Optimising the size and quality of Sardines through real-time harvest monitoring

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PREMIUM FOOD AND WINE FROM OUR CLEAN ENVIRONMENT

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Principal Investigator and Objectives

013/746: Optimising the size and quality of Sardines through real-time harvest monitoring

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Project Objectives:

1. To empower industry to conduct real-time monitoring of fish size and quality in relation to key environmental parameters.
2. To determine the key environmental factors influencing the spatial distribution and size of fish.
3. To establish a co-management system for optimising the size, quality and value of fish harvested by the South Australian Sardine Fishery using industry collected data and near real-time map underlays of key environmental variables.

Non-Technical Summary

In order to improve the commercial profitability and sustainability of the South Australian Sardine Fishery (SASF) there was a need to establish improved monitoring and harvest management practices based on an understanding of Sardine habitat preferences. In this project, the South Australian Sardine Industry Association Inc. (SASIA) was empowered with the resources to autonomously implement near real-time monitoring of fish movement in relation to changes in environmental conditions. As a part of the harvest management optimisation, an understanding of the environmental conditions which characterise the habitat preferences of juvenile, adult and spawning Sardines was investigated.

This project was developed at the request of SASIA and comprises two inter-related components with the common objectives of improving the economic value and ecological sustainability of the fishery.

Firstly, the SASIA was assisted in developing and implementing an autonomous near real-time harvest management system. The system is composed of three inter-connected components; fish measurement, data storage and spatial mapping. SASIA collected data on fish length (caudal-fork length) are efficiently measured and stored directly into a database using an electronic fish measurement board. The database has been designed to store and present information related to the location and size of the commercial catch from which sample measures of fish length are collected. Finally, GIS spatial mapping software is linked with the database to provide maps showing the spatial distribution of target and non-target sized fish. Maps detailing changes in the spatial distribution of target and non-target size are updated fortnightly and used by the SASIA to optimise the size of fish harvested.

Secondly, to augment the adopted real-time harvest management system, habitat suitability studies using generalised additive models (GAMs) were undertaken to understand the environmental conditions that explain the habitat preferences of juvenile and adult Sardines, as well as the summer-time spawning habitat. Historical datasets used in the modelling studies included 1) Sardine egg densities and coincident oceanographic measurements made during Daily Egg Production Method (DEPM) surveys conducted since 2004, and 2) fish length measurements made by independent observers aboard commercial vessels since 2004 and corresponding satellite measures of sea surface temperature and surface chlorophyll *a* concentrations.

In common with similar studies of Sardine habitat suitability undertaken elsewhere around the world, our results show spatial (i.e. depth) and environmental variables (i.e. sea surface temperature, surface chlorophyll *a* concentrations) can be used to explain and differentiate the habitat preferences of juvenile (i.e. small, non-target size) and adult (i.e. large, target size) Sardines and spawning habitat. The probability of agreement between observations and predictions demonstrated that the GAMs had an acceptable level of predictive capability for juvenile and adult habitat and a good level of predictive capability for spawning habitat. The inclusion of available additional environmental factors (e.g. surface salinity and depth of the chlorophyll *a* maximum) provided small, yet significant, improvements in the capacity to predict the distribution of spawning habitat.

Importantly, the modelling studies demonstrated that daily satellite observations of key environmental predictors (i.e. sea surface temperature, surface chlorophyll *a* concentration) can provide an acceptable level of habitat prediction for juvenile and adult Sardines. To make full use of readily available satellite information, the SASIA has been trained to incorporate observations of relevant satellite environmental parameters, averaged over time-scales ranging from several days to months, into maps showing the spatial distribution of target (adult) and non-target sized (juvenile) fish in relation to shifts in identified environmental drivers.

OUTCOMES ACHIEVED

The key outcome from this project is the empowerment of the SASIA to autonomously manage the size and quality of fish harvested by establishing the tools, capability and procedures to monitor catches efficiently in near real-time. The integrated fish length measurement, data storage and spatial mapping system that was established will reduce fishing mortality rates on juvenile Sardine and improve the overall size, quality and value of fish that are taken. This outcome will enhance the ecological, economic and social sustainability of the South Australian Sardine Fishery.

The ability to predict the spawning habitat of Sardine that was developed in this project will also assist the optimisation of future DEPM surveys by helping to ensure that sampling effort is targeted on areas likely to support high densities of Sardine eggs and spawning adults.

The overall increase in our understanding of the habitat preferences of Sardine developed in this project will enhance the future management of South Australia's fishery resources and ecosystems by assisting modelling, prediction and interpretation of future spatial and temporal shifts in Sardine distribution and abundance that may occur under a variety of scenarios, including climate change.

LIST OF OUTPUTS PRODUCED

1. An autonomous integrated fish measurement, database and spatial mapping system that has enabled the SASIA to manage the size and quality of fish harvested in near real-time. The system includes an automated fish length measurement board, ArcGIS spatial mapping software and a Microsoft Excel database.
2. Statistical models that increased our understanding of the environmental conditions which define the habitat preferences of Sardines. These models have the capability to use satellite information and/or ocean model forecasts of environmental variables to predict the preferred habitat of spawning Sardines, adults and juveniles.

Acknowledgements

This work was a project of the Australian Seafood Cooperative Research Centre (ASCRC) and received funds from the Fisheries Research and Development Corporation (FRDC). Thank you to the Integrated Marine Observing System (http://www.imos.org.au/) for providing the satellite datasets via the IMOS portal (http://imos.aodn.org.au) and for maintaining and updating the "Accessing IMOS Satellite Data" document by Redondo Rodriguez *et al.* presented in Appendix 2. Dr. Stephen Mayfield, Assoc. Prof. John Middleton, John Feenstra and two anonymous reviewers provided valuable comments which helped improve the quality of the final report. The report was approved for publication by Prof. Gavin Begg.

1. Introduction

The distribution of Australian Sardines (*Sardinops sagax*) extends across the cool, temperate waters of southern Australia and into sub-tropical waters as far north as Rockhampton, Queensland in the east and Shark bay, Western Australia in the west. Comprised of four separate stocks, the southern Australian stock is centred in waters off South Australia and contributes the majority of the Australian Sardine population (Ward *et al.* 2006c). Accordingly, the South Australian Sardine Fishery (SASF) is Australia's largest commercial fishery by volume and has an annual production of around 34,000 t with an estimated value of $20.7 million (Econsearch 2014). To further ensure stock sustainability and improve the commercial quality (i.e. size) of fish taken, the South Australian Sardine Industry Association Inc. (SASIA) has sought assistance to develop; (i) an autonomous fish length monitoring and harvest management system, and (ii) a better understanding of the environmental conditions which influence the habitat preferences of Sardine.

In addition to their commercial value, Sardines play a key ecological role in many marine food webs by transferring energy from plankton to higher trophic levels (Cury *et al.* 2000). In South Australian waters, Sardines provide an important food source for a variety of predatory fishes (Ward *et al.* 2006c), squid (O'Sullivan and Cullen 1983), seabirds (Crawford 2003) and marine mammals (Page *et al.* 2005). Hence, elucidation of the environmental conditions that define the habitat preferences of Sardines will improve our understanding of the ecology of Sardines and is intrinsic to fisheries management (Boyd *et al.* 2006). Globally, habitat suitability studies have demonstrated that a range of common spatial and environmental variables, such as bottom depth, temperature and phytoplankton biomass define the preferred habitat of juvenile (Tsagarakis *et al.* 2008, Giannoulaki *et al*. 2011) and spawning (Schismenou *et al.* 2008, Weber and McClatchie 2010) Sardines. Ultimately, patterns of Sardine distribution are complicated by spatial and temporal shifts and lags between the interaction of environmental (i.e. pelagic bio-physical environment) and biological processes (i.e. population sizes changes, larval development) (Gremillet *et al.* 2008). For these reasons, determining the habitat preferences of Sardines requires information collected over extensive spatial and temporal scales (Planque *et al.* 2007).

In South Australia, the need to better understand the environmental conditions that define the distribution and habitat of Sardines is important for several reasons. Firstly, the distribution of Sardines affects predator-prey relationships and is expected to have regional trophodynamic implications (Goldsworthy *et al.* 2013). Secondly, such knowledge is needed to inform the optimisation and planning of effective stock assessment surveys. If areas where spawning is most likely to occur could be identified before a survey cruise, the design of the sampling program could be optimised to provide better egg abundance measures and improved spawning biomass estimates for a given effort and/or cost. Finally, reductions in the size (and age) of Sardines caught over recent years from southern Spencer Gulf suggest that the high proportion of fish being caught from this region may be impacting on stock status (Ward *et al.* 2012). Improving our understanding of the environmental preferences and distribution of juvenile and adult Sardines offers an opportunity to identify key areas for stock management (i.e. nursery grounds) and optimise commercial fishing in order to reduce impacts on stocks whilst improving the overall size and commercial quality of fish taken.

1.1 Need

Understanding the effect of fishing and environmental factors in determining the distribution and abundance of target-size Sardines is essential to the ecologically and economically sustainable development of the South Australian Sardine Fishery (SASF).

In response to recent reductions in fish length (and quality), SASIA has sought assistance to increase the productivity and profitability of the fishery through the development and implementation of an industry-led, near real-time harvest monitoring system.

To address these needs industry has requested help to:

1. Establish the skills and systems required to conduct near real-time monitoring of fish harvesting.

2. Identify and obtain advice on the oceanographic factors affecting the distribution of juvenile and adult Sardine size classes.

3. Obtain ongoing access to identified, readily available satellite oceanographic information for inclusion in developed near real-time harvest monitoring system to further optimise the size and quality of fish taken.

2. Methods

2.1 Objective 1: To empower industry to conduct real-time monitoring of fish size and quality in relation to key environmental parameters.

Objective 3: To establish a co-management system for optimising the size, quality and value of fish harvested by the SASF using industry collected data and near real-time map underlays of key environmental variables.

The development of an autonomous fish size measurement and harvest monitoring system for the SASIA involved the linking of three components (Figure 1).

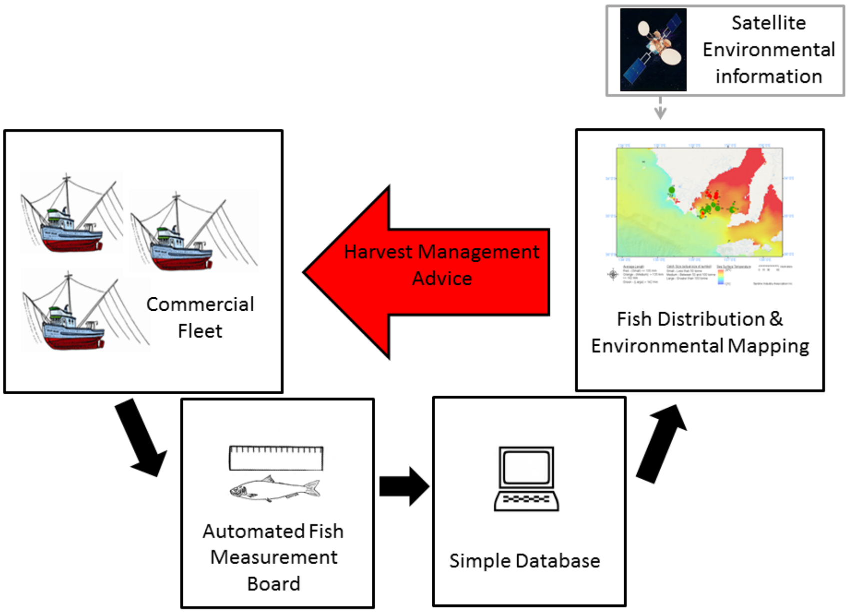

Figure 1. Schematic diagram describing the SASIA led monitoring and harvest co-management system. Samples taken from commercial vessels are measured for fish length in port by industry representatives using a single electronic fish measurement board. The measurement board is linked wirelessly to a database which stores measures of fish length and additional data necessary for the spatial management of the fishery. Mapping software is linked to the database to provide maps showing the distribution of Sardines by different size classes. Maps can incorporate coincident satellite measures of environmental variables (e.g. sea surface temperature) as underlays. Maps are updated fortnightly to provide near real-time information on shifts in the distribution of Sardines in relation to environmental drivers. This information is used as part of a co-management system between Industry managers, SARDI and PIRSA Fisheries and Aquaculture to optimise harvest practices.

Firstly, the size (length) of fish obtained from commercial catch is measured by the SASIA using a single customised electronic fish measurement board (SciElex Pty. Ltd). Fish sample bags, containing up to 50 individual fish and a waterproof tag referencing the samples to the SARDI log book entry, are prepared at sea by fishers. Sample bags are then collected from each vessel on their return to port by an industry representative and fish lengths are measured using the electronic measurement board. Measures of fish length, given by the caudal-fork length (mm), are 'wirelessly' logged directly from the measurement board into a Microsoft Excel worksheet. Industry representatives received training by SARDI scientists to accurately measure fish length. Referencing of the samples to the SARDI logbook entry allows for the quarterly evaluation of industry measures against fish length measures processed by SARDI from samples taken by independent observers aboard commercial vessels.

Secondly, to exploit the full potential of the fish measurement board, a simple Microsoft Excel database was developed around the Microsoft Excel worksheet that fish length measures are automatically logged to. The database allows for the entry and storage of additional metadata relevant to the spatial management of the fishery. These data are obtained from the SARDI log book number accompanying each set of samples. Required metadata includes the GPS location, date/time and total tonnage caught for each respective shot and vessel. The database has graphical features that allow for simple plots of temporal and spatial patterns in fish length to be easily updated. SASF management representatives completed a Microsoft Excel training course to ensure the full uptake of the database.

Thirdly, the SASIA has adopted and received training in the use of ArcGIS spatial mapping software (ESRI Australia). ESRI, in discussion with the SASIA and SARDI scientists, has customised the software used by the SASIA. The mapping package allows for routinely displaying the spatial distribution of fish length, weight, total catch size and environmental variables. Data are loaded directly from the database into mapping software. A 'traffic light' and 'symbolic' system is used to map the distribution of fish length and catch tonnages, respectively. Selection of fish length categories was based on the size and age at which Sardines reach sexual maturity (Ward and Staunton-Smith 2002) and are consistent with the management guidelines given in the South Australian *Fisheries Management Act 2007* (http://www.legislation.sa.gov.au/LZ/C/A/Fisheries%20Management%20Act%202007.aspx). Measures of the average fish length (mm) and total catch size (t) by vessel, shot and location are binned into one of three categories. Fish length categories were defined as 'red' for small fish less than 135 mm, 'orange' for medium fish between 135 and 142 mm and 'green' for large fish greater than 142 mm. Symbol sizes for total catch size categories were defined by a 'small' symbol for a catch less than 50 t, 'medium' symbol for a catch between 50 and 100 t and a 'large' symbol for catches greater than 100 t.

The mapping package is able to incorporate map underlays of relevant satellite environmental information (i.e. sea surface temperature and chlorophyll *a* concentration) available from the IMOS ocean data portal (https://imos.aodn.org.au/). SARDI has provided, and continue to provide, support in accessing, incorporating and interpreting satellite data from the IMOS portal (see Appendix 2). Information presented in Appendix 2 regarding accessing IMOS satellite data is maintained and updated by the eMarine Information Infrastructure (eMII) facility and is available to the public from the IMOS website (http://imos.org.au/emii.html). Satellite information is updated daily on the IMOS portal with approximately a 6-day lag between observations and data availability. Furthermore, owing to factors such as cloud cover which limit the extent of daily spatial coverage, composite images averaged over time scales of 3-days are typically required for full spatial coverage over the South Australian region. Currently, maps showing changes in the spatial distribution of target and non-target size fish in relation to time-averaged satellite environmental information are updated each fortnight by SASIA. These fortnightly updates are communicated to fishers by SASIA management and provide near real-time information to optimise harvest management by avoiding the triggering of size based rules.

2.2 Objective 2: To determine the key environmental factors influencing the spatial distribution and size of fish.

2.2.1 General Analytical Approach

The study of Sardine spatial distributions was undertaken using generalised additive models (GAM; Hastie and Tibshirani 1990, Wood 2006). GAMs were used to examine relationships between environmental variables and the presence/absence of 1) Sardine eggs and 2) Sardine juveniles and adults. GAMs have been widely applied in ecological studies investigating the relationships between species and their environments (Guisan *et al.* 2002). In fisheries studies, GAMs have been successfully applied to predict the spatial distribution of eggs as a proxy for spawning habitat for Sardine (Wood and Augustin 2002, Planque *et al.* 2007) and other small pelagic fish species (Stoner *et al.* 2001, Zagaglia *et al.* 2004), as well as the distribution of juvenile Sardines as a proxy for nursery grounds (Tsagarakis *et al.* 2008, Giannoulaki *et al*. 2011).

GAMs fit smoothers to relationships between the response and predictor variables. In this study, we use a binomial error distribution and a logit link function in the GAM models. Binomial GAMs have been successfully applied to fish habitat suitability studies and perform better than similar models using abundance data (Francis *et al.* 2005, Weber and McClatchie 2010).

All GAMs were fitted using the 'gam' function in the 'mgcv' library (version 1.8-0, Wood 2006) in the R statistical software (R version 3.1.1; R Core Team, 2014). The general form of the model was:

$$E(y) = \beta_0 + \sum_k S_k\,(X_k)$$

Where $E(y)$ is the expected value of the response (dependent) variable (y), β_0 is the intercept, S_k is the smoothing function and X_k is the value of the k^{th} predictor variable. For each predictor variable, thin plate regression splines were used (Wood 2006) and overfitting was prevented by restricting the degrees of freedom to 3. This ensured the fitted smoothers remained biologically realistic for the expected response of Sardines to an environmental stimulus (Weber and McClatchie 2010).

Before commencing GAM modelling, predictor variables were checked for co-linearity using multi-panel scatterplots and Pearson correlation coefficients following the methods of Zuur *et al.* (2010). The building and testing of GAMs then followed the general approach taken by Chust *et al.* (2014). First, a GAM was built for each predictor variable independently. Combined GAM models were then improved in a forward stepwise manner by adding variables. Predictor variables that did not improve the explained deviance by >1%, or were not statistically significant, were excluded. The percentage of deviance explained by the model is calculated as, 1–residual model deviance/null model deviance) times 100; where the deviance is -2 times the log likelihood of the model.

Model validation was based on an assessment of predictive capability through an iterative process that excluded one year of data at a time from the model build for validation. The predictive capability of the model was evaluated using the explained deviance and area under the receiver operating characteristic curve (AUC; Fielding and Bell 1997). AUC values range between 0 and 1, where a value of 1 indicates perfect prediction accuracy and a value of 0 indicates perfectly inaccurate predictions. An AUC of 0.5 represents a model that predicts no better than random. As a second test, accuracy measures were derived from an error matrix. Here, the modelled probability of a correct prediction was converted to ei*t*her presence or absence using a probability threshold value. The receiver operating characteristic curve (ROC) was used to determine an optimum threshold that maximises model sensitivity and specificity (Fielding and Bell 1997). The error matrix is then given as a cross-tabulation of the modelled presence/absence against the observed data. An accuracy value (percentage) is estimated as the portion of the presence and absence records correctly predicted.

2.2.2 Spawning Habitat

Eggs and measures of environmental variables were obtained at stations sampled during daily egg production method (DEPM) surveys (Ward *et al.* 2011). DEPM surveys are conducted in the waters of South Australia between February and March during the peak spawning period (Ward *et al.* 2012) and coincide with summer upwelling season (Kaempf et al. 2004). The final dataset included seven survey years (i.e. 2004 - 2007, 2009, 2011 and 2013) and each survey year included between 237 and 256 stations located in southern Spencer Gulf and shelf waters (Figure 2). DEPM surveys were not conducted in 2008, 2010 or 2012.

Eggs are collected as a part of plankton samples obtained using paired Californian Vertical Egg Tow (CalVET) plankton nets. Each CalVET net had an internal diameter of 0.3 m, 330 µm mesh size and plastic cod ends for sample collection. Nets are lowered to a depth of approximately 70 m or to 10 m from the bottom in water less than 80 m. Plankton seawater samples are preserved in 5% buffered formaldehyde for identification in the laboratory following the methods of Neira et al. (1998). Environmental variables were measured using a SeaBird Conductivity-Temperature-Depth profiler (CTD) fitted with a fluorometer. CTD profiles were made from the surface to a depth of approximately 90 m or to 10 m from the bottom in water less than 90 m. Fluorescence gives an un-calibrated measure of chlorophyll *a* concentration (chl *a*). Due to fluorometer sensor drift and calibration limitations, daily measures of satellite surface chl *a* were used to replace CTD surface fluorescence values where possible to form a single dataset. Satellite chl *a* data was obtained at each location by averaging the available chl *a* data within a 5x5 pixel grid (centered on the target location), using the standard 4 km resolution MODIS-Aqua level-3 chl *a* product (http://oceancolor.gsfc.nasa.gov/).

Six predictor variables were used to model the presence of Sardine eggs. Environmental variables included; sea surface temperature (SST, ^{o}C), surface salinity (Salinity, PSU), surface chlorophyll *a* (chl *a*, µg L^{-1}), depth at which the maximum chlorophyll concentration occurred (DCM, m) and the mixed layer depth (MLD, m). Bottom depth (depth, m) was included as a spatial variable. SST and salinity were used as predictors of the physiological suitability of the habitat. Chl *a* provides an indicator of phytoplankton biomass and was included as a predictor of the food availability. Mixed layer depth and depth of the chlorophyll maximum provided environmental predictors related to internal stratification and nutrient shoaling processes (e.g. upwelling) that are likely to influence primary productivity. Mixed layer depth was estimated from the CTD profiles following the method of Holte and Talley (2009). Depth information was interpolated from the ETOPO2v2 dataset (National Geophysical Data Center 2006) available from the NOAA website (www.ngdc.noaaa.gov).

The final dataset included 1,857 sampled stations.

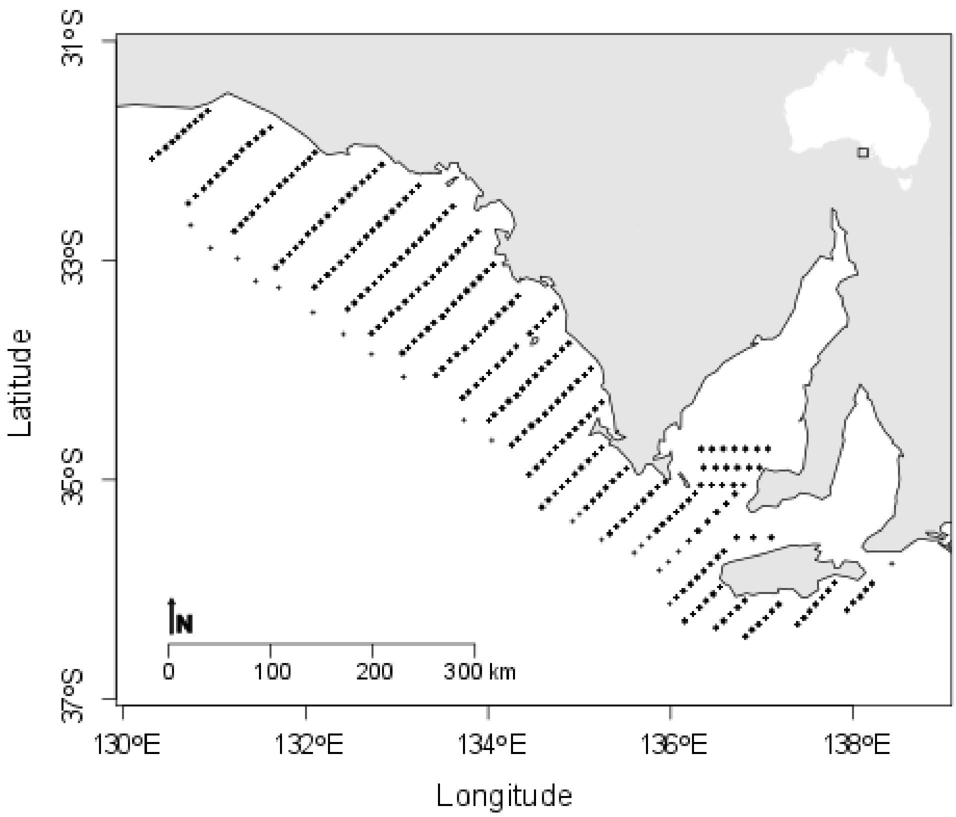

Figure 2. Map of the South Australian Sardine stock assessment survey region. The locations of sampling sites included to derive the egg presence/absence data for each survey year are shown.

2.2.3 Juvenile and Adult Habitat

Three predictor variables were used to model the presence/absence of juvenile and adult Sardines. Measures of fish length were obtained from commercial catch samples taken by independent observers on fishing vessels during 2004 to 2013 (Figure 3). No data are available for 2007. Independent observers were present on approximately 10% of fishing trips. Fish length was measured as the caudal-fork length (mm). Sardine were divided into juvenile (<135 mm) and adult (>142 mm) fish length classes to form two separate binomial datasets for the GAM modelling. Juvenile and adult fish were classified according to the size and age at which local Sardines reach sexual maturity (Ward and Staunton-Smith 2002) and was kept consistent with the size classification management system used by the SASF.

Environmental variables included those readily available from satellite observations; sea surface temperature (SST, ^{o}C), and surface chlorophyll *a* (chl *a*, µg L^{-1}). Bottom depth (depth, m) was included as a spatial variable. SST was used as a predictor of the physiological suitability of the habitat. Chlorophyll *a* provides an indicator of phytoplankton biomass and was included as a predictor of the food availability. Satellite SST and chl *a* data are obtained at each location by averaging the available data within a 5x5 pixel grid (centred on the target location), using the standard 4 km resolution MODIS-Aqua level-3 chl a product (http://oceancolor.gsfc.nasa.gov/). Depth information was interpolated from the ETOPO2v2 dataset (National Geophysical Data Centre 2006) available from the NOAA website (www.ngdc.noaaa.gov). Sites for which corresponding SST and chl *a* matchups were unavailable (i.e. due to cloud cover) were excluded from the analysis. Sites situated in water depths shallower than 20 m were also excluded due to problems such as bottom reflectance which lead to the overestimation of chl *a* in shallow waters (Bierman *et al.* 2009). the final dataset included 12,337 measures of fish length and coincident values of environmental and spatial variables.

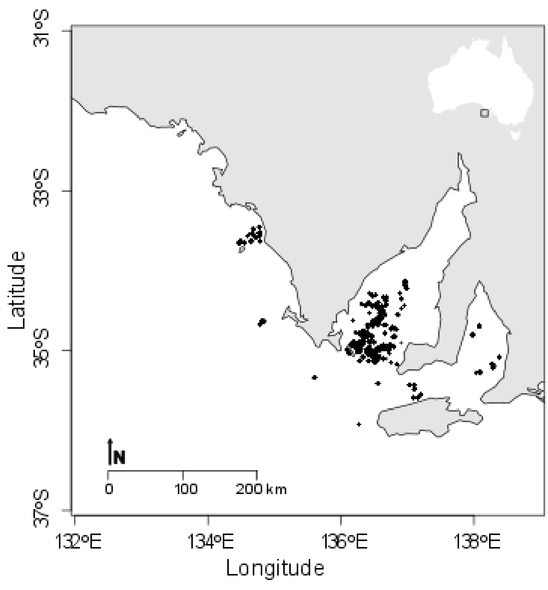

Figure 3. Map of the South Australian region showing the location of commercial catch sites used to derive the presence/absence data for small and large size class Sardines.

Results and Discussion

3.1 Objective 1: To empower industry to conduct real-time monitoring of fish size and quality in relation to key environmental parameters.

Objective 3: To establish a co-management system for optimising the size, quality and value of fish harvested by the SASF using industry collected data and near real-time map underlays of key environmental variables.

3.1.1 Results

The establishment of the SASIA with integrated measurement and harvest monitoring system was initiated through the purchase of an automated electronic finfish measuring board (Figure 4). The board measures and wirelessly logs data on fish length and weight directly into a Microsoft Excel spreadsheet. This automated measurement and data storage capability has decreased measurement errors and eliminated the need for manual data entry, thereby reducing errors and providing significant time and cost savings.

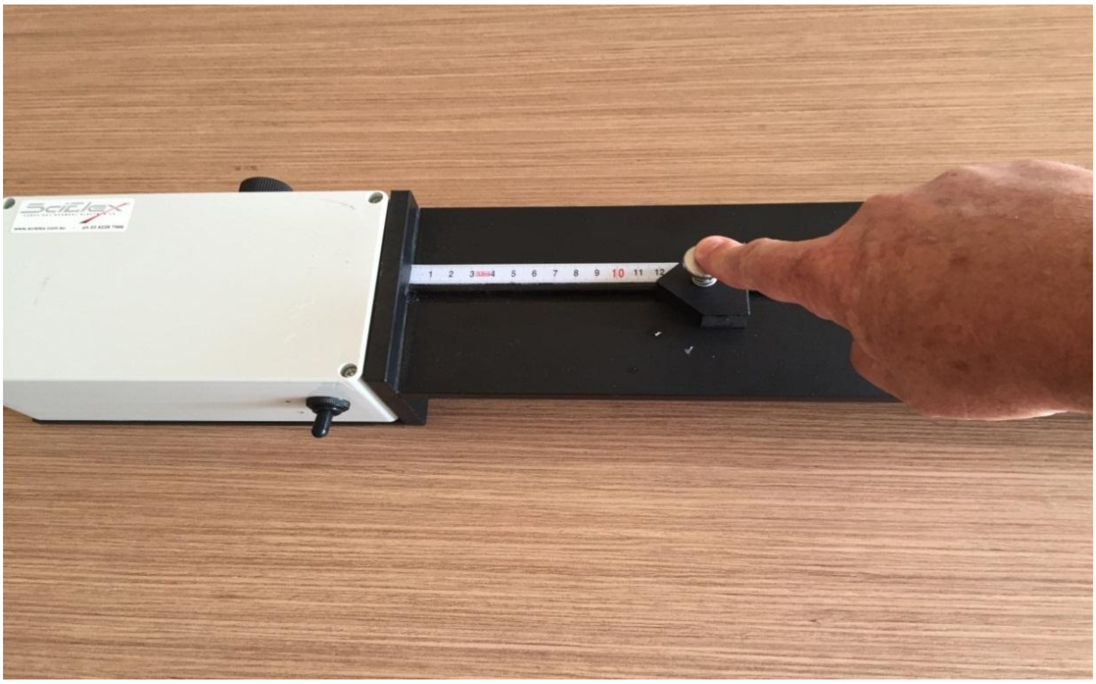

Figure 4. The SciElex electronic fish measurement board purchased by the SASIA. The board wirelessly logs individual measures of fish (caudal-fork) length and weight to a Microsoft Excel worksheet.

The Microsoft Excel database completes the establishment of SASIA with tools for measuring and storing data. The easy-to-use database has been designed with additional graphical presentation features which can be simply updated to provide data summaries. Figure 5 shows an example of the database's graphical features and shows temporal changes in the average size of fish caught each month across 2012 and 2013 for fishing in and outside of Spencer Gulf. Clearly, the average length of fish caught each month is smaller inside Spencer Gulf relative to those caught outside of the gulf. Moreover, for fishing in Spencer Gulf, a comparison of monthly averaged sizes between years show a general increase of fish length in 2013 relative to 2012.

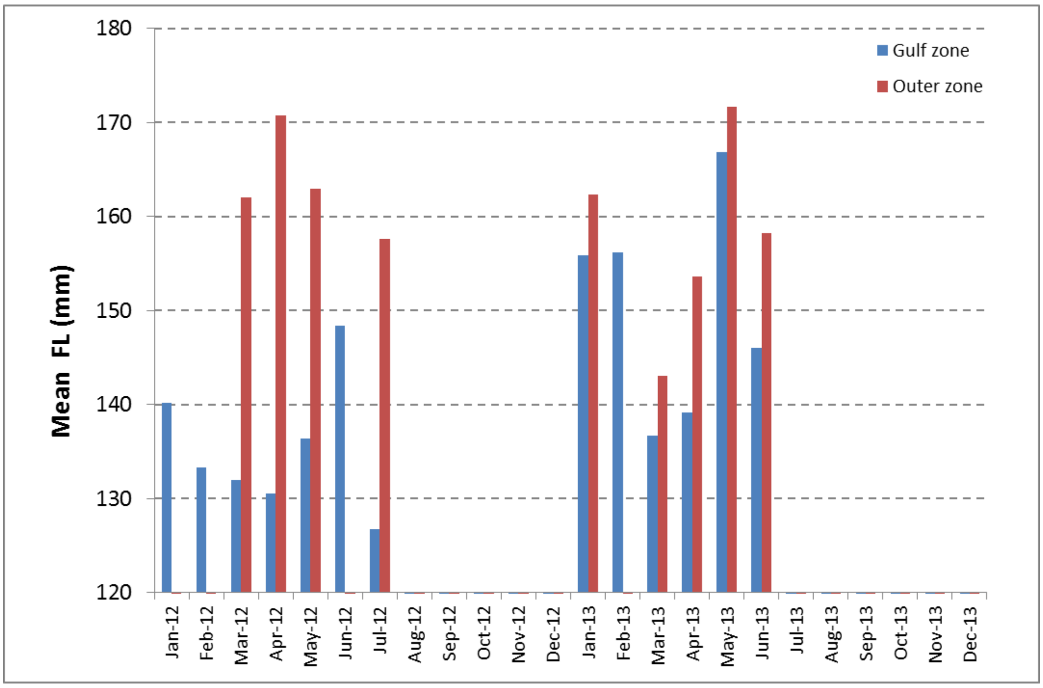

Figure 5. Time-series of monthly changes in the mean fish length (mm) of Sardines measured by the SASIA showing the course-scale spatial distribution of Sardines sizes caught in (Gulf zone) and outside (Outer zone) of Spencer Gulf.

Finally, the database is linked with ArcGIS mapping software to accurately map the spatial distribution of fish lengths and total catch. Figure 6 provides an example map showing the distribution of fish length and total catch size classes measured by the SASIA using the electronic measurement board for commercial fishing undertaken in March 2014. The map shows juvenile fish were caught in shallower, warmer waters to the north. Larger (adult) Sardines were caught in deeper, cooler waters closer to the mouth and outside of Spencer Gulf.

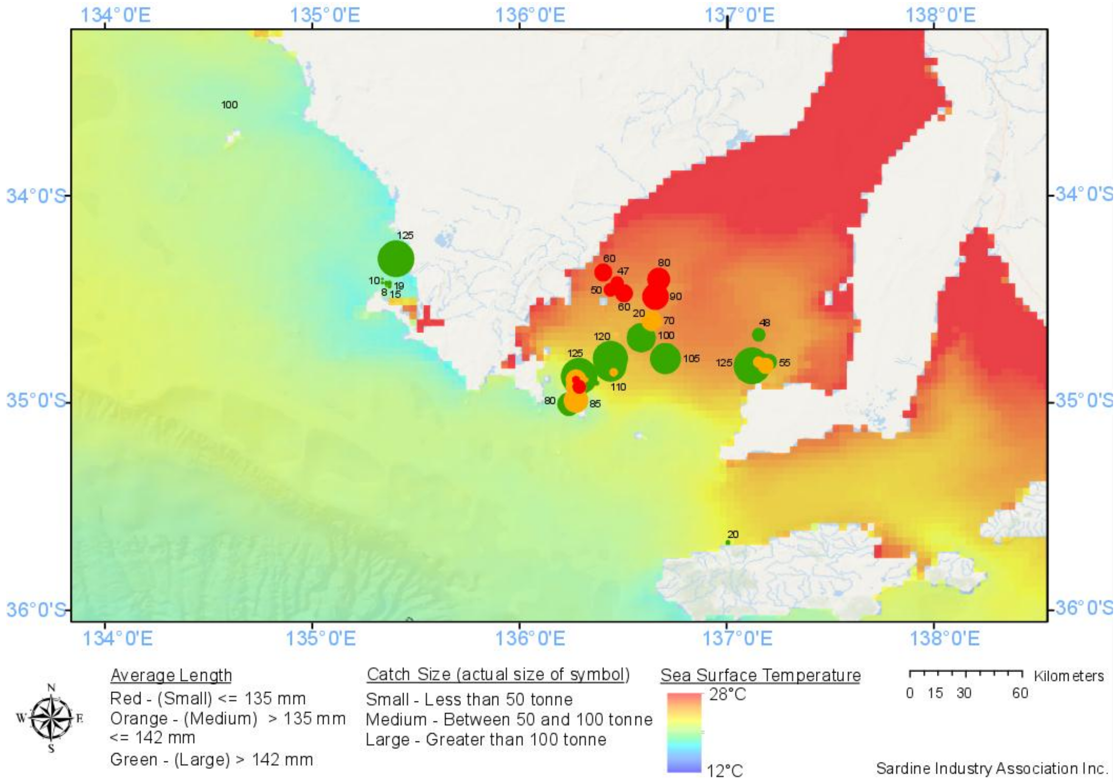

Figure 6. SASIA measured distribution of Sardines caught during commercial fishing during March 2015 with satellite derived underlay of March averaged SST (°C). The colour of the symbol depicts the average length of fish measured classified: small (<= 135 mm; red marker), medium (135-142 mm; orange marker) and large (>142 mm; green marker). The size of the symbol depicts the size of the catch classified as; small (<50 t), medium (50-100 t), large (>100 t).

3.1.2 Discussion

The developed measurement, monitoring and mapping system has been fully adopted by the SASIA and used operationally since January 2015. Through regular fortnightly updates, the spatial mapping ability has allowed the SASIA to provide near real-time advice to skippers as to developing trends on shifts in the location of small, non-target sized fish (e.g. Figure 6). As a result, the capacity to direct fishing effort away from small fish has been improved. Continuation of the measurement and harvest management system is expected to provide an improved understanding of the shifts in the habitat preferences and boundaries of juvenile and adult Sardines in relation to changes in environmental drivers.

3.2 Objective 2: To determine the key environmental factors influencing the spatial distribution and size of fish.

3.2.1 Results: Spawning Habitat

The percentage deviance explained by each individual predictor variable was tested using a GAM and shown in Table 1. With exception of the mixed layer depth (MLD), all environmental and spatial (i.e. depth) predictors provided a significant contribution to the explained deviance of greater than 1%. Depth was the strongest individual explanatory variable accounting for 11.4% of the explained deviance.

Table 1. Variable range and explained deviance of Sardine egg presence/absence by each factor.

Predictor Variable	Observed Range	Explained Deviance (%)
SST (^oC)	15.0 – 22.8	1.27
Salinity (PSU)	35.3 – 37.8	2.93
chl *a* (µg/l)	0.06 - 1.14	1.85
MLD (m)	10 - 72	0.21
DCM (m)	11 - 89	1.12
Depth (m)	35 – 150	11.4

Subsequently, combined GAMs were fitted to explain egg presence/absence according to the described methodology and the explained deviance compared (Table 2). Environmental variables and depth all provided significant contributions and improvement to the explained deviance. Combined models of varying complexity accounted for 13.0 - 16.6% of the explained deviance. The final model contained depth, SST, surface salinity, surface chl *a* and depth of the chlorophyll maximum (DCM). An additional model restricted to depth, SST and chl *a* was included as an example of a model which could be used operationally to predict spawning habit based on readily available satellite information. For the final combined model, Table 2 shows the estimated degrees of freedom (EDF) and *p*-value for each predictor variable.

Table 2. (Top) Explained deviance for multiple predictor GAMs. The full model retained for spawning habitat prediction is highlighted in grey. (Bottom) Estimated degrees of freedom (EDF) and *p*-value for each predictor variable used in the full model for spawning habitat prediction.

Predictor Variables Selected	**Explained Deviance (%)**	
Depth + Salinity	13.0	
Depth + Salinity + log(chl *a*)	14.1	
Depth + Salinity + log(chl *a*) + SST	15.3	
Depth + Salinity + log (chl *a*) + SST + DCM	16.6	
Full GAM	**EDF**	***p* - value**
Depth	1.99	< 0.0001
Salinity	1.82	< 0.0001
chl *a*	1.93	0.0003
SST	1.87	0.0075
DCM	1.90	< 0.0001

Estimates of the partial effects of predictor variables (i.e. the relationship between each predictor variable and egg presence) are shown in Figure 7. Sardines were preferentially likely to spawn in mid-shelf regions in waters between approximately 50 - 70 m deep. Sardines showed a preference of water masses defined by mid-range SST and surface salinities within the range of 19 - 20 ^{o}C and 36.1 - 36.6 PSU, respectively. Sardines were more likely to be present in areas of intermediate phytoplankton biomass defined by chl *a* concentrations in the range of 0.4 - 0.9 µg chl *a* /l (approximately -1.4 to -0.9 on the log scale). The modelled probability of finding eggs also increased with the deepening of the deep chlorophyll maximum to depths between 60 and 90 m.

The predictive capability of the full and operational GAMs according to the explained deviance, AUC and overall accuracy measure (Table 3), demonstrated that both models showed a good level of agreement between occurrence predictions and observations (AUC Full: 0.74 – 0.78, AUC Operational: 0.73 – 0.77). This level of predictability was supported by a cross validation accuracy measure averaged across years of 71% and 68% for the full and operational models, respectively. With the exception for 2013, the levels of model predictability remained consistent across years.

Demonstrations of maps of potential Sardine spawning habitat constructed by interpolating the predicted values of Sardine egg presence are shown in Figure 8. Maps are shown for the 2006 and 2013 survey years which demonstrated the highest (81%) and lowest (56%) measures of accuracy (Table 3). The overall patterns of Sardine presence and absence were reasonably well captured by the environmental GAM. For the 2006 survey year, the model distinguished between the presences of Sardines in the west and their absence in eastern shelf waters. This contrasts with the 2013 survey year that predicted a distinct shift and increase in Sardine egg presence to the central and eastern Great Australian Bight region, but overpredicted the probability of their presence in the west. Both years indicate the entrance to

Spencer Gulf between Port Lincoln and Kangaroo Island to be a region of increased egg probability. Similarly, the probability of Sardine egg presence drops rapidly beyond the 70 m isobath, particularly in the eastern GAB region.

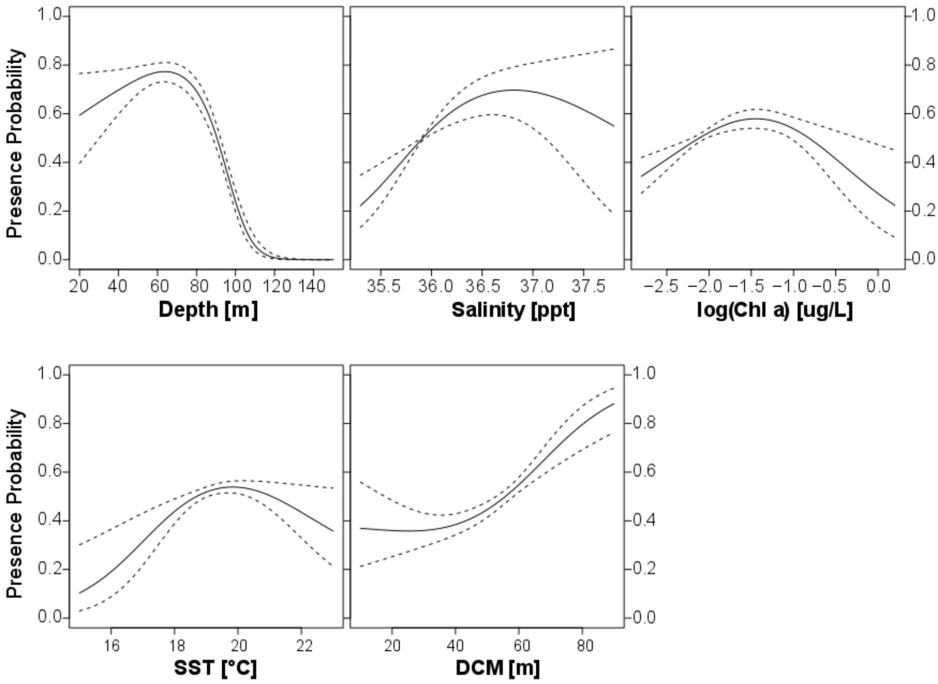

Figure 7. Partial effects of predictor variables on the logistic GAM model to predict presence/absence of Sardine eggs. Solid lines indicate the predicted probability of egg presence across the range of predictor variable values. Dashed lines indicate 95% confidence limits on the estimates.

Table 3. Results of the GAM validation for potential spawning habitat showing the percentage explained deviance, cross-validation AUC and accuracy measures. Model validation was based on an assessment of predictive capability by excluding each tested years data from the model build for validation. Values are provided for the full GAM model which included the 5 predictor variables shown in Table 2 and an operational model based on 3 predictor variables (i.e. depth (m) and satellite measures of sea surface temperature (°C) and chlorophyll *a* (µg/l)).

Survey Year	**Overall Deviance Explained (%) Full / Operational**	**AUC Full / Operational**	**Accuracy (%) Full/Operational**
2004	16.7 / 15.3	0.76 / 0.75	77 / 75
2005	18.2 / 16.2	0.77 / 0.76	69 / 68
2006	15.0 / 13.5	0.74 / 0.73	81 / 80
2007	16.5 / 14.2	0.76 / 0.74	72 / 72
2009	17.2 / 15.6	0.77 / 0.76	71 / 69
2011	18.7 / 17.6	0.78 / 0.77	65 / 64
2013	21.6 / 19.7	0.79 / 0.77	56 / 55
Average	**17.7 / 16.0**	**0.77 / 0.76**	**71 / 68**

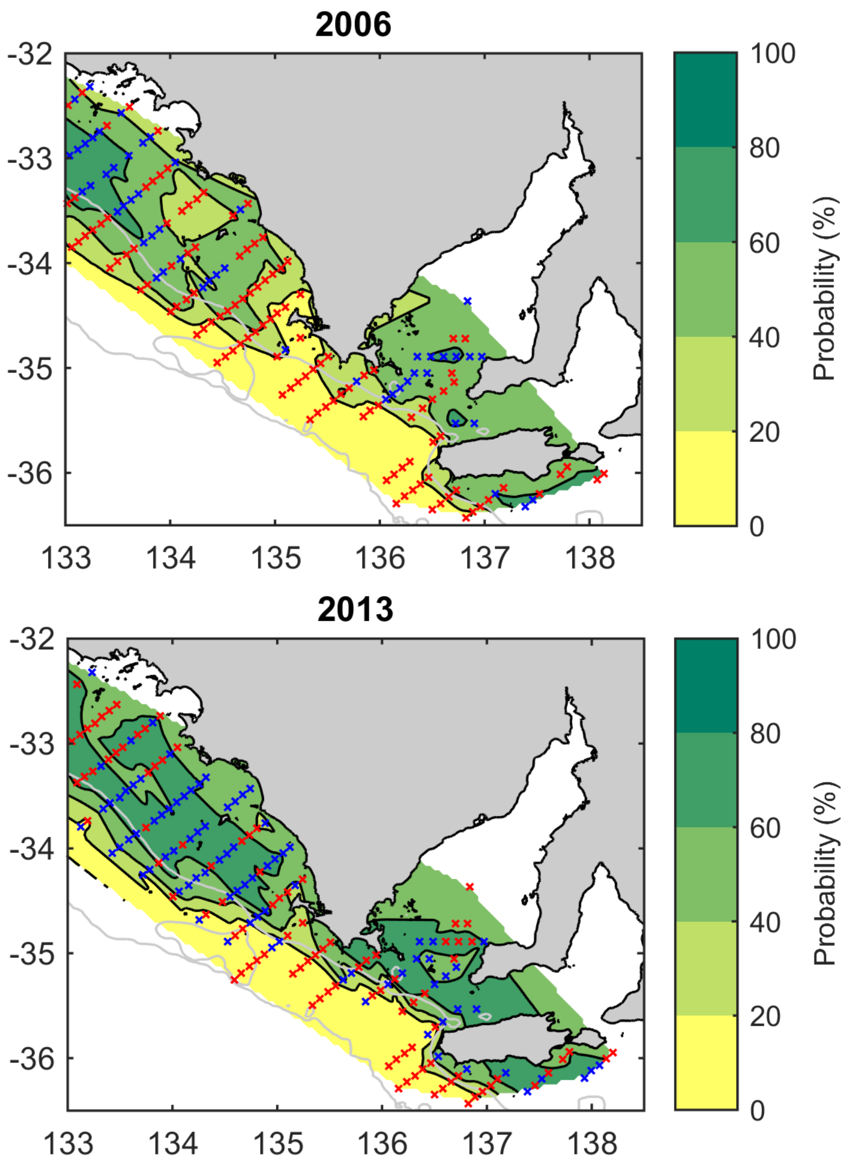

Figure 8. Predicted probability (%) of potential Sardine spawning habitat overlaid with the presence (blue circle) and absence (red cross) of eggs sampled during the DEPM surveys in 2006 (top) and 2013 (bottom). Each habitat prediction map was constructed by excluding the respective year's survey data from the model build. 200 m and 70 m isobaths are shown as grey lines.

3.2.2 Discussion: Spawning Habitat

The objective of this research was to define the environmental conditions which are potentially suitable for spawning Sardines in the coastal waters of South Australia during summer. The application of GAMs showed a reasonable ability to predict the presence/absence of eggs which is assumed to be directly related to the potential spawning habitat (Planque *et al.* 2007). Overall, the percentage of explained deviance (~17%) and levels of predictability (AUC ~0.77) provided by the model are within the lower range of values previously reported for the application of GAMs to predict Sardine spawning habitat (Schismenou *et al*. 2008, Weber and McClatchie 2010, Zwolinski *et al.* 2010).

In common with similar studies (e.g. Weber and McClatchie 2010, Zwolinski *et al.* 2010), our models required information on depth, surface temperature, surface chl *a* concentration and surface salinity to predict spawning habitat. The model presented here, based on Sardine egg presence/absence over a 7 year survey period, demonstrates that spawning Sardine are likely to be found between 50 - 70 m depth where SST lie between 19 - 20 ^{o}C and surface salinities between 36.1 - 36.6 PSU. The range of preferred surface temperature and salinity values are within the range of physiological tolerance limits of Sardine (Martinez-Porchas *et al.* 2009). Reported preferred hydrographic conditions for spawning Sardines vary globally (Ginnoulaki *et al.* 2005, Petitgas *et al.* 2006, Weber and McClatchie 2010, Zwolinksi *et al.* 2010), indicating the observed temperature and salinity preferences may not be directly related to physiological benefits but may be indicative of a correlation to other variables that affect adult Sardines, such as larval development temperatures and food availability. Sardines were more likely to be in areas of intermediate phytoplankton biomass defined by chl *a* concentrations in the range of 0.4 - 0.9 µg/l. This apparent avoidance of high chlorophyll areas by spawning Sardines is consistent with previous studies (Reiss *et al.* 2008, Weber and McClatchie 2010). In contrast to Weber and McClatchie (2010), our results show that the inclusion of the depth of the chlorophyll maximum provided a small, yet significant improvement to the model. Weber and McClatchie (2010) included the depth of the chlorophyll maximum as an index of primary production; assuming the depth of the chlorophyll maximum will be shallower during periods of high productivity and becomes progressively deeper towards the end of the upwelling season as phytoplankton balance their need for light and nutrients. Our collective finding of a preferred Sardine spawning habitat consisting of a deep chlorophyll maximum (>60 m), intermediate chl *a* concentrations and warmer SST values suggest Sardines may avoid areas of cool, upwelled water of high primary productivity.

The majority of predictor variables used in our study are obtained from satellite information. Moreover, we have demonstrated that surface values of SST and chl *a* are adequate to provide useful predictors of spawning habitat. For historical studies, the inclusion of additional parameters such as surface salinity and depth of the chlorophyll maximum could be further obtained from ocean models for the region (Middleton *et al.* 2013). From an operational view-point, the models developed here can be used with near real-time satellite information to construct potential spawning habitat predictions with temporal and spatial resolutions of days to weeks and kilometres to hundreds of kilometres. The future inclusion of information from forecasting ocean models currently planned for development in the region will only improve predictions of spawning habitat. The benefits of such predictive models include optimising DEPM survey-sampling effort, understanding seasonal migration patterns and regional trophodynamic relationships, as well as predicting changes in spawning habitat under climate change scenarios.

3.2.3 Results: Juvenile and Adult Habitat

Measures of fish (caudal-fork) length included in the analysis ranged from 83 to 223 mm with a mean size of 148 mm and a modal value of 142 mm. Juveniles (<135 mm) and adults (>142 mm) accounted for 18% and 36% of the total sample size (n = 12,338) used for model construction. Each predictor variable was first separately tested for predicting juvenile and adult presence using a GAM (Table 4). All environmental and spatial (i.e. depth) predictors provided a significant contribution to the explained deviance of greater than 1%. For juvenile fish, SST was the strongest explanatory variable accounting for 5.3% of the explained deviance. For adult fish, depth was the strongest explanatory variable accounting for 2.16% of the explained deviance. Both SST and depth accounted for a greater percentage of the explained deviance for juveniles and adults. Chlorophyll *a* accounted for the smallest percentage of the explained deviance for juveniles and adults.

Table 4. Variable range and explained deviance of Sardine length classes (juvenile/small and adult/large) presence/absence by each factor.

Predictor Variable	Observed Range	Explained Deviance (%) Small / Large
SST (^{o}C)	13.8 – 24.5	5.3 / 2.06
Chl *a* (µg/l)	0.1 - 4.9	1.1 / 1.76
Depth (m)	20 – 129	4.07 /2.16

Subsequently, combined GAMs were fitted to explain the presence of juvenile and adult fish according to the described methodology and the explained deviances are compared (Table 5). Environmental variables and depth provided highly significant contributions to the combined models. The final full model consisted of SST, depth and chl *a* and accounted for 8.4% and 5.5% of the explained deviance for juvenile and adult fish, respectively. This result indicates that environmental variables are requisite to reconstruct the habitat suitability of Sardines. For the full combined model, Table 5 shows the estimated degrees of freedom (EDF) and *p*-value for each predictor variable.

Table 5. (Top) Explained deviance for multiple predictor GAMs. The model retained for size class (Small/Large) habitat prediction is highlighted in grey. (Bottom) Estimated degrees of freedom (EDF) and *p*-value for each predictor variable used in the full model for spawning habitat prediction.

Predictor Variables Selected	Explained Deviance (%) Small / Large	
Depth + SST	7.3 / 4.2	
Depth + SST + log (chl *a*)	8.4 / 5.5	
FULL GAM	**EDF**	***p* - value**
Depth	1.98 / 1.99	< 0.0001/ < 0.0001
SST	2.00 / 2.00	< 0.0001/ < 0.0001
chl *a*	1.98 / 1.72	< 0.0001/ < 0.0001

Estimates of the partial effects of predictor variables suggest that juvenile (Figure 9) and adult (Figure 10) Sardines have different preferential habitats. Juvenile Sardines are more likely to be in shallow waters less than approximately 35 m depth and SST less than 17 ^{o}C or greater than 22 ^{o}C. Juvenile Sardines also showed a preference to be in areas of very low or very high phytoplankton biomass inferred by chl *a* concentrations below <0.25 µg/l (approximately -1.3 on the log scale) and above 1.65 µg/l (approximately 0.5 on the log scale). Inversely, adult Sardines are more likely to be present in waters between 40 and 85 m depth and SST ranging from approximately 17.5 to 21 ^{o}C. Adult Sardines showed a preference to be in areas of low phytoplankton biomass defined by chl *a* concentrations below 0.45 µg/l (approximately -0.8 on the log scale).

The predictive capability of the juvenile and adult based GAMs according to the AUC and overall accuracy measure (Table 6) demonstrated that both models showed an acceptable level of agreement between the occurrence of predictions and observations (AUC: juvenile 0.65 – 0.72, adult 0.62 – 0.69). The higher levels of predictability indicated by the accuracy measures averaged across the years (juvenile 85%, adult 72%) suggests the models have good predictive capability. However, it is likely the high accuracy percentages reported for some years may be influenced by the relative length of the datasets used for the model build and validation. Measures of fish length for individual years ranged between 4% in 2006 and 33% in 2010 of the total dataset used in the analysis.

Demonstrations of maps of the potential habitat for juvenile and adult Sardines, estimated from satellite SST and chl *a* information averaged over February and March of each corresponding year, were constructed by interpolating the predicted values of Sardine presence and are shown in Figure 11. Figure 12 shows the corresponding maps of SST and chl *a*. Differences are shown in the average SST and chl *a* environmental conditions between years. Specifically, 2013 represented an abnormally warm summer period where SST experienced across South Australian waters were 1 to 2 ^{o}C warmer than long term climatological conditions. In response to the warm SST, chl *a* concentrations were generally higher within Spencer Gulf and reduced offshore in shelf waters.

The overall patterns of predicted presence for juveniles and adults showed a general inverse relationship with each other as expected from the partial predictors shown in Figures 9 and 10. Juvenile Sardines showed a preference for the shallower waters of the gulfs and bays, whilst adult Sardines are more likely found in deeper waters on the continental shelf. Shifts in the predicted distribution of juveniles and adults between years are driven by changes in the distribution and magnitude of SST and chl *a*. For juveniles the probability of finding Sardines increased throughout the gulfs in 2013, with regions of predicted probabilities >60% extending further offshore in gulf waters in response to the warmer SST and increased chl *a* concentrations. Moreover, as a result of warmer SST, the probability of finding adult Sardines in 2013 decreased across the mid-shelf region, particularly in the far west and into Spencer Gulf.

The distribution of the juvenile and adult Sardines caught during commercial fishing for the corresponding February/March periods of 2006 and 2013 are presented as an overlay in Figure 11. Here, measures of fish length made by independent observers aboard commercial vessels were averaged and the average binned into small (juvenile), medium and large (adult) size classes. To demonstrate the capability of GAMs to predict juvenile and adult Sardine habitat, only the distribution of fish lengths binned into the juvenile and adult size classes are plotted. Notwithstanding the small sample size, the overall patterns of observed juvenile and adult Sardine distribution appear to be generally captured by the environmental GAMs. During 2006, on average, only adult fish were caught. Adults were located in areas where there was a predicted low probability (<20%) of finding juvenile fish and a high probability (>60%) of finding adult fish. Similarly for 2013, adult fish were generally found in areas predicted to have a low probability of juvenile fish and higher probability of adult fish. The single observation of juvenile fish was located on the interface of predicted juvenile and adult habitats which displayed some overlap, particularly near the entrance to Spencer Gulf.

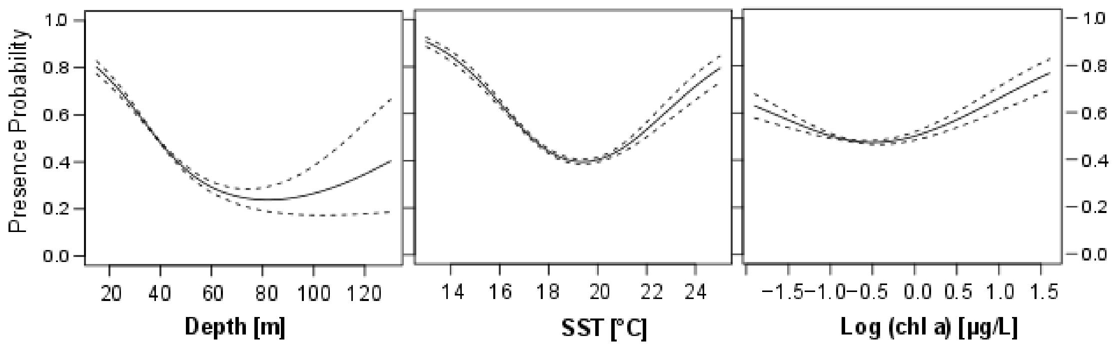

Figure 9. Partial effects of predictor variables on the logistic GAM model to predict presence/absence of small (juvenile) size class Sardines. Solid lines indicate the probability of juvenile presence across the range of each predictor variables values. Dashed lines indicate 95 % confidence limits on the estimates.

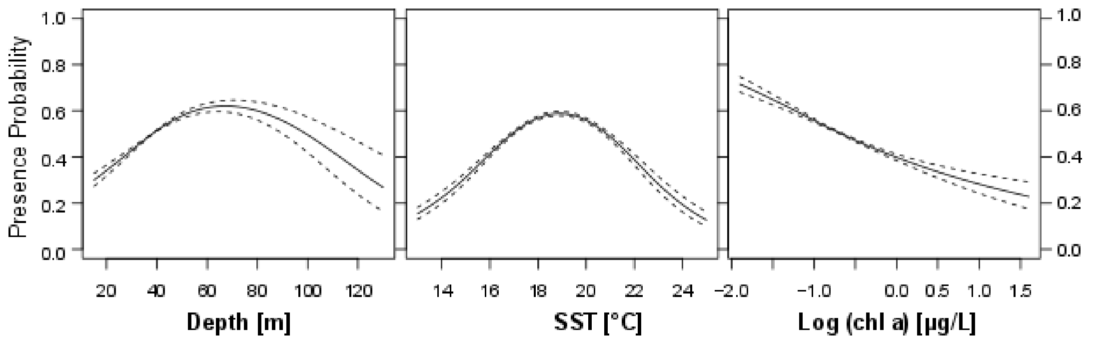

Figure 10. Partial effects of predictor variables on the logistic GAM model to predict presence/absence of large (adult) size class sardines. Solid lines indicate the probability of adult presence across the range of each predictor variables values. Dashed lines indicate 95 % confidence limits on the estimates.

Table 6. Results of the full GAM validation showing the explained deviance, AUC and cross-validation accuracy measure for small (juvenile) and large (adult) fish length classes. Model validation was based on an assessment of predictive capability by excluding each tested years data from the model build for validation.

Year	Overall Deviance Explained (%) Small / Large	AUC Small / Large	Accuracy (%) Small / Large
2004	5.9 / 4.0	0.65 / 0.62	97 / 73
2005	8.0 / 5.5	0.68 / 0.65	97 / 75
2006	8.1 / 4.9	0.67 / 0.63	98 / 85
2008	8.3 / 5.7	0.68 / 0.65	88 /65
2009	10.5 / 6.8	0.72 / 0.67	93 / 72
2010	12.1 / 7.3	0.72 / 0.65	82 / 59
2011	7.4 / 4.5	0.67 / 0.63	69 / 89
2012	11.6 / 8.6	0.70/ 0.69	59 / 67
2013	9.5 / 6.1	0.69 / 0.66	86 / 63
Average	**9.0 / 5.9**	**0.69 / 0.65**	**85 / 72**

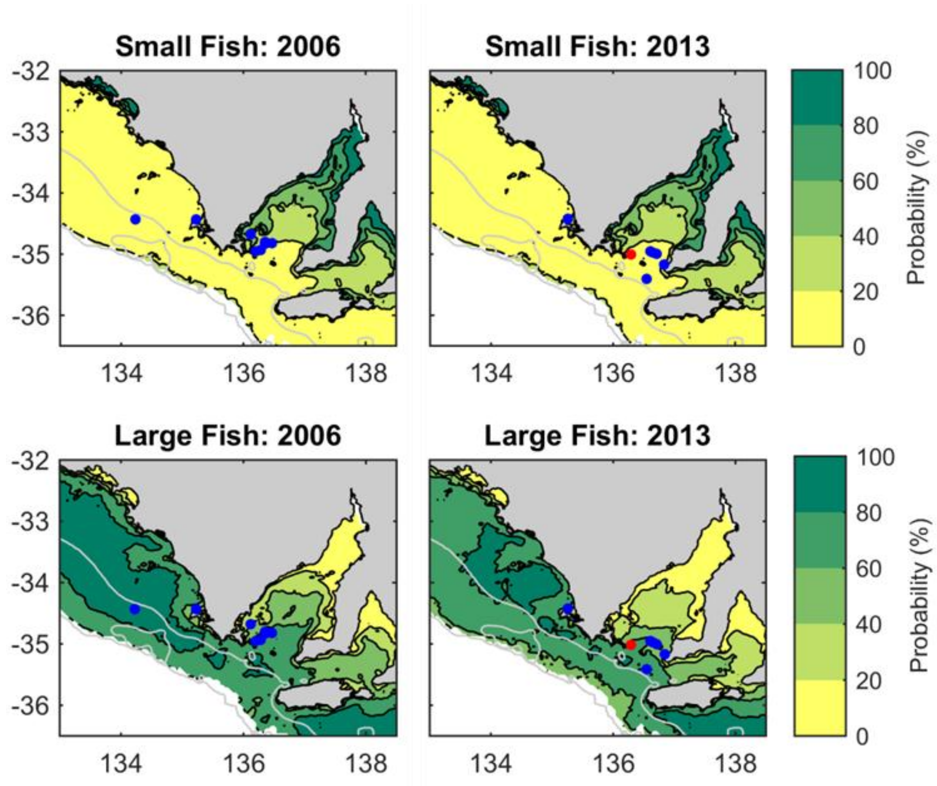

Figure 11. Predicted probability (%) of potential habitat for (top) juvenile and (bottom) adult Sardines estimated from the 2-month averaged satellite measures of SST and chl *a* shown in Figure 12. Habitat maps are overlaid with the location of juvenile (red marker) and adult (blue marker) fish caught by commercial vessels during the corresponding period.

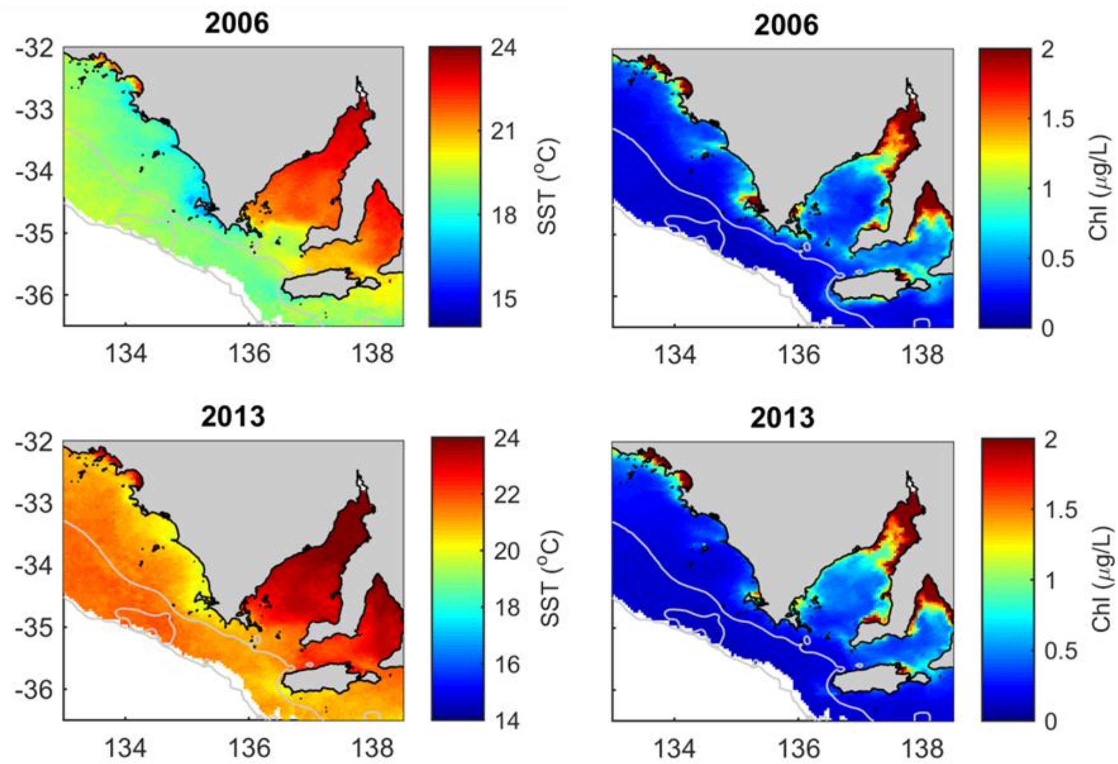

Figure 12. February-March time-averaged distributions of sea surface temperature (SST) and surface chlorophyll (chl) measured by the MODIS Aqua satellite for (top) 2006 and bottom (2013).

3.2.4 Discussion: Juvenile and Adult Habitat

The objective of this research was to define the environmental conditions which are potentially suitable for adult (large) and juvenile (small) Sardines in the coastal waters of South Australia. The application of GAMs showed an acceptable ability to predict the presence/absence of juveniles, and to a slightly lesser extent, adult Sardines. Overall, the low percentage of explained deviance (small: ~9%, large 5.9%) and levels of predictability (AUC: small ~0.69, large ~0.65) provided by the model are lower than previously reported for GAMs applied to predict Sardine juvenile habitat (Giannoulaki *et al.* 2011). However, Giannoulaki *et al.* (2011) used measures of juvenile distribution and environmental conditions measured more regularly over a wider spatial extent and included additional variables not available for this study.

In common with similar studies (Tsagarakis *et al.* 2008, Giannoulaki *et al.* 2011), our models used information on depth, and satellite derived SST and chl *a* concentration to predict juvenile Sardine habitat. The model presented here, based on measures of fish length taken by independent observers aboard commercial vessels over an 9 year survey period, demonstrates there are differences in the preferred habitat of juvenile and adult Sardines. Juvenile Sardines are more likely to be present in shallow waters less than 35 m depth, SST less than 17 ^{o}C or greater than 22 ^{o}C and in areas of either very low or very high chl *a* concentrations. These results are consistent with previous findings that show the preferred juvenile habitat of Sardines in the Mediterranean Sea occurs in inshore coastal areas of adjacent gulfs (Tsagarkis *et al.* 2008, Giannoulaki *et al.* 2011). Adult Sardines were shown to more likely to be present in waters between 40 and 85 m depth, SSTs ranging from approximately 17.5 to 21 ^{o}C and in areas of low to intermediate chl *a* concentrations. Importantly, these environmental conditions are consistent with the preferred habitat characteristics of spawning adults identified using a separate dataset in Section 3.2.3.

Spatial differences identified in the areas predicted to be juvenile and adult habitats have important implications for the management of stocks and the target harvesting of larger, adult fish of greater commercial value. Whilst certain hotspots of juvenile habitat appear to be consistent features (e.g. Boston Bay, Sir Joseph Banks group, Coffin Bay) the distribution of juvenile and adult fish habitats also overlap to varying degrees. The most common region of overlap was found to be near the entrance to Spencer Gulf (Figure 11). This finding is consistent with other studies of Sardine and small pelagic fish habitat preferences (Machias *et al.* 2007, Tugores *et al.* 2010, Giannoulaki *et al.* 2011), with regions of overlap appearing to be centred around sources and/or the accumulation of nutrients (Giannoulaki *et al.* 2011). This may be the case for the mouth of Spencer Gulf where ocean frontal features have been shown to enhance biological concentrations of chl *a* (Petrusevics *et al.* 2011) and larvae (Bruce and Short 1991). As the entrance to Spencer Gulf is also an active spot for commercial fishing a criterion such as >50% of juveniles in the catch may provide an indication of nursery grounds under changing environmental conditions.

Environmental variables used in this study are easily obtained from satellite information and we have demonstrated that surface values of SST and chl *a* are sufficient to provide an adequate level of juvenile and adult habitat prediction. From an operational view-point, the models can be used with near real-time satellite information to construct potential spawning habitat predictions with temporal and spatial resolutions of days to weeks and spatial resolutions of kilometres to hundreds of kilometres. The future inclusion of information from forecasting ocean models, such as salinity, are likely to improve predictions of juvenile and adult habitat. The benefits of such predictive models include optimising commercial harvest strategies, identifying priority areas for stock management and conservation, as well as understanding seasonal and climatic scale spatial shifts in Sardine habitat and their inferences for regional trophodynamic relationships.

3. Conclusion

This project has successfully achieved its three objectives.

The SASIA is now autonomously conducting the monitoring of fish length using a system that includes a custom-built electronic fish measuring board linked directly to a purpose-designed Microsoft Excel database. The database is linked to ArcGIS spatial mapping software. Maps showing the distribution of target and non-target sized fish are currently updated fortnightly to provide in near real-time information for use in optimising harvest management strategies. In addition, the mapping package has the capability to produce map underlays of relevant satellite environmental data (e.g. SST, chl *a*), identified as a part of this project, with sufficient spatial coverage available for the region obtained using 3-day composite images.

The project has successfully identified a range of environmental factors (i.e. depth, SST, chl *a*) that determine the habitat preferences of juvenile and adult Sardines as well as the preferred spawning habitat. The models provide an acceptable capability for predicting the distribution of juveniles, adults and the spawning habitat using satellite data (i.e. SST, chl *a*). These findings directly feeds back into the harvest monitoring system as the inclusion of satellite data provides an additional source of near-real time information on which to base harvest management decisions. Additional oceanographic measurements (e.g. surface salinity, depth of the chlorophyll maximum) taken during DEPM surveys further improve our capacity to predict spawning habitat. We have a high level of confidence in these results because the variable ranges that determine the presence of adults and define spawning habitat were similar, despite being derived from independent datasets.

This project has also enhanced co-management of the South Australian Sardine Fishery. SASIA is now using the near real-time monitoring system consisting of fortnightly maps of fish length distribution and 3-day composite maps of satellite environmental variables developed under Objective 1 to; a) inform fishers whether or not the fish they have taken meet the agreed size criteria,, and b) advise fishers about fishing areas that should be avoided because they contain large numbers of juvenile Sardines. The resultant decrease in fishing pressure on small Sardines is expected to: a) enhance the ecological sustainability of the fishery by reducing the number of fish harvested per unit weight of catch; b) increase the economic performance of the fishery by increasing the quality and value of the catch; and c) augment the community support for the fishery by demonstrating increased stewardship of the resource.

The capability to predict spawning habitat developed in this project also has the potential to optimise the design of future DEPM surveys by helping to ensure that sampling effort is targeted on areas likely support high densities of Sardine eggs and spawning adults. The general increase in our understanding of habitat preferences of Sardine developed in this project will also assist modelling, prediction and interpretation of future spatial and temporal shifts in Sardine distribution and abundance that may occur under a variety of scenarios, including climate change.

4. Benefits and Adoption

This project will enhance the ecological, economic and social sustainability of the SASF by reducing the impacts of fishing on the stock, improving the quality and value of the catch and demonstrating the industry's increasing stewardship of the resource.

The co-management approach taken in this project has led to the near real-time monitoring and harvest co-management system being adopted by SASIA during the course of the project. The monitoring system consisting of measurement, database and mapping components will be continued by the SASIA. Evaluation of the industry measures of fish length against measures made by independent observers and processed by SARDI occurs quarterly. Harvest management strategies will be made in consultation with SARDI and PIRSA Fisheries and Aquaculture.

The ability to predict spawning habitat developed in this project has the potential to assist in optimising the design of future DEPM surveys and improve the accuracy of future estimates of spawning biomass that are used to manage the fishery.

5. Further Development

There is a need to measure the effectiveness of the near real-time monitoring system established in this project in reducing the capture of juvenile Sardines in the SASF. This will be evaluated as part of the ongoing assessment of the fishery against the formal fish length performance indicator as measured and annually reviewed by SARDI after each fishing season when Total Allowable Catch (TAC) targets are set.

Knowledge of the environmental factors that define the spawning habitat of Sardine will be used to inform a project that is aiming to improve the accuracy and precision of estimates of spawning biomass obtained using the DEPM (FRDC 2014/026 Improving the precision of estimates of egg production and spawning biomass obtained using the Daily Egg Production Method).

6. Planned Outcomes

This study has successfully achieved the planned objectives and is well positioned to deliver outcomes which will enhance the sustainability and profitability in several ways.

1. Empowering industry with the tools, capability and procedures to collect, store, interpret, present and communicate information on the distribution of juvenile Sardines in relation to spatial and environmental factors in near real-time.

2. Identifying environmental factors which influence the distribution of juvenile, adult and spawning Sardines.

3. Enhancing co-management of the SASF and demonstrate stewardship of the resource by establishing within industry the capacity to reduce the capture rates of juvenile Sardines.

4. Potentially increasing commercial value of the fishery by ensuring that fish of optimum size and quality are taken for a range of end products (e.g. tuna aquaculture feed, human consumption).

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Appendices

1. PROJECT STAFF

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2. ACCESSING IMOS SATELLITE DATA

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[1]SARDI Aquatic Sciences

[2] Integrated Marine Observing System

This is a working document. The document is maintained and updated by the eMarine Information Infrastructure (eMII) facility and is available to the public from the Integrated Marine Observing System (IMOS) website (http://imos.org.au/emii.html).

We appreciate any feedback from industry.

Several satellite datasets are available from the IMOS portal: (http://imos.aodn.org.au). Data include sea surface temperature and OceanColour (chlorophyll-*a* concentration) and can be downloaded from the IMOS portal in the form of NetCDF files.

NetCDF (network Common Data Form) is a file format for storing multidimensional scientific data (variables) such as temperature, and each of these variables can be displayed through a dimension (such as time). This format is widely used in MATLAB applications.

Panoply, a JAVA application developed by NASA, is used for

a) viewing NetCDF files that allows plotting and
b) exporting data into a csv or txt file.

The software for Panopy and further information can be found at

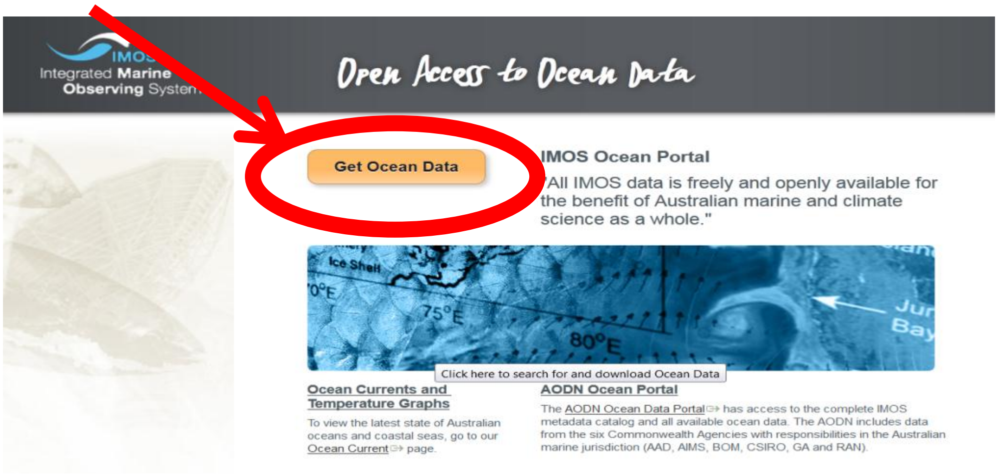
http://www.giss.nasa.gov/tools/panoply/.

<u>In this document:</u>

a. 'How to' guide for downloading satellite data from the IMOS portal
b. 'How to' guide for using Panoply to view a NetCDF file
c. 'How to' guide to create monthly means from daily data
d. 'How to' guide to export csv files from a NetCDF file

a. DOWNLOADING DATA FROM THE IMOS PORTAL

Go to https://imos.aodn.org.au/imos123/ and click '*Get Ocean Data*'. Note that the IMOS portal won't work from internet explorer, need to use Mozilla firefox (address already stored as a bookmark)



To select the data, first choose the following options on the left menu:

<u>Measured parameter:</u>

For **SST** select:

+Physical-Water

-Temperature

- Skin temperature of the water body

For **Chlorophyll-*a*** select*:*

+Biological

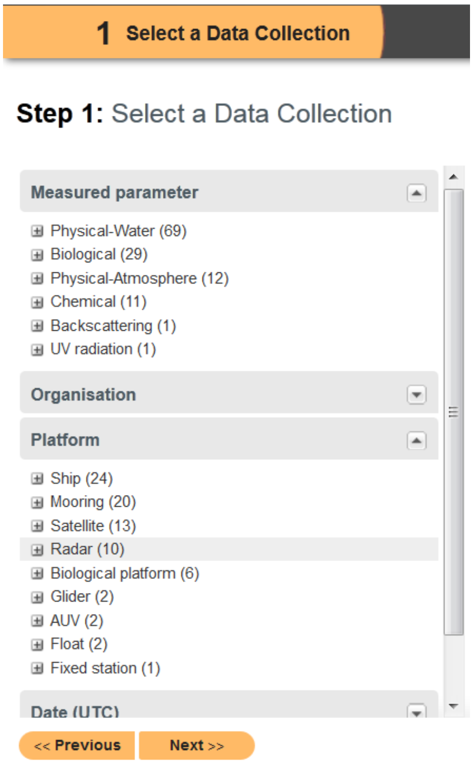
-Chlorophyll

-Concentration of chlorophyll per unit volume of the water body

<u>Platform:</u>

Select:

+Satellite



-orbiting satellite

Then find and select (click next) the desired product from the list on the right (scroll down if necessary), as follows:

For Sea surface temperature (SST):

To create the monthly means (from daily data) to be used on the PDF files: use either:

(1) daily images of day-time SST from the sensor MODIS onboard the Aqua satellite (**IMOS - SRS Satellite – OC MODIS –01 day- Ocean Colour - SST**)

OR

(2) daily images of day+night time SST from the AVHRR sensor onboard the NOAA satellites (**IMOS - SRS Satellite - SST L3S - 01 day composite – day and night time composite)**.

Note that the day-time SST is affected by the **"**warm skin" effect, especially under weak winds and high amounts of incoming sunlight, leading to SST measurements significantly different from the bulk surface temperature. Therefore **option 2 is preferred**.

To create the videos: use either

(1) daily images of day-time SST from the sensor MODIS onboard the Aqua satellite
(**IMOS - SRS Satellite – OC MODIS –01 day – Ocean Colour - SST**)

OR

(2) daily images of day+night time SST from the AVHRR sensor onboard the NOAA satellites
(**IMOS - SRS Satellite - SST L3S - 01 day composite – day and night time composite)**

OR

(3) 3-day composite of day+night time SST from the AVHRR sensor onboard the NOAA satellites (**IMOS - SRS Satellite –SST L3C -03 Day composite - NOAA-19 – day and night time composite**)

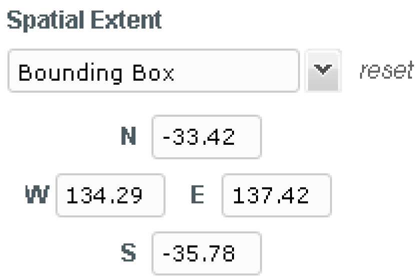
Note that daily products usually show poor coverage (high number of unavailable data) due to cloud cover, therefore **option 3 is preferred**.

For chlorophyll-*a* concentration:

For both the monthly means and the animations, use the daily images of chlorophyll-a from the MODIS sensor onboard Aqua satellite and based on the standard OC3M algorithm (**IMOS - SRS SATELLITE - OC MODIS - Chlorophyll a concentration algorithm (OC3)).**

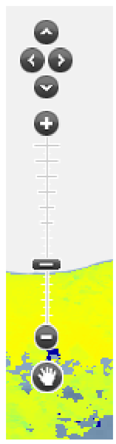
The standard OC3M algorithm (O'Reilly *et al*. 1998) is an empirical algorithm developed for global applications. It is reliable in open waters but **<u>may be inaccurate in shallow or coastal waters</u>** due to bottom reflectance and interaction with colored dissolved organic matter (CDOM), therefore the limitations for applications in shallow waters must be taken into

Create a spatial subset using the bounding box with the following coordinates:



Click interface to save changes (else your values will not be stored). Then choose the temporal extent (select the date range, the UTC time cannot be changed as this is related to the time of satellite overpass on a particular day), **<u>click interface to save changes</u>** (else your values will not be stored) and then click **NEXT**.

<u>For the animations</u>, select the temporal extent corresponding to your data, for example: 03/Jan/2014 to 06/Jun/2014

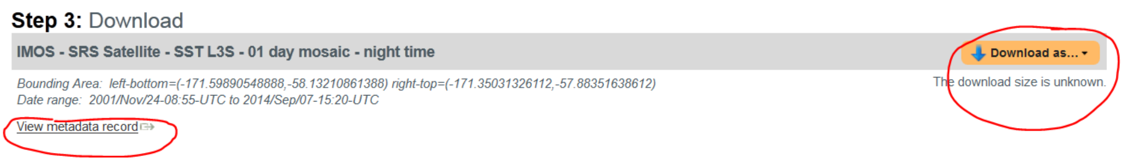


<u>For the monthly means</u>, select the whole month (ex 1 to 31st Jan 2014). Note that you can make a mean of any period of time you want (for example 10 day means) for presentation purposes, just select your dates and follow the steps below.

Note that you can zoom in and out of the map to check the selected area, but you need to click on the hand symbol to move the map around, otherwise it will start drawing a new box.

Download the data (available only as NetCDF format) and/or view the metadata record. The download size is unknown (it depends on the period and region requested) and subsetting the data may take a long time. You will be asked to provide an email address to be notified when your data is ready to download.

Note: If a selection is greater than 2GB, it will fail and you will receive an email error message.



Once the subsetting is finalized, you will receive an email with a link to download the file (or an error message if the download was not successful. Note that it may be due to the file size). Download and store the file into the Netcdf_files folder (either SST or Chlor subfolders) with a meaningful name (and always with the extension ".nc")

Recommended name conventions:

Parameter_year_monthNum+MonthName_ otherInfo**.nc**

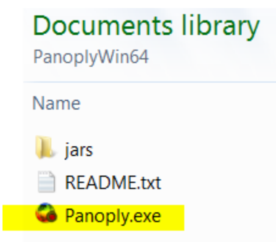
SST_2014_01Jan_1dNightTime.nc (if downloading new data from NOAA)

SST_2014_01Jan_JuntoJun_3dNightTime.nc (if downloading the 3-day composites from NOAA for animations)

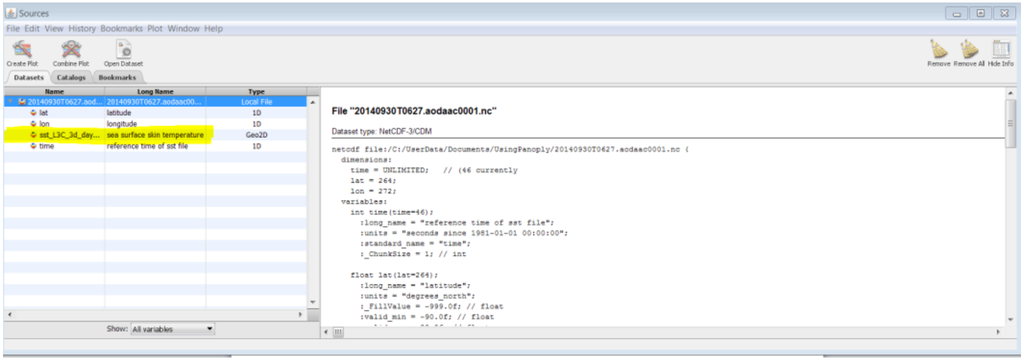
b. READING NETCDF DATA (using Panoply)

Panoply is a program that can be used to check the netcdf files quickly. In addition, it can also be used to extract data from a netcdf file and stored in a .csv file that can be read by matlab (see appendix 1 for instructions on how to extract the data into an excel file)

To open NetCDF files simply double-click on the Panoply.exe application to run the program and then go to file->open and choose the Netcdf file of interest.



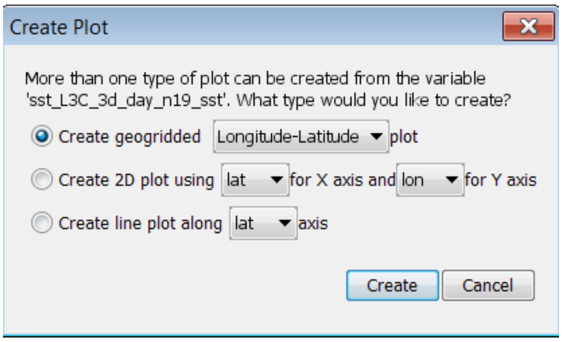
The Loaded file looks like:



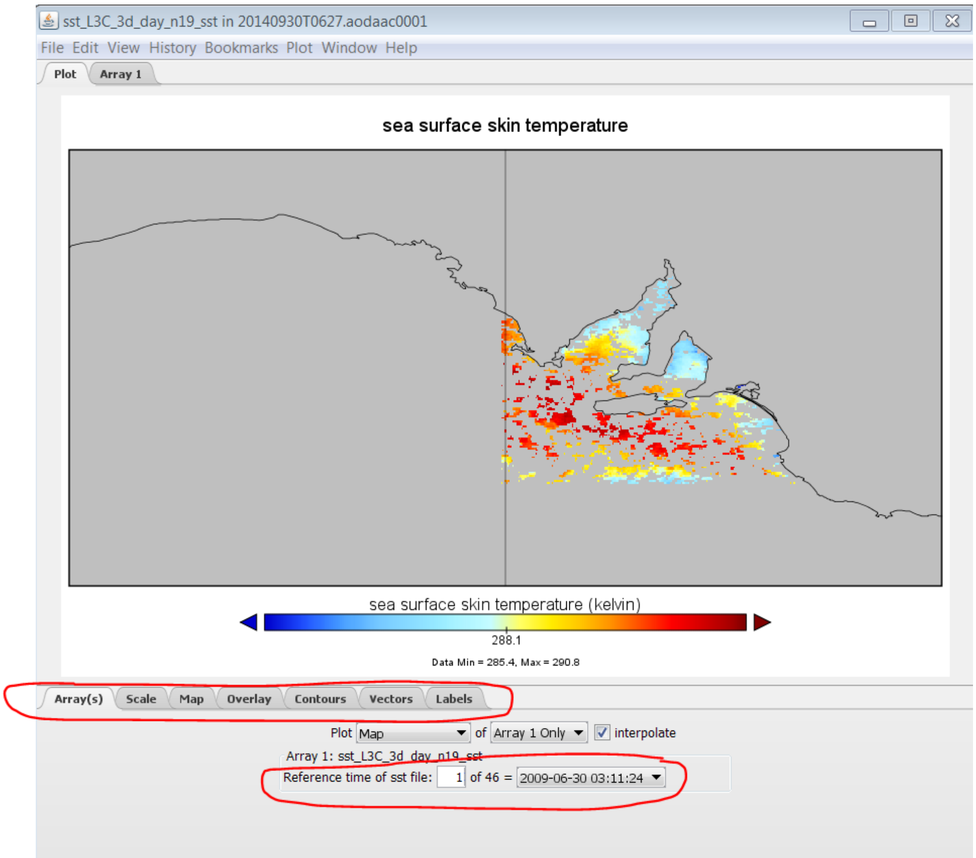
The left panel displays the variables within the file, in the example: lat, lon, sst_L3C_3d_day_n19_sst (SST data) and time. The right panel displays the metadata (info on what who and when about the data).

Clicking on each of the variables will display the attributes of the selected variable on the right panel. It is important to **check the attributes** to get critical information such as the units.

To plot the data into a map double click on the variable (For ex. sst_L3C_3d_day_n19_sst), then choose '*Create geogridded plot'.*



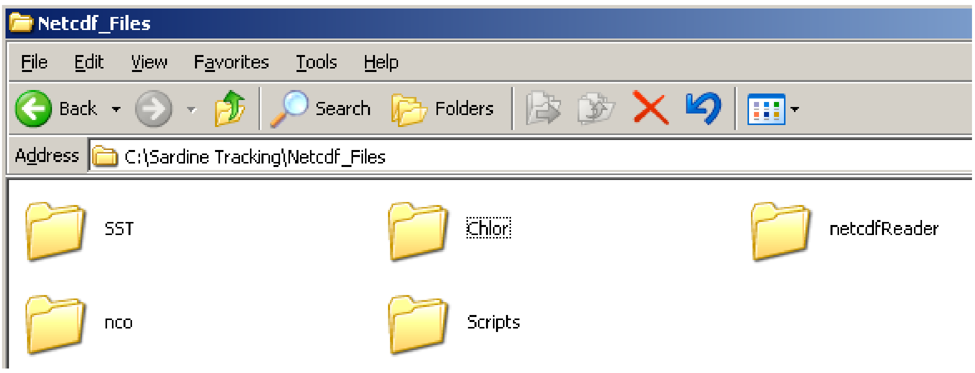
Panoply will display a lat/lon map with your selected parameter for the first of the time references. You can change the displayed dates under the '*Array(s)* ' tab located below the image. To zoom into your area of interest, press the *control* key while clicking over the area of interest in the map. You can further personalize the displayed map (color scale, map projection, land overlay, lables, etc…) using the rest of the tabs ('*scale*', '*overlay*', …) and save the displayed map in a number of formats (*file->save image as*), including png, pdf and ps.



c. CREATE MONTHLY MEANS FROM DAILY FILES

(to be used on the pdf files)

Go to the *Netcdf_Files* folder, then into *Scripts* folder and then open a template text files (eiher **SST_MonMean_Template.txt** or **Chlo_MonMean_Template.txt**)



Find the line that reads:

set my_file=my_netcdf_file

and change *my_netcdf_file* for the name of your file containing the daily data (without the .nc extension), for example:

set my_file=SST_2014_01Jan

Once you have changed that, save the file as a .bat file:

go to file-> save as,
save as type: All files

Choose a name (be consistant) example: create_SST_2014_01Jan.bat

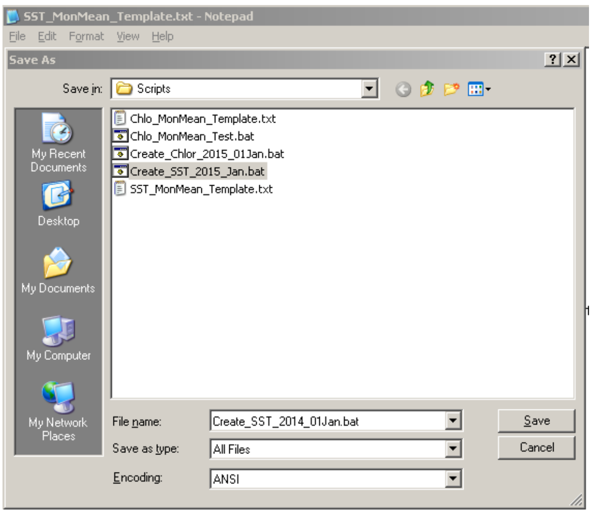
Double click on the created .bat file (ex Create_SST_2014_01Jan.bat). If everything goes well, after you double click on the file, it will authomatically create a new netcdf file containg the monthly mean. You will find the new netcdf file in the folder *Netcdf_files->SST* or *Netcdf_files->Chlor* with the same name as the orignal file followed by _MonMean, for example: *SST_2014_01Jan_MonMean.nc*

Use Panoply to check the new file (if desired, recommended)

d. EXPORT CSV DATA USING PANOPLY

To export the data, load the NetCDF file with Panoply (as shown before) and select (click on) the variable (For example. sst_L3C_3d_day_n19_sst), then go to '*file->export data-> Export data as labelled text',* which will create a txt file with four columns: time, longs, lats and data values.

Note: the time will be saved as a code number in the units specified in the attributes:



<u>For MODIS data</u> (chlorophyll and SST) time units are "days since 1800-01-01 00:00:00.0" (Gregorian calendar). For example:

01 Jan 1800 will = 1
02 Jan 1800 = 2
03 Jan 1800 = 3
(…)
01 Jan 2014= 78162
02 Jan 2014=78163

Excel can convert dates to code numbers and vice versa, but it uses "days since 01-01-1900" as units, hence:

to convert the number to a calendar date using excel do:

a. Create a new column detracting 36522 to the code numbers,
   e.g. for the 01 Jan 2014 =>78162 – 36522=41640
b. Select the new column and right click to change the format cells to date ('*home->format->format cells*')

<u>For NOAA data</u> (SST), time units are " seconds since 1981-01-01 00:00:00" (365-day calendar). For example:

01 Jan 1981 00:00:00 will = 1
02 Jan 1981 00:00:00= 86400 (=24h * 60' * 60'')
03 Jan 1981 00:00:00=172800
(…)
01 Jan 2014 15:20:00=1041434400
02 Jan 2014 15:20:00=1041520800

Excel can convert dates to code numbers and vice versa, but it uses "days since 01-01-1900" as units, hence:

to convert the number to a calendar date using excel do:

a. Create a new column to convert seconds to days (since 1981) by dividing the code numbers by 86400 (=24h * 60' * 60'')
   e.g. for the 01 Jan2014=>1041434400/86400=12053.63889
b. Create a new column adding 29587 to the new code numbers (days since 1981)
   e.g. for the 01 Jan2014=>12053.63889+29587=41640.64
c. Select the new column and right click to change the format cells to date ('*home->format->format cells*')

Note: SST data from NOAA is stored as Kelvin rather than degrees Celsius so use the conversion (1°C = 1°K - 273.15) in another column of your csv file.

Note: "NaN" stands for "not a number" and it is the value assigned to missing data within the satellite image (eg., due to cloud cover etc)

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