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Craig Mundy

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Australian Government
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Using GPS technology to improve fishery dependent data collection in abalone fisheries

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Australian Government
Fisheries Research and Development Corporation

Project No. 2006/029

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1. Non-technical summary

2006/029	**Using GPS technology to improve fishery dependent data collection in abalone fisheries**

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OBJECTIVES:

1. Develop protocols and/or tools to automate conversion and interpretation of high resolution data.
2. Develop and test technology derived indicator variables.
3. Evaluate high resolution data for assessment of spatially-structured abalone populations.
4. Commence mapping commercially productive abalone populations.
5. Preliminary investigations of spatial dynamics of abalone fisheries.
6. Incorporation of electronically derived indicator variables into the Tasmanian Abalone Management Plan.

NON TECHNCAL SUMMARY

OUTCOMES ACHIEVED TO DATE

This research has improved management of the wild-catch abalone industry through improving quality and resolution of fishery data, specifically:

1. Development and implementation of a secure RDBMS for archival, management and retrieval of GPS and depth logger data acquired by abalone fishers,
2. Distribution of the AbTrack database to all abalone producing states,
3. Identification of spatial performance indices and spatial analyses of use in management of abalone dive-fisheries.
4. Development of software scripts and procedures for automated data analysis of spatial fishery-dependent data from abalone diver fisheries;
5. Preliminary testing of spatial performance measures using pilot study data from the Tasmanian Wild Harvest Abalone Fishery.

This is immediately evident through the adoption and use of the AbTrack database in Tasmania, South Australia, Victoria and New South Wales; and the adoption of GPS and Depth data loggers as a mandatory component of fishery-dependent data reporting in Tasmania.

This project has successfully developed a range of scripts and procedures to automate the processing of raw spatial data, to provide spatial performance measures useful for abalone fisheries assessment. Importantly, the data that can be obtained using GPS and depth data loggers is highly quantitative, and not subject to bias of any kind. It is also a low cost system, with the cost of GPS and depth logger expected to reduce to around $700 per diver. The data, logger management and preliminary analysis tasks for the Tasmanian fishery should be achievable by a single full time Technical Officer. The GPS and depth logger has minimal impact on the catching sector operations, with the exception of remembering to turn the GPS logger on and off, and recharging the GPS.

This project has also developed and established a multi-purpose RDBMS that can a) maintain a register of loggers and fishers using unique identifiers, b) manage the deployment of loggers to individual fishers, and c) provide an upload portal to a secure database in SQL Server 2008. The tools developed have intentionally utilised the capacity of free and open source software (FOSS), such that uptake of the concept is not limited by the financial cost required if they were developed entirely within more commonly used but corporate RBDMSs such as Oracle (with Oracle Spatial), or corporate GIS software such as ESRI's ArcGIS.

This project has established the logic process behind the use of an objective fishery-dependent data collection program focusing on acquiring spatial data of fishing events. Spatial methods of this type have not previously been applied to small vessel fisheries. While there has been some spatial analysis of VMS derived fishery dependent data to date, such analyses are limited by the low temporal resolution of sampling. The advantage of the system outlined here is that it is designed specifically for the needs of fishery assessment, rather than for compliance.

The development of these methods facilitate the use of low-cost spatial performance measures to assess abalone dive fisheries at one tenth the cost of a fishery-dependent density estimation program to achieve similar management outcomes.

In addition to activities in Tasmania, the project has also provided an extension service to New South Wales, Victoria and South Australia, that has included provision of the AbTrack RBDMS, SQL Server 2008 SQL and R scripts, and training.

KEYWORDS: Abalone, dive fishery, GPS, data-logger, *Haliotis rubra,* spatial performance indices, kernel utilisation distribution, GIS, hotspot analysis.

2. Acknowledgments

Funding for this project was provided by the Fisheries Research and Development Corporation and the University of Tasmania. Managers, divers and investors in the Tasmanian Abalone Fishery provided continual encouragement for the development of the analytical processes and provided extensive feedback on the practicality of using GPS and depth data logger hardware under typical abalone fishery conditions. Michael Porteus provided exceptional support with logger ‘wrangling’ and extracting loggers from fishers ‘who were going to send it back after their next trip’.

The AbTrack RDBMS would not have come to fruition without the skill and expertise of Mr Peter Walsh, especially his capacity to take my ideas and turn them into reality. Dr Malcolm Haddon provided encouragement to continue pursuing this concept when all appeared to be for naught.

3. Background

Catch and effort (CPUE) data are used in most fisheries around the world for assessing stock abundance. The adequacy of CPUE as a proxy for stock abundance is therefore entirely dependent on the quality and spatial resolution of the catch and effort components. This is especially true for abalone, where CPUE trend data are considered an unreliable estimate of abalone abundance (Karpov et. al 2000). However, the use of CPUE for abalone stock assessment persists because fishery independent estimates of abundance are logistically difficult and considerably more expensive to obtain.

The poor quality of CPUE data is due to two primary issues. The first and most important is that the scale at which fishing effort is reported (block, map code etc.) is much larger than the area fished by a diver on a given day (1 – 10 km's vs. 100's of metres). The mismatch between scale of unit stocks and scale of data collection on fishing effort is recognised as a key management weakness for most fisheries (Hilborn et. al 2005). The second issue relates to quality of CPUE data and that catch and/or effort are rarely recorded accurately. In Australian abalone fisheries it is normal practice to obtain an accurate weight of each divers catch. The effort recorded however is an estimate of the hours fished, and may be of variable quality. Consequently CPUE data can provide a poor resolution picture of stock trends.

In order to improve the quality and spatial resolution of catch and effort data, research staff at the University of Tasmania (UTAS) trialled GPS technology and an automatic depth sensor to obtain fine-scale data on fishing location and an accurate record of effort. Fishing dinghy position was recorded at 10 second intervals using a GPS receiver connected to a data logger placed on a diver's boat. An automatic depth/time recorder (DTR) attached to the divers harness was used to quantify effort accurately by automatically recording the actual time each diver spends in the water and the depth profile of each dive. In addition to improving CPUE data resolution and quality, these technology based data capture tool enable researchers to address many more issues that have not previously been possible. Preliminary trials during the UTAS pilot study indicate the GPS & DTR loggers are robust, and a minor imposition on the diver/deckhand team. In Victoria, data on fishing location have been acquired via GPS units integrated into electronic shellfish measuring boards used for sampling catches during commercial abalone diving operations.

The issue of scale of catch reporting is critical and must be addressed because of the interaction between the scale of reporting and abalone biology. Abalone populations are aggregated at small scales, grow slowly, and have limited post-recruitment dispersal. If fishing mortality (F) is too high, local stocks become serially depleted, and serial depletion cannot be detected with current low resolution data capture. This problem and the expense of obtaining quality fishery-independent data over large spatial scales was described by Prince (2003) as the "Tyranny of Scale".

The UTAS pilot study clearly demonstrated that simple GPS units can provide an affordable option to capture of high quality data. The spatial resolution of GPS data is currently around 10m to 20m, and data capture rate can be set at intervals from 1 second to several minutes. The GPS data logger performs a similar function to the Vessel Monitoring System (VMS) in use on larger trawl vessels, with two key differences. GPS position data are more accurate than VMS, but data captured by GPS are not available to managers in real time. VMS systems are also significantly more expensive (x 10) than GPS and require a major power source, and are therefore not suitable for installation on small fishing dinghies.

Massive amounts of data are generated with GPS/DTR technology and manual or semi-manual processing and analysis of data to date is highly time-consuming. Therefore to maximise the research and management potential of the new data, software tools to automate data processing and analysis are essential.

The GPS/DTR approach has potential applications for a broad range of research questions, and applications. A key example is the ability to use high resolution catch location data to ensure research sites are located within commercial fishing grounds. The difficulty in locating appropriate research sites is a key issue for all stakeholders. The GPS/DTR concept also has application other small vessel based fisheries where VMS is inappropriate. For example, this approach could also be used in urchin, beche de mere, calamari, and spatially structured demersal finfish fisheries.

The primary goal of this project is to develop and utilise new technology to improve abalone fishery management and research through capture of high resolution catch and effort data. It is envisaged this project will provide a platform from which further development can be undertaken, and as a demonstration of the value of affordable, high resolution catch data to other fisheries.

4. Need

Strategic R&D Plans

TasFRAB 2005 Theme 3: Improving the scale of data collection and development of performance measures.

Tasmanian Abalone Strategic Research Plan (2005 – 2009) - Need for fine-scale data on fishing effort.

Catch and effort data are either important components of model-based stock assessment (NSW, VIC, SA, NZ) or form the primary basis for trend-based stock assessment (TAS). Because of the current low quality and resolution of effort reporting in abalone fisheries, CPUE data are insensitive to serial depletion. Low resolution catch effort data decreases the ability to identify stock declines, and increases the risk that stocks will collapse, or be diminished for long periods. Low resolution data will also increase the risk that major management intervention is required because of late confirmation a fishery is in decline.

Acquisition of fine-scale data on fishing location is an essential component of flexible management for abalone fisheries, and provides managers and industry with the capacity to continue broad scale management at larger scales (zones), but also to manage elements of the fishery at a fine scale if required. A flexible scale of management will enable the current natural dynamic of fishing effort within regions to continue.

CPUE is the primary fishery dependent indicator variable that is used to measure performance. Because CPUE is not linearly related to stock abundance, there is an important need for alternate indicator variables. This need could be resolved through the development of new technology derived indicator variables that can be calculated using the combined GPS and DTR data. High resolution location and effort data based on GPS/DTR data will increase the precision of stock assessments by improving quality of CPUE data, and by development of additional indicator variables.

5. OBJECTIVES:

1. Develop protocols and/or tools to automate conversion and interpretation of high resolution data.
2. Develop and test technology derived indicator variables.
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6. Methods

6.1 Data logger hardware for capturing location, effort and depth of dive events in abalone fisheries

The use of position data loggers on commercial fishing vessels is not a new concept. Satellite based (Inmarsat, Argos etc.) Vessel Monitoring Systems (VMS) have been in place for pelagic and trawl fleets around the world for about 15 years. Initial testing of satellite based position communication methods began in the 1980's with several countries conducting trials by the early 1990's (Anonomous 1998). The earliest experimental application of passive GPS data loggers for collection of spatial position information was conducted on a single vessel in the Clyde Sea *Nephrops* trawl fishery in 1998 (Marrs et al. 2003). The GPS data logger used in the *Nephrops* trawl study was a combined external GPS receiver and data logger system designed for the aero industry, recording Latitude and Longitude every 10 minutes.

Commercially available hardware for capture of spatial position of fishing vessels or other small fishing vessels are currently reliant on the satellite transmission based Vessel Monitoring System (VMS). VMS hardware is expensive to purchase, has a high power supply requirement, and is expensive to operate in the context of cost of an appropriately short polling interval (i.e. five minutes or less). Consequently, a VMS based approach is entirely unsuitable for capturing the spatial information of small-vessel based fishing fleets such as those active in abalone dive fisheries. These vessels typically have no power, or are limited to basic 12v power systems run from generators on outboard motors.

The initial GPS data loggers in use in the Tasmanian Abalone Fishery were constructed from individual components, typically a standalone micro 12 or 20 channel GPS receiver connected to a data logger via serial interface, and an independent portable 12V power supply. The construction of an integrated GPS receiver/data logger unit with internal battery was commissioned after initial testing of the early composite logger systems, and these integrated receiver/logger units were used for the majority of this study. Three years later, there remains no commercially available portable GPS data logger units designed for use on small vessels. However, with the advent of geo-tagging of digital photographs, a variety of small personal GPS receiver/data logger units are now commercially available. For several reasons, these amateur units, while functional, are not well suited for the purposes of deployment on commercial abalone fishery vessels.

An important component of monitoring activity of abalone divers is the depth at which abalone are harvested. Even fewer options are available for automated monitoring of diver depth than there are for capturing spatial position. The only affordable depth/time logger available to date is the Reefnet Sensus depth/time/temperature logger (ReefNet 2002b). Comparable loggers are available from other manufacturers at approximately 6 times the cost of those from Reefnet.

This chapter describes the specifications of the various logger hardware used, and the performance in field trials on commercial abalone vessels. Recommendations for hardware standards and specifications are provided should GPS and/or depth logger systems be utilised on a fishery wide scale as part of the fishery- dependent data collection process.

6.1.1 Logger hardware specifications and configuration

6.1.1.1 GPS logger design and specifications

An initial GPS Datalogger (MK0) was developed to UTAS specifications in 2004 by SciElex, and trialled by IMAS research staff during research field trips. Subsequent to the initial version, two progressively more flexible models of GPS datalogger were developed (MKI, MKII). All of the GPS loggers have an integrated non-differential 12 channel GPS receiver. The Haicom Hi-204S was used in all earlier models (MK0 and MKI loggers). The MK0/MKI loggers record standard National Marine Electronics Association (NMEA) output data from the receiver with date and time in UTC0, and have a capacity of 1,048,576 records (approximately 120 days of continuous recording at 10 sec intervals, 24 hours/day). The datum for Latitude and Longitude is WGS84. The manufacturer's specifications for the Hi-204S list accuracy as 25m (Haicom_Electronics_Corporation 2005). Both MK0 and MKI GPS loggers (Figure 1) require an external 12V power supply. On diver's boats, power is supplied to MK0/MKI GPS loggers either from on-board power or from an external sealed lead-acid 7Ah 12V battery. The MKII GPS loggers are powered internally by 4 x Flat 4/3A NiMh 4500mAh 1.2v batteries in series providing 4.8V for approximately 40 hours of run time, and use a Fastrax uPatch100-S GPS receiver (Rogers et al. 1984, Fastrax_Limited 2006) . Standard NMEA strings are stored in sequence on the memory module. MKII loggers have an Atmel 8bit Flash based microcontroller with 4kByte RAM, running at 7.3728MHz. Memory in the MKII loggers is a 128MByte Multimedia Card Flash Card providing capacity for more than 2 million samples (Verdouw 2007). GPS receivers and loggers are encased in a robust, waterproof FIBOX housing (Figure 1).

Data is downloaded from the MK0 and MKI GPS dataloggers via a serial port using the Windows HyperTerminal interface. The MK0/MKI datalogger firmware, supplied by SciElex, provides an interface with the ability set unique ID codes for each logger, sampling frequency, data download and memory erase functions. The ID codes and additional information is saved along with the standard NMEA strings to a CSV file. The MKII GPS loggers have a USB interface, which includes all functions available on MKI loggers, and the option to select/deselect certain NMEA fields. The MKII logger has its own download software, which performs some basic data management functions such as conversion of raw time and date fields into a combined date/time field in a user selected UTC time zone (Verdouw 2007).

Figure 1. A MKI GPS datalogger with Haicom Hi-204S GPS receiver and external 12v power supply.

6.1.1.2 GPS: Choice of Sampling Interval

Provided that there is adequate satellite reception, the GPS dataloggers are capable of recording a constant stream of position data at any sampling interval up from one second intervals. Ideally, when sampling movement paths the sampling interval should match the scale of change or the scale of movement (Turchin 1998, Cain et al. 2005). As this research project is focussed on capturing and quantifying diver behaviour during single fishing events (i.e. for example, the amount of area searched and the complexity and concentration of fishing activity) the GPS datalogger sampling frequency was chosen to capture the scale of vessel movement during a dive. Under-sampling can occur when position data is recorded at a temporal scale that is too coarse, leading to loss of important movement information. Under-sampling has been recognised in a fisheries context during analysis of Vessel Monitoring System (VMS) position information collected from vessel operating in a trawl fishery (Deng et al. 2005) and can underestimate track lengths by up to 50% in the case of African penguin tracking (Ryan et al. 2004). Over-sampling can occur when position data is recorded at a finer temporal scale than the scale of movement and leads to repetitive sampling of the same position (Turchin 1998). There is also a trade-off between sampling rate and battery lifespan and memory capacity. Over-sampling in the field is recognised as less of a problem than under-sampling because over-sampled data sets can be sub-sampled later and no information is lost (Turchin 1998).

In a pilot study, testing against under-sampling was performed on data collected at a very high temporal resolution, i.e. at 5 second intervals. As suggested by (Kareiva and Shigesada 1983), the data were sub-sampled at several different time intervals and the sampling interval chosen that provided movement parameters which most accurately reflected the complexity of the vessel path while minimising the number of data points to be analysed. This was a subjective, visual assessment. Subsequently, the recording frequency of GPS loggers was set to an interval of 10 seconds.

For most of the project, divers were asked to leave the GPS dataloggers running for the full duration of a fishing day which would provide a continuous 10 second data stream for full days of fishing and commuting activity. However, early issues with unreliable power supply, unstable battery connections and/or insufficient battery charge for MK0 and MKI dataloggers resulted in many of the divers switching the GPS loggers off after each dive.

6.1.1.3 GPS Logger output

The GPS loggers start recording when the integrated GPS receiver received the first positive fix from available satellites. The loggers record receiver position at 10 second intervals until turned off again. If the GPS receivers lost reception from satellites, they did not record any more data until a valid GPS signal was received. The text files (comma-separated values (csv)) downloaded from a MKII GPS logger using manufacturer firmware contained the following fields:

- **Diver_Code:** Entered by researchers when equipment was deployed
- **Divers:** Optional, flagged if more than one diver used the logger
- **Event:** Flagged 'start/end' by the 'waypoint' buttons (see Section 2.4)
- **UTC_time:** Position time stamp from the GPS receiver
- **UTC_date:** Position date stamp from the GPS receiver
- **Corrected_Time:** Firmware calculated time from user selected UTC zone
- **Corrected_Date:** Firmware calculated date from user selected UTC zone
- **Log_lat:** Latitude from GPS receiver
- **Log_long:** Longitude from GPS receiver
- **Speed:** Calculated by the GPS receiver, given in knots
- **Course:** Calculated by the GPS receiver

6.1.1.4 Depth/time/temperature loggers

The depth and temperature recorders used in the UTAS data collection program were produced by a Canadian company, Reefnet (www.reefnet.ca). The loggers were small and compact and recorded depth (pressure), temperature (degrees K), and time (with an internal crystal clock counter). Data were obtained using both SensusPro and SensusPro Ultra models of depth loggers. These models differ from each other only in data storage capacity (see Table 1 for depth logger specifications). Sensus Pro and Sensus Pro Ultra loggers are depth tested as waterproof to 500 feet (152.4 metres) by the manufacturer (ReefNet 2002b). They have solid state flash memory with a capacity to store either 100 or 1500 hours respectively of depth and temperature data (when set to record at 10 second intervals), before beginning to rewrite over old data. The sensors and logger are housed in a fibreglass reinforced polycarbonate case and were attached to a diver's vest with a Velcro tab strip, or stainless steel ring (Figure 2). Data was downloaded via three small metal pads on the lower surface of the loggers using a dedicated download serial interface download cradle.

Table 1. Specifications of ReefNet depth and temperature loggers (ReefNet 2002b).

Logger	Projected battery life	Memory	Accuracy of depth sensors	Accuracy of temperature sensors
SensusPro	2 - 5 years	100 Dive Hrs (@10sec)	+/- 1 ft (resolution of 0.5 inches of water)	+/- 0.8 C (resolution of 0.01 C)
SensusPro Ultra	2 - 5 years	1500 Dive Hrs (@10sec)	+/- 1 ft (resolution of 0.5 inches of water)	+/- 0.8 C (resolution of 0.01 C)

The 'Ultra' model loggers, with greater data storage capacity than the SensusPro loggers, began to be produced part-way through this program and were immediately adopted. The greater memory substantially reduced the risk of data loss, through overwriting, which was a hazard that has been identified while using the SensusPro model with smaller data storage capacity.

Figure 2. Sensus Ultra depth/time/temperature logger from Reefnet. Sensus

A pressure sensor acts as the primary driver in the Sensus loggers. The Sensus loggers are user-configurable, to turn on when a user-selected pressure threshold is detected, at which point the logger will begin recording pressure, temperature and clock count until measured pressure drops below the user-defined pressure threshold. When this occurs, the logger continues to record for a user-defined number of intervals, and then switches off. For this study, the default settings were a pressure threshold of 1111 mbar (~approximately 3 feet), 10 second sampling interval, and 15 samples following the logger ascending shallower than approximately 3 feet below the surface.

6.1.1.5 Automation of download of Reefnet Sensus depth loggers.

Reefnet provide a software interface (Manager.exe) and serial download cradle to alter settings and retrieve data from the Sensus logger. The initial free software (Manager.exe) provided by Reefnet to download data from the SENSUS depth loggers did not include a bulk/automated export option. Raw data from individual divers could be displayed, and using cut and past actions, data can be transferred to Excel or text files. This was very slow, required additional data manipulation to construct date/time information, and when a single diver may have completed more than 100 dives each month, this is an unacceptably tedious process. Reefnet have always provided a developers manual to enable third party software to be developed to interact/download information from the Sensus loggers. Prior to the commencement of 2006/029 the PI (CM) contracted SciElex to develop a software interface to download data from the Sensus-Pro depth logger in a form that could easily be imported into a database with no additional processing. While this was relatively straight forward, Reefnet released a new version of the Sensus logger (Sensus-Ultra), which required a modification of the SciElex software. At this time Reefnet were contacted with a request to provide an export function from within their SENSUS MANAGER software. Reefnet obliged and provided the Export function free of charge (Figure 3).

Output from the ReefNet export function had the following fields;

Index: Sequential ID number for each dive, starting at 1 for each download
Device_ID: Identification code for the logger
Year: Year in 4 digits
Month: Month in 2 digits
Day: Day in 2 digits
Hour: Hour in 24 hour time
Minute: Minutes
Second: Seconds
Offset: Seconds elapsed since start of dive
Pressure: Pressure in millibars
Temperature: Temperature in degrees Kelvin

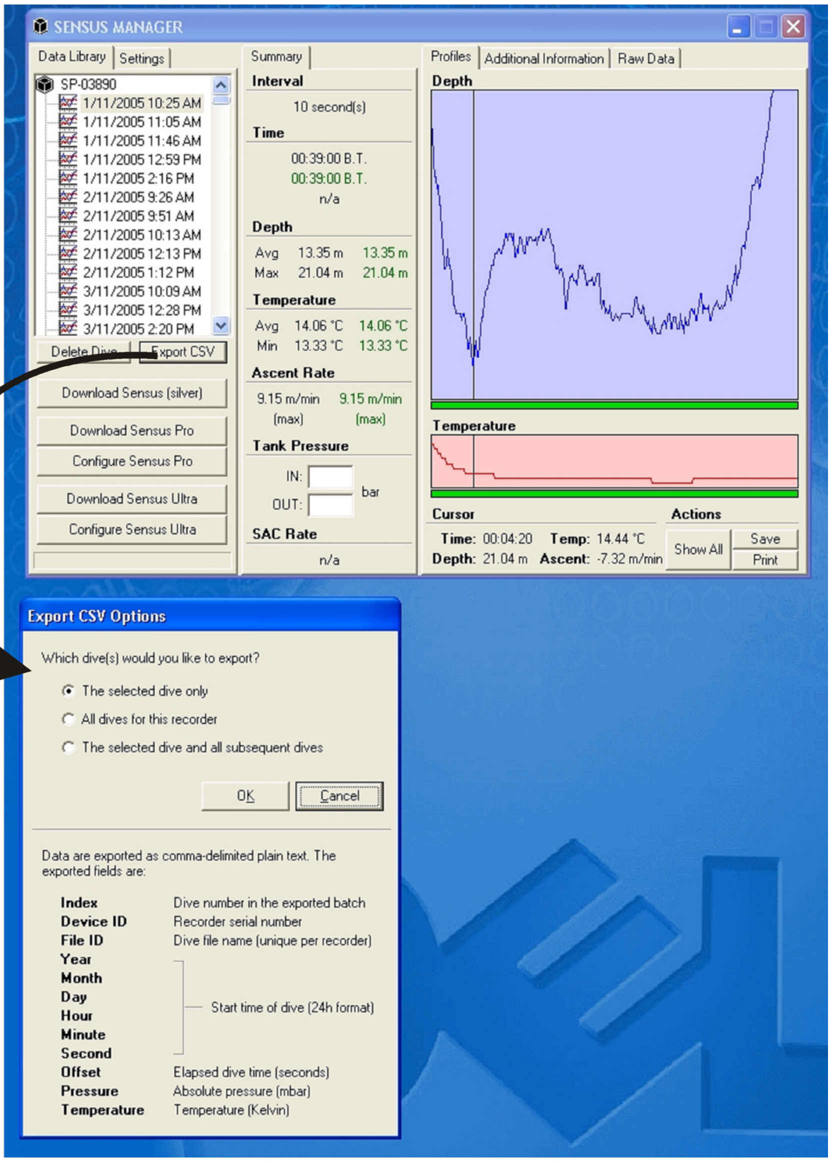

Figure 3. Export button provided by REEFNET in Sensus Manager software, and options for export of indivudal dives, all dives or, dives from a particular date onwards.

6.1.1.6 Clock Drift in Depth Loggers

SensusPro depth loggers do not have a real time clock. Instead, the internal clock functions as a timer. At the moment of power-up during manufacture, the clock commences counting. When loggers detect a change in pressure above a given threshold (indicating that the logger is underwater), the clock count (in seconds since power up) is recorded. When data is downloaded from the loggers to a computer that has been synchronised to NMEA time, the real time at download and logger clock count at download are recorded in the download data file. Sensus Manager software calculates the real time at the start of a dive and a time stamp for every depth record by subtracting the difference in clock count from the real time at download (ReefNet 2002a).

Drift in the frequency of the crystal clock used in the depth loggers was detected, although not unusual in small devices with internal crystal clocks (Serway and Jewett 2003). The manufacturer's specifications for the crystal used in the Sensus loggers is ± 20 ppm (pulses per million) which equates to an error of up to ± 2 seconds/day. The crystal counters in the depth loggers suffered from time drift at varying rates in each logger. As a consequence, each logger required independent calibration, and a correction applied to the data prior to matching depth logger data with the GPS position data. Without correction, a disparity in boat speed and diver depth was observed, where the vessel was apparently travelling very quickly for several minutes when the diver was supposedly several metres below the surface.

As data is not deleted from the loggers at download, the clock drift between two downloads could be calculated by downloading the same dive on two or more occasions separated by several weeks. The accrued difference (in seconds) in the start time of a specific dive between the two download events was calculated as the clock drift for that period. Clock drift for each deployment was assumed to be linear and as a function of the number of days elapsed allowed calculation of the drift in seconds/day. Correction per second elapsed was calculated for each deployment and applied to the time/date field of the downloaded data. In applying this correction to each downloaded data set, the disparity between boat speed and diver depth was eliminated.

6.1.2 Testing for error in GPS data

Non-differential 12 channel GPS receivers have limited accuracy due to errors in the satellite signal reception caused by ionospheric delays, geometric dilution of precision, time ambiguities, and multipath reflections (Jeffrey and Edds 1997). Accuracy is generally considered to be in the order of ±5 - 10 m, although the MKI logger Haicom receiver used in the MKI and MKIIA loggers is less accurate: specifications lists accuracy of 25 m (Haicom_Electronics_Corporation 2005).

During data collection trials where GPS loggers were placed together at a fixed location, it was observed that data from some loggers had a greater scatter of position points over a short time interval than data from other loggers. To test whether error was being introduced to the precision of data by the dataloggers, two MKII GPS dataloggers were installed side by side in a stationary position for a period of 4 hours. The loggers were set to record position at 10 second intervals and the point data was projected in WGS84 UTM Zone 55S using ESRI ArcMap 9.2 (see Figure 4).

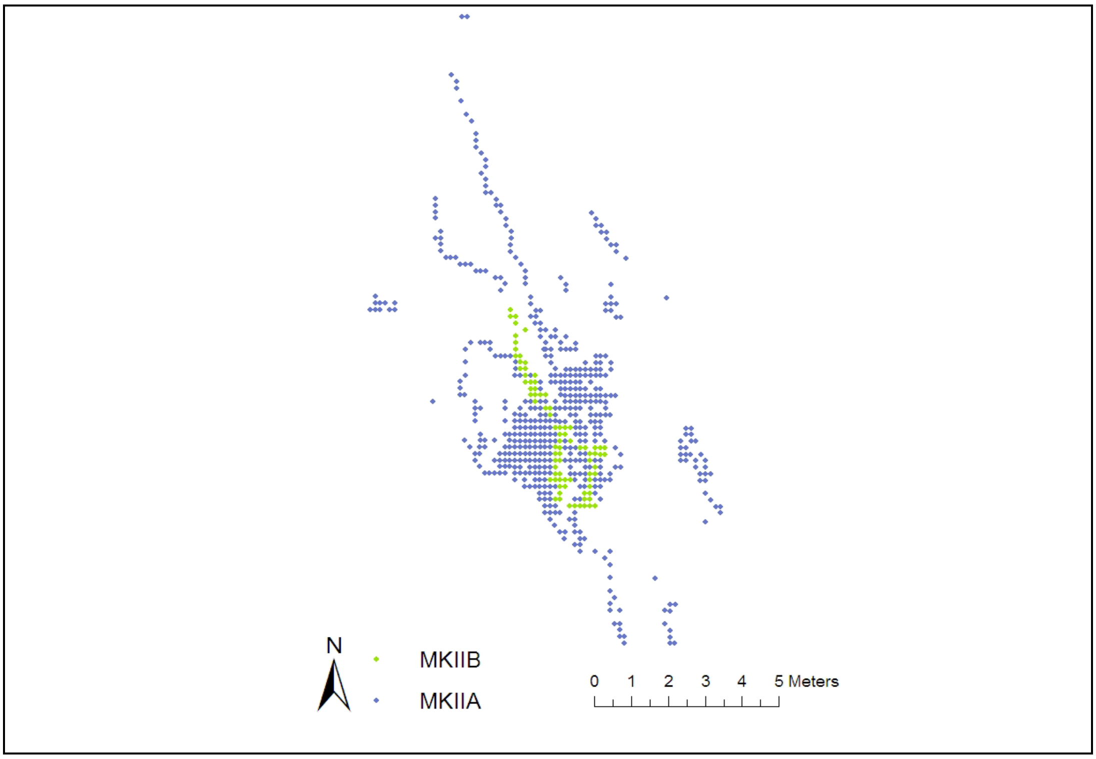

Figure 4. Scatter of recorded GPS locations (projected in WGS84) from two stationary SciElex MKII GPS dataloggers continuously recording position at 10 second intervals for 4 hours in May 2007.

GPS receiver accuracy – the accuracy of the receiver chips in the SciElex MKII has improved over the SciElex MK0 and MKI units. Increased performance was also achieved in the commercial GlobalSat GPS data loggers which utilised the low power, high sensitivity (-158dBm) GPS receivers produced by SiRFStar and MTK respectively. Variation in coordinate fix at a stationary point was ~ 8m, for the MKII and GlobalSat units, down from ~30m with the earlier Sirfstar II and Fastrax chipsets. One of the benefits of the high resolution GPS receiver chipsets is that accurate positions are obtained when fishers are close to cliff lines. However, none of the GPS receiver chips will obtain an accurate position when the vessel is shielded by cliff lines at times of the day when satellites are closer to the horizon behind the cliff line.

Overall, the units produced by SciElex are sufficiently robust to be used in abalone fishing dinghies with an expected life of at least 3 years. The commercially produced loggers (GlobalSat BT335) housed in Pelican 1010 waterproof cases have also proven to be a reliable and robust to typical use under abalone fishing conditions, although they are susceptible to water damage when divers switch off units with wet hands after diving.

6.2 AbTrack – a custom RDBMSs for logger management, data upload and archival

6.2.1 Background

Automated collection of fishery-dependent data by deploying data loggers across a large group of divers generates two challenges 1) keeping track of which logger was issued to which diver and over what time period so that data is correctly associated with the diver; and 2) managing the large volumes of data that will be generated. If data loggers are to be distributed across a fishing fleet an efficient process for managing allocation of data loggers and managing and archiving data collected must be established. For the purposes of this study, an interim MS Access database was developed by the PI to manage allocation and retrieval of data loggers and to process and store data from GPS and depth loggers. This interim database structure was then updated and converted to MS SQL Server 2005 and a front end created for managing allocation of loggers to fishers and for uploading of data (AbTrack), by a contract database programmer.

6.2.1.1 Data generation expectations

Data logging frequencies in the order of 10 seconds were determined to be optimal to avoid over-sampling, and to capture sufficient detail of a the dynamic of a fishing event to be useful. In the context of the Tasmanian Abalone Fishery, if all divers were to us GPS and depth dataloggers, set to record either position or depth at 10 second intervals, the dataset for a single fishing year contain approximately 15 million records as a minimum, for each data type. A dataset of this magnitude requires a professional RDBMSs approach, and is well beyond the capabilities of products such as MS Access.

6.2.1.2 Requirement to capture logger allocation to fishers

An essential component of deploying position and depth data loggers across a fleet is confidence that data are correctly attributed to a particular diver during a particular time period. Without a robust system for managing the allocation of loggers to divers, the objective of investigating fleet dynamics or individual fisher behaviour are not possible, and catch cannot be allocated to a set of electronic position/depth records. The nature of the depth logger design also requires the exact date and time of download to be recorded in the database, as this time stamp is utilised in the correction of the Sensus date/time data stream (adjustment for Sensus daily clock error). For this reason, an efficient front end for capture of logger allocation and retrieval details was considered a critical issue in the development of AbTrack.

6.2.1.3 Database platform options

There are currently a relatively large number of suitable RDBMSs platforms to choose from. Several common RDBMSs platforms are however costly, and would be cost prohibitive for small research groups or industry bodies to utilise. ESRI ArcGIS versions 9.2 to 9.3 utilised MS SQL Server Express edition as the default RDBMSs system for ArcSDE in the ArcMAP Desktop edition. For this reason, the flexibility of effective integration with ArcGIS and low cost, and the option to use .NET Framework for development of front ends was the final reason for choosing MS SQL Server as the RDBMSs platform for AbTrack.

Following the beta release of the AbTrack RDBMS, MS SQL Server 2008 (SS08) was released, incorporating native spatial data types for the first time in a major RDBMSs system, adding a major benefit to our SQL Server based data management system. The spatial data types (Geography and Geometry) and associated functions also conform to widely accepted industry standards set by the Open GeoSpatial Consortium (OGC). The new Geography and Geometry data types are implemented as Microsoft .NET Framework Common Language Runtime (CLR) types (Anon 2008). The Geography data type is suitable for Latitude/Longitude data (e.g. WGS84, GDA94), whereas the Geometry data type is suitable for use with data in projected form (e.g. UTM or MGA coordinate systems). These spatial data types store points, lines and polygons in either WKB or WKT formats. Microsoft also provides a free version (SQL Server Express) that is more than sufficient for the requirements of this project. For those research or industry groups that don't have access to Agency or Institute managed database systems, The SQL Server 2008 Express edition is free, and the Small Business Server premium edition which includes the Standard edition retails for approximately for A$2000.

6.2.2 AbTrack features and operation

The AbTrack software comprises a Visual Basic (VB6) compiled front end coupled to a SQL Server database (Currently developed in SQL Server 2008, but is compatible with the 2005 and 2000 versions). All data logger specific import processing is performed in SQL Server using T-SQL scripts with the VB application acting as a conduit for the raw data. This means new or changed data logger models can be incorporated with changes to T-SQL scripts and do not require modification of the from end VB application (thus providing a high level of flexibility to add new logger types, or to change the processing scripts, without having to alter the front end VB software, a much more tedious and costly process). Data validation is also performed using T-SQL scripts and, in the event of a data validation error, offers the user the option to remove the offending data or retain for further investigation. Using the AbTrack software, data can be easily calibrated, merged (for separate data loggers with matching time stamps) and extracted to Excel or CSV format. Additionally, the software provides functionality for managing data logger allocation and inventory tracking.

6.2.2.1 Welcome and feature access screen

The features within the AbTrack front end are arranged in three groups; 1) Sampling data, 2) Supporting Data, and 3) Administration (Figure 5). Each tab is described in brief below. A relationships diagram for the SQL Server AbTrack database and table metadata is provided in Appendix 3: Relationships diagram and metadata for AbTrack.

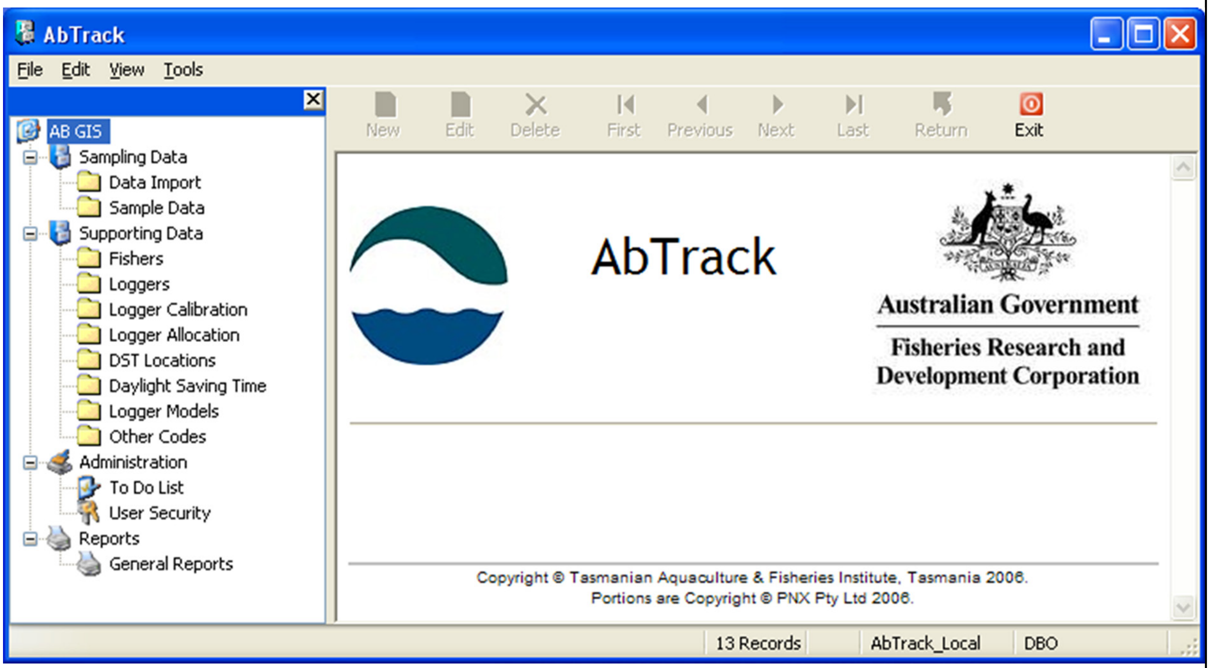

Figure 5. AbTrack start-up screen.

6.2.2.2 *Sampling Data features*

6.2.2.2.1 Data Import

The data import screen (Figure 6) allows selection of the diver the data belongs to and identification of the details of the loggers used. The screen also requires input of the file names and critically, the date and time of download for the Sensus depth loggers. The date/time of download is essential for the calibration process, which is completed prior to uploading the data to the database.

When the **Start Import** button is clicked, the front end passes the details and the data through to a T-SQL script within SQL Server. During this process, the T-SQL script also rounds the time data to the nearest 10 seconds, and creates a join between the two data streams.

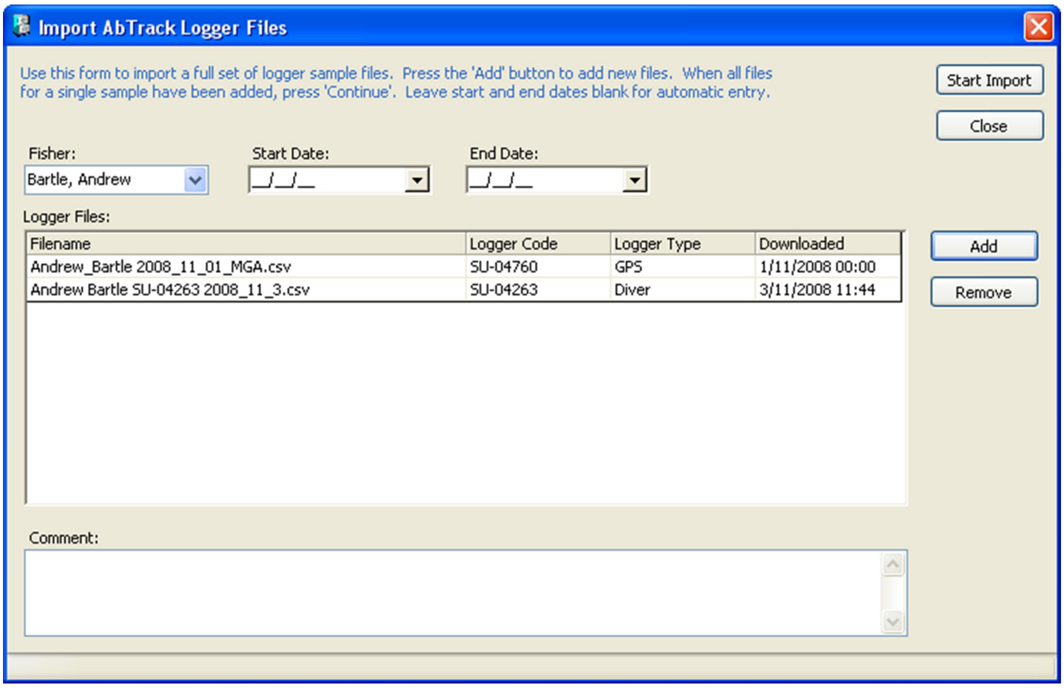

Figure 6. Data import window. This panel enables selection of fisher, logger serial number, raw csv files for upload, and the time of download.

6.2.2.2.2 Sample Data

Double clicking on the Sample Data icon in the menu panel opens a window listing all of the files uploaded to date (Figure 7). Double clicking on any entry will open a further screen (Figure 8) showing details of the files uploaded. Double click on any of the entries in this screen will retrieve the data associated with the chosen upload in either GPS priority view (Figure 9) which will retrieve all GPS data and any associated depth data, or in Depth priority view, which will retrieve all Depth data, and any associated GPS data. The data retrieved is displayed in table form, and can be saved to a csv file by choosing File / Save as in the menu options at the top of the screen.

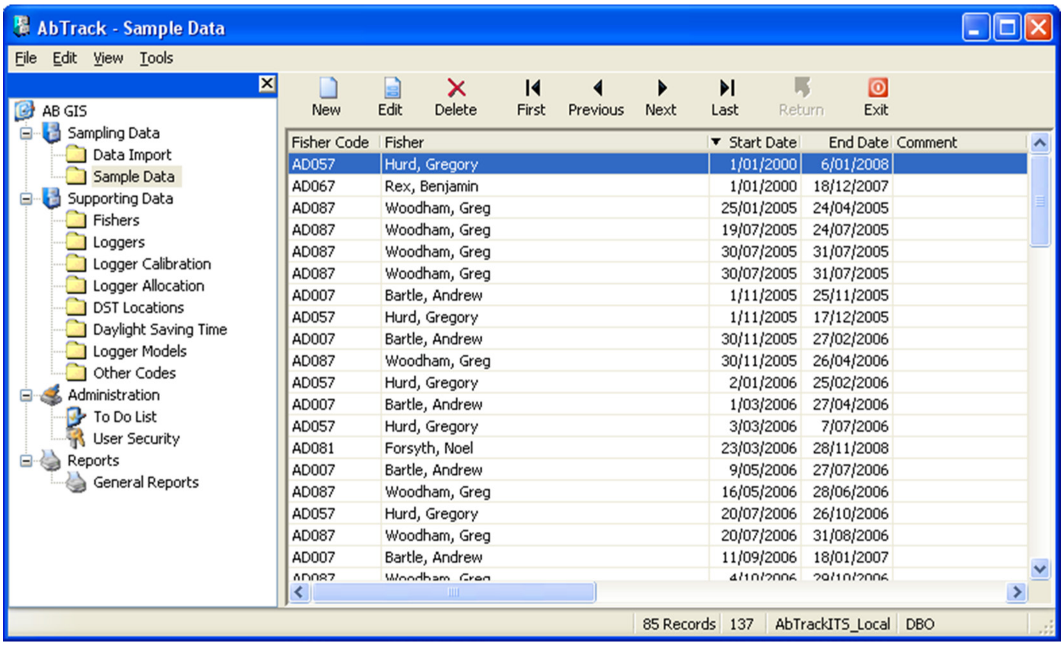

Figure 7. Sample Data window. This window provides a list of all data upload events, which can be explored in further detail by double clicking on any row.

Data can be deleted from the database by selected the desired upload from the list of files uploaded, for example in Figure 8. This will also delete all of the records in the relevant tables, and provides a cleaner system of removing data than by removing data directly from within SQL Server.

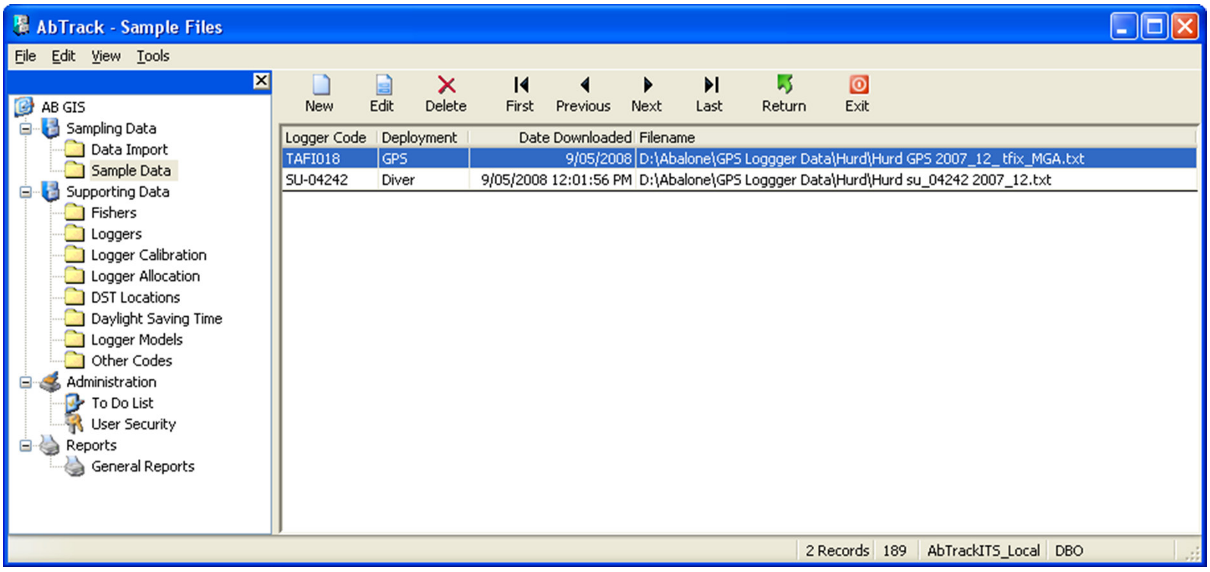

Figure 8. Sample Data detail window. This window provides a list of al data uploaded, which can be explored in further detail by double clicking on any row.

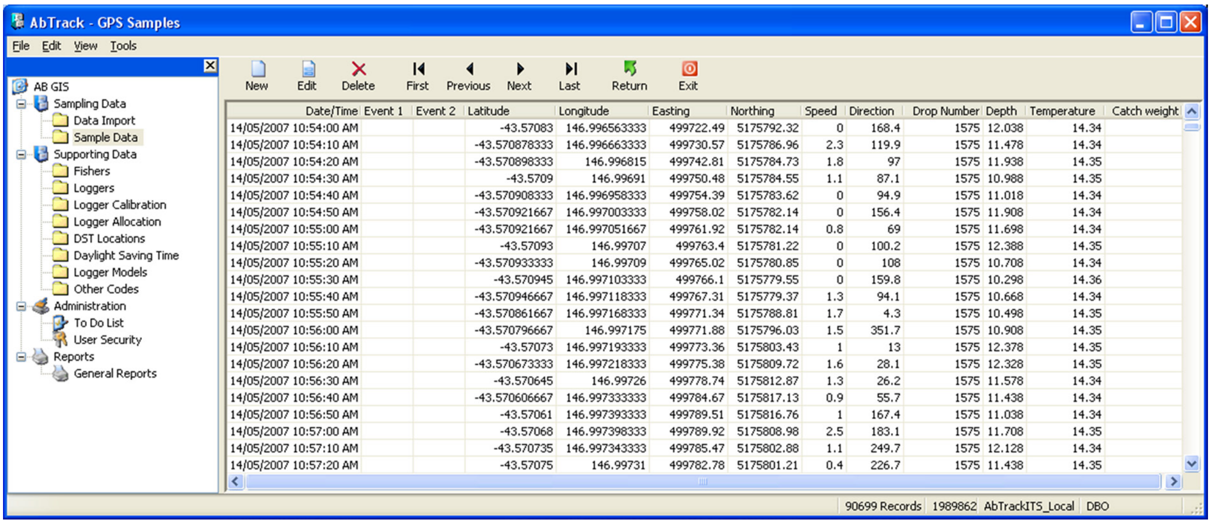

Figure 9. Sample Data retrieval window. This window retrieves all data associated with an upload file (GPS or depth, and displays it in table form.

6.2.2.3 Supporting Data features

6.2.2.3.1 <u>Fishers</u>

AbTrack is able to maintain a list of all divers in the fleet, with contact details and a record of the License ID the fisher was working on. Each Fisher is given a unique ID, which is retained throughout, and never re-allocated. The fisher name and license ID are used to link the e-data to the DPIPWE abalone catch record system. These details are entered in the Fisher panel, available from the Supporting Data section accessed by the navigation pane (Figure 10).

6.2.2.3.2 Loggers

The Loggers window (Figure 11) enables entry of details for all logger types, and for recording when loggers are commissioned or decommissioned. Once loggers are decommissioned they cannot be allocated to a fisher.

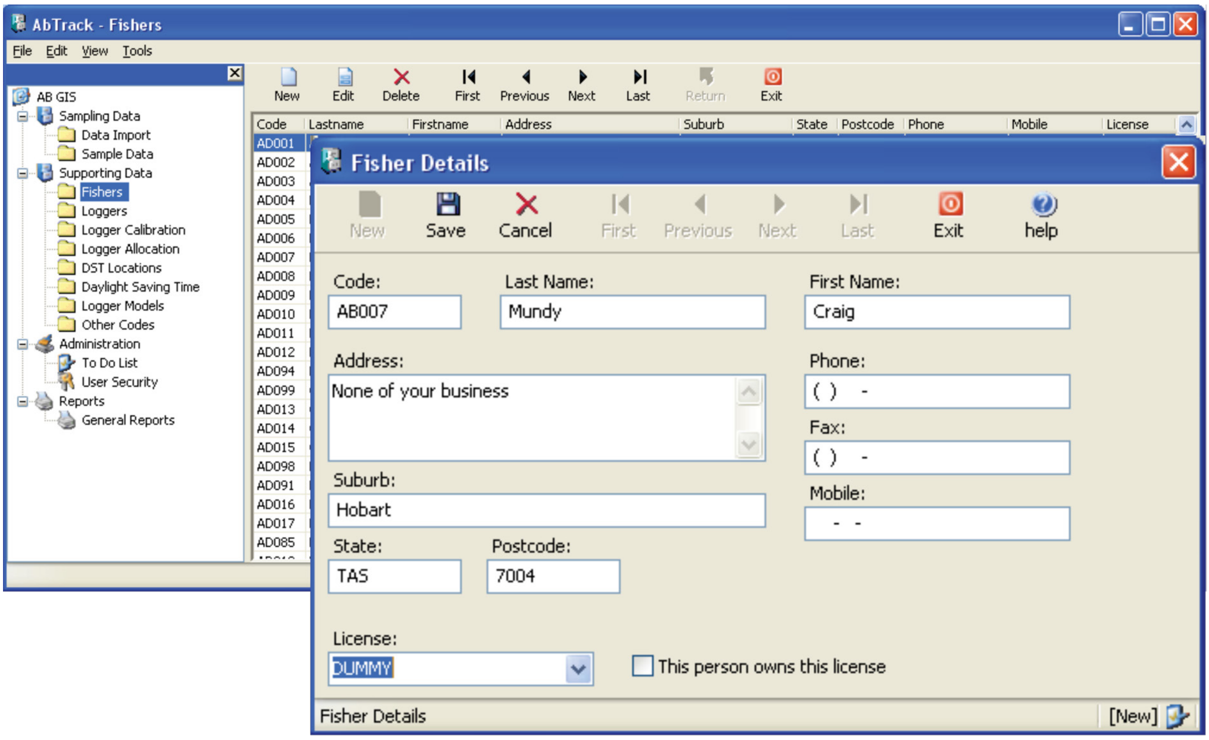

Figure 10. Fisher details entry window. This window enables input of unique identification code and contact details for individual fishers.

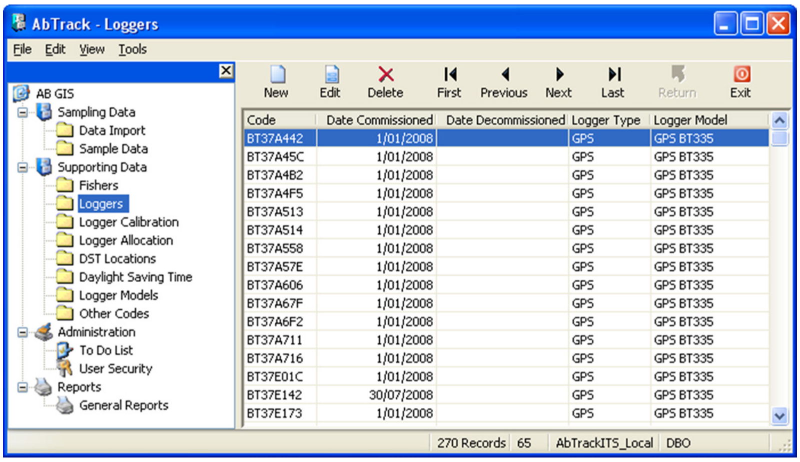

Figure 11. Logger details entry window, for input of logger type, model and serial number.

6.2.2.3.3 Logger calibration

The Calibration window (Figure 12) enables input of the calibration coefficient for each Sensus depth logger. The calibration coefficient is critical for correcting clock drift prior to the pairing of depth data with the GPS data, and subsequent upload.

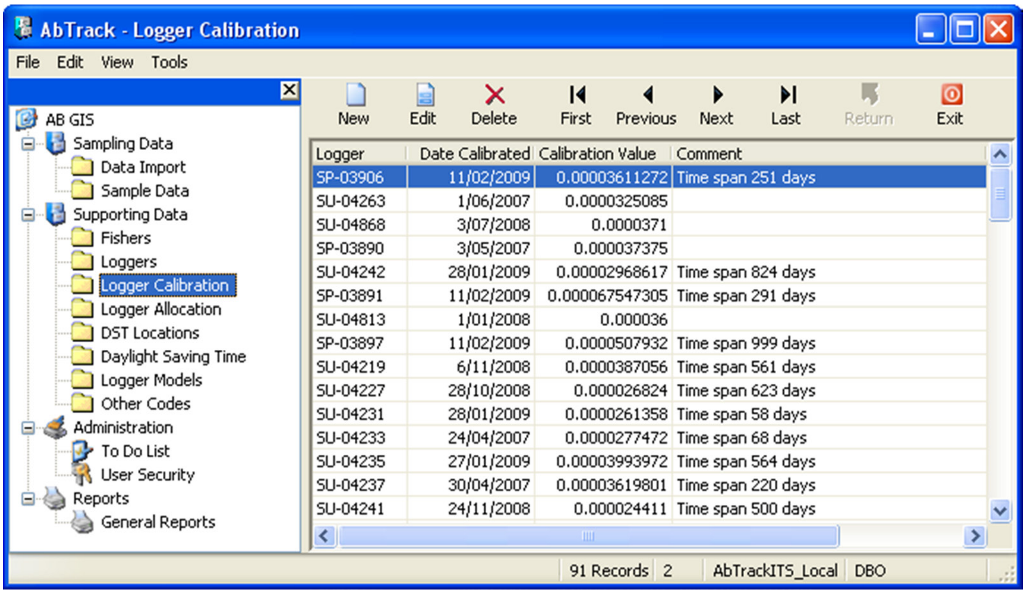

Figure 12. Logger calibration entry window. This window enables input of the calibration coefficient, and details of the calibration for each logger

6.2.2.3.4 Logger Allocation

Once loggers and fishers have been entered into the database, the Logger Allocation window (Figure 13) enables issuing of a logger to an individual diver. The date the loggers were issued and retrieved are also recorded to ensure that a logger is not allocated to another fisher (within the database) prior to the actual logger being returned and made available for re-issue.

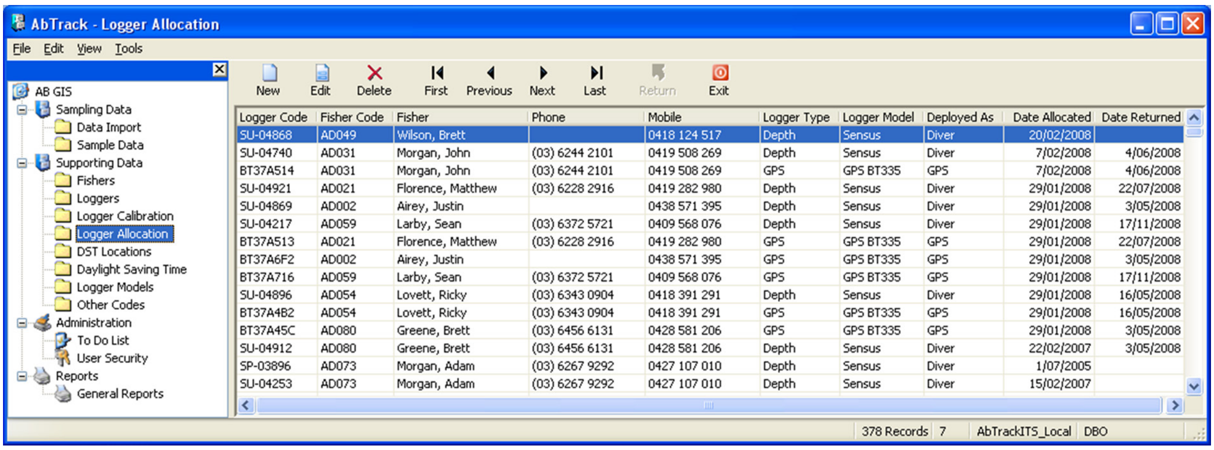

Figure 13. Logger allocation window. This window enables allocation of individual or sets of loggers to specific fishers.

6.2.2.3.5 Daylight Savings Zones and start/end of Daylight Savings periods

All data in the database are retained at a time zone of AEST, or UTC +10:00hrs.The NMEA string received from the GPS is always in UTC 0, thus the time correction for GPS data is taken from the UTC offset recorded in the DST Locations window (Figure 14). GPS data are corrected by 10 hours during upload. The date/time stamp attached to the depth data however, is however taken from the host computer at the time of logger download. Thus the data may or may not require correction. Any data downloaded during the daylight savings period will require correction, whereas data downloaded outside of the daylight savings period do not require correction. For this reason, the start and end dates of Daylight Savings (Figure 15) is an essential component of managing the data/time stamp for the depth loggers.

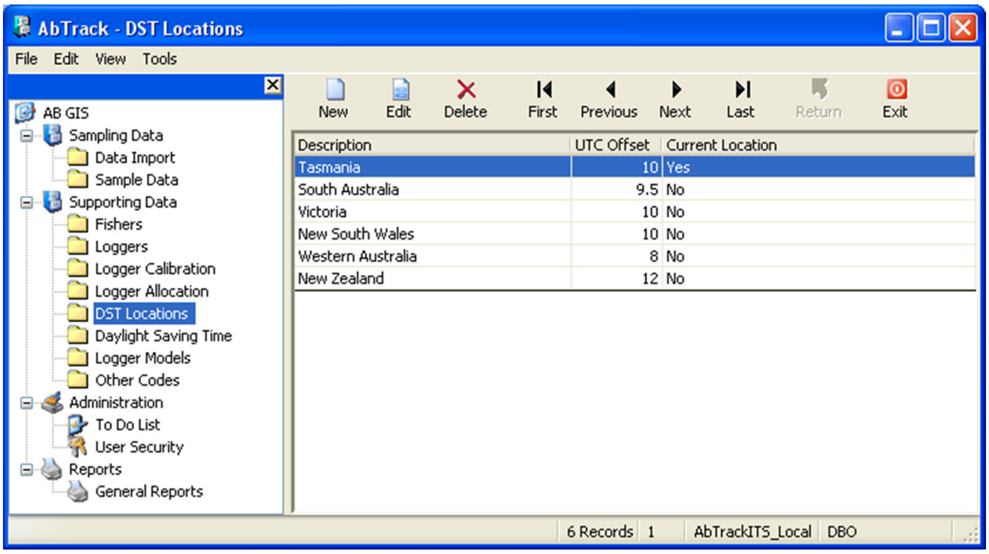

Figure 14. Daylight Savings Location window for setting the current location, to ensure the correct UTC offset is used, and the correct set of Daylight Savings start and end dates are used.

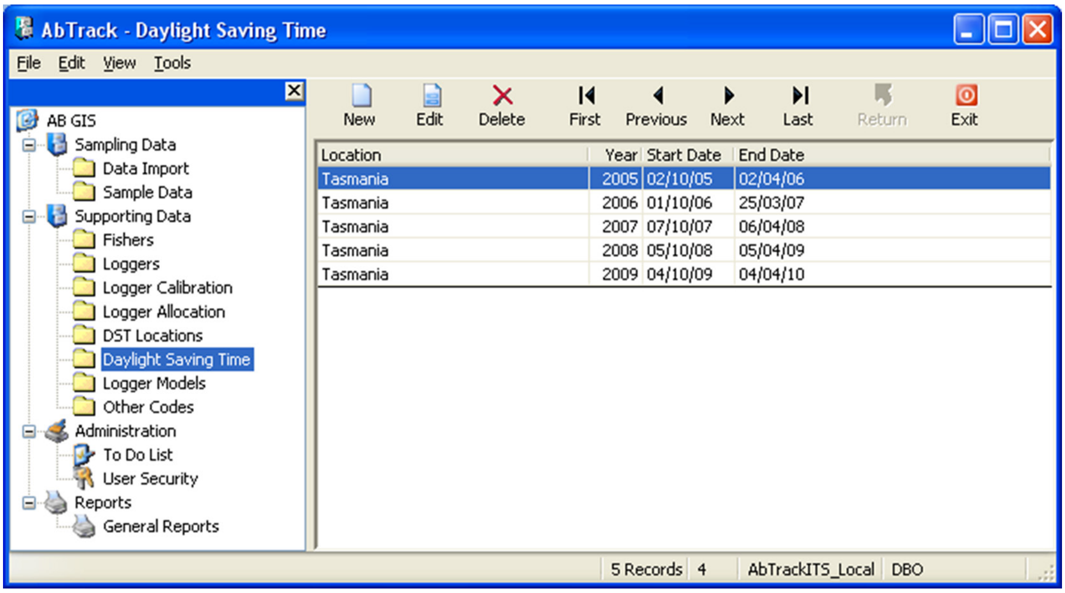

Figure 15. Daylight Savings details window for input of start and end dates for a given state in a specified year.

6.2.2.3.6 <u>Logger Models</u>

The logger model and the associated T-SQL import script are entered into through the Logger Models screen (Figure 16). This must be done before a new type of logger can be registered in the Loggers window (Figure 11). The T-SQL script is relatively straight forward and can be edited and modified by any person with a good understanding of RBDMs and SQL. The script does not require compiling prior to execution.

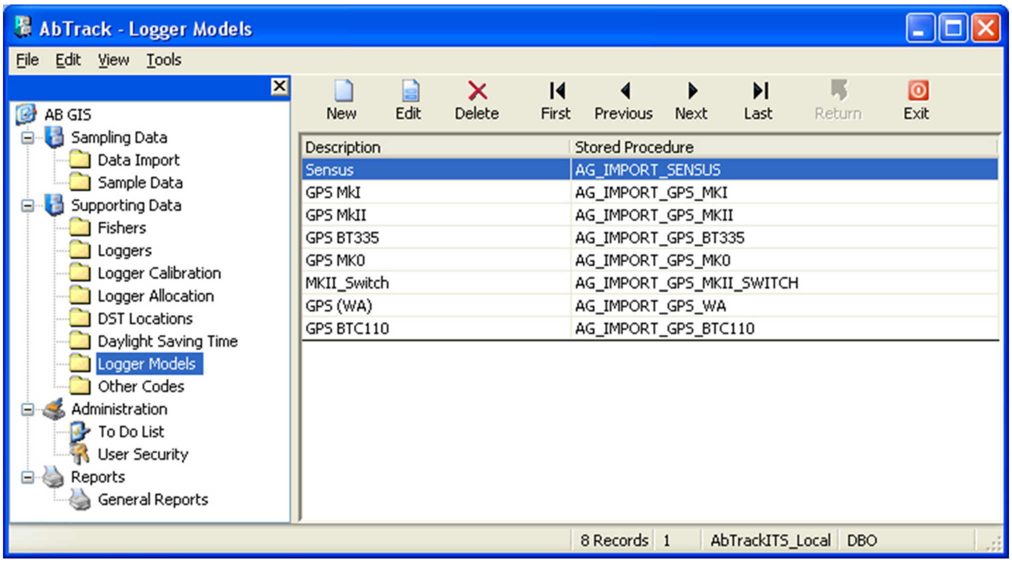

Figure 16. Logger type input window. Model types and the T-SQL import script are recorded through this window.

6.2.2.4 Administration

6.2.2.4.1 To-Do List

The administration section provides options for adding and removing users, and for setting the level of access for different users (admin, read only etc.). This section also provides a ToDo function (Figure 17), where tasks that require attention can be entered, and accessed by all users. Each of the screens above also has a ToDo list at the lowest level. ToDo records created in other screens can also be accessed here.

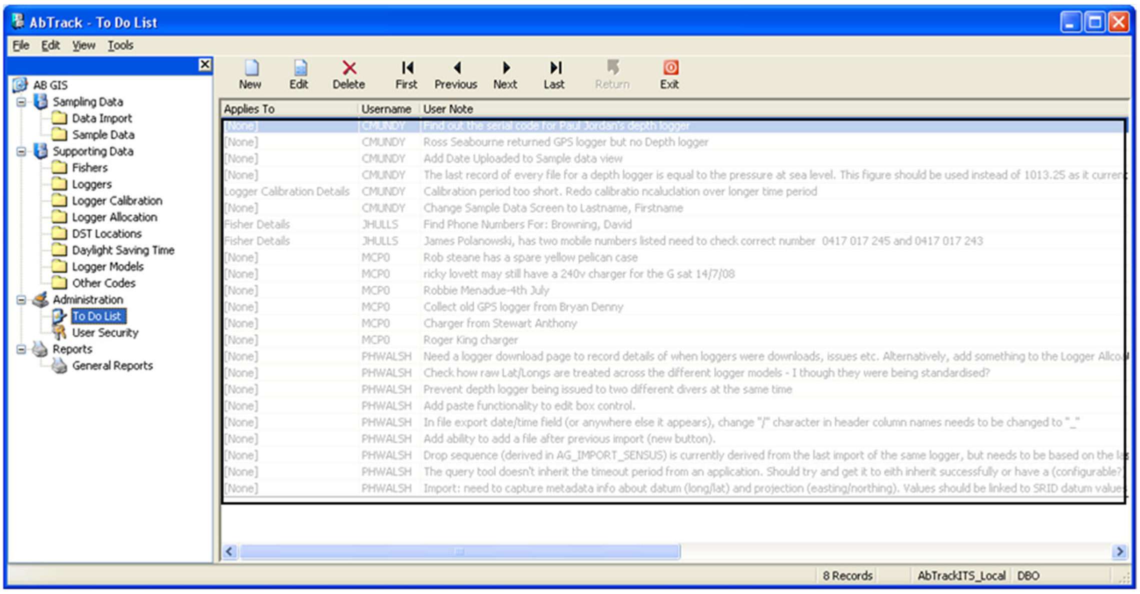

Figure 17. To Do list entry and management screen.

6.3 Calculation of spatial performance Indices: Dive events

The majority of the world's fisheries report catch, effort and location in one or more aggregated forms, such as trip, day, reporting blocks or 1 degree grids. 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 these smaller scales. Processing of data on grid systems has several advantages (see Section 6.4), although certain analyses are not possible, or more difficult when data are processed by grids and grid cells.

The alternative to aggregated sampling, is reporting of fishing activity (effort, catch, location) by discrete fishing event. Reporting of each individual trawl, pot, net shot, hang location, or dive provides greater spatial and temporal resolution of fishing activity, and therefore fishery performance. The downside of reporting at such fine scale however is accuracy. To achieve high resolution fine scale data therefore requires a mechanism that does not significantly impact on the catching sector, and, provides an objective unbiased estimate of the fishing event. This is particularly important in the context of small fishing vessels with limited space to locate sensitive and fragile electronic equipment, and where the crew may be restricted in their movement around the vessel.

The data obtained from a passive GPS position logger provides an excellent raw data platform to capture details (effort and location) of fishing effort in dive fisheries (and could be applicable to any gear type used in small vessel 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, in particular movement in relation to home range size (Cagnacci et al. 2010, Urbano et al. 2010). Two common functions for describing the home range of target animals are Minimum Convex Polygons, and more recently, bivariate Kernel Density Estimators (KDE). KDE functions are now widely accepted as the preferred analytical tool for home range analysis as it generates a more accurate Home Range estimate, and, can provide an estimate of concentration. The KDE algorithm is effectively a function that describes point density in space, and has a broad mathematical background, and is the function chosen in this study to define the area of a dive event.

This aims of this chapter are to a) describe the process for calculating a KDE isopleths, as an descriptor for individual fishing event in the Tasmanian abalone dive fishery, and b) illustrate the metrics and analytical processes that can then be applied to the KDE derived spatial polygon.

6.3.1 Use of bivariate Kernel Density Estimators to define the area fished per dive

The application of Kernel Density Estimators (KDE) for estimating probability densities was first described by (Silverman 1986), and adapted for use in home range analysis by (Worton 1989). A variety of KDE forms have been proposed and tested. Here we use the GPS position data to generate fixed bivariate normal kernel density utilisation distributions (KUD) to produce a polygon that describes an individual fishing event. We also adopt the recommendation of Borger et al. (2006) and use 90% isopleths, rather than the more commonly used 95% isopleth to spatially define each fishing event. Thus the 90% isopleth effectively defines the total activity space for the dive and the 50% isopleth defines the core area of the dive.

The KUDs of the total and core activity space for each dive were calculated using function `hrkde` in the *adehabitat* package (Calenge 2006) for R. Function `hrkde` requires two input data frames, one containing the *xy* coordinates, and the other containing unique identifier for each dive event for batch processing. Two additional parameters must be set, the grid cell size and the smoothing parameter h. In order to compare multiple KUDs, a common grid size and h must be used. In this study, a standard grid cell size of 5m and a smoothing parameter of $h = 7$ is used in the calculation of all KUDs. The script used to generate the KUDs is provided in Box 1. For more detail on the use of KDE for home range analysis, see (Worton 1989, Calenge 2006, Gitzen et al. 2006, Millspaugh et al. 2006, Fieberg 2007).

Box 1. R script to generate Kernel Utilisation Distributions (KUD) using the hrkde function in the R package *adehabitat.*

```
library(adehabitat)
library(shapefiles)

# Read position and id fields from csv file
# Key fields required are Eastings and Northings, and an ID field
abxyid <- read.csv("D:/R_Stuff/RKDE/data.csv", header=TRUE, sep=',', dec='.')

# Generate a standard grid for each individual dive event
# Step 1: Find Min and Max Eastings and Northings, and output to dataframe
MinE <- aggregate(abxyid[,c(6)],by=list(idcd=abxyid$DROP_NUMBER), min)
MaxE <- aggregate(abxyid[,c(6)],by=list(idcd=abxyid$DROP_NUMBER), max)
MinN <- aggregate(abxyid[,c(7)],by=list(idcd=abxyid$DROP_NUMBER), min)
MaxN <- aggregate(abxyid[,c(7)],by=list(idcd=abxyid$DROP_NUMBER), max)

#Step 2: Merge Min/Max Eastings & Northings for each dive into a single list
my.mergelist <- list(MaxE, MinN, MaxN)
grids <- MinE
for ( .df in my.mergelist ) {
  grids <-merge(grids,.df,by.x="idcd", by.y="idcd", all=T)
 }
colnames(grids) <- c("idcd", "MinE","MaxE", "MinN","MaxN")
names(grids)
grids

#summary info about dives if required
abxyidsorted <- abxyid[order(abxyid$DROP_NUMBER),]
numdives <- length(grids[,1])

#Step 4: Set buffer size for grid so that contour isopleths are not truncated
buffer<- 100

#Step 5: Create separate grid for each dive, & output grids as class asc
ascgrid <- lapply(1:numdives, function(i) {
    extent <- data.frame (x=c(grids[i,2] - buffer, grids[i,3] + buffer),
y=c(grids[i,4] - buffer,
    grids[i,5] + buffer))
    ascgen(extent, cellsize=resolution)
  })
names(ascgrid) <- grids[,1]

#Set Grid cell size in metres (for data in Eastings and Northings)
Resolution <- 5

# Create Kernel Utilisation Distributions for each dive event
hrkde <- kernelUD(abxyid[,c("EASTING","NORTHING")],
id=abxyid[,c("DROP_NUMBER")], h=7, grid=ascgrid, same4all=FALSE)

#Create 90% & 50% isopleth contours
hrver90 <- getverticeshr(hrkde, 90)
hrver50 <- getverticeshr(hrkde, 50)

# Export 50% and 90% KUD isopleth polygons to shapefiles
hrver90shape <- kver2shapefile(hrver90)
       write.shapefile(hrver90shape, "D:/R_Stuff/RKDE/abxyid90", arcgis=TRUE)
hrver50shape <- kver2shapefile(hrver50)
       write.shapefile(hrver50shape, "D:/R_Stuff/RKDE/abxyid50", arcgis=TRUE)
```

6.3.1.1 Spatial metrics calculated from KUD isopleths

Following the generation of KUDs (Figure 18) to describe the activity space of a dive, there are several metrics that can be derived from the KUD that can be used as spatial performance measures. These metrics can be easily calculated either within SQL Server using relatively simple SQL scripts. For convenience, these scripts are usually established as a view. Alternatively, the metrics could be calculated within R, or for those willing to wrestle with the larger GIS platforms, within your favourite GIS package.

6.3.1.2 Perimeter/Area ratio as a measure of KUD complexity

The field of fragmentation statistics offers a large number of metrics developed for analysis of fragmentation in forest habitats, both in the context of effect of habitat destruction on animal populations, but also on re-generation and productivity of forest systems. Several of those metrics can be applied to our KUD 90% isopleth polygons. The most useful metric worth pursuing is the corrected perimeter/area ratios (PAC). The PAC ratios are an accepted quantitative metric in the patch analysis literature, and are calculated as;

$$PAC = P \div \sqrt{4 \times pi \times A}$$

Where;
P =perimeter of polygon
pi = Pi constant
A = area of polygon

A perfect circle has a PAC equal to 1, a square has a PAC equal to 1.1, and PAC is very large for polygons that are long and skinny. The value of the PAC can be used in combination with KUD area and length, to characterise the shape of a dive event in the context of the dive time.

6.3.1.3 KUD area and shape parameters

The area of a KUD for a given dive describes the activity space that the diver fished within. It is important to note that the actual area fished by the diver will be considerably less than the area of the KUD. The KUD area, catch and effort associated with a dive could be used to calculate Kg/Ha or Ha/Hour, but these indices should not be considered as a direct index for use in biomass calculation.

The length of the KUD however, provides a meaningful descriptor of the length of reef travelled. Divers frequently talk of having to swim further, and cover a greater length of coast line in the same time to achieve the same catch as abalone abundance declines. Area could also be used in this regard for reef systems that are broader, rather than for example linear strip reefs that closely follow steep cliff lines. Several free tools are available for ArcGIS to calculate polygon length and the width perpendicular to the longest axis. The Enclosing Rectangles function within Manifold GIS will create a rectangle with the longest axis parallel to the major axis of the polygon. A query to determine the length and width of the longest/shortest sides will achieve a similar result.

6.3.1.4 KUD Isopleth ratios as a measure of within dive effort concentration

Depending on the distribution of abalone (clustered or dispersed) on the reefs fished, the ratio of the 50% isopleth area against the 90% isopleth area provides an indication of the degree of concentration of the fishing activity within a dive event. For example if abalones are distributed uniformly or randomly in space then the 50% isopleth should cover approximately 50% of the area fished. Abalones however are typically highly clustered, such that fishing effort will be concentrated in one or more areas within the total area fished (Figure 18).

6.3.1.5 KUD centroid

Analysis of fleet dynamics and fisher decisions in the context of factors such as travel time and cost, CPUE, weather conditions and product value will require a single point representation of the location of a fishing (dive) event. The most appropriate single point representation of a KUD 90% isopleth polygon is the centroid. In the Tasmanian abalone fishery, nomination of the port (boat ramp, wharf) of departure is a requirement of the daily catch docket report to be submitted to DPIPWE. Position coordinates of each approved port, along with centroid of the KUD polygon provides the base data from which fisher harvest strategies can be explored. Polygon centroids can be calculated within any of the major GIS platforms, various packages available for R, or by the native SQL SERVER 2008 function `STCentroid()`.

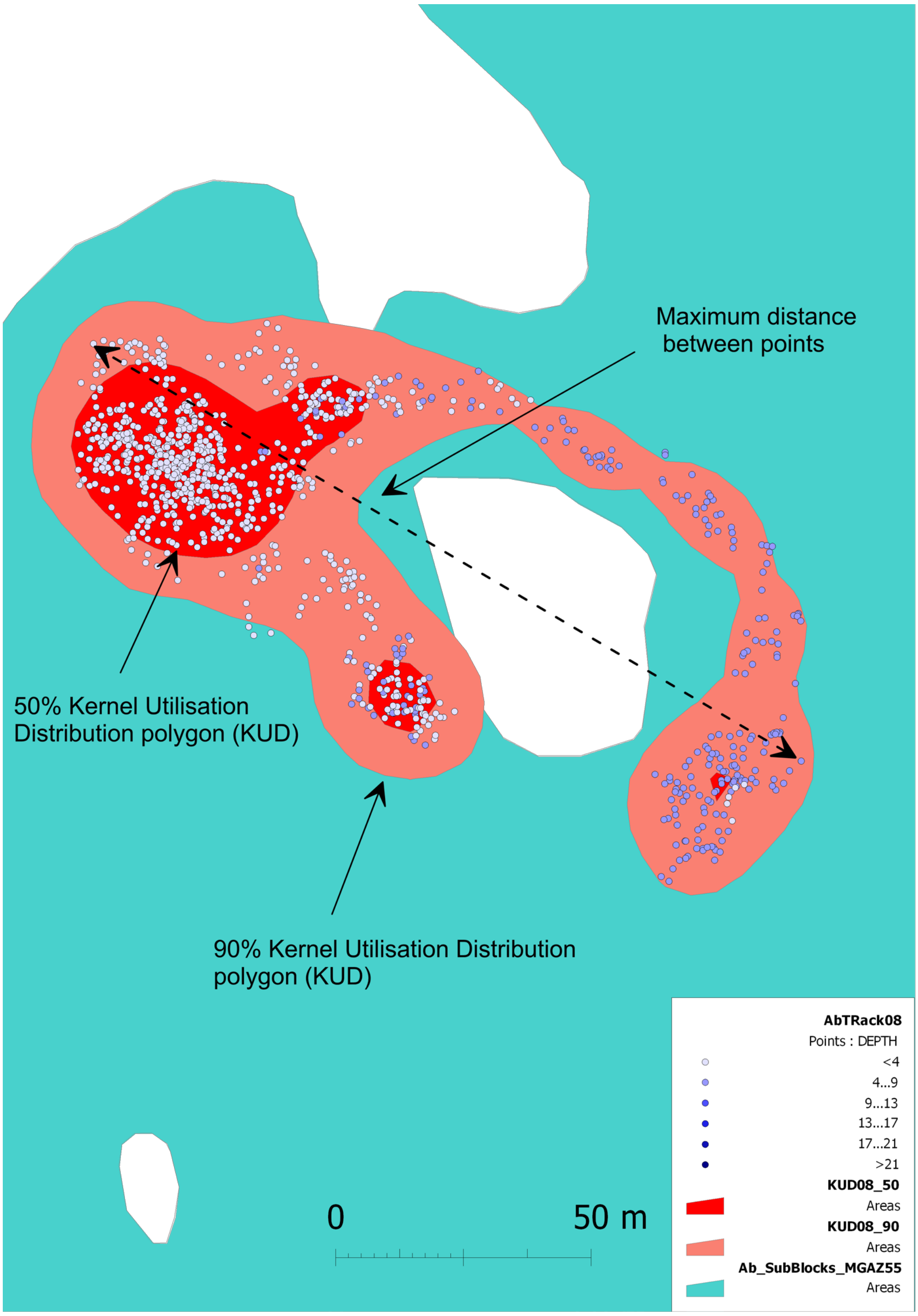

Figure 18. Example of Kernel Utilisation Distribution (KUD). Outer polygon (light red) represents the 90%KUD. Inner polygon (dark red) represents the 50% KUD. Note 50% KUD is represented by three separate polygons located where point density is greatest.

6.3.2 Evaluation of linear indicator variables

6.3.2.1 Sinuosity, Fractals and Mean turning angles

Evaluation of two linear indicator variables has resulted in the rejection of the fractal and sinuosity indices as suitable for performance measures of diver activity. As the data path obtained by the GPS data logger relates to the vessel rather than the diver, it is not feasible to accurately determine the diver path from this data, and fractals or sinuosity should not be used to interpret or ascribe a behavioural pattern to the diver.

The vessel path in order of influence will be driven by wind, swell, deckhand behaviour, abalone abundance, and lastly diver position. There is a possibility however parameters that quantify the complexity of the vessel path could be used as a proxy for wind conditions to provide a parameter to standardise CPUE data. Turning angles and segment length are two parameters that have been used in the analyses of VMS data from trawl fisheries. Further work on the use of these functions extracting information from GPS position data is required, before consideration can be given to using linear parameters as performance measures.

6.4 Calculation of spatial performance Indices: Grid type analyses

While assessing the logic of how to analyse and interpret the GPS data, a grid based approach was developed that takes into account the limitations in spatial resolution of the data, and provides new opportunities for development of spatial performance measures. The two key limitations on interpretation of the spatial data are the inherent accuracy of the GPS receiver (~ 20m), and, that the data represent the vessel track rather than the diver track. By using a grid cell size of 1.Ha (100m x 100m), quantitative data can still be obtained at a scale appropriate to the patch size of abalone, but without over stating the spatial accuracy of the data given the above limitations. At grid cell sizes smaller than 1Ha should be considered with appropriate caution.

Grid based analysis of VMS position and fishery dependent data has been trialled in several fisheries. Most are simple systems based on large scale grids, and typically either map catch through time, for example mapping of the pelagic Tuna fishery around American Samoa (Riolo 2006), or mapping of effort in different trawl fisheries north of the UK (Lee et al. 2010). Some have applied more sophisticated functions to develop spatial indicators (e.g. Woillez et al. 2007) but these primarily involve examining mean location of populations, and the spatial dispersion using calculations of anisotropy and isotropy. Some of the methods trialled by (Woillez et al. 2007) may have application at the smaller scale, although the patchy nature of commercially productive abalone populations may make interpretation of patterns more complex, and will require more data than is currently available.

6.4.1 Description of activity per unit area of reef

The KUD isopleth approach described in section 6.3 is a useful approach to quantify the activity space of a single dive event. An alternate approach to quantifying the exploitation of a resource in a spatial context is to examine activity within a defined area of reef. As the GPS data logger captures data every 10 seconds, every point is equal to 10 seconds of fishing effort. As the catch in kg for the day is also known, a weight in grams can also be attributed to every point. By overlaying the GPS vessel data with a defined grid (e.g. 1hectare grid cell size), standard spatial join functions can be used to look at the dynamics of exploitation within each cell. For example the total number of points within a grid cell multiplied by 10 (= total seconds effort) and divided by 60 returns the total effort in minutes for that cell. Similarly, the sum of the weight value associated with each point returns the total catch in each cell. Through the flexibility of SQL, additional information can be extracted such as the number of different divers active in a cell, the number of days a cell was fished, or the number of times any one diver returned to the cell.

The information derived from the grid approach can then be further utilised to provide a precise description of the extent and patchiness of the fishery, and provide an understanding of the harvest strategy of the fleet, rather than of an individual diver. A key example is documenting ‘hotspots’ where visitation rates are high, and determining whether visitation is a function of convenience (proximity to boat ramp) or productivity. Grid based approaches are common in trawl approaches (e.g. Riolo 2006), but usually because effort and catch reporting structures for pelagic fisheries are grid based, with a cell size of 30 minutes or 1 degree. One of the advantages of the electronic position data collected here is that the grid can be re-scaled to suit the needs of the investigator.

6.4.2 Grid Methods

6.4.2.1 Creating a grid

When creating a grid, it is necessary to decide on the form of the grid. In the case of a grid with square cells, each cell as eight adjacent cells. The distance from the centroid of the centre cell to the centroid of each neighbour cell depends on whether the cell is directly adjacent to the centre cell (i.e. north, south, east or west), or a corner cell (NW, NE, SE, SW). This adds a degree of complexity when exploring the relationships among adjacent cells. The alternative is to use a hexagonal cell, where the distance between the centroid of a cell and the centroid of all neighbouring cells is identical.

For this study, vector grids with hexagon shaped cells were created using the `Repeating shapes` freeware tool for ArcGIS (Jenness 2010). A hexagon grid network extending from the coast to a distance of two kilometres offshore was created for the entire coast of Tasmania and all offshore islands. Similar networks were produced for the New South Wales and South Australian coastlines. A minimum cell size of 1Ha was used for all grids created, which gives an edge length of 62 metres, or a width of 107.45 metres. The vector grids were then imported to MS SQL Server 2008 for processing.

6.4.2.2 Views to extract data from AbTrack and generate a Geometry spatial data type field

The first stage of the process of extracting data from AbTrack for analysis is to construct a query or view to provide a flat table of the information required. Typically the fields of interest will be one or more unique identifiers (Diver name, License code, Drop Number, etc.), a Date/Time field, position in projected form (Eastings and Northings), and any additional attribute data required (Depth, Catch, Vessel Speed etc.). The code to achieve this given in Box 2. The flat table (Table 2) produced from the code in Box 2 forms the basis for all subsequent analyses. For this reason, the SQL code in Box 2 is saved as a permanent View in the SS08 database. The view can then either queried and the result exported to a .csv file for the KDE analyses described in Chapter 6.3, or used in further analyses within MS SQL Server 2008 using native MS SS08 spatial functions.

In order to utilise the spatial capability of SS08, the GPS position (Eastings and Northings) of each individual point must be converted to a Geometry spatial data type field. This is achieved with the native SS08 function `geometry::Point(X, Y, 28355)`. The example code is given in Box 3, and the example output is shown in Table 3. The integer number within brackets (e.g. `28355`) is the SRID value. The SRID is a unique identifier representing the coordinate system of the data. In this case 28355 is the unique integer identify for MGA94 Zone55. The SRID values are based on a coding system developed by the European Petroleum Survey Group (EPSG), and is now the global standard system spatial identifier reference system for most Database and GIS platforms.

Box 2. SQL script to extract data from AbTrack in the form of a flat table suitable for further analysis. This query is saved as a view named `GPSData` in the SS08 database.

```
SELECT
      ROW_NUMBER() OVER (ORDER BY P_GPS.DATE_LOCAL) AS ID,
      P_PER.CODE,
      P_PER.LASTNAME,
      P_PER.FIRSTNAME,
      P_GPS.DATE_LOCAL,
      P_GPS.EASTING,
      P_GPS.NORTHING,
      P_GPS.SPEED,
      P_DEPTH.DROP_NUMBER,
      P_DEPTH.DEPTH,
      P_DEPTH.TEMPERATURE
FROM
      dbo.AG_SAMPLE_GPS AS P_GPS
      INNER JOIN dbo.AG_SAMPLE_DEPTH AS P_DEPTH ON P_GPS.ID =
      P_DEPTH.AG_SAMPLE_GPS_ID
      INNER JOIN  dbo.AG_SAMPLE_FILE AS P_SAMPFILE ON
      P_GPS.AG_SAMPLE_FILE_ID = P_SAMPFILE.ID
      INNER JOIN dbo.AG_SAMPLE AS P_SAMP ON
      P_SAMPFILE.AG_SAMPLE_ID = P_SAMP.ID
      INNER JOIN dbo.CM_PERSON AS P_PER ON P_SAMP.CM_PERSON_ID =
      P_PER.ID
      INNER JOIN dbo.AG_SAMPLE_FILE AS P_SAMPFILE_1 ON
      P_DEPTH.AG_SAMPLE_FILE_ID = P_SAMPFILE_1.ID
      INNER JOIN dbo.AG_SAMPLE AS P_SAMP_1 ON
      P_SAMPFILE_1.AG_SAMPLE_ID = P_SAMP_1.ID
      INNER JOIN dbo.CM_PERSON AS P_PER_1 ON P_SAMP_1.CM_PERSON_ID
      = P_PER_1.ID
WHERE
      (P_SAMPFILE_1.AG_SAMPLE_DEPLOYMENT_TYPE_ID <> 3)
```

Table 2. Example of flat table produced from SQL code in Box 2

ID	CODE	LASTNAME	FIRSTNAME	DATE_LOCAL	EASTING	NORTHING	SPEED	DROP_NUMBER	DEPTH	TEMPERATURE
1	AB007	Dan	Diver	00:50.0	445226.7	5180356.94	1.38	24	2.538	12.37
2	AB007	Dan	Diver	00:50.0	445226.7	5180356.94	1.38	24	3.468	12.37
3	AB007	Dan	Diver	01:00.0	445218.26	5180352.06	1.78	24	2.848	12.37
4	AB007	Dan	Diver	01:00.0	445218.26	5180352.06	1.78	24	2.848	12.37
5	AB007	Dan	Diver	01:10.0	445217.33	5180350.02	0	24	3.158	12.37
6	AB007	Dan	Diver	01:10.0	445217.33	5180350.02	0	24	2.848	12.37
7	AB007	Dan	Diver	01:20.0	445217.47	5180349.09	0	24	2.848	12.37
8	AB007	Dan	Diver	01:20.0	445217.47	5180349.09	0	24	2.848	12.37
9	AB007	Dan	Diver	01:30.0	445217.87	5180349.65	0.37	24	3.158	12.37
10	AB007	Dan	Diver	01:30.0	445217.87	5180349.65	0.37	24	2.848	12.37

Box 3. SQL code to create a spatial Geometry field from Eastings and Northings using the native `geometry::Point()` function.

```
SELECT       ID,
             CODE,
             LASTNAME,
             FIRSTNAME,
             DATE_LOCAL,
             EASTING,
             NORTHING,
             SPEED,
             DEPTH,
             DROP_NUMBER,
             TEMPERATURE,
             geometry::Point(EASTING, NORTHING, 28355) AS GEOM
FROM         Abtrack.dbo.GPSDATA
```

Table 3. Example output from SQL code given in Box 3. A new field (GEOM) stores the Eastings and Northings as a Geometry spatial data field (not shown here) in Well Known Binary (WKB) format.

ID	CODE	LASTNAME	FIRSTNAME	DATE_LOCAL	EASTING	NORTHING	SPEED	DROP_NUMBER	DEPTH	TEMP
1	AB007	Dan	Diver	00:50.0	445226.7	5180356.94	1.38	2.538	24	12.37
2	AB007	Dan	Diver	00:50.0	445226.7	5180356.94	1.38	3.468	24	12.37
3	AB007	Dan	Diver	01:00.0	445218.26	5180352.06	1.78	2.848	24	12.37
4	AB007	Dan	Diver	01:00.0	445218.26	5180352.06	1.78	2.848	24	12.37
5	AB007	Dan	Diver	01:10.0	445217.33	5180350.02	0	3.158	24	12.37
6	AB007	Dan	Diver	01:10.0	445217.33	5180350.02	0	2.848	24	12.37
7	AB007	Dan	Diver	01:20.0	445217.47	5180349.09	0	2.848	24	12.37
8	AB007	Dan	Diver	01:20.0	445217.47	5180349.09	0	2.848	24	12.37
9	AB007	Dan	Diver	01:30.0	445217.87	5180349.65	0.37	3.158	24	12.37
10	AB007	Dan	Diver	01:30.0	445217.87	5180349.65	0.37	2.848	24	12.37

6.4.2.3 *Using spatial queries to conduct grid based analyses of GPS points*

A normal SQL query might find all records where the surname matches a given condition such as;

```
SELECT surname, firstname, birthday, address
FROM STAFF
WHERE Surname = "Mundy"
```

A spatial query uses the spatial relationship between objects to select the desired set of records. Most GIS products offer functions that perform several forms of spatial joins. Spatial joins can the take several forms including the ability to query a spatial database to return all points that are within a specified distance of a line or boundary, or return all points that are contained within a polygon.

The primary analysis of interest here is to quantify the number of points within each grid cell, and to summarise various attributes attached to each point (e.g. calculate the mean depth of all points within each cell). This is achieved by utilising the flexibility of SQL and the spatial query function `STWithin()` available within MS SQL Server 2008. An identical function is available within the open source PostgreSQL database enabled with the open source spatial extension PostGIS. The `STWithin()` function creates a spatial join between the flat table of GPS points created in Box 3, and the hexagon grid table covering the coastal regions of the fishery of interest (see 6.4.2.1).

Where possible, views are used in the batch processing of position information to minimise the production of temporary tables. The grid analysis is done in two parts, an initial view (or query) which generates a flat table with the desired information (e.g. count of points, average depth etc.) referenced by a unique summary (Box 4), and a subsequent View (or query) that links the summary information to a spatial object such as a grid cell via the unique identifier, for visualisation purposes (Box 5).

With most database queries, indexing can dramatically reduce the execution time, and this is just as important for spatial queries. For this reason the SQL code in Box 3 is used to create a new temporary table rather than a view, and a spatial index is created on the Geometry field `GEOM` to maximise the efficiency of subsequent queries using this data set. Spatial indexes also need to be created for the grid network tables, prior to executing any queries.

Visualisation of attribute values (effort, catch etc.) can be achieved by using a colour ramp to indicate various bin classes (Figure 19)

Note: The field `geodb_oid` is an integer code that uniquely identifies each individual grid cell in the grid network table.

Box 4. SQL code to create a spatial join between a table containing individual GPS points and a spatial table containing the hexagon grid. This query is stored as a view `PointCountinHex` in the SS08 database, or can be run as a standalone query.

```
SELECT
      h.geodb_oid,
      COUNT(d.DEPTH) AS pnt_count,
      AVG(d.DEPTH) AS avg_depth,
      COUNT(DISTINCT d.LASTNAME) AS Num_divers,
      COUNT(DISTINCT CONVERT(date, d.DATE_LOCAL, 103)) AS fish_date,
      MIN(CONVERT(date, d.DATE_LOCAL, 103)) AS MinDate
FROM
      CoastInf.dbo.Hex_1Ha AS h INNER JOIN
      AbTrack.dbo.Data_09_07_17 AS d WITH (INDEX (gidx_Data_09_07_17))
      ON d.GEOM.STWithin(h.GEOM) = 1
WHERE
      (YEAR(d.DATE_LOCAL) =   2008)
GROUP BY
      h.geodb_oid
```

Table 4. Example output from code given in Box 4. For each hexagon cell a count of the number of points, the average depth of each point, the number of different divers active, the number of days the cell was fished, and the first date for the year the cell was fished.

geodb_oid	pnt_count	avg_depth	Num_divers	fish_date	MinDate
493825	70	11.420571	1	2	11/03/2008
493987	158	8.202303	3	3	22/02/2008
493988	406	8.668615	2	3	12/03/2008
493989	103	7.343048	3	5	1/02/2008
493990	619	9.562798	3	9	11/03/2008
493991	52	10.964923	1	1	1/10/2008
494153	115	10.919652	1	1	25/09/2008
494154	254	7.987251	2	5	22/02/2008
494155	107	7.360523	2	2	1/02/2008
494156	959	8.988135	3	9	1/02/2008

Box 5. SQL code to visualise the point in polygon count summary data from the code generated in Box 4. This query is stored as a view `PointCountinHexVisual` in the SS08 database, or can be run as a standalone query.

```
SELECT
      h.geodb_oid,
      s.pnt_count,
      s.avg_depth,
      s.Num_divers,
      s.fish_date,
      s.Mindate,
      h.GEOM
FROM  CoastInf.dbo.Hex_1Ha h INNER JOIN AbTrack.dbo.PointCountinHex S
ON h.geodb_oid = S.geodb_oid
```

Table 5. Example output from code given in Box 5.

geodb_oid	pnt_count	avg_depth	Num_divers	fish_date	MinDate
493825	70	11.420571	2	3	11/03/2008
493987	158	8.202303	3	3	22/02/2008
493988	406	8.668615	2	3	12/03/2008
493989	103	7.343048	3	5	1/02/2008
493990	619	9.562798	3	9	11/03/2008
493991	52	10.964923	1	1	1/10/2008
494153	115	10.919652	1	1	25/09/2008
494154	254	7.987251	2	5	22/02/2008
494155	107	7.360523	2	2	1/02/2008
494156	959	8.988135	3	9	1/02/2008

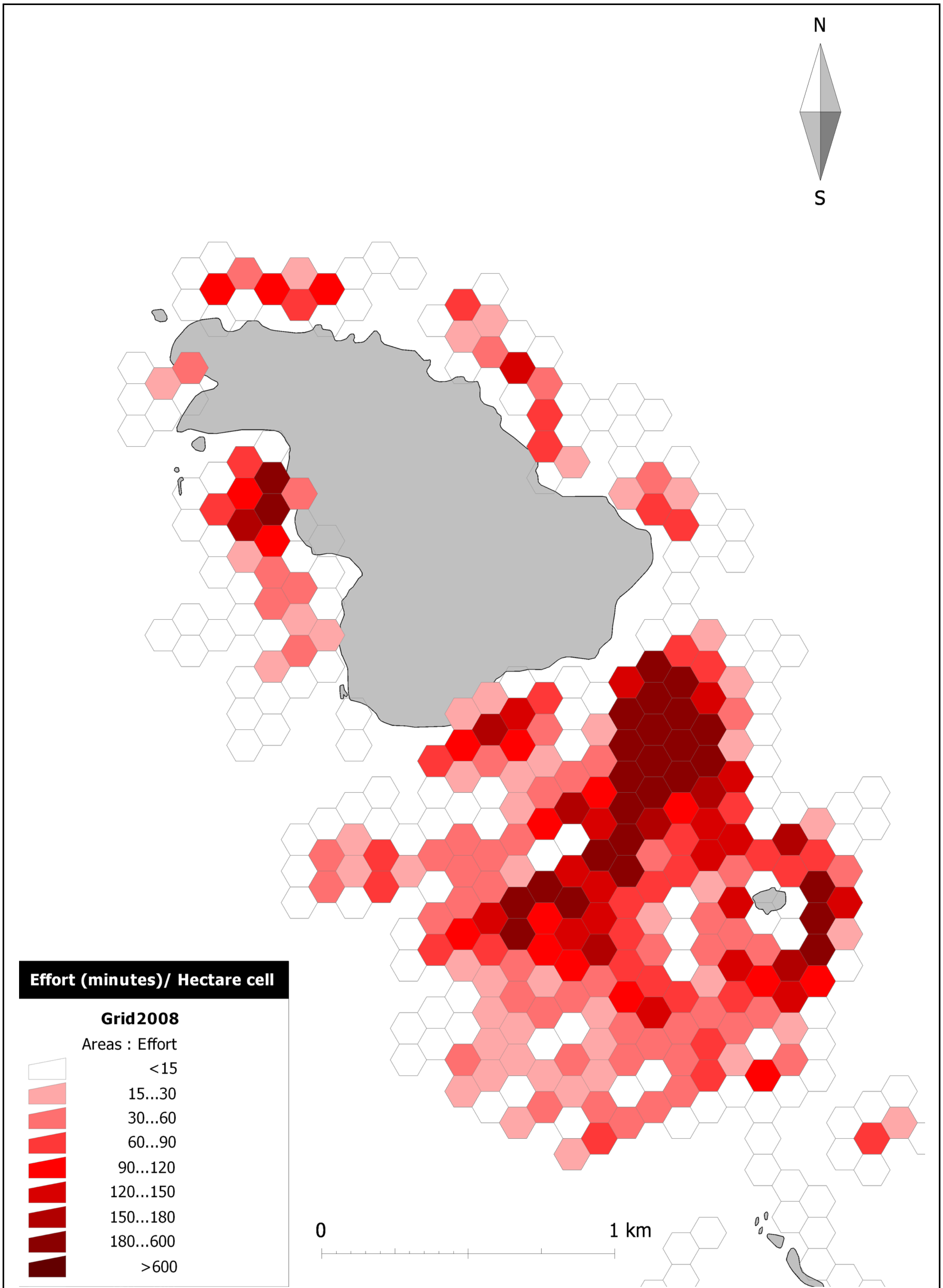

Figure 19. Graphic display of the point-in-polygon analysis achieved through SQL code in Box 2 to Box 5. Cells are colour coded in bins of minutes/cell. Graphic representation prepared in Manifold GIS.

6.5 Case Study: Spatial Performance Measures applied to the North West Tasmania Block 5 Experimental Fishery

If we consider the three essential components of fishery-dependent data in abalone fisheries - catch, effort and the scale of reporting, we can identify the latter two (effort and scale of reporting) as being imprecise or unreliable. Catch is reported accurately, because the catch is weighed at the boat ramp, using certified scales as part of the transfer of catch from diver to abalone processor. For many small-vessel fisheries, the catch and effort reporting required by regulators has remained unchanged for decades. We also recognise that in many circumstances it can be challenging for divers or deckhands to record effort, particularly when there are multiple short drops, with short surface intervals, in rough conditions. Standard dive computers may not be helpful if the time between drops (surface interval) is short, for example less than 5 or 10 mins, as most dive computers will treat these short intervals as part of the previous dive. The biggest issue however with reporting of catch-effort data in the Tasmanian abalone fishery is the mismatch in scale between the area exploited during a dive fishing event (small) and the statistical reporting block or sub-block (very large). For example, even the smallest sub-block might cover more than 20 km^2 or a stretch of coast 15- 20 km long, whereas the average dive length is typically less than. When we receive multiple catch records from the same or different divers for a particular block, we don't know whether some patches are fished multiple times, or whether every dive is in a different location. This is perhaps the key reason why serial depletion can occur in abalone fisheries and why it is difficult to detect

The mismatch between the scale of fishing, the scale of reporting and the capacity of research teams to collect independent data has aptly described this problem as the "Tyranny of Scale" (Prince 2003). Interestingly, all fisheries are inherently spatial in context yet we, fishers, regulators and researchers, have always neglected this critical component in fisheries reporting and assessment? Fine-scale data on fishing activity was sought from Tasmanian fishers in 2002, but it was clearly an impractical and largely impossible task for the industry to achieve manually. With affordable, easy-to-use technology and the right analytical skills high quality and high resolution space and time data can be achieved. This then has the potential to provide a powerful tool to examine both fishery and fleet dynamics in small-vessel fisheries, particularly those susceptible to serial depletion. Here we describe a range of quantitative metrics that can be derived from geo-referenced fishery-dependent data.

6.5.1 Block 5 Experimental Fishery

The catch history for Block 5 North-West Tasmania has fluctuated greatly over the past three decades (Figure 20). Catch taken has varied as a consequence of stock rise and decline, imposition of quota, introduction of spatial zoning, change to the minimum legal size limit, and the perceived low suitability of abalone from this area for the live market. Major reductions in catch through the late 1980's were a consequence of stock decline, size limit increases and quota reductions, and continued low catches in the 2000's were largely due to live market issues. The increased catch in 2008 to 2010 is a consequence of management initiated re-distribution of effort and TAC into Block 5, and a size limit reduction.

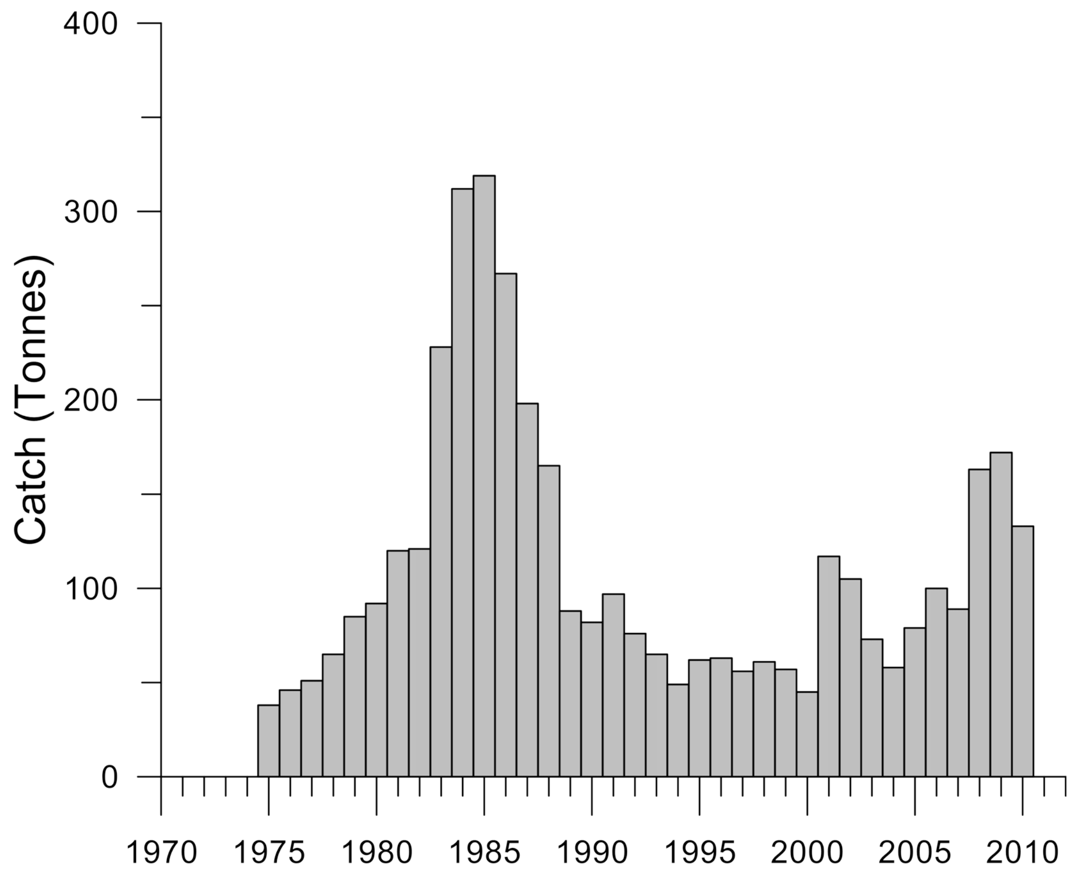

Figure 20. Catch history for Block 5, North West Tasmania

An argument was made by a key industry member that the peak catches in the early 1980's were sustainable, and that the large subsequent reductions were a consequence of size limit increases, and not due to stock declines. Growth rates of populations in this area vary over a broad range within short spatial proximity, and identifying a single 'compromise' size limit is problematic. To address the industry proposal, an experimental fishery for Block 5 commenced in 2008, with a size limit reduction from 132mm MLL to 127mm MLL, and the block catch lifted to a maximum of 150 tonnes, which is approximately 50 tonnes greater than the average annual catch over the previous decade.

6.5.2 Mandatory use of loggers

As part of the Block 5 Experimental Fishery, fishers had the opportunity to fish at the reduced size limit of 127mm MLL, provided they obtained a permit from Fisheries Branch, DPIPWE to fish at the lower size limit, and, that they carried a functioning GPS data logger and a depth data logger. Fishers could choose to not use the logger equipment, and continue to fish this area at the established size limit of 132mm MLL. The Block 5 Experimental Fishery commenced in 2008, and continues in 2011. Data are presented for the period 2008 to 2010.

Fishers were able to collect or exchange Logger kits at the DPIPWE Fisheries Licence Office or by direct post from IMAS-FAC where fishers did not reside in Hobart.

6.5.3 Logger configuration

The GPS and depth loggers had a pre-set recording interval of 10 seconds. Returned loggers were downloaded and data uploaded to AbTrack database.

6.5.4 Spatial performance measures

A list of potentially useful spatial performance indices (SPI) based on geo-referenced fishery-dependent diver data is provided in Table 6. The SPI's are grouped according to interest in either quantifying the parameters associated with each discrete dive event (Section 6.3) or quantifying the fishing activity at a specific geographic location (Section 6.4). These SPI's were chosen for their potential to quantify spatial aspects of diver fishing patterns that are suggested to change with change in stock abundance. For example shifts into deeper or shallow water as populations are exploited, length of shore accessed (max length of vessel footprint, area of vessel footprint), or measures of spatial effort concentration within a dive (KDI).

Table 6. List of current and new spatial performance measures planned for the Tasmanian abalone fishery, based on live fishing practices with vessels utilising GPS and diver depth loggers recording at 10 second intervals.

	Metric	**Method**	**Spatial Scale**
Current	Catch	Manual Docket	Block
Current	CPUE	Manual Docket	Block
New	KUD Area KUD Length KDI effort concentration indice KUD shape metrics Proximity/Nearest neighbour	GPS & Depth loggers	Dive Event
New	Number of cells fished Frequency distribution of cells fished Divers/cell Days Fished/cell Mean depth/cell Effort/cell Effort spread/cell ~Catch/cell	GPS & Depth loggers, & Manual Docket	1Ha Grid Cell (flexible)
New	Reef or cell replenishment time	GPS & Depth loggers, & Manual Docket	1Ha Grid Cell (flexible)
New	Distribution of Effort with depth	Depth logger	1Ha Grid Cell (flexible)

6.5.4.1 Local Indicators of Spatial Autocorrelation (LISA) and Local Spatial Clustering

Abalone abundance is well known to vary over several spatial scales. Abalone fisheries are typically characterised by regional scale variation in abundance and productivity, as well as a high level of patchiness at very small spatial scales (10s of meters). A key issue of concern with existing reporting systems for abalone fisheries is the inability to identify spatial contraction in the area that supports commercial abalone fishing, and, whether anecdotal reports of contraction are permanent.

Classic spatial autocorrelation metrics Moran's I and Geary's C provide a measure of global spatial structure and scaling within a dataset, but do not enable identification of local spatial clusters. Over the past two decades several methods were developed to quantify spatial structure at local scales (Premo 2004). LocalG/LocalG* (Getis and Ord 1992, Ord and Getis 1995, Sokal et al. 1998) provides a relative measure of the sum of neighbourhood values (Premo 2004) i.e. a local clustering of high or low values. LocalMoran's I (*Ii*) provides a measure of similarity between a target point and the neighbouring points (Anselin 1995, Premo 2004), and is often referred to as Local Indicator of Spatial Autocorrelation (LISA).

Here, we use the Getis-Ord statistic (G_i*) and LocalMorans I (I_i) using R (R Development Core Team 2011) and the spatial analysis package `spdep` (Bivand et al. 2011). The LISA and Local spatial clustering techniques are applied here to identify 'Hot Spot' locations in the fishery, quantify change in location and size of the hot spots through time. Data used in this analysis utilised the grid methods outlined in Section 6.4. The centroid of each hex cell provides the spatial information and the numeric variable of interest was minutes of effort logged in each cell. A nearest neighbour distance of 300m was used for both *G** and *Ii* (Box 6)

Box 6. R script to generate LISA values. This script imports data from AbTrack, and uses the *spdep* package to calculate LocalG, LocalG* (including pivot cell), LocalMorans I, and outputs the result to a shapefile.

```
library(spdep) #Load required libraries
library(RODBC)
library(sp)
library(rgdal)

#Suck in centroid values from hexgrid table in AbTRack to a dataframe via ODBC
channel1 <- odbcConnect('AbTRackAnalysis') #Establish ODBC connection
centroids  <- "Select Geom.STCentroid().STX as Easting, Geom.STCentroid().STY as
Northing, Pnt_Count, Effort, Num_Divers, Fish_Date, geodb_oid
           from AbTrackAnalysis.dbo.Grid2010
           ORDER BY geodb_oid"
xycent <- sqlQuery(channel1, centroids)
close(channel1)

#Make col names Shapefile friendly (i.e. <= 8 characters)
colnames(xycent) <- c('Easting', 'Northing','Pnt_Cnt', 'Effort', 'N_Dvrs',
'Fsh_Days',    'geodb_oid')
#Set GeoID as rowname (transfers through to the SpatialPointsDataFrame)
row.names(xycent) <-xycent$geodb_oid

#Convert dataframe to class SpatialPointsDataFrame
#reminder: make sure x,y fields are the first two fields in xycent
spcent <- SpatialPointsDataFrame(xycent[c("Easting","Northing")],
xycent[c("Pnt_Cnt", "Effort", "N_Dvrs","Fsh_Days","geodb_oid")], match.ID = TRUE )
proj4string(spcent) <- CRS(SRID)
SRID <- "+init=epsg:28355" #Set variables

#Create a nearest neighbor object (class nb) using dnearneigh or knearneigh
#need to decide on distance to search for neighbors, or the number of neighbors.
# A distance band of 250m will include two rings of hex cells around the pivot.
dnb300 <- dnearneigh(spcent, 0, 250)
#knb12 <-knearneigh(spcent, k=12, RANN=TRUE)

#LOCALG
# Local G including the pivot cell (include.self function)
G300s <- localG(spcent$Pnt_Cnt, nb2listw(include.self(dnb300), style="B",
zero.policy=TRUE), zero.policy=TRUE)

#LOCALMORAN
lm300 <- localmoran(spcent$Pnt_Cnt, nb2listw(dnb300, style="B",
zero.policy=TRUE),zero.policy=TRUE, p.adjust.method="bonferroni")

#bind LocalG & LOCALMoran fields with SPatialPointsDataFrame
spcent@data$G300 <- as.vector(G300[])
spcent@data$G300s <- as.vector(G300s[])
lm300df <-  as.data.frame(lm300[])
colnames(lm300df) <- c('Ii', 'E_Ii','Var_Ii', 'Z_Ii', 'Pr_z')
spcent@data$Ii <- lm300df$Ii
spcent@data$E_Ii <- lm300df$E_Ii
spcent@data$Var_Ii <- lm300df$Var_Ii
spcent@data$Z_Ii <- lm300df$Z_Ii
spcent@data$Pr_z <- lm300df$Pr_z

#Write to Shapefile
writeOGR(spcent, dsn=paste('D:/Abtrack/SpatialEDA/Block5/', 'LISA10_300.shp',
sep='/'), layer='spcent', driver='ESRI Shapefile' )
```

7. Results and Discussion

7.1 Evaluation of Effort data obtained from Sensus depth/time loggers

To understand the accuracy that effort was been reported in the Tasmanian Abalone Fishery, daily effort data (hours) derived from logbook and depth logger sources from divers with fishing experience ranging from more than 20 years to just a few weeks were compared. Interestingly, there was a broad range of differences in the average difference in effort reported manually by the divers and the effort captured using electronic depth loggers. Importantly, years of fishing experience was not a good predictor of the accuracy to which divers logged their effort (Figure 21). When the two different effort data sources were then used to calculate CPUE, again the patterns suggest fishing experience was not a good indicator of reliability of manual recording of fishing effort (Figure 22). Importantly, the magnitude of the difference is considerable, with variation in greater than 30Kg/hr observed between manual and electronic effort records. One consistent pattern however, was that most divers, and particularly the more experience divers, tended to overestimate the actual effort expended in fishing (Figure 23).

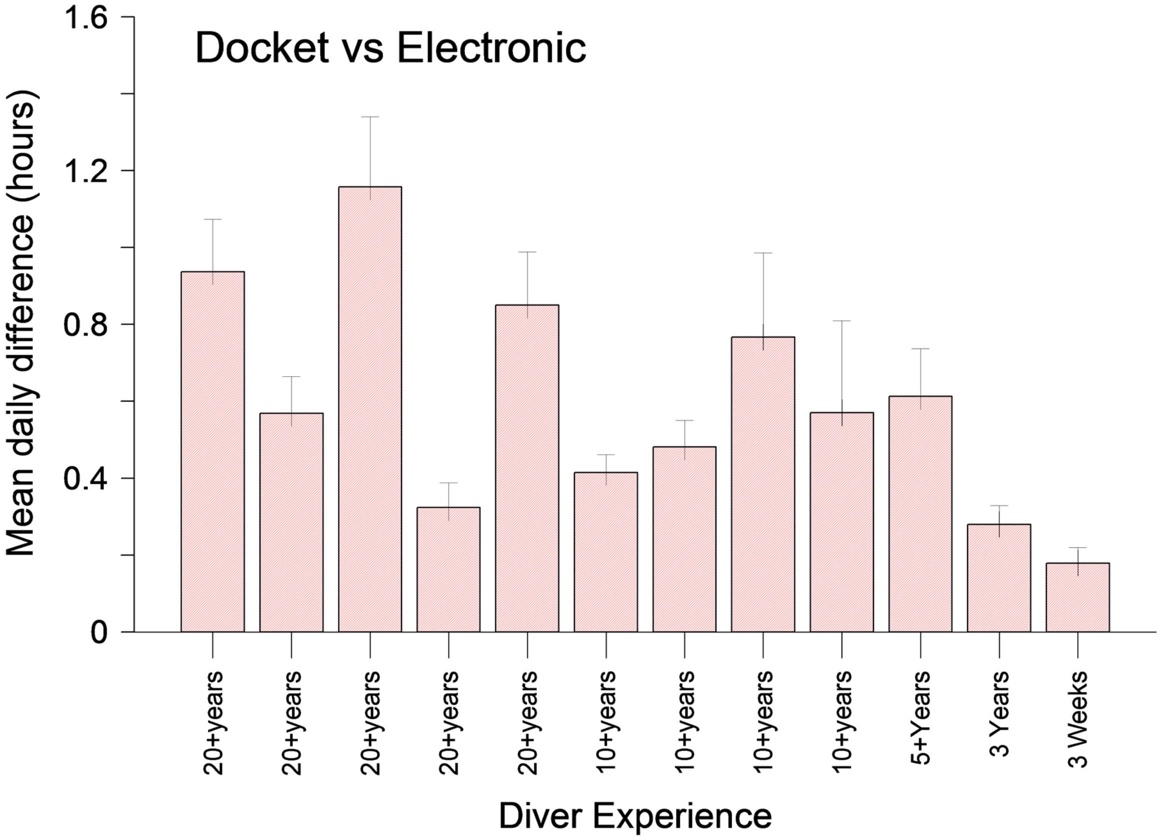

Figure 21. Mean daily difference (hours) between logbook effort data and depth logger data, for 12 divers with varying levels of abalone fishing experience

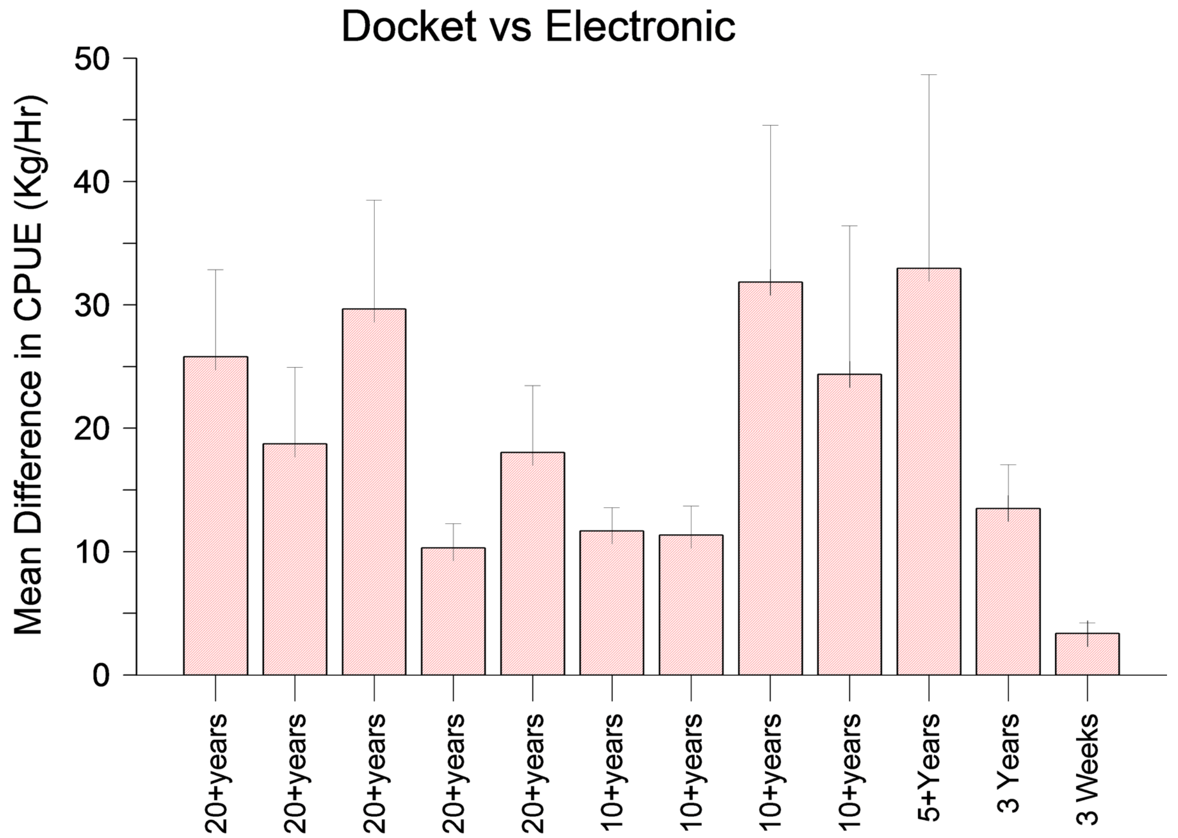

Figure 22. Average difference in CPUE calculated using manual and electronic systems, for 12 divers with varying levels of experience in the Tasmanian abalone fishery. The absolute difference value was used in these calculations.

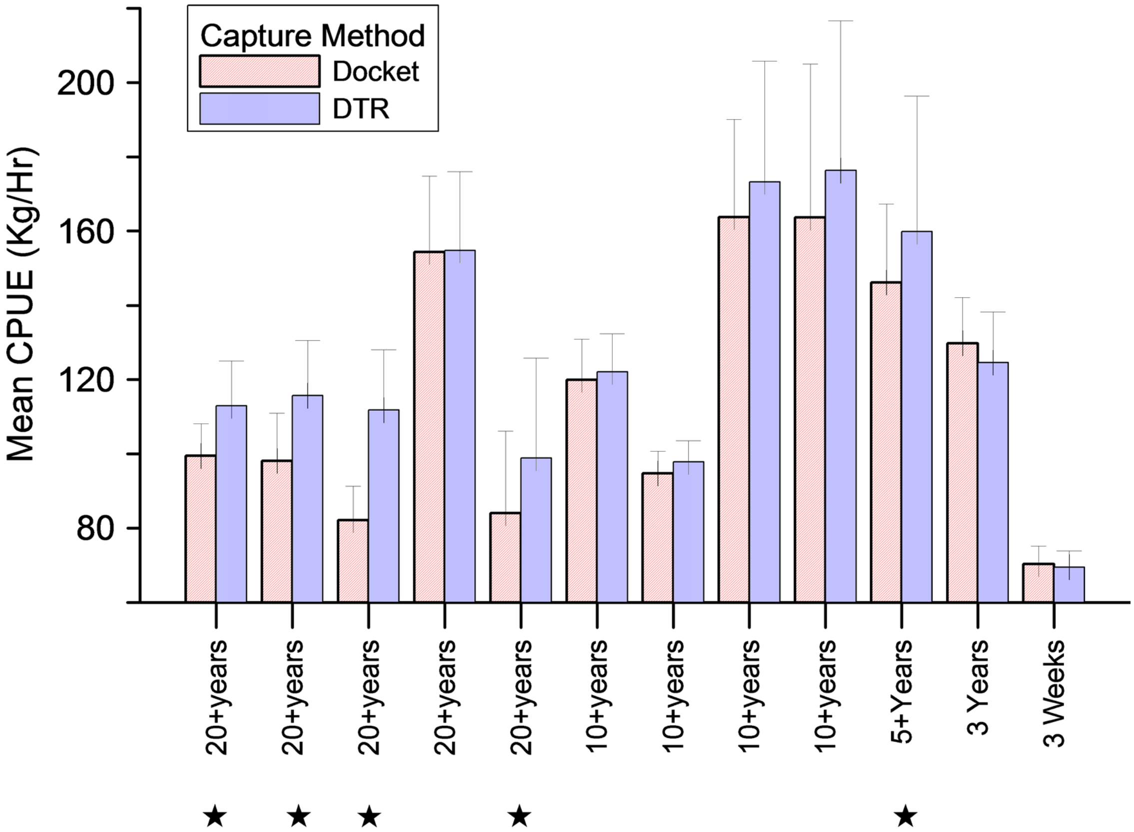

Figure 23. Mean CPUE calculated from manually recorded effort on diver dockets, and the Sensus Ultra depth loggers, for 12 divers with varying levels of experience in the Tasmanian abalone fishery.

7.2 Logger hardware recommendations

7.2.1 GPS hardware issues

Power supply issues have been the single most significant issue with implementing GPS data loggers in the Tasmanian abalone fisheries. Significant corrosion of terminals, leads and copper wires were experienced with the initial externally powered units, and drove the development of internal battery powered GPS loggers. A flow on consequence of the requirement for internal battery systems is that battery capacity is limited by the available space within the logger housing. Thus battery life is now the key limiting factor. The NiMH battery cells used in the SciElex MKII GPS loggers have had an unacceptable high failure rate, and the continued use of NiMH batteries will be avoided where possible. Sealed lead acid batteries offer an unacceptably low weight to power storage ratio, and are not seen as a viable alternative to NiMH. Access to affordable lithium ion battery technology is much cheaper now (2009) than at the commencement of the study. Compact battery capacities of

600 to 6000 mAh are now affordable options for GPS hardware, and combined with low power GPS receiver chips will provide a runtime of about 20 to 200 hours depending on capacity. There are however safety issues associated with the use of Lithium Ion battery cells, as they are less stable at high temperatures, and have lower impact resistance.

By keeping the logger capacity to a minimum, power supply issues can be adequately addressed now using lithium ion or Lithium polymer battery technology. However, if the GPS Logger hardware evolves towards an electronic logbook with LCD screens and keypad input (as trialled with the SciElex MKII GPS loggers), then power supply issues will need to be revisited for situations where the catcher vessel has no on-board 12v power.

7.2.2 Sensus depth/temperature logger hardware issues

The depth loggers produced by Reefnet have been very reliable, with a failure rate of less than 1% out of 150 loggers over 3 years. Comparable depth/time loggers produced by Star-Oddi (DST Centi TD) are available, although the Star Oddi 7 times more expensive (~ US$700/logger). Local companies are unable to produce a comparable commercial product at a competitive price, and the ReefNet loggers continue to be the unit of choice.

7.2.3 GPS and Depth logger overview

The key weakness in the solutions currently adopted and operational in Tasmanian, New South Wales and South Australia is loss of the depth loggers. The depth logger provides several functions: accurate recording of effort and depth, and, through the date/time stamp, identifying the segment of the GPS position track when divers are fishing. Initial attempts to have deckhands record entry/exit from the water using buttons on the GPS loggers were inadequate as deckhands frequently forget to identify the diver has entering or exiting the water, particularly under difficult or challenging sea conditions. It was for this reason that the depth loggers were incorporated, as the automated the process of identifying when divers were in the water fishing, and when they were travelling between dive sites.

A potential solution to this problem is to consider numerical algorithms to classify the GPS vessel path as fishing or travelling (*see Appendix 5: Classification Tool to decode GPS stream into 'dive' and 'travel' segments in the absence of Depth logger data*.). Vessel speed is very effective in this regard, although the addition of step length and turning angles should improve the classification process. Developing classification algorithms using turning-angle, step length and vessel speed data is a high priority for any further research on the use of GPS and depth loggers in dive fisheries. The classification algorithms will also have application for small vessels using other gear types such as trapping, potting and line fishing.

Future GPS logger designs should consider a USB based connection where the logger appears as an external drive, much the same as a portable USB memory stick, and utilise a customisable configuration file. This would alleviate many of the problems associated with a download interface, and increase the ease with which multiple parties can download data and transfer the contents of the logger to a safe data repository. Power supply issues may be assisted with small solar charging systems, particular as the development of micro GPS receivers for mobile devices has also significantly reduced the power requirements of the receiver.

7.3 Case Study: Spatial Performance Measures applied to the North West Tasmania Block 5 Experimental Fishery

7.3.1 Logger use

Logger uptake was relatively high, with over loggers issued to over 60 divers in 2008, for fishing under the experimental fishery in Block 5. Failure to turn loggers on, battery charge issues, hardware faults, loss of loggers and corrupted data all contributed to a loss of data in all three years of the study reported here (Table 7). The return time frame of loggers was highly variable, with loggers returned within days of the completion of fishing, to several years after fishing. No return time frame was specified in the experimental permit conditions.

A further complication in data processing in this experimental fishery was the unexpected relatively high level of team-diving, whereby two divers worked from the same tender, each using a depth logger but using only single a GPS logger. This practice was within the regulations and the experimental permit conditions, but made attribution of data to individual divers too complicated to resolve easily. Thus without substantial manual processing, much of the data reflects team dive activity, and much of the apparent missing data relates to the team dive operation with a single GPS logger.

Table 7. Number of divers that reported catch from Block 5 between 2008 and 2010 and the number of divers where GPS and depth data were obtained.

	Docket	GPS
Year	Number of Divers	Number of Divers
2008	61	30
2009	67	35
2010	57	21

7.3.2 Catch and Catch Rate changes within Block 5

The level of catch harvested varied across the sub-blocks (5A, 5B, 5C) within the Block 5 experimental fishery, and, the pattern also changed over the three year study period (Figure 24a). Catch in sub-block 5B was relatively uniform across the three years, whereas catch from sub-blocks 5A and 5C varied substantially. In contrast, catch rates varied little across the three years. A small reduction of approximately 10 Kg/Hr was observed in sub-blocks 5A and 5C between 2009 and 2010 (Figure 24b). A similar catch rate reduction was observed in sub-block 5B between 2008 and 2009, which was maintained into 2010. The average dive duration declined across the three study years in all three sub-blocks (Figure 24c). The number of dives (drops) per day in sub-block 5A was constant through the study period at an average of three drops/day (Figure 24d). The number of drops/day in sub-block 5B increased from an average of 2/day to 4/day over the study period, whereas the drops/day in sub-block 5C only increased from an average of 3/day to 4/day in the final year (2010).

7.3.3 Spatial Performance Indices - comparison across sub-blocks 5A to 5C

A selection of spatial performance indices were calculated from the geo-referenced diver data and summarised by year and by sub-block. The number of cells where activity was logged and considered to contribute significantly to the catch, declined in 5A and 5B, but not 5C (Figure 25). Sub-blocks 5A and 5C were comparable across most SPI's with the exception of depth (Figure 29a), where the mean depth of dives was marginally lower, and more consistent in sub-block 5A than in 5B or 5C. SPI's for sub-block 5B typically were different from both 5A and 5B. In sub-block 5B, abalone were more concentrated than in the other sub-blocks: it had the lowest catch, but the highest catch per unit effort (CPUE) (Figure 24), and the catch was taken from proportionally fewer cells (Figure 25).

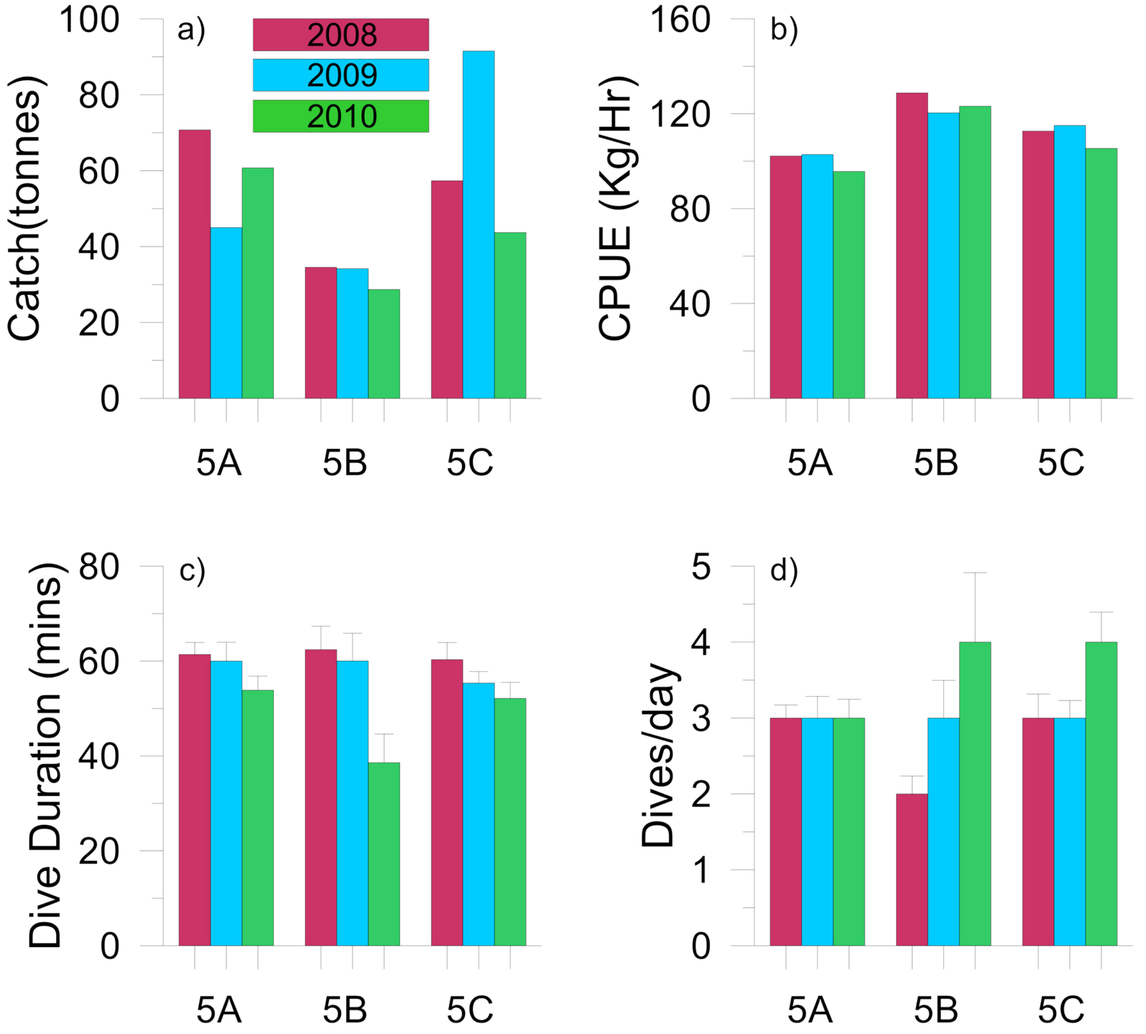

Figure 24. Summary information on a) Catch, b) Catch Rate, c) mean dive duration, and d) mean number of dives/day across the fleet for the Bock 5 Experimental Fishery. Catch and Catch Rate data are derived from quota docket returns provided by the abalone divers. Dive duration and number of dives/day obtained from depth data loggers. Error bars indicated Standard Errors.

The temporal pattern in the proportion of cells with effort between 10 and 15 minutes per cell, and up to 30 minutes per cell was not consistent in the three sub-blocks. In sub block 5A, there as increase in the number of cells fished for 15min and 30 min over the three year study period, and a coincident decline in the number of cells fished for 60 minutes or more (Figure 26). A different pattern was observed in sub-block 5B, with a decrease in the number of cells fished for less than 15min in each year, and an increase in the number of cells fished for 30 minutes and 60 minutes (Figure 27). In sub-block 5C the number of cells fished for 15minutes or less was stable across the three years, with a substantial increase in the number of cells fished for 30minutes or less, and a reduction in the proportion of cells fished at greater levels of effort across the three years.

The mean vessel footprint/dive derived from the KUD (Figure 29c) and longest axis of each dive event in 5B (Figure 29e) was shorter on average than in either 5A or 5C, and distance from the coast to the centroid of each dive event was shorter than for sub-blocks 5A and 5C (Figure 29b). This pattern is consistent with reefs in this part of the coast dropping away more quickly, rather than the more gentle shelving reefs in 5A and 5C. PAC and KDI indices which characterise dive event shape complexity effort concentration however, were comparable across all sub-three blocks.

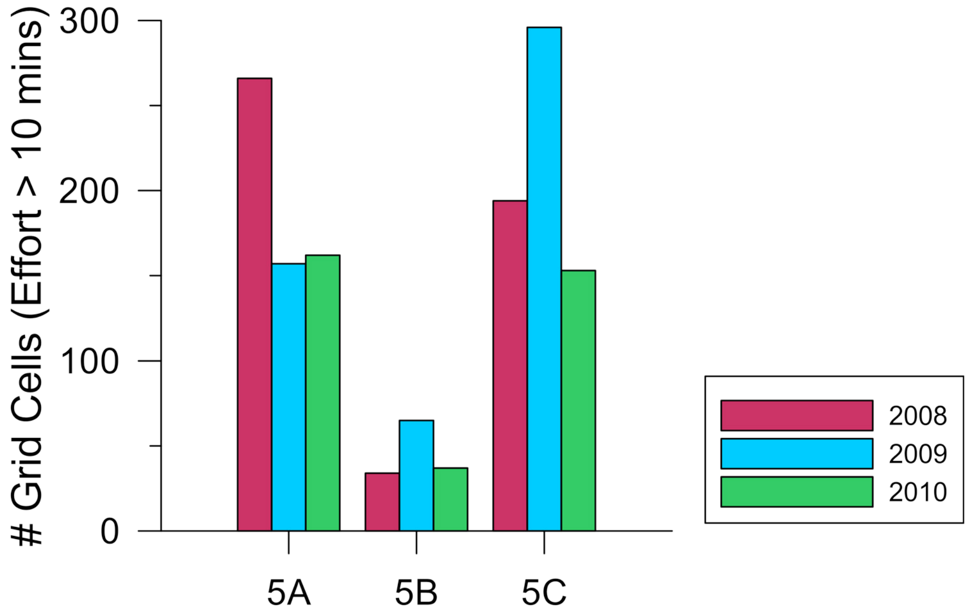

Figure 25. Number of Hex cells where >10 minutes of fishing effort was logged.

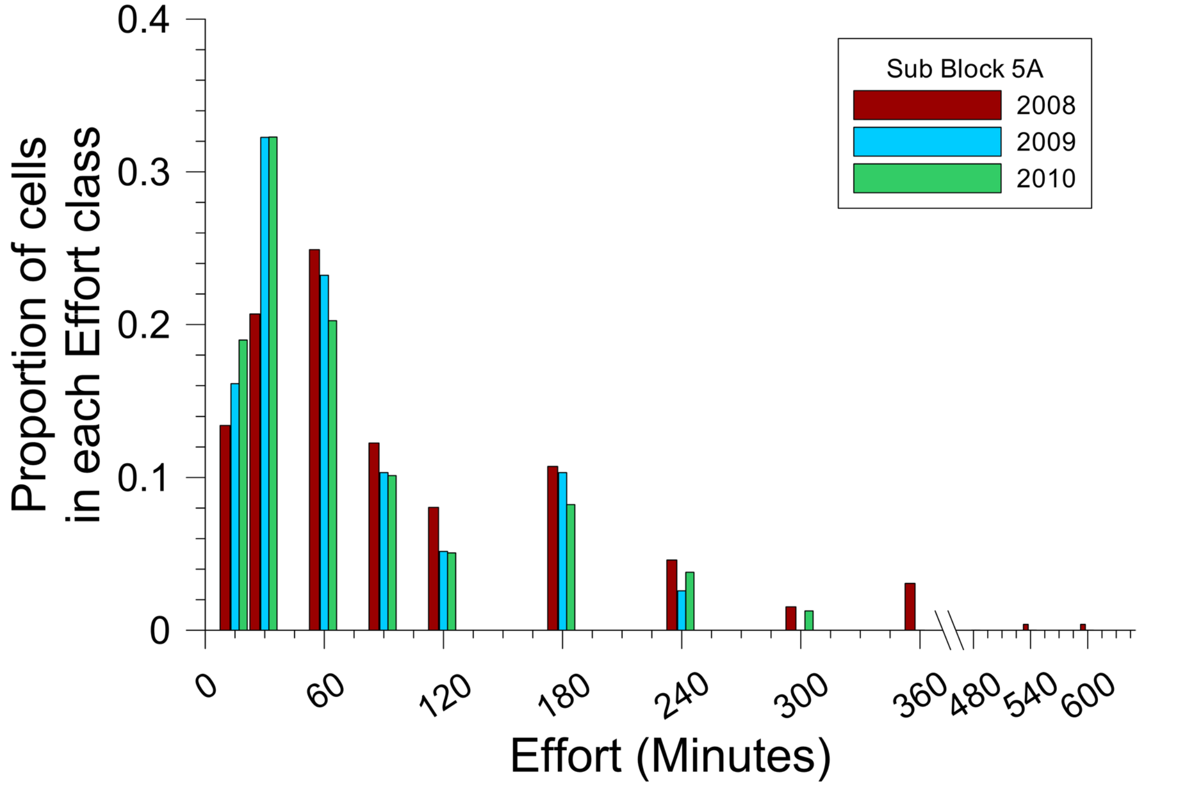

Figure 26. Proportion of cells fished in Sub Block 5A. The first two bin classes are 15min and 30min. All cells with less than 10min of logged effort are excluded from this analysis.

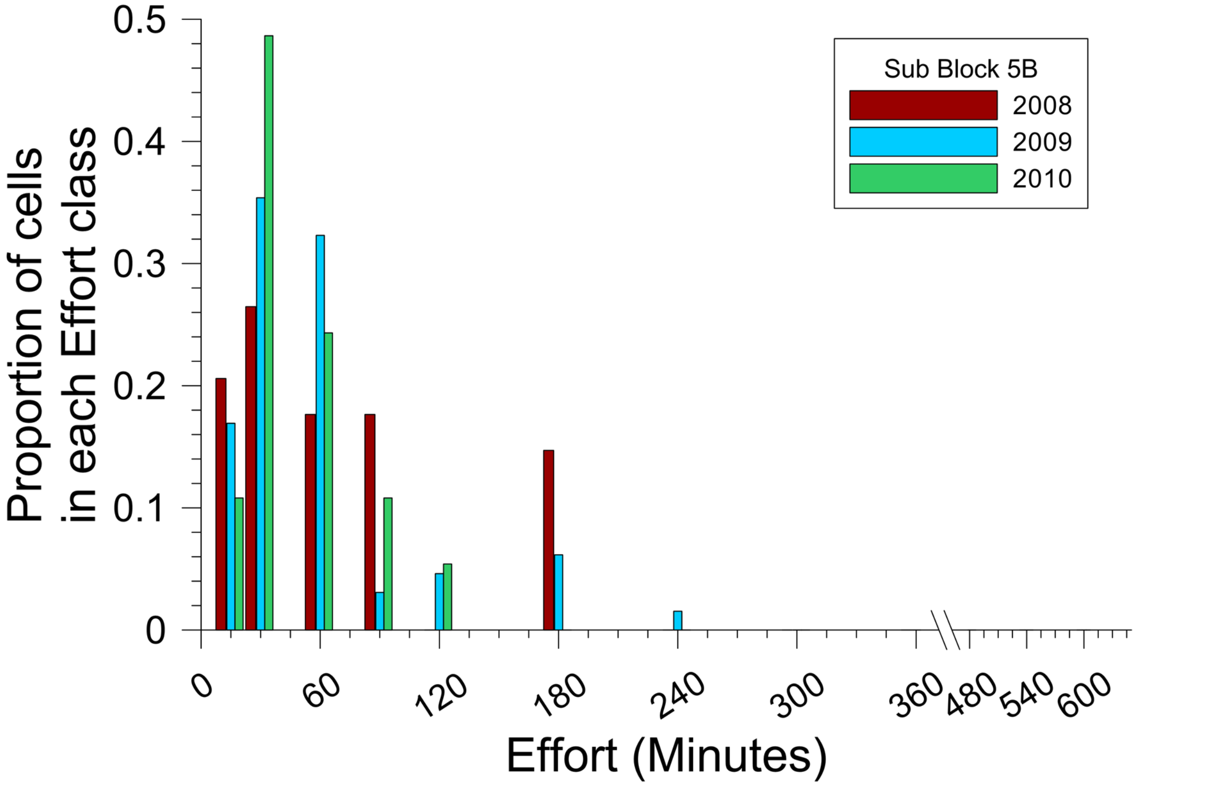

Figure 27. Proportion of cells fished in Sub Block 5B. The first two bin classes are 15min and 30min. All cells with less than 10min of logged effort are excluded from this analysis.

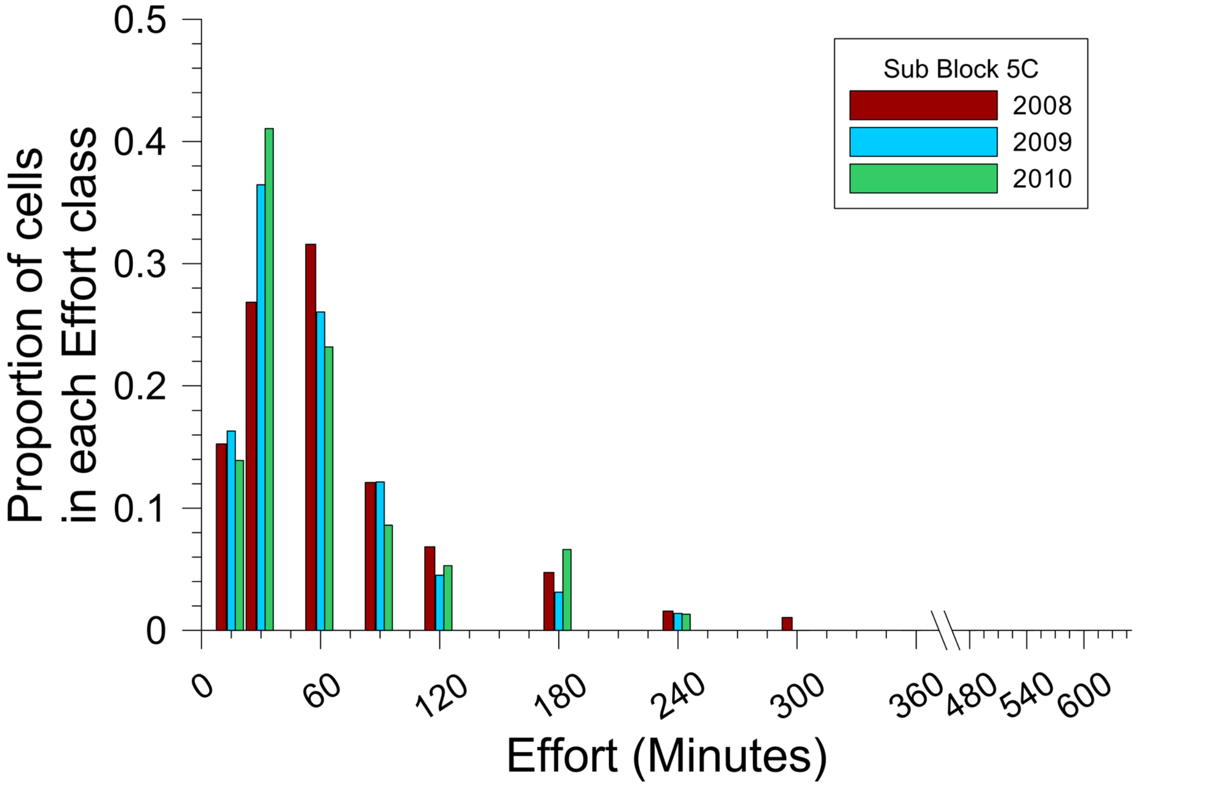

Figure 28. Proportion of cells fished in Sub Block 5C. The first two bin classes are 15min and 30min. All cells with less than 10min of logged effort are excluded from this analysis.

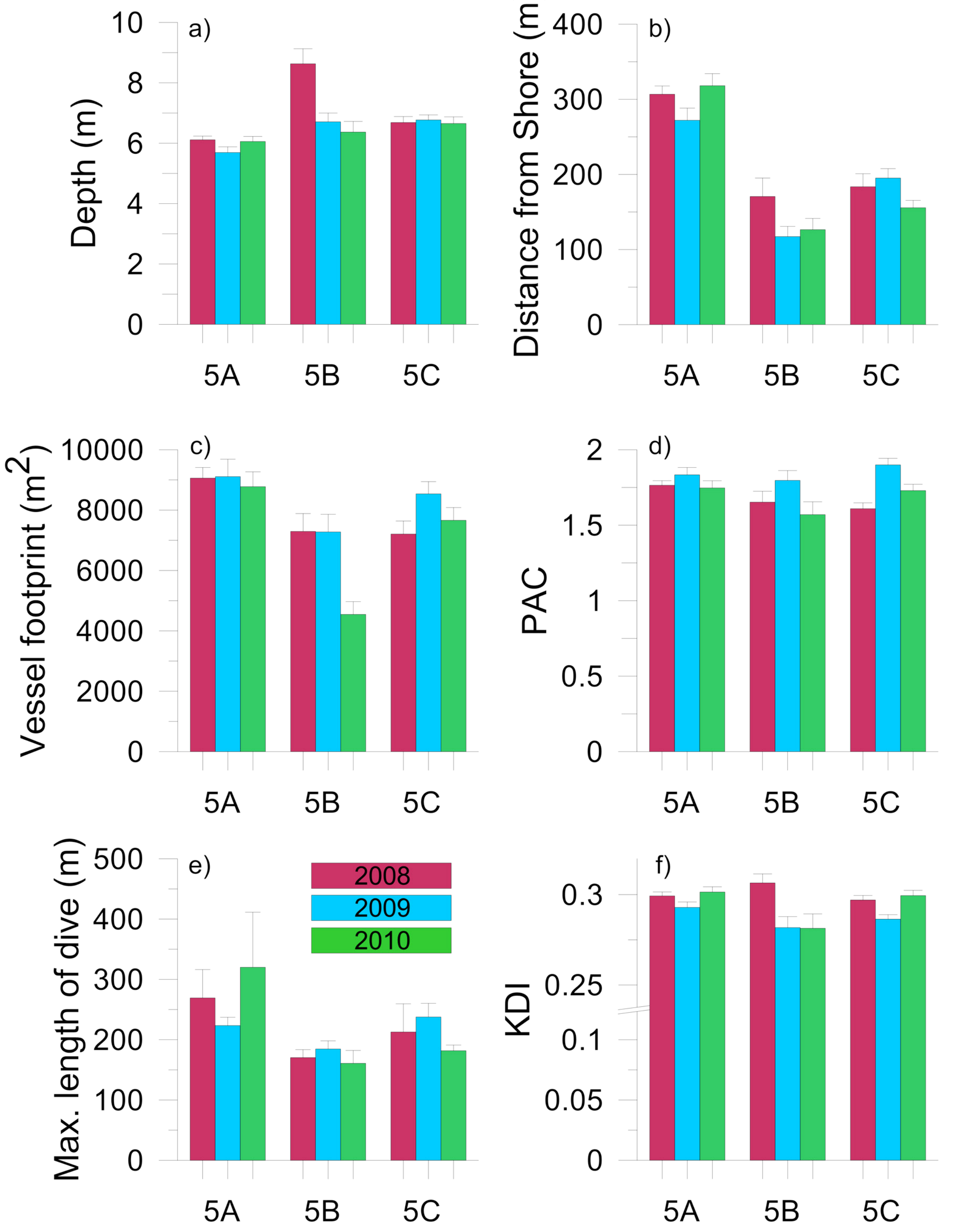

Figure 29. Average Spatial Performance Indices grouped by Sub Block and year (2008 to 2010 for Block 5. a) mean dive depth, b) Mean distance of dive centroid to nearest shore, c) mean vessel footprint (from KUD), d) mean PAC, e) mean maximum dimension of KUD, and f) mean KDI. Data are pooled across the fleet. All SPI's derived from returned GPS and depth data logger data. Error bars indicated Standard Errors.

The pattern of fishing effort with depth over the three year study period was remarkably consistent in sub-blocks 5A and 5C (Figure 29). In sub-block 5B however, there was substantial effort around the 15m depth band in the first year (2008), but not in subsequent years, where effort increased in the 7m to 10m depth band (Figure 30).

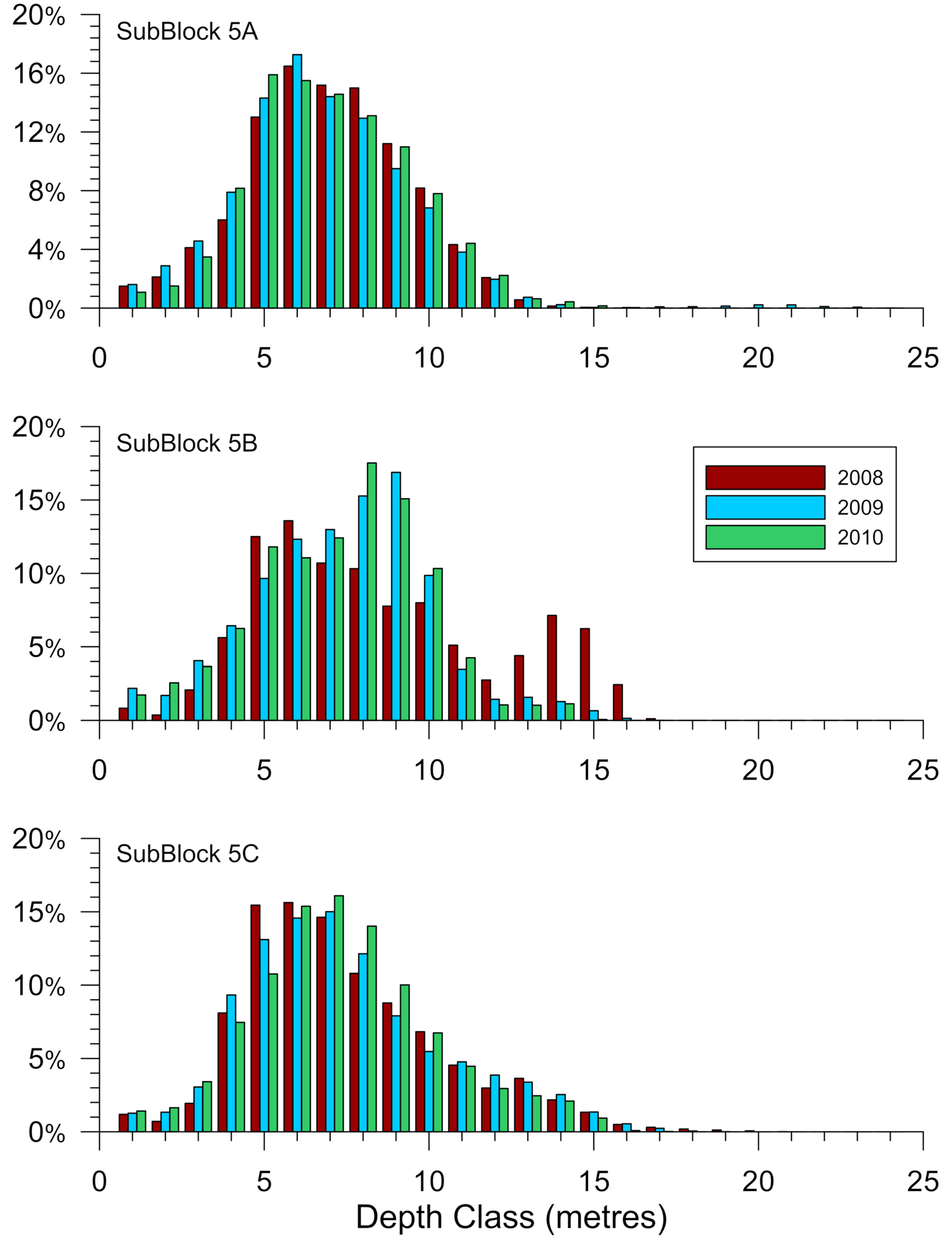

Figure 30. Frequency distribution of effort at depth (entire fleet pooled) within each sub-block and year. Depth size class interval is 1m.

7.3.4 Comparison of resource space use among years

An advantage of the geo-referenced diver data is the capacity to explore the spatial pattern of resource use, or intensity of resource use through time. In the context of the 90% KUD polygons, this involves a spatial approach referred to as 'overlay analysis' where the overlap of the KUD (90% or 50%) polygons from each year (pooled across the fleet) is quantified. In the context of the hexagon grid cell analysis, it the effort or attributed catch within each cell can be compared across years. If fishing intensity and/or productivity is constant through time, with exploitation or effort applied at a particular location also consistent through time, then we expect a high level of correlation in the effort within a given cell among years. However, individual abalone divers typically have an informal rotational policy driven by local knowledge and experience. We might therefore expect to see an absence of strong correlation in resource use among years for individual divers, although at the fleet level, the correlations may still exist depending on the number of productive patches of abalone are exploited to reach the allowable catch.

Data from the Block 5 experimental fishery (all sub-blocks) were pooled across the fleet, and the effort (in minutes) within each cell for the three years was compared. The minutes spent in each cell for 2008 was plotted against the minutes spent in the same cell for 2009, for 2009 vs. 2010, and for 2008 vs. 2010 (Figure 31). While there are clearly some areas where a similar level of fishing effort occurred in both years, there are many cells which were fished in one year but not the other. The extent of return and consistency of resource exploitation by the fleet in block 5 was surprisingly small between 2008 and 2009, however the pattern of resource use between 2008 and 2010 (Figure 31) and 2009 and 2010 (Figure 31) suggests continued high use of preferred locations. The relationships among years in terms of resource use at the scale of 1Hectare cells is consistent with comments from divers that they have a rotational harvest strategy on time scales of one to two years.

When data are split by sub-block, a similar overall pattern is evident. However, in Sub-block 5A, there is a pattern of correlated fishing intensity within 1 Ha cells between 2008 and 2010 (Figure 32b), suggesting a 'filtering' of non-productive sites by the divers through time. No such pattern is emerging in sub-block 5C. Approximately 50% of the total fleet visiting Block 5 (~ 60 divers -Table 7) had rarely fished in this area prior to the commencement of this experimental fishery, and some learning and gathering of local knowledge is expected over the course of the study.

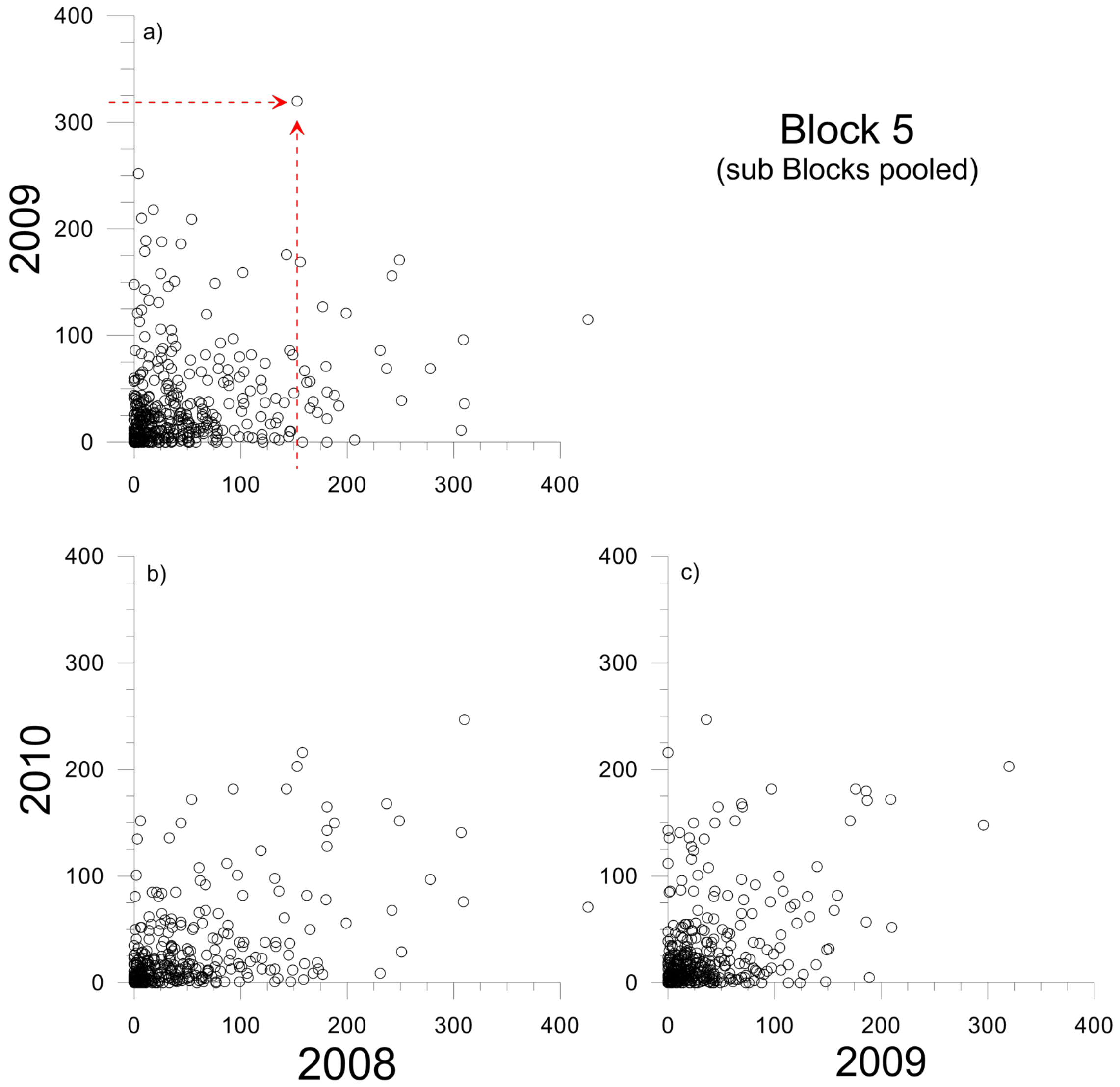

Figure 31. Comparison of resource use through time for the entire fleet in Block5. X and Y axes represent effort in minutes. Each symbol (+) represents the effort in a cell for the two years. a) effort in 2008 (x-axis) vs effort 2009 (y-axis); b) effort in 2008 (x-axis) vs effort 2010 (y-axis); c) effort in 2009 (x-axis) vs effort 2010 (y-axis). For example: the uppermost point in panel a) identified by the red arrows illustrates that ~150 minutes was logged in this cell in 2008 and ~ 320 minutes was logged in the same cell in 2009.

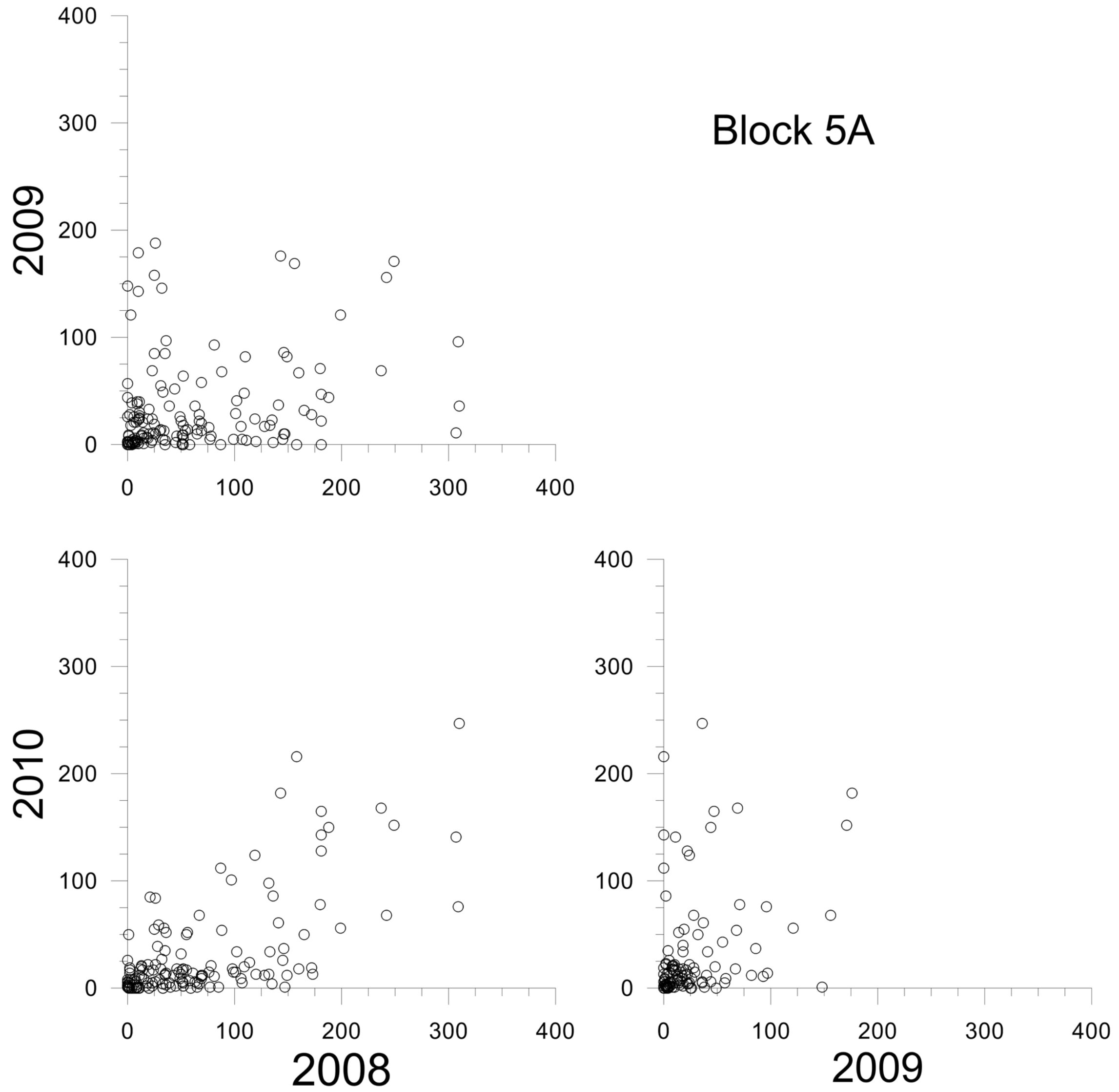

Figure 32. Comparison of resource use through time for the entire fleet in Sub-Block5A. X and Y axes represent effort in minutes. Each symbol (+) represents the effort in a cell for the two years. a) effort in 2008 (x-axis) vs effort 2009 (y-axis); b) effort in 2008 (x-axis) vs effort 2010 (y-axis); c) effort in 2009 (x-axis) vs effort 2010 (y-axis).

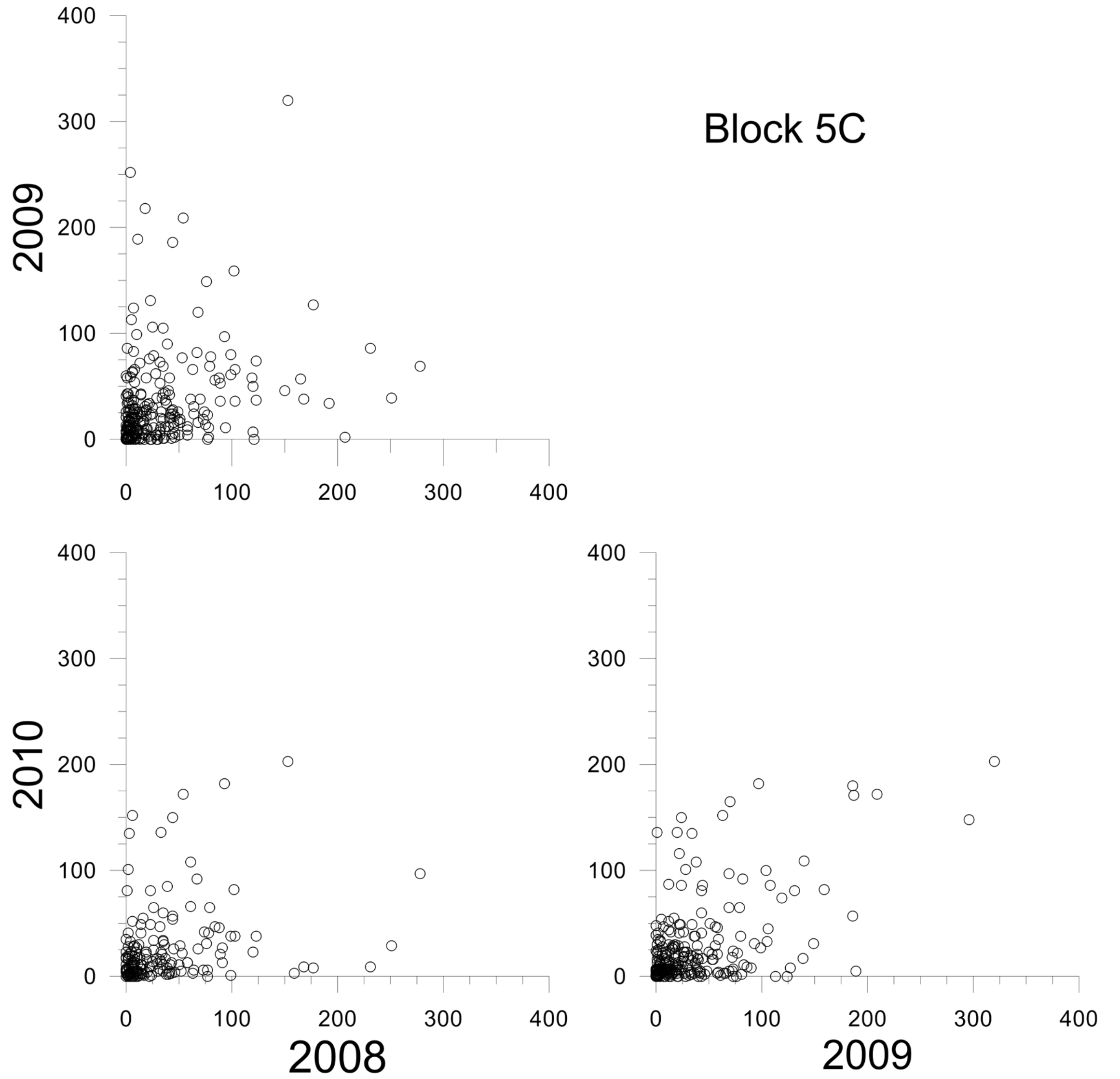

Figure 33. Comparison of resource use through time for the entire fleet in Sub-Block5C. X and Y axes represent effort in minutes. Each symbol (+) represents the effort in a cell for the two years. a) effort in 2008 (x-axis) vs effort 2009 (y-axis); b) effort in 2008 (x-axis) vs effort 2010 (y-axis); c) effort in 2009 (x-axis) vs effort 2010 (y-axis).

7.3.5 Application of LISA and HotSpot Analysis to identify critical areas to the fishery

Local spatial clustering and LISA techniques identified major HotSpots of fishing intensity between Woolnorth and Trefoil Island in sub-block 5A (Figure 34, Figure 35). LISA and local spatial clustering techniques also identified HotSpots in fishing intensity in Sub-blocks 5B and 5C, but are not shown here. The Local G* statistic (G_i*) identified substantial changes in the Woolnorth hotspot over the three year study period. While the location of the hotspot was stationary through time, the size of the hotspot and the intensity of fishing (as identified by lower G_i* values) diminished substantially between 2008 and 2009, despite little change in the catch rate (Figure 34). The intensity and size of the Woolnorth hotspot increased between 2009 and 2010, but did not approach the intensity of fishing seen in 2008. Local Moran's I_i identified similar patterns to that observed with the LocalG statistic G_i* (Figure 35). No cold spots were identified in Block 5 during the study period. In 2008 several cells had very low (negative) I_i values, indicating that there was substantial variation between the target or pivot cell, and its neighbours. These low I_i values are on the boundary of the Woolnorth hot spot and suggest there is a very rapid transition from highly productive reef to moderate or low productive reef.

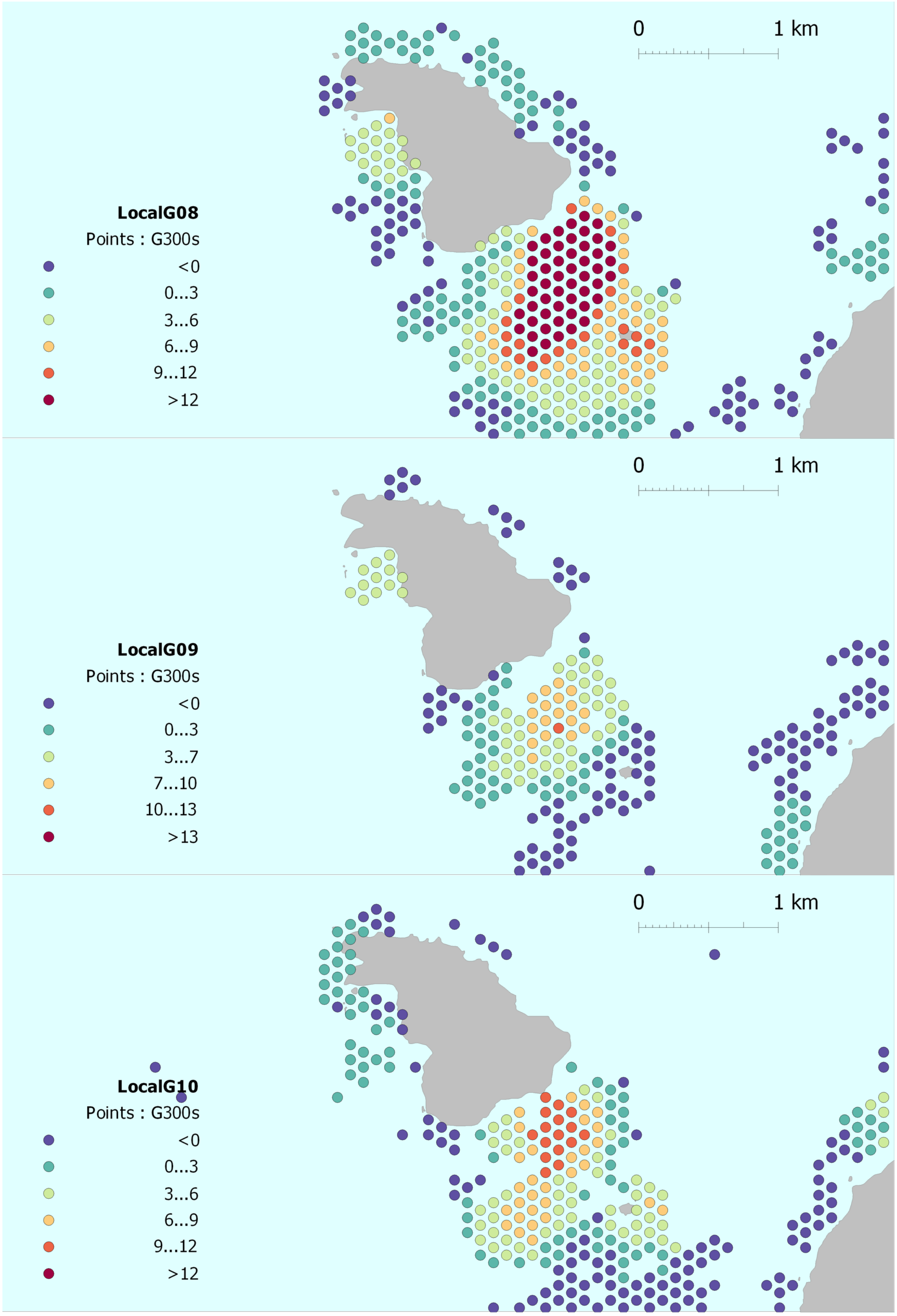

Figure 34. Values of the *Gi** statistic from HotSpot analysis (local spatial clustering) for fishing activity in 2008, 2009, 2010 at Woolnorth Point. Data used for input was effort (minutes)/Hectare cell. Values > 4 are significant at 0.05. A positive G_i* value indicates spatial clustering of high values, and a negative G_i* value indicates spatial clustering of low values.

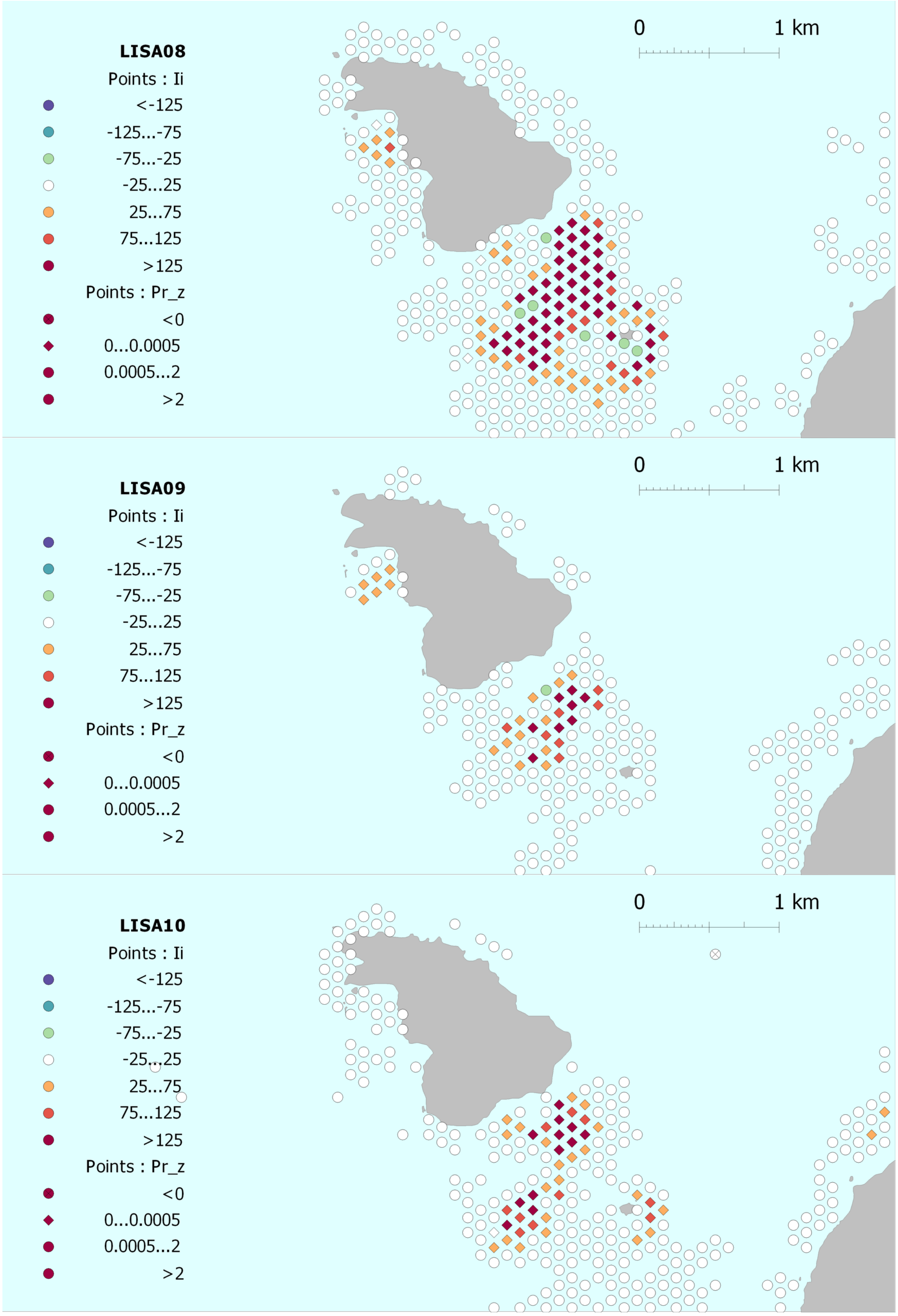

Figure 35. Values of the I_i *statistic* from LISA analysis (LocalMoran's I) for fishing activity in 2008, 2009, 2010 at Woolnorth. Circles indicate non-significant I_i values, diamonds indicate significant Ii values (normal approximation). Data used for input was effort (minutes)/Hectare cell. A positive I_i value indicates spatial clustering of similar values (either high or low), negative I_i value indicates clustering of dissimilar values (for example, a location with high values surrounded by neighbors with low values).

7.3.6 Discussion

7.3.6.1 Traps for young players: Establishing a framework for Mandatory use of data loggers

A major problem encountered during the Block 5 Experimental fishery was retrieving the GPS and depth loggers on a timely basis, to enable uploading, processing and analysis of the data in a timely manner. Additionally, the mandatory use arrangements were not sufficiently clear on the use of GPS logger when two divers operated as a team from the same vessel. This resulted in a mix-and-match outcome in terms of GPS and depth logger data that hindered the data processing, and assigning catch data to the geo-referenced diver data. For example, one fisher worked as part of two different teams over two consecutive days, using his issued depth logger but using his partners issued GPS logger rather than his own on both days. On the third day the fisher worked alone, using his own GPS and depth loggers. To accurately process and assign reported catch data from each diver to the spatial data requires manual cut and paste operations that were too cumbersome to attempt in this analysis due to the relatively common practice of team diving in this area during the study period. Future mandatory use arrangements need to consider regulations providing for the return of the logger data to enable frequent processing and analysis to inform adaptive management processes.

The GPS and depth data streams provided by the data loggers provide a range of new spatial performance indices (SPI) that incorporate the inherently spatial nature of commercial abalone fishing. While it is expected these SPI's will be substantially more sensitive for detecting change in fishery performance, and or exploitation rate, it is not possible to place the improvements in a particular context without fishery wide data. Most of the new performance measures (Table 6) identified requires data from all fishers for the full fishing year to be effective at characterising the dynamic nature of the fishery, and any within-year trends that suggest management action is required.

7.3.6.2 Utility of Spatial Performance Indicators

Individual SPI's, comparisons of common reef use through time and hotspot analyses all illustrated a level of among-year dynamic in the fishery that was not evident on the basis of catch-rates. In particular the hotspot analyses were able to identify the location and intensity of several hotspots of fishing activity, and to quantify a contraction in that hotspot through time. In the context of fishery management, clear indicators that highly productive fishing grounds (hotspots) are becoming less productive highlights an issue for future TAC decisions. If there is no indication that other areas within the fishery can absorb the reduction in yield from the hotspot areas, then the expected yield for that reporting area (block, reef code etc.) would need to be revised downward.

In the context of reference points and decision rules associated with SPI's and spatial analyses, a learning curve of several years is expected before researchers and managers will have a clear understanding of the value of individual SPI's vary, and the acceptable boundaries within which those SPI's might vary naturally, and under conditions of stock improvements or stock declines. For example, it might be reasonable to expect the number of cells fished per year, in a fully exploited fishery, to remain relatively constant. Similarly the number, location and intensity of HotSpots might vary annually within some range for a stable and sustainable fishery. How quickly and hotspots might contract or expand is not yet understood.

The shape of the frequency distribution of cells fished in a stable fishery in equilibrium is likely to be temporally constant. As a fishery improves from a low level, a shift in the shape of the frequency distribution would be expected, with more cells receiving more effort, and fewer cells receiving low levels of effort. In the case of a declining fishery, divers would tend to explore more reef areas as abundance begins to decline, in order to maintain catch rates. This would result in a decreased reliance of a small number of cells, and a spreading of effort across the cells that make up the fishery. As the fishery declines further, the shape of the distribution will shift back again with greater reliance on a few well known cells and with minimal effort other than exploratory fishing effort across other cells to gauge recovery.

Where a fishery wide logger deployment program is initiated, it will be possible to gain an early understanding of the status of different parts of the fishery, prior to a time-series is available to gauge trends. Analysis of the spatial performance measures in areas of comparable reef can be contrasted in the context of catch and catch rates. For example, do areas with lower catch rates have larger vessel footprints (area or length of footprint)? Reef systems where abalone is highly patchy are also expected to have a mean KDI that is lower than reef systems where abalone abundance is more homogeneous across reef systems. Trends in KDI's may not be useful in the context of changes in the performance of the fishery, but KDI may provide an index of habitat complexity, and enable a classification of reefs based on similar KDI values.

8. Benefits

This project has developed the analytical systems to enable batch processing of raw data to provide spatial performance measures for abalone fisheries, and for any other dive fishery. The primary benefit of automation of the analytical tasks within a secure software environment is to make available the use of spatial performance measures, without prior knowledge of GIS, RDBMSs, or spatial analysis procedures.

The concepts developed in this study have been adopted in Tasmania, New South Wales and South Australia thus far, and the AbTrack front end has also been distributed to Western Australia and Victoria. Within Tasmania, the use of GPS and Depth data loggers is now mandatory for fishing in Blocks 5 and Blocks 6 in North West Tasmania, involving approximately 200 tonnes of the Northern and Central Western Zone catch. In New South Wales, the uptake of GPS and depth data loggers is nearing 100% on a voluntary basis, and is currently in a trial phase as the primary data fishery dependent data collection system, other than reporting of daily catch weights. In South Australia, use of GPS and depth data loggers is also mandatory for blacklip abalone fishing, within constrained areas of the South Australian Fishery.

From January 1 2012, the use of GPS and depth loggers will become mandatory for the entire Tasmanian Abalone fleet, for all abalone fishing across the state. This coincides with a reduction in the information to be provided by divers on their daily docket returns as certain key information can now be extracted from the GPS and depth logger data (e.g. effort at depth, number of drops).

Extensive support for installation and training on use of the AbTrack front end has been provided by the PI and by the contract database programmer to South Australia and New South Wales, and these states are well advanced in terms of uploading and archival of data. Substantial training in the use of the RBDMS and R scripts has been provided to New South Wales, and this state is almost operating independently at the time of writing.

9. Further development

There are a range of issues requiring further development of spatial statistical methods, in particular the use of Multi-Criteria Decision Analyses to provide an objective assessment of potential TAC, and the application of spatial linear modelling to provide a predictive capacity of local catch. Some key areas for future development are;

1) Hardware optimisation for the GPS data loggers and improving the reliability of the equipment used.

2) Further automation of scripts within T-SQL stored procedure inside the AbTrack database for certain tasks e.g. post-processing of Virtual Dive data outputs from the Discriminant Function Analyses (see Appendix 5: Classification Tool to decode GPS stream into 'dive' and 'travel' segments in the absence of Depth logger data.).

3) Acquisition of fleet wide geo-referenced fishery data for complete fishing years to enable more thorough testing of performance measures and spatial techniques across

4) Careful consideration of a framework for mandatory use of loggers for catch and effort reporting.

10. Planned outcomes

This project was successful in developing a system for the acquisition, storage and analysis of fine-scale fishery-dependent data in abalone diver fisheries. The analytical tools will not only deliver benefits for research and management of abalone fisheries in all States, but also for all spatially structured fisheries that operate from small fishing vessels (< 10m).

The new geo-referenced diver data can be used as a base platform in any fishery, with subsequent treatment of the data falling in line with the management plans and harvest strategy of any jurisdiction that chooses to adopt this approach. The spatial RDBMS and automated analyses were designed to accommodate significant volumes of data annually (e.g. in in excess of 10 million records per year are expected in the Tasmanian Fishery in 2012).

The spatial data platform developed and described in this report provides a launch pad for extensive quantitative based spatial performance measures, reference points and control rules to be developed, specifically targeted the spatial nature of abalone fisheries. An original objective (Objective 6) of this project was to incorporate electronic variables into the Tasmanian Abalone Management Plan. This specific objective was not completed, partly because this project (2006/029) did not intend to review the existing out-dated Harvest Strategy, and because the existing Control Rule and Trigger point system was based on reference years. As we do not have a sufficient time series to provide reference years, incorporation of Electronic Indicator Variables into the current Management Plan is not a sensible process. However, a new Harvest Strategy and associated control rules utilising the spatial performance measures developed here, is being developed within two additional FRDC funded projects, specifically 2007/020 “Identification and Evaluation of Biological Performance Indicators for Abalone Fisheries “ and 2011/201 “Implementing a spatial assessment and decision process to improve fishery management “.

11. Conclusions

This project has successfully developed a range of scripts and procedures to automate the processing of raw spatial data, to provide spatial performance measures useful for abalone fisheries assessment. Importantly, the data that can be obtained using GPS and depth data loggers is highly quantitative, and not subject to bias of any kind. It is also a low cost system, with the cost of GPS and depth logger expected to reduce to around $500 per diver, and with the data, logger management and preliminary analysis tasks for the Tasmanian fishery achievable by a single full time Technical Officer. The GPS and depth logger has minimal impact on the catching sector operations, with the exception of remembering to turn the GPS logger on and off, and recharging the GPS logger batteries.

This project has also developed and established a multi-purpose RDBMS that can a) maintain a register of loggers and fishers using unique identifiers, b) manage the deployment of loggers to individual fishers, and c) provide an upload portal to a secure database in SQL Server 2008. The tools developed have intentionally utilised the capacity of free and open source software (FOSS), such that uptake of the concept is not limited by the financial cost required if they were developed entirely within more commonly used but corporate RBDMSs such as Oracle (with Oracle Spatial), or corporate GIS software such as ESRI's ArcGIS. The decision to utilise the recently implemented capabilities of SQL Server 2008 Spatial data types has provided a very high level of flexibility and customisation. Additionally, the ease of using SQL and spatial functions to create spatial queries for the grid based analyses is greatly superior to that available within ArcGIS, and with similar levels of performance. The use of R to perform the KDE analysis to identify the activity space of each individual fishing event opens the possibility of extensive customisation, in a highly flexible and rapidly evolving software environment.

Importantly, it is the temporal trends in these new spatial measures that will be most useful to fishery assessments in the longer term, although the information can also be used in the short term to understand the complex spatial nature of the commercially productive reef systems. There will need to be substantial innovation in the modelling frameworks used to incorporate the spatial information derived from the loggers. While it may not be immediately apparent, several of the spatial performance measures, are likely to combine with CPUE and Catch distribution to better inform models of recruitment pulses and failures. In particular recovery times of cells or groups of cells will be highly informative of the spatial variation in the resilience of reefs to support and recover from fishing.

The data obtained during the Block 5 North-west Tasmania experiment between 2008 and 2010 provided an ideal opportunity to test technology derived indicator variables, and evaluate the potential for high resolution data to improve the assessment of abalone fisheries. The geo-referenced fishery-dependent data and derived spatial performance indices identified clear patterns of serial depletion at scales smaller that the scale of reporting units. HotSpot analyses have identified the presence of intense fishing zones (hotspots), and provided preliminary evidence for both fixed location hotspots in some regions, whereas in other regions the location of the hotspots is dynamic.

A baseline map has been obtained for several key areas in the Tasmanian Abalone Fishery, with more the location of more than 5000 commercial abalone fishing events mapped and analysed around the Tasmanian coastline.

While data was collected over a much broader area within the Tasmanian Abalone Fishery than is presented here (> 3450 dive events), outside of Block 5, the use of the loggers was haphazard and insufficient coverage for any one diver or area was achieved to expand the analyses beyond the examples given here. The issue of voluntary vs. mandatory use of GPS and depth data logging equipment as part of the fishers reporting requirements is a critical issue for the uptake of the technology within any fishery. Without adequate incentives to use the equipment, or disincentives to avoid using the equipment, apathy will severely limit the potential of the concept to improve fisheries assessment. If use of the logger systems in not close to 100% either voluntarily or through mandatory requirements there is little to be gained from pursuing this process.

There are two primary options available to enable 100% uptake and use of the loggers by fishers. Either use of the equipment is regulated by industry by inclusion in Codes of Practise required by peak industry bodies, or use is mandated by the Government agency responsible for the fishery. The preferable arrangement is both options apply. Currently, the method of adoption and regulations for use is under review in Tasmania by DPIPWE and the Tasmanian Abalone Council, in order to achieve 100% uptake by fishers should the decision to be made to implement spatial performance measures within the Tasmanian abalone fishery.

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13. Appendix 1: Intellectual property

No commercially valuable intellectual property arose from the research. Steps were taken to avoid release of private information, or inclusion of maps that might enable third parties to identify fishing sites that were not widely known, so that there is little need to restrict distribution of results. The AbTrack front end utilises corporate software (Nexus) owned by PNX Ltd. IMAS has purchased the IP rights to Nexus under a not-for-profit arrangement. Use of the Nexus based AbTrack front end has been granted only to the participants in this project (i.e. Australasian Wild Harvest Abalone fisheries), for the purposes intended, and described in this project. The AbTrack front end may not be distributed beyond the participants in this project without the permission of IMAS, Peter Walsh and/or PNX Ltd.

The database structure developed within SQL Server 2008 does not carry any restrictions and is free for distribution. The SQL and R scripts also carry no restriction, with the exception that the PI requests that he is notified of any improvements in the content of the scripts or SQL statements. The PI is continually updating the scripts provided in this document to keep pace with developments in R and the R packages used for these analyses. Please contact the PI for the latest version.

14. Appendix 2: Staff

Project staff were:

Dr Craig Mundy, Tasmanian Aquaculture and Fisheries Institute, University of Tasmania (Marine Research laboratories).

Mr Peter Walsh, Tasmanian Aquaculture and Fisheries Institute, University of Tasmania (Marine Research laboratories) and PNX Ltd.

15. Appendix 3: Relationships diagram and metadata for AbTrack

The AbTrack database has been designed from the ground up, with Primary and Foreign Key fields linking tables. The relationships between tables are articulated within SQL Server (Figure 36), and assists with query design and execution.

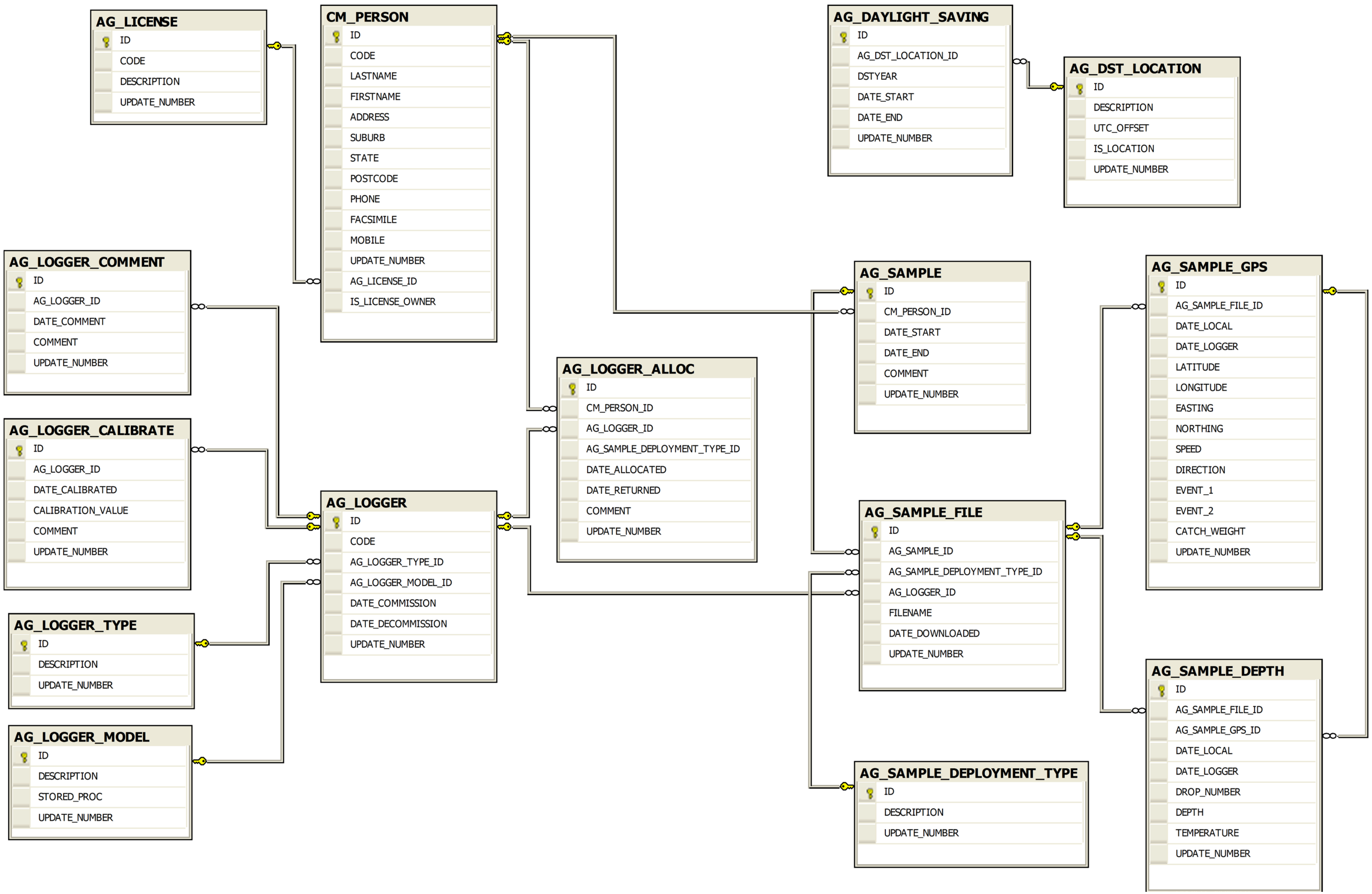


Figure 36. AbTrack RDBMS Relationship Diagram

AG_DAYLIGHT_SAVING

Contain daylight saving information for different locations.

15.1.1.1 Keys

Key	Type	Related Table	Related Column
PK_AG_DAYLIGHT_SAVING	Primary	N/A	N/A
FK_AG_DAYLIGHT_SAVING_AG_DST_LOCATION	Foreign	AG_DST_LOCATION	ID

15.1.1.2 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
AG_DST_LOCATION_ID	int	10	0	NO	Foreign Key AG_DST_LOCATION
DSTYEAR	int	10	0	NO	Numeric year
DATE_START	datetime	23	3	NO	Date DST starts (spring)
DATE_END	datetime	23	3	NO	Date DST ends (Autumn)
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_DST_LOCATION

Contains information about DST locations/zones

15.1.1.3 Keys

Key	Type	Related Table	Related Column
PK_AG_DST_LOCATION	Primary	N/A	N/A

15.1.1.4 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
DESCRIPTION	char	50		NO	Daylight savings location/zone (normally a state or country)
UTC_OFFSET	numeric	10	2	NO	Offset from UTC in hours (non-DST time)
IS_LOCATION	smallint	5	0	NO	Flag to denote local time zone. Can only be set for one record in the table.
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_LICENSE

Contains license information

15.1.1.5 Keys

Key	Type	Related Table	Related Column
PK_AG_LICENSE	Primary	N/A	N/A

15.1.1.6 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
CODE	varchar	10		NO	License code
DESCRIPTION	char	50		YES	Description/Details for this license.
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_LOGGER

Contains information about individual loggers (all types and models)

15.1.1.7 Keys

Key	Type	Related Table	Related Column
PK_AG_LOGGER	Primary	N/A	N/A
FK_AG_LOGGER_AG_LOGGER_MODEL	Foreign	AG_LOGGER_MODEL	ID
FK_AG_LOGGER_AG_LOGGER_TYPE	Foreign	AG_LOGGER_TYPE	ID

15.1.1.8 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
CODE	char	10		NO	Code for identifying this logger
AG_LOGGER_TYPE_ID	int	10	0	NO	Foreign Key AG_LOGGER_TYPE
AG_LOGGER_MODEL_ID	int	10	0	NO	Foreign Key AG_LOGGER_MODEL
DATE_COMMISSION	datetime	23	3	NO	Date this logger was commissioned
DATE_DECOMMISSION	datetime	23	3	YES	Date this logger was decommissioned
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_LOGGER_ALLOC

Contains information about loggers allocated to divers

15.1.1.9 Keys

Key	Type	Related Table	Related Column
PK_AG_LOGGER_ALLOC	Primary	N/A	N/A
FK_AG_LOGGER_ALLOC_AG_LOGGER	Foreign	AG_LOGGER	ID
FK_AG_LOGGER_ALLOC_CM_PERSON	Foreign	CM_PERSON	ID

15.1.1.10 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
CM_PERSON_ID	int	10	0	NO	Foreign Key CM_PERSON
AG_LOGGER_ID	int	10	0	NO	Foreign Key AG_LOGGER
AG_SAMPLE_DEPLOYMENT_TYPE_ID	int	10	0	NO	Foreign Key AG_SAMPLE_DEPLOYMENT_TYPE
DATE_ALLOCATED	datetime	23	3	NO	Date the logger was allocated to the diver
DATE_RETURNED	datetime	23	3	YES	Date the logger was returned by the diver
COMMENT	char	255		YES	Comment
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_LOGGER_CALIBRATE

Contains calibration information for a logger. Only used for depth loggers. Loggers are calibrated at irregular intervals.

15.1.1.11 Keys

Key	Type	Related Table	Related Column
PK_AG_LOGGER_CALIBRATE	Primary	N/A	N/A
FK_AG_LOGGER_CALIBRATE_AG_LOGGER	Foreign	AG_LOGGER	ID

15.1.1.12 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
AG_LOGGER_ID	int	10	0	NO	Foreign Key AG_LOGGER
DATE_CALIBRATED	datetime	23	3	NO	Date the depth logger was calibrated
CALIBRATION_VALUE	numeric	18	12	NO	Correction value for logger calibration
COMMENT	char	4096		YES	Comment
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_LOGGER_COMMENT

Contains comments (with dates) about individual loggers.

15.1.1.13 Keys

Key	Type	Related Table	Related Column
PK_AG_LOGGER_COMMENT	Primary	N/A	N/A
FK_AG_LOGGER_COMMENT_AG_LOGGER	Foreign	AG_LOGGER	ID

15.1.1.14 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
AG_LOGGER_ID	int	10	0	NO	Foreign Key AG_LOGGER
DATE_COMMENT	datetime	23	3	NO	Date relevent to this comment
COMMENT	char	4096		NO	Comment
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_LOGGER_MODEL

Contains information about the different models of loggers used in AbTrack

15.1.1.15 Keys

Key	Type	Related Table	Related Column
PK_AG_LOGGER_MODEL	Primary	N/A	N/A

15.1.1.16 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
DESCRIPTION	char	50		NO	Description of this logger model
STORED_PROC	char	50		NO	Name of the stored procedure used to import data from this logger
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_LOGGER_TYPE

Contains information about the different types of loggers used in AbTrack (normally GPS or depth)

15.1.1.17 Keys

Key	Type	Related Table	Related Column
PK_AG_LOGGER_TYPE	Primary	N/A	N/A

15.1.1.18 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
DESCRIPTION	char	50		NO	Description of this logger type
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_SAMPLE

Contains information about a sample run. Each sample run will have one associated GPS logger data file and one or more associated depth logger data files.

15.1.1.19 Keys

Key	Type	Related Table	Related Column
PK_AG_SAMPLE	Primary	N/A	N/A
FK_AG_SAMPLE_CM_PERSON	Foreign	CM_PERSON	ID

15.1.1.20 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
CM_PERSON_ID	int	10	0	NO	Foreign Key CM_PERSON
DATE_START	datetime	23	3	NO	Start date for this sample recording
DATE_END	datetime	23	3	NO	End date for this sample recording
COMMENT	char	4096		YES	Comment
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_SAMPLE_DEPLOYMENT_TYPE

Contains information about the types of logger deployment (normally GPS, diver or drop line).

15.1.1.21 Keys

Key	Type	Related Table	Related Column
PK_AG_SAMPLE_DIVER_TYPE	Primary	N/A	N/A

15.1.1.22 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
DESCRIPTION	char	50		NO	Description for this deployment type.
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_SAMPLE_DEPTH

Contains information recorded by a depth logger.

15.1.1.23 Keys

Key	Type	Related Table	Related Column
PK_AG_SAMPLE_DIVER	Primary	N/A	N/A
FK_AG_SAMPLE_DIVER_AG_SAMPLE_FILE	Foreign	AG_SAMPLE_FILE	ID
FK_AG_SAMPLE_DIVER_AG_SAMPLE_GPS	Foreign	AG_SAMPLE_GPS	ID

15.1.1.24 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
AG_SAMPLE_FILE_ID	int	10	0	NO	Foreign Key AG_SAMPLE_FILE
AG_SAMPLE_GPS_ID	int	10	0	YES	Foreign Key AG_SAMPLE_GPS. Created during import, this key matches records to the closest time stamp between loggers.
DATE_LOCAL	datetime	23	3	NO	Local date/time (DST adjusted as required. i.e. the true local time)
DATE_LOGGER	datetime	23	3	NO	Date/Time as read from the logger
DROP_NUMBER	int	10	0	NO	Drop number for this sample (starts at 1 for each day OR starts at 1 for each logger).
DEPTH	numeric	18	3	NO	Depth (m)
TEMPERATURE	numeric	18	3	NO	Temperature (degrees Celsius)
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_SAMPLE_FILE

15.1.1.25 Keys

Key	Type	Related Table	Related Column
PK_AG_SAMPLE_FILE	Primary	N/A	N/A
FK_AG_SAMPLE_FILE_AG_LOGGER	Foreign	AG_LOGGER	ID
FK_AG_SAMPLE_FILE_AG_SAMPLE	Foreign	AG_SAMPLE	ID
FK_AG_SAMPLE_FILE_AG_SAMPLE_DEPLOYMENT_TYPE	Foreign	AG_SAMPLE_DEPLOYMENT_TYPE	ID

15.1.1.26 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
AG_SAMPLE_ID	int	10	0	NO	Foreign Key AG_SAMPLE
AG_SAMPLE_DEPLOYMENT_TYPE_ID	int	10	0	YES	Foreign Key AG_SAMPLE_DEPLOYMENT_TYPE
AG_LOGGER_ID	int	10	0	NO	Foreign Key AG_LOGGER
FILENAME	char	255		NO	Source filename including path
DATE_DOWNLOADED	datetime	23	3	NO	Date/Time the file was downloaded from the logger
UPDATE_NUMBER	int	10	0	NO	Update Number

AG_SAMPLE_GPS

15.1.1.27 Keys

Key	Type	Related Table	Related Column
PK_AG_SAMPLE_GPS	Primary	N/A	N/A
FK_AG_SAMPLE_GPS_AG_SAMPLE_FILE	Foreign	AG_SAMPLE_FILE	ID

15.1.1.28 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
AG_SAMPLE_FILE_ID	int	10	0	NO	Foreign Key AG_SAMPLE_FILE
DATE_LOCAL	datetime	23	3	NO	Local date/time (DST adjusted as required. i.e. the true local time)
DATE_LOGGER	datetime	23	3	NO	Date/Time as read from the logger
LATITUDE	numeric	18	9	NO	Latitude (decimal degrees)
LONGITUDE	numeric	18	9	NO	Longitude (decimal degrees)
EASTING	numeric	18	2	NO	Easting
NORTHING	numeric	18	2	NO	Northing
SPEED	numeric	10	2	NO	Speed (knots)
DIRECTION	numeric	10	2	YES	Compass direction/heading (degrees)
EVENT_1	char	5		YES	Event 1
EVENT_2	char	5		YES	Event 2
CATCH_WEIGHT	int	10	0	YES	Catch weight (kg)
UPDATE_NUMBER	int	10	0	NO	Update Number

CM_PERSON

Contains details about individual divers

15.1.1.29 Keys

Key	Type	Related Table	Related Column
PK_CM_PERSON	Primary	N/A	N/A
FK_CM_PERSON_AG_LICENSE	Foreign	AG_LICENSE	ID

15.1.1.30 Columns

Fieldname	Type	Size	Scale	Null	Comment
ID	int identity	10	0	NO	Primary Key
CODE	char	5		NO	Diver code
LASTNAME	char	50		NO	Last name
FIRSTNAME	char	50		NO	First name
ADDRESS	char	255		YES	Address
SUBURB	char	50		YES	Suburb
STATE	char	3		YES	State
POSTCODE	char	4		YES	Postcode
PHONE	char	20		YES	Phone
FACSIMILE	char	20		YES	Fax
MOBILE	char	20		YES	Mobile
UPDATE_NUMBER	int	10	0	NO	Update Number
AG_LICENSE_ID	int	10	0	YES	Foreign Key AG_LICENSE
IS_LICENSE_OWNER	smallint	5	0	YES	Denotes if this person owns the license selected in AG_LICENSE_ID (1=Yes, 0=No).

16. Appendix 4: Modifications to AbTrack database to incorporate SciElex and VADA measuring board length measurements.

16.1.1 Modification of AbTrack database tables and relationships to accept length measuring board data.

At the request of Victorian and New South Wales representatives, the AbTrack database was modified to allow uploading and archiving of GPS enabled electronic length data from the Victorian Central Zone measuring boards, the SciElex measuring boards in use by WADA, and the SciElex measuring boards in use in NSW by abalone processors.

This update required a structural change to the database, and was achieved by the inclusion of an additional Table named AG_SAMPLE_OTHER (Figure 37. AbTrack RDBMS Relationship Diagram, modified to include a table to house GPS enabled measuring board data.), and creation of input scripts specific to the logger model of choice. These modifications have been completed, tested and are now operational.

While undertaking this modification, the opportunity was taken to update several AbTrack tables, with additional features. Primarily, this involved modifications to the AG_LOGGER_ALLOCATION table to include the date and time of download for each logger, inclusion of a table AG_SRID to store SRID (Spatial Reference Identifier) values that identify the datum and coordinate reference system of the data being uploaded (e.g. 28355 for Tasmania and Central Zone Victoria, 2356 for New South Wales and 28353 and 28354 for South Australia). The AG_SAMPLE_FILE table was also modified to include a field that captured the date and time of upload of csv files to the SQL SERVER database to assist with auditing purposes.

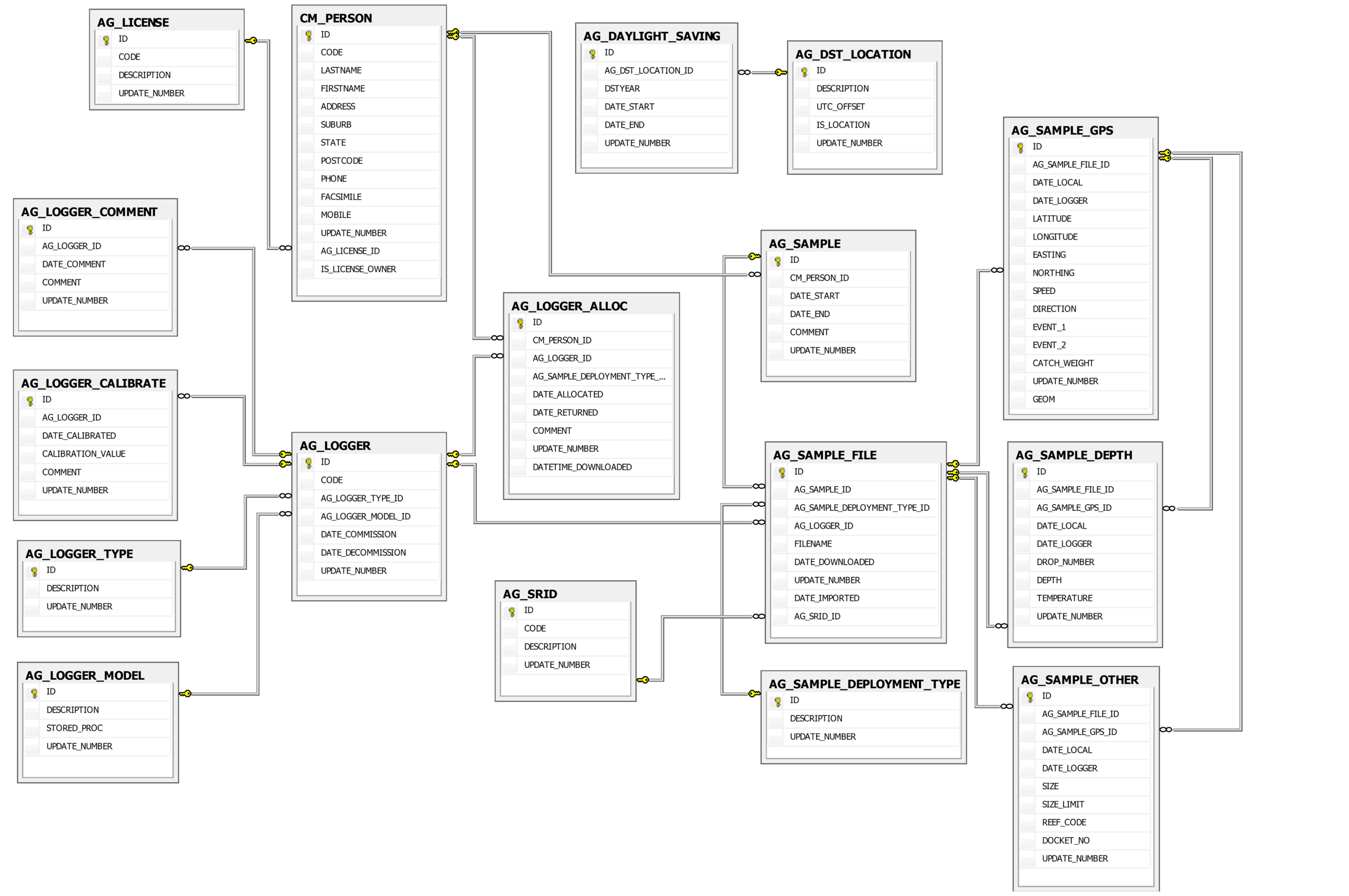


Figure 37. AbTrack RDBMS Relationship Diagram, modified to include a table to house GPS enabled measuring board data.

16.1.1.1 Output of spatially referenced data from the VADA measuring board data sets.

All available Victorian Central Zone spatially referenced length measurements were uploaded to a dedicated VADA AbTrack database by IMAS staff. The spatial information for each abalone length record in the VADA database identifies the location at which the abalone was measured, which is not always the location where it was harvested. For this reason, many of the analyses and spatial performance measures described in Chapter 6.3 above cannot be applied to this data set. However, summary information based on fishing activity within each reef code can be easily displayed in graphical form, such as the average length of abalone caught in each reef code using spatial query functions. For example, if a spatial layer containing the boundaries of all reef codes is overlayed with the location of measurement of all abalone, a link can be created grouping all measurements within the boundary of each reef code to that reef code. This is called a spatial join, and allows a range of calculations on the measurement data (shell length) to be made on the basis of the inherited reef code through the spatial join (Figure 39Figure 38).

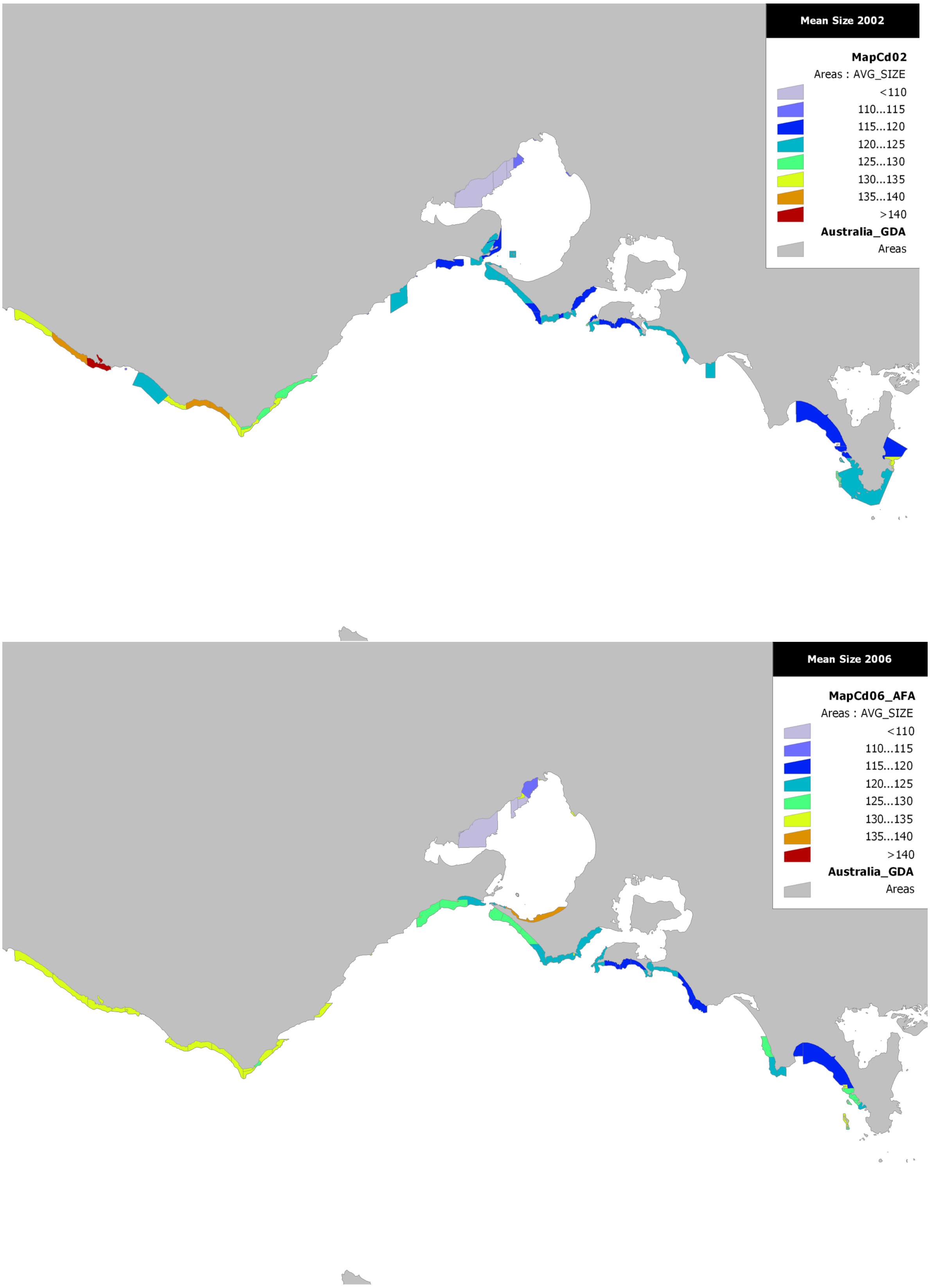
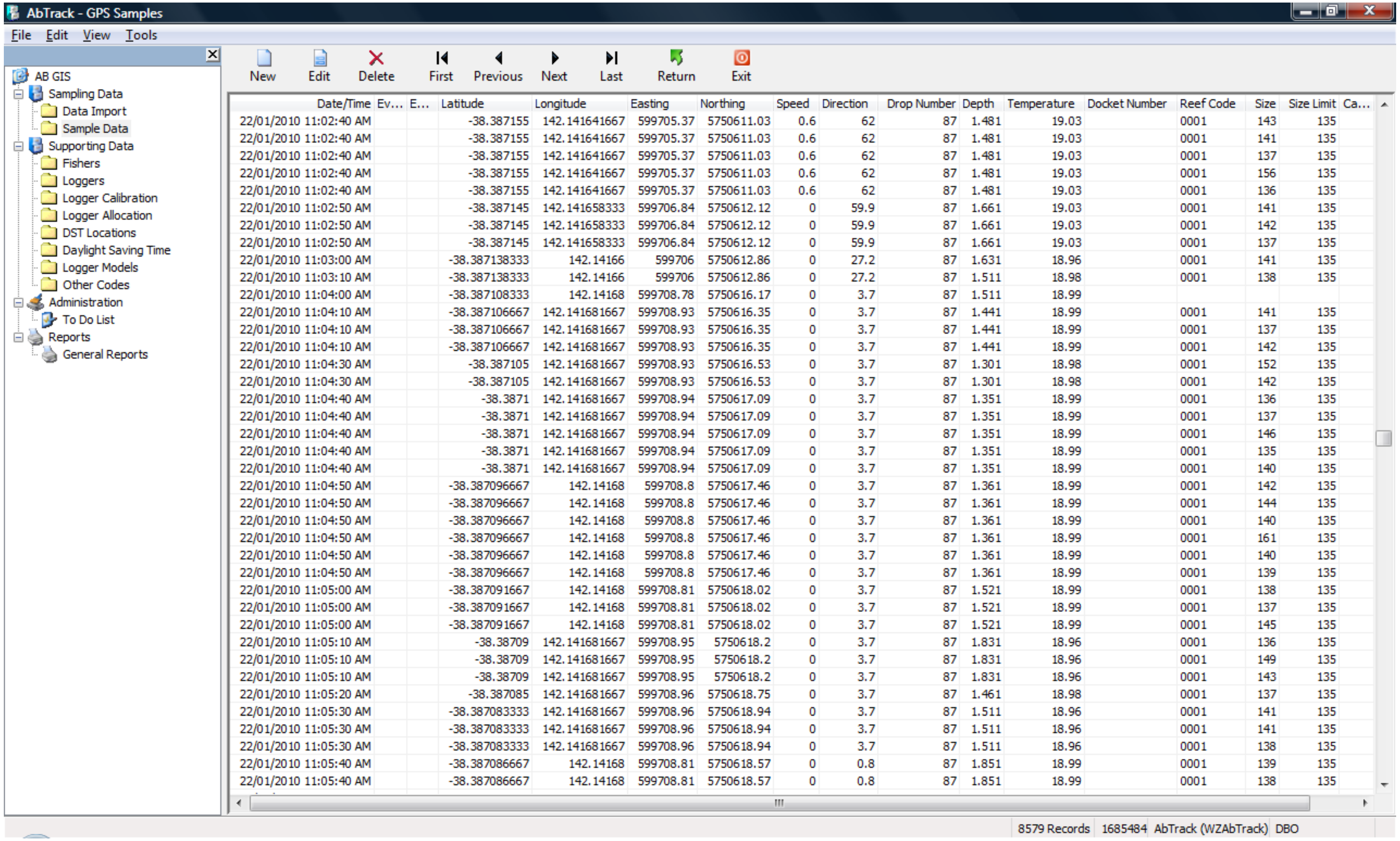


Figure 38. Mean size of abalone measured in 2002 (upper Panel) and 2006 (lower Panel) within each Map code

16.1.1.2 Output of spatially referenced data from the WADA measuring board data sets.

Spatial referenced length data () were collected as part of the WADA structure fishing TRF project (Figure 39). These data were obtained though fishing on anchor, at pre-determined locations in the Victorian Western Zone abalone fishery. Spatial Performance measures described in Section 6.3 above cannot be applied to this data set. However the spatial information can be used to provide a geographical summary of the data collected. Maps of abalone shell length data from structured fishing locations can be created from the spatially referenced data to show graphical trends in the size distribution, catch rates, and/or spatial relationships between adjacent and distant sites (Figure 40).



Date/Time	Ev...	E...	Latitude	Longitude	Easting	Northing	Speed	Direction	Drop Number	Depth	Temperature	Docket Number	Reef Code	Size	Size Limit	Ca...
22/01/2010 11:02:40 AM			-38.387155	142.141641667	599705.37	5750611.03	0.6	62	87	1.481	19.03		0001	143	135	
22/01/2010 11:02:40 AM			-38.387155	142.141641667	599705.37	5750611.03	0.6	62	87	1.481	19.03		0001	141	135	
22/01/2010 11:02:40 AM			-38.387155	142.141641667	599705.37	5750611.03	0.6	62	87	1.481	19.03		0001	137	135	
22/01/2010 11:02:40 AM			-38.387155	142.141641667	599705.37	5750611.03	0.6	62	87	1.481	19.03		0001	156	135	
22/01/2010 11:02:40 AM			-38.387155	142.141641667	599705.37	5750611.03	0.6	62	87	1.481	19.03		0001	136	135	
22/01/2010 11:02:50 AM			-38.387145	142.141658333	599706.84	5750612.12	0	59.9	87	1.661	19.03		0001	141	135	
22/01/2010 11:02:50 AM			-38.387145	142.141658333	599706.84	5750612.12	0	59.9	87	1.661	19.03		0001	142	135	
22/01/2010 11:02:50 AM			-38.387145	142.141658333	599706.84	5750612.12	0	59.9	87	1.661	19.03		0001	137	135	
22/01/2010 11:03:00 AM			-38.387138333	142.14166	599706	5750612.86	0	27.2	87	1.631	18.96		0001	141	135	
22/01/2010 11:03:10 AM			-38.387138333	142.14166	599706	5750612.86	0	27.2	87	1.511	18.98		0001	138	135	
22/01/2010 11:04:00 AM			-38.387108333	142.1168	599708.78	5750616.17	0	3.7	87	1.511	18.99					
22/01/2010 11:04:10 AM			-38.387106667	142.141681667	599708.93	5750616.35	0	3.7	87	1.441	18.99		0001	141	135	
22/01/2010 11:04:10 AM			-38.387106667	142.141681667	599708.93	5750616.35	0	3.7	87	1.441	18.99		0001	137	135	
22/01/2010 11:04:10 AM			-38.387106667	142.141681667	599708.93	5750616.35	0	3.7	87	1.441	18.99		0001	142	135	
22/01/2010 11:04:30 AM			-38.387105	142.141681667	599708.93	5750616.53	0	3.7	87	1.301	18.98		0001	152	135	
22/01/2010 11:04:30 AM			-38.387105	142.141681667	599708.93	5750616.53	0	3.7	87	1.301	18.98		0001	142	135	
22/01/2010 11:04:40 AM			-38.3871	142.141681667	599708.94	5750617.09	0	3.7	87	1.351	18.99		0001	136	135	
22/01/2010 11:04:40 AM			-38.3871	142.141681667	599708.94	5750617.09	0	3.7	87	1.351	18.99		0001	137	135	
22/01/2010 11:04:40 AM			-38.3871	142.141681667	599708.94	5750617.09	0	3.7	87	1.351	18.99		0001	146	135	
22/01/2010 11:04:40 AM			-38.3871	142.141681667	599708.94	5750617.09	0	3.7	87	1.351	18.99		0001	135	135	
22/01/2010 11:04:40 AM			-38.3871	142.141681667	599708.94	5750617.09	0	3.7	87	1.351	18.99		0001	140	135	
22/01/2010 11:04:50 AM			-38.387096667	142.14168	599708.8	5750617.46	0	3.7	87	1.361	18.99		0001	142	135	
22/01/2010 11:04:50 AM			-38.387096667	142.14168	599708.8	5750617.46	0	3.7	87	1.361	18.99		0001	144	135	
22/01/2010 11:04:50 AM			-38.387096667	142.14168	599708.8	5750617.46	0	3.7	87	1.361	18.99		0001	140	135	
22/01/2010 11:04:50 AM			-38.387096667	142.14168	599708.8	5750617.46	0	3.7	87	1.361	18.99		0001	161	135	
22/01/2010 11:04:50 AM			-38.387096667	142.14168	599708.8	5750617.46	0	3.7	87	1.361	18.99		0001	140	135	
22/01/2010 11:04:50 AM			-38.387096667	142.14168	599708.8	5750617.46	0	3.7	87	1.361	18.99		0001	139	135	
22/01/2010 11:05:00 AM			-38.387091667	142.14168	599708.81	5750618.02	0	3.7	87	1.521	18.99		0001	138	135	
22/01/2010 11:05:00 AM			-38.387091667	142.14168	599708.81	5750618.02	0	3.7	87	1.521	18.99		0001	137	135	
22/01/2010 11:05:00 AM			-38.387091667	142.14168	599708.81	5750618.02	0	3.7	87	1.521	18.99		0001	145	135	
22/01/2010 11:05:10 AM			-38.38709	142.141681667	599708.95	5750618.2	0	3.7	87	1.831	18.96		0001	136	135	
22/01/2010 11:05:10 AM			-38.38709	142.141681667	599708.95	5750618.2	0	3.7	87	1.831	18.96		0001	149	135	
22/01/2010 11:05:10 AM			-38.38709	142.141681667	599708.95	5750618.2	0	3.7	87	1.831	18.96		0001	143	135	
22/01/2010 11:05:20 AM			-38.387085	142.141681667	599708.96	5750618.75	0	3.7	87	1.461	18.98		0001	137	135	
22/01/2010 11:05:30 AM			-38.387083333	142.141681667	599708.96	5750618.94	0	3.7	87	1.511	18.96		0001	141	135	
22/01/2010 11:05:30 AM			-38.387083333	142.141681667	599708.96	5750618.94	0	3.7	87	1.511	18.96		0001	141	135	
22/01/2010 11:05:30 AM			-38.387083333	142.141681667	599708.96	5750618.94	0	3.7	87	1.511	18.96		0001	138	135	
22/01/2010 11:05:40 AM			-38.387086667	142.14168	599708.81	5750618.57	0	0.8	87	1.851	18.99		0001	139	135	
22/01/2010 11:05:40 AM			-38.387086667	142.14168	599708.81	5750618.57	0	0.8	87	1.851	18.99		0001	138	135	

Figure 39. Screenshot of WADA TRF spatially referenced abalone length data, within the modified AbTrack database. (Courtesy Duncan Worthington).

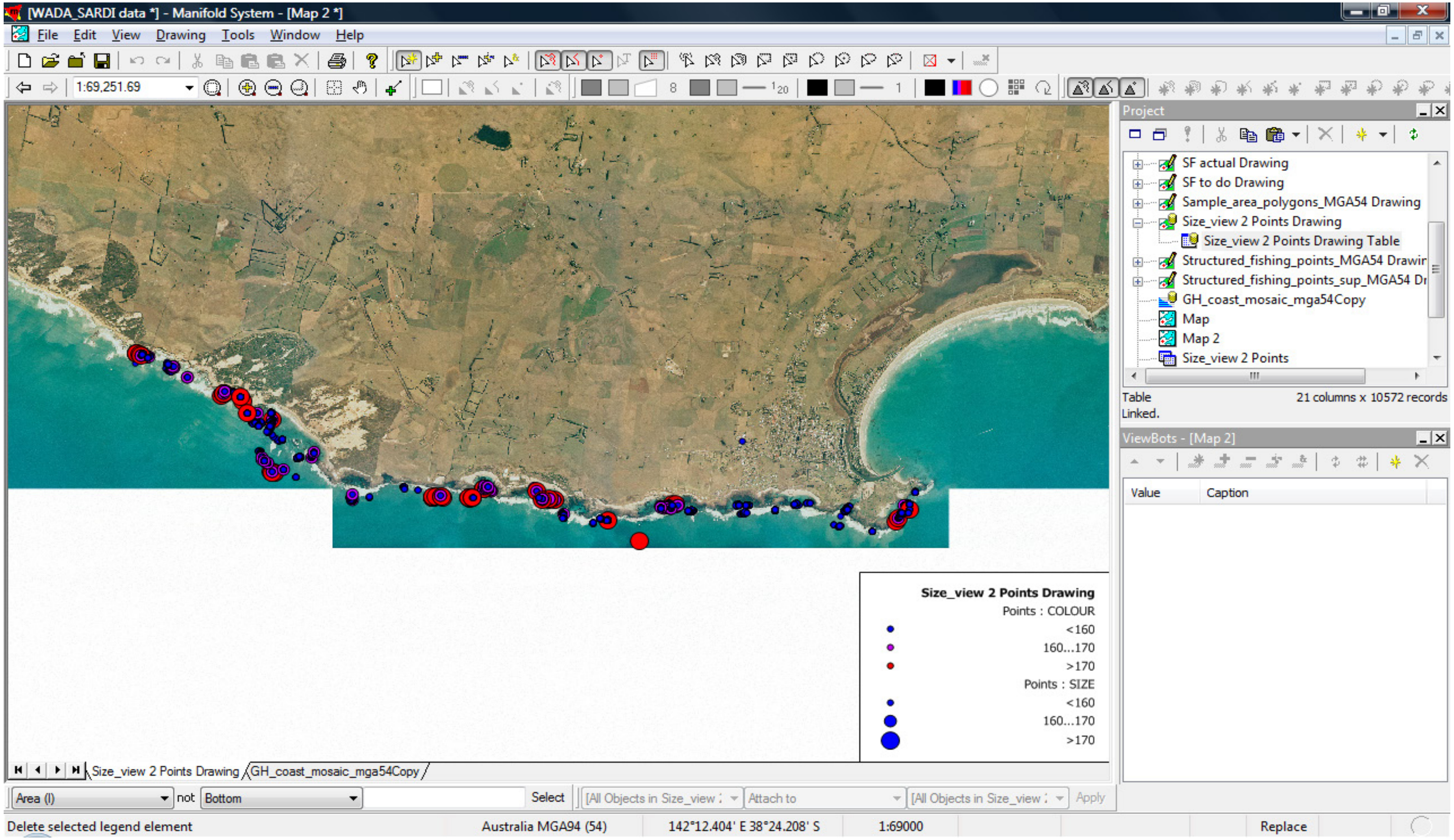


Figure 40. Map of abalone length data from WADA TRF, color coed by size, overlayed on satelite image. (Courtesy Duncan Worthington).

17. Appendix 5: Classification Tool to decode GPS stream into 'dive' and 'travel' segments in the absence of Depth logger data.

17.1.1 Background and problem definition

Central to processing of GPS data logger based spatial information on fishing activity is the information obtained from depth data loggers. The depth data loggers provide depth and temperature information during a dive, but more importantly, they provide the start time and completion time of each dive. The start and end points of each dive are then used to automate the stripping of unwanted data (i.e. travel from port to fishing location, between fishing locations) from the dataset. On occasions, depth data loggers are lost during shallow dives in rough conditions or damaged (rarely), resulting in GPS derived location data, but with no companion depth data to define the start/end points of each dive.

Options for utilising the GPS based spatial information currently are limited to manual, subjective identification of sections of the GPS data stream as either diving or fishing. This is a time consuming process, and, as it takes place outside of the AbTrack database, the data are not subsequently integrated with the full AbTrack dataset. An objective means of classifying GPS data streams into 'travelling' vs. 'diving' components, or at least a partially objective system for this purpose, that can then allow upload of the classified GPS data into AbTrack would enable GPS data in the absence of depth data to be fully integrated into AbTrack and fully utilised.

17.1.2 Linear Discriminant Analysis

17.1.2.1 Description of analysis

There are characteristic 'data signatures' of the GPS points during diving, which provide a possible mechanism to classify a GPS track in the absence of depth logger data as either 'diving' or travelling' The logical analytical approach for this is Linear Discriminant Function Analysis (LDA), which provides an objective process for predicting group membership, based on a set of continuous predictor variables (Tabachnick and Fidell 1989).

LDA is completed in a two-step process. The first step uses a training data set where depth logger data are available to identify one more discriminant functions and to test the success of the classification function based on the training data set. The second step classifies the target data set based on the functions developed for the training data set. Wherever possible, the training data set and target data sets should come from the same diver, and the same location, to avoid confounding spatial and behavioural components with the diving vs. travelling signature.

17.1.2.2 Description of data inputs

Several components of the GPS data stream could be used in an LDA classification of GPS data into 'diving' or 'travelling'. Firstly vessel speed tends to be much slower, in the order of two to three knots during diving, and much greater when travelling from port to dive locations or between dive locations. Vessel speed can be obtained in two ways – from the raw NMEA output from the GPS receiver (vessel speed), or by calculating speed from the distance travelled between two points and the time elapsed (hereafter referred to as ground speed).

The spatial position of the vessel at consecutive points in the data stream offer further information in the form step length (distance between each pair of consecutive points), and turning angle. The turning angle can be calculated as either the absolute angle made between the slope of a line between two points and the x (horizontal) axis, or the relative angle made between three successive points (Calenge et al. 2009). The package `ltraj` data class in the R package `adehabitatLT` (Calenge 2006) provides functions for calculating step length, absolute angle, and relative angle from spatial coordinates. Speed, Ground Speed, Step Length, Turning Angle and Absolute Angle form the set of potential continuous predictor variables used in the LDA classification.

The value of the above data variables within a diving component of a GPS data stream can vary for brief bursts. For example, when a vessel speeds in to pick up a catch bag, or away to avoid a wave, or up manoeuvring up current when divers are working in high tidal flow areas. For this reason, running means of the data variables of interest were calculated with a window of 30 points. This equates to an approximately 5 minute window of GPS stream data, and smooths over the short 10 or 20 second bursts observed in the raw data set.

17.1.2.3 GPS data stream classification workflow

The application of Discriminant Function Analysis and subsequent classification of an un-coded GPS data stream is completed within the R statistical package (R Development Core R Development Core Team 2011). The process is broken into a workflow comprised of 12 discrete steps (Figure 41). The complete R code for the analysis from import of data to export to final *.csv* file, with each step labelled as indicated in the workflow diagram is provided in Section 17.1.2.5.

The success of the linear discriminant analysis classification on training datasets varied depending on parameters of the moving window size for calculating running means, and the linear predictors including in the `lda` function. Success rates of the discriminant function for correctly classifying 'diving' components were typically greater than 95%. However, success rates for correctly classifying the 'travelling' component were much lower, typically around 50%. This is primarily because there are periods pre- and post- diving when vessel movement patterns are indistinguishable (slow speed, short step length, sharper turning angles) from that the pattern observed during diving. These periods most likely relate to gearing up and preparation prior to the dive, packing and storing gear or abalone on completion of the dive, site assessment, or drifting during surface intervals. The final steps of the code provided in Section 17.1.2.5 produce a csv file complete with Eastings/Northings, a variable containing the classification ('diving', 'travelling'), and a variable containing a sequential 'drop number'. This file can be imported into Manifold and assessed and edited visually. In most circumstances this can be completed in less than 1 hour. The need to undertake this process will be low, and a small amount of manual processing is therefore tolerable.

The final .csv file can then be filtered to exclude non-diving component and uploaded to SQL Server via the AbTrack interface.

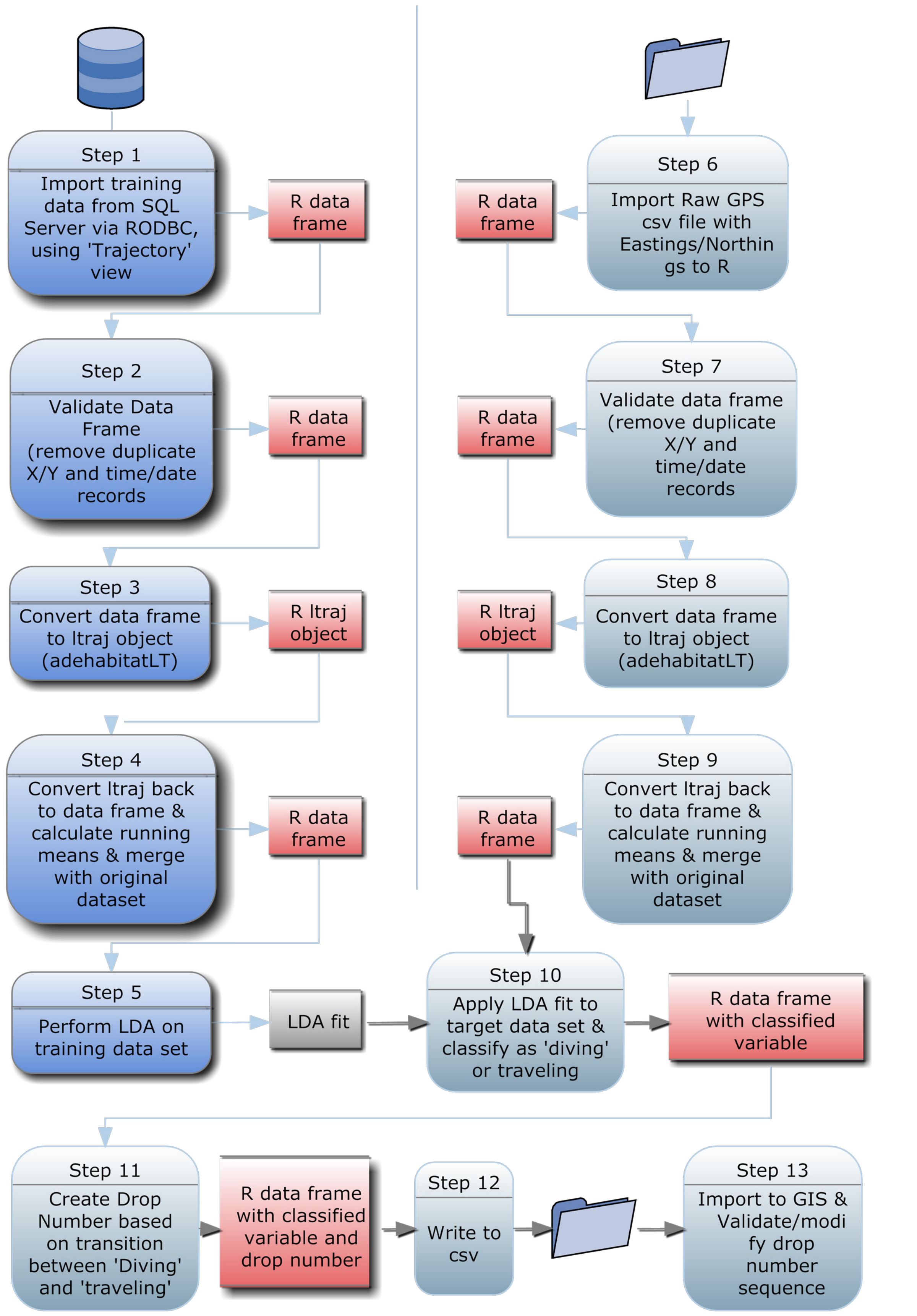


Figure 41. Workflow diagram for application of linear discriminant function analysis to classify un-coded GPS data as 'Diving' or 'Travelling'.

17.1.2.4 SQL query for extracting training data from AbTrack SQL SERVER database

For the purposes of extracting training data for classification of GPS data as 'Diving' or 'Travelling' with Discriminant Function Analysis, all data from a data series for a particular diver is required. The SQL code used for the database view *Trajectory* is given in Box 7.

Box 7. SQL script to extract training data from AbTrack in the form of a flat table for use in Discriminant Function Analysis. This query is saved as a view named `Trajectory` in the SQL SSERVER 2008 AbTrack database.

```
SELECT
      ROW_NUMBER() OVER (ORDER BY P_GPS.DATE_LOCAL) AS ID,
      P_PER.CODE, P_PER.LASTNAME,
      P_PER.FIRSTNAME,
      P_GPS.DATE_LOCAL,
      P_GPS.DATE_LOGGER,
      P_GPS.EASTING,
      P_GPS.NORTHING,
      P_GPS.SPEED,
      P_DEPTH.DROP_NUMBER,
      P_DEPTH.DEPTH,
      P_DEPTH.TEMPERATURE,
      LTRIM(P_PER.CODE) + '_' + CONVERT(CHAR(10),
      P_GPS.DATE_LOCAL, 120) + '_' + LTRIM(STR(P_DEPTH.DROP_NUMBER)) AS DiveID
FROM
      dbo.AG_SAMPLE_GPS AS P_GPS LEFT OUTER JOIN
      dbo.AG_SAMPLE_DEPTH AS P_DEPTH ON P_GPS.ID = P_DEPTH.AG_SAMPLE_GPS_ID LEFT OUTER JOIN
      dbo.AG_SAMPLE_FILE AS P_SAMPFILE ON P_GPS.AG_SAMPLE_FILE_ID = P_SAMPFILE.ID LEFT OUTER JOIN
      dbo.AG_SAMPLE AS P_SAMP ON P_SAMPFILE.AG_SAMPLE_ID = P_SAMP.ID LEFT OUTER JOIN
      dbo.CM_PERSON AS P_PER ON P_SAMP.CM_PERSON_ID = P_PER.ID LEFT OUTER JOIN
      dbo.AG_SAMPLE_FILE AS P_SAMPFILE_1 ON P_DEPTH.AG_SAMPLE_FILE_ID = P_SAMPFILE_1.ID LEFT OUTER JOIN
      dbo.AG_SAMPLE AS P_SAMP_1 ON P_SAMPFILE_1.AG_SAMPLE_ID = P_SAMP_1.ID LEFT OUTER JOIN
      dbo.CM_PERSON AS P_PER_1 ON P_SAMP_1.CM_PERSON_ID = P_PER_1.ID
```

17.1.2.5 R code

```
##Required R packages
library(adehabitatLT)
library(rgdal)
library(RODBC)
library(MASS)
library(rrcov)
library(caTools)
library(gdata)
library(car)
library(mvnormtest)
library(mvoutlier)

## STEP 1:EXTRACT TRAINING DATA SEET FROM VIEW "TRAJECTORY" IN ABTRACK DATABASE
#Specify ODBC connection details and extract data
channel1 <- odbcConnect('AbTRackLocal')
traindata <- "SELECT *
  FROM [AbTrack].[dbo].[Trajectory]
  where LASTNAME = 'Rex' and year(DATE_LOCAL) = 2010 and month(DATE_LOCAL) =1 and day(DATE_LOCAL) = 2
   ORDER BY DATE_LOCAL"
gpstrain <- sqlQuery(channel1, traindata)
close(channel1)
 gpstrain$GEOM <- NULL
#Trim leading/trailing spaces and sort by date/time
gpstrain$LASTNAME <- trim(gpstrain$LASTNAME)
gpstrain$FIRSTNAME <- trim(gpstrain$FIRSTNAME)
gpstrain <- gpstrain[order(gpstrain$DATE_LOCAL),]

## STEP 2: DATA VALIDATION
NROW(gpstrain$EASTING) # count of rows before duplicate removal
#Remove duplicate rows based on identical EASTING/NORTHING values
#NOTE: change numbers in the next line to correspond with column numbers for EASTING, NORTHING
gpstrain <-gpstrain[!duplicated(gpstrain[,7:8]),]
NROW(gpstrain$EASTING) # count of rows after duplicate removal
#remove duplicate dates
NROW(gpstrain$EASTING) # count of rows before duplicate removal
gpstrain <-gpstrain[!duplicated(gpstrain[,5]),]
NROW(gpstrain$EASTING) # count of rows after duplicate removal

#Optionally, remove data where depth < 0.5m, and check number of rows
#gpstrain <- gpstrain[-c(which(gpstrain$DEPTH < 0.5 & gpstrain$TEMPERATURE > 0)), ]
#NROW(gpstrain$EASTING)
```

```
## STEP 3: CONVERT TO LTRAJ CLASS
# Converting to ltraj class using as.ltraj from package adehabitatLT calculates step length, turning angles, etc.
# Default is to use DiveID to separate training data into bursts, to prevent large jumps between data points
gpstrainlt<- as.ltraj(gpstrain[,c("EASTING","NORTHING")],date=gpstrain[,c("DATE_LOCAL")],id=gpstrain[,c("CODE")],
burst=gpstrain[,c("DiveID")], typeII=TRUE, slsp="remove")

#gpstrainlt<- as.ltraj(gpstrain[,c("EASTING","NORTHING")],date=gpstrain[,c("DATE_LOCAL")],id=gpstrain[,c("CODE")], typeII=TRUE,
slsp="remove")
is.regular(gpstrainlt)
gpstrainlt <- setNA(gpstrainlt, gpstrainlt[[1]]$date[1], units=c("sec"),10)
is.regular(gpstrainlt)
trajdyn(gpstrainlt)

NROW(gpstrainlt)
## STEP 4: CONVERT TO DATAFRAME AND CALCULATE MOVING WINDOW MEAN/SD
gpstrainltdf <- ld(gpstrainlt)
# Remove rows where rel.angle is null
gpstrainltdf<-gpstrainltdf[-c(which(is.na(gpstrainltdf$rel.angle))),]
NROW(gpstrainltdf)
# NOTE: Speed from GSP is the speed of the vessel at the single second the data were written to memory
# Therefore, we calculate and use ground speed (x distance travelled in y time) rather than use speed from NMEA GPS
gpstrainltdf$grspeed <- (gpstrainltdf$dist/gpstrainltdf$dt)*60*60/1000
#set moving window size
#NOTE window size of 20 equates to a moving window of ~ 3 minutes & 20 seconds - you can adjust this to optimise your data set
varwinsize <- 20
#Calculate Mean of Moving Window (window set by varwinsize parameter) using runmean function from package(caTools)
gpstrainltdf$rmrelang <- runmean(cos(gpstrainltdf$rel.angle), varwinsize, alg=c("exact"), endrule=c("constant"))
gpstrainltdf$rmabsang <- runmean(cos(gpstrainltdf$abs.angle), varwinsize, alg=c("exact"), endrule=c("constant"))
gpstrainltdf$rmdist <- runmean(gpstrainltdf$dist, varwinsize, alg=c("exact"), endrule=c("constant"))
gpstrainltdf$rmspeed <- runmean(gpstrainltdf$grspeed, varwinsize, alg=c("exact"), endrule=c("constant"))
#Standard Deviation of Moving Window (window set by varwinsize paramter) using runsd function from package(caTools)
gpstrainltdf$rsdrelang <- runsd(cos(gpstrainltdf$rel.angle), varwinsize, center = runmean (cos(gpstrainltdf$rel.angle),varwinsize),
endrule = c("constant"))
gpstrainltdf$rsdabsang <- runsd(cos(gpstrainltdf$abs.angle), varwinsize, center = runmean (cos(gpstrainltdf$abs.angle),varwinsize),
endrule = c("constant"))
gpstrainltdf$rsddist <- runsd(gpstrainltdf$dist, varwinsize, center = runmean (gpstrainltdf$dist,varwinsize), endrule =
c("constant"))
gpstrainltdf$rsdspeed <- runsd(gpstrainltdf$grspeed, varwinsize, center = runmean (gpstrainltdf$grspeed,varwinsize), endrule =
c("constant"))
colnames(gpstrainltdf) <- c( 'EASTING', 'NORTHING', 'DATE_LOCAL','dx', 'dy', 'dist', 'dt', 'R2n', 'abs.angle', 'rel.angle', 'id',
'burst','pkey','grspeed', 'rmrelang','rmabsang','rmdist', 'rmgrspeed', 'rsdrelang','rsdabsang','rsddist','rsdgrspeed')
NROW(gpstrain$EASTING)
```

```
#MERGE MOVING WINDOW CALCULATED VARIABLES WITH ORIGINAL DATA
gpstrainset <-merge(gpstrainltdf,gpstrain, by =c("DATE_LOCAL")) #,by.x=c("date","x","y"),by.y=c("DATE_LOCAL","EASTING","NORTHING"))
gpstrainset <- gpstrainset[order(gpstrainset$DATE_LOCAL),]
colnames(gpstrainset) <- c('DATE_LOCAL', 'EASTING.lt', 'NORTHING.lt', 'dx', 'dy', 'dist', 'dt', 'R2n', 'abs.angle', 'rel.angle',
'id', 'burst','pkey', 'grspeed', 'rmrelang','rmabsang', 'rmdist', 'rmgrspeed', 'rsdrelang','rsdabsang','rsddist','rsdgrspeed', 'ID',
'CODE', 'LASTNAME', 'FIRSTNAME', 'DATE_LOGGER', 'EASTING.dat', 'NORTHING.dat', 'SPEED', 'DROP_NUMBER', 'DEPTH',  'TEMPERATURE',
'DiveID')

#Create Diving" field and Classify track as Diving=Yes or Diving=No using DEPTH information
NROW(gpstrainset)
gpstrainset$Diving <-ifelse(gpstrainset$DEPTH > 0.5, "Yes", "No")
gpstrainset$Diving[is.na(gpstrainset$Diving)]<-"No"
gpstrainset$Diving <- as.factor(gpstrainset$Diving)


## STEP 5: PERFORM DESCRIMINANT FUNCTION ANALYSIS
#Linear Discrimant analysis model - fit model to training dataset using package(MASS)
divelda <-lda(Diving ~ rmabsang + rmdist + rmgrspeed + rsddist + rsdgrspeed + rsdabsang, data = gpstrainset, na.action=na.omit)
#Apply discriminant function to training dataset and create classification field based on lda model fit
gpstrainset$classified <- predict(divelda,gpstrainset, method="predictive")$class
#Create a new field and assign the discriminant scores from the model fit
gpstrainset$scores <- predict(divelda, gpstrainset)$x
#Calculate Observed vs Predicted group membership to check accuracy of prediction
ctest <- table(gpstrainset$Diving, gpstrainset$classified)
ctest
diag(prop.table(ctest,1))
# total percent correct
sum(diag(prop.table(ctest)))


## STEP 6: READ RAW GPS DATA FROM CSV FILE
#ADJUST col names() for required GPS logger model
#Note: use the projected data file with EASTINGS/NORTHINGS, not Lat/Long
gpsdat <- read.csv("D:/AbTrack/RawData/Archived_data_files/GPS_2009/Rex_2009_02_03_MGA.csv", header=TRUE, sep=',', dec='.')
#BTC colnames(gpsdat) <- c( 'Longitude', 'Latitude', 'Speed','Course', 'NumberOfSats', 'HDOP', 'Altitude', 'Date', 'TIME',
'Distance','EASTING','NORTHING')
colnames(gpsdat) <-
c('Diver_Code','Divers','Event','Catch','UTC_time','UTC_date','Corrected_Time','Corrected_Date','Status','Log_lat','Log_long','Speed'
,'Course','EASTING','NORTHING') #SciElex
#Convert paste UTC_date & UTC_time, convert to POSIXct and add/subtract time
# use %Y for 4 digit year and %y for 2 digit year
#BTC110 gpsdat$LoggerDate <- as.POSIXct(strptime(paste(gpsdat$Date, gpsdat$TIME), "%d/%m/%Y %H:%M:%S"))
gpsdat$LoggerDate <- as.POSIXct(strptime(paste(gpsdat$UTC_date, gpsdat$UTC_time), "%d/%m/%y %H:%M:%S")) #SciElex MKII
#Convert from UTC0 to UTC10
gpsdat$LoggerDate <- gpsdat$LoggerDate + (10*60*60)
```

```
#Create a diveid code based on date
#BTC110 gpsdat$LogId <-paste("BTC")
gpsdat$LogId <-gpsdat$Diver_Code

## STEP 7: DATA VALIDATION of raw GPS data
NROW(gpsdat$EASTING) # count of rows before duplicate removal
#Remove duplicate rows based on identical EASTING/NORTHING values
#NOTE: change numbers in the next lineto correspond with column numbers for EASTING, NORTHING
gpsdat <-gpsdat[!duplicated(gpsdat[,14:15]),]
NROW(gpsdat$EASTING) # count of rows after duplicate removal
#remove duplicate dates
NROW(gpsdat$EASTING) # count of rows before duplicate removal
gpsdat <-gpsdat[!duplicated(gpsdat[,16]),]
NROW(gpsdat$EASTING) # count of rows after duplicate removal


## STEP 8: CONVERT raw GPS data TO LTRAJ CLASS
# Converting to ltrasj class using as.ltraj from package(adehabitatLT) clculates step length, turning angles, etc
gpsdatlt<- as.ltraj(gpsdat[,c("EASTING","NORTHING")],date=gpsdat[,c("LoggerDate")],id=gpsdat[,c("LogId")],typeII=TRUE, slsp="remove")
NROW(gpsdatlt)


## STEP 9: CONVERT TO DATAFRAME AND CALCULATE MOVING WINDOW MEAN/SD
gpsdatltdf <- ld(gpsdatlt)
# Remove rows where rel.angle is null
gpsdatltdf<-gpsdatltdf[-c(which(is.na(gpsdatltdf$rel.angle))),]
# NOTE: Speed from GPS is the speed of the vessel at the single second the data was written to memory
# Therefore, we calculate and use ground speed (x distance travelled in y time) rather than use speed from NMEA GPS
gpsdatltdf$grspeed <- (gpsdatltdf$dist/gpsdatltdf$dt)*60*60/1000
#set moving window size
#NOTE window size equates to a moving window of ~ 3 minutes & 20 seconds - you can adjust this to optimise your data set
varwinsize <- 20
#Calculate Mean of Moving Window (window set by varwinsize paramter) using runmean function from package(caTools)
gpsdatltdf$rmrelang <- runmean(gpsdatltdf$rel.angle, varwinsize, alg=c("exact"), endrule=c("constant"))
gpsdatltdf$rmabsang <- runmean(gpsdatltdf$abs.angle, varwinsize, alg=c("exact"), endrule=c("constant"))
gpsdatltdf$rmdist <- runmean(gpsdatltdf$dist, varwinsize, alg=c("exact"), endrule=c("constant"))
gpsdatltdf$rmspeed <- runmean(gpsdatltdf$grspeed, varwinsize, alg=c("exact"), endrule=c("constant"))
#Standard Deviation of Moving Window (window set by varwinsize paramter) using runsd function from package(caTools)
gpsdatltdf$rsdrelang <- runsd(gpsdatltdf$rel.angle, varwinsize, center = runmean (abs(gpsdatltdf$rel.angle),varwinsize), endrule =
c("constant"))
gpsdatltdf$rsdabsang <- runsd(gpsdatltdf$abs.angle, varwinsize, center = runmean (abs(gpsdatltdf$abs.angle),varwinsize), endrule =
c("constant"))
gpsdatltdf$rsddist <- runsd(gpsdatltdf$dist, varwinsize, center = runmean (gpsdatltdf$dist,varwinsize), endrule = c("constant"))
gpsdatltdf$rsdspeed <- runsd(gpsdatltdf$grspeed, varwinsize, center = runmean (gpsdatltdf$grspeed,varwinsize), endrule =
c("constant"))
```

```
colnames(gpsdatltdf) <- c( 'EASTING', 'NORTHING', 'LoggerDate','dx', 'dy', 'dist', 'dt', 'R2n', 'abs.angle', 'rel.angle',  'id',
'burst','pkey', 'grspeed', 'rmrelang','rmabsang','rmdist', 'rmgrspeed', 'rsdrelang','rsdabsang','rsddist','rsdgrspeed')

#MERGE MOVING WINDOW CALCULATED VARIABLES WITH ORIGINAL DATA
gpsdatset <-merge(gpsdatltdf,gpsdat, by =c("LoggerDate")) #,by.x=c("date","x","y"),by.y=c("DATE_LOCAL","EASTING","NORTHING"))
gpsdatset <- gpsdatset[order(gpsdatset$LoggerDate),]
#BTC110 colnames(gpsdatset) <- c('LoggerDate', 'EASTING.lt', 'NORTHING.lt', 'dx', 'dy', 'dist', 'dt', 'R2n', 'abs.angle',
'rel.angle', 'grspeed', 'rmrelang', 'rmdist', 'rmgrspeed', 'rsdrelang','rsddist','rsdgrspeed','Longitude', 'Latitude',
'Speed','Course', 'NumberOfSats', 'HDOP', 'Altitude', 'Date', 'TIME', 'Distance','EASTING.dat','NORTHING.dat','LogId')
colnames(gpsdatset) <- c('LoggerDate', 'EASTING.lt', 'NORTHING.lt', 'dx', 'dy', 'dist', 'dt', 'R2n', 'abs.angle', 'rel.angle',  'id',
'burst','pkey','grspeed', 'rmrelang','rmabsang', 'rmdist', 'rmgrspeed', 'rsdrelang','rsdabsang','rsddist','rsdgrspeed',
'Diver_Code','Divers','Event','Catch','UTC_time','UTC_date','Corrected_Time','Corrected_Date','Status','Log_lat','Log_long','Speed','
Course','EASTING','NORTHING','LogId') #SciElex MKII

## STEP 10: Apply LDA fit to target GPS dataset
#applies model fit from training dataset to GPS dataset and creates a new field called classified
gpsdatset$classified <- predict(divelda,newdata=gpsdatset, dimen=1)$class
tapply(gpsdatset$rmgrspeed, list(Diving=gpsdatset$classified), mean, na.rm=TRUE)
tapply(gpsdatset$rmdist, list(Diving=gpsdatset$classified), mean, na.rm=TRUE)

gpsdatset$SpeedTrap <-ifelse(gpsdatset$rmgrspeed > 5, "No", "YES")
gpsdatset$SpeedTrap[is.na(gpsdatset$SpeedTrap)]<-"YES"

ctest <- table(gpsdatset$SpeedTrap, gpsdatset$classified)
ctest
diag(prop.table(ctest,1))
# total percent correct
sum(diag(prop.table(ctest)))

##STEP 11: CREATE DROPNUMBER field and add to dataframe
ptm <- proc.time()
InstantDepth <- subset(gpsdatset, select=c(Diver_Code:NORTHING,classified))
InstantDepth$DropNumber <- as.numeric(NA)
InstantDepth$DiveLength <- as.numeric(NA)
LastClass  <- InstantDepth$classified[[1]]
  DropNumberCnt <- 1
  DiveLengthCnt <- 1

for (i in 2:length(InstantDepth$classified)) {
      if (InstantDepth$classified[[i]] == "No") {
        if(InstantDepth$classified[[i]] != LastClass) {
          DropNumberCnt <- DropNumberCnt + 1
          DiveLengthCnt <- 1
        }
        LastClass <- InstantDepth$classified[[i]]
```

```
        }
       else {
         InstantDepth$DropNumber[[i]] <- DropNumberCnt
         InstantDepth$DiveLength[[i]] <- DiveLengthCnt
         DiveLengthCnt <- DiveLengthCnt + 1
         LastClass <- InstantDepth$classified[[i]]
        }
   }
cputime <-proc.time() - ptm
cputime

#End processing for incremental Drop Numbers


## STEP 12: Write to csv file
write.csv(InstantDepth, file = "y:/AbTrack/RawData/VirtualDepth/InstantDepthRex.csv", quote=FALSE, row.names=FALSE, na="")
```