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# Investment dynamics of the Western and Central Pacific Ocean US purse seine fleet

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## Executive Summary

Understanding fisher decision making in a competitive but changing market is becoming increasingly important when developing management plans for sustainable fisheries. In the Western and Central Pacific, catches of tuna by weight are dominated by the purse seine fleet. To investigate the key drivers that influence the behaviour of the US purse seine fleet operating in the complex Western Central Pacific Ocean tuna fishery, multivariate methods were applied to identify candidate predictor variables in 2 separate 7 year periods and the 14 year time series to be applied in a discrete choice multinomial model. By integrating available cost data, interest rates and other factors that were likely to influence future anticipated benefits or losses, it was possible to identify key important drivers influencing whether operators chose to enter (invest in), remain (stay and continue fishing) or exit (tie-up for a period or remain under a different flag) the US fleet. Results show the importance of capturing the changes of the fisher dynamics over the time period. Early years show that vessel engine power was an important factor (a proxy for capital investment) in contrast to the later time period where vessel tonnage was of greater importance potentially due to fuel prices increases (cost), a drop in interest rates (financing decisions), increased revenues (net benefits) to offset the increase in costs. Fishers Willingness To Pay (WTP) estimated by the 3 models estimates increased from US$29 to US$7290 per day, which shows the perceived value placed on the fishery by fishers wanting to invest in. These models may assist fisheries managers when considering potential strategic long-term policies for balancing licence sales, and hence revenues for pacific island nations without displacing large amounts of capacity.

## 1. Introduction

When natural resources such as fish stocks are poorly regulated and are limited, a race to exploit them occurs because of excess competition. For fisheries to remain sustainable and profitable, the fishing effort applied by fishers must be in proportion with the fishing opportunities i.e. excess fishing capacity needs to be reduced to an optimum level for those fishing opportunities (FAO, 2003). While progress has been made in developing a precautionary approach to fisheries management to move towards this optimum, in most cases this has been confined to biological elements. A more balanced application is needed to address important social and economic risks (FAO, 2005-13). As stated by several authors, for fisheries management to be successful, that understanding fisheries dynamics and the drivers that influence the behaviour of fishers is necessary (Wilen, 1979; Hilborn and Walters, 1992; Charles, 1993; Fulton *et al.,* 2011).

Economic theory in the past has suggested that decisions to 'enter' a fishery have largely been based on the assumption of fishers reallocating to the most profitable fisheries and those who 'exit' a fishery are non-profitable and subsequently seek capital investment elsewhere (Gordon, 1954). Nowadays entry and exit decisions are said to depend on investment in terms of e.g. the availability of licences (opportunity costs), economic performance relating to the relative size of fish stocks they harvest, the value of landings, as well as financial costs (Le Floc'h *et al.,* 2011). A fleet's response to management's decisions cannot be predicted with absolute certainty because the drivers that influence strategic and tactical behaviour change over time. In a management context it is important to understand fisher behaviour in the face of a changing environment in order to manage the system better. Fisher tactics can be described as short-term decisions, such as where and when to go fishing (Vermard *et al.,* 2008; Ran *et al.,* 2011), what gear(s) to deploy (Eggert and Tveteras, 2004; Bene and Tewfik, 2001), and where to land the fish (all of which can be affected by fuel costs (Poos *et al.,* 2013), weather (Campbell and Hand, 1999), crew availability and market price (Asche *et al.,* 2008). In contrast, fisher strategies associated with long-term decision-making include factors such as fuel price rises (Abernethy *et al.,* 2010), costs for replacing gears, modifications to vessel (Mesnil, 2008) (including general refurbishment as well as changes to allow deployment of other gears), stock status (Asche *et al.,* 2008), catch prices and incentives such as decommissioning schemes (Frost *et al.,* 1995), investment or disinvestments for modernisation (Anderson, 2007). Using models to assess a fleet's responses to management measures can provide essential information on fleet dynamics that can be used then to inform the management decision-making process (e.g. Pelletier and Mahévas, 2005; Bastardie *et al.,* 2010).

The Western and Central Pacific Ocean (WCPO) purse seine fishery is one of the most important oceanic tuna fisheries with catches in 2004 representing 66 % of the world's tuna (Hamilton *et al.,* 2011). The fishery consists of 4 main target species, albacore (*Thunnus alalunga*), skipjack (*Katsuwonus pelamis*), yellowfin (*Thunnus albacares*), and bigeye tuna (*T. obesus*). Small yellowfin and bigeye are caught together with skipjack close to the surface of in tropical and sub-tropical waters of the equatorial region (between +/- 10º). *El Niño* and *La Niña* climate conditions influence the distribution of tuna within the Western and Central Pacific Ocean and its availability to fishing gears, and subsequently can have huge implications for all stakeholders in the fishery especially the Pacific islanders that rely on tuna production in terms of income (Barclay *et al.,* 2007). The main fishing fleet targeting the displacements during these events are the Western Pacific purse seine fleet tightly concentrated along the equatorial plane between 5°N - 10°S and from 135°E to 150°W (Figure 1). The fleet is large in size and has around 300 vessels which include vessels from other pacific island nations, the US, Japan, Philippines and New Zealand catching over 80% of the tuna in the Western Pacific (Harley *et al.,* 2012). The US fleet operates under a specific multilateral agreement with Pacific Island Country and Territory members of the Forum Fisheries Agency (FFA). Past arrangements have included a capacity cap on the number of vessel licences (set at 40 vessels in 2002; WPFMC, 2009) and Total Allowable Effort (TAE) limits. Since 2007 the Vessel Day Scheme

(VDS) has been in operation as a means to control effort levels. The VDS arrangement allocates a total number of days and these days are then apportioned among Pacific nations on an annual basis or in some instances up to 3 years in advance. While setting limits on days, Pacific Island nations benefit in terms of increasing revenues from access fees paid by the Distant Water Fishing Nations (DWFNs), which result in the creation of infrastructure and it is hoped that the catches of tunas are reduced. The current minimum benchmark fishing day fee is now up to $8000 and the number of days set at a total of 44,623 days per year (http://www.pnatuna.com/node/142).

Historically the US fleet during the 1980-1990s consisted of 30-50 vessels and was catching on average 144,000 to 203,000 metric tonnes of tuna, which accounted for 15-25% of the tuna caught (Gillett *et al.,* 2002), but a large proportion of vessels left early 2000's due to market forces (Hamilton *et al.,* 2011). Today the US fleet makes up around 10% of the 300 vessels after a re-emergence due to an arrangement with US nationals and foreign investors in 2007. In 2009 this fleet caught over 280,000t (Hamilton *et al.,* 2011).

The rationale for this study is to identify factors that influence the strategic investment behaviour of fishers in the short and longer term where there have been lots of changes in terms of an ever changing environment e.g. financial markets, climate change and excessive rises in fuel prices, together with vessel modernisation and technological uptake (Fissel and Gilbert, 2010) (e.g. better storage facilities, increases in vessel power, sonar etc.) which increase fishing efficiency and thus may provide incentives to enter the fishery. The US purse seine fleet was chosen due to the data availability and because the fleet is economically important because of its access arrangements which have led to a growth in employment in the region. Pradhan and Leung (2004) used the multinomial logit framework (polytomous discrete choice model or random utility model - RUM (McFadden, 1974)) to predict the strategic behaviour of the US Hawaiian longline fleet to better understand fisher behaviour (enter/exit) relative to staying in the fishery. The same framework is employed for the US WCPO purse seine fishery, and the analysis extended to include model variable selection approaches and an estimation of Willingness To Pay (WTP) to enter the fishery, as an increase in effort (number of vessels entering) will subsequently lead to an increase in ratio to the total value placed on the fishery. Thus the model will assist fisheries managers in the development of strategic long-term policies that anticipate fisher behaviour.

## 2. Methods

### 2.1 The data

The Secretariat of the Pacific Community (SPC) Catch and Effort query System (CES) database for fishing activity and the FFA fleet register were used to select commercial landing and vessel data of the United States of America purse seine fleet operating in the WCPO between 1997 and 2010. The fleet register contains information on vessel characteristics such as gross registered tonnage, grt, vessel length, and date of registration. Price per metric tonnes data (US$) of the main target species, skipjack, yellowfin and bigeye tuna were acquired from FFA (Bangkok prices). The Southern Oscillation Index (SOI) was obtained from the Australian government bureau of meteorology[1]. US gulf prices (US$) per barrel were obtained from the US energy information administration[2] and information on interest rates were sourced from the federal reserve[3], the data were combined by year and a database was produced.

[1] http://www.bom.gov.au/climate/current/soihtm1.shtml
[2] http://www.eia.gov/petroleum/data.cfm
[3] http://research.stlouisfed.org/fred2/series/FEDFUNDS

## 2.2 Response variable selection

Economic theory suggests that fishers make their strategic choices based on changing stock biomass levels, management regulations (effort controls), market prices, and fuel costs. Ideally individual vessel cost data would be necessary to conduct a full bio-economic model; however much of these data are not available. As a result, several variables were used as surrogates, e.g. value as a proxy for economic viability and fuel price as a proxy for cost. Annual fuel prices were calculated per vessel based on Fuel Use Intensity (FUI) estimates (Tyedmers and Parker, 2012) for the 3 species as a weighted average of catch. US Gulf prices were used as they include barge and/or ex-pipe fees. Fisher skills, knowledge, and experience are expected to relate to the annual revenues of the target species of the fleet. Age of vessel was included, because it is assumed that older vessels may exit because of higher costs of maintenance and operation and that newer vessel will enter. Physical factors such as length, number of crew, number of auxiliary boats, engine power and gross registered tonnage were included to see the behaviour of a particular size or power group of vessel influenced fisher behavior. Size/power is correlated with capital investment and may affect a decision. SOI was included to track the climatic effects. Interest rates were included in the database to capture capital investment and financing decisions. One would assume that a large increase in the interest rate could potentially have implications in terms of exit strategies. Figure 2 and 3 shows results of the data exploration.

## 2.3 Variable reduction for models

Here we propose multivariate methods to identify candidate variables for 2 separate 7 year periods 1997-2003, 2004-2010 and the full time series (1997-2010). The rationale for doing so was that some variables can be considered non-stationary and nonlinear due to the variability of their nature and thus maybe diluted, which can cause problems when fitting over a long time series. Variable selection for input into the RUM was explored using a sequence of multivariate techniques e.g. Principle Component Analysis (PCA) (Hotelling, 1933), correlation matrices and random forests (Breiman, 2001). The purpose of this was to simplify the interpretation of multivariable datasets.

### Step 1 – Random Forests

Random forest theory (Breiman, 2001) is based on single decision trees, but rather than one decision tree they are based on an 'ensemble' or forests in order to reduce high variances (which are produced with single trees) by averaging across the forests. It does this by bootstrapping a random sample of the input data, and then fitting a tree (or as many as the analyst requires) for each classification, accuracies and error rates are computed for each observation using out of bag predictions (OOB). The Random Forests differs from other traditional variable selection techniques as it gives equal weighting to collinear variables that are good predictors of the response. As such it prevents elimination of equal good predictors which are also correlated. However it should be noted that variable importance is a ranking not an absolute value. Values are ranked if the value is above the lowest scoring value, these values can also be negative, generally however, variables approaching 0 are irrelevant. Here 20000 bootstrapped samples were used.

### Step – 2 Correlation matrices

A correlation matrix describes the correlation amongst n variables based on a square n x n matrix. The higher or lower the correlation coefficient the more strongly it's correlated positively or negatively correlated with another variable. For instance the diagonal element relates to correlations amongst themselves, so will give a correlation coefficient of 1. A cut off ≤ 0.3 is used to identify pairs of variables that are weakly correlated.

### Step 3 - PCA

Problems when selecting variables for use in the RUM are correlation between variables, high noise and a lack of contrast in the variables. Here a PCA was applied to help alleviate the problems of multi-colinearity in the dataset by converting correlated variables into uncorrelated components representing linear combinations of co-varying variables. A loading cut off at 0.3 was used to assess which variables were important, and scree plots used to identify the fraction of total variance in the data as explained by each principal component, a cut off > 1 was used (Westad *et al.,* 2003).

In summary the steps taken for variable selection are as follows:

*Step 1 is based on all the random variable trees that have been permuted for the OOB which are passed down the trees to perform predictions and undergo an algorithm test for variable importance based on OOB misclassification rate and its standard error (all variables are treated with equal weighting even though they maybe correlated).The mean decreasing accuracy output table is used and each variable systematically selected in combination with step 2 and step 3.*

*Step 2 will give an indication of the scale of correlation, the closer to zero in the matrix imply conditional independence of the variables. If the selected variable in step 1 is assessed as correlated i.e., having a correlation coefficient > 0.3 then it is omitted.*

*Step 3 supports step 2, variables in the same component can be considered correlated, however if correlation coefficient is ≤ 0.3 then is selected. Also some variables which are seen as important in step 1 may not appear in the components that explain the most variation so are excluded.*

*Final model selection of variables was based upon the Akaike information criteria (AIC; Akaike, 1974).*

## 2.4 The model

The RUM used is based on the conditional logit choice model (McFadden, 1974, 1981), where $U$ is the utility, $i$ the individual, $j$ the choice (such as a fishing trip), $w_i$ are attributes of individual $i$, $\varepsilon_{ij}$ is the stochastic error component, which is random, and $\beta_j$ is a coefficient. A set of unordered choices is assumed, and this can be written as:

$$U_{ij} = \beta_j w_i + \varepsilon_{ij}\,. \tag{1}$$

The probability that an individual $i$ makes choice $j$ is then

$$\Pr\text{ob}(\gamma_i = j) = \frac{\exp(w_i \beta_j)}{\sum_{j=1}^{J} \exp(w_i \beta_j)}, \tag{2}$$

where $\gamma_i$ is an indicator variable (with the same length as vector $\mathbf{J}$) referring to the choice $(j)$ made by individual $i$. The discrete choice dependent variable $j$ is a polytomous variable parameterized on a year-by-year basis and assumes the unique values 'entry', 'exit', or 'stay' in the purse seine fishery. Based on the paper by Pradhan and Leung (2004) their decision rules were applied e.g. A vessel enters a WCPO fishery if it was not in the previous year's US fleet but is in the current fleet. A vessel that enters is assumed to already be in the fishery, under a different flag or tied up due to operational reasons based on their year of build which is present in the vessel history database. A dummy variable in the predictor variables captures new entrants (lag of 5 years since their build year). A vessel which assumes the value 'exit' is one which is currently in the US fleet but is not in the fleet the subsequent year (potentially tied up for operational reasons or re-flagged, however there are no ways to capture this information as 'unique' license information changed with owner), in contrast to stay which is a vessel that stays in the current year and the subsequent year. The fishery is potentially one of the most profitable fisheries in the world, so one would assume that fishers are highly likely to exit it. The model assumes regulated access (Homans and Wilen, 1997), i.e. that they purchase a vessel and the licence with the entitlement to fish. Taking into account the objective to identify factors that influence fisher decision making over the 2 separate time periods and the full time series WTP can be estimated for change in investment attributes on the entry decision (mean) over cost (entry) attributes resulting from the coefficients (e.g. see Train, 1998).

$$U_{\text{entry}} = \bar{\beta}_{\text{attributes}} + \beta_{\text{costs}} = 0 = -\frac{\bar{\beta}_{attributes}}{\beta_{\text{costs}}} = \text{-WTP} \qquad (3)$$

R software (R-development team, 2010) was used in the model estimation (mlogit package).

## 3. Results

The results from the PCA analysis in all cases identified >10 new variables (components) which explained the same amount of information as the original 15 variables (Table 1). The amount of variance each component (eigenvalues) accounts for can be determined by plotting components against the variance (Figure 4).

The dataset 1997-2003 show that components 1-6 display the most variation, in contrast to 2004-2010/1997-2010 which shows the most variation in the first 5 components. The loadings of coefficients that make up each component are displayed in Tables 2-4. For instance component number 1 (dataset 1997-2003) contains the variables skjval and yftval so when one increases/decreases so does the other, this is reconfirmed by the correlation matrices (Figure 5) which have a correlation coefficient of +0.38. However some variables can be considered non-stationary and nonlinear and are positively correlated in the dataset 1997-2003 (e.g. soi and int.rates), however in the 2004-2010 dataset they are slightly negatively correlated (Figure 5).

Results from the random forest are displayed in Figure 6. The variables of higher mean decreasing accuracy are considered the more important variables. The top mean decreasing accuracy scores >0 were used to classify exit, entry or stay. In the dataset 1997-2003 the variable fuelcostyr was considered the most important in contrast to vsl_length which was the least important. Fuel cost was the first selected variable, it also featured in the first 3 components of the PCA with a loading greater than 0.3. The second variable to be selected from the random forest (Figure 6) was vsl_fuel_capacity featuring on the 5th component of the PCA and has a correlation coefficient of -0.01 with fuelcostyr (Figure 5) so was selected. Engine power was identified as the next important variable (Figure 6), and features on the second component of the PCA (Table 2). Engine power was selected based on weak association with the selected variables above. The next 3 variables, vsl_grt (same component as engine power with which it has correlation ≥0.5), totrev (on a different component to all of the pre-selected components but is highly positively correlated with fuelcostyr 0.45) and skjval which is correlated with fuelcostyr and as such are removed. Vsl_age was on the same PCA component as fuelcostyr, however vsl_age was selected due to weak associations (0.2). Soi (featuring on PCA component 4 and 5) and vsl_storage_capacity (component 2) were selected due to weak association with the already selected variables; however yftval which was next in sequence was omitted due to correlations with soi. Auxillary boat count was the next variable to feature from the random forest variable importance; this was selected due to weak associations with all pre-selected variables even though it was found in the same component as fuelcostyr and vsl_age. The last remaining variables were either considered unimportant (vsl_length) or were correlated with the candidate variables and as such were omitted from further analyses. Subsequently the final model contained vsl_engine_power, fuelcostyr, vsl_fuel_capacity, vsl_age, soi, vsl_storage_capacity and psv_auxillary_boat_count. Note that classification variables (entus) could not be included for the above analysis and thus enter the AIC procedure. Final selection of the variables was then based on their statistical significance at a level of α of 0.05, following stepwise backward selection using the multinom package and the R function stepAIC. This approach was adopted for all of the datasets until a reduced selection of the variables were selected.

The significant variables and their estimated coefficients for each of the RUM models are listed in Table 5. The results from the multinomial models showed a range of McFadden's $R^2$ of 0.20 - 0.32, suggesting the models fitted the data well (McFadden, 1979). Several variables had a significant influence on the utility and probability of entry 'vs' stay and exit 'vs' stay choices, including fuelcostyr, vsl_engine_power/vsl_grt/vsl_length, the significance of new investment (entus), and vsl_age.

The model for the period 1997-2003 suggests that as vessel engine power increased, fishers aligned their decision to enter marginally more than exit, i.e. coefficient for enter 0.003 compared to 0.002 to exit ($p < 0.01$ )(Table 5). While the decision to exit or enter vs stay relationship for fuelcostyr was weak (i.e a low negative number), model outputs suggest that as the fuel prices increase (along with their operating costs), vessels are marginally more likely to exit the fishery. In contrast, when the fleet contained few psv_auxillary_boats there was a higher probability of exiting. Vsl_storage_capacity is obviously an important characteristic and will reflect on the fishers' economic performance and hence investment decisions, hence the marginally more positive sign on entering rather than exiting (i.e the more storage space the longer the boat can stay out and fish).

The model for the period 2004-2010 contained more, and generally different, covariates than that for 1997-2003, but similarly the fuel variable showed weak relationships with entry and exit response variables. Nevertheless both exit and entry decisions associated with this variable were significant at ($p < 0.001$) and had negative signs on the coefficients. Marginally more boats entered (Figure 2) than exited when fuel prices increased (thereby making it more costly to fish) but also more appealing to sell at higher prices to recoup their investment. Figure 3 suggest that fishers were encouraged to enter the fishery with the decline in interest rates experienced during this period; however interest rates didn't enter the model due to it being omitted at the variable selection stage. Vessel tonnage and vessel length in this period replaced engine power/storage_capacity as the proxy for capital investment which was a key driver in the model for 1997-2003. Figure 3 would suggest that as fuel prices increased, and when past stock biomass levels were high, prices for skipjack and yellowfin tunas may have decreased. One would also assume from the results that fishers were looking for bigger less fuel intensive boats in order to control the supply and demand market to offset the increase in costs. The results show that there was major investment in this period with the increase in boat size came the increase in auxiliary vessels, the coefficient on entering is significant ($p < 0.001$) and positive relative to the exit coefficient ($p < 0.001$) which was small and negative.

Model 1997-2010 shows a combination of all the factors discussed in the 2 study periods with the exception of vessel age, fuel capacity becoming a prominent factor over time. The results for the variable vessel age indicate, as expected, that younger vessels are more likely to enter the fishery, resulting in an increase in the efficiency of the fleet. In contrast the model suggests that older vessels are not more likely to exit over this period.

The results from WTP were calculated using equation (3) for the 3 separate year periods and are as follows:

1997-2003 the surplus amount fishers were willing to pay was US$29, in the year period 2004-2010, it was US$5394 and over the whole period it was US$7290 per day. These results show the value of the fishery to the fishers.

# 4. Discussion

Worldwide, previous attempts to control fishing capacity have resulted in the use of programs to restrict fleet expansion (or fishing power) and fishing effort targets via Individual Transferable Quotas (ITQ's), whereby a reduction in capacity and effort is hoped to lead to a reduced fishing mortality on the main target stocks (Cunningham and Greboval, 2001). Nowadays there is more of a requirement of member states to develop cooperation among the various stakeholders and to rationalise and devolve management of fisheries more regionally. Whilst it is necessary to build on existing capabilities to ensure implications of our advice are explained in socio-economic terms as well as environmental considerations, many tools are necessary to improve cooperation amongst various stakeholders and need to be developed.

Within the VDS there is a need for stakeholders to be able to evaluate alternatives prior to implementation to show that management objectives can be met within a cost effective and equitable framework. The Western Central Pacific is one of the most important fisheries in the world (Hamilton *et al.,* 2011), it is potentially the most profitable and as a consequence attracts fishing effort rather than losing it, and thus makes exit decisions difficult to predict. Therefore controlling effort levels in the future will be of great importance to this fishery, and as such understanding how fishers invest will be of increasing importance for fisheries managers when trying to manage and balance capacity with fishing opportunities.

The outcomes of one of the papers main objectives was to estimate fishers investment preferences and from this calculate what fishers were WTP beyond what they actually pay to procure fishing rights within the Pacific Island territories. Results from the model (2004-2010) suggest that fishers are willing to pay more than the US$8000 market price of up-to US$5394, this is assuming fuel prices (or other factors not included in the model i.e. maintenance costs, wages and salaries etc..) don't change. In contrast the results from model (1997-2003) show those US fishers were only willing to pay US$29 dollars for access rights. Figure 2 shows that a large portion of this fleet left during this period potentially due to the increased costs and decrease in market prices. Overall however fishers perceived this a valuable fishery willing to pay in excess of US$7290. This is of course an estimate and further analysis would be needed for the development of strategic long term policies in balancing licence sales without displacing a large amount of capacity, as the implications of charging this additional access fee could be costly opportunity for the pacific island nations in terms of forgone access fees and the domestic benefits from US fishers landing into island nation ports.

Most fisher behaviour analyses based on decision theory has been constructed via theoretical economic theory and/or knowledge that's been published (Abernethy *et al.,* 2007). Here 3 multinomial models are presented with variable selection to select the best set of predictors and to remove colinearity in order accurately capture strategic behaviour of the US Purse seine fleet. The results described offer insights into this fleet's investment decisions where changes in important external forcing factors have occurred e.g. fluctuations in oil prices, stock levels and interest rates. By integrating available cost data, interest rates and other factors that were likely to influence future anticipated benefits or losses, it was possible to identify key important drivers influencing whether operators chose to enter, remain or exit.

Important factors considered in the analysis included future revenues and operating costs (e.g. potential fuel price increases), vessel characteristics and the impact of interest rates. In the late 1990s it was apparent from the results that engine power played a pivotal role in the decision to enter the fishery, however as time preceded, engine power within the fleet decreased, while in contrast vessel tonnage increased[4]. Engine power can be considered a proxy for capital investment

4 (According to WPFMC (2009), US vessels in 2009 had an average grt of 1500t in contrast to 1995 when the average was just 1181t (see also Figure 2)

and an older vessel can be fitted with a new engine, reducing maitenance costs. During this time period the purse seine fleet had an average age of 23 years without any new entrants to the fishery since 1990 and as such, the cost of replacing a purse seiner at that time would have cost US$15 million (Gillett *et al.,* 2002). Several authors in the past (Hutton, 1984; Suzuki, 1988; Campbell and Nicoll, 1994) discussed US fishers' preference for faster vessels to target free-schooling tunas which generally had a higher proportion of yellowfin which traditionally obtained better market prices, and subsequently they maximised their resource rent.

If the stock biomass of yellowfin and skipjack declined it provided less opportunities for this fleet and so it would then either decline in size or diversify (in terms of fishing areas and/or species) which is potentially what happened towards the end of 2001. Coupled with the increase in fuel price and low price per ton of the target species resulted in fewer opportunities for the fleet and so they either exited or simply reflagged. Over the study period fuel prices rose from US$ 25 per barrel in 1997 up to US$100 per barrel in 2009. During this period improvements in fishing vessel power occurred to offset the increase in fishing costs through the use of Fishing Aggregation Devices (FAD), associated sonar technology (Fonteneau *et al.,* 2013) (thereby reducing search time and thus fuel costs) and increasing storage capacity and vessel length mirroring increases in vessel tonnage and the investment of more vessels to this fleet (age being a significant variable), which were significant outcomes from the analysis. Also of note were the increases in prices per ton of the target species coupled with low interest rates encouraged investment behavior as well as government subsidies (not included in the study) allocated to US purse seiners (Sharp and Sumalia, 2009). Interestingly the *El Niño* (soi) wasn't a significant factor in the strategic thinking of these fishers potentially due to the amplitude in inter-annual variability (see, http://www.bom.gov.au/climate/current/soihtm1.shtml) that has occurred in the last 2 decades which could have been viewed as an unreliable factor to base their decision making on in an already profitable fishery. In contrast Campbell and Hand (1999) showed that this particular fleet based their short term decision making (tactics) on this phenomenon.

Over the study period changes in correlation amongst the different variables exist and so changing one variable may result in a change in another. Therefore collinearity can lead to erroneous parameter estimation in statistical models (Weisberg, 1985). Here collinearity in the models was reduced to negligible amounts by adopting multivariate processes resulting in variable reduction for input into the models. However it should be noted that alternative models may equally be supported by the data, in which case model choice is not necessarily about choosing the best model since the recognition of the fact there may be several equally good explanatory models which are important in developing a better understanding of system dynamics (Grant, 1986; Pitelka and Pitelka 1993).

As a suggested way of improving future models, a qualitative survey would enrich the analysis as assumptions had to be made in the models constructed. Several authors have stressed the importance of including fisher knowledge in models that are to be used for management decision-making (McGoodwin, 2006; Menzies and Butler, 2006). Fisher knowledge was absent from this study because there was no time or resource to conduct a qualitative survey. Data on pre-entry and post-exit performance related to revenues in other fisheries would be useful (e.g. the Eastern pacific or under a different flag). Furthermore, there may be impacts on other stocks, for example the spatial distribution of fishing effort may change as some vessels exit a particular fishery and move to exploit other stocks/regions. This will result in fishing mortality changes on different ages of the new target stock and by-catch, and the subsequent discard levels. As some of the fleet exit others do not, it still results in the most profitable remaining with money from buybacks or government grants used for more investment i.e. larger storage facilities, technological FAD advancements or extra subsides towards license and fuel costs resulting in greater impacts on the stocks. Social changes also happen, as those that do not exit the fleet can be bought up by other national or international fishers/investors, which is what happened to a large portion of this fleet. This can have implications in terms of changes in targeting and hence fishing mortality. Overall, the model has potential to be used as a strategic planning tool that can be used to help develop management plans to align fleet capacity with fishing opportunities.

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## 7. Tables and Figures

Table 1. Description of variables in the database.

| variable | description |
|---|---|
| vsl_grt | Gross registered tonnage of the vessel |
| vsl_length | Vessel length |
| vsl_speed | Vessel speed in knots |
| vsl_crew_count | Vessel crew count (number of persons) |
| vsl_engine_power | Vessel engine power in kW |
| vsl_fuel_capacity | Vessel fuel capacity in $m^3$ |
| vsl_storage_capacity | Vessel storage capacity in $m^3$ |
| psv_auxiliary_boats_count | Number of auxiallary boats |
| vsl_age | Age of vessel |
| fuelcostyr | Fuel cost per vessel per year (US$) |
| int.rates | Average % interest rate |
| totrev | Combined total of skj, bet and yft per vessel per year (US$) |
| skjval | Skipjack tuna value per per vessel per year (US$) – Bangkok prices |
| yftval | Yellowfin tuna value per vessel per year (US$) – Bangkok prices |
| betval | Bigeye tuna value per vessel per year (US$) – Bangkok prices |
| Soi | Southern oscillation index |

Table 2. PCA loadings 1997 – 2003 where loading ≥ 0.3.

| variable | Comp.1 | Comp.2 | Comp.3 | Comp.4 | Comp.5 | Comp.6 |
|---|---|---|---|---|---|---|
| vsl_grt | | -0.398 | | | | |
| vsl_length | | | | | | 0.575 |
| vsl_speed | | | | 0.437 | -0.385 | |
| vsl_crew_count | | -0.373 | | | | |
| vsl_engine_power | | -0.323 | | | | |
| vsl_fuel_capacity | | | | | 0.585 | |
| vsl_storage_capacity | | -0.357 | | | | |
| psv_auxiliary_boats_count | | | -0.422 | | | -0.422 |
| vsl_age | | | -0.392 | | | |
| fuelcostyr | | | -0.384 | 0.41 | | |
| int.rates | | | 0.596 | | | |
| skjval | -0.455 | | | 0.31 | | |
| yftval | -0.418 | | | | | |
| betval | | | | | | -0.305 |
| totrev | -0.525 | | | | | |
| soi | | | | 0.506 | 0.388 | |

Table 3. PCA loadings 20042010 where loading ≥ 0.3.

| **variable** | **Comp.1** | **Comp.2** | **Comp.3** | **Comp.4** | **Comp.5** |
|---|---|---|---|---|---|
| vsl_grt | | -0.433 | | | -0.317 |
| vsl_length | | | | 0.581 | |
| vsl_speed | | -0.345 | | | 0.343 |
| vsl_crew_count | -0.343 | | | | |
| vsl_engine_power | | -0.54 | | | |
| vsl_fuel_capacity | | -0.389 | | -0.396 | 0.426 |
| vsl_storage_capacity | | -0.391 | | | |
| psv_auxiliary_boats_count | | | -0.369 | | 0.442 |
| vsl_age | | | 0.383 | | |
| fuelcostyr | -0.386 | | | | |
| int.rates | | | | 0.344 | 0.432 |
| skjval | -0.389 | | | | |
| yftval | | | | 0.376 | 0.323 |
| betval | | | 0.452 | | |
| totrev | -0.395 | | 0.305 | | |
| soi | | | | | |

Table 4. PCA loadings 1997-2010 where loading ≥ 0.3.

| **variable** | **Comp.1** | **Comp.2** | **Comp.3** | **Comp.4** | **Comp.5** |
|---|---|---|---|---|---|
| vsl_grt | -0.425 | -0.347 | -0.315 | | |
| vsl_length | 0.679 | 0.582 | | | |
| vsl_speed | -0.401 | 0.328 | 0.344 | -0.477 | 0.371 |
| vsl_crew_count | -0.372 | | | | |
| vsl_engine_power | -0.504 | -0.303 | | | |
| vsl_fuel_capacity | -0.34 | -0.367 | 0.467 | 0.379 | 0.315 |
| vsl_storage_capacity | -0.452 | -0.678 | | | |
| psv_auxiliary_boats_count | -0.331 | 0.348 | -0.553 | -0.355 | |
| vsl_age | -0.469 | -0.319 | | | |
| fuelcostyr | -0.417 | | | | |
| int.rates | 0.44 | -0.392 | -0.679 | | |
| skjval | -0.412 | | | | |
| yftval | 0.628 | -0.491 | | | |
| betval | -0.506 | -0.668 | 0.301 | | |
| totrev | -0.403 | | | | |
| soi | -0.656 | -0.427 | | | |

Table 5. Parameter estimates from the multinomial logit model.

| Model 1997-2003 | Estimate | Std. Error | |
|---|---|---|---|
| enter:(intercept) | -15.589 | 5.3373 | ** |
| exit:(intercept) | -10.17 | 3.6015 | ** |
| enter:fuelcostyr | -2.82E-05 | 7.27E-06 | *** |
| exit:fuelcostyr | -1.44E-05 | 4.67E-06 | ** |
| enter:vsl_engine_power | 0.003595 | 0.001297 | ** |
| exit:vsl_engine_power | 0.002286 | 0.000941 | * |
| enter:psv_auxiliary_boats_count | 0.90663 | 0.41863 | * |
| exit:psv_auxiliary_boats_count | 0.49695 | 0.25849 | . |
| enter:vsl_storage_capacity | 0.000794 | 0.000407 | . |
| exit:vsl_storage_capacity | 0.000643 | 0.000324 | * |
| **Log-Likelihood: -60.081** | | | |
| **McFadden R^2: 0.32417** | | | |

| Model 2003 - 2010 | Estimate | Std. Error | |
|---|---|---|---|
| enter:(intercept) | -6.809437 | 2.02E-07 | *** |
| exit:(intercept) | -0.636176 | 2.96E-07 | *** |
| enter:fuelcostyr | -1.62E-06 | 6.25E-07 | ** |
| exit:fuelcostyr | -1.76E-06 | 8.03E-07 | * |
| enter:vsl_length | 0.020147 | 1.5E-05 | *** |
| exit:vsl_length | 0.015062 | 2.01E-05 | *** |
| enter:vsl_grt | 0.001781 | 0.000359 | *** |
| exit:vsl_grt | -0.000198 | 0.000421 | |
| enter:psv_auxiliary_boats_count | 0.586298 | 6.83E-07 | *** |
| exit:psv_auxiliary_boats_count | -0.293133 | 7.73E-07 | *** |
| enter:entus | 12.13128 | 1.11E-11 | *** |
| exit:entus | -1.506471 | 1.66E-12 | *** |
| **Log-Likelihood: -90.00391** | | | |
| **McFadden R^2: 0.2416361** | | | |

| Model 2003 - 2010 | Estimate | Std. Error | |
|---|---|---|---|
| enter:(intercept) | -3.170228 | 5.26E-07 | *** |
| exit:(intercept) | -4.77779 | 6.05E-07 | *** |
| enter:fuelcostyr | -1.17E-06 | 4.07E-07 | ** |
| exit:fuelcostyr | -1.48E-06 | 5.75E-07 | * |
| enter:vsl_length | 0.022226 | 3.64E-05 | *** |
| exit:vsl_length | 0.022166 | 3.61E-05 | *** |
| enter:vsl_age | -0.092643 | 1.42E-05 | *** |
| exit:vsl_age | 0.028548 | 1.75E-05 | *** |
| enter:vsl_storage_capacity | 0.000534 | 0.000289 | . |
| exit:vsl_storage_capacity | 0.000874 | 0.000263 | *** |
| enter:vsl_fuel_capacity | 0.001781 | 0.000697 | * |
| exit:vsl_fuel_capacity | 5.59E-05 | 0.000711 | |
| enter:entus | 15.68829 | 2.96E-14 | *** |
| exit:entus | -1.655642 | 6.59E-16 | *** |
| **Log-Likelihood: -169.7683** | | | |
| **McFadden R^2: 0.2013186** | | | |

Statistical significance at ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 .

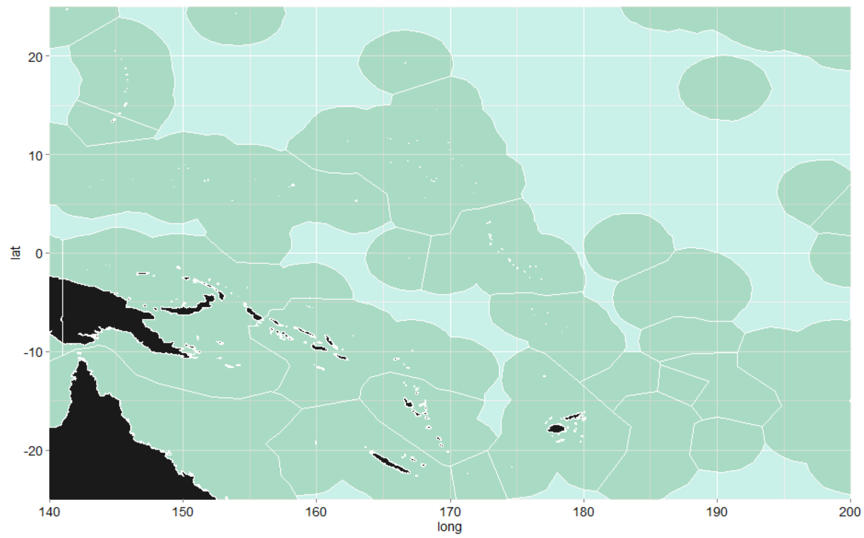



Figure 1. The Western and Central Pacific Ocean with Pacific island regions.

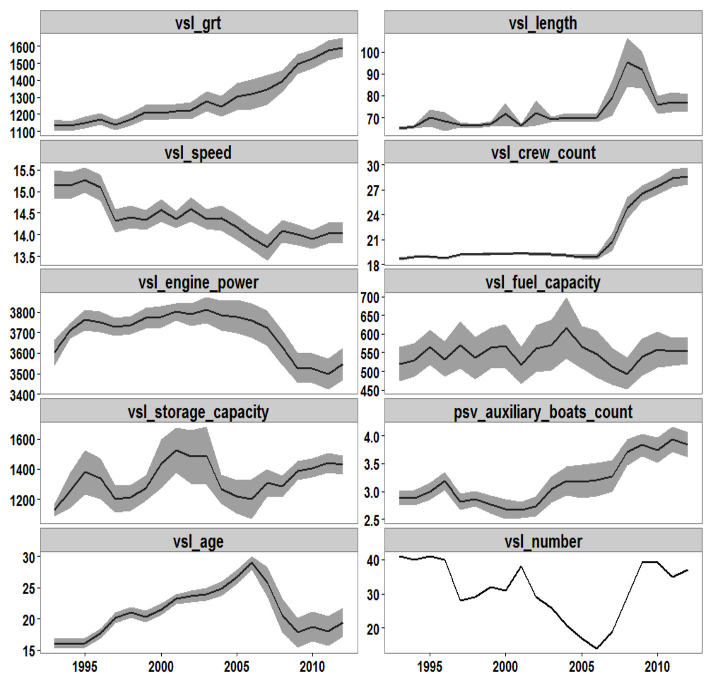



Figure 2. The US purse seine physical characteristics, the thin black line represents the mean surrounded by standard error bar in light grey. (see Table 1 for list of covariates)

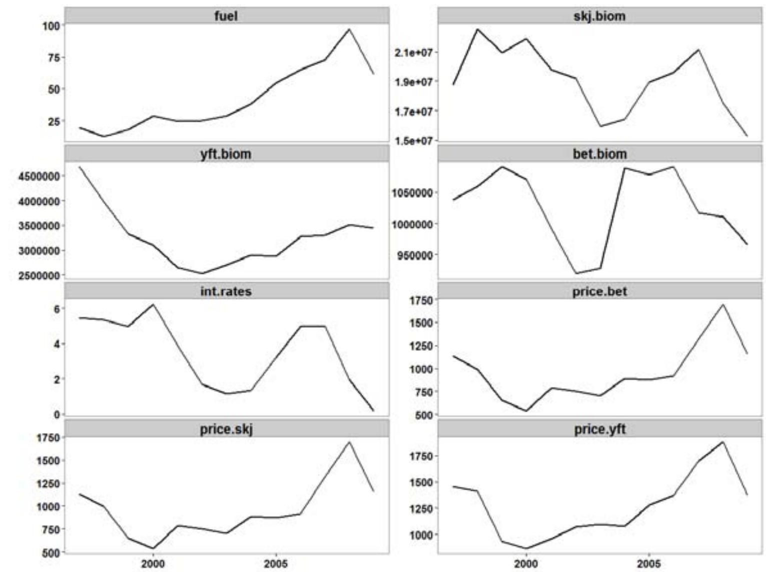



Figure 3. Price per tonne (price.skj = skipjack, price.bet = bigeye, price.yft=yellowfin), fuel price in dollars per barrel, interest rates as (%) (int.rates) and biomass estimates in tonnes, (skj.biom=skipjack, bet.biom=bigeye, yft.biom=yellowfin). (See Table 1 for list of covariates)

**PCA 1997-2003** **PCA 2004-2010** **PCA 1997-2010**

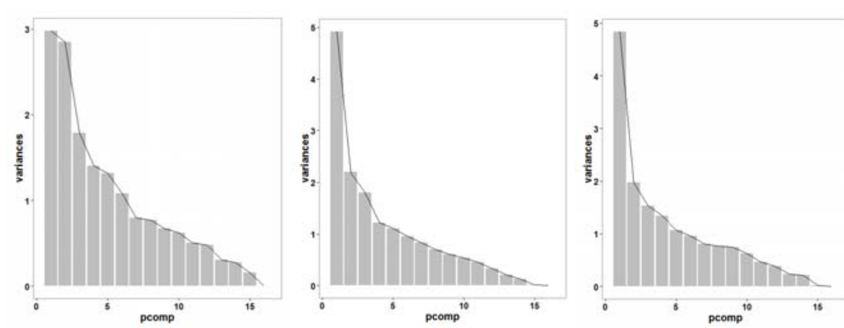
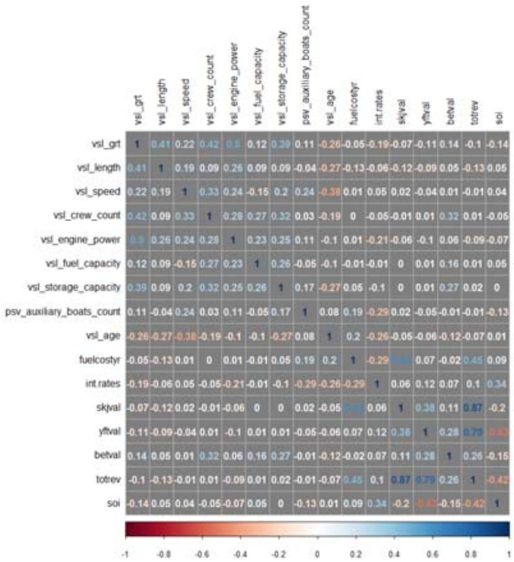
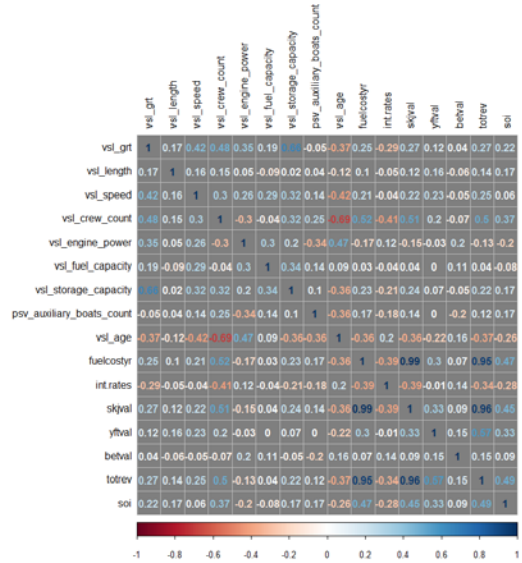



Figure 4. Scree plots displaying the variance of each component for each dataset.

**Correlation matrix 1997-2003**




**Correlation matrix 2004-2010**




**Correlation matrix 1997-2010**

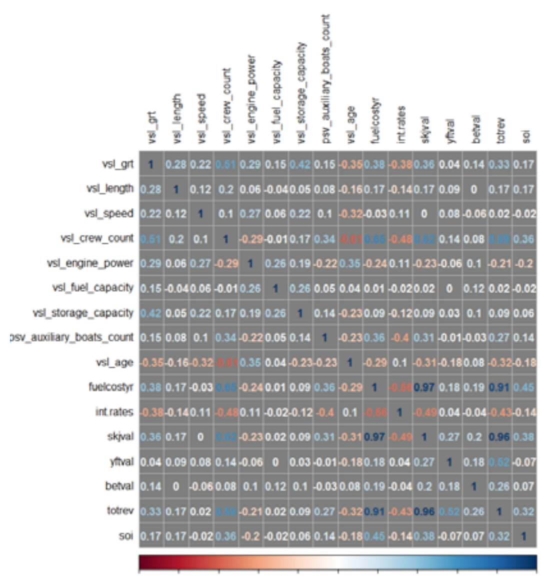



Figure 5. Correlation matrices of the 3 data sets.

**Random forest 1997-2003** **Random forest 2004-2010** **Random forest 1997-2010**

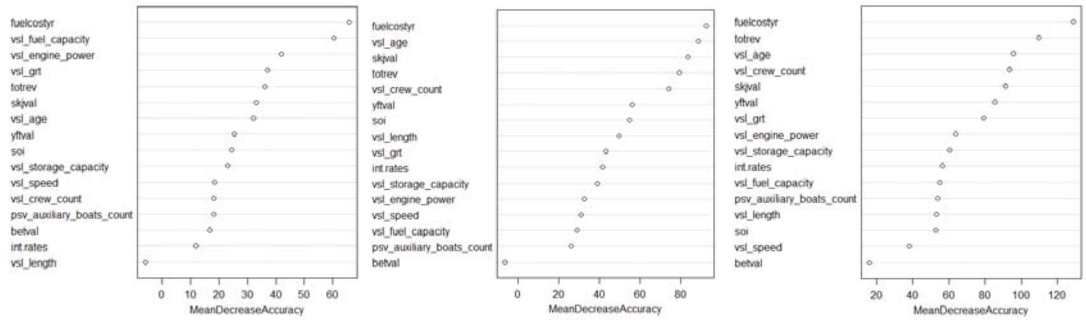



Figure 6. Variable importance plots for the predictor variables from the RF.