and size measurements (Harvey et al. 2002; Langlois et al. 2010). It is however biased by the presence of an observer in the water which influences the behaviour of large predatory fish, as has been highlighted with traditional UVC (Willis et al. 2000). Stereo-DOV appears to sample smaller and cryptic species more effectively than stereo-BRUV (Watson et al. 2005, 2010), however, stereo-BRUV is better at surveying the larger-bodied fisheries species (Watson et al. 2010) and produces more precise relative abundance data making it more cost-effective (Langlois et al. 2010).

Some characteristics that affect the precision and accuracy of count data are common to several methods. For example, methods that do not provide an instantaneous measure of abundance will over-estimate the density of fish (Ward-

Paige et al. 2010). Similarly, methods that use bait to attract fish do not produce acute abundance estimates, even though the precision is typically very high. On the other hand, data characterised by low abundances are typically variable and zero-inflated, thereby complicating statistical analysis and reducing the precision of the data (Cunningham and Lindenmayer 2005), while rare species are associated with much lower detection probabilities than abundant ones, increasing the potential for bias in the data (McNeil et al. 2008). As such, methods that allow individuals to accumulate over time (i.e. FT, CA, RUV, BRUV) will overestimate abundance but have a lower variability in the data, while methods that provide a more instantaneous measure of abundance (i.e. UVC, ROV) will provide accurate abundance estimates but be plagued by high levels of variability and high number of zeros.

This means that data often reflect the observed trends rather than the actual trends in the abundance and distribution of species and patterns in biodiversity (Monk et al. 2012). Accordingly, ecological datasets collected with different methods cannot be compared as the observed patterns will be biased by the detectability of species by the different methods. In a similar vein methods that incorrectly estimate abundance can have serious consequences if the data is to inform management decisions (Ward-Paige et al. 2010). By reporting an over, or underestimated abundance, the data could instil false security or false pessimism in the status of a stock, and the resultant management interventions could negatively impact the actual status of the stock, or the stakeholders who rely on the resource, respectively.

As a result, method evaluation is fundamental to ecological research (Elphick 2008), which is in turn the cornerstone to effective EMB and resource management (Pikitch et al. 2004). It enables researchers to select the most appropriate method(s) needed to answer a question, and provides a comprehensive understanding of the biases of the method, which then aids the interpretation of observed patterns in the data (Yoccoz et al. 2001). Comparative method assessments are particularly useful as they provide a direct comparison of the ability that different methods have to detect fish, and enable the cost-effectiveness of the different methods to be determined through statistical power analysis and sample size estimation (Ellis and deMartini 1995; Willis et al. 2000; Watson et al. 2005, 2010; Götz et al. 2007; Bennett et al. 2009; Langlois et al. 2010; Pelletier et al. 2011; Harvey et al. 2012).

Ideally, the cost of collecting accurate, precise, spatially comprehensive and long-term data should not feature in the experimental design and method selection process. However, marine research is expensive and long-term programmes require sustainable funding, and time, over decades before the data begins to show its true value (Vos et al. 2000; Molloy et al. 2010). Consequently, financial constraints and long-term feasibility are important considerations when selecting how, when and what to monitor to meet specified research objectives (Langlois et al. 2010; Murphy and Jenkins 2010). To know what the relative costs of different methods are, and to measure the trade-off between cost and improved knowledge, systematic cost-benefit analyses are required that provide general guidelines on which approach is best suited to answer a type of question (Elphick 2008). What is evident from past work, and research presented in this thesis, is that local environmental conditions (i.e. habitat structure and temperature), and biological characteristics (i.e. community structure and biogeography) influence the quality of data collected by a method (Willis et al. 2000; Harvey et al. 2007; Colton and Swearer 2010; Pelletier et al. 2011). It is therefore important to assess how the different methods perform under local conditions, and not assume that global experience will dictate which method will provide the most comprehensive assessment of the local fish community.

A method's performance will be gauged against the data's ability to answer the specified research question with a certain power (or certainty) and statistical significance level. Power analysis, in its narrow sense, refers to the probability of rejecting the null hypothesis when it is false (Bolker 2007). However, in its broader sense, power analysis investigates how the quality and quantity of data, and the true properties of the ecological system, influence the reliability of the findings to questions about the ecosystem (Bolker 2007). Bolker (2007) provides a detailed philosophical and theoretical account to modelling of ecological data and assessing the power of an analysis. Here, it is worthwhile considering certain aspects of this book:

The amount of information that you can extract from data is dependent on factors such as: (i) the number of data points, (ii) the spatial and temporal distribution of data (experimental design), (iii) the amount of variation within the data, and (iv) the effect size (the distance between the observed value and the null-hypothesis value).

Typically, datasets that are large; balanced; wide ranging; spatially and temporally comprehensive (extent size); with a minimum distance between samples without evoking pseudo-replication (fine grain) are best (Bolker 2007). Similarly, the larger the effect size, the less important are factors (i) – (iii). Better datasets usually come at a cost of increased effort, and as such experimental design typically juggles the trade-offs between the effort (or cost) and the number of samples collected, the extent size covered or the grain between the samples (Bolker 2007).

The reliability of answers from the analysis depends on both the precision and accuracy of the data. Precise data will be associated with narrow confidence intervals (high certainty) around the answers, while with accurate data, answers are more likely to be correct (or true). Both are important, as precise and inaccurate data will provide misleading confidence in an incorrect answer, while accurate and imprecise data will provide a correct answer, but with insufficient confidence to draw any reliable (or meaningful) conclusions (Bolker 2007).

Aspects that affect the precision and accuracy data include:

- **Bias** (accuracy) is the expected difference between the data points and the true value of the parameter being measured.
- **Variance** (precision) is the measure of deviance between the individual data points and the mean of the data points.
- **Confidence interval width** (precision) is the distance between the upper and lower confidence interval estimates. If the confidence interval is estimated correctly then the width will be related to the deviance in the observed and predicted data points. Expressing the confidence interval width as a proportion of the estimate value provides information on the precision of the estimate. A similar measure of precision to the coefficient of variation that expresses the standard deviation as a proportion of the mean (McArdle et al. 1990).
- **Mean squared error** (precision) is the combination of bias and variance and is the total variation around the true value of the parameter being measured, rather than around the mean estimated form the observed data points. It provides and overall sense of quality of the estimator.
- **Coverage** (accuracy) measures the accuracy of the confidence intervals estimated through simulation. “Coverage describes the proportion or percentage of simulations in which the confidence intervals actually include the true value of the parameter being measured.

- **Power** (precision), in its narrow sense, gives the probability of correctly rejecting the null hypothesis.

All of these aspects are important to consider when examining patterns in data. Power analysis has additional benefits in that it can be used to explore the sample size needed to get a precise estimate for a parameter, and to explore how variations in experimental design will influence the ability to answer a research question (Bolker 2007). Typically, a number of monitoring methods will be able to provide statistically robust data so long as sufficient samples are collected. The sample size necessary to achieve an acceptable level of robustness will vary with the most cost-efficient methods requiring the fewest samples.

Through comparative field experiments this chapter will directly compare the ability of a wide range of reef fish monitoring methods to estimate species diversity and relative abundance, and determine the power of the data to detect long-term changes in the fish communities.

The results in this chapter have been divided into two parts, based on location, as the experimental design was different between the Castle Rock study area, in the Table Mountain National Park (TMNP) MPA, and the Rheeders Reef study area, in the Tsitsikamma National Park (TNP) MPA. Each result section will be accompanied by an independent specific discussion .The final chapter (Chapter 6) will then present a cost-benefit analysis and identify cost-efficient methods most suited for reef fish monitoring programmes in the Agulhas Ecoregion of South Africa.

5.2 Part I: Method comparison, and sensitivity to detect a reserve effect in a small, established no-take zone in the Table Mountain National Park Marine Protected Area

5.2.1 Study Aim

The aim of this field experiment was to compare the ability of three subtidal monitoring methods to survey the fish community, and assess the sensitivity to detect differences in abundance depending on habitat protection status.

5.2.2 Study objectives

The main objectives of the experiments were to:

- Compare the fish community sampled (presence/ absence and relative abundance) using BRUV, FT and volunteer UVC surveys.
- Compare the ability of the three methods to detect a protection effect on selected dominant species of fish recorded by all methods
- Conduct a power analysis to assess the variability in the data and the number of samples required by each method to detect a 10 % growth in the populations over a five-year period.

5.3 Materials and methods

5.3.1 Study area and experimental design

The experiments were conducted at the Castle Rock study area in the TMNP MPA described in Chapter 2 (section 2.2.1, Fig. 2.1b, c), and will not be described in detail here. Equally, the mapping and stratification of the sampling area was based on the approach described in Chapter 2 (section 2.2.2 and 2.2.3), and will not be presented in detail here. The habitat strata, considered important for the experimental design, included protection status with two levels: 'no-take' and 'exploited', and reef profile with two levels: 'high' and 'low'. Sample stations were randomly selected with an even allocation between each strata combination.

The research was conducted during daylight hours over a period of 25 days during autumn (March/April) 2010. The sampling effort was standardised at four days per method to account for different sampling efficiencies of the three methods. Only one method was used throughout a day and the succession based on a random sequence of the three methods.

The experiments were conducted off a small (4.5 m length) semi-rigid ski boat, provided by the South African National Parks (SANParks). Although greater sampling effort would have been desirable, poor weather conditions combined with a small research platform restricted the maximum number of days where data could be collected (i.e. only 12 of the 25 days spent in the field were suitable for data collection).

5.3.2 Fish sampling methods

Three reef fish monitoring techniques were employed: (1) FT (2) volunteer based UVC and (3) BRUV. The methods were selected for the following reasons:

- The Castle Rock study area is partly within a no-take MPA and as such the methods selected needed to be non-destructive.
- The study area is in a prominent tourist area and it was felt that conducting controlled angling surveys would draw unnecessary attention from concerned

residents. Due to their more discrete nature, FT was selected over controlled angling.
- Volunteers were used for the UVC surveys as they constitute a large and affordable alternative to experienced researchers.
- Following the results from the remote video method assessment, the BRUV was selected over the RUV method. Although it was originally planned to use the RUV method in conjunction with the other three, the limited field time meant that the method was excluded from this study.

5.3.2.1 Fish traps (FT)

The FT employed in the experiments were the same as those used during the method assessment (Chapter 4), however the funnel opening was standardised to 15cm and the soak time to 80 minutes, following the recommendations from Chapter 4. The research vessel had a carrying capacity of three FT which enabled a total of 48 samples to be collected during the allotted four-day sampling period.

5.3.2.2 Volunteer Underwater Visual Census (UVC)

The UVC technique was identical to that described in Chapter 2 (namely: paired-transects). However, only one dataset per paired-transect was randomly selected for the analysis. To control for variability in the quality of observers, only volunteers that had conducted more than five paired-transects previously were invited to collect the data. This resulted in a total of 11 volunteers taking part in the survey with 45 transects being completed within the allotted four sampling days.

5.3.2.3 Baited Remote Underwater Video (BRUV)

The BRUV system and deployment procedure was standardised and described in Chapter 3. A 50-minute deployment time was selected in accordance with the results from Chapter 3. As only one BRUV station could be conducted at a time a total of 16 samples was collected during the allotted four-day sampling period.

5.3.3 Environmental variables

At each sampling station the water temperature was measured either with a temperature logger at BRUV and FT stations or with a dive computer at UVC stations. The underwater visibility was only measured at UVC and BRUV stations.

For the UVC stations it was estimated by measuring the horizontal distance at which the yellow dive reel became visible to a diver, while for the BRUV stations it was calculated by estimating the relative change in length of individual roman, *Chrysoblephus laticeps*, after the method described in Chapter 3. Water depth was measured with a boat-based echo-sounder at BRUV and FT stations, and with a dive computer at UVC stations.

5.3.4 Data analysis

5.3.4.1 Multivariate community analysis

The multivariate analysis was conducted with PRIMER v6 (Clarke & Warwick 2001) and the PERMANOVA+ add-on package for PRIMER v6 (Anderson et al. 2008). A two-way non-parametric multivariate analysis of variance (PERMANOVA) tested for differences in the fish assemblage (presence/absence and relative abundance) sampled by the FT, UVC and BRUV methods and between samples from the no-take and exploited zones. The data were transformed prior to analysis with a Log 2 modified Gower dissimilarity matrix as it is more appropriate for dealing with multivariate heterogeneity of variance (Anderson et al. 2006, Goetze et al. 2011). Due to the low number of samples for the BRUV, unrestricted permutations on the raw data (n=4999) were computed for each term in the analysis to estimate the p-values (Anderson 2008). Where factors were significant, pairwise comparisons were conducted in PERMANOVA to identify which levels were significantly different from each other.

Principle coordinate ordination (PCO) analysis was performed to visualize the unconstrained grouping of stations and show the broad patterns between the samples and predetermined grouping variables. To visualise the effect of significant factors from the PERMANOVA analysis and to identify the species driving the observed differences, a constrained canonical analysis of principle coordinates (CAP) was conducted (Anderson and Willis 2003). For both the PCO and CAP procedures a Pearson's correlation of 0.4 was chosen to show the correlation between the dominant species and the canonical axis.

5.3.4.2 Univariate method comparison

Detailed exploratory analysis was conducted following the approach of Zuur et al. (2010). The schooling species, massbanker (*Trachurus trachurus*) was associated with extremely high standard error estimates (>10 times the coefficient estimate), reflecting extreme variability in abundance. This is indicative of a poorly fitting model (Bolker et al. 2008) and as a result the species was excluded from the analysis. Harvey et al. (2007) found a similar negative effect of schooling species dominating sample variance and blurring underlying patterns during analysis.

Poisson Generalised Linear Models (GLMs) were selected to model the interaction effect of *Method* and protection *Status* together with the main effect of water *Temperature* on the species richness, total count and relative abundance of hottentot *Pachymetopon blochii*, roman, catsharks *Scyliorhinidae* and fingerfins *Cheilodactylidae*. The full Poisson GLM was described as:

$$Y_i \sim P(\mu_i)$$

$$E(Y_i) = \mu_i \quad \text{and} \quad var(Y_i) = \mu_i$$

$$log(\mu_i) = \alpha + \beta_1(Method_i \times Status_i) + \beta_2(Temperature_i) \qquad \text{(equ. 6.1)}$$

, where the estimated relative abundance, $E(Y_i)$, is μ_i, and the variance is assumed to be equal to the mean, μ_i. The interaction effect, $\beta_1(Method_i \times Status_i)$, was included as it was thought that the detection probability would vary within and between the different method in the no-take zone and the exploited zone. The main effect of temperature was included to account for variability in the data that was not controlled for in the stratified random sampling design.

Regression diagnostic tests and model selection were carried out according to the methods described by Logan (2010). Here the Akaike information criterion (AIC), for all possible combinations of covariates included in the full model, were calculated and the combination with the lowest AIC score was considered to be the most parsimonious model. When the Poisson models were characterised by overdispersed residuals, the GLMs were redone using the negative binomial distribution family with a log link. The negative binomial distribution can be seen as a

combination of the Poisson and Gamma distributions, where Y is assumed to be Poisson distributed and μ to follow a Gamma distribution (Zuur et al. 2009). The mean and variance for Y are given by:

$$Y_i = NB(\mu_i, k)$$

$$E(Y_i) = \mu_i \quad \text{and} \quad var(Y_i) = \mu_i + \frac{\mu_i^2}{k}. \qquad \text{(equ. 6.2)}$$

Unlike the Poisson distribution where the variance is equal to the mean, the negative binomial distribution incorporates an overdispersion parameter, k, into the calculation and is thus better suited for modelling overdispersed count data (Zuur et al. 2009).

Where colinearity was identified between covariates, the covariates with the highest variance inflation factor (VIF) were sequentially removed from the model until all the VIFs were less than the threshold of 3 (Zuur *et al*. 2010). All analyses were conducted in the R environment (version 2.13.0, R Development Core Team 2011) using the MASS package (Venables and Ripley 2002). All graphs were created with the Lattice and LatticeExtra packages (Sarkar 2008).

5.3.4.3 Power analysis

The power analysis employed in this chapter differs from the method of Willis et al. (2003) that was used in the preceding chapters. This was because the method of Willis et al. (2003) assumed that data followed the Poisson distribution, and most of the data from this experiment was found to better follow the negative binomial distribution.

As such, in this chapter the power analysis was conducted to assess the number of samples needed annually to detect a 10 % per annum population increase over five years, with 80 % power and a significance level of $\alpha < 0.05$. These values were selected to define an experimental design able to detect population growth of 10 % per annum in the absence of fishing. A time frame of five years was chosen to represent a theoretical MPA evaluation cycle. The power analysis was based on a Monte Carlo approach after the method of (Porch et al. 2004; Bolker 2007; Blanchard et al. 2007). A deterministic increase in average relative abundance (μ_i) was based on the following equation:

$$(\mu_i)_{t+1} = (\mu_i)_t \times e^r \quad \text{(equ. 6.3)}$$

, where $(\mu_i)_t$ is the relative abundance value predicted for year t, and r is +0.1 (i.e. 10 % growth). Based on this, 500 iterations were generated to calculate the power associated with a sample size of n (where n is the number of samples taken per annum). For each iteration, n relative abundance measurements were generated from the appropriate distribution for each of the five years. The parameters of the distributions were derived from the most parsimonious models. Due to the small sample size for BRUV, it was decided to run the models with only one covariate, *Status*, included in the model. This allowed for the effect of protection status to be taken into account when predicting the data variability, but ensured that the model was not over fitted. The simulation was based on a random-stratified design with even allocation of samples between the strata, while for the continuous covariates the observed data was replicated for each year.

The structure of the GLM (based on the full model) for each iteration was:

$$ln(\mu_i) \pm \ error = \propto + \beta_1(Status_i) + \beta_2(r) \times t \quad \text{(equ. 6.4)}$$

, where r is the estimated growth rate (i.e. the slope). The p-value for the estimated slope $\beta(r)$ was recorded for each iteration. The number of iterations for which $p<0.05$, and for which the direction of $\beta(r)$, negative or positive, agreed with the deterministic *r* value were recorded and expressed as a fraction of 500. The power of detecting a significant increase (or decrease) was indicated by this fraction, i.e. a power of 80 % would be equivalent to 400 trials with a significant slope $\beta(r)$ out of the total 500 trials.

5.4 Results

5.4.1 Sampling and Environmental characteristics

A total of 109 samples was collected consisting of 16 BRUV stations, 48 trap deployments, and 45 UVC transects. The highest daily sampling effort was achieved with FT (12 deployments per day), followed by UVC (11 samples per day), while the sampling effort was particularly low using BRUV (four samples per day). This difference is attributed to the higher number of volunteer divers (n = 11) and FT (n = 3) available to collect samples at a time. Of the 109 samples, 53 were collected from the exploited zone and 56 were collected from the no-take zone (Table 5.1).

Table 5.1: Distribution of sampling effort between the three methods, the protection *Status*, and the reef *Profile*. FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

Status	No-take		Exploited	
Profile	High	Low	High	Low
FT	13	12	11	12
UVC	12	11	11	11
BRUV	4	4	4	4

The average (± SD) water temperature during the field survey was 13.7 ± 2.7 ºC, with a range of 10.0 to 18.9 ºC. The water temperature average was slightly higher for the FT samples (14.7 ± 2.8 ºC), but similar for the UVC (12.8 ± 2.6 ºC) and BRUV (13.0 ± 1.3 ºC) samples. Sampling depth ranged between 4.0 and 28.2 m, with an average depth around 13 m for all samples. The average depth sampled was within one meter for all methods (FT = 13.4 ± 5.3; UVC = 12.6 ± 4.2; BRUV = 12.8 ± 5.2 m). Average water visibility recorded during the survey was greater than five meters for both the BRUV and UCV methods. Water visibility was not recorded during FT deployments.

5.4.2 Description of the fish community sampled

A cumulative total of 30 species of fish were recorded during the survey, with BRUV and UVC recording 19 species, and FT 13 species. Only six species were common to all three methods (Fig. 5.1), four of which were bony fish and two cartilaginous species (Table 5.2). Underwater visual census sampled the highest number of species unique to a method, with seven bony fish and one cartilaginous species. Four species were unique to BRUV, one of which was a cartilaginous species, while only three bony fish species were unique to the FT method. This included species from the families Gobidae and Clinidae which were not included as target families during the UVC surveys (Table 5.2)

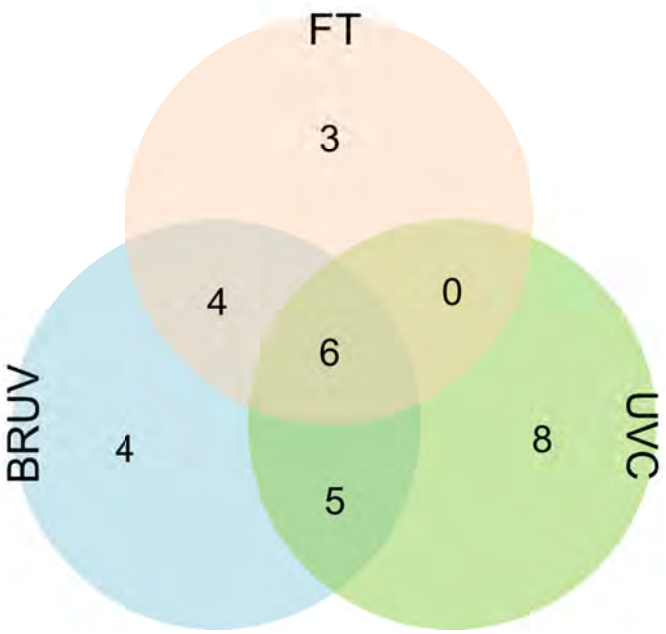

Figure 5.1: Schematic illustration showing the number of species recorded by each of the monitoring methods. The numbers in the overlapping sections of the circles indicate how many species were shared by two or all methods. FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

Table 5.2: List of all species of fish recorded using fish traps, UVC and BRUV. The occurrence is the number of samples where the species was recorded (n), as well as the frequency of occurrence (%) in relation to the number of samples collected per method. The relative abundance is calculated from the samples in which the species were recorded. Species are sorted taxonomically and according to their cumulative frequency of observation (Total N). FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

		Species information		Total	FT						UVC						BRUV					
					Occurrence		Relative abundance				Occurrence		Relative abundance				Occurrence		Relative abundance			
Type	Family	Scientific name	Common mane	N	n	%	Mean	SD	Min	Max	n	%	Mean	SD	Min	Max	n	%	Mean	SD	Min	Max
Osteichthyes	Sparidae	*Pachymetopon blochii*	Hottentot[1]	78	27	54.0	4.19	5.54	1	28	35	77.8	12.57	18.77	1	97	16	100.0	16.13	12.33	4	44
Osteichthyes	Sparidae	*Chrysoblephus laticeps*	Roman[1]	42	3	6.0	1.00	0.00	1	1	29	64.4	4.41	3.76	1	18	10	62.5	2.30	1.42	1	5
Osteichthyes	Sparidae	*Spondyliosoma emarginatum*	Steentjie	42	24	48.0	7.29	6.77	1	27	5	11.1	3.00	1.58	1	5	13	81.3	12.31	12.76	1	43
Osteichthyes	Cheilodactylidae	*Chirodactylus brachydactylus*	Twotone fingerfin	20	–	—	–	–	–	–	18	40.0	3.67	3.88	1	16	2	12.5	1.00	NA	1	1
Osteichthyes	Sparidae	*Boopsoidea inornata*	Fransmadam	14	–	—	–	–	–	–	12	26.7	23.67	32.11	1	100	2	12.5	1.00	NA	1	1
Osteichthyes	Cheilodactylidae	*Cheilodactylus fasciatus*	Redfingers	14	–	—	–	–	–	–	14	31.1	3.71	3.20	1	12	–	–	–	–	–	–
Osteichthyes	Clinidae	*Clinidae spp.*	Klipfish spp.	11	11	22.0	1.55	0.82	1	3	–	—	–	–	–	–	–	–	–	–	–	–
Osteichthyes	Carangidae	*Trachurus trachurus*	Maasbanker	7	–	—	–	–	–	–	1	2.2	1.00	NA	NA	NA	6	37.5	104.33	148.49	16	400
Osteichthyes	Sparidae	*Rhabdosargus globiceps*	White stumpnose[1]	7	–	—	–	–	–	–	–	—	–	–	–	–	7	43.8	1.71	0.95	1	3
Osteichthyes	Parascorpididae	*Parascorpis typus*	Jutjaw	5	–	—	–	–	–	–	5	11.1	1.80	0.45	1	2	–	–	–	–	–	–
Osteichthyes	Sparidae	*Diplodus capensis*	Blacktail[1]	5	–	—	–	–	–	–	3	6.7	1.00	0.00	1	1	2	12.5	1.50	NA	1	2
Osteichthyes	Sparidae	*Petrus rupestris*	Red steenbras[1]	5	–	—	–	–	–	–	5	11.1	1.00	0.00	1	1	–	–	–	–	–	–
Osteichthyes	Sparidae	*Gymnocrotaphus curvidens*	Janbruin[1]	4	–	—	–	–	–	–	4	8.9	1.50	0.58	1	2	–	–	–	–	–	–
Osteichthyes	Ariidae	*Galeichthys feliceps*	White seacatfish	4	3	6.0	1.33	0.58	1	2	–	—	–	–	–	–	1	6.3	1.00	NA	NA	NA
Osteichthyes	Sparidae	*Pterogymnus laniarius*	Panga[1]	4	1	2.0	1.00	NA	NA	NA	2	4.4	15.00	NA	6	24	1	6.3	2.00	NA	NA	NA
Osteichthyes	Sparidae	*Argyrozona argyrozona*	Carpenter[1]	2	–	—	–	–	–	–	–	—	–	–	–	–	2	12.5	2.50	NA	1	4
Osteichthyes	Sparidae	*Sarpa salpa*	Strepie	2	–	—	–	–	–	–	1	2.2	1.00	NA	NA	NA	1	6.3	12.00	NA	NA	NA
Osteichthyes	Cheilodactylidae	*Cheilodactylus pixi*	Barred fingerfin	1	–	—	–	–	–	–	1	2.2	1.00	NA	NA	NA	–	–	–	–	–	–
Osteichthyes	Sparidae	*Pachymetopon aeneum*	Blue hottentot[1]	1	1	2.0	1.00	NA	NA	NA	–	—	–	–	–	–	–	–	–	–	–	–
Osteichthyes	Coracinidae	*Dichistius capensis*	Galjoen[1]	1	–	—	–	–	–	–	1	2.2	1.00	NA	NA	NA	–	–	–	–	–	–
Osteichthyes	Sparidae	*Chrysoblephus gibbiceps*	Red stumpnose[1]	1	–	—	–	–	–	–	–	—	–	–	–	–	1	6.3	1.00	NA	NA	NA
Osteichthyes	Gobidae	*Gobidae spp.*	Gobi spp.	1	1	2.0	1.00	NA	NA	NA	–	—	–	–	–	–	–	–	–	–	–	–
Osteichthyes	Oplegnathidae	*Oplegnathus conwayi*	Cape knifejaw[1]	1	–	—	–	–	–	–	1	2.2	4.00	NA	NA	NA	–	–	–	–	–	–
Condrichthyes	Scyliorhinidae	*Haploblepharus edwardsii*	Puffadder shyshark	36	20	40.0	2.85	2.56	1	12	3	6.7	1.33	0.58	1	2	13	81.3	1.31	0.48	1	2
Condrichthyes	Scyliorhinidae	*Haploblepharus pictus*	Dark shyshark	23	18	36.0	1.67	0.91	1	4	–	—	–	–	–	–	5	31.3	1.60	0.89	1	3
Condrichthyes	Scyliorhinidae	*Poroderma africanum*	Striped catshark	21	15	30.0	1.67	1.35	1	6	1	2.2	1.00	NA	NA	NA	5	31.3	1.20	0.45	1	2
Condrichthyes	Scyliorhinidae	*Poroderma pantherinum*	Leopard catshark	14	12	24.0	1.08	0.29	1	2	–	—	–	–	–	–	2	12.5	1.00	NA	1	1
Condrichthyes	Hexanchidae	*Notorynchus cepedianus*	Spotted sevengill cowshark	4	–	—	–	–	–	–	–	—	–	–	–	–	4	25.0	1.50	0.58	1	2
Condrichthyes	Carcharhinidae	*Triakis megalopterus*	Spotted gullyshark	1	–	—	–	–	–	–	1	2.2	1.00	NA	NA	NA	–	–	–	–	–	–
Agnatha	Myxinidae	*Eptatretus hexatrema*	Six-gill hagfish	2	1	2.0	1.00	NA	NA	NA	–	—	–	–	–	–	1	6.3	1.00	NA	NA	NA

1: Fisheries targets

Of the bony fish, hottentot, steentjie *Spondyliosoma emarginatum* roman and panga *Pterogymnus laniarius* were recorded by all three methods. Hottentot was the most frequently observed species, occurring in all BRUV samples, 54 % of the FT and 78 % of the UVC samples. Steentjies appeared to be under-sampled by UVC occurring in only 11 % of samples, in comparison to the 81 % and 48 % occurrence in the BRUV and FT samples, respectively. Similarly, roman were under-sampled by FT (6 %), in relation to their frequency of occurrence in the BRUV (63 %) or UVC, samples (64 %). Underwater visual census was the only method able to adequately survey the fingerfin species, with none being present in the FT samples, while only the twotone fingerfin *Chirodactylus brachydactylus* was recorded in the BRUV samples (13 %).

The catsharks were the most frequently observed cartilaginous species in the BRUV and FT samples, with the puffadder shyshark *Haploblepharus edwardsii* present in 81 % and 40 % of the samples, respectively. Only BRUV was able to sample the dominant large species of reef associated shark, the spotted sevengill cowshark *Notorynchus cepedianus*, that was present in 25 % of the samples. Very few sharks were recorded by UVC (11 %).

5.4.3 Multivariate community analysis

There was a highly significant effect of method on the observed fish community for both the presence/absence ($MS = 3.06$, $F = 10.91$, $p<0.001$) and the relative abundance data ($MS = 18.72$, $F = 8.72$, $p<0.001$). In both instances the pairwise tests showed significant separation of communities between all the methods (Table 5.3). There was no significant effect of protection *Status* on the fish communities sampled by FT and BRUV in the presence/absence (FT: $t = 1.11$, $p=0.29$; BRUV: $t = 0.75$, $p=0.76$) and the relative abundance data (FT: $t = 1.13$, $p=0.28$; BRUV: $t = 1.00$, $p=0.41$). However, with the UVC data, PERMANOVA identified a significant difference in community structure between the exploited and no-take zones for both the presence/absence ($t = 1.97$, $p<0.05$) and the relative abundance data ($t = 1.74$, $p<0.05$).

Table 5.3: PERMANOVA pairwise tests on Modified Gower Log2 dissimilarities of the presence/absence and relative abundance of the species sampled by the different methods. P(perm) = p-value calculated during the permutational analysis. FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

	Presence/ Absence			Relative abundance		
Pairwise test	t	P(perm)		t	P(perm)	
BRUV vs FT	2.111	0.000	***	2.977	0.000	***
BRUV vs UVC	3.037	0.000	***	1.8695	0.010	*
FT vs UVC	4.033	0.000	***	3.4847	0.000	***

*Significance level: "***"<0.001, "**"<0.01, "*"<0.05,"▪"<0.1*

The differences in the communities sampled by the three methods are clearly evident in the PCO ordination for the presence/absence (Fig. 5.2a) and for the relative abundance data (Fig. 5.3a). Roman, puffadder shyshark and dark shyshark *Haploblepharus pictus* were the main species (R ≥ 0.4) that contributed to the observed differences in the presence/absence data, with the shysharks correlating with BRUV and FT samples and roman correlating with UVC samples (Fig. 5.2a). The situation was somewhat different in the abundance data reflecting strong correlations of hottentot with UVC samples, and puffadder shyshark and steentjie with the FT samples while BRUV samples occupied the mid-ground between the different sample trajectories (Fig. 5.3a).

The CAP analysis found significant separation between the methods for the presence/absence data (tr(Q_m'HQ_m): 1.22, p = 0.0002) (Fig. 5.2b) and the relative abundance data (tr(Q_m'HQ_m): 0.74, p = 0.0002) (Fig. 5.3b). Nine species were isolated as contributing to the observed differences (R ≥ 0.4) in the presence/absence data. For the UVC data, this illustrated the methods ability to survey the dominant large sparid, roman, together with the dominant large cryptic species, the twotone fingerfin and the redfingers *Cheilodactylus fasciatus* (Fig. 5.2b). Three species of catshark (striped *Poroderma africanum* and leopard *Poroderma pantherinum* catsharks, and dark shyshark) accounted for the separation of the FT samples, while three species of sparid (white stumpnose *Rhabdosargus globiceps*, steentjie and blacktail *Diplodus capensis*) were influential in distinguishing the BRUV samples (Fig. 5.2b).

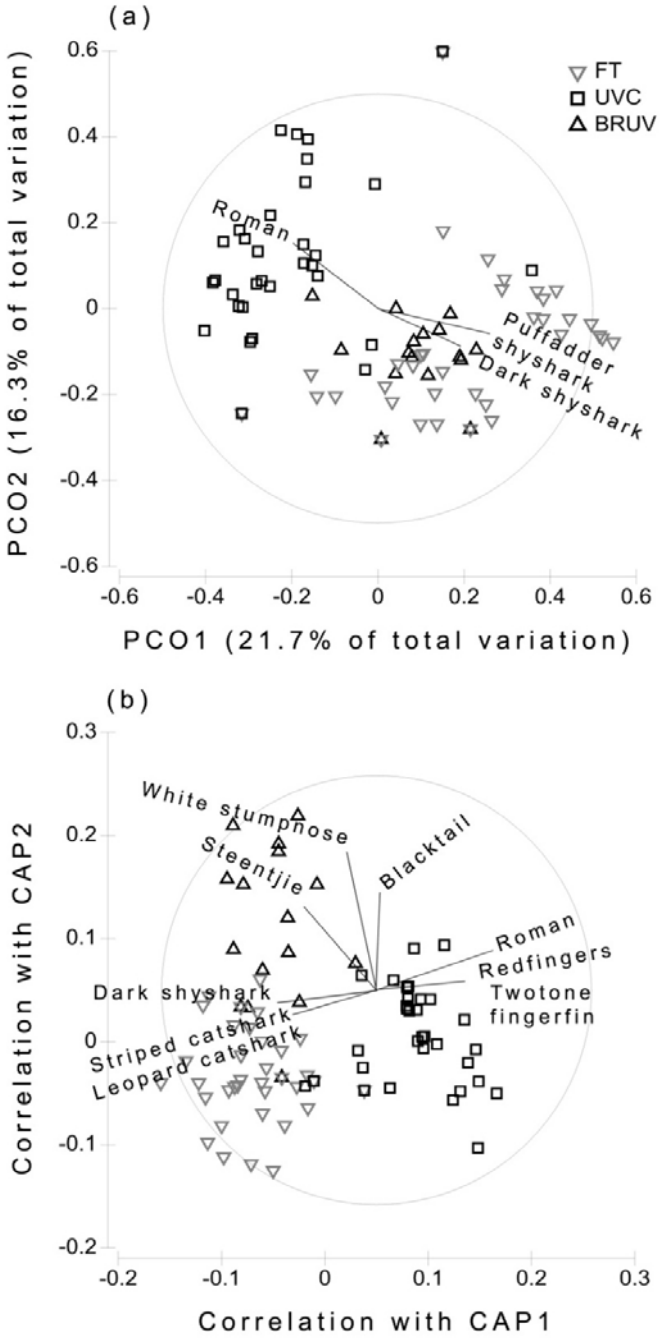

Figure 5.2: Results from (a) the principal coordinate ordination (PCO) and (b) the canonical analysis of principal coordinates (CAP) ordination based on modified Gower Log2 dissimilarities for species presence/absence. Species correlations (Pearson *R* value greater than 0.4) with the canonical axis are represented as vectors indicating the affinity of the species to the method (e.g. catsharks are positively correlated with fish traps). FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

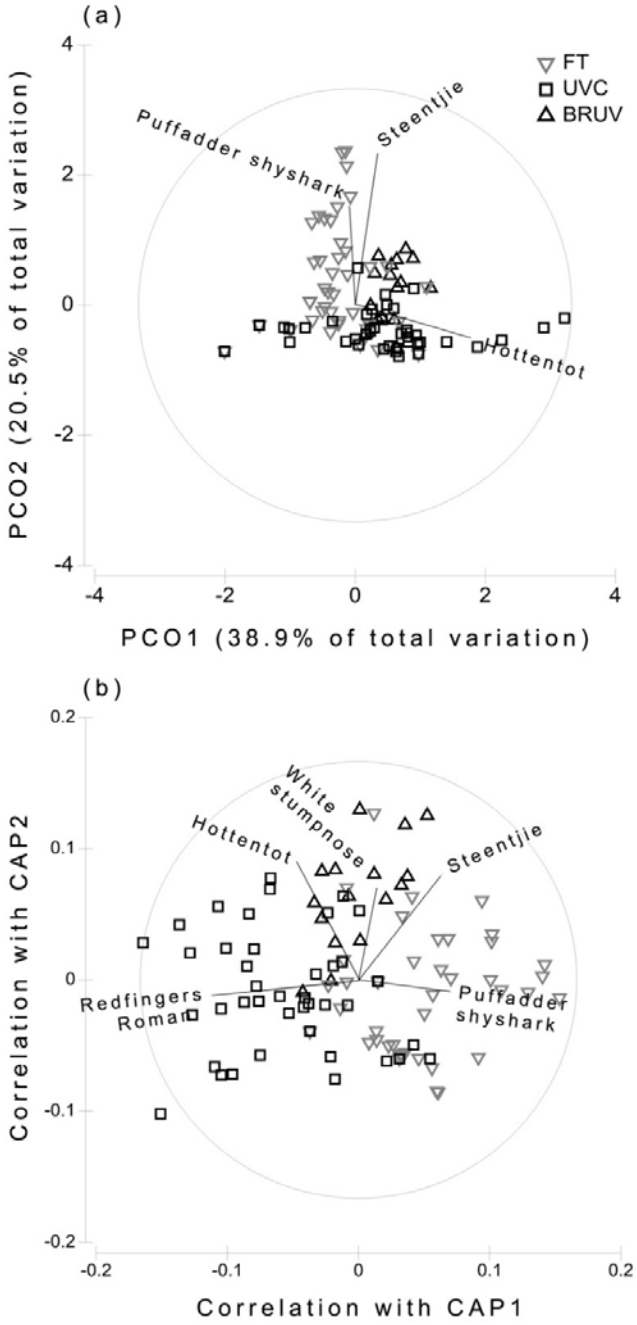

Figure 5.3: Results from (a) the principal coordinate ordination (PCO) and (b) the canonical analysis of principal coordinates (CAP) ordination based on modified Gower Log2 dissimilarities for relative abundance. Species correlations (Pearson *R* value greater than 0.4) with the canonical axis are represented as vectors indicating the affinity of the species to the method. FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

Only six of these species were important when the relative abundance was considered with roman and redfingers, white stumpnose and puffadder shyshark correlating with the UVC, BRUV, and FT method, respectively (Fig. 5.3b). Steentjie and hottentot appeared to occupy the mid-ground between BRUV and FT, and between BRUV and UVC, respectively (Fig. 5.2b).

5.4.4 Univariate method comparison

5.4.4.1 Species richness

On average (± SD) BRUV recorded the highest species richness (5.9 ± 2.0), followed by UVC (3.2 ± 2.1) and FT (2.8 ± 1.6). Baited remote underwater video also recorded the most species in a sample (10), compared to UVC (8) and FT (7), and was the only method where at least one species was recorded in every sample.

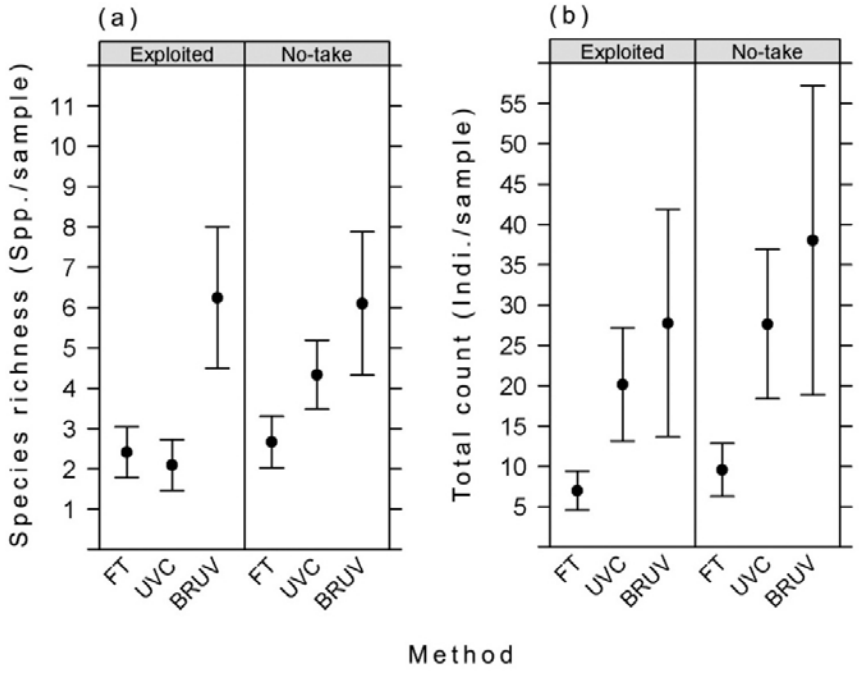

Figure 5.4: The effects of *.Method* and *Status* on the predicted mean (± 95 % confidence intervals) species richness (a) and total count of fish (b). FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

Assessment of the VIF found that none of the covariates in the full model showed sufficient variation to warrant their exclusion. In addition, assessment of the overdispersion parameter showed that the Poisson error distribution was suitable to model the species richness data. The model selection process indicated that the full model was the most parsimonious:

$$\log(Species\ richness_i) = \alpha + \beta_1(Method_i \times Status_i) + \beta_2(Temperature_i).$$

Together, the interaction effect between *Method* and *Status* and the main effect of *Temperature* was able to explain 37.7 % of the observed variability in the data. The likelihood ratio test identified that the effect of *Method* was highly significant (X^2= 29.83, p<0.001), with the BRUV recording significantly more species than both UVC and FT (Fig. 5.4a) in the exploited zone, and BRUV and UVC recording significantly more species than FT in the no-take zone (Fig. 5.4a). The interaction effect between *Method* and *Status* was significant (X^2 = 9.32, p<0.01), with UVC detecting significantly more species in the no-take zone compared to the exploited zone (Fig. 5.4a). On the other hand, BRUV and FT did not detect any significant effect of *Status* (Fig. 5.4a). Temperature had a significant (X^2 = 8.34, p<0.01) positive effect (Odds ratio ± SE = 0.06 ± 0.02) on species richness with more species observed in warmer water (Table 5.4).

5.4.4.2 Total count

The average (± SD) total number of fish recorded was similar between BRUV (31.9 ± 16.9) and UVC (23.3 ± 27.2), however, the variability was much greater in the UVC data. Fish traps provided the lowest number of fish per sample (9.0 ± 8.2).

The Poisson model was characterised by highly overdispersed residuals and, as a result, the total counts were modelled with the negative binomial distribution. The model selection process identified that *Temperature* played little role in explaining the observed variability in the data and it was excluded from the predictive model. Similarly, the interaction between *Method* and *Status* was dropped from the model. The most parsimonious model,

$$log(Total\ count_i) = \alpha + \beta_1(Method_i) + \beta_2(Status_i),$$

was able to explain 20.8 % of the observed variability in the data. *Method* had a significant effect on the total count (X^2= 27.69, p<0.001), with BRUV and UVC recorded significantly more individuals per sample than the FT method in both the exploited and no-take zones (Fig. 5.4b). The effect of *Status* was found to be significant (X^2=3.88, p<0.05), with more fish recorded in the no-take zone. However the confidence intervals (CIs) around the predicted mean total counts were large suggesting that the precision of the data was low (Fig. 5.4b).

Table 5.4: Parameter estimates for the selected covariates, and information on the model fit from the generalised linear model (GLM) on the relative abundance of the dominant species and groups of species. FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

	Species richness				Total count				Hottentot			
	Estimate[2]	SE	t value[3]		Estimate	SE	t value		Estimate	SE	t value	
Method: FT	0.032	0.341	0.095		1.991	0.179	11.093	***	3.174	0.901	3.523	***
Method: UVC	-0.139	0.206	-0.674		0.939	0.208	4.505	***	1.193	0.445	2.682	**
Method: BRUV	0.952	0.196	4.861	***	1.253	0.286	4.379	***	1.022	0.586	1.744	.
Status: No-take	0.102	0.175	0.584		0.380	0.192	1.978	.	-0.534	0.448	-1.192	
UVC:No-take	0.062	0.021	2.936	**					-0.146	0.059	-2.451	*
BRUV:No-take	0.623	0.253	2.459	*					-0.285	0.615	-0.463	
Temperature	-0.126	0.271	-0.465						1.369	0.825	1.660	
Theta (k) [1]					1.1352				0.6464			
Null deviance	162.24 on 108 DF				162.63 on 108 DF				171.44 on 108 DF			
Residual deviance	101.05 on 102 DF				128.76 on 105 DF				120.20 on 102 DF			

	Roman				Catsharks				Targets			
	Estimate	SE	t value		Estimate	SE	t value		Estimate	SE	t value	
Method: FT					0.544	0.203	2.679	**	1.786	0.879	2.033	*
Method: UVC	-2.257	0.795	-2.839	**					1.641	0.327	5.017	***
Method: BRUV	-0.485	0.341	-1.420		-0.187	0.290	-0.645		1.996	0.429	4.656	***
UVC:No-take	0.962	0.294	3.266	**	0.645	0.249	2.591	*				
UVC:No-take												
BRUV:No-take												
Temperature	0.196	0.057	3.414	**					-0.064	0.058	-1.095	
Theta (k)	1.654				1.8064				0.7815			
Null deviance	102.422 on 60 DF				78.703 on 63 DF				179.70 on 108 DF			
Residual deviance	69.364 on 57 DF				71.627 on 61 DF				124.18 on 105 DF			

1: Theta (k) = shape parameter of the negative binomial distribution. Small k = distribution closer to gamma; Large k = distribution closer to

2: Estimate = log(Odds ratio)

3: Significance level: "***"<0.001, "**"<0.01, "*"<0.05,"▪"<0.1

5.4.4.3 Hottentot

Baited remote underwater video recorded the highest mean (± SD) hottentot abundance (16.1 ± 12.3), followed by UVC (9.8 ± 17.3) and the FT method (2.3 ±

4.6). The highest abundance was recorded by UVC (97), and BRUV was the only method to record hottentot in every sample.

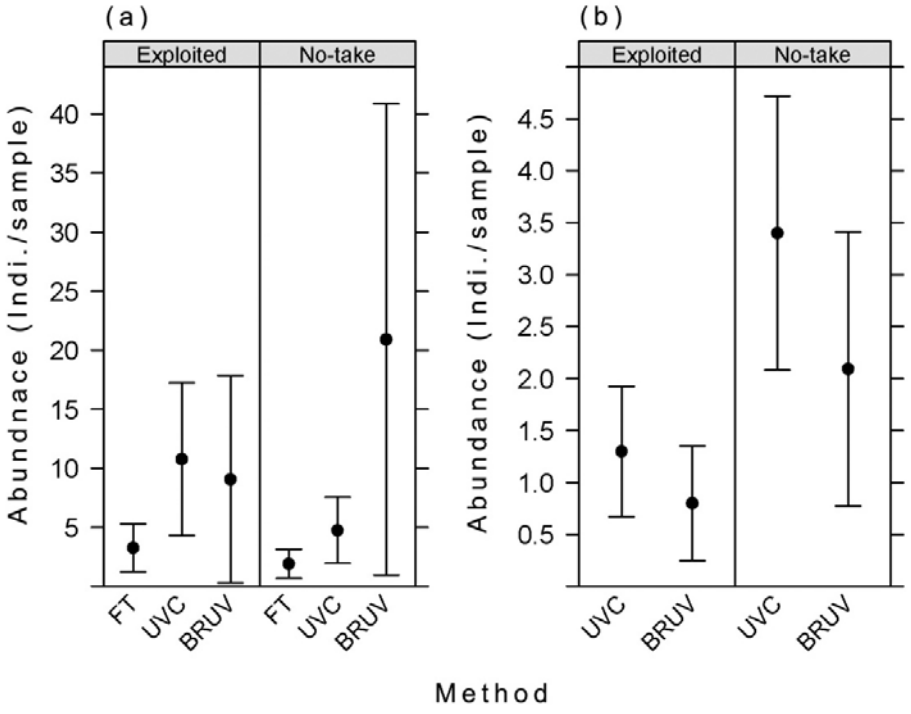

Figure 5.5: The effects of *Method* and *Status* on the predicted mean (± 95 % confidence intervals) relative abundance for hottentot (a) and roman (b). FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

As with total count, the abundance data of hottentot was highly overdispersed and was accordingly modelled with the negative binomial distribution. The model selection process identified that the full model was the most parsimonious model:

$$log(Abundance_i) = \alpha + \beta_1(Method_i \times Status_i) + \beta_2(Temperature_i).$$

The model was able to explain 29.9 % of the observed variability in hottentot abundance. The likelihood ratio test identified that *Method* had a significant effect on hottentot abundance ($X^2 = 7.11$, $p<0.05$). However the width of the CIs around the predicted means was large and blurred separation between the abundance data from the different methods (Fig. 5.5a). The effect of *Status* was not found to be significant ($X^2 = 1.39$, $p>0.2$), however the interaction effect between *Method* and

Status (X^2 = 4.06, p>0.1) showed contrasting effects of *Status* on hottentot abundance when measured with the different methods (Fig. 5.5a). The BRUV data suggested that the abundance of hottentot was greater in the no-take zones, while the data from both FT and UVC suggested the opposite, with more hottentot in the exploited zone compared to the no-take zone. The effect of *Temperature* was significant (X^2 = 4.26, p<0.05), with a negative correlation (Odds ratio ± SE = -0.14 ± 0.06) with the relative abundance of hottentot (Table 5.3).

5.4.4.4 Roman

The highest average abundance (± SD) of roman was recorded by UVC (2.8 ± 3.7), followed by the BRUV (1.4 ± 1.6) and the FT method (0.1 ± 0.2). For the analysis of the variability in roman abundance only the data from UVC and BRUV were used, as insufficient roman were recorded by the FT method (6 % of the samples). The exploratory analysis identified that the distribution of the residuals was highly overdispersed, and as a result the roman abundance data were modelled with the negative binomial distribution. The model selection process resulted in the interaction effect between *Method* and *Status* being dropped from the most parsimonious model:

$$log(Abundance_i) = \alpha + \beta_1(Method_i) + \beta_2(Status_i) + \beta_3(Temperature_i).$$

Together, *Method*, *Status* and *Temperature* were able to explain 32.3 % of the observed variability in roman abundance. *Method* did not significantly influence the relative abundance of roman (X^2 = 1.99, p>0.1) (Fig. 5.5b). The effect of *Status* was significant (X^2= 10.98, p<0.001), however, this was only true for UVC as there was considerable overlap in the predicted CI from the BRUV data (Fig. 5.5b). The effect of water *Temperature* was significant (X^2 = 14.19, p<0.001), with higher abundances of roman predicted in warmer water (Odds ratio = 0.19 ± 0.06).

5.4.4.5 Catsharks

Average (± SD) catshark abundance was similar in the FT (2.5 ± 2.7) and the BRUV samples (2.1 ± 2.1). Underwater visual census recorded very few catsharks (0.1 ± 0.4). As such, the analysis on the abundance of catsharks excluded UVC as there was insufficient data. The exploratory analysis revealed overdispersed residuals and

as a result the negative binomial distribution family was used to analyse the observed variability in catshark data. The model selection process excluded the covariates *Temperature* from the most parsimonious model:

$$log(Abundance_i) = \alpha + \beta_1(Method_i) + \beta_2(Status_i),$$

Together, *Method* and *Status* were able to explain 10.0 % of the observed variability in catshark abundance. The likelihood ratio test identified that *Method* did not significantly ($X^2 = 0.41$, $p>0.5$) affect catshark abundance (Fig. 5.6a). The effect of *Status* was significant ($X^2 = 6.76$, $p<0.01$), with greater abundances of catsharks predicted to occur in the no-take area (Fig. 5.6a).

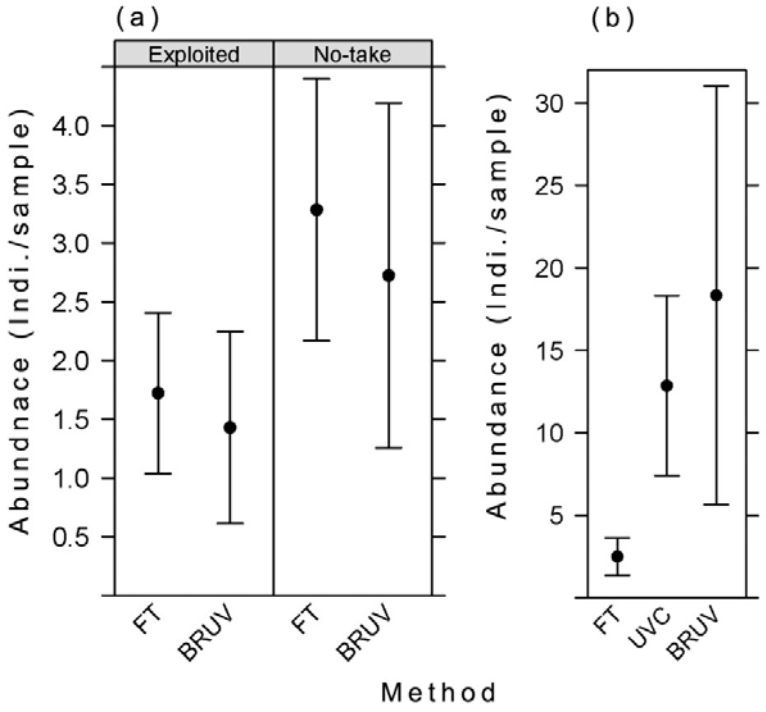

Figure 5.6: The effects of *Method* and *Status* on the predicted mean (± 95 % confidence intervals) relative abundance for catsharks (a) and the effect of *Method* on the relative abundance of primary fisheries targets (b). FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

5.4.4.6 Primary fisheries species

The grouping of primary fisheries targets consisted of carpenter *Argyrozona argyrozona*, galjoen *Dichistius capensis*, panga, red steenbras *Petrus rupestris*, red stumpnose *Chrysoblephus gibbiceps* and roman. The highest average (± SD) abundance of primary fisheries targets was recorded by BRUV (19.0 ± 12.2), followed by UVC (13.7 ± 18.0), with FT recording the lowest abundance of primary fisheries targets (2.4 ± 4.7).

The exploratory analysis revealed overdispersed residuals and as a result the negative binomial distribution family was used to model the observed variability in primary fisheries targets abundance. The model selection process excluded the covariate *Status* from the most parsimonious model:

$$log(Abundance_i) = \alpha + \beta_1(Method_i) + \beta_2(Temperature_i),$$

Together, *Method* and *Temperature* were able to explain 30.9 % of the observed variability in the abundance of primary fisheries targets. The likelihood ratio test identified that *Method* had a highly significantly affect ($X^2 = 30.98$, $p<0.001$), with BRUV and UVC recording significantly higher abundances than FT (Fig. 5.6b). The effect of *Temperature* was not significant ($X^2 = 1.06$, $p>0.2$).

5.4.5 Protection effect and Power analysis

The power analysis was designed to enable the detection of significant trends in abundance of a species or group of species over a period of five years. The scale of the trend in abundance was set to a 10 % population growth. To limit variation in the structure of the GLMs used to predict the power of the data, the power analyses were conducted on a standardised model containing only the effects of protection *Status* and *Year*.

5.4.5.1 Species richness

The model residuals for all species richness datasets showed no signs of overdispersion and the Poisson distribution was used to model the variance and conduct the power analysis.

Protection *Status* had no measureable effect on species richness from the FT data ($X^2 = 0.55$, $p>0.4$), with the exploited zone averaging (± SD) 2.6 ± 1.6 species, and the no-take zone 2.9 ± 1.6 species. Baited remote underwater video demonstrated the same pattern ($X^2 <0.001$, $p = 1$), with the same number of species recorded in the exploited zone (5.5 ± 2.5) compared to the no-take zone (5.5 ± 1.7), although there was considerably less variation between the samples from the no-take zone. The effect of protection *Status* on species richness was significant ($X^2 = 16.40$, $p<0.001$) for the UVC method, with significantly more species recorded in the no-take zone (4.2 ± 1.7) compared to the exploited zone (2.1 ± 1.5).

The results from the power analysis showed that all methods collected sufficient samples to have confidence in the precision of the data. Baited remote underwater video was estimated to require the lowest sampling effort (n = 7 samples) to detect the 10 % growth in species richness over a five year period (Table 5.5) (Fig. 5.7a). Underwater visual census ranked second requiring 11 samples, followed by FT which required 13 samples to detect the specified change in community structure (Table 5.5) (Fig. 5.7a).

Table 5.5: Minimum number of samples required for the different methods to detect a 10 % population growth over a period of five years at a significance level of $\alpha = 0.05$ with a power of 0.8. FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

Method	FT	UVC	BRUV
Replicate samples	48	45	16
Species richness	13	11	**7**
Hottentot	128	83	**13**
Roman	—	62	**45**
Steentjie	152	264	**79**
Catsharks	41	—	**32**
Fingerfins	—	**147**	—
Primary fisheries targets	—	77	**23**

5.4.5.2 Hottentot

The model residuals for all hottentot datasets were overdispersed and the negative binomial distribution was used to model the variance and conduct the power analysis.

Average (± SD) hottentot abundance recorded in the FT was greater in the exploited (3.0 ± 6.0) compared to the no-take zone (1.6 ± 2.9), however this effect was not significant ($X^2 = 1.60$, $p>0.2$). A significant effect of protection *Status* was identified in the UVC data ($X^2 = 4.92$, $p<0.05$) with greater abundances in the exploited (14.1 ± 23.6) compared to the no-take zone (5.6 ± 5.4). In contrast, average (± SD) hottentot abundance sampled with BRUV was significantly ($X^2 = 9.59$, $p<0.01$) greater in the no-take zone (22.8 ± 14.2), with fewer individuals recorded in the exploited zone (9.5 ± 4.9).

The results from the power analysis showed that the BRUV required the lowest sampling effort to produce data with the desired precision to detect long-term change in the hottentot community (Table 5.5) (Fig. 5.7b). The fact that BRUV required greater than six, and nine times fewer samples than UVC and FT, respectively, suggests that caution should be placed when interpreting the results from the analysis on the effect of protection *Status* on abundance. In this regard it is more likely that the pattern observed in the BRUV data is accurate, while the negative effect of protection *Status* identified by the UVC and, to a lesser degree, FT was misleading.

5.4.5.3 Roman

Overdispersion of the residuals was evident in the roman abundance data for both the UVC and BRUV methods, and the negative binomial distribution was used to model the variance in the data.

Average (± SD) roman abundance from the UVC samples was significantly ($X^2 = 8.34$, $p<0.01$) greater in the no-take (4.2 ± 4.0) compared to the exploited zone (1.4 ± 2.7). The BRUV data showed the same pattern, with average (± SD) roman abundance greater in the no-take (1.9 ± 1.9) compared to the exploited zone (1.0 ± 1.2), however the scale of the effect was not significant ($X^2 = 1.31$, $p>0.2$).

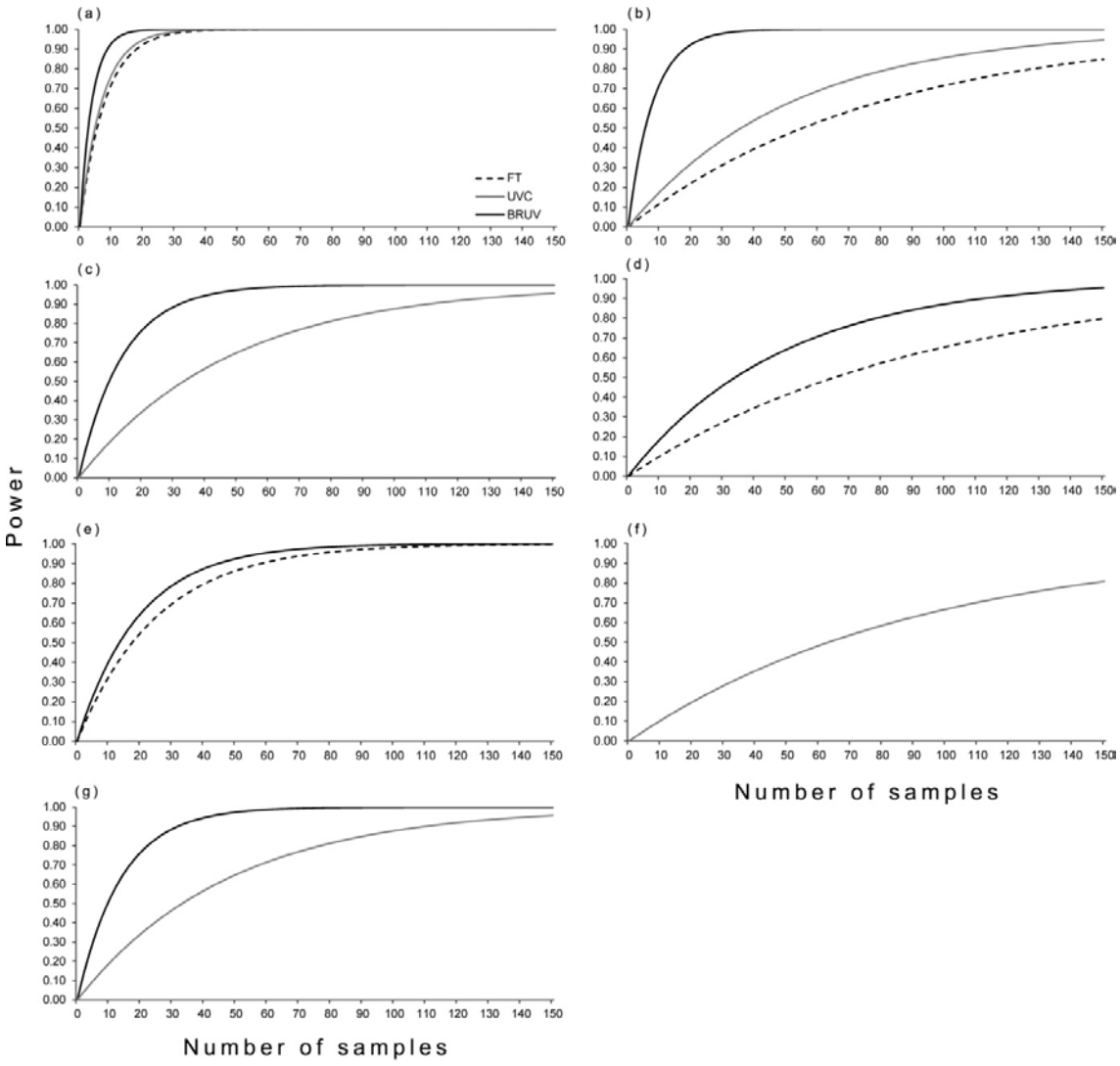

Figure 5.7: Predicted power with increasing sample size do detect a 10 % growth in species richness (a), hottentot (b), roman (c), steentjie (d), catsharks (e), fingerfins (f) and primary fisheries targets (g) over a period of five years. FT = fish traps, UVC = underwater visual census, BRUV = baited remote underwater video.

Although UVC recorded more roman that BRUV, the higher degree of variability in the UVC data meant that BRUV required fewer samples to detect the 10 % growth in roman population size over a period of five years (Table 5.5) (Fig. 5.7c).

5.4.5.4 Steentjie

Overdispersion of the residuals was evident in the steentjie abundance data for both the FT and BRUV methods, and the negative binomial distribution was used to model the variance in the data.

Both the BRUV and FT datasets showed that there was no significant effect of protection *Status* on the relative abundance of steentjie (BRUV: $X^2 = 0.02$, $P>0.8$; FT: $X^2 = 1.23$, $p>0.2$). However, their data was characterised by high levels of variability (FT: no-take zone = 4.9 ± 7.6, exploited zone = 2.5 ± 3.4; BRUV: no-take zones = 10.5 ± 15.4, exploited zone = 9.5 ± 9.7), and it is possible that this may have blurred any potential patterns in the data, especially for the FT. The results from the power analysis indicated that both methods required considerably greater sampling effort to have sufficient power to detect a 10 % growth in steentjie abundance (Table 5.5), with FT requiring almost double the sampling effort predicted for BRUV (Table 5.5) (Fig. 5.7d).

5.4.5.5 Catsharks

Overdispersion of the residuals was evident in the catshark abundance data and as a result the negative binomial distribution was used to model the variance in the data.

Average (± SD) catshark abundance from the FT was significantly ($X^2 = 5.00$, $p<0.05$) greater in the no-take (3.3 ± 3.2) compared to the exploited zone (1.7 ± 1.7). As with the FT data, the average (± SD) was greater in the no-take (2.6 ± 2.3) compared to the exploited zone (1.5 ± 1.9), however the scale of the effect was found not to be significant ($X^2 = 1.46$, $p>0.2$).

The power analysis suggested that sufficient samples were collected to have confidence in the patterns observed in the FT data (Table 5.5). The power analysis indicated that BRUV required double the sampling effect achieved during this study to confidently predict patterns in catshark abundance (Table 5.5). In comparison to TFs, however, BRUV was predicted to require fewer samples to detect a 10 % growth in catshark abundance (Table 5.5) (Fig. 5.7e).

5.4.5.6 Fingerfins

Only the UVC method was able to detect the fingerfin species (namely: twotone, barred and redfingers) that occurred within the study area. Overdispersion of the residuals was evident in the fingerfin abundance data and as a result the negative binomial distribution was used to model the variance in the data.

Average (± SD) abundance was found to be significantly ($X^2 = 4.3$, $p<0.05$) greater inside the no-take (4.0 ± 5.2) compared to the exploited zone (1.2 ± 4.4). However the power analysis indicated that insufficient samples were collected during this study to have sufficient power and certainty in the analysis (Table 5.5) (Fig. 5.7f).

5.4.5.7 Primary fisheries targets

Only the UVC and BRUV datasets were used to assess the effect of protection *Status* and conduct the power analysis. Overdispersion of the residuals was evident in the abundance data and, as a result, the negative binomial distribution was used to model the variance in the data.

UVC measure significantly ($X^2 = 7.6$, $p<0.01$) more primary fisheries target inside the no-take area (5.5 ± 6.2), than in the adjacent exploited zone (1.7 ± 3.4). In contrast, BRUV showed no effect of protection *Status* ($X^2 = 0.69$, $p>0.4$) on the abundance of primary fisheries targets (no-take = 3.1 ± 2.8; exploited: 2.3 ± 1.3). The power analysis identified that both methods required greater sampling effort to have confidence in the results and the BRUV required fewer samples to achieve the same diagnostic power as UVC (Table 5.5) (Fig. 5.7g).

5.5 Discussion

5.5.1 Comparison of methods

The first question that this chapter aimed to address was whether there was a measurable difference in the fish community sampled by the different methods. The comparative field experiment clearly demonstrated differences in the ability of the three methods to survey the reef fish community within the study area. While UVC sampled the most unique species, BRUV appeared to be able to sample the largest portion of shared species (i.e. those common to BRUV and UVC, or BRUV and FT) resulting in the same total number of species observed as in UVC. Fish traps were notably ineffective at sampling the reef fish community, however, they were able to sample the highest number of catshark species, which were poorly sampled with UVC. The basic pattern observed, with UVC sampling the most unique species and FT the least, was highlighted in the PCO and CAP analyses with the strongest separation in sample dissimilarities observed between these two methods. Even though BRUV showed stronger similarity to both UVC and the FT method, the PERMANOVA analysis suggested that the difference between all three methods was significant, when comparing both species richness and relative abundance. The clear contrast in the communities sampled by the different methods is important, as it highlights the variable detection probabilities of different species by different methods. This conclusion is well documented from past research (Willis et al. 2000; Watson et al. 2005; Colton and Swearer 2010), and reinforces the need to understand the relative strengths and weaknesses of a sampling method before employing it to answer an ecological question.

The distinct differences between the methods were further demonstrated with the univariate analysis of species richness and relative abundance. Here, it showed that BRUV, on average, recorded more species than UVC or the FT method. This was particularly true for samples from the exploited zone, where BRUV was predicted to record significantly more species than UVC or the FT method. In Chapter 2 it was shown that UVC is particularly prone to observer bias, with low detection probabilities for rare species. It is possible that the low number of species recorded reflects this reduced ability to detect the species occurring at lower abundances in

the exploited zone compared to the no-take zone. In line with this, there was no significant difference between the number of species recorded by UVC and BRUV in the no-take zone. One of the strengths of BRUV is the consistency, or increased precision, between samples (Harvey et al. 2007), and this trend was evident throughout the analysis.

The pattern in the total count data was equally distinct with both UVC and BRUV, recording significantly more individuals per transect than the FT method. Although BRUV recoded higher abundances on average there was insufficient evidence to suggest a significant difference to the UVC data. This pattern was mirrored when only the hottentot data were analysed. While there was no marked effect of *Method* on the roman data when comparing BRUV and UVC, and on the catshark data when comparing BRUV and FT.

Overall, FT appeared to be in a lower league to BRUV and UVC, when it came to surveying the reef fish assemblages in both zones. This result is in agreement with Harvey et al. (2012) who found that stereo-BRUV was a much more powerful tool than FT in measuring various fish community parameters on the tropical continental shelf of Australia. The ability of the FT method to survey and collect catsharks, showed that there is value in the method. Although BRUV also provided some information on catsharks, FT allowed the different sexes to be separated and accurate length measurements for the individuals. However, using the BRUV in stereo-video configuration (see Harvey and Shortis 1996) would equally provide accurate measurements of catshark size.

Baited remote underwater video was the most consistent performer, either out-sampling both UVC and FT, or producing equitable data. There was one exception, with UVC being the only method to produce data suitable for analysis of the fingerfin population in the area. The inability of the BRUV method to survey the fingerfin group was highlighted in Chapter 3, where the unbaited remote underwater video (RUV) consistently recorded the family more efficiently than BRUV. Fingerfins appear to be an important component of the rocky reef communities in the Agulhas Ecoregion of South Africa, occurring from the shallows to depths in excess of 80m. Studies intending to investigate the ecology and processes that structure these reef habitats would need to include a method that can survey this species. The depth

distribution of fingerfins exceeds safe diving depths, thereby limiting the use of UVC, and as such, unbaited remote underwater video (RUV) may present a more effective option to monitor this component of the community.

5.5.2 The effect of protection status and power analysis

The results from the second (presence of a reserve effect) and third (power to detect long-term patterns) objectives from this field experiment will be discussed together.

The multivariate PERMANOVA analysis delivered equivocal results for BRUV and FT suggesting that there was little difference between the fish communities in the exploited and no-take zone. On the other hand, UVC detected significant differences between the composition of the fish communities within the no-take and exploited zone. This effect was driven by the dominant species in the UVC samples, the roman and fingerfins, which were poorly represented outside the no-take zone. Similarly, UVC was able to detect a significant effect of protection status on the observed species richness. Both, FT and BRUV, failed to detect any clear differences. While for the FT, this likely reflects the inability of the method to survey the broader fish community. For the BRUV, the situation may be accurate, highlighting the inability of UVC to survey species when they are rare. Alternatively, BRUV data is biased by bait, and this may have reduced the accuracy of the data, attracting species from deeper waters or from the adjacent no-take zone.

The response of hottentot to protection status was inconsistent between the methods, with both UVC and FT suggesting that abundance was greater outside the protected zone than within, while BRUV suggested the opposite. The power analysis indicated that both, UVC and the FT method, required considerably greater sampling effort (n = 83 and 128, respectively) than what was conducted (n = 45 and 48, respectively), to have any real confidence in the results. On the other hand, sufficient BRUV samples were collected (n = 16), suggesting that the significant effect of protection was more likely to be accurate. While at first glance this might seem like a positive result, the recommended sampling effort for BRUV to detect a growth or decline in the hottentot population is alarmingly low (n = 7). This suggests that the model may be underestimating the variability in hottentot abundance, and could again reflect a bias associated with bait.

Hottentot in the TMNP MPA can be considered equivalent to the steentjie in the Tsitsikamma National Park (TNP) MPA. The results from Chapter 3 indicated that steentjie showed a disproportionate response to the presence of bait relative to all other species sampled. This bias may also be working on the hottentot abundance data, resulting in the BRUV method dampening the actual variability in the population by consistently overestimating abundance. In the introduction, the principles of accuracy and precision were discussed (Bolker 2007). In this instance, the BRUV may provide the desired precision at the cost of accuracy, and it is a trait that abundant small generalist carnivores, such as steentjie and hottentot, may be particularly vulnerable too.

Roman abundances were greater inside the no-take zone than in the adjacent fished zone. Bennett et al. (2009) found a similar pattern, when comparing roman abundance measured in the TNP MPA, and an adjacent exploited area at Plettenberg Bay. Although the protection effect was present in both, the UVC and BRUV data, it was identified most strongly by UVC. Past research has suggested that roman are a suitable indicator of fishing pressure on reef habitats in the Agulhas Ecoregion (Smith et al. 2007; Götz et al. 2008; Bennett et al. 2009). The results from the power analysis demonstrate the improved efficiency of BRUV over UVC to survey this important indicator species. This result is in agreement with the findings from the TNP MPA (Chapter 3), where the required sampling effort for BRUV to detect a doubling or halving of the roman population was considerably lower (n = 8) than what was recommended for UVC (n= 15; Bennett et al. 2009).

The results suggested that both BRUV and the FT method detected declines in the abundance of catsharks between the no-take and exploited zones. Catsharks are not the target of any fishery and are typically considered a by-catch species. The significantly lower abundances of catsharks detected by the FT outside the no-take zone suggest that fishing is resulting in a noticeable depletion of these endemic shark species. This agrees with recent reports, which indicate declines in the abundance of the striped catshark on the Agulhas Bank (Sink et al. 2012). Catsharks are by far the most dominant species of shark on rocky reefs in the Agulhas Ecoregion and as such the protection afforded to these species within no-take MPAs should not be overlooked. An interesting trend was observed for the fingerfins, a

group which is not captured by any fishery. Underwater visual census found significantly more fingerfins in the no-take zone than in the adjacent exploited habitat. The areas were highly comparable in terms of structure and location, pointing to a negative indirect effect of fishing on fingerfin abundance. This study did not attempt to investigate causal links, but it is worth investigating these potential indirect effects further with greater sample replication.

The inconsistency amongst methods is of concern, as it is difficult to gauge which method is providing the correct answer. However, it may be possible to use results from a power analysis to determine the precision of the data, and the reliability of the outputs. Accuracy, on the other hand, is harder to gauge, but experience and knowledge (i.e. where fishing occurs, target species should have a lower abundance), in combination with the precision of the data should assist to determine the reliability of the outputs.

5.5.3 Conclusions

The power analysis was designed to facilitate the selection of sampling intensity for each method to detect annual increase in population size of 10 % per year over a period of five years. The results showed that BRUV required considerably lower sampling effort than UVC or the FT method. Underwater visual census' core strength lay in its ability to survey the fingerfin group, as it was the only method that observed sufficient individuals to warrant a statistical analysis. While the strength of the FT method was to survey the different species of catshark, BRUV was still more efficient at measuring the relative abundance of this group.

Typically, it is recommended that multiple methods be used to capture the trends in the entire fish community (Watson et al. 2005; Colton and Swearer 2010). While the results from this study are in agreement, the logistical implications are often not considered. Using multiple methods would come at an increased cost in the short-term (as several types of equipment and training will be required), and long-term (as each method would require dedicated field-time). For most research bodies this financial strain would not be feasible, and as a result costs would be saved by reducing the extent or grain of the sampling programme per method, ultimately reducing the statistical power to detect long-term trends. While knowledge on

biodiversity and species richness are important, a long-term monitoring programme may be better served by (i) focussing on one method, (ii) understanding the limitations of the method, and (iii) using indicator species that reflect both the direct and indirect effects of fishing on reef communities. The question “what should we monitor?” then becomes relevant.

This question was not thoroughly investigated during this study, but example indicator species could include primary fisheries targets, by-catch species and non-targets. Candidates from this study would be roman, catsharks and fingerfins. In this instance BRUV is the logical choice as it was associated with the highest precision, enabling it to detect trends more effectively for roman and catsharks. The indirect effect of protection status on the abundance of fingerfins suggested broader ecological implications of fishing on reef communities. The inability of BRUV to survey this component of the community suggests that even if indicator species are targeted, selecting only one method would still not provide sufficient data to capture long-term trends, and the impact of exploitation and global change on the reef communities. Somewhere along the line a compromise would need to be made either to sacrifice the ecological coverage of a monitoring programme or the statistical power to detect trends. The logical sacrifice is the former.

5.6 Part II: Method comparison and assessment of spatial variability in the Tsitsikamma NP MPA

5.6.1 Study Aim

To compare the ability of five shallow-water, and three deep-water monitoring methods to survey the fish community and assess their cost effectiveness for long-term monitoring on the Rheeders Reef (shallow) and Middle Bank reef (deep) complexes through power analysis.

5.6.2 Study objectives

The main objectives of the field experiment were to:

- Compare the fish community sampled (presence/ absence and relative abundance) using fish traps (FT), controlled angling (CA), underwater visual census (UVC), remote underwater video (RUV) and baited RUV (BRUV) at shallow-water areas on Rheeders Reef.
- Compare the fish community sampled (presence/ absence and relative abundance) using RUV, BRUV and remotely operated vehicle (ROV) at deep-water areas on Middle Bank.
- Conduct a power analysis to assess the variability in the data and determine the number of samples required by each method to detect an annual 10 % growth in the population of selected fish populations over a five-year period.

5.7 Materials and methods

5.7.1 Study area and experimental design

This research was conducted in the Tsitsikamma NP MPA (TNP MPA), at the Rheeders Reef (see Chapter 2) and Middle Bank study areas (Fig. 5.8). The Middle Bank study area is situated approximately four kilometres offshore from Storms River mouth, and five kilometres from the Rheeders Reef study area (Fig. 5.8a). Both study areas were mapped with a GPS linked echo sounder to identify suitable reef habitat (Fig. 2.1e, Fig. 5.8b). Possible sample stations were identified by superimposing a grid, with the cell dimensions of 150 x 150 m for Rheeders Reef, and 300 x 300m for Middle Bank, onto the map. At the Rheeders Reef study area, each grid-cell was classified according to reef profile (high and low) and depth (deep and shallow) (Fig. 2.1e), while only reef profile was used to stratify the Middle Bank study area (Fig. 5.8b). Only grid-cells that contained more than 50 % reef were considered for selection (Chapter 2). Within each study area, sample stations (cells) were randomly selected, with an even allocation between the different strata.

Sampling was conducted during daylight hours over a period of 34 days in winter (July/August) 2010. Due to adverse sea conditions, only 17 days were suitable to conduct field research. Only one method was employed per day, with the method selection based on a random sequence of the five methods for the shallow study area, and the three methods for the deep study area. The research was conducted off two platforms, one used solely for the ROV survey (13 m powered catamaran), and the other used for the remaining survey types (9 m powered semi-rigid inflatable). It was the original intention to allocate three sampling days to each method, however due to the adverse sea conditions this was not achieved for all methods and some of the sampling days were cut short, further limiting the sampling effort.

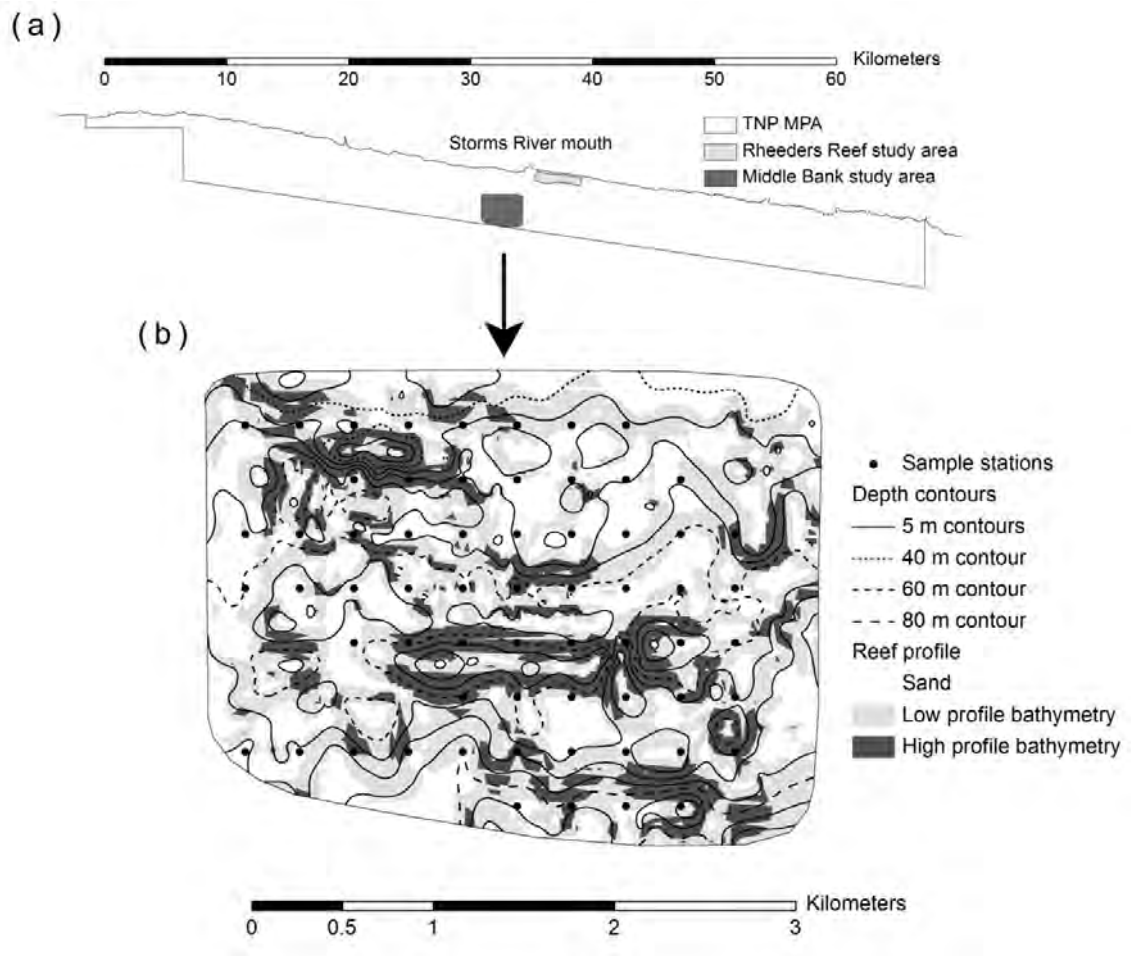

Figure 5.8: Map showing the position of the Middle Bank study area relative to Storms River mouth, and the Rheeders Reef study area in the Tsitsikamma National Park marine protected area (TNP MPA) (a), together with the depth contours and the distribution of high and low profile bathymetry (b). The positions of the potential samples sites are included.

5.7.2 Fish sampling methods

5.7.2.1 Fish traps (FT)

The FT used in this field experiment was the same as those described in Part I of this chapter. Three FT were used simultaneously, which enabled a total of 25 trap samples to be collected over a period of two fieldwork days.

5.7.2.2 Controlled angling (CA)

The CA method was based on the approach by Götz et al. (2007) and Bennett et al. (2009). At each station, four anglers were simultaneously bottom fishing for 30 minutes, with the combined angler effort of two angler hours per station. The fishing gear consisted of a single barbless 4/0 circle hook, baited with sardine, *Sardinops sagax*. Captured fish were brought to the surface where they were placed in a PVC sling, and covered with a damp cloth to avoid exposure to sunlight. The fish were identified and the fork length (FL: tip of snout to midpoint of tail) measured to the nearest millimetre before being released. Where fish appeared to suffer from barotrauma, the swimbladders were deflated using a 15-gauge hypodermic needle. A total of 16 CA samples was collected over a period of three fieldwork days.

5.7.2.3 Underwater visual census (UVC)

The UVC method was based on the same principles used in Part I of this chapter, however only one observer in a pair collected the data, with the second diver swimming behind the observer and measuring the length of the transect. In this way the fish community was not disturbed before conducting the count. With the paired-transect technique (Part I), the line transect was measured out initially before the observers conducted the survey. It is possible that this may have disturbed the fish community and influenced the composition of the observed community. While this was not a problem when calculating observer bias, it was not necessary for the between method comparisons. At each sampling station, two 50 m line transects were conducted, in opposite directions, and separated by at least 20 m. A total of 30 samples was collected over a period of three fieldwork days. A total of four different observers, each with over five years of experience in conducting UVC surveys was used to collect the data.

5.7.2.4 Remote underwater video (RUV)

The RUV method was the same as described in Chapter 3, but was adjusted in accordance with the recommendations for the method performance optimisation. As such, the deployment time at each station was restricted to 35 minutes. A total of ten samples was collected over a period of two fieldwork days at the Rheeders Reef

study area. For the deep-water stations from the Middle Bank study area, five samples were collected during one fieldwork day.

5.7.2.5 Baited remote underwater video (BRUV)

The BRUV method was the same as described in Part I of this chapter. A total of ten samples was collected over a period of two fieldwork days at the Rheeders Reef study area, and seven samples were collected at the Middle Bank study area during two fieldwork days.

5.7.2.6 Remotely operated vehicle (ROV)

A SAAB Seaeye Falcon 12177 with electric propulsion via thrusters, was used to conduct the ROV survey. The ROV was fitted with a high resolution, low light, colour video camera (SAAB CAM04P), with live feed to the surface for control and recording of footage. The camera was mounted at an angel of -15° to the horizontal to ensure that both the reef and water column were in the field of view at all times. During all ROV operations lights were used to aid navigation in the low light environment. The lighting system consisted of two 36 W (2520 lumens) cool white LED lights.

An anchored line transect method was employed as wind and currents prevented the vessel from safely operating in the vicinity of the ROV and precluded the use of the continuous line transect approach ('live boating'). The sampling approach was roughly based on the method used by Karpov et al. (2006, 2010) and Trenkel et al. (2004) and adapted to suite the ROV system used and sea conditions experienced during the fieldwork.

At each sampling station the vessel would anchor and the ROV would descend to the ocean floor using the position directly under the boat as the starting point for the line transect. The ROV would then fly, approximately 0.5 m above the reef, in a randomly selected direction for a distance of 50 m, with the camera recording the fish community directly in front of the ROV. The ROV would then return to the starting position and repeat the process in the opposite direction. The swimming speed was restricted to between 0.17 and 0.2 m per second, equating to a total time of between eight and ten minutes for the 100 m transect. With the ROV swimming at

0.5 m above the reef a consistent field of view was maintained, creating a standard measure of relative abundance for each sample. The ROV camera had a horizontal angle of view of 54.4° which translated into a field of view of approximately 3.2 m transect width and 0.7 m distance in front of the ROV. A total of seven samples was collected during two days of fieldwork.

5.7.3 Environmental variables

At each sampling station the water temperature was measured either with a Hobo temperature logger, for the FT, CA, RUV, BRUV and ROV surveys, or with personal dive computers for the UVC surveys. The underwater visibility was only measured at the UVC, RUV and BRUV stations. For the UVC stations it was estimated by measuring the distance at which a yellow hand-size dive reel became visible, while for the BRUV surveys by estimating the relative change in length of individual roman, *Chrysoblephus laticeps*, after the method described in Chapter 3. The ROV surveys were conducted at the same time as the BRUV surveys in the Middle Bank study area. As such the underwater visibility for the ROV was assumed to be the same as that for the BRUV. Water depth was measured off the personal dive computers during UVC surveys or off the boat-based echo-sounder for all other survey types.

5.7.4 Data analysis

5.7.4.1 Multivariate community analysis

Multivariate analysis was performed as described in Part I of this chapter.

5.7.4.2 Univariate method comparison

The univariate method comparison followed the approach described in Part I of this chapter. There was a slight difference in the structure of the generalized linear model (GLM) with the covariate protection “Status” not relevant here. Due to the limited number of samples collected per method only covariates that were considered relevant to the specific question being addressed (and those not taken into account in the stratified sampling schedule) were included in the model. The full Poisson GLM was described as:

$$log(\mu_i) = \alpha + \beta_1(Method_i) + \beta_2(Temperature_i), \quad \text{(equ. 6.5)}$$

where the effect of *Method* was the focus of the assessment and the variability in water temperature as a random effect could not be taken into account in the stratified sampling schedule. In cases where the Poisson GLM fit was characterised by overdispersion of residuals, it was substituted by the negative binomial model, as in Part I of this chapter.

5.7.4.3 Power analysis

The general structure of the power analysis followed the approach described in Part I of this chapter. The difference here was the exclusion of protection *Status* as a covariate in the power analysis. As a result, no environmental covariates were included in the GLM, and the power analyses were run on the null model:

$$log(\mu_i) \pm error = \alpha + \beta_1(r) \times t, \quad \text{(equ. 6.6)}$$

where r is the slope for the change in abundance extrapolated over a five-year period (t).

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5.8 Results

5.8.1 Sampling effort and environmental characteristics

A total of 91 samples was collected during 12 days of fieldwork at the Rheeders Reef study area. Due to logistical constraints associated with poor sea conditions, the planned sampling strategy could not be followed exactly, and as such the sampling effort for the different methods, and the distribution of samples between the low and high profile reef stations was unbalanced (Table 5.6). Sampling depth ranged from 9 to 34 m, with an average (± SD) of 20.6 (± 6.3) m. The average sampling depth was similar for most methods, with the exception being RUV deviating by +2.7 m from the average (Table 5.6). Water temperature ranged between 11 and 18 ˚C, with an average of 13.7 (± 1.7) ˚C. The average water temperature for FT and CA samples deviated the most from the average water temperature, -1.2 and +1.3 ˚C respectively (Table 5.6).

Table 5.6: Distribution of sampling effort at the Rheeders Reef study area, between the five methods and levels of reef profile (# of samples), together with the average (SD) sample depth (m) and temperature (˚C). FT = fish traps; CA = controlled angling; UVC = underwater visual census; RUV = remote underwater video; BRUV = baited RUV.

Method	*Profile* (low/high)	*Depth* (SD)	*Temperature* (SD)
FT	11/14	19.88 (6.40)	12.48 (0.93)
CA	6/10	20.44 (6.07)	15.01 (2.69)
UVC	10/20	20.32 (6.17)	14.22 (0.61)
RUV	3/7	23.30 (5.60)	13.18 (1.75)
BRUV	5/5	21.00 (7.76)	13.82 (1.02)

A total of 19 samples was collected during five days of fieldwork at the Middle Bank study area. Again, the poor sea conditions resulted in an unbalanced number of samples collected with each method, and between levels of reef profile, with more samples collected on high profile reef (Table 5.7). Sampling depth ranged between 44 and 75 m, with an average of 56.5 ± 11.0 m. The ROV samples were taken from slightly deeper reefs (+2.6 m) from the average, and the RUV from slightly shallower reefs (-2.1 m) from the average (Table 5.7). Water temperature was considerably

lower and more stable at the deep study area (10.4 ± 0.5 ˚C), compared to the shallow water study area (13.7 ± 1.7 ˚C). There was little variation in average water temperature for the samples collected with the different methods (Table 5.7).

Table 5.7: Distribution of sampling effort at the Middle Bank study area, between the three methods and levels of reef profile, together with the average (SD) sample depth (m) and temperature (˚C). RUV = remote underwater video; BRUV = baited RUV; ROV = remotely operated vehicle.

Method	*Profile* (low/high)	*Depth* (SD)	*Temperature* (SD)
RUV	2/3	54.40 (10.69)	10.28 (0.33)
BRUV	3/4	55.43 (13.23)	10.51 (0.84)
ROV	2/5	59.14 (9.81)	10.31 (0.18)

5.8.2 Description of the fish community

Thirty-three species were identified in the 91 samples (collected with all methods) from the Rheeders Reef study area (Table 5.8). Roman was the most frequently observed species occurring in 52.7 % of all samples. Steentjie, *Spondyliosoma emarginatum*, (40.7 %), fransmadam, *Boopsoidea inornata*, (37.4 %) and twotone fingerfin, *Chirodactylus brachydactylus*, (36.3 %) were the only other species to occur in more than one third of all samples. The striped catshark, *Poroderma africanum*, was the most frequently observed shark, occurring in 15.4 % of all samples (Table 5.8).

Baited remote underwater video recorded the most species (n = 28), followed by RUV (n = 20), UVC (n = 15) and CA (n = 14). Fish traps were only able to detect 27 % (n = 9) of all the species recorded (Fig. 5.8a). Steentjie was the only species recorded with all five methods.

Table 5.8: List of all species of fish recorded using the fish traps (FT), controlled angling (CA), underwater visual census (UVC), remote underwater video (RUV) and baited RUV (BRUV) at the shallow water sampling stations on the Rheeders Reef sampling area. The number of samples where the species was recorded (n), as well as the % occurrence in relation to the number of samples collected per method is provided. Species are sorted taxonomically and according to their overall frequency of observation (Overall N).

				Overall		FT		CA		UVC		RUV		BRUV	
Type	Family	Scientific name	Common name	N	%	n	%	n	%	n	%	n	%	n	%
Osteichthyes	Sparidae	*Chrysoblephus laticeps*	Roman	48	52.7			11	68.8	21	70.0	7	70.0	9	90.0
Osteichthyes	Sparidae	*Spondyliosoma emarginatum*	Steentjie	37	40.7	9	36.0	4	25.0	9	30.0	6	60.0	9	90.0
Osteichthyes	Sparidae	*Boopsoidea inornata*	Fransmadam	34	37.4			7	43.8	13	43.3	5	50.0	9	90.0
Osteichthyes	Cheilodactylidae	*Chirodactylus brachydactylus*	Twotone fingerfin	33	36.3					24	80.0	6	60.0	3	30.0
Osteichthyes	Sparidae	*Diplodus capensis*	Blacktail	23	25.3			1	6.3	15	50.0	3	30.0	4	40.0
Osteichthyes	Cheilodactylidae	*Cheilodactylus fasciatus*	Redfingers	21	23.1					19	63.3	1	10.0	1	10.0
Osteichthyes	Sparidae	*Pachymetopon aeneum*	Blue hottentot	16	17.6	1	4.0			6	20.0	3	30.0	6	60.0
Osteichthyes	Cheilodactylidae	*Cheilodactylus pixi*	Barred fingerfin	13	14.3					10	33.3	2	20.0	1	10.0
Osteichthyes	Sparidae	*Gymnocrotaphus curvidens*	Janbruin	13	14.3					7	23.3	3	30.0	3	30.0
Osteichthyes	Sparidae	*Chrysoblephus cristiceps*	Dageraad	11	12.1			2	12.5	3	10.0	2	20.0	4	40.0
Osteichthyes	Ariidae	*Galeichthys feliceps*	White seacatfish	10	11	4	16.0	2	12.5	2	6.7			2	20.0
Osteichthyes	Sparidae	*Petrus rupestris*	Red steenbras	8	8.79			1	6.3	1	3.3	2	20.0	4	40.0
Osteichthyes	Sparidae	*Rhabdosargus holubi*	Cape stumpnose	6	6.59	1	4.0					2	20.0	3	30.0
Osteichthyes	Haemulidae	*Pomadasys olivaceum*	Piggy	5	5.49	1	4.0	1	6.3					3	30.0
Osteichthyes	Serranidae	*Acanthistius sebastoides*	Koester	5	5.49			2	12.5	2	6.7			1	10.0
Osteichthyes	Oplegnathidae	*Oplegnathus conwayi*	Cape knifejaw	4	4.4					2	6.7	1	10.0	1	10.0
Osteichthyes	Sparidae	*Lithognathus mormyrus*	Sand steenbras	4	4.4			1	6.3			1	10.0	2	20.0
Osteichthyes	Sparidae	*Sarpa salpa*	Strepie	4	4.4							1	10.0	3	30.0
Osteichthyes	Parascorpididae	*Parascorpis typus*	Jutjaw	3	3.3					1	3.3	2	20.0		
Osteichthyes	Sparidae	*Diplodus hottentotus*	Zebra	3	3.3							2	20.0	1	10.0
Osteichthyes	Sparidae	*Chrysoblephus gibbiceps*	Red stumpnose	2	2.2									2	20.0
Osteichthyes	Sparidae	*Pagellus bellottii natalensis*	Red tjor-tjor	2	2.2			2	12.5						
Osteichthyes	Sparidae	*Argyrozona argyrozona*	Carpenter	1	1.1									1	10.0
Osteichthyes	Sparidae	*Cheimerius nufar*	Santer	1	1.1									1	10.0
Osteichthyes	Sparidae	*Rhabdosargus globiceps*	White stumpnose	1	1.1									1	10.0
Condrichthyes	Scyliorhinidae	*Poroderma africanum*	Striped catshark	14	15.4	8	32.0	1	6.3			1	10.0	4	40.0
Condrichthyes	Scyliorhinidae	*Haploblepharus edwardsii*	Puffadder shyshark	7	7.69	2	8.0	2	12.5					3	30.0
Condrichthyes	Carcharhinidae	*Mustelus mustelus*	Smooth-hound	5	5.49			3	18.8			2	20.0		
Condrichthyes	Scyliorhinidae	*Haploblepharus pictus*	Dark shyshark	3	3.3									3	30.0
Condrichthyes	Carcharhinidae	*Carcharhinus brachyurus*	Copper shark	2	2.2									2	20.0
Condrichthyes	Scyliorhinidae	*Poroderma pantherinum*	Leopard catshark	2	2.2	1	4.0							1	10.0
Condrichthyes	Dasyatidae	*Dasyatis brevicaudata*	Shorttail stingray	1	1.1							1	10.0		
Agnatha	Myxinidae	*Eptatretus hexatrema*	Six-gill hagfish	1	1.1	1	4.0								

Table 5.9: List of all species of fish recorded using remote underwater video (RUV), baited RUV (BRUV) and remotely operated vehicle (ROV) at the deep water sampling station on the Middle Bank sampling area. The number of samples where the species was recorded (n), as well as the % occurrence in relation to the number of samples collected per method is provided. Species are sorted taxonomically and according to their overall frequency of observation (Overall N).

				Overall		RUV		BRUV		ROV	
Type	Family	Scientific name	Species	N	%	n	%	n	%	n	%
Osteichthyes	Sparidae	*Pterogymnus laniarius*	Panga	13	68.4	2	40.0	7	100.0	4	57.1
Osteichthyes	Sparidae	*Chrysoblephus laticeps*	Roman	10	52.6	2	40.0	6	85.7	2	28.6
Osteichthyes	Sparidae	*Spondyliosoma emarginatum*	Steentjie	10	52.6	2	40.0	6	85.7	2	28.6
Osteichthyes	Sparidae	*Argyrozona argyrozona*	Carpenter	8	42.1	1	20.0	6	85.7	1	14.3
Osteichthyes	Sparidae	*Pachymetopon aeneum*	Blue hottentot	8	42.1	2	40.0	5	71.4	1	14.3
Osteichthyes	Sparidae	*Pachymetopon blochii*	Hottentot	6	31.6			6	85.7		
Osteichthyes	Sparidae	*Petrus rupestris*	Red steenbras	6	31.6	2	40.0	4	57.1		
Osteichthyes	Sparidae	*Chrysoblephus gibbiceps*	Red stumpnose	5	26.3	2	40.0	3	42.9		
Osteichthyes	Parascorpididae	*Parascorpis typus*	Jutjaw	4	21.1	1	20.0	3	42.9		
Osteichthyes	Cheilodactylidae	*Cheilodactylus fasciatus*	Redfingers	3	15.8					3	42.9
Osteichthyes	Carangidae	*Trachurus trachurus*	Maasbanker	2	10.5					2	28.6
Osteichthyes	Sparidae	*Boopsoidea inornata*	Fransmadam	2	10.5			2	28.6		
Osteichthyes	Sparidae	*Rhabdosargus globiceps*	White stumpnose	2	10.5			2	28.6		
Osteichthyes	Ariidae	*Galeichthys feliceps*	White seacatfish	1	5.3			1	14.3		
Osteichthyes	Cheilodactylidae	*Chirodactylus brachydactylus*	Twotone fingerfin	1	5.3			1	14.3		
Osteichthyes	Cheilodactylidae	*Cheilodactylus pixi*	Barred fingerfin	1	5.3					1	14.3
Osteichthyes	Congiopodidae	*Congipodus spp.*	Horsefish spp.	1	5.3					1	14.3
Condrichthyes	Scyliorhinidae	*Haploblepharus edwardsii*	Puffadder shyshark	4	21.1			3	42.9	1	14.3
Condrichthyes	Hexanchidae	*Notorynchus cepedianus*	Spotted sevengill cowshark	2	10.5			2	28.6		
Condrichthyes	Scyliorhinidae	*Poroderma africanum*	Striped catshark	2	10.5			2	28.6		
Condrichthyes	Carcharhinidae	*Carcharhinus brachyurus*	Copper shark	1	5.3			1	14.3		

Baited remote underwater video recorded the most unique species (i.e. those not detected by the other methods), four of which were bony fish (Osteichthyes) and two were cartilaginous species (Condrichthyes) (Fig. 5.9a). Fish traps, CA and RUV each recorded a single unique species, while no unique species were detected by UVC (Fig. 5.9a).

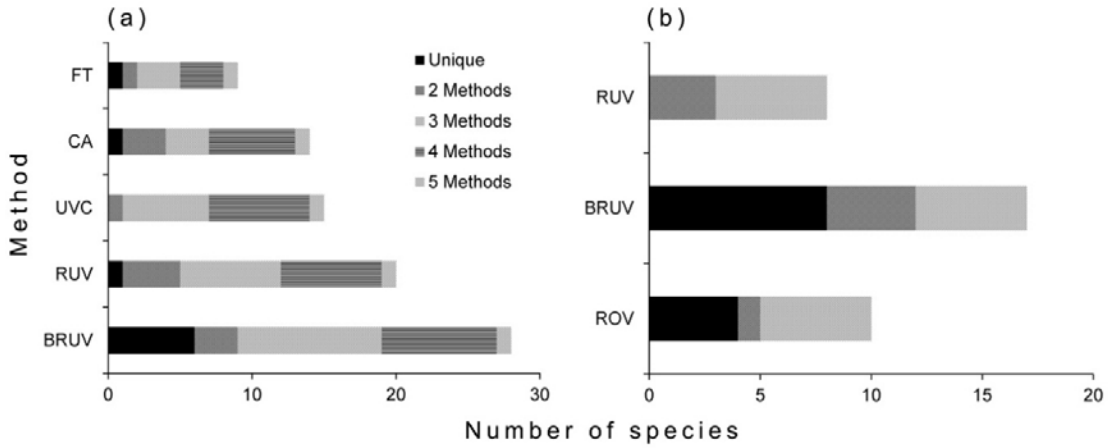

Figure 5.9: Total number of species recorded together with the number of unique species, species common to two methods, three methods, four methods, and all five methods at the Rheeders Reef study area (a), and those common to two methods and all three methods at the Middle Bank study area (b). FT = fish traps; CA = controlled angling; RUV = remote underwater video; BRUV = baited RUV; ROV = remotely operated vehicle.

A total of 21 species was identified from the samples at the Middle Bank study area. The five most common species were panga *Pterogymnus laniarius* (68.4 %), roman (52.6 %), steentjie (52.6 %), carpenter *Argyrozona argyrozona* (42.1 %) and blue hottentot *Pachymetopon aeneum* (42.1 %). These listed species were the only ones common to all methods. This highlights a marked difference in the community recorded at the Rheeders Reef study area (Table 5.8) and the Middle Bank study area (Table 5.9). Puffadder shyshark *Haploblepharus edwardsii* was the most frequently observed shark species occurring in 21.1 % of the 19 samples.

Of the 21 species recorded, BRUV was able to sample 81 % (n = 17), followed by the ROV, which recorded 48 % (n = 10) and RUV, which recorded 28 % (n = 8).

Baited remote underwater video sampled the highest number of unique species (n = 8), five of which were bony fish and three cartilaginous fish (Fig. 5.9b). The ROV was able to record four species of unique bony fish, while no species were unique to the RUV samples (Fig. 5.9b).

Table 5.10: PERMANOVA pairwise tests on modified Gower log2 dissimilarities of the presence/absence and relative abundance of the species sampled by the different methods at the Rheeders Reef study area. FT = fish traps; CA = controlled angling; RUV = remote underwater video; BRUV = baited RUV.

		Pairwise tests			
	Methods	CA	UVC	RUV	BRUV
Presence/ Absence	FT	2.34[1] (0.000)[2] ***[3]	3.67 (0.000) ***	1.67 (0.021) *	2.24 (0.001) **
	CA	—	2.65 (0.000) ***	1.33 (0.064) .	1.63 (0.001) ***
	UVC	—	—	1.66 (0.011) *	2.39 (0.000) ***
	RUV	—	—	—	1.17 (0.191)
Relative abundance	FT	2.07 (0.013) *	2.59 (0.000) ***	1.17 (0.261)	2.96 (0.001) ***
	CA	—	2.29 (0.000) ***	1.56 (0.042) *	2.31 (0.001) ***
	UVC	—	—	1.57 (0.032) *	2.83 (0.000) ***
	RUV	—	—	—	1.92 (0.022) *

1: t-value

2: P(perm)

*3: Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1*

5.8.3 Multivariate analysis of the fish community

5.8.3.1 Shallow water communities (Rheeders Reef)

The PERMANOVA analysis identified a highly significant effect of *Method* on both the presence/absence (MS = 1.73, F = 5.55, p<0.001) and the relative abundance data (MS = 9.30, F = 5.12, p<0.001). The pairwise tests showed no significant difference in the species presence/absence when sampled by RUV and BRUV, and RUV and CA (Table 5.10). Similarly, no significant difference was identified in the relative abundance data for the fish community when sampled with FT and RUV (Table 5.10). For all remaining pairwise comparisons significant differences in community structure were detected (Table 5.10).

Distinct fish communities sampled by the different methods were further evident in the PCO analysis for the presence/absence (Fig. 5.10a) and the relative abundance data (Fig. 5.10b). The presence/absence data indicated that striped catshark was recorded more frequently in the FT samples, while twotone fingerfin and redfingers *Cheilodactylus fasciatus* were more frequently observed in the UVC, and to a lesser degree the RUV samples. The presence of roman in both the BRUV and CA samples contributed to the separation of these methods (Fig. 5.10a). The relative abundance data showed that higher abundances of steentjie, fransmadam and roman contributed to the separation of the CA and BRUV samples, while the higher abundances of redfingers further distinguished the UVC samples from the rest (Fig. 5.11a).

The CAP analysis indicated a significant separation between the methods for the presence/absence data (tr[Q_m'HQ_m] = 13.25, p = 0.0002) (Fig. 5.11b), and the relative abundance data (tr[Q_m'HQ_m] = 6.90, p = 0.0002) (Fig. 5.11b). In the presence/absence data, red steenbras, *Petrus rupestris*, dageraad, *Chrysoblephus cristiceps* and roman were associated with BRUV samples and to a lesser degree UVC and RUV samples (Fig. 5.10b). Similarly, steentjie and fransmadam were associated with BRUV, RUV and UVC (Fig. 5.11b). The relative abundance data of white seacatfish (*Galeichthys feliceps*) and striped catshark contributed to the separation seen in the FT samples. Roman accounted for separation observed in the UVC and CA samples. The higher relative abundance of dark shyshark, *Haploblepharus pictus*, blacktail, *Diplodus capensis*, copper shark, *Carcharhinus brachyurus*, blue hottentot, strepie, *Sarpa salpa*, steentjie and red steenbras contributed to the separation of the BRUV samples (Fig. 5.11b).

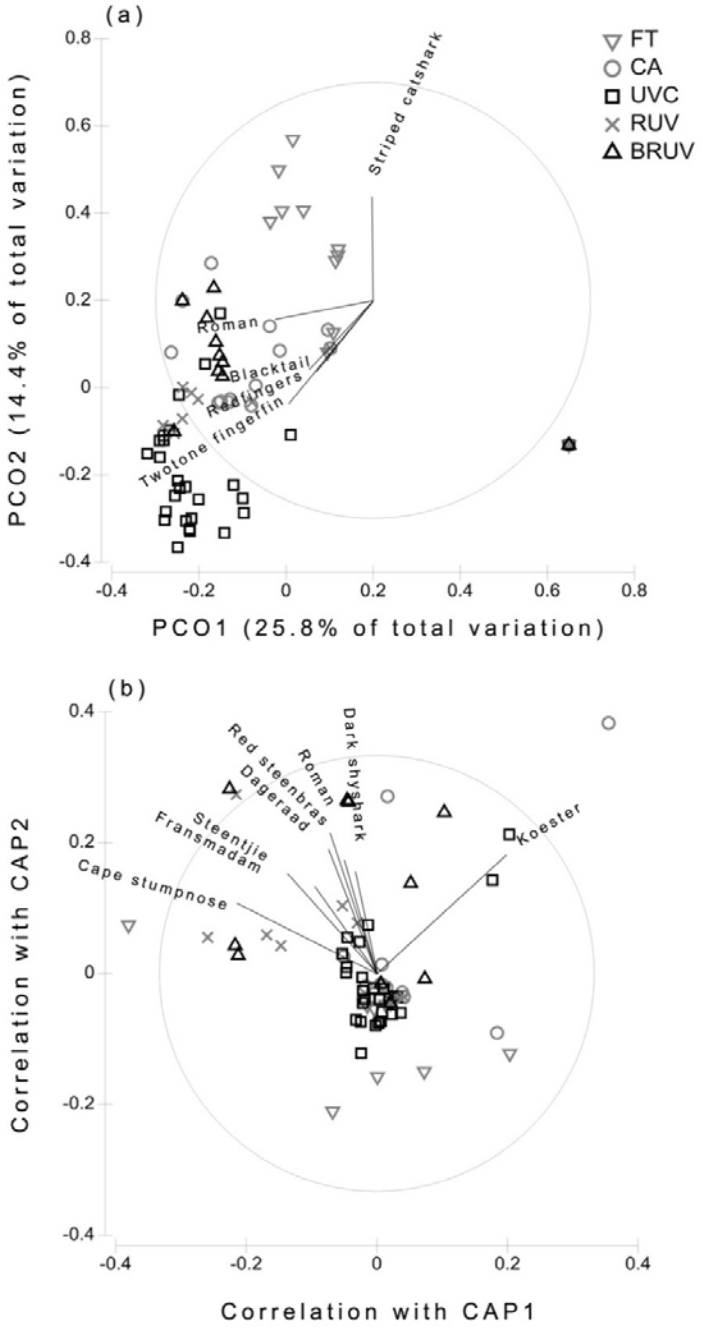

Figure 5.10: Results from the principle coordinate ordination (PCO) (a) and the Canonical analysis of principal coordinates (CAP) ordination (b) based on modified Gower log2 dissimilarities for species presence/absence from the Rheeders Reef study area. Species correlations (Pearson *R* value > 0.4) with the canonical axis are represented as vectors indicating the affinity of species to the method. FT = fish traps; CA = controlled angling; RUV = remote underwater video; BRUV = baited RUV.

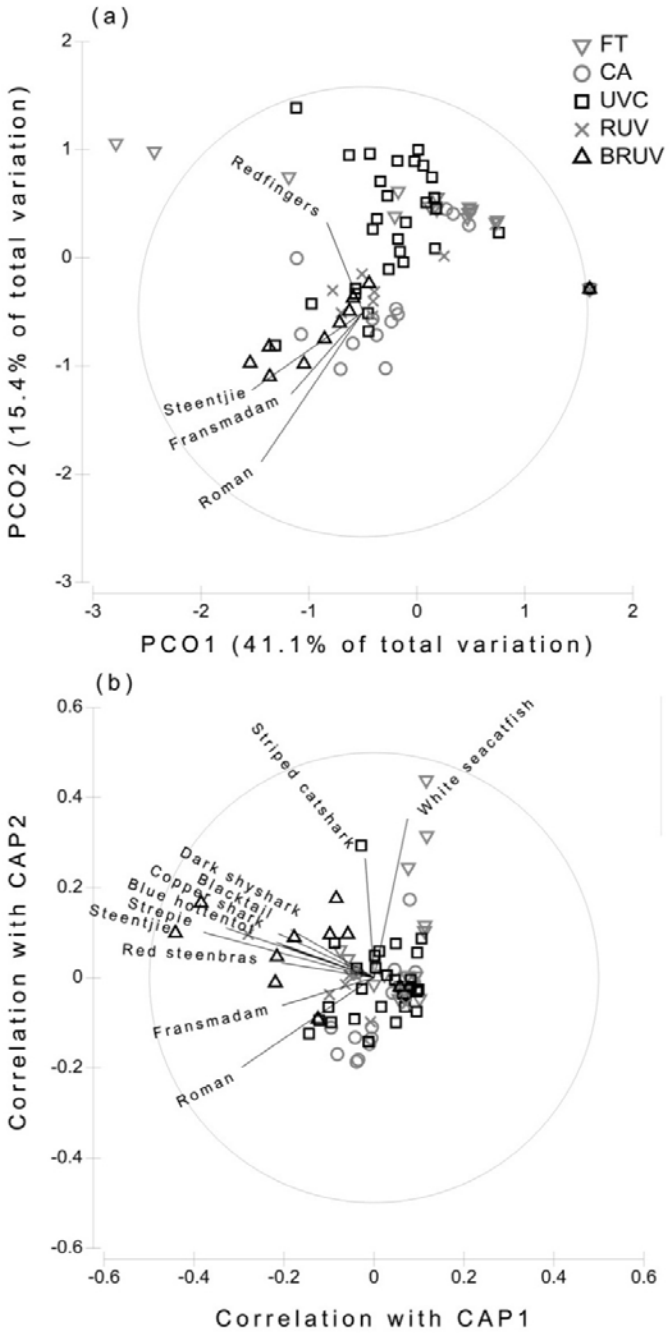

Figure 5.11: Results from the principle coordinate ordination (PCO) (a) and the canonical analysis of principal coordinates (CAP) ordination (b) based on modified Gower log2 dissimilarities for species relative abundance from the Rheeders Reef study area. Species correlations (Pearson *R* value > 0.4) with the canonical axis are represented as vectors indicating the affinity of species to the method. FT = fish traps; CA = controlled angling; RUV = remote underwater video; BRUV = baited RUV.

5.8.3.2 Deep water communities (Middle Bank)

Due to the low sampling effort and a high degree of variability between the different methods PERMANOVA was performed on a log10 transformed modified Gower resemblance matrix. The analysis on the samples collected on Middle Bank showed significant differences between the communities sampled by the methods when analysing the presence/absence data (MS = 0.83, F = 2.52, $p<0.05$) and the relative abundance data (MS = 1.61, F = 2.66, $p<0.05$).

Table 5.11: PERMANOVA pairwise tests on modified Gower log10 dissimilarities of the presence/absence and relative abundance of the species sampled by the different methods at the Middle Bank study area. RUV = remote underwater video; BRUV = baited RUV; ROV = remotely operated vehicle.

	Presence/ Absence			Relative abundance		
Pairwise tests	t	P(perm)		t	P(perm)	
BRUV vs RUV	1.800	0.042	*	1.701	0.074	.
BRUV vs ROV	1.625	0.016	*	1.859	0.010	*
RUV vs ROV	1.391	0.096	.	1.291	0.131	

*Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "."<0.1*

The pairwise tests on the PERMANOVA results identified significant differences in the community presence/absence data between the BRUV and RUV, and the BRUV and ROV methods, while no significant difference was evident between the RUV and ROV methods (Table 5.11). For the community relative abundance data no significant difference was identified between the RUV and BRUV methods, and RUV and ROV methods, however, a significant difference was identified between the BRUV and ROV methods (Table 5.11).

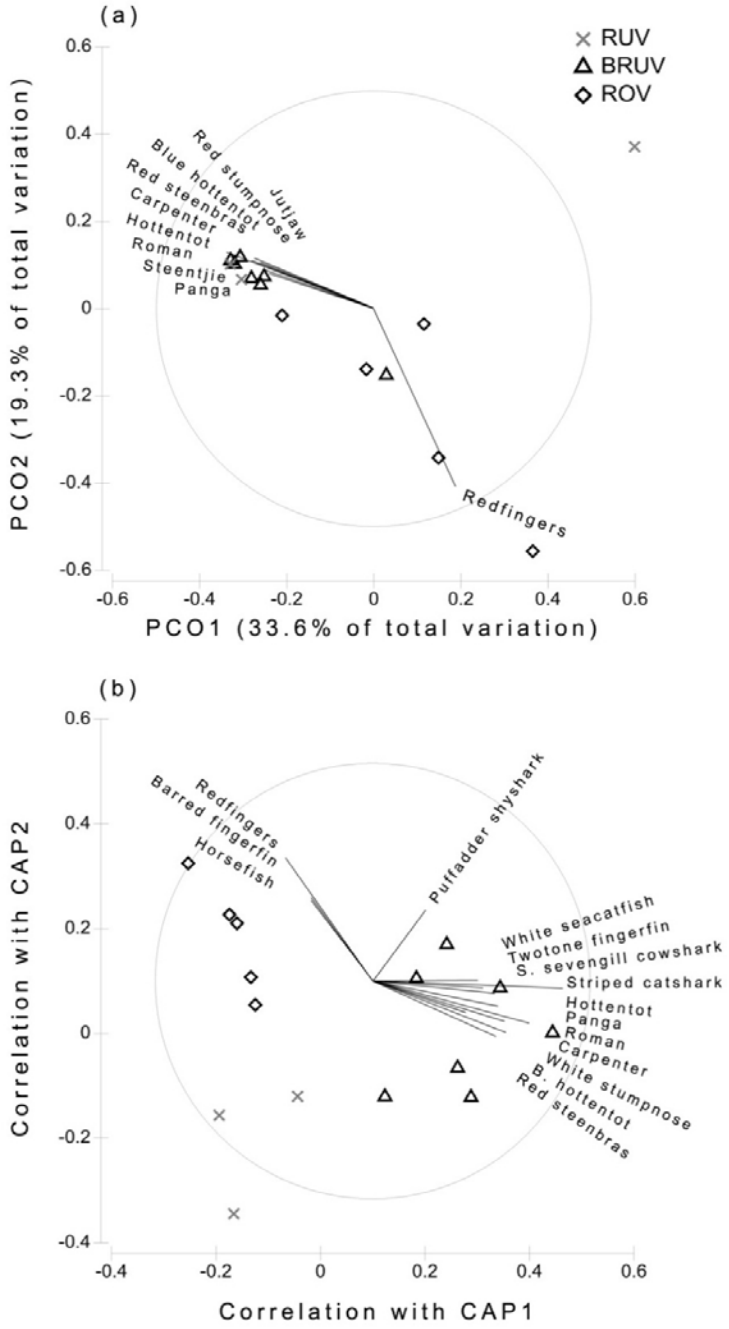

Figure 5.12: Results from the principle coordinate ordination (PCO) (a) and the canonical analysis of principle coordinates (CAP) ordination (b) based on modified Gower log10 dissimilarities for species presence/absence from the Middle Bank study area. Species correlations (Pearson *R* value > 0.4) with the canonical axis are represented as vectors indicating the affinity of species to the method. RUV = remote underwater video; BRUV = baited RUV; ROV = remotely operated vehicle.

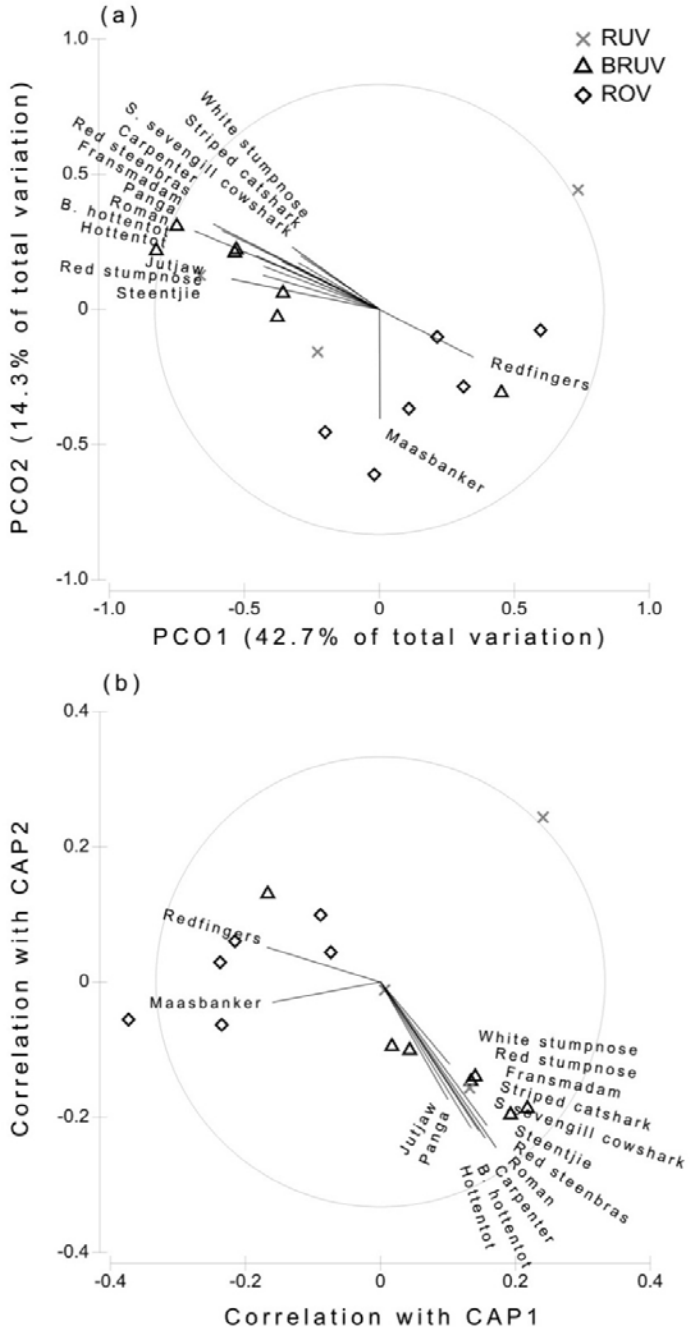

Figure 5.13: Results from the principle coordinate ordination (PCO) (a) and the canonical analysis of principle coordinates (CAP) ordination (b) based on modified Gower log10 dissimilarities for species relative abundance from the Middle Bank study area. Species correlations (Pearson *R* value > 0.4) with the canonical axis are represented as vectors indicating the affinity of species to the method. RUV = remote underwater video; BRUV = baited RUV; ROV = remotely operated vehicle.

The CAP analysis on the presence/absence data, showed strong separation between the samples collected with the ROV and those collected with the RUV and BRUV (Fig. 5.12a). The separation appeared to be driven by the presence of redfingers in the ROV samples and the presence of numerous sparids (panga, steentjie, roman, hottentot, carpenter, red steenbras, blue hottentot and red stumpnose *Chrysoblephus gibbiceps*) in the BRUV, and to a lesser degree RUV, samples (Fig. 5.12a).

The CAP analysis on the relative abundance data (Fig. 5.13a) showed similar separation between the methods, with the ROV samples distinct from the BRUV and to a lesser degree the RUV samples. The relative abundance of redfingers, together with maasbanker *Trachurus trachurus* accounted for the separation of the ROV from the BRUV samples. The higher relative abundance of 13 species (Fig. 5.13a) was identified as contributing to the observed separation between the BRUV and ROV samples.

The CAP analysis found significant separation between the methods for both the presence/absence data (tr[Q_m'HQ_m] = 1.65, p = 0.0004) (Fig. 5.12b) and the relative abundance data (tr[Q_m'HQ_m] = 1.08, p = 0.0004) (Fig. 5.13b). The presence of redfingers, barred fingerfin (*Cheilodactylus pixi*), and an unidentified horsefish (*Congipodus sp.*), accounted for the separation of the ROV samples (Fig. 5.12b). The separation of the BRUV samples was driven by the presence of 11 species (Fig. 5.12b). The higher relative abundance of maasbanker and redfingers contributed to the separation of the ROV from the BRUV and RUV samples (Fig. 5.13b), while higher relative abundances from a much more diverse assemblage (n = 13) drove the separation of the BRUV samples (Fig. 5.13b).

5.8.4 Univariate method comparison

5.8.4.1 Shallow water communities (Rheeders Reef)

5.8.4.1.1 Species richness

On average (± SD) BRUV recorded the most species per sample (8.7 ± 5.1) followed by RUV (5.3 ± 4.3) and UVC (4.5 ± 2.5). Controlled angling and FT recorded the fewest species per sample, averaging 2.5 ± 1.3 and 1.1 ± 1.2, respectively. Assessment of the VIF (variance inflation factor) found that none of the covariates in the full model exhibited sufficient co-variation to warrant exclusion from the full model. In addition, the assessment of the residual deviance found the residuals to be overdispersed, and as a result the negative binomial distribution was used to model the data.

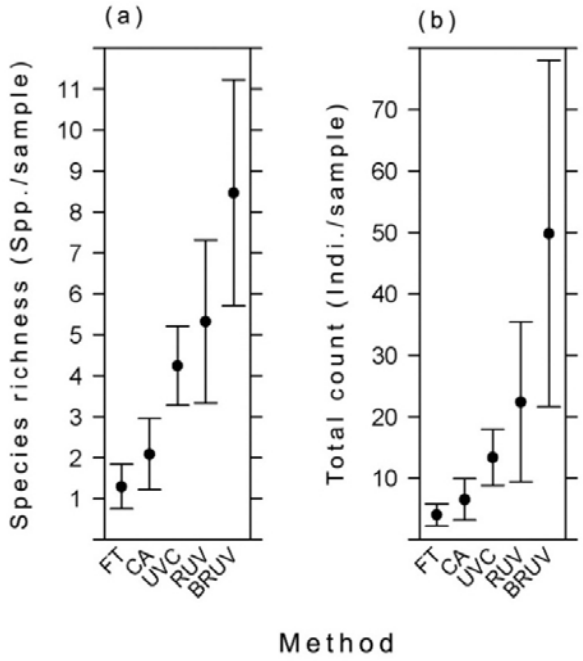

Figure 5.14: The effects of survey method on the species richness (a) and total count of individuals per sample (b) from the shallow water sample stations in the Rheeders Reef study area. Displayed data are the predicted mean (± 95 % confidence intervals). FT = fish traps; CA = controlled angling; RUV = remote underwater video; BRUV = baited RUV.

Table 5.12: Results from the negative binomial generalized linear models investigating the effect of *Method* and water *Temperature* on the diversity of the fish community from the Rheeders Reef study area. FT = fish traps; CA = controlled angling; RUV = remote underwater video; BRUV = baited RUV.

	Species richness				Total count				Roman				Fransmadam			
	Estimate[2]	SE	t value[3]		Estimate	SE	t value		Estimate	SE	t value		Estimate	SE	t value	
FT	-1.381	0.711	-1.943	▪	-1.704	0.935	-1.822	▪	—	—	—		—	—	—	
CA	0.478	0.321	1.486		0.481	0.374	1.287		-0.806	1.446	-0.557		-4.480	2.247	-1.994	▪
UVC	1.188	0.250	4.743	***	1.199	0.298	4.025	***	-0.516	0.372	-1.387		1.405	0.573	2.450	*
RUV	1.414	0.282	5.015	***	1.715	0.365	4.701	***	-0.501	0.516	-0.971		2.393	0.738	3.244	**
BRUV	1.878	0.273	6.885	***	2.514	0.369	6.804	***	0.306	0.473	0.648		2.185	0.702	3.111	**
Temperature	0.119	0.054	2.205	*	0.226	0.073	3.106	**	0.161	0.093	1.729	▪	0.275	0.140	1.964	▪
Theta (k)[1]	6.1812				1.0985				0.9875				0.4555			
Null deviance	195.42 on 90 DF				186.88 on 90 DF				85.690 on 65 DF				79.329 on 65 DF			
Residual deviance	109.10 on 85 DF				109.25 on 85 DF				75.117 on 61 DF				63.547 on 61 DF			

	Steentjie				Catsharks				Fingerfins				Primary fisheries targets			
	Estimate	SE	t value		Estimate	SE	t value		Estimate	SE	t value		Estimate	SE	t value	
FT	-5.146	2.196	-2.344	*	-0.386	0.329	-1.172		—	—	—		—	—	—	
CA	-1.542	0.916	-1.683	▪	—	—	—		—	—	—		1.781	0.284	6.269	***
UVC	-0.801	0.639	-1.254		—	—	—		-1.702	2.138	-0.796		-0.639	0.359	-1.782	▪
RUV	0.446	0.765	0.583		—	—	—		-1.384	0.380	-3.646	***	-0.618	0.473	-1.307	
BRUV	2.211	0.750	2.949	**	0.722	0.564	1.280		-2.316	0.468	-4.945	***	0.416	0.452	0.920	
Temperature	0.424	0.172	2.473	*	—	—	—		0.251	0.150	1.674		—	—	—	
Theta (k)	0.3634				0.5208				2.0458				0.8572			
Null deviance	119.730 on 90 DF				30.990 on 34 DF				96.856 on 49 DF				83.449 on 65 DF			
Residual deviance	76.463 on 85 DF				29.634 on 33 DF				53.278 on 46 DF				74.811 on 62 DF			

1: Theta (k) = shape parameter of the negative binomial distribution. Small k = distribution closer to gamma; Large k = distribution closer to Poisson

2: Estimate = log(Odds ratio)

3: Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

The model selection process identified that the full model was the most parsimonious:

$$\log(Species\ richness_i) = \alpha + \beta_1(Method_i) + \beta_2(Temperature_i).$$

Together, *Method* and *Temperature* were able to explain 44.17 % of the observed variability in the species richness data (Table 5.12). *Method* had a highly significant effect (X^2 = 72., p<0.001) on the predicted species richness, with separation of the confidence intervals (CIs) indicating that BRUV recorded significantly more species than UVC, CA or FT (Fig. 5.14a), and RUV and UVC recording significantly more species than CA and FT (Fig. 5.14a). *Temperature* had a significant (X^2 = 4.80, p<0.05) effect on species richness, with more species recorded at higher water temperatures (Odds ratio ± SE = 0.12 ± 0.05).

5.8.4.2 Total count

On average (± SD) BRUV recorded the most fish per sample (52.2 ± 31.6), followed by RUV (26.2 ± 27.2), UVC (14.7 ± 12.2), CA (9.3 ± 6.9) and FT (3.1 ± 3.8).

The model selection process identified that the full model was also the most parsimonious model:

$$\log(Total\ count_i) = \alpha + \beta_1(Method_i) + \beta_2(Temperature_i).$$

Together, *Method* and *Temperature* were able to explain 41.6 % of the observed variability in the total count data (Table 5.12). The effect of *Method* was highly significant (X^2 = 65.86, p<0.001), with BRUV predicted to record significantly more fish per sample than UVC, CA or FT (Fig. 5.14b). Although more fish were recorded per sample with RUV compared to UVC, there was considerable overlap in the CIs suggesting the difference was not significant (Fig. 5.14b). Water *Temperature* was found to have a significant (X^2 = 8.01, p<0.01) positive relationship with total count (Odds ratio ± SE = 0.23 ± 0.07).

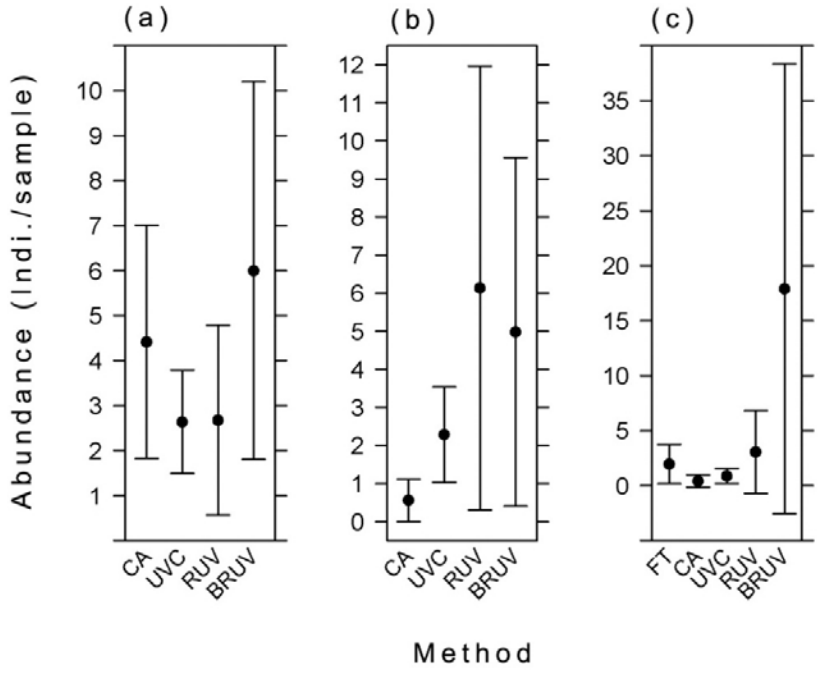

Figure 5.15: The effect of *Method* on the predicted mean relative abundance (± 95 % confidence intervals) for roman (a), fransmadam (b) and steentjie (c) from the shallow water sample stations in the Rheeders Reef study area. CA = controlled angling; UVC = underwater visual census; RUV = remote underwater video; BRUV = baited RUV.

5.8.4.3 Roman

No romans were captured in the FT so the method was omitted from the subsequent analysis. The highest average abundances of roman were recorded by BRUV (5.7 ± 3.3) and CA (5.6 ± 5.5), however, the variability around the mean was considerably lower for BRUV. Underwater visual census and RUV recorded a similar average abundance of 2.6 ± 3.6 and 2.5 ± 2.3, respectively.

The model selection process identified the full model as the most parsimonious model:

$$\log(Roman_i) = \alpha + \beta_1(Method_i) + \beta_2(Temperature_i).$$

Together, *Method* and *Temperature* were able to explain 12.3 % of the variation in roman abundance data (Table 5.12). The effect of *Method* was not significant (X^2 = 5.18, p>0.05) (Fig. 5.15a). Increasing water *Temperature* coincided with increases in

the abundance of roman (Odds ratio ± SE = 0.16 ± 0.09), however, this effect was not found to be significant (X^2 = 2.51, p>0.05)

5.8.4.4 Fransmadam

No fransmadams were captured with the FT and the method was omitted from the analysis. The highest average (± SD) abundance of fransmadam was recorded by RUV (7.0 ± 9.4), however, the data showed considerable variability between the samples. Abundance of fransmadam in the BRUV samples averaged 4.5 ± 3.4 followed by UVC (2.3 ± 4.1) and CA (0.7 ± 0.9). As with RUV, the abundance estimates from UVC and CA were highly variable.

The model selection process identified that the full model was the most parsimonious model:

$$\log(Fransmadam_i) = \alpha + \beta_1(Method_i) + \beta_2(Temperature_i).$$

The most parsimonious model was able to explain 24.4 % of the variability in fransmadam abundance (Table 5.12). The effect of *Method* was significant (X^2 = 15.86, p<0.01), with UVC recording significantly more fransmadam than CA (Fig. 5.15b). Although CA recorded considerably fewer fransmadam than both RUV and BRUV (Fig. 5.15b), the data were characterised by wide CIs and there was no evidence for separation between the methods. Water *Temperature* had a positive effect, with higher abundance of fransmadam recorded in warmer waters (Odds ratio ± SE = 0.27 ± 0.14). The effect of *Temperature* was, however, not significant (X^2 = 2.52, p>0.1).

5.8.4.5 Steentjie

The average (± SD) abundance of steentjie in the BRUV samples (18.0 ± 11.0) was more than six times greater than that recorded in the RUV samples (2.8 ± 3.4), which recorded the second highest abundance. Fish traps captured the third highest abundance (1.5 ± 3.2) followed closely by UVC (1.0 ± 2.4) and CA (1.0 ± 2.4). The abundance of steentjie was highly variable for all methods.

The model selection process identified the full model as the most parsimonious model:

$$\log(Steentjie_i) = \alpha + \beta_1(Method_i) + \beta_2(Temperature_i).$$

Together, *Method* and *Temperature* were able to explain 36.1 % of the variability in the steentjie abundance (Table 5.12). The likelihood ratio tests (Chi-squared) identified that the effect of *Method* was highly significant ($X^2 = 34.10$, $p<0.001$), however as with the previous analysis, the width of the CIs around the predicted mean abundances for the different methods, particularity the BRUV, was large and reduced the confidence in the significance of the results (Fig. 5.15c). Steentjie abundance was predicted to significantly ($X^2 = 5.26$, $p<0.05$) increase with increasing water temperature.

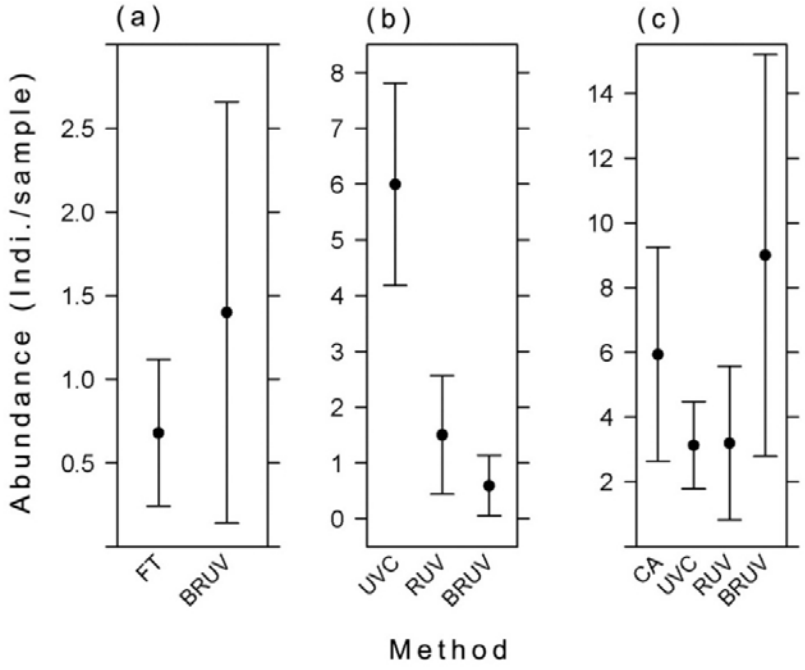

Figure 5.16: The effects of *Method* on the relative abundance of catsharks (a), fingerfins (b) and primary fisheries targets (c) from the shallow water sample stations in the Rheeders Reef study area. Displayed data are the predicted mean (± 95 % confidence intervals). FT = fish traps; CA = controlled angling; UVC = underwater visual census; RUV = remote underwater video; BRUV = baited RUV.

5.8.4.6 Catsharks

The species of catshark included in the grouping were the striped catshark, leopard catshark (*Poroderma pantherinum*), puffadder shyshark and dark shyshark. The dark shyshark was only recorded with BRUV. The striped catshark, leopard catshark and puffadder shyshark were recorded with both, FT and BRUV. Although catsharks were recorded with CA and RUV they were rarely detected and as a result the methods were excluded from the analysis. No species of shark were detected with UVC and it too was excluded from the analysis. Baited remote underwater video recorded catsharks at an average (± SD) abundance of 1.4 ± 1.9 per sample, while FT recorded a considerably lower average abundance of 0.7 ± 1.1 per sample.

The model selection process resulted in *Temperature* being dropped from the most parsimonious model:

$$\log(Catsharks_i) = \alpha + \beta_1(Method_i).$$

Although included in the model, the effect of *Method* was not significant ($X^2 = 1.70$, $p>0.1$) (Fig. 5.16a), and as a result *Method* was only able to explain 4.4 % of the observed variability in the data (Table 5.12).

5.8.4.7 Fingerfins

The species that were recorded from the fingerfin family included the twotone fingerfin, redfingers and barred fingerfin. Each species was recorded with UVC, RUV and BRUV. The highest average (± SD) abundance of fingerfins was recorded with UVC (6.4 ± 4.8), more than four times higher than that recorded with RUV (1.4 ± 1.5) and more than ten times higher than that recorded with BRUV (0.6 ± 0.8).

The model selection process resulted in *Temperature* being dropped from the most parsimonious model:

$$\log(Fingerfins_i) = \alpha + \beta_1(Method_i) .$$

The effect of *Method* was highly significant ($X^2 = 45.40$, $p<0.001$) and able to explain 42.5 % of the observed variability in fingerfin abundance (Table 5.12). Underwater visual census recorded significantly more fingerfins than both RUV and BRUV (Fig.

5.16b). Although more fingerfins were recorded with RUV compared to BRUV, the overlap of the CIs indicated that there was no clear difference (Fig. 5.16b).

5.8.4.8 Primary fisheries targets

The primary fisheries targets included roman, dageraad, red steenbras, red stumpnose, carpenter, santer (*Cheimerius nufar*), white stumpnose (*Rhabdosargus globiceps*) and blue hottentot. None of these species were recorded on sufficient occasions in the FT survey, and as a result FT was omitted from this analysis. Of these species, red stumpnose, carpenter, santer and white stumpnose were only recorded with BRUV.

Table 5.13: Results from the negative binomial generalized linear models investigating the effect of *Method* and *Temperature* on the observed fish community from the Middle Bank study area. RUV = remote underwater video; BRUV = baited RUV; ROV = remotely operated vehicle.

	Species richness				Total count			
	Estimate[2]	SE	t value[3]		Estimate	SE	t value	
Method: RUV	1.030	0.395	2.604	*	-13.192	4.619	-2.856	*
Method: BRUV	1.119	0.481	2.325	*	1.880	0.605	3.107	**
Method: ROV	-0.085	0.522	-0.163		-0.196	0.610	-0.322	
Temperature	—	—	—		1.469	0.447	3.288	**
Theta (k) [1]	2.6478				0.744			
Null deviance	34.326 on 18 DF				34.810 on 18 DF			
Residual deviance	23.648 on 16 DF				21.867 on 15 Df			

1: Theta (k) = shape parameter of the negative binomial distribution. Small k = distribution closer to gamma; Large k = distribution closer to Poisson

2: Estimate = log(Odds ratio)

3: Significance level: "***"<0.001, "**"<0.01, "*"<0.05, "▪"<0.1

The highest average (± SD) abundance for the primary fisheries targets was recorded with BRUV (9.0 ± 6.1), followed by CA (5.9 ± 6.1), RUV (3.2 ± 3.2) and UVC (3.1 ± 4.4). The lower level of variability typical to BRUV was again evident as it is the only method where the SD was less than the observed mean abundance for this group of species.

The model selection process resulted in *Temperature* being omitted from the most parsimonious model:

$$\log(Targets_i) = \alpha + \beta_1(Method_i).$$

The most parsimonious model was able to explain 10.4 % of the observed variability in primary fisheries target abundance (Table 5.12). The effect of *Method* was significant ($X^2 = 12.68$, $p<0.01$), however, high levels of uncertainty in the data resulted in wide CIs, which blurred true separation between the different methods (Fig. 5.16c). The similarity between the predicted mean abundance of primary fisheries targets (Fig. 5.16c) and roman (Fig. 5.15a), reflects the dominance of roman as a primary fisheries species in the study area.

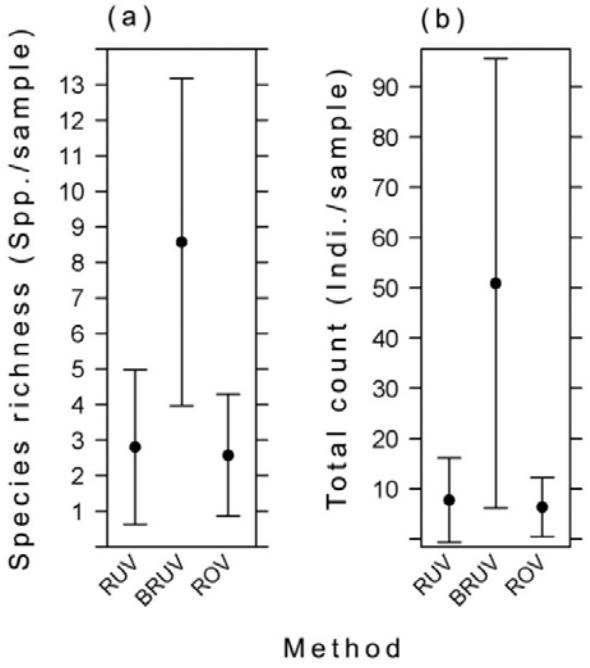

Figure 5.17: The effect of *Method* on the predicted mean (± 95 % confidence interval) species richness (a) and total count of fish in a sample (b) from the deep water sample stations in the Middle Bank study area. RUV = remote underwater video; BRUV = baited RUV; ROV = remotely operated vehicle.

5.8.5 Deep water communities (Middle Bank)

Due to the few samples collected in the deep water study area and high variability between the methods in terms of the number of species and the relative abundance the method comparison was only conducted on the species richness and total count data.

5.8.5.1 Species richness

Average (± SD) species richness was greatest for BRUV (8.6 ± 4.0). The species richness recorded with both the ROV (2.8 ± 3.9) and RUV (2.6 ± 1.8) were more than three times lower than that recorded with BRUV.

The model selection process resulted in *Temperature* being dropped from the most parsimonious model:

$\log(Species\ richness_i) = \alpha + \beta_1(Method_i)$.

Method was able to explain 31.1 % of the observed variability in the species richness data (Table 5.13). The effect of *Method* was significant ($X^2 = 10.04$, $p<0.01$), with BRUV recording more species than the ROV or RUV, however as with the preceding analyses, a lack of precision in the data (indicated by the width of the CIs) increased the uncertainty in this conclusion (Fig. 5.17a).

5.8.5.2 Total count

The average (± SD) total number of fish recorded per sample was greatest for the BRUV (48.6 ± 32.7). The average total count for RUV (11.2 ± 19.1) and the ROV (6.6 ± 6.6) were four times and seven times lower than that observed in the BRUV samples, respectively.

The model selection process identified that the full model was also the most parsimonious model:

$\log(Total\ count_i) = \alpha + \beta_1(Method_i) + \beta_2(Temperature_i)$.

Together, *Method* and *Temperature* were able to explain 37.2 % of the observed variability in the total count data (Table 5.13). The effect of *Method* was significant

(X^2 = 11.57, p<0.01), however, the CIs overlapped between the different methods suggesting that the variability in the data was obscuring the true trends (Fig. 5.17b). The effect of *Temperature* was not significant (X^2 = 2.44, p>0.1), but the correlation indicated that more individuals were predicted to be recorded in warmer waters (Odds ratio ± SE = 1.5 ± 0.44).

Table 5.14: Minimum number of samples required for the different methods to detect an annual 10 % population growth over a period of five years at a significance level of $\alpha = 0.05$ with a power of 0.8. FT = fish traps; CA = controlled angling; UVC = underwater visual census; RUV = remote operated vehicle; BRUV = baited RUV.

Method	FT	CA	UVC	RUV	BRUV
Replicate samples	25	16	30	10	10
Species richness	35	14	**11**	39	18
Roman	—	71	73	35	**13**
Fransmadam	—	67	194	—	**22**
Steentjie	235	364	264	101	**25**
Catsharks	152	—	—	—	**92**
Fingerfins	—	—	**26**	46	64
Primary fisheries targets	—	65	72	49	**21**

Table 5.15: Number of samples required for the different methods to detect an annual 10 % population growth decline over a period of five years at a significance level of $\alpha = 0.05$ with a power of 0.8. RUV = remote underwater video; BRUV = Baited RUV; ROV = remotely operated vehicle.

Method	RUV	BRUV	ROV
Replicate samples	5	7	7
Species richness	13	**9**	15
Panga	149	**39**	47
Roman	136	**24**	150
Steentjie	—	62	—
Carpenter	—	38	—
Red steenbras	—	43	—
Red stumpnose	—	61	—

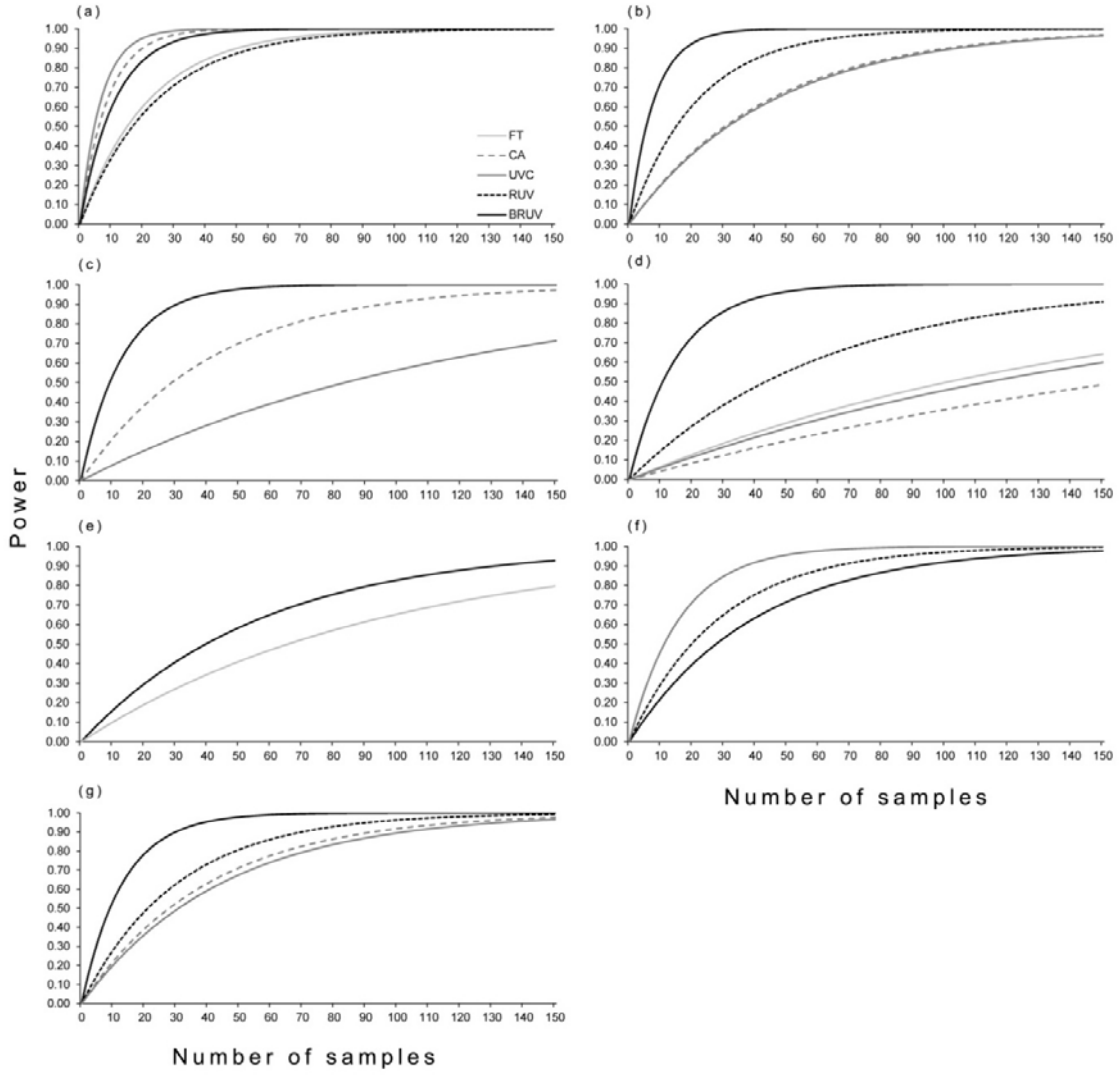

Figure 5.18: Predicted power with increasing sample size to detect an annual 10 % population growth in species richness (a), roman (b), fransmadam (c), steentjie (d), catsharks (e), fingerfins (f) and primary fisheries targets (g) for fish traps (FT), controlled angling (CA), underwater visual census (UVC), remote underwater video (RUV) and baited-RUV (BRUV).

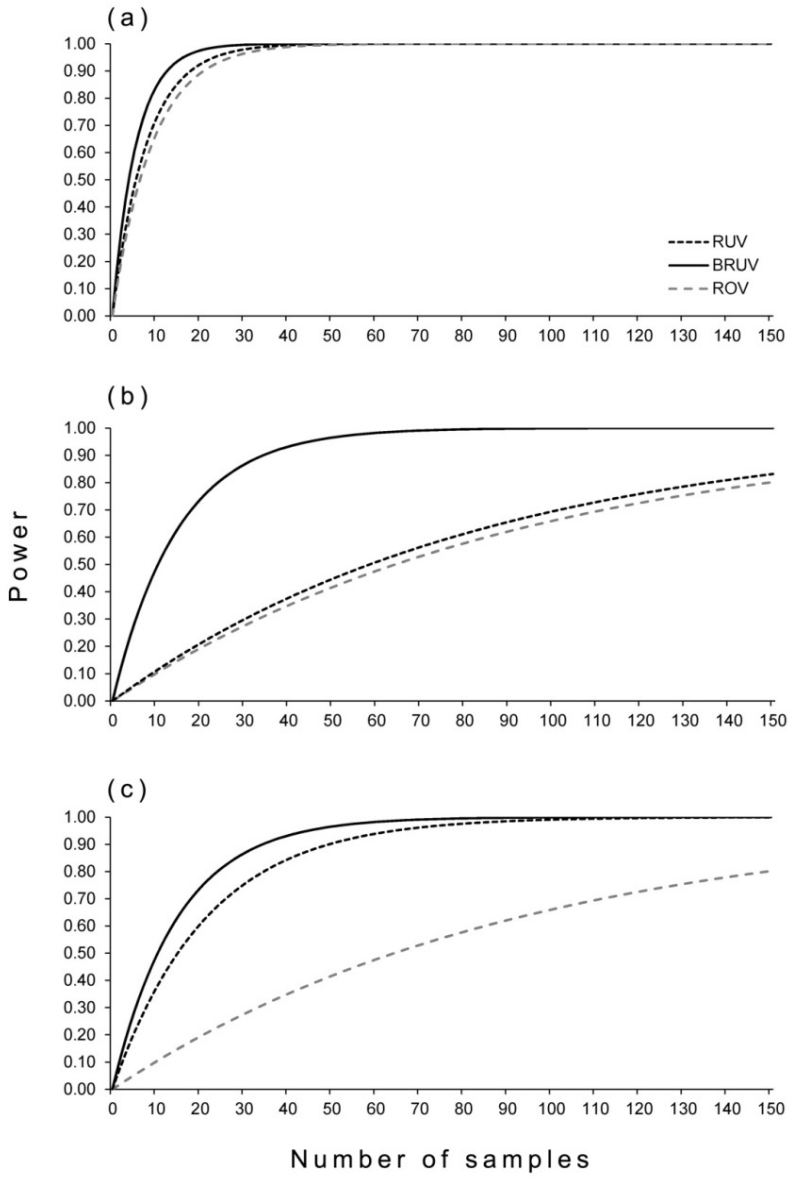

Figure 5.19: Predicted power with increasing sample size to detect an annual 10 % population growth in species richness (a), panga (b) and roman (c) for remote underwater video (RUV), baited-RUV (BRUV) and the remotely operated vehicle (ROV).

5.8.6 Power analysis

5.8.6.1 Rheeders Reef study area

The minimum number of samples to detect a 10 % growth per annum in species richness was 11 samples for UVC (Table 5.14) (Fig. 5.18a). Controlled angling required 14 while BRUV required 18 samples (Table 5.14) (Fig. 5.18a). The highest sampling effort was required by FT (n = 35 samples) and RUV (n = 39 samples). Care should be taken when interpreting the species richness power analysis as the number of species recorded by the different methods differs drastically. In this study BRUV recorded 46 % and 50 % more species than UVC and CA, respectively. As such the probability of BRUV to detect the arrival of a new species, or the probability that a species which becomes locally extinct was originally detected by BRUV is almost double that of UVC or CA.

Baited remote underwater video was predicted to require the fewest samples to detect a 10 % per annum population growth for roman (Fig. 5.18b), fransmadam (Fig. 5.18c), steentjie (Fig. 5.18d), catsharks (Fig. 5.18e) and the primary fisheries species (Fig. 5.18g). The fingerfin grouping was most efficiently sampled by UVC, followed by RUV and BRUV (Table 5.14) (Fig. 5.18f).

5.8.6.2 Middle Bank study area

Due to data limitations it was only possible to conduct the power analysis on the species richness, panga and roman data for the three methods. In all instances BRUV proved to be the most efficient (Table 5.15) (Fig. 5.19a, b).

In addition, the power analysis was conducted on a number of other species that were only recorded on sufficient occasions by the BRUV. These species mostly consisted of primary fisheries targets (carpenter, red steenbras and red stumpnose), and the results suggest that a minimum of 61 samples within a deep study area would be sufficient to detect a population growth of 10 (Table 5.15) (Fig. 5.19c).

5.9 Discussion

5.9.1 Method comparison

5.9.1.1 Rheeders Reef study area

The results from the research in the Rheeders Reef study area showed significant differences between the fish communities recorded with the different methods. In the PERMANOVA pairwise comparison of methods there were isolated cases where no significant difference was detected between methods. These cases included the comparison between BRUV and RUV as well as RUV and CA, in terms of the species recorded, and the FT and RUV in terms of the relative abundance of the species. However, the majority of pair-wise comparisons showed that the different methods measure dissimilar components of the fish community. Baited remote underwater video sampled the most species (85 % of the total number of species recorded), almost a third more than RUV which recorded the second most species. Importantly, the results for BRUV and RUV came from the lowest sampling effort during the study (n = 10 samples for both methods), compared to UVC where three times as many samples were collected and only 15 species were recorded. Due to the large number of methods used in this assessment, there were fewer species unique to a specific method, compared to what was observed at the Castle Rock study area (Chapter 5, Part I), where UVC recorded eight unique species, BRUV recorded four unique species and FT recorded three unique species. Nevertheless, BRUV recorded six unique species, while FT, CA and RUV recorded a single unique species each.

There is agreement in the correlation of species with specific methods between the results from the Castle Rock study area (Chapter 5, Part I) and the results from the Rheeders Reef study area. The PCO and CAP analyses performed on the Modified Gower sample dissimilarity scores, showed that the presence and relative abundance of striped catshark contributed to the separation of the FT samples from the other methods, while the presence and relative abundance of twotone fingerfin and redfingers contributed to the separation of the UVC samples from the other methods. The presence and relative abundance of roman contributed to the

separation of the UVC, BRUV and CA samples from the other methods. In addition to roman, the PCO and CAP analyses indicated that the dissimilarity scores for BRUV samples were strongly influenced by the presence and relative abundance of primary fisheries targets, including red steenbras, blue hottentot and dageraad.

The univariate analysis reiterated the differences in the number of species and the relative abundance of species recorded by the alternative methods. In terms of highest species richness and total count of fish, BRUV ranked at the top followed by RUV, UVC, CA and FT. Baited remote underwater video not only recorded the highest average number of species per sample but also the highest abundance for all fish, roman, steentjie, catsharks and the grouping of primary fishery targets. This is in agreement with the results from the Castle Rock study area (Chapter 5, Part I). Past studies have compared the ability of BRUV and UVC to survey specific fish species (Willis et al. 2000), as well as the entire fish community (Stobart et al. 2007; Colton and Swearer 2010). The results from this study contrast with those from Stobart et al. (2007), and Colton and Swearer (2010), which both reported that UVC was more effective than BRUV at surveying the entire fish community. Both these studies were conducted in tropical/sub-tropical environments and reported considerably greater species richness compared to what was detected during this study in a temperate environment. It is possible that BRUV was unable to effectively survey the more specious tropical and subtropical communities where there are more specialist species that may not have been attracted to the bait. The results from this study agree with the findings from Willis et al. (2000) where BRUV collected more precise data than UVC for generalist carnivores. This pattern was not true for species from different trophic groups, with UVC recording the highest abundances for fingerfins (a microinvertebrate carnivore). This trend was identified in Part I of this chapter, and it appears that both UVC and RUV produce more reliable data than BRUV for the different species of fingerfin.

Comparisons of the efficiencies of stereo-BRUV and FT at sampling demersal fish have found that stereo-BRUV is a much more powerful tool to measure population structure (Harvey et al. 2012). The results presented in this chapter are in agreement, with FT not detecting, or under-sampling most of the dominant species present within the survey area. The results from the Rheeders Reef study area agree

with the results from Chapter 4, and Part I of this chapter, that FT are effective at capturing the different species of catshark that occur on the warm-temperate reefs of South Africa. However, BRUV appears to be equally, or more effective, at doing this. As a result, it is likely that the FT method has become mostly redundant unless specimen samples, length measurements or sexing is required. The use of stereo-BRUV for length measurements (Harvey and Shortis 1996) will further negate the role of FT in sampling subtidal fish assemblages.

Controlled angling was highly selective in terms of the species captured, with samples dominated by roman, and to a lesser extent fransmadam and steentjie. The relative abundance of roman recorded by CA was the second highest during this study, suggesting that the method was effective at surveying this species. This result is in agreement with past finding that have demonstrated that CA is highly effective at surveying the roman population on rocky reefs in the Agulhas Ecoregion of South Africa (Götz et al. 2007; Bennett et al. 2009). Willis et al. (2000) noted that inter-specific competition for baited hooks would negatively affect CA data, and depress the abundance of the less dominant species. Comparing the CA, RUV and BRUV data from this study, there is strong similarity in relative abundance for roman, but it appears that CA significantly underestimates the abundance of common, but smaller species such as steentjie and fransmadam in comparison to RUV and BRUV. It is likely that interspecific competition around the baited hook contributed to this disparity. Controlled angling was able to collect data on the presence of sharks within the survey area, however, the frequency of observation was too low to allow for any subsequent analysis.

Controlled angling and FT were the only extractive methods tested during this research. Both methods were highly selective in the species that were recorded, while the variability in the data was high. The inability of these extractive methods to provide accurate information on the entire community limits their use to studies that focus on certain species or biodiversity. Both CA and FT are cheap, logistically simple and required limited specialised training and experience. While it is recommended that FT is not used for any ecological monitoring activity, CA does produce valuable data for species such as roman and can be used for cost-effective long-term monitoring.

Although UVC recorded fewer species and lower abundances of fish than BRUV, it was able to effectively survey species that were not attracted to bait. These species were predominantly the benthic or microinvertebrate carnivores, and included the fingerfins, as well as species such as janbruin *Gymnocrotaphus curvidens*, cape knifejaw *Oplegnathus conwayi* and jutjaw *Parascorpis typus*. Colton and Swearer (2010) found similar results with fingerfins occurring in 89 % of UVC samples, but infrequently in BRUV data. Remote underwater video was the only other method that did not depend on bait to attract fish into the survey area. Although RUV consistently detected all these species, they were typically recorded at lower abundances. Interestingly, BRUV recorded all of the above mentioned species, excepting jutjaw, however, their occurrence was unpredictable and their abundance low. The UVC was the only method not to detect any elasmobranch. This appears typical for UVC, transects or point counts, as sharks rarely enter the survey boundaries (Ward-Paige and Lotze 2011). While this is understandable for the larger, roaming species of sharks (e.g. smooth hound *Mustelus mustelus* or copper shark *Carcharhinus brachyurus*), the species of catshark that occurred in the Rheeders Reef study area appear relatively resident and would have been present on the reef. Crypticity and shyness are known to reduce detectability of fish during UVC (Bozec et al. 2011) and it is likely that the shysharks were overlooked during the UVC surveys.

As opposed to the other methods tested, RUV recorded similar species as BRUV. However, RUV data were characterised by higher levels of variability between samples, and the species were typically observed at lower abundances. Watson et al. (2005) and Harvey et al. (2007) identified that RUV is characterised by high variability and required greater sampling effort to provide data able to detect a 25 % change in the total number of individuals. The results from this study, as well as those presented in Chapter 3, support these findings, with RUV requiring considerably greater sampling effort to have the same diagnostic power as BRUV.

As was the case with UVC, there were exceptions to the superiority of the BRUV method with the RUV being more effective at recording the microinvertebrate cornivores. Francour et al. (1999) showed that RUV and UVC point counts recorded similar dominant species, although UVC typically recorded twice as many species than the remote video technique. This difference in diversity was attributed to the

RUV only sampling at the base level of the kelp forest where the study took place, whereas the divers sampled the fish community throughout the water column (Francour et al. 1999). The results from this study indicated that RUV recorded more species than UVC line transects. The difference between the results from Francour et al. (1999) and this study could be attributed to the different UVC approaches that were used, but also to the fact that only species occurring within three meters above the reef were counted by all methods. This aside, RUV and UVC appeared to provide similar data for the dominant species. As such RUV may provide a suitable alternative to UVC, and a valuable addition to BRUV to conduct baseline surveys of fish assemblages where depth precludes UVC.

5.9.1.2 Middle Bank study area

The data from the deep water study area (44-75 m) add support to the superiority of BRUV at measuring a broader range of species (81 % of the 21 species recorded by all three methods), in comparison to RUV (28 %) and ROV (48 %). The majority of species recorded by BRUV are considered important components of the hook and line fishery (line-fishery) in South Africa. A large number of these species are considered over-exploited or collapsed, however, in most cases there is a need to update stock status (Mann 2000; DAFF 2010; Sink et al. 2012). In addition, these species are associated with rocky reefs that occur throughout the region, and are known to move and migrate between shallow and deep water habitats driven by ontogenetic habitat shifts and spawning (Mann 2000). The ability of BRUV to non-destructively survey the deep and shallow water components of the community make it an ideal method to conduct these surveys in a comparative and standardised manner. It was mentioned earlier that stereo-BRUV enables highly accurate length estimates for fish (Harvey and Shortis 1996). The use of stereo-BRUV, rather than the mono-camera BRUV as employed during this study, would further improve the collection of population data for fisheries management.

The RUV appeared to measure only a small component, in terms of number of species and their abundance, of the deep water fish community sampled by all three methods. On the other hand, the ROV contributed four unique species to the overall species richness. These included two species of fingerfin, redfingers and barred fingerfin, the schooling maasbanker, and an unidentified species of horsefish. While

maasbanker feed on plankton, the remainder feed on benthic invertebrates and these species may have avoided the heightened activity around the baited videos. A similar pattern was observed in the Rheeders Reef study area where both RUV and UVC appeared to be more effective at surveying the microinvertebrate carnivores. The ability of the ROV to sample a greater area and encounter species that are not attracted to bait provides an advantage over the static BRUV and RUV methods that depend on attraction and chance encounters, respectively. However, the ROV data were characterised by high levels of variability providing little confidence in its ability to efficiently sample the fish community. Interestingly, the ROV was unable to detect the twotone fingerfin (the dominant microinvertebrate carnivore from Rheeders Reef) and the jutjaw (a zooplanktivore) that were both present in the BRUV samples. Although this suggests that the BRUV method can detect these species on deeper water reefs, it is understood that the dataset suffered from the low sample replication (particularly the RUV where only five samples were collected), and additional samples will shed further light onto the true capabilities of the different remote video techniques to survey deep water reef habitats.

Although all census techniques are associated with biases, very little is known about the biases associated with the ROV method. Past work has identified that the lights, sounds, movement and speed of an ROV attracts or repels different components of the fish community which leads to variable and biased abundance estimates (Trenkel et al. 2004; Stoner et al. 2008). Biases associated with other methods, such as UVC, RUV and BRUV, are relatively well known, and understanding these biases enables researchers to account for them during quantitative analysis. There is a need to conduct more methodological research with ROVs to identify and measure the influence of these biases on the observed fish community (Stoner et al. 2008). Until this has been completed it is doubtful that ROVs will be able to provide quantitative population data of a similar quality to BRUV or even RUV, and the method should be restricted to qualitative exploratory surveys.

5.9.2 Power analysis

5.9.2.1 Rheeders Reef study area

A total of six separate analyses was run on individual species (n = 3) and groupings of species (n = 3) that differed in feeding biology, behaviour and fisheries importance. The results were conclusive, with five of the six power analyses indicating that BRUV required the lowest sampling effort to detect the +10 % in abundance, over a period of five years, at a power of 80 % and an alpha level of 0.5. The species and groupings included roman, steentjie, fransmadam, catsharks and the primary fisheries targets. The only exception was the fingerfin grouping, where UVC and RUV required fewer samples than BRUV. Interestingly the RUV method was identified as the second most cost-effective method from all the power analyses that were run on this dataset (n = 4, as not all species or groups had sufficient data for the power analysis to be conducted). This included roman, fingerfins, steentjie and the grouping of primary fisheries targets.

In addition, the power analysis was run on the species richness data as per the approach of Langlois et al. (2010). However, power to detect change in species richness may mislead method selection for long-term sampling plans, unless the methods detect the same suite of species. During this study, UVC and CA were identified as requiring the fewest samples to detect the 10 % growth in species richness, however, the results show that both methods sampled less than 50 % of the total number of species recorded at the Rheeders Reef study area. Baited remote underwater video, on the other hand, required a greater sampling effort to detect long-term change in species richness, but it detected 85 % of all the species recorded on Rheeders Reef. In this instance long-term monitoring would be better served by first selecting the method that most effectively surveys the broader fish community and then designing a sampling strategy based on minimum number of samples required for that method to detect a predetermined level of change in species richness.

5.9.2.2 Middle Bank study area

The high level of consistency in BRUV data together with the high levels of variability in RUV and the ROV data were reflected in the power analysis from Middle Bank, with the lowest sampling effort required for panga and roman when using BRUV. Although BRUV appeared to be the most effective, data from the deeper water study area were characterised by higher levels of variability than data from the shallow water study area. As a result roman and steentjie both required considerably more samples from the Middle Bank study area (24 and 62, respectively) compared to the Rheeders Reef study area (13 and 25, respectively) to detect an annual 10 % growth in relative abundance over a period of five years.

5.9.3 Conclusions

Compared to FT, CA, UVC and RUV, BRUV provides the most comprehensive assessment of the subtidal reef fish communities in the TNP MPA. This is not only true for the shallow photic (5-30 m), but also down to depths of 75 m. While no samples were collected from reefs beyond 75 m depth, it is likely that BRUV will be equally more effective at surveying these habitats. Baited remote underwater video not only recorded the highest species richness, but also recorded most species at higher abundances than the other methods. The consistency of these findings make BRUV the most effective method, as the least number of samples were required to produce statistically robust data. There is general agreement between the results from Part I and Part II of this chapter. As a result, BRUV is recommended as the most suitable method for surveying the subtidal reef fish communities in the warm-temperate regions of South Africa.

It is important to remember that BRUV data are biased by the presence of bait which alters the behaviour of fish. This results in the BRUV underestimating the abundance of microinvertebrate carnivores, and overestimating the abundance of generalist carnivores. Although UVC was found to produce the best data for the microinvertebrate carnivores, the method’s performance was weak as it was unable to detect most species and the data was characterised by high levels of variation between the samples. In addition the use of UVC is restricted to shallow sampling depths (< 30 m) due to safety considerations. For many species, RUV was found to

collect data similar to BRUV and UVC, and the unbaited video method offers a number of advantages. Remote underwater video can survey the microinvertebrate carnivores as well as the larger fish species that avoid divers. Furthermore, RUV is also able to sample throughout the depth range of a species. The shortfall is that RUV samples fewer species than BRUV and the data is highly variable making it considerably less effective. As such long-term monitoring objectives would be better met with the BRUV method. However, where baseline biodiversity assessments are required, researchers should consider conducting a combination of RUV and BRUV surveys.

There was considerable dissimilarity in the fish community structure from the BRUV data between the shallow study area (Rheeders Reef) and the deep water study area (Middle Bank). The presence of many adult carpenter and panga was in stark contrast to what was observed in the inshore study area where few juveniles of these species were recorded. Although no size estimates were possible, the populations of roman, blue hottentot and red steenbras were dominated by larger individuals on the deeper reefs. Adult hottentot *Pachymetopon blochii* were consistently recorded in the Middle Bank study area, while no hottentot have ever been observed at the shallow Rheeders Reef study area. The ability of the BRUV and to a lesser extent the RUV methods, to non-destructively sample reef habitats throughout the depth distribution of a fish species make them ideal tools to conduct detailed ecological research into the pattern and processes that structure reef fish communities. By using the stereo-video configuration, the quality and quantity of data from these surveys will be further enhanced.

Chapter 6

Cost-benefit analysis of reef fish monitoring methods to address ecosystem and fisheries monitoring objectives

6.1 Introduction

Selecting the most suitable methods to conduct monitoring is one of the most important steps during the design phase of a monitoring programme (Vos et al. 2000; Yoccoz et al. 2001; Elphick 2008). There are numerous methods to collect data on the abundance and size of reef fish species (Murphy and Jenkins 2010). The research within this thesis investigated and compared six different fisheries-independent and theoretically non-destructive approaches, with an emphasis on their ability to detect species and measure abundance.

The selected methods included two extractive techniques, controlled angling (CA) and fish traps (FT), and four *in situ* observational techniques, underwater visual census (UVC), remote underwater video (RUV), baited RUV (BRUV) and remotely operated vehicle (ROV). This represents a wide assortment of methods which have all been used to survey fish populations on rocky reefs around the world (Francour et al. 1999; Edger et al. 2004; Trenkel et al. 2004; Watson et al. 2005; Götz et al. 2008; Bennett et al. 2009; Harvey et al. 2012), and are considered suitable to survey the reefs in the Agulhas Ecoregion of South Africa (Griffiths and Wilke 2002; Götz et al. 2007, 2008; Smith et al. 2007; Bennett et al. 2009). There are a few alternative methods, including acoustic cameras (e.g. duel-frequency identification sonar = DIDSON) and different approaches to UVC (e.g. point-counts and diver operated video) (Murphy and Jenkins 2010). However, as presented in the general introduction (Chapter 1), it was felt that the selected methods provided sufficient coverage in terms of the available options, technology types and costs.

It is well known that the quality of data varies between different methods, and that each method surveys a specific component of the fish community more effectively than others (Francour et al. 1999; Willis and Babcock 2000; Willis et al. 2000; Cappo et al. 2004; Edgar et al. 2004; Watson et al. 2005, 2010; Götz et al. 2007; Harvey et al. 2007, 2012; Bennett et al. 2009; Colton and Swearer 2010; Langlois et al. 2010, 2012b; Pelletier et al. 2011). Results from this thesis agree with these findings, with the results from Chapter 5 illustrating clear differences between methods in the observed fish communities and extreme variation in the levels of sampling replication needed to produce data with equivalent diagnostic power.

The long-term success of a monitoring programme depends on its cost-efficiency (Caughlan and Oakley 2001). Cost-efficiency can be described as the cheapest way to achieve a target outcome. The cost of data collection will represent a substantial part of a monitoring programme's budget, compared to the cost of programme management (Caughlan and Oakley 2001). Consequently, decisions on what method to use should take into account the cost-efficiency of the data collection. An effective way of achieving this is by comparing the sampling effort required to produce data with a standardised diagnostic power against the cost of collecting the samples (Langlois et al. 2010). While cost-efficiency can be used to direct method selection, the suitability of a method to address the monitoring objectives, as well as provide additional data that will aid in the interpretations of the results need to be kept in mind.

6.1.1 Aim and objectives

The aim of this chapter is to identify a method, or group of methods, most suited for long-term monitoring of reef fish communities in the Agulhas Ecoregion of South Africa, to address the following objectives:

1. Monitor the change in composition and abundance of multiple components of the reef fish community to measure; (i) the impact of climate change, (ii) the patterns in biodiversity, or (iii) the response to ecosystem based management.
2. Monitor the change in population abundance and structure for reef fish species of fisheries importance.

6.2 Methods

To achieve the aims of this chapter, the suitability of a method for long-term monitoring of reef fish was determined though a cost-benefit analysis (CBA), that takes into account the cost-efficiency together with the additional benefits gained from using a particular method.

The cost and cost-efficiency component of the CBA takes into account the once off initial cost to purchase all the required equipment and provide relevant training to personnel, together with the annual sampling and data processing cost, based on the estimated number of samples required to detect a 10 % population growth per year over a period of five years. The benefit component of the CBA investigated the methods ability to detect the different trophic and functional groups present in the reef fish community, and developed a simple scoring system to rank the inherent capabilities of the different methods, independent from the results of the cost-efficiency analysis.

6.2.1 Cost and cost-efficiency

The cost was calculated as the estimated costs to conduct reef monitoring over a five-year period based on the data and field records from the Rheeders Reef and Middle Bank study areas in the Tsitsikamma National Park (TNP) marine protected area (MPA), and the Castle Rock study area in the Table Mountain National Park (TMNP) MPA. Where possible, the costs were taken from field trip reports and experience. Where no first-hand information was available the costs were taken from the literature and communications with relevant sources. To estimate the relative cost-efficiency of the different methods the following aspects were taken into account:

1. Establishment of research capabilities
2. Cost of collecting a sample
3. Required sampling effort and sampling efficiency
4. Time spent in the field
5. Processing of data

Following the results presented in this thesis, the FT method was excluded from the CBA as they were found to be ineffective at sampling the reef fish community as a whole, or the species of fisheries importance. There is a potential that the FT method could be used in combination with other methods, for example CA, to provide a broader assessment of the reef fish community. However, FT did not sample the relevant components of the fish community to be complementary to any other method.

6.2.1.1 Establishing research capabilities

The establishment of research capabilities is considered to be a once-off cost, with all equipment and trained personnel assumed to have an average working lifespan of five years (at the financing organisation). The costs include all the capital equipment to set up the research capabilities within an organisation, as well as specialised training for personnel where required. Where applicable, the equipment was designed to enable data collection to a maximum depth of 100 m.

For CA, capital equipment requirements were specified to meet the protocol of Bennett et al. (2009), and employed in the method comparison chapter of this thesis (Chapter 5). Sufficient funds were included to equip four anglers with the required fishing gear (for details see Appendix 7.1).

Research diving in South Africa is considered to be commercial diving and as such has to abide by the commercial diving regulations (Department of Labour 2008). Under these regulations a dive team consists of a supervisor (who oversees the dive operation) and four divers (two pairs), all of whom have to have the relevant Class IV commercial supervisor and diver qualifications (Department of Labour 2008). An alternative approach is to have two supervisors and two divers in a team with the supervisors alternating between dives. Although this reduces the team size for the UVC surveys, it requires two divers with suitable experience to be trained as supervisors, which is not always feasible and will come with its own associated costs. Therefore, the former dive team setup is used for the CBA. Sufficient funds were included to purchase equipment for four divers, provide training for supervisor and divers, provide specialised first aid equipment and enable refilling of cylinders as required (for details see Appendix 7.1).

The capital equipment costs were identical for RUV and BRUV, and will be discussed together. The data presented in this thesis were collected with a system that provided a live feed to the surface where the video was recorded. Although this was sufficient to address the research questions, more recent RUV and BRUV systems consist of self-contained video recorders, which greatly increases the cost-efficiency of the method (Watson et al. 2005, 2010; Langlois et al. 2010; Harvey et al. 2012). Research in the TMNP MPA has demonstrated the suitability of GoPro Hero2 action cameras for mono-camera RUV and BRUV research (de Vos *pers. com.*). The off-the-shelf housing for GoPro cameras has a maximum operating depth of 60 m, and as such the equipment cost includes the purchase of deeper rated housings (≥ 100 m). Sufficient funds were allocated to purchase equipment for four mono-camera GoPro RUVs and four mono-camera GoPro BRUVs (see Appendix 7.1), to enable simultaneous deployment and increase the sampling effort. In addition, funds were allocated for the purchase of video analysis software, EventMeasure (SeaGIS 2011). The software allows for fast and efficient video analysis and standardises the analysis and data-entry process, thereby reducing the scope for observer error.

The capital equipment needed for ROV surveys was based on the methodology employed in Part II of Chapter 5. The size of the ROV used (SeaEye Falcon) was relatively large (length = 100 cm, width = 60 cm, height = 50 cm) and technically advanced, with respect to the tasks it was required to perform, although it is still in the 'observation class' of ROVs. There are alternative smaller and cheaper mini-ROVs, such as the VideoRay P4 (www.videoray.com), which can provide a more cost-effective alternative. However, mini-ROVs are typically restricted for use in calm sea conditions and are most manoeuvrable at shallower depths. The oceanographic conditions within the Agulhas Ecoregion are treacherous, with high seas, strong surge and powerful currents. As such, the SeaEye Falcon is considered to be the more suitable option for conducting standardised monitoring of reef fish communities in the region. Sufficient funds were allocated to cover the cost of the complete ROV system, with surface control facilities and the training of two pilots to operate the vehicle (see Appendix 7.2).

In addition to the methods tested in this thesis, the CBA was extended to determine the cost-efficiency of stereo-RUV and stereo-BRUV (see Harvey and Shortis 1996). Stereo-BRUV is rapidly emerging as the most comprehensive reef fish sampling tool available for researchers and managers (Murphy and Jenkins 2010). As the stereo-camera techniques estimate abundance using the exact same methods, MaxN (Cappo et al. 2003), as the mono-camera techniques, it is assumed that the results from the power analyses apply to both camera configurations. The advantage of the stereo-camera configuration is that it allows for the size of fish to be measured from the MaxN frame, and for the visible area to be calculated accurately (Harvey and Shortis 1996). Both these measurements are not possible with the mono-camera configuration. As with RUV and BRUV, sufficient funds were allocated to assemble four stereo-RUV and four stereo-BRUV systems, together with the required software licences and calibration tools (SeaGIS 2011) (see Appendix 7.1).

6.2.1.2 Cost per sample

For each method a cost per sample was calculated, based on consumable materials needed in the field, and time for processing the sample after collection. Where bait was required, it was standardised to 0.8 kg per sample. With CA there is a moderate rate of material loss (i.e. hooks, sinkers and swivels) at each station. To account for this a value of R 2.7 was added to the CA samples. A standardised cost per sample of 0.5 rand was applied for all other consumable material (i.e. cable ties, duck-tape). Employee's time was calculated at a cost of R 12,000 month^{-1}, which equates to an hourly rate of R 69.2 hour^{-1}, or R 553.6 day^{-1}. This salary scale is in line with that of a field technician with the minimum required qualification and experience working at a South African National Research Facility (Dr T Bornman pers. com.). Where data processing involved only data-entry (CA and UVC), 0.25 hours were allocated per sample. For RUV and BRUV, where processing involved video analysis for abundance, 1.5 hours were allocated for the unbaited samples and 2.5 hours were allocated for the baited samples. The video processing times are considerably shorter than what was reported in Chapter 3 (RUV = 2.4 hours; BRUV = 5.7 hours). The reason for this is that specialised video analysis software is available (EventMeasure, see SeaGIS 2011), which greatly reduces the time for video processing (Prof E Harvey *pers. comm.*). Where processing involved video analysis

for abundance and size measurements (stereo-RUV and stereo-BRUV), 2.0 hours were allocated for the unbaited samples and 3.0 hours were allocated for the baited samples (Prof E Harvey *pers. comm*.). For the ROV samples, a data processing time of 0.75 hours was allocated.

6.2.1.3 Cost per day

The cost per day incorporated subsistence, size of the monitoring team, number of days spent in the field, running cost of the vessel, number of samples collected per day, average distance travelled between sample sites based on the stratified random sample site allocation, and the daily distance travelled to and from the study site.

The size of the monitoring team varied between the different methods. Four team members are required for CA (four anglers), five team members are required for UVC (one supervisor and four divers) and three team members are required for RUV, BRUV (three deckhands) and ROV (two pilots and one deckhand) surveys. In addition to this, a boat skipper is required for each method. Staff time while in the field was cost at the same rate as that for the video analysis (R 69.2 $hour^{-1}$, or R 553.6 day^{-1}).

The average distance travelled between stations depends on the size of the study area. Using a standard 6 x 3 km study area, divided into 150 x 150 m blocks classified according to depth and reef profile, the average (±SD) distance between 100 randomly selected sampling points from all strata was estimated to be 2.9 ± 2.0 km. For the RUV and BRUV methods, stations had to be visited twice, for deployment and collection, and as such an average distance of 5.8 km was applicable. The ROV requires a larger (> 9 m length) vessel with a watertight cabin for the topside control electronics, and a generator with a running cost of R 50 km^{-1}. The remaining methods can all be conducted off a typical skiboat (≤ 9 m length) with a running cost of R 15 km^{-1}.

The number of hours spent at sea was standardised to six hours per day for each method. Based on this, the feasible number of samples was estimated for each method. Controlled angling was set to seven samples per day, with 20 minutes for transit between stations, anchoring and preparation of equipment. Underwater visual census was set to five samples per day, with the divers working in separate pairs,

and taking turns to collect two and three samples per day. The predicted number of samples for the UVC method was high (see Chapter 5), and as such this conservative estimate of samples per day accounts for the cumulative risk of multiple dives on consecutive days for an extended period of time (Department of Labour 2008). For RUV and stereo-RUV it was estimated that 17 samples could be collected per day with four systems using a 35 minute deployment time and 20 minutes between deployments for transit and preparation of the equipment. For BRUV and stereo-BRUV is was estimated that 16 samples could be collected per day with four systems, each deployed for 50 minutes with 20 minutes between successive deployments to allow for transit and preparation of equipment. For the ROV an achievable sampling effort was predicted to be six samples per day, with 40 minutes required for transit, anchoring and preparation of equipment, and 20 minutes of flying the ROV.

The number of field days required was then calculated as the required number of samples divided by the estimated number of samples collected per day. In addition to the cost per day of field work, loss of days due to bad weather was considered. Experience from both TNP and TMNP show that bad weather doubles the required number of field days needed to collect sufficient data (see Chapter 5). For each method, the required number of field days was assumed to be equivalent to the expected number of bad weather days, and the cost of bad weather days was taken as the employee's daily rate and subsistence for the monitoring team with no additional expenses.

6.2.1.4 Sampling effort

The required sampling effort was derived from the power analyses performed in Chapter 5. The power analysis was designed to identify the minimum number of samples required to detect a 10 % growth in abundance per year for a specific method, over a period of five years. Two separate CBAs were conducted, with the aim of providing information relevant to programmes aiming to (i) monitor population changes in multiple species in the reef fish assemblage, and programmes aiming to (ii) monitor changes in populations of reef fish important to fisheries.

The power analyses performed in Chapter 5 were run on multiple components of the fish community representing different trophic or functional groups. These groups included: (i) dominant large generalist carnivores (primary fisheries targets: roman *Chrysoblephus laticeps*, carpenter *Argyrozona argyrozona* and panga *Pterogymnus laniarius*); (ii) scarce large generalist carnivores (primary fisheries targets: red steenbras *Petrus rupestris*, dageraad *Chrysoblephus cristiceps* and red stumpnose *Chrysoblephus gibbiceps*), (ii) small and medium generalist carnivores (steentjie *Spondyliosoma emarginatum*, fransmadam *Boopsoidea inornata* and hottentot *Pachymetopon blochii*), (iv) benthic invertebrate carnivores (fingerfins *Cheilodactylidae*), and (v) cryptic reef sharks (catsharks *Scyliorhinidae*). The trophic and functional groups missing from the power analyses were the omnivores and herbivores, and the large sharks, skates and rays, as insufficient species and numbers were detected during the comparative method assessments to permit a power analysis. As such, the optimum level of sampling was taken to be the minimum number of replicates needed to effectively monitor the populations of species in the respective tropic and functional groups (Table 6.1). Of the methods considered in the CBA, only the BRUV was able to detect the catsharks. As a result the sampling effort required for the catsharks was excluded from the calculation of cost-efficiency for the BRUV, as it would have biased the comparison with the other methods.

There was the option to run the power analysis on the abundance of the different trophic and functional groupings of species, rather than the individual species, as this would have produced more generalised results. However, by grouping different species that occur at different abundances and levels of variation together, sensitivity to detect species level changes in the population is lost for all but the most abundant species. To illustrate this, the sampling effort required to detect a 10 % population growth in the grouping of primary fisheries targets (n = 31 samples, see Chapter 5 Part II) from Middle Bank, compared to individual species that make up the grouping (roman = 24, panga = 39, carpenter = 38, red steenbras = 43 and red stumpnose = 61), is only sufficient to adequately capture the variability in the roman population, and is roughly 50 % of that required to detect changes in the red stumpnose population. Considering this it was felt that the species specific approach would provide more realistic estimates for the number of samples required. The power

analyses for steentjie indicated that an exceptionally high level of sample replication was necessary to monitor this species (n > 300 samples). Consequently, only the fransmadam and hottentot power analyses results were used as an indication of the sampling effort required for small and medium generalist carnivores.

The second CBA was conducted to select the most cost-efficient method to monitor the long-term change in fisheries resources. The optimum sampling effort was identified as the minimum number of samples to effectively survey the dominant large generalist carnivores (roman, carpenter and panga) and the scarce large generalist carnivores (red steenbras, dageraad and red stumpnose) for each of the different methods (Table 6.1).

Table 6.1: Results from the power analysis providing the required minimum sampling effort from each study area to detect long-term changes in the abundance of multiple species from the reef fish community, and the species of fisheries importance.

	TMNP- Castle Rock		TNP- Rheeders Reef		TNP- Middle Bank	
	Community	Fisheries	Community	Fisheries	Community	Fisheries
CA	—	—	—	71	—	—
UVC	83	77	194	73	—	—
RUV	—	—	137	49	—	149
BRUV	45	45	64	21	—	61
ROV	—	—	—	—	—	150

6.2.2 Method benefits

6.2.2.1 Detectability

For each of the trophic and functional groups described above, a detectability score was calculated by measuring the frequency of occurrence that the different groups were detected by the different methods (see Appendix 7.2 for lists of species within each trophic/functional group). The groupings are somewhat different from those used in previous chapters, with the invertebrate carnivores and microinvertebrate carnivores grouped into a benthic invertebrate carnivore group. This was done to

reduce the number of levels in the functional/ trophic classification, and to simplify the subsequent analysis. The fingerfin family was used to represent the group when it came to considering the number of samples required. To expand the applicability of the detectability scores, and reduce any potential biases from only using data from a single study area, all available data from TMNP and TNP for each of the different methods were combined (n = 634 samples). Groups were classified as abundant when they occurred in greater than 60 % of the samples, common when they occurred in between 30 and 60 % of the samples, and scarce if they were recorded in fewer than 30 % of the samples for each method. Methods were then ranked according to the number of abundant, common and scarce trophic and functional groups that were detected. In addition, the average percentage occurrence across all trophic and functional groups, and the groups of fisheries importance were measured.

Table 6.2: Weaknesses and strengths useful to ascribe to aspects of reef fish sampling methods highlighting the difference between data types and collection process, and data quality and processing time.

	Weakness	Strength
Data collection and impact	Ex situ (extractive)	In situ (observe fish in their environemnt)
	Barotrauma	No barotrauma
	External physical damage	No external damage
	High levels of mortality	No mortality
	Localised damage to reef habitat (trampelling effect)	Limited localised damage to reef habitat
	Logistically complex	Logistically simple
	Safety risks	Limited safety risks
	Specialised training	No specialised training
	Restricted operating depth	No depth restrictions
	Prone to technical issues	Limited technical issues
	Achievable sample replication low	Achievable sample replication high
	Limited control of sampling environment	Good control of sampling environment
Data and processing	Large observer bias	Limited observer bias
	Biased by bait	No bait used
	Biased by noise and movement	Limited noise and movement bias
	No measure of field of view	Accurately measures field of view
	Many zero-counts	Few zero-counts
	High data variability	Low data variability
	Highly species specific	High species richness
	No length measurements	Accurate length measurements
	No additional information on habitat from where the sample was taken	Provides additional information on habitat from where the sample was taken
	Extensive data processing time	Short data processing time

6.2.2.2 Method capabilities

The inherent strengths and weaknesses of the different methods (Table 6.2) were taken from the results of this thesis, and the relevant literature (Thompson and Mapstone 1997, 2002; Vos et al. 2000; Willis et al. 2000; Yoccoz et al. 2001; Edgar et al. 2004; Cunningham and Lindenmayer 2005; Watson et al. 2005, 2010; Bolker 2007; Harvey et al. 2007, 2012; Elphick 2008; Götz et al. 2008; Bennett et al. 2009; Edgar and Stuart-Smith 2009; Colton and Swearer 2010; Kulbicki et al. 2010; Langlois et al. 2010, 2012b; Murphy and Jenkins 2010; Pelletier et al. 2011; Moore et al. 2011; Johnson et al. 2012; Monk et al. 2012).

The methods were then scored on a three scale system according to their ability to meet the characteristics considered as strengths. Method characteristics that fell into the ‘weakness’ category were scored zero, those that fell in between the two categories were scored 0.5 and those that fell into the ‘strength’ category were scored one. The scores were based on both the results from this thesis and the relevant literature (listed in the preceding paragraph).

6.3 Results

6.3.1 Cost

Controlled angling required the lowest initial investment (R 14 400), five times lower than that required for RUV or BRUV (R 75 750). Underwater visual census required an initial investment of R 199 900, while the stereo-RUV or stereo-BRUV required R 257 900 to acquire four systems. The ROV was by far the most expensive, requiring R 2 625 000 to purchase the equipment and train two pilots (Table 6.3).

Table 6.3: Summary of the costs associated with the examined sampling methods. CA = controlled angling, UVC = underwater visual census, RUV = remote underwater video, BRUV = baited RUV, ROV = remotely operated vehicle, stereo-B/RUV = stereo configuration to enable length and survey area estimates.

	Initial outlay	Cost per sample	Cost per field day	Cost per non-field day
	Rheeders Reef and Castle Rock study areas			
CA	R 14 400.0	R 28.5	R 3 564.4	R 3 143.0
UVC	R 199 900.0	R 17.8	R 4 106.9	R 3 771.6
RUV	R 75 750.0	R 121.8	R 4 012.0	R 2 514.4
BRUV	R 75 750.0	R 199.0	R 4 098.1	R 2 514.4
stereo-RUV	R 257 900.0	R 156.4	R 4 012.0	R 2 514.4
stereo-BRUV	R 257 900.0	R 233.6	R 4 098.1	R 2 514.4
	Middle Bank study area			
RUV	R 75 750.0	R 121.8	R 4 578.1	R 2 514.4
BRUV	R 75 750.0	R 199.0	R 4 492.0	R 2 514.4
ROV	R 2 625 000.0	R 59.9	R 6 236.4	R 2 514.4
stereo-RUV	R 257 900.0	R 156.4	R 4 578.1	R 2 514.4
stereo-BRUV	R 257 900.0	R 233.6	R 4 492.0	R 2 514.4

The stereo-BRUV was predicted to have the highest cost per sample (R 233.6), due mostly to the three hours allocated for data processing. Underwater visual census had the lowest cost per sample of R 17.8, with the time allotted for data entry making up the majority of this amount (Table 6.3). The bulk of the daily costs reflect the size of the monitoring team. The cost per field day was highest for the deeper water study area and reflected the greater distance travelled to and from the study area. The

highest cost per field day was for the ROV method, which can be attributed to the running cost of the larger vessel necessary for ROV operations (R 50 km^{-1}), compared to the vessel type applicable for all other methods (R 15 km^{-1}). For the shallow water study sites (Castle Rock and Rheeders Reef) the cost per field day ranged between R 3 500 and R 4 100. The cost per field day for RUV and BRUV (mono- and stereo-camera configurations) reflected the greater distance travelled per research day, as more samples could be collected (RUV: n = 17; BRUV: n = 16), together with the fact that each station had to be visited twice, to deploy and retrieve the systems. The cost per field day for CA and UVC reflected the large monitoring teams (n = 5 and 6 including the skipper, respectively). Variability in the cost per bad weather day reflected variation in the size of the monitoring teams required for each of the methods (Table 6.3).

6.3.2 Cost-efficiency

Baited remote underwater video and stereo-BRUV were identified as the most cost-efficient methods to monitor multiple components of the fish community and the species of fisheries importance in the Castle Rock study area within the TMNP MPA (Table 6.4). For monitoring multiple components of the community BRUV and stereo-BRUV were four times more cost-efficient than UVC. This difference is driven by the high number of field days required to complete the sample collection, and the size of the monitoring team required to collect the necessary UVC samples (1 dive supervisor, 4 divers, 1 skipper), compared to the BRUV and stereo-BRUV (3 deckhands, 1 skipper). Comparing person-days, the UVC required 207 days while the BRUV and stereo-BRUV only required 39 and 41 person days, respectively, of which 17 were assigned for data processing. A slightly less extreme result was obtained for monitoring the species of fisheries importance (Table 6.4).

The results from the Rheeders Reef study area in the TNP MPA (Table 6.5) reiterate the preceding results, with BRUV and stereo-BRUV being the most cost-efficient to monitor multiple components of the community and the fisheries species. Remote underwater video and stereo-RUV were the second most cost-efficient, however, in comparison to the BRUV and stereo-BRUV the annual sampling cost of the unbaited video methods was almost double when it came to monitoring multiple components

of the fish community. Although RUV and stereo-RUV appeared more cost-efficient at monitoring the fisheries species than the multiple components of the fish community, they were still 50 % more expensive than the BRUV and stereo-BRUV, respectively (Table 6.5).

Underwater visual census was again associated with the lowest cost-efficiency with predicted monitoring costs eight times greater than that predicted for BRUV or stereo-BRUV when monitoring multiple components of the fish community, and seven times greater when monitoring the fisheries species (Table 6.5). As before, this difference is driven by the high number of samples required to detect the 10 % increase in the population, together with the low number of samples that can be collected per day. When the number of samples per day is theoretically increased to 17 (i.e. to what is achievable by the BRUV), BRUV is still twice as cost-effective as UVC.

Table 6.4: Results from the cost-efficiency analysis for the Castle Rock study area in the Table Mountain National Park marine protected area. UVC = underwater visual census, BRUV = baited remote underwater video, stereo-BRUV = stereo configuration to enable length and survey area estimates.

		Method		
		UVC	BRUV	stereo-BRUV
Multiple components of the community	Samples required	83	45	45
	Samples/day	5	16	16
	Field work days	17	3	3
	Bad weather days	17	3	3
	Data processing (days)	3	15	17
	Annual cost	*R 135 411.1*	*R 28 534.2*	*R 30 091.2*
	Five year cost	*R 677 055.3*	*R 142 671.0*	*R 150 456.0*
Species of fisheries importance	Samples required	77	45	45
	Samples/day	5	16	16
	Field work days	16	3	3
	Bad weather days	16	3	3
	Data processing (days)	3	15	17
	Annual cost	*R 127 425.8*	*R 28 534.2*	*R 30 091.2*
	Five year cost	*R 637 129.0*	*R 142 671.0*	*R 150 456.0*

Table 6.5: Results from the cost-efficiency analysis for the Rheeders Reef study area in the Tsitsikamma National Park marine protected area. CA = controlled angling, UVC = underwater visual census, RUV = remote underwater video, BRUV = baited RUV, stereo-B/RUV = stereo configuration to enable length and survey area estimates.

		Method					
		CA	UVC	RUV	BRUV	stereo-RUV	stereo-BRUV
Multiple components of the community	Samples required	—	194	137	64	137	64
	Samples/day	—	5	17	16	17	16
	Field work days	—	39	9	4	9	4
	Bad weather days	—	39	9	4	9	4
	Data processing (days)	—	7	26	20	35	24
	Annual cost	—	*R 310 712.8*	*R 76 199.1*	*R 38 841.6*	*R 80 939.3*	*R 41 056.0*
	Five year cost	—	*R 1 553 563.8*	*R 380 995.5*	*R 194 208.0*	*R 404 696.5*	*R 205 280.0*
Species of fisheries importance	Samples required	71	73	49	21	49	21
	Samples/day	7	5	17	16	17	16
	Field work days	11	15	3	2	3	2
	Bad weather days	11	15	3	2	3	2
	Data processing (days)	3	3	10	7	13	8
	Annual cost	*R 75 800.8*	*R 119 476.2*	*R 25 805.7*	*R 17 231.8*	*R 27 501.1*	*R 17 958.4*
	Five year cost	R 379 004.0	R 597 380.8	R 129 028.5	R 86 159.0	R 137 505.5	R 89 792.0

Table 6.6: Results from the cost-efficiency analysis for the Middle Bank study area in the Tsitsikamma National Park marine protected area. A detailed explanation for the CBA is provided in the text. RUV = remote underwater video, BRUV = baited RUV, ROV = remotely operated vehicle, stereo-B/RUV = stereo configuration to enable length and survey area estimates.

		Method				
		RUV	BRUV	ROV	Stereo-RUV	stereo-BRUV
Species of fisheries importance	Samples required	149	61	150	149	61
	Samples/day	17	16	6	17	16
	Field work days	9	4	25	9	4
	Bad weather days	9	4	25	9	4
	Data processing (days)	28	20	15	38	23
	Annual cost	*R 81 980.7*	*R 40 164.6*	*R 227 755.0*	*R 87 136.1*	*R 42 275.2*
	Five year cost	R 409 903.5	R 200 823.0	R 1 138 775.0	R 435 680.5	R 211 376.0

Controlled angling was included as an option to monitor the species of fisheries importance at Rheeders Reef in the TNP MPA. However, results showed BRUV and stereo-BRUV both to be four times more cost-effective than CA at monitoring the fisheries species (Table 6.5).

The final cost-efficiency analysis was conducted on the data from Middle Bank in the TNP MPA (Table 6.6). The analysis was only run on the sampling effort required to monitor changes in fisheries species, as they dominated the community and no species from other trophic or function groups were detected on sufficient occasions to allow for the power analysis to be run. Baited remote underwater video and stereo-BRUV were again identified as the most cost-efficient methods. Remote underwater video and stereo-RUV both cost more than twice their baited counterparts. The cost for ROV surveys was over 170 % more than that predicted for RUV, making it the least cost-effective method to achieve monitoring objectives.

6.3.3 Detectability of trophic and functional groups

The comparison of the methods' ability to detect the different trophic and functional groups in the community highlighted the superiority of BRUV to detect all groups, with an average detection of 58.8 % across all groups (Table 6.7). In addition, BRUV was the only method that recorded all groups in more than 30 % of the samples. The same result was found for the detection of species of fisheries importance, where they were detected in 68.1 % of the BRUV samples. Remote underwater video ranked second, with an average occurrence of 50.5 % for all trophic and functional groups, while the groups of fisheries importance were detected in 60.5 % of RUV samples. Furthermore, the RUV and BRUV were the only methods to detect the scarce species of fisheries importance in more than 30 % of samples. Underwater visual census recorded all functional and trophic groups in 46.8 %, while the groups of fisheries importance were detected in 50.8 % of samples. Baited remote underwater video was the only method to detect the sharks, skates and rays, and the cryptic reef sharks in more than 30 % of samples. Underwater visual census and RUV appeared most effective at detecting species classified as benthic invertebrate carnivores. The groupings of omnivores and herbivores, large sharks, skates and rays were not abundant in the data from any of the methods (Table 6.7).

The selective nature of CA was highlighted in the analysis, with a low average detection rate (24 %) of all trophic and functional groups. The trophic and functional groups comprising species of fisheries importance were only recorded in 42 % of the CA samples, which is considerably lower than that observed for BRUV (68.1 %). The results for the ROV highlight its inability to detect the different trophic and functional groups in the community or the groups of fisheries importance (Table 6.7).

Table 6.7: Probability (ranked: common, scarce or absent) that a functional group will be represented in a sample, together with an average detection probability (%) for functional groups in the community (i.e. the ability to detect groups a-g), and the average detection probability (%) of the functional groups of fisheries importance (i.e. the ability to detect groups a-b). All available data from Tsitsikamma and Table Mountain National Park marine protected areas were used (n = 634 samples)

		Abundant	Common	Scarce	Presence in samples	
Method	n	(>60%)	(30-60 %)	(<30 %)	Community	Fisheries
Controlled angling (CA)	144		a,c	b,f,e,g,d	24.0	41.3
Underwater visual census (UVC)	136	c,d,a	e	b,g,f	46.8	50.8
Remote underwater video (RUV)	43	a,c,d	e,b	f,g	50.5	60.5
Baited RUV (BRUV)	61	c,a,g	b,f,e,d		58.8	68.1
Remotely operated vehicle (ROV)	16		c,a	d,b,g,e,f	17.0	21.9

Functional groups: a = Dominant large generalist carnivores, b = Scarce large generalist carnivores, c = Small & medium sized generalist carnivores, d = Benthic invertebrate carnivores, e = Omnivores and herbivores, f = Sharks, skates and rays, g = Cryptic reef sharks

6.3.4 Method capabilities

The results from the assessment of the different methods theoretical capabilities indicated that the stereo-RUV and stereo-BRUV were mostly characterised by factors considered to be strengths (75 %) (Table 6.8). Remote underwater video and BRUV ranked tied second (69 %) behind the stereo-video techniques, which have the advantage in that they can provide accurate information on the size of the field of view and the size of the counted fish. The UVC method partially met, or failed to meet numerous criteria associated with both the data collection process and the quality and quantity of the data provided, and ranked fifth (59.1 %) overall. Remotely operated vehicle and CA (both 50 %) were associated with many factors considered to be methodological weaknesses for the assessment of reef fish populations (Table 6.8).

Table 6.8: Method characteristics scores for the employed methods, as well as the stereo-RUV and stereo-BRUV methods. Weakness = 0, Strength = 1, Neither weakness nor strength = 0.5.

	Weakness	Strength	CA	UVC	RUV	BRUV	ROV	stereo-RUV	stereo-BRUV
Data collection and impact	Ex situ (extractive)	In situ (observe fish in their environemnt)	0	1	1	1	1	1	1
	Barotrauma	No barotrauma	0	1	1	1	1	1	1
	External physical damage	No external damage	0.5	1	1	1	1	1	1
	High levels of mortality	No mortality	0.5	1	1	1	1	1	1
	Localised damage to reef habitat (trampelling effect)	Limited localised damage to reef habitat	0.5	1	0.5	0.5	0.5	0.5	0.5
	Logistically complex	Logistically simple	1	0.5	1	1	0	1	1
	Safety risks	Limited safety risks	1	0	1	1	1	1	1
	Specialised training	No specialised training	1	0	1	1	0	0.5	0.5
	Restricted operating depth	No depth restrictions	1	0	1	1	1	1	1
	Prone to technical issues	Limited technical issues	1	0.5	0.5	0.5	0	0.5	0.5
	Achievable sample replication low	Achievable sample replication high	0	0	1	1	0	1	1
	Limited control of sampling environment	Good control of sampling environment	0	1	0	0	1	0	0
Data and processing	Large observer bias	Limited observer bias	0.5	0	0.5	0.5	0.5	0.5	0.5
	Biased by bait	No bait used	0	1	1	0	1	1	0
	Biased by noise and movement	Limited noise and movement bias	1	0	0.5	0.5	0	0.5	0.5
	No measure of field of view	Accurately measures field of view	0	0.5	0	0	0.5	1	1
	Many zero-counts	Few zero-counts	0.5	0.5	0.5	1	0	0.5	1
	High data variability	Low data variability	0.5	0.5	0.5	1	0	0.5	1
	Highly species specific	High species richness	0	1	1	1	0	1	1
	No length measurements	Accurate length measurements	1	0.5	0	0	0.5	1	1
	No additional information on habitat from where the sample was taken	Provides additional information on habitat from where the sample was taken	0	1	1	1	1	1	1
	Extensive data processing time	Short data processing time	1	1	0	0	0	0	0
		Score (% of total)	50.0	59.1	68.2	68.2	50.0	75.0	75.0

6.4 Discussion

6.4.1 Monitoring multiple components of the reef fish community

Long-term monitoring programmes that aim to detect ecosystem level changes in reef communities, will require species and abundance information from multiple components of the reef fish community. These community level changes can be driven by global climate change, or anthropogenic disturbance such as fisheries. These monitoring programmes are essential to meet management and scientific research objectives.

Based on the results presented in this chapter, RUV and BRUV (thus indirectly the not tested stereo-RUV and stereo-BRUV) were identified as most likely to detect the different trophic and functional groups from the reef communities in both examined MPAs. Underwater visual census was unable to effectively sample the cartilaginous species and as a result the method should only be considered as an option when a programme specifically aims to monitor the different species of bony fish that occur on rocky reefs in the region. The majority of the trophic and functional groups were classified as scarce in the CA and ROV data, and these methods were not considered useful to monitor long-term trends in multiple components of the fish community.

Underwater visual census was characterised by a number of features that impede its capabilities as a monitoring tool. These included, the need for specialised training, depth restrictions, safety risks for divers and a limited number of replicate samples that could be collected per day. In addition, the method was considered to be biased by the presence of the divers in the water, and by the capabilities of the divers to collect accurate data. Similarly, the cost-efficiency analysis identified that UVC was the least cost-effective of the five methods (Castle Rock: R 135 411.1 $year^{-1}$ or 207 person days; Rheeders Reef: R 310 72.8 $year^{-1}$ or 475 person days). While the cost of the annual monitoring is high, the time to collect the data is not considered to be feasible as UVC required between 17 and 39 field work days. Considering the stipulated one-to-one ratio of bad weather days to field work days, it is unlikely that any implementing organisation will be able to commit staff for such lengthy periods. It

is possible that better cost-efficiency is achieved by employing volunteers to collect the data (see Edgar and Stuart-Smith 2009). However, this may not always be possible due to the target location of the monitoring programme and the size and availability of the local recreational SCUBA diving community. Equally, in South Africa, involving volunteers may not comply with the implementing organisation's occupational health and safety requirements (Department of Labour 2008). As a result the costs are considered to greatly outweigh the benefits of UVC.

Colton and Swearer (2010) found that UVC was more cost-effective than BRUV when it came to estimating temperate reef fish diversity. The results from this study suggest that this may not apply to all temperate reef fish assemblages with BRUV proving to be between three and seven times more cost-effective in the TMNP and TNP, respectively.

Remote underwater video and BRUV were identified as having the same scores in terms of the inherent capabilities of the monitoring method, however, the BRUV was considerably more cost-efficient (R 38 841.6 $year^{-1}$ and 52 person days) than the RUV (R 76 199.1 $year^{-1}$ and 98 person days). Comparing the ability of BRUV and RUV to detect the different trophic and functional groups shows that the cartilaginous functional groups (sharks, skates and rays, and the cryptic reef sharks) were infrequently (< 30 % of the samples) detected by RUV, while all trophic and functional groups were commonly (> 30 %) detected with BRUV. Given the above, BRUV should be preferred over RUV for monitoring the relative abundance of multiple components of the reef fish community. Past research has come to similar conclusions, with sample variability lower in BRUV compared to RUV data, making BRUV the more cost-efficient option (Watson et al. 2005, 2010; Harvey et al. 2007; Langlois et al. 2010, 2012b).

Stereo-RUV scored high with respect to its capabilities as a monitoring method, however, it was considerably less cost-efficient than stereo-BRUV (stereo-RUV: R 80 939.3 $year^{-1}$ and 107 person days; stereo-BRUV: R 41 056.0 $year^{-1}$ and 56 person days). While the overall method capability scores were the same (75 %), there are a number of differences between the methods that make stereo-RUV more appealing. Firstly, the survey area cannot be calculated in the baited video stations due to uncertainties regarding the extent of the area from where the fish are

attracted into the field of view (Colton and Swearer 2010). This confines the count data to relative abundance rather than density measures. In addition, bait biases the observed abundances of different species of fish, with certain species drawn towards the bait, while others are deterred by the increased activity around the bait (Chapter 3). The selection between stereo-RUV and stereo-BRUV depends strongly on the objectives of the monitoring programme. While density estimates are considered important for effective management of exploitable resources, relative abundance will be sufficient to meet programme objectives that require monitoring of multiple components of the fish community to determine natural variability in spatial and temporal abundance distributions or detect the indirect effects of fisheries. Considering the ability of stereo-BRUV to more effectively measure the different components of the fish community, the benefits gained using the stereo-RUV to measure the fish community under near-natural conditions (or as close to natural as any method will allow) do not outweigh its lower cost-efficiency.

Apart from the initial costs to establish the research capabilities there is only negligible differences in the running cost for BRUV or stereo-BRUV to monitor multiple components of the fish community. The inherent capabilities of stereo-BRUV were estimated to be greater than those of BRUV, due to the ability of the stereo configuration to provide accurate measurements of the lengths of the counted fish. A population's size structure is highly sensitive to fisheries impacts, and knowledge thereof valuable for effective management of fisheries resources (Shin et al. 2005). On the other hand, information on fish length is not necessary to monitor long-term changes in relative abundance of different components of the reef fish community. Consequently, BRUV is considered adequate to meet the objectives for long-term monitoring of multiple components of the fish community, where the size structure of populations is less important.

6.4.2 Monitoring species of fisheries importance

Monitoring long-term abundance trends of species targeted through fishing activity is critical for effective resource management. Such trends not only provide insights into the effectiveness of implemented actions (such as MPAs) (Buxton and Smale 1989; Willis et al. 2003; McLean et al. 2011), but also support early warning systems by

informing managers and direct policy makers on how best to adapt management plans to emerging threats (Lindenmayer and Likens 2009). In addition to the knowledge on the abundance of fish species, fisheries management often requires information such as biomass and trophic biology (Jennings 2005; Shin et al. 2005, 2010). Size estimates are of particular value to measure the direct and ecosystem effects of fishing, as they can provide data for numerous fisheries indicators, such as the biomass of the surveyed species, the relationship between biomass and landings, the mean length of fish in the community and numerous other size-based indicators that can be used (Shin et al. 2005, 2010).

The assessment of the detectability for the species of fisheries importance suggested that only RUV and BRUV (thus, indirectly, the not tested stereo-RUV and stereo-BRUV) were able to detect the dominant and scarce large generalist carnivore groups (Table 6.7). Although RUV and BRUV are effective at measuring the relative abundance of the dominant and scarce fisheries species, neither provides a measure of fish size and are thus unsuitable to meet most fisheries monitoring objectives.

Although the species classified as scarce large generalist carnivores were poorly detected by UVC, the species from the dominant large generalist carnivore group were frequently detected. Underwater visual census is commonly used to monitor the status of reef species targeted in shallow water (< 30 m) fisheries (Buxton and Smale 1989; Edger et al. 1999; Barrett et al. 2007; Kulbicki et al. 2007; Edgar and Stuart-Smith 2009), and the results from this study suggest that UVC can provide data for the dominant species. However, UVC had the lowest cost-efficiency of all the methods (Castle Rock: R 127 425.8 $year^{-1}$ and 195 person days; Rheeders Reef: R 119 476.2 $year^{-1}$ and 183 person days). Controlled angling was considerably more cost-effective (R 75 800.8 year-1 and 113 person days), compared to UVC. However, CA was the only method where both the dominant and scarce species of fisheries importance were observed in less than 60 of the samples. Controlled angling is often used for monitoring reef fish species (Willis et al. 2000; Götz et al. 2008; Bennett et al. 2009; James et al. 2012; Langlois et al. 2012b; Maggs et al. 2012), and it is capable of collecting abundance and accurate size information for the dominant large generalist carnivores. In addition, the initial cost for the method is

low, giving it the appearance of a suitable option for programmes running off a limited budget.

Selection between CA and UVC depends strongly on the specific objectives of a programme, with objectives primarily requiring relative abundance information of dominant large generalist carnivores better served by employing CA. However, when a programme has more specific requirements that rely on density estimates, measurements of the abiotic and biotic environment where the sample was collected, or in areas where angling is not permitted, UVC is the better choice.

While UVC is a more versatile fisheries species monitoring tool than CA, its weaknesses are highlighted in comparison with the stereo-RUV and stereo-BRUV methods. Stereo-RUV collected similar data for the dominant and scarce large generalist carnivores compared to UVC, however, the inherent strengths of the stereo-RUV as a monitoring method were considerably greater than that of UVC. Of particular importance is the fact that the stereo-RUV is not restricted by depth and can collect a large number of samples per day. In addition, stereo-RUV is less vulnerable to observer bias, and the least intrusive of all examined methods. Furthermore, the data collection with stereo-RUV was predicted to be 175 % more cost-effective (Rheeders Reef: R 27 501.1 year^{-1} and 37 person days) compared to UVC.

The range of most reef fish species targeted in fisheries extends into deep water (>30m, but typically <250m) offshore habitats, and often spawning activities are concentrated here (e.g. red steenbras) (Mann 2000). Subsequently, fisheries monitoring objectives will often require standardised sampling throughout the depth range of a target species. The inability of UVC to be conducted at depths greater than 30 m further limits the applicability of the method. Although the initial investment for UVC is R 58 000 less than that required for stereo-RUV, this benefit is negated after the first year of monitoring making stereo-RUV the recommended method out of the two.

The core benefit gained from conducting monitoring with stereo-BRUV rather than stereo-RUV is greater cost-efficiency, with the baited technique being 53 and 106 % more cost-efficient than the unbaited technique at the Rheeders Reef and Middle

Bank study areas, respectively. Bait also increases the observed average abundance of most fisheries species (see Chapters 3 and 5). In both stereo-video techniques the size of individuals from a species is only measured in the frame where the MaxN abundance measure is taken. As such, higher abundances result in more length measurements and less uncertainty in the size structure of populations.

On the other hand, the relative abundance data from stereo-BRUV cannot be converted to a density measure as it is impossible to estimate the size of the bait plume and account for variability in the response of different species to bait with reasonable accuracy (Colton and Swearer 2010). Stereo-RUV data is not biased by bait and it is possible to convert the abundance data to density by calculating the area visible in the field of view. In the comparative assessment of RUV and BRUV presented in Chapter 3, it was suggested that the MaxN measure of relative abundance from RUV overestimated the actual density of fish within the visible area. Consequently, it may not be feasible to convert MaxN abundances to density until further research has determined the extent of this inaccuracy, or developed a more suitable instantaneous measure of abundance from the stereo-RUV data. Relative to the costs and uncertainties associated with other methods, the costs associated with stereo-BRUV are considered minimal, and where finances allow for the initial investment, stereo-BRUV is recommended to monitor species of fisheries importance.

6.4.3 Conclusions

Baited remote underwater video is the most cost-efficient method to monitor the warm-temperate rocky reef fish community in the Agulhas Ecoregion of South Africa. Remote underwater video had numerous favourable attributes that made it appear to be a viable alternative to BRUV. Most notably is the fact that the data aren't biased by bait. However, the high variability in the RUV data and its lower ability to detect species of fisheries importance negated this benefit. Although not tested during this research, it is predicted that stereo-BRUV will most likely strengthen the value of the data obtained from the mono-camera BRUV setup. Where size data are required to meet a monitoring objective only stereo-BRUV can be recommended.

It is important to bear in mind that the setups for BRUV and RUV, and stereo-BRUV and stereo-RUV differ only in the addition of a bait arm. As a result, investment in the baited method automatically means the unbaited option is available. While the RUV and BRUV pairing is a powerful monitoring suite, the stereo-RUV and stereo-BRUV combination is considerably more powerful and offers the flexibility to collect data valuable to address community and fisheries monitoring objectives. Where budget permits, stereo-video should be favoured over mono-video setups.

6.5 Appendices

Appendix 6.1: Details of the items included in the initial outlay for the different monitoring methods included in the cost benefit analysis

Controlled Angling (CA)

#	Item	Quantity	Unit	Cost	Total
1	Rods	4.00	#	R 850.00	R 3 400.00
2	Reels	4.00	#	R 1 100.00	R 4 400.00
3	Line	4.00	Spools	R 217.00	R 868.00
4	Measuring board	2.00	#	R 250.00	R 500.00
5	Lappies	10.00	#	R 15.00	R 150.00
6	Training	4.00	Experience	R 0.00	R 0.00
7	Miscellaneous extras	1.00	Lump sum	R 5 000.00	R 5 000.00
				Total	**R 14 318.00**

Underwater Visual Census (UVC)

#	Item	Quantity	Unit	Cost	Total
1	Training	4.00	Course	R 8 000.00	R 32 000.00
2	Supervisor	1.00	Course	R 8 000.00	R 8 000.00
3	Cylinders	9.00	#	R 3 000.00	R 27 000.00
4	DVs	4.00	#	R 11 000.00	R 44 000.00
5	BCs	4.00	#	R 4 000.00	R 16 000.00
6	Dive computers	4.00	#	R 3 000.00	R 12 000.00
7	Fins	4.00	#	R 1 000.00	R 4 000.00
8	Wetsuits	4.00	#	R 2 500.00	R 10 000.00
9	Masks	4.00	#	R 500.00	R 2 000.00
10	Weights	4.00	Belts	R 210.00	R 840.00
11	Knives	4.00	#	R 350.00	R 1 400.00
12	Data slates	10.00	#	R 15.00	R 150.00
13	Compressor	1.00	#	R 35 000.00	R 35 000.00
14	DAN and first aid	1.00	Kit	R 2 000.00	R 2 000.00
15	Dive reel	1.00	#	R 500.00	R 500.00
16	Miscellaneous extras	1.00	Lump sum	R 5 000.00	R 5 000.00
				Total	**R 199 890.00**

Appendix 6.1: Continued

Remote Underwater Video (RUV) and Baited RUV (BRUV)

#	Item	Quantity	Unit	Cost	Total
1	Cameras	4	#	R 3 000.00	R 12 000.00
2	Housings	4	#	R 1 500.00	R 6 000.00
3	Frame	4	#	R 4 000.00	R 16 000.00
4	Rope	600	m	R 4.00	R 2 400.00
5	Big buoys	4	#	R 500.00	R 2 000.00
6	Small buoys	4	#	R 150.00	R 600.00
7	SD cards (8GB)	40	#	R 50.00	R 2 000.00
8	EventMeasure	1	Licence	R 29 750.00	R 29 750.00
9	Miscellaneous extras	1	Lump sum	R 5 000.00	R 5 000.00
				Total	**R 75 750.00**

stereo-RUV and stereo-BRUV

#	Item	Quantity	Unit	Cost	Total
1	Cameras	8	#	R 8 000.00	R 64 000.00
2	Wide-angle lenses	8	#	R 1 000.00	R 8 000.00
3	Housings	8	#	R 6 500.00	R 52 000.00
4	Synchronizing diodes	4	#	R 500.00	R 2 000.00
5	Frame	4	#	R 8 000.00	R 32 000.00
6	Calibration cube	1	#	R 26 350.00	R 26 350.00
7	CAL software	1	Licence	R 29 750.00	R 29 750.00
8	EventMeasure	1	Licence	R 29 750.00	R 29 750.00
9	Rope	600	m	R 4.00	R 2 400.00
10	Big buoys	4	#	R 500.00	R 2 000.00
11	Small buoys	4	#	R 150.00	R 600.00
12	SD cards (8GB)	80	#	R 50.00	R 4 000.00
13	Miscellaneous extras	1	Lump sump	R 5 000.00	R 5 000.00
				Total	**R 257 850.00**

Remotely operated vehicle (ROV)

#	Item	Quantity	Unit	Cost	Total
1	ROV	1	#	R 2 500 000.00	R 2 500 000.00
2	Training	2	Course	R 60 000.00	R 120 000.00
16	Miscellaneous extras	1	Lump sum	R 5 000.00	R 5 000.00
				Total	**R 2 625 000.00**

Appendix 6.2: List of the species grouped within the different trophic and functional groups.

Code	Trophic and functional grouping	Family	*Scientific name*	Common name
a	Dominant large generalist carnivore	Sparidae	*Chrysoblephus laticeps*	Roman
		Sparidae	*Pterogymnus laniarius*	Panga
b	Scarce large generalist carnivore	Carangidae	*Lichia amia*	Garrick
		Carangidae	*Seriola lalandi*	Giant yellowtail
		Genypterus	*Genypterus capensis*	Kingklip
		Pomatomidae	*Pomatomus saltatrix*	Elf
		Sciaenidae	*Argyrosomus japonicus*	Dusky kob
		Sciaenidae	*Atractoscion aequidens*	Geelbek
		Serranidae	*Epinephelus marginatus*	Yellowbelly rockcod
		Sparidae	*Argyrozona argyrozona*	Carpenter
		Sparidae	*Cheimerius nufar*	Santer
		Sparidae	*Chrysoblephus cristiceps*	Dageraad
		Sparidae	*Chrysoblephus gibbiceps*	Red stumpnose
		Sparidae	*Petrus rupestris*	Red steenbras
		Sparidae	*Rhabdosargus globiceps*	White stumpnose
c	Small & medium sized generalist carnivore	Ariidae	*Galeichthys ater*	Black seacatfish
		Ariidae	*Galeichthys feliceps*	White seacatfish
		Carangidae	*Trachurus trachurus*	Maasbanker
		Clinidae	*Clinidae spp.*	Klipfish spp.
		Haemulidae	*Pomadasys olivaceum*	Piggy
		Scombridae	*Scomber japonicus*	Chub mackerel
		Serranidae	*Acanthistius sebastoides*	Koester
		Serranidae	*Serranus cabrilla*	Comber
		Sparidae	*Boopsoidea inornata*	Fransmadam
		Sparidae	*Pachymetopon aeneum*	Blue hottentot
		Sparidae	*Pachymetopon blochii*	Hottentot
		Sparidae	*Pagellus bellottii natalensis*	Red tjor-tjor
		Sparidae	*Porcostoma dentata*	Dane
		Sparidae	*Rhabdosargus holubi*	Cape stumpnose
		Sparidae	*Spondyliosoma emarginatum*	Steentjie
		Tetraodontidae	*Amblyrhynchotes honckenii*	Evileye blaasop
		Triglidae	*Chelidonichthys kumu*	Bluefin Gurnard
d	Benthic invertebrate carnivore	Chaetodontidae	*Chaetodon marleyi*	Doublesash butterflyfish
		Cheilodactylidae	*Cheilodactylus fasciatus*	Redfingers
		Cheilodactylidae	*Cheilodactylus pixi*	Barred fingerfin
		Cheilodactylidae	*Chirodactylus brachydactylus*	Twotone fingerfin
		Cheilodactylidae	*Chirodactylus grandis*	Bank steenbras
		Congiopodidae	*Congipodus spp.*	Horsefish spp.
		Coracinidae	*Dichistius capensis*	Galjoen
		Parascorpididae	*Parascorpis typus*	Jutjaw
		Sparidae	*Cymatoceps nasutus*	Black musselcracker
		Sparidae	*Lithognathus lithognathus*	White steenbras
		Sparidae	*Lithognathus mormyrus*	Sand steenbras
		Sparidae	*Sparodon durbanensis*	White musselcracker
e	Herbivore & omnivore	Oplegnathidae	*Oplegnathus conwayi*	Cape knifejaw
		Scorpidae	*Neoscorpis lithophilus*	Stonebream
		Sparidae	*Diplodus capensis*	Blacktail
		Sparidae	*Diplodus hottentotus*	Zebra
		Sparidae	*Gymnocrotaphus curvidens*	Janbruin
		Sparidae	*Pachymetopon grande*	Bronze bream
		Sparidae	*Sarpa salpa*	Strepie
f	Sharks, skates & rays	Myxinidae	*Eptatretus hexatrema*	Six-gill hagfish
		Carcharhinidae	*Carcharhinus brachyurus*	Copper shark
		Carcharhinidae	*Carcharhinus obscurus*	Dusky shark
		Carcharhinidae	*Galeorhinus galeus*	Soupfin shark
		Carcharhinidae	*Mustelus mustelus*	Smooth-hound
		Carcharhinidae	*Triakis megalopteris*	Spotted gullyshark
		Dasyatidae	*Dasyatis brevicaudata*	Shorttail stingray
		Dasyatidae	*Gymnura natalensis*	Diamond ray
		Hexanchidae	*Notorynchus cepedianus*	Spotted sevengill cowshark
		Myliobatidae	*Myliobatis aqulia*	Eagleray
		Myliobatidae	*Pteromylaeus bovinus*	Bullray
		Myliobatidae	*Pteromylaeus bovinus*	Duckbill ray
		Rhinobatidae	*Rhinobatos annnulatus*	Lesser guitarfish
		Sphyrnidae	*Sphyrna spp.*	Hammerhead spp.
g	Crypitic reef sharks	Scyliorhinidae	*Halaelurus natalensis*	Tiger catshark
		Scyliorhinidae	*Haploblepharus edwardsii*	Puffadder shyshark
		Scyliorhinidae	*Haploblepharus fuscus*	Brown shyshark
		Scyliorhinidae	*Haploblepharus pictus*	Dark shyshark
		Scyliorhinidae	*Poroderma africanum*	Striped catshark
		Scyliorhinidae	*Poroderma pantherinum*	Leopard catshark
		Scyliorhinidae	*Scyliorhinus capensis*	Yellowspotted catshark

Chapter 7

General Discussion: Cost-efficient monitoring of subtidal reef fish populations in the Agulhas Ecoregion of South Africa

7.1 Synopsis

7.1.1 Thesis rationale

The purpose of this thesis was to identify a reef fish monitoring method, or suite of methods, most appropriate for use in long-term monitoring (LTM) programmes in the Agulhas Ecoregion of South Africa. The motivation for conducting this research came from the need to accurately and precisely monitor the reef fish populations that are impacted by fisheries in exploited areas and are deemed to recover in no-take marine protected areas (MPAs). In addition, it was identified that there was a need to monitor the impacts of climate change on reef fish communities. All of these impacts work over large spatial and temporal scales, and effective monitoring will require a standardised approach to identify regional scale spatial trends over the long-term.

Long-term monitoring is expensive and it is unlikely that any one research or management agency will be able to sustain effective regional scale monitoring. It is more likely that multiple agencies, each with their own specific management or scientific monitoring objectives, will be involved. Through the provision of a standardised protocol for collecting reef fish data, management or research agencies will be able to design monitoring programmes that best achieve their own objectives. At the same time, any data collected with the standardised protocol will be comparable and suitable for use in regional scale analyses.

7.1.2 Approach

To achieve the aim of this thesis, six monitoring methods covering a broad range of technologies were identified. Where necessary and possible, the different methods were independently assessed to optimise performance. Following this, all six methods were simultaneously compared during two field experiments to identify which methods were able to detect the majority of the reef fish species typical to the Agulhas Ecoregion, and which methods were the most cost-efficient at achieving a desired level of sampling precision.

7.2 Core findings

A considerable amount of research has been presented in this thesis. Although the end results are straightforward there are numerous other findings that are worth summarising here before advocating a most suitable monitoring method(s).

7.2.1 Method assessments

Independent assessments were conducted on the fish trap (FT), underwater visual census (UVC), remote underwater video (RUV) and baited RUV (BRUV) methods.

7.2.1.1 Underwater visual census (UVC)

The assessment of the UVC strip-transect method (Chapter 2) involved directly comparing the precision of data collected by researchers and volunteers using a novel double-observer technique (paired-transects). In essence the paired-transects can be viewed as an independent and simultaneously repeated analysis of a closed sample, where both analyses are expected to produce identical results. By constructing a dissimilarity score calculated from the two analyses of a sample, collected either by two volunteers or two researchers, the accuracy and precision of data from these different observer types could be measured and compared. In addition, the paired-transect method allowed for the detection probability of different species of fish to be calculated and for the effect of diversity and species abundance on the detection probability and sample dissimilarity score to be measured.

The results indicated that there was considerable error in both the researchers' and volunteers' data, however, the volunteers produced data that were significantly less precise for the whole community. There was also considerable variability in the data, suggesting that certain volunteers or researchers were markedly better or worse than the average. The distinction between researchers and volunteers was not evident in the data for the dominant species of fish, suggesting that errors observed in the volunteer data may be attributed to the rare species in the survey area. For all observers, the abundance of a species in the sample had a significant influence on its detectability, with locally scarce or rare species poorly detected.

While it was not directly addressed during this research, paired-transects can be used to account for detection error in abundance estimates by applying capture-mark-recapture models, such as the Royle Biometrics (Riddle et al. 2010). Therefore, future research with UVC may benefit by adopting this approach.

7.2.1.2 Remote underwater video (RUV) and baited RUV (BRUV)

The ability of the RUV and BRUV methods to survey the reef fish was assessed in the Tsitsikamma National Park (TNP) MPA (Chapter 3). As this was the first time the method had been used in South Africa to monitor reef fish, the research addressed basic, but fundamental questions relating to the optimal deployment time, and the effect of bait on the observed community structure and variability between samples. A repeated measures design was implemented that allowed for the direct comparison of the efficiency of the two methods by first measuring the sample with the RUV followed by the BRUV.

The results demonstrated that BRUV was more efficient at surveying the entire fish community, specifically the invertebrate carnivores, generalist carnivores, and cartilaginous species. On the other hand, RUV was more effective at surveying the microinvertebrate carnivores. High variability in the RUV data resulted in the method requiring a greater number of samples to achieve the same diagnostic power as BRUV. However, RUV required a shorter deployment (35 minutes) and post-sampling video analysis time (2.4 hours) making it more time efficient (BRUV = 50 minutes and 5.7 hours). Baited remote underwater video was more sensitive in the detection of differences in abundance between habitat types, while the RUV data were more prone to an intra-species methodological bias linked to visible reef in the frame of view. The scale of the response to the presence of bait was inconsistent between species, indicating that behaviour determined the area surveyed within the bait plume of BRUV.

The RUV was identified as an appealing monitoring method as it allowed the fish community to be sampled under near natural conditions. However, due to the low species richness and the high variability in the data, the benefits gained by sampling the fish community with the RUV do not outweigh those obtained by altering the community through the presence of bait.

7.2.1.3 Fish traps (FT)

The assessment of the FT method was conducted in the TNP MPA (Chapter 4). The study aimed to identify the optimal soak time for the traps, and whether or not the size of the funnel entrance to the trap affected the species composition and abundance of the species captured.

The results showed that the data collected with FT were highly variable, while the method was only able to survey a few selected species with a moderate efficiency. The larger funnel entrance (15 cm diameter) to the traps recorded more species and significantly higher abundances of fish than the smaller funnel entrance (10 cm diameter). On the other hand, the smaller funnel entrance required shorter soak times (35 minutes), compared to the larger funnel entrance (77 minutes) to maximise the catch per unit effort. Although this would suggest that the smaller entrance was more efficient, the lower species richness and abundance recorded with the smaller entrance, together with the overall high variability in the FT data, meant that the larger funnel was the preferred design for monitoring.

7.2.2 Method comparisons

Two field experiments were conducted to compare the structure of the reef fish community and the precision of the abundance data obtained by the different methods (Chapter 5, Part I and Part II). The first field experiment was conducted in the Castle Rock no-take zone in the Table Mountain National Park MPA. Due to weather limitations only three methods could be compared and these included FT, UVC and BRUV. The second field experiment was conducted at two sites, one shallow (10 – 30 m = Rheeders Reef) and one deep (40 – 80 m = Middle Bank), in the TNP MPA. Five methods (FT, controlled angling [CA], UVC, RUV and BRUV) were compared at the Rheeders Reef study area and three methods (RUV, BRUV and remotely operated vehicles [ROV]) were compared at the Middle Bank study area.

The results from all experiments revealed that the different methods sampled different components of the reef fish community with varying efficiency. As should be expected, the methods that used bait to attract fish into the sample area (CA and

BRUV) recorded higher richness and abundances of piscivores and generalist carnivores. On the other hand, the unbaited methods (UVC, RUV and ROV) recorded higher abundances of the non-carnivorous species and the microinvertebrate carnivores. With regards to overall species richness, BRUV recorded considerably more species than all other methods tested at the Rheeders Reef and Middle Bank study areas in the TNP MPA. However at the Castle Rock study area in the TMNP MPA, UVC and BRUV recorded that same number of species, although only 58% of these were common to both methods.

At all three study areas the BRUV recorded the most species per sample compared to all other methods. Equally, the BRUV method was associated with the highest total abundance measures per sample and the lowest levels of variability between samples when looking at the overall fish assemblage and for most of the species that were analysed individually. The only consistent exception was the microinvertebrate carnivores (i.e. fingerfins Cheilodactylidae) that were better represented in the UVC and RUV samples. The data produce by RUV and UVC were similar in terms of the species composition and levels of variability between samples, although the UVC typically recorded fish at higher abundances. This, however, was based on the comparison from only one site (Rheeders Reef) and may not be broadly representative. Fish traps, CA and ROV were all unable to effectively survey the reef fish community in comparison to BRUV, RUV and UVC.

A power analysis was employed to measure the number of samples required to detect a significant trend under a simulated population growth of 10% per year over a period of five years. The low levels of variability in the BRUV data resulted in the method requiring the lowest number of sample replication within a study area, of all the methods. The only exception, again being the fingerfins. For the fingerfins, UVC was identified as requiring the lowest number of sample replication to detect a significant growth in the population over a period of five years.

7.2.3 Cost-benefit analysis

To determine the cost-efficiency and the additional benefits associated with each of the methods a comprehensive cost-benefit analysis (CBA) was conducted (Chapter 6). The CBA took into account the initial outlay together with the predicted annual

monitoring costs based on the results of the power analysis and the cost of collecting a sample for each method. In addition, the analysis considered the strengths and weaknesses of each of the methods as well as their ability to detect the different trophic and functional groups of fish that are typical to the Agulhas Ecoregion. Following this, the most suitable and cost-efficient methods were identified for monitoring objectives looking at (i) multiple components of the fish community (i.e. for biodiversity monitoring or monitoring for ecosystem based management) or (ii) reef fish species of fisheries importance (i.e. for fisheries management monitoring).

Baited remote underwater video was identified as the most cost-efficient method to achieve both monitoring objectives, while RUV ranked second requiring between 50% and 100% more money to achieve the annual monitoring requirements. The high levels of variability in the UVC data, together with the limited number of samples that can be safely collected on one day meant that UVC was not a feasible option for LTM of subtidal reef fish in the Agulhas Ecoregion of South Africa. Equally, the CBA indicated that CA and ROV had poor cost-efficiency and were outcompeted by both, the RUV and BRUV methods.

Prior to and during the course of this research stereo-BRUV, and to a lesser extent stereo-RUV, have gained considerable support as effective reef fish monitoring methods (Harvey and Shortis 1996; Watson et al. 2005; Murphy and Jenkins. 2010; Langlois et al. 2010; McLean et al. 2011). The major advantage over single camera RUV and BRUV is that the stereo camera configuration provides accurate size measurements for the fish in the MaxN frame, as well as an accurate estimate of the area within the camera's field of view (Harvey and Shortis 1996; Murphy and Jenkins 2010). By providing an estimate of fish size, stereo-BRUV can produce valuable data for fisheries management (Harvey et al. 2012; Langlois et al. 2012b). The ability to estimate the area within the cameras' field of view allows the sampling area to be standardised between samples that differ in underwater visibility and permits true comparisons of relative abundance data within and between sampling areas. However, the initial outlay costs for stereo video systems are more than three times higher than that required for the single camera systems. Therefore, selection between the two methods will depend strongly on the objectives and the available budget of the monitoring programme.

7.3 Cost-efficient monitoring of reef fish

Two alternative monitoring objectives were used to determine the cost-efficiency of the different monitoring methods in Chapter 6. It would not have been feasible to provide protocols for all possible combinations of objectives that may practically occur in real monitoring programmes, so the intent was to provide general and likely examples relevant to the themes reiterated in this thesis. Through this, the optimal number of samples and the costs to monitor species of fisheries importance, or monitor multiple components of the fish community, were calculated. The fisheries monitoring objective is relatively specific. It is felt that the monitoring requirements to detect changes in multiple components of the fish community is sufficiently broad to encompass most biodiversity monitoring objectives as well. Here it is assumed that by collecting sufficient samples to monitor the trends in individual species from different trophic and functional groups, sufficient samples will be collected to obtain accurate information on species richness and diversity.

In the sections that follow, methods and protocols will be proposed that address these contrasting monitoring objectives. Although the number of samples and the costs provided are relatively specific, it needs to be kept in mind that these are based on the results from this thesis and the power analysis provided herein. As such the costs are not inflexible and should be considered a guideline. It is, however, certain that the choice of methods, BRUV and stereo-BRUV, are in fact the most suitable methods for monitoring reef fish communities in the Agulhas Ecoregion of South Africa. While this thesis has focussed on the need of monitoring programmes, the methods proposed will be equally applicable for field experiments conducted over shorter time scales.

7.3.1 Monitoring multiple components of the reef fish community

7.3.1.1 Applicable monitoring objectives

Examples of objectives that would benefit from monitoring multiple components of a fish community would typically be those investigating the ecology and structure of

reef fish communities, or the ecological implications of predator removal and ecosystem based management actions. Examples of these objectives would be:

1. Monitoring patterns in biodiversity
2. Monitoring patterns in ecological interactions
3. Monitoring the ecological implications, or indirect effects, of fisheries exploitation, and
4. Monitoring the impacts of climate change on reef fish communities

7.3.1.2 Selected method

The results from this thesis are conclusive in that BRUV is considerably more effective, in terms of cost-efficiency, quality and quantity of data, than traditional fish community monitoring methods such as UVC. This contradicts some past comparisons from other regions of the world that concluded UVC to be more effective at monitoring tropical and subtropical reef fish communities than BRUV (Stobart et al. 2007; Colton and Swearer 2010). It is possible that the relatively depauperate reef communities in the warm temperate Agulhas Ecoregion of South Africa are better suited to video monitoring techniques, in comparison to the diverse and species rich tropical counterparts. Remote underwater video collected equivalent data to that obtained from UVC, and to a lesser degree BRUV, which agrees with past results (Fancour et al. 1999; Watson et al. 2005; Harvey et al. 2007). However, RUV is considerably less cost-efficient than BRUV, which would ultimately compromise the sustainability of a LTM programme.

Stereo-BRUV provides more information on the fish within a sample, compared to BRUV, and there is little difference in the annual monitoring cost between methods. In addition, the stereo-BRUV offers a simple and reliable means to standardise the area within which the fish are counted, as the field of view can be calculated accurately. Although this standardisation does not allow the estimation of density, as fish are attracted into the field of view by the bait, it allows for accurate comparison of samples collected under varying visibility conditions. A crude method was employed during this study to estimate underwater visibility in the BRUV samples by measuring the change in size of an individual roman *Chrysoblephus laticeps* while feeding at the bait container compared to its size at the limit of visibility. Although this

was sufficient for the objectives of this study, it required one species to be present in ideally all the samples which may not be the case in other studies. In contrast, stereo-RUV data are not biased by bait, and can theoretically be converted from a relative abundance measure to a density estimate. However it is unlikely that the MaxN measure of abundance can be used for this as it is considered to overestimate the abundance of fish in RUV (and by association the stereo-RUV) samples. The stereo-RUV method would benefit from future research addressing this issue.

The disadvantage of stereo-BRUV is that it is over three times more expensive to establish the research capabilities. Where the objectives of a monitoring programme are solely to observe changes in the relative abundance of multiple components of the fish community, BRUV is the optimal method. However, if data on the size of fish are required, or if there is no alternate way to standardise the visible area, stereo-BRUV is the recommended method.

7.3.1.3 Expected costs

The costs were discussed in the CBA (Chapter 6 and relevant appendices) and the reader should refer to that chapter if exact details are required.

An initial outlay of approximately R 76 000 is required to set up four BRUV systems. The cost includes all field equipment as well as the standardised video analysis software and data storage hard drives. The video analysis software takes up a considerable portion of this cost (R 30 000), however, it provides a standardised platform upon which the videos can be analysed and reduces the possibility for observer errors, as the data capture is automated. In addition, the software allows for easy quality control as the MaxN frames are linked to the data entries. It also reduces the time taken to process the videos which reduces the cost of the annual monitoring.

Results from this study suggest that BRUV requires a maximum of 64 samples to detect an annual 10% growth in the fish populations over a period of five years. This level of replication was predicted for a study area of approximately six square-kilometres and will be lower for smaller study areas. For example, 45 samples were required for BRUV from the Castle Rock study area in the TMNP MPA which covered an area of about two square-kilometres. Alternatively, data from study areas

characterised by lower abundances of fish will show higher variability and will require higher sample replication to produce data with comparable statistical power. As such, the value of 64 samples should be used as a guideline, and monitoring programmes should determine their site specific requirements for sample replication within the first year of data collection.

With four BRUVs it is possible to collect 16 samples per day, with a 50 minute deployment time during six hours at sea. This equates to four sea-going days to collect the data, while a further 20 eight-hour-days will be required for one person to process the videos. The total cost of the annual sampling is predicted to be approximately R 40 000.

The only marked difference in the cost for the stereo-BRUV is the initial outlay that is estimated to be approximately R 260 000 for four systems with all the relevant software and hardware. The time taken to process the 64 samples is 24 days, which is four days more than that required for the BRUV as it includes the time necessary for the extraction of size estimates.

7.3.2 Monitoring reef fish species of fisheries importance

7.3.2.1 Applicable monitoring objective

Management of fisheries resources relies on accurate data on population status for the different components of the fisheries. Monitoring efforts to achieve this objective would be most efficiently addressed by surveying only the species of concern. Likewise, many MPAs are proclaimed with the aim to protect fisheries resources. Under this management objective, monitoring of single or multiple species of fisheries importance would be sufficient to provide data relevant to management.

Many shortcomings of current management strategies for reef fish resources are as a result of a historical lack of understanding around the controlling factors of line-fish distribution and abundances, and their interactions with other components of the ecosystems. Considering the drive to establish more holistic ecosystem-based management (EBM), there is a dire need to understand the fundamental ecological structure of reef ecosystems to place the distribution and abundance patterns of reef fisheries resources in context (Johnson et al. 2012). Where feasible, monitoring

programmes should look beyond the species of commercial importance and collect data on their habitats and associations with other components of the fish community.

If a monitoring programme aims to collect data to inform EBM then the guidelines described above for monitoring multiple components of the fish community should be used.

7.3.2.2 Most suitable method(s)

Methods considered valuable for monitoring reef fish of commercial importance include CA, UVC, stereo-RUV and stereo-BRUV. All the methods provide a measure of fish size, while UVC is the only method that allows extrapolation of the relative abundance data to density information. Although this is theoretically possible with the stereo-RUV method, there is concern (see Chapter 3) around the accuracy of MaxN as measure of abundance, as it is not instantaneous. However, UVC and stereo-RUV are not cost-efficient. In addition, UVC is prone to observer bias, is limited to shallow water and has been shown to underestimate the abundance of fisheries species (Thompson and Mapstone 1997; Willis et al. 2000; Edgar et al. 2004). The range of many of South Africa's line-fish species extends into deep water (>30m, but typically <200m) offshore habitats and often spawning activities are concentrated here (e.g. red steenbras *Petrus rupestris*) (Mann 2000). As a result, UVC is not considered suitable for use in programmes with objectives to monitor exploited fish stocks on the reefs in the Agulhas Ecoregion of South Africa.

Controlled angling appears to be an effective tool for monitoring the dominant species of fisheries importance on the reefs in the Agulhas Ecoregion (i.e. roman, carpenter *Argyrozona argyrozona* and panga *Pterogymnus laniarius*), however, its inability to detect the scarce fisheries species (i.e. red steenbras, dageraad *Chrysoblephus cristiceps* and red stumpnose *C. gibbiceps*) limits the use of the method when relative abundance data for multiple fisheries species are required.

Baited remote underwater video was identified as the most cost-efficient method for monitoring the relative abundance of reef fisheries species, however, the method is unable to provide size information for the fish. Fish length is considered a highly sensitive measure of fishing pressure, and size-based indicators can provide relevant information for the indirect effects of fishing on ecosystem structure and

processes (Shin et al. 2005; Langlois et al. 2012). Although more expensive to purchase, stereo-BRUV will provide the most suitable data for monitoring the direct effects of fishing on target populations and will be equally effective at monitoring the indirect effects.

7.3.2.3 Expected costs

Between 21 and 45 samples from the shallow water study areas (10 – 30 m) were required for BRUV to detect an annual 10 % growth in the abundance of fisheries species over a period of five years. The considerably lower level of replication required for the large Rheeders Reef study area (21 samples, 6 km^2), compared to the small Castle Rock study area (45 samples, 2 km^2), illustrates how low abundances of target species will affect the design of a monitoring programme. Equally, 61 replicate samples were required from the deep water (45 – 75 m) Middle bank study area. This demonstrates that even within a study area, depth related changes in abundance will alter the variability in the abundance of fish and this needs to be kept in mind when designing a study or LTM programme and determining the cost.

As a guideline, surveys conducted at depths shallower than 30 m should budget for approximately R 30 000 $year^{-1}$, while surveys in deeper waters (45-80 m) would require in the region of R 40 000 to collect sufficient samples to monitor the changes in abundance of reef species of fisheries importance.

7.3.3 Additional considerations for reef fish monitoring

It is recognised that monitoring programmes must consider more than just the selection of suitable methods (Ward and Jacoby 1992). Controlling for, and measuring environmental and biological parameters that will influence the abundance and size patterns in the target populations will reduce noise in the data (which will in turn reduce the variability and cost of effective monitoring) and aid in the explanation of the observed trends. Additional environmental and biological parameters include the identification of habitat structure, depth, patterns in environmental variability and the biotic community coexisting with the fish. In addition, monitoring programmes should install suitable quality control mechanisms

to ensure that all data contributing to the programme meet a minimum standard. These are briefly discussed below.

7.3.3.1 Habitat maps

Having at least a basic understanding of the nature of the fixed properties of the reef habitat within the survey area is essential to enable a focused experimental design (Murray et al. 2001). There are numerous methodologies for obtaining bathymetric maps (e.g. single-beam sonar, side-scan sonar and multibeam sonar (Murphy and Jenkins 2010)). Although highly detailed and accurate maps can be obtained from side-scan and multibeam sonar the purchase cost of these techniques is very high in comparison to single-beam sonar. However they are more efficient and cover a wider area in a fraction of the time that is required for single-beam sonar surveys, thereby making them more cost-efficient (Murphy and Jenkins 2010).

During this research all the above mentioned hydroacoustic mapping techniques were used at the different sites. While no direct comparisons were made of the quality and accuracy of the maps created by the different methods, verification of the habitat maps was conducted with the fish sampling methods that allowed for simultaneous habitat assessments (i.e. UVC, RUV, BRUV and ROV). For the most part there seemed to be strong agreement between the habitat characteristics identified in the maps from all the methods and the actual nature of the habitat at the different sample sites. Although the side-scan and multibeam sonar maps provided the most detail, the maps created with single-beam sonar were suitably reliable to enable effective experimental design and stratification on the permanent features of the habitat.

7.3.3.2 Stratification on permanent features

Stratification of a survey area according to the permanent or fixed features of the habitat (i.e. depth, bottom type, or reef profile) ensures that any random sampling will produce data that are representative for the entire survey area, and are not unduly biased towards a habitat feature that will markedly skew the community composition and abundance (Vos et al. 2000; Yoccoz et al. 2001).

Reef profile was consistently identified as having an influence on the abundance of the dominant species of fish recorded during this research. Typically, a high profile reef was associated with higher abundances. However, this was not always the case, with species such as the smooth-hound shark *Mustelus mustelus* occurring in higher numbers in a low profile habitat. Incorporating reef profile into the design of a sampling approach will control for the effect of habitat structure on abundance estimates. At the same time ensuring that all samples are collected from sites containing reef, will reduce the probability of false zeros (i.e. a zero count for reef fish because the sample was collected on sand) in the data.

Reef depth was also identified as contributing to observed variability in the abundances of different species. For example red steenbras was more abundant in the deeper strata (18-30 m) at the Rheeders reef study area in the TNP MPA, compared to the shallower area (10-17 m). Equally, red steenbras was even more abundant at the Middle Bank study area in the TNP MPA at depths of 45-70 m, compared to the Rheeders Reef study area. Setting the range for the depth strata is not a simple task. The shallow photic, or inshore zone along the South African coastline is considered to be between five and 30 m in depth, with the inner shelf occupying the depth range between 30 m and 100-150 m, and the outer shelf extending to the shelf-break at a maximum depth of 350 m (Sink et al. 2012). Data from this study suggested that difference in abundance of fish can be detected between 10 and 30 m depth, and as a result these depth strata may be too broad, particularly for shallow water monitoring. It is thus recommended that within the inshore zone at least two depth strata are applied for stratification. For work in deeper waters, broader depth bins may be suitable, but future research would benefit from the identification of ecologically meaningful depth bins.

Although seasonality was not directly assessed during this research, it may be important for certain monitoring objectives. For example, understanding the seasonal change in community structure associated with ontogenetic or foraging migrations will provide valuable information on periodicity in recruitment and the abundance distributions of species at different life-history stages (Holbrook et al. 1994; McCormick et al. 1998; Shima et al. 2012). Stratification of sampling effort between seasons will enable these objectives to be addressed. It is important to remember

that, if understanding the abundance distributions of different life-history stages is required, a method that provides size estimates for the sampled fish will also be necessary.

7.3.3.3 Variability of the physical environment

During this study, rough seas and strong winds limited the number of sea going days to approximately 50% of the time spent in the field. This places a considerable burden on the monitoring costs as it doubles the time taken to collect the required number of samples. All the field work in this study took place over the summer and winter months as it was conducted concurrently with a seasonal LTM programme. Along the south coast of South Africa, the summer months are characterised by strong winds, while during the winter months cold fronts and sea storms from the Southern Ocean reach the coast at regular intervals. If seasonal sampling is not required then a monitoring programme may benefit from choosing the period of the year where sea and weather conditions are the most stable. In South Africa, this would be during autumn, March and May.

Water temperature was found to consistently explain observed variability in fish abundance. The significantly lower abundance measures associated with cold water are caused by the fish sheltering in caves and crevices (Kerwath et al. 2007). This is an example of detectability bias, as the fish are present in the survey area, but they are not available for detection (Elphick 2008). Within the Agulhas Ecoregion localised, wind-driven upwelling can result in water temperature dropping by as much as 11.2 °C over the course of a day. Upwelling is most prominent between October and March (Fig. 7.1), however, suitable winds that induce upwelling do occur throughout the year. Ideally, monitoring activities should not take place during upwelling events as the variability in the abundance measures will add considerable uncertainty to the trends in population size. A potential way to standardize this is to establish a cut-off point, based on the standard deviation in temperature for the month or season during which the sampling is conducted. For example, at the Rheeders Reef study area in the TNP MPA, the water temperature averages 15.3 ± 3.7 °C during the summer months (November - March), and the lower cut-off limit would be 11.6 °C. Alternatively, in winter (June - August), the water temperature averages 15.6 ± 1.4 °C and the appropriate cut-off limit would be 14.2 °C. This

provides a standardised approach to deal with short-term temperature variability but allows flexibility to account for seasonal patterns and variation between study areas.

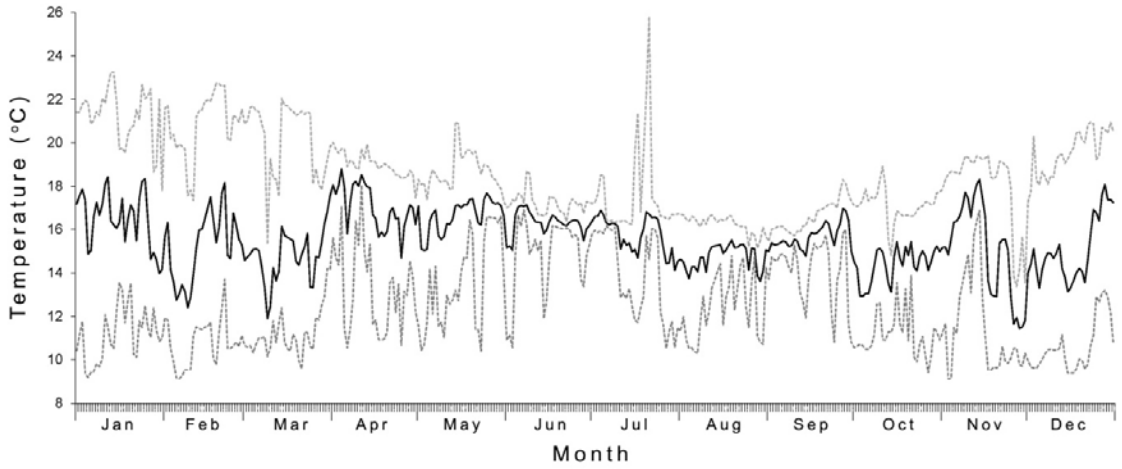

Figure 7.1: Annual variation in water temperature (°C) showing the daily three year average (solid black line), min and max (grey dotted lines) values recorded at a depth of 20 m in the Rheeders Reef study area. The data was collected during this study using a hobo temperature logger mounted to a permanent sampling station approximately 30 cm above the reef.

Underwater visibility is another environmental variable that is not fixed as it can vary between sampling stations and over short time scales. Visibility determines the area in which fish can be accurately identified and counted, and variability in visibility between sampling stations results in sample area changing. For methods such as UVC strip transects or CA this is not a problem, as for the strip transect the survey area is fixed, while for the CA the samples are not collected by visual observations as bait is used to lure the fish to the hook. For methods that rely on visual counts, but do not have a fixed survey area (i.e. RUV and BRUV), it is an imperative to control for variability in visibility by placing a lower cut-off limit that restricts sampling below a certain threshold. In the Agulhas Ecoregion of South Africa, underwater visibility is typically poor, and a cut-off visibility would need to be set as low as four meters. However, it is still necessary to control for variation in visibility above the threshold, and for this, the visible area would need to be calculated for every sample to enable

standardisation. This is an additional strength of the stereo-BRUV method over the single camera BRUV.

7.3.3.4 Measurement of biotic components of the environment

Spatial management interventions, such as no-take MPAs are viewed as key tools for EBM (Pikitich et al. 2004). Effective EBM requires knowledge on the relationship between fish and the biotic and abiotic features of the habitats where they occur (Johnson et al. 2012; Langlois et al. 20012b). In South Africa, the drive to establish MPAs has outpaced the generation of knowledge and it is a research priority to "improve the science base of South Africa's MPAs through coordinated monitoring initiatives" (Sink et al. 2012).

While there is a need for applied research to identify the relationship between the fish assemblage and the abiotic (i.e. bottom type, reef profile and depth) and biotic environment (i.e. invertebrate community and sources of primary productivity) (Johnson et al. 2012), collection of monitoring data should include information on the dominant benthic invertebrate and algal functional groups from where the sample was collected. This basic information can be obtained in the video footage from respective methods, and if and when necessary can be considered to explain variation in the patterns of fish community structure and abundance.

7.3.3.5 Quality control

All monitoring programmes should establish a quality control policy to ensure that the data collected meet a minimum standard (Vos et al. 2000; Yoccoz et al. 2001). As with all methods, there is opportunity for observer error to enter the BRUV data during the collection and analysis process. The advantage of BRUV over other methods is that these sources of error are easy to manage as the video samples can be revisited to validate the data.

Although not discussed in detail in this thesis, monitoring programme managers should ensure that specific protocols are developed and followed to standardise the data collection, data processing and data storage procedures. This will reduce the scope for individuals to use their personal interpretations of how they think the work should be done.

7.4 Conclusion

The research within this thesis successfully addressed the aim to identify a method, or suite of methods, most suited to monitor the populations of reef fish in the Agulhas Ecoregion of South Africa.

Although the research would have benefited from additional study areas and higher levels of sample replication during the comparative methods assessments, the results from both the TNP and TMNP MPAs support the conclusion that BRUV and, by association stereo-BRUV, are superior to the presently employed reef fish monitoring methods.

Without considering the costs, stereo-BRUV provides more data per sample compared to BRUV and where budgets allow, it is preferred to BRUV for LTM. In addition, with future technological improvements the costs of stereo-BRUV will likely drop making it more accessible to programmes operating on a restricted budget. Where equipment budgets dictate what method can be used, programmes should look to employ BRUV. Importantly, the abundance data from BRUV and stereo-BRUV are comparable allowing programmes to adapt their methodology if and when budgets allow.

The process of identifying the most suited method for the LTM of reef fish in the Agulhas Ecoregion was the first step in the aim to establish a network of LTM programmes. There is still much work to be done, and stakeholder meetings need to be conducted with relevant research, management and conservation agencies to present the method and protocol. Through these meetings and workshops frameworks for LTM programmes can be designed to meet the specific requirements of each agency, and guidance and assistance can be provided to ensure that the interested agencies are able to establish LTM programmes.

Chapter 8

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