IMPLEMENTING A SPATIAL ASSESSMENT AND DECISION PROCESS TO IMPROVE FISHERY MANAGEMENT OUTCOMES USING GEO-REFERENCED DIVER DATA

Craig Mundy, Hugh Jones and Duncan Worthington

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Researcher Contact Details

Name: Dr Craig Mundy
Address: IMAS-FA,
University of Tasmania
Phone: +61 3 62277232
Fax: +61 3 62278035
Email: Craig.Mundy@utas.edu.au

FRDC Contact Details

Address: 25 Geils Court
Deakin ACT 2600
Phone: 02 6285 0400
Fax: 02 6285 0499
Email: frdc@frdc.com.au
Web: www.frdc.com.au

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1. Contents

1. Acknowledgements

Funding for this project was provided by the Fisheries Research and Development Corporation, the Tasmanian Department of Primary Industries, Parks, Water, Environment and the University of Tasmania. Managers and fishers in the Tasmanian, New South Wales and Victorian abalone fisheries provided support and direction for the use of the spatially referenced fishery-dependent data. This project operated at a high level of success of data capture, due entirely to the efforts of Ruari Colqhuon, Luisa Forbes and Michael Porteus in managing the logger allocation program. Peter Walsh has provided invaluable assistance with keeping the Microsoft SQL Server database humming.

2. Executive Summary

Fishing activity was captured across 53,852 one Hectare hex grid cells across Tasmania. A total of 113,164 diving hours were recorded across 125,536 individual fishing events (Table 1). Between 2012 and 2016, the Tasmanian Geo-Fishery Dependent Data (GFDD) program captured between 85 % and 90 % of the fishing effort across the entire fishery. Four spatial Indicators obtained from the GFDD - linear swim rate (Lm/hr), area search rate (Ha/hr), catch landed per Hectare (KgLa/Ha), and drops per day offer significant promise as new performance measures in addition to classic catch and effort based CPUE indicators (Chapter 6). Catch landed per unit area (KgLa/Ha) and Maximum linear extent of the dive displayed consistent and interpretable trends that parallel trends in CPUE, and the relationship with CPUE appeared to be global in nature. Linear swim rate as Lm/Hr appeared to have a local rather than global relationship with CPUE (Kg/Hr), highlighting the importance of underlying assumptions when determining TRPs and LRPs for these new spatial indicators. The GFDD through the linear swim rate indicator was able to detect a change in intensity of selective fishing practices (i.e. fisher diving patterns) in the Perkins Bay greenlip fishery. This finding is an important demonstration of the capacity of GFDD to identify change in fishing behaviour that has a spatial signature. The primary impediment to utilising these indicators in Harvest Strategies or ad hoc decision processes (for states with data available) is the limited time-series from which to develop meaningful Limit and Target reference Points (LRP and TRP).

This project has achieved the first significant quantitively description of spatially structured, spatially discrete hand-harvest fisheries across Tasmania, New South Wales and Victoria. Serial depletion is often presented as a theoretical explanation for the demise of fisheries, but that concept is rarely supported with empirical data. Chapter 10 demonstrated that the Tasmanian abalone fishery was comprised of several hundred discrete reef systems across the Tasmanian coastline, and that catch was largely proportional to area. While there were several outlier reefs, this relationship between reef area and reef production hints at some underlying base productivity. Strong relationships between catch and effort are routinely observed, but this is the first demonstration that such a relationship also exists for catch and area.

The proportion of fishable reef utilised each year and the degree of overlap between successive years was previously unknown, and researchers and management relied on industry participants to provide input on long-term changes. However results obtained from diver overlap analyses suggest that asking fishers their opinion on whether the global fishable reef is changing is an unfair question, as there is relatively little overlap in where fishers work, and particularly in large fisheries with many divers, any one diver may only fish a small fraction of the total area. Analytical tools developed in this project enable researchers to exploit the GFDD datasets and provide a precise measure of the extent of reef used in any one year. This project demonstrated that the area of reef fished in anyone year may be only half the known productive fishing grounds. This should not be interpreted as potential for expansion, but rather highlights the process of cycling through fishing grounds, enabling some reefs to escape fishing in some years.

There has been considerable attention given in Victoria and New South Wales to develop a predictive tool utilising previous history to determine future catch. While this is a potentially exciting application of the GFDD data, there appears to be considerable spatial and temporal dynamic in predictability of catch. The Geographic Weighted Regression analyses (Chapter 8) were very useful in identifying local areas of temporal persistence, and/or areas where catch is highly variable mong years. These types of analyses may have greater utility in understanding how productivity of exploited reef systems change through time in a backward-looking investigation than in any future predictive capacity. The challenge with using spatial linear modelling of whole of year spatial fishing patterns to predict catch in future years is that TACC decisions are often made prior to completion of the fishing year. There would need to be a clear demonstration that partial years data provided the same overall pattern as the full year data, and that is likely to be dependent on how much quota was left to catch at the time of the analyses.

Several analytical tools were developed to examine fleet behaviour and diver movement patterns, local variability in harvest levels and spatial structure of the reef systems being exploited. Separating normal fleet patterns driven by fisher preference, effects of inter-annual variation in exploitable biomass, and long-term changes in stock levels will require a much longer time series than currently available. Short term shifts in fleet movements and temporal variability in structure of fishing may be easily confused with normal cycling of fishing grounds. There is considerable impatience to utilise Geo-referenced fishery-dependent data in decision making processes and Harvest Strategies, despite no defensible mechanism to develop reference points from the short time series available. Similarly, the proportion of the known fishable reef area utilised each year and the degree of overlap among subsequent years are likely to be enormously informative for understanding one of the key unknown questions in abalone fisheries – is the footprint of the fishery and/or density changing through time. The capacity to identify areas of high persistence of commercially productive stocks will also improve our ability to understand and monitor key drivers of productivity and local regions critical to achieving the TACC.

Project has facilitated the collection of geo-referenced fishery dependent data across Tasmania, New South Wales and Victoria. A companion project was also run in the South Australian Central Zone abalone fishery where use of the Tasmanian GPS and Depth data loggers was made mandatory in 2013. The success of GFDD in improving the confidence in determining stock status ultimately relies on the high level of data coverage achieved, particularly in Tasmania. While the KUD derived spatial indicators may be useful with lower levels of coverage, the grid derived indicators will be of little use without high levels of data coverage as they rely on capturing activities of the entire fleet across a fishing year. In particular the Index of Persistence developed in Chapter 9 is not viable without a high level of data coverage. If spatial indicators are to be considered as part of annual assessments of fishery status there must be a commitment to ongoing collection of the data to generate a time-series that is useful, and that there is some certainty of these data streams being available for assessment into the future.

3. Introduction

3.1. Matching fishery assessment and management to appropriate biological scales in abalone fisheries

The goals of this project were to improve abalone fishery management through capture of high resolution fishery dependent catch and effort data via position and depth data loggers, and, through implementation of a decision framework based on spatial and non-spatial measures of fishery performance. It is envisaged this abalone specific project will provide a platform from which extension to other types of fisheries can be achieved, and particularly as a demonstration of the value of affordable, high resolution catch and effort data to other S-fisheries (Parma et al. 2003, Orensanz et al. 2005). The term S-fisheries was coined by Parma et al. (2003) to describe small-vessel inshore fisheries, as they are commonly described by 'S' words, e.g. small-vessel, spatially structured, small-scale, sedentary, serial depletion. The current project builds heavily on, and extends, previous IMAS and FRDC funded research completed within FRDC 2006/029 "Using GPS Technology to Improve Fishery Dependent Data Collection in Abalone Fisheries"

The idea of position data loggers as a tool for fisheries research is not new (Marrs et al. 2003). What is new are the analytical methods proposed here to calculate spatial indicators appropriate to abalone dive fisheries, and the application of spatial linear modelling and/or Multi Criteria Decision Analysis techniques to assist with calculation of a bottom-up based estimate of a sustainable TACC. The incorporation of fine-scale electronic data into assessment techniques will for the first time, appropriately match the scale of assessment to biological scales of abalone populations (Miller et al. 2009). The new system is likely to capture most change in fisher harvest strategies, and detect spatial changes (e.g. serial depletion) in stock productivity at appropriate time and spatial scales. Other abalone fisheries in Australia have used data loggers for some time, incorporating data into workshop processes. Two primary differences between this project and datalogging ventures in other states is the structure of the data logging recording process, and, the ability to use the position data to develop spatial indicators and apply spatial statistical methods (e.g local spatial clustering, geographic weighted regression etc) to the data sets.

Hyper-stability in CPUE is a common feature of abalone fisheries, but remains a largely theoretical argument, both in abalone fisheries research and the broader fisheries literature due to difficulty of obtaining precise spatial information on location of fishing activity. Serial depletion at arrange of spatial scales (of patches within reefs, productive reefs, or high production or high value regions) is principally a spatial issue and is in effect the sequential depletion of fishing grounds by fishers. Serial depletion is a common and significant risk factor to S-fisheries (Orensanz et al. 2005), primarily because of the mis-match between scale of fishing and scale of reporting. In S-fisheries, we rarely have the information to accurately determine the sustainable TAC across the fishery, or TAC at the scale of local populations. In practice, we use past experience, and examine catch and effort data for signals that indicate a mis-match between TAC and sustainable yield. This is particularly important when fishers adjust their fishing strategy on the basis of recent fishing success (Daw 2008), masking signals of change in stock abundance. Hyper-stable CPUE data are common in S-fisheries, and are principally a failure to capture the behavioural (spatial) change in fisher activity in response to stock decline. Hyper-stability in CPUE can result either from serial depletion of populations which may occur at a range of spatial scales, and/or, through changes in fishing behaviour which masks change in abundance while maintaining CPUE (e.g. swim further and faster, shorter periods between visiting fishing sites). For this reason, capture of high-resolution spatial information on fishing activity in abalone fisheries with time, position and depth data loggers is considered critical for provision of sustainable advice to those fisheries.

The impact of increasing demands from live markets for specific products influences selectivity in the fishery and further strengthens the need to capture spatial information on our small-scale fisheries. Live-markets are more discerning, creating price differentials for perceived high- and low-value seafoods. This creates an incentive for fishers to target stocks from particular regions that attract a higher price. Rising operational costs such as fuel price creates additional incentives to minimise travel, impacting areas close to ports or boat ramps. The social and economic pressures created by these two key factors alone create strong pressure for fisher behaviour that leads to serial depletion, as has occurred in the abalone fishery in southern Tasmania.

A common problem with existing fisheries data aggregated at the reporting block scale is that shifts in effort driven by stock abundance or by market preferences are difficult to isolate. When geo-referenced diver data is available, it will be possible to distinguish between these two key factors, by examining trends in spatial performance indices at sub- reporting block scale.

3.2. Objective management systems utilising spatial performance indices, MCDA and spatial linear modelling.

As part of the evolving management framework in Australian fisheries, spatial information on the activities of fishers will take on a much more influential role in the broader management of coastal ecosystems. Multiple use management concepts, marine protected areas, indigenous rights, are all growing issues that will impact on the established fishing grounds. Unfortunately, because of the typical spatial scale of reporting in coastal fisheries, areas that have historic importance are poorly described, and fishers have few accepted means to demonstrate historic use and reliance on fishing grounds in debates over access rights (e.g. Marine Protected Areas, indigenous land rights, alternate coastal zone use).

Historical trends and responses to exploitation may provide little insight to future responses of fisheries to exploitation given apparent and predicted climate change. Thus assessment will need to be less reliant on historical data, and focus on new techniques utilising short to medium term trends in productivity of our fisheries. Spatial linear modelling or geographic regression techniques that explicitly incorporate spatial information provide the potential to explore the relationship between activity (catch, catch rate, number of divers, fishing period and intensity) at a particular reef location and the subsequent catch. Multi Criteria Decision Analysis (MCDA), likewise combines critical criteria and evaluation rules at a local scale, which can then be aggregated to a larger spatial scale for TACC determination.

3.3. Relationship to previous project FRDC 2006/029 "Using GPS technology to improve fishery dependent data collection in abalone fisheries"

Project 2006/029 extended the research underway at IMAS (formally TAFI) in the Tasmanian Abalone Fishery to other abalone dive fisheries in Australia and New Zealand. Having recognised the ease of collecting large volumes of data, this project went some way to automating the process of converting data to information. Finally, 2006/029 began the process of developing spatial indicators for use in Management Strategy Evaluation (MSE), and Fishery Assessments, and development of a logger management and spatial database management system. Project 2006/029 was never a vehicle for data collection, and while volunteer uptake of the GPS and depth loggers has been encouraging, consistent use of the units has been less so, leading to incomplete and patchy data sets.

Transfer of technology and concepts from Tasmania to South Australia, Victoria and New South Wales in particular has led to the adoption and/or trialling of electronic data collection for abalone fisheries in these states. However, ongoing Industry concerns over ownership of data, data sharing agreements and fears that other fishers may gain access to their spatial data (and hence local knowledge) remain a major impediment to uptake.

4. Project Objectives

1. To introduce geo-referenced fishery-dependent data collection using the Digital Toolbox across the fishing fleets in South-Eastern Australia
2. To develop, test and implement an objective decision making framework using geo-referenced fishery-dependent data
3. To adapt advances in spatial fishery management from other jurisdictions into the decision framework
4. Extension of geo-referenced data decision systems to Tasmanian industry and other abalone jurisdictions underpinned by robust management science
5. Develop and provide an E-resource to enable individual fishers with access to their data

5. Acquisition of fishery-wide geo-referenced fishery-dependent data

Author: Craig Mundy

5.1. Introduction

Three states were signatories to this project, and endeavoured to expand collection of geo-referenced fishery-dependent data. Use of GPS and Depth dataloggers became mandatory in Tasmania at the commencement of the project, but remained voluntary in New South Wales and Victoria. The methods outlined in Sections 5.2 to 5.4 apply to data collected across all three states. Use of the data varied however, depending on the sphere of interest and degree of coverage.

5.2. Data collection

A robust GPS receiver/data logger unit with internal Lithium Ion battery, encased in an IP65 housing was deployed on each of 125 commercial abalone fishers' vessels. The position data loggers were pre-set to record standard National Marine Electronics Association (NMEA) strings (RMC, GSA) at 10 second intervals to a standard min-SD memory card. An important component of monitoring activity of a dive fishery is the depth profile at which fishing occurs. To capture fishing depth profiles, depth data loggers (Sensus Ultra, Reefnet Inc), also pre-set to record at 10 second intervals, were attached to each fishers weight vest. The dive loggers commence logging when pressure exceeds a pre-set pressure threshold, typically equivalent to 0.5m depth (1111 mBar), and cease logging when pressure drops below that threshold, providing an automated system for determining when fishing is taking place. At three monthly intervals the GPS and dive loggers, are replaced to enable data retrieval. The separate position and depth data streams are merged on the date/time stamp, and position data are filtered so that only position information is used where fishers are diving. This provides a data stream of date/time, position, depth and temperature at 10 sec intervals for the duration of every dive (Figure 1). The data are archived in a SQL Server database utilising Open Geospatial Consortium (OGC) compliant geometry data types to store the raw position data as spatial points.

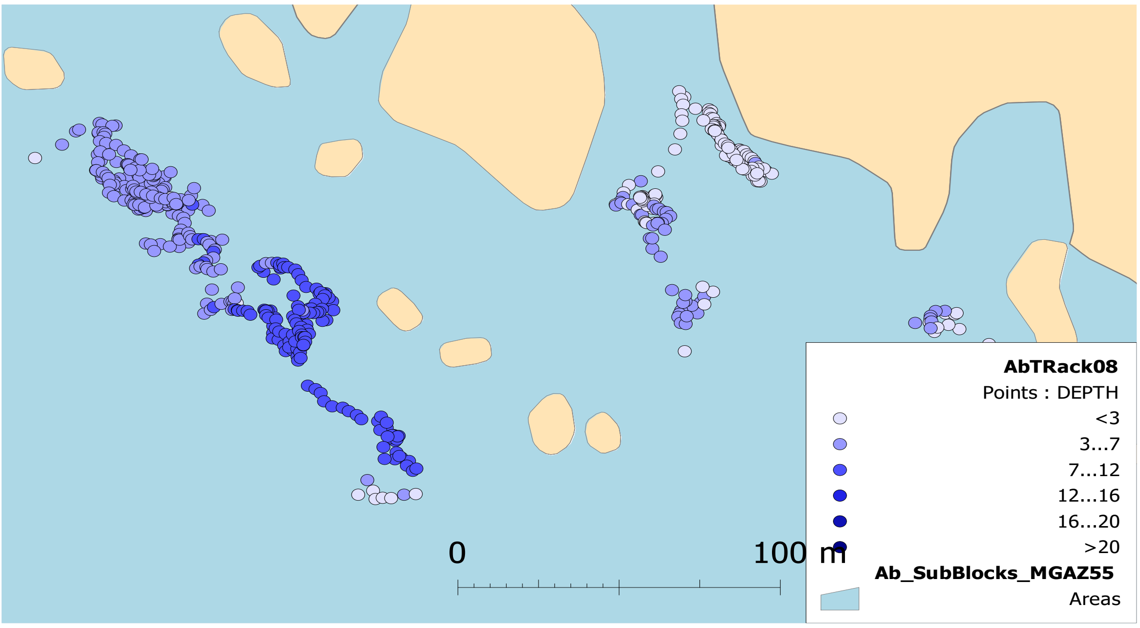


Figure 1. Raw filtered data stream, with locations colour coded by depth [turn into black and white picture with colour points, and reduce the legend].

5.3. Catch mapping & filtering

In the Tasmanian abalone fishery, catch is reported daily through logbooks with landed weights accurate to the nearest gram. Catch in kilograms for each diver on each day of fishing is allocated pro-rata to the filtered spatial data, such that where a fisher dives multiple times on a single day, the proportion of the catch allocated to each dive was done on the basis of the duration of each dive as a proportion of the total dive time. Thus each record in the data stream represents 10 seconds of fishing effort and a harvest weight, tagged with position, date/time and depth and forms the basis of the abalone fishery geo-referenced fishery-dependent dataset. Data from 2012 to 2016 is analysed here, using subsets of data to contrast different components of the program.

A limitation on this dataset is that catch is reported by day, and allocated across multiple dives within a day pro-rata based on the duration of each dive. Thus where catch (and catch rates) vary across individual dive events within a day, the actual catch (and catch rate) may differ from the inferred distribution of catch and catch rate based on the pro-rata allocation process. This introduces a smoothing effect to catch and catch-rates across dives. Further research is required to test the potential of spatial metrics such as swim rate to provide a better weighting for the allocation of catch across dives rather than use the proportional allocation function.

5.4. Spatial processing

The majority of the world's fisheries report catch, effort, location, and time stamp in one or more aggregated forms, such as trip, day, statistical reporting blocks or 1 degree grids (or larger). This leads to a loss of spatial resolution (Piet and Quirijns 2009) and a loss of behavioural information such as changes in the number of discrete fishing events to achieve a desired yield, and the spatial separation or clustering of fishing events at smaller scales. Access to detailed geo-referenced fishery-dependent data enables fishing activity to be examined in two distinct forms; by individual fishing events (dives), or activity at discrete spatial locations such as within a cell on a grid.

5.4.1. Grid

A grid based approach enables exploitation of a resource to be examined within a defined area of reef through time. Here we use a hexagonal grid (1 hectare cell size) overlayed on the geo-referenced fishery data as the basis for grid analyses, with one advantage of a hexagonal grid being that the distance between the centroid of a cell and the centroid of all neighbouring cells is identical. For each cell, the effort, implied catch, mean depth, number of fishers, and number of fishing days are obtained using a spatial join on the spatial point geometry of the position data with a hexagonal grid polygon geometry. A count of all points falling within each cell provides total effort/cell. A sum of the catch weight value assigned to each point provides the total catch/cell. The mean daily catch rate , mean fishing depth, number of fishers, and number of fishing days are also calculated for each cell. One advantage of the electronic position data is that the grid can be re-scaled to suit assessment needs.

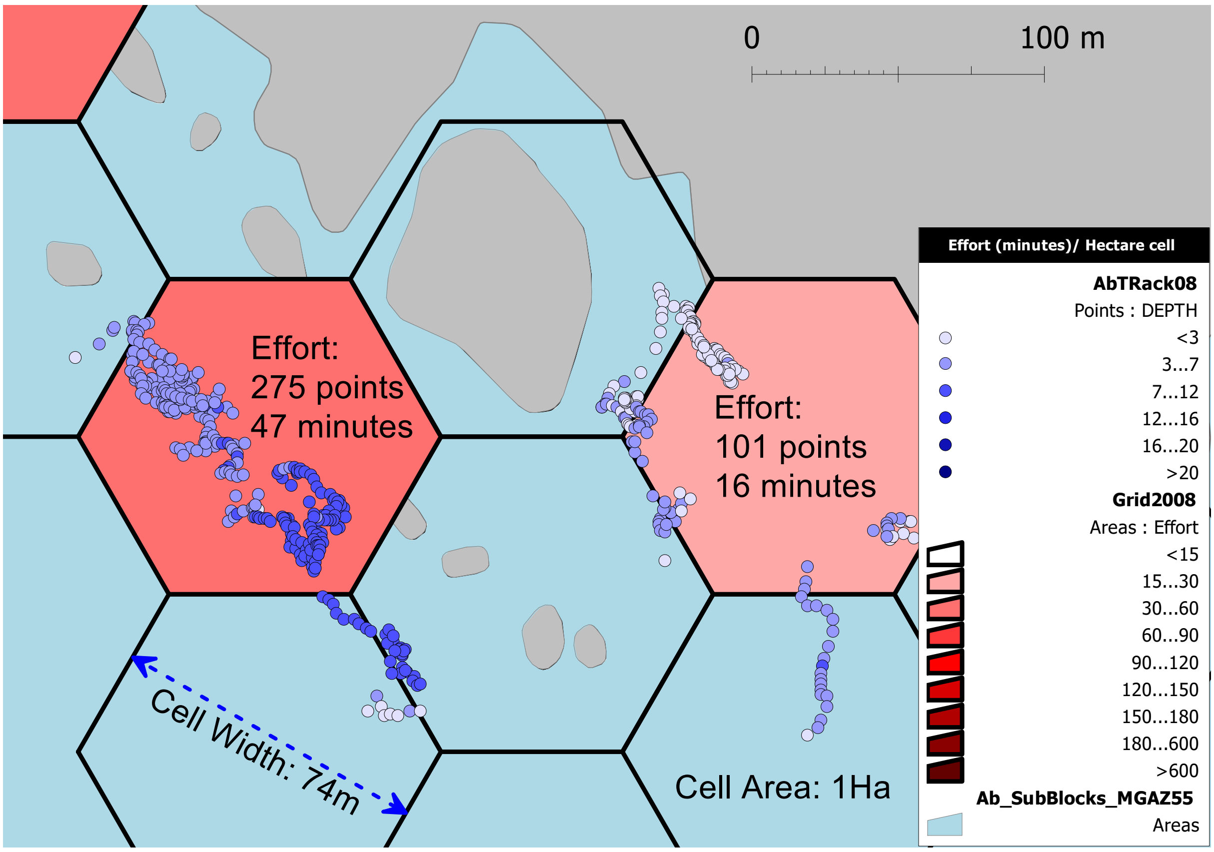


Figure 2. Extraction of summary metrics by overlaying gps points with a regular hexagonal grid.

5.4.2. Dive finprint: KUD

An alternative to aggregated grid based sampling is reporting of fishing activity (effort, catch, location) by discrete fishing event (trawl, pot, net shot, or dive). Reporting of each individual dive provides a different spatial and temporal resolution of fishing activity by enabling individual and fleet level investigation of fishing patterns. This has not previously been possible in a dive fishery, and rarely achieved in most fisheries. The data obtained from GPS position data loggers placed on fishing vessels are comparable to data that is typically recorded in studies of animal movement, where locations of individual animals are used to calculate each animals home range (Cagnacci et al. 2010, Urbano et al. 2010).

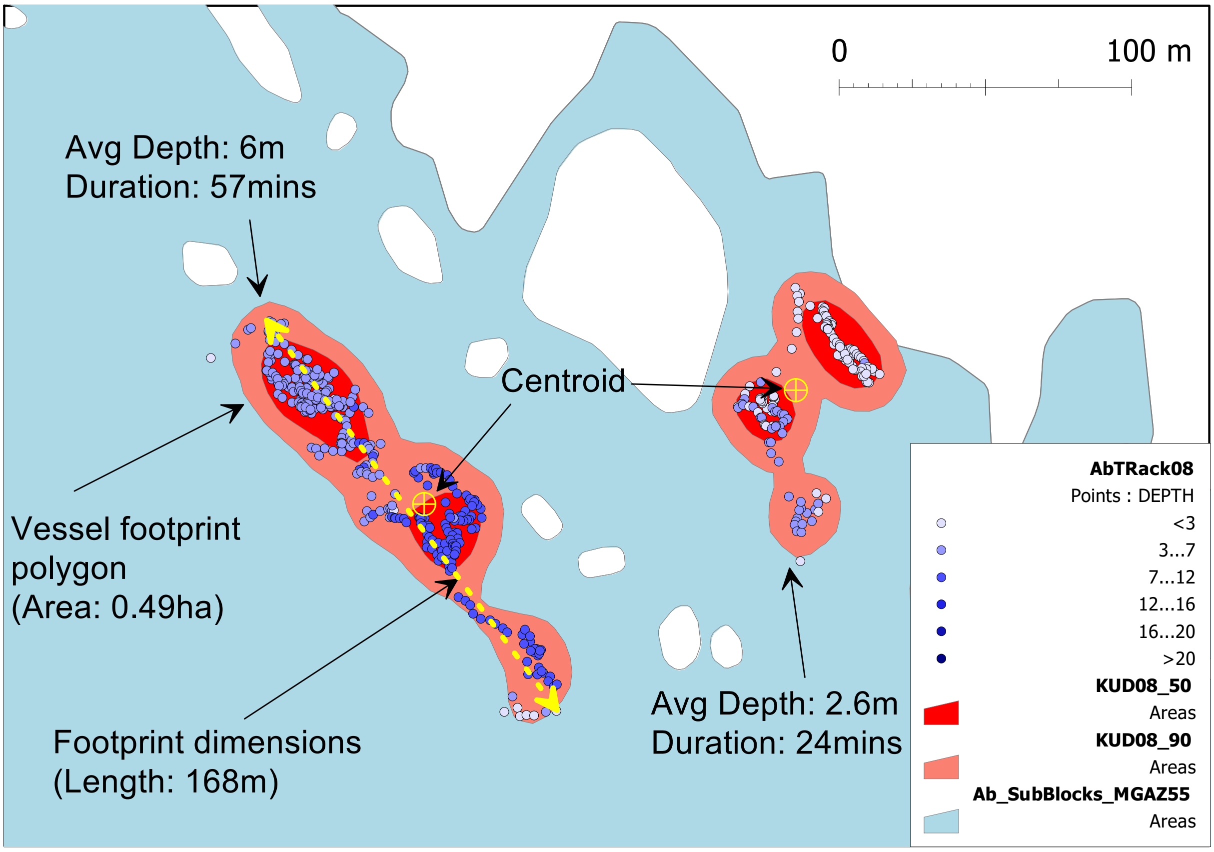


Figure 3. Summary metrics obtained from individual KUD isopleths.

The position data from each individual dive are used to generate fixed bivariate normal kernel density utilisation distributions (KUD) to produce a polygon that describes the maximum 'finprint' of each individual fishing event (unique dive). We adopt the recommendation of Borger et al. (2006a) and use 90% isopleths rather than the more commonly used 95% isopleth, to spatially define the maximum finprint of each fishing event. Thus the 90% isopleth effectively defines the total activity space and the 50% isopleth defines the core area of each fishing event. In order to compare KUDs across divers and through time, a common grid size and smoothing factor *h* must be used. In this study, a standard square grid cell size of 5m (25 m^2) and a smoothing parameter of *h* = 7 is used in the calculation of all KUDs. All KUD analyses were conducted using the `RODBC` (Ripley and Lapsley 2015), `adehabitatHR` (Calenge 2006), and `rgdal` (Bivand et al. 2011) packages for R statistical software (Core-Team 2015).

5.5. Results and Discussion

5.5.1. Data acquired during the project

Due to delays in signing of contracts, the GPS data loggers were not ready until late January 2012. This affected capture of data for January 2012 in the Tasmanian Western Zone as there is substantial demand for live abalone for the Chinese New Year, and weather is usually more benign. There was no loss of data for the Eastern Zone as there was a seasonal closure in this fishery from January 1st to March 31st. Only light fishing occurs in the Northern Zone and in the greenlip fishery through January due to warm sea and air temperatures and a perception that these regions did not supply live-quality abalone to the export market during summer. Data loss was limited in in these areas.

Fishing activity was captured across 53,852 one Hectare hex grid cells across the five year project. A total of 113,164 diving hours were recorded across 125,536 individual fishing events (Table 1). Between 2012 and 2016, the Tasmanian GFDD program captured between 85 % and 90 % of the fishing effort across the entire fishery. Hardware failures account for around 3% to 5% each year, and occurred in both Depth and GPS data-loggers. The Depth data logger failures were due only to failing battery power. The Reefnet Sensus Pro loggers use volatile RAM, and once the battery charge drops below approximately 3.4v, they are unable to either function or communicate via the download cable. Depth data loggers were not re-issued if voltage approached this threshold. Failures in the GPS data-loggers were primarily in two areas; 1) faulty battery packs would lead to rapid decline in the charge, failure to charge, or failure to start up; and 2) the connector port type used initially were prone to failure, and these were replaced as they failed over the life of the project. The removable memory module design was adequate for the purpose of the project, although many of the hardware failures were associated with this feature as it is the primary means of water ingress to the GPS datalogger. The remaining data losses occurred primarily through fishers forgetting to turn the GPS loggers on, or to take the GPS loggers with them in the vessel.

Table 1. Summary of data capture between 2012 and 2016 in the Tasmanian abalone fishery.

Year	Hours	Number of fishing events (dives)
2012	22,133.79	23,991
2013	23,169.41	25,482
2014	23,115.12	25,415
2015	23,457.26	26,446
2016	21,289.84	24,202
Total	113,164.40	125,536

6. Key Spatial indicators for use in assessment of abalone fisheries

Author: Craig Mundy

6.1. Introduction

Catch per unit effort (Kg/Hr) is the primary fishery-dependent indicator used in abalone fisheries assessment world-wide. Acceptance of CPUE as reliable fishery indicator varies among (and within) fishers, managers, research fund providers and researchers. Despite the lack of evidence that CPUE is a reliable proxy for abundance in abalone fisheries, CPUE is frequently referred to and assumed to be a proxy for either abundance or biomass. CPUE is considered a lag indicator due to the capacity of fishers to adjust fishing strategy to maintain catch rates while overall abundance declines. Again, this is largely hypothetical as there is no robust examples of this occurring in any abalone fishery. A key and valid criticism of the use of CPUE is that effort on a given day is not entirely driven by target species abundance, and may be influenced by a range of variables such as conditions on the day (swell, wind, turbidity, algal biomass) and efficiency of the fishing team (experience of the deckhand, fatigue).

A large number of spatial indicators may be derived from the geo-referenced fishery dependent data (GFDD) for use in fishery assessments (Haddon et al. 2014). A subset of those indicators are considered likely to be useful for assessing fishery performance (Table 2). In the first instance, spatial indicators reflective of dive activity that are simple to interpret and have good coherence with catch rates will gain support. These are the simple performance measures that involve various combinations of catch, time, and area. Several combinations such as catch per area are not directly subject to the effort based issues identified above, but may still be affected indirectly (e.g. slow progress due to swell will also impact area utilised).

Spatial indicators that attempt to provide fleet level patterns are more complex, substantially different to the information that fishers are familiar with and have little basis elsewhere in the fisheries literature due to being entirely novel. This chapter provides a brief summary of the simple spatial indicators, and chapters 7 to 9 provided more detailed analysis of fleet level behaviours or patterns.

Table 2. Spatial indices of fishing events as alternate and complimentary measures of fishery performance.

Spatial Indicator	**Description**	**Origin**
MaxDist	Maximum 1 dimensional extent of the dive	KUD
LmpHr	MaxDist / dive duration in minutes	KUD
ShortDives	Proportion of dives where dive duration < 15 minutes	KUD
KgHaK	Catch in Kg / Hectare	KUD
KgHaG	Catch in Kg / Hectare	Hex
FreqDist	Frequency distribution of variables obtained from the hexagonal grid, e.g. number of active divers/cell.	Hex

CC	Concentration area curve	Hex
Gini	Gini coefficient as an index of inequality in the distribution of fishing effort	Hex

6.2. Methods and input data

A five-year time series of geo-referenced fishery dependent data from across Tasmania was explored to provide example of spatial indicators that appear to be indicative of fishery performance. Detailed descriptions of the methods for each spatial indicator are provided in (Mundy 2012). Spatial indicators were derived from two sources; 1) one Hectare hexagonal grid data where the number of points observed in each grid cell form the basis of the potential indicator; 2) the 90% isopleth of the bivariate kernel density function for each independent dive event;.

6.2.1. Choice of KUD polygon isopleth

Consideration of the end use of the KUD isopleths should be an important driver of which particular isopleth level is chosen. The original intended use of the KUD isopleth was as a spatial representation of the maximum possible footprint of a dive event, consistent with the use in the animal movement literature (Borger et al. 2006b, Cagnacci et al. 2010, Urbano et al. 2010), from which spatial indicators of performance could be calculated (e.g. linear swim rate, hectares utilised per hour). For this reason, the chosen isopleth level was 90% as described in section 5.4.2. Over time, there has been an evolution of the use of the KUD isopleth to include calculations of abalone density in terms of Kilograms/m^2 and/or reef biomass. As the data represent the nominal catch landed from a dive and the area of the chosen KUD isopleth, any metrics calculated from these data represent a harvest metric and may be unrelated or least not easily related to the actual reef biomass in terms of Kg/m^2.

In order to evaluate the characteristics of the KUD isopleth polygon in the context of a fishing event and how a KUD isopleth polygon might reasonably be used, an overlay analysis was conducted for all dive events (21,514) in 2017. For each dive event, four different isopleths were extracted (25%, 50%, 75% and 90%) using functions in the `sp` and `rgeos` libraries (Colloca 2009, Bivand and Rundel 2017). For each dive, the proportion of raw xy data points contained by the respective isopleth was calculated. A dataframe was compiled containing the percent of points contained, polygon area, maxdist, and duration in minutes for each of the 21,514 dive events.

6.3. Results and Discussion

6.3.1. Simple spatial indicators

Evaluation of several spatial indicators across the Tasmanian Western and Eastern Zone abalone fisheries show complimentary trends to traditional CPUE (Kg/Hr). In particular, catch per unit area Kg landed per Hectare fished from the KUD isopleth (*KgLa/HaK*), the maximum distance of reef traversed per dive

(MaxDist), and the swim rate (*LmpHr*) which is the time taken to traverse MaxDist appear informative. For example, CPUE in Block 10 declined between 2012 and 2016, and increased in 2017, suggesting mean availability has declined over most of the time-series. On the basis of the CPUE trend we might normally infer that overall, the mean abundance is changing. We find that mean Kg/Ha harvested mirrors the CPUE trend (Figure 5; a & c). Depending on the physical structure and extent of the habitat, and based on reports from experienced divers we also expect, and find, that the maximum extent of the major axis of the dive event (maxdist) will increase when CPUE declines, and the rate (Lm/Hr) at which the divers move over the reef will also increase (Figure 4; b & d). Conversely, when abalone abundance increases through time, we expect that divers will not cover the reef as quickly as they spend more time harvesting, and the rate at which they move across the reef will decrease, while the mean Kg harvested per hectare should increase. In contrast to Block 10, in Block 21 where CPUE increased between 2012 and 2014, the mean Kg/Ha harvested increased across the three years (Figure 4; a & b), the maximum extent of dives decreased and the rate at which fishers cover the reef also decreased (Figure 4; c & d). The majority of reporting blocks where CPUE was increasing or decreasing followed the above trend, however there were anomalies in a few sub-blocks, with trends in the spatial indicators departing from the trends in CPUE.

Spatial Indicators appear to show trends in the performance of the fishery that are consistent, but not identical to the classic CPUE performance measure of Kg/Hr. They also appear able to provide insight to some factors that contribute to change in CPUE, in addition to change in abundance. Classic catch rates in the greenlip fishery in Perkins Bay north-west Tasmania declined gradually over the period 2012 to 2017 (Figure 6). Within this time period a behavioural change in fishing occurred with an increase in selective fishing for larger animals. While change in KgLa/Ha mirrored the change in CPUE (Kh/Hr), the trend in swim rate (Lm/Hr) increased and was inverse to Kg/Hr and KgLa/Ha between 2012 and 2014 as expected. From 2015 to 2017 however the swim rate declined (Figure 6). This anomalous trend in swim rate is consistent with a known change in fishing behaviour, where divers increased the frequency of measuring while searching for larger animals and slowing progress along the reef. The extent of reef (MAxDist) also increased gradually over the same time period, indicating more reef was being utilised to obtain the required size structure of catch. Need to switch order of Figures 4 & 5.

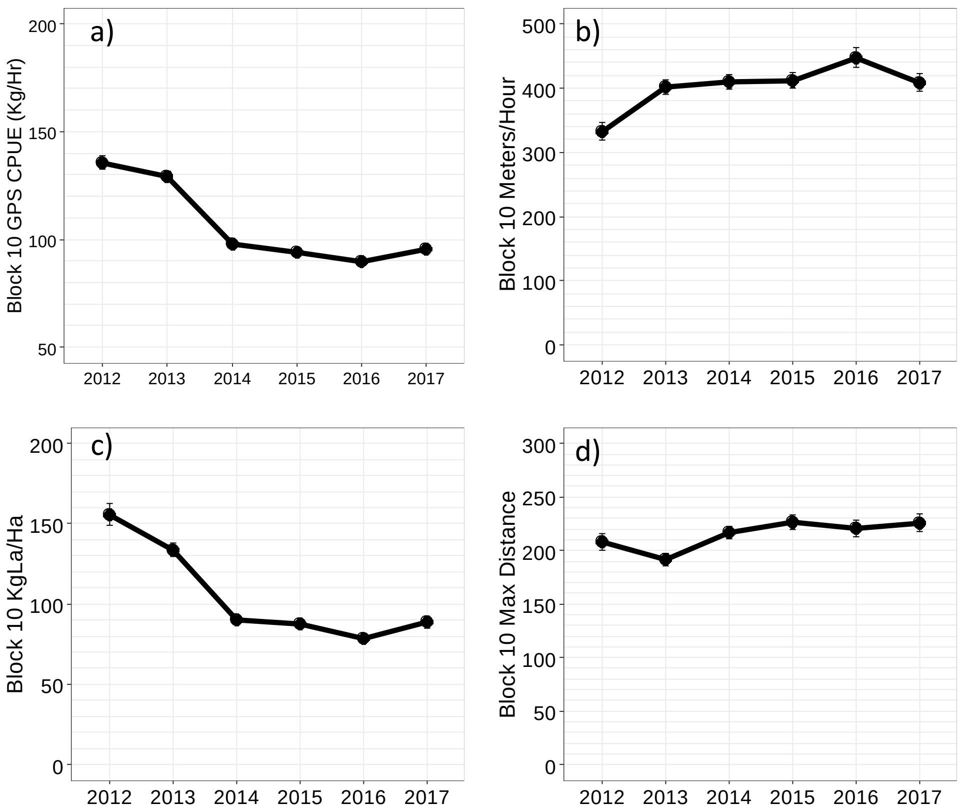


Figure 5. Classic and spatial performance measures for Block 10, south-west Tasmania. a) CPUE Kg/Hr; b) swim rate Lm/hr; c) mean Kg landed per Hectare, d) mean extent of the maximum linear axis of dive events.

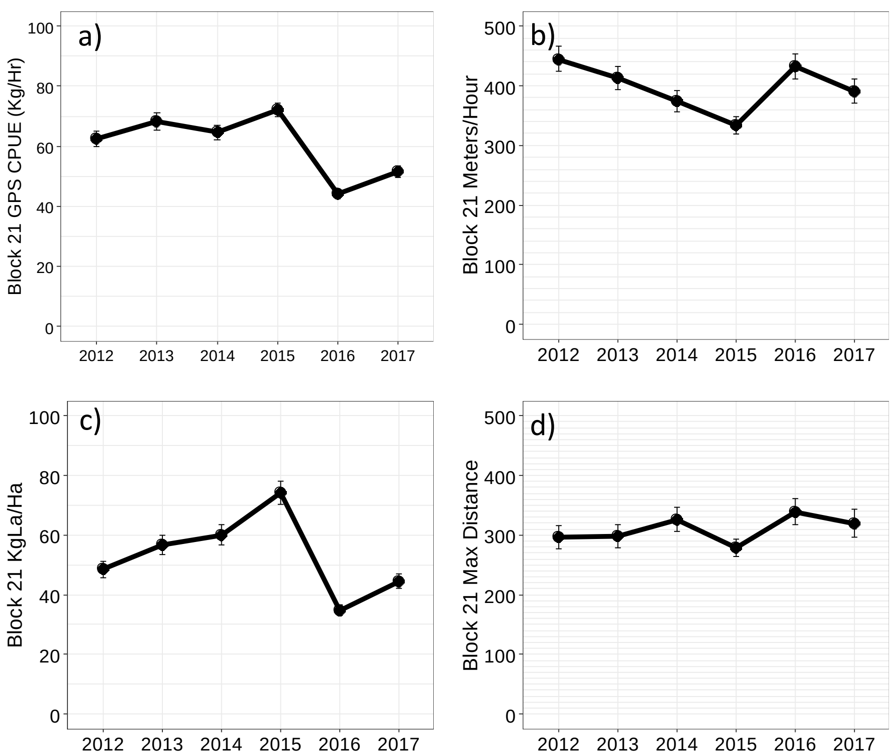


Figure 4. Classic and spatial performance measures for Block 21. a) CPUE Kg/Hr; b) swim rate Lm/hr; c) mean Kg landed per Hectare, d) mean extent of the maximum linear axis of dive events.

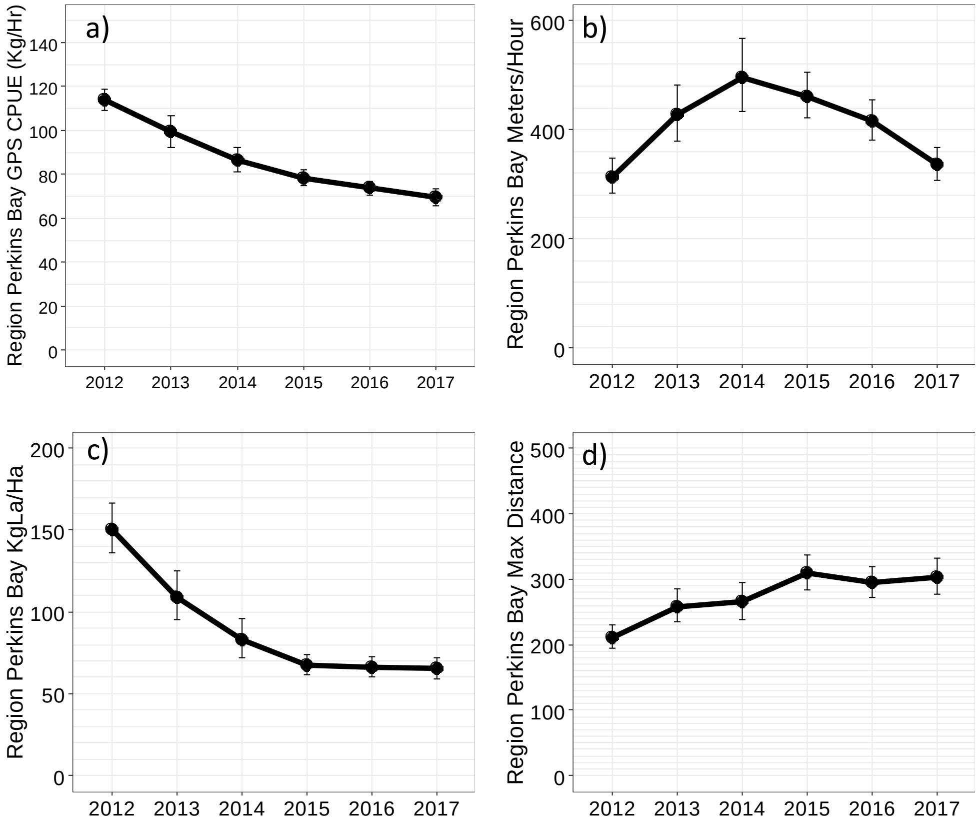


Figure 6. Classic and spatial performance measures for Perkins Bay greenlip fishery, north-west Tasmania. a) CPUE Kg/Hr; b) swim rate Lm/hr; c) mean Kg landed per Hectare, d) mean extent of the maximum linear axis of dive events.

6.3.2. Coherence among CPUE and select spatial indicators

Exploring coherence among the spatial indicators identified some complex patterns. Metrics such as Kg/Ha (derived from KUD and from hex grids) correspond well with CPUE (Kg/Hr), and when considered across various reporting blocks, a continuous trend is clearly evident (Figure 7). This suggests that the relationship between Kg/Hr and Kg/Ha is not specific to individual reporting blocks, and a general relationship between these two indicators exists across the western zone, and perhaps more widely. The two forms of KgLa/Ha (KUD vs grid) also show relatively good coherence across the western zone blocks (Figure 8).

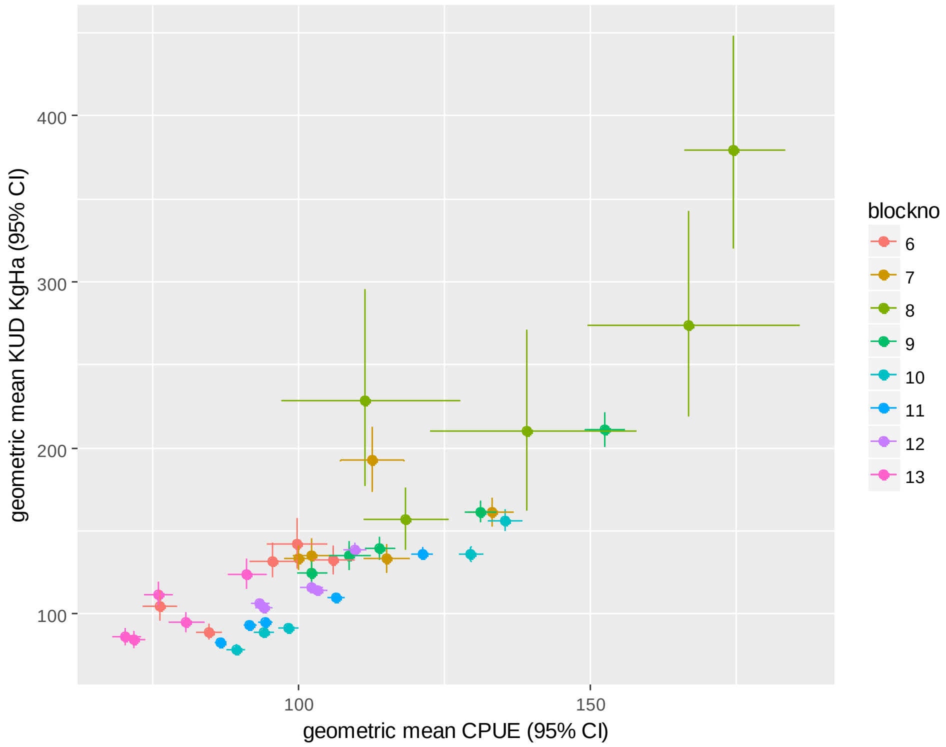


Figure 7. Relationship between dive CPUE and kud KgLa/Hr for Western Zone reporting blocks. Replicated points for each block are years 2012 – 2016 inclusive).

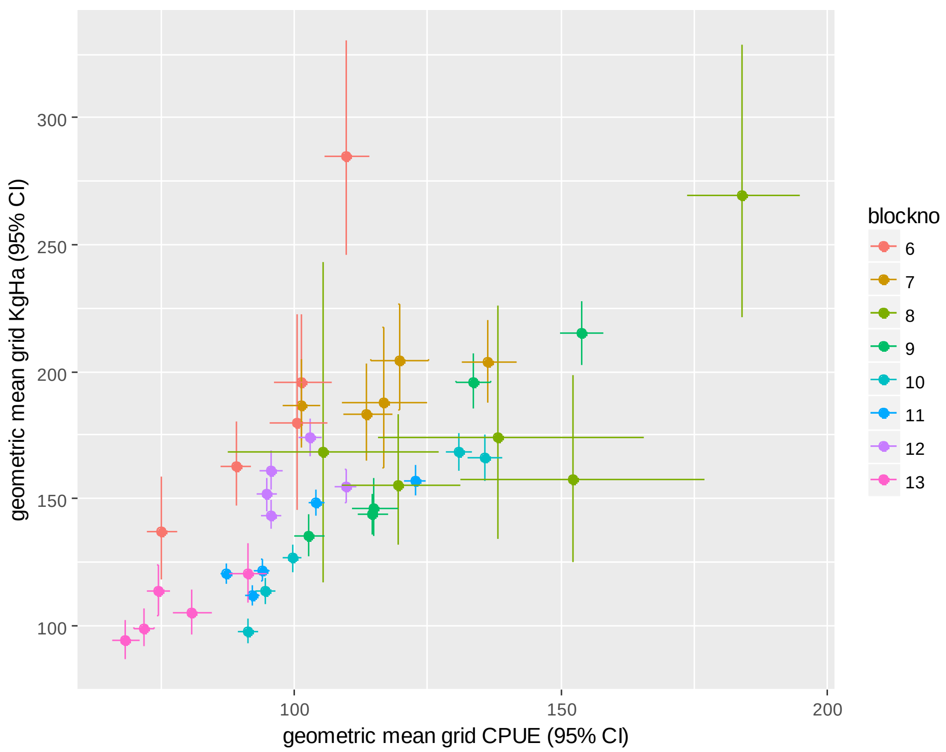


Figure 8. Relationship between grid CPUE and grid KgHa for Western Zone reporting blocks. Replicated points for each block are years 2012 – 2016 inclusive). Grid CPUE was calculated as total yield/total mins per hex cell within each year.

An approximately inverse linear relationship between CPUE and the mean maximum dive distance is apparent (Figure 9), suggesting CPUE declines as fishers have to cover greater distances. The relationship between CPUE and maximum distance also appears to be generalised rather than localised as observed for the KgLa/Ha indicator. In contrast, the relationship between CPUE and the swim rate in linear m/Hr is less clear (Figure 10), and a general relationship between these two indicators appears unlikely. When these data are reconsidered by individual block, it appears that there is an inverse relationship between catch rates and swim rates, but this relationship is specific to individual blocks (Figure 11). For blocks 9 – 13, 2012 has the highest CPUE and the slowest swim rate, but as CPUE declines over subsequent years the order of years among blocks is not consistent although, the inverse relationship between CPUE and swim rate remains apparent (Figure 11). Confidence intervals around the geometric mean CPUE appear to be larger than for maximum distance and linear meters per hour, although this pattern does not hold for KgLa/Ha.

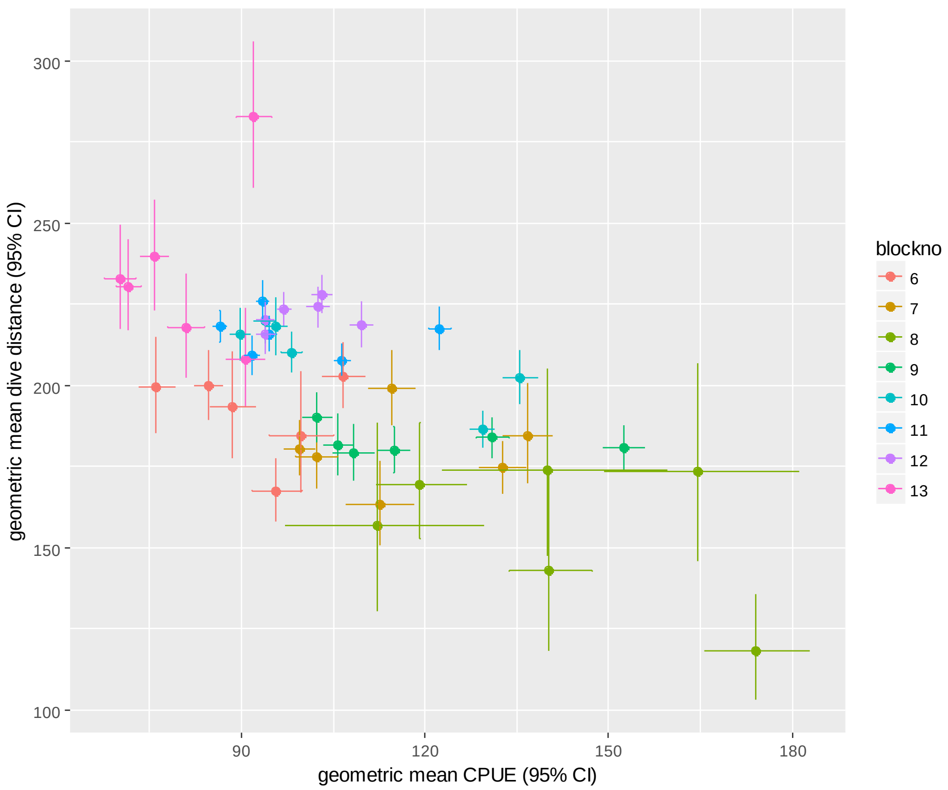


Figure 9. Relationship between dive CPUE and mean maximum dive distance for Western Zone reporting blocks. Replicated points for each block are years 2012 – 2016 inclusive).

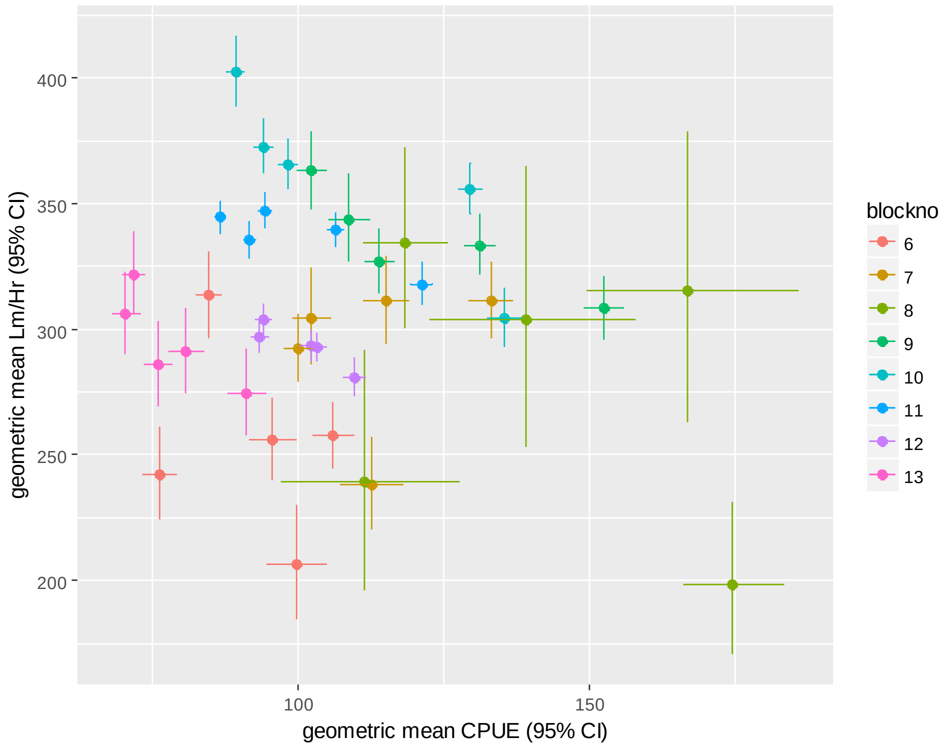


Figure 10. Relationship between dive CPUE and linear Meters/Hr for Western Zone reporting blocks. Replicate points of the same colour for each block are years 2012 – 2016 inclusive.

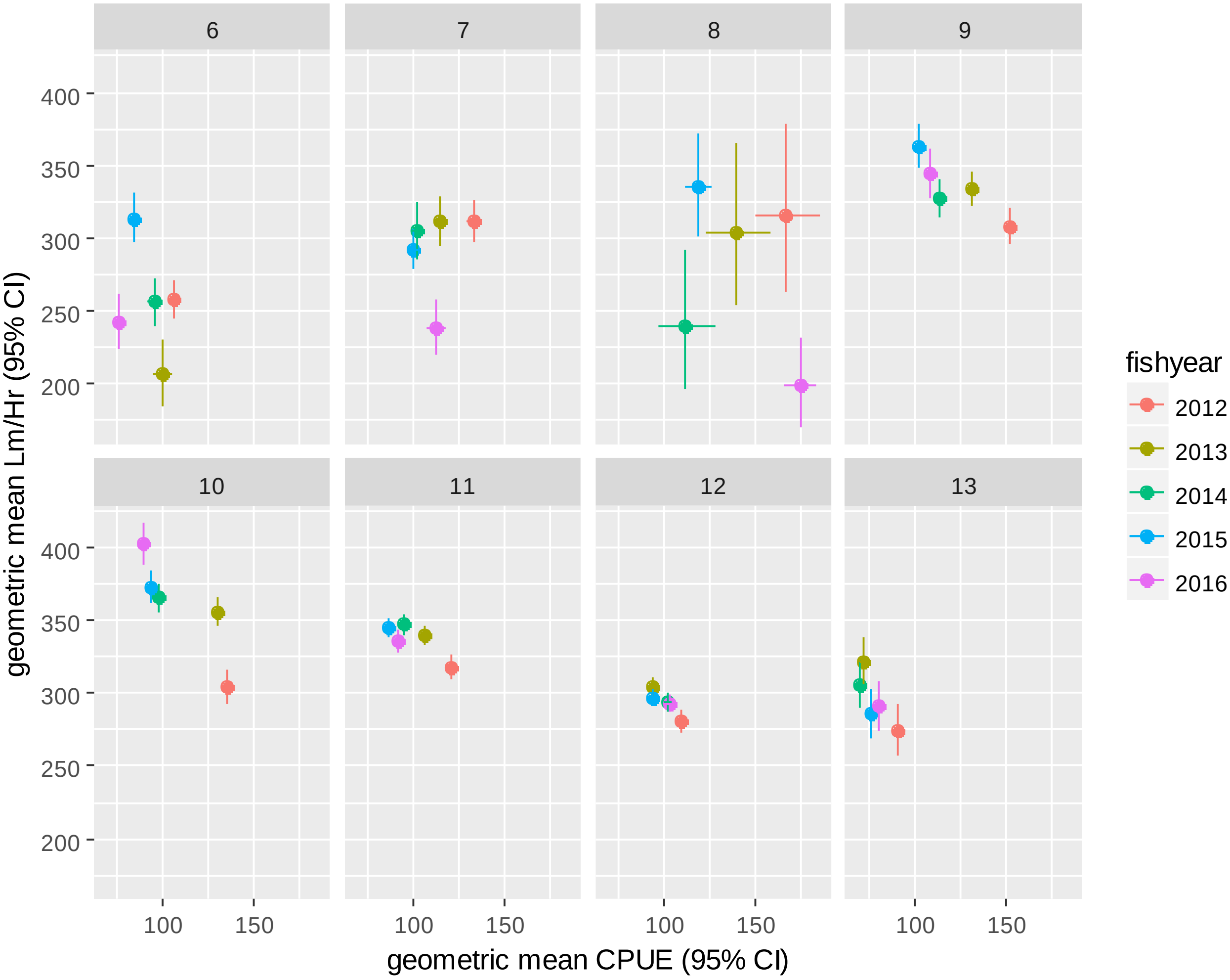


Figure 11. Relationship between CPUE (Kg/Hr) and LmHr (Linear meters per hour), when considered by individual reporting block from the Western Zone. Blocks 6 – 8 have relatively small annual catches with considerably fewer dive events, and lack a clear trend, whereas blocks 9 – 13 have much larger catches and consequenty have a a higher sample size of dive events.

While LmpHr, MaxDist and KgHaK show good potential as informative indicators, two of the proposed indicators (drops per day, and frequency of short dives) appear to show less coherence with catch rates. The frequency of very short dives of less than 15mins duration in block 6 was largely invariant over time (Figure 12), despite a rapid and continuous decline in catch rates (Figure 13) over the same time period. During the final year of the time series, there was a 3% increase in proportion of short dive events but the magnitude of change suggests this metric may be less informative than catch rates. Changes in the number of dives per day per diver in block 6 showed a weak pattern of increasing number of dives per day as catch rates declined, with the inter-quartile range increasing from 3 to 5 dives/day to 3 to 7 dives/day. This change is more consistent with the catch rate decline in this block. In a more complex example, these two spatial indicators suggest a more significant deterioration of fishery performance in the Eastern block 27 fishery (Figure 14), where the frequency of short dives increased by approximately 5% and the median and inter-quartile range of dives per day increased steadily over the five-year time-series. However, catch rates over the same period rather than showing a continuous directional trend, initially increased in 2012 and 2013 to a high in 2014, then declined in 2015 and 2016 (Figure 15). Where there is less coherence with, or a different pattern to that shown by the traditional CPUE indicator, there remains a challenge to determine which indicator is providing the most precise and accurate measure of the state of the fishery. With a time-series of only five years, there is most likely insufficient data to be certain whether these simple spatial indicators are more or at least as reliable than catch per unit effort.

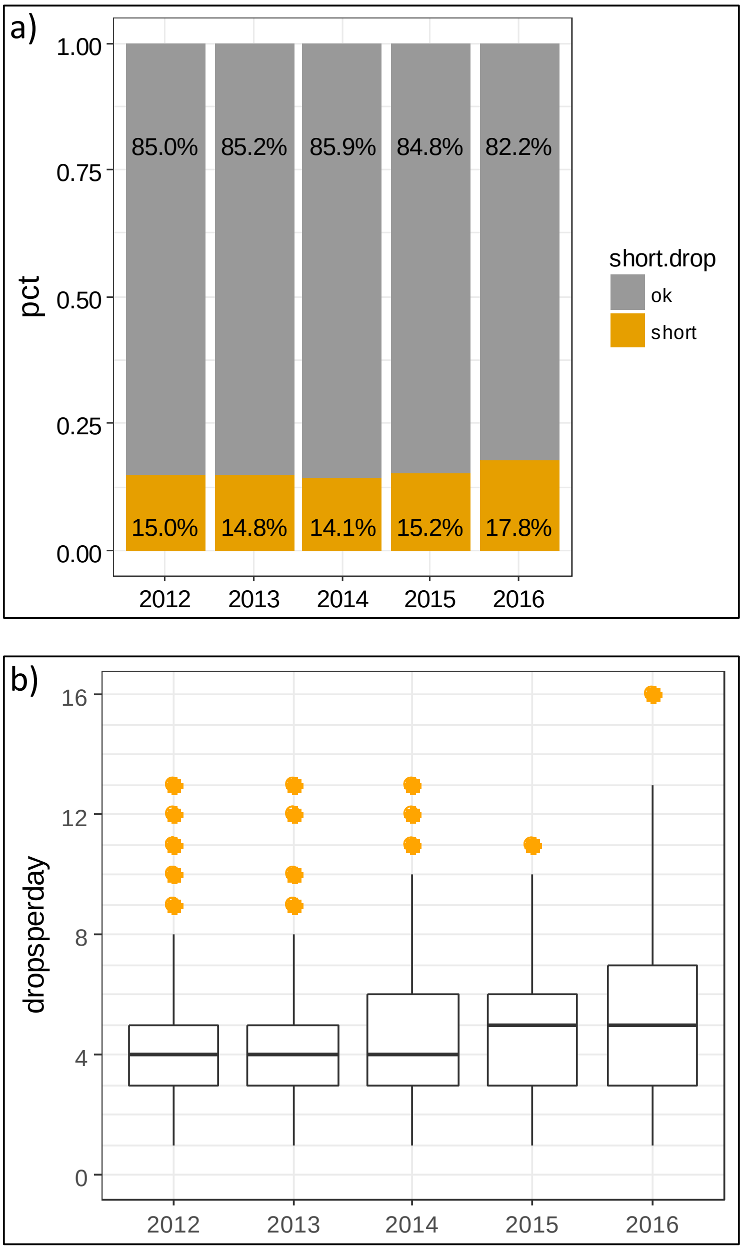


Figure 12. Spatial indicators of the number of dives per day and the prevalence of very short dives in Block 6 Central Western Zone; a) Bar chart of the proportion of dives across the fleet that were less than 15 minutes in duration, b) Box plot of the number of drops per day per dive. N.b. Over the period 2012 – 2016, catch rates in this reporting block have almost halved.

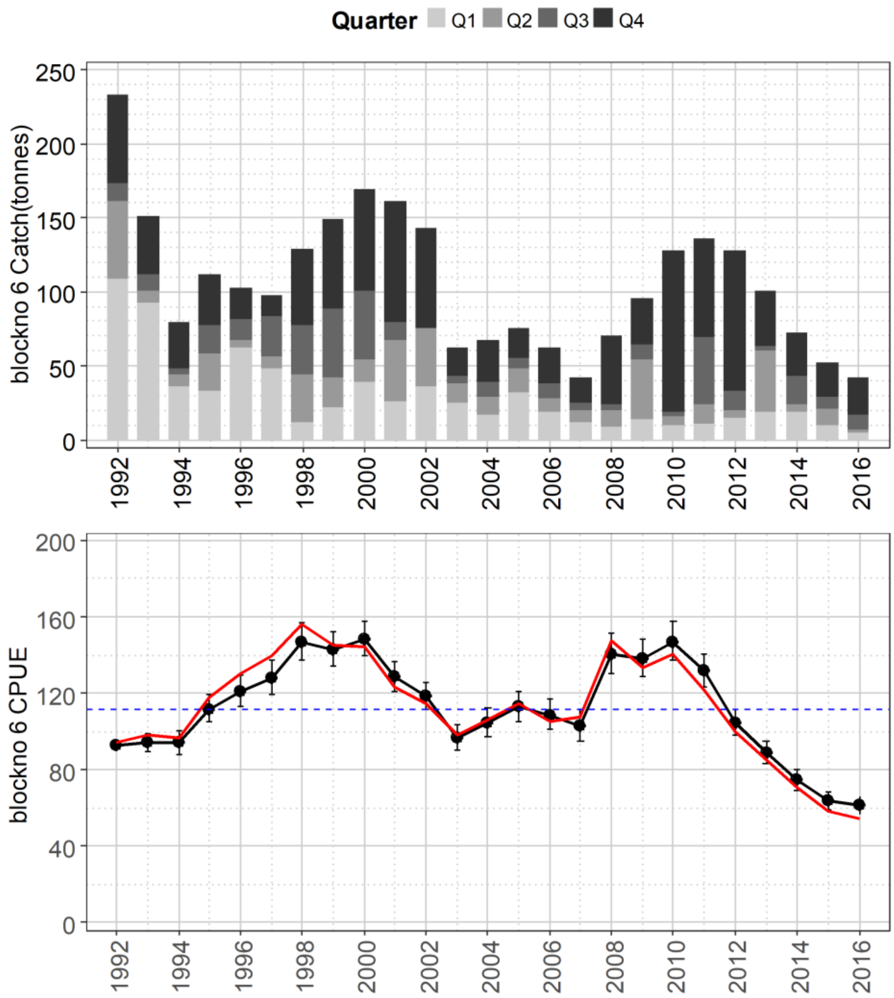


Figure 13. Catch and catch rate trends in Block 6 Central Western Zone. Top plot - catch taken during each quarter of each year; Bottom plot - standardised CPUE (black line) and geometric mean CPUE (red line).

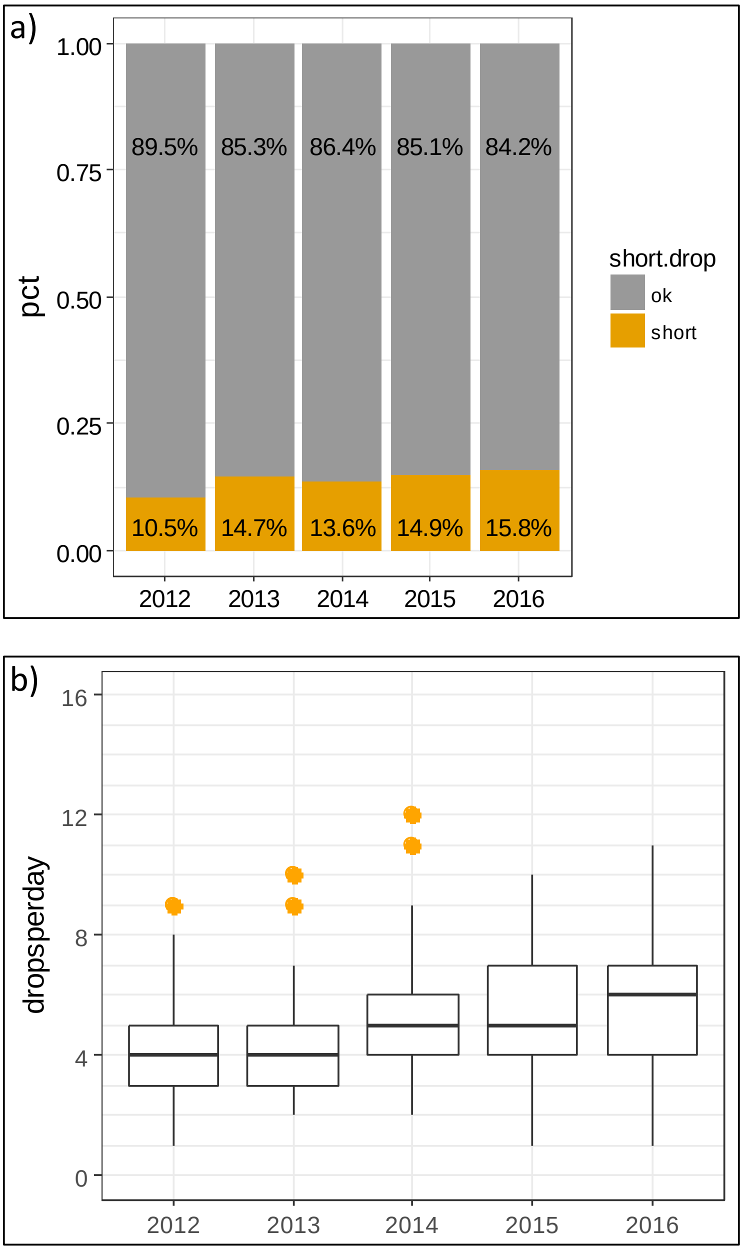


Figure 14. Spatial indicators of the number of dives per day and the prevalence of very short dives in Block 27 Eastern Zone; a) Bar chart of the proportion of dives across the fleet that were less than 15 minutes in duration, b) Box plot of the number of drops per day per dive. N.b. Over the period 2012 – 2016, catch rates increased between 2012 and 2014, and then declined to a level below w012 in this reporting block incresed to a peak in 2014, and then declined through to 2016.

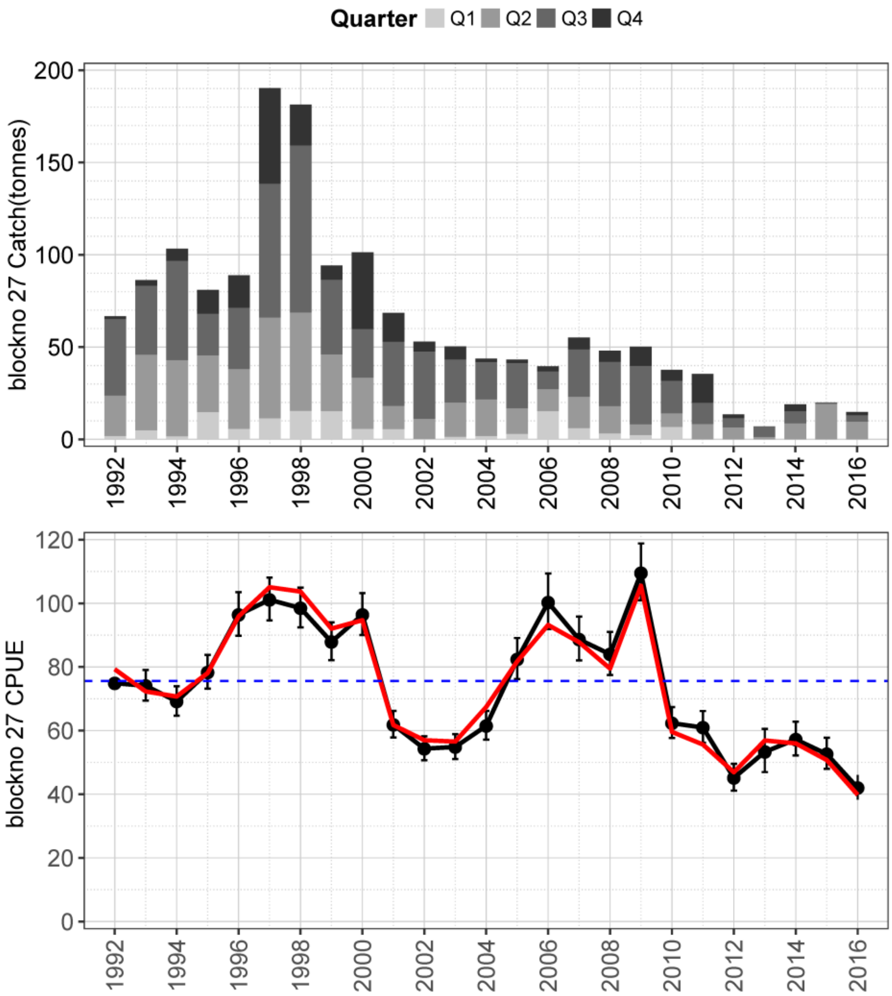


Figure 15. Catch and catch rate trends in Block 27 Eastern Zone. Top plot show catch taken during each quarter of each year. Bottom plot shows standardised CPUE (black line) and geometric mean CPUE (red line).

6.3.3. Evenness of catch distribution across fishing grounds

Access to fine-scale spatial information about commercial abalone fishing provides an opportunity to describe the area supporting commercial abalone fishing. By mapping daily catch onto the spatial data, we are able to describe the spatial distribution of fishing effort within each spatial assessment unit (SAU). The spatial structure of fishing and harvest can be addressed in several ways, the simplest of which is the shape of the frequency distribution of catch (or effort) within 1 Hectare hex cells. Across all areas of the Tasmanian abalone fishery, a small number of hex cells contribute a large amount of catch, and the majority of reef only supports low levels of catch. Cells with high catches are rare, and in the case of block 6, Central Western Zone where catch rates are falling, there is a substantial increase over the time series in the number of cells that yield small catches (Figure 16). When stocks are increasing such as in block 21, Eastern Zone, more reef cells yield higher catches and fewer cells yield low catches (Figure 17) as the fishery improved between 2012 and 2015. In 2016, catch rates fell sharply in response to a significant marine heat wave event, and there was a corresponding shift in the distribution of catches towards higher number of cells yielding relatively little catch.

Changes in the intensity of fishing within a reporting region such as increasing levels of effort in fewer reef areas can indicate changes in stock levels. Increasing reliance on a few small productive reefs in association with declining indicators such as catch rates strengthen the capacity to identify declining stock levels, whereas a greater spread of catch across the reef area in combination with increasing catch rates is indicative of an improving stock. The heavily skewed distribution suggests caution and careful selection of measures of central tendency.

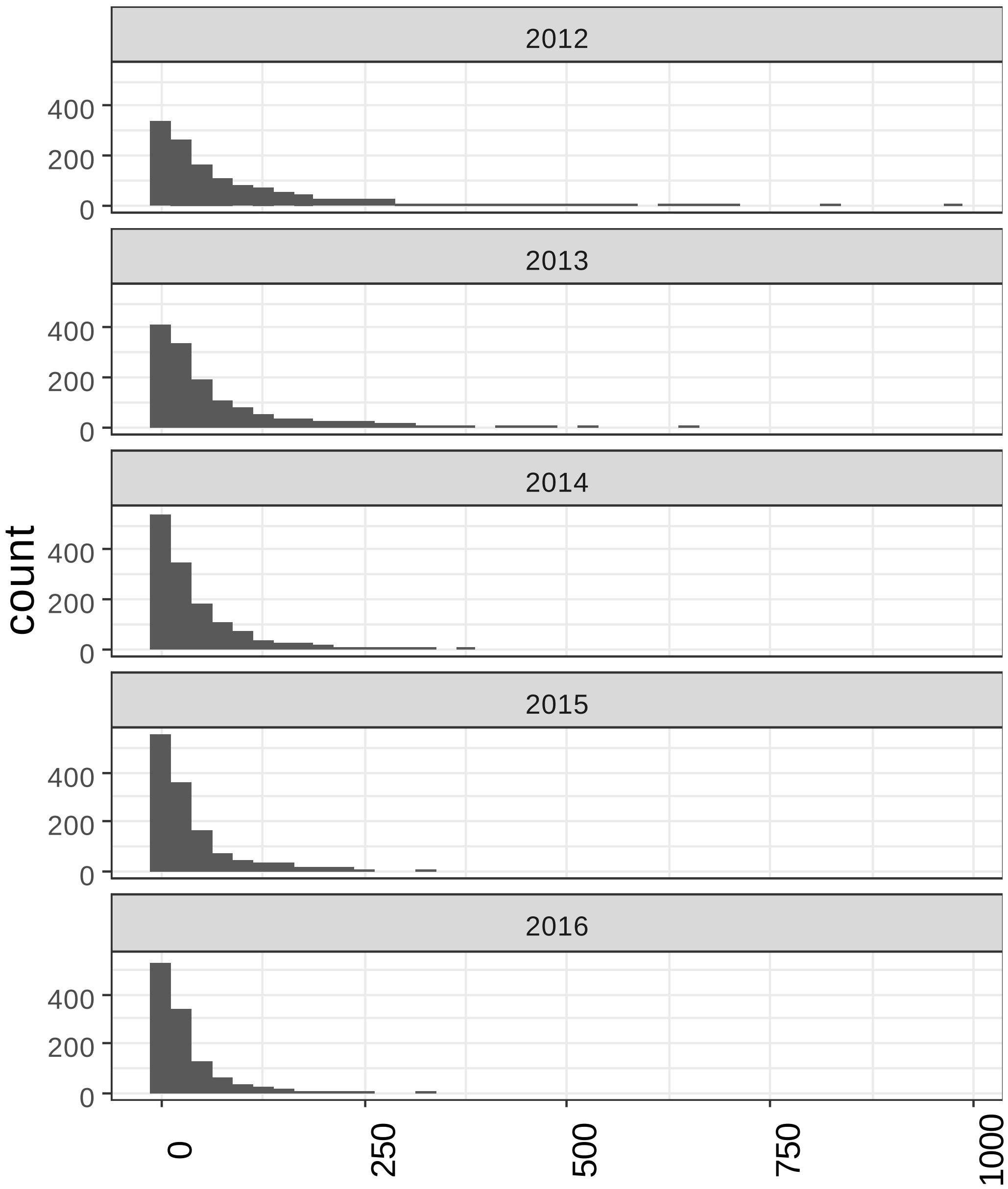


Figure 16. Histogram of KgLa/Ha in block 6, Central Western Zone. Bin size is 25 KgLa/Ha.

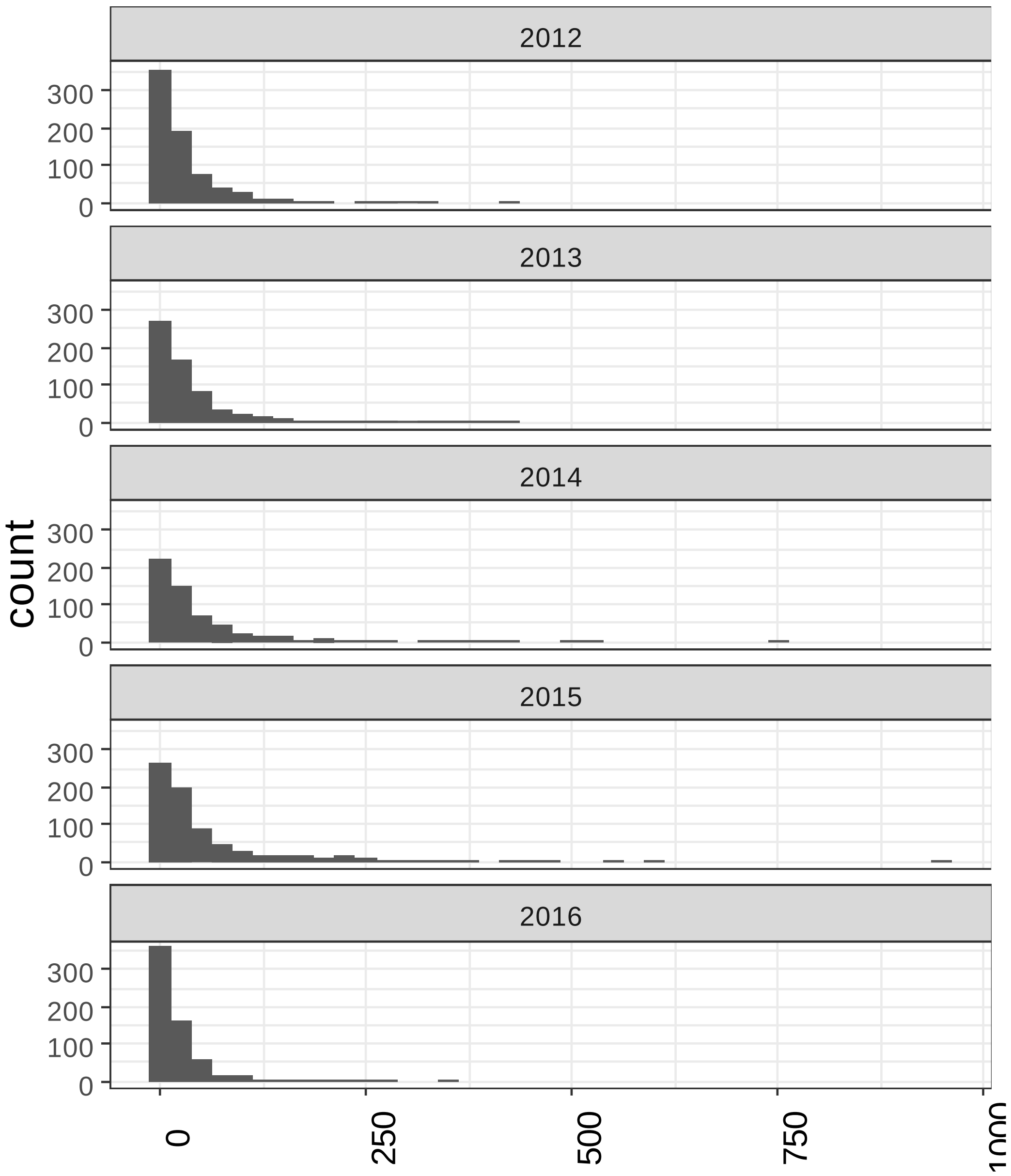


Figure 17. Histogram of KgLa/Ha in block 21, Eastern Zone. Bin size is 25 KgLa/Ha

6.3.4. The importance of spatial scale at which metrics are summarised

All of the Australian abalone fisheries summarise indicators or performance measures within long established spatial units (blocks, spatial assessment units, spatial management units, reefcodes, map codes etc). The rationale for the precise location of the boundaries between neighbouring units and the size of the boundary units is not well documented and largely lost as agencies responsible for managing fisheries transition across departments, or staff retire or move on to other activities. When summaries are presented for defined spatial units there is a tendency to assume that, with some variation, most of the reefs within a spatial unit follow the same trend through time. To explore this concept, we use block 12 in the Tasmanian Western Zone to illustrate that there is often considerable spatial dynamic within a large reporting block.

Catch rate as Kg/Hr was summarised for the whole of Block 12 for the period 2012 – 2016 (Figure 18). A series of sequential equal geographic divisions were made, breaking Block 12 into two spatially equal parts, then four, then 8, then 16 and finally 64 hypothetical blocks. At each new scale, mean catch rates were re-calculated for each cell and the trend examined relative to the original whole block trend (Figure 18). At the four hypothetical block subdivision (Figure 19) none of the cells mirrored the full block trends, except hypothetical subblock 4 which had a similar shape, but at a much higher catch rate. At the 16 hypothetical block subdivision (Figure 20), only hypothetical subblock 11 mirrors the original whole of block pattern (Figure 18), and as for hypothetical subblock 4 in the four hypothetical block subdivision, this subblock has a much higher catch rate than the full block trend. One important outcome from this exercise is to highlight that different fishers may fish the same large reporting block yet experience rather different levels of abundance and changes through time. It also highlights the complexity of attempting to scale up data collected at a handful of spot locations across a fishing ground.

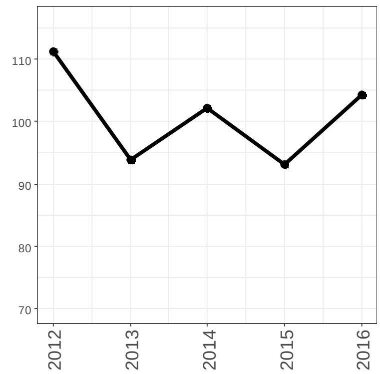


Figure 18. Catch rate trend for all of block 12 Western Zone.

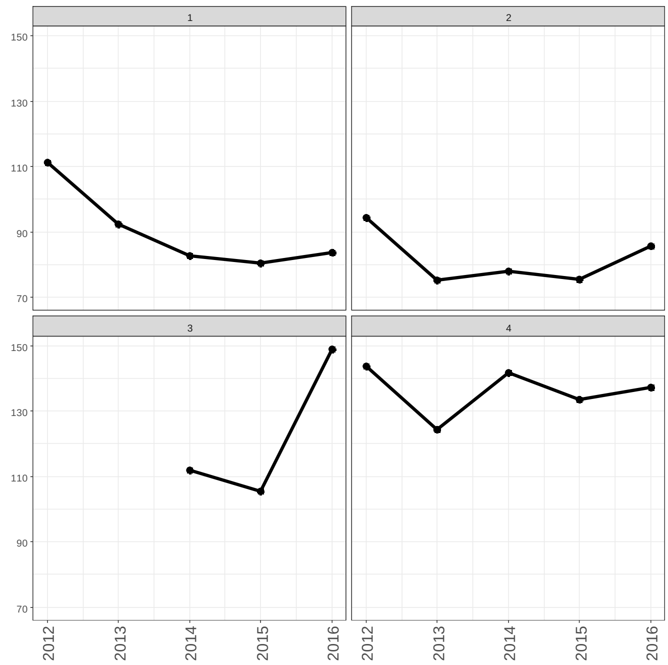


Figure 19. Catch rate trends for block 12 broken into 4 equal spatial cells. Not all of the subdivided cells ultimately included fishing activity.

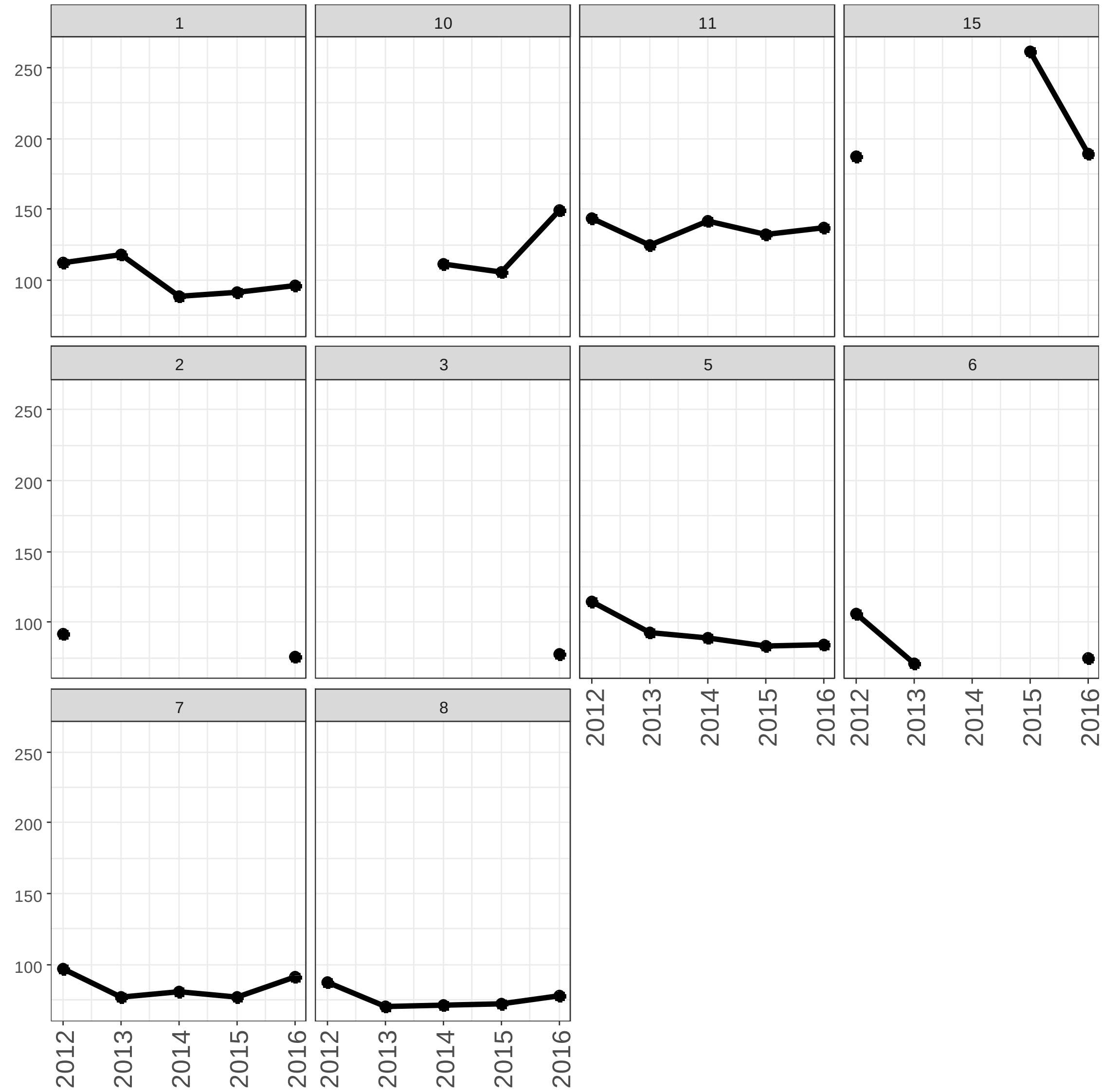


Figure 20. Catch rate trends for block 12 broken into 16 equal spatial cells. Not all of the subdivided cells ultimately included fishing activity.

6.3.5. KUD polygons: choice of isopleth

The isopleth polygon is calculated from the bivariate kernel density utilisation distributions rather than the spread of the raw data points. Thus the 90% isopleth of the distribution maps the distribution function, and this may or may not translate directly to the proportion of raw points covered. For example, in 2017 the 90% isopleth KUD typically contained more than 90% of the data points, with one third of all dive events containing 100% of the data points, and the remaining two-thirds of dive events containing 95% or more of the raw data points (Figure 21). Similarly, The 50% KUD isopleth contained between 55% and 100% of the raw data points, with a mode of around 65% (Figure 21). In all cases, the respective isopleths contained more of the raw data points than the probability distribution function might indicate, and therefore the area of the KUD is larger than might be anticipated by the isopleth value alone.

The area of any 90% KUD isopleth is the area traversed by the fishing vessel, not the diver. Sanders and Beinssen (1998) used a search rate of $20m^2$/Minute for abalone divers in the Victorian abalone fishery. To understand the extent that the KUD isopleth polygons may overestimate the actual fished area, comparing the expected dive area based on the dive duration multiplied by the Sanders and Beinssen (1998) search rate ($20m^2$ / Min) to the area of a polygon is instructive. Taking a data point from Figure 21 with a dive duration of 122.5 minutes as an example, the area swept by the diver according to Sanders and Beinssen (1998) is 2,250 m^2 based on 20 m^2 / minute. Adjusting for handling time in a fishery with 100 Kg/Hr and an average individual weight of 600g, the area swept is reduced by less than 3% to 2,187 m^2. The measured area of the dive isopleth was 3,067 m^2, 8,713 m^2 and 26,359 m^2 for the 25%, 50% and 90% KUD isopleths respectively. The area of the 90% isopleth is an order of magnitude larger than the area swept calculation, the 50% isopleth is 4 times higher than area swept, while the area of the 25% isopleth is 1.5 times higher than the theoretical area swept. The search rate per minute for this dive if the 25% isopleth is a reasonable proxy for the area actually fished by the diver is 27 m^2 / Minute, and for the 50% isopleth the search rate would be 71 m^2 / Minute. A hypothetical search rate based on a 50% isopleth or greater is impossible for normal productive abalone reef with healthy kelp communities and a species that is semi-cryptic to cryptic. If we calculate the hypothetical dive time based on Sanders and Beinssen (1998) area swept rate and the area of the KUD isopleth, it is apparent that only the 25% isopleth returns a plausible hypothetical dive time (Figure 23). Thus, when used as an estimator of total reef biomass the 90%, 75% and 50% isopleths in effect underestimate the actual mass/m^2 on the reef. To use the isopleth area values in a calculation of Kg/Ha for biomass, we must also know the level of heterogeneity at a range of scales from 10s of meters to 100s of meters to kilometres to make use of this data as a proxy for reef biomass, rather than as a simple spatial indicator in the form of Kg landed per Hectare (KgLa/Ha). Ultimately, a scaling parameter that addresses the 'patchiness' at multiple spatial scales is required to use KUD isopleth areas for calculation of reef biomass, but such a scaling parameter is unlikely to be derived from the spatial data derived from the logger program.

The choice of isopleth has much less effect on the two primary spatial indicators Lm/Hr and Ha/Hr derived from the KUD isopleth polygons. The Lm/Hr calculated from different isopleth levels as the maximum extent of vertices of the KUD isopleth polygon divided by the dive duration was largely proportional (Figure 24). Similarly, Ha/Hr calculated from different isopleth values as the area utilised per hour as the area of the KUD isopleth polygon divided by the dive duration was largely invariant, with the exception of a few outliers (Figure 25). Thus use of different isopleths has relatively little impact when the KUD isopleth polygons are used as a spatial performance indicator.

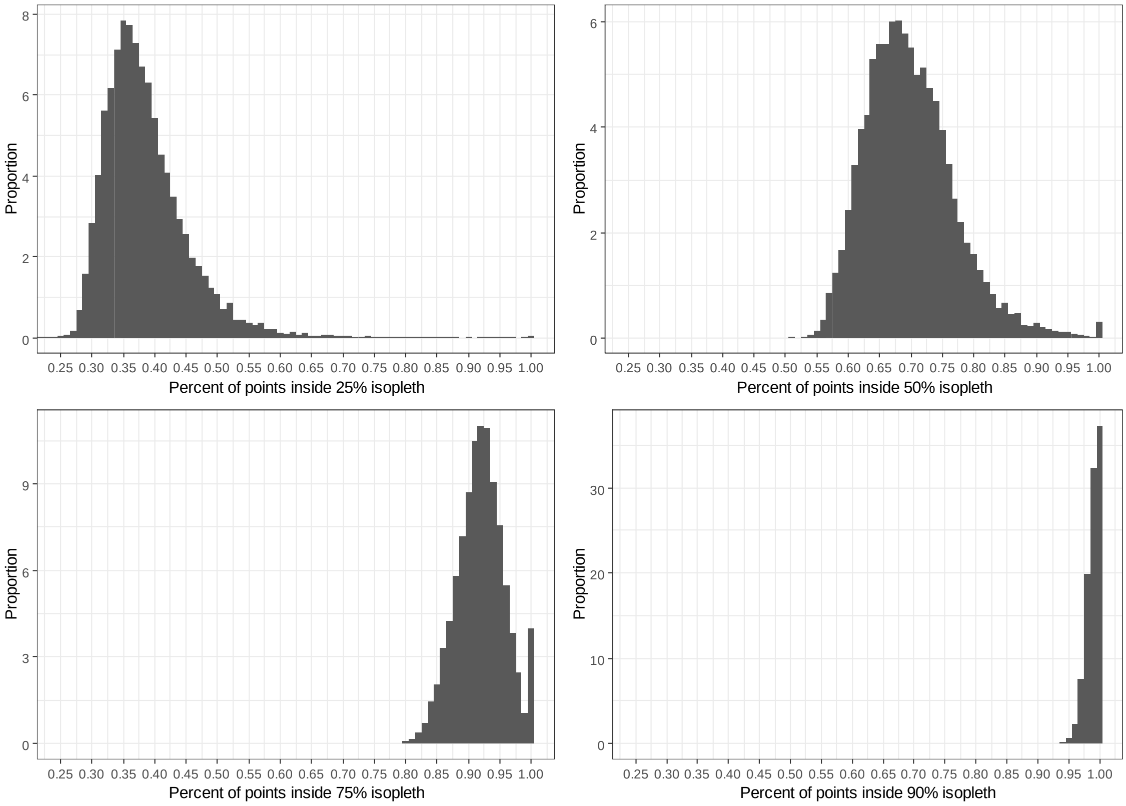


Figure 21. Frequency distribution of the percentage of points contained within 25%, 50%, 75% and 90% KUD isopleths. Data are from all dives recorded during 2017.

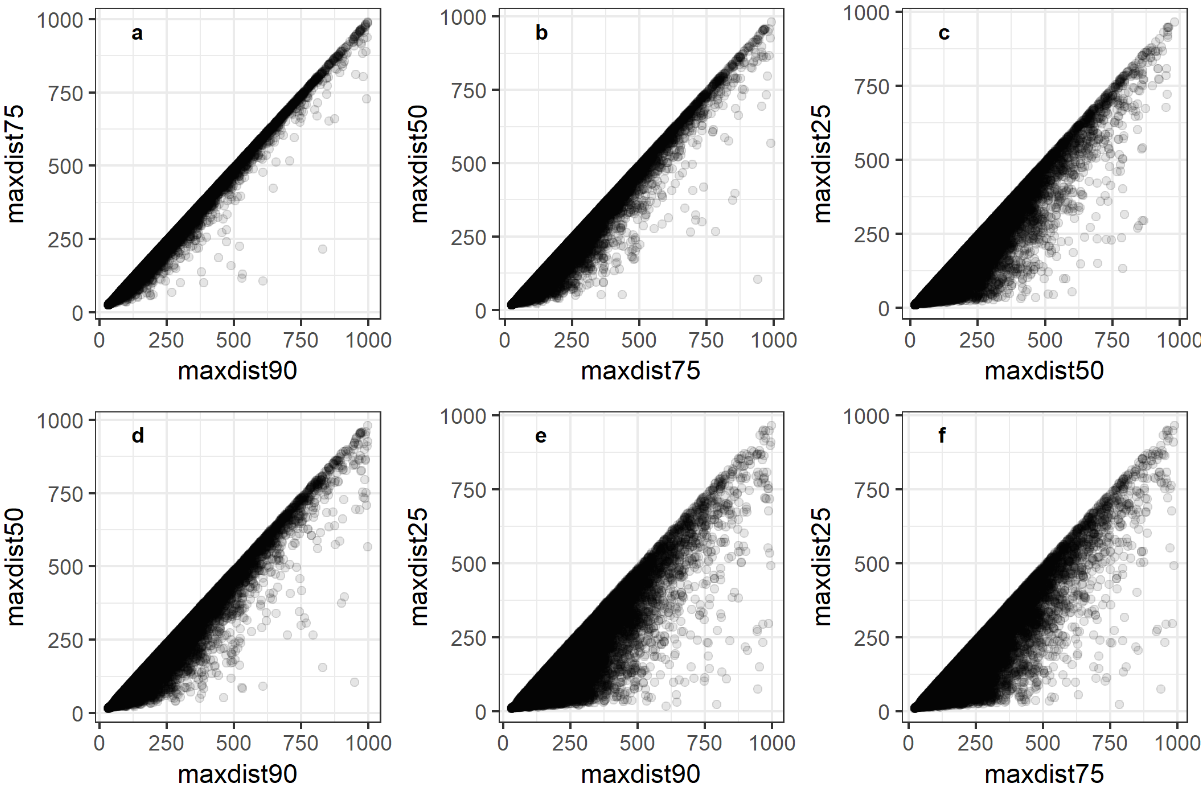


Figure 22.Relationship between the MaxDist indicator derived from 90%, 75%, 50% and 25% KUD isopleths. a) 90 vs 75, b) 75 vs 50, c) 50 vs 35, d) 90 vs 50, e) 90 vs 25, f) 75 vs 25

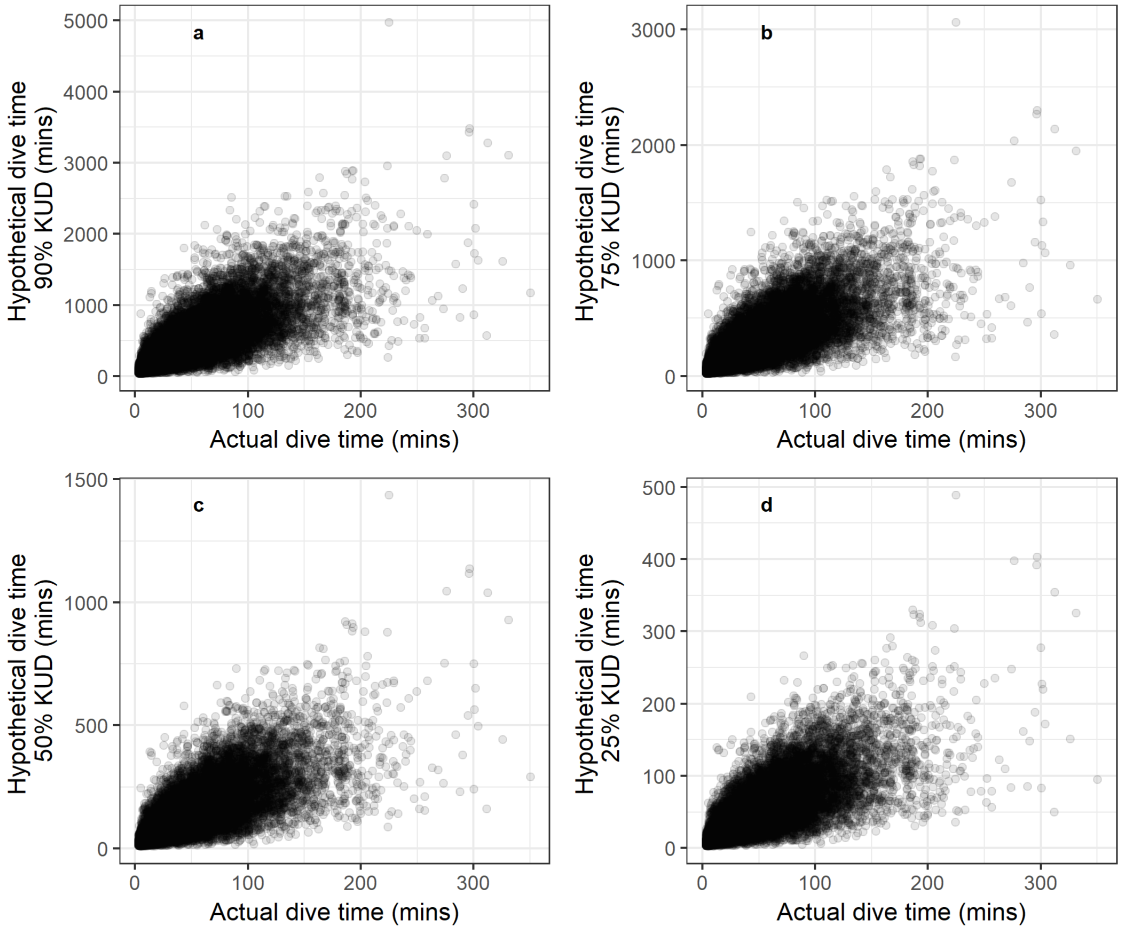


Figure 23. Relationship between actual dive time (X axis) and the hypothetical dive time (Y axis) based on the area of a given KUD isopleth. a) 90% isopleth; b) 75% isopleth; c) 50% isopleth; d) 25% isopleth.

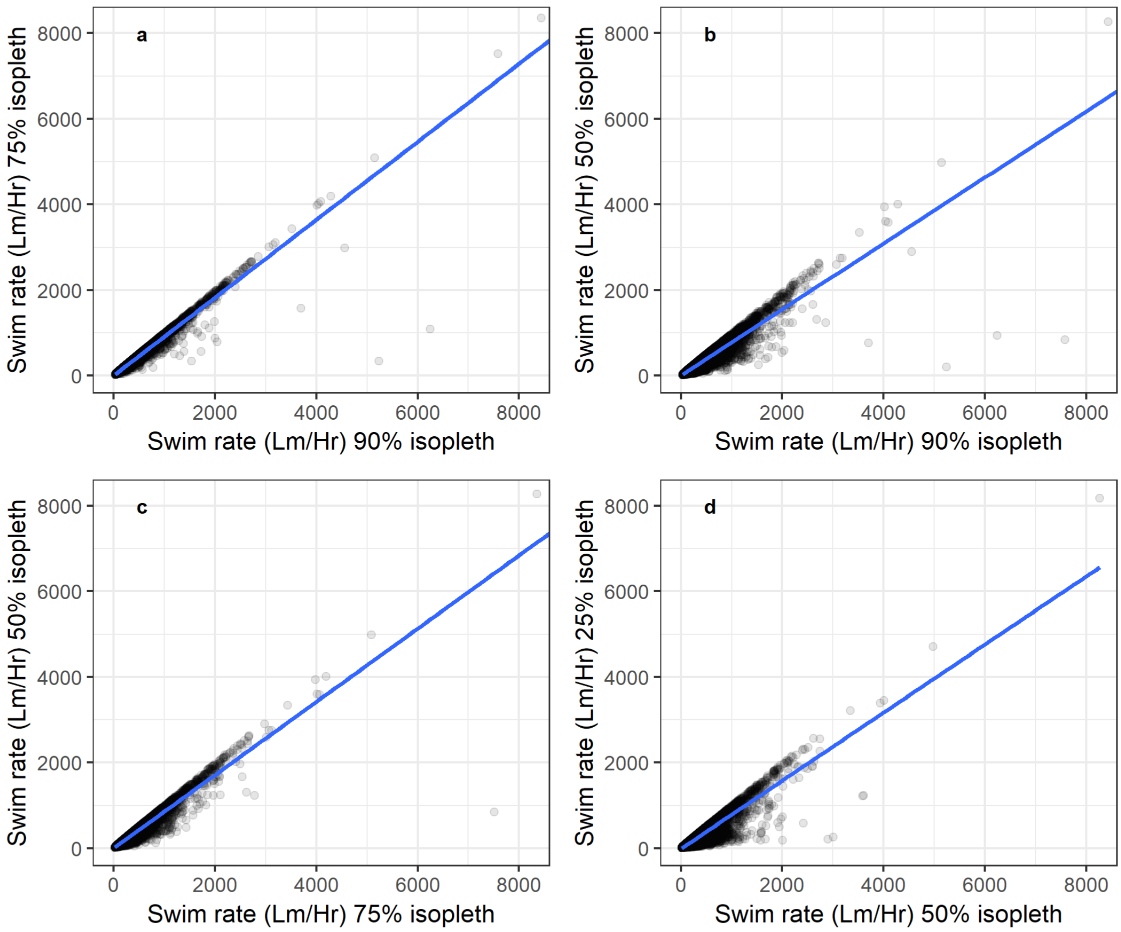


Figure 24. Relationship between swim rate Lm/hr spatial indicator variable calculated from different KUD isopleths. a) 90% vs 75%; b) 90% vs 50%, c) 75% vs 50%, d) 50% vs 25%.

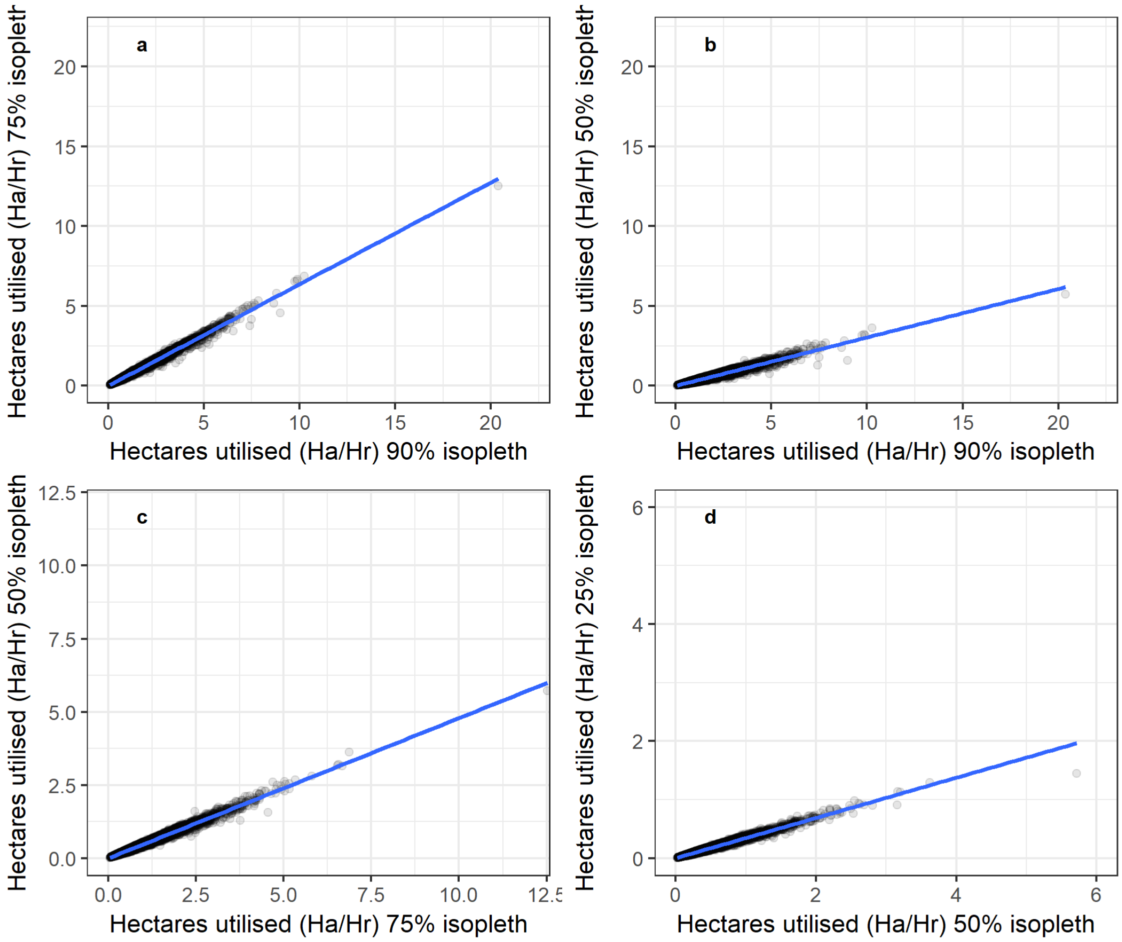


Figure 25. Relationship between Hectare/Hr spatial indicator variable calculated from different KUD isopleths. a) 90% vs 75%; b) 90% vs 50%,

7. Spatial structure of fishing: spatial autocorrelation, hotspots and outlier cells

Author: Craig Mundy

7.1. Introduction

Abalone fisheries are thought to be highly spatially structured with individual fishing events occurring over relatively short sections of reef, driven by habitat patchiness, sea conditions, abundance of the target species, and time limitations imposed by depth. Haliotids also have biological and ecological characteristics (limited immigration/emigration and localised larval dispersal) that further contribute to the notion of a highly structured stock. Tobler's first law (TFL) of geography states '*everything is related to everything else, but near things are more related than distant things*'. TFL has largely held up across a broad range of applications (Miller 2004), but the definition of TFL in itself was intentionally a little vague (Tobler 2004). Of interest here is whether Tobler's first law applies to abalone fisheries, and, the scale at which local homogeneity decays to randomness. Analysis of fishery-independent research survey datasets suggest there is high levels of local heterogeneity in abundance, exhibited as substantial variation in abundance of abalone among replicate transects within sites (Mundy et al. 2006). Whether this observed micro-scale variation in heterogeneity propagates through to local heterogeneity in harvest has not previously been addressed quantitatively. Several classical approaches may be used to examine and quantify spatial structure, and the extent to which TFL applies to abalone fisheries. In this chapter we explore patterns in spatial structure of annual harvest across a grid of 1 Hectare cells using spatial autocorrelation methods.

7.2. Methods

7.2.1. Testing for presence of spatial auto-correlation

Evidence of spatial structure is explored through a cascading series of analyses. Firstly, presence of global spatial autocorrelation using Moran I was examined in the hexagonal grid dataset, using the centroid as the geographic reference point for each cell. Where global Moran I is significant, the scale of spatial structure was further explored using correlograms.Local Indicators of Spatial Autocorrelation (LISA) were then used to identify clusters of high and low catches (hotspots and coldspots) and outlier regions using Local Moran I. Significant hot/cold spots are areas where the neighbouring hex cells are highly positively correlated with the target cell (hot/hot or cold/cold). Whereas outlier cells are identified as target cells which are highly negatively correlated with the neighbouring cells (hot/cold or cold/hot).

Input data for the investigation of spatial autocorrelation was a SpatialPolygonDataFrame (SPDF) of one Hectare hexagonal polygon grid cells covering the extent of the fishery. The SPDF contains variables of interest at the grid level, including total annual harvest per cell, for each year from 2012 to 2016 inclusive. In this analysis, the dependent variable of interest is total catch in Kg of abalone per cell. Cells that contained more than 25Kg total catch pooled over the five-year study period were included in the analysis. Data were analysed for blocks 13, 22, 24 and 29 from the Eastern Zone and blocks 9, 10, 11 and 12 from the Western Zone, using kg Landed in 2016 as the dependent variable.

For each fishing block, a D-Nearest Neighbour object was created in R (R-Core-Team 2017) using package `spdep` (Bivand et al. 2011) with a distance band of 107 m, which captures the six adjoining hex cells to each target hex cell. Global Moran I was calculated using `spdep` and significance testing done by permutation (Bivand et al. 2011). Spatial correlograms were calculated in `spdep` with 15 lag distances. The primary SPDF data were then exported to GeoDa (Anselin et al. 2006) using the GeoPackage (Open-Geospatial-Consortium 2018) driver implemented in `rgdal` (Bivand et al. 2015).

7.2.2. Examining temporal correlation in the harvest

Of considerable interest is whether catch or effort in grid cells are correlated among years. Temporal correlation in patterns of harvest were examined by calculating Lee's L (Lee 2001, 2004), using R package `spdep` (Bivand et al. 2011), and using the D-nearest neighbour object obtained from Section 7.2.1 above. Lee's L integrates the Pearson's correlation coefficient and Moran I coefficient, to enable a robust test for correlation between two time periods, taking into account any spatial autocorrelation. Lee's L ranges between -1 and 1, and significance is tested by permutation (n = 1000).

7.3. Results and Discussion

7.3.1. Global spatial structure

Global Moran I was statistically significant in all major blocks examined, confirming that spatial structure of fishing effort is non-random and that there is significant spatial structure in abalone fisheries (Table 3). Moran I was much lower in Western Zone blocks compared to Eastern Zone blocks, suggesting the magnitude and intensity of spatial structuring differed between the two zones examined.

7.3.2. Magnitude of spatial structuring of catch

Detailed investigation of spatial structure of catch via Spatial Correlograms identified a clear difference in the scale of spatial structuring between the Eastern and Western zones. All four blocks examined within the Eastern zone displayed significant positive Moran I values at lag numbers up to at least 7, and up to 15 for block 13 (Figure 26). In contrast, Western zone blocks displayed significant Moran I values at only the first two lag numbers, except for block 12, which displayed a spatial structure similar to that observed in Eastern Zone blocks (Figure 27). Moran I at the first lag distance was greater than 4 in all Eastern Zone blocks, but Moran I was less than 4 in three of the four Western zone blocks, with block 12 again as the anomaly. Within

Block 12, the overall block spatial structure results appear to be driven by spatial patterns in Sub-Block 12C (Figure 28), which currently is the most productive part of Block 12 and has the highest mean CPUE.

Table 3. Global Moran I for key fishing blocks in the Western and Eastern Zones of the Tasmanian Abalone fishery. Moran I was based on a D nearest neighbour network, with D set at 107 m which identifies the six adjoining hexagonal cells to each target cell in the grid.

ZONE	BLOCK	MORAN I	P-VALUE
EASTERN	13	0.66	0.001
	22	0.48	0.001
	24	0.42	0.001
	29	0.55	0.001
WESTERN	9	0.25	0.001
	10	0.27	0.001
	11	0.25	0.001
	12	0.47	0.001

There are several plausible explanations for the differing patterns across the two zones. The patterns could be indicative of the relative status (depleted, recovering, healthy) of the two fisheries, be a product of the pattern of exploitation (e.g. weather limitations on access to reefs), or be substantially driven by habitat related productivity. Fisheries experiencing consistently high levels of fishing mortality may now have a more homogenous spatial structure, whereas fisheries that are healthy may show more spatial heterogeneity in spatial structure as local populations increase or decline. Under this hypothesis, Eastern Zone Block 13 would be expected to show a pattern more similar to the Western Zone blocks, given CPUE is increasing and continues to be productive. Patterns in Block 13 will however be dominated by sub-block 13E, which has a large and unusual two-dimensional reef structure. The alternative explanation is that these differing patterns in spatial structure are driven by habitat type, with larger areas of more uniform habitat type on the East than the West. Reef type in the Eastern blocks examined here is primarily complex dolerite and granite boulder strips with interspersed with large slab reef. The Western Zone blocks are largely on quartzite parent rock with a range of ridge and boulder habitats that may be more fragmented.

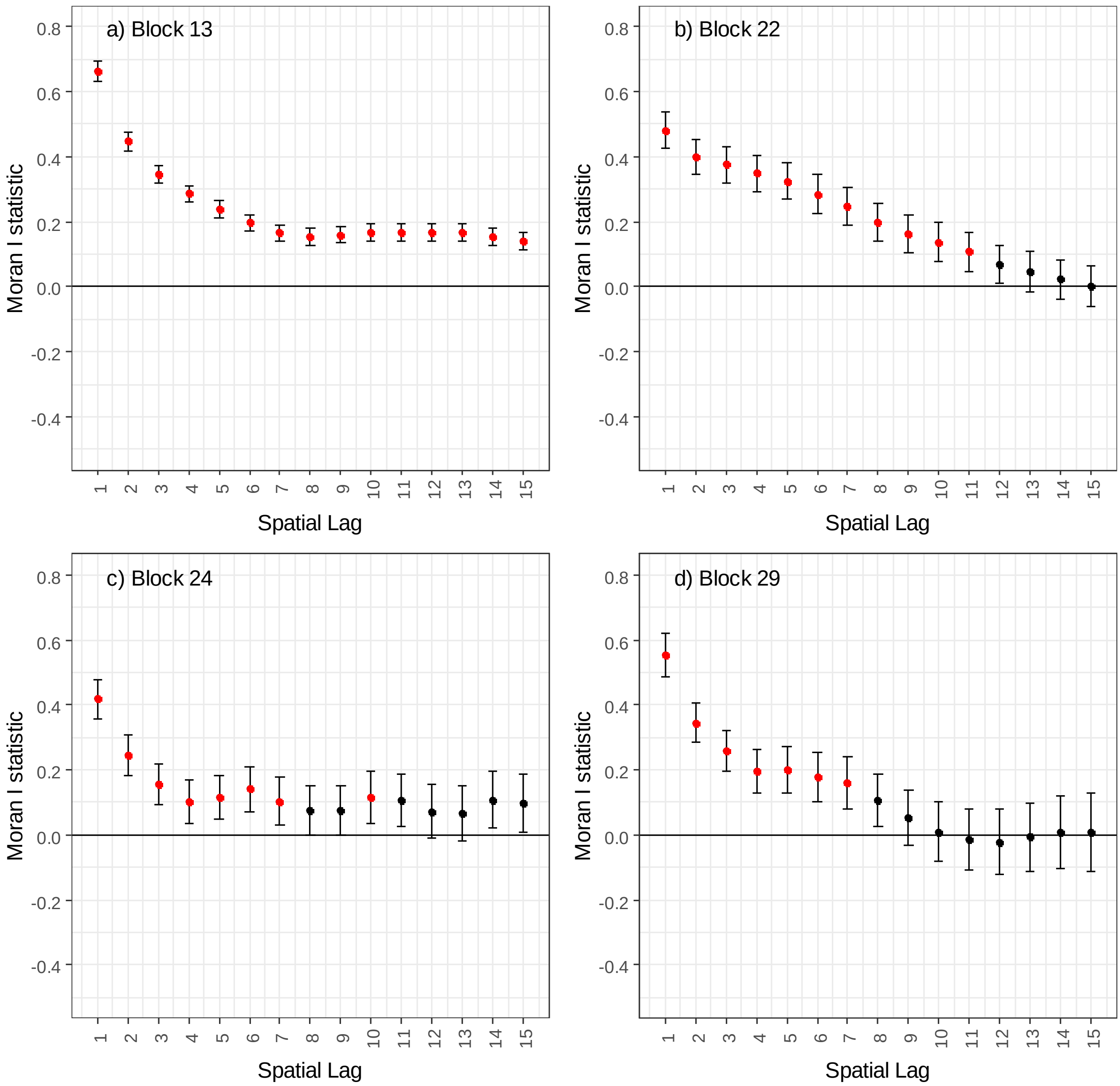


Figure 26. Spatial corellogram of 2016 blacklip harvest per cell, with 15 lag intervals for Eastern Zone blocks (13, 22, 24, 29). Red dots indicate significant departure of Moran I from zero (NB. Each lag number equates to ~ 107 metres).

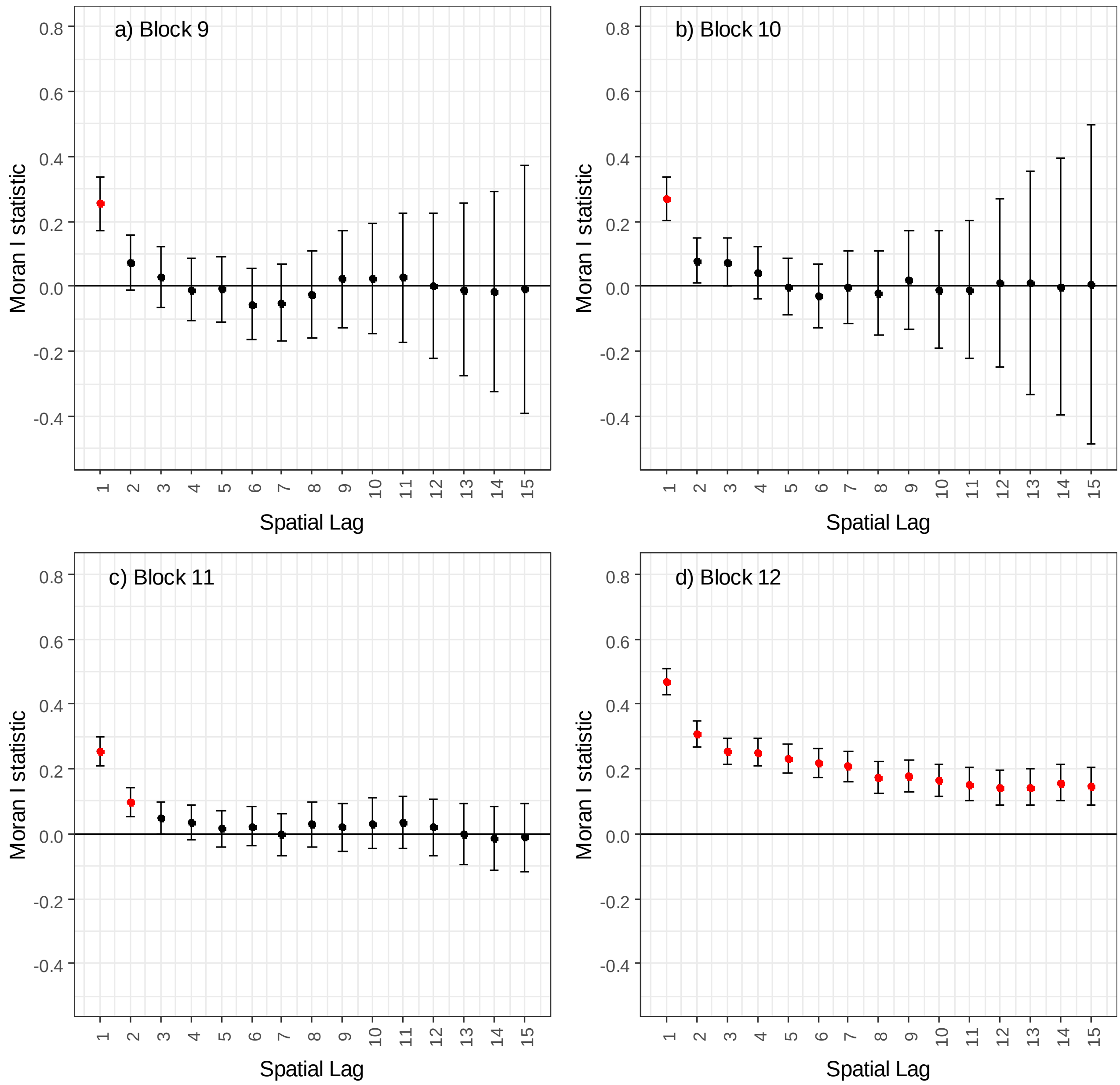


Figure 27. Spatial Corellogram of 2016 blacklip harvest per cell, with 15 lag intervals for Western Zone blocks (9, 10, 11, 12). Red dots indicate significant departure of Moran I from zero (NB. Each lag equates to ~ 107 metres).

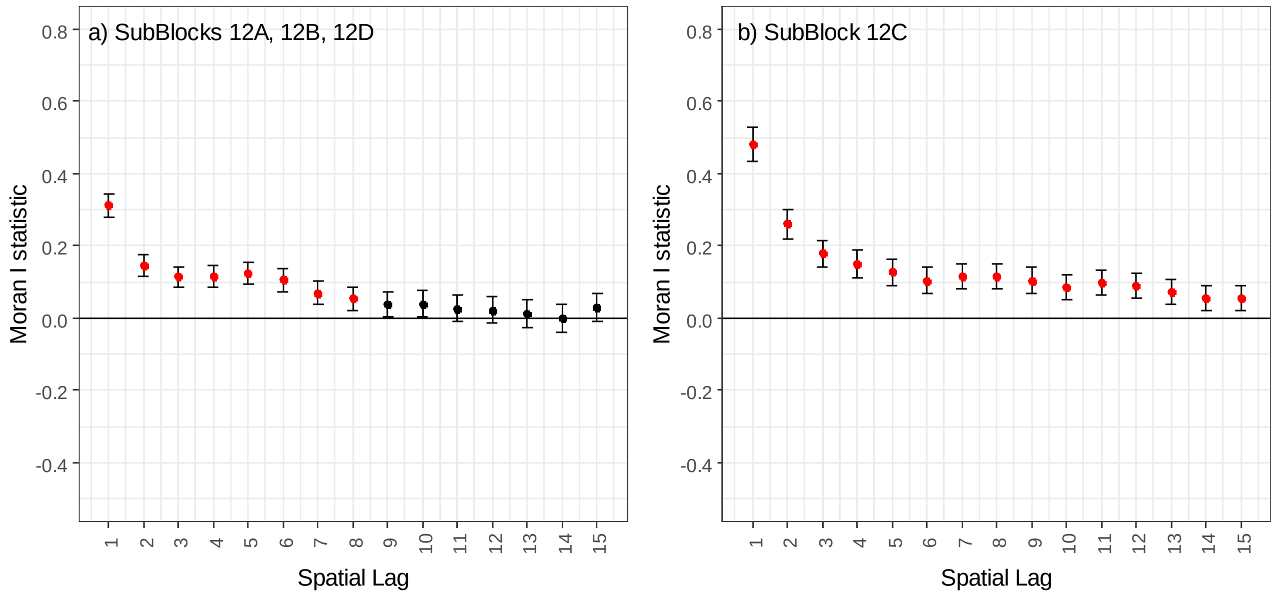


Figure 28. Spatial corellogram of 2016 blacklip harvest per cell, with 15 lag intervals for Western Zone block 12; a) subblocks 12A, 12B, 12D, b) subblock 12C. Red dots indicate significant departure of Moran I from zero (NB. Each lag number equates to ~ 107 metres).

7.3.3. Hotspots, coldspots and outliers

Thematic maps with color-ramped indicators of variables of interest can provide a useful means of data exploration. Local Indicators of Spatial Auto-correlation (LISA) statistics are also useful tools to identify spatially contiguous areas with similar properties (hotspots, coldspots) but also outlier areas that don't conform to expectation. LISA methods have an additional advantage in providing permutation-based classification of data into groups which could be used as a spatial indicator. Here we apply LISA methods to the spatial grid dataset of Kg landed per one hectare hexagon in 2016. A thematic map of catch landed per hexagon cell in Block 13 Eastern Zone illustrates areas of high and low catch, and that there are clusters of high cells and low cells (Figure 29a). LISA analysis identifies some of these patches as significant hot and cold spots (Figure 29b), but also large areas where there is no substantial local correlation. Proportionally, Local Moran I for most hexagon cells in both Western and Eastern Zone fisheries is not significant (Table 4), and there are relatively few cells that have high catches where their neighbours also have high catches (typically < 10%). Block 13 Eastern Zone however has almost double the proportion of High-High catch cells compared to all other blocks tested. The Eastern and Western Zones show different patterns in the proportion of Low-Low cells across the fished area. Between 12% and 17% of cells in the Eastern Zone blocks were classified as Low-Low, whereas in the Western Zone the proportion of Low-Low cells was 5% or less.

The Eastern and Western Zone fisheries again display different spatial structure, with commonalities across blocks within each zone. LISA analyses identified a greater proportion of Coldspots (Low-Low clusters) in the Eastern Zone. This outcome is consistent with the lower CPUE and depleted state of most of the Eastern Zone fishery (Mundy & Jones 2017). Block 13 is clearly different from all other blocks, with up to 14% of cells clustering in HotSpots.

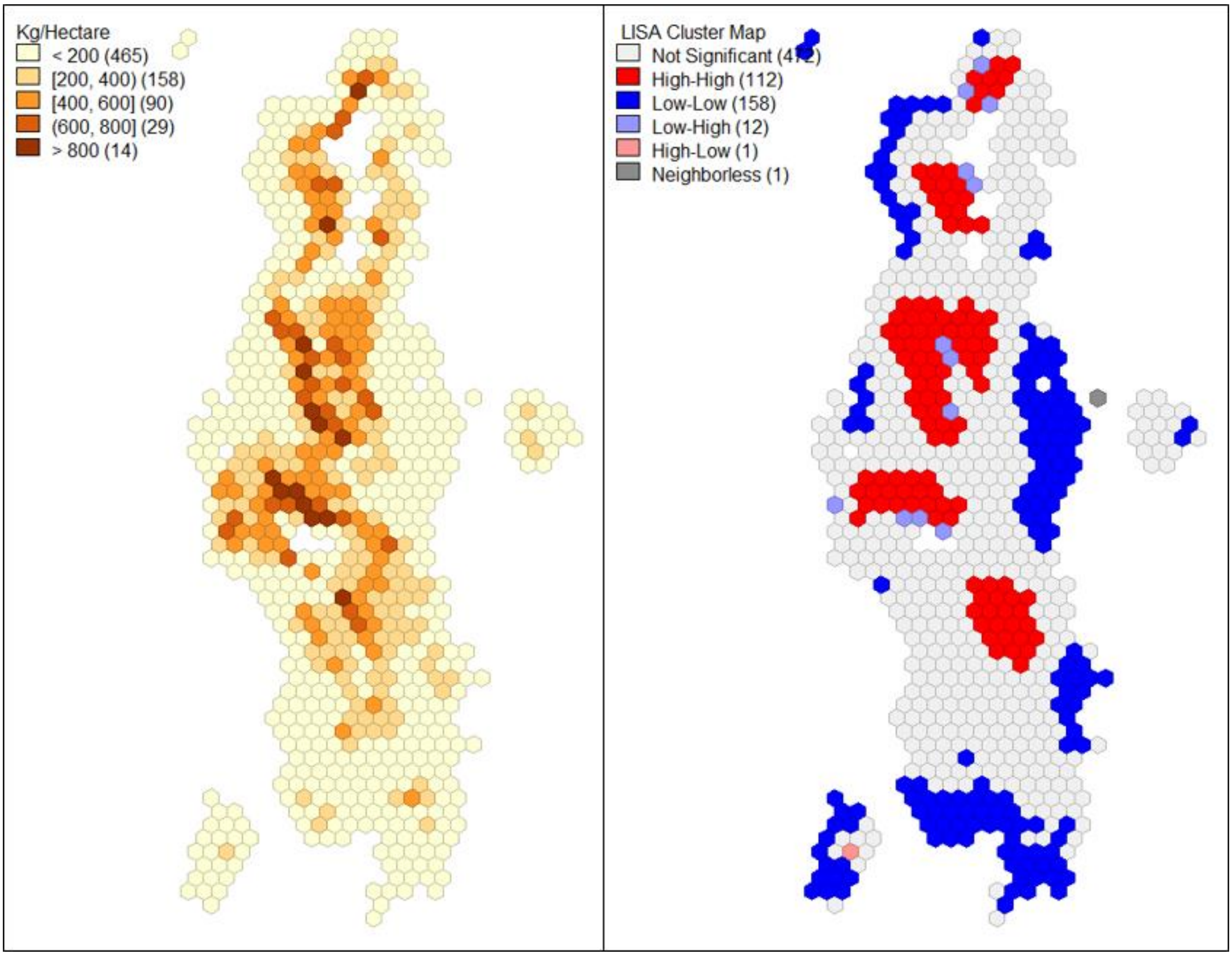


Figure 29. Thematic map of Kg/Hectare harvest from sublock13E during 2012 and matching LISA cluster map. Left panel displays annual harvest per 1 Hectare cell in 5 colour bands with 200Kg increments. Right Panel displays the colour coded LISA category for each cell. Locations of hotspots and coldspots change through time. For confidential reasons, the thematic catch and LISA maps are based on 2012 for graphical illustration, whereas the analyses presented in Table 4 are based on the 2016 dataset.

Table 4. Proportion of cells Cell in each of five LISA categories for annual harvest in 2016. NS = Non-significant, H-H = High-High, L-L = Low-Low, L-H = Low-High, H-L = High-Low, NO-NB = No neighbours.

Zone	Block	Total Cells	NS	H-H	L-L	L-H	H-L	No-Nb
Eastern	13	1659	0.67	0.14	0.17	0.01	0.00	0.01
	22	761	0.80	0.06	0.12	0.02	0.00	0.00
	24	769	0.77	0.07	0.12	0.03	0.00	0.01
	29	508	0.76	0.05	0.15	0.03	0.00	0.01
Western	9	468	0.84	0.05	0.03	0.03	0.00	0.04
	10	749	0.85	0.07	0.03	0.03	0.00	0.03
	11	1518	0.84	0.06	0.04	0.03	0.01	0.02
	12	1725	0.82	0.09	0.05	0.02	0.01	0.01

7.3.4. Temporal correlation in harvest

In Section 7.3.3 we demonstrated the existence of a small proportion of areas in each fishery as hotspots and cold spots. Of further interest is the likelihood that these patterns are persistent through time i.e. cold spots are always coldspots. One approach to this question is to use simple measures of correlation, as positive correlations among years could be assumed to indicate temporal stability in the spatial distribution of effort, and or, temporal stability in spatial productivity of populations. Lee's L follows a similar pattern to Moran I. Accounting for spatial autocorrelation, Eastern Zone displays higher levels of inter-annual correlation (double) than the Western Zone. While Block 12 Western Zone showed a spatial structure more similar to the Eastern Zone, the temporal pattern in correlation of harvest is consistent with other western zone blocks.

Table 5. Lee's L tests of local correlation in catch between2013 and 2014, and between 2015 and 2016, accounting for any spatial autocorrelation.

ZONE	BLOCK	2013 VS 2014		2015 VS 2016	
		Lee's L	p-value	Lee's L	p-value
EASTERN	13	0.54	0.001	0.50	0.001
	22	0.47	0.001	0.64	0.001
	24	0.34	0.001	0.23	0.02
	29	0.39	0.001	0.57	0.001
WESTERN	9	0.21	0.001	0.29	0.01
	10	0.18	0.001	0.21	0.001
	11	0.19	0.001	0.21	0.001
	12	0.14	0.001	0.27	0.001

8. Is harvest at local scales affected by fishing history?

Author: Craig Mundy

8.1. Introduction

In chapter 7, we demonstrated that abalone harvest was spatially structured at very local scales, but at moderate distances there was no autocorrelation present. We also found that the scale of structuring was different between the Western and Eastern Zone fisheries. The divergence in spatial structure between the two zones was also evident in metrics of temporal correlation. Together these findings suggest further exploration of the spatial and temporal dynamics and/or scaling effects in catch across fishing grounds is required to understand how best to make use of spatially mapped catch as a predictive variable. If there is no persistent relationship in local catch among years, then utilising local scale catch from the current year as a basis for future catch becomes problematic. Understanding the consequences of previous fishing activity on future catch is also important for example, if high levels of harvest at a local scale in one year are followed by reduced levels of harvest in the following year.

The inter-annual patterns in local catch may change as stock levels increase or decrease. When stocks are high, and TACC is below the sustainable harvest fraction, prior fishing effort is unlikely to dampen subsequent fishing activity, and some populations may remain unfished. When stocks are declining, catch may be depressed at the local scale where fishing pressure exceeds locally sustainable levels and negative coefficients may be expected. At very low stock levels, the relationship may switch back to positive coefficients, as all parts of the fishery revert back to natural production, with all areas being fished i.e. the TACC set is approximately equal to or greater than the sustainable harvest fraction. The local scale patchiness in habitat quality and environmental conditions combined with abalone biology are expected to generate some level of spatial autocorrelation and spatial structure in harvest data. Whether environmental drivers over ride fishing history as the major determinant of future catch has not been explored empirically.

Regression methods provide an opportunity to explore the extent to which local catch can be explained by prior fishing history. Contrasting Ordinary Least Squares regression with two forms of spatial regression (spatial autoregressive models and geographic weighted regression), can highlight the contribution of local spatial dynamics, to the empirical relationship between catch and fishing history. Parametric analyses assume that samples and/or error terms are independent. With spatially derived datasets, this assumption is likely to be compromised unless spatial autocorrelation is accounted for. When addressing spatial autocorrelation in datasets, the appropriate analytical approach is dependent on whether spatial variation is of inherent interest or considered a nuisance factor, and whether the autocorrelation affects either the dependent or independent variables, or both. In the case of spatial heterogeneity in the data where nearby observations are affected by (or effect) neighbouring observations, we would apply a Spatial Lag model (Ward and

Gleditsch 2008). Spatial Lag models effectively treat spatial variation, as a component of interest. In the case of spatial dependence where data are linked to neighbouring data through an unspecified process, we apply a Spatial Error model. Spatial error models are often referred to as mis-specified models because there are factors of importance that have not been captured that affect the local value of data. For this reason, spatial error models treat spatial autocorrelation as a nuisance factor. Where the spatial influence is considered to act on both the independent and dependent variables, then a Spatial Durbin model is more appropriate. There seem few plausible arguments that the magnitude of catch level in one grid cell could have a direct affect in a neighbouring grid cell in the same year (i.e. Spatial Lag Model). More likely, catch in a grid cell is locally correlated either because habitat allows similar levels of productivity, or, the local scale of targeted fishing drives high and low intensities of fishing pressure (i.e. Spatial Error Model, or Spatial Durbin Model). In this chapter we explore the application of spatial regression methods to quantify the relationship between prior fishing history and catch at the local scale. Geographic Weighted Regression (GWR) seeks to account for non-stationarity in the dataset using a form of moving window regression, and has some similarity to the approach used for Regression Kriging. GWR is a relatively new method in the regression family and has been suggested as a useful exploratory analysis tool, with some caution advised on interpretation of results.

8.2. Methods

8.2.1. Prior harvest as a predictor of future harvest

Our specific interest here is whether fishing history in recent years is a strong driver of catch in future years at the local scale. To achieve this, we explored catch per one Ha grid cell between 2013 and 2015 (independent variables) to explain catch per cell in 2016 (dependent variable). Four different models were tested to explore the relationship between catch landed in 2016 and fishing during the previous three years; 1) 2016 ~ 2015, 2) 2016 ~ sum(2015, 2014), 3) 2016 ~ sum(2015, 2014, 2013), and 4) 2016 ~ 2015 + 2014 + 2013. We used a simple linear model (OLS) as a starting point, acknowledging that we are likely to have both temporal and spatial auto-correlation concerns. Geographic Weighted Summary Statistics (GWSS) and Geographic Weighted Regression (GWR) was applied to the hexagonal grid dataset using the R package `GWmodel` (Lu et al. 2014, Gollini et al. 2015).

Three spatial management units are used to contrast different reef structures. Fishing sub-block 6C is a relatively small but productive reef system on Tasmania's North West coast. Fishing sub-block 13E is a large two-dimensional fishing ground approximately 8Km long and 1.5Km wide. Fishing sub-block 11C is comprised of a mix of linear coastal reefs and offshore reefs. The total fished area and total landed weight of Blocks 11 and 13 are approximately equal, although CPUE in block 11 is approximately double the observed CPUE in Block 13. In Chapter 7 we found the highest level of spatial autocorrelation at the first lag number (i.e. adjacent hex cell neighbours to the target cell of interest). A D-nearest neighbour network was built using a distance *D* of 108 m, with a starting distance of 0 m (see section 7.2) and converted to a spatial weights matrix for the spatial autoregressive model. A bandwidth of 108 m was also used for the Geographic Weighted Regression to be comparable.

8.3. Results and Discussion

8.3.1. Evidence of heterogeneity in local correlation among years

Mapping of geographic weighted summary statistics (GWSS) suggests strong spatial structure in correlation between the dependent variable (catch in 2016) and the three independent variables (catch in each of 2013, 2014, and 2015) (Figures 30, 31). In both the north-west and south-east example, local areas of high correlation are observed, along with regions of no correlation or mild negative correlation. While spatial pattern in local correlation varies across years, broad regions of strong positive or neutral correlation appear to be persistent.

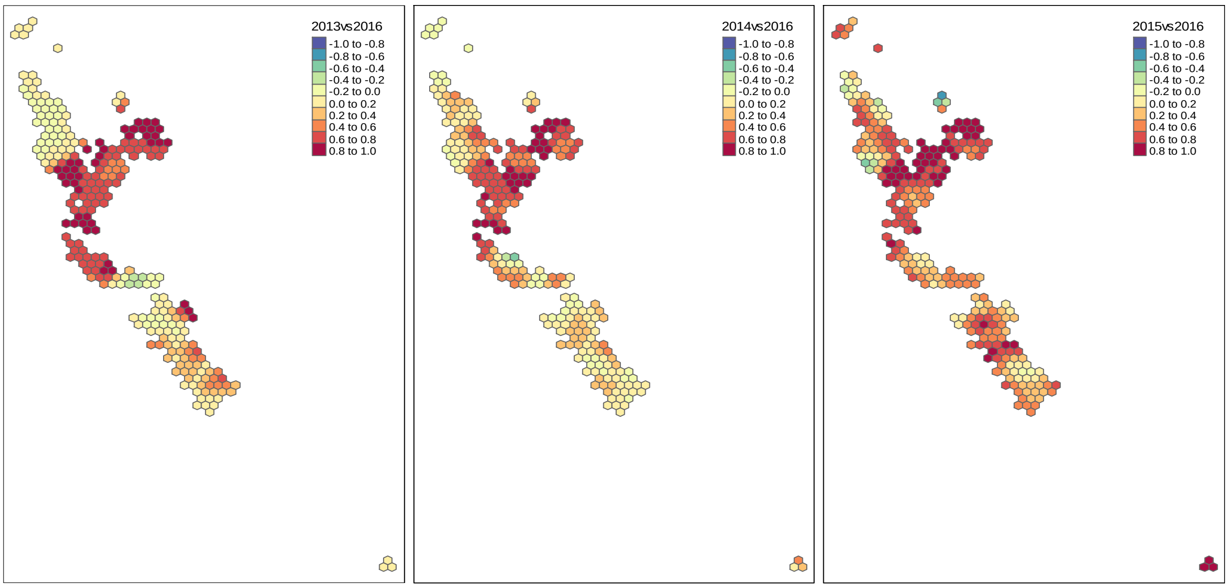


Figure 30. Local correlation in annual catch harvested among years in fishing sub-block 6C, North West Tasmania. Left: 2013 vs 2016, Middle: 2014 vs 2016, Right: 2015 vs 2016. Magnitude of the local correlation coefficient (-1 to 1) indicated by colour ramp.

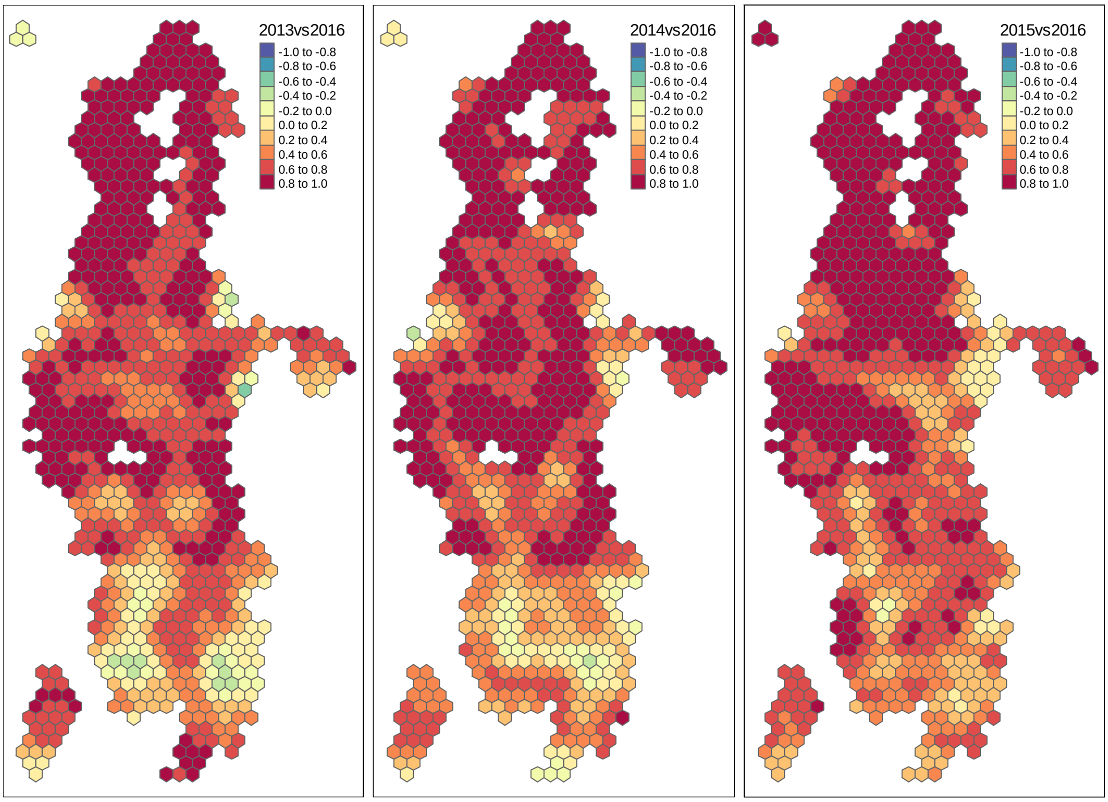


Figure 31. Local correlation in catch harvested among years in fishing sub-block 13E, South East Tasmania. Left: 2013 vs 2016, Middle: 2014 vs 2016, Right: 2015 vs 2016. Magnitude of the local correlation coefficient (-1 to 1) indicated by colour ramp.

8.3.2. Evidence of non-stationarity

Geographic weighted regression demonstrated clear evidence of non-stationarity in all three case studies (Sub-block 6C, 11C, and 13E). Adjusted R^2 was always higher and AIC was lower for GWR compared to OLS for all four models tested (Tables 6, 7, and 8). The full model with catch in 2013, 2014 and 2015 as independent variables achieved the highest Adjusted R^2 for both OLS and GWR, and this model is used here for further exploration of spatial pattern in catch (note figures are not provided for sub-block 11c for reasons of brevity). Studentised residuals did not show any strong spatial clustering (Figures 32, 33), whereas clustering of high and low Local R^2 was much more apparent (Figures 32, 33). Mapping of coefficients identify clear interannual variation in sign and magnitude at the local scale (Figures 34, 35) at sub-block 6C and sub-block 13E.

Collectively these results demonstrate substantial spatial non-stationarity in the relationship between catch in a target year and the catch in previous years and highlight the difficulty in utilising prior fishing history as a predictor of future catch. The fit of the third model tested (2016 Catch ~ sum(2015 + 2014+ 2013) which captures the previous three years of fishing effort in one variable was only marginally less than the optimum full model. Use of a multi-year pooled variable may have better application as a generic model, assuming that overall there is temporal consistency in the spatial pattern of coefficients. This would need further exploration to determine whether there was a generally applicable relationship. Use of the data in this way will be dependent on a high level of data capture across years, and variation in data also may compromise the overall capacity of this approach.

Table 6. Comparison of linear modelling and Geographic Weighted Regression for fishing sub-block 6C on Tasmania's North West coast. The variables $yHat_{LM}$, $yHat_{GWR}$, and Catch are for the 2016 fishing year.

Formula	$AdjR^2_{LM}$	$AdjR^2_{GWR}$	AIC_{LM}	AIC_{GWR}	$yHat_{LM}$	$yHat_{GWR}$	Catch
2016 ~ 2015	0.25	0.60	1726	1454	14.67	17.08	19.34
2016 ~ sum(2015 + 2014)	0.40	0.71	1650	1350	15.69	17.77	19.34
2016 ~ sum(2015 + 2014 + 2013)	0.44	0.72	1633	1347	15.88	17.8	19.34
2016 ~ 2015 + 2014 + 2013	0.45	0.73	1634	1265	15.92	18.17	19.34

Table 7. Comparison of linear modelling and Geographic Weighted Regression for a section of reef in sub-block 13E on Tasmania's South East coast. The variables $yHat_{LM}$, $yHat_{GWR}$, and Catch are for the 2016 fishing year.

Formula	$AdjR^2_{LM}$	$AdjR^2_{GWR}$	AIC_{LM}	AIC_{GWR}	$yHat_{LM}$	$yHat_{GWR}$	Catch
2016 ~ 2015	0.68	0.87	4562	3722	152.65	161.03	166.5
2016 ~ sum(2015 + 2014)	0.73	0.89	4433	3599	154.71	161.82	166.5
2016 ~ sum(2015 + 2014 + 2013)	0.76	0.89	4347	3547	155.91	161.80	166.5
2016 ~ 2015 + 2014 + 2013	0.76	0.90	4346	3357	155.98	163.53	166.5

Table 8. Comparison of linear modelling and Geographic Weighted Regression for fishing sub-block 11C on Tasmania's South West coast. The variables $yHat_{LM}$, $yHat_{GWR}$, and Catch are for the 2016 fishing year.

Formula	$AdjR^2_{LM}$	$AdjR^2_{GWR}$	AIC_{LM}	AIC_{GWR}	$yHat_{LM}$	$yHat_{GWR}$	Catch
2016 ~ 2015	0.11	0.56	5621	4688	26.61	36.02	44.28
2016 ~ sum(2015 + 2014)	0.17	0.62	5560	4561	27.68	37.25	44.28
2016 ~ sum(2015 + 2014 + 2013)	0.18	0.63	5542	4530	27.98	37.74	44.28
2016 ~ 2015 + 2014 + 2013	0.17	0.67	5552	4180	27.88	39.57	44.28

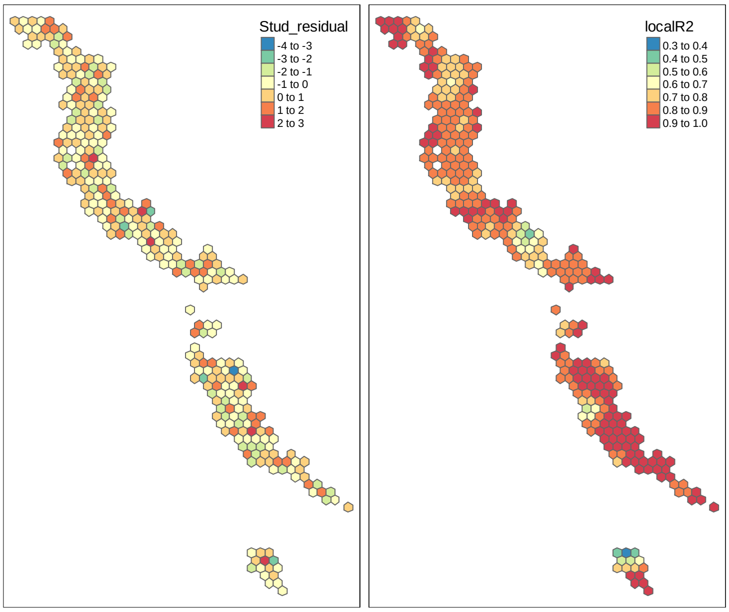


Figure 32. Studentised residuals and local R^2 from a Geographic Weighted Regression analyses of annual catch in fishing sub-block 6C, North West Tasmania. GWR model: 2016 ~ 2015 + 2014 + 2013. Left: Studentised Residuals, Right: Local R^2.

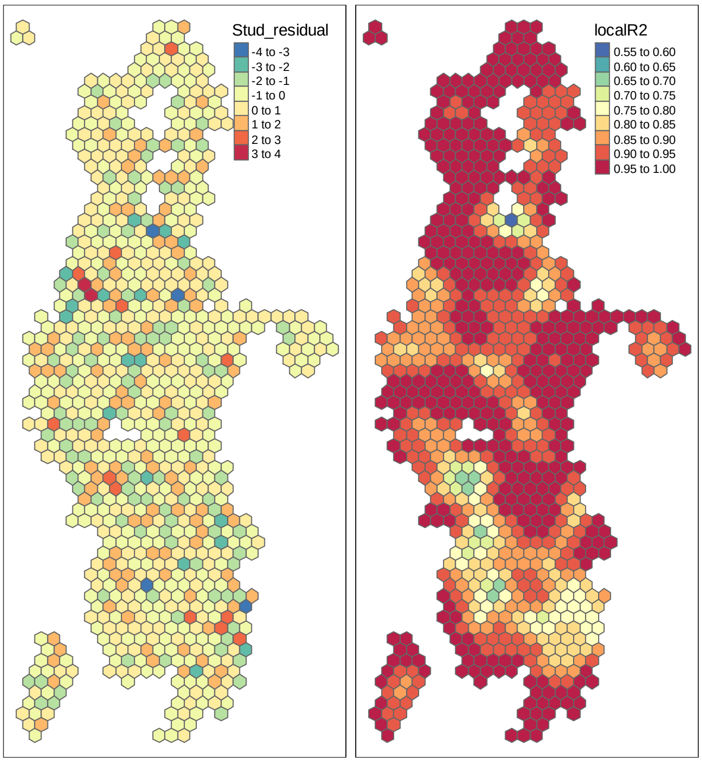


Figure 33. Studentised residuals and local R^2 from a Geographic Weighted Regression analyses of annual catch in fishing sub-block13E, South East Tasmania. GWR model: 2016 ~ 2015 + 2014 + 2013. Left: Studentised Residuals, Right: Local R^2.

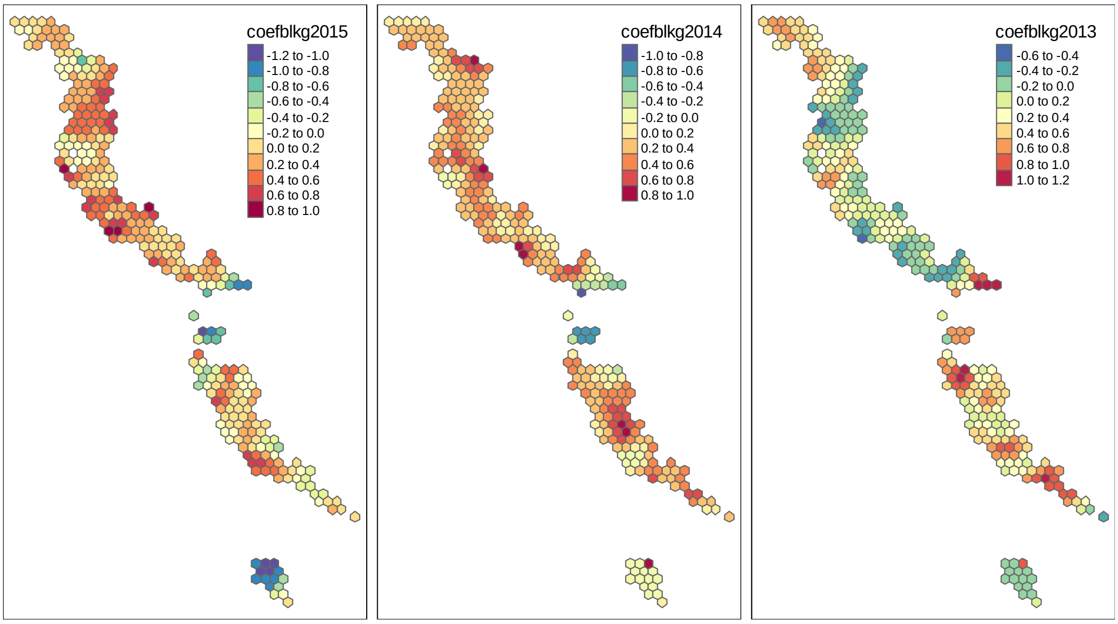


Figure 34. Coefficients for independent variables (catch 2013, 2014, 2015) included in the Geographic Weighted regression of 2016 catch in sub-block 6C.

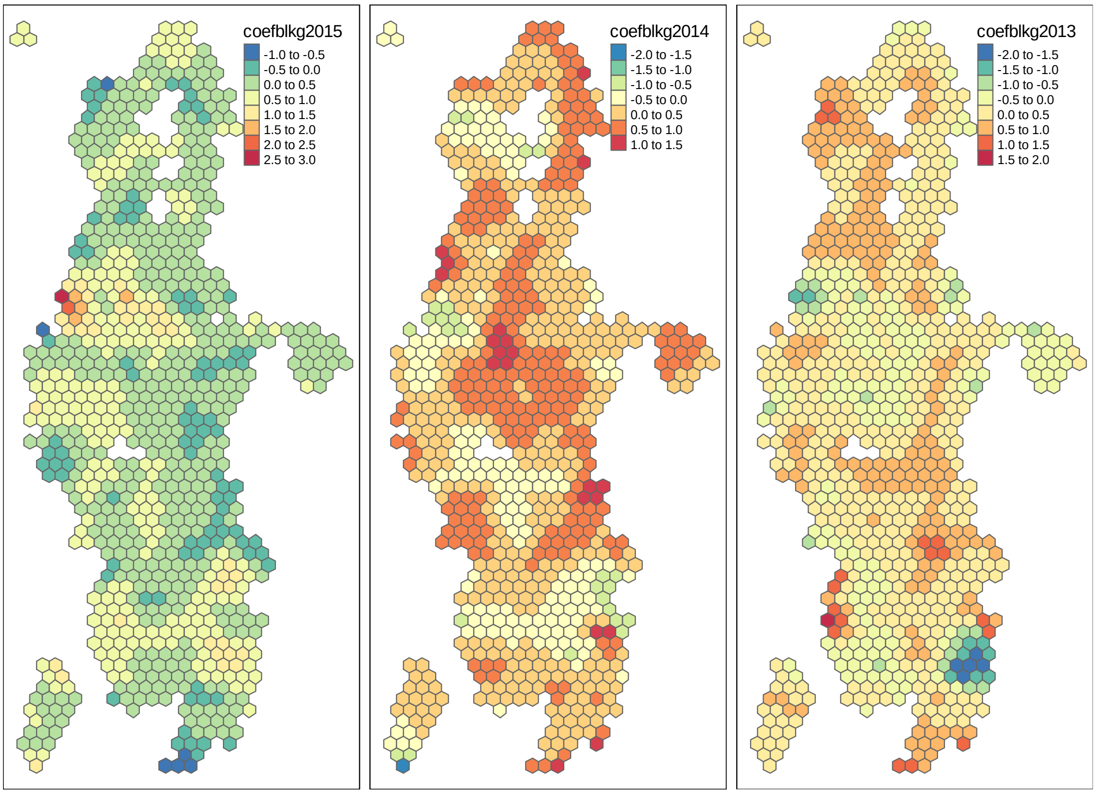


Figure 35. Coefficients for independent variables (catch 2013, 2014, 2015) included in the Geographic Weighted regression of 2016 catch in sub-block 13E.

9. Development of an Index of Persistence (IOP) for quantifying reef resilience.

Author: Hugh Jones and Craig Mundy

9.1. Introduction

Dive fisheries are part of a group of small-scale benthic fisheries known as 'S-fisheries' (Orensanz et al. 2005) that are characterised by complex spatial heterogeneity of stocks and location specific effects of harvest (Fernández-Boán et al. 2013). To understand the effects of such fisheries on stocks and ecosystems, fisheries data needs to be spatially resolved at a much finer scale than is currently acheived (Russo et al. 2013). Increased spatial resolution assists in the sub-division of fishing effort and identification of meta-populations, thereby providing opportunities for reducing uncertainty in any stock assessments. Abalone (*Haliotis sp.*) represent an important example of such dive fisheries and identifying the correct scale at which to assess abalone fisheries has long been debated, primarily as a result of the disjunction between the spatial scales of biological parameters, fisheries management, and harvest (Prince 2005, Bedford et al. 2013, Helidoniotis and Haddon 2013).

The key to identifying the optimal assessment scale within these fisheries is understanding the distribution, biology and productivity of stocks at individual population scales as well as the characteristics of harvest at differing scales. Understanding these dynamics enables a clarification of the trade-offs between the increased costs of finer-scale management relative to the realised economic benefit (catch rates, yield) and the long-term fishery productivity and sustainability. To do this requires spatially explicit information on the fishing process at scales finer than those generated by the current fishery-dependent mechanisms (e.g. log-books) and as a result fisheries dependent data for abalone fisheries is often viewed as inadequate (McShane et al. 1994, Hart and Gorfine 1997a, Perry et al. 2002). This view is also held because catch-per-unit-effort (CPUE) in such fisheries has previously been found to be hyper-stable relative to stock size (Hobday *et al.*, 2011), caused in part by the coarse spatial resolution of the current data.

The CPUE in abalone fisheries is typically recorded at a day's end in the form of the total day's catch matched against total day's dive time within a management area which may be many kilometres in dimension. Measurement of the "area effectively harvested" per unit of effort (e.g. 1 h of diving) is not available from such data and therefore how harvest rates affect individual reefs is unknown. Consequently, this may allow the depletion of individual reefs without any short-term signals in the exploitation rates over the smallest managed territory. Fishery independent assessments can identify such localized depletion events but are constrained by expensive and logistical practicalities. Diver surveys are also subject to considerable debate with regard to their robustness and sensitivity to stock changes, as well as their applicability to the wider fishery (Nash 1992, McShane 1996, Hart and Gorfine 1997b, Hart et al. 1997). As a result of these limitations abalone fisheries management tends to be viewed as data poor (Prince et al. 2008) and continues to be managed primarily through setting annual catch limits following an examination of CPUE at the smallest scale available.

One potential solution that is gathering interest in other S-fisheries is the use of data generated by the fishers themselves (Fernández-Boán et al. 2013). This is a process adapted from industrial fishing where vessel monitoring systems (VMS) define discrete fishing opportunities and fishing intensity at individual locations (Branch et al. 2005, Lambert et al. 2012). GPS data loggers provide an analogous opportunity to VMS in dive fisheries (Mundy 2012) with added precision in allocation of fishing time through time-matched depth loggers. The spatial variability of both stock dynamics and fleet tactics present in abalone fisheries suggests that spatially explicit assessment tools may be most suited to ascertaining their stock status. Potential spatial assessment tools include geo-statistical aggregation curves (or concentration area curves - CACs) used in fisheries science to describe aggregated patterns of abundance (Petitgas 1998, Tamdrari et al. 2010, Russo et al. 2013) and effort allocation (Jennings and Lee 2012, Fernández-Boán et al. 2013). CACs provide a spatial measure to assess how uniformly fishing effort is applied among areas (Russo et al. 2013) and can be used to classify the persistence of area use over time (Colloca 2009, Colloca et al. 2015). CACs are common place as part of management strategies in VMS based fisheries of pelagic and demersal stocks and are one of the ecological indicators used in the European Union common fishery policy (Woillez et al. 2007, Russo et al. 2013). Within dive fisheries, their use in urchin fisheries has led to better understanding of fishery mobility and resource use (Moreno et al. 2007) and provided evidence for the review of the acceptability of current broad scale management practices (Ourens et al. 2015). Current application of CACs within S-fisheries has been at either relatively broad scales without GPS (Moreno et al. 2007) or over short time frames with only a proportion of the fishing fleet participating (Fernández-Boán et al. 2013).

A number of CAC indices have been formally examined (Gini Index - Russo et al. 2013, Space Selectivity Index - Petitgas 1998, and the Selective Index - Woillez et al. 2007) which all share a common base model from the Lorenz Curve (Myers and Cadigan 1995). Fundamentally, these are all indices that characterize the spatial distribution of the target species by relating the cumulative total of catch or abundance to the cumulative area from where it was taken. The primary differences between the indices relates to whether the index includes 'zero' or null values and whether other spatial metrics that are not CACs (e.g. centre of gravity - Woillez et al. 2009) form part of a suite of spatial indices that describe a fishery. The Gini index is the most widely recognised of the CAC indices when zero values are removed and is the benchmark for describing the evenness of the spatial distribution of a given variable across multiple disciplines (e.g. financial inequality, housing inequality) (Gini 1921). In addition to CACs being used to examine spatial variability, the temporal persistence of individual areas can be assessed using CACs by identifying high density spatial units and tracking their progress through time, and has been used to identify persistent nursery areas in demersal and pelagic fisheries (Colloca et al 2009, Colloca et al 2015).

The mandatory use of a submersible data logger and companion GPS logger (Amendment to the Fisheries (Abalone) Rules 2009, Department of Primary Industries, Parks, Water and Environment, Tasmania) for Tasmanian commercial abalone divers since 2012 has provided a near complete time series of fishing activity and location for this fishery (Mundy in press). Cross referencing of the geo-spatial dataset against daily catch records across the entire fishery has provided GPS derived CPUE and catch to specific locations. For species such as blacklip abalone (*H. rubra*) where local-scale variation of key population parameters (growth, maturity, recruitment, morphometrics) are evident at scales of a few hundred metres (McShane 1995, Haddon et al. 2008, Saunders et al. 2009, Helidoniotis and Haddon 2014) this information offers the promise of providing fishery indicators at effective scales of harvest. However, just how small a management unit should be chosen is not well defined. The spatial concentration of effort (the scale of diving for a population inside the fishing ground), may vary with topography, population dynamics, and previous fishing effort. In this work we use CACs to characterise the detailed spatial distribution of catches within the Tasmanian abalone fishery while evaluating the sensitivity of CACs at four spatial scales. We use CACs to develop a catch persistence index to identify areas of multiannual high production and examine the spatial distribution of persistent catches in relation to total fishing area. Within this work, CAC results along with estimations of reef area are used to provide context to the CPUE trends and examine if they provide additional information on fishery performance beyond that currently available from paper catch and effort log-books.

9.2. Methods

Statistical and graphical analyses were conducted through the R statistical software (R Core Team, 2015). The R packages used for data extraction and analysis were `sp` (Bivand et al. 2011), `ade4` (Dray and Dufour 2007), `reshape` (Wickham and Hadley 2007), `sqldf` (Grothendieck 2014), `lubridate` (Grolemund and Wickham 2011), `ggplot2` (Wickham 2009) and custom functions. Spatial mapping of grid cells was completed using the Manifold GIS (manifold.net).

The Tasmanian blacklip abalone fishery is divided into 57 fishing blocks with catch and CPUE data reported at this scale. For this current work six of the fishing blocks were selected from the fishery Eastern Zone fishery. Block 13 was selected on the basis of it being the highest producing block in the fishery, and its status as the principal day return fishing block in south eastern Tasmania. (Blocks 20, 21 and 22 were chosen based on their proximity to each other, the similarity of their fishing areas (narrow near-shore reefs confined by deep water on the seaward edge) and their contrasting catch and CPUE records between 2012-2015 (Figure 37). Block 24 and 29 were selected on the basis of being two of the principal fishing grounds on the Tasmanian East coast.

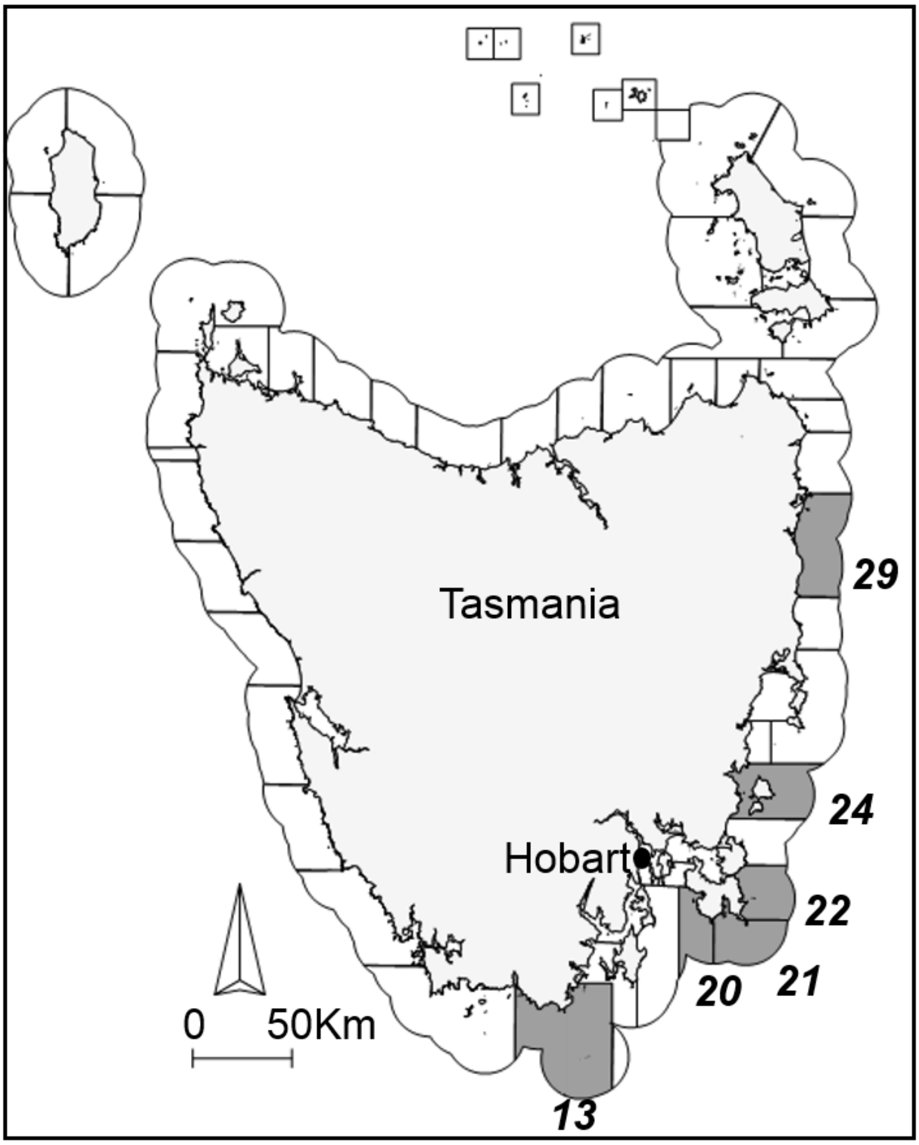


Figure 36. Tasmania, Australia blacklip abalone (*Haliotis rubra*) fishing blocks. Blocks examined in this work shown in grey with accompanying block number.

9.2.1. Pre-processing of geo-referenced spatial data

The time series of data examined in this work covers four years from 2012 to 2015. Time-stamped data streams with position and depth information for the duration of each dive event in the fishery, were stored in a SQL Server database utilising OGC compliant geometry data types as spatial points (Mundy et al., *in press*). These data streams were cross-referenced against the catch landing database with catch in kilograms for each diver on each day of fishing allocated pro-rata to the spatial data. Where a fisher dived multiple times on a single day, the proportion of the catch allocated to each dive was made on the basis of the duration of each dive as a proportion of the total dive time. Thus each record in the data stream represents 10 seconds of fishing effort and a harvest weight, tagged with position, date/time, depth and diver identification. Grid cells of size 1, 2, 5 and 100 hectares (ha) were used to allocate the spatial distribution of fishing effort into regular tessellating cells. These cells were hexagon in shape with sides 107.46 m, 151.97 m, 240.28 m, and 1074.57 m respectfully. A one Hectare grid cell size was selected based on evidence from the geo-referenced dataset of mean dive distances being on average 200 m in length and therefore each side of the 1ha grid is approximately equal to half of one dive length. Geo-referenced spatial data frames forming the grid cells were built in R (R core team 2015) and mapped in Manifold (manifold.net) before being exported to a MS SQL Server database for overlay analysis. The grid cell catch-effort allocations were then extracted back into R using library RGDAL (Bivand et al. 2015) and RODBc (Ripley and Lapsley 2015), and the data trimmed to exclude any dive <10 minutes duration or with zero catch allocation. The final extracted data contained data streams comprised of unique grid cell identification with associated fishing year, fishing block, catch weight in kilograms (Kg), dive time in minutes and number of licenced divers who had fished that grid cell.

The boundaries of suitable fishing grounds for abalone in Tasmania were defined by the total extent of all active grid cells with catch allocation across the multi-year dataset. This provided the total fishable reef area (TFRA). The extent to which the TFRA represented the true limit of suitable habitat for commercial abalone fishing was examined by calculation of the number of additional new 1Ha cells per annum. Within an individual year not every grid cell in the TFRA was fished and where this occurred the cell was allocated zero catch for that year. Only active grid cells (e.g. catch >0) within year were considered as part of the annual fished area (AFA). Annual standardised geometric mean CPUE was calculated at a fishing block scale using the catch and total dive time in minutes per block. Catch per grid cell was calculated by dividing total annual block catch by the AFA.

9.2.2. Concentration Area Curves and Gini Index.

The CACs were calculated at the block fishery management scale. CACs were produced by scaling catch and area between 0 and 1 where P_y is the cumulated catch, ranked in decreasing order, T_y the corresponding cumulated area occupied by the catch values. Two CACs were produced per block one based on TFRA and a second based on AFA. CACs expressed against the TFRA provided evidence of the proportional use of the total fishery area each year, while by scaling concentration area curves to the AFA each year it was possible to remove the effect of annual differences in AFA. This allowed temporal comparisons between years where catch and number of grid cells fished varied. Gini Index (G) calculations were produced from the AFA CACs with confidence intervals provided by 1000 bootstrapped iterations (Dixon 1987) and through R library reldist (Handcock 2015). The G index is bound between 0 to 1 where a higher G value indicates that more of the catch is being taken from fewer grid cells suggesting an aggregated distribution and increased spatial inequality.

$$G = \sum_{i=1}^{n}(2i - n - 1)x_i/n^2\mu \qquad \text{Equation 1}$$

Where x_i are abalone catch values sorted from smallest to largest, n is the number of grid cells and μ is the mean catch. *G* values and 95 % confidence intervals were calculated for each year at each grid cell size (1ha, 2ha, 5ha and 100ha). Spatial and temporal variation in the Gini index was assessed by lack of overlap in confidence intervals between years or spatial areas. Analysis of variance (ANOVA) was used to compare *G* values between grid sizes (fixed effect). Assessment of the spatial distribution of cumulative catches (P_y) and impact of grid cell size on estimates of TFRA was achieved by mapping 1ha grid cells against 2ha grid cells.

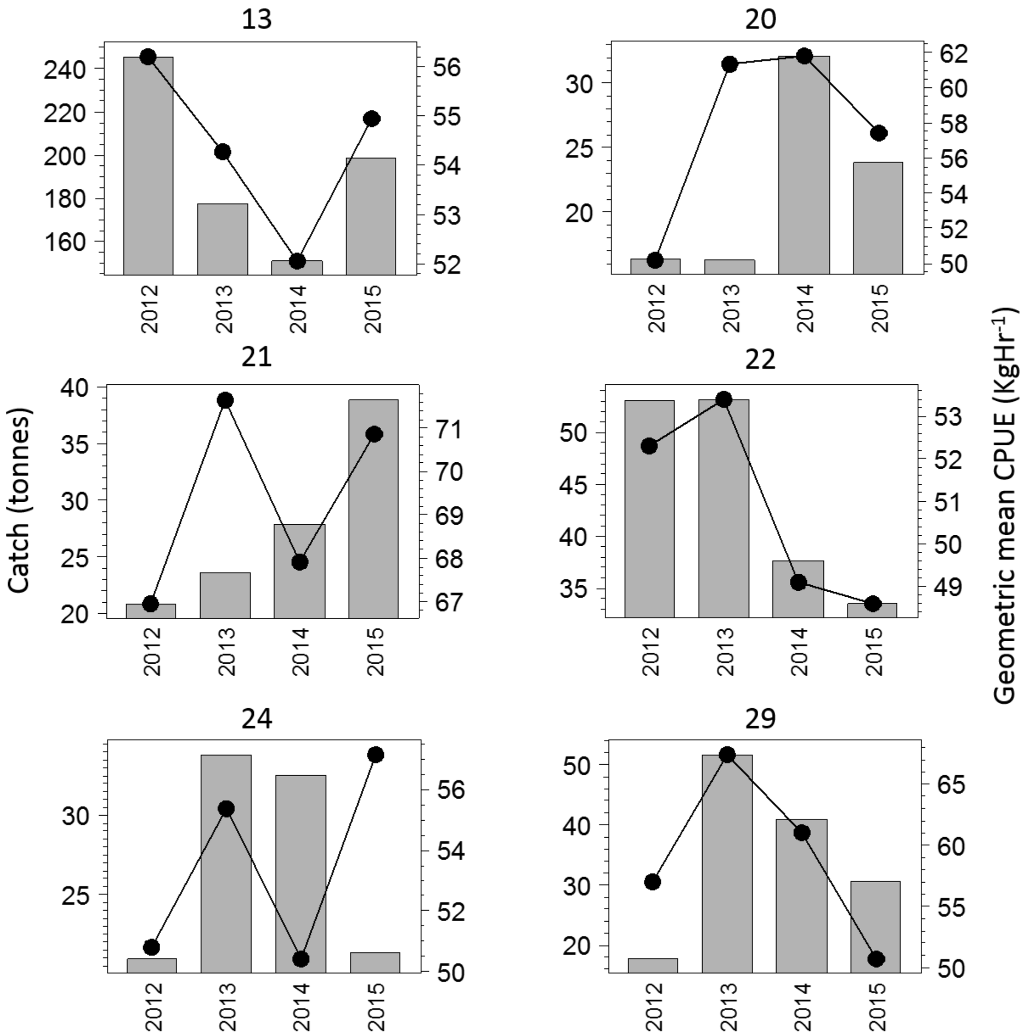


Figure 37. Catch (grey bars, left-hand y-axis) and catch per unit effort (CPUE, black dots with lines right-hand y axis) for selected blacklip abalone (*Haliotis rubra*) fishing blocks from the Tasmanian commercial geo-referenced fishing records 2012-2015. Note the y-axes do not start at zero and each can have a different scale.

9.2.3. Persistence.

The index of persistence (*IoP*) was adapted from the work of Colloca et al., (2009). Using the annual TFRA CACs, the point at which the curve reached a 45^0 angle was identified and considered the tangent or threshold of persistence for cells within a fishery block in any given year (Figure 38). Each curve up to the tangent contains a specific proportion of cells and corresponding percentage of catch (Figure 38). The tangent represents the point at which the cumulative catch of abalone switches from one of relatively aggregated distribution to one of relatively dispersed distribution. For cells prior to the tangent, catch increases proportionally quicker than area, whereas above the threshold the reverse is true; a relative increase in the area is followed by a proportionally lower increase in the catch of abalone. For each cell a binomial persistence score was allocated per year. Let $\delta_{ij} = 1$ if the grid cell i is included prior to the persistence catch threshold in year j, otherwise $\delta_{ij} = 0$. The *IoP* which measures the relative persistence of that cell over time can then be calculated, where n is the total number of annual datasets considered.

$$IoP = \frac{1}{n}\sum^{n} \delta ij \qquad \text{Equation 2}$$

Subsequently the percentage of cells in the TRFA that had *IoP* = 1 (IoP_1) and *IoP* = 0 (IoP_0) was calculated along with the proportion of total catch across all years from these grid cells. The mean number of divers who fished IoP_1 and IoP_0 cells was also determined. Spatial distribution of *IoP* within blocks was assessed by transfer of the spatial dataframe from R into Manifold.

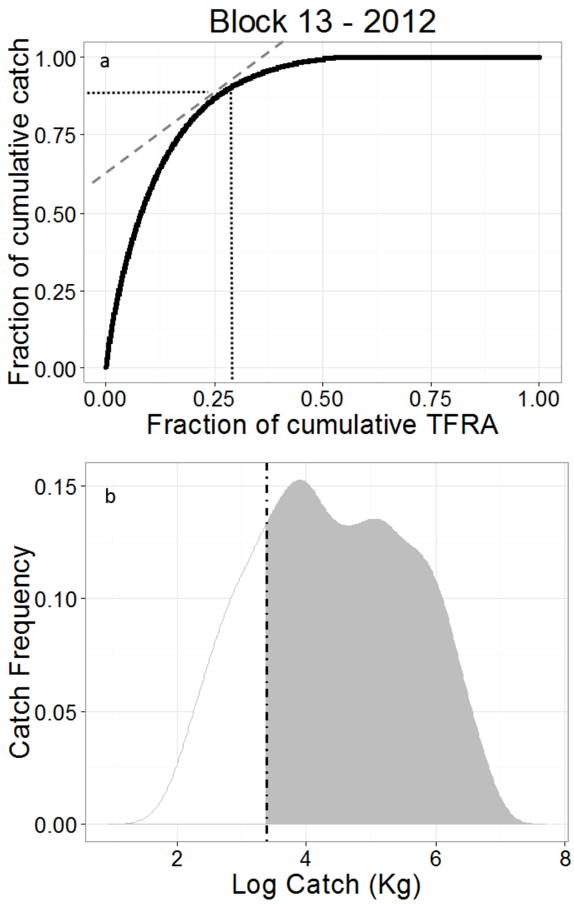


Figure 38. (a) Concentration area curve based on total fishable reef area (TFRA) of blacklip (*H. rubra*) abalone for block 13 from the Tasmanian fishery 2012. Grey dashed line is the 45^{o} tangent line, vertical black dotted line indicates fraction of TFRA at tangent (29.8%) and horizontal black dotted line indicates fraction of catch at tangent (83.6%). (b) Log-frequency distribution of catch with related fraction of catch up to the tangent (vertical dot-dash line - grey shaded area).

9.3. Results

The geo-referenced dataset for the six fishing blocks consisted of 14,889 geo-referenced records across the four-year sample period. Catch associated with the geo-referenced points amounted to a mean of 86.4% (± 7.8 s.d.) of log book catch records across blocks and years. Catch varied within and between blocks through time; the highest recorded catches were in block 13 with the highest individual year being 2012 (245.8 tonnes). The lowest catches recorded were <17 tonnes in blocks 20 in 2012-2013 (Table 9, Figure 37). Annual standardised geometric mean CPUE ranged from 48.6-71.7 KgHr^{-1} ($\bar{x}$ = 57.5 KgHr^{-1}) across the blocks with temporal trends in CPUE being dependent on block (Table 9, Figure 37). Block 13 had elevated catch per hectare compared to other blocks (Table 9).

With the 1 ha grid scale used as the base estimate of TFRA, block 13 had the largest estimated TFRA (1700 ha) whilst block 21 had the smallest TFRA (600 ha). The size of the TFRA increased each year in each block but the number of new grid cells added per annum declined with time in all cases except 2013 in block 29 (Figure 39). Across the blocks the percentage increase in the fishable reef area decreased from 24.9 % in 2013 to 7.2 % by 2015. The AFA was on average 67.7 % of the TFRA (range 82.5 – 79.8) with the highest AFA percentage recorded in block 13 and the lowest in block 29 (Table 9). Catch per grid cell varied between years within blocks and between blocks (Table 9). The highest recorded catch per grid cell was found in block 13 in 2012 (182.9 $KgHa^{-1}$) with the lowest in block 24 in 2012 (38.3 $KgHa^{-1}$) (Table 9).

Table 9. Summary statistics for the geo-referenced dataset for select Tasmanian blacklip abalone blocks (BLK) from 2012-2015. Catch per unit effort (CPUE), catch (tonne), total fishable reef area (TFRA), annual fished area (AFA), percentage of area with aggregated catch (%AAC), kilograms per grid cell (Catch 1Ha), Gini Index and percentage of aggregated catch (% AGG. CATCH). The figures are based on the 1Ha grid size. CPUE is the standardised geometric mean CPUE. TFRA is the sum of all grid cells where fishing has taken place over the four-year dataset. AFA is the number of grid cells actively fished per annum, with the corresponding percentage of those cells to the TFRA given in brackets. %AAC is the percentage of TFRA or AFA (in brackets) at which the cumulative catch of abalone switches from one of aggregated distribution to one of dispersed distribution. % AGG. Catch is corresponding percentage of total catch at the point at which cumulative catch switches from aggregated to dispersed distribution. Kilograms per grid cell is catch divided by AFA. Gini index (± confidence interval (1000 bootstraps)) is bound between 0 and 1 with 0 = an even distribution of catch across the block and 1 = all catch from a single grid cell within block.

Blk	*Year*	*CPUE*	*Catch t*	*TFRA*	*AFA*	*Gini (±C.I)*	*Catch 1 ha*	*% ACC*	*% AGG Catch*
13	2012	57.1	245.8	1700	1344 (79.1)	0.56 (0.55-0.56)	182.9	32.4 (41.0)	82.9
	2013	61.2	177.6	1700	1230 (72.4)	0.58 (0.57-0.58)	144.4	29.6 (40.9)	84.3
	2014	51.8	150.6	1700	1258 (74.0)	0.55 (0.540.56)	119.7	31.1 (42.1)	82.7
	2015	50.9	198.8	1700	1402 (82.5)	0.53 (0.52-0.54)	141.8	33.5 (40.6)	79.9
20	2012	54.0	16.3	606	363 (59.9)	0.52 (0.50-0.54)	45.0	28.1 (46.8)	82.2
	2013	57.8	16.2	606	333 (55.0)	0.47 (0.44-0.50)	48.7	31.4 (57.1)	85.4
	2014	54.1	32.1	606	463 (76.4)	0.51 (0.49-0.53)	69.4	31.7 (41.5)	77.7
	2015	58.5	23.8	606	433 (71.5)	0.51 (0.49-0.52)	55.1	32.0 (44.8)	80.3
21	2012	50.6	20.8	641	414 (64.6)	0.47 (0.45-0.49)	50.3	32.3 (50.0)	81.4
	2013	65.2	23.6	641	383 (59.8)	0.51 (0.49-0.52)	61.6	30.6 (51.2)	84.2
	2014	47.9	27.9	641	382 (59.6)	0.50 (0.48-0.52)	73.0	29.6 (49.7)	82.9
	2015	55.6	38.9	641	496 (77.4)	0.55 (0.53-0.56)	78.4	28.1 (36.3)	77.4
22	2012	53.9	53.1	863	691 (80.1)	0.50 (0.49-0.52)	76.8	34.0 (42.4)	79.0
	2013	68.8	53.2	863	688 (79.7)	0.52 (0.50-0.53)	77.3	33.6 (42.2)	79.1
	2014	49.3	37.6	863	654 (75.8)	0.49 (0.48-0.50)	57.5	32.7 (43.1)	78.1
	2015	68.4	33.5	863	597 (69.2)	0.54 (0.52-0.56)	56.0	28.0 (40.5)	78.9
24	2012	50.7	20.9	946	546 (57.7)	0.43 (0.41-0.44)	38.3	33.5 (58.1)	84.7
	2013	65.2	33.9	946	614 (64.9)	0.48 (0.47-0.49)	55.1	31.2 (48.0)	81.6
	2014	50.1	32.5	946	678 (71.7)	0.48 (0.46-0.49)	48.0	33.1 (46.2)	80.0
	2015	60.5	21.3	946	447 (47.3)	0.47 (0.45-0.48)	47.7	29.4 (62.2)	88.4
29	2012	62.2	17.6	600	211 (35.2)	0.57 (0.55-0.59)	83.6	21.7 (61.6)	92.2
	2013	72.4	51.7	600	425 (70.8)	0.57 (0.55-0.58)	121.7	29.3 (41.4)	82.6
	2014	57.1	41.0	600	425 (70.8)	0.51 (0.49-0.52)	96.4	33.0 (46.6)	82.8
	2015	50.6	30.6	600	412 (68.7)	0.57 (0.54-0.59)	74.3	27.5 (40.0)	80.9

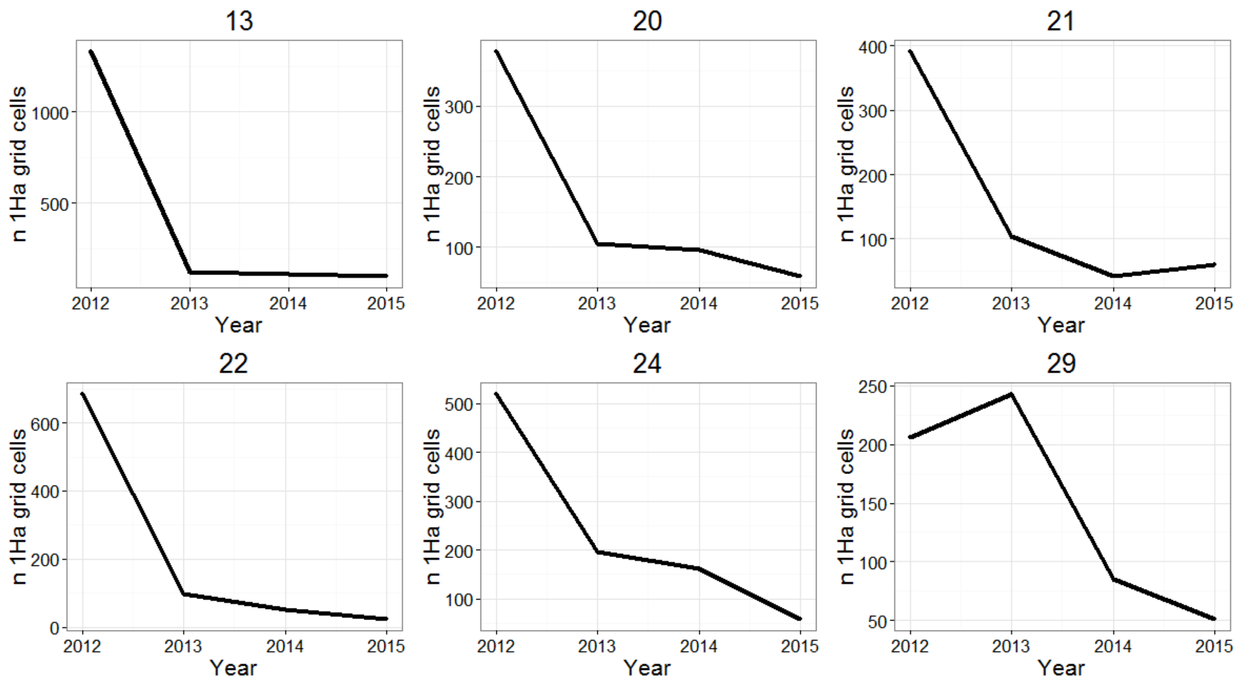


Figure 39. Increase in total fishable reef area per annum for six blacklip abalone (*Haliotis rubra*) fishing blocks from the Tasmanian commercial geo-referenced fishing records 2012-2015. Note the y-axes do not start at zero and each can have a different scale.

9.3.1. TFRA and Gini Index

The estimated TFRA increased with grid size in all blocks (Table 10, Figure 40) while examination of the spatial distribution of cumulative catch (Py) showed that heterogeneity evident at 1 ha was lost within the 2 ha grids. Mapping of the TFRA revealed that the width of the TFRA was limited to a few hundred metres (3 to 4 1 ha grid cells) in width across a large portion of the coastline (Figure 40). A significant increase in the Gini index was evident with increased grid scale (ANOVA $F_{3,92}$ = 13.94, P = <0.01) (Figure 41). All further analysis in this work utilised the 1 ha grid size. The highest spatial unevenness in catches (higher G values) were found in block 29 (Figure 42). Temporal variation, distinguished by lack of overlap in bootstrap confident intervals, was evident in all of the blocks examined, except block 20 which had a consistent *G* value in all years despite large variations in catch (Figure 42). No common temporal trend in *G* was evident across blocks nor did the trend in G index mirror changes in CPUE or catch. For instance in Block 13 a similar *G* in 2012 and 2014 resulted from catch totals being lower by 61.3% and CPUE reduced by 7 $KgHr^{-1}$ (Table 9,Figure 42. Annual Gini index ± confidence intervals (c.i.) calculated by 1000 bootstraps of blacklip abalone in six blocks of the Tasmanian fishery between 2012-15. Catch (tonnes) per annum is displayed above year for each block. Figure 42).

Table 10. Estimated total fishable reef area (TFRA) in Hectares for six blacklip abalone blocks in Tasmania, based on geo-referenced diver data between 2012-2015. TFRA based on grid sizes of 1, 2, 5 and 100 ha.

Block	***1***	***2***	***5***	***100***
13	1700	2034	2610	6400
20	606	902	1435	5300
21	641	802	1230	5600
22	863	1100	1560	5500
24	946	1280	1950	9200
29	600	748	1140	4900

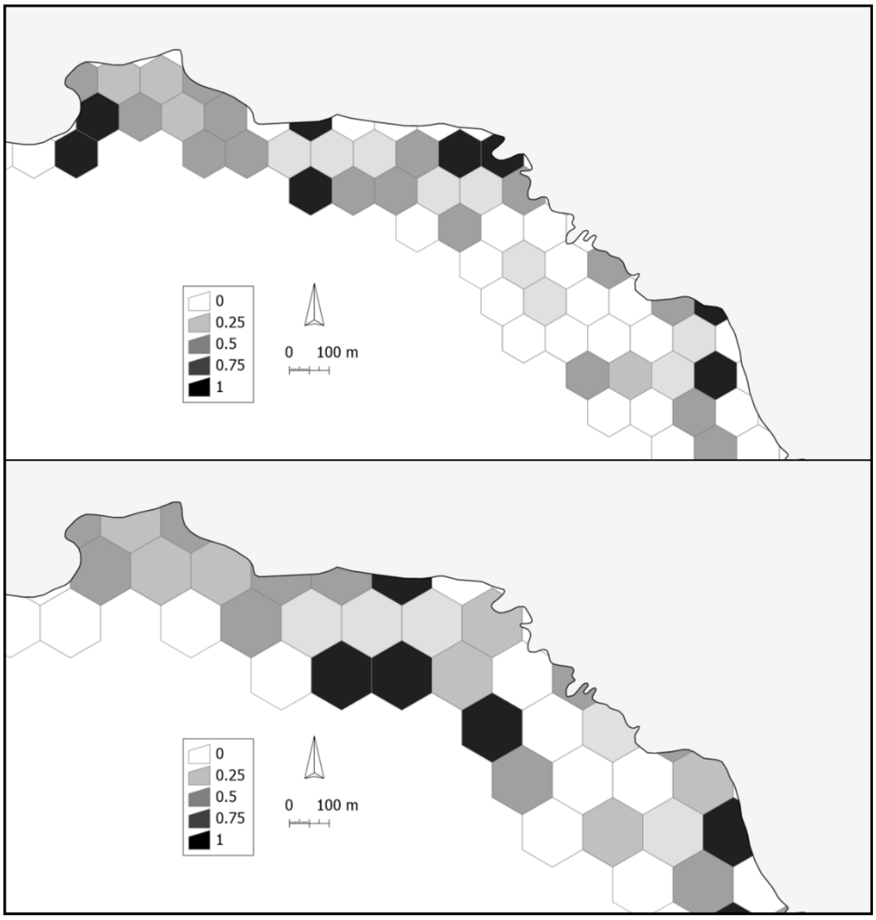


Figure 40. Subsection of coastline of the blacklip abalone (*Haliotis rubra*) showing the fishable reef area at 1 ha (top) and 2 ha (bottom) scales. Grey scale applied to the grid cells shows cumulative catch (P_y) for cells within block across all years (2012-2015). The grey scale groups cells according to rank on a 0 to 1 scale for catch, where cells with lowest catch (white) are closest to 0 and those with the highest catch are closest to 1 (Black).

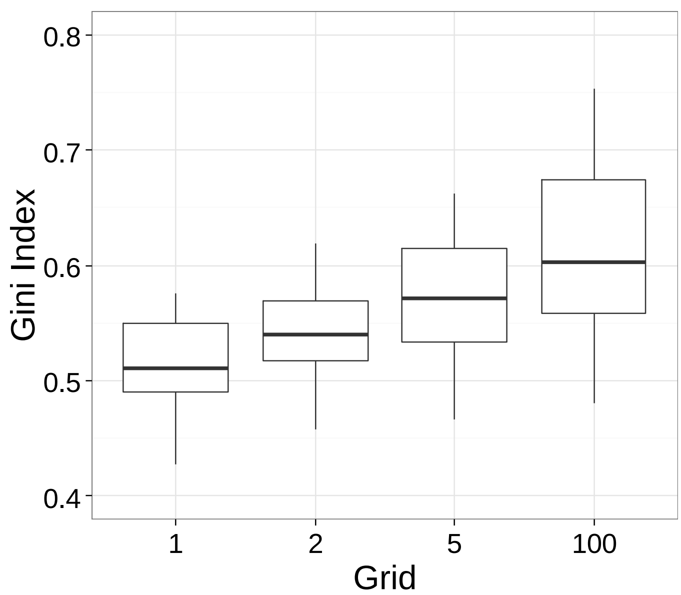


Figure 41. Comparison of Gini indexes of Blacklip abalone spatial distributions from six Tasmanian fishing blocks at four grid scales (1 ha, 2 ha, 5 ha and 100 ha) from years 2012-2015. Each sample's data is represented by a central line which is the median value, a box which is the interquartile range, vertical lines which are the 2.5th and 97.5th percentiles, and black circles which are outliers.

Total catch in any block was taken from <85 % of the TFRA in any year, with 75 % of the catch coming from <35 % of the TFRA (Figure 43). The proportion of TFRA fished each year varied among blocks although was consistently > 70 % in block 13. Variation among years in Block 29 was up to 35.6 % (Table 9, Figure 43). Temporal differences in the annual catch within blocks (Table 9) was in some blocks associated with similar changes in the percentage of the TFRA required to fish the catch (Figure 43). For example in block 20, the larger catches in 2014-15 were associated with a comparatively larger percentage of the TFRA than the preceding years (Table 9, Figure 43). The increase in catch and AFA in block 20, however, had no influence on the AFA CAC shape or subsequent *G* value (Table 9, Figure 43). Plotting of CACs where AFA was used as the measure of area, removed effects of changes in the proportion of area fished per annum which are evident in the TFRA CACs (Figure 43). Curve shape differences in TFRA CACs between years in block 13, 22, 24 and 29 were reduced when CACs were expressed as AFA indicating similarities in spatial distributions of catches despite changes in AFA and catch (Figure 43). For example, in block 29 the AFA CAC for 2012 had a similar shape to 2013 and 2014 indicating a similar spatial distribution of catch despite a much reduced annual catch total and TFRA fished (Figure 43, Table 9). Dynamic changes in curve shape for AFA CACs were evident in block 29 (2014) and block 21 (2015). For the 2014 AFA CAC in block 29 the fraction of cumulative catch per unit of cumulative AFA decreased despite the overall AFA remaining similar to 2013 (Figure 43, Table 9). This reduction in cumulative catch per unit area of the AFA was associated with a reduction in catch compared to 2013 (Figure 43, Table 9). For the 2015 AFA CAC in block 21, the fraction of cumulative catch per cumulative AFA increased compared to the three previous years (Figure 43). This was a response to an increase in catch as divers expanded the AFA compared to previous years (Figure 43, Table 9). As a result CPUE for 2015 increased over 2014 (Figure 43, Table 9).

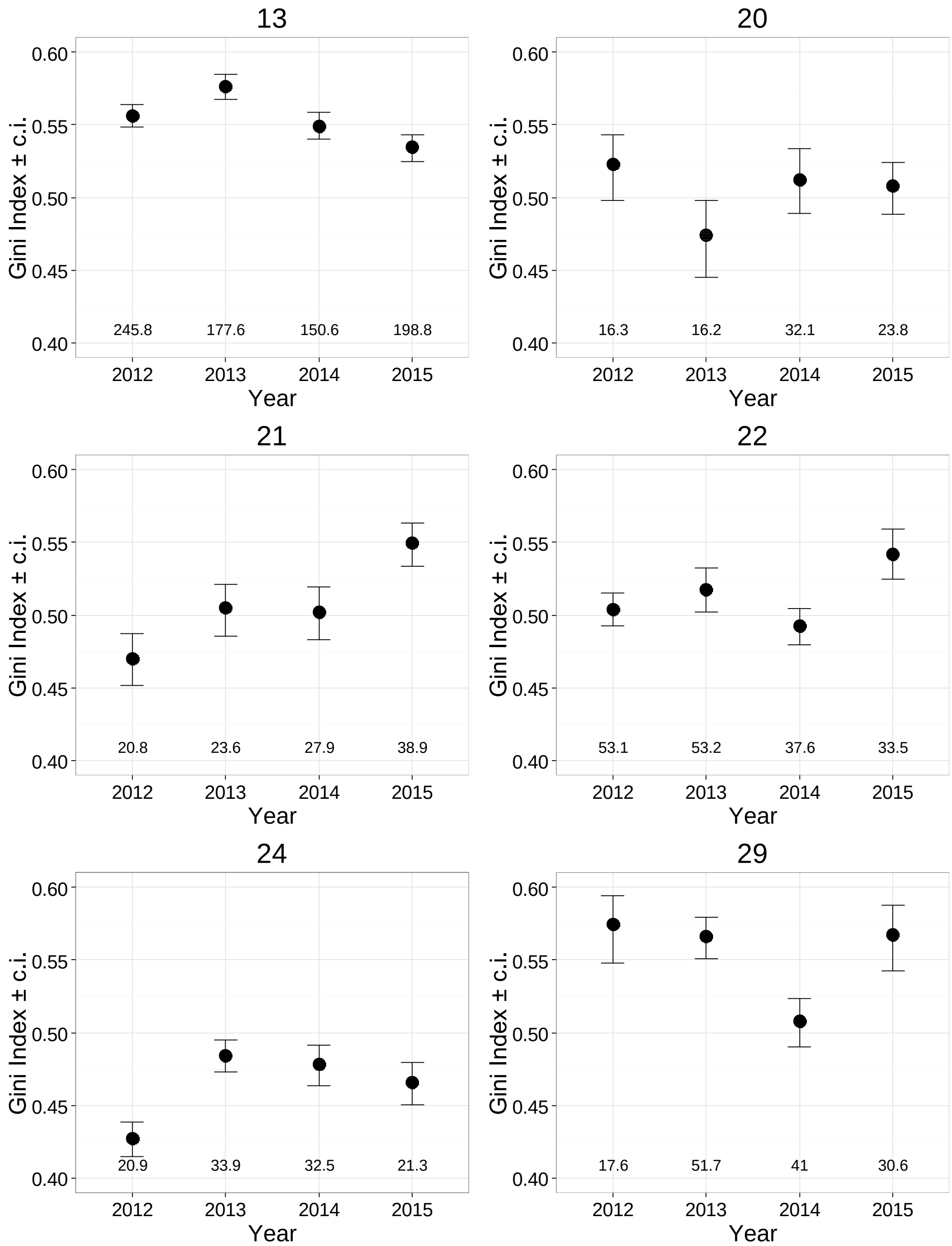


Figure 42. Annual Gini index ± confidence intervals (c.i.) calculated by 1000 bootstraps of blacklip abalone in six blocks of the Tasmanian fishery between 2012-15. Catch (tonnes) per annum is displayed above year for each block.

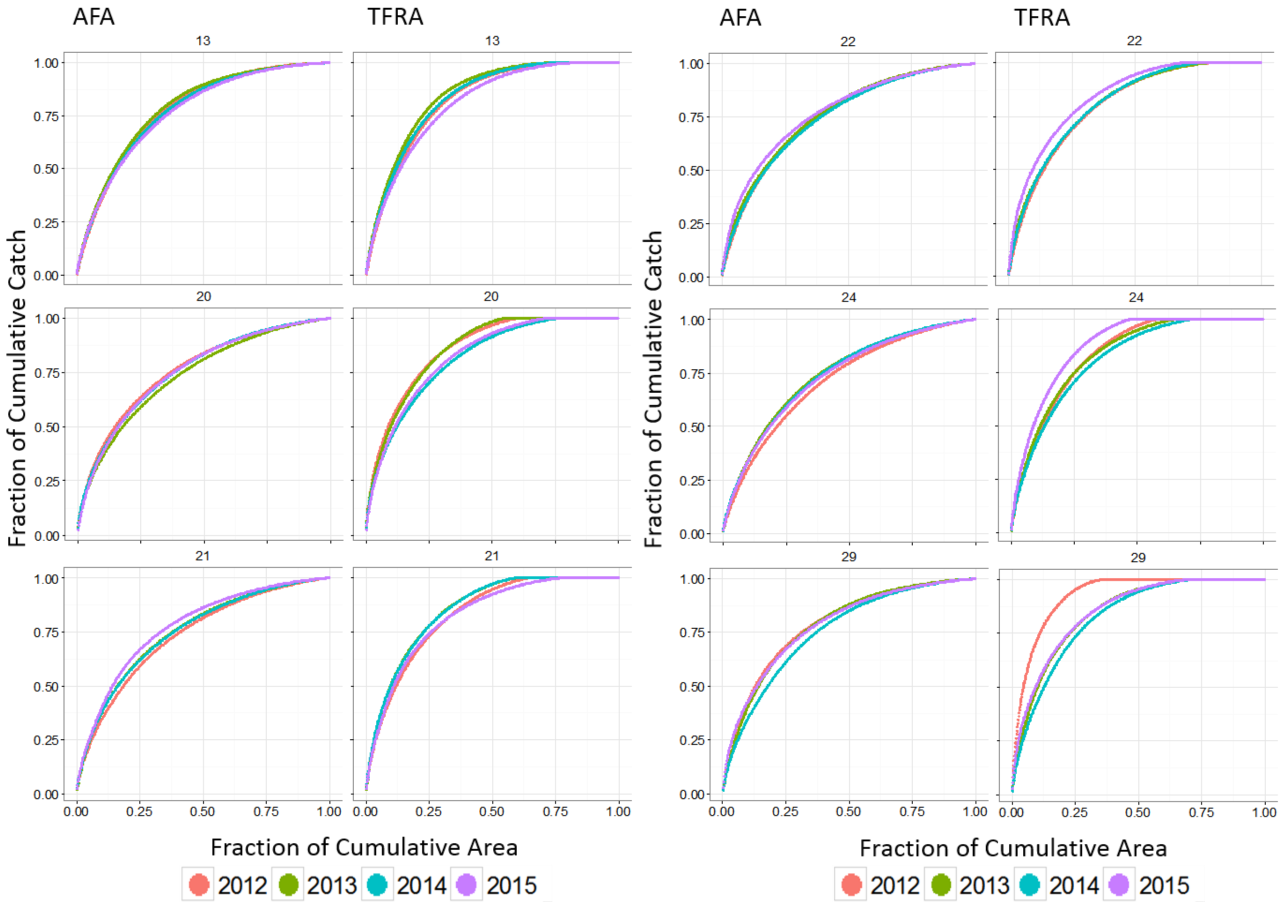


Figure 43. Concentration area curves (CACs) for six Tasmanian blacklip abalone fishery blocks (13, 20, 21, 22, 24, 29) between 2012-2015. Paired CACs with left-hand figures showing the fraction of cumulative area expressed as the active fished area (AFA) within each year. Right-hand figures show the fraction of cumulative area expressed as the total fishable reef area (TFRA) across all years.

9.3.2. Persistence.

The mean proportion of grid cells with an aggregated catch distribution (e.g. cells which occur prior to the 45° tangent on the TFRA CAC) across all blocks and years was 30.7 % (± 2.8) of the TFRA and 46.4 % (± 7.1) of the AFA (Table 9). Catch from these grid cells accounted for a mean of 82.1 % (± 3.4) of the block catch within each year (Table 9). The average *IoP* score of grid cells between blocks was stable and ranged from $\bar{x} = 0.28$ to 0.32 with block 29 lower than the other blocks (Table 11). The percentage of grid cells scoring IoP_1 (e.g. cells with aggregated catch in each of the four years) varied between blocks between 9.7 % (block 20) and 19.9 % (block 13) with IoP_1 grid cells contributed between 35 % (block 24) and 62 % (block 13) of the annual catch (Table 11). The percentage of the TFRA that didn't produced aggregated catch totals in any year (IoP_0) ranged from 43.2 % (block 24) to 53.6 % (block 13). These IoP_0 cells contributed between 9.4 % (blocks 24 and 29) and 11.7 % (block 22) of annual block catch totals (Table 11). Blocks 13 and 22, the two largest catching blocks, had elevated percentages of cells with IoP_1 and higher numbers of divers fishing IoP_1 cells compared to other fishing blocks (Table 11). Mapping of *IoP* scores showed that IoP_1 cells were not randomly distributed across the TFRA but were typically found in aggregated patches (Figure 44). In block 13 the TFRA included locations around island masses and offshore reefs where patches of IoP_1 cells were located at the centre of these areas with the borders of the TFRA occupied by IoP_0 cells (Figure 44). In the other blocks the TFRA was typically constrained to a linear dimension parallel to the shoreline with IoP_1 cells located in discrete patches along length of the shore (Figure 44).

Table 11. Index of persistence (*IoP*) summary for six blacklip abalone fishing blocks in Tasmania for years 2012-15. *IoP* ± standard error is the mean *IoP* score for all cells with the fishing block. *IoP* is bound between 0 and 1 where 1 represents a cell which had aggregated catch totals in all years and 0 represents a cell with dispersed catch totals in all years. Separation of aggregated and dispersed catch totals each year were assessed through the 45° tangent on total fishable reef area concentration area curves (TFRA CAC). Percentage persistent grid cells (% *IoP* = 1) is the percentage of all grid cells which occur prior to the 45° tangent on the TFRA CAC in all years and the associated percentage of total catch (% Catch *IoP* = 1) across years represented by these cells. The mean number of divers that fished the *IoP* = 1 grid cells is also given ($\bar{x}$ no. divers *IoP* = 1). % *IoP* = 0 is the percentage of total grid cells that never occurred prior to the 45° tangent and their associated percentage catch (% Catch *IoP* = 0). The mean number of divers that fished the *IoP* = 0 grid cells is also given ($\bar{x}$ no. divers *IoP* = 0).

Block	***IoP (± s.e.)***	***% IoP = 1***	***% IoP = 0***	***% Catch IoP = 1***	***% Catch IoP = 0***	***$\bar{x}$ no. divers IoP = 1***	***$\bar{x}$ no. divers IoP = 0***
13	0.32 (0.01)	19.9	53.6	62.3	10.2	59.6	9.8
20	0.31 (0.01)	9.7	45.4	38.6	10.6	23.2	5.0
21	0.30 (0.01)	12.6	47.2	47.2	10.2	29.1	4.7
22	0.32 (0.01)	17.1	48.4	54.0	11.7	37.2	8.7
24	0.32 (0.01)	10.5	43.2	35.0	9.4	18.6	4.2
29	0.28 (0.01)	10.7	52.2	45.4	9.4	22.3	4.2

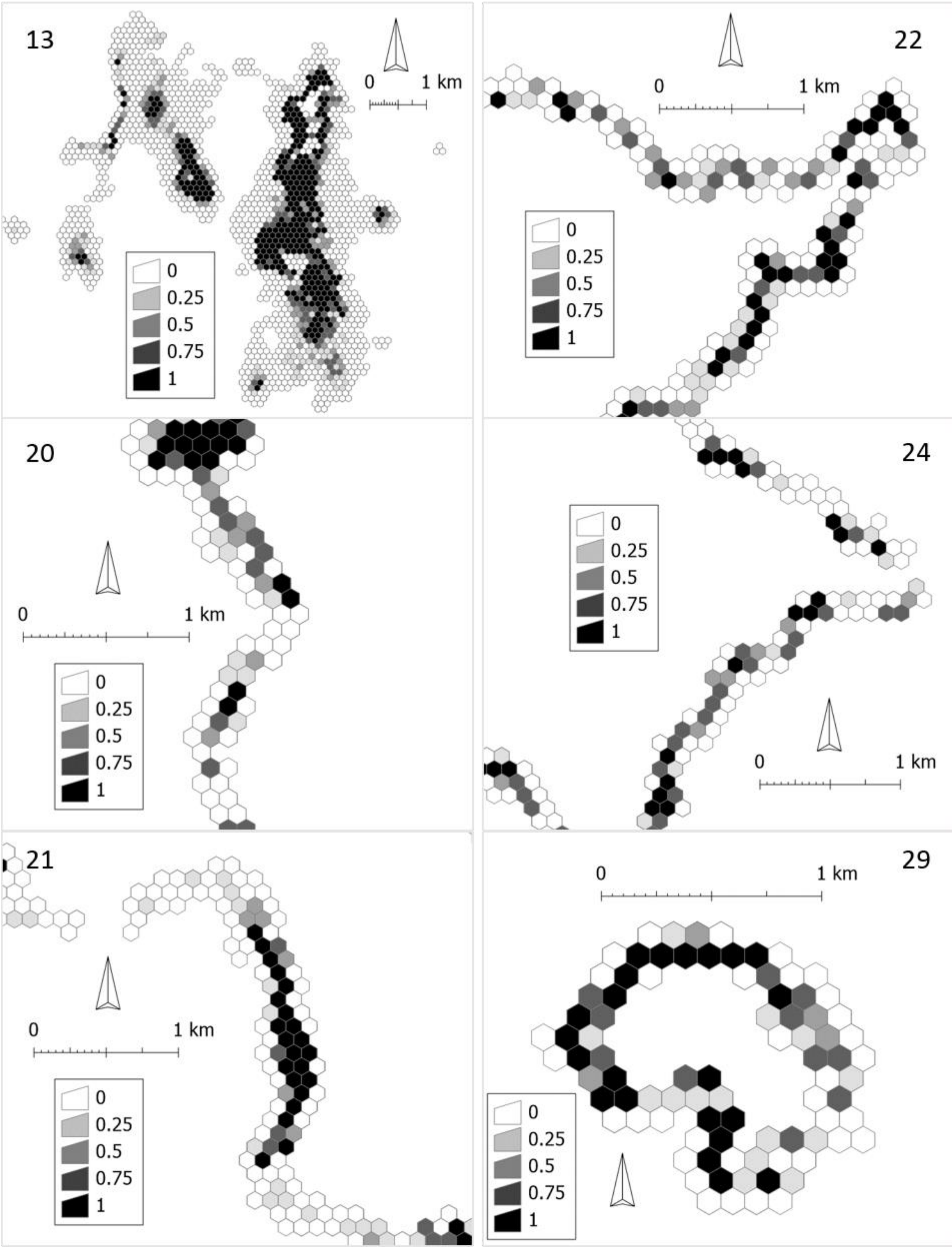


Figure 44. Spatial distribution of Index of Persistence (*IoP*) from select sections of coastline from six Tasmanian blacklip abalone fishery blocks between 2012-2015. Grid scale is 1 ha. Block *IoP* is bound between 0 and 1 where 1 represents a cell which had aggregated catch totals in all years and 0 represents a cell with dispersed catch totals in all years. Separation of aggregated and dispersed catch totals each year were assessed through the 45° tangent on total fishable reef area concentration area curves.

9.4. Discussion

Identification of new measures of fishery performance are especially important given the difficulty in sustainably harvesting many S-fishery species (Perry et al. 2002, Orensanz et al. 2005), significant concerns regarding the overreliance on CPUE data (McShane et al. 1994, Hart and Gorfine 1997a, Perry et al. 2002), and, in Tasmania, the recent reductions in abalone harvest (Mayfield et al. 2012, Mundy et al. 2014). GPS technology has previously been used in dive fisheries to compile CACs (Moreno et al. 2007, Fernández-Boán et al. 2013). Without depth-logger units, previous work has relied on boat speed profiles to estimate fishing activity, whereas the addition of the depth-logger units used in this fishery provides precise characterisation of fishing activity both in space and time. Here we used CACs, Gini (*G*) index and estimates of TFRA at a hierarchy of scales to assess which base unit of spatial measurement is the most suitable for examining fishery dynamics. As the scale of the spatial grid system increased from 1 ha to 100 ha there was progressive increments in the mean *G* index and spread of *G* values suggesting that at larger scales the attribution of abalone catches appear more aggregated than at finer spatial scales of assessment.

The biological structuring of blacklip abalone stocks includes evidence of low degrees of adult movement (Prince et al. 1988), growth and shape variability (Saunders et al. 2009) and restricted larval dispersal (Prince et al. 1987, Temby et al. 2007, Miller et al. 2009, 2014) at scales of a few hundred metres. The high *G* values evidenced in the larger grid cells of this work derive from merging high catch and low catch sections of reef into single grid cells and imply that larger grid cells are out of spatial synchrony with the scale of the blacklip abalone population dynamics and fishery. Furthermore, mapping of the TFRA at the 1 ha gird scale (hexagon length 107 m) indicated that a substantial portion the estimated TFRA in blocks 20, 21, 22 and 24 was only a few hundred metres in width from the shoreline to TFRA seaward extent. Use of the larger grid scales to assess spatial variability in these regions enlarged the seaward extent of the estimated TFRA beyond that of the 1Ha estimate resulting in significant overestimation of the TFRA and including areas that are not actually fished. Consequently, the inclusion of non-fished areas inflated *G* values. This also implies that using the larger grid cells to assess catch contributions of reef areas would likely limit the ability to identify depletion of individual stocks and any short-term signals in the exploitation.

The fine scale structuring of blacklip abalone populations has led to calls for assessment tools to be implemented at similar scales to those of the individual fishing operations (Prince and Shepherd 1992, Prince 2005, Bedford et al. 2013). Although the 2, 5 and 100 ha scales provide a significantly improved spatial resolution over current scales of management, the 1 ha scale improves the spatial resolution further, reducing overestimation of the TFRA and is within good spatial synchrony with the biological structuring of the resource. Though the 1 ha grid scale appears the most satisfactory spatial scale for blacklip abalone populations assessed in this work, it may not be so for other abalone species with differing population structuring (Miller et al. 2014) or for blacklip populations outside of Tasmania. Theoretically it is possible to reduce the scale of the grid system further, but with GPS accuracy in some parts of the Tasmanian fishery limited to ≈ 10 m and diver boats operating up to 20 m away from the divers, assessment at a finer scale becomes subject to greater uncertainty. This work establishes the impact of spatial scale on *G* values. It also emphasizes that identifying the spatial scale most closely akin to the population dynamics of the target species and the scale of fishing is an important prerequisite to avoid misrepresentation of fishing areas and the spatial distribution of catch and effort.

CPUE data collated at coarse spatial scales is the primary fishery monitoring tool in abalone fisheries (Bedford et al. 2013). Current interpretation of CPUE trends requires the assumption that the CPUE exhibited in a block is representative of the whole block, but it lacks any information on the specific area effectively harvested and how areas of reef respond to serial harvest. To effectively interpret CPUE data, knowledge of both the resource's spatial distribution and whether fishing is evenly spread, or otherwise, over that distribution (Petitgas 2001). Changes in fishing location and tactic are potential indicators of changes in resource status (Fernández-Boán et al. 2013). The *IoP* utilized in this study is an adaptation of the work of Colloca et al. (2009) where it was used to identify persistent nursery areas. We implemented this index to identify persistent aggregated catch areas and examine the resilience of grid cells to serial harvesting. In doing so we showed that significant proportions of the annual blacklip abalone catch from 2012 to 2015 came from approximately 35 % of the TFRA and that these areas are frequented by a large number of divers. With less than 18 % of the TFRA sustaining aggregated catch across the regions examined this method highlights that relatively few individual grid cells were resilient to serial harvest across the four-year sample period. That the fishery is heavily reliant on a few key reef areas (cells persistent in all years produced up to 62 % annual catch) should be noted and that if fishing pressure or environmental change were to reduce catch from these cells there could be consequences for the stability of future catches from this part of the fishery. This work also displayed evidence that within the fishing grounds these productive cells were not randomly distributed but show a high degree of spatial clustering. Importantly, the *IoP* data suggest the clustering of persistent cells and the increased fishing activity around them compared to non-persistent cells is not reflected in the current management of this important fishery but should be incorporated into future strategies to enhance the current resource management components.

Understanding the vital environmental drivers which promote productive grid cells is key to future management of this fishery at finer scales. Recruitment survival, growth and size-at-maturity of abalone have been linked to wave exposure (McShane and Naylor 1995, Naylor and McShane 2001): growth and fecundity exhibit variation with temperature (Steinarsson and Imsland 2003, Grubert and Ritar 2005) and abalone catches have been linked to reef structure (Chick et al. 2012, Jalali et al. 2015). Mapping of *IoP* by grid cell provided a defined spatial area to which fishery independent survey resources maybe directed to investigate these assumptions. Furthermore, monitoring of persistent areas using a combination of the CACs indexes and fishery independent surveys may provide early warning of fine scale stock depletion and recruitment that could significantly influence future catches and therefore management decisions.

Previous to geo-spatial estimation of commercial fishing ground extent knowledge of productive abalone areas was limited to interpretations of diver knowledge which have been shown to be not always precise (Jalali et al. 2015). The AFA and TFRA used in this work depict localization of fishing events and extent of fishing grounds which are broadly based on the spatial indicators of fishing pressures developed for the EU common fishing policy framework (Russo et al. 2013). Our TFRA is similar to that proposed by Russo et al. (2013) in it approximates the total area of fishing activity. However, it varies from previous geo-spatial estimation of abalone fishing ground extent, which used light detection and ranging (LiDAR) to estimate potential grounds (Jalali et al. 2015). Our calculation of the TFRA varies from Russo et al. (2013) and other work on benthic species (Fernández-Boán et al. 2013) as a result of the lack of bathymetric data to define fishing ground extent. Neither a LiDAR nor bathymetric dataset were available for the entire Tasmanian coastline at a spatial resolution suitable for assessing abalone fishing grounds. Therefore, an alternative method was developed using all available geo-referenced fishing records covering the time since GPS tracking has become mandatory in the Tasmanian abalone fishery. One potential result of using this method is that as the TFRA may be underestimated against the true TFRA but the declining number of hex cell additions with each year in this data set suggest that these increases will diminish each successive year. The impact of such increases in TFRA on the *G* index are minimal as it is dependent on the AFA not TFRA, but the percentage of the AFA to the TFRA and the *IoP* score could potentially decrease.

The integration of diver derived geospatial fishing data into a tessellating grid system and the subsequent calculation of CAC indices provides evidence of delineation of fishing activity at a fine scale within an abalone fishery. The *IoP* established here offers new opportunities to assess fishery performance and assist in teasing apart the cause of hyperstability in CPUE data and changes in catch. Furthermore, coupled with TFRA and AFA provide a valuable asset in describing changing patterns of resource availability and fishery tactic in a fishery which is traditionally perceived as data poor. Application of these methods is not limited to the abalone fishery and could equally be applied to other S-fisheries globally that vary at fine spatiotemporal scales.

10. Delineation of fishing grounds: identifying discrete reef systems

Author: Craig Mundy

10.1. Introduction

All fisheries have instituted a spatial grid or spatial structure within which fishers are obliged to report their fishing activity. In some fisheries, these divisions are cells within a regular grid typically based on Latitude and Longitude (e.g. Tasmanian rock lobster, scale-fish and commercial dive fisheries) whereas for most Australian abalone fisheries the spatial reporting units (blocks, maps) are irregular in size and shape. Boundaries between irregular sized spatial units in abalone fisheries were presumably hand selected based on convenience and ease for fishers to determine their position while fishing. Subsequent analysis and summary of fishery-dependent data using these artificial spatial subdivisions could create artefacts when fishers distribute their effort within known contiguous reef systems, rather than by reporting block.

The spatial structure of commercially productive rocky reef varies regionally in Tasmania. In the North East and North West, and some offshore islands there are large expanses of sandy beach interspersed with headlands or rocky sections of coast. The southern half of Tasmania is characterised by large stretches of rocky coast with relatively few stretches of sandy beach. A small number of offshore 'platforms' such as the Actaeons in south-east Tasmania and the gap between the coast and Trefoil Island in the north-west offer unique, but often productive abalone reef systems. The distribution and the degree of fragmentation of productive abalone habitat may drive spatial patterns of harvest by divers, and potentially constrain spatial indicators (SPI) such as MaxDist. Similarly, the width of reef (how quickly the reef descends to a sand edge or to deeper water) will place constraints on how the diver progresses along a reef system. For example, if the reef descends sharply to a sand edge or quickly to depths too deep to fish safely, the diver has few choices if maintaining a particular depth profile. This local constraint may introduce local relationships between lmphr and CPUE for example, or other spatial indicators.

The shape and distribution of rocky reef could be provided by various forms of habitat mapping, whether that involves simple systems such as those used for Seamap Tasmania, or more complex multibeam or Lidar based methods for quantifying habitat extent and habitat type. As not all rocky reef supports commercially productive abalone populations, habitat mapping information may overestimate the potential reef available to the fishery. Similarly, extent of reef mapped using spatial data loggers used by fishers is likely to underestimate the extent of rocky reef along a coastline. Access to both forms of data would provide the most complete assessment of productive abalone reef, but access to both types of data is not available in any single state as yet. Here we characterise the extent and fragmentation of productive abalone reef by identifying discrete fishing grounds and describing their structure, independent of report block boundaries.

Two options could be pursued for identifying areas of contiguous reef habitat on the basis of use by commercial abalone divers. Quantifying the spatial structure of abalone reef can be achieved by using nearest neighbour metrics or, by using overlay and intersection based analyses applied to the KUD polygon datasets. Alternatively, identifying contiguous clusters of hex grid cells could also be used to identify contiguous reef systems by building a topological network based on adjoining hex cells. The hex grid dataset has the potential however to inflate the actual area of reef fished. Here we use nearest neighbour analyses to build a neighbourhood network of KUD 90% isopleth polygons as a case study for identifying individual reef systems.

10.2. Methods

10.2.1. Use of D Nearest Neighbour networks to describe spatial extent of abalone reefs

The KUD 90% isopleth (dive polygons) for individual dives are complex in shape and may comprise several separate sub-polygons. The centroid of the dive polygon is a convenient and easily calculated reference point for each dive. Identifying the dive polygons that make up a contiguous reef structure was achieved by applying D nearest neighbour analysis to the dive polygon centroids. A nearest neighbour network (dNNBN) is created by identifying all neighbour dive polygons whose centroid falls within a specified distance of a dive, repeated across all dive events. Here the distance range used is 0 to D, where D is 2 x the median *MaxDist* (length of a dive event) value for dive polygons within the dataset being analysed. The dNNBN is then deconstructed to separate disconnected clusters of polygons where neighbour link distance is greater than D, resulting in a list of polygons that are connected by a distance of less than D. Each cluster of dive polygons that make up a contiguous reef system is assigned a unique cluster identifier (cluster ID). Each of the original individual dive polygons is then assigned the cluster ID for the cluster which it is a member of. All dNNBN analyses were conducted in R (Core-Team 2016) using the package `spdep` (Bivand et al. 2011).

10.2.2. Inter-annual overlap in reef utilisation

The dNNBN method described above was used to identify all discrete reef systems in the Tasmanian abalone fishery, using the 90% KUD isopleth polygons from all dive events between 2012 and 2016. This created a dataset to describe the total fished area, the number of discrete reefs, and the area of each individual reef. As all events are tagged with reef cluster ID and year, the proportion of each reef utilised in a single year can be calculated, as well as the overlap in use of a specific reef between consecutive years. Here we use the four largest reefs as a case study for the extent of overlap in reef use among consecutive years.

10.3. Results and Discussion

10.3.1. Contiguous reef systems

The nearest neighbour network approach identified 979 distinct reef systems across the Tasmanian abalone fishery. Less than 5% of these reefs (32) accounted for 50% of the total fished area (Figure

45), while less than 2% of reefs account for 50% of the total harvest between 2012 and 2016. There is a general relationship between individual reef area and total reef catch (Figure 46), but there are several substantial outlier reefs which are either much more or less productive than expected on the basis of reef area alone. This analysis was based on the 90% KUD isopleth and a D nearest neighbour network using D equivalent to 2 times the median dive extent. From Section 6.3.5, we know that the 90% isopleth is an overestimate of the actual area likely to be used by a fisher during a dive. Changing two key parameters the isopleth (e.g. 50% KUD) and D may result in different outcomes for different reasons. A smaller KUD isopleth polygon reduced the overall area slightly and may increase the number of discrete reefs as a consequence. Increasing the value of D i.e. requiring greater separation between polygon centroids is expected to reduce the number of discrete reef systems. Use of the 50% Isopleth polygons and a larger separation distance reduced the number of discrete reefs to under 600 but increased the fit of the relationship between catch and area (Figure 47). Optimum isopleth level and D value used in this analysis will be different across Australian abalone fisheries, particularly where different dive practices are used (e.g. live fishing, anchored fishing, motorised cage fishing), and different habitats utilised (e.g. wave exposed shores, high tidal flow regions).

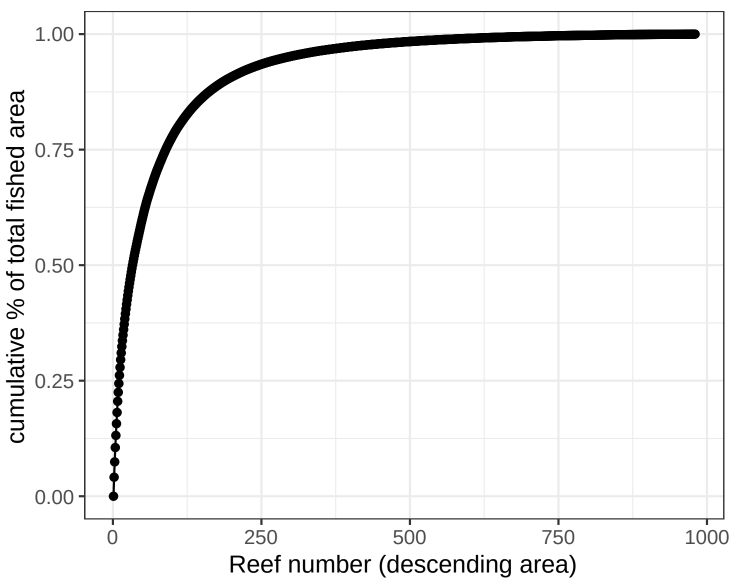


Figure 45. Cumulative area of individual contiguous reefs (all fishing events pooled 2012-2016).

The dNNBN analyses tested here demonstrate another facet of the complexity in spatial structure of the Tasmanian abalone fishery, with a few very large reef systems accounting for the majority of the total harvest. Combined with a meta-population based inter-reef connectivity (Miller et al. 2009, 2014), these results provide strong evidence that it is highly improbable that abalone fisheries would conform to a Dynamic Pool fishery model, and that outputs of approaches that assume a Dynamic Pool relationship exists should be interpreted with caution.

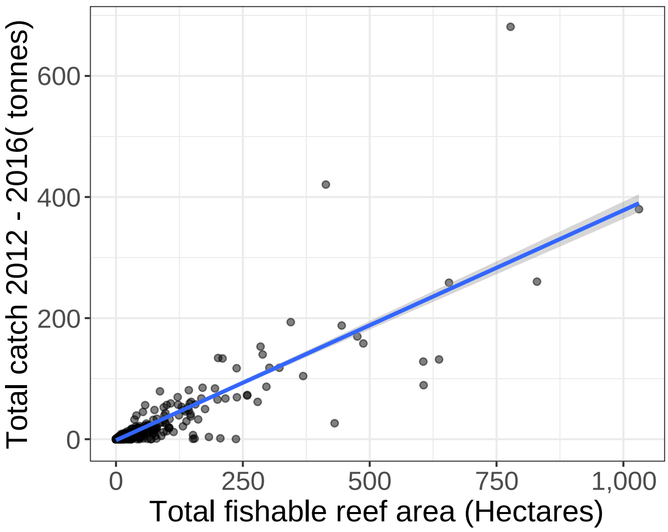


Figure 46. Relationship between total fished area and total catch per cluster (pooled over five years 2012 - 2016). Data input: 90% KUD isopleth, D=400m. Adj R^2 = 0.73, Slope = 0.38, p < 0.001.

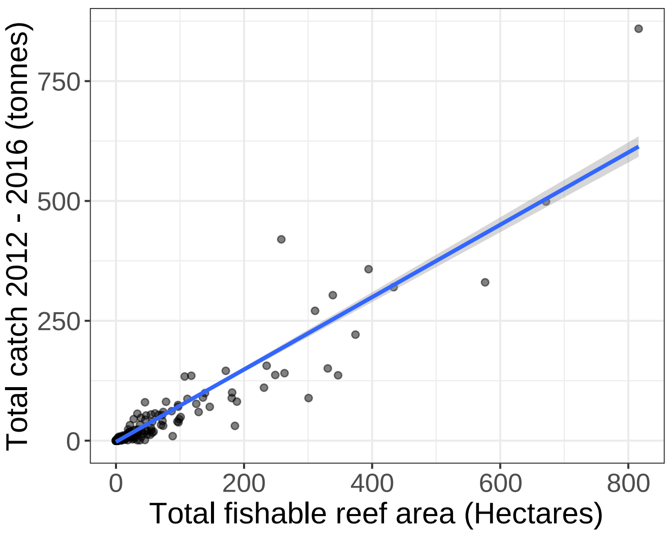


Figure 47. Relationship between total fished area and total catch per cluster (pooled over five years 2012 - 2016). Data input: 50% KUD isopleth, D=758m. Adj R2 = 0.88, Slope = 0.75, p < 0.001

10.3.2. Inter-annual patterns in reef use

The ability to identify contiguous reef structures independent of artificial reporting area for management convenience opens up the possibility of better understanding how reef systems are utilised through time. A key question for abalone fisheries is the extent of reef used each year and the level of inter-annual overlap. Fisheries Scientists routinely calculate annual summary statistics without consideration (or knowledge) of whether the data used in their analyses are comparable i.e. summary catch rates in two consecutive years are based on the same fished area.

A smaller than expected proportion of the total fishable reef area was utilised in any one year for the two largest reefs. On Reef 1 annual usage of the total fishable area ranged from 36% to 46% (excluding 2012), and on Reef 2 the annual usage ranged from 37% to 51% (excluding 2012) (Figure 48). For the largest reef in the Eastern Zone (Reef 3), the annual usage of the total fishable reef area was almost double that of Reefs 1 and 2, ranging between 62% and 80% annually. Inter-annual overlap in reef usage among consecutive years also varied substantially between Reef 1 and Reef 3. Overlap in consecutive years for Reef 1 was approximately 40% (excluding 2012), whereas for Reef 3, the overlap among consecutive years was between 78% and 87%.

As reported in previous chapters, substantial differences in spatial patterns between East and west coast fisheries are again observed in this study. The Western Zone abalone fishery are in a recovery phase, with increasing catch rates and a relatively stable long-term TACC, in contrast to the Eastern Zone fishery which has experienced a 50% decline in catch rates and 40% decline in TACC between 2010 and 2016. Whether the high annual level of exploitation of the total fishable reef area in the Eastern Zone is a function of stock levels, or the physical nature of the habitat is unknown. The generally low catch rates and high accessibility of most Eastern Zone reefs suggests that the level of exploitation of total fishable reef may be a function of stock status. If stock status does influence the area utilised in a given year, we should expect that the proportion of the total fishable reef area exploited annually should decline as the stocks rebuild.

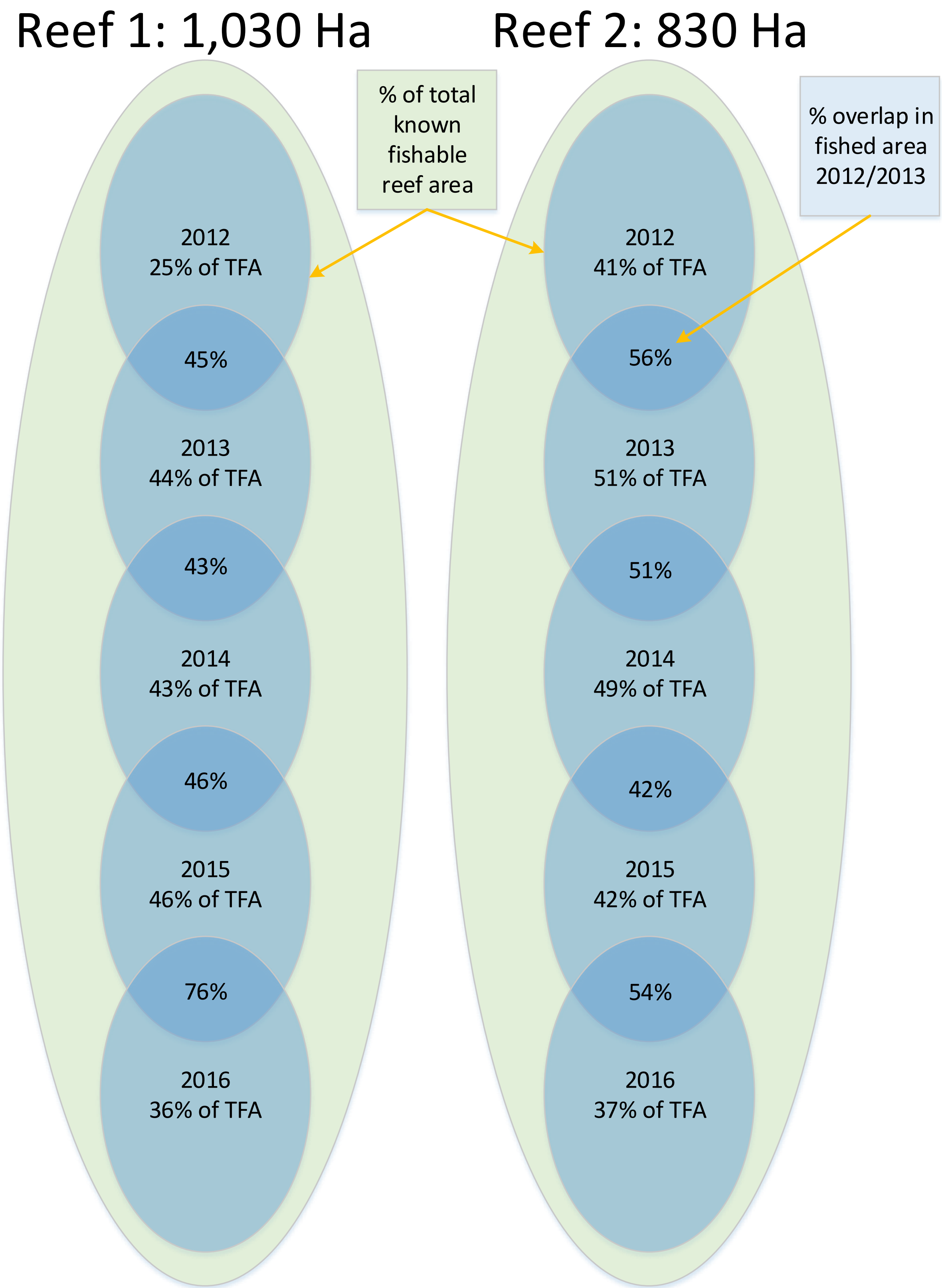


Figure 48. Total fished area, fished area in each fishing year (2012 - 2016) and proportion overlap among consecutive years of the two largest reefs in the Tasmanian fishery. Reef 1 and 2 are located on the south and south-west coast in the Western Zone. Note- usage of Reef 1 in 2012 is artificially low due to data loss associated with the late distribution of loggers at the commencement of the project. The south coast is subjected to high fishing pressure in January.

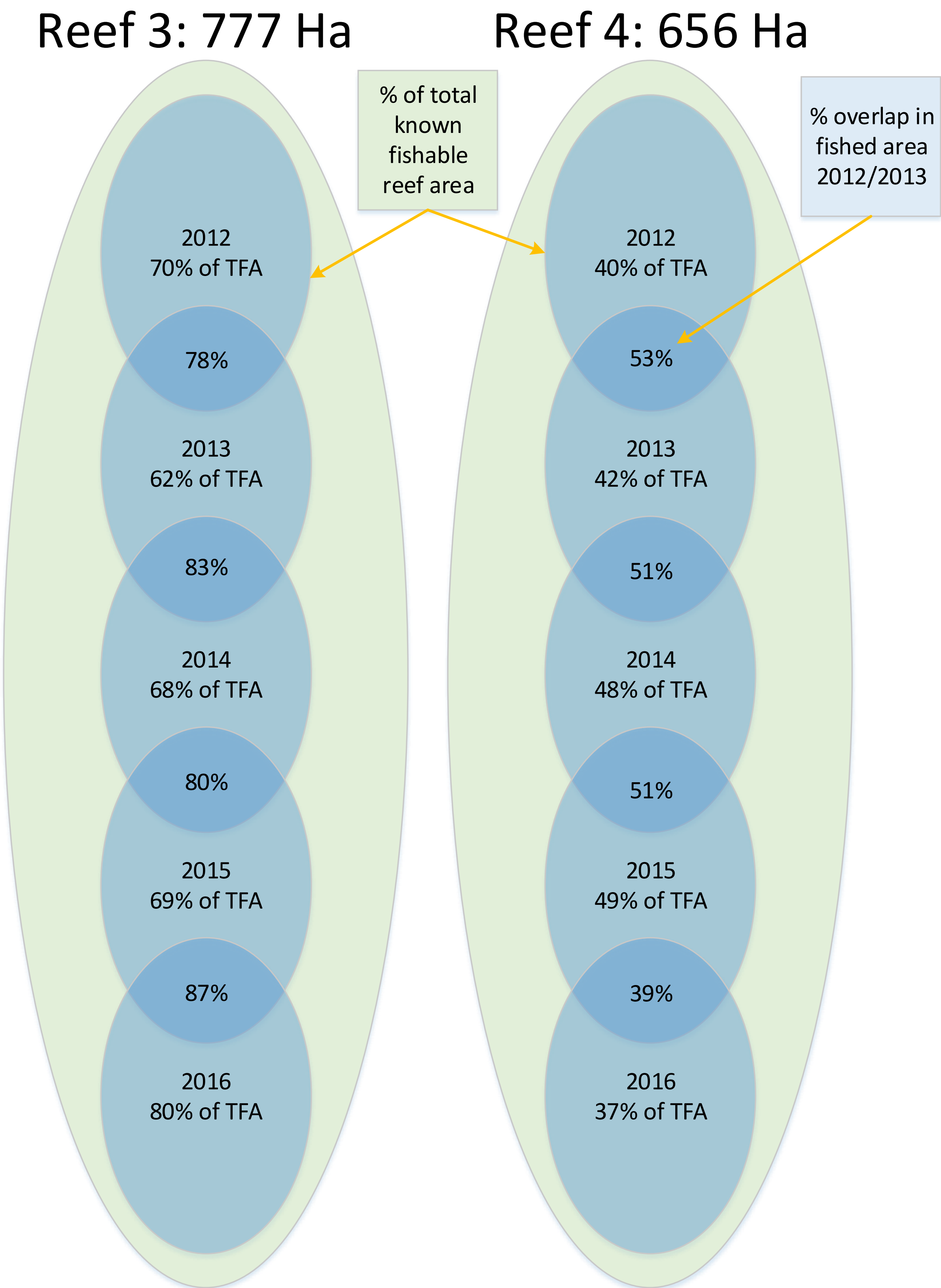


Figure 49. Total fished area, fished area in each fishing year (2012 - 2016) and proportion overlap among consecutive years of the third and fourth largest reefs in the Tasmanian abalone fishery. Reef 3 (Actaeons) is located in the Eastern Zone and reef 4 is in the Western Zone. Note – There is no data loss for Reef 3 associated with late distribution of loggers, as the Eastern Zone is closed to fishing from January to March inclusive.

11. Patterns in use of reefs: Characteristic return time to known sites

Author: Craig Mundy

11.1. Introduction

The Tasmanian abalone fishery transitioned from an input controlled (licenses capped at 125 divers in 1972) to a quota managed owner diver arrangement in 1985 and to a full ITQ system in 1992. Under this framework, highly motivated divers with appropriate vessels and access to quota could maximise their catch and focus fishing in areas of high catch rates. Resource management frameworks where multiple fishers have access to the same fishing ground inevitably lead to competition. The level of competition within the Tasmanian abalone fishery has reached extreme levels in 2017, with 45 divers fishing a spatially managed area and reaching the catch limit of 25 tonnes in five fishing days. Such intense competition for a common resource is an extreme example of the 'tragedy of the commons' (Berkes 1985, Prince 2005, Jensen et al. 2012), and places the Tasmanian fishery in that rare class of 'Olympic fisheries'. The factors driving this intense competition are yet to be understood but illustrate the importance of understanding the use of the resource by the fleet, and how that pattern of use may change over time in response to management action.

Within Australian haliotid fisheries it is common to hear fishers describe a normal pattern of cycling through known fishing locations. Typically, this will be 12months but may be as long as four years for less productive sites. It is also common for fishers to describe a shortening in the return time to known locations as a resource declines. Theoretically this would be the initial phase of serial depletion, particularly if the number of locations visited each year also increased, with the end result being hyper-stability in catch rates while the stock levels decline. The capacity to detect increasing frequency of visits to known locations by an individual or increases in the number of locations visited annually by divers could provide an early warning of serial depletion. However, distinguishing between a normal pattern of cycling through known fishing locations and a pattern suggestive of serial depletion as a consequence of a mis-match between the TACC and sustainable harvest fraction is likely to require a substantial time series involving transitions from high to low stock status.

11.2. Methods

11.2.1. Site Fidelity: How often do fishers return to the same sites?

The frequency of revisits to the same location was determined by examining the number of times there was close overlap between two dives. A D-nearest neighbour network (dNNBN) is created by identifying all neighbour dive polygons (KUD 90% isopleth) whose centroid falls within a specified distance of the centroid of the target dive, repeated across all dive events. Here the distance range used is 0 to D (where D = 40.0 m).

D is calculated as 0.2 x the median *MaxDist* (length of a dive event) value for dive polygons within the reef being analysed. All dive events between 2012 and 2016 were included in this analyses. All dNNBN analyses were conducted in R (Core-Team 2016) using the package `spdep` (Bivand et al. 2011).

The unique ID of the diver for both the target and neighbour dives was then identified, and a range of difference parameters calculated for the target and neighbour dives; specifically, differences in time between the overlapping events, CPUE and swim rate in LmpHr. As the practice of 'doubling up' (two fishers diving together on a T-piece) is becoming more common, and, divers often move sequentially along the coast during the day, neighbour pairs occurring on the same day were excluded from subsequent analyses. Overlap events are then split into 1) those involving different divers fishing in the same place, or 2) the same diver returning to the same place at least 24 hours after the initial event. Frequency histograms of overlapping dive events were used to examine the extent of site fidelity and spatial overlap in visitation by divers in the Tasmanian abalone fishery for a selection of key reefs (see Chapter 11) on the Eastern and Western coasts.

11.3. Results and Discussion

11.3.1. Frequency of overlap in fishing sites

Repeat visits to fishing grounds by the same diver and by different divers varied around the coast. Fishing site overlap analyses found that most locations are fished relatively infrequently by different divers. On some reefs however (e.g. Reef 15 in the Actaeons), there is substantial spatial overlap by divers with one single location fished up to 60 times over a six-year period (Figure 50). Reef 15 had almost double the number of fishing events as Reef 28, but only half the number of dive events with no effective neighbours within 40m of the dive centroid (Figures 50, 51). Return visits to the same location by the same divers were very different across the two reef case studies. Where dive locations were only visited once by the same diver over the six-year period, this occurred 400 times on Reef 28, and more than 2100 times on Reef 15.

The effect of prior fishing events on CPUE appeared to be negligible on both Reefs 15 and 28 (Figures 52a, 53a). The exception being a slight short-term improvement in CPUE where the same fisher returned to the same location within the 40 day window (Figure 53b). These results highlight the unusual nature of Reef 15 in the Actaeons where the extent of spatial overlap in fishing events is substantial, but with relatively few consequences. While the absence of a strong effect on CPUE was unexpected, it may well highlight the fact that the KUD polygons represent the path of the vessel, and while the vessel path may overlap among visits, the actual path of the divers may be quite different. Where reefs slope quickly from the shore to a sand edge or unworkable depths, effectively constraining where divers may search for abalone, we would expect to find more substantial effects of fishing events on subsequent fishing events at a location within short time period. Further analyses are required for this aspect of the fleet dynamics, contrasting effects of spatial overlap on

CPUE in narrow vs wide reef systems.

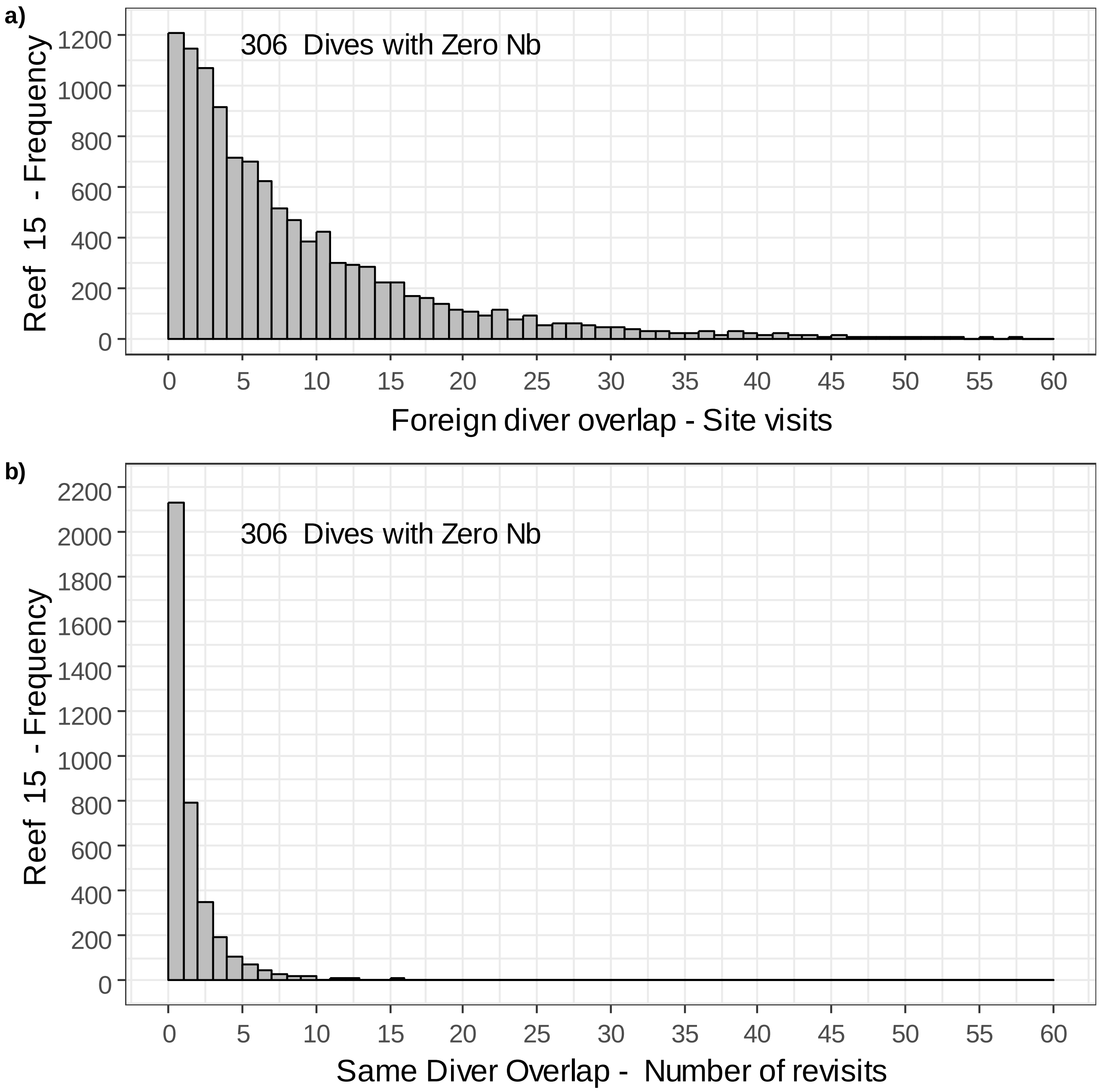


Figure 50. Frequency of revisits to the same location within reef 15 (sub-block 13E, Eastern Zone) between 2012 and 2016. A total of 13,542 were recorded on reef 15, with only 306 dives having no neighbour dives within 40m. a) Frequency distribution of overlapping fishing events where the identity of the diver of the target dive is different to all neighbouring dive events (overlap among fishers). b) Frequency distribution of overlapping fishing events where the identity of the diver of the target dive is the same as the neighbouring dive events (repeat visits).

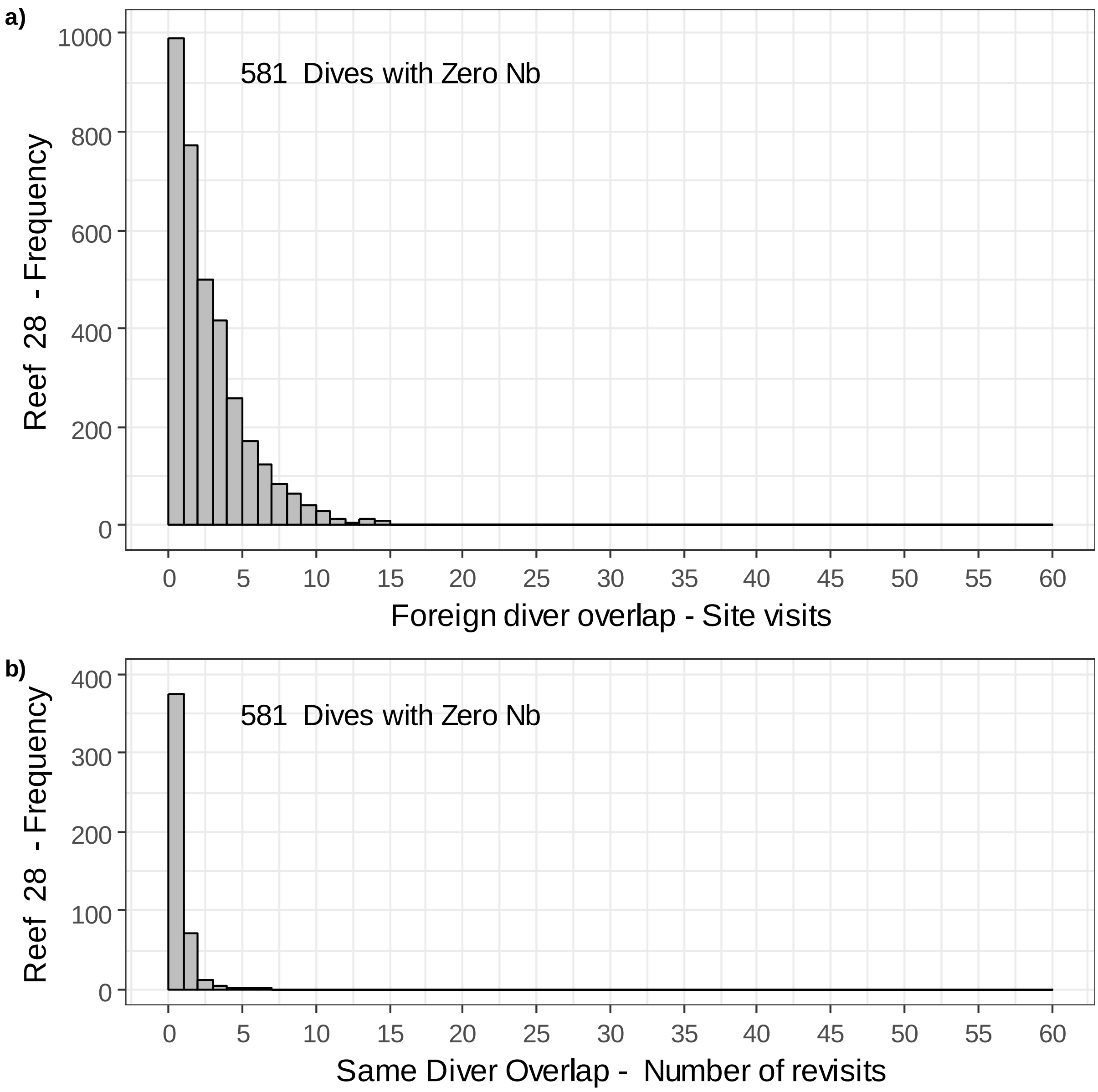


Figure 51. Frequency of revisits to the same location within reef 28 (sub-block 10C, Western Zone) between 2012 and 2016. A total of 6,379 dive events were recorded, with only 581 dives having no neighbour dives within 40m. a) Frequency distribution of overlapping fishing events where the identity of the diver of the target dive is different to all neighbouring dive events (overlap among fishers). b) Frequency distribution of overlapping fishing events where the identity of the diver of the target dive is the same as the neighbouring dive events (repeat visits).

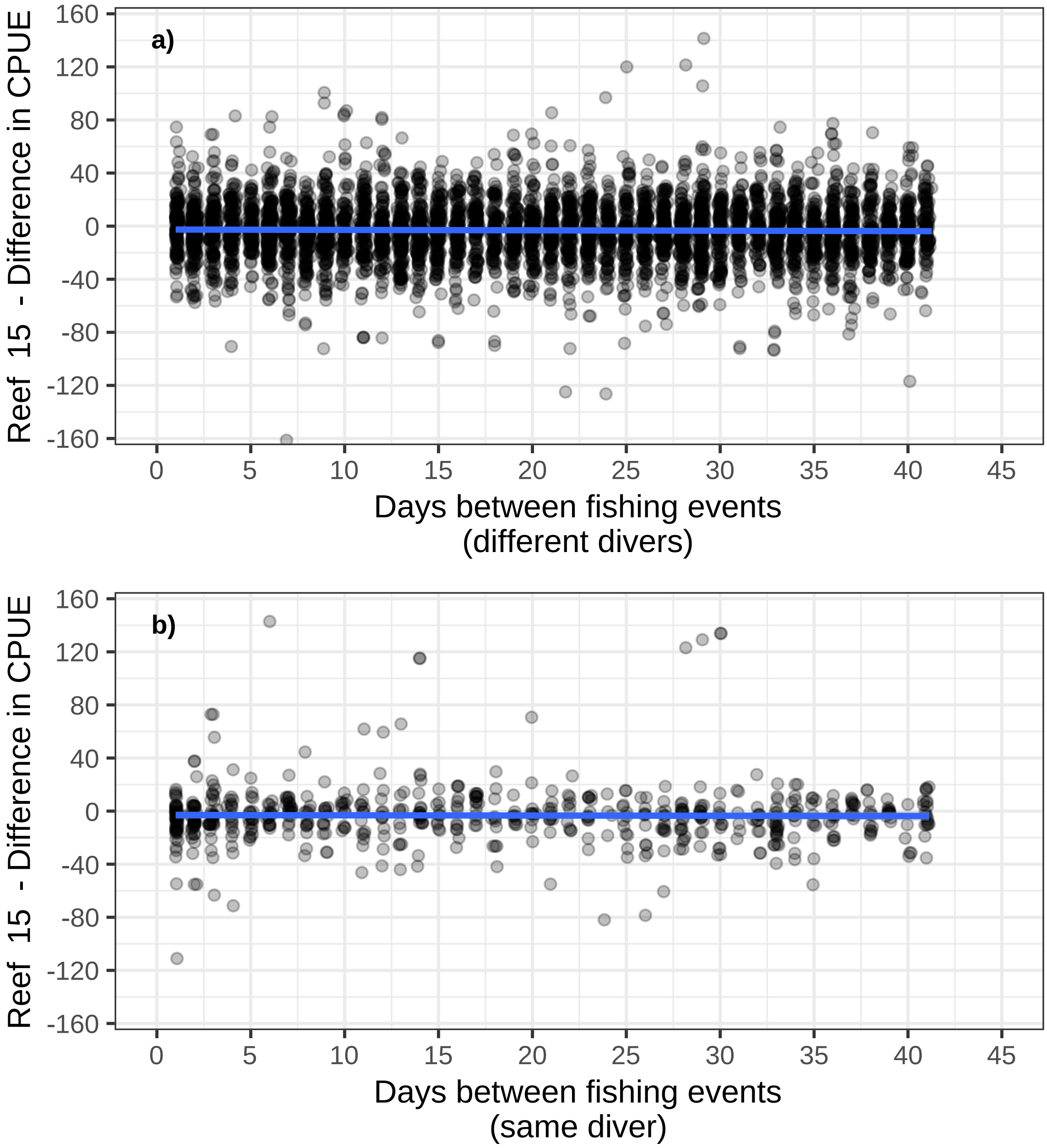


Figure 52. Effect of fishing the same location within a short time window (40 days) at Reef 15, Eastern Zone. a) Overlapping fishing events by different divers; b) Overlapping fishing event by the same diver. Note: same diver pairs pooled across all divers.

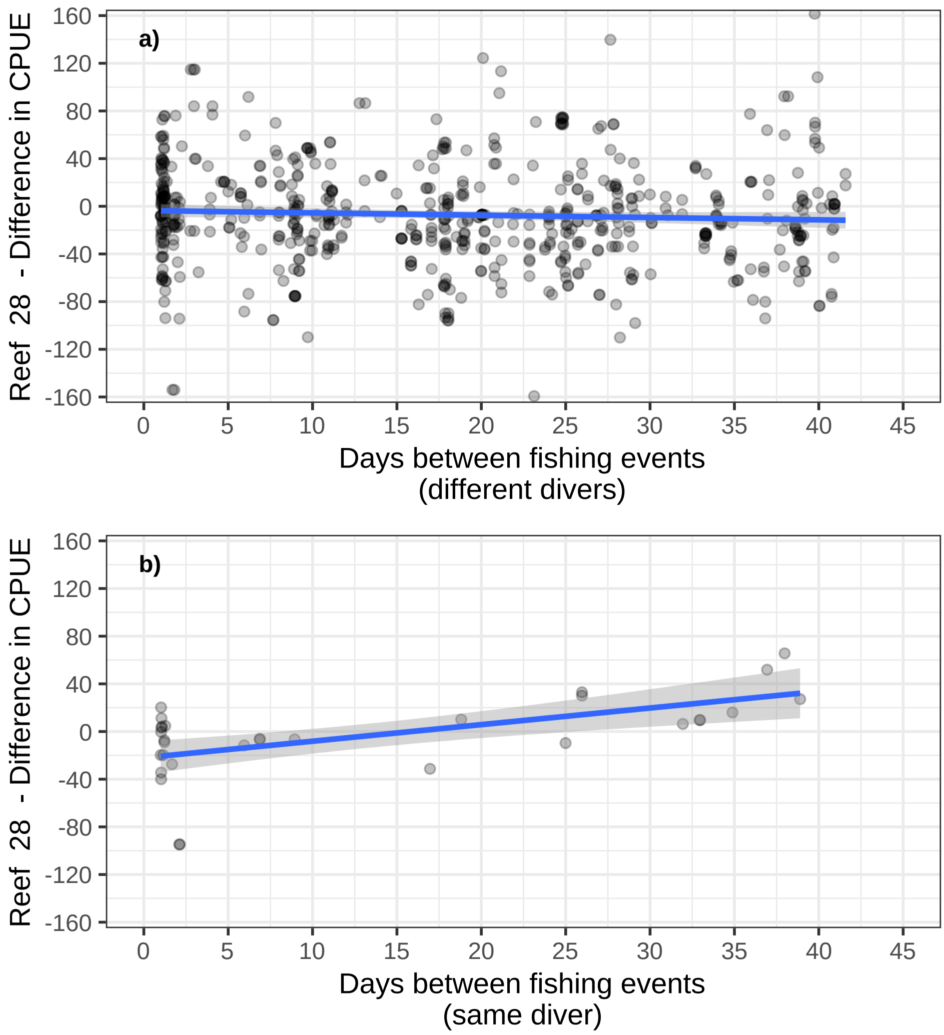


Figure 53. Effect of fishing the same location within a short time window (40 days) on Reef 28, Western Zone. a) Overlapping fishing events by different divers; b) Overlapping fishing event by the same diver. Note: same diver pairs pooled across all divers.

12. Development of a Multi-Criteria Decision Analysis based harvest strategy for the Tasmanian abalone fishery.

Author: Craig Mundy and Hugh Jones

12.1. Background

Prior to 2008, the Total Allowable Commercial Catch (TACC) was determined using a top-down process, where the TACC from the previous year was allocated across blocks. Where catch rates in specific blocks were declining and considered unlikely to support that level of catch, attempts were made first to shift the catch to other blocks, and as a last resort, reduce the overall TACC. Commencing in 2008, the Zone TACC was determined by a bottom-up process of summing the catch considered sustainable at each reporting block in the Fisheries Resource Advisory Group (FRAG) workshop process. The FRAG involved a multi-workshop process (four workshops annually) where two empirical indicators (catch and CPUE), diver opinions, are used in an ad hoc 'weight of evidence' approach based on "expert opinion".

Since the commencement of formal assessments for this fishery, there has been opposition to TACC reductions where changes are likely to have substantial economic impacts on the investor sector. As a result the final TACC recommendation is a compromise between environmental sustainability and economic tolerance. In the past, the distinction between a precautionary TACC and the final TACC recommendation has been blurred. In 2014, this practice was modified with IMAS providing a document recommending Statistical Block level TACCs for 2015. This IMAS view is discussed and either accepted or modified with the justification for any changes recorded explicitly. While the 2014 process is an improvement, this ad hoc weight of evidence approach has several weaknesses:

1. It is highly dependent on the mix of divers, quota owners and processor managers present at the workshop and the financial impact of change on those present. The absence or presence of individuals can alter the outcome of discussion on some areas substantially.
2. There is no explicit weighting of the performance measures (PM) (typically catch, CPUE, catch size structure, diver opinion) being considered, and the weighting given to each of these performance measures can often depend on how convinced individuals, including IMAS researchers and, at times the Department, are of their view.
3. There is insufficient regard for the data quality of the PMs in use, for example the accuracy and relevance of CPUE or associated biases are not well understood by all, and whether

'expert' diver opinion represents a few individuals or has general acceptance across the harvest sector.

4. While the workshop structure, which is common to most states, provides a record of the consensus decision for a given reporting block, map code, or reef code, it does not provide a clear audit trail of how the final TACC was determined and which PMs or economic factors were most influential, or of any departures from an independent more evidence driven process

At the commencement of this project, Tasmania did not have a formal harvest strategy although for a brief period (1999-2000), trigger points associated with upper and lower reference periods were used. However these were not well designed and the reference periods were not always appropriate for all blocks. Reliance on reference periods must explicitly assume (but typically this is implicit) that the physical and biological environment has not changed between now and the reference periods used and that fishing power and fishing efficiency remains constant. In the case of the east coast of Tasmania, the assumption of a static physical and biological environment is most certainly not valid. The reference period approach was abandoned in 2001, and an ad hoc expert driven process evolved in the absence of any further development of a formal harvest strategy.

12.2. A new flexible MCDA based Harvest Strategy

To address the weaknesses in the current ad hoc approach described above, a formal empirical Harvest Strategy is required to ensure TACCs are set within an objective decision process based on best available data. An effective empirical Harvest Strategy (eHS) for Tasmania must be capable of including more than two PMs and incorporate a PM weighting (or importance) component. It should also be sufficiently flexible to allow selection of a local suite of PMs as appropriate for an area, rather than a global set of PMs. To this end, a draft Harvest Strategy based on Multi-Criteria Decision Analysis (MCDA) methods has been developed. There are a large number of different forms of MCDA and associated terminology which all have a common approach – to provide an objective decision outcome based on multiple criteria through a repeatable and defensible process. Typically, MCDA uses multiple qualitative criteria to evaluate a set of options. Here, the MCDA implemented utilises quantitative criteria (= empirical Performance Measures) to develop an overall single index of stock performance against agreed performance criteria for each spatial assessment area, with a control rule applied to that single index to indicate whether the TACC for the following year should remain unchanged, be reduced, or be increased, and where change is recommended, by how much. There is an extensive literature on systems for weighting individual criteria and these may be applied if required while the MCDA based Harvest Strategy concept is developed.

Implementation of the MCDA based Harvest Strategy process follows several logical steps (Box 1). An opportunity for stakeholders to provide input to the process, including input on the selection of PMs, the scoring functions, and the weighting of PMs is important for the acceptance of any Harvest Strategy.

1. Establish the decision context.
    1.1. Establish aims of the empirical Harvest Strategy, and identify decision makers and other key players.
    1.2. Consider the context of the status assessment, such as addressing depletion or rebuilding phase.
    1.3. Identify explicit objectives for the fishery.
2. Identify the spatial assessment areas to which the MCDA will be applied
3. Identify PMs.
    3.1. Identify PMs for assessing the relative fishery status through time.
    3.2. Organise the PMs by clustering them under high-level categories in a hierarchy.
4. 'Scoring'. Assess each PM against the agreed performance criteria and targets.
    4.1. Develop a scoring process for each PM
    4.2. Provide opportunity for input and approval of selection of PMs, and scoring system
5. 'Weighting'. Assign weights to each PM reflecting their relative contribution to decisions.
    5.1. Provide opportunity for input to determine weighting matrix
6. Combine the weights and scores for each PM to derive an overall index value.
    6.1. Calculate weighted scores at each level in the hierarchy.
    6.2. Calculate weighted composite index score.
7. Apply Decision Rule to composite index
8. Examine the results.
9. Sensitivity analysis.
    9.1. Conduct a sensitivity analysis: do alternate scoring functions or weights affect the final composite index score.
    9.2. Assess effect of inclusion/exclusion of PM

Box 1. Process for implementing a MCDA based Harvest Strategy

The Harvest Strategy has been reviewed (Buxton et al. 2015) and subjected to testing via Management Strategy Evaluation (Haddon et al. 2014, Haddon and Mundy 2016). This HS identifies aspirational targets for the fishery and attempts to manage the fishery towards that target. The HS is run at the scale of individual reporting Blocks to arrive at a combined score, followed by a Control Rule to assign a recommended management action based on the combined score.

12.3. Worked example of the MCDA eHS in the Tasmanian Abalone fishery.

12.3.1. Selection of Performance Measures

Selection of individual Performance Measures (PMs) to be used when assessing the fishery performance in each spatial assessment area should include PMs reflecting particular concerns of management and industry. Likewise the scoring functions for each PM should include input from the divers, particularly divers with extensive experience in specific areas. Existing PMs that could be utilised in an MCDA context are derived from CPUE data, but other PMs currently under development could also include for example inter-quartile distances of commercial catch length frequency data and spatial PMs derived from diver GPS units.

To provide a worked example of the MCDA process here we focus on three performance measures that form the basis of ad hoc discussions on fishery performance in the Fisheries Resource Advisory Group meetings in 2014:

1. Target CPUE: the current CPUE scored against a target CPUE defined by Block
2. Gradient 1: Percent change in CPUE in the current year over the previous year
3. Gradient 4: Gradient of change in CPUE over the past four years including year to date.

12.3.2. Performance measure scoring functions

The scoring functions in the proposed MCDA process incorporate targets and limits that are analogous to classical target and limit reference points. A scoring function is established for each PM, with the value of the PM (e.g. Target CPUE) scoring between 0 and 10. For all PMs the target is always a score of 5, with 0 implying the worst under-performance and 10 the highest over-performance. The relationship can be linear or non-linear, and may be a positive or inverse function. The MCDA process can also include constraints, such as zero TAC when combinations of PMs result in certain critical values. Where possible the scoring function and the target score will be derived empirically. However, for the new spatial PMs where there is only a short time-series, empirical derivation of scoring functions is not currently feasible, and choice of target score and the scoring function will be derived via expert opinion as an interim measure.

12.3.3. Performance Measure Weighting

A level of importance must be assigned to each PM in the MCDA, and the weights must sum to 1. The weighting values for a given PM can incorporate a confidence or data quality consideration. Techniques for stakeholder input to the weightings are well established, and are typically based on ranking systems. The final MCDA based index of performance is then a sum of the criterion score x criterion weight, for all PMs (Table 12).

12.3.4. Control Rule for TACC Adjustment

A control rule system is applied to the composite MCDA index, to determine the action to be taken. The control rule system proposed is based on a similar system suggested by Dichmont and Brown (2010). If the composite index score is close to the target score of 5, there is no change in TACC for a given spatial assessment unit (e.g. Block). A TACC reduction is required if the composite index score is less than 5, and a TACC increase may be taken if the score is greater than 6 (Table 12).

The Control Rule decision structure is intentionally asymmetric around the Composite Score target of 5 with TACC increases ranging from 5% to 15% while TACC decreases range from 5% to 80%. The level of increase/decrease is determined by the extent of departure from the target score of 5. Where the control rule results in a TACC decrease, the Control Rule specifies the minimum reduction required given the Composite Score, whereas for TACC increases, the Control Rule specifies the maximum increase. TACC increase could optionally not be taken if arguments can be rationalised to support the status quo (e.g. market dynamics). The logic here is that for long-lived species such as commercially exploited haliotids where adult mortality is relatively low, from a biological stand point there is little to be lost in delaying a TACC increase by 12 months.

	TARGET CPUE	GRADIENT 1	GRADIENT 4CPUE
PM SCORE	a	b	c
PM WEIGHT	0.7	0.15	0.15
PM TOTAL	a x 0.7	b x 0.15	c x 0.15
COMPOSITE INDEX SCORE	$\Sigma((a \times 0.7) + (b \times 0.15) + (c \times 0.15))$		

HARVEST CONTROL RULE

Score	< 0.5	0.5 – 1.5	1.5 – 2.5	2.5 – 3.5	3.5 – 4.5	4.5 – 5.5	5.5 – 6.5	6.5 – 7.5	7.5 – 8.5	8.5 – 9.5	> 9.5
TACC Adjust	-25%	-20%	-15%	-10%	-5%	NC	5%	10%	15%	20%	25%

Table 12. Weightings, composite scoring function (upper panel) and Control Rule (lower panel). Upper panel- MCDA index calculation based on three PMs with unequal weights, resulting in a composite index score. Lower panel – symmetric decision rule system applied to the composite index score.

Consideration of individual scoring systems, weighting coefficients, the control rules and any constraints are on-going through a series of informal workshops with experienced fishers. Ultimately, components of this Harvest Strategy will be tested within the MSE under development in Tasmania.

12.3.5. Calculation of the three current PMs and their associated scoring functions

12.3.5.1. **Target CPUE**

The objective of the Target CPUE PM is to maintain CPUE at or above a tar- get value (i.e. 5 or greater on the PM scoring function). Following initial presentations of the MCDA Harvest Strategy at the June 2014 FRAG meeting, and at a subsequent workshop re- search/industry workshop (19/06/2014) it was agreed that an empirical process would be used to determine CPUE targets for each reporting block, based on mean annual CPUE back to 1985. A range of options for establishing appropriate CPUE targets were proposed included median annual CPUE (50th quantile), and more precautionary targets such as the 55th, 65th and 75th quantile of the annual CPUE. As the time series of data used to determine the CPUE target excludes the period of low CPUE during the late 1980’s and early 1990’s, a mildly precautionary approach using the 55th percentile was adopted.

The Target CPUE was determined for each statutory block, and scoring function implemented according to the magnitude of the CPUE Target (Figure 54). Where the current standardised CPUE is below the target CPUE, a low score is achieved (red arrow), and when the current CPUE exceeds the CPUE Target a high score is achieved (green arrow).

$CE_{b,T}$ is the target CPUE in Block *b*, and ΔCE, when added or subtracted from $CE_{b,T}$ is the upper and lower bounds of CPUE expected in Block *b* in the fishery. Thus if the $CE_{b,T}$ = 110kg/hr with a ΔCE of 50kg/hr the range of CPUE for which scores are defined would be between 60 – 160 kg/hr. Given $CE_{b,y}$ is the CPUE in block *b* in year *y* then:

$$score = \left(\frac{5}{\Delta CE}\right) CE_{b,y} + \left(5 - \frac{5}{\Delta CE} CE_{bT}\right) \quad (1)$$

It is important to note the difference between the actual CPUE in a year, $CE_{b,y}$, and the Target CPUE, $CE_{b,T}$. When the two are the same then, as designed, the score would be 5. This is a general relationship for all combinations of target CPUE and ΔCE, given the assumptions that $CE_{b,T} > \Delta CE$, and that both are always positive.

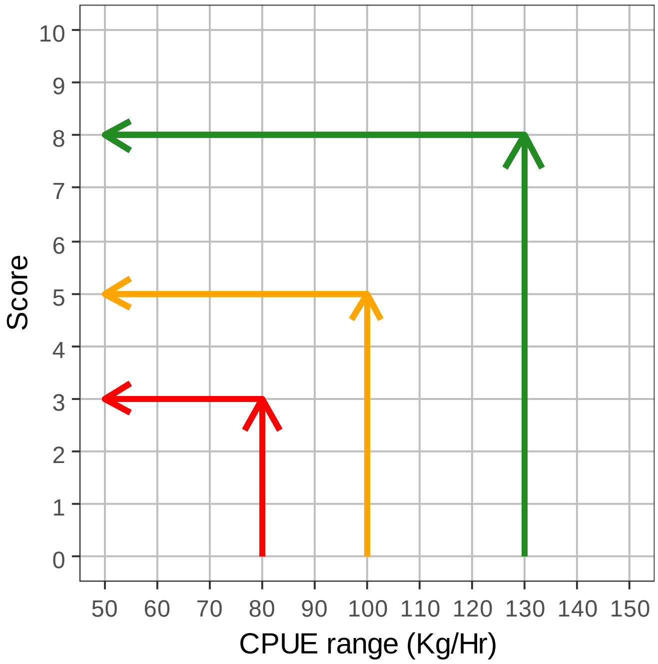


Figure 54. Illustration of the translation of an observed CPUE relative to a defined Target CPUE into an MCDA score. Three instances are shown, the CEb;T is 100 Kg/Hr (score 5). At 80 Kg/Hr and 130 Kg/Hr, the scores are 3 and 8 respectively.

12.3.5.2. **Gradient 1**

The objective of this scoring function is to recommend positive increases in the TACC if there are rapid increases in CPUE between the current year and the previous year and conversely recommend decreases in the TACC if there are recent decreases in CPUE.

$CE_{b,y}$ is the CPUE in block *b* in year *y* and this is used to calculate the performance measure Gradient 1:

$$rate1 = \left(\frac{CE_{b,y}}{CE_{b,y-1}} - 1 \right) \qquad (2)$$

The output for each PM is required as a score between 0 – 10, so assuming a symmetric distribution of scores around the changes in CPUE (Figure 55), given an expected maximum percentage increase or decrease of *a* or –*a* between years, this can be translated to a score as:

$$score = \frac{a}{5} \times rate1 + 5 \qquad (3)$$

With limits imposed such that the score is constrained between 0 – 10. If these limits are reached often then the range of potential changes (*a* – -*a*) would need to expand. Initially a range from -0.4 – 0.4 will be used.

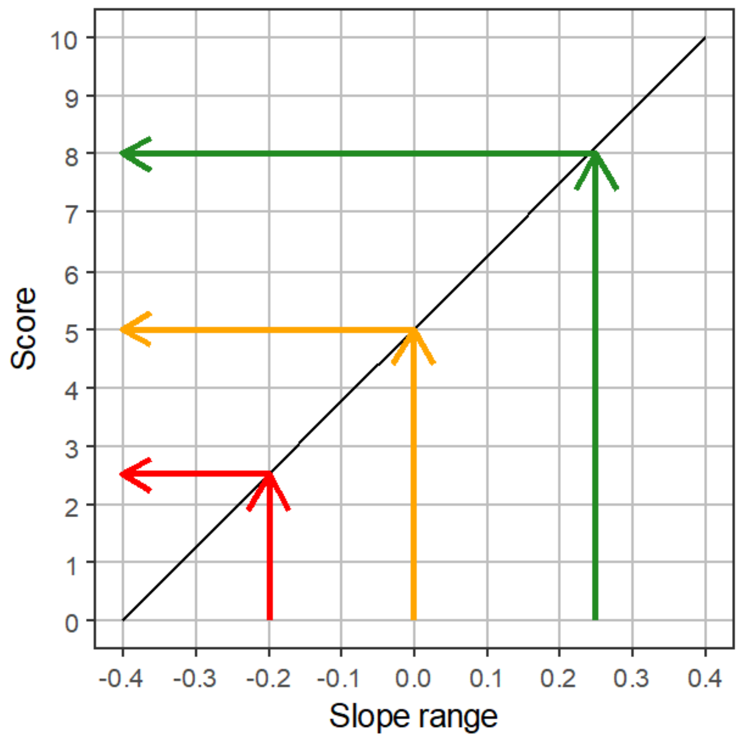


Figure 55. Illustration of the translation of an observed CPUE 4 year slope into an MCDA score. Three instances are shown, the CEb;T is 0.0 slope (score 5). At a slope of -0.2 and + 0.25, the scores are 3 and 8 respectively.

12.3.5.3. **Gradient 4 CPUE**

The objective of this scoring function is to recommend positive increases in the TACC if the gradient of CPUE over a four year period is increasing (provisionally n = 4) and conversely it recommends decreases in the TACC if that gradient is negative (Figure 55). The assumption is that where TACC is constant or decreasing, and a negative CPUE gradient is observed, the harvest level is likely to exceed recruitment to the fishery. As CPUE is a relative measure for particular spatial assessment units, so the changes in CPUE through time need to be converted to proportional changes through time otherwise areas of different productivity would be treated differently.

With limits imposed such that the score is constrained between 0 – 10. If these limits are reached often or never reached, then the range of potential changes (−*a*–*a*) would need to be modified. For this assessment, the range of observed slopes over the reference period for each individual block is extended by 15%, with −*a* and *a* set as the lower and upper extent of the extended range. As for the CPUE Target example, where the current CPUE gradient is below the target of zero a low score is achieved (red arrow), and when the current CPUE gradient exceeds the Target a high score is achieved (green arrow).

12.3.6. Block Based MCDA eHS and setting of TACC

Each reporting Block (= spatial assessment unit) within a fishing zone has a different long term productivity and catch rate, thus the MCDA process is applied by to each Block. The zone-wide TACC is determined by summing the recommended catch to be taken from each Block. The question arises about which Block catch should be modified to determine the projected Block catch for the following year. In practice, the TACC decision made in year$_t$ for the fishing year$_{t+1}$ must be made in October of year$_t$. Thus the final catch and CPUE for a given block is not known at the time of the decision, and the CPUE analysis must be conducted on either partial year data (January – September), or the full years data from the previous year (i.e year$_{t-1}$). When the fishery is declining or rebuilding rapidly, then there is a strong argument and preference by Industry to utilise all available data especially the data obtained in the year to date. In terms of the Block catch value that the adjustment will be applied to, when the analysis includes the partial year data, then the allocated catch for year$_t$ (defined during the assessment in year$_{t-1}$) will form the base value for Block catch adjustment.

12.4. Retrospective Evaluation of MCDA HS against Fishery Decisions 2001 – 2014

Development of an objective decision process for TACC setting as part of a formal Harvest Strategy for the Tasmanian Abalone Fishery is essential for the provision of defensible management advice for this fishery. The process of evaluating and fine-tuning the MCDA Harvest Strategy calculations including PM weightings will be an iterative process running over several months or years and will include MSE modelling and industry discussion. The intension of this pilot evaluation is to provide an example of the interactions and power of the PMs to adjust TACC recommendations through the MCDA eHS process.

This pilot assessment of the MCDA HS model is split into three sections, each addressing a key question concerning the retrospective analysis of the MCDA harvest strategy. Section 1 considers the implications of applying the MCDA on full year data versus current partial year data. Section 2 evaluates the Target CPUE performance measure (MP) at three different target levels and how this impacts MCDA outcomes. Section 3 considers the effect of PM weighting on the MCDA outcomes. These evaluations of the MCDA Harvest Strategy were based on CPUE data between 2000 and 2014 for the Western and Eastern Zones (Figure 56).

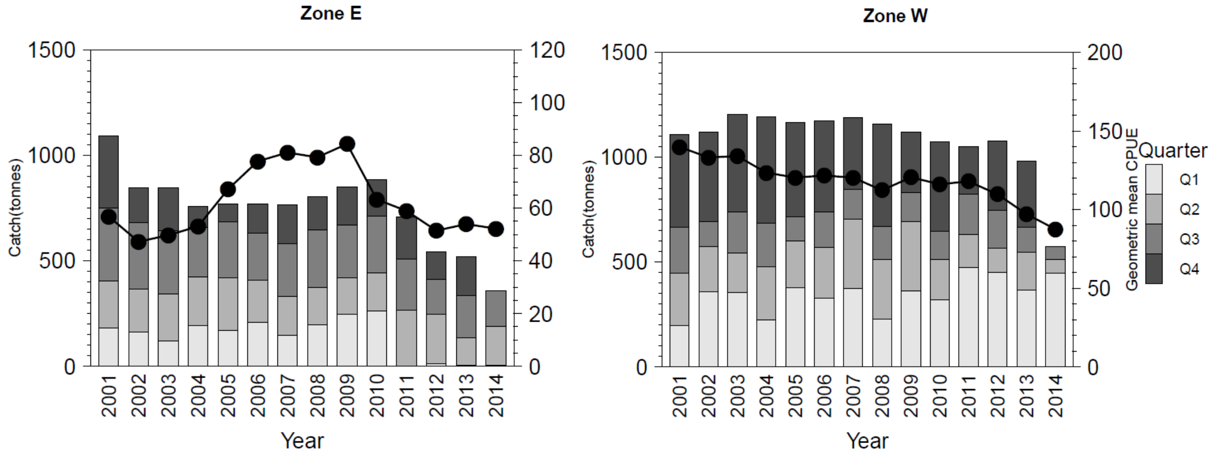


Figure 56. CPUE (solid line with dots) and commercial catch of Blacklip abalone for the Eastern Zone (E) and Western Zone (W) for the Tasmanian Abalone fishery from 2001 - 2014. Year 2014 represents data from January to October inclusive.

12.4.1. Evaluation of partial year vs full year in the MCDA HS

The current fishery assessment and TACC setting process within Tasmania involves four Fisheries Resource Advisory Group (FRAG) workshops through the year, with a final workshop in October where a TACC recommendation is determined. This provisional TACC is presented to the peak industry group (Tasmanian Abalone Council) AGM and to the Minsters Fishery Advisory Group (AbFAC). Recommendations on future TACC are provided to the minister by the AbFAC, usually in late October or early November, but prior to the full year's data being available. This creates a dilemma of whether or not to incorporate the partial data available at the time of the final workshop, or place greater reliance on the full year's data from the previous fishing year.

Originally (early 2000s) the TAC recommendations were based on the full year data from the previous year, largely ignoring the data year to date, resulting in a one-year implementation delay. Since the inception of the FRAG review process, t the current ad-hoc TACC setting for the next year (Cy^{+1}) are made on year to date (January-September) CPUE data (*CPUEp*) and the zone TACC recommendation from the previous November (Cy^{-1}) A complication when using the partial year data to assess the fishery status, is the total catch (*C*) from each reporting block is also unknown, and the block catch adjustment (& Zone TACC) must be made on either the catch allocated to a block or a modified value based on catch against expected catch at that time of year.

CPUE in the Tasmanian fishery is seasonally and spatially variable at a Block level. For instance divers report higher fourth quarter CPUE in parts of the Western Zone as a result of improved weather conditions and reduced fishing pressure through winter. In contrast, the Actaeons region in the Eastern Zone (Block 13) can have lower CPUE in summer and spring due to greater kelp biomass and possibly to reduction in density of abalone through autumn and winter fishing pressure. In order to evaluate how reliance on year to date CPUE data (*CPUEp*) may effect MCDA outputs a retrospective analysis of the 2000-2014 data was completed comparing partial year CPUE (*CPUEp*) against full year CPUE (*CPUEy*). The *CPUEp* dataset was limited to the January-September CPUE data, equivalent to that which would be available at the October workshop, while the *CPUEy* used full year CPUE data for each year.

With *CPUEy* of the current year not available for normal fishery assessments, future TACC setting via the MCDA (or any other method) must adopted one of two possible routes with regard to the CPUE data, The decision process could;

1. Utilise year to date CPUE data (*CPUEp)* (zero implementation delay)
2. Utilise full year CPUE data from the previous completed fishing year ($CPUEy^{-1}$) with full year catch the previous year (Cy^{-1}) to estimate the TACC for the next year (Cy^{+1}) (one-year implementation delay).

Both of these possible applications have issues with regard to implementation error with the *CPUEp* option subject to final quarter CPUE variation and the $CPUEy^{-1}$ option being one year out of step with the current CPUE trends. In order to evaluate how this may effect MCDA outputs a separate retrospective analysis of the 2000-2014 data was completed comparing *CPUEp* and $CPUEy^{-1}$ MCDA outputs against each other and against the TACC decisions made in the fishery.

In both retrospective analysis each of the three PMs (Target CPUE, Gradient 4 CPUE and Gradient 1) were equally weighted and used to calculate Cy^{+1}. For example to calculate the Gradient 4 CPUE PM in 2005 for the *CPUEy* dataset CPUE data from 2001-2004 was used in the linear regression. While in the *CPUEp* dataset nine month CPUE for 2001-2004 was used and for the $CPUEy^{-1}$ dataset CPUE data from 2000-2003 was used. This was applied to each year in succession to produce *CPUEp* and $CPUEy^{-1}$ TACC adjustments within zone between 2005-2014 using the MCDA eHS control rule. The Gradient 4 CPUE MP requires minimum of four years data prior to implementation preventing MCDA results prior to 2005. Within these analysis Target CPUE was set at the 65th quantile for each Block (see Table 14).

The retrospective analysis of the *CPUEy* and *CPUEp* data showed differences in MCDA outcomes across both zones (Figure 57). In both Eastern and Western zones the MCDA driven TACC outcomes show only minor departures from the TACC's actually implemented. Within the Eastern Zone no consistent trend of over- or under-conservatism was evident for either *CPUEy* or *CPUEp* TACC adjustments. In some years the *CPUEy* dataset providing more conservative TACC adjustments than the *CPUEp* (2004, 2005, 2013) and in others the *CPUEp* dataset provided more conservative estimates (2010-2011) (Figure 57 a-b). The difference between these scenarios was on occasion substantial, for example in 2011 *CPUEy* suggested a TACC of 900t versus a

CPUEp TACC of 760t (Figure 57 a-b). This implies that in the Eastern zone block CPUE variation in the final quarter of each year can be quite significant but can vary in both directions, both increasing and decreasing CPUE. The implementation error between *CPUEp* and *CPUEy* therefore is not consistent through time and is difficult to quantify, however if a quarterly implementation within the MSE is possible, modelling of these scenarios may provide a more thorough examination of this error. In the Western Zone *CPUEy* and *CPUEp* outputs were much closer and more stable between years (Figure 57 c-d). In general the *CPUEp* data appeared fractionally more conservative which may reflect the diver opinion that CPUE increases in some Blocks in the spring. This analysis of the discrepancy between *CPUEy* and *CPUEp* highlights the limitations of basing any TACC setting method on *CPUEp* data. It suggests that in an ideal scenario the MCDA should set next year's TACC on *CPUEy* data but as this is not possible under the current arrangements the alternatives of *CPUEp* and $CPUEy^{-1}$ must be considered.

Under the *CPUEp* or $CPUEy^{-1}$ scenarios Eastern Zone TACC adjustments were again annually variable (Figure 57 a-b). Under the $CPUEy^{-1}$ scenario the TACC adjustments appeared less conservative than the *CPUEp* data when the catch (2010-3013, Figure 57a-b) and zone CPUE (Figure 56) trend was in decline but more conservative when the catch (2007-2010 Figure 57 a-b) and CPUE (Figure 56) was increasing. Essentially this pattern is the result of the Gradient 4 CPUE MP delaying MCDA control rule response in the $CPUEy^{-1}$ model. Within the Western Zone this delay in $CPUEy^{-1}$ control rule response is also evident particularly in years 2012-2014 where a sharp decline in catch and continued zone CPUE decline (Figure 56) does not result in further TACC reductions (Figure 57 c-d). In both zones the *CPUEp* MCDA output follows the actual fishery decisions more closely than the $CPUEy^{-1}$ model as might be expected given that the ad hoc decisions were based on the same data. However, importantly the *CPUEp* does appear to be slightly more conservative in nature than the ad-hoc decision process when zonal CPUE is in decline and is also more conservative than the $CPUEy^{-1}$ model. Given that both of these major zones within the fishery still show low (Eastern) and declining (Western) CPUE, consideration of the most conservative method of CPUE application is probably advisable. Given this result and that the partial year data has been used routinely in the FRAG process for the past 5 years, the *CPUEp* model is used in all further sections of this document.

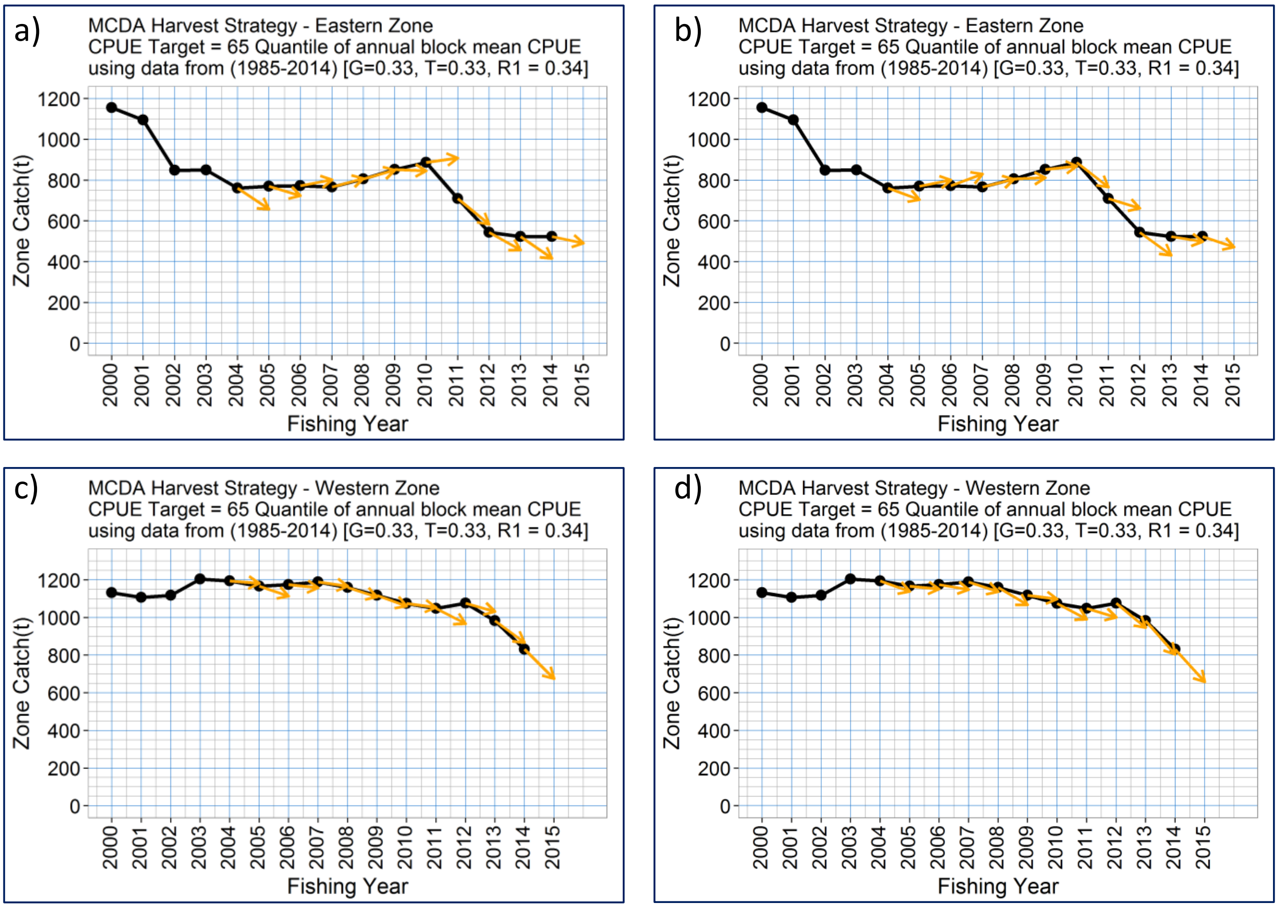


Figure 57. Eastern (a-b) and Western Zones (c-d) MCDA HS under two scenarios of MCDA application: full year CPUE data (*yr*) (a and c) and 9-month current year CPUE data (b and d). The black line plots the annual catch taken, and the orange arrow indicates the proposed catch for the following year based on the selected MCDA eHS output. Performance measures have equal weighting G= Gradient 4 CPUE, T = Target CPUE, R1= Gradient 1.

Evaluation of Target CPUE PM value used in the MCDA eHS.

The objective of this analyses was to evaluate the relative performance of three potential target values for the Target CPUE performance measure (PM). Initial testing of the MCDA used a global CPUE target value for each Zone, based on an understanding of good, acceptable, poor CPUE levels in recent years. However, an empirical process for determining CPUE for each individual block was considered more defendable and is explored here. One possibility is for the Target CPUE to be derived for each block from the 50th, 65th and 75th quantiles of observed mean annual CPUE from 1985-2014. However, as TACCs and associated CPUE have varied substantially over the past 35 years, along with improvements in fishing efficiency, the merits of inclusion of data over such a wide temporal range is subject to much discussion.

The upper and lower limits of the Target CPUE scoring function (i.e. 0 & 10) was expressed as a proportion of the target CPUE. For this exercise, when the target CPUE was below 90 Kg/hr, the upper and lower limits were set at ± 50% of the target CPUE, and for target CPUE above 90 Kg/hr, the upper and lower limits were set at ± 45% of the target CPUE. In order to observe the effect of different target CPUE values the MCDA was run with Target CPUE allocated a 70% weighing score with a minor weighting of 15% for each of Gradient 4 CPUE and Gradient 1.

The 50th, 65th and 75th quantile annual CPUE varied substantially among zones with the Western Zone having substantially higher rates of catch than the Eastern Zone at each of the quantile Target CPUEs (Table 13). The range of CPUE targets among blocks within the two major zones (Eastern, Western), was substantially different, with relatively little variation among blocks in the Eastern Zone (Table 14). In contrast the lowest block Target CPUE in the western zone was almost half the Target CPUE in the highest block (Table 14), confirming the need to develop block based targets rather than use global values.

Table 13. Quantiles of annual CPUE by Zone in the two primary fishing zones in the Tasmanian abalone fishery. Data drawn from 1985-2014

Quantile of CPUE	Eastern Zone (Kg/hr)	Western Zone (Kg/hr)
50	58	125
65	66	137
75	71	145

Table 14. Effect of different selection thresholds on magnitude of Target CPUE. Target CPUE by Block for 50th, 65th and 75th quantiles. NOTE - Block 13 has Sub-Blocks in both the Eastern and Western Zones

Block Western Zone	nYears	50th	65th	75th
6	31	110	120	135
7	31	145	150	150
8	31	150	150	150
9	31	150	150	150
10	31	145	150	150
11	31	125	145	150
12	31	110	115	125
13	31	70	80	85
Eastern Zone				
13	31	70	80	85
14	31	55	65	70
15	30	50	55	60
16	31	60	75	75
17	31	60	65	70
18	20	50	55	60
19	31	55	60	60
20	31	70	75	80
21	31	70	80	80
22	31	60	65	70
23	31	55	60	65
24	31	60	70	80
25	21	50	50	55
26	27	55	60	75
27	31	60	75	85
28	31	55	60	65
29	31	60	65	70
30	28	55	60	65
31	31	60	70	80

Analysis of the Target CPUE performance under the three scenarios followed expectations that the lower the quantile used the less conservative the MCDA HS recommendations for TACC adjustments. In the Eastern Zone, for the 11 years considered, the 50th quantile target CPUE value recommended higher catches than the TACC actually taken on four occasions and a lower TACC of a similar magnitude on two occasions (Figure 58 a). In contrast the 75th quantile recommended a lower catch in the Eastern Zone on seven years examined and on four occasions recommended an increase in TACC (Figure 58c). In the Western Zone, the 50th quantile closely followed the decisions made by the fishery for the period 2003-2008 but suggested a decreased catch from 2010 onwards than that implemented within the fishery (Figure 59a). At the 75th quantile in the Western Zone 10 of the 11 years had a reduced TACC compared to the actual catch taken (Figure 59c). In both zones the 65th quantile provided an intermediate measure in TACC between the conservative nature of the 75th quantile model and the 50th quantile (Figure 58b, Figure 59**Error! Reference source not found.**b).

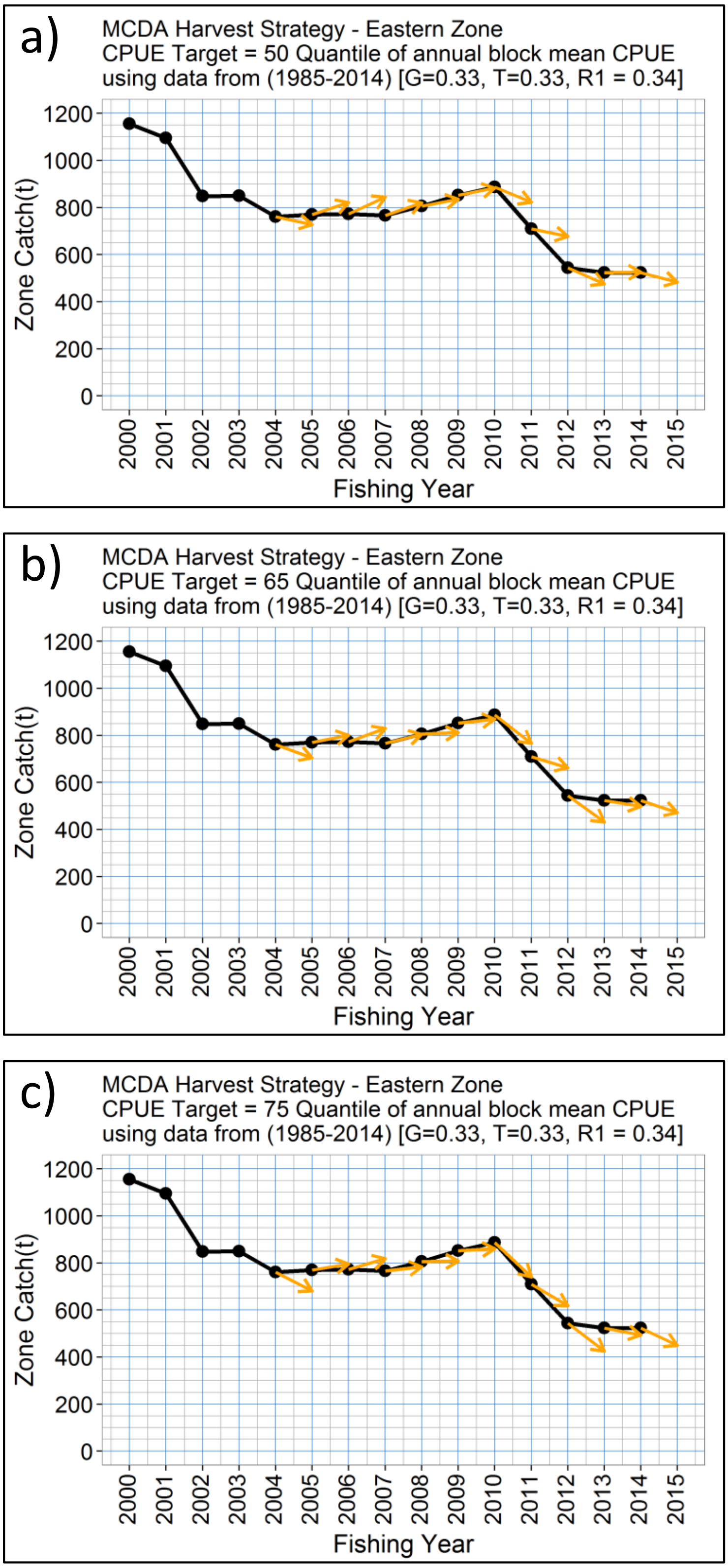


Figure 58. Eastern Zone MCDA HS under three scenarios of the Target CPUE performance measure 50th (a), 65th (b), 75th (c) quantile annual CPUE. The black line plots the annual catch taken, and the orange arrow indicates the proposed catch for the following year based on the selected MCDA Harvest Strategy.

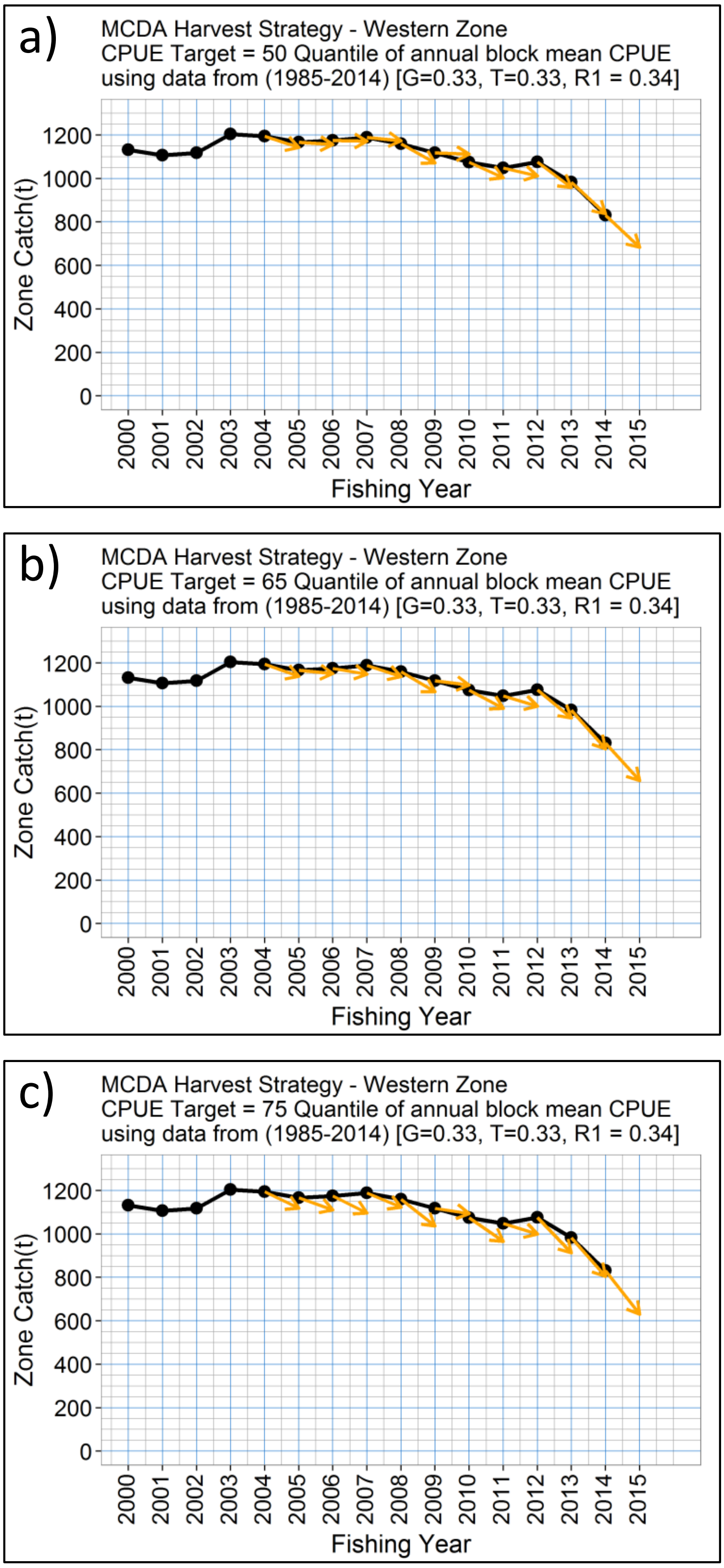


Figure 59. Western Zone MCDA HS under three scenarios of the Target CPUE performance measure 50th (a), 65th (b), 75th (c) quantile annual CPUE. The black line plots the annual catch taken, and the orange arrow indicates the proposed catch for the following year based on the selected MCDA Harvest Strategy

The decline in the CPUE in the Eastern Zone since 2010 is of considerable concern in the fishery (Figure 56) and suggests the current ad-hoc management practice has been unable to arrive at a TACC position to arrest this decline and trigger stock rebuilding. Therefore any management system evoked through the MCDA would need to provide greater protection than the current ad-hoc method. Within the MCDA evaluation the 50th quantile in the Eastern Zone provided a less conservative TACC recommendation in all but two of the years of the current method and importantly recommended a higher TACC than that taken in years 2010 and 2011 despite a rapidly declining CPUE. The 50th quantile model therefore may be considered less conservative than the current regime and may not provide a suitable sustainable method for future TACC allocation in this zone. The Western Zone has seen a declining CPUE since 2001 (Figure 56) which is mirrored by a declining annual TACC suggesting a management process which again has been unable to provide a sustainable target catch. The 50th quantile Target CPUE MCDA model suggested similar catch targets as that implemented by the fishery, and while it did suggest lower TACC's than the current management strategy in 2010 – 2011 it appears unlikely to provide a long term sustainable management outcome. The 75th quantile model provides the most conservative model of this analysis and would significantly reduce the TACC in both the Eastern and Western Zones to historic low catch levels if implemented. While this is the most likely model of the three scenarios to allow fishery stock recovery, it may place the industry at economic risk and as such is unlikely to be an acceptable solution for either the investor or harvest sector. This empirical pilot evaluation of using 50th, 65th and 75th quantile annual CPUE values suggests that the 65th quantile target would be best placed to be adopted as a minimum to ensure, in the short term, that TACC's are set to enable stock rebuilding, while being more acceptable to the catching sector than the 75th quantile. More detailed analysis on the Target CPUE quantile analysis and time frames required to achieve rebuilding targets will take place within the MSE model.

12.4.2. Performance measure weighting in the MCDA eHS

The three PMs trialled in this exercise have different characteristics and are likely to impart different outcomes depending on the weightings used in the MCDA. To test the effective power of each performance measure (PM) in altering a TACC recommendation the MCDA eHS was run sequentially with each PM given a major weighting of 70%, with the other two PMs weighed equally at 15%. A further MCDA eHS with all PMs having equal weighting (33%, 33% and 34%) was also run. The three PMs tested on the 2000-2014 dataset were Target CPUE, Gradient 1 and Gradient 4 CPUE. Based on the evaluation of the Target CPUE (Section 1) the 65 quantile was used as the Target CPUE in all MCDA scenarios here. In this analysis the use of the Gradient 4 CPUE PM requires four years of data in order to be calculated therefore for each MCDA the analysis period starts at 2000 but MCDA eHS recommendations begin from 2003.

With Gradient 4 CPUE as the major PM the model reaction to changes in CPUE were similar to the Gradient

1 CPUE model, but less conservative than when the Target CPUE has majority weighting (Figure 60). The Gradient 4 CPUE model appeared to create a time lag between CPUE change and TACC effect (Figure 60a). With the Target CPUE as the major PM, the Eastern Zone TACC broadly followed the ad-hoc methods currently applied in the fishery. Where CPUE declined significantly away from the Target CPUE (66 Kg/hr), the Target CPUE majority weighting suggested greater declines in TACC than those implemented (2004-2005, 2012-2014) (Figure 60b). Gradient 1 was the least conservative of the models tested in the Eastern Zone over the majority of the years when CPUE was relatively stable (2004-2007) but reacted to reduce TACC significantly when CPUE fell rapidly in 2010 (Figure 60c). Equal weighting of the PMs moderated the large decreases in TACC allocated by the Target CPUE major weighting model and the increases allocated by the Gradient 1 major weighted model (Figure 60d). The equally weighted model in the Eastern Zone most closely followed the Gradient 4 CPUE PM but with less time lag (**Error! Reference source not found.**d). In the Western Zone a similar pattern was evident with the Target CPUE the most conservative model suggesting a reduced TACC compared to the other two models when used as the major MP (Figure 61 b). In this zone when Gradient 4 CPUE was applied as the major PM it broadly followed the ad-hoc fishery decisions (Figure 61a) but also showed a weak time lag oscillation as seen in Eastern Zone. With Gradient 1 as the major PM the model provided an intermediary TACC compared to the Gradient 4 and Target CPUE major weighting model runs being more conservative than the ad-hoc approach (Figure 61 c). The equally weighted model (Figure 61d) provided a moderated model to the extremes provided by the most conservative Target CPUE model and the least conservative Gradient 4 CPUE model (Figure 61d).

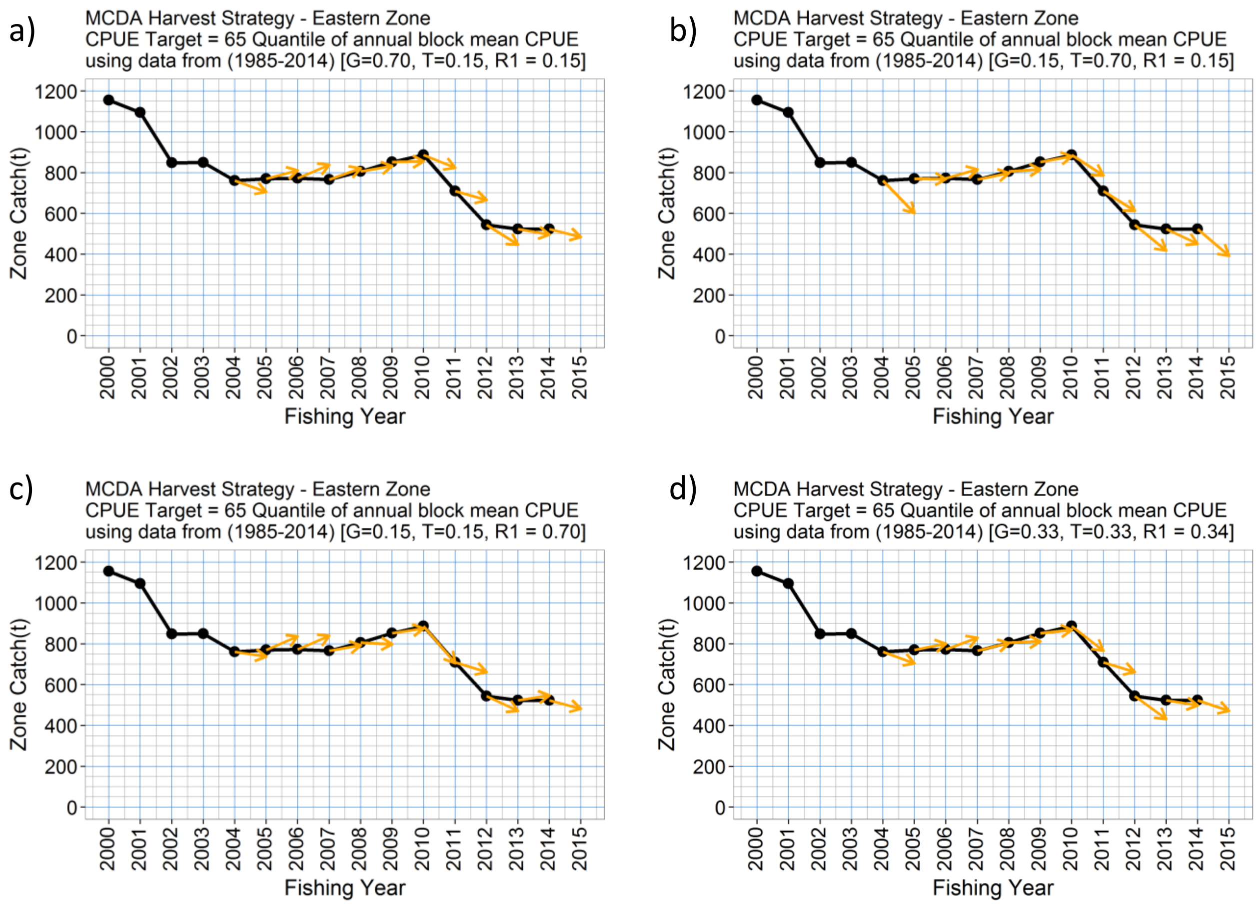


Figure 60. Eastern Zone MCDA HS under four scenarios of the performance measure weighting. Figures a-c major weighting = 70%, minor weightings =15%, figure d equal PM weighting 33%. G= Gradient 4 CPUE, T = Target CPUE, R1= Gradient 1. The black line plots the annual catch taken, and the orange arrow indicates the proposed catch for the following year based on the selected MCDA Harvest Strategy.

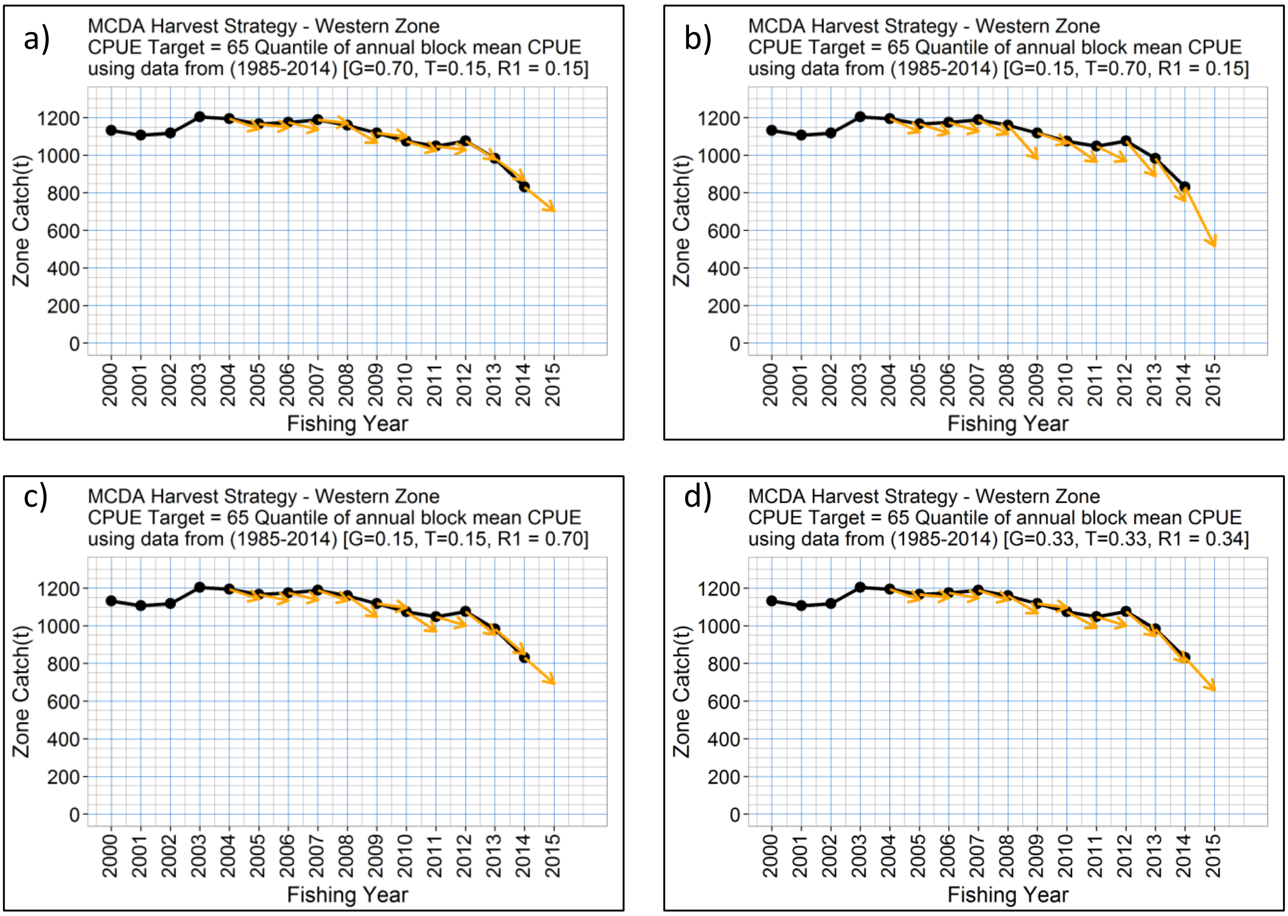


Figure 61. Western Zone MCDA HS under four scenarios of the performance measure weighting. Figures a-c major weighting = 70%, minor weightings = 15%, figure d equal PM weighting. G= Gradient 4 CPUE, T = Target CPUE, R1= Gradient 1. The black line plots the annual catch taken, and the orange arrow indicates the proposed catch for the following year based on the selected MCDA Harvest Strategy

12.5. Discussion

The retrospective analysis of MCDA outcomes against decisions made over the past decade suggests that when the Target CPUE is based on the 65th quantile (CPUE 1985 – 2014) and set as the major weighted PM it offers a more precautionary TACC. Setting the Gradient 4 CPUE as the major weighting PM results in a time lag oscillation effect resulting in delayed reactions to TACC adjustments. This could be viewed as a dangerous artefact in fisheries such as abalone which can experience hyper-stable CPUE values and sudden collapse. The Gradient 1 PM offers a similar mechanism of CPUE evaluation to the Gradient 4CPUE MP, but over a shorter time frame and is more likely to react to sudden CPUE changes.

Over the course of the next two decades, this fishery is likely to experience further increases and decreases in stock biomass, and thus management action may shift between a stock rebuilding phase, TACC maintenance phase, or a TACC building phase. To achieve different aims within the same eHS a decision tree process that alters the PM weights could be used in a defensible process to achieve different management objectives (e.g. Figure 62). The conditions that trigger action along a particular branch of the decision tree need further discussion and evaluation. While the geo-referenced fishery-dependent data provides significant opportunity for new PMs to improve the response of this process to stock biomass changes, even if restricted to the three PMs used in this exercise, it would be an improvement over past practice.

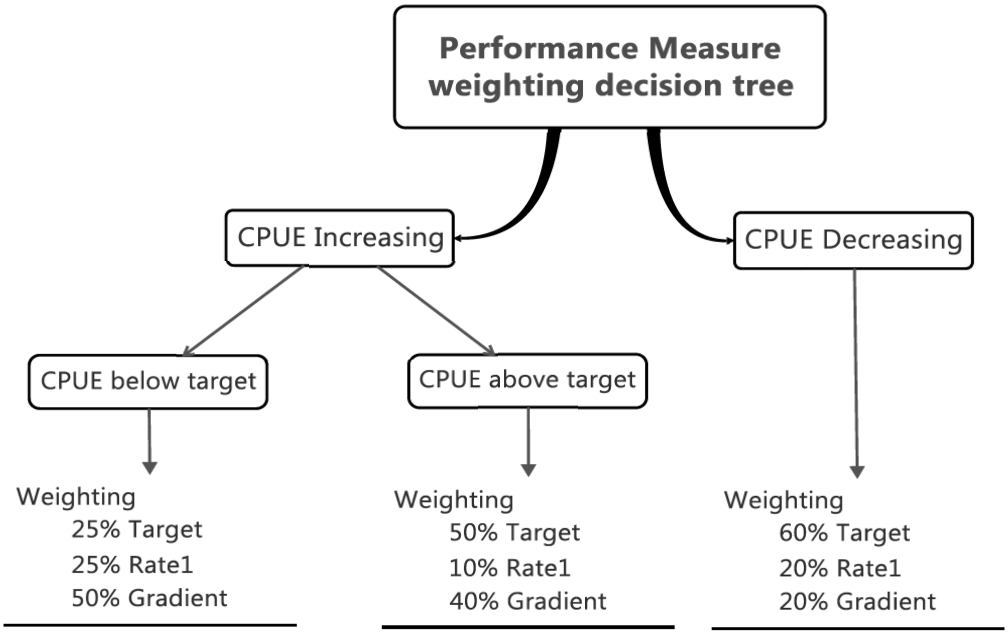


Figure 62. Performance Measure weighting decision tree. Depending on the state of the fishery, the weighting of PMs can be altered to direct the MCDA towards particular outcomes.

13. Developing the use of GPS loggers for TAC advice in the NSW abalone fishery

Author: Duncan Worthington

13.1. Background

A component of the FRDC Project 2011-201, "Implementing a Spatial Assessment and Decision Process to Improve Fishery Management Outcomes Using Geo-Referenced Diver Data" , was implemented in the NSW abalone fishery. Objectives of the project in NSW related to the development of GPS loggers with Structured Fishing designs, extension and development of techniques of analysis of GPS logger data, and its incorporation within a decision-making framework to provide TAC advice in the fishery. This chapter provides a summary of the history and project work completed to address those objectives.

GPS loggers have now been used voluntarily and with consistent coverage in the fishery since 2009-10. For several years, the data collection, analysis and interpretation has attempted to follow recommendations of earlier independent reviews, the TAC Committee, DPI, Industry and other stakeholders. Structured Fishing designs in NSW have involved structuring additional data collection with GPS loggers at over 100 sites selected by divers and revisited through time, in contrast to the approach in WZ Victoria where Structured Fishing involved advising diver to fish at selected sites following AVG, but have not been continued through time. Several different approaches have been developed to make the most of GPS logger usage, by collecting fine-scale information about catches, linking different data collection methods (e.g. estimate from loggers, catch logbooks and independent abundance surveys) and analyses, to provide comparable information about stocks allowing a weight of evidence approach to stock assessment. A novel, informative and cost-efficient framework has evolved to incorporate these data and analyses into advice about catch planning and TAC setting in the fishery, and which will continue to develop during the years ahead.

13.1.1. GPS and depth loggers

Fine scale location of diving effort is collected through the voluntary use of GPS (Global Positioning System) and DTS (Depth and Temperature sensors) loggers by most divers in the fishery. GPS and depth logger data are collected regularly from divers and stored in the purpose-built AbTrack SQL server database. This requires manipulation and coordination of files before upload, and the database and raw data files are backed up on and off-site (raw data files and Google Earth files of dive events with summary Performance Indicators are also provided to divers). Manifold GIS is used to link and query the database to produce Performance Indicators (PI) for dive events in each Area and Year (i.e. July-June to provide a full year's data to TAC setting process). PI include the average area of dive events and the area covered per hour during dive events, the overlap of different dive events (i.e. % of total dive event area that is overlapping with other dive events within the year and area), the area of dive events compared to the total fished area (i.e. total area within the year and area as a proportion of all years for that area), the proportion of short dive events (i.e. <15 min), the concentration of dive events (i.e. ratio of the area of 50% and 90% of GPS points per dive event), and the depth of dive events. These basic Performance Indicators can easily be extended or revised to include different spatial or temporal grouping. For example, a grid of 1 Ha hexagons is also available, allowing the calculation of all PI for dive events within each hexagon. Two new logger Performance Indicators have been presented this year, including the nearest neighbour in time, which shows the average number of days between dive events with centroids within 500 m of each other, and the nearest neighbour in space, which shows the average distance between centroids of dive events within 50 days of each other. Current development is also continuing to investigate the standardisation of logger PI to remove confounding by consistent differences among divers similar to the catch data, and among Structured Fishing sites, and the use of loess smoothers to describe trends through time, similar to the catch data.

The GPS logger database can also be linked to the Logbook catch database, through the reported time of each bin being filled by each diver, and the time recorded on the GPS logger. In this way, PI available from the Logbook catch data, including catch, effort, catch rate (raw and standardised) and mean weight can be directly related to spatial information, including GPS points, dive events, subzones and a hexagonal grid. The linked databases are also used in producing Google Earth files for all and each diver, and summarising PI from loggers and logbook on detailed maps of the coast.

While all divers have been provided with GPS and Depth loggers, not all divers operate them on all days fishing. In recent years, there have also been several new divers enter the fishery, and some have taken time to settle down and run loggers consistently. In 2014-15, there has also been some significant loss of data cause by logger malfunction to GPS and measuring loggers (e.g. logger data was lost because of breakage of loggers from two key divers in 2015). The data set summarised here currently has logger data for 50-60% of diver-days during 2014-15, although several loggers remain to be downloaded. While coverage has remained high for several years, logger operation remains voluntary and several divers have not been operating loggers on all days fishing, mostly because batteries run flat and are not recharged immediately. All divers except one have provided verbal support for operating loggers, although he supports others operating them, although two additional divers have not provided any logger data in 2014-15. Ongoing support and encouragement for divers to operate loggers is required to ensure coverage is kept high.

Data available from loggers is also being used to develop a method to estimate the density and total biomass of legal-sized abalone available to the fishery, with potential for use in a Harvest Strategy. Estimates of the density of biomass (i.e. calculated as daily catch in kg from the logbook divided by the daily area of dive events in Ha estimated by the 50% KUD of GPS points per dive event) are extrapolated over an estimate of the area of productive reef (i.e. calculated from logger activity within a 100 m grid) to provide an estimate of the total biomass. Estimates of density are standardised by extracting the relevant data, removing outliers with density <50 kg/Ha or >1500kg/Ha, and implementing the R command glm, with ln(daily Catch/Dive event area) described by the terms Year x Area +Diver, with normal errors. For comparison, a similar model is also fitted to catch rate data (i.e. logbook kg/h). Estimates of density were calculated from the GLM for the average diver (i.e. 50% diver cdf) and for a diver that provided a density estimate for Area 20 and 21 similar to that found in the abundance survey in 2013-14 (i.e. 597 kg/Ha) and the average of unstandardized density estimates (i.e. 524 kg/Ha). Estimates of density for the average diver in Area 20 and 21 in 2013-14 were 314 kg/Ha, while all estimates presented unless noted otherwise, were standardised to a diver that estimated a density of 553 kg/Ha (i.e. 70% of diver cdf or the mean effect + 0.5SD). A model is also being developed to investigate further fine-scale spatial standardisation, including the terms Year x Area + Diver + Site x Area, where the centroid of a day's dive events is used to allocate the data to a Structured Fishing site within subzones and areas, and is presented here for comparison (i.e. for a 70% diver at an average Site within each Area).

13.1.2. Measuring GPS loggers

Data about the lengths of abalone are collected with Measuring loggers in two ways. First, Measuring loggers are operated in abalone processors to provide data about the length of abalone landed that can be associated (i.e. through docket ID) with diving effort per Subzone in the Catch Reporting and then GPS logger databases. The sampling design attempts to concentrate sampling in winter-spring, and sample the lengths of abalone in proportion to the catch coming from different Areas. Receivers are directed to measure abalone from about 220 bins of abalone, and progress is monitored and adjusted in an attempt to match the sample to the catch distribution among areas. In addition, any catch from northern areas of the fishery is given a high priority for measuring. Second, Measuring loggers are operated by divers while fishing to provide data about the spatial location of lengths of abalone landed that can be associated with GPS logger data (i.e. through time fields in both databases) and then Catch Reporting data. Measuring by divers is mostly ad-hoc, although some divers are using them as part of the Structured Fishing design, providing information from multiple data sources from the same site and diver through time.

Measuring Board loggers record the length of abalone for each abalone passed through them, and data are downloaded and stored in a SQL server database. Length data can be linked either to a GPS point if measured by a diver with a GPS and depth logger, or to a dive event (first bin of the day linked to first dive event) if tagged by the diver and measured by a receiver. Data from Receivers and divers are combined, and converted to weight to compare directly with other indicators of the size of abalone (i.e. mean weight per bin from logbook). Data from receivers and divers are combined by weighting that includes calculation of the mean length of abalone per diver day, before averaging across spatial area (i.e. not weighted by the number of abalone measured per day). Several PI are calculated including the mean length and proportion ≥130 mm, with estimates first calculated per diver day and then across diver days (i.e. the mean length for an area is the average across diver days from both processor and diver measuring). For several reasons, it is possible for the measuring loggers to record data below the minimum length and above plausible maximum lengths (e.g. measuring error). PI are calculated by limiting data to less than 160 mm and greater than 115 mm. To enable comparison of PI from measured lengths with those of mean weight per bin from logbook catch reporting, individual lengths (i.e. mm) are converted to weight (i.e. g) using 0.000334 x Length ^2.857356.

13.2. GPS logger performance indicators

Performance indicators from GPS logger data are still being developed in NSW, and other fisheries including Tas, Vic and NZ. GPS and depth loggers collect data about the behaviour of divers in response to the stock, among other influences. As a result, changes in the abalone stock can lead to changes in diver's behaviour that can be recorded by the GPS loggers. As logger data can provide information about stocks, it can be used in performance indicators for the fishery. While there are a range of performance indicators available from logger data, which appear to offer significant potential for monitoring fine-scale diver behaviour and stocks, it remains unclear exactly how each of these will respond to changes in the stock. Current monitoring is only beginning to understand the relationship between logger-based performance indicators and the abalone stock in NSW.

GPS logger data and the behaviour of divers may be particularly important to understanding changes in the stock, as divers are able to quickly change their behaviour in response to change in the stock (e.g. area fished, rate of movement, and visitation or overlap among dives). As a consequence, changes in the stock, such as a reduction in biomass caused by reduced recruitment, are likely to quickly translate into changed behaviour of divers attempting to maintain their catch rate, and so into performance indicators derived from logger data. This is in contrast to regulated, broad scale, logbook catch reporting, which provides little understanding of diver's behaviour other than the number of hours fished, and catch rates that can often be maintained at the broader scale despite a decline in biomass. As a consequence, it is hoped that GPS loggers monitoring diver behaviour as it changes in response to the stock, using the performance indicators that can be produced, may be able to give earlier indications of changes in stocks than logbook catch data. Finally, a method is being developed to use the data from GPS loggers, combined with logbook catch data, to provide estimates of available biomass. Estimates of biomass from GPS loggers provide the opportunity for their use in the draft Harvest Strategy to guide the catch planning workshop and TAC discussions.

13.2.1. Density estimates by Area

Estimates of the density of legal-sized abalone can be calculated from the logger data, by combining the daily logbook catch with an estimate of the area fished (i.e. daily kg/Ha). The area fished is calculated from the GPS logger data (i.e. position of the logger on the boat every 10 seconds) by fitting a spatial model (i.e. kernel density) to GPS points from each dive event and estimating the area that encloses 50% of the GPS points. This attempts to estimate the likely area fished by the diver (i.e. with a hookah hose attached to the boat) from the GPS data. Daily estimates of density vary among divers, in a similar way to catch rates (i.e. kg/h), and are standardised in an attempt to remove this variation and allow better comparison of Areas through time. Estimates of density standardised to the average diver (i.e. 50% of diver cdf, 314 kg/Ha in 2013-14) were significantly lower than estimates of density from the abundance survey in Area 20-21 (i.e. 597 kg/Ha) and the average of unstandardized density estimates (i.e. 524 kg/Ha). All estimates of density, unless noted otherwise, were standardised to a diver that estimated a density of 553 kg/Ha in Area 20-21 in 2013-14 (i.e. 70% of diver cdf or the mean effect + 0.5SD).

Estimates of the density of legal-sized abalone from logger data have increased in all Areas since 2009-10 (Figure 63). Increase in density between 2009-10 and 2014-15 ranged from a 154% increase in Area 11, near Tathra, to a 32% increase in Area 14, near Eden, and averaged 88% among areas. In some Areas, estimates of density have increased every year (e.g. Area 10, Bermagui), some Areas have been relatively stable since 2010-11 (e.g. Area 13, Long Beach), and others have fluctuated in a predictable way to management changes, such as the increase in size limit in early 2012-13 within Areas 19-21, south of Wonboyn. Several Areas, particularly Area 14-16 (i.e. Eden to Green Cape) declined in recent years, following several years of increase in density, and following ongoing increases in catch (Figure 63). Since peaks in density 1-2 years ago in Areas 14-16, density has declined by an average of 14.8% in 2014-15. Effects of standardisation can be seen by comparing the raw (i.e. black dots) and standardised estimates of density (i.e. blue lines), and are consistent with patterns in effort of divers with different catch rates. For example, standardised estimates of density are higher than raw values in Area 10, as the area has not been worked by higher catch rate divers in recent years. Further, the standardisation has reduced the decline in density in recent years in Area 14-16, to a more stable level consistent with densities in 2012-13, and also suggesting some effect of changing patterns of effort by higher catch rate divers (Figure 63).

For comparison, estimates of catch rate (i.e. logbook kg/h) were also standardised using the same factors and at the same scale as the logger density estimates (Figure 64). Estimates of standardised catch rate have much smaller confidence intervals than the density estimates, but a similar relationship to raw values, suggesting generally consistent standardisation effects among the data types. Despite increasing catch in most areas, catch rate increased every year in all areas, except in Areas 17-21 (i.e. Disaster Bay and south of Wonboyn) in one year, which was also coincident with the size limit increase south of Wonboyn. Catch rate (kg/h) has also continued to increase in areas where density estimates have stabilised or declined (Figures 63, 64).). For example, in Area 13-16, density estimates in 2014-15 have been stable or declined from their peak to levels similar to 2012-13, while catch rates have continues to increase by an average of 4.3% (density declined 14.8%). In comparison to estimates of density, increases in catch rate from 2009-10 to 2014-15 were much less variable among Areas, ranging from a 128% increase in Area 13 (density ranged up to a 154% increase in Area 11, with only a 79% increase in Area 13), to a 65% increase in Area 18, (density ranged down to a 32% increase in Area 14, with a 68% increase in Area 18) and averaged 91% among areas (density averaged 88%). Change in catch rates was most different from change in estimates of density in Areas 13 and 14, near Eden, where the catch rate increase was higher than density (i.e. 1.6 and 3.3 times higher), and in Areas 11 and 16, where the density increase was higher than catch rate (i.e. 0.61 and 0.61 times lower). In other words, while overall increases in density and catch rate were similar, estimates of catch rate did not vary as much among areas, or in a consistent spatial pattern with the estimated changes in density, particularly where density showed recent declines around Eden, while standardised catch rates continued to increase. A repeat of the abundance survey in Area 20-21 could provide further validation that the estimated changes in density are consistent with changes in the stock, and this is being considered for 2016.

Figure 63. Standardised density of abalone (dark blue line) +SE (light blue line) for 12 Areas since 2009-10. Unstandardised estimates of density (black dots) and catch (grey bars) are also shown.

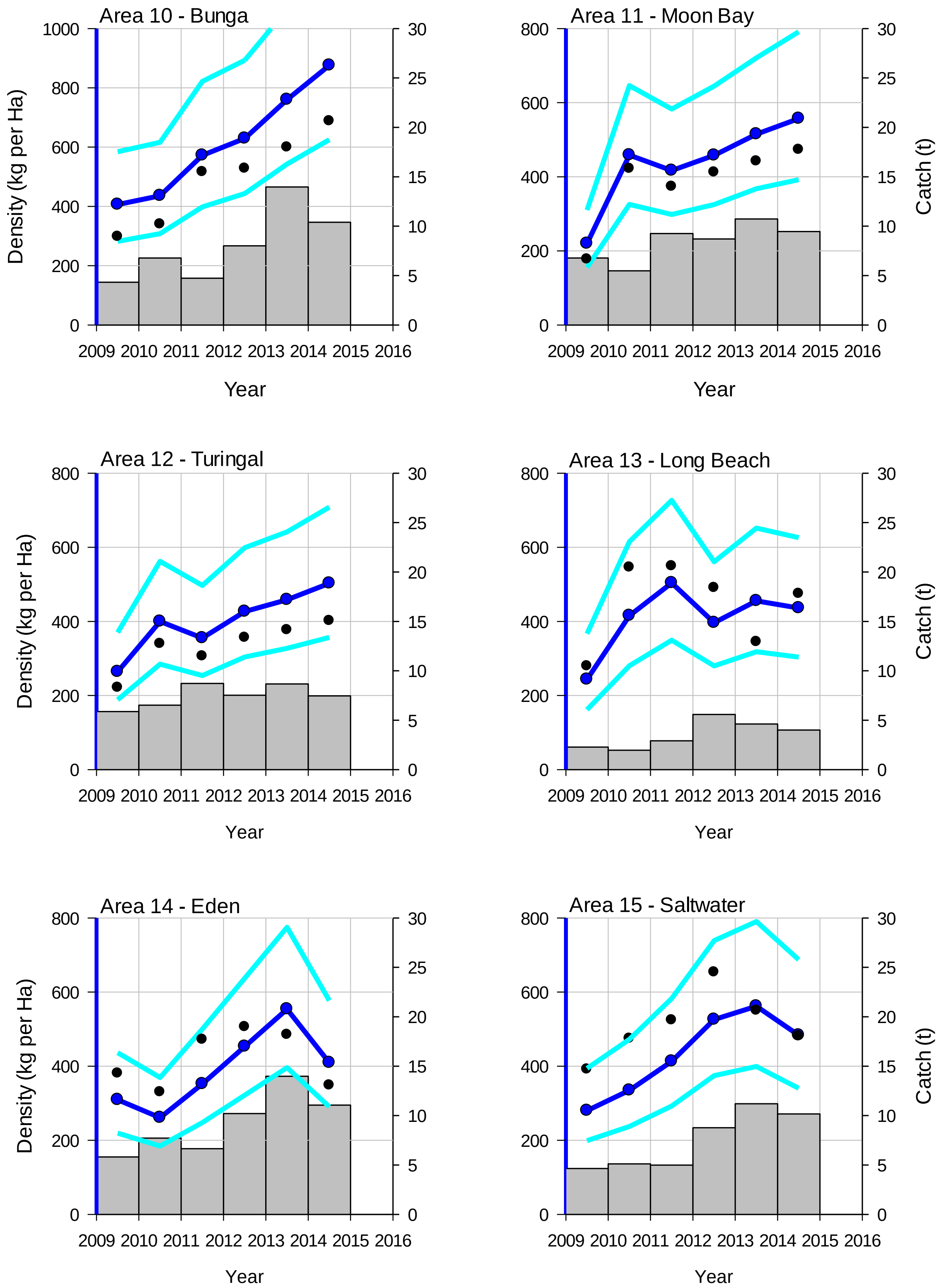


Figure 63, continued. Standardised density of abalone (dark blue line) ±SE (light blue line) for 12 Areas since 2009-10. Unstandardised estimates of density (black dots) and catch (grey bars) are also shown.

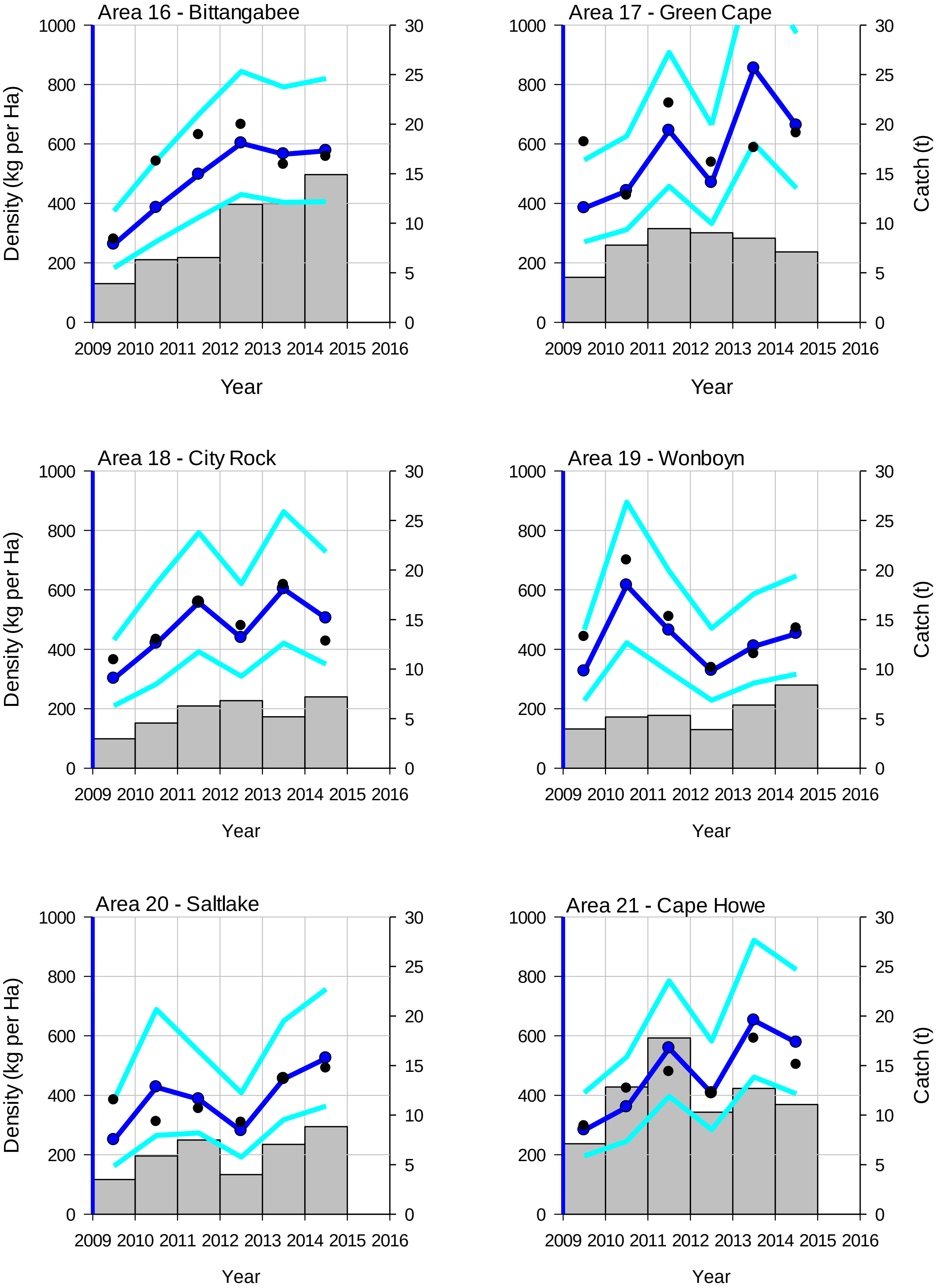


Figure 64. Standardised catch rate of abalone (dark red line) +SE (light red line) for 12 Areas since 2009-10. Unstandardised estimates of catch rate (black dots) and catch (grey bars) are also shown.

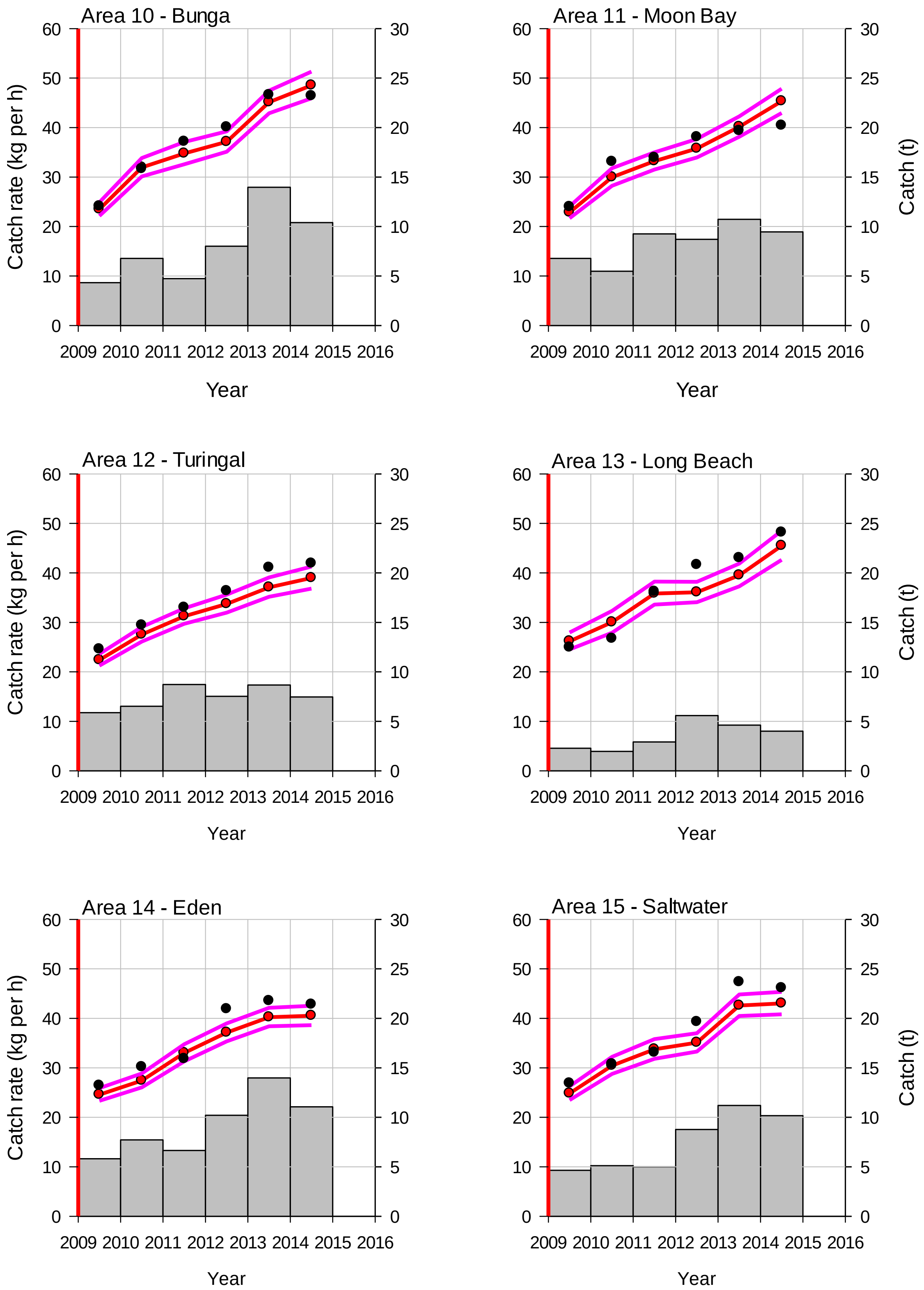
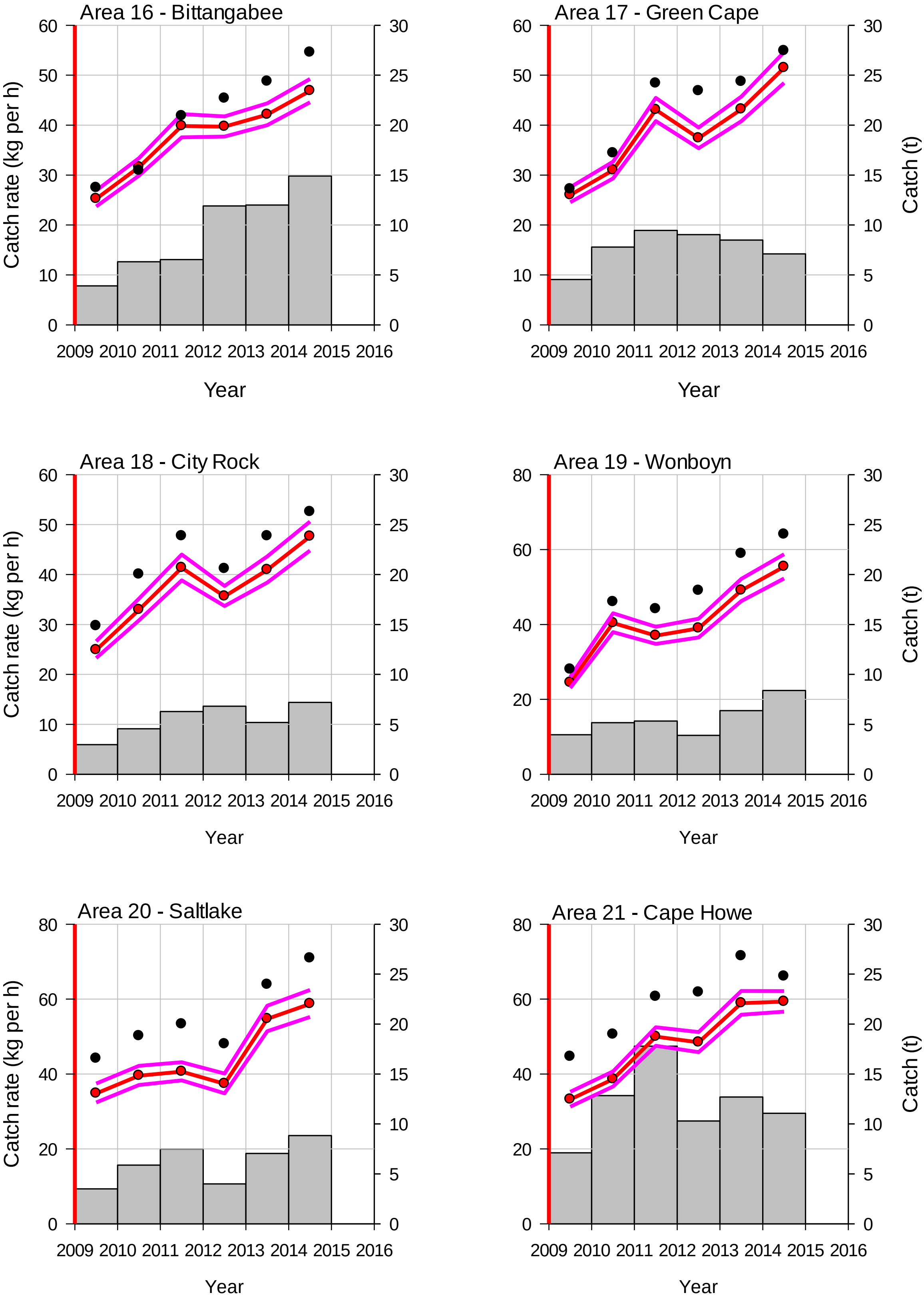


Figure 64, continued. Standardised catch rate of abalone (dark red line) +SE (light red line) for 12 Areas since 2009-10. Unstandardised estimates of catch rate (black dots) and catch (grey bars) are also shown.



13.2.2. Performance Indicators for dive events by Area

Several key performance indicators derived from logger data have been presented within selected areas for several years. A similar set of performance indicators are again presented for 3 Areas, including Area 11 (i.e. Moon Bay near Tathra) and Area 15-16 (i.e. Saltwater and Bittangabee on Green Cape) in Figure 65. The figure shows the 6 individual graphs which display i) annual catch and the standardised logger estimate of density, ii) the average (+SE) area and the average area per hour of dive events, iii) the average distance or time to the nearest dive event, iv) the annual area fished as a percent of the total area (i.e. from logger data in all years) and the annual area of dive events that overlapped as a percent of the area of the year's dive events, v) the number of short dives as a proportion of all dives and an index of the shape of dive events (i.e. area of 50% of GPS points as a proportion of the area of 90% of GPS points), and vi) the average (+SE) depth of dive events. Changes in these performance indicators through time may suggest changes in diver behaviour that reflect changes in the stock, although differences in these indicators among divers may confound this comparison, and methods of standardisation are being considered.

As understanding is still developing of the behaviour of logger performance indicators in response to the stock, it is useful to consider changes in the indicators in areas with contrasting trends in the stock and fishing. Since 2009, catch has been more stable in Area 11, and catch has increased markedly in Area 15 and 16 (Figure 65). Logger estimates of density suggest ongoing increases in Area 11, while density has more recently stabilised or declined in Area 15 and 16. The area and area per hour of dive events has generally been declining in Area 11, while generally increasing in Area 15 and 16 (Figure 65). The nearest dive event in time and space was generally closer in each Area in 2012-13, following some increases in catch in each Area, before nearest dive events moved further apart in each area since then, coincident with catch rates continuing to increase (Figure 65). The area fished and overlap of dive events has been generally declining in Area 11, and generally increasing in Area 15 and 16, before a sharp decline in Area 16 in 2014-15 (i.e. note this may be related to some recent data loss from logger malfunction from two key divers in this area).

In Area 16, annual catch has increased about 300% since 2009-10, while the area fished and overlap of dive event has remained relatively consistent. This has been possible through a large increase in the average catch per dive event, which increased from under 40 kg per dive event in 2009-10 to about 110 kg per dive event in 2014-15 (Figure 65, iv green). The proportion of short dives and shape of dive events has generally increased in Area 15 and 16 (i.e. 50% area proportionally larger, less focussed), while short dives have been stable and shape declining in Area 11 (i.e. 50% area proportionally smaller, more focussed). The average depth of dive events has generally been more consistent through time in the three areas, although the average depth in Area 16 has declined slightly (i.e. about 1 m less, Figure 65), and confounding among divers with different depth preferences may also influence change through time. Methods are being developed to standardise these performance indicators, using similar factors to the logger density standardisation.

Figure 65. Performance Indicators for dive events derived from GPS logger data, and catch, for 3 Areas since 2009. Note, each Area has an average of about 100 dive events logged per year, Area 11 is about 25 km long with 220 Ha of productive reef, while Area 15-16 are about 6-7 km with 130 Ha.

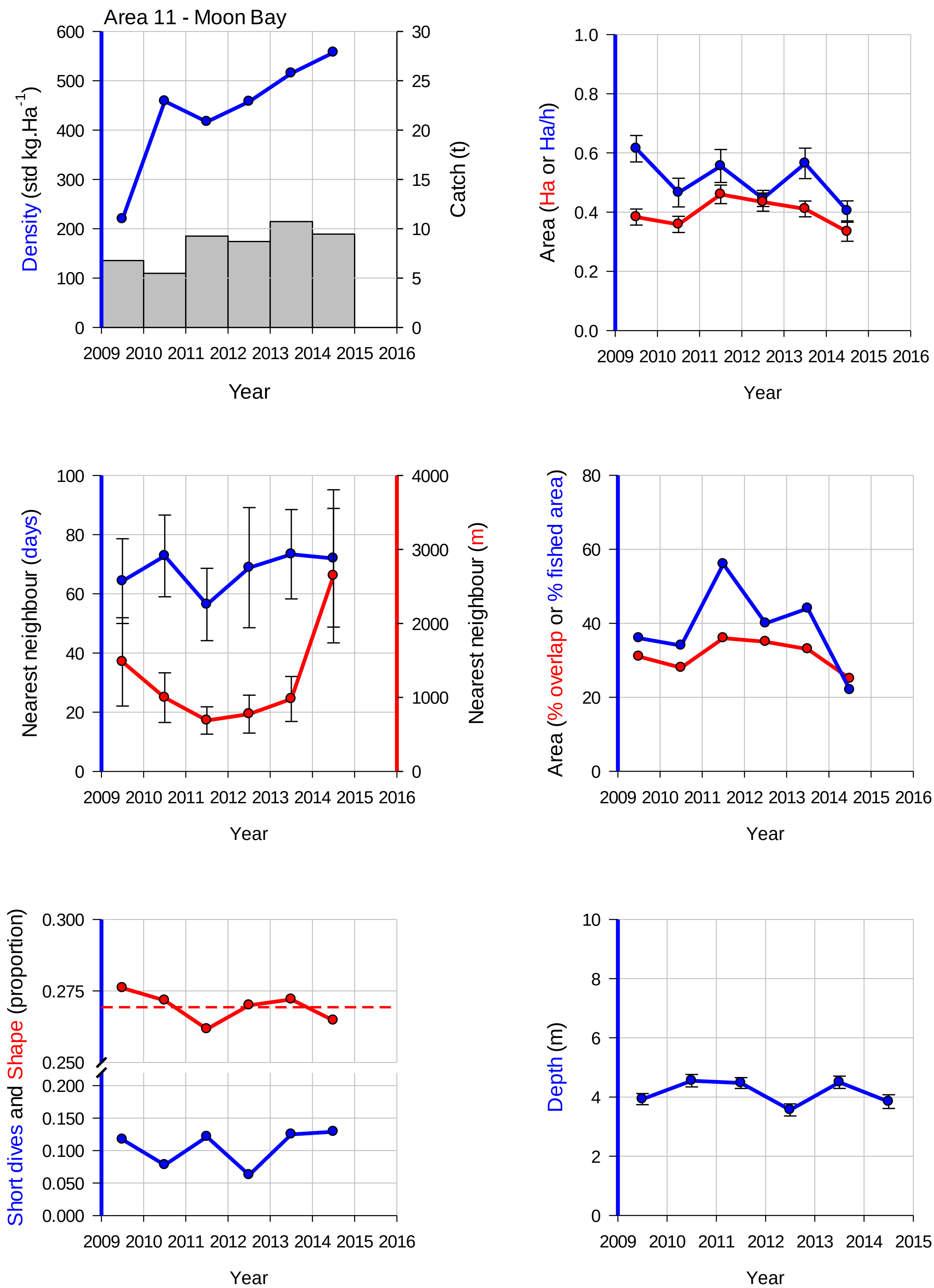


Figure 65, continued. Performance Indicators for dive events derived from GPS logger data, and catch, for 3 Areas since 2009. Note, each Area has an average of about 100 dive events logged per year, Area 11 is about 25 km long with 220 Ha of productive reef, while Area 15-16 are about 6-7 km with 130 Ha.

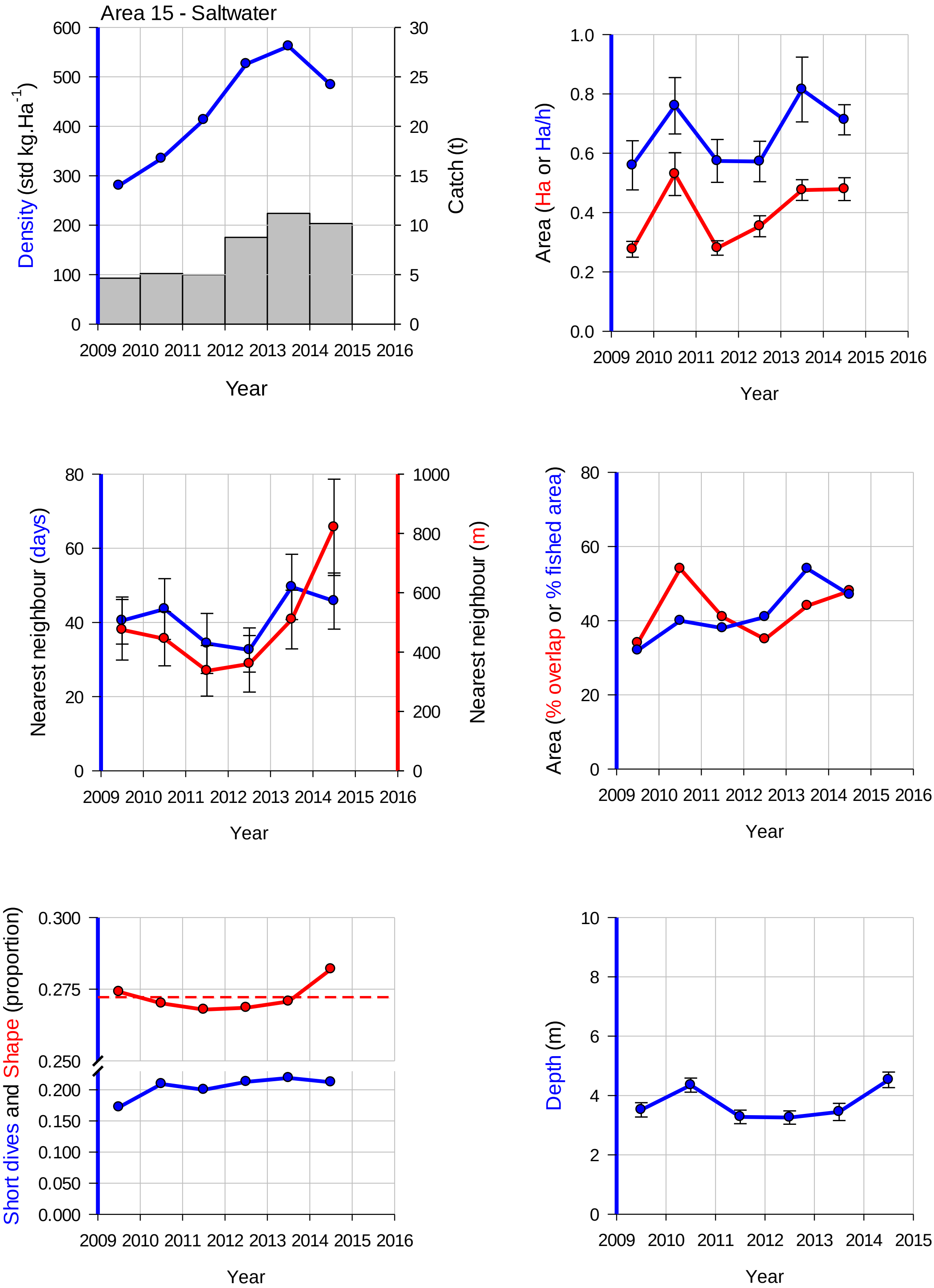
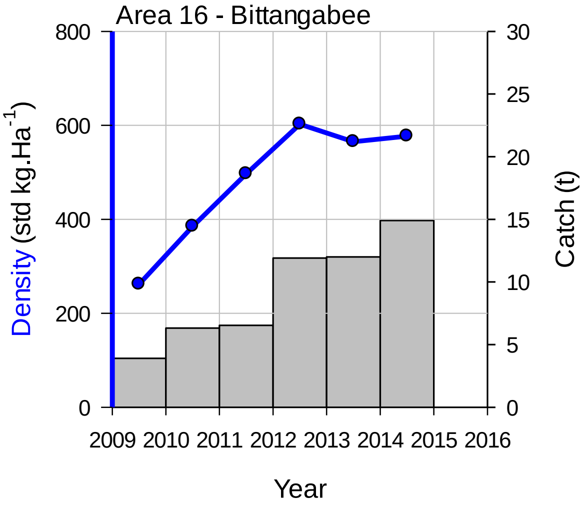
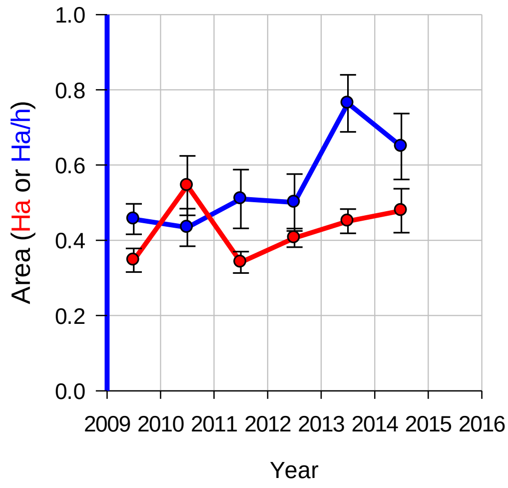
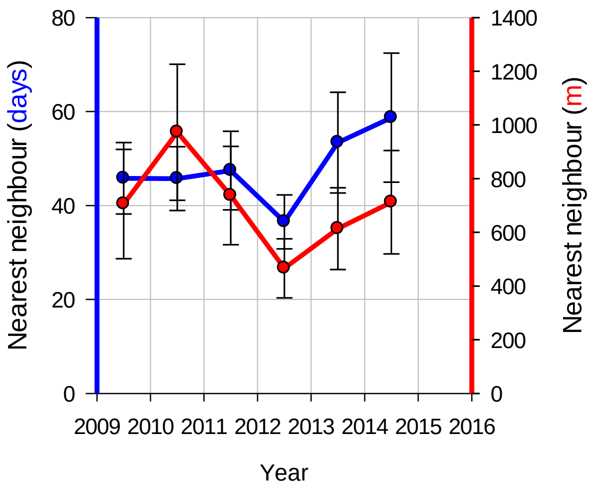
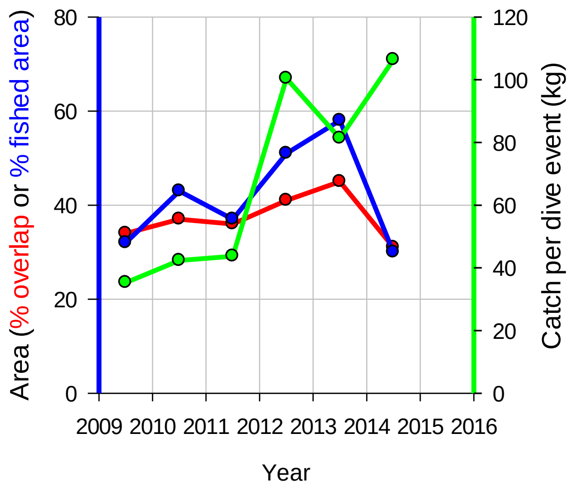


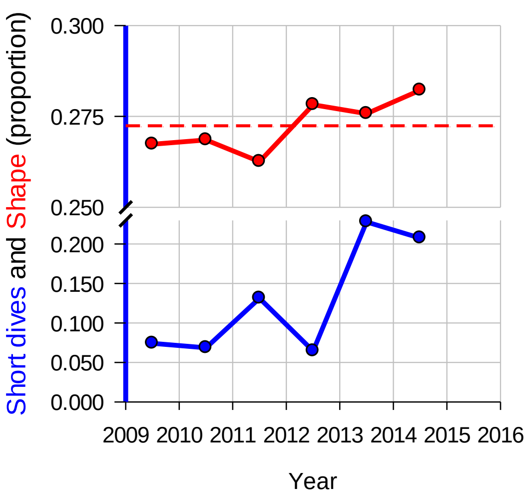
Figure 65, continued. Performance Indicators for dive events derived from GPS logger data, and catch, for 3 Areas since 2009. Note, each Area has an average of about 100 dive events logged per year, Area 11 is about 25 km long with 220 Ha of productive reef, while Area 15-16 are about 6-7 km with 130 Ha.

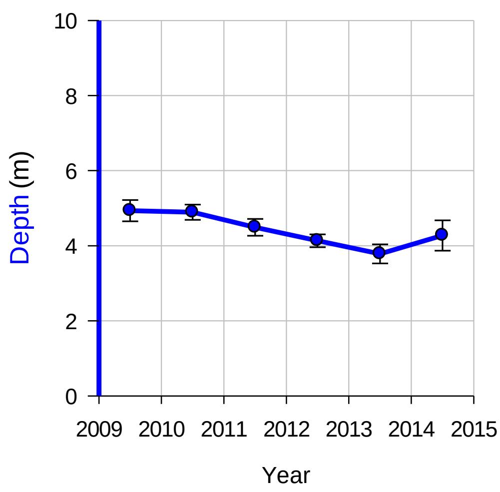












13.2.3. Fine scale Performance Indicators and density estimates

Logger performance indicators can also be investigated at a finer spatial scale within Areas and Subzones. To facilitate fine spatial scale comparisons, about 100 sites have been defined to enable grouping of logger performance indicators at a fine scale during normal fishing and Structured Fishing designs. Fine scale logger data has been presented for the Short Point site within Area 12 near Merimbula, and the Stinkys site within Area 10 north of Tathra (Figure 66). These sites were chosen again because of their contrasting trends in the stock and fishing. The figures include estimates of catch and catch rate from the combination of logger data and the time each bin was filled from the logbook. Estimates of standardised logger density and other logger performance indicators are also presented (Figure 66).

Catch, catch rate and logger density has increased markedly at Stinkys since 2010, while they have been more stable at Short Point (Figure 66). Estimated logged catch has increased from under 1 t at Stinkys to about 4 t per year, while catch rate and logger density has also increased by a similar proportion. Over the same time, catch at Short Point has increased from just over 0.5 t to about 1 t, while catch rates have been more stable, despite a large increase in 2014-15. Logger performance indicators at Short Point suggest a change in the behaviour of divers that may reflect stock conditions from the years with lower catches including and prior to 2012-13, where the rate of area coverage per dive event was lower, nearest neighbour dive events were on average furthest apart, dive events covered a lower percentage of the total fished area, there were very few short dives and the dive event shape index was lower (Figure 66). As catch increased, the rate of movement across the dive event increased, dive events became closer together in space and time, the area fished as a percent of the total fished area increase (but overlapping of dive events did not), the proportion of short dives and shape index increased. Logger performance indicators at Stinkys have also changed as catch has increased markedly over the years. The rate of area coverage per dive event has decreased, as have the nearest dive events in space and time, and the dive event shape index increased (Figure 66). In contrast, the overlap of dive events decreased markedly, while the area fished remained relatively constant, and the catch per dive event increased from about 20 kg to 80 kg (Figure 66). A days dive events including Stinkys decreased from an average of 7 dive events per day across 3 sites, to under 3 dive events across an average of about 1.5 sites per day. Further, as well as the increase in catch from Stinkys, the catch from Stinkys also increased as a proportion of catch (and logger activity) from the sub-zone, increasing from 20% of the catch from the sub-zone to 60% between 2010 and 2015 (Figure 67).

As catch has increased in these two areas, there has been a changing pattern of logger performance indicators, including contradictory changes among the two areas (e.g. increasing catch with both decreasing and increasing area per dive event). This suggests interpretation of logger performance indicators will not always be simple, and may need to include local, site-related factors, such as local habitat and fishing conditions. While changes were visible at the an annual scale, change may have also been occurring at many shorter time scales, as divers made decisions and fished the area in response to very recent previous catch, weather and market conditions. Investigating these within year patterns becomes difficult at finer spatial scales as data becomes limited, while pooling greater spatial areas may confound comparisons through time with more external factors. Despite that, the annual pattern of change observed is a combination of the shorter term changes, some of which are visible at the annual scale while others are not, and represent the ongoing sporadic harvest and rest activity of abalone fishing and stocks.

Figure 66. Performance Indicators for dive events derived from GPS logger data, and catch, for two SF sites within Area 12 and 10 since 2008, selected as examples. Note, each Area has about 20-35 dive events logged per year, with 10-15 Ha of reef over 900-1300 m.

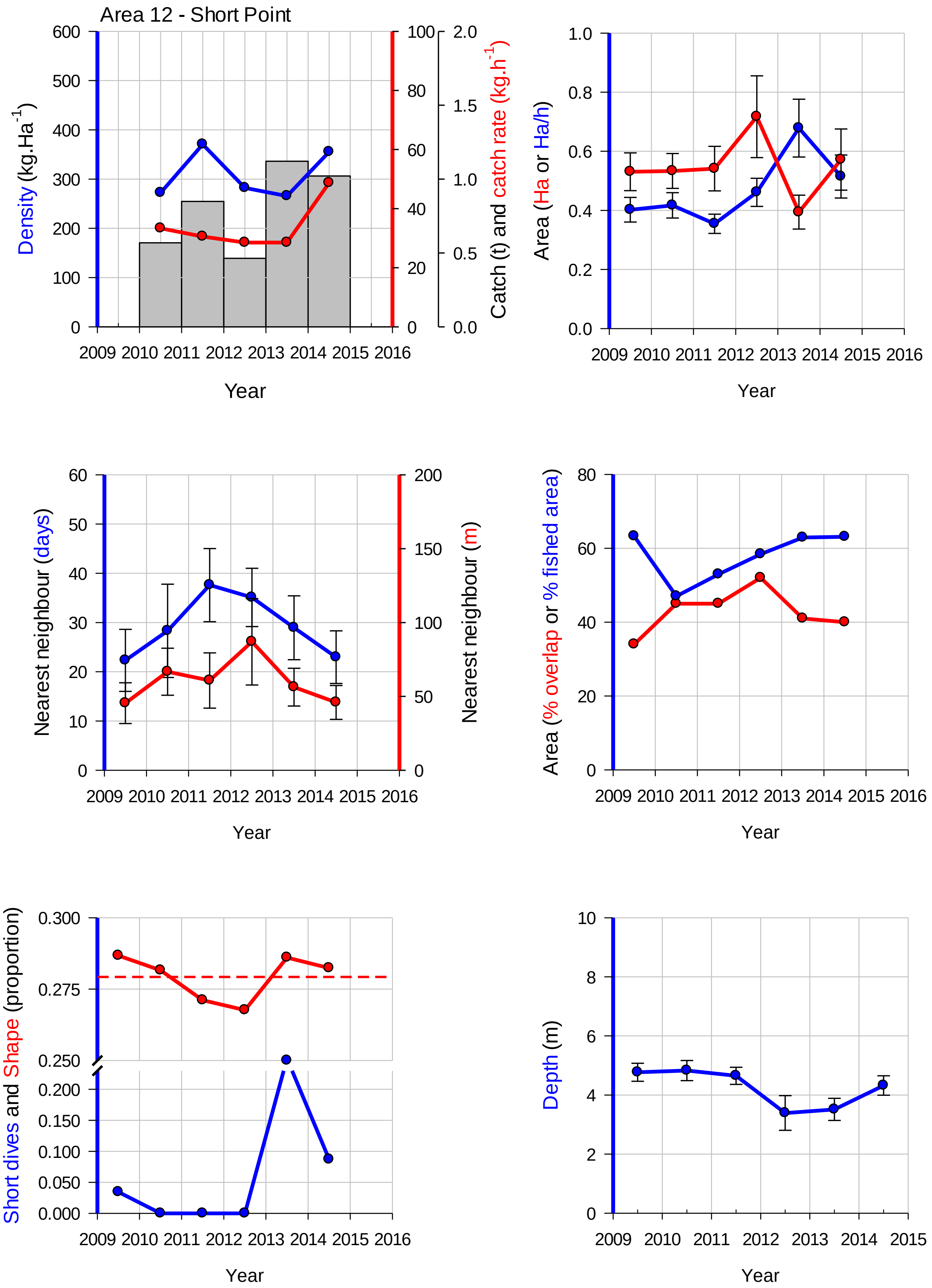
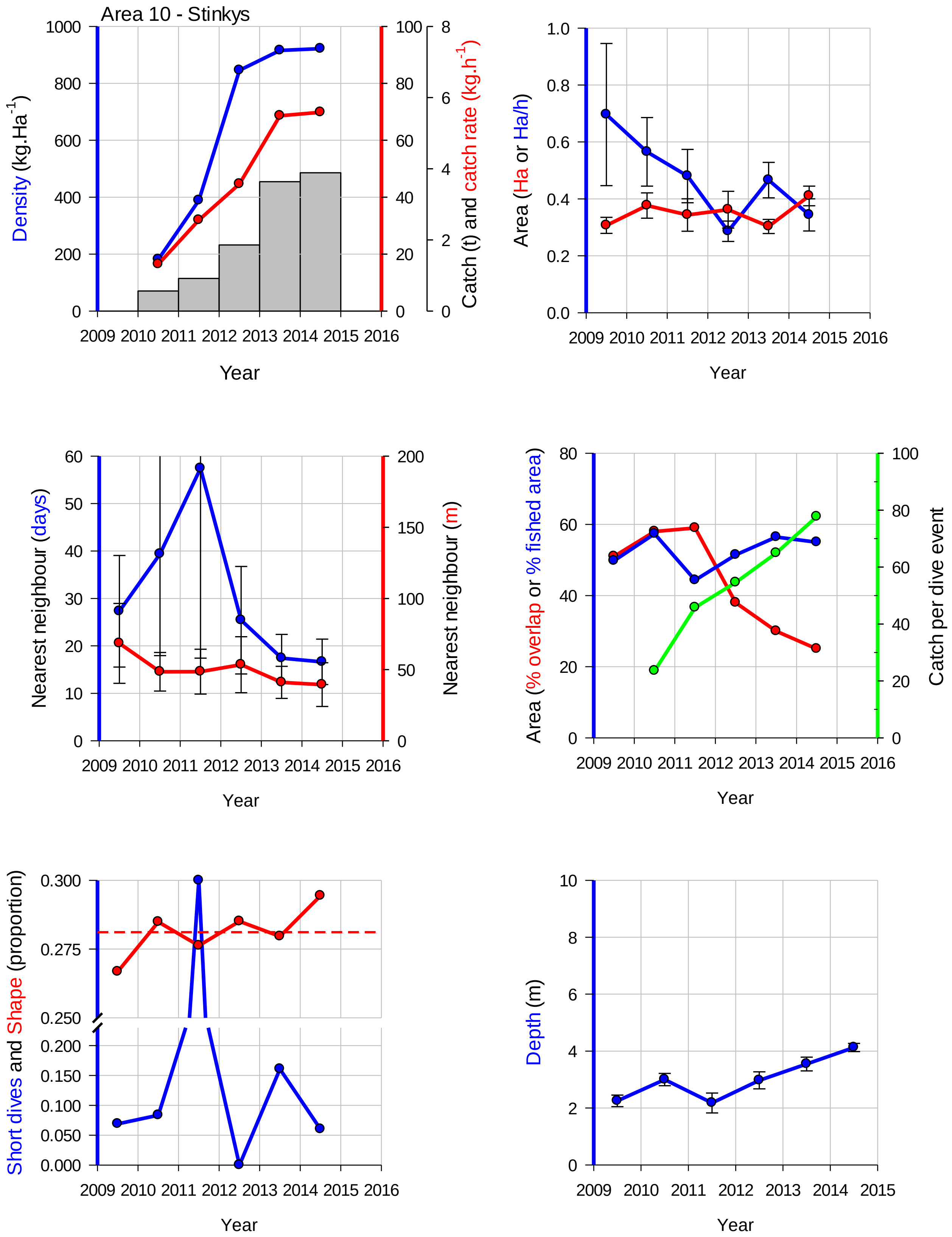


Figure 66, continued. Performance Indicators for dive events from GPS logger data, and catch, for two SF sites within Area 12 and 10 since 2008, selected as examples. Note, each Area has about 20-35 dive events logged per year, with 10-15 Ha of reef over 900-1300 m.



Because of the possible importance of fine scale, within Subzone factors and their influence on logger performance indicators and assessment of the stock, the standardisation of logger density has been extended to the influence of sites within sub-zones and areas. Each days dive events were allocated to a site (i.e. by the position of their centroid) and standardised in the same way as Area-based estimates, plus an additional factor of Site nested within each Area. This analysis attempted to standardise estimates of density for differences in diving effort among sites. For example, as Stinkys is a known high catch rate site within its sub-zone, an increase in catch from Stinkys would increase the apparent catch rate for the zone, even without a change in catch rate at any site. Estimates of the effect of different divers and different sites on estimates of density were similar in magnitude, and ranged from about below 0.5 to 3 (i.e. from about 50-300% the average diver and site, Figure 67). Stinkys is an outstanding site within its sub-zone, and with a logger density generally about 30% higher than the average site, although some sites in other Areas were up to 3 times the density of the average site (Figure 67).

Stinkys is a high density site within its subzone and Area 10, where it is estimated that catch has increased from about 20% of the subzone catch, up to about 60% (Figure 67). This change in distribution of catch, with greater concentration on a high catch rate site, will influence estimates of catch rate at the Area scale. Standardising estimates of density and catch rate by Site allows better comparisons of the subzone or Area through time, without the confounding effect of consistent site differences, and are shown for 5 Areas and 1 SMU (Figure 68). Standardisation including the Site factor led to some large changes in estimates of density for different Areas (i.e. green line in Figure 68), compared to broader-scale Area-based standardisation as blue line). For example, the changes with greater catch from Stinkys, a high density site within Area 10, were confounded in the Area-based estimates of density (i.e. blue line), but when standardised for the Site factor, the estimate of density is reduced from 2012-13 (i.e. green line below blue line), during the period when the proportion of sub-zone catch from Stinkys increased (Figure 68). As a result, the estimate of density in Area 10 during 2014-15 is about 25% lower if standardised for the fine scale Site factor. Similarly, Stinkys and Area 10 are within Region 3 (=SMU 2), where standardisation by Site also decreased estimates of density by a greater effect through time (Figure 68). In contrast, standardisation by Site led to an increased estimate of density in Area 11 and 14, similar estimates in Area 12, and for the important Area 16 a slight decline in recent estimates of density (i.e. blue line) was changed to a slight increase (i.e. green line) with standardisation by Site, although estimated density in 2014-15 was very similar. The pattern of raw, standardised by Diver, and standardised by Diver and Site observed in Area 16 is consistent with a change through time in the catch by high catch rate divers at high catch rate sites, as may have occurred with recent changes in the fishery (Figure 68). Methods of fine scale spatial standardisation deserve further development and evaluation for standardisation approaches used in the fishery.

Figure 67. Variation in standardised density (kg.Ha^{-1}) among a) effects of 30 divers and b) effects of 99 Structured Fishing sites, shown as a frequency distribution of effects relative to average (i.e. average effect = 1, effect of 0.5 = 50% of average and 2 = 200% of average, with Stinkys shown in red at 1.3), c) Estimated catch at Stinkys SF site, with catch from Stinkys as a proportion of Area 10 catch (blue line, from logger dive event centroid allocation method), and d) mean number of SF sites fished per diver day (±se), and dive events per diver day (±se) when fishing Stinkys within Area 10 since 2007.

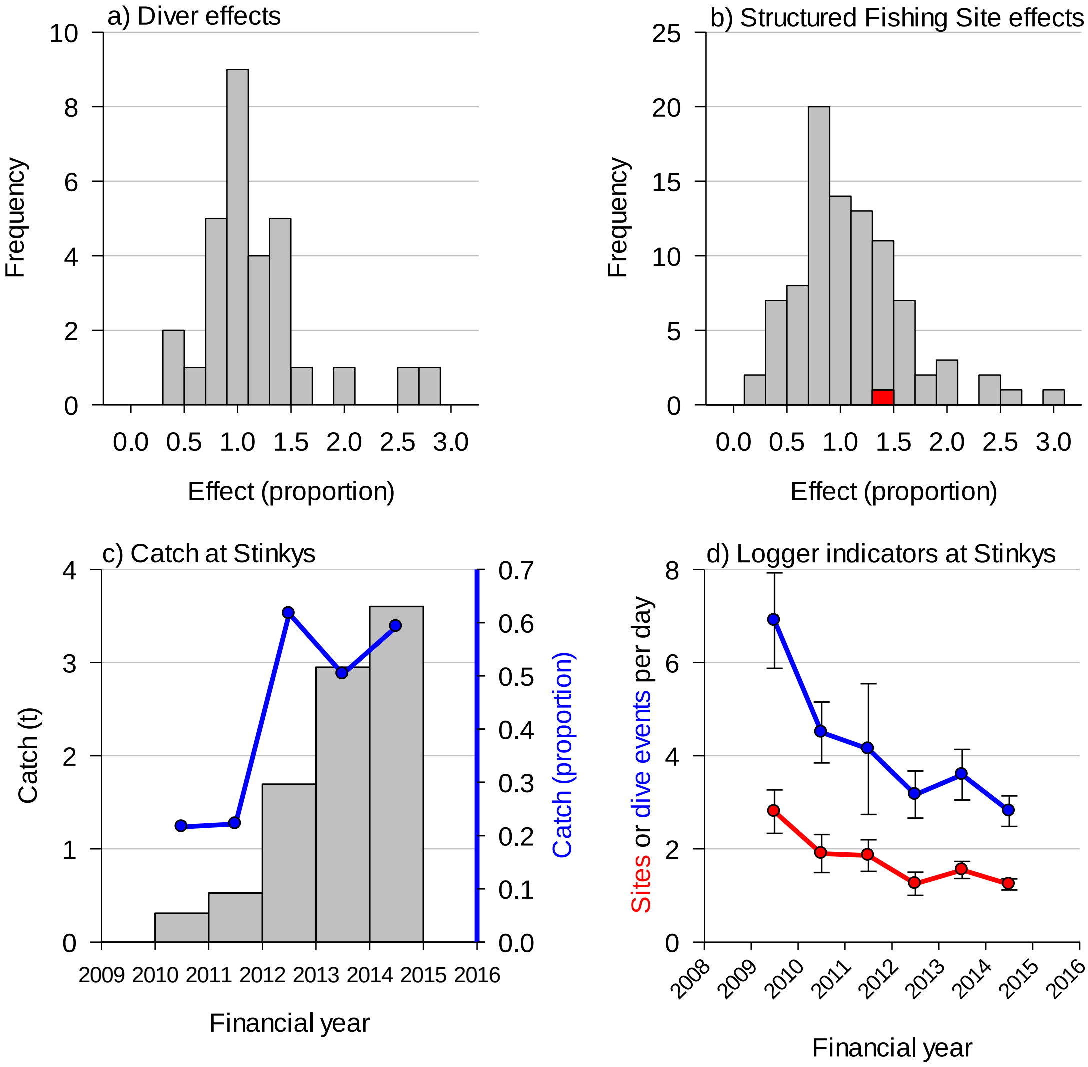
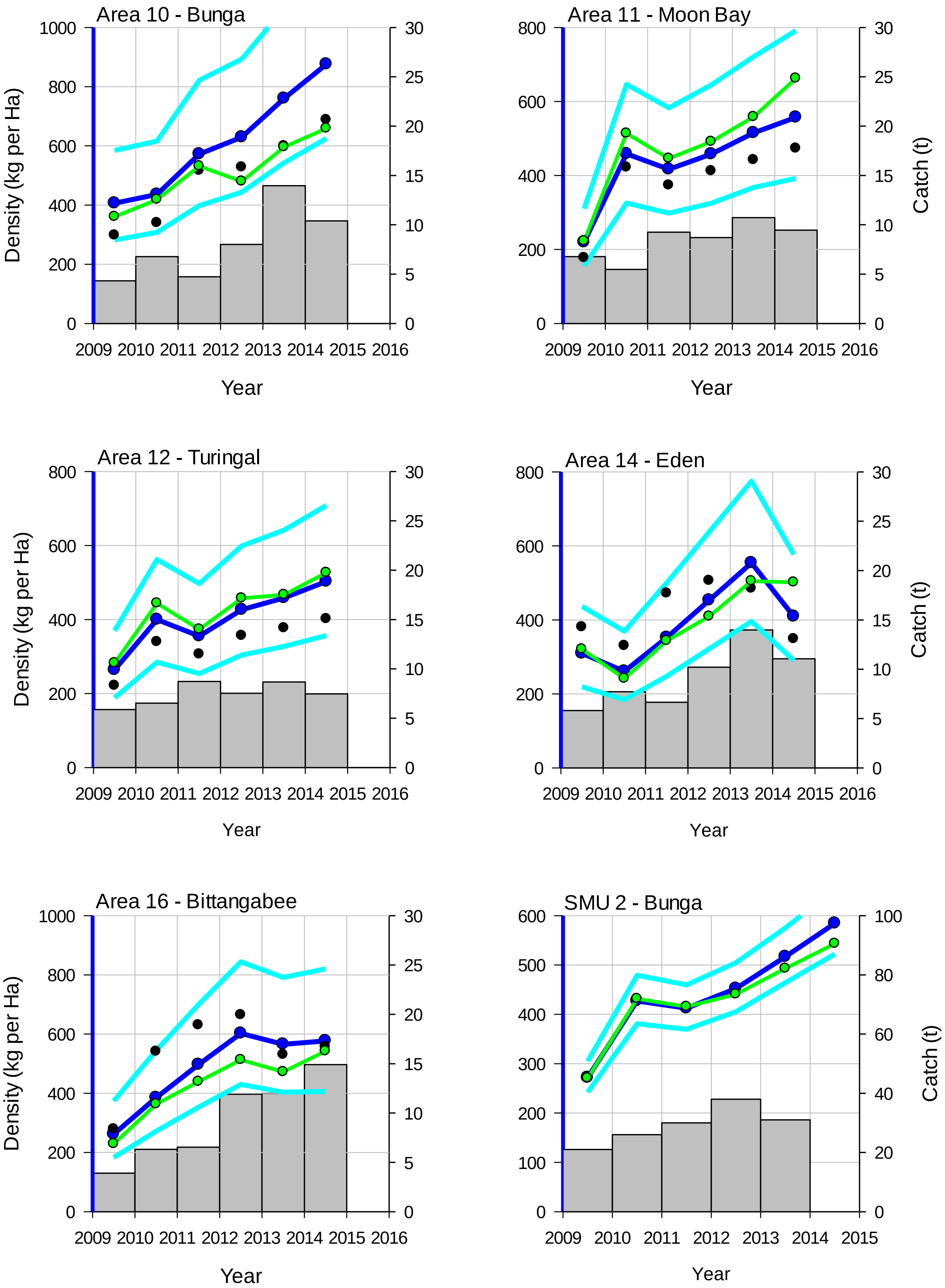


Figure 68. Standardised density of abalone (dark blue line) +SE (light blue line), and standardised density of abalone from model with additional fine-scale spatial standardisation (green line), for 5 Areas and 1 SMU, as examples, since 2009-10. Unstandardised estimates of density (black dots) and catch (grey bars) are also shown.



13.2.4. Estimating biomass from density and area

Data available from loggers is being used to develop a method to provide estimates of the density and total biomass of legal-sized abalone available to the fishery, with potential for use in a Harvest Strategy. Estimates of the density of legal-sized abalone can be calculated from the logger data, by combining the daily logbook catch with an estimate of the area fished (i.e. daily kg/Ha). The area fished is calculated from the GPS logger data (i.e. position of the logger on the boat every 10 seconds) by fitting a spatial model (i.e. kernel density) to each dive event and estimating the area that encloses 50% of the GPS points (see above). This attempts to estimate the likely area fished by the diver (i.e. with a hookah hose attached to the boat) from the GPS data. Estimates of density are then extrapolated to an estimate of the area of productive reef, which is also estimated from logger data. The area of productive reef used to extrapolate density estimates is calculated from the logger activity within a 100 m hexagonal grid. Standardised density estimates were described above, and here productive reef areas are described, and densities extrapolated to produce estimates of total biomass and harvest fraction (i.e. catch as a proportion of total biomass).

Estimates of the productive area of reef from logger data are summarised per year and Region (Table 15) and the accumulating area per year and region (Table 16). The area of productive reef used by the fishery in Regions 4-6 has been relatively stable each year, while it has varied and declined in Regions 1-3, including a large decline in recent years in Region 2, and some increase in Region 1 and 3. Throughout NSW in 2014-15, 1139 Ha of reef were estimated to be productive based on logged dive event activity within a 100 m grid, and this has been declining since reaching a peak in 2011-12 (Table 16). This estimate of the productive area of reef is influenced by both the activity of the fishery and the level of use of loggers, although this has been relatively consistent through time. The cumulative area of reef used has increased each year, although further annual increases in the cumulative area of reef are slowing considerably (Table 16). Throughout NSW to the end of 2014-15, a total of 3425 Ha of reef were estimated to be productive based on logged dive event activity within a 100 m grid. Two alternative estimates of productive reef area are provided for each Region (Table 17, and Regions have been grouped into possible Spatial Management Units, SMU, as used in Victoria), the higher is based on the total cumulative reef area identified per region, and the lower as 90% of that value, although for Region 1-3 the lower value was calculated from the cumulative area of the last 3 years. Cumulative area of the last 3 years represents between 78-87% of total cumulative reef area for each of Region 4-6. These alternative estimates are provided to allow investigation of the sensitivity of biomass estimates to uncertainty in reef area.

Table 15. Estimated area of productive reef (Ha) per Region per year, calculated from logged dive event activity within a 100 m grid, since 2009-10. Note the total area for all Regions in 2014-15 is 1139 Ha.

	Region	1	2	3	4	5	6
	Area	**1-3**	**3-7**	**7-10**	**10-13**	**14-16**	**17-21**
	Subzone	**A-L**	**M-R**	**S-U**	**V-X**	**Y1-Y2**	**Y3-Z**
Year							
2009-10		1	244	192	401	270	263
2010-11		108	213	175	363	310	220
2011-12			157	235	434	300	349
2012-13		19	205	62	380	329	307
2013-14		22	136	87	405	401	330
2014-15		49	82	101	324	290	293

Table 16. Cumulative estimated area of productive reef (Ha) per Region, calculated from logged dive event activity within a 100 m grid, since 2006-07. Note the total area for all Regions in 2014-15 is 3425 Ha.

	Region	1	2	3	4	5	6
	Area	**1-3**	**3-7**	**7-10**	**10-13**	**14-16**	**17-21**
	Subzone	**A-L**	**M-R**	**S-U**	**V-X**	**Y1-Y2**	**Y3-Z**
Year							
<2009		338	147	146	227	104	103
2009-10		339	343	282	438	304	295
2010-11		427	440	346	543	417	346
2011-12		427	482	437	646	458	432
2012-13		440	553	451	684	497	480
2013-14		454	574	464	724	553	532
2014-15		484	599	477	740	571	554

Estimates of the standardised density of legal-sized abalone from logger data are summarised per year and Region (Table 17), and Regions have been grouped into possible Spatial Management Units (SMU) as are used in Victoria. Two alternative estimates of density are provided for each year, and include an estimate of density based on the average diver (i.e. noting this estimate of density was well below that observed in the abundance survey) and a diver that produced a very similar estimate of density to the abundance survey. These alternative estimates are provided to allow investigation of the sensitivity of biomass estimates to uncertainty in density. Density estimates in all Regions have increased significantly since 2009-10, although there are several differences to this general trend (Table 17). A decline in density, and its recovery, is clear in Region 6 in 2012-13 following the increase in size limit and the size of fish included in the density estimate related to legal-sized abalone (i.e. size limit change, changed the definition of biomass from ≥120 mm to ≥123 mm). A decline in density is also apparent in Region 5 during 2014-15, that is coincident with recent increased catch in the area. In comparison, density in 2014-15 has remained stable in Region 6 and Region 1-3, although limited data is available because of reduced catches, but has continued to increase in Region 4.

The alternative estimates of density and productive reef area are used to calculate a range of estimates of total biomass, to investigate sensitivity to the alternatives (Table 17). For each alternative estimate of biomass, the productive area of reef is held constant among years, so changes in biomass among years are only proportional to changes in density. As a consequence, like estimates of density, estimates of biomass have increased significantly since 2009-10 in all Regions, and in 2014-15 range from 150-520 t per SMU, or using the base density estimate, a total of about 1500 t of legal-sized abalone throughout NSW (i.e. noting uncertainty particularly in the 520 t estimated in Region 1-3). These estimates of current legal-sized abalone above the 117-123 mm size limits can be compared to previous DPI model-based estimates of biomass above the 115 mm size limit in 2007, of about 1100 t for Region 2-6 (e.g. compared to 1200 t from current logger estimates excluding Region 1). Unfortunately, a logger-based estimate of biomass is not available for 2007, but considering the large increase in commercial catch rates between 2007 and 2014-15, and increase in density estimated from loggers since 2009, it is likely that the logger-based method would provide a considerably more conservative estimate of biomass in 2007 than that from the population model. Workshop catch targets and actual catch for the last two years, including catch to date in 2015 and extrapolated to a 130 t catch equivalent to the TAC, are also presented for each SMU (Table 17).

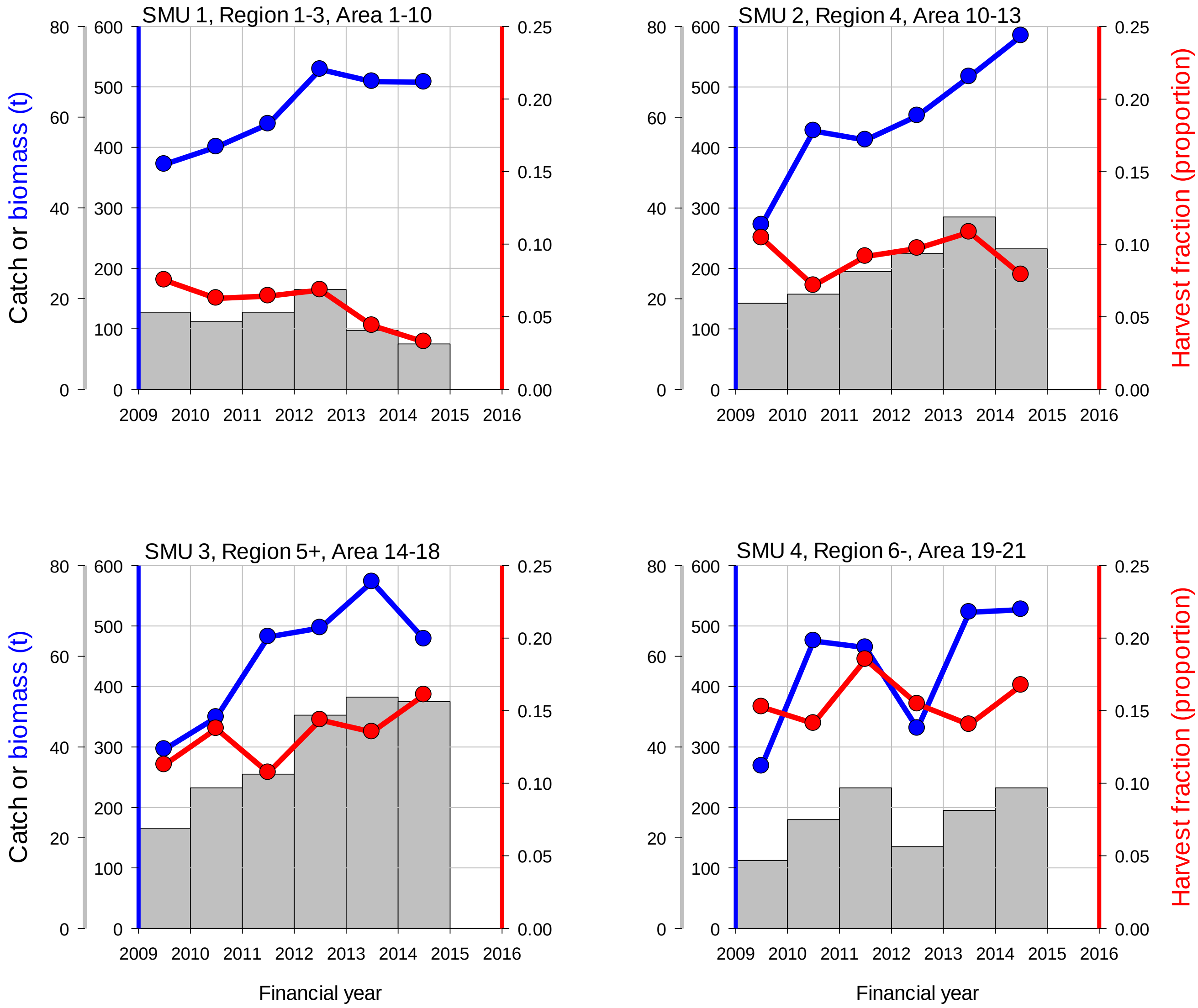
Table 17. Range of estimates of biomass of legal-sized abalone, for alternative assumptions about estimates of density and productive reef area. Alternative assumptions are explained in the text, and include two density options that are combined with two productive area options, with the range of resultant biomass estimates shown. Note 123.1 t was caught in 2014-15, estimates of productive area from 2015-16 are included, and Y3 has been removed from Region 6 and included in Region 5.

	SMU 1	**SMU 2**	**SMU 3**	**SMU 4**
	Region 1-3	**Region 4**	**Region 5+**	**Region 6-**
	Area 1-10	**Area 10-13**	**Area 14-18**	**Area 19-21**
	Subzone A-U	**Subzone V-X**	**Subzone Y1-Y3**	**Subzone Z**
Year				
	Density (kg/Ha)			
2009-10	303-372	222-272	241-296	219-268
2010-11	326-401	348-427	284-349	387-475
2011-12	357-438	336-412	393-482	378-464
2012-13	431-529	369-452	405-497	270-331
2013-14	415-509	421-517	573-467	426-523
2014-15	414-508	476-584	390-478	429-527
	Area (Ha)			
All years	601-1024	679-754	656-729	356-396
	Biomass (t)			
2009-10	182-380	150-205	158-216	78-106
2010-11	196-410	236-322	187-254	138-188
2011-12	215-449	228-311	258-351	135-184
2012-13	259-541	250-341	265-362	96-131
2013-14	249-521	286-390	306-418	152-207
2014-15	249-520	323-441	256-348	153-208
	Catch and targets (t)			
2014 Workshop targets	25	31	49	32
2013-14 catch	13	38	51	26
2015 Workshop targets	21	33	50	32
2014-15 catch	10	31	50	31
2015 catch to end Aug for 88.7 t	9	21	35	23
2015 catch to end Aug extrapolated to 130 t	13	31	51	34

Estimates of biomass density, catch and resultant harvest fraction are summarised by year in Figure 69. With limited catch in Regions 1-3, there are less data available to estimate biomass, but estimates suggest biomass has been increasing with the reduced catch in recent years, and that as a result the harvest fraction has been decreasing to less than 5%. In Region 4 (i.e. SMU 2), estimates suggest the biomass has been increasing strongly for several years and in 2014-15 (noting the reduced estimate of biomass in this region when fine-scale logger information was included in the standardisation). Catch has also increased in Region 4, slightly more than in proportion to the biomass increases, so the estimated harvest fraction has remained stable or increased slightly for several years, although a reduced catch and increased biomass in 2014-15 has led to a reduction in estimated harvest fraction (Figure 69). Since 2011-12, catches in Region 5 (i.e. SMU 3) have increased faster than the biomass, although in 2014-15 the biomass was estimated to have declined despite the catch reducing slightly. In Region 6 (i.e. SMU 4), the catch and biomass declined sharply in 2012-13, coincident with the size limit increase, but recovered and was stable in 2014-15, leading to a slight increase in harvest fraction with the increase in catch. Absolute harvest fractions in 2014-15 were around 15% in Region 5-6, 10% in Region 4, and below 5% in Region 1-3, although the influence of using the same methodology to calculate biomass among the different regions, and possible confounding (e.g. by habitat etc) is less clear (e.g. particularly with uncertainty about estimates of productive area in Region 1-3).

The development of a method of using GPS logger data to estimate biomass provides an opportunity to estimate change in biomass through time, and relate them to the earlier model-based estimates for the fishery prior to 2007. This goes some way to trying to address the TAC Committee's comments about the need to develop interpretation of the logger data to enable assessment of the current status of the population relative to earlier assessments and times. The method used to estimate biomass from GPS logger data appears to provide a simple and intuitive way of estimating biomass and its change through time, enabling the application of simple approaches, such as harvest fractions, to provide advice and guide catch within a broader harvest strategy. While the method offers promise, there are still several directions for possible further development, including particularly the spatial and temporal scale of application (e.g. SMU or Area) and need for standardisation of density estimates by diver and site. Finally, the estimated biomass and harvest fractions in NSW appear within the range of those tested in a MSE of harvest fractions in WZ that would lead to ongoing recovery in that fishery.

Figure 69. Catch (grey bars), standardised biomass density (blue line, for a 70% diver) and estimated harvest fraction (red line), assuming a constant productive area equal to the lower estimates presented in Table 3, for 4 SMU since 2009.



13.3. Measuring logger performance indicators

13.3.1. Length and weight of abalone landed by Area

Loggers are used to measure the length of abalone from bins landed at Receivers, and at sites chosen by divers while fishing. These two data sets are combined to present estimates by Area of the length (Figure 70) and weight (i.e. conversion using length-weight relationship), and allow comparison with other indicators of size (e.g. mean weight per bin from logbook, Figure 71). Further, recent and historical data have been presented using the same methods to allow direct comparison and recent length-frequency distributions have also been presented. Measuring by divers also includes fine scale information from GPS data, and the fine scale information from measuring through time is also presented separately (Figures 72, 73).

Estimates of the length of abalone landed are shown for Areas where there are reasonable samples and include all areas south of Bermagui (Figure 70). Direct comparison among the years for each Area is confounded to some extent by variation among diver-days, particularly with several Areas having less than 5 diver-days sampled. Despite that, there was an increase in the estimated length of abalone in most Areas between 2009-10 and 2014-15 (Figure 70), and to levels well above those in 1999. Lengths of abalone showed little, if any increase, in Areas 12, 14 and 21 (Figure 70). Lengths of abalone declined slightly in all Areas north of Bittangabee during 2014-15, but increased in most areas south of Bittangabee. Changes through time in the two indicators of abalone lengths (i.e. mean length and proportion $\geq$130 mm) were generally very similar in all areas, suggesting little change in the shape of length-frequency distributions, although differences did occur in some Areas, such as in Area 16 where the proportion of abalone $\geq$130 mm increased more than the mean length, suggesting a greater increase in the frequency of larger abalone (Figure 70).

Changes in the length of abalone landed estimated from logger measuring, following conversion to weight, were generally consistent with changes in the mean weight of abalone per bin calculated form logbook data (Figure 71). Mean weight of abalone per bin increased from 2009-10 to 2014-15 in all Areas (Figure 71). For Areas north of Wonboyn, where the size limit was not changed during this period, mean weight increased 2.2-8.1% (mean = 5.9%) from 2009-10 to 2014-15, and south of Wonboyn, where the size limit was changed from 120-123 mm, abalone weight increased 14.5-21.4% (mean = 18.7%) among Areas. A very large sample of abalone were measured in 1999, which was the first year that reporting of the weight and number of individuals per bin was required for logbook recording, and allowing calculation of mean weight. Estimates of the change in weight from measuring (i.e. and conversion by length-weight relationship) in 1999 to 2014-15 were calculated for all Areas south of Bermagui, and compared to estimates of change in mean weight from logbook data (i.e. both including abalone of all sizes, and not limiting by size limit changes). Estimates of weight change from measuring ranged among areas from 5.7-46.3% (mean = 16.1%, and mean south of Wonboyn = 32.2%) from 1999 until 2014-15, while estimates of weight change from logbook data ranged among areas from 12.4-37.2% (mean = 18.6%, and mean south of Wonboyn = 32.5%), suggesting generally similar estimates of change among the independent methods. Estimates of weight from length measuring are based on much smaller samples of abalone, and so are associated with greater uncertainty than estimates from logbook data which are available for all bins and abalone landed in the fishery each year, but can be influenced by uncertainty related to the type of bin used to hold abalone.

Figure 70. Mean length of abalone (blue line, ±SE) and proportion >130 mm (green line, ±95% CI) from processor and diver measuring in 12 Areas since 2010-11. Note, because of size limit changes, only fish ≥117 mm, and ≥123 mm in areas 19-21, are used in calculations.

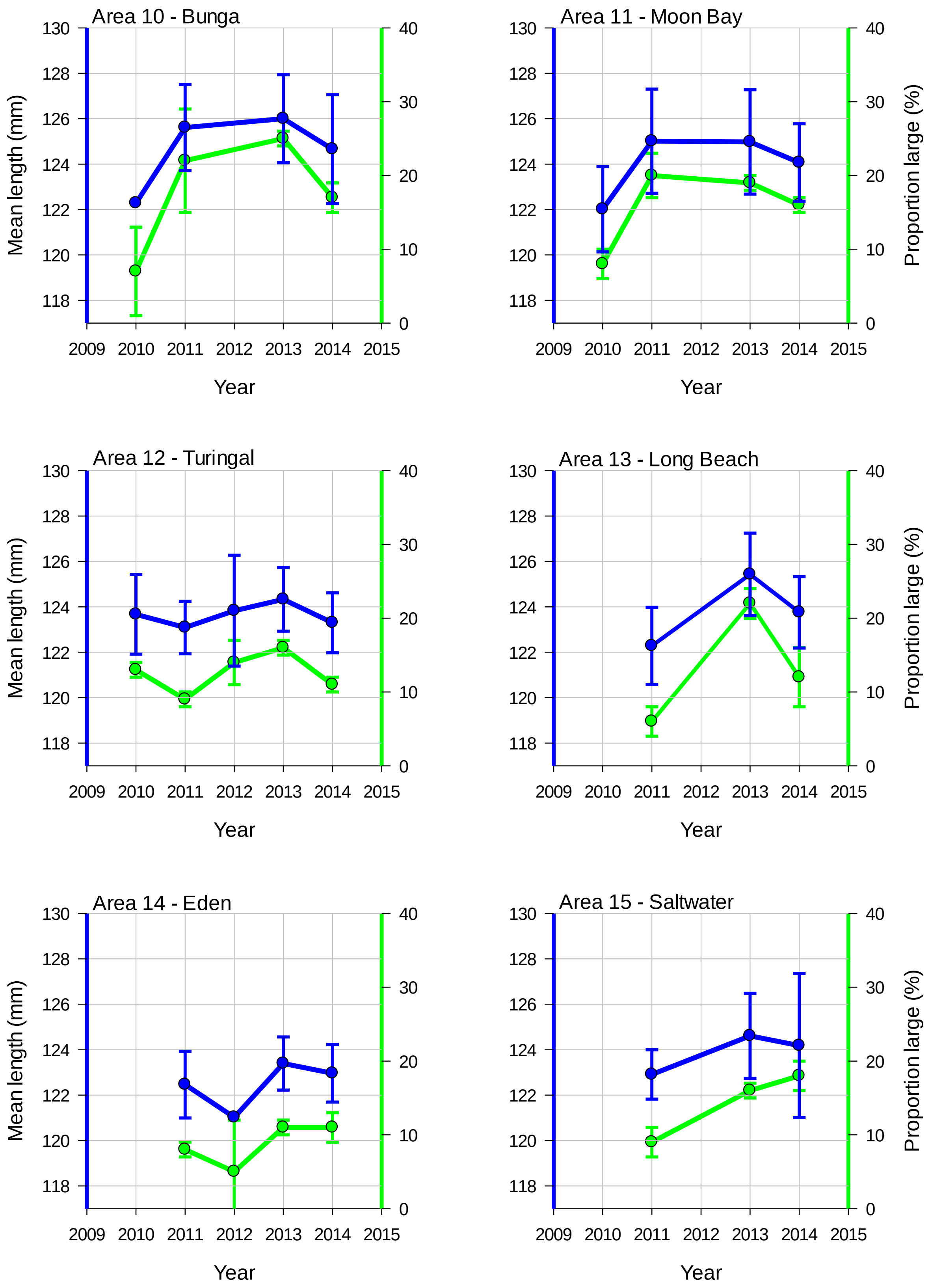


Figure 70, continued. Mean length of abalone (blue line, ±SE) and proportion >130 mm (green line, both ±95% CI) from processor and diver measuring in 12 Areas since 2010-11. Note, because of size limit changes, only fish ≥117 mm, and ≥123 mm in areas 19-21, are used in calculations.

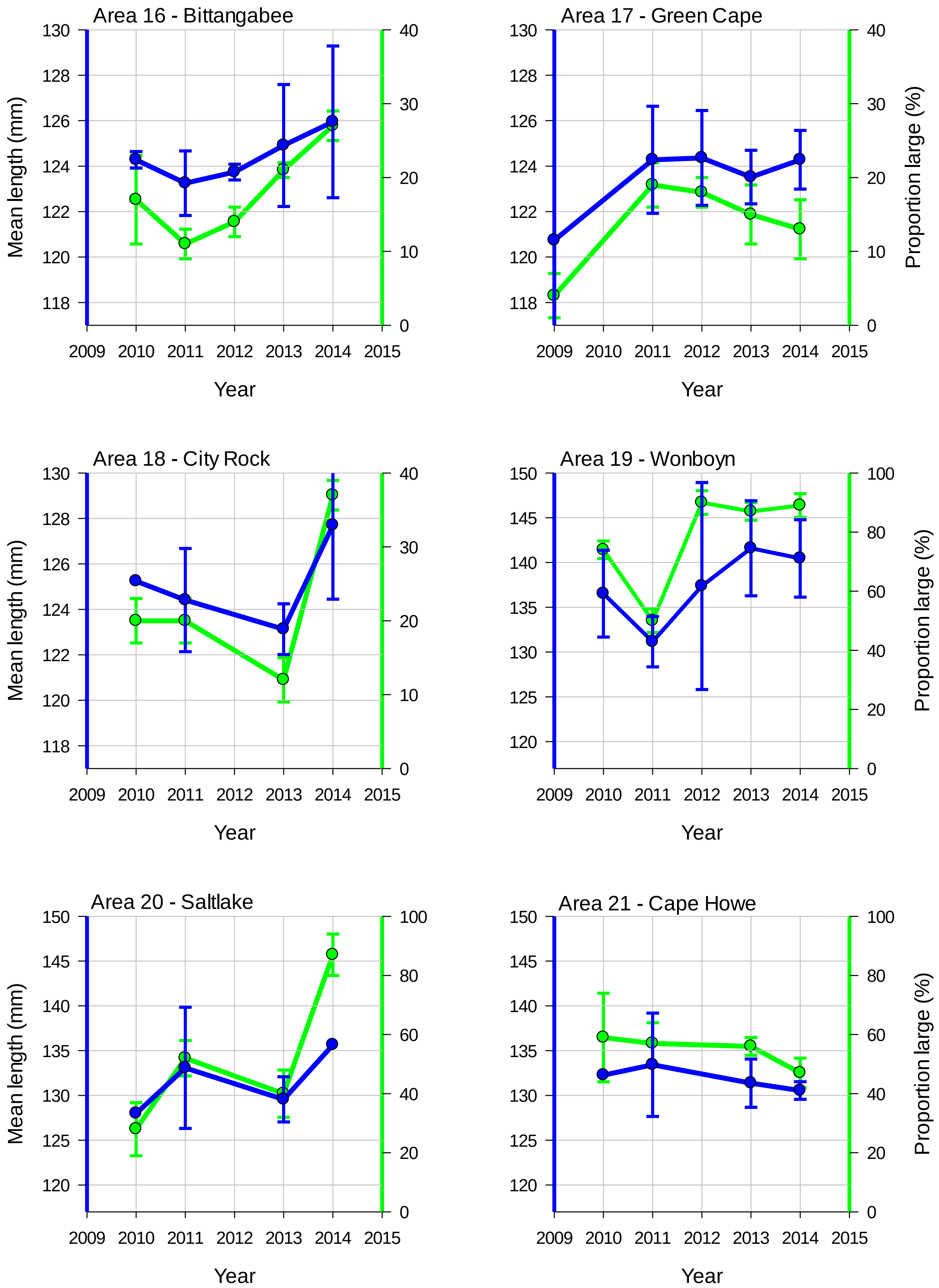


Figure 71. Mean weight of abalone (±SE) estimated from processor and diver measuring (blue line) and logbook bin data (green line) in 12 Areas since 2009-10.

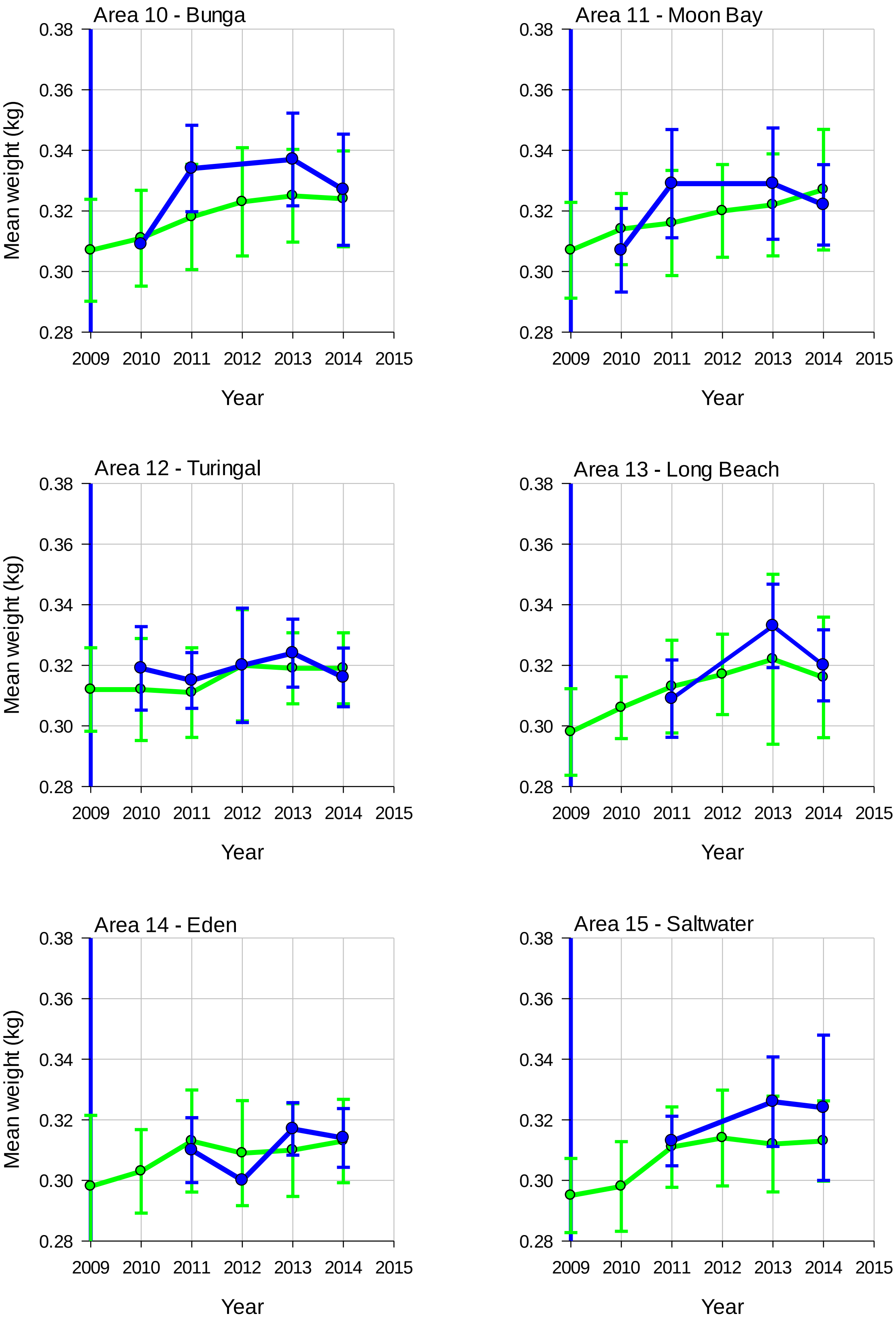
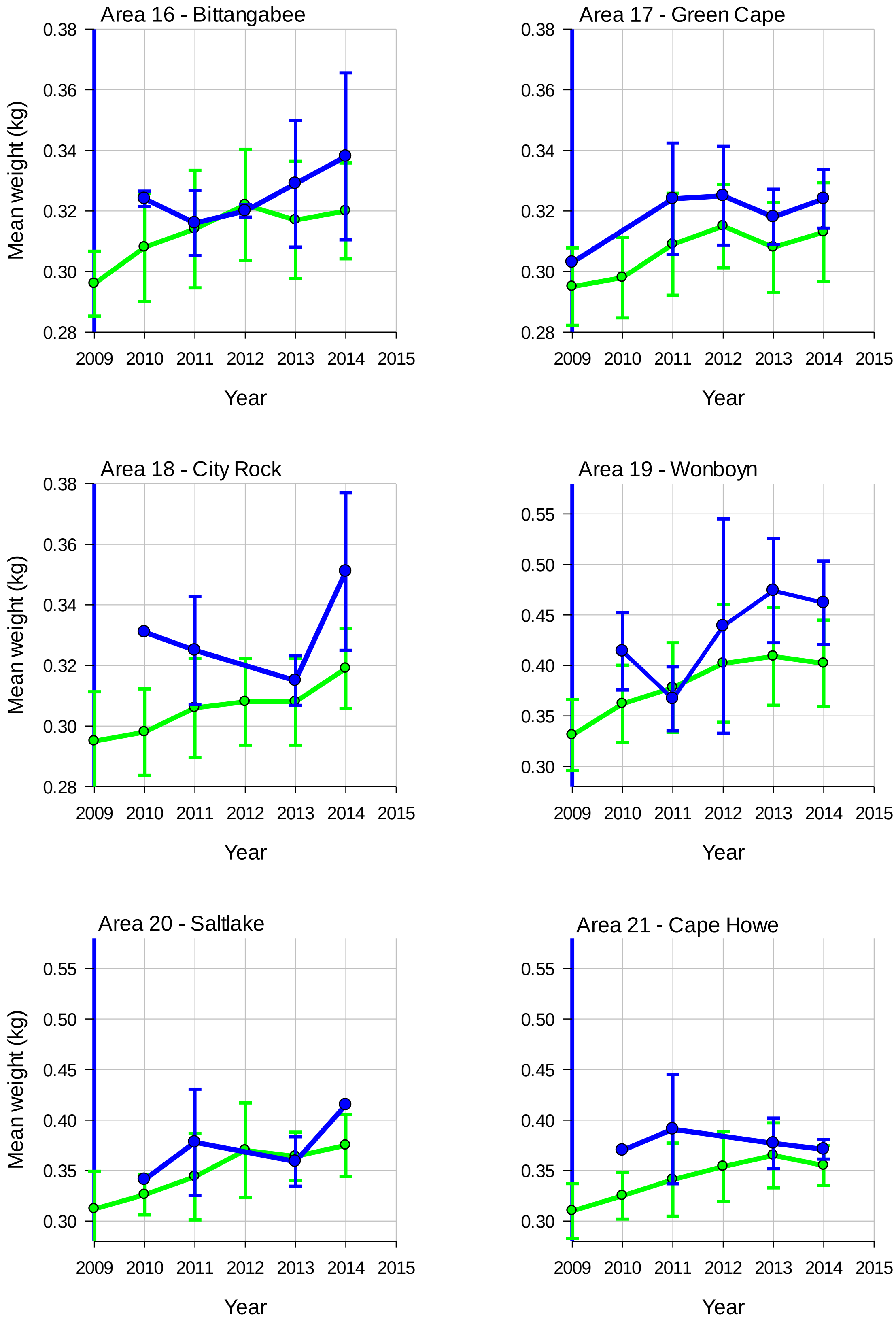


Figure 71, continued. Mean weight of abalone (+SE) estimated from processor and diver measuring (blue line) and logbook bin data (green line) in 12 Areas since 2009-10.



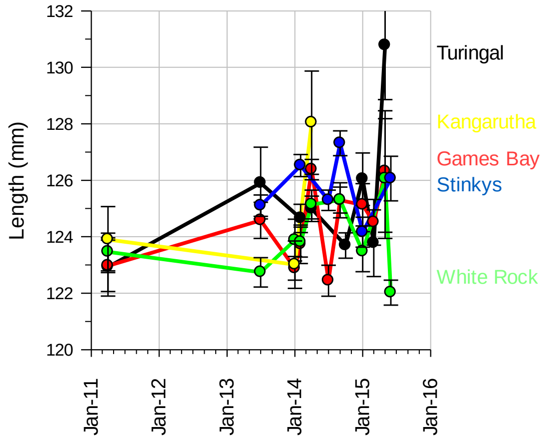
13.3.2. Fine scale length of abalone landed

Measuring of abalone by divers with GPS-enabled loggers provides important additional and complimentary fine-scale information about changes in the length of abalone. GPS location provides an ability to make fine-scale comparisons of the length of abalone caught at the same site by the same diver through time. Measuring at Receivers confounds comparisons through time with the significant fine-scale spatial variation that often dominates abalone populations, and when attempting to represent broad areas or the whole fishery, can be limited by available sample sizes (i.e. improvements could be made by rotating concentrated sampling of Areas among years). By concentrating the significant measuring effort of divers at a selection of sites, better samples at a fine-scale should enable more valid comparisons through time. This information can also combined with other fine-scale indicators to increase knowledge of stocks at these sites, and particularly those from the structured fishing program, and potentially then extrapolate changes to broader scales.

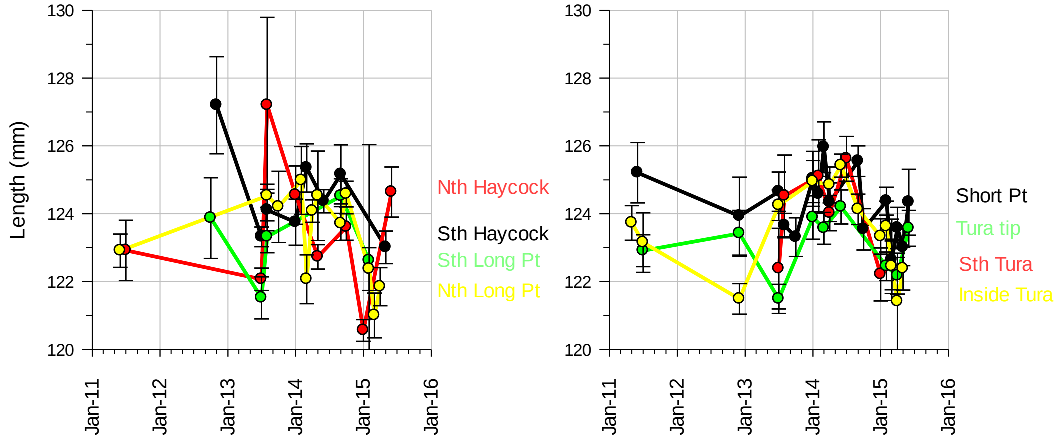
Estimate of change in mean length and the proportion of abalone ≥130 mm are presented for 27 sites within 8 Areas (Figures 72, 73). Lengths of abalone have increased at most sites, with lengths increasing (mean = 2.8%) at 13 of 19 sites with data in 2011-12 or 2012-13 and 2014-15. At the remaining 6 of 19 sites, there was a decrease in length over the same period (mean = 2.1%), and 5 of the 6 sites with a decrease in length were located in Area 12, where 5 of the 6 sites declined. Estimates of changes in length available from the fine-scale measuring program can also be compared to estimates of change by Area from measuring (see above), and following conversion to weight, to estimates of change in weight by Area from logbook data, and through allocation by GPS data and time bins are filled, to estimates of change in weight by site from logbook and logger data. For example, within Area 12 there was an average decrease in length of 1.1% and weight of 1.0% from 5 sites between 2011-12 and 2014-15, while measuring at the Area-scale estimated a 0.3% increase in weight, and logbook data estimated a 2.2% increase in weight at the Area-scale, and a 1.0% increase in weight at the site-scale. Similarly, within Area 16, there was an average increase in length of 2.1% and weight of 6.0% from sites between 2011-12 and 2014-15, while measuring at the Area-scale estimated a 7.0% increase in weight, and logbook data estimated a 2.9% increase in weight at the Area-scale, and a 3.0% increase in weight at the site-scale. Each of the data sources have uncertainties related to sampling and their representivity of the landed catch and abalone stock, but the fine-scale measuring adds an additional component to the weight of evidence approach to assessing data sources and their implications for the stock and its assessment.

Figure 72. Mean length of abalone (±95% CI) per month from diver measuring at 28 Structured Fishing sites within 8 Areas since 2010-11. Note, the average number of abalone measured per month ranges from 64 to 585, with an average of 240 abalone, and 75% of estimates were from 1 diver day.

Area 10-11, Bunga and Tathra



Area 12, Merimbula



Area 14, Eden

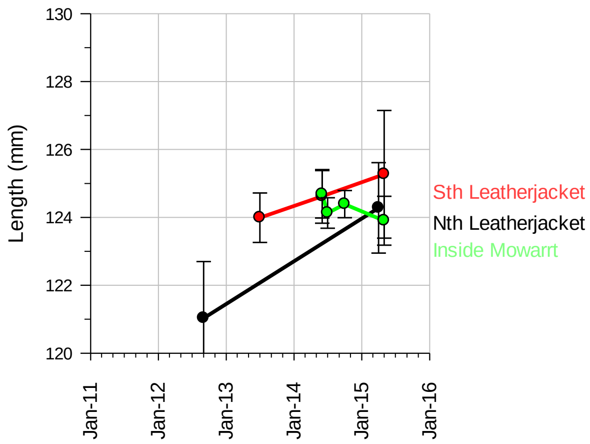
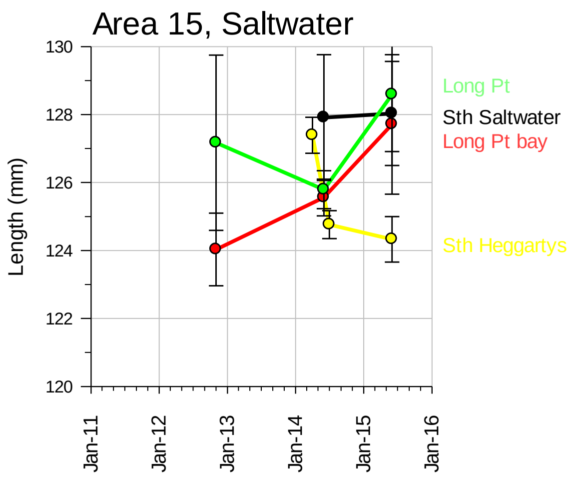
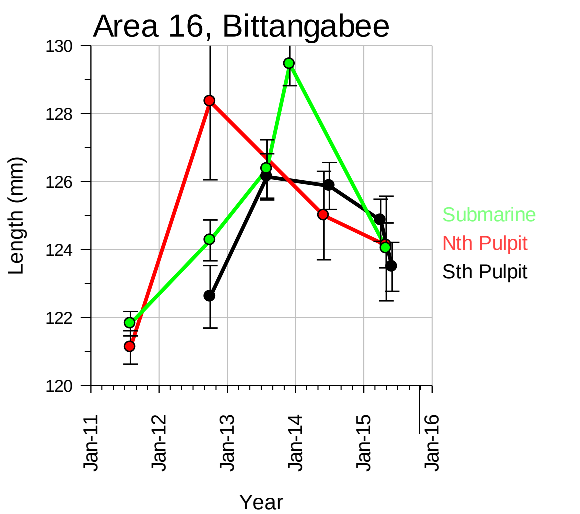


Figure 72, continued. Mean length of abalone (±95% CI) from diver measuring at 28 Structured Fishing sites within 8 Areas since 2010-11. Note, the average number of abalone measured per month ranges from 64 to 585, with an average of 240 abalone, and 75% of estimates were from 1 diver day.





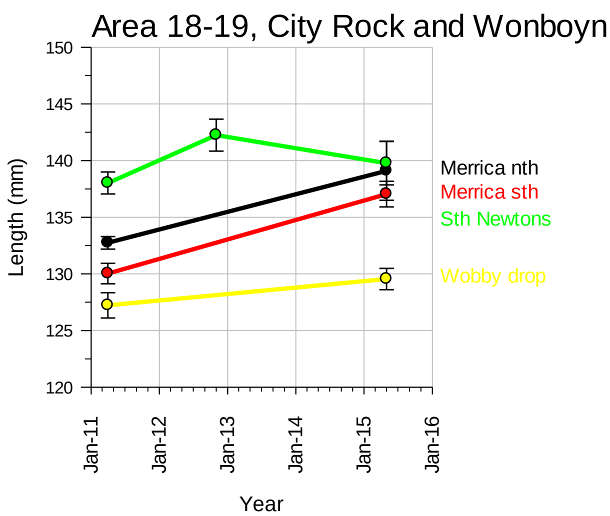
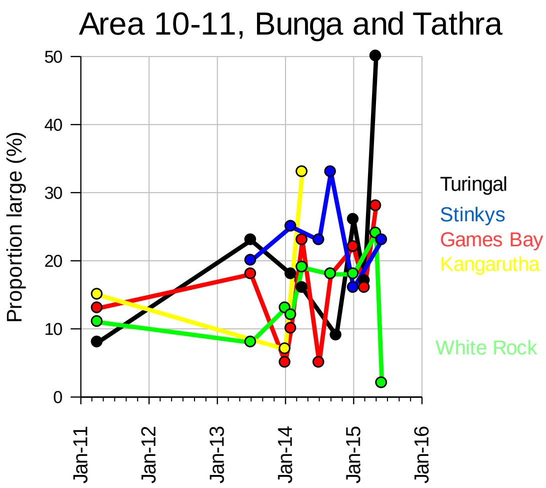
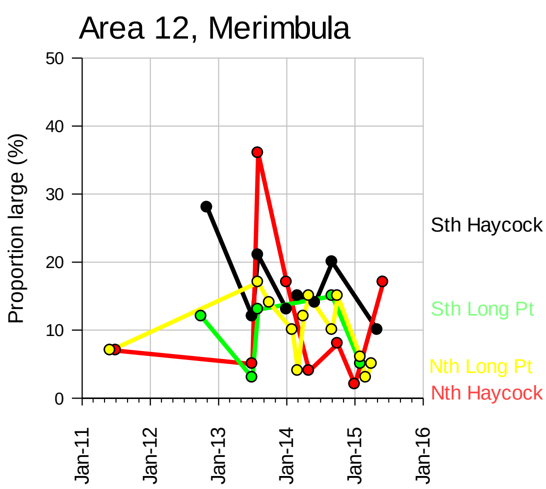
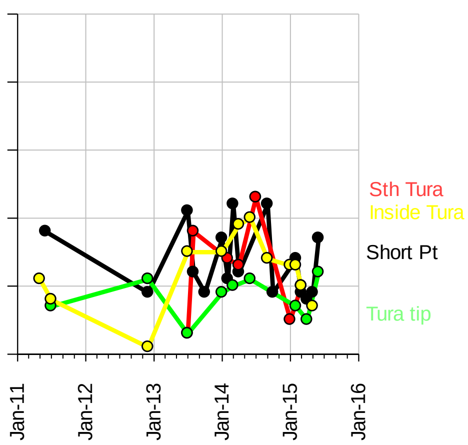


Figure 73. Proportion of abalone >130 mm from diver measuring at 28 Structured Fishing sites within 7 Areas since 2010-11. Note, the average number of abalone measured per month ranges from 64 to 585, with an average of 240 abalone, and 75% of estimates were from 1 diver day.







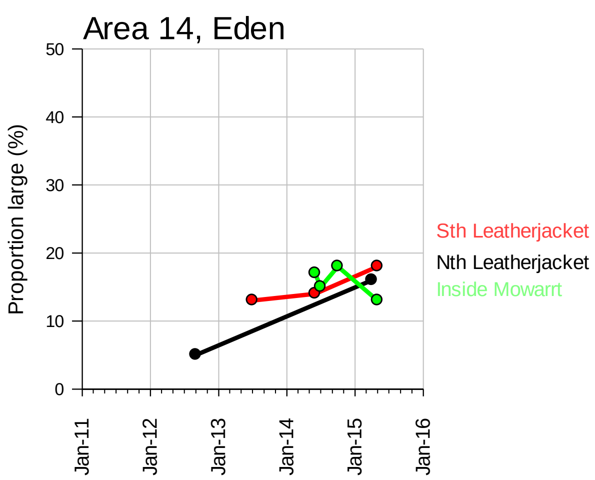
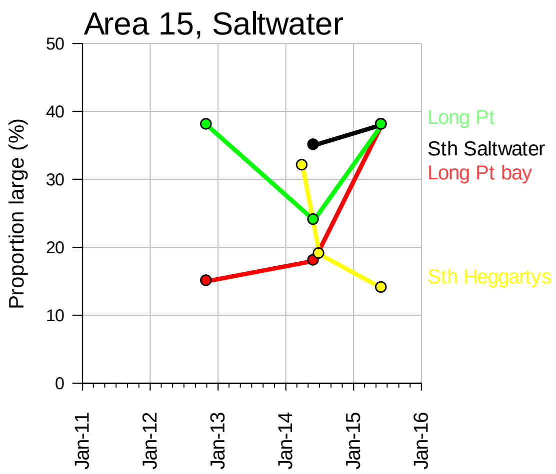
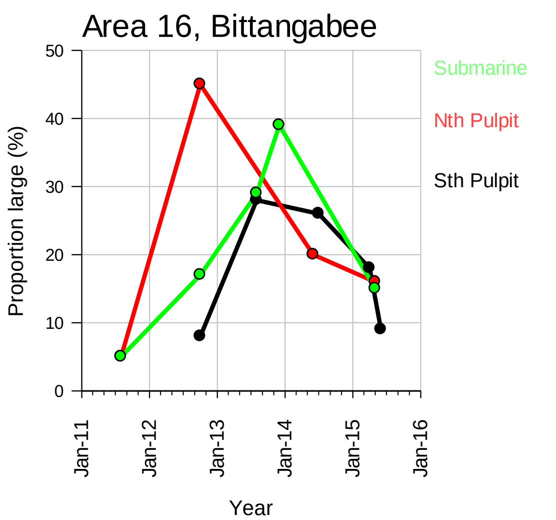
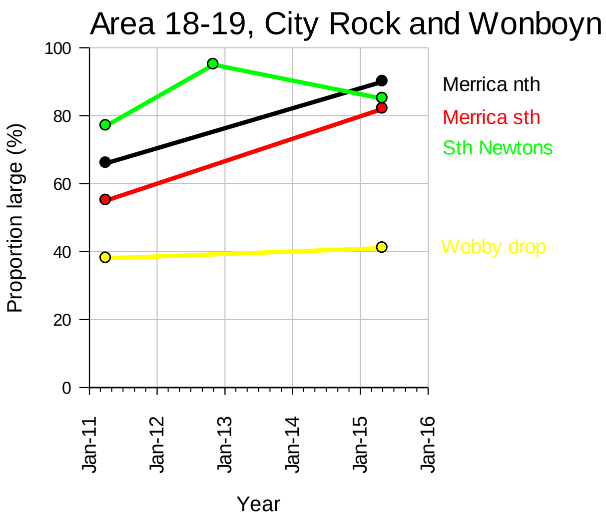


Figure 73 continued. Proportion of abalone ≥130 mm from diver measuring at 28 Structured Fishing sites within 7 Areas since 2010-11. Note, the average number of abalone measured per month ranges from 64 to 585, with an average of 240 abalone, and 75% of estimates were from 1 diver day.







13.4. Summary

This chapter has summarised progress of the project with data available, technical detail of analyses and interpretation for an assessment of stocks of abalone in NSW based on data collected using GPS loggers. This information was presented as part of the TAC setting process for the fishery in 2016, during November 2015. For several years, the data collection with GPS loggers, analysis and interpretation has attempted to follow recommendations of earlier independent reviews, the TAC Committee, DPI, Industry and other stakeholders. A novel, informative and cost efficient framework has evolved to provide advice about catch setting in the fishery, particularly with information from GPS logger, and which will continue to develop during the years ahead.

After declining from 333 t in 1999, the TAC and catch has increased from 75 t in 2009-10 to 130 t in 2015 and remains well below historical levels, but concentrated in areas south of Bermagui (Areas 10-21), because of the ease of catching and processing in the south. Catch rates and the sizes of abalone landed have been increasing for several years and are at record highs, although increases have stabilised or declined in some areas, particularly where catch has been concentrated. Estimates of biomass based on GPS logger data, and other performance indicators, have been developed and are generally consistent with other data showing a pattern of strong increases over several years, although some areas where catch has been concentrated have stabilised or declined in 2014-15. Comparatively little information is available about recovery of stocks where there is little fishing or use of GPS loggers, north of Bermagui.

The Catch Planning Workshop, with information from GPS loggers and other sources, recommended a further increase in TAC for 2016 up to 140 t, with many Shareholders suggesting this was conservative, particularly considering the large areas of coast with little catch. The Workshop agreed on the need for a separate quota for northern areas of the fishery, as it has done for about 5 years, to ensure catch was spread with greater amounts taken in the north. The Workshop also agreed that the current distribution of catch south of Bermagui was appropriate, and believed it was more appropriate for Industry to manage catch distribution at the fine scale of Sub-zones and Areas, while regulatory approaches could be considered at broader spatial scales, such as a northern quota. There is still broad support within Industry for the operation of GPS loggers managed by an Industry entity, as recommended by previous independent reviews. NSW DPI has recently sought tenders to provide the service of managing and interpreting the GPS logger information in the years ahead. Both Industry and DPI are committed to the ongoing use and development of GPS loggers to provide spatial stock assessment and contribute to decision processes improving fishery management outcomes with geo-referenced diver data.

14. Developing the use of GPS loggers for TAC advice in the Victorian WZ abalone fishery

Author: Duncan Worthington

14.1. Background

A component of the FRDC Project 2011-201, "Implementing a Spatial Assessment and Decision Process to Improve Fishery Management Outcomes Using Geo-Referenced Diver Data" , was implemented in the Western Zone (WZ) abalone fishery of Victoria. Objectives of the project in WZ related to the completion of Structured Fishing surveys at Portland and Warrnambool, extension and development of techniques of analysis of GPS logger data, and its incorporation within a decision-making framework to provide TAC advice in the fishery. This chapter provides a summary of the history and project work completed to address those objectives.

Following the spread of Abalone Viral Ganglioneuritis (AVG), a decision was made in 2006 to stop commercial fishing in the areas where abalone populations were seriously affected. In early 2009, a decision was made to attempt to recommence fishing, within a broader plan to ensure and demonstrate the continued recovery of stocks through a conservative harvest strategy, including a higher length limit, greater spatial control of catch, and development of improved and cost-efficient data collection using GPS loggers to provide TAC advice. WADA started development of a project to collect information about stocks and to advise reopening and management of fishing. This occurred initially through the Finer Scale Management FRDC project in April 2008, then a related workshop in May 2008. An application to the FRDC TRF was submitted in August 2008, and was approved in October, before the first project meeting in November 2008.

A successful FRDC TRF application helped fund the establishment of a WADA abundance survey at Port Fairy (i.e. 40 sites), that used the same methodology with sites complimentary to the existing DEPI abundance survey (i.e. 7 sites). The WADA abundance survey was combined with estimates of productive reef area provided by commercial divers, to calculate estimates of the biomass of abalone available above various possible minimum legal lengths (Table 18 and 19), and advise an initial catch limit for the Port Fairy area for the 2009-10 fishing period. A total of 28 t of abalone ≥135 mm in length were estimated within the survey area in 2009 (i.e. this survey estimate was based on a probability of 90% that the true biomass was at least this amount or greater). Initially, catch at Port Fairy was set to 7 t to ensure it would not be possible to catch all abalone estimated to be available within 4 years (i.e. in the absence of further population production from either recruitment or growth, and which would be equivalent to an annual harvest fraction of 25%). Catches for the first two years of fishing at Port Fairy were arranged as part of a Structured Fishing program, that involved divers fishing from GPS points and providing detailed catch, GPS logger and other information about sites. GPS points were selected based on a design to allow comparisons among sites, and at the same site by the same diver through time. Information from the Structured Fishing survey was then used to advise subsequent catch planning and setting (see final report from FRDC 2008-077).

Table 18. WADA abundance survey summary for Portland, Warrnambool and Port Fairy, showing the general design of the survey and estimates of the density of individuals (i.e. m^{-2}) above different lengths.

	Portland					
	Bridgewater		Nelson		Grant	
Sites	12		10		4	
Transects	48		40		16	
	Density of individuals	SD	Density of individuals	SD	Density of individuals	SD
All individuals	0.52	0.10	0.39	0.28	0.31	0.16
>120 mm	0.32	0.08	0.25	0.17	0.16	0.08
>125 mm	0.25	0.07	0.21	0.16	0.12	0.10
>130 mm	0.19	0.06	0.14	0.11	0.07	0.08
>135 mm	0.12	0.05	0.09	0.08	0.05	0.08
>140 mm	0.07	0.03	0.04	0.04	0.02	0.03

	Warrnambool				Port Fairy	
	Mills-Killarney		Levys-WPier			
Sites	4		6		40	
Transects	16		24		80	
	Density of individuals	SD	Density of individuals	SD	Density of individuals	SD
All individuals	0.56	0.35	0.25	0.23	0.83	0.55
>120 mm	0.30	0.19	0.17	0.13	0.38	0.31
>125 mm	0.18	0.11	0.12	0.08	0.30	-
>130 mm	0.08	0.01	0.09	0.05	0.20	-
>135 mm	0.02	0.05	0.05	0.04	0.12	-
>140 mm	0.00	0.00	0.02	0.02	0.06	-

Table 19. WADA abundance survey summary for Portland, Warrnambool and Port Fairy, showing the general design of the survey and estimates of the density of biomass (i.e. kg per m-2) above different lengths.

	Portland					
	Bridgewater		Nelson		Grant	
Area	212 ha		208 ha		43 ha	
Sites	12		10		4	
	Density of biomass	SD	Density of biomass	SD	Density of biomass	SD
>120 mm	149	80	119	81	74	46
>125 mm	133	69	106	79	59	50
>130 mm	106	54	81	62	39	47
>135 mm	77	43	55	46	28	45
>140 mm	54	34	27	27	12	25

	Warrnambool				Port Fairy
	Mills-Killarney		Levys-WPier		
Area	265 ha		218 ha		56 ha
Sites	4		6		40 (2 transects)
	Density of biomass	SD	Density of biomass	SD	Density of biomass
>120 mm	134	86	82	58	143
>125 mm	86	58	64	40	124
>130 mm	39	32	49	30	92
>135 mm	13	12	30	23	61
>140 mm	3	3	12	15	na

In 2011, as part of FRDC 2011-201, a similar process was initiated in areas of reef near Warrnambool (i.e. Mills to Lady Bay) and Portland (i.e. Whites to Lawrence Rocks) that were impacted by AVG and closed to fishing. WADA implemented abundance surveys at Warrnambool and Portland, using the same methodology and with complimentary sites to the existing DEPI abundance survey sites. Estimates of density were combined with estimates of productive reef area provided by commercial divers, to calculate estimates of the biomass of abalone available above various possible minimum legal lengths, and advise an initial catch limit for the Warrnambool area in 2010-11 and Portland in 2011-12 fishing periods. A total of 47 t of abalone ≥135 mm in length were estimated within the Warrnambool survey areas in May 2011 (i.e. this survey estimate was based on a probability of 90% that the true biomass was at least this amount or greater), an initial harvest fraction of 5% was applied and combined with Industry advice to produce an initial catch of 4.2 t. Similarly in the Portland area, a total of 206 t of abalone ≥135 mm in length were estimated within the survey areas in August 2011 (i.e. this survey estimate was based on a probability of 90% that the true biomass was at least this amount or greater), an initial harvest fraction of 5% was applied and combined with Industry advice to produce an initial catch of 11 t. Initial catches from Warrnambool and Portland were from a Structured Fishing program similar to Port Fairy, which involved catches being taken from sites identified by GPS points, and the provision of detailed information about fishing. Sites were selected to be complimentary to DPI survey sites, including some of the same sites (Figure 74). Estimates of catch rate in $kg.h^{-1}$ and $kg.Ha^{-1}$ were calculated from data sheets and logger data provided by divers (e.g. Figure 75). Divers were provided with Google Earth files summarizing the data provided (Figure 76), which allowed very fine-scale comparisons of fishery Performance Indicators for individual divers through time (e.g. Figure 77).

Figure 74. Design of Warrnambool Structured Fishing survey sites (numbered green points) in Mills, Killarney and Cutting reefcodes, together with WADA abundance survey sites (white-yellow points overlaying green Structured Fishing sites).

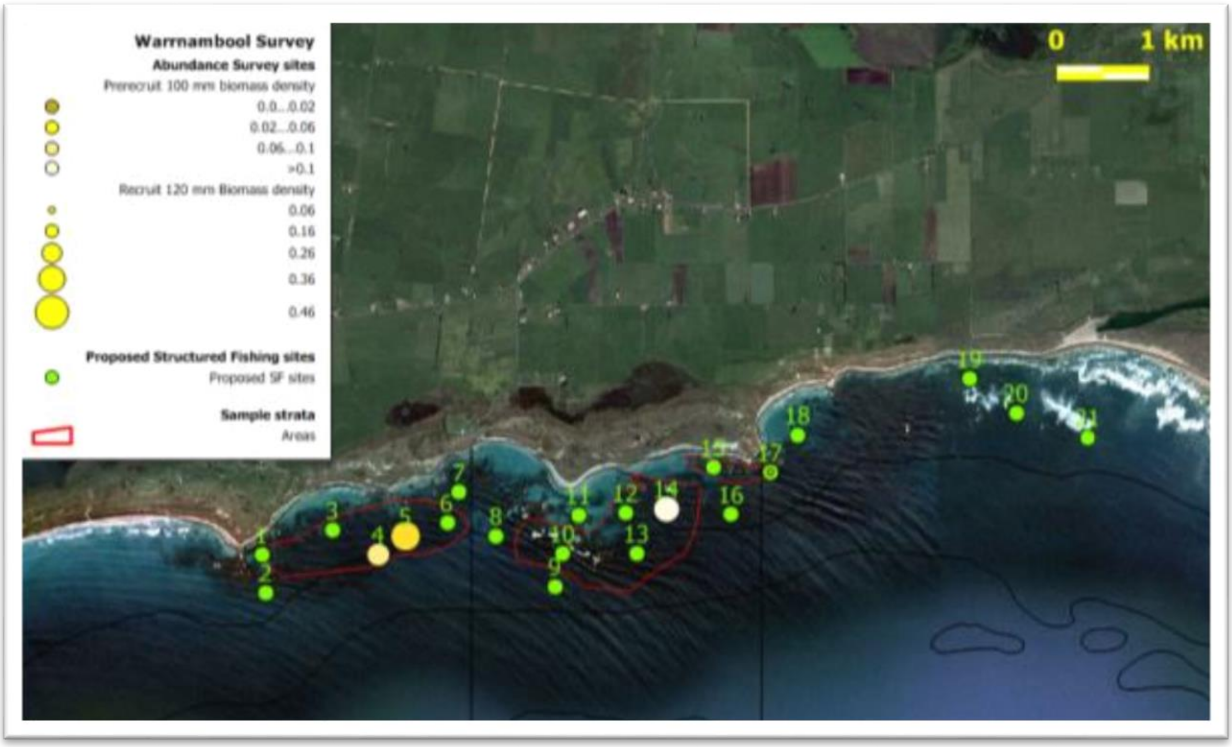


Figure 75. Catch rate of abalone at Warrnambool Structured Fishing survey in Mills, Killarney and Cutting reefcodes.

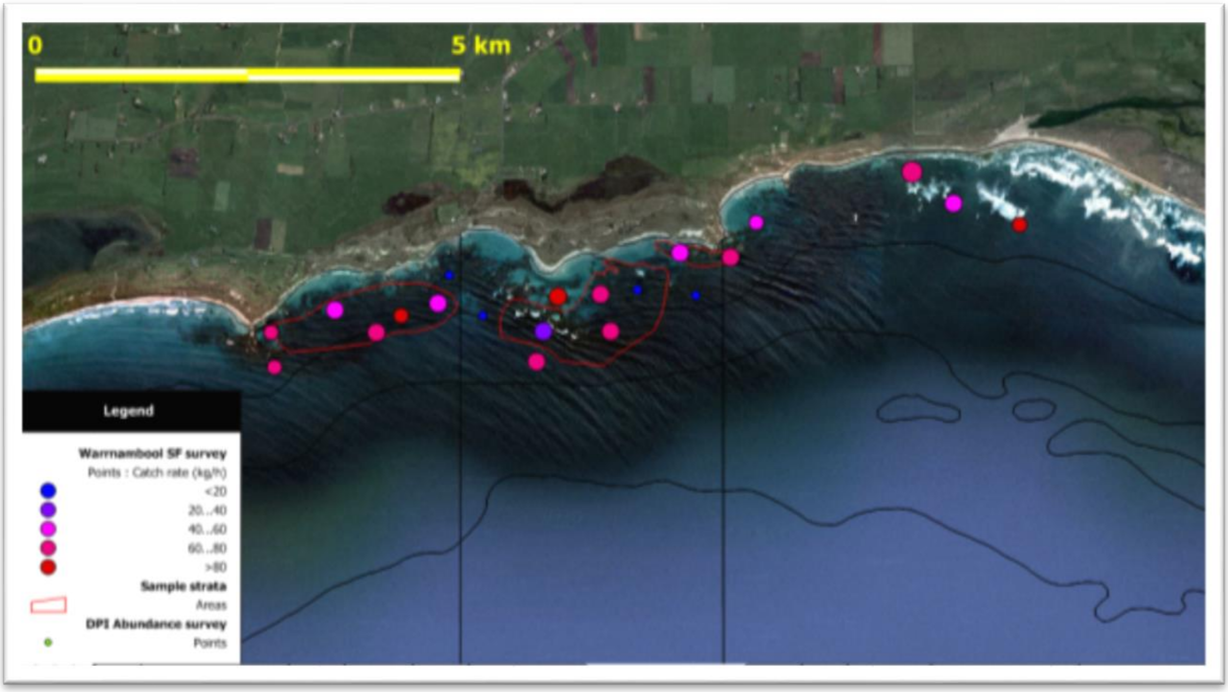


Figure 76. Snapshot of Google Earth files provided to divers showing logged dive events (yellow shapes) and logged abalone measured (points coloured by length) as part of the Structured Fishing survey .

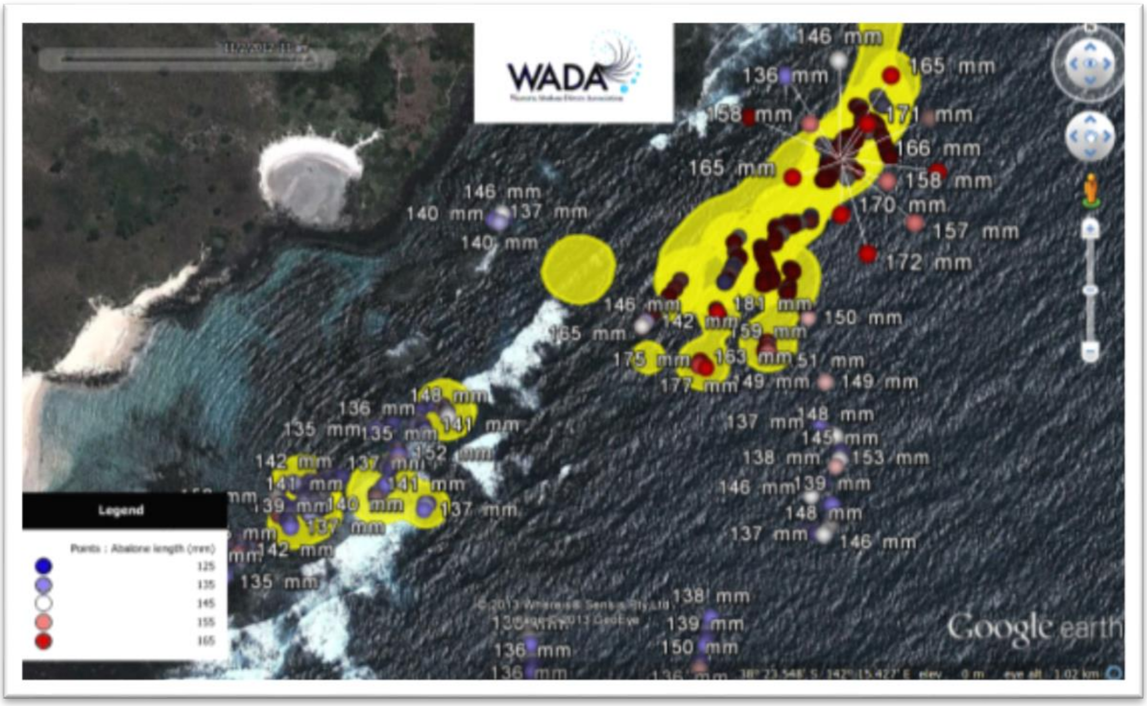


Figure 77. Snapshot of fine-scale data, showing area of reef (pixelated to retain privacy) and position of logged abalone measured during 3 Structured Fishing surveys (SF1-SF3), with the mean length and number of abalone measured summarised in the top left.

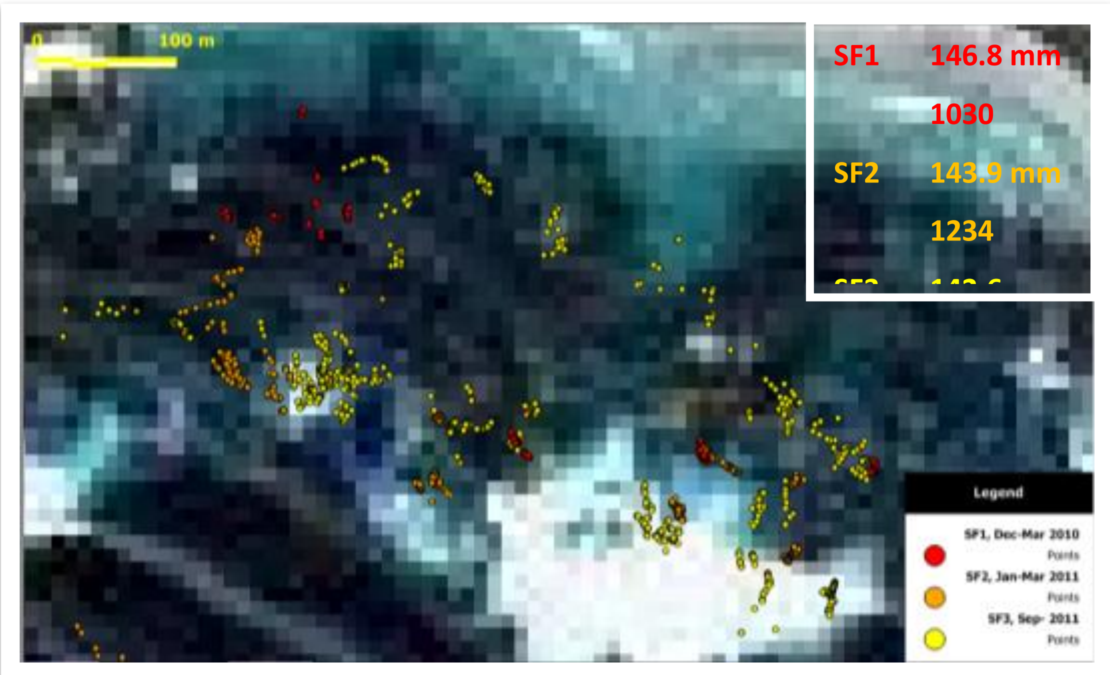


Table 20. Estimates of the probability of different levels of biomass (t), and the corresponding catch (t) for different harvest fractions and minimum length limits, calculated from the WADA abundance survey for three areas at Portland.

		Bridgewater				Nelson				Grant		
		Probability (%)				Probability (%)				Probability (%)		
>120 mm		10	50	90		10	50	90		10	50	90
Biomass (t)		253	316	379		178	247	315		19	32	45
Harvest fraction (%)	1	3	3	4	1	2	2	3	1	0	0	0
	5	13	16	19	5	9	12	16	5	1	2	2
	10	25	32	38	10	18	25	31	10	2	3	4
>125 mm												
Biomass (t)		228	282	336		154	221	288		12	26	40
Harvest fraction (%)	1	2	3	3	1	2	2	3	1	0	0	0
	5	11	14	17	5	8	11	14	5	1	1	2
	10	23	28	34	10	15	22	29	10	1	3	4
>130 mm												
Biomass (t)		184	226	268		116	168	220		4	17	30
Harvest fraction (%)	1	2	2	3	1	1	2	2	1	0	0	0
	5	9	11	13	5	6	8	11	5	0	1	1
	10	18	23	27	10	12	17	22	10	0	2	3
>135 mm												
Biomass (t)		130	164	198		76	115	154		0	12	25
Harvest fraction (%)	1	1	2	2	1	1	1	2	1	0	0	0
	5	7	8	10	5	4	6	8	5	0	1	1
	10	13	16	20	10	8	11	15	10	0	1	2
>140 mm												
Biomass (t)		89	116	142		34	57	80		-2	5	12
Harvest fraction (%)	1	1	1	1	1	0	1	1	0	0	0	0
	5	4	6	7	5	2	3	4	1	0	0	1
	10	9	12	14	10	3	6	8	2	0	1	1

Following initial catches during Structured Fishing surveys at Port Fairy, Warrnambool and Portland, information collected during the surveys from data sheets and loggers, and ongoing monitoring of abundance and length-structure, was used to revise the estimates of biomass and advise catch setting. At Port Fairy, information from Structured Fishing suggested that there were extensive areas of reef outside the original survey areas (i.e. 56 Ha estimated prior to fishing from diver estimates of historically-productive areas) that also contained productive abalone populations. With this information from the Structured Fishing survey, and ongoing good catch rates and the length-structure of fish landed, industry proposed an increase in catch from the initial 7 t to 21 t in 2012-13. Although the original biomass estimate suggested this would be a very high harvest fraction, the survey estimate of biomass could be revised (i.e. density estimate revised to survey average, and productive reef area expanded to all shallow reef) to suggest a harvest fraction of about 10% was possible. Subsequent fishing at Port Fairy has seen catch restricted to about half the shallow reef area at Port Fairy, with the productive reef area further revised during the TAC setting process (i.e. 181 Ha) to produce a biomass estimate in 2014 of 47 t of abalone ≥135 mm and more than 87 t available to the fishery at the current length limits (i.e. >130 and 132 mm, Tables 20 - 22), with a harvest fraction of about 10%.

The estimate productive reef area for the Crags of 71 t currently used in the WZ Harvest Strategy was calculated from an estimate of half the total shallow reef area at Port Fairy (i.e. 188 Ha), and the catch taken from the Crags reefcode as a proportion of the Port Fairy catch in 2011-12, and was similar to an estimate of half the total shallow reef area for the Crags (75 Ha). Estimates of productive reef area used for all Port Fairy reefcodes were originally based only on diver's estimates (i.e. 56 Ha with 40 Ha at the Crags), but were expanded based on structured fishing results which showed most sites fished at Port Fairy contained productive abalone populations. Estimates of productive area of reef currently used in the WZ Harvest Strategy at Warrnambool and Portland are still based on diver's estimates of historically productive reef, as structured fishing and more recent fishing have not suggested expanded areas of reef may be productive. Formal review of the area of productive reef and density estimates are planned for a three year rotation among the three areas (i.e. Port Fairy, Warrnambool and Portland), and the Port Fairy estimate was revised in 2013-14.

Table 21. Estimates of density, productive area and biomass, with corresponding catch for different harvest fractions calculated from the WADA abundance survey, and the 2012-13 catch. This Table was presented to the 2013 Workshop.

Area	Scenario	Density ($g.m^{-2}$)		Area (Ha)	Biomass (t)	Catch (t) at each harvest fraction			Catch 2012-13 (t)
		lo	av			1%	5%	10%	
Port Fairy	Strata	47	61	72	34-44	**0.3-0.4**	**1.7-2.2**	**3.4-4.4**	21
(2009 survey	All reef	47	61	376	177-229	**1.8-2.3**	**8.8-11.5**	**17.7-22.9**	
catch 7, 7, 11, 21)	>130->135	51	65	376	192-244	**1.9-2.4**	**9.6-12.2**	**19.2-24.4**	
Warrnambool	>135	10	21	483	47-101	**0.5-1.0**	**2.4-5.1**	**4.8-10.1**	4.5
(2011 survey	>125->140	22	40	483	106-193	**1.1-1.9**	**5.3-9.7**	**10.6-19.3**	
catch 4.2, 4.5)									
Portland	>135	45	55	463	206-255	**2.1-2.5**	**10.4-12.7**	**20.8-25.5**	8.6
(2011 survey catch 8.6)	>130->135	50	60	463	232-278	**2.3-2.8**	**11.6-13.9**	**23.2-27.8**	

A similar process was used to consider changes in biomass and catch at Warrnambool and Portland. At

Warrnambool there was an initial biomass estimate of 47 t (i.e. with 90% probability that biomass was higher) and catch of 4.1 t of abalone above a 135 mm length limit (i.e. including $\geq$140 mm at Levys), although the length limit has now been adjusted to 130 mm (i.e. still $\geq$140 mm at Levys), with an increase in biomass and catch to 141 t (i.e. with 50% probability biomass was higher) and 10.1 t, respectively. There is some concern at Warrnambool that the actual biomass may not be as high as that estimated, because of biomass estimates (i.e. density and productive area) in the Levy's to Hopkins River area which was badly impacted by AVG. At Portland, there was an initial biomass estimate of 206 t (i.e. with 90% probability that biomass was higher) and catch of 8.6 t of abalone above a 135 mm length limit. The length limit has now been adjusted to 130 mm, with an increase in available biomass and catch to 304 t and 29.5 t, respectively. There is some concern at Portland that the actual biomass may not be as high as that estimated, because fishing is not distributed evenly through the identified productive area of the fishery. Some areas identified as productive are being heavily fished, while other areas have not been fished. It is proposed to continue to review and revise as needed the density and productive area assumptions on which the biomass estimates are based, including a full formal review at least every 3 years.

Coordination of the initial TRF project with the annual TAC setting and catch planning process led from the development of the initial plan for abundance and Structured Fishing surveys, to further development and incorporation of the outputs into the WADA catch planning and TAC setting processes. The Workshop process received and worked through the plans, outputs and advice from this project, and ensured its integration with the understanding of industry, and particularly its divers, to interpret and apply a fine-scale catch planning and TAC approach consistent with the intent of the broader-scale biomass calculations. There is now an opportunity to formalise the biomass-based approach within a broader harvest strategy for the WZ fishery.

Table 22. Estimates of density, productive area and biomass, with corresponding catch for different harvest fractions calculated from the WADA abundance survey, and the 2013-14 catch. This Table was presented to the 2014 Workshop.

Area	Scenario	Density (kg.Ha^{-1})	Area (Ha)	Biomass (t)	Catch 2013-14	Harvest fraction		
						5%	**7.5%**	**10%**
Mills-Killarney	≥130	390	265	103	9.7	5.2	7.8	10.3
Levys-Wpier	≥130	490	78	38	0.1	1.9	2.9	3.8
Grant-LwRx	≥130	390	43	17	1.2	0.8	1.3	1.7
Nelson	≥130	810	121	98	8.1	4.9	7.4	9.8
Bridgewater	≥130	1060	88	93	10.2	4.7	7.0	9.3
	≥135	770	124	96	0.9	4.8	7.2	9.6
Port Fairy	≥130	920	117	108	8.3	5.4	8.1	10.8
	≥135	610	71	43	5.2	2.2	3.2	4.3
Port Fairy	≥130	593	117	69	8.3	3.5	5.2	6.9
(rev biomass)	≥135	252	71	18	5.2	0.9	1.4	1.8
Total					**43.7**	**29.9**	**44.9**	**59.6**
(rev biomass)						**26.7**	**40.2**	**53.2**

Table 6. Estimates of density, productive area and biomass, with corresponding catch for different harvest fractions calculated from the WADA abundance survey, and the 2014-15 catch. This Table was presented to the 2015 Workshop.

Area	rf-cds	Density (kg.Ha^{-1})	Area (Ha)	Biomass (t)	Catch (target)	Harvest fraction		
						7.5%	10%	15%
Mills-Killarney	3.09-3.11	480u	265	127	6.8 (8.6)	**9.5**	**12.7**	**19.1**
Levys-Wpier	3.12-3.14	490	78	38	0 (0)	**2.9**	**3.8**	**5.7**
Grant-LwRx	2.08-2.10	390	43	17	1.2 (1.2)	**1.3**	**1.7**	**2.5**
Nelson	2.01-2.07	514d	121	62	9.1 (8.2)	**4.7**	**6.2**	**9.3**
Bridgewater	1.01-1.07	1012u	212	215	15.1 (20.1)	**16.1**	**21.5**	**32.2**
Port Fairy	3.05	671u	71	48	3.7 (3.2)	**3.6**	**4.8**	**7.1**
	2.15-3.08	807u	134	119	5.9 (9.5)	**8.9**	**11.9**	**17.9**
Julia Percy	3.01-3.04	643n	59n	38	2.0 (2.8)	**2.9**	**3.8**	**5.7**
Total					44.46 (56.08)	**49.9**	**66.4**	**99.5**

Table 23. Estimates of sensitivity of density, productive area and biomass to alternative methods of estimation, with corresponding catch for different harvest fractions calculated from the WADA abundance survey, and the 2014-15 catch. This Table was presented

Area	Density (kg.Ha^{-1})	Area (Ha)	Biomass (t)	Catch (target)	Harvest fraction		
					7.5%	10%	15%
Mills-Killarney	480 (480) 326	265 (113)	127 (54)	6.8 (8.6)	9.5	**12.7 (5.4)**	19.1
Levys-Wpier	490 (285) NA	78 (28)	38 (14)	0 (0)	2.9	**3.8 (1.4)**	5.7
Grant-LwRx	390 (NA) 728	43 (16)	17 (6)	1.2 (1.2)	1.3	**1.7 (0.6)**	2.5
Nelson	514 (298) 553	121 (73)	62 (38)	9.1 (8.2)	4.7	**6.2 (3.8)**	9.3
Bridgewater	1012 (562) 623*	212 (143)	215 (145)	15.1 (20.1)	16.1	**21.5 (15)**	32.2
Port Fairy 3.05	671 (632) 626*	71 (95)	48 (64)	3.7 (3.2)	3.6	**4.8 (6.4)**	7.1
2.15-3.08	807 (863) 595*	144 (141)	119 (114)	5.9 (9.5)	8.9	**11.9 (11)**	17.9
Julia Percy	643 (643) 791	63 (63)	38 (58)	2.0 (2.8)	2.0	**2.7 (2.7)**	4.0
Total	current (survey)	logger		44.46 (56.08)	49.0	**65.3 (46.2)**	97.8

14.2. Developing empirical estimates of biomass in the WZ abalone fishery

14.2.1. Background

A harvest strategy based on a range of data sources and information, including biomass estimates, has been developed and investigated in association with the annual assessment and TAC setting process for the Western Zone (WZ) abalone fishery. After the impact of Abalone Viral ganglioneuritis (AVG) in 2006, commercial fishing was stopped in impacted areas. After 3 years closure, an abundance survey was used to advise the development of a survey involving commercial divers fishing to a spatially-structured design. The Structured Fishing survey made use of Global Positioning System (GPS) and depth loggers to record dive events, for combination with detailed records of catch, abalone lengths and other observations. These surveys provided complimentary information to a long-term abundance survey at much fewer sites. Since the recommencement of fishing in 2009-10, estimates of the biomass of abalone have informed the TAC setting process, and by 2012 a biomass-based harvest strategy was established.

Estimates of biomass were calculated from abundance surveys and GPS logger information from structured fishing surveys. This was done by combining estimates of the density and size of abalone, with estimates of the area of productive reef, to extrapolate survey densities and estimate biomass available to the fishery. While both data sources have proven useful, resources are not available to continue abundance surveys at the spatial and temporal scale necessary to inform further development of a biomass-based harvest strategy. Similarly, it has been difficult to continue a structured fishing survey, because of the level of support and resources required. GPS loggers are now used for all commercial fishing in the WZ fishery. As a consequence, WADA have been investigating the potential of GPS logger and catch data from normal commercial fishing operations, to provide information about the density and spatial extent of productive abalone populations, and so to estimate their biomass through time. This section provides a summary of the recent use of estimates of biomass in the fishery, and the development of new methods based on information available from GPS loggers during normal commercial fishing, including their use in a simple harvest strategy.

Biomass is not frequently estimated for abalone populations, particularly because of the difficulties caused by size-dependent crypsis of abalone, survey selectivity (including effects from both variable detection by divers, and the uncertain representivity of sites through time), large variation in density at a range of spatial scales, and the need to extrapolate density estimates from very small scale surveys to much larger areas of reef. Similarly, fitting population models to estimate biomass, with the complex spatial structure of abalone populations and limited data, has also proved difficult. The development and use of GPS loggers in recent years may provide an additional method to estimate biomass of abalone populations, which can be compared and calibrated with existing methods to provide validation.

Biomass estimates available from logger information collected during commercial fishing can have important benefits over abundance surveys. In particular they make use of the extensive searching time and broad spatial coverage of commercial divers during fishing (i.e. equivalent to about a thousand hours per year in WZ, and usually covering a large fraction of productive reef), so that density estimates are based on much larger samples of abalone over much broader areas than is feasible using small transects at a limited number of sites. Despite that, information from loggers can be influenced by many of the same factors that can influence interpretation of commercial catch rates, and which require careful interpretation. As a consequence, it is clear that each of the methods that can estimate biomass (i.e. abundance surveys, modelling and GPS loggers) have their own strengths and weaknesses, and so can provide complimentary information for interpretation and cross validation.

In this section we describe the data and different methods used to calculate density, productive area and biomass of abalone in the WZ fishery since the resumption of fishing after AVG. We also summarise a novel method that uses information from GPS loggers to estimate the biomass of abalone, and compare these estimates to those from abundance surveys and population modelling in an attempt to calibrate and validate the estimates produced. Comparisons of logger-based estimates of biomass with other methods are made within the Crags reefcode, both because it has the greatest coverage by abundance surveys and, unlike most reefcodes, both abundance survey and model-based estimates of biomass have been calculated. With appropriate validation, the use of logger data offers a simple and intuitive method to estimate biomass through time and guide catch within a broader harvest strategy.

14.3. Calculating density of abalone

14.3.1. Scientific abundance and length surveys

Estimates of density and biomass of abalone in WZ have been made using several different approaches to data collection and analysis. To facilitate consideration using a weight-of-evidence approach, estimates of biomass are calculated from several different data collection methods and are presented separately. These include estimates of undersize, mature and legal density from WADA and DEPI abundance surveys, estimates of legal density from GPS and depth loggers, and estimates of productive area from loggers, divers and Lidar. Estimates of the density of biomass are calculated from the abundance surveys by combining data on the density of abalone and their sizes, while estimates of density from loggers are calculated from the density of legal-sized abalone, using daily catch and dive event area. Estimates of density are then applied across a productive area of reef which has been estimated using several approaches including diver-knowledge of historically-productive reef, Lidar estimates of reef area and habitat suitability, and GPS logger data. GPS logger data is considered the most reliable method of estimating the area of productive reef used by the fishery.

In recent years, both DEPI and WADA have implemented surveys of the abundance and length-structure of abalone in WZ. DEPI surveys have been completed since 1992, but at relatively few sites (i.e. 39 in 2015) concentrated in key reefcodes (e.g. 5 at Crags and 3 at Watersprings). DEPI added an additional site in 2014, but data from this site were not included in calculations. WADA surveys were completed in 2009 at Port Fairy and 2011 at Warrnambool and Portland, at many more sites (i.e. 78 in total, and 13 at Crags). The WADA surveys used the same sampling methodology, but selected sites that were complimentary to the DEPI surveys, particularly in areas where there were few DEPI sites. DEPI has 7 survey sites at Port Fairy, 10 at Warrnambool and 19 at Portland, while WADA established 42, 10 and 26 complimentary sites in these areas respectively. The WADA surveys were designed to increase the number of sites within most productive reefcodes to at least 2, although this is still considered well below the number required to precisely estimate the density of abalone within a reefcode.

Both DEPI and WADA surveys involve divers counting the abundance of abalone in two size classes (i.e. Prerecruits <120 mm, and Recruits $\geq$120 mm) on six, radial 30 x 1 m transects per site (i.e. 180 m^2 sampled per site, or with 5 sites in the Crags about 0.1% of the estimated productive reef area). This data provides an estimate of the density of abalone (i.e. individuals.m^{-2}) in the two size classes. The shell length is also measured from all abalone collected in a 5 minute swim, up to a total of 25 abalone, at the end of each transect, or up to 150 abalone per site. To estimate the broader-scale density of different length-classes of abalone, the estimates of density from the survey were combined with the length-frequency distribution at each site, and averaged across sites within a reefcode or broader-area. This was done by multiplying the density of abalone in the Prerecruit and/or Recruit classes by the proportion of individuals of the appropriate length class in the length-frequency sample. That is,

$$DI_{class} = DI_{Prerecruit}\left(\frac{N_{class}}{N_{Prerecruit}}\right) + DI_{Recruit}\left(\frac{N_{class}}{N_{Recruit}}\right)$$

where DI_{class} is the density of individuals.m^{-2}in a chosen length class, N_{class} is the number of individuals in the chosen length class from the length-frequency sample, and Prerecruit and Recruit subscripts refer to the survey length classes. For example, this method was used to calculate the density of legal-sized (i.e. $\geq$130 mm or 132 mm at the Crags, and available to the fishery), mature (i.e. $\geq$102 mm, the length at 50% maturity from Haddon and Helidoniotis) and under-size (i.e. $\geq$100 and <120 mm, expected to be fully visible to the survey and provide an estimate of likely recruitment) individuals. The density of individuals in different length classes was also combined with a length-weight relationship (i.e. Weight = 3.34×10^{-4} x $Length^{2.857}$ from Haddon and Helidoniotis) to provide an estimate of biomass density (i.e. kg.m^{-2} or kg.Ha^{-1}) using,

$$DB_{class} = DI_{class} \left(\frac{W_{class}}{N_{class}}\right)$$

where DB_{class} is the density of biomass in kg.m^{-2}in a chosen length class, W_{class} is the sum of weights from the length-weight relationship for abalone in 1 mm length classes from the length-frequency sample, and this is applied separately for Prerecruits and Recruits before summing across appropriate length-classes to produce indices of the density of biomass for undersize (≥100-<120), mature (≥102) and legal abalone (≥130-132) at each site, which are then averaged across sites within groups of reefcodes and SMU. All sites are included in calculations, except site 147 which was removed to make the distribution of sites more representative of the commercial catch (i.e. as there are 3 sites sampled in reefcodes 1.07 and 1.08, where there is currently very little commercial catch). These calculations have used estimates of abundance that have not been standardized by a GLM, although both standardised and un-standardised data could be presented.

Estimates of total biomass are calculated by applying the estimate density of biomass in the chosen size class to an area of reef (i.e. A) selected to estimate the area of the effective productive population.

$$B_{class} = A \times DB_{class}$$

The productive area of reef can be estimated using several approaches based on GPS logger and Lidar data and derived habitat models (see below). Estimates of the productive area of reef can also be further validated by calibration of estimates of total biomass from this method and other independent methods (e.g. population model).

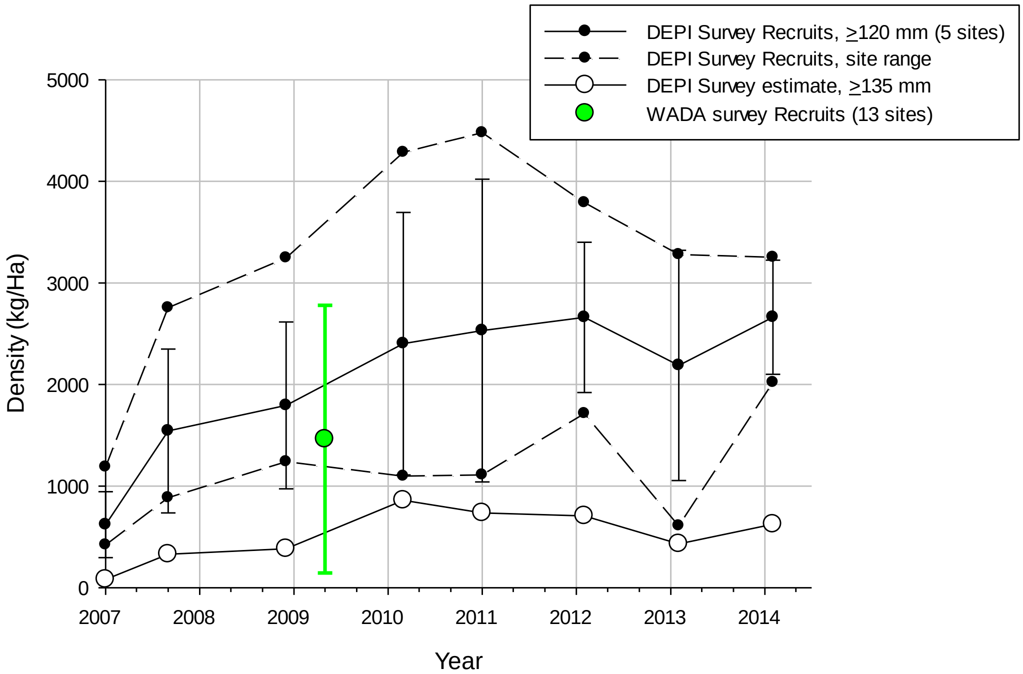
Estimates of the density of biomass of undersize, mature and legal abalone were averaged across sites within areas and within broader Spatial Management Units, and scaled up by an area of reef estimated as historically-productive. The area of historically-productive reef was estimated by divers prior to the WADA abundance survey and structured fishing, and has been reviewed as further data on the area of productive reef has become available from structured fishing and ongoing GPS logger use, and revised at Port Fairy. Estimates of historically-productive reef at Portland and Warrnambool have not yet been revised, although logger data has shown little commercial diving activity in several areas. Estimates of the productive area of reef are calculated each year from activity using two approaches (i.e. >20 abalone measured per year, and presence of a logged dive event) within a 100 m hexagonal grid, and unique grids are summed across years. The combination of estimates of density applied across an area of productive reef then provides a time-series of estimates of biomass from DEPI surveys which commenced in 1992, from the WADA surveys at Port Fairy in 2009, and Warrnambool and Portland in 2011, that are adjusted by change in the DPI surveys, and logger-based estimates. To date, densities have been applied across a constant productive area estimated using several approaches, but could be reviewed (i.e. regularly, or as needed, e.g. density at Port Fairy was reviewed in 2014 and as size limits changed, and productive area was reviewed at Port Fairy in 2012-13)or allowed to vary through time.

Three estimates of the density of biomass are presented in the TAC Setting process, together with three estimates of the area of productive reef. Estimates of the density of biomass include those calculated from the WADA abundance survey in 2009-11 (i.e. as used since the recommencement of fishing), that are modified by the proportional change in density in the DPI surveys (i.e. proportional change in two year average from WADA survey year until current year), the current year estimate from the DEPI survey, and the current year estimate from GPS loggers. For example, at Mills-Killarney the density of biomass was calculated as 390 kg/Ha in the 2011 WADA survey, and DPI surveys estimated a 23% increase from 2011-12 to 2013-14, so a density of 480 kg/Ha (i.e. 390*123% kg/Ha) and both estimates are applied across the estimated 265 Ha of productive reef. Estimates of productive area include the existing estimates used in TAC setting in previous years (i.e. mostly based on diver estimates, but revised at Port Fairy), an estimate from GPS loggers (i.e. summed unique areas with activity over each of past three years), and Lidar estimates of reef area and suitable habitat (i.e. all reef and suitability $\geq$0.25). As there was no WADA survey at Julia Percy Island, or historically-productive area estimate, an estimate of biomass is calculated from the DEPI survey density in the current year, applied to the area of reef used by the fishery in 2011-12 (i.e. the only year of extensive GPS logger data at Julia Percy).

Estimates of the density of abalone in the Recruit ($\geq$120 mm) length-class were averaged across the 5 DEPI survey sites within the Crags through time since AVG, and compared with the WADA survey estimate from 13 sites at the Crags in May 2009 (Figure 75). Density of Recruits in the DPI survey at the Crags were lowest (i.e. 620 kg.Ha^{-1}) in early 2007 after AVG, and increased to a peak of 2661 kg.Ha^{-1} in early 2012. The WADA survey completed in May 2009 provided a similar, but lower estimate of the density of Recruits compared to the DEPI surveys immediately before and after the WADA survey. Sites sampled in the WADA survey extended further west than those in the DEPI survey, but areas of shallow reef west of the WADA surveys are known to contain smaller areas of productive reef with high densities of abalone, suggesting both WADA and DEPI density estimates may be biased lower by not sampling these areas. Despite that, the estimates of density from the two surveys broadly overlapped, suggesting reasonably consistent estimates of the density of abalone within the reefcode.

Densities of Recruits in the DEPI survey averaged about 2282 kg.Ha^{-1} in the 4 years prior to AVG, when the regulated length limit was 120 mm and all individuals in the Recruit length class were available to the fishery. In comparison, the density of abalone available to the fishery after AVG when a larger regulated length limit was applied (i.e. ≥135 mm length limit) increased from a low of 80 kg.Ha^{-1} in 2007, to a peak of 860 kg.Ha^{-1} in 2010, before declining to 623 kg.Ha^{-1} in early 2014. In the 4 years prior to AVG, densities of ≥135 mm abalone in the DPI survey averaged about 375 kg.Ha^{-1}. Both DEPI and WADA abundance surveys were concentrated near the main fishing area at the Crags, and no abundance survey estimates are available from the reefs further west, although significant catches have come from these areas in recent years.

Figure 78. Estimated density of abalone (kg.Ha^{-1}) in the Recruits size-class (i.e. ≥120 mm) averaged across 5 sites in the DEPI survey since 2007 (filled circles ±SD among sites, with range shown by dashed lines), and across 13 sites in the WADA survey in 2009 (green circle ± SD among sites). Open circles show the density of abalone ≥135 mm calculated from the DEPI survey and length-frequency.



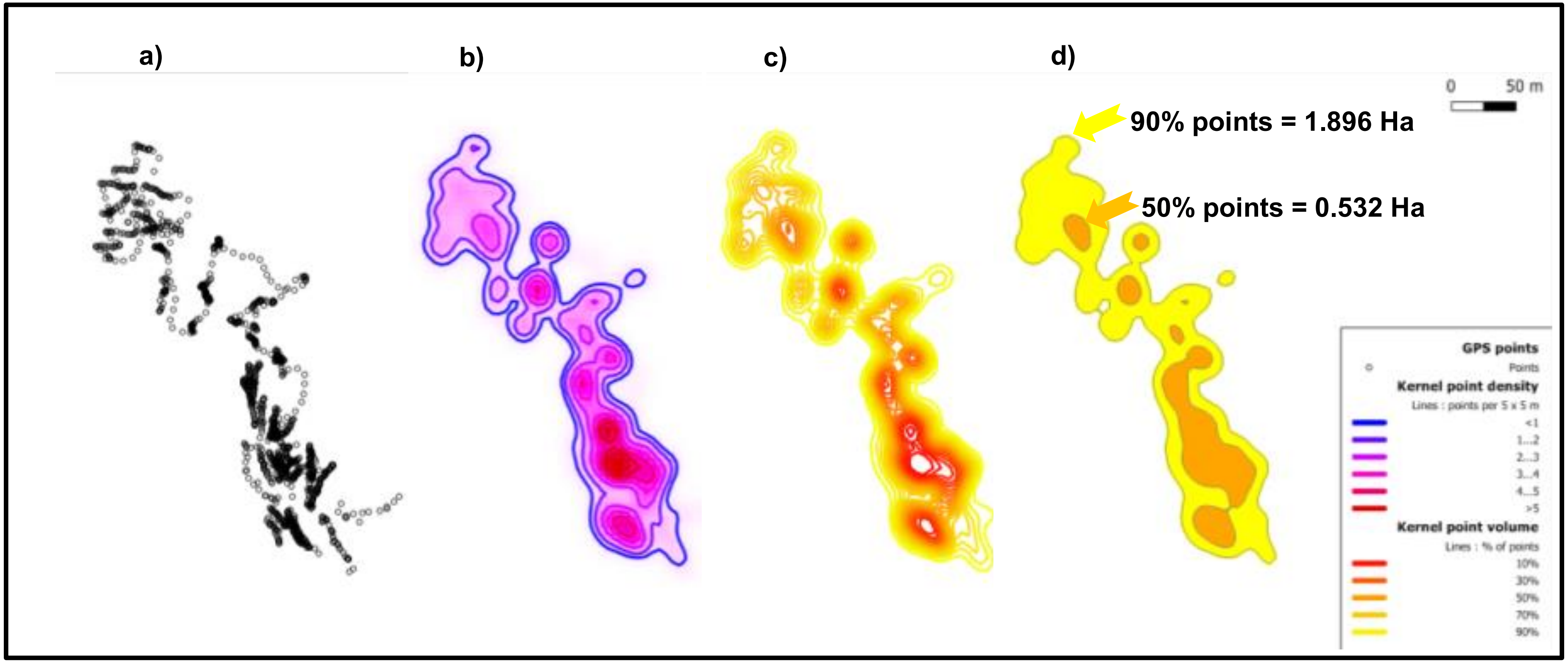
14.3.2. Fishing with loggers

Estimates of the density of abalone can be calculated from the data provided by GPS loggers. The GPS loggers used in WZ are held on the diver's boat, and the diver is tethered to the boat by a hookah hose of ~50 m. As the boat moves during the day, the spread of GPS points can provide an estimate of the area of reef visited by the diver during a day. In addition, daily catch (i.e. kg) is reported to DEPI and can be linked to the daily area of reef visited by the diver (i.e. Ha) to produce an estimate of the density of abalone (i.e. kg.Ha^{-1}). Similar to abundance surveys and commercial catch rates (i.e. kg.h^{-1}), such estimates of density are likely to be affected by selectivity/crypsis, diver-specific effects, weather and other factors.

GPS loggers in WZ collect the GPS position of the boat at regular time intervals (e.g. 10 sec and 1 min) and when abalone are measured with a GPS-enabled measuring board. Depth loggers are also attached to divers and used to log when they are at depths >0.5 m (i.e. actual depth is not recorded on the logger, but can be estimated from the GPS position and known depth contours), which are defined as a dive event. The time of dive events are then used to isolate the times of GPS points associated with the dive event. The GPS records from individual dive events (i.e. boat GPS locations when the diver was >0. 5m) were summarised using Kernel Density Estimation (Mundy 2012) to describe the spatial density of GPS points during the dive event. This was done by estimating spatial, bivariate-normal distributions for each GPS point from a dive event, which are then combined for all points within the dive event and normalised to produce contours of the area enclosing different percentages of the points from the dive event (Figure 79). The area searched by the diver during the dive event can then be estimated by the area of different percent contours. For example, areas enclosing 50% and 90% of the estimated density of GPS points from each dive event are routinely calculated here. These areas (i.e. Ha) can be summed for all dive events by each diver during a day to provide an estimate of the total area searched by the diver per day, and linked to the reported daily catch (i.e. kg), to provide an estimate of the density of abalone encountered by the diver (i.e. $kg.Ha^{-1}$) each day.

To increase the information available about abalone stocks following the resumption of fishing, a program of Structured Fishing was implemented in three broad areas of the fishery. These areas were Port Fairy in 2009-10 and 2011-12, Warrnambool in 2011-12 and Portland in 2012-13. Divers were allocated GPS points selected to a sampling design, and asked to catch a specified quantity of abalone from those locations while logging GPS and depth data, measuring all collected abalone and recording several general observations. Divers were also given some prescribed opportunity to identify and fish some sites of their own choosing while collecting the same data. The sampling design specifically enabled spatial comparisons (e.g. within, near and far from identified historically productive areas), comparisons of individual divers through time (e.g. same fishing method, by same diver at same site) and comparisons of pre-selected survey sites with those selected by divers on the day. The design included survey sites in reef areas that from historical records and diver experience had never been historically-productive, and so density estimates from the survey are likely to be representative of all shallow reef areas rather than just historically-productive areas.

Figure 79. Method of developing a summary of a dive event, showing a) GPS points every 10 seconds where diver depth is >0.5 m, b) kernel point density (i.e. estimated density of points per 5 x 5 m shown by pink-red colours) and contours (i.e. estimated density of points per 5 x 5 m grid shown by blue lines), c) kernel point volume contours (i.e. enclosing estimated percent of points with highest density from dive event) and d) kernel point volume contours enclosing estimated 50% and 90% of points, with related area (i.e. Ha).

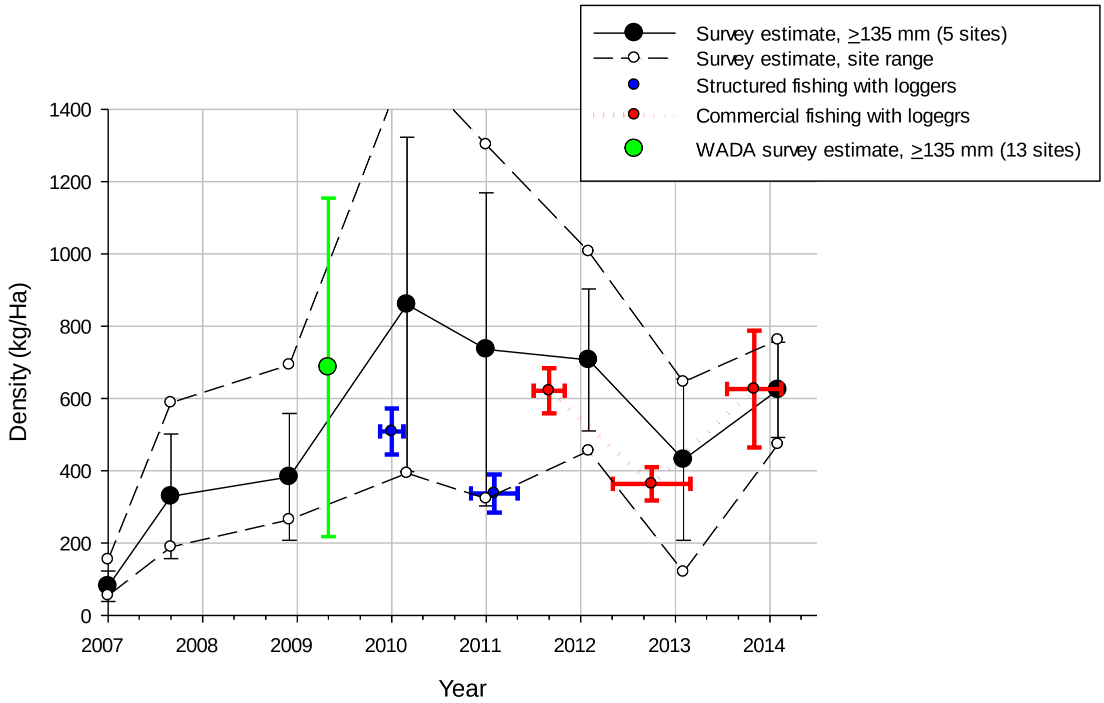


Estimates of the density of abalone from logged dive events during structured fishing and normal commercial fishing within the Crags reefcode for each fishing period were compared to estimates of density from the DEPI and WADA abundance surveys (Figure 80). Estimates of the density of abalone from logged dive events were most similar to estimates from abundance surveys when the area used for calculation was that estimated to enclose 50% of points from the dive event, which is consistent with a-priori expectation (i.e. Mundy pers comm). All estimates of density from loggers presented here are based on daily catch reported to DEPI, and the area estimated to enclose 50% of points from logged dive events on that day.

Estimates of the density of abalone from logged dive events during Structured Fishing programs were available in the 2009-10 and 2010-11 fishing periods (blue circles in Figure 80). The design of the Structured Fishing programs (i.e. and differences in design between the Structured Fishing programs) will influence the likely density estimates, and they are more likely to be representative of all shallow reef area, rather than historically-productive areas where DEPI surveys and commercial fishing are targeted. Estimates of the density of abalone from loggers during the two Structured Fishing programs were lower than those from DEPI and WADA surveys completed at the same time, although both types of surveys recorded declines between 2009-10 and 2010-11. As depth loggers were not used for normal fishing at the time, there are not yet any years with logger-based density estimates from both structured fishing and commercial fishing, so a direct comparison cannot be made. From the comparisons that are possible it is likely that the Structured Fishing estimates are lower than those from commercial fishing, as expected.

Estimates of the density of abalone from logged dive events during normal commercial fishing are available for 3 years from the 2011-12 fishing period (red circles in Figure 80). Estimates of the density of abalone from loggers were very similar to those from DEPI abundance surveys in each of the three years (i.e. each within 16% of survey estimate, with 3 year difference of 12.5%), including the estimated decline of about 40% in 2013-14 coincident with an increased catch in the area. The 5 DEPI survey sites are all closely located near the main fishing area of the Crags reefcode, while estimates from commercial fishing in each year represent a much larger proportion of historically-productive and total reef area within the reefcode (i.e. abundance survey sampling fraction of 0.1%, with logged 90% dive-event coverage of about 17-40% of estimated productive reef per year). Further, there is no DEPI abundance survey information from the productive reef areas with relatively high abalone density in the west of the reefcode, which represent about half of the total productive reef in the reefcode. In other words, density estimates from loggers are more likely to be representative of the full productive area of reef, and appear to provide more precise (i.e. lower SE) estimates of density than the DEPI survey. Despite that, logger-based estimates from normal commercial fishing, and their change through time, are very similar to those from the abundance surveys.

Figure 80. Estimated density of abalone ≥135 mm (kg.Ha^{-1}) within the Crags reefcode from 5 sites in the DEPI survey since 2007 (filled circles ±SD among sites = population SE, with range shown by dashed lines), from 13 sites in the WADA survey in 2009 (green circle ± SD among sites = population SE), from loggers used in Structured Fishing during 2009-2011 (blue circle ±SE) and from loggers used in commercial fishing from 2011-12 to 2013-14 (red circle ±SE). Horizontal error bars on logger-based estimates show the approximate range of time of the fishing.

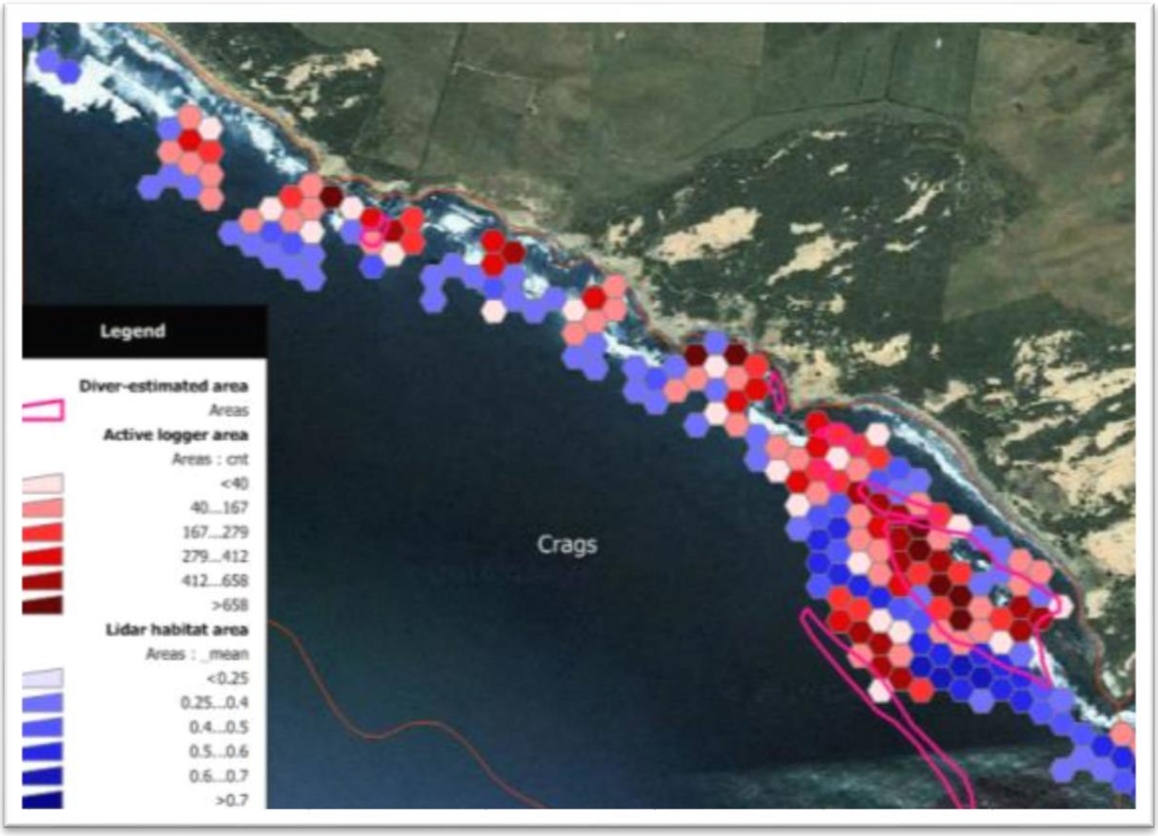


14.4. Calculating area of productive reef

14.4.1. Estimates from divers

To calculate the biomass of abalone available to the fishery, the estimated density must be extrapolated from survey sites, or areas fished with loggers, to an appropriate area of reef. After the impact of AVG, and to help design the initial WADA abundance surveys and structured fishing, and to estimate biomass, active commercial divers were asked to identify the most historically-productive areas of reef. This was done by collaboratively identifying the areas on over-head imagery, digitizing and reviewing (Figure 81). Estimates of historically-productive areas were made by divers for reefs at the Crags, the rest of Port Fairy, Warrnambool and Portland.

Figure 81. Overhead imagery of the Crags reefcode (i.e. boundaries shown as red lines), with estimates of most historically-productive reef estimated by divers prior to fishing after AVG (purple lines), over-laying a 100 m hexagonal grid with logged fishing activity (i.e. >20 abalone measured per year, over 4 years, coloured white to red), overlaying the same hexagonal grid with a Lidar-derived habitat suitability model (>0.25 coloured blue). Estimates of reef area varied from the most historically-productive areas estimated by divers of 40 Ha, to areas with active logger use of 95 Ha, and a Lidar-derived habitat model of 71-146 Ha.



14.4.2. Fishing with loggers

GPS loggers provide information about the area of reef visited by commercial divers, and this can also be used to estimate the productive area of reef in several ways. For example, the area of individual dive events can be combined across all divers (e.g. union of dive events summarised by the area estimated to enclose 50% or 90% of points from the dive event) within a year. Alternatively, the presence of a dive event in an area could be recorded by the presence of a GPS record or number of records from a dive event, or contours of the dive event, within a grid of contiguous hexagonal areas of reef (e.g. 1 Ha grid in Figure 81, or a grid of any defined size and shape). Grid cells with such activity can then be summed within a time period to provide an estimate of the area of productive reef. A range of such approaches have been used here to investigate the sensitivity of estimates of productive reef area to the approach used.

Estimates of the area of productive reef within the Crags reefcode varied among different methods of estimation (Table 24). Diver's estimates of the area of the most historically-productive abalone reef totaled 40 Ha, while an independent estimate of reef habitat likely to be suitable for abalone based on LIDAR mapping and a habitat suitability model, provided an estimate of 135 Ha (i.e. 71-146 Ha). Logger-based estimates of the area of productive reef were strongly dependent on the level of catch in each year, with a greater area of reef visited by divers in years with higher catch (e.g. Table 25). For example, the method of estimating area based on 100 m hexagonal grid cells with activity of at least 20 lengths logged, produced estimates varying from 44 Ha in 2011-12 to 83 Ha in the 2012-13 fishing period with much higher catch, and 95 Ha from the union of areas in the 3 years. As annual catch can influence the estimate of the area of productive reef, and the WZ fishery currently has limited catch, estimates of the area of productive reef from multiple years of logger data are likely to be more reliable in estimating the total area of productive reef.

Table 24. Estimate of productive reef area (Ha) within the Crags reefcode from several different methods and time periods using logger data, and two independent methods.

Estimation Method	Estimate of productive reef area (Ha)
>20 lengths per grid cell	
2011-12	44
2012-13	83
2013-14	46
Union of grid cells from annual estimates, 3 years	95
Dive event area	
Union of dive events with 50%, 3 years	18
Union of dive events with 50% and 25 m buffer, 3 years	59
Union of dive events with 50% and 50 m buffer, 3 years	101
Union of dive events with 90%, 3 years	47
Union of dive events with 90% and 25 m buffer, 3 years	92
Union of dive events with 90% and 50 m buffer, 3 years	134
Dive event within 1 Ha grid	
1 Ha grid contains dive event centroid, 3 years	73
1 Ha grid touches dive event, 3 years	161
Independent Estimation Methods	
LiDAR habitat suitability model (Ierodiaconou et al)	135
2013-14 WZ TAC Setting Process	71

Logger-based estimates were also influenced by the particular method used to estimate the productive area of reef from the data available. All logger-based methods were able to provide estimates of the productive area of reef that were similar to the area currently used in biomass estimation as part of the current WZ Harvest Strategy. For example, the method recording presence of activity from the centroid of each dive event in a 1 Ha hexagonal grid provided an estimate of 73 Ha, which was very similar to the 71 Ha used in 2013-14 as part of the WZ Harvest Strategy. There are limited other independent data with which to calibrate and validate the logger-based methods of estimating the area of productive reef. Lidar-based data and derived habitat suitability models can provide some validation for the estimates produced from loggers. Lidar data about reefcode area, estimates of reef area, and two habitat suitability models have been calculated for all reefcodes in WZ, and can be compared to estimates produced by divers and logger-based estimates for all reefcodes (Table 25). While estimates of reef area among the different method are generally similar and consistent among reefcodes, calculations based on logger data are the only method that uses data that relates to actual use of the reef during abalone fishing, and so are likely to be a more reliable indicators of the current area of productive abalone reef.

Table 25. Estimated area (Ha) per reefcode in WZ of the Reefcode, Lidar, Reef, abalone habitat, historically productive reef and logger use. Further detail about calculation of each measure are summarised below the table. A – indicates data are not available or not calculated.

Reefcode	Name	i) Total Reefcode area	ii) Total Lidar area	iii) Reef and Reef-sediment 5 x 5 m	iv) Reef 5 x 5 m	v) Suitable habitat (WZ) 5 x 5 m	vi) Suitable habitat (WZ) 100 m grid	vii) Suitable habitat (Vic) 5 x 5 m	viii) Suitable habitat (Vic) 100 m grid	ix) Most historically productive	x) Logger activity while fishing
1.01	Discovery Bay	15576	10873	3439	160	841	-	4187-10872	-	0	171
1.02	Whites	47	40	30	8	20	15-24	26-40	40	11	23-27
1.03	Water Springs	97	87	63	14	29	19-35	54-87	83	21	47-54
1.04	Blowholes	138	85	63	6	11	2-13	55-84	92	5	19-26
1.05	The Tits	263	105	93	37	51	51-79	79-100	141	40	18-24
1.06	Sth Bridgewater	91	51	34	12	21	24-36	27-40	53	17	8-10
1.07	Seal Caves	1470	1468	8	2	18	5-13	6-42	13	11	5-12
1.08	Horseshoe	1135	979	6	2	26	1-9	7-82	14	3	5-6
2.01	Murrels	1582	1421	101	26	81	25-72	34-156	37	2	0-3
2.02	Jones Bay	402	396	56	17	33	25-41	46-64	74	9	24-30
2.03	Outside Nelson	125	50	45	13	24	22-46	38-45	80	3	40-41
2.04	Devils Kitchen	355	219	35	8	13	8-16	17-50	30	7	9-9
2.05	Inside Nelson	112	103	20	8	29	19-37	11-22	21	14	2-2
2.06	Killer Waves	990	861	25	7	16	16-19	10-34	22	26	
2.07	Yellow Rock	473	428	32	7	60	19-56	13-35	25	15	
2.08	Cape Grant	288	265	18	5	26	20-37	11-20	27	0	4-4
2.09	Passage	1503	591	313	121	194	202-251	124-224	224	115	3-5
2.10	Lawrence Rocks	38	7	7	3	5	10-11	5-6	15	15	4-5
2.11	Blacknose	2174	2043	26	9	89	10-66	5-24	3	2	

2.12	Hospital Reef	1028	878	427	49	147	55-166	30-100	26	129	58-84
2.13	Dutton Way	1062	980	814	183	184	10-133	18-98	-	266	23-36
2.14	Julia Bank	18828	7635	3968	475	1525	608-1550	699-1559	770	0	202-288
2.15	Yambuk	1978	806	452	119	289	142-313	95-244	82	0	20-27
2.16	Minerva	10383	4924	3635	442	976	116-871	322-838	44	22	9-29
3.01	JP North	66	-	-	-	-	-	-	-	21	21-24
3.02	JP Northeast	107	-	-	-	-	-	-	-	8	10-12
3.03	JP East	181	-	-	-	-	-	-	-	17	14-15
3.04	JP Prop Bay	58	-	-	-	-	-	-	-	16	30-33
3.05	Crags	950	788	167	56	135	71-146	71-141	90	31	90-110
3.06	Burnets	303	220	94	57	69	52-67	43-79	67	20	24-28
3.07	Watertower	582	236	210	97	110	74-123	98-161	168	37	64-72
3.08	Lighthouse	566	316	92	39	46	36-70	45-81	82	12	31-42
3.09	Mills	1320	768	134	55	121	74-109	51-117	62	14	40-47
3.10	Killarney	505	275	163	63	112	88-121	68-131	109	14	54-63
3.11	Cutting	2688	1781	738	128	301	152-308	193-493	194	4	16-18
3.12	Thunder Pt	901	528	283	100	219	171-228	143-242	221	41	11-17
3.13	Lady Bay	1178	958	826	399	635	435-699	203-480	193	22	7-8
3.14	Levys Point	152	143	45	17	44	16-42	21-44	21	10	10-11

i) Total area of Reefcode (note, shape file used by Deakin Uni, out to depth contour).

ii) Total area of Lidar data (note, DEPI shape file used unless otherwise noted, out to depth contour).

iii) Area of Reef and Reef-sediment from 5 x 5 m raster. Classification model from Lidar and ground-truth, with Reef $\geq$70% reef and Reef-sediment $\geq$25% reef.

iv) Area of Reef from 5 x 5 m raster. Classification model from Lidar and ground-truth, with Reef $\geq$70% reef.

v) Area of Suitable habitat with score >0.25 from 5 x 5 m raster (note, shape file used by Deakin to depth contour). Classification as Suitable habitat from model based on logger data for WZ (i.e. WZ classification model), and dominated by depth, rugosity (i.e. surface v planar area) and complexity (i.e. change in slope).

vi) Area of Suitable habitat (from WZ classification model) from 5 x 5 m raster averaged by 100 m hexagonal grid, and counted for grids with mean score $\geq$0.25 and $\geq$0.4.

vii) Area of Suitable habitat (from Vic classification model) from 5 x 5 m raster for grids with mean score $\geq$120 and $\geq$140. Classification as Suitable habitat from model based on DPI survey data for Vic (i.e. Vic classification model), and dominated by complexity, SST and sediment.

viii) Area of Suitable habitat (from Vic classification model) from 5 x 5 m raster averaged by 100 m hexagonal grid, and counted for grids with mean score $\geq$140. Classification as Suitable habitat from model based on DPI survey data for Vic (i.e. Vic classification model), and dominated by complexity, SST and sediment.

ix) Area of most historically-productive abalone reef estimated by McShane (1981).

x) Area with GPS logger activity (i.e. >20 abalone measured within a year from 2011-14) while abalone fishing, within a 100 m hexagonal grid.

14.5. Using GPS logger to estimate of biomass and the uncertainty

Estimates of the density of abalone and area of productive reef from loggers can be used to produce an estimate of the biomass of abalone available to the fishery. It appears estimates of biomass from loggers can be relatively simple and cheap (i.e. in-kind contribution by divers to the operation of loggers), intuitive in their calculation and interpretation, and can produce similar estimates to other methods of estimating biomass. When provided in an intuitive decision-structure, together with other complimentary information, as has been developed in the WZ abalone fishery TAC setting process, estimates of biomass from GPS loggers appear to provide a useful contribution to TAC setting advice that may also contribute to the implementation of a formal harvest strategy in WZ.

There are a range of different methods to combine logger and catch data to estimate the density of abalone, and the appropriate area of productive reef to extrapolate density and calculate biomass. In the WZ fishery, the density of abalone was estimated from the combination of daily catch and the area visited by a diver, which was determined from the estimated area of 50% of the GPS points from dive events during each day. While other methods could be used, this method provided estimates of density similar to those from independent abundance surveys. Further, the productive area of reef was estimated by a variety of methods, but historical estimates by divers and the method based on the presence of >20 abalone measurements in a 1 Ha grid, have been used in development of TAC advice in WZ. While there are few other methods able to provide estimates of the productive area of reef for comparison and verification (e.g. Lidar and habitat models), there are independent methods available to calculate biomass (e.g. population models) that can provide further information for calibration and validation of methods to use data collected by GPS loggers during commercial fishing to calculate biomass available to the fishery. A recent national Workshop considering strategic priorities for harvest strategy development rated further calibration of these methods a high priority.

Methods to estimate biomass have been developed here within the Crags reefcode. These techniques are now applied to estimate biomass within other reefcodes within WZ, and within other fisheries, such as NSW. Within WZ, following Structured Fishing surveys in each area, there are now 4 years of commercial fishing with loggers at Port Fairy and Warrnambool, and 3 years at Portland, so information is still limited in time and with little contrast in the data. In other fisheries, estimates of biomass from loggers could be directly compared to estimates available from abundance surveys and other methods estimating biomass in southern NSW and Tipara Reef in SA. The comparison of estimates of biomass from loggers with estimates from other techniques presented here, has provided guidance on the specific methods that may be most appropriate for using logger data to estimate biomass. These comparisons have also provided some verification that logger information can provide similar biomass estimates to other methods, and that these methods provide accurate estimates of biomass.

Despite these benefits, many uncertainties remain about the preferred technique of combining the logger data to calculate biomass, and their influence on accuracy and precision of that estimate. These uncertainties range from technical issues (e.g. how to determine and deal with lost logger data within a day, standardization, scale of calculation and application, timing of data collection, analysis and review) to factors such as the crypsis of abalone, selectivity of different divers and weather conditions, all of which will clearly influence estimates of density from the combination of logger and catch data, but importantly these factors will influence any measure, including relatively expensive independent survey estimates of density. These factors are similar to those that influence the interpretation of simple fishery catch rates, but the spatial information available from loggers provides the opportunity to remove some key confounding factors (e.g. area visited or swept by the diver estimated by the area of the dive even) and make direct fine-scale comparisons (e.g. at a site within a reefcode) through time. Perhaps most importantly, as divers are often able to maintain catch rates (i.e. logbook $kg.h^{-1}$), it will be important to determine how estimates of density from logger data (i.e. fine-scale, standardised $kg.Ha^{-1}$) compare, and whether they can provide an early warning of other changes.

A harvest strategy to catch a specific proportion of the available biomass will result in catch that is too high if estimates of biomass are biased too high. As a consequence, it is appropriate to use techniques that produce more conservative estimates of biomass, particularly because of uncertainty in the methods to calculate biomass from logger data and their unknown accuracy. Techniques developed here include estimates of density calibrated to abundance survey estimates, but estimates of productive area may have greater uncertainties because there are few other methods available for comparison. The current application of biomass estimates in the WZ harvest strategy uses a productive area estimate 44% lower than estimated by the preferred technique using logger data, as part of an approach to ensure conservative estimates of productive area, and so biomass, are used in guiding catch.

Estimate of biomass from GPS logger data are calculated from estimates of density and productive area, which can also be estimated by independent methods (e.g. density by abundance surveys, area by Lidar habitat models). Estimates of biomass through time are also made during fitting of population model, and these estimates provide a further opportunity for calibration and validation of estimates produced by GPS loggers. Several estimates of biomass are available from population models developed in WZ, including those developed by DEPI (i.e. prior to AVG and in FRDC 2007/066) and CSIRO (FRDC 2012/225). Preliminary comparison of estimates of biomass from GPS loggers and population models were similar, but more detailed comparison was beyond the scope of this project. Despite that, there remains a need to extend comparisons of biomass among methods to provide further calibration and validation of both methods. A recent national Workshop considering strategic priorities for harvest strategy development rated further calibration of methods a high priority. Further development of methods for estimating biomass from GPS loggers, that could be used in TAC setting and catch controls as part of a harvest strategy, are still required and will depend on several other factors including the level of logger use, resources for analysis, frequency of review and level of precaution required.

Following the impacts of AVG, and in the absence of an agreed strategy to guide catch for the fishery, WADA have been instrumental in developing data collection, analysis and use of data in guiding appropriate management of the WZ fishery. This also follows their role in developing finer scale management and Industry-based assessment workshops prior to the impacts of AVG. Development of a method to use data from GPS loggers to estimate biomass has provided guidance on its conceptual and practical implementation in a simple and intuitive decision structure for TAC advice and a developing harvest strategy. With ongoing use and development, WADA may be ready to move with DEPI and other stakeholders to formalise a harvest strategy for the WZ fishery using GPS logger information with other sources.

15. Conclusion

15.1. Evaluation of Mandatory use of Loggers

The success of this project ultimately relies on the high level of data coverage achieved, particularly in Tasmania. While the KUD derived spatial indicators may be useful with lower levels of coverage, the grid derived indicators will be of little use without high levels of data coverage as they rely on capturing activities of the entire fleet across a fishing year. In particular the Index of Persistence developed in Chapter 9 is not viable without a high level of data coverage. If spatial indicators are to be considered as part of annual assessments of fishery status there must be a commitment to ongoing collection of the data to generate a time-series that is useful, and that there is some certainty of these data streams being available for assessment into the future.

15.2. Spatial indicators of fishery status

On the basis of a five-year time-series (2012 – 2016) several spatial indicators appear to be strong candidates as alternate and complimentary measures of fishery performance (Chapter 6). Several spatial Indicators displayed consistent and interpretable trends that parallel trends in CPUE. One Spatial Indicator, swim rate as Lm/Hr appeared to have locally important properties, whereas others such as Kg/ha appeared to have a more general relationship across fishing grounds. Whether these Spatial Indicators are locally or generally applicable has important consequences for the approach used to determine TRPs and LRPs.

15.3. Challenges with inclusion of spatial indicators in an empirical harvest strategy.

At the outset of this project the PI naively focused on the collection of a time-series of data from which to demonstrate the utility of spatial indicators for supporting classic fishery-dependent catch per unit effort (CPUE) derived performance measures. While demonstration that spatial indicators have diagnostic capacity for determining stock status is helpful, establishing appropriate Limit and Target Reference Points for these variables is questionable when limited by a time series of six years. For the MCDA based empirical harvest strategy using classic catch per unit effort data, we have a long-time series (Reference Period) from which to draw meaningful metrics (quantiles, medians, means). The greatest impediment to incorporating these spatial indicators in an assessment process is the limited time series available to use as a Reference Period to determine Limit and Target Reference Points. Creative solutions to using these unique spatial data sets with a limited time series will need to be the subject of ongoing research on the use of spatial indicators for fishery assessment.

The challenge with using spatial linear modelling of whole of year spatial fishing patterns to predict catch in future years is that TACC decisions are often made prior to completion of the fishing year. There would need to be a clear demonstration that partial years data provided the same overall pattern as the full year data, and that is likely to be dependent on how much quota was left to catch at the time of the analyses. The Geographic Weighted Regression analyses (Chapter 8) were very useful in identifying local areas of temporal persistence, and/or areas where catch is highly variable mong years. These types of analyses may have greater utility in understanding how productivity of exploited reef systems change through time.

15.4. Spatial structure of fishing – empirical evidence of spatial structure

This project has achieved the first significant quantitively description of a spatially structured, spatially discrete hand-harvest fishery. Serial depletion is often presented as a theoretical explanation for the demise of fisheries, but that concept is rarely supported with empirical data. Chapter 10 demonstrated that the Tasmanian abalone fishery was comprised of several hundred discrete reef systems across the Tasmanian coastline, and that catch was largely proportional to area. While there were several outlier reefs, this relationship between reef area and reef production hints at some underlying base productivity. Strong relationships between catch and effort are routinely observed, but this is the first demonstration that such a relationship also exists for catch and area.

15.5. Properties and metrics to describe Fleet Behaviour

Several analytical tools were developed to examine fleet behaviour and diver movement patterns, local variability in harvest levels and spatial structure of the reef systems being exploited. Separating normal fleet patterns driven by fisher preference, effects of inter-annual variation in exploitable biomass, and long-term changes in stock levels will require a much longer time series than currently available. Short term shifts in fleet movements and temporal variability in structure of fishing may be easily confused with normal cycling of fishing grounds. There is considerable impatience to utilise Geo-referenced fishery-dependent data in decision making processes and Harvest Strategies, despite no defensible mechanism to develop reference points from the short time series available. Similarly, the proportion of the known fishable reef area utilised each year and the degree of overlap among subsequent years are likely to be enormously informative for understanding one of the key unknown questions in abalone fisheries – is the footprint of the fishery and/or density changing through time. The capacity to identify areas of high persistence of commercially productive stocks will also improve our ability to understand and monitor key drivers of productivity and local regions critical to achieving the TACC.

16. Recommendations

16.1. Further Development

16.1.1. Hardware

Timely access to the spatial data from GPS and depth data loggers is essential to enable time-senstive processing and analyses of the data. The current hardware format of using returnable memory modules was a cost-effective approach to capture data for pilot studies, but is an impediment to use in regular assessment meetings and for the TACC setting process. Development of logging hardware that enables daily return of data to researcher is essential maximise benefits of the spatial data, especially if the intention is to incorporate the data in empirical harvest control rules.

16.1.2. Software

The current SQL Server database front end is nearing the end of its useful life. The University of Tasmania has committed to developing a new Django browser based front end to future proof the management of the logger allocations to divers. This would also permit the development of a browser-based dashboard to display and deliver the processed spatial data to fishers in a similar form to that developed in New Zealand by DragonFly ltd. However, at this time, there appears to be only minor interest in the development of that capacity in Tasmania.

17. Extension and Adoption

17.1. Project Coverage and adoption

From February 1, 2012 there has been mandatory use of the GPS and Depth data loggers in Tasmania, and high level voluntary use in Victoria and New South Wales. Use of the logging technology has continued in all three states, with an ongoing commitment by Tasmania to make use of the GPS and Depth dataloggers mandatory. The spatial data are also routinely used in the Western Zone Victoria and New South Wales abalone fishery assessments and TACC determination process.

Trends in spatial indicators have been included in the 2015, 2016, and 2017 annual Tasmanian Fishery Assessment, and in the 2017 assessment Concentration Area Curves were included to provide an overview of the extent of reef used each year by fishing zone.

A flexible multi-criteria based Empirical Harvest Strategy (EHS) and Control Rule system was developed as part of this project. This EHS has been trialled during the 2017 and 2018 TACC setting process, with support from the Minister, Tasmanian Government Department of Primary Industries, Parks, Water an Environment. The EHS has been adopted in the DPIPWE Harvest Strategy Policy document (currently under review) and forms the starting point for discussion on TACC for each reporting Block during the Tasmanian Abalone Fishery Resource Advisory Group (AbFRAG).

The geo-referenced fishery-dependent data has also been spatial used to create new reporting blocks, identify new block and zone boundaries, and assist with developing catch targets in some regions. It has also been used to highlight changes in the depth distribution of fishing activity and quantify the improvements in catch rates when fishers move into new fishing grounds (i.e. deeper reefs).

18. Project materials developed

This project inherited the SQL Server database backend and Nexus database frontend for data storage and management from project 2006/029. During this project, R and SQL Server scripts were further developed to improve efficiency or created to address primary questions being asked of the data. These scripts have been committed to a GitHub repository, and could be developed into an R Package at some stage if funding and time commitments allow.

19. References

Anselin, L., I. Syabri, and Y. Kho. 2006. GeoDa: An Introduction to Spatial Data Analysis. Geographical Analysis 38:5–22.

Bedford, R. A., J. W. Hearne, and H. K. Gorfine. 2013. Implications of the dichotomy between the spatial scales at which abalone are managed and harvested. Fisheries Management and Ecology 20:338–345.

Berkes, F. 1985. Fishermen and 'The Tragedy of the Commons. Environmental Conservation 12:199–206.

Bivand, R., M. Altman, L. Anselin, R. Assunção, O. Berke, A. Bernat, G. Blanchet, E. Blankmeyer, M. Carvalho, B. Christensen, Y. Chun, C. Dormann, S. Dray, R. Halbersma, E. Krainski, P. Legendre, N. Lewin-Koh, H. Li, J. Ma, G. Millo, W. Mueller, H. Ono, P. Peres-Neto, G. Piras, M. Reder, M. Tiefelsdorf, and D. Yu. 2011. spdep: Spatial dependence: weighting schemes, statistics and models.

Bivand, R., T. Keitt, and B. Rowlingson. 2015. rgdal: Bindings for the Geospatial Data Abstraction Library.

Bivand, R., and C. Rundel. 2017. rgeos: Interface to Geometry Engine - Open Source (GEOS).

Borger, L., N. Franconi, G. de Michele, A. Gantz, F. Meschi, A. Manica, S. Lovari, and T. Coulson. 2006a. Effects of sampling regime on the mean and variance of home range size estimates. Journal of Animal Ecology 75:1393–1405.

Borger, L., N. Franconi, G. de Michele, A. Gantz, F. Meschi, A. Manica, S. Lovari, and T. Coulson. 2006b. Effects of sampling regime on the mean and variance of home range size estimates. Journal of Animal Ecology 75:1393–1405.

Branch, T. A., R. Hilborn, and E. Bogazzi. 2005. Escaping the tyranny of the grid: a more realistic way of defining fishing opportunities. Canadian Journal of Fisheries and Aquatic Sciences 62:631–642.

Buxton, C. D., I. Cartright, C. Dichmont, S. Mayfield, and E. E. Plaganyi. 2015. Review of the Harvest Strategy and MCDA process for the Tasmanian Abalone Fishery. . Insitute for Marine and Antarctic Studies.

Cagnacci, F., L. Boitani, R. A. Powell, and M. S. Boyce. 2010. Animal ecology meets GPS-based radiotelemetry: a perfect storm of opportunities and challenges. Philosophical Transactions of the Royal Society B-Biological Sciences 365:2157–2162.

Calenge, C. 2006. The package adehabitat for the R software: a tool for the analysis of space and habitat use by animals. Ecological Modelling 197:516–519.

Chick, R. C., S. Mayfield, P. Burch, S. N. Turich, and R. McGarvey. 2012. Detecting change in density and biomass of a benthic marine invertebrate following commercial fishing. Fisheries Research 129â€"130:94–105.

Colloca, F., V. Bartolino, G. J. Lasinio, L. Maiorano, P. Sartor, and G. Ardizzone. 2009. Identifying fish nurseries using density and persistence measures. Marine Ecology Progress Series.

Colloca, F., G. Garofalo, I. Bitetto, M. Facchini, F. Grati, A. Martiradonna, and others. 2015. The Seascape of Demersal Fish Nursery Areas in the North Mediterranean Sea, a First Step Towards the Implementation of Spatial Planning for Trawl Fisheries. PLoS ONE 10:e0119590.

Colloca, G. F. Bartolino V. Lasinio G. J. Maiorano L. Sartor P. Ardizzone. 2009. Identifying fish nurseries using density and persistence measures. Marine Ecology Progress Series.

Core-Team, R. 2015. R: A Language and Environment for Statistical Computing. . R Foundation for Statistical Computing, Vienna, Austria.

Core-Team, R. 2016. R: A Language and Environment for Statistical Computing. . R Foundation for Statistical Computing, Vienna, Austria.

Daw, T. M. 2008. Spatial distribution of effort by artisanal fishers: Exploring economic factors affecting the lobster fisheries of the Corn Islands, Nicaragua. Fisheries Research 90:17–25.

Dixon, R. W. Philip M. Jacob Weiner Thomas Mitchell-Olds. 1987. Bootstrapping the Gini Coefficient of Inequality. Ecology 68:1548–1551.

Dray, S., and A. B. Dufour. 2007. The ade4 package: implementing the duality diagram for ecologists. Journal of Statistical Software 22:1–20.

Fernández-Boán, M., J. Freire, A. M. Parma, L. Fernández, and J. M. Orensanz. 2013. Monitoring the fishing process in the sea urchin diving fishery of Galicia. ICES Journal of Marine Science: Journal du Conseil.

Gini, C. 1921. Measurement of inequality of incomes. The Economic Journal:124–126.

Gollini, I., B. Lu, M. Charlton, C. Brunsdon, and P. Harris. 2015. GWmodel: An R Package for Exploring Spatial Heterogeneity Using Geographically Weighted Models. Journal of Statistical Software 63:1–50.

Grolemund, G., and H. Wickham. 2011. Dates and Times Made Easy with lubridate. Journal of Statistical Software 40:1–25.

Grothendieck, G. 2014. Manipulate R data frames using SQL.

Grubert, M. A., and A. J. Ritar. 2005. The effect of temperature and conditioning interval on the spawning success of wild-caught blacklip (Haliotis rubra, Leach 1814) and greenlip (H-laevigata, Donovan 1808) abalone. Aquaculture Research 36:654–665.

Haddon, M., S. Mayfield, F. Helidoniotis, R. Chick, and C. Mundy. 2014. Identification and Evaluation of Performance Indicators for Abalone Fisheries. FRDC Final Report 2007/020. . Commonwealth Scientific and Industrial Research Organisation (CSIRO), Hobart.

Haddon, M., and C. Mundy. 2016. Testing abalone empirical harvest strategies, for setting TACs and associated LMLs, that include the use of novel spatially explicit performance measures. CSIRO Oceans and Atmosphere, Hobart.

Haddon, M., C. Mundy, and D. Tarbath. 2008. Using an inverse-logistic model to describe growth increments of blacklip abalone (Haliotis rubra) in Tasmania. Fishery Bulletin 106:58–71.

Handcock, M. S. 2015. Relative Distribution Methods. . Los Angeles, CA.

Hart, A. M., and H. K. Gorfine. 1997a. Abundance estimation of blacklip abalone (Haliotis rubra) II. A comparative evaluation of catch-effort, change-in-ration, mark-recapture and diver-survey methods. Fisheries Research 29:171–83.

Hart, A. M., and H. K. Gorfine. 1997b. Abundance estimation of blacklip abalone (haliotis rubra) II. A comparative evaluation of catch-effort, change-in-ratio, mark-recapture and diver-survey methods. Fisheries Research 29:171–183.

Hart, A. M., H. K. Gorfine, and M. P. Callan. 1997. Abundance estimation of blacklip abalone (Haliotis rubra) I. An analysis of diver-survey methods used for large-scale monitoring. Fisheries Research 29:159–69.

Helidoniotis, F., and M. Haddon. 2013. Growth Models for Fisheries: The Effect of Unbalanced Sampling Error On Model Selection, Parameter Estimation, and Biological Predictions. Journal of Shellfish Research 32:223–235.

Helidoniotis, F., and M. Haddon. 2014. The effectiveness of broad-scale legal minimum lengths for protecting spawning biomass of Haliotis rubra in Tasmania. New Zealand Journal of Marine and Freshwater Research 48:70–85.

Jalali, M. A., D. Ierodiaconou, J. Monk, H. Gorfine, and A. Rattray. 2015. Predictive mapping of abalone fishing grounds using remotely-sensed LiDAR and commercial catch data. Fisheries Research 169:26–36.

Jennings, S., and J. Lee. 2012. Defining fishing grounds with vessel monitoring system data. ICES Journal of Marine Science: Journal du Conseil 69:51–63.

Jensen, O. P., T. A. Branch, and R. Hilborn. 2012. Marine fisheries as ecological experiments. Theoretical Ecology 5:3–22.

Lambert, G. I., S. Jennings, J. G. Hiddink, N. T. Hintzen, H. Hinz, M. J. Kaiser, and L. G. Murray. 2012. Implications of using alternative methods of vessel monitoring system (VMS) data analysis to describe fishing activities and impacts. Ices Journal of Marine Science 69:682–693.

Lee, S.-I. 2001. Developing a bivariate spatial association measure: An integration of Pearson's r and Moran's I. Journal of Geographical Systems 3:369–385.

Lee, S.-I. 2004. A Generalized Significance Testing Method for Global Measures of Spatial Association: An Extension of the Mantel Test. Environment and Planning A: Economy and Space 36:1687–1703.

Lu, B., P. Harris, M. Charlton, and C. Brunsdon. 2014. The GWmodel R package: further topics for exploring spatial heterogeneity using geographically weighted models. Geo-spatial Information Science 17:85–101.

Marrs, S. J., I. D. Tuck, R. J. A. Atkinson, T. D. I. Stevenson, and C. Hall. 2003. Position data loggers and logbooks as tools in fisheries research: results of a pilot study and some recommendations. Fisheries Research 58:109–117.

Mayfield, S., C. Mundy, H. Gorfine, A. M. Hart, and D. Worthington. 2012. Fifty Years of Sustained Production from the Australian Abalone Fisheries. Reviews in Fisheries Science 20:220–250.

McShane, P. E. 1995. Recruitment variation in abalone: its importance to fisheries management. Marine and Freshwater Research 46:555–570.

McShane, P. E. 1996. Patch dynamics and effects of exploitation on abalone (Haliotis iris) populations. Fisheries Research 25:191–9.

McShane, P. E., S. F. Mercer, and J. R. Naylor. 1994. Spatial variation and commercial fishing of New Zealand abalone (Haliotis iris and H. australis). New Zealand Journal of Marine and Freshwater Research 28:345–355.

McShane, P. E., and J. R. Naylor. 1995. Depth can effect post-settlement survival of Haliotis iris (Mollusca: Gastropoda). Journal of Experimental Marine Biology and Ecology 187:1–12.

Miller, H. J. 2004. Tobler's First Law and Spatial Analysis. Annals of the Association of American Geographers 94:284–289.

Miller, K. J., B. T. Maynard, and C. N. Mundy. 2009. Genetic diversity and gene flow in collapsed and healthy abalone fisheries. Molecular Ecology 18:200–211.

Miller, K. J., C. N. Mundy, and S. Mayfield. 2014. Molecular genetics to inform spatial management in benthic invertebrate fisheries: a case study using the Australian Greenlip Abalone. Molecular Ecology 23:4958–4975.

Moreno, C. A., N. Barahona, C. Molinet, J. M. (Lobo) Orensanz, A. M. Parma, and A. Zuleta. 2007. From Crisis to Institutional Sustainability in the Chilean Sea Urchin Fishery. Pages 43–67 Fisheries Management. . Blackwell Publishing Ltd.

Mundy, C. 2012. Using GPS technology to improve fishery dependent data collection in abalone fisheries. FRDC Report 2006/029. Institute for Marine and Antarctic Studies, University of Tasmania.

Mundy, C., M. Haddon, and T. Karlov. 2006. Linking Fishery-Dependent and Fishery-Independent

Assessments of Abalone Fisheries. . University of Tasmania.

Mundy, C., S. Mayfield, H. Gorfine, and G. Liggins. 2014. Blacklip abalone Haliotis rubra. Pages 80–92 *in* M. Flood, I. Stobutzki, J. Andrews, C. Ashby, G. Begg, R. Fletcher, C. Gardner, L. Georgeson, S. Hansen, K. Hartmann, P. Hone, P. Horvat, L. Maloney, B. McDonald, A. Moore, A. Roelofs, K. Sainsbury, T. Saunders, T. Smith, C. Stewardson, J. Stewart, and B. Wise, editors. Fisheries Research and Development Corporation, Canberra.

Myers, R. A., and N. G. Cadigan. 1995. Was an increase in natural mortality responsible for the collapse off northern cod? Canadian Journal of Fisheries and Aquatic Sciences 52:1274–1285.

Nash, . W.J. 1992. An evaluation of egg-per-recruit analysis as a means of assessing size limits for blacklip abalone (Haliotis rubra) in Tasmania. Pages 318–338 *in* S. A. Shepherd, M. J. Tegner, and S. A. GuzmÃ¡n del PrÃ³o, editors. Abalone of the World: Biology, Fisheries and Culture. Fishing News Books:Blackwell Scientific Publications., Cambridge,.

Naylor, J. R., and P. E. McShane. 2001. Mortality of post-settlement abalone Haliotis iris caused by conspecific adults and wave exposure. New Zealand Journal of Marine and Freshwater Research 35:363–369.

Open-Geospatial-Consortium. 2018. An Open Format for Geospatial Information.

Orensanz, J. M., A. M. Parma, G. Jerez, N. Barahona, M. Montecinos, and I. Elias. 2005. What are the key elements for the sustainability of “S-fisheries”? Insights from South America. Bulletin of Marine Science 76:527–556.

Ourens, R., I. Naya, and J. Freire. 2015. Mismatch between biological, exploitation, and governance scales and ineffective management of sea urchin (Paracentrotus lividus) fisheries in Galicia. Marine Policy 51:13–20.

Parma, A. M., J. M. (Lobo) Orensanz, I. Elías, and G. Jerez. 2003. Diving for shellfish and data: incentives for the participation of fishers in the monitoring and management of artisanal fisheries around southern South America. *in* S. J. Newman, D. J. Gaughan, G. Jackson, M. C. Mackie, B. Molony, J. S. John, and P. Kailola, editors. Australian Society for Fish Biology Workshop Proceedings - Towards Sustainability of Data-Limited Multi-Sector Fisheries.

Perry, J. N., A. M. Liebhold, M. S. Rosenberg, J. Dungan, M. Miriti, A. Jakomulska, and S. Citron-Pousty. 2002. Illustrations and guidelines for selecting statistical models for quantifying spatial pattern in ecological data. Ecography 25:578–600.

Petitgas, P. 1998. Biomass-dependent dynamics of fish spatial distributions characterized by geostatistical aggregation curves. ICES Journal of Marine Science 55:443–453.

Petitgas, P. 2001. Geostatistics in fisheries survey design and stock assessment: models, variances and applications. Fish and Fisheries 2:231–249.

Piet, G. J., and F. J. Quirijns. 2009. The importance of scale for fishing impact estimations. Canadian Journal of Fisheries and Aquatic Sciences 66:829–835.

Prince, J. 2005. Combating the tyranny of scale for haliotids: Micro-management for microstocks. Bulletin of Marine Science 76:557–577.

Prince, J. D., H. Peeters, H. Gorfine, and R. W. Day. 2008. The novel use of harvest policies and rapid visual assessment to manage spatially complex abalone resources (Genus Haliotis). Fisheries Research 94:330–338.

Prince, J. D., T. L. Sellers, W. B. Ford, and S. R. Talbot. 1987. Experimental-Evidence for Limited Dispersal of Haliotid Larvae (Genus Haliotis, Mollusca, Gastropoda). Journal of Experimental Marine Biology and Ecology 106:243–263.

Prince, J. D., T. L. Sellers, W. B. Ford, and S. R. Talbot. 1988. Recruitment, Growth, Mortality and Population-Structure in a Southern Australian Population of Haliotis-Rubra (Mollusca, Gastropoda). Marine Biology 100:75–82.

Prince, J. D., and S. A. Shepherd. 1992. Australian abalone fisheries and their management. Pages 407–426 *in* S. A. Shepherd, M. J. Tegner, and S. A. Guzman del Prao, editors. Abalone of the world: biology, fisheries and culture. Proceedings of the 1st International Symposium on Abalone.

R-Core-Team. 2017. R: A Language and Environment for Statistical Computing. . R Foundation for Statistical Computing, Vienna, Austria.

Ripley, B., and M. Lapsley. 2015. RODBC: ODBC Database Access.

Russo, T., A. Parisi, and S. Cataudella. 2013. Spatial indicators of fishing pressure: Preliminary analyses and possible developments. Ecological Indicators 26:141–153.

Sanders, M. J., and K. H. Beinssen. 1998. A comparison of management strategies for the rehabilitation of a fishery: Applied to the fishery for blacklip abalone Haliotis rubra in the Western Zone of Victoria (Australia). Fisheries Research 38:283–301.

Saunders, T., S. D. Connell, and S. Mayfield. 2009. Differences in abalone growth and morphology between locations with high and low food availability: morphologically fixed or plastic traits? Marine Biology 156:1255–1263.

Steinarsson, A., and A. K. Imsland. 2003. Size dependent variation in optimum growth temperature of red abalone (Haliotis rufescens). Aquaculture 224:353–362.

Tamdrari, H., M. Castonguay, J.-C. Brêthes, and D. Duplisea. 2010. Density-independent and -dependent habitat selection of Atlantic cod (Gadus morhua) based on geostatistical aggregation curves in the northern Gulf of St Lawrence. ICES Journal of Marine Science: Journal du Conseil 67:1676–1686.

Temby, N., K. Miller, and C. Mundy. 2007. Evidence of genetic subdivision among populations of blacklip abalone (Haliotis rubra Leach) in Tasmania. Marine and Freshwater Research 58:733–742.

Tobler, W. 2004. On the First Law of Geography: A Reply. Annals of the Association of American Geographers 94:304–310.

Urbano, F., F. Cagnacci, C. Calenge, H. Dettki, A. Cameron, and M. Neteler. 2010. Wildlife tracking data management: a new vision. Philosophical Transactions of the Royal Society B-Biological Sciences 365:2177–2185.

Ward, M. D., and K. S. Gleditsch. 2008. Spatial regression models. . Thousand Oaks : Sage Publications.

Wickham, H. 2009. ggplot2: Elegant Graphics for Data Analysis. . Springer-Verlag New York.

Wickham, and Hadley. 2007. Reshaping data with the reshape package. Journal of Statistical Software 21.

Woillez, M., J.-C. Poulard, J. Rivoirard, P. Petitgas, and N. Bez. 2007. Indices for capturing spatial patterns and their evolution in time, with application to European hake (Merluccius merluccius) in the Bay of Biscay. ICES Journal of Marine Science 64:537–550.