Studies on ecological and climatic conditions as drivers of stock dynamics of fisheries resources

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STUDIES ON ECOLOGICAL AND CLIMATIC CONDITIONS AS DRIVERS OF STOCK DYNAMICS OF FISHERIES RESOURCES

A Dissertation presented

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CHAPTER 1

Introduction and overview of the study

1.1. INTRODUCTION

Over the past few decades, there has been growing interest in development better and more efficient techniques to assess commercial fisheries stocks. Although there are a number of fisheries across the globe that is managed quite successfully, there are hardly any natural fish species whose ecological characteristics and interaction with biotic and environmental factors are completely understood. A fish population is affected by numerous intrinsic and extrinsic factors interacting at different levels to result in its population dynamics over a time series.

Prior to the rise of numerous commercial fisheries in the early 1900s, most fisheries resources were in abundant supply and due to this most fisheries around the world have exploited fisheries resources for economic gains without attempting to understand the underlying mechanisms which drive these populations. It was not until various fisheries industries around the world started to collapse, that fishery managers decided to invest in understanding the biological and ecological characteristics of the commercial fish species in order to better manage the fishery. As a result numerous mathematical and statistical techniques have been developed over the years for assessing fisheries stocks and are still developing as there are no techniques at present that can completely explain a fisheries stock.

A lot of fishery around the world is managed by regulating the fishing pressure, catch sizes and fishing season. In recent years numerous studies have shown that alterations in local ecological factors and various climatic conditions play a significant role in shaping the distribution and abundance of various fish species over a time series. While fishing effort does have impact on fishery resources and regulating it may work for some fisheries, understanding the importance of ecological and environmental factors in shaping these fishery resources is imperative to provide fishery managers the tools necessary to effectively manage a fishery for now and the future.

This study was aimed at elucidating the ecological and environmental variables which affect the time series trajectory of four commercially important fish species and develop suitable models using those variables to reconstruct the time series trajectory of the stocks.

1.2. BIOLOGY OF FOUR ECNOMOICALLY IMPORTANT FISH SPECIES

1.2.1. Japanese Pond Smelt *Hypomesus nipponensis*

The Japanese pond smelt, *Hypomesus nipponensis* McAllister (revised by Saruwatari *et al.*, (1997)) is a commercially important lake fish in Japan (Ibaraki Prefecture, 2012; Katayama *et al.*, 2001; Ibaraki Prefecture, 1996; Hamada, 1961; Shiraisi, 1960). It is distributed substantially among the Lakes Ogawara, Abashiri, Suwa, Kasumigaura and Kitaura as well as coastal sea areas around Japan (Katayama and Kawasaki, 1994; McDowall, 1988; Hamada, 1961). The pond smelt is of cultural importance as a symbol for freshwater fisheries in the area around Lake Kasumigaura and Kitaura (Ibaraki Prefecture, 2012). Spawning occurs annually in the two lakes between mid-January to mid-March and pond smelts recruit to the fishery when they are four to six months old. They have a life span of one year and the fishermen harvest pond smelt in the two lakes annually from July to December using trawl net (Ibaraki Prefecture, 2012; Nemoto, 2012; Arayama, 2011; Nemoto, 1993; Kasebayashi and Nakano, 1961).

1.2.2. Peruvian anchoveta *Engraulis ringens*

The Peruvian anchoveta *Engraulis ringens* Jenyns 1842 is a small dominant nekton species with a short lifespan and high mortality rate in the coastal region of the northern Humboldt Current System (HCS) off Peru with spawning area located between 8ºS and 14ºS (Barange *et al*., 2009; Braun *et al*., 2005; Oliva *et al*., 2001). Peak spawning occurs between August and September, but spawning activity spreads throughout the year (Braun *et al*., 2005). *E. ringens* is of significantly high ecological importance as it feeds mainly on zooplankton and acts as prey for higher trophic levels channeling energy between trophic levels in the process (Van der Lingen *et al.*, 2009; Espinoza and Bertrand, 2008; Pauley *et al*., 1989).

1.2.3. Yellowfin Tuna *Thunnus albacares*

Yellowfin tuna (*Thunnus albacares*) is one of the highly migratory species of tuna which has been of significant commercial importance to the nations that fall within the Western and Central Pacific Convention Area (WCPCA) including the South Pacific Island countries and territories where yellowfin tuna forms one of the major revenue contributors for the fisheries sector (Bell *et al.*, 2013; Hampton, 2010; Silbert and Hampton, 2003; Gillett *et al.*, 2001; Aaheim and Signa, 2000; Lawson, 2000). After skipjack tuna (*Katsuwonus pelamis*), yellowfin tuna accounts for the second highest catch in the Western and Central Pacific Ocean (WCPO). They start spawning at lengths approximately >100cm in preferable water temperatures >26ºC and are relatively fast growing reaching maximum size of up to 180cm fork length during their lifespan of around 5 to 8 years (Zhu *et al.*, 2011; Hampton and Fournier, 2001; Itano, 2000; Lehodey and Leroy, 1999).

1.2.4. Albacore Tuna *Thunnus alalunga*

Albacore tuna (*Thunnus alalunga*) is a commercially important species of tuna to the economy of various countries in the WCPCA in the South Pacific (Amoe, 2005; Aaheim and Signa, 2000). They are also highly migratory with sexual maturity, age, seasonally and their catch varies both seasonally and spatially (Langley and Hoyle, 2008; Polovina *et al.*, 2001; Jones, 1991). Albacore tuna mature at lengths approximately >80cm and spawning in the South Pacific occurs from around 10ºS to 25ºS with recruitment occurring after around one year in the coastal waters of New Zealand when the fish are about 40cm to 50cm in length or Fork Length (FL) (Langley, 2004; Ramon and Bailey, 1996). Over their lifespan albacore tuna reach maximum lengths of up to 120cm FL. Albacore tuna fisheries has expanded considerably in the South Pacific Ocean with almost three fold increase in catch the past two decades from 1990 to 2010 (Harley *et al.*, 2011).

1.3. OVERVIEW OF THE STUDY

This study was focused at identifying the ecological and environmental variables which affect the time series trajectory patterns of four different commercially important fish species. Utilizing these variables and incorporating them into models to explain a significant proportion of the stock time series fluctuation pattern for each species. The concept of the existence of regimes was also reanalyzed with alternative methods for verification.

Chapter 2 looks at the relationship of the biotic and abiotic variables with the stock time series pattern of the Japanese pond Smelt *Hypomesus nipponensis* in Lake Kasumigaura and Kitaura of the Ibaraki prefecture, Japan and discusses the suitable representatives for the Japanese pond smelt stock dynamics. Significant intrinsic and environmental variables are used to develop stock reproduction models to significantly reconstruct the trajectory of the pond smelt stock for the two lakes.

Chapter 3 discusses the claim of the existence of regimes and the presence of different density dependent effects in the stock time series of the Peruvian anchoveta (*Engraulis ringens*) off Peru and uses alternative methods to test the validity of the claim. The relationship of the environmental variables with the Peruvian anchoveta is also explored and recruitment forecasting models are developed with significant fitness to the referred recruitment.

Chapter 4 examines the effects of different climatic conditions on a long time series stock fluctuation pattern for the yellowfin tuna *Thunnus albacares* in three regions of the Eastern and Western South Pacific Ocean. Data and results are sufficiently explored to ensure that statistical and process errors are not present. Climatic variables which exhibit relationship with the yellowfin tuna stock trajectory are used for construction of stock reproduction models to significantly fit the stock time series of the yellowfin tuna in the three regions.

Chapter 5 investigates the relationship of climatic conditions with the time series dynamics of the albacore tuna *Thunnus alalunga* stock in three regions of the Eastern and Western South Pacific Ocean. Suitable stock reproduction models are constructed using Generalized Linear Model (GLM) and Response Surface Methodology (RSM) to fit the stock trajectory of the albacore tuna in the three regions.

Chapter 6 discusses the results of the studies on the four species and highlights the main outcomes and points from the four studies. Recommendations and difficulties in stock assessments for the four species are also discussed.

CHAPTER 2

Factors Affecting Japanese Pond Smelt (*Hypomesus nipponensis*) Stock Trajectory in Lake Kasumigaura and Kitaura

Keywords: Pond smelt, Lake Kasumigaura, Lake Kitaura, phosphorus, surface temperature

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Singh, A.A., Sunoh, N., Niwa, S., Tokoro, F., Sakamoto, D., Suzuki, N., and Sakuramoto, K., 2014. Driving factors behind the fluctuation mechanisms of the Japanese pond smelt *Hypomesus nipponensis* in Lake Kasumigaura and Kitaura: Catch Forecasting Model. Abstract, Book of Abstracts, Development of Fisheries and Marine Technology for Sustainable Biodiversity, Conservation and Responsible Aquaculture Industries, International Fisheries Symposium - IFS2014, Universitas Airlannga, Surabaya, Indonesia.

2.1. ABSTRACT

The Japanese pond smelt (*Hypomesus nipponensis*) stock has been observed to fluctuate quite rigorously over the years with sustained periods of low catch in Lake Kasumigaura and Kitaura of the Ibaraki prefecture, Japan which would adversely affect the socioeconomic livelihood of the local fishermen and fisheries industry. This study was aimed at determining the factors affecting the stock fluctuation of the pond smelt through the different years in the two lakes. Through exploratory analysis it was found that the pond smelt had significant relationship with total phosphorus (TP) level in both lakes. The global mean land and ocean temperature index (LOTI) was also found to be indirectly related to the pond smelt stock in Lake Kasumigaura and Kitaura at the latitude band of 24°N to 90°N (*l*). Both TP and LOTI had inverse relationship with pond smelt trajectory in both lakes. For both Lake Kasumigaura and Kitaura, TP for the individual lakes and LOTI (*l*) were used as independent variables using generalized linear model and response surface methods for modeling the stock dynamics of the pond smelt in the two lakes. Model selection was based on significant parameter estimates (p<0.05), Akaikes Information Criterion and R^2 values. Phosphorus loading is an indication of increasing anthropogenic activities in the surrounding area having negative impact on the pond smelt population. When management decisions are being made regarding pond smelt fishery and sustainability plans in the Ibaraki prefecture, the effects of TP and LOTI should be taken into account. Future research needs to be directed towards deeper understanding the mechanisms by which TP and LOTI affect pond smelt population in Lake Kasumigaura and Kitaura for more effective management.

2.2. INTRODUCTION

The Japanese pond smelt, *Hypomesus nipponensis* McAllister (revised by Saruwatari *et al.*, (1997)) is a commercially important lake fish in Japan (Ibaraki Prefecture, 2012; Katayama *et al.*, 2001; Ibaraki Prefecture, 1996; Hamada, 1961; Shiraisi, 1960). It is distributed substantially among the Lakes Ogawara, Abashiri, Suwa, Kasumigaura and Kitaura as well as coastal sea areas around Japan (Katayama and Kawasaki, 1994; McDowall, 1988; Hamada, 1961). The pond smelt is of cultural importance as a symbol for freshwater fisheries in the area around Lake Kasumigaura and Kitaura (Ibaraki Prefecture, 2012). Their population has been observed to fluctuate quite intensively over time in the two lakes and has reached comparatively low levels and sustained low over a number of years in recent history. Understanding of such patterns is important for effective management and for both economical and biological sustainability of the pond smelt.

Lake Kasumigaura, the second largest lake in Japan (after Lake Biwa) and the much smaller nearby Lake Kitaura (**Figure 2-1**) are freshwater shallow lakes with an average depth of four meters, located on the East side of the Kanto plain in Ibaraki prefecture, Japan (Sakamoto *et al.*, 2014; Matsushita *et al.*, 2006). The landscape around the two lakes is dominated by forest, paddy fields, plowed fields and water, with the traditional industries of the area being livestock management, agriculture and fishery production (Matsushita *et al.*, 2006). Matsushita *et al.*, 2006 studied the changes in land use from 1979 to 1996 around the Lake Kasumigaura and Kitaura Basin and reported significant increase in human land use such as agricultural activities, residential homes and recreational facilities.

Pond smelts have been shown to be affected by biological and environmental factors previously (Hasenbein *et al.*, 2013; Sharma *et al.*, 2011; Toda and Wada, 1990; Hanazato *et al.*, 1989). In a study by Hanazato *et al.*, (1989), in Lake Yunoko it was found that the population of pond smelt are almost absent in anoxic areas where the dissolved oxygen was below 3mg/l, showing that dissolved oxygen concentration of lake water has a strong influence on the population dynamics of the pond smelt (*Hypomesus olidus*). Hasenbein *et al.*, (2013) showed that negative correlation exists between turbidity of water and feeding frequency of juvenile delta smelt (*Hypomesus transpacificus*) from the San Francisco Bay Delta, USA. Sharma *et al.*, (2011) studied the impact of changes in climatic condition (air temperature) and invasion of rainbow smelt (*Osmerus mordax*) on cisco (*Coregonus artedii*) population for over 13,000 lakes in Winsconsin, USA. Results showed that the negative impact of changes in air temperature on cisco will be much larger than invasion of rainbow smelt by the year 2100. Heithaus *et al.*, (2009) and Atkinson *et al.,* (2008) concluded that the vulnerability to predation is a significant factor in determining the survival and mortality of fish stocks in lakes and rivers. Toda and Wada (1990) showed that the seasonal change in size of prawn *(macrobrachium nipponense),* goby (*Tridentiger obscurus*), pond smelt (*Hypomesus transpacificus*) and zooplankton show similar patterns in Lake Kasumigaura.

Bryan and Ludsin (2013) studied the impact of different nutrient levels and introduction of a predatory species on the food web structure in three lakes in Ohio, USA. Results showed that changes in nutrient content including phosphorus had higher impact on lake food web structure compared with changes in predatory species. Human land use and developments have probably resulted in the increased loading of nutrients including phosphorus in Lake Kasumigaura and Kitaura (Matsushita *et al.*, 2006). Phosphorus loading has been shown to be the leading cause of eutrophication in lake ecosystems, which leads to anoxia, increase in turbidity and changes in the community structure of primary producers, eventually leading to changes in the dynamics of higher trophic level vertebrates (Jeppensen *et al.*, 2010; Xu *et al.*, 2010; Schindler *et al.*, 2008; Ludsin *et al.*, 2001).

In understanding population dynamics it is important to study the habitat of the fish as this plays a significant role in their survival both as juveniles and as they grow into adult forms (Grol *et al.*, 2011). Here, a habitat is the interaction of a fish species with biotic and abiotic factors to support a healthy population (Hayes *et al.*, 1996). The mechanisms behind the trajectory pattern of fish are complex as various biotic and abiotic factors might be interacting and operating together resulting in annual changes in population. It is critical to understand the relationship of a fish to its habitat and long-term data are essential to compare trends of variables and identify their linkages to fish population dynamics (Rose, 2000; Feyrer *et al.,* 2007) in order to better manage a fishery.

The purpose of this study was to determine the intrinsic and environmental factors affecting the fluctuation patterns of the Japanese pond smelt (*H. nipponensis*) through the years for Lake Kasumigaura and Kitaura. The objectives were to: (1) carry out exploratory analysis and determine if relationships exist between pond smelt stocks and variables from data on nutrient levels in lake, physiochemical data for each lake and biological data on organisms; (2) determine if the climatic condition of surface temperature of the latitude band above the two lakes have any relation to pond smelt stock as the effect of air temperature above lakes on lake fish has been shown in Sharma *et al.*, (2011); (3) use variables exhibiting significant relationships to pond smelt stock trajectory to develop reasonable stock reproduction model for the Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura and Lake Kitaura respectively.

2.3. MATERIALS AND METHODS

2.3.1. Data

The catch data for the stock of the Japanese pond smelt *H. nipponensis* in Lake Kasumigaura and Kitaura for the range of years from 1972 to 2008 was obtained from the Ibaraki Prefectural Fisheries Experiment Station (IFES), Ibaraki, Japan and as calculated by Nemoto, (1995) and Kubota, (2002). Spawning occurs annually in the two lakes between mid-January to mid-March and pond smelts recruit to the fishery when they are four to six months old. They have a life span of one year and the fishermen harvest pond smelt in the two lakes annually from July to December using trawl net (Ibaraki Prefecture, 2012; Nemoto, 2012; Arayama, 2011; Nemoto, 1993; Kasebayashi and Nakano, 1961) and provide the catch data to IFES. IFES also carries out trawl surveys just before the initiation of the fishing season. Catch size of pond smelt ranges from ~6cm in July to ~10cm from August to December (Kasebayashi and Nakano, 1961) and they are distributed throughout Lake Kasumigaura and Kitaura encompassing an area of approximately 220km^2 (**Figure 2-1**).

Figures 2-2A and **2-2B** show the trajectory of the Japanese pond smelt (*H. nipponensis*) from the year 1972 to 2008 for Lake Kasumigaura and Kitaura respectively. For Lake Kasumigaura (**Figure 2-2A**), there was a decreasing trend of catch for the years 1974-1976, 1986-1988, 1993-1995 and 1997-2000, while the years 1980-1984, 1988-1991 and 1995-1997 followed an increasing trend. For the other years, the trend fluctuated annually. The catch peaked in 1984 followed by a sharp decline, while other significant peaks for catch of pond smelt can be observed for the years 1974, 1977 and 1986. In the year 2000 the catch volume was at its lowest point and seemed to recover to some extent by the year 2007. For Lake Kitaura (**Figure 2-2B**), a decreasing trend can be observed for the years 1972-1975, 1979-1981, 1986-1988, 1989-1994 and 1997-2000, while an increasing trend was seen for the years 1975-1977, 1981-1982, and 1994-1997. For the other years, the trend had an annual fluctuation of higher and lower catch. The peak catch of pond smelt for Lake Kitaura can be seen in the year 1979 which was followed by a sharp decline. Other significant peaks can be observed for the years 1972, 1977 and 1986. The lowest catch volume was observed for the year 2000, following which the stock recovered to some extent by the year 2007 before declining again by the year 2008.

From **Figures 2-2A** and **2-2B** a similar pattern can be observed. Before 1988, the catch trend for both lakes showed two peaks that are quite similar. Around 1977 and 1986, the catches in Lake Kasumigaura were significantly high. Similarly, around 1977 and 1986, the catches in Lake Kitaura were also significantly high. From 1986 to 1989 the catch trajectory pattern for both lakes were almost identical and after 1990, catches in both lakes generally showed a decreasing pattern which continued up to the year 2004.

The catch per unit effort (CPUE) is a suitable representative of the pond smelt stock for Lake Kasumigaura and Kitaura but the effort data from IFES was only available from 1998 to 2008. This limited the CPUE calculation for a period of only 11 years which would be insufficient to effectively compare trends and linkages between variables. On the other hand, the catch data was available for a period of 37 years for both Lake Kasumigaura and Kitaura, hence it would be better suited for trend analysis and comparisons with variables. To justify the suitability of catch data as representative of pond smelt stock trajectory for the two lakes, it was compared with the CPUE data.

Other variable data obtained for Lake Kasumigaura and Kitaura from IFES included; i) data on the nutrient levels such as chemical oxygen demand, dissolved oxygen, total nitrogen and total phosphorus (mg/l); ii) *in situ* data including water temperature (ºC), turbidity (cm), chlorophyll (µg/l) and pH; iii) biological catch data (tonnes) included grasscarp (*Ctenopharyngodon idellus*), crusian carp (*Carassius auratus*), eel (*Anguilla japonica*), borakind mullet (*Mugil cephalus*), prawn (*Macrobachium nipponense*), catfish (*Sarcocheilichyhys variegates microoculus*), clam (*Corbicula japonica*) and icefish (*Salangichthys microdon*) as the fish and shellfish species. Climatic data for global mean land and ocean temperature index (LOTI) for the latitude band of 24°N to 90°N was obtained from the National Aeronautics and Space Administration (NASA), Goddard Institute for Space studies, Goddard Space Flight Center, Science and Exploration Directorate, Earth Science Division (http://data.giss.nasa.gov/gistemp).

2.3.2. Regression Analysis and Unit Root Test

Regression analysis was carried out to screen all the variables and determine which individual independent variables correlated to the dependent variables of pond smelt catch and CPUE time series in Lake Kasumigaura and Kitaura. In order to determine if catch data could be used as a representative of pond smelt stock in Lake Kasumigaura and Kitaura it was compared with the available CPUE data from 1998 to 2008. The CPUE data from 1998 to 2008 for Lake Kasumigaura and Kitaura (P_x and P_y) was subjected to regression analysis against nutrient, *in situ*, biological and climatic data. The same treatment was applied to catch data from 1998 to 2008 for the two lakes (C_x and C_y) for comparison. The determination coefficient was also calculated between the CPUE and catch for pond smelt in both lakes from 1998 to 2008 to examine how well they align with each other.

Regression analysis was applied to the pond smelt catch data from 1972 to 2008 for Lake Kasumigaura and Kitaura (C_u and C_v) against the various nutrient, *in situ*, biological and climatic data. Variables which belonged exclusively to a particular lake, such as catch data for a fish species in a particular lake, were used in regression analysis just for that particular lake as this made sense ecologically. These results were also compared with the regression results of CPUE from 1998 to 2008.

Time series data which have a deterministic trend have a stationary process where changes in time series trend or shocks have transitory effects. When shocks have permanent effect the time series have a stochastic trend or unit root. The presence of a unit root in a time series can result in spurious correlations in statistical techniques such as regression analysis (MacKinnon, 1996; Kwiatkowski *et al.*, 1992; Dickey and Fuller, 1979). Pond smelt catch and CPUE data for Lake Kasumigaura and Kitaura as well as variables which exhibited significance correlation with pond smelt data in each lake were subjected to MacKinnons and Augmented Dickey-Fuller unit root tests to confirm whether any of the time series data had a non-stationary process (MacKinnon, 1996; Kwiatkowski *et al.*, 1992; Dickey and Fuller, 1979).

2.3.3. Stock Reproduction Model

Independent variables which individually showed significant relationships to the catch and CPUE in regression analysis were fitted together to reconstruct the time series stock trajectory or stock reproduction model for the pond smelt in Lake Kasumigaura and Kitaura. One or more variables were to be selected from each group which included; i.) data on the nutrient levels ii.) *in situ* data iii.) biological data and iv.) climatic data for each lake. Variables which exhibited sufficient correlation with pond smelt catch data for each lake and had lowest AIC values in each group were to be used as independent variables for the stock reproduction model for the individual lakes. Variables with $p<0.05$ were recognized as significant relationship of the independent variable with the dependent variable (C_u and C_v). In cases where $p\geq0.05$ but $p<0.1$ the variables were treated as weakly significant and also considered for modeling. Variables were rejected for $p\geq0.1$ and in cases where all variable for an entire group had $p\geq0.1$, no variables were selected from the group. The parent formula used for the stock reproduction model for Lake Kasumigaura was a Generalized Linear Model (GLM) shown below

$$\ln\left(C_{u,t}\right) = \ln(\alpha_0) + \alpha_1 m_{1,t-n} + \alpha_2 m_{2,t-n} + \cdots + \alpha_k m_{k,t-n} + \varepsilon \qquad (1)$$

where C_u is the catch data for pond smelt in Lake Kasumigaura, α_0 is the intercept parameter, α_1, $\alpha_{2\ldots}\alpha_k$ are parameter estimates, m_1, $m_{2\ldots}m_k$ are the independent variables selected based on the results of the regression analysis for Lake Kasumigaura, t is the year with n=0,1 and ε is a normally distributed random variable. The response surface methodology (RSM) which has been previously described (Bezerra *et al.*, 2008; Myers *et al.*, 2009; Buchanan and Phillips, 1990; Box and Behnken, 1960) is a set of statistical and mathematical techniques which uses linear and polynomial functions to fit variables in order to describe data or system being studied. RSM was used to modify the Equation (1) to incorporate second and third order polynomials to investigate if the variables fit better with this method (Equation 2)

$$\ln\left(C_{u,t}\right) = \ln(\alpha_0) + \alpha_1 m_{1,t-n} + \alpha_2 m_{2,t-n} + \alpha_3 m_{1,t-n}^2 + \alpha_4 m_{2,t-n}^2 + \cdots + \alpha_k m_{k,t-n}^s + \varepsilon \qquad (2)$$

where s=1,2,3. We also used the GLM (Equation 3) and RSM (Equation 4) as the parent formulas for stock reproduction model for Lake Kitaura as shown below

$$\ln\left(C_{v,t}\right) = \ln(\alpha'_0) + \alpha'_1 q_{1,t-n} + \alpha'_2 q_{2,t-n} + \cdots + \alpha'_k q_{k,t-n} + \varepsilon' \qquad (3)$$

$$\ln\left(C_{v,t}\right) = \ln(\alpha'_0) + \alpha'_1 q_{1,t-n} + \alpha'_2 q_{2,t-n} + \alpha'_3 q_{1,t-n}^2 + \alpha'_4 q_{2,t-n}^2 + \cdots + \alpha'_k q_{k,t-n}^s + \varepsilon' \quad (4)$$

where C_v is the catch data for pond smelt in Lake Kitaura, α_0' is the intercept parameter, α_1', α_2'…α_k' are parameter estimates, q_1, $q_{2,\ldots}q_k$ are the independent variables selected based on the results of the regression analysis for Lake Kitaura and ε' is a normally distributed random variable.

Various possible combinations of variables for Equations (1-4) were used by elimination to reach the optimum model for the catch dynamics of the pond smelt for each lake. The CPUE for pond smelt in Lake Kasumigaura from 1998 to 2008 (P_x) and Lake Kitaura from 1998 to 2008 (P_y) was also modeled by substituting C_u and C_v in Equations (1-4) with P_x and P_y. Each combination of variables was checked for significant parameter estimates at p<0.05. The actual CPUE and catch dynamics and the predicted dynamics from the selected models were plotted for both Lake Kasumigaura and Kitaura. The Akaike Information Criterion (AIC) and R^2 value were used to evaluate each model and form a basis for model selection at $p<0.05$ (Akaike, 1981).

All statistical analysis for this study was carried out using the statistical software “R”, version 3.0.1 (R Core Team, 2013).

2.4. RESULTS

2.4.1. Catch and CPUE Comparison

The abbreviated forms of variables that are of interest and the independent variables which showed correlations with dependent variables are shown in **Table 2-1** with their descriptions. The regression results of the pond smelt CPUE from 1998 to 2008 for Lake Kasumigaura and Kitaura (P_x and P_y) against independent variables are shown in **Table 2-2**. For Lake Kasumigaura the CPUE showed significant correlation with the LOTI latitude band 24ºN to 90ºN (l_t) and weak correlation with total phosphorus (w_t). For Lake Kitaura significant correlation of the CPUE was observed for LOTI latitude band l_t and grasscarp (*C. idellus*) (b_t) with weak correlation against total phosphorus (z_t). In all cases the independent variables had higher correlation in year t and weaker relationship with lag of one year at t-1. When we compare these results with the regression of pond smelt catch from 1998 to 2008 for each lake against independent variables shown in **Table 2-3**, the results are almost identical.

Figure 2-3 shows the correlation between the pond smelt catch and CPUE for Lake Kasumigaura and Kitaura respectively for the years 1998 to 2008. The determination coefficients are 0.927 and 0.952 with $p<0.05$. CPUE and catch showed very high correlation and both showed correlation to the same variables (**Table 2-2** and **Table 2-3**), therefore we assumed that catch could possibly be a suitable representative for pond smelt stock trajectory for the two lakes. Due to the limitation of available effort data, the range of data for CPUE was only available for a short period from 1998 to 2008 whereas the catch data available from 1972 to

2008 was quite extensive which made it more suitable for comparing trends and identifying linkages against various variables over long time series compared to short time series for CPUE data.

2.4.2. Regression Analysis and Unit Root Test

The results for regression analysis are shown in **Table 2-4** for individual variables against the Japanese pond smelt (*Hypomesus nipponensis*) catch for Lake Kasumigaura and Kitaura for the years 1972 to 2008. **Table 2-1** can be referred to for the definitions of the variables. In **Table 2-4**, we only show the results for variables with $p<0.05$. From group i.) data on nutrient levels, TP in Lake Kasumigaura (w_{t-1}) and Lake Kitaura (z_{t-1}) showed most significant relationships with pond smelt (*H. nipponensis*) catch in Lake Kasumigaura ($C_{u,t}$) and Lake Kitaura ($C_{v,t}$) respectively. From group ii.) *in situ* data, no significant relationship was observed with pond smelt dynamics in either lake. From group iii.) biological data on the different fish and shellfish species, no significant relationships were detected for Lake Kasumigaura with only grasscarp (*C. idellus*) (b_t) exhibiting significant relationship with pond smelt catch in Lake Kitaura (**Table 2-4**). From group iv.) climatic data, LOTI for the latitude band 24ºN to 90ºN (l_t) showed significant relationship with pond smelt for both Lake Kasumigaura and Kitaura. The relationship of pond smelt for both lakes with this latitude band made ecological sense as Japan (including the two lakes) falls within this latitude band.

For Lake Kitaura we carried out further analysis to confirm if grasscarp really affects pond smelt trajectory or whether its dynamics is affected by the same variables as pond smelt. The results are presented in **Table 2-5** where it can be seen that grasscarp is affected by the same variables as pond smelt in Lake Kitaura for the years 1972 to 2008 (**Table 2-4**) and 1998 to 2008 (**Table 2-2** and **2-3**). Grasscarp cannot be used as independent variable for pond smelt in Lake Kitaura as both pond smelt and grasscarp are affected by the same factors.

In regression analysis sometimes spurious correlation can arise. Unit root tests are statistical methods to identify such cases (MacKinnon, 1996; Kwiatkowski *et al.*, 1992; Dickey and Fuller, 1979). **Table 2-6** shows the unit root test results for the independent and dependent variables used to determine relationships for this study. The value for the t-test (t-value) in all cases was <0 for MacKinnon's test (M-test) and Augmented Dickey-Fuller test (ADF-test) and significant at p<0.05 level which showed that all the variables tested had stationary processes and the relationships shown in **Table 2-2, 2-3, 2-4** and **2-5** are reliable and non-spurious.

2.4.3. Stock Reproduction Model

Table 2-7 shows the results for stock reproduction models using variables which showed most significant relationships within each group of variables with pond smelt catch in Lake Kasumigaura and Kitaura in **Table 2-4**. For Lake Kasumigaura we used l_t and $w_{t\text{-}1}$ and for Lake Kitaura we used l_t and $z_{t\text{-}1}$ as independent variables for pond smelt in each lake. From **Table 2-7**, model **2-i** had the highest R^2 and lowest AIC value for pond smelt in Lake Kasumigaura and model **2-iv** for Lake Kitaura. Both models incorporated TP as an independent variable which made sense ecologically since the variable belonged intrinsically to the two lakes. Both models also included LOTI for the latitude band which incorporates Lake Kasumigaura and Kitaura within the band. LOTI can be said to have indirect correlation to pond smelt since it is a climatic variable which can be said to be a climatic indicator of pond smelt trajectory to some degree.

Figure 2-4 shows the trajectory of the referred pond smelt catch in Lake Kasumigaura and the trajectory resulting from model **2-i, Table 2-7**). The predicted catch seems to fit quite well with the referred catch for Lake Kasumigaura. In **Figure 2-5** the predicted and referred catch from model **2-iv (Table 2-7**) for pond smelt in Lake Kitaura are shown. The fitness of the predicted catch with referred catch is quite good.

Figure 2-6 shows the linear correlation of the predicted and referred catch of pond smelt for Lake Kasumigaura from model **2-i (Table 2-7**) and Lake Kitaura from model **2-iv (Table 2-7**). The determination coefficients were 0.654 and 0.721 respectively. The correlations for both the lakes were quite significant statistically.

Table 2-8 shows the results of stock reproduction models for the pond smelt CPUE in Lake Kasumigaura and Kitaura from 1998 to 2008 using independent variables of TP and LOTI from **Table 2-2**. Model **2-vii** and **2-ix** are most significant for Lake Kasumigaura and Kitaura respectively and their plots against the referred CPUE for pond smelt in each lake shows significantly high fitness (**Figure 2-7** and **2-8**). Despite the differences in time lags for TP data, the structure of the models for the CPUE in **Table 2-8** and for the assumed case for catch in **Table 2-7** are very similar with both models incorporating the same independent variables which provides further credibility to the assumption of catch as being a suitable representative of the stock dynamics of pond smelt in Lake Kasumigaura and Kitaura.

2.5. DISCUSSION

For effective management planning of any fishery, it is critical to first understand the underlying factors behind the fluctuation pattern of the organism over a time series. Once the pattern is understood, a much more informed management plan can be strategized. This study was carried out with the intention of determining the factors affecting the fluctuation pattern of the Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura and Kitaura for a time series of 37 years. The pond smelt population fluctuates quite vigorously over the years between the extremes of highs and lows as can be seen from **Figure 2-2A** and **2-2B**. While periods with high abundance of stock are probably most beneficial to the fishermen and the fisheries industry of Ibaraki, it is the sustained periods of low catch that can have detrimental impact on the socioeconomic livelihood of the fishermen and the local fisheries industry. For this reason, it is imperative to gain a better understanding of the reasons behind the population fluctuation pattern of the Japanese pond smelt in Lake Kasumigaura and Kitaura.

From the results of this study it was observed that TP levels had the strongest correlation with pond smelt in both Kasumigaura and Kitaura with a lag of one year (**Table 2-4**). Since pond smelt has an average life span of one year (Kasebayashi and Nakano, 1961), TP might have direct impact on the pond smelt spawning stock biomass in the previous year or it causes changes in the lake ecosystem which affects pond smelt population in the following year. LOTI (*l*) has higher correlation with pond smelt in Lake Kasumigaura and Lake Kitaura in the same year compared to a lag of one year (**Table 2-4**).

The most suitable models which can significantly reproduce pond smelt trajectory for Lake Kasumigaura and Kitaura from 1973 to 2008 incorporate the variables TP for individual lakes and LOTI for the latitude band 24ºN to 90ºN respectively (**Table 2-7**). The same variables are incorporated into the models for pond smelt CPUE from 1998 to 2008 for Lake Kasumigaura and Kitaura (**Table 2-8**) which provides further support for the models shown in **Table 2-7**. In the case of LOTI, the two lakes fall within the latitude band incorporated into the final models. Sharma *et al.*, (2011) showed that changes in air temperature have negative impact on cisco (*C. artedii*) population for over 13,000 lakes in Wisconsin, USA. Since, LOTI which is an index of the global mean land (air) and ocean surface air temperature, does not intrinsically belong to either lakes, it is evident that the impact it has on pond smelt stock fluctuation is indirect in nature. Pond smelt spawning occurs between mid-January to mid-March and harvesting begins in July when they are 4 to 6 months old (Arayama, 2011; Kasebayashi and Nakano, 1961). LOTI might have indirect effect on the ecological processes affecting the early life stages of pond smelt in the two lakes.

From **Table 2-7** and **2-8** it is clear that both TP level and LOTI affect pond smelt stock and the overall effect of the two variables resulted in a good fitness of the predicted catch/CPUE to the referred catch/CPUE of pond smelt in Lake Kasumigaura and Kitaura (**Figure 2-4, 2-5, 2-7** and **2-8**). For Lake Kitaura, grasscarp (*C. idellus*) exhibits a strong relationship with pond smelt (**Table 2-2, 2-3** and **2-4**) and using it as an independent variable could have resulted in models with higher correlations. Aquatic ecosystems are complex and are affected by numerous intrinsic and extrinsic factors interacting (Grol *et al.*, 2011) to result in the dynamic behavior of biological populations. The fact that grasscarp shows correlation to pond smelt might be due to both fish species being influenced by the same variables.

As this was true in the case of grasscarp (**Table 2-5**), it could not be used as an independent variable for modeling pond smelt in Lake Kitaura. It is interesting to note that while grasscarp is present in both Lake Kasumigaura and Kitaura, its correlation to pond smelt although false was only detected for one lake (**Table 2-2, 2-3** and **2-4**). Also, even though the models in **Table 2-7** and **2-8** incorporate the same independent variables, their determination coefficients are different. Based on this it can be inferred that although the two lakes are located close to each other geographically, they have some differences in their individual ecosystem dynamics and food web structures.

In this study, pond smelt in both Lake Kasumigaura and Lake Kitaura are impacted by changes in phosphorus content according to the models in **Table 2-7** and **2-8**. The relationship of phosphorus content to fish biomass in lakes has also been reported by Jeppesen *et al.*, (2010) and Yurk and Ney, (1989). Alterations in phosphorus level in lakes is strongly linked to increase in population and human land use activities such as agriculture and development around the lake environment (Xu *et al.*, 2010; Evans *et al.*, 1996; Johnson *et al.*, 1989; Wilson, 1989; Wilson and Ryan 1988). Havens *et al.*, (2001) reported a strong link between phosphorus loading in Kasumigaura and human developmental activities around the lake.

One recommendation for rehabilitating the pond smelt population in Lake Kasumigaura and Kitaura would be the implementation of abatement programmes for phosphorus loading to the two lakes. This may lead to the recovery of the pond smelt population, however such a step should be taken with great caution. While reduction in phosphorus loading of Lake Kasumigaura and Kitaura may cause the pond smelt population to recover, it can also have adverse effects on other commercially and ecologically important species. Ludsin *et al.*, (2001) studied the effect of reduced phosphorus loading on fish community dynamics in Lake Erie, USA from 1969 to 1996. While some species of fish recovered in abundance through time, other species decreased in abundance. Anthropogenic activities have caused significant negative alterations of freshwater fish communities over the last century (Carpenter *et al.*, 1998; Naiman *et al.*, 1995) and in order to reverse these effects, a deeper understanding of the mechanisms underlying the functioning of freshwater ecosystems is critical.

The structure of the stock reproduction model of pond smelt (*H. nipponensis*) is very similar for Lake Kasumigaura and Kitaura (**Table 2-7**). The catch dynamics of the Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura and Kitaura can be effectively determined in proportion to the biotic and abiotic factors, LOTI (l_t) and total phosphorus ($w_{t\text{-}1}$) for Lake Kasumigaura and LOTI (l_t) and total phosphorus ($z_{t\text{-}1}$) for Lake Kitaura respectively. The dynamics of the pond smelt for both lakes can be written as

$$F_{t,g} = f(e_{1,t-n}, e_{2,t-n}, \cdots, e_{k,t-n}) \tag{5}$$

where $F_{t,g}$ is the catch or CPUE in year t lake g, and f () is the function determined by the biotic and abiotic factors e_i (i = 1, 2, …, k) with n=0,1. The structure shown by equation (5) is the same for the Japanese pond smelt in both Lake Kasumigaura and Kitaura.

This study provides evidence that nutrient content and climatic factors can have significant effect on the time series trajectory of fisheries populations in lake environments. This helps to recognize and appreciate the importance of such factors in fishery management. For Lake Kasumigaura and Kitaura investigation efforts need to be directed towards understanding the underlying pathways by which TP and LOTI affect pond smelt populations which will increase understanding of this important lake species for the Ibaraki Prefecture of Japan and provide better management options. From the results of this study it can be said that LOTI is an important climatic factor which has indirect influence on pond smelt stock dynamics in Lakes Kasumigaura and Kitaura and phosphorus loading in the two lakes has adverse impact on pond smelt stock.

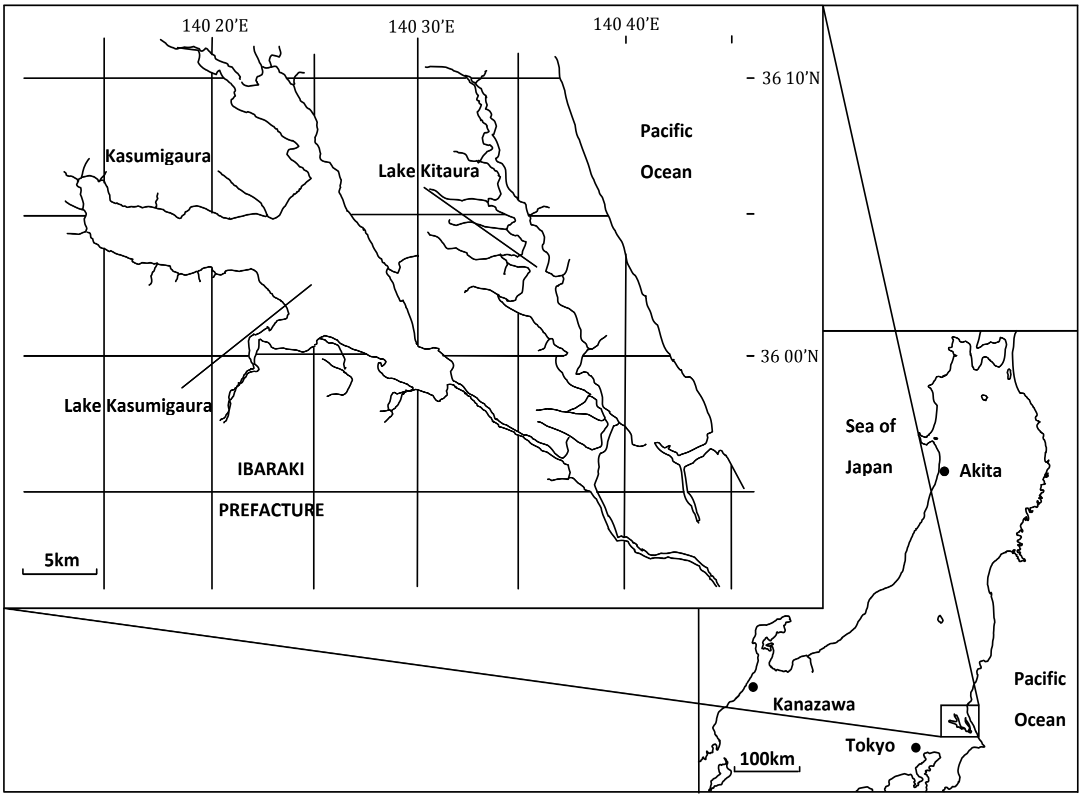

Figure 2-1. Map of Kasumigaura, Ibaraki Prefecture, Japan, showing the location of Lake Kasumigaura and Kitaura, the study site and stock distribution for the Japanese pond smelt (*H. nipponensis*).

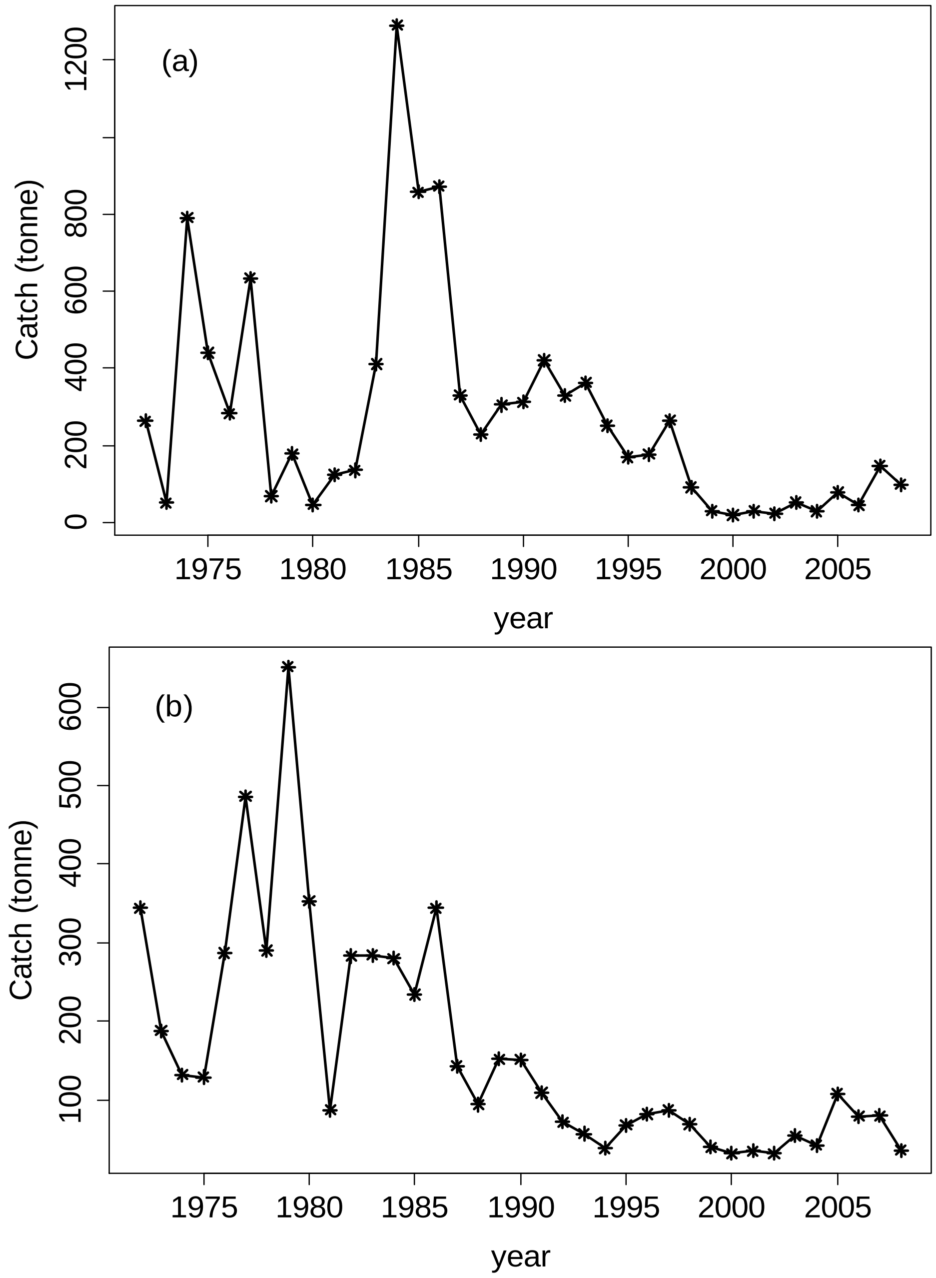

Figure 2-2. (a) The catch dynamics of the Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura from 1972 to 2008. (b) The catch dynamics of the Japanese pond smelt (*H. nipponensis*) in Lake Kitaura from 1972 to 2008.

Table 2-1. Table showing variables of interest for this study relating to Lake Kasumigaura and Kitaura.

Type	Variable	Description
Dependent	C_u	Japanese pond smelt (*H. nipponensis*) catch 1972-2008 Lake Kasumigaura
	C_v	Japanese pond smelt (*H. nipponensis*) catch 1972-2008 Lake Kitaura
	C_x	Japanese pond smelt (*H. nipponensis*) catch 1998-2008 Lake Kasumigaura
	C_y	Japanese pond smelt (*H. nipponensis*) catch 1998-2008 Lake Kitaura
	P_x	Japanese pond smelt (*H. nipponensis*) CPUE 1998-2008 Lake Kasumigaura
	P_y	Japanese pond smelt (*H. nipponensis*) CPUE 1998-2008 Lake Kitaura
Independent	w	Total phosphorus Lake Kasumigaura
	z	Total phosphorus Lake Kitaura
	b	Grasscarp (*C. idellus*) Lake Kitaura
	l	Global mean land and ocean temperature index (LOTI) for the latitude band 24ºN to 90ºN

Table 2-2. Regression results for the Japanese pond smelt (*H.nipponensis*) CPUE in Lake Kasumigaura and Kitaura against independent variables for the years 1998 to 2008. Variables with p<0.05 are highly significant and those with 0.05≤p<0.10 are weakely significant.

Lake Kasumigaura (year t)					Lake Kasumigaura (year t-1)				
Variables	R	R^2	p-value	AIC value	Variables	R	R^2	p-value	AIC value
$P_{x,t}$, l_t	-0.886	0.785	2.82×10^{-4}	72	$P_{x,t}$, $l_{t\text{-}1}$	-0.381	0.145	2.77×10^{-2}	81
$P_{x,t}$, w_t	-0.329	0.108	3.24×10^{-2}	79	$P_{x,t}$, $w_{t\text{-}1}$	-0.138	0.019	7.05×10^{-2}	89
Lake Kitaura (year t)					Lake Kitaura (year t-1)				
$P_{y,t}$, l_t	-0.772	0.596	5.40×10^{-3}	81	$P_{y,t}$, $l_{t\text{-}1}$	-0.412	0.170	2.37×10^{-2}	82
$P_{y,t}$, z_t	-0.225	0.051	5.07×10^{-2}	80	$P_{y,t}$, $z_{t\text{-}1}$	-0.113	0.012	7.56×10^{-2}	84
$P_{y,t}$, b_t*	0.786	0.618	1.20×10^{-2}	66	$P_{y,t}$, $b_{t\text{-}1}$*	0.132	0.018	7.55×10^{-2}	67

*Data only available from 1998 to 2006

Table 2-3. Regression results for the Japanese pond smelt (*H.nipponensis*) catch in Lake Kasumigaura and Kitaura against independent variables for the years 1998 to 2008. Variables with p<0.05 are highly significant and those with 0.05≤p<0.10 are weakely significant.

Lake Kasumigaura (year t)					Lake Kasumigaura (year t-1)				
Variables	R	R^2	p-value	AIC value	Variables	R	R^2	p-value	AIC value
$C_{x,t}$, l_t	-0.752	0.565	7.64×10^{-3}	108	$C_{x,t}$, $l_{t\text{-}1}$	-0.571	0.326	8.48×10^{-2}	104
$C_{x,t}$, w_t	-0.338	0.114	3.10×10^{-2}	116	$C_{x,t}$, $w_{t\text{-}1}$	-0.257	0.065	4.74×10^{-2}	107
Lake Kitaura (year t)					Lake Kitaura (year t-1)				
$C_{y,t}$, l_t	-0.766	0.587	5.98×10^{-3}	98	$C_{y,t}$, $l_{t\text{-}1}$	-0.387	0.150	2.69×10^{-2}	97
$C_{y,t}$, z_t	-0.205	0.042	5.85×10^{-2}	107	$C_{y,t}$, $z_{t\text{-}1}$	-0.139	0.019	6.69×10^{-2}	98
$C_{y,t}$, b_t*	0.729	0.531	2.59×10^{-2}	82	$C_{y,t}$, $b_{t\text{-}1}$*	0.292	0.085	4.83×10^{-2}	80

*Data only available from 1998 to 2006

Table 2-4. Regression results for individual variables against the Japanese pond smelt (*H.nipponensis*) catch in Lake Kasumigaura and Kitaura for the years 1972 to 2008 (year t) and 1973 to 2008 (year t-1). Variables with p<0.05 are highly significant.

Lake Kasumigaura (year t)					Lake Kasumigaura (year t-1)				
Variables	R	R^2	p-value	AIC value	Variables	R	R^2	p-value	AIC value
$C_{u,t}$, l_t	-0.548	0.301	5.50×10^{-4}	503	$C_{u,t}$, $l_{t\text{-}1}$	-0.516	0.267	1.10×10^{-3}	517
$C_{u,t}$, w_t	-0.579	0.336	1.72×10^{-4}	514	$C_{u,t}$, $w_{t\text{-}1}$	-0.585	0.342	1.78×10^{-4}	500
Lake Kitaura (year t)					Lake Kitaura (year t-1)				
$C_{v,t}$, l_t	-0.657	0.431	1.01×10^{-5}	456	$C_{v,t}$, $l_{t\text{-}1}$	-0.606	0.368	8.89×10^{-5}	447
$C_{v,t}$, z_t	-0.503	0.253	1.52×10^{-3}	466	$C_{v,t}$, $z_{t\text{-}1}$	-0.582	0.338	2.00×10^{-4}	449
$C_{v,t}$, b_t*	0.707	0.499	2.10×10^{-6}	428	$C_{v,t}$, $b_{t\text{-}1}$**	0.661	0.437	2.09×10^{-5}	419

*Data only available from 1972 to 2006

**Data only available from 1973 to 2006

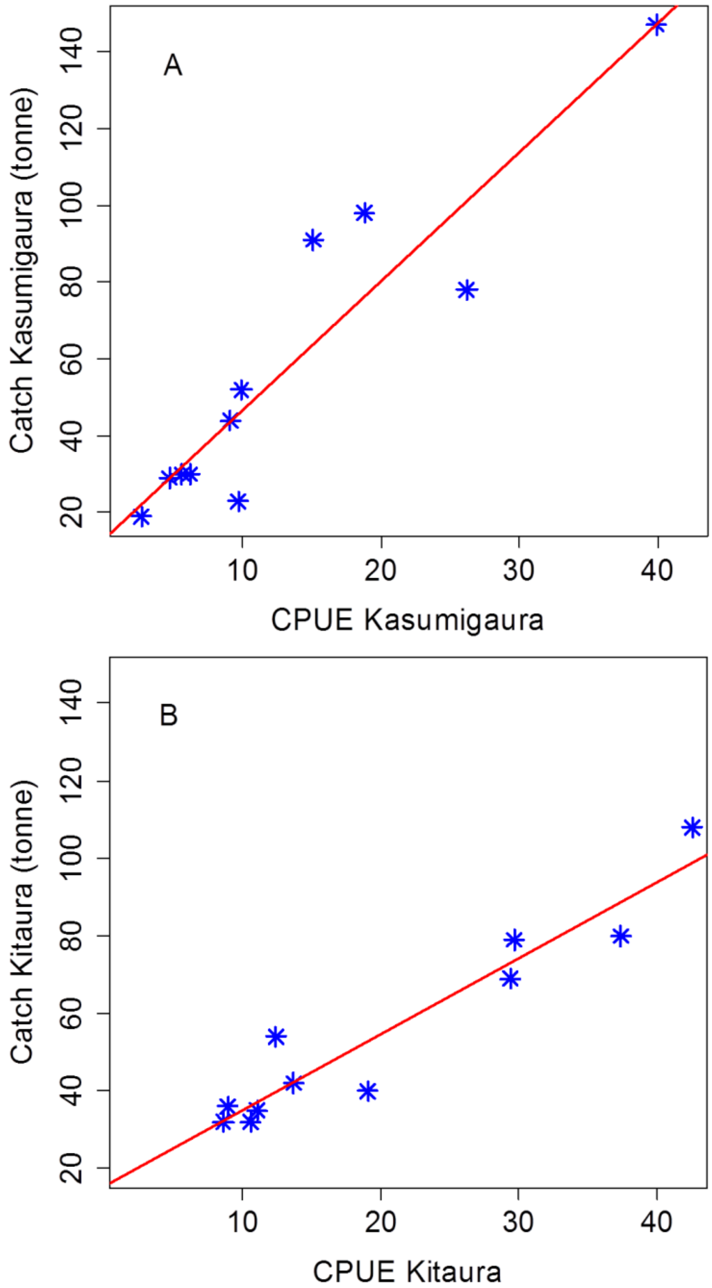

Figure 2-3. The relationship between the Japanese pond smelt (*H.nipponensis*) catch and CPUE for Lake Kasumigaura (A) and Kitaura (B) from 1998 to 2008. The determination coefficients are 0.927 and 0.952 respectively.

Table 2-5. Relationship of grasscarp catch for Lake Kitaura with independent variables.

Dependent variable	Independent variable	R	R^2	p-value	AIC value
b_t (1972-2006)	l_t	-0.458	0.210	5.60×10^{-3}	380
	z_t	-0.466	0.217	4.78×10^{-3}	379
b_t (1998-2006)	l_t	-0.606	0.368	8.35×10^{-2}	79
	z_t	-0.078	0.006	9.41×10^{-2}	83

Table 2-6. Results of unit root tests for variables used in regression analysis from **Table 2-2, 2-3, 2-4** and **2-5**.

Series	M-test		ADF-test	
	t-value	*p*-value	t-value	*p*-value
C_u 1972-2008	-9.341	1.17×10^{-10}	-9.341	$<1.00\times10^{-2}$
C_v 1972-2008	-6.776	1.38×10^{-07}	-6.776	$<1.00\times10^{-2}$
C_x 1998-2008	-5.740	7.05×10^{-4}	-5.740	$<1.00\times10^{-2}$
C_y 1998-2008	-3.523	9.68×10^{-3}	-3.523	1.81×10^{-2}
P_x 1998-2008	-5.474	9.32×10^{-4}	-5.474	$<1.00\times10^{-2}$
P_y 1998-2008	-2.497	4.12×10^{-2}	-2.497	1.47×10^{-2}
w 1972-2008	-7.073	5.06×10^{-8}	-7.073	$<1.00\times10^{-2}$
z 1972-2008	-6.879	1.04×10^{-07}	-6.879	$<1.00\times10^{-2}$
w 1998-2008	-5.946	5.73×10^{-4}	-5.946	$<1.00\times10^{-2}$
z 1998-2008	-8.747	5.14×10^{-5}	-8.747	$<1.00\times10^{-2}$
l 1972-2008	-9.874	3.09×10^{-11}	-9.874	$<1.00\times10^{-2}$
l 1998-2008	-4.383	3.22×10^{-3}	-4.383	$<1.00\times10^{-2}$
b 1972-2006	-6.948	8.55×10^{-8}	-6.948	$<1.00\times10^{-2}$
b 1998-2006	-3.860	1.19×10^{-2}	-3.860	$<1.00\times10^{-2}$

Table 2-7. Models using multiple variables selected from **Table 2-4** for Lake Kasumigaura and Kitaura. Some parameters are shown for different models for the Japanese pond smelt (*H. nipponensis*) showing the highest R^2 and lowest AIC values. Values are only shown for models exhibiting significant parameter estimates and model significance at $p < 0.05$.

	Lake Kasumigaura Model	R	R^2	p-value	AIC value
2-i)	$\ln\left(C_{u,t}\right) = 7.08 + 4.93 \times 10^{-4} \times l_t^2 - 4.14 \times 10^{-6} \times l_t^3 - 19.24 \times w_{t-1}$	0.654	0.427	1.55×10^{-5}	495
2-ii)	$\ln\left(C_{u,t}\right) = 6.13 + 5.34 \times 10^{-4} \times l_t^2 - 4.50 \times 10^{-6} \times l_t^3 - 866.90 \times w_{t-1}^3$	0.639	0.408	2.76×10^{-5}	497
2-iii)	$\ln\left(C_{u,t}\right) = 5.75 + 0.193 \times (l_t \times w_{t-1})$	0.560	0.315	3.74×10^{-4}	502
	Lake Kitaura				
2-iv)	$\ln\left(C_{v,t}\right) = 8.56 - 0.039 \times l_t - 4.24 \times 10^{-6} \times l_t^3 - 108.0 \times z_{t-1} + 88.5 \times z_{t-1}^2 + 1.01 \times (l_t \times z_{t-1})$	0.721	0.521	6.87×10^{-7}	437
2-v)	$\ln\left(C_{v,t}\right) = 6.30 + 5.67 \times 10^{-4} \times l_t^2 - 5.39 \times 10^{-6} \times l_t^3 - 15.29 \times z_{t-1}$	0.696	0.484	2.48×10^{-6}	440
2-vi)	$\ln\left(C_{v,t}\right) = 5.56 + 6.09 \times 10^{-4} \times l_t^2 - 5.66 \times 10^{-6} \times l_t^3 - 63.01 \times z_{t-1}^3$	0.684	0.467	4.34×10^{-6}	441

Table 2-8. Models using multiple variables selected from **Table 2-2** for Lake Kasumigaura and Kitaura. Some parameters are shown for different models for the Japanese pond smelt (*H. nipponensis*) CPUE from 1998 to 2008 with highest R^2 and lowest AIC values. Values are only shown for models exhibiting significant parameter estimates and model significance at $p < 0.05$.

	Model	R	R^2	p-value	AIC value
	Lake Kasumigaura				
2-vii)	$\ln(P_{x,t}) = 14.04 + 1.96 \times 10^{-3} \times l_t^2 - 298.20 \times w_t + 3.82 \times (l_t \times w_t)$	0.919	0.844	6.40×10^{-5}	69
2-viii)	$\ln(P_{x,t}) = 1.31 + 0.424 \times (l_t \times w_t)$	0.909	0.827	1.04×10^{-4}	70
	Lake Kitaura				
2-ix)	$\ln(P_{y,t}) = 2.28 - 4.55 \times 10^{-2} \times l_t - 30.35 \times z_t$	0.887	0.786	2.75×10^{-4}	74
2-x)	$\ln(P_{y,t}) = 2.63 + 3.06 \times 10^{2} \times l^2 + 0.417 \times (l_t \times z_t)$	0.880	0.774	3.54×10^{-4}	75

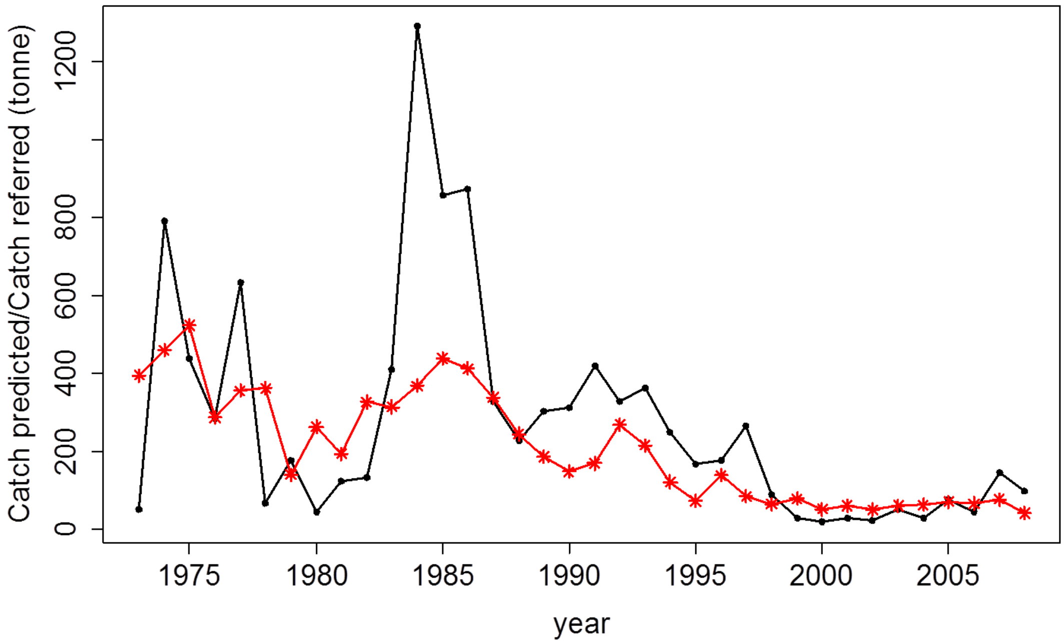

Figure 2-4. Graph showing the actual catch dynamics of the Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura in black and the dynamics resulting from model **2-i** (**Table 2-7**) in red for the years ranging from 1973 to 2008.

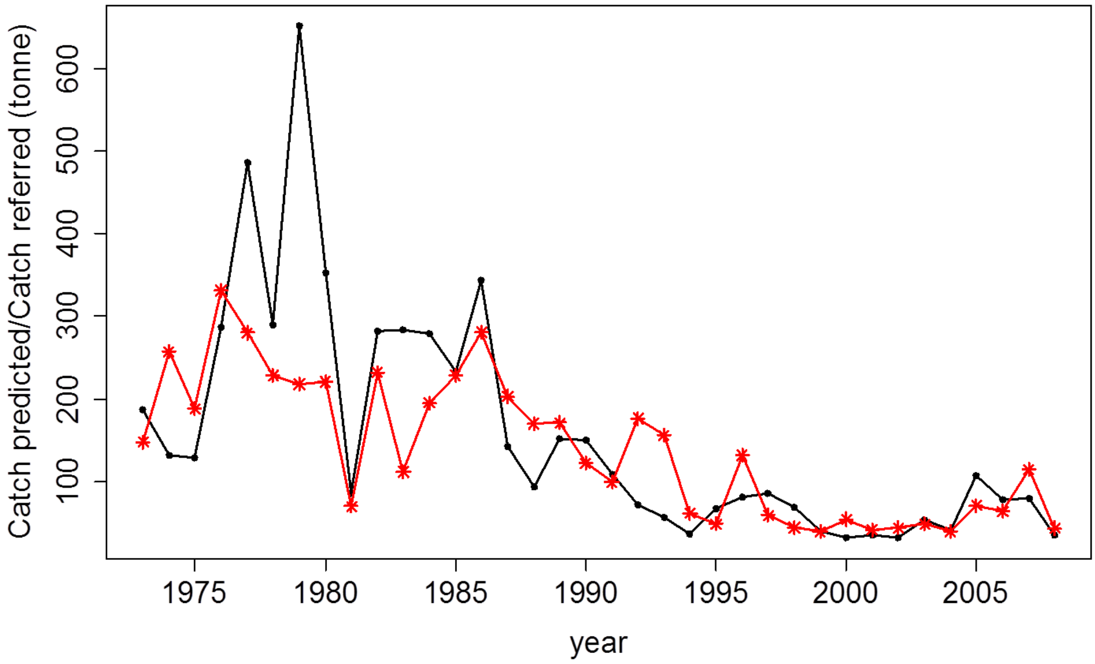

Figure 2-5. Graph showing the actual catch dynamics of the Japanese pond smelt (*H. nipponensis*) in Lake Kitaura in black and the dynamics resulting from model **2-iv** (**Table 2-7**) in red for the years ranging from 1973 to 2008.

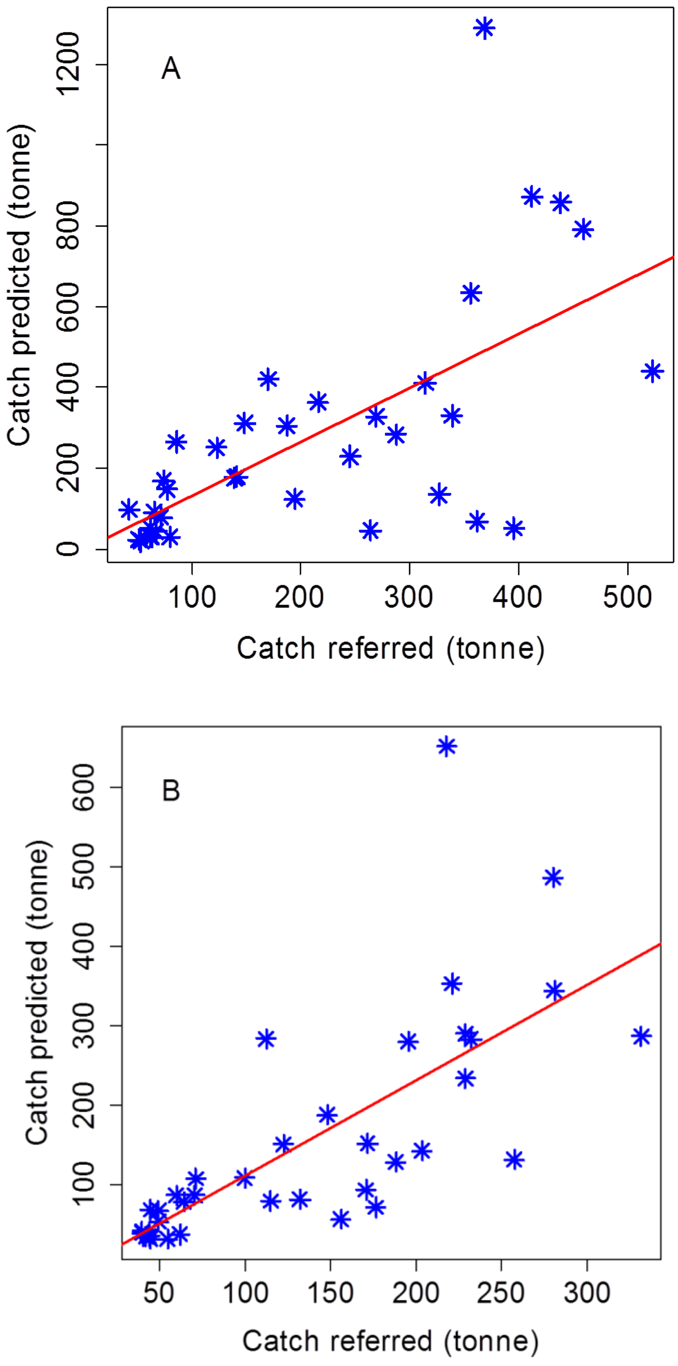

Figure 2-6. Graph showing the relationship between the catch predicted and catch referred the Japanese pond smelt (*H. nipponensis*) for Lake Kasumigaura (a) from model **2-i** (**Table 2-7**) and Lake Kitaura (b) from model **2-iv** (**Table 2-7**).

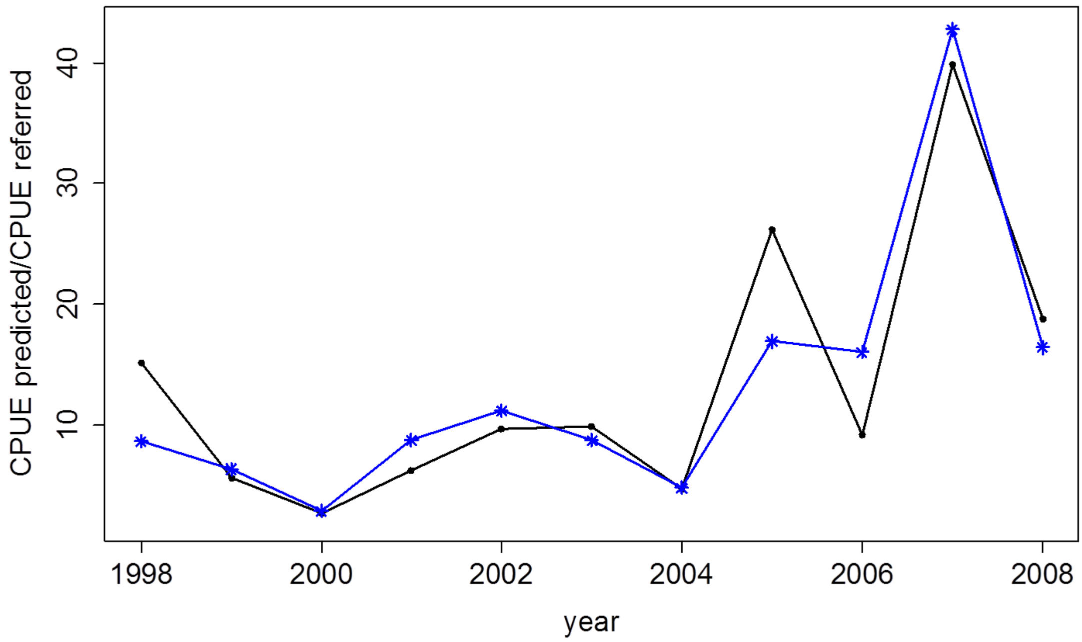

Figure 2-7. Graph showing the referred CPUE dynamics of the Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura in black and the dynamics resulting from model **2-vii** (**Table 2-8**) in blue for the years ranging from 1998 to 2008.

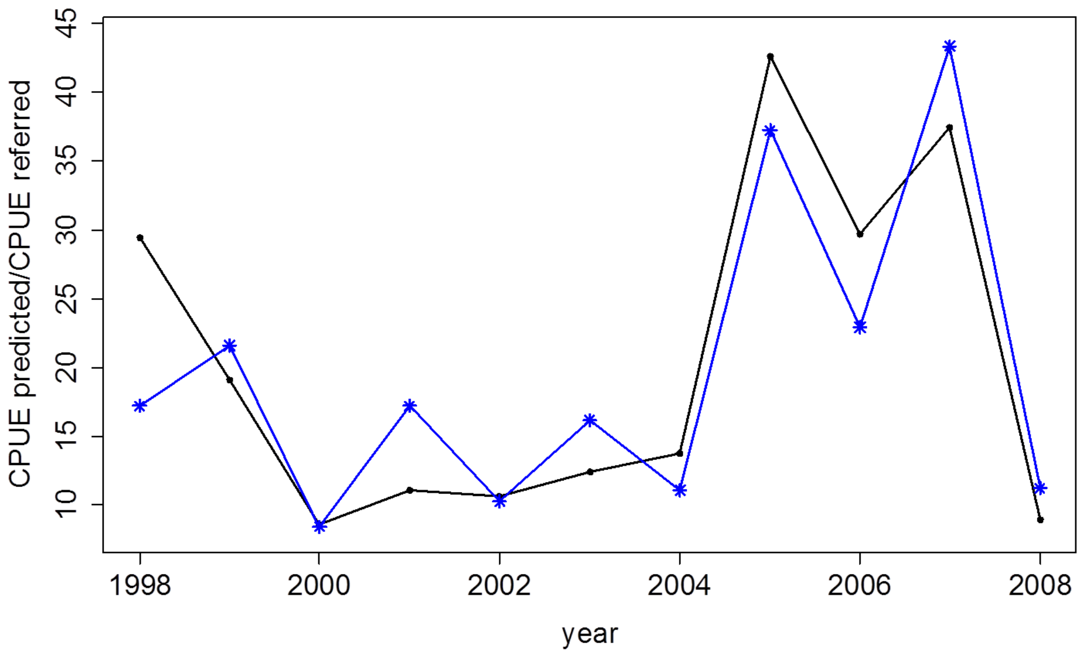

Figure 2-8. Graph showing the referred CPUE dynamics of the Japanese pond smelt (*H. nipponensis*) in Lake Kitaura in black and the dynamics resulting from model **2-ix** (**Table 2-8**) in blue for the years ranging from 1998 to 2008.

CHAPTER 3

Model for stock-recruitment dynamics of the Peruvian anchoveta *Engraulis ringens* off Peru

Keywords: Anchoveta, Density-Dependent, Recruitment, Regimes, Reproductive Success, Sea Surface Temperature, Southern Oscillation Index

Publication

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Singh, A.A., Sakuramoto, K., and Suzuki, N., 2013. Model for stock-recruitment dynamics of the Peruvian anchoveta, *Engralis ringens* off Peru. Abstract, Book of Abstracts, Shaping Fisheries and Aquaculture Today for a Healthier Tomorrow, International Fisheries Symposium - IFS2013, Kasetsart Univeristy, Bangkok, Thailand.

3.1. ABSTRACT

This study was aimed at re-examining the validity of the results from Cahuin *et al.* (Estuar. Coast. Shelf Sci. 84, 2009) and identify a model to describe the stock-recruitment relationship of the Peruvian anchoveta (*Engraulis ringens*). Regression analysis was used to determine if density-dependent effects were present. The analysis did not show the existence of any density dependent effects. It is important to use environmental factors and take observational and process errors into account when attempting to identify density-dependent effects in fish populations. Sea surface temperature (SST) and Southern Oscillation Index (SOI) were used as independent variables to fit the recruitment dynamics of the anchoveta. Both SST and SOI were found to be significantly important parameters in structuring anchoveta dynamics according to Akaike Information Criterion (AIC) and R^2 values. The results of this study do not correlate with the findings of Cahuin *et al.*, (2009), where density-dependent effects and the presence of regimes were detected. In conclusion, the recruitment R_t is essentially determined in proportion to spawning stock biomass S_t, and the environmental factors in year t further change the recruitments. This mechanism is completely same with that for Japanese sardine proposed by Sakuramoto (The Open Fish. Sci. 5, 2012).

3.2. INTRODUCTION

Marine ecosystems are complex and are affected by numerous intrinsic and extrinsic environmental factors. Fish populations have a tendency to fluctuate over time and the mechanisms behind these fluctuation patterns can be understood by investigating relationship of the recruitment (R) to the spawning stock biomass

(SSB) and environmental factors. Jacobson and MacCall (1995) have shown that the recruitment of Pacific sardine in the coastal area of North America is significantly influenced by both the SSB and the sea surface temperature (SST). SST has been shown to be correlated to anchovy population dynamics previously (Takasuka *et al.*, 2008; Takasuka and Oozeki, 2007; Takasuka *et al.*, 2005; Lluch-Belda *et al.*, 1991). The impact of sea surface temperature on the recruitment dynamics of other species of fish has also been identified (Funamoto *et al.*, 2013; Funamoto, 2007). Climatic conditions such as wind direction index, North Atlantic oscillation and Southern oscillation index (SOI) have also been correlated with the dynamics and regimes of anchovy as well as other fish species (Funamoto *et al.*, 2013; Cahuin *et al.*, 2009; Santojanni *et al.*, 2006; Borja *et al.*, 1996; Fromentin and Plaque, 1996).

Cahuin *et al.*, (2009) examined the reproductive success (RPS) and SSB relationship of the Peruvian anchoveta (*Engraulis ringens*) from 1963 to 2004 and discussed their fluctuation mechanisms. They explained the longterm fluctuations by the concept of “regime shift” and separating the data series into two periods of “favorable regimes” and one period of “unfavorable regime”. Separate regression lines of ln(RPS) against SSB were calculated for each regime. They stated that the long-term dynamics of the anchoveta are caused by regime shifts and the existence of different carrying capacities or density-dependent effects during these regimes.

Wada and Jacobson (1998) identified the existence of regimes in the RPS dynamics of the Japanese sardine (*Sardinops melanotictus*) over a long time series from 1951 to 1995. The data for the time series was divided into two and separate regression lines were constructed and identified as regimes characterized as “favorable” and “unfavorable”. Based on the slope of the regression lines for the regimes the conclusion was drawn that density-dependent effects on recruitment does exist for *Sardinops* species. Density-dependent effects can only be measured for long-term data series if there is evidence of large (>1000-fold) difference between the maximum and minimum abundance in the data series (Hilborn and Walters, 1992). Sakuramoto (2012) discussed the validity of the results from Wada and Jacobson (1998) and proposed a new concept for the stock-recruitment relationship of the *Sardinops* species. It was reported that the false decreasing trend indicating the existence of density-dependent effects was due to observational error. When the data were adjusted for observational errors and regression analysis was applied to the full data series, the slope of the regression line did not differ significantly from unity indicating the absence of density-dependent effects as well as the absence of two different carrying capacities or regimes. Sakuramoto and Suzuki (2012) provide a detailed report on the effect of observation and/or process error which in most cases results from environmental variables on recruitment and/ or SSB in the selection of a stock-recruitment relationship.

Cahuin *et al.*, (2009) used the General Additive Model (GAM) to model the RPS of anchovy with SSB, SST, SOI and other environmental variables. They stressed the importance of the SST, however, they identified the SOI as the environmental variable to best explain the recruitment dynamics of the Peruvian anchoveta.

The purpose of this study was to re-examine the assessment of the Peruvian anchoveta by Cahuin *et al.*, (2009). The objectives are to: 1) re-examine the basis of separation of the anchovy data into the two regimes; 2) test the validity of the existence of density-dependent effects; 3) find out the best model for explaining the recruitment, by using SSB, SST and SOI as the environmental variables.

3.3. MATERIALS AND METHODS

3.3.1. Data

The data on the spawning stock biomass and recruitment of the North-Central stock of anchoveta (*E. ringens*), was obtained from Cahuin *et al.*, (2009) (**Table 3-1**). The stock distribution of the Peruvian anchoveta is shown in **Figure 3-1**. The recruitment (R) is the number of fish at age 0 and the spawning stock biomass (SSB) is the weight of reproductive adult fish at the initialization of the spawning season. The actual raw data for R and SSB was collected by the Instituto del Mar del Peru (IMARPE). More information regarding the landings of Peruvian anchovy is available from the IMARPE database (**Table 3-2)**.

The data for monthly mean sea surface temperature (SST) was obtained for the years ranging from 1963 to 2004 at Nino 1 + 2 (0˚ - 10˚ South) (90˚ West - 80˚ West), from the NOAA website. Data for the monthly Southern Oscillation Index (SOI) was also obtained from 1963 to 2004 and the annual averages were calculated from this. Both the SST and SOI data were calculated from this. The SST and SOI data as reported by the National Weather Service, Climate Prediction center were obtained from NOAA database (**Table 3-2**). The monthly anomalies from the standardized data series from 1963-2004 were used to calculate the annual means.

Descriptions of databases that were accessed for retrieving raw datasets used for this study are shown in **Table 3-2**.

3.3.2. Regimes and Density-Dependent Effects

Cahuin *et al.*, (2009) reported the existence of regimes and density-dependent effect in the anchovy population dynamics. To re-examine the validity of this, we began by plotting the log of recruitment, SSB and RPS of the anchovy for the data series from 1963-2004. The data were log transformed to reduce the effects of outliers and skewness. We replicated the method of Cahuin *et al.*, (2009) to separate the data into the "favorable" and "unfavorable" regimes. Linear regression was applied to ln(RPS) against the SSB, for (a) recognizing the existence of the two regimes and (b) ignoring the regimes. In addition to this we carried out a reselection of the data based on the data points above and below the regression line for the graph of ln(RPS) against (SSB) and applied linear regression analysis to it. The coefficients of all three regression analysis were reported.

For validation of the existence of density-dependent effects, we used simple regression with least squares method. We tested the slope of the regression line for the plot of ln(RPS) against ln(SSB) for zero. This method has some limitations as the RPS is sensitive to observational errors for short data series (Sakuramoto, 2012; Stöckl *et al.*, 1998). To confirm the results we applied regression analysis to ln(R) against ln(SSB) to test for unity as this method is more resistant to observational errors.

3.3.3. Recruitment Forecasting Model

The generalized linear model (GLM) was used to explain the recruitment dynamics of the Peruvian anchoveta. The basic model was

$$\ln\left(\frac{R_t}{S_t}\right) = \ln(\alpha) + \gamma \times (T_t) + \delta \times (I_t) + \varepsilon_t \tag{1}$$

where (R_t/S_t) is the reproductive success (RPS), t is the year, α is the intercept parameter, T and I are the environmental variables for SST and SOI respectively, and ε_t is a normally distributed random variable. The other model for the RPS that was used, was derived from a linearized Ricker (1975) model and it was modified to incorporate the environmental variable

$$\ln\left(\frac{R_t}{S_t}\right) = \ln(\alpha') + \beta \times (S_t) + \gamma' \times (T_t) + \delta' \times (I_t) + \varepsilon_t' \tag{2}$$

where (R_t/S_t) is the reproductive success (RPS), S is the spawning stock biomass and β is the parameter estimate for S. T and I represent the environmental variables for SST and SOI respectively. Different modifications of the two models were used for exploratory analysis to find out the best model for the recruitment fluctuations of anchoveta. The Akaike Information Criterion (AIC) was used to evaluate each model and form a basis for model selection (Akaike, 1981). The models exhibiting smallest AIC values and some of their parameters were reported. The actual recruitment dynamics from **Table 3-1** and the recruitment resulting from the model was plotted.

All statistical analysis for this study was carried out using the statistical software "R", version 3.0.1 (R Core Team, 2013).

3.4. RESULTS

3.4.1. Regimes and Density-Dependent Effects

The fluctuations patterns for ln(R), ln(SSB) and ln(RPS) are shown in **Figures 3-2(a)**, **(b)** and **(c)** respectively. The ln(R) shows a decreasing trend in the years 1970-1974, 1979-1982 and from 1992-1996. For the other years, the trend is either increasing or fluctuating with a decrease followed by an increase every following year. The fluctuation pattern for ln(R) is similar to ln(SSB). The pattern for ln(SSB) seems to be followed by ln(R) after a lag of one year. Cahuin *et al.*, (2009) identified regimes in the years 1963-1971, 1986-2004 for favorable regime and the years 1972-1985 for unfavorable regime. The plot of the ln(RPS) (**Figure 3-2(c)**) shows decreasing and increasing patterns to be randomly distributed for the range of year from 1963-2004 and does not show the regimes identified by Cahuin *et al.*, (2009).

The plots of ln(RPS) against SSB in **Figure 3-3** is replicated from Cahuin *et al.*, (2009). It shows two regression lines for the data based on the favorable and unfavorable regime. We connected the data points for the two regimes following the year series. **Figure 3-3** also shows a single regression line for the whole data series without separation into regimes. We used the regression line for the whole data series to select the data points above and below the regression line and plot separate regression lines for each in **Figure 3-4**.

The model coefficients and other parameters for the plots in **Figure 3-3** and **Figure 3-4** are presented in **Table 3-3**. According to Cahuin *et al.*, (2009), the model recognizing the presence of the regimes is better than a model ignoring the regimes. The AIC selects the model with regime over a model without regimes (**Table 3-3**), however, it is unclear how the selection of the data points of regimes were made. The presence of regimes is unclear from **Figure 3-2(c)**, and in **Figure 3-3**, it can be observed that the RPS for the unfavorable regime does not remain continuously low for long periods of time (years). The fluctuations between low RPS and high RPS are too short to claim the existence of regimes.

The pattern is similar for the unfavorable regime. It is not clear what the basis of separation of the data into regimes really was.

If regimes do exist, then the method of separation of data by Cahuin *et al.*, (2009) in **Figure 3-3**, should be the best fit for the data points. This means that, any alternative way of separation of data should give a higher AIC value than the model of Cahuin *et al.*, (2009) (**Table 3-3** (**Model 3-i**)). To test this, we performed an alternative selection of the data based on the data points above and below the regression line from the plot of ln(RPS) against SSB for the full data series and applied separate regression analysis to each (**Figure 3-4**).

When we compare the AIC value that was calculated for the single regression line without regimes with that of double regression lines which resulted from two different regimes, the latter AIC was smaller than the former one (**Table 3-3**).

However, this does not represent the validity of the latter model as being more optimal than the former one. In other words, it is not reasonable to compare the one line model with the two lines one. We should carry out comparisons between models which consist of two lines. One example of an alternative two lines model is shown in **Table 3-3** (**Model 3-iii**). One group is constructed with the data points above the regression line for full data series in **Figure 3-4**. The other group is constructed with the data points below the regression line. The former group indicates the years when ln(RPS) was high, and the latter one indicates the years when ln(RPS) was low. When we assumed this grouping method, and calculated the AIC, the AIC of this model (**Table 3-3** (**Model 3-iii**)) was much lower than the model which considered the presence of regimes and adapted two lines (**Table 3-3** (**Model 3-i**)). This is evidence that the proposal of the existence of density-dependent effects in each regime is questionable.

To further elucidate whether density-dependent effects exist for the Peruvian anchovy data, we adopted the method employed by Sakuramoto (2012). Regression analysis was applied to ln(RPS) against ln(SSB) for the data separated into regimes from Cahuin *et al.*, (2009). The slope for the favorable regime (**Figure 3-5**) was (slope = −0.673) and significantly negative (p = 0.032) and for the unfavorable regime the slope was (slope = −0.878) and significantly negative (p = 0.097) under the 10% significant level. When we applied a single linear regression to the whole data series from 1963-2004 for ln(RPS) against ln(SSB), the resulting regression line (slope = −0.067) did not differ significantly from zero (p = 0.718) and density-dependent effects could not be detected (**Figure 3-5**). The pattern in **Figure**

3-5 coincided well with the simulations shown by Sakuramoto (2012).

Same results can be obtained when the linear regression of ln(R) against ln(SSB) was conducted. For the plot of ln(R) against ln(SSB), the slope of the regression line for the favorable regime (slope = 0.327) was significantly different from zero and less than unity with a 95% confidence interval of (−0.282, 0.936). The slope for the unfavorable regime (slope = 0.122) was not significantly different from zero and unity with a 95% confidence interval of (−0.944, 1.188). When regression was applied to the full data set the slope for this regression was (slope = 0.923) with the 95% confidence limit of (0.561, 1.305), which is not significantly different from unity (**Figure 3-6**). According to the results, the claim of the existence of density-dependent effects in each regime is highly questionable for the anchovy data series.

3.4.2. Recruitment Forecasting Model

Cahuin *et al.*, (2009) used the Generalized Additive Model (GAM) for modeling the anchovy dynamics with the SSB and having SOI and SST as the environmental parameters. They used the full time series from 1963-2004 in one approach and came up with the following model:

$$\log\left(\frac{R}{S}\right) = s \times (\mathrm{SSB}) + s \times (I) \tag{3}$$

where (R/S) is the reproductive success (RPS), and SSB is the spawning stock biomass. I represent the environmental variable for SOI and s is a spline smoother parameter obtained using penalized regression splines analysis. Equation (3), when applied to full time series for anchovy data had a value of R^2 = 0.251. In another approach, Cahuin *et al.*, (2009) used data only from the years 1963-1971 and 1986-2004 which were identified as the favorable regimes. The preferred model was produced with the years of the favorable regime and SOI and SSB as the independent parameters. The resulting model was the same as Equation (3), with a value of $R^2 = 0.494$. The difference between the two approaches is the proportion of data used for analysis. The best model by Cahuin *et al.*, (2009) was one with only the data from the favorable regimes that did not include the anchovy data for 14 years which is 33.33% of the total data. This is a major proportion of the stock-recruitment data series which was not incorporated for the modeling of the data, more importantly since the presence of regimes has now been put into question. The resulting model and the basis of selection of the best model are highly debatable.

In our approach, the fluctuation dynamics of the whole time series of the Peruvian anchovy was modeled through GLM and linearized Ricker model. We used various modifications of the models to incorporate the environmental variables of SOI and SST. In the study by Cahuin *et al.*, (2009), the SST at 4 different experimental stations across the coastal region of Peru was used. Since we did not have access to this data, in our study we used the SST from Nino 1 + 2 (0˚ - 10˚ South) (90˚ West - 80˚ West) available from the NOAA website. We used the SST from the month of July as exploratory analysis showed July SST to be mostly strongly correlated to anchovy recruitment.

AIC values, R^2 and significant parameter estimates were used to determine the best model for explaining the dynamics of anchovy recruitment from 1963-2004. Some of the parameters and AIC values are shown for models that exhibited strong correlations and lowest AIC values in **Table 3-4**. The table shows only the results expressed by Equation (1), as the AIC values for Equation (1) were much lower compared to Equation (2).

Models, (a), (b), (d) and (e) were the only models having significant parameter estimates with reference to their *p*-values. The difference in the AIC values between the models was <0.4, which is not enough to select one model over the other. We selected model (d) as it had the highest R^2 value and incorporated both the SST and the SOI as the independent variables (**Table 3-4**). The best model by Cahuin *et al.*, (2009) had the SSB and SOI as the independent variables and in our case the selected model has SOI and SST as the independent variables.

The recruitment of the Peruvian anchovy was calculated from Model (d) and it was plotted against the actual recruitment from **Table 3-1** in **Figure 3-7**. The actual recruitment dynamics seem to fit well with the model recruitment dynamics. It seems that the reproductive success of the Peruvian anchoveta *Engraulis ringens* from 1963 to 2004 can be explained well by the SST and SOI.

3.5. DISCUSSION

Figures 3-3, **3-5** and **3-6** show the relationship between ln(RPS) and SSB, ln(RPS) and ln(SSB) and ln(R) and ln(SSB), respectively. In all these figures, the plots can be separated into two groups. One is the group plotted at the higher SSB or ln(SSB) and the other at the lower SSB or ln(SSB), which corresponds to Cahuin *et al.*, (2009) who defined favorable and unfavorable regimes. With reference to the SSB levels, the data can be separated into two regimes, however for the two regimes, the ln(R) and ln(RPS) fluctuated significantly above and below the regression line for the full data series. Particularly, when the SSB levels were low, the variation in the ln(RPS) levels were extremely high, which could have been produced by observational errors as was explained by Sakuramoto (2012) in his simulations. On the contrary, with reference to **Figure 3-2(c)**, it can be seen that the trajectory of ln(RPS) cannot be separated into the two regimes as the RPS levels fluctuate around average RPS except for the years 1981-1983 and 1985. Therefore, we agree that the data can be separated into two different periods with high and low SSBs, however this does mean that these periods really indicate the existence of two regimes.

We did not detect the presence of density-dependent effects or regimes in our analysis of the Peruvian anchoveta through regression analysis. Sakuramoto (2012) showed with simple deterministic relationships that RPS is quite sensitive to measurement errors even for small data series and can result in a false trend in the stock-recruitment relationship. For the short data series of the regimes identified by Cahuin *et al.*, (2009), we see a significant decreasing trend for ln(RPS) against ln(SSB) in **Figure 3-5**, but when the whole data series is used, there was no decreasing trend present. To confirm our results we applied regression analysis to recruitment. The results coincide well with regression analysis of the RPS and do not detect density-dependent effects. Sakuramoto (2012) similarly used regression analysis on the recruitment of sardine to confirm the results of least squares regression for the RPS relationship.

Cahuin *et al.*, (2009) separated the anchovy data into two sets and applied separate regression analysis to the RPS. They showed that according to the AIC, the model recognizing the two regimes was better that a model with a single regression, without any separation of data (**Table 3-3** (**Models 3-i** and **3-ii**)). In our study, we separated the data into two sets based on the data points above and below the regression line for the RPS in **Table 3-3** (**Model 3-iii**) and **Figure 3-4**. When all three models were compared with AIC, our model was selected as the better model. In both cases, the superior model was a result of separation of the data into two sets. This may be due to the impact of the environmental factors and changes in the climatic conditions. This needs further investigation to verify why exactly this occurs and we should also be careful when using RPS to explain stock-recruitment relationships as previously stated, it is quite sensitive to observational errors (Sakuramoto, 2012).

Upon selection of the model with two regimes, Cahuin *et al.*, (2009) fit the RPS data with the model of Ricker. Sakuramoto and Suzuki (2012) explain in detail that when the actual model for a stock-recruitment relationship is a proportional model, observational and/or process errors can result in the selection of a Ricker (1975) or Beverton and Holt (1957) model. On the contrary, when the actual model is a Ricker (1975) or Beverton and Holt (1957) model, observational and/or process errors seldom resulted in the selection of a proportional model. In this study, the expanded proportional model, which incorporated the environmental factors, SST and SOI, was selected as the optimal model, it strongly indicates a possibility that the actual stock recruitment relationship is the proportional model and does not have a density dependent effect (**Figure 3-6**).

In this study we attempted to explain the recruitment dynamics of the Peruvian anchovy from 1963-2004 with modifications of the GLM and expanded proportional model to incorporate the environmental variables. In our analysis we based our model selection through the AIC, R^2 and significant parameter estimates. The R^2 value for our model was much higher (R^2 = 0.557) in comparison to the model with full data series (Equation (3)) by Cahuin *et al.*, (2009) (R^2 = 0.251). Our selected model incorporated both the SST and SOI as the independent variables (**Table 3-4**, **Model (3-vii)**). Both SST and SOI have a strong influence in structuring the dynamics of the anchoveta.

Sea surface temperature has established its importance as an environmental factor in structuring the dynamics of various fish species (Sakuramoto *et al.*, 2010; Takasuka *et al.*, 2008; Funamoto, 2007; Takasuka and Oozeki, 2007; Takasuka *et al.*, 2005; Cianelli *et al.*, 2005; Cianelli *et al.*, 2004; Liluch-Belda *et al.*, 1991). Indeed, exploratory analysis showed strong negative correlation of SOI with SST. Funamoto *et al.*, (2013) and Funamoto (2011) showed that SST and wind indexes had significant bivariate relationship with fish recruitment. The SST, Pacific Decadal Oscillation and Arctic Oscillation have been shown to have significant relationship with drastic reductions in fish populations in the Kuroshio Extension

(Sakuramoto *et al.*, 2010).

Cahuin *et al.*, (2009) showed the importance of SST and SOI in modeling the dynamics of the Peruvian anchoveta. Their overall best model had SOI as the independent variable and the model selection was based on the percentage deviance. Their model did not incorporate 33.33% of the data which was stated as belonging to the unfavorable regime. However, they did show that the resulting best model was still the same when the whole range of data was used (Equation (3)). Our model show both SST and SOI as important environmental variables for modeling the recruitment dynamics of the Peruvian anchoveta. We used numerous variations of the modifications of the GLM and expanded proportional model to reach our final models, whereas the analysis of Cahuin *et al.*, (2009) do not show much variation for model selection. Also, our SST data was different from theirs and this may have affected the outcome. The variation in the fit of the model with actual data may be due to the influence of other environmental factors not incorporated in this study and is subject to further investigation.

From 1979 to 1989 rapid changes can be observed in ln(R), ln(SSB) and ln(RPS) dynamics. According to Mysak (1984), the catastrophic decline in the population of the Peruvian anchoveta is a result of strong El Niño events. Klyashtorin (2001), showed that strong El Niño events are followed by a sharp decline in the population of the Peruvian anchoveta. In our study, we were able to generate a suitable model for explaining the dynamics of anchovy. However, we did not incorporate El Niño as one of the modeling variables, this needs further investigation to validate the influence of El Niño in structuring the dynamics of the Peruvian anchoveta.

In conclusion, the recruitment of the Peruvian anchoveta, *Engraulis ringens* off Peru R_t is essentially determined in proportion to spawning stock biomass S_t, and then environmental factors, SST and SOI, in year t further change the recruitments. That is, it can be written by

$$R_t = S_t . f(e_1, e_2, \dots, e_k) \tag{4}$$

where R_t is the recruitment in year t, S_t is the spawning stock biomass in year t and $f()$ is the function determined by environmental factors e_i (i = 1, 2, … , k), where k is the number of environmental factors related to the recruitment. The mechanism shown by Equation (4) is completely same with that for Japanese sardine proposed by Sakuramoto (2014) and Sakuramoto (2013).

Table 3-1. Recruitment and spawning stock biomass of the North-Central stock of the Peruvian anchoveta *Engraulis ringens* from 1963 to 2004 (source: Cahuin *et al.*, (2009)).

Year	Spawning biomass (10^6) tons	Recruits (10^9) fish	Year	Spawning biomass (10^6) tons	Recruits (10^9) fish
1963	7.997	1477	1984	2.741	563
1964	10.069	824	1985	5.703	57
1965	7.739	1304	1986	7.254	557
1966	9.998	1399	1987	5.751	929
1967	12.340	1083	1988	9.586	267
1968	11.124	1250	1989	6.544	556
1969	10.639	1681	1990	5.556	443
1970	13.644	1676	1991	5.530	990
1971	12.637	495	1992	9.232	1509
1972	5.665	461	1993	11.581	1430
1973	4.926	414	1994	15.792	1226
1974	5.877	151	1995	15.643	1039
1975	3.090	281	1996	14.227	317
1976	2.355	168	1997	6.525	677
1977	1.118	187	1998	4.986	521
1978	1.750	191	1999	8.670	910
1979	2.383	432	2000	11.581	746
1980	3.365	138	2001	8.517	1216
1981	3.179	27	2002	9.272	882
1982	1.539	10	2003	7.873	900
1983	0.561	266	2004	8.412	1294

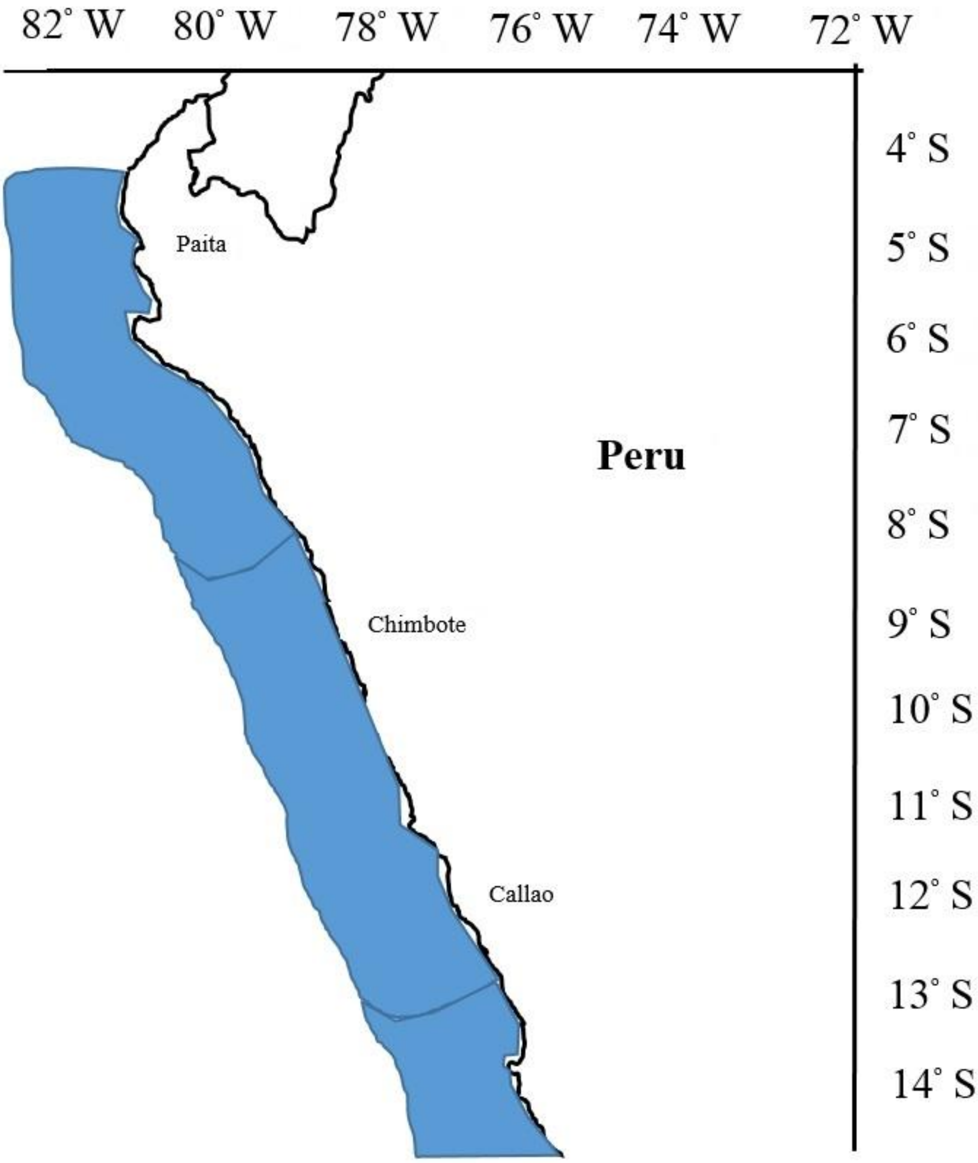

Figure 3-1. Map of Peru showing the stock distribution of the Peruvian anchoveta *Engraulis ringens* off Peru (4º-14ºSouth). The shaded area (in blue) is the major anchovy fishing area to which the data used in this study belongs to, based on the information from Cahuin *et al.*, (2009) and IMARPE database. The fishing area is approximate and not to scale.

Table 3-2. Table showing details about the sources of the different data used for this study.

Data	Source	Description
Spawning Stock Biomass (SSB)	http://dx.doi.org/10.1016/j.ecss.2009.07.027	SSB data was obtained from the article by Cahuin *et al.*, (2009), Table 1
Recruitment (R)	http://dx.doi.org/10.1016/j.ecss.2009.07.027	Recruitment data was obtained from the article by Cahuin *et al.*, (2009), Table 1
Sea surface Temperature (SST)	http://www.cpc.ncep.noaa.gov/data/indices	SST monthly data was obtained from the National Weather Service, Climate Prediction center NOAA website for the years ranging from 1963 to 2004 at Nino 1+2 (0-10ºSouth) (90º West-80ºWest)
Southern Oscillation Index (SOI)	http://www.cpc.ncep.noaa.gov/data/indices	SOI monthly data was obtained from the National Weather Service, Climate Prediction center NOAA website from 1963 to 2004.
Anchovy stock Distribution	http://www.imarpe.pe	Information on the distribution of Anchovy stock was obtained from IMARPE database.

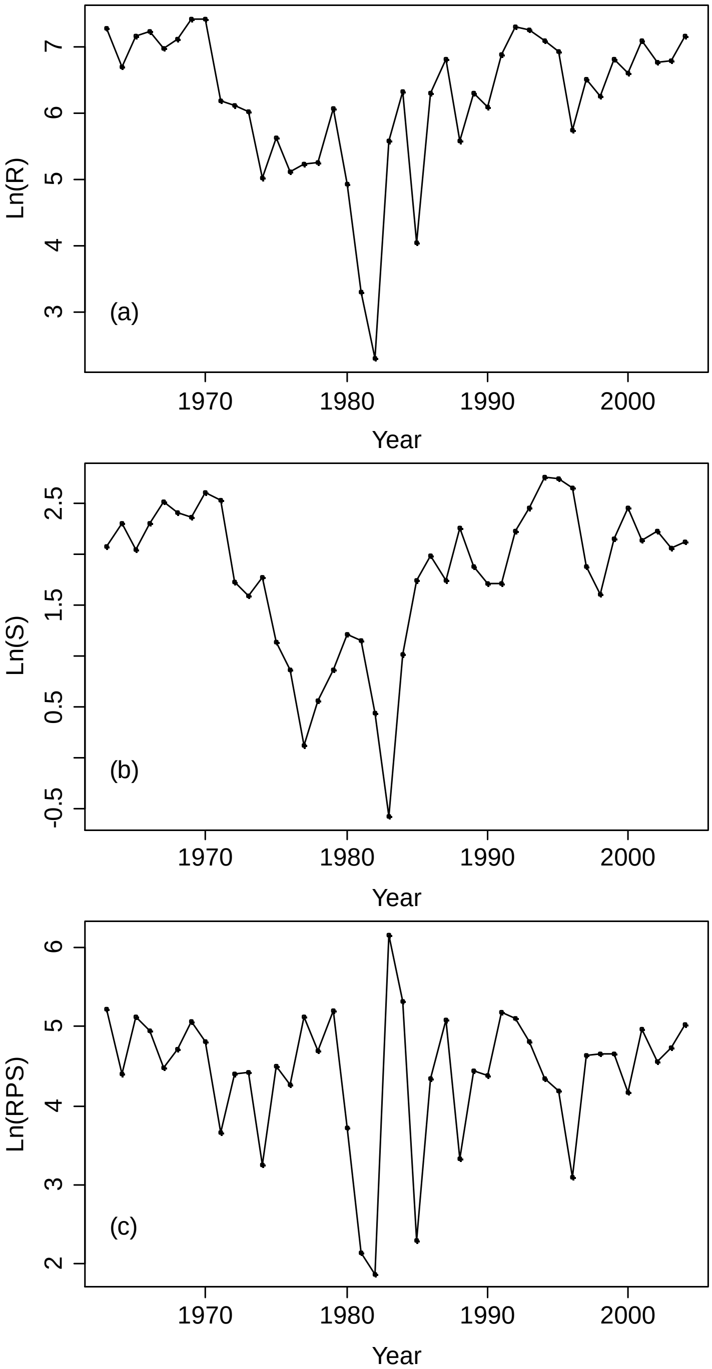

Figure 3-2. The dynamics of Peruvian anchoveta *Engraulis ringens* from 1963-2004. (a) ln(R), (b) ln(SSB), (c) ln(RPS). The fluctuations patterns are similar for ln(R) and ln(SSB). The plot ln(RPS) does not show regimes indentified by Cahuin *et al.*, (2009).

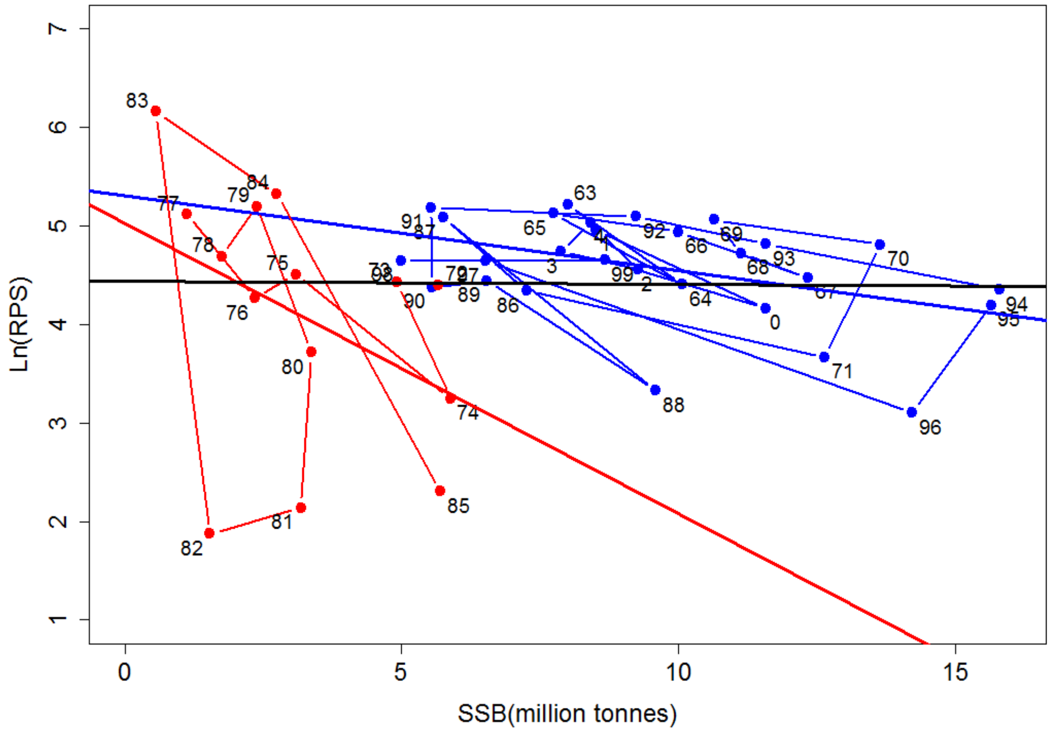

Figure 3-3. Graph of ln(RPS) plotted against the SSB of the Peruvian anchoveta *Engraulis ringens* showing data selection based on the two regimes. The regression line in blue represents the favorable regime "F" and red represents the unfavorable regime "U" from Cahuin *et al.*, (2009). The regression line in black represents the full data series. The lines connecting the data points for the favorable regime (in blue) and unfavorable regime (in red) show the annual variation of the data.

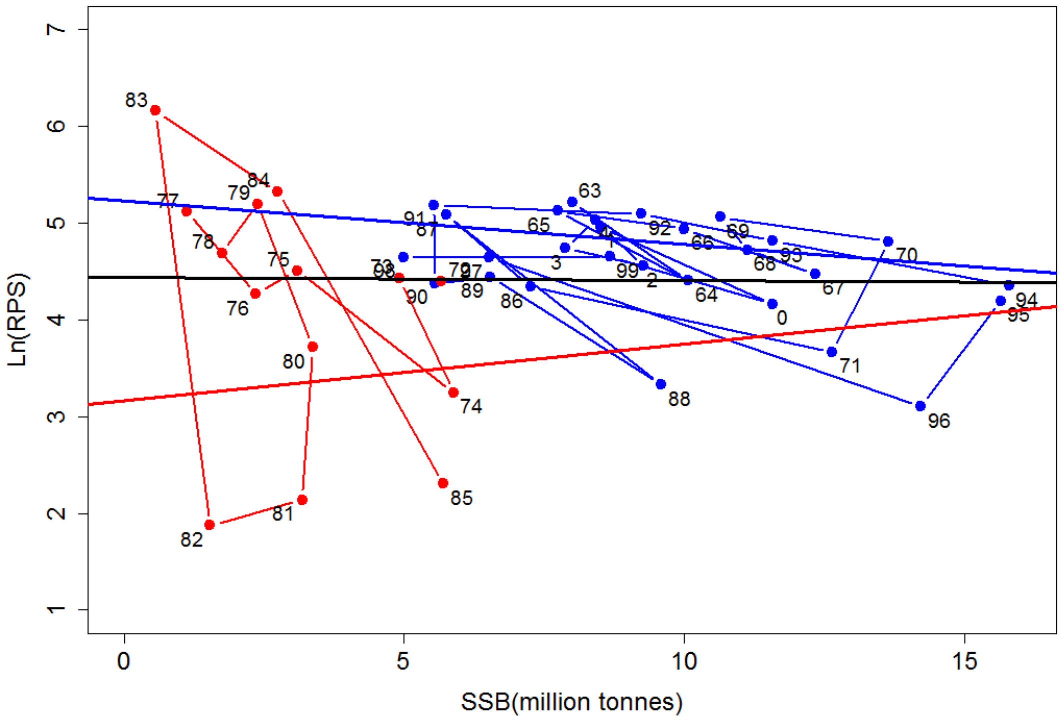

Figure 3-4. Graph of ln(RPS) plotted against the SSB of the Peruvian anchoveta *Engraulis ringens* showing regression plots for two sets of data selected based on the data points above (regression line in blue) and below (regression line in red) the regression line for the full data series (in black). The lines connecting the data points for the favorable regime (in blue) and unfavorable regime (in red) show the annual variation of the data.

Table 3-3. Comparison of model coefficients for ln(RPS) as a function of the SSB for the full model without regimes, with regimes and a model with two data sets having data points selection based on points above and below the regression line for the full data series.

Model	Coefficients	Estimate	Std. error	t value	Pr (>|t|)
3-i) Two regimes[a]	Intercept	5.149	0.336	15.33	$<2 \cdot 10^{-16}$
	Slope (F)[a]	-0.061	0.035	-1.73	0.092
	Slope (U)[a]	-0.324	0.102	-3.19	0.003
	Null deviance	31.496	(41df)		
	Residual deviance	24.552	(39df)		
	AIC	**104.64**			
3-ii) Without regimes[a]	Intercept	4.440	0.289	15.378	$<2 \cdot 10^{-16}$
	Slope	-0.003	0.034	-0.088	0.93
	Null deviance	31.400	(41df)		
	Residual deviance	31.390	(40df)		
	AIC	**112.97**			
3-iii) Without regimes[b]	Intercept	4.200	0.286	20.942	$<2 \cdot 10^{-16}$
	Slope (A)[c]	-0.045	0.019	-2.39	0.025
	Slope (B)[d]	0.058	0.046	1.264	0.227
	Null deviance	29.840	(40df)		
	Residual deviance	26.142	(38df)		
	AIC	**66.25**			

[a]Replicated model from Cahuin *et al.*, (2009). “F” represents the favorable regime and “U” represents the unfavorable regime. [b]Model based on separation of data points above and below the regression line for full data series. [c]Regression line for data points above the regression line for full data series in **Figure 3-4**. [d]Regression line for data points below the regression line for full data series in **Figure 3-4**.

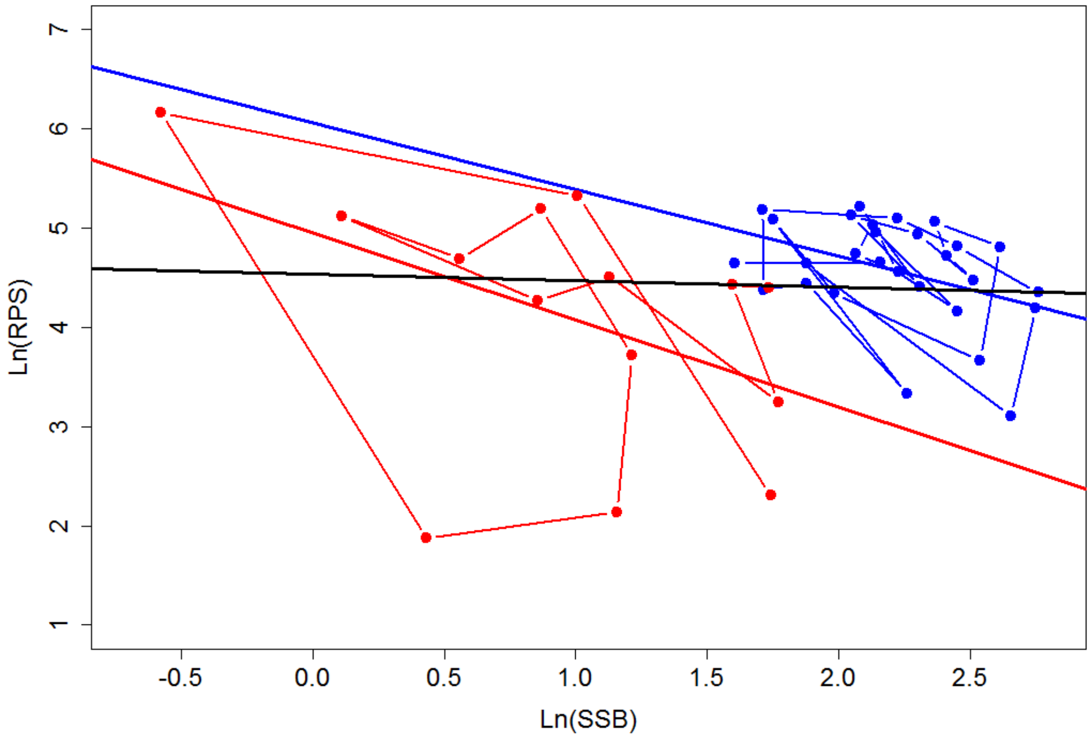

Figure 3-5. Graph of ln(RPS) plotted against the ln(SSB) of the Peruvian anchoveta *Engraulis ringens*. The slope for the favorable regime (in blue) was (slope = −0.673) and significantly negative (p = 0.032). For the unfavorable regime (in red) the slope was (slope = −0.878) and significantly negative (p = 0.097) under 10% significant level. The slope of the regression line for full data series (in black) was (slope = −0.067) and not significantly different from zero (p = 0.718). Density-dependent effects and regime shift are not detected. The lines connecting the data points for the favorable regime (in blue) and unfavorable regime (in red) show the annual variation of the data.

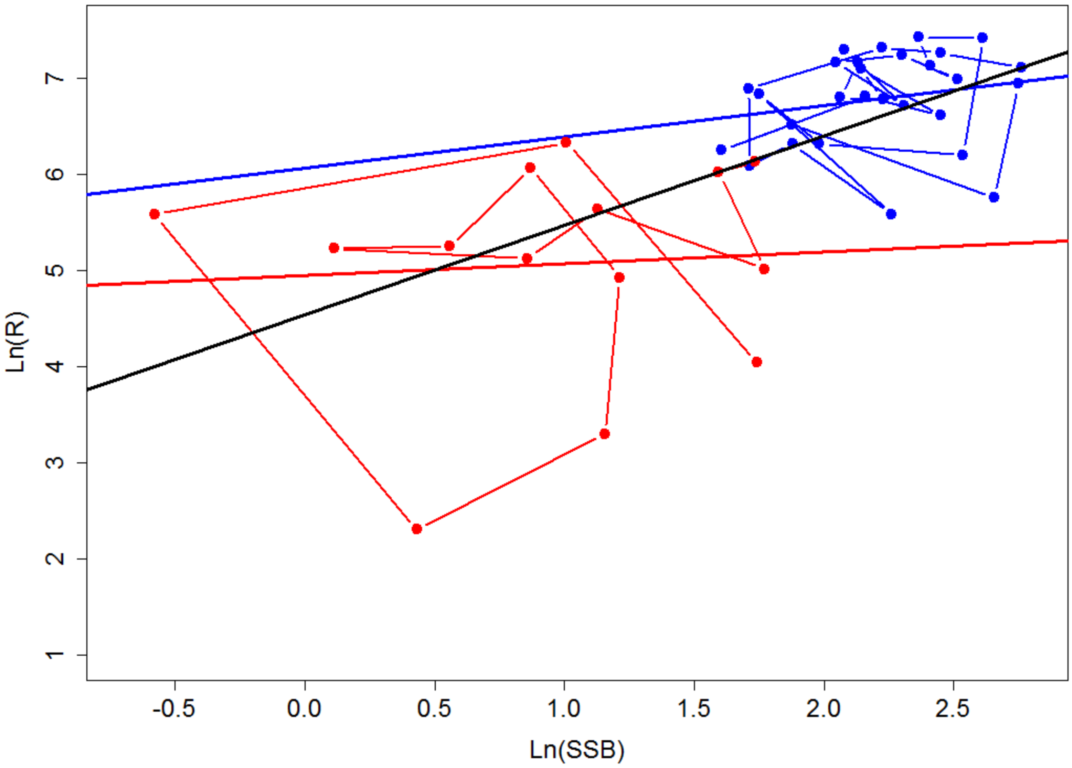

Figure 3-6. Graph of ln(R) plotted against ln(SSB) of the Peruvian anchoveta *Engraulis ringens*. The slope of the regression line for the favorable regime (in blue) was (slope = 0.327) with a 95% confidence interval of (−0.282, 0.936). The slope for the unfavorable regime (in red) was (slope = 0.122) with a 95% confidence interval of (−0.944, 1.188). The regression line for the full data set had a slope of (slope = 0.923) with the 95% confidence limit (0.561, 1.305). This indicates the absence of density-dependent effects. The lines connecting the data points for the favorable regime (in blue) and unfavorable regime (in red) show the annual variation of the data.

Table 3-4. Table showing the different models used for modeling the recruitment dynamics of the Peruvian anchoveta *Engraulis ringens* and the Akaike Information Criterion (AIC) values. The model with the lowest AIC value, significant parameter estimates, highest R^2 and incorporating most variables was selected. R is the recruitment, a0 is the intercept, a_1, b_1 and c_1 are the parameter estimates for the independent variables, S is the spawning stock biomass, T is the sea surface temperature and I is the Southern Oscillation Index.

Model	R^2	Parameter estimates	p-value	AIC value
3-iv) $\ln(R/S) = \ln(a_0) + a_1 \cdot T^2$	0.419	a_0= 2.084, a_1= 0.005	a_0=0.067[f] , a_1=0.040[e]	108.496
3-v) $\ln(R/S) = \ln(a_0) + a_1 \cdot T^3$	0.413	a_0=2.925, a_1=$1.426 \cdot 10^{-04}$	a_0=$2.040 \cdot 10^{-04}$[e], a_1=0.040[e]	108.498
3-vi) $\ln(R/S) = \ln(a_0) + a_1 \cdot T$	0.426	a_0=-0.433, a_1=0.223	a_0=0.851, a_1=0.040[e]	108.508
3-vii) $\ln(R/S) = \ln(a_0) + c_1 \cdot T \cdot I$	0.557	a_0=4.430, c_1=-0.020	a_0=<$2.000 \cdot 10^{-16}$[e], c_1=0.047[e]	108.763
3-viii) $\ln(R/S) = \ln(a_0) + b_1 \cdot I$	0.555	a_0=4.438, b_1=-0.437	a_0=<$2.000 \cdot 10^{-16}$[e], b_1=0.050[e]	108.891
3-ix) $\ln(R/S) = \ln(a_0) + a_1 \cdot T^2 + b_1 \cdot I^2$	0.478	a_0=2.195, a_1=$4.963 \cdot 10^{-03}$ b_1=-0.394	a_0=0.054[f], a_1=0.037[e] b_1=0.242	109.002
3-x) $\ln(R/S) = \ln(a_0) + a_1 \cdot T + b_1 \cdot I^2$	0.483	a_0=-0.3477, a_1=0.2251 b_1=-0.3910	a_0=0.880, a_1=0.038[e] b_1=0.245	109.036
3-xi) $\ln(R/S) = \ln(a_0) + a_1 \cdot T^3 + b_1 \cdot I$	0.513	a_0=3.416, a_1= $9.690 \cdot 10^{-05}$ b_1=-0.267	a_0=$2.840 \cdot 10^{-04}$[e], a_1=0.235 b_1=0.305	109.349
3-xii) $\ln(R/S) = \ln(a_0) + a_1 \cdot T^3 + c_1 \cdot T \cdot I$	0.511	a_0=3.441, a_1= $9.399 \cdot 10^{-05}$ c_1=$-1.231 \cdot 10^{-02}$	a_0=$3.310 \cdot 10^{-04}$[e], a_1=0.260 c_1=0.311	109.377
3-xiii) $\ln(R/S) = \ln(a_0) + a_1 \cdot T^2 + b_1 \cdot I$	0.516	a_0=2.850, a_1=$3.314 \cdot 10^{-03}$ b_1=-0.265	a_0=0.039[e], a_1=0.239 b_1=0.312	109.381

[e]Statistically significant at p = 0.05; [f]Statistically significant at p = 0.10.

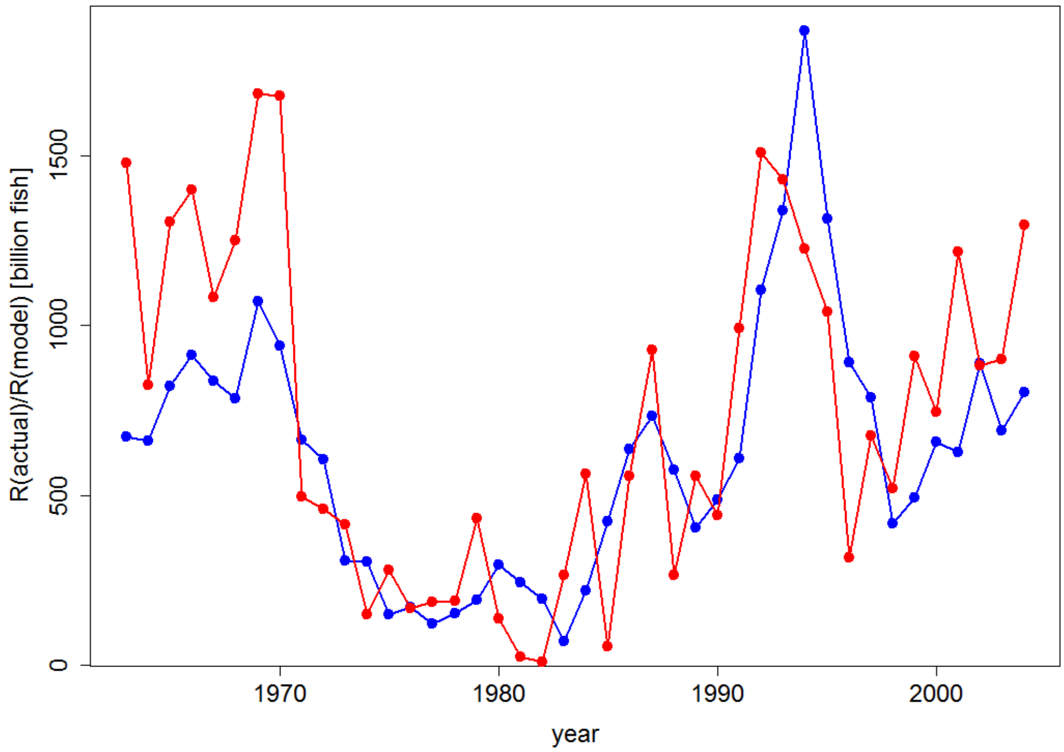

Figure 3-7. Graph showing the actual dynamics (in red) of the Peruvian anchoveta *Engraulis ringens* from 1963 to 2004 and the dynamics resulting from model **3-vii**, (**Table 3-4**) shown in blue.

CHAPTER 4

Influence of Climatic Conditions on the Time Series Fluctuation of Yellowfin Tuna *Thunnus albacares* in the South Pacific Ocean

Keywords: Yellowfin tuna, Global mean Land and Ocean Temperature Index, Pacific warm pool Index, Southern Oscillation Index, *Thunnus albacares*

Publication

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Singh, A.A., Suzuki, N., and Sakuramoto, K., 2014. Impact of climatic and environmental conditions on the dynamics of the yellowfin tuna *Thunnus albacares* in the Pacific Ocean and the Exclusive Economic Zone of Fiji. Abstract, ICOR Book of Abstracts, Oceans and Rivers in Common: Building Nations…Sustaining, International Conference on Oceans and Rivers – ICOR2014, Fiji National University, Nadi, Fiji.

4.1. ABSTRACT

Yellowfin tuna (*Thunnus albacares*) is one of the most commercially important fish species for South Pacific island nations and territories and for effective conservation efforts it is important to understand the factors which affect their time series pattern. Our research was aimed at elucidating the climatic factors which affect the trajectory of the yellowfin tuna stock in the Eastern and Western South Pacific Ocean. We utilized various climatic factors for the years t-n with n=0, 1,…,8 and investigated their statistical relationship to the catch per unit effort (CPUE) of yellowfin tuna stock from 1957-2008 for three South Pacific zones ranging from the East to the West Pacific Ocean within the coverage area of the Western and Central Pacific Convention Area. Results showed that the climatic conditions of; (i) the global mean land and ocean temperature index (LOTI), (ii) the Pacific warm pool index (PWI) and (iii) Southern Oscillation Index (SOI) had significant relationship with the CPUE of yellowfin tuna in all three zones. LOTI, PWI and SOI were used as independent variables and fitted through modeling to replicate the CPUE trajectory of the yellowfin tuna in Zone 1, Zone 2 and Zone 3. Model selection was based on significant parameter estimates (p<0.05), Akaikes Information Criterion (AIC) and R^2 values. Models selected for all three zones had LOTI, PWI and SOI as the independent variables. This study showed that LOTI, PWI and SOI are climatic conditions which have significant impact on the fluctuation pattern of the yellowfin tuna CPUE in the Eastern and Western South Pacific Ocean. From the findings of this study it can be recommended that when management decisions are being made for yellowfin tuna fishery conservation and sustainability in the Eastern and Western South Pacific, it is imperative to take the effect of climatic factors into account.

4.2. INTRODUCTION

Yellowfin tuna (*Thunnus albacares*) is one of the highly migratory species of tuna which has been of significant commercial importance to the nations that fall within the Western and Central Pacific Convention Area (WCPCA) including the South Pacific Island countries and territories where yellowfin tuna forms one of the major revenue contributors for the fisheries sector (Bell *et al.*, 2013; Hampton, 2010;

Silbert and Hampton, 2003; Gillett *et al.*, 2001; Aaheim and Signa, 2000; Lawson, 2000). As a migratory species yellowfin tuna has a median displacement of 337-380 nautical miles and a large proportion of the population moves beyond the exclusive economic zone (EEZ) of most countries (Schaefer *et al.*, 2007; Silbert and Hampton, 2003). However, estimates of half-life show that the residence period of yellowfin tuna within the EEZ of Pacific Island states is approximately 6 months and due to their high growth rates, this period is sufficient to cause substantial production of the species within a single EEZ (Silbert and Hampton, 2003). After skipjack tuna (*Katsuwonus pelamis*), yellowfin tuna accounts for the second highest catch in the Western and Central Pacific Ocean (WCPO). The global demand for tuna has been increasing and effort levels for tuna harvests in the WCPCA have been intensifying as other oceanic areas are becoming overharvested (Lehodey *et al.*, 2011). This exposes the Pacific tuna species to greater fishing pressure and increases vulnerability to declining of stock levels beyond sustainability limits. However, the stock assessment of tuna species is complicated as alternations in climatic conditions also affect their stock dynamics.

El Niño-Southern Oscillation (ENSO) and El Niño and La Niña events have been observed to affect the stock distribution and abundance of tuna species by altering primary productivity of oceanic areas (Lehodey, 2001; Lehodey *et al.*, 1997). Significant impact of various climatic conditions has been documented over the years for different commercially important tuna stocks. Changes in the climatic conditions of the North Atlantic Oscillation (NAO) and Northern Hemisphere Temperature anomaly caused significant changes in the migration and spatial distribution of the North Atlantic albacore (*Thunnus alalunga*) and Eastern Atlantic bluefin (*Thunnus thynnus*) tuna over a period of 40 and 25 years respectively in the Northeast Atlantic Ocean (Dufour *et al.*, 2010). In the Pacific Ocean, Lehodey *et al.*, (2003) showed that positive Pacific Decadal Oscillation (PDO) and El Niño events frequency are favorable for the recruitment of yellowfin and skipjack tuna while albacore tuna recruitment is enhanced by negative PDO and La Niña events. During El Niño events which are followed by La Niña events, catches of skipjack tuna has been observed to be high in the Pacific region where the Warm Pool and the Pacific

Equatorial Divergence converge. The Southern Oscillation Index (SOI) which is related to El Niño and La Niña events has also been shown to be related to skipjack tuna stock and yellowfin tuna catch time series (Kumar *et al.*, 2014; Lehodey *et al.*, 2011; Corbineau *et al.*, 2010; Senina *et al.*, 2008; Lehodey *et al.*, 1997).

The fluctuation patterns of fish are complex and result from interaction of various intrinsic and extrinsic factors working together. It is important to understand the role of climatic conditions on the stock dynamics of commercially important fish species and make the information available to fishery decision makers as the significance of climatic factors in fisheries stock abundance and distribution cannot be ignored. The aim of this study is to explore the relationships of climatic conditions with the stock trajectory of yellowfin tuna (*T. albacares*) in the South Pacific region. To use environmental factors as independent variables and develop suitable stock reproduction models to explain the fluctuation pattern of the yellowfin tuna time series.

4.3. MATERIALS AND METHODS

4.3.1. Data

Catch and effort data for the yellowfin tuna (*T. albacares*) in the Eastern and Western South Pacific region from 1957 to 2008 was obtained from the Western and Central Pacific Fisheries Commission (WCPFC) public domain data (https://www.wcpfc.int/) aggregated in 5º by 5º spatial grids. The stock distribution of the yellowfin tuna selected for this study is shown in **Figure 4-1**.

Only the longline data for yellowfin tuna was utilized for this study as it was the most extensive with reference the time series range and the possibility of observation errors for the effort were much less compared to pole and line and purse seine data. The type of effort data for longline was by the number of hooks which was preferable over the effort data for pole and line and purse seine which was by the number of fishing days. The data for yellowfin tuna were separated into three areas; Zone 1 (2.5ºN – 47.5ºS, 162.5ºW – 152.5ºW, 7.5ºS – 47.5ºS, 152.5ºW – 132.5ºW), Zone 2 (2.5ºN – 47.5ºS, 172.5ºE – 162.5ºW) and Zone 3 (2.5ºN – 47.5ºS, 147.5ºE – 172.5ºE) (**Figure 4-1)** by geolocating and isolating the latitude and longitude coordinates which fell within each zone. Annual catch and effort for the yellowfin tuna in Zone 1, 2 and 3 were calculated from aggregated longline monthly data by latitude and longitude coordinates. From the catch and effort data, the catch per unit effort (CPUE) for Zone 1, Zone 2 and Zone 3 were calculated (**Figure 4-2A**, **Figure 4-2B** and **Figure 4-2C**). For CPUE calculation, the catch data used was in tonnes and effort was the number of hooks used. Exploratory analysis showed differences in the CPUE, catch magnitude and catch and effort relationship for yellowfin tuna time series in the three zones which made it essential to treat Zone 1, Zone 2 and Zone 3 as three different stocks.

The CPUE time series fluctuation pattern for the yellowfin tuna in Zone 1 can be seen in **Figure 4-2A** for the years 1957 to 2008. From 1960-1964, 1970-1972, 1974-1976, 1981-1983, 1984-1986, 1988-1990, 1992-1994 and 1995-1997 there is an increasing trend and for the years 1958-1960, 1964-1967, 1968-1970, 1972-1974, 1976-1978, 1979-1981, 1986-1988, 1990-1992, 1997-1999, 2000-2003 and 2006-2008 a decreasing trend can be observed with the maximum peak in 1964 and minimum in 2008. For the trajectory of yellowfin tuna in Zone 2 (**Figure 4-2B**) we can see an increasing trend for the years 1958-1960, 1974-1978 and 1981-1983 while a decreasing trend can be observed for the years 1963-1967, 1968-1971, 1972-1974, 1978-1981, 1985-1989, 1992-1995, 1996-1999, 2000-2003 and 2004-2006. The CPUE is at peak for the years 1960 and 1963, however from this point an overall gradual decline in the yellowfin tuna in Zone 2 can be seen until 2008 with the lowest point for the CPUE in the years 1974, 1981, 1991, 2003 and 2008. Finally for Zone 3 (**Figure 4-2C**) the CPUE has an increasing trend for the years 1962-1964, 1974-1978, 1986-1988 and 1993-1996 with a decreasing trend from 1957-1959, 1960-1962, 1971-1974, 1988-1991, 1996-1999 and 2002-2004. CPUE is highest in 1957, 1960 and 1964 and lowest in 1974 and 1999. The CPUE trends in Zone 2 and Zone 3 have more similarities with each other compared with Zone 1 where the CPUE fluctuates intensively between high and low peaks over the time series.

Global Mean Land and Ocean Temperature Index (LOTI) for the latitude band 0ºN to 24ºS from 1949 to 2008 was obtained from the National Aeronautics and Space Administration (NASA), Goddard Institute for Space studies, Goddard Space Flight Center, Science and Exploration Directorate, Earth Science Division (http://data.giss.nasa.gov/gistemp). Monthly data for the Pacific warm pool index (PWI) from 1949 to 2008 and Southern Oscillation Index (SOI) from 1951 to 2008 were obtained from the National Oceanic and Atmospheric Administration (NOAA), Earth System Research Laboratory, Physical Sciences Division (http://www.esrl.noaa.gov).

4.3.2. Exploratory Analysis and Unit Root Test

To identify if relationships existed between dependent and independent variables, we applied regression analysis of the dependent variables of yellowfin tuna CPUE in Zone 1 (Y_{z1}), Zone 2 (Y_{z2}) and Zone 3 (Y_{z3}) against the independent variables of LOTI (L), monthly and annual PWI (P) and SOI (I). Y_{z1}, Y_{z2} and Y_{z3} were tested against climatic conditions for year t-n where n=0, 1,…,8 as the lifespan of yellowfin tuna is around 5 to 8 years (Zhu *et al.*, 2011; Hampton and Fournier, 2001). Regression results with $p<0.05$ were considered as significant relationships. Dependent variables as well as independent variables which showed significant relationships to dependent variables were tested for the presence of outliers using boxplots and scatterplots and correlations among independent variables as outlined in Zurr *et al.*, 2010. Coefficient of correlation with $R>0.500$ was considered as significant. The protocol for data exploration was followed as outlined by Zurr *et al.*, 2010 to avoid violations of assumptions from the statistical techniques utilized.

Time series data can have either a deterministic trend which is a stationary process or stochastic trend which is non-stationary process. When alteration or shocks in trend have transitory effects on a time series with deterministic trend the time series remains a stationary process and when these shocks causes permanent alterations to a trend the time series is categorized as having a stochastic process or a unit root. For a given time series the presence of a unit root can cause unauthentic correlations in analysis techniques such as regression analysis (MacKinnon, 1996; Dickey and Fuller, 1979). Yellowfin tuna CPUE in Zone 1, Zone 2 and Zone 3 as well as the independent variables which exhibited significance correlation with the dependent variables were analyzed with the Augmented Dickey-Fuller and MacKinnons unit root test to confirm whether any of the time series data were a non-stationary process (MacKinnon, 1996; Kwiatkowski *et al.*, 1992; Dickey and Fuller, 1979).

4.3.3. Stock Reproduction Model

From exploratory analysis the individual independent variables which showed significant relationship at $p<0.05$ with yellowfin tuna CPUE in Zone 1, Zone 2 and Zone 3 with highest R^2 and lowest AIC values were incorporated into stock reproduction models. Here, the stock reproduction model is an attempt to reconstruct the CPUE trajectory of yellowfin tuna in the three South Pacific zones by fitting climatic data as independent variables. The parent formula used for the stock reproduction model for Zone 1, Zone 2 and Zone 3 was a Generalized Linear Model (GLM) shown below

$$\ln\left(Y_{zi,t}\right) = \ln(\alpha_0) + \alpha_{1,n}x_{1,t-n} + \alpha_{2,n}x_{2,t-n} + \cdots + \alpha_{k,n}x_{k,t-n} + \varepsilon_{zi,t} \qquad (1)$$

where $Y_{zi,t}$ is the yellowfin tuna CPUE with z= Zone 1, Zone 2 and Zone 3 with i = 1, 2, 3, α_0 is the intercept parameter, α_1, $\alpha_2,\ldots,\alpha_k$ are parameter estimates, x_1, $x_2,\ldots,x_k$ are the independent variables, t is the year with n= 0, 1,…,8 and $\varepsilon_{zi,t}$ is a random variable which is normally distributed and cannot be explained.

The response surface methodology (RSM) uses linear and polynomial functions to incorporate independent variables into mathematical and statistical models to describe a system or data which is under investigation (Myers *et al.*, 2009; Bezerra *et al.*, 2008; Buchanan and Phillips, 1990; Box and Behnken, 1960). Equation (1) was modified and expanded using RSM by incorporation of polynomials of the second and third order to determine if variables could be better fit with this technique (Equation 2).

$$\ln(Y_{zi,t}) = \ln(\alpha_0) + \alpha_{1,m,n}x_{1,t-n}^{m} + \alpha_{2,m,n}x_{2,t-n}^{m} + \cdots + \alpha_{k,m,n}x_{k,t-n}^{m} + \varepsilon_{zi,t} \quad (2)$$

where m=1, 2, 3. The dependent variable and y-intercept were log transformed to reduce the effects of skewness and outliers. Various combination or the independent variables were investigated by successive elimination for the linear model and with polynomial combinations of the independent variables for Equation (1) and Equation (2) to identify suitable models for explaining the trajectory of the yellowfin tuna stock in the three zones of the South Pacific region. The residuals of the model against the fitted values were tested for homogeneity of variance. If the range of variance were ≥4.00 then the least square estimators will be significantly degraded [26]. For model selection criteria, we used the Akaikes Information Criterion (AIC) and R^2 values at p<0.05 with condition of significant parameter estimates at p<0.05 [27]. The referred trajectory of the CPUE was plotted with the predicted CPUE of the yellowfin tuna in Zone 1, Zone 2 and Zone 3 and compared. All statistical analysis for this study was carried out using the statistical software "R", version 3.0.1 (R Core Team, 2014).

4.4. RESULTS

4.4.1. Catch and Effort Trajectory

For this study only the CPUE was used for regression analysis and model development as it better represented the actual fluctuation pattern of the yellowfin tuna stock in the South Pacific Zone 1, Zone 2 and Zone 3 compared to the catch time series (**Figure 4-3**). From **Figure 4-3** it can be seen that the yellowfin tuna effort shows similar fluctuation pattern with the catch in all three cases. The correlation between catch and effort of yellowfin tuna in Zone 1, 2 and 3 can be seen in **Figure 4-4** where the points above the slopes refer mostly to the years where the catch was high at low effort and most of the points below the slopes refer to the years where catch was low and effort levels were high. Points which recline on or close to the slope line are the years where catch and effort corresponded more closely to each other. From **Figure 4-3** and **Figure 4-4** the effort trajectory in Zone 1 seems to better fit the catch trajectory compared to that of Zone 2 and Zone 3. The determination coefficient for Zone 1 (0.745) is significantly higher compared to Zone 2 (0.343) and Zone 3 (0.327). As the catch and effort are correlated for the three zones, it can be said that the catch dynamics of the yellowfin tuna in the three fishing zones are influenced by the fishing effort. Since CPUE is defined as the catch for each unit of effort it is a much better standard representative of the true trajectory of yellowfin tuna compared to the catch time series for this study.

Figure 4-5 shows the similarities and differences in the yellowfin tuna catch and CPUE time series magnitudes in Zone 1, Zone 2 and Zone 3. Catch levels in Zone 3 have remained significantly higher for most of the time series from 1957-2008 compared to Zone 2 and Zone 3. Catch in Zone 2 remained higher than in Zone 1 until around the mid-1980s from which point the catch in both zones remained at similar scales up to 2008. Similarly, the CPUE in Zone 3 mostly remained significantly higher than in Zone 2 and Zone 1 until around the mid-1990s after which the CPUE in all three zones remained at similar levels. CPUE in Zone 2 was much higher than in Zone 1 until the early 1970s and remained more or less similar to Zone 1 from this point. On average it can be said that the stock level in Zone 3 has been the highest followed by Zone 2 and with the lowest in Zone 1 until recently where the stock levels in all three zones have been at similar levels.

4.4.2. Exploratory Analysis and Unit Root Test

In **Table 4-1** the results of the regression analysis of the CPUE for the yellowfin tuna in Zone 1, Zone 2 and Zone 3 of the South Pacific region against the independent climatic conditions variables for the years t-n (n=0, 1,…,8) are shown. We have only included the variables which exhibited correlations according to the highest R^2 and lowest AIC values at $p<0.05$. The dependent variables Y_{z1}, Y_{z2} and Y_{z3} had significantly high correlations with the independent variables of LOTI for the latitude band 0ºN to 24ºS (L), PWI for the month of September (P_s) and November (P_n) and SOI for the month of April (I_a), July (I_j) and August (I_g). LOTI had highest correlation at year t-8 for all three zones while PWI had strongest correlation at year t-4 in all three cases with P_s for Y_{z1} and P_n for Y_{z2} and Y_{z3}. SOI showed most significant correlation for I_a at year t-1 with Y_{z1}, I_j at year t-4 for Y_{z2} and I_g at year t-2 for Y_{z3}. These independent variables were also accepted on the basis that these are climatic conditions fall within or in close proximation the data coverage zone for the CPUE of the yellowfin tuna in Zone 1, Zone 2 and Zone 3.

When regression analysis is used sometimes spurious correlations may arise. To detect this we performed unit root tests which are statistical methods to identify cases of unauthentic correlations (MacKinnon, 1996; Kwiatkowski *et al.*, 1992; Dickey and Fuller, 1979) for all the time series data used in this study. Results of MacKinnon's test (M-test) and Augmented Dickey-Fuller test (ADF-test) having t-test value (t-value) of <0 and significance level of $p<0.05$ were positive for having stationary process (**Table 4-2**). The outcome of the unit root tests showed that all the time series variables from **Table 4-1** showed stationarity and did not have a unit root processes and the relationships shown in **Table 4-1** are authentic.

4.4.3. Stock Reproduction Model

The results for stock reproduction models for the CPUE of the yellowfin tuna in the South Pacific Zone 1, Zone 2 and Zone 3 using the independent variables from **Table 4-1** are shown in **Table 4-3**. We have only shown three models for each area which had the highest R^2 and lowest AIC values with $p<0.05$. For the yellowfin tuna in Zone 1 model (i) has the highest R^2 and lowest AIC value and it incorporates the independent variables $L_{t\text{-}8}$, $P_{s,t\text{-}4}$ and $I_{a,t\text{-}1}$. For Zone 2 model (iv) is most significant with respect to R^2, AIC and p-value and incorporates $L_{t\text{-}8}$, $P_{n,t\text{-}4}$ and $I_{j,t\text{-}4}$. The most suitable model for the yellowfin tuna in Zone 3 is model (vii) which incorporates $L_{t\text{-}8}$, $P_{n,t\text{-}4}$ and $I_{g,t\text{-}2}$ as the independent variables (**Table 4-3**).

Collinearity tests did not show any significantly high correlations between any of the independent variables incorporated into the final models in **Table 4-3**. Homogeneity tests showed that all model residuals shown in **Table 4-3** have a variance of <0.1 which fulfills the requirements of homogeneity where variance needs to be <4.00 for the least square estimators to be reliable (Fox, 2008) (**Figure 4-6**).

Figure 4-7 shows the plot of CPUE of the yellowfin tuna (*T. albacares*) in Zone 1 and the CPUE trajectory from model **4-i** (**Table 4-3**). The CPUE predicted seems to fit quite well with the CPUE referred. In **Figure 4-8** and **Figure 4-9** the referred CPUE trajectory of yellowfin tuna in in Zone 2 and Zone 3 are shown with the CPUE trajectory resulting from model **4-iv** and **4-vii** (**Table 4-3**). The fitness of the predicted CPUE with the referred CPUE is highest for Zone 3 followed by Zone 2 and Zone 1. The linear correlations of the models shown in **Table 4-3** are shown in **Figure 4-10**. The determination coefficients for the yellowfin tuna CPUE referred for Zone 1, Zone 2 and Zone 3 against the CPUE predicted from models **4-i**, **4-iv** and **4-vii** (**Table 4-3**, **Figure 4-10**) are 0.602, 0.698 and 0.797 respectively. The slope for (**Figure 10**(i)) is 1.064 with 95% confidence interval of (0.663, 1.465), for (**Figure 10**(iv)) the slope is 1.104 with 95% confidence interval of (0.782, 1.425) and for (**Figure 10**(vii)) the slope is 1.098 with 95% confidence interval of (0.862, 1.335). In all three cases the slopes are not significantly different from unity.

Figure 4-11 shows the time series fluctuation patterns for the independent variables *L*, *P* and *I* which resulted in the most statistically significant models for the CPUE trajectory of the yellowfin tuna in the South Pacific Zone 1, Zone 2 and Zone 3 from models (i), (iv) and (vii) (**Table 4-3**). Both LOTI and PWI seem to have a gradually increasing pattern from 1949 to 2008 while SOI seems to fluctuate between highs and lows while running approximately parallel to the x-axis from 1951 to 2008. Exploratory analysis showed the presence of relationship of the SOI incorporated into the models for Zone 1 (I_a), Zone 2 (I_j) and Zone 3 (I_g) with the climatic conditions of the Pacific Decadal Oscillation (PDO) for the month of September and Niña 3 which is the Eastern Tropical Pacific sea surface temperature (5ºN-5ºS, 150ºW-90ºW) (**Figure 4-12**). Due to their interrelation and high collinearity only SOI was selected for modeling as it was most significant among these variables.

4.5. DISCUSSION

Before making management plans and mitigation procedures for the conservation and sustainability of any fishery stock it is imperative to first understand the underlying factors behind its time series fluctuation pattern. This study was carried out in order to better understand the stock dynamics of the yellowfin tuna in the Eastern and Western South Pacific Ocean Zone 1, Zone 2 and Zone 3 (**Figure 4-1**) from 1957 to 2008. From **Figure 4-5** the differences in stock dynamics in the three zones are evident. The catch levels are significantly higher in Zone 3 compared to Zone 1 and Zone 2 where the catch levels differed to a lesser magnitude with catch levels in Zone 1 being the lowest. Similar pattern can be observed for CPUE trajectory where the CPUE in Zone 3 is significantly higher than Zone 2 and Zone 1 which had smaller differences with Zone 1 having the lowest CPUE. From this it can be inferred that historically stock levels have been considerably higher in Zone 3 compared to Zone 2 and Zone 1. In the mid-1990s the CPUE in Zone 3 reached lower levels and became analogous with Zone 2 and Zone 1 up to 2008. Conversely the catch levels in Zone 3 have been retained high during this period through significant increase in exploitation efforts (**Figure 4-3** and **Figure 4-5**) which if left unchecked could lead to the overexploitation of the yellowfin tuna stock in Zone 3. Such assumptions for tuna stocks based on fishing effort alone may be true to some extent but it is not precise as the effect of climatic conditions in altering tuna stock dynamics has been documented which needs to be further studied and taken into account (Lehodey *et al.*, 2011; Corbineau *et al.*, 2010; Senina *et al.*, 2008; Lehodey *et al.*, 2003; Lehodey *et al.*, 1997).

For this study we decided to use the CPUE data over the catch data for regression analysis and developing the stock reproduction model. From **Figure 4-3** it can be seen that the effort does not remain constant over time and follows a similar pattern to the catch trajectory with different degrees of similarities for each zone (**Figure 4-4**) whereas the CPUE is the catch calculated for each unit of effort. The CPUE is therefore a better representative of the stock dynamics of the yellowfin tuna compared to catch. When using CPUE to represent stock status of a fishery it is assumed that the strength of a unit of effort used to exploit the fishery remains constant over time. Hampton and Fournier, (2001) have shown that the longline catchability of yellowfin tuna in the Western and Central Pacific Ocean (WCPO) area have remained relatively constant over time and that CPUE is a suitable representative of the stock abundance of the exploitable biomass.

From regression analysis the climatic condition variables, PWI, LOTI and SOI have significantly high correlation with the yellowfin tuna CPUE in Zone 1, Zone 2 and Zone 3 (**Table 4-1**). The PWI is the sea surface temperature index for a specific and substantial area in the WCPCA where the temperature is higher than average. The LOTI is an Index of the sea and land surface air temperature for the latitude band 0ºN to 24ºS which cut across the South Pacific and falls within the data coverage area. SOI comprises of large scale alterations in atmospheric mass or air pressure anomalies between the Western and Eastern tropical and sub-topical Southern Pacific. It is calculated based the sea level pressure anomalies differences at Darwin (12ºS to 130ºE) and Tahiti (17ºS to 149ºW) (Trenberth, 1984). La Niña episodes occur during positive SOI while El Niño events happen during negative SOI (**Figure 4-12**). The relationship of PWI, LOTI and SOI to yellowfin tuna makes ecological sense as all three of these climatic conditions are located within Zone 1, Zone 2 and Zone 3 data coverage area.

For all three zones the final models incorporate L, P and I as the independent climatic variables (**Table 4-3**) with different months and lag periods. LOTI results in most significant models with lag period of t-8 ($L_{t\text{-}8}$) for Zone 1, Zone 2 and Zone 3. This falls within the lifespan of yellowfin tuna which is around 5 to 8 years (Hampton and Fournier, 2001; Zhu *et al.*, 2011). It can be inferred that LOTI influences the spawning and early life stages of the yellowfin tuna in all three zones of the South Pacific Ocean. PWI fits to the most significant models for Zone 1 for the month of September (P_s) and for Zone 2 and Zone 3 for the month of November (P_n) with lag of t-4 for all three zones. Lehodey *et al.*, (2003) has shown that the yellowfin tuna population is linked to the Pacific warm pool. Graham *et al.*, (2007) and Maldenya, (1996) investigated the stomach contents of yellowfin tuna and found that their diet changes significantly between 45cm and 50cm fork length. Kuhnert *et al.*, (2012) showed that the dietary preferences of yellowfin tuna differed in relation to their size, sea surface temperature and latitude. It is possible that the alteration in PWI influences the prey distribution and availability for the yellowfin tuna when they make transformations in their diet. The SOI incorporated into the most suitable models (**Table 4-3**) differed by month and lag periods for Zone 1 ($I_{a,t-1}$), Zone 2 ($I_{j,t-4}$) and Zone 3 ($I_{g,t-2}$). Lehodey *et al.*, (2003) showed that primary production and prey distribution for tuna is influenced by changes in SOI. The difference in the lag periods for the SOI might be attributed to its influence on the spatial distribution of various prey in relation to the different dietary preferences and life stages of the yellowfin tuna in Zone 1, Zone 2 and Zone 3 (Kuhnert *et al.*, 2012; Graham *et al.*, 2007; Maldeniya, 1996). The effect of SOI on small fish species has been previously reported (Singh *et al.*, 2014; Ho *et al.*, 2013). Lehodey *et al.*, (2003) showed that the recruitment of yellowfin tuna is favorable during positive Pacific Decadal Oscillation (PDO) and El Niño events and unfavorable during negative PDO and La Niña events. El Niño and La Niña events result in the easterly and westerly migrations of the Pacific warm pool and causing changes in the temperature and salinity of the water in the area (Sudre *et al.*, 2013; Hansen *et al.*, 2006; Picaut *et al.*, 1996). Indeed, exploratory analysis showed strong link between yellowfin tuna in Zone 1, Zone 2 and Zone 3 and the climatic condition of SOI, El Niño, La Niña and PDO as they are interrelated climatic conditions (**Figure 4-12**).

The time series trajectory of yellowfin tuna in Zone 1, Zone 2 and Zone 3 can be written in relation to the climatic conditions as

$$Y_{zi,t} = f(v_{1,t-n}, v_{2,t-n}, \dots, v_{k,t-n}) \tag{3}$$

where $Y_{zi,t}$ is the CPUE in the coverage zone zi with i = 1, 2 and 3, in year t and f () is the function determined by the climatic factors v_i (i = 1, 2,…, k) with n=(0, 1,…,8). Equation (3) shows the mechanism which is followed for the yellowfin tuna in all three zones of the Eastern and Western South Pacific. The models for all three zones fit quite well to the referred CPUE from **Figure 4-7**, **Figure 4-8** and **Figure 4-9**.

From **Table 4-3** and **Figure 4-10** it can be seen that the fitted models for yellowfin tuna get more significant from Zone1 to Zone 2 and Zone 3 being the most significant. From **Figure 4-3** and **Figure 4-4** the relationship of between catch and effort is highest for Zone 1 followed by Zone 2 and the lowest for Zone 3. This phenomenon can be observed in **Figure 4-4** and **Figure 4-10** where the closer (further) the points scatter from the slope line the lower (higher) the bias between the relationship of the catch and effort and the predicted and referred CPUE. Based on this we can state that the larger proportion of the stock time series pattern for yellowfin tuna in Zone 3 is due to the alterations in the climatic conditions of LOTI, PWI and SOI with the trajectory for Zone 2 being affected less than Zone 3 and Zone 1 although significant, being the least affected by the three climatic conditions. This coincides with the catch and effort relationship where the catch trajectory in Zone 1 is mostly determined by the effort level followed by Zone 2 with the lowest being Zone 3. The effect of the climatic conditions of LOTI, PWI and SOI on yellowfin tuna stock gets more pronounced as we move from the Western to the Eastern South Pacific Ocean.

It might be possible that the Island nations and territories which fall within the WCPCA might not be taking the declining stock status of the yellowfin tuna with reference to the CPUE (**Figure 4-5**) more seriously and making significant conservation efforts as it can be seen from **Figure 4-5** that even until recently catch levels can still be maintained high. The increase in catch is significantly determined by the increase in effort (**Figure 4-3** and **Figure 4-4**) especially for Zone 1. Miyake, (2004) outlines the rapid development of yellowfin tuna commercial fisheries in the WCPO from the mid-1980s. As shown in Hampton and Fournier, (2001) yield analysis of yellowfin tuna data for the WCPO area show that catches have been quite high and may have even exceeded the maximum sustainable yield (MSY) over the three decades from the 1970s to 1990s.

From the stock reproduction models for the yellowfin tuna in Zone 1, Zone 2 and Zone 3 it is evident that a significantly high proportion of the CPUE time series fluctuation patterns are due to changes in the LOTI, PWI and SOI. The slopes in **Figure 4-10** are not significantly different from unity and this is further evidence that these climatic conditions have a strong influence on the stock trajectory of yellowfin tuna in all three areas. As the trajectory for yellowfin tuna has historically been affected by LOTI, PWI and SOI (**Figure 4-7**, **Figure 4-8** and **Figure 4-9**), if the climatic pattern continues, it can be expected that the future CPUE especially for Zone 2 and Zone 3 might continue to decrease in the future. Since it is highly improbable to control the trajectories of climatic conditions and even less without international cooperation, conservation efforts should be directed at factors that can be controlled more practically by human intervention such as the fishing effort. Sustainability efforts for future yellowfin tuna stock should be done by reducing the effort levels to increase the CPUE rather than increasing effort levels to increase catch. While adherence to such recommendation can lead to the biological sustainability of the yellowfin tuna stock, it will probably have negative impact on the economic gains from yellowfin tuna harvest for countries within the Eastern and Western South Pacific. It is necessary to develop suitable plans to control the effort level such as to ensure both the biological and economical sustainability of the yellowfin tuna stock.

Miller, (2007) has outlined the effects of various climatic conditions on the abundance and distribution of various pelagic fish stocks. It was also noted that tuna species including yellowfin tuna abundance and spatial distribution are quite sensitive to changes in climatic condition. Tropical tuna including yellowfin need continuous access to rich food sources because of their high metabolic rate, production and short life spans. They are constantly swimming in search of food and their distribution is highly dependent on aquatic processes which result in high concentration of food resources. These processes are a result of short term and long term variability in climatic conditions (Lehodey *et al.*, 2003; Sharp, 1992; Stéquert, 1989).

The resulting dynamic behaviors of biological populations in aquatic ecosystems are complex and are affected by the interaction of numerous intrinsic and extrinsic factors (Grol *et al.*, 2011). Further work needs to be done in order to establish how the climate variables interrelate to affect yellowfin tuna fishery in the South Pacific Ocean. The understanding of the effects of these processes on the trajectory and distribution pattern of the yellowfin tuna will help to make more informed decisions regarding the yellowfin tuna fisheries in the Eastern and Western South Pacific.

With the models developed in this study, the climatic condition of LOTI, PWI and SOI combined with the effects of fishing pressure (effort) accounts for a major proportion of the abundance of exploitable yellowfin tuna stock in the Eastern and Western South Pacific. When management decisions are made regarding the fisheries of yellowfin tuna including fishing quotas in these areas it is imperative to also take the effect of climatic conditions into account. From the resulting stock dynamics in this study and due to the substantial residency and production of yellowfin tuna within each EEZ in the WCPO according to Silbert and Hampton, (2003), it can be said that while international managements arrangements are necessary for the sustainability of yellowfin tuna stocks in the South Pacific, domestic conservation policies are imperative for management of yellowfin tuna stocks within the EEZs of South Pacific Island nations and territories.

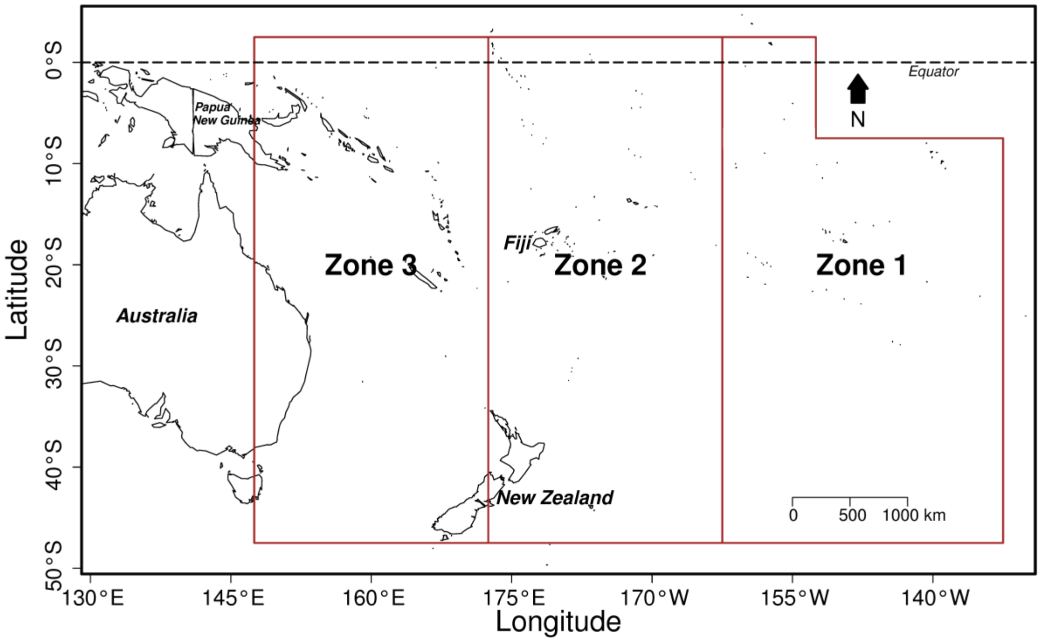

Figure 4-1. Map of the Eastern and Western South Pacific region showing the stock distribution of the yellowfin tuna (*T. albacares*). The region is divided into Zone 1, Zone 2 and Zone 3 shown by the enclosure polygons.

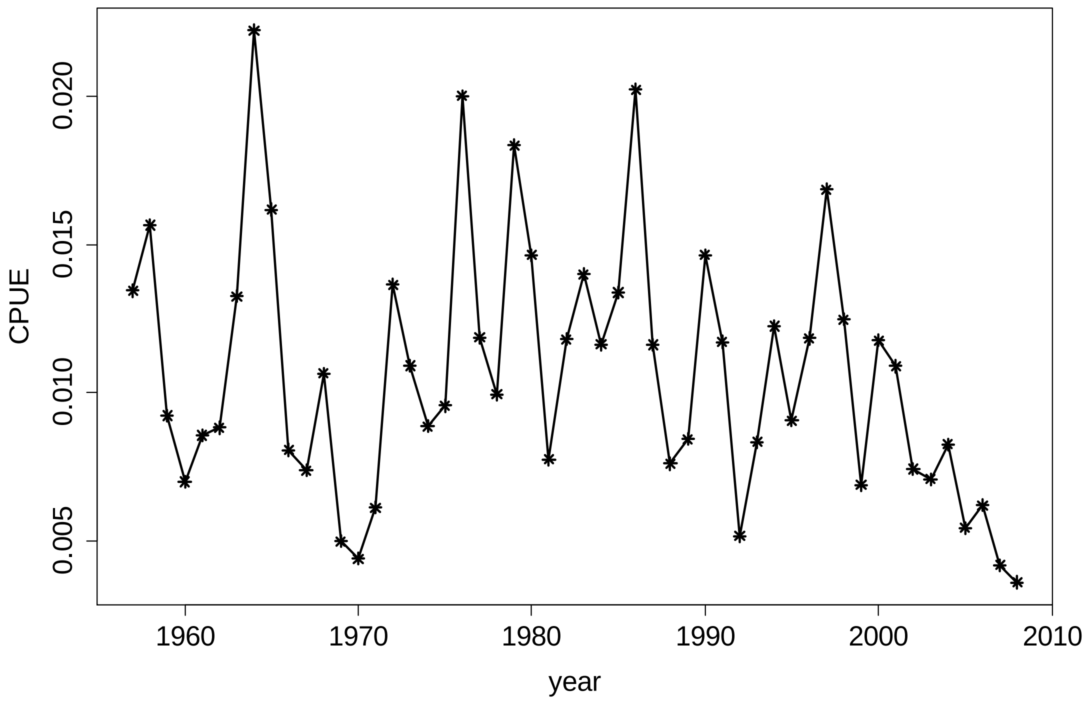

Figure 4-2A. The CPUE time series trajectory of the yellowfin tuna (*T. albacares*) stock in Zone 1. Time series is shown for the years ranging from 1957-2008.

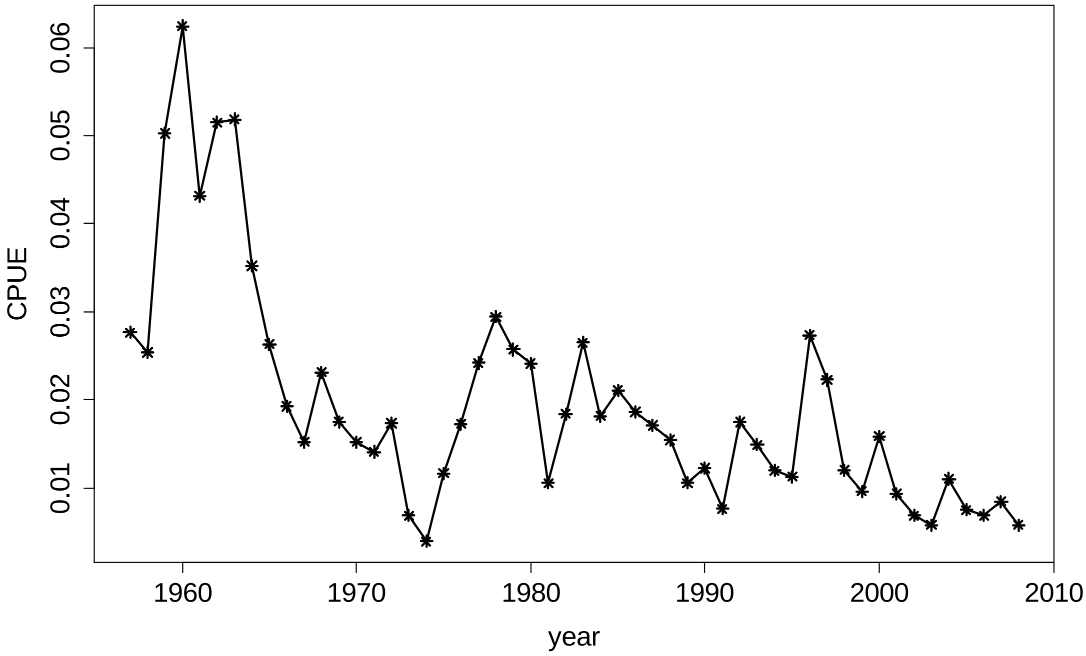

Figure 4-2B. The CPUE time series trajectory of the yellowfin tuna (*T. albacares*) stock in Zone 2. Time series is shown for the years ranging from 1957 to 2008.

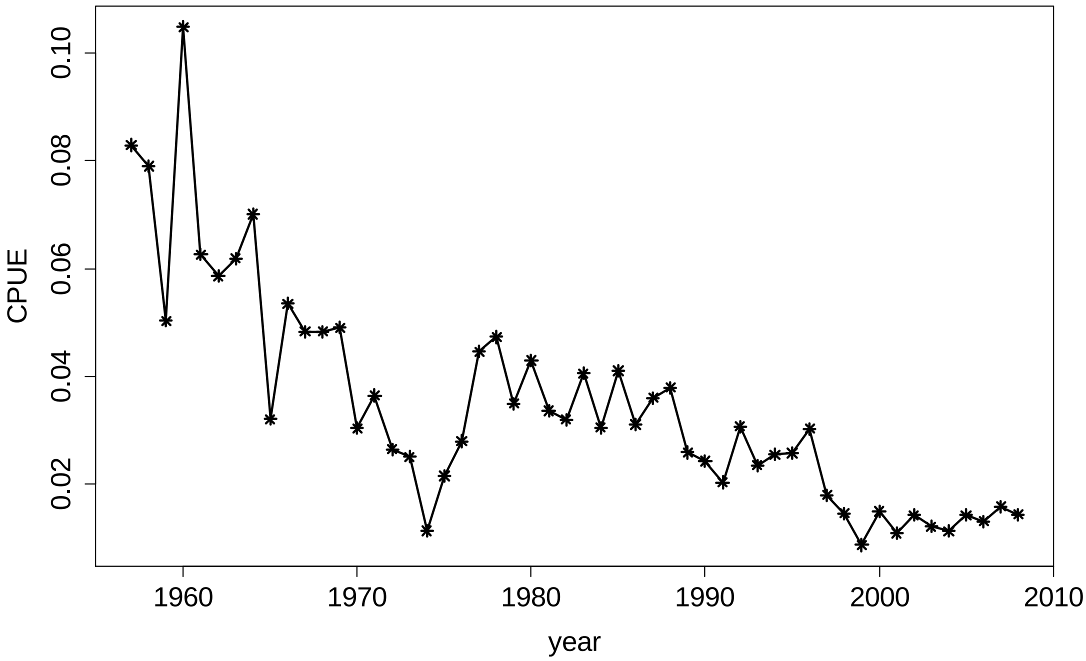

Figure 4-2C. The CPUE time series trajectory of the yellowfin tuna (*T. albacares*) stock in Zone 3. Time series is shown for the years ranging from 1957 to 2008.

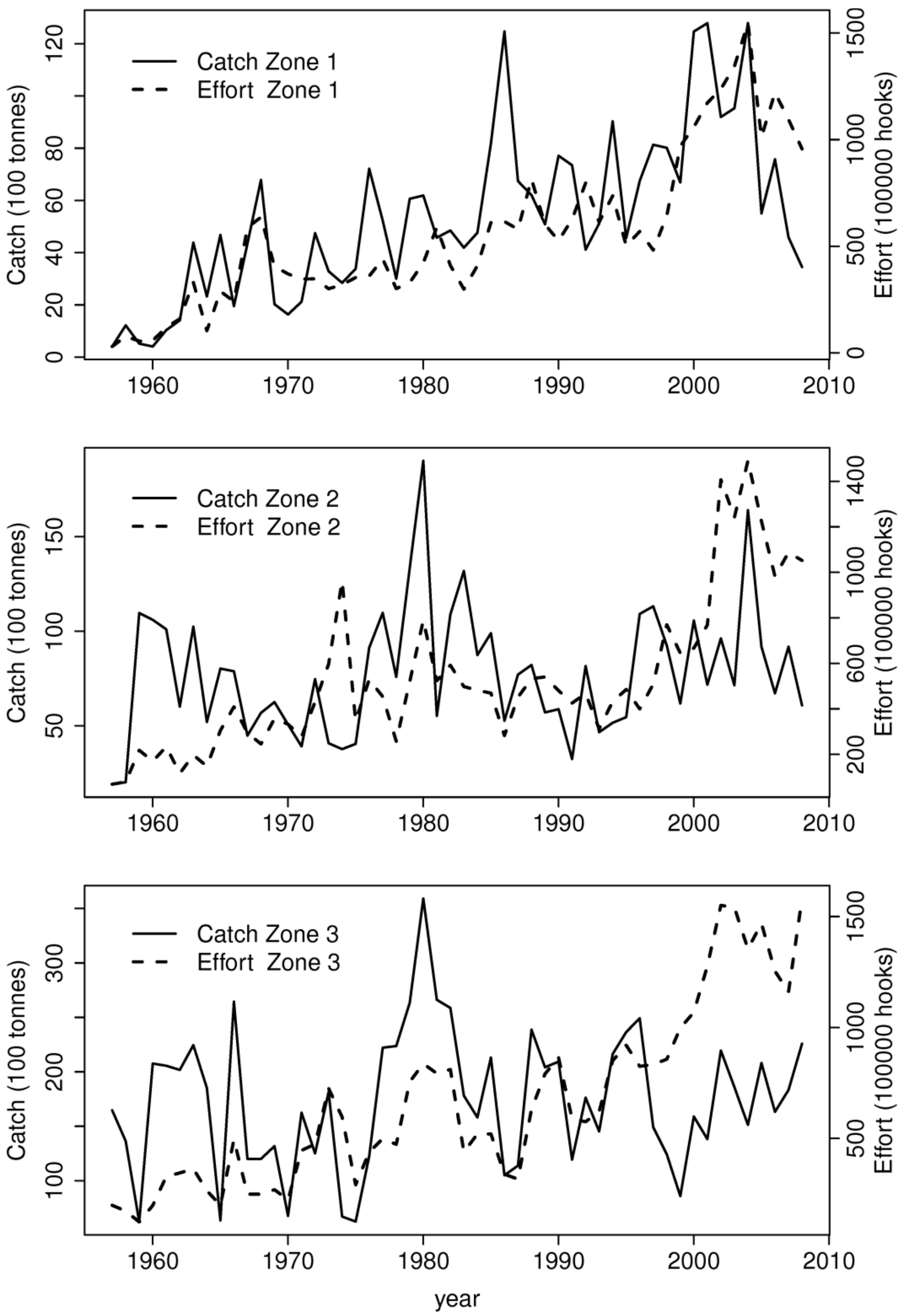

Figure 4-3. The catch and effort time series trajectory of the yellowfin tuna (*T. albacares*) stock in Zone 1, Zone 2 and Zone 3 from 1957-2008. The similarities and differences in the trajectory patterns can be observed.

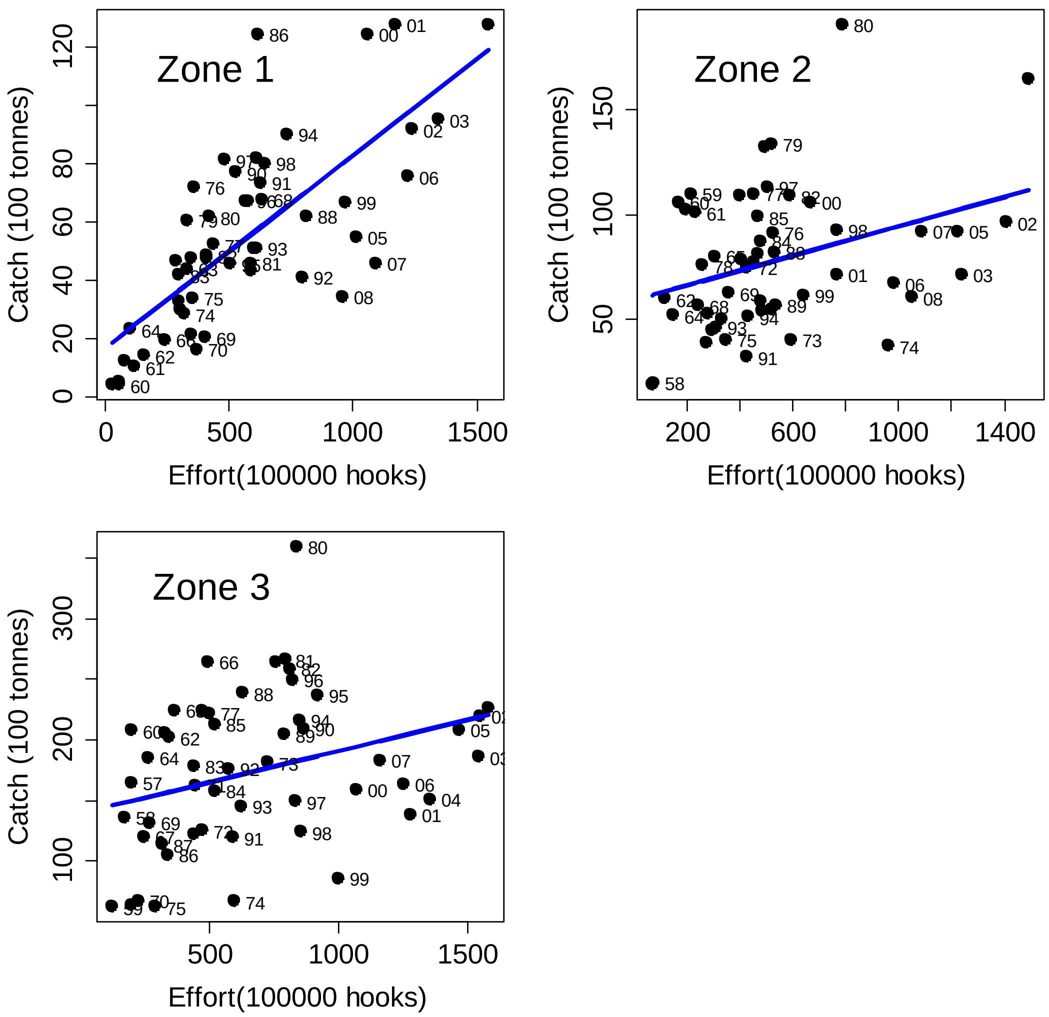

Figure 4-4. The relationship between the catch and effort for the yellowfin tuna (*T. albacares*) stock in Zone 1, Zone 2 and Zone 3 from 1957-2008. The determination coefficients are 0.745, 0.343 and 0.327 respectively.

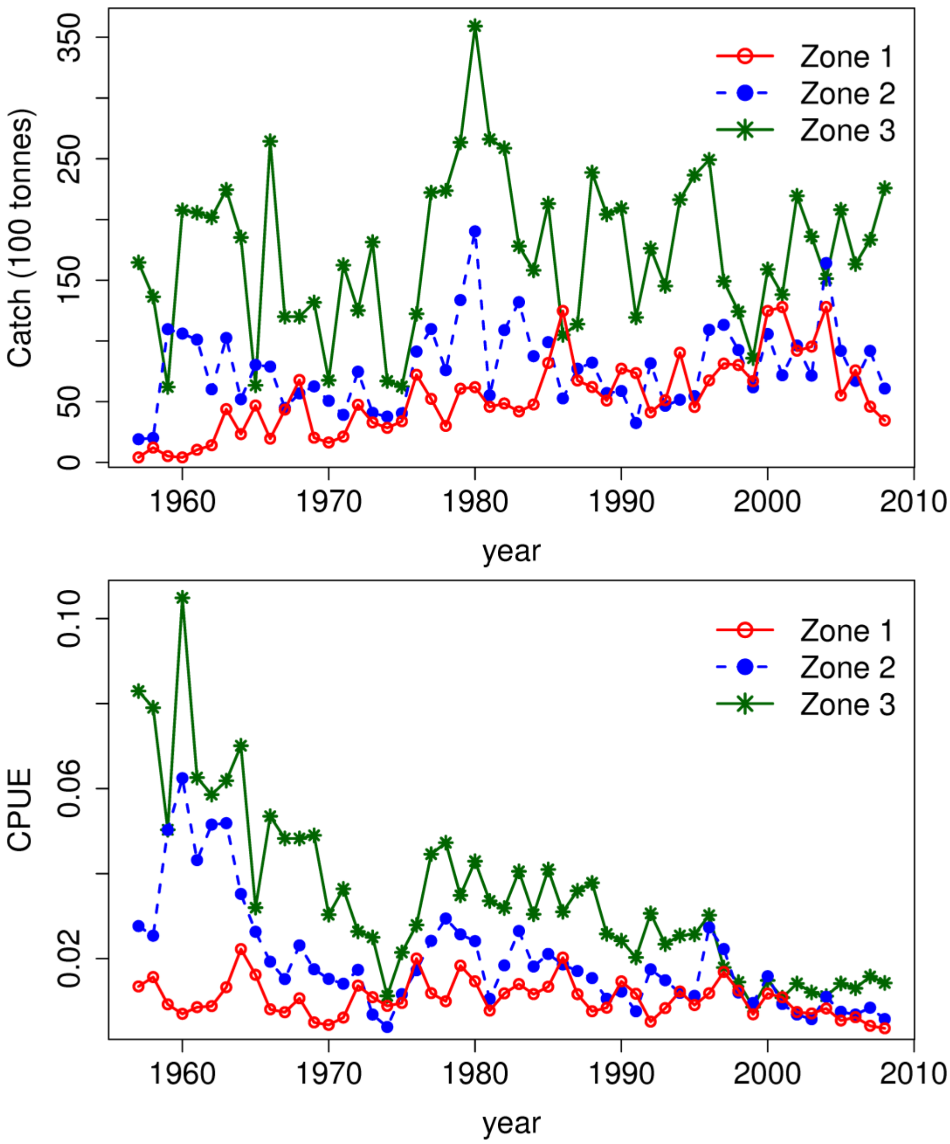

Figure 4-5. The catch and CPUE time series trajectory of the yellowfin tuna (*T. albacares*) stock in Zone 1, 2 and 3from 1957 to 2008. On average, both catch and CPUE magnitudes were highest for Zone 3 followed by Zone 2 and the smallest for Zone 1.

Table 4-1. Regression results for independent climate variables against the yellowfin tuna (*T. albacares*) stock in Zone 1, 2 and 3. Variables exhibiting values with p<0.05 are regarded as significant.

Year	Y_{z1}, L			Y_{z1}, P_s			Y_{z1}, I_a		
	R^2	p-value	AIC	R^2	p-value	AIC	R^2	p-value	AIC
				Zone 1					
t	0.023	2.79×10^{-1}	-415	0.128	9.29×10^{-3}	-422	0.001	7.93×10^{-1}	-415
t-1	0.151	4.37×10^{-3}	-423	0.063	7.31×10^{-2}	-418	0.181	1.67×10^{-3}	-425
t-2	0.090	3.07×10^{-2}	-420	0.006	5.95×10^{-1}	-415	0.008	5.22×10^{-1}	-415
t-3	0.008	5.07×10^{-1}	-415	0.043	1.41×10^{-1}	-417	0.050	1.12×10^{-1}	-417
t-4	0.042	1.43×10^{-1}	-417	0.173	2.16×10^{-3}	-424	0.004	6.73×10^{-1}	-415
t-5	0.091	2.94×10^{-2}	-420	0.083	3.82×10^{-2}	-419	0.047	1.25×10^{-1}	-417
t-6	0.009	4.93×10^{-1}	-415	0.035	1.86×10^{-1}	-416	0.027	2.47×10^{-1}	-416
t-7	0.002	7.57×10^{-1}	-415	0.138	6.77×10^{-3}	-422	0.047	1.26×10^{-1}	-408
t-8	0.176	1.98×10^{-3}	-425	0.119	1.21×10^{-2}	-421	0.023	2.90×10^{-1}	-399
				Zone 2					
	Y_{z2}, L			Y_{z2}, P_n			Y_{z2}, I_j		
t	0.182	1.62×10^{-3}	-310	0.181	1.69×10^{-3}	-310	0.001	8.13×10^{-1}	-300
t-1	0.223	4.03×10^{-4}	-313	0.259	1.19×10^{-4}	-315	0.006	5.87×10^{-1}	-300
t-2	0.192	1.15×10^{-3}	-311	0.297	2.95×10^{-5}	-318	0.020	3.14×10^{-1}	-301
t-3	0.228	3.41×10^{-4}	-313	0.313	1.60×10^{-5}	-319	0.008	5.22×10^{-1}	-300
t-4	0.326	9.91×10^{-6}	-320	0.403	4.39×10^{-7}	-327	0.109	1.66×10^{-2}	-306
t-5	0.295	3.22×10^{-5}	-318	0.398	5.45×10^{-7}	-326	0.082	3.93×10^{-2}	-304
t-6	0.257	1.27×10^{-4}	-315	0.289	3.91×10^{-5}	-318	0.003	2.87×10^{-1}	-301
t-7	0.290	3.83×10^{-5}	-318	0.287	4.26×10^{-5}	-317	0.034	1.94×10^{-1}	-295
t-8	0.337	6.43×10^{-6}	-321	0.296	3.01×10^{-5}	-318	0.047	2.68×10^{-2}	-289
				Zone 3					
	Y_{z3}, L			Y_{z3}, P_n			Y_{z3}, I_q		
t	0.301	2.58×10^{-5}	-271	0.361	2.48×10^{-6}	-275	0.040	1.55×10^{-1}	-254
t-1	0.371	1.64×10^{-6}	-276	0.382	1.04×10^{-6}	-277	0.001	8.87×10^{-1}	-252
t-2	0.355	3.13×10^{-6}	-275	0.467	2.39×10^{-8}	-285	0.115	1.39×10^{-2}	-258
t-3	0.419	2.18×10^{-7}	-280	0.516	2.09×10^{-9}	-290	0.031	2.11×10^{-1}	-254
t-4	0.425	1.65×10^{-7}	-281	0.532	8.62×10^{-10}	-291	0.046	1.26×10^{-1}	-254
t-5	0.353	3.45×10^{-6}	-275	0.438	9.10×10^{-8}	-282	0.034	1.90×10^{-1}	-254
t-6	0.391	7.08×10^{-7}	-278	0.389	7.88×10^{-7}	-278	0.030	2.19×10^{-1}	-254
t-7	0.390	7.41×10^{-7}	-278	0.309	1.91×10^{-5}	-271	0.005	6.19×10^{-1}	-252
t-8	0.465	2.56×10^{-8}	-284	0.392	6.93×10^{-7}	-278	0.024	2.82×10^{-1}	-253

Table 4-2. Results of unit root tests for variables used in regression analysis from **Table 4-1**.

Series	M-test		ADF-test	
	t-value	p-value	t-value	p-value
Y_{z1} 1957-2008	-7.749	5.28×10^{-10}	-7.749	$<1.00\times10^{-2}$
Y_{z2} 1957-2008	-7.851	3.70×10^{-10}	-7.851	$<1.00\times10^{-2}$
Y_{z3} 1957-2008	-11.390	3.02×10^{-15}	-11.390	$<1.00\times10^{-2}$
L 1949-2008	-8.656	6.51×10^{-12}	-8.656	$<1.00\times10^{-2}$
P_s 1949-2008	-13.370	$<2.20\times10^{-16}$	-13.369	$<1.00\times10^{-2}$
P_n 1949-2008	-10.750	3.12×10^{-15}	-10.750	$<1.00\times10^{-2}$
I_a 1951-2008	-9.221	1.11×10^{-12}	-9.221	$<1.00\times10^{-2}$
I_j 1951-2008	-11.546	3.31×10^{-16}	-11.546	$<1.00\times10^{-2}$
I_g 1951-2008	-13.230	$<2.20\times10^{-16}$	-13.230	$<1.00\times10^{-2}$

Table 4-3. Stock reproduction models and some parameters using the independent variables L, P and I from **Table 4-1** for the yellowfin tuna (*T. albacares*) stock in Zone 1, Zone 2 and Zone 3 of the South Pacific Ocean. Values are only shown for statistically most significant model at p<0.05.

	Model	R^2	t-value	p-value	AIC
	Zone 1				
4-i)	$\ln(Y_{z1,t}) = -4.69 + 2.38 \times 10^{-4} \times L_{t-8}^2 - 3.43 \times 10^{-6} \times L_{t-8}^3 - 0.63 \times P_{s,t-4} + 9.31 \times 10^{-2} \times I_{a,t-1}$	0.362	5.326	2.39×10^{-6}	-438
4-ii)	$\ln(Y_{z1,t}) = -4.70 + 2.60 \times 10^{-4} \times L_{t-8}^2 - 3.89 \times 10^{-6} \times L_{t-8}^3 - 0.66 \times P_{s,t-4} + 1.86 \times 10^{-2} \times I_{a,t-1}^3$	0.341	5.090	5.45×10^{-6}	-436
4-iii)	$\ln(Y_{z1,t}) = -4.74 + 2.34 \times 10^{-4} \times L_{t-8}^2 - 3.78 \times 10^{-6} \times L_{t-8}^3 - 0.73 \times P_{s,t-4} + 4.40 \times 10^{-2} \times I_{a,t-1}^2$	0.320	4.845	1.27×10^{-5}	-435
	Zone 2				
4-iv)	$\ln(Y_{z2,t}) = -4.11 - 1.25 \times 10^{-2} \times L_{t-8} + 3.25 \times 10^{-4} \times L_{t-8}^2 + 4.06 \times P_{n,t-4}^2 - 5.68 \times P_{n,t-4}^3 - 5.51 \times 10^{-2} \times (L_{t-8} \times P_{n,t-4}) + 8.48 \times 10^{-2} \times I_{j,t-4}$	0.487	6.893	8.83×10^{-9}	-334
4-v)	$\ln(Y_{z2,t}) = -3.97 - 1.48 \times 10^{-2} \times L_{t-8} + 2.85 \times 10^{-4} \times L_{t-8}^2 - 3.87 \times 10^{-2} \times (L_{t-8} \times P_{n,t-4}) + 0.115 \times I_{j,t-4}$	0.443	6.299	7.49×10^{-8}	-330
4-vi)	$\ln(Y_{z2,t}) = -3.95 - 8.98 \times 10^{-3} \times L_{t-8} - 4.35 \times P_{n,t-4}^3 + 9.20 \times 10^{-2} \times I_{j,t-4}$	0.438	6.238	9.32×10^{-8}	-330
	Zone 3				
4-vii)	$\ln(Y_{z3,t}) = -3.38 - 1.42 \times 10^{-6} \times L_{t-8}^3 - 1.54 \times P_{n,t-4} + 6.37 \times 10^{-2} \times I_{g,t-2}$	0.635	9.323	1.61×10^{-12}	-304
4-viii)	$\ln(Y_{z3,t}) = -3.34 - 9.65 \times 10^{-5} \times L_{t-8}^2 - 1.53 \times P_{n,t-4} + 6.44 \times 10^{-2} \times I_{g,t-2}$	0.624	9.115	3.30×10^{-12}	-303
4-ix)	$\ln(Y_{z3,t}) = -3.39 - 1.55 \times 10^{-4} \times L_{t-8}^2 + 2.87 \times P_{n,t-4}^2 - 10.72 \times P_{n,t-4}^3 + 6.48 \times 10^{-2} \times I_{g,t-2}$	0.573	8.186	8.58×10^{-11}	-296

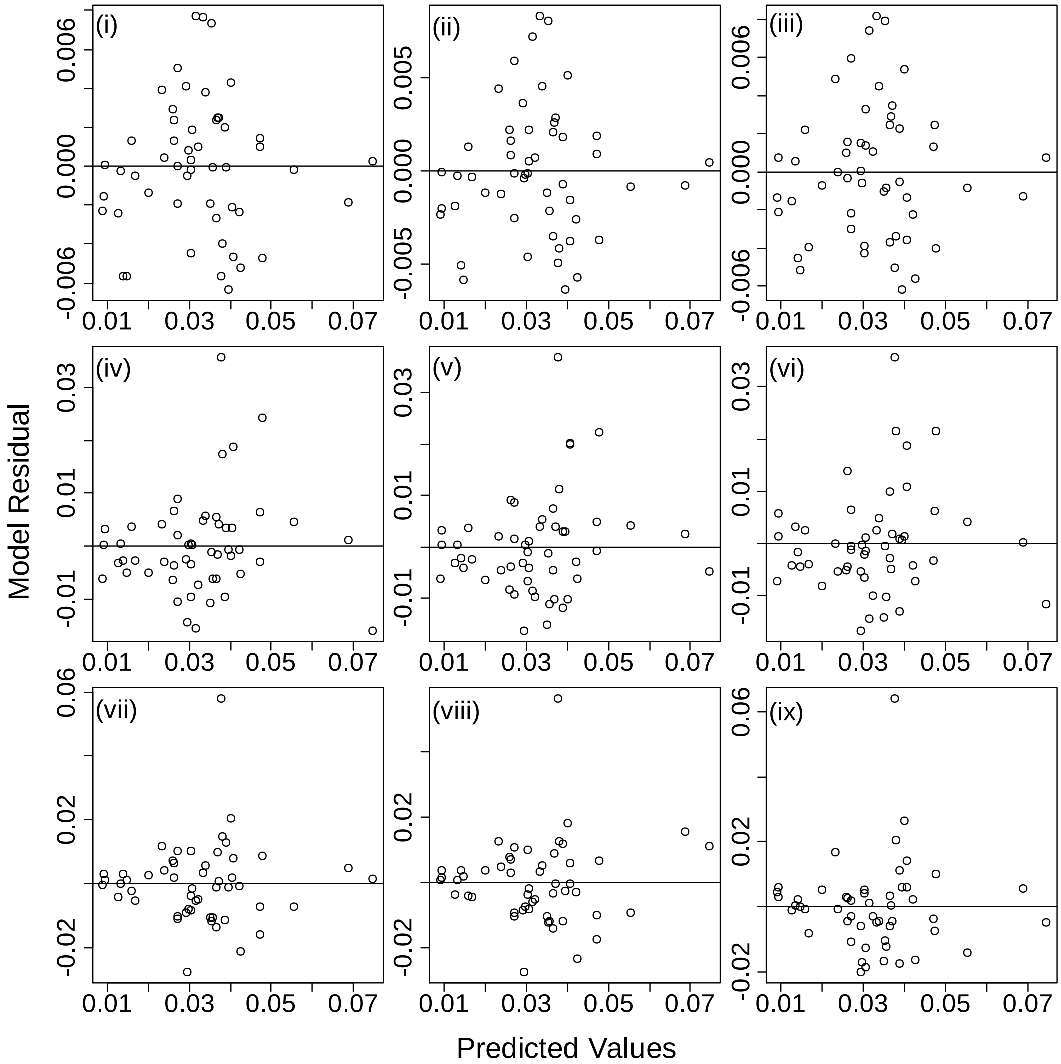

Figure 4-6. The residuals of models from **Table 4-3** against the predicted values. Top panel are for Zone 1, middle panel for Zone 2 and bottom panel for Zone 3. The residual variance in all cases is <0.08.

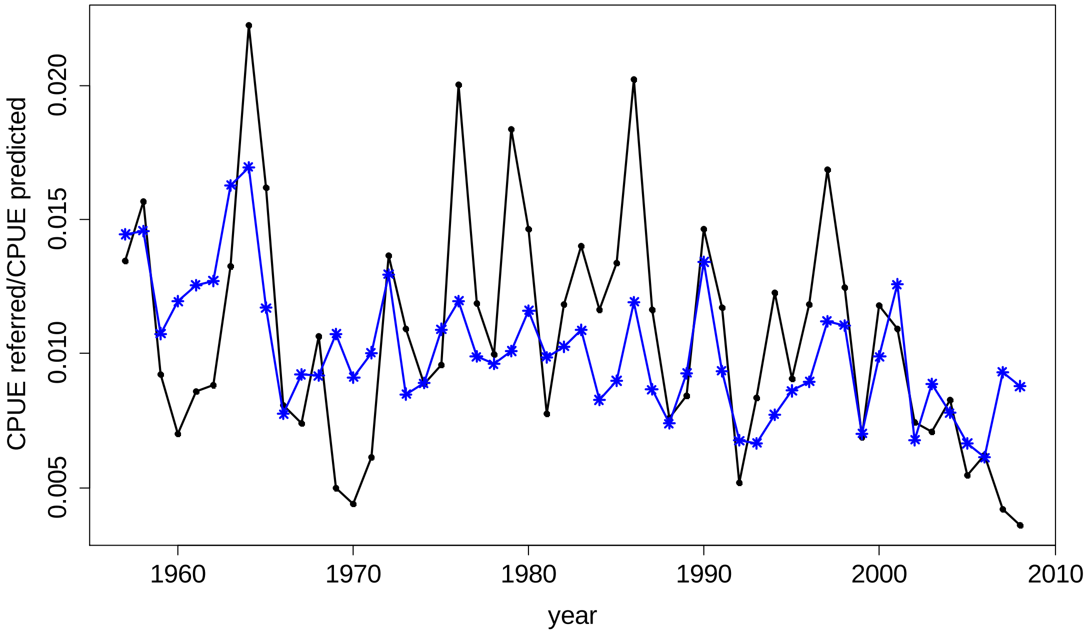

Figure 4-7. Graph showing the CPUE time series trajectory of the yellowfin tuna (*T. albacares*) stock in Zone 1 for the years 1957-2008. The referred CPUE is shown in black and the trajectory which resulted from model **4-i** (**Table 4-3**) is shown in blue.

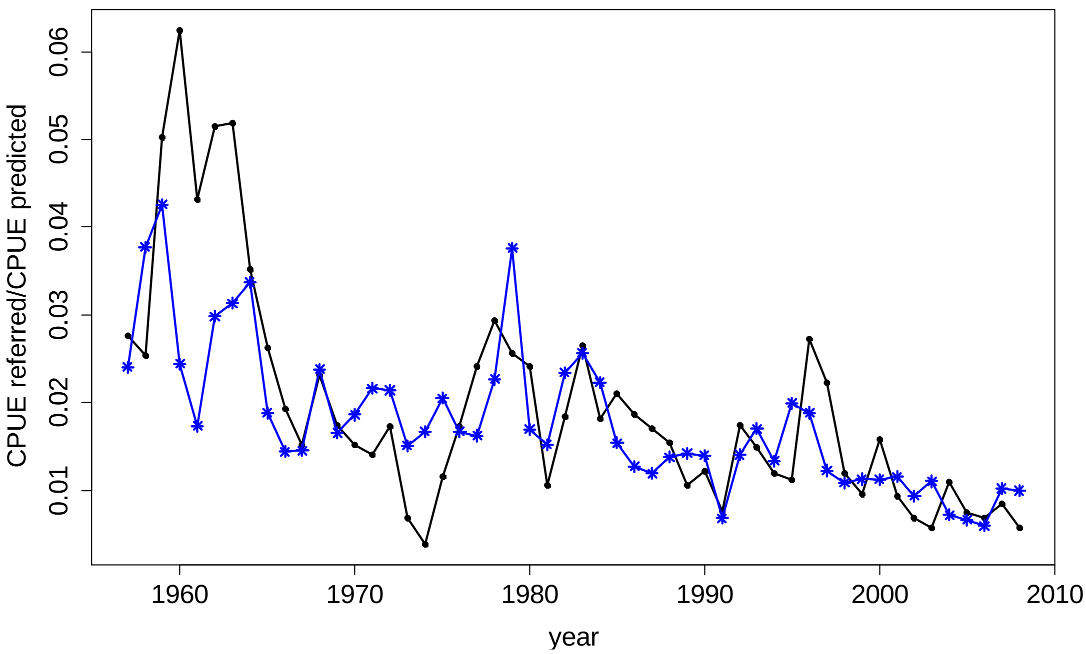

Figure 4-8. Graph showing the CPUE time series trajectory of the yellowfin tuna (*T. albacares*) stock in Zone 2 for the years 1957-2008. The referred CPUE is shown in black and the trajectory which resulted from model **4-iv** (**Table 4-3**)is shown in blue.

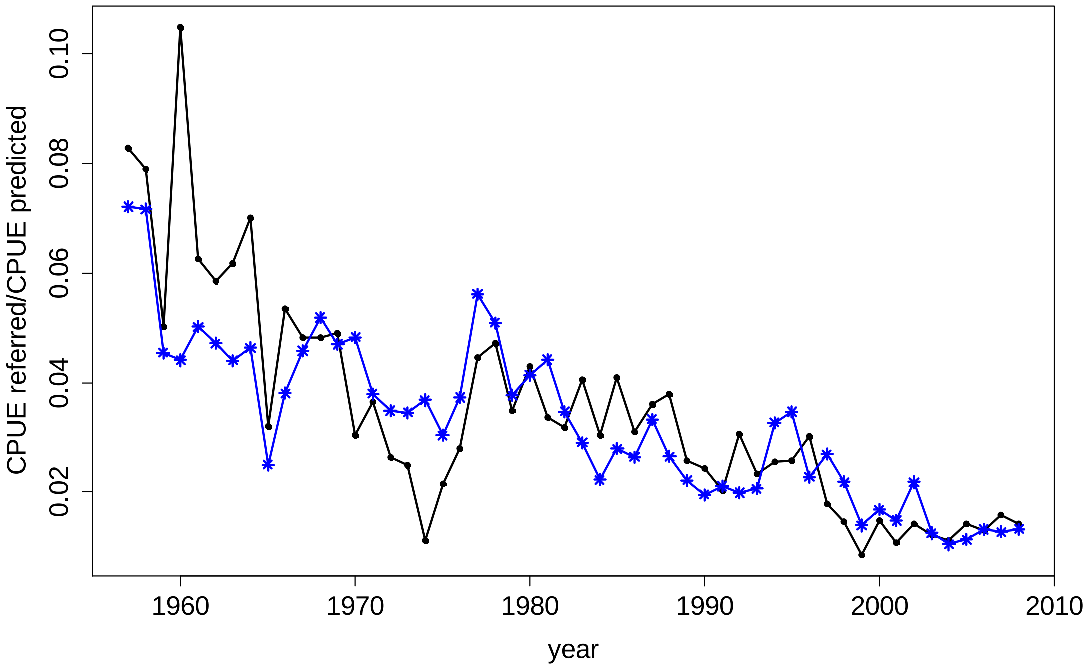

Figure 4-9. Graph showing the CPUE time series trajectory of the yellowfin tuna (*T. albacares*) stock in Zone 3 for the years 1957-2008. The referred CPUE is shown in black and the trajectory which resulted from model **4-vii** (**Table 4-3**) is shown in blue.

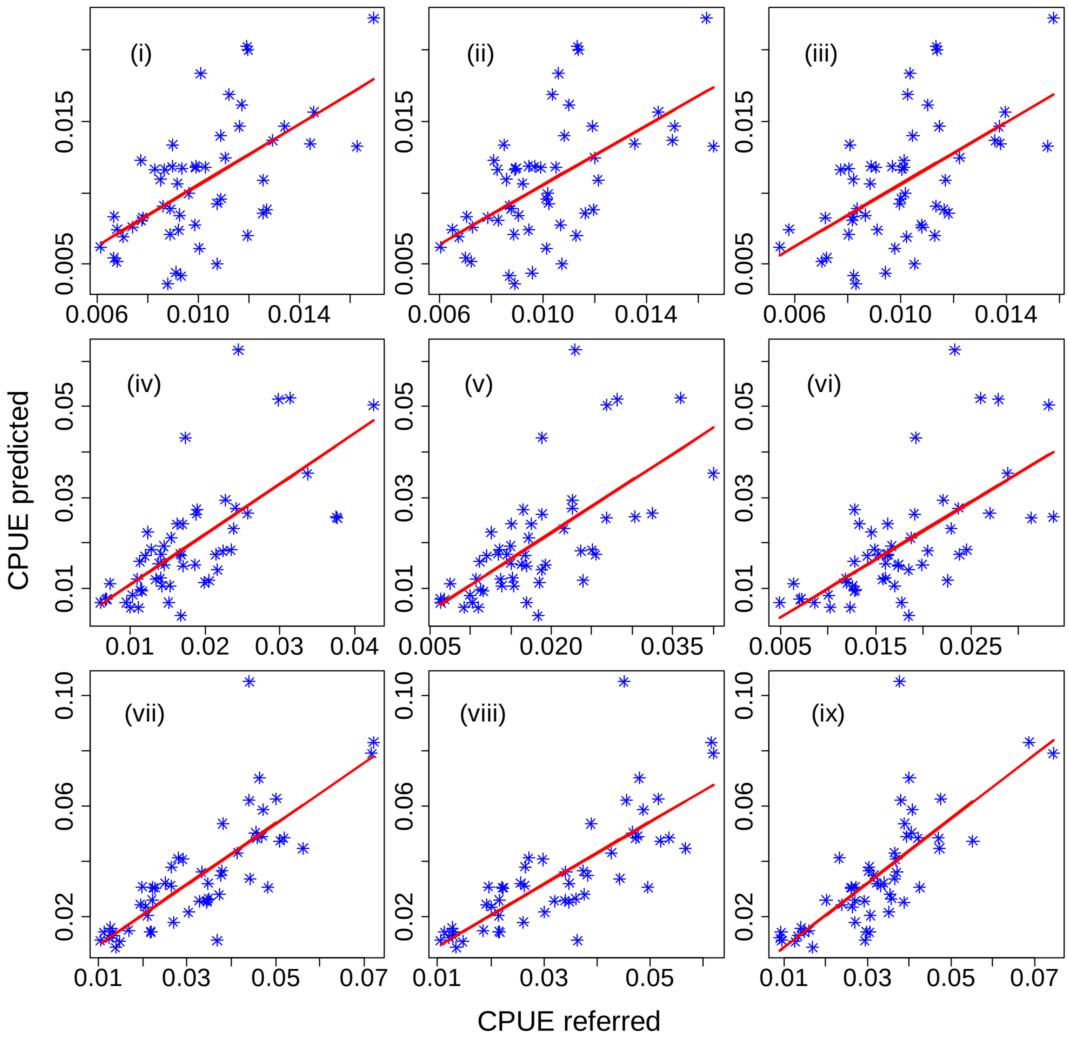

Figure 4-10. The linear relationship between the CPUE predicted and CPUE referred for the yellowfin tuna (*T. albacares*) stock in the South Pacific Ocean Zone 1 (top panel), Zone 2 (middle panel) and Zone 3 (bottom panel). The numbers refer to the models presented in **Table 4-3**.

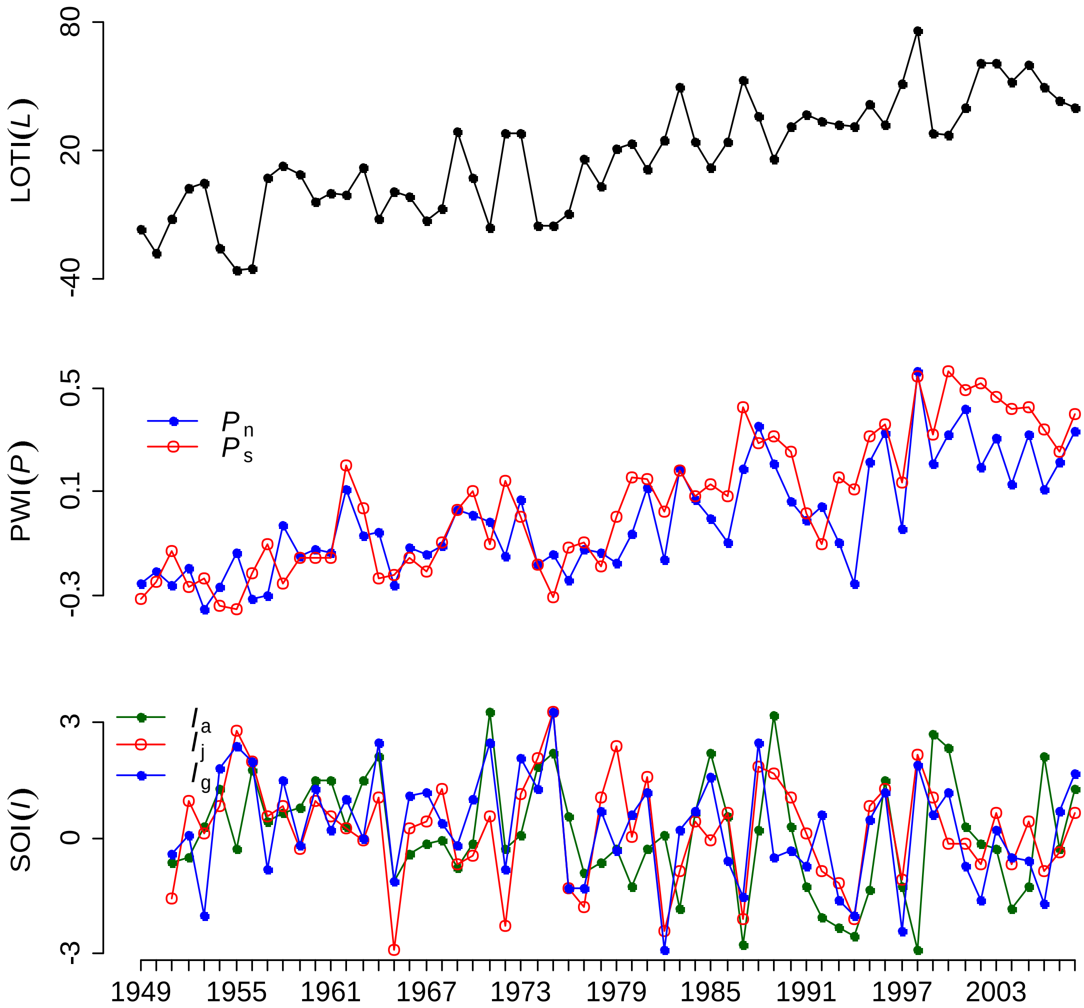

Figure 4-11. Time series pattern of the climatic conditions. Graphs from top; the global mean land and ocean temperature index LOTI for the latitude band 0ºN to 24ºS (*L*), Pacific warm pool index (PWI) for the month of September (P_s) and November (P_n) and Southern Oscillation Index (SOI) for the month of April (I_a), July (I_j) and August (I_g).

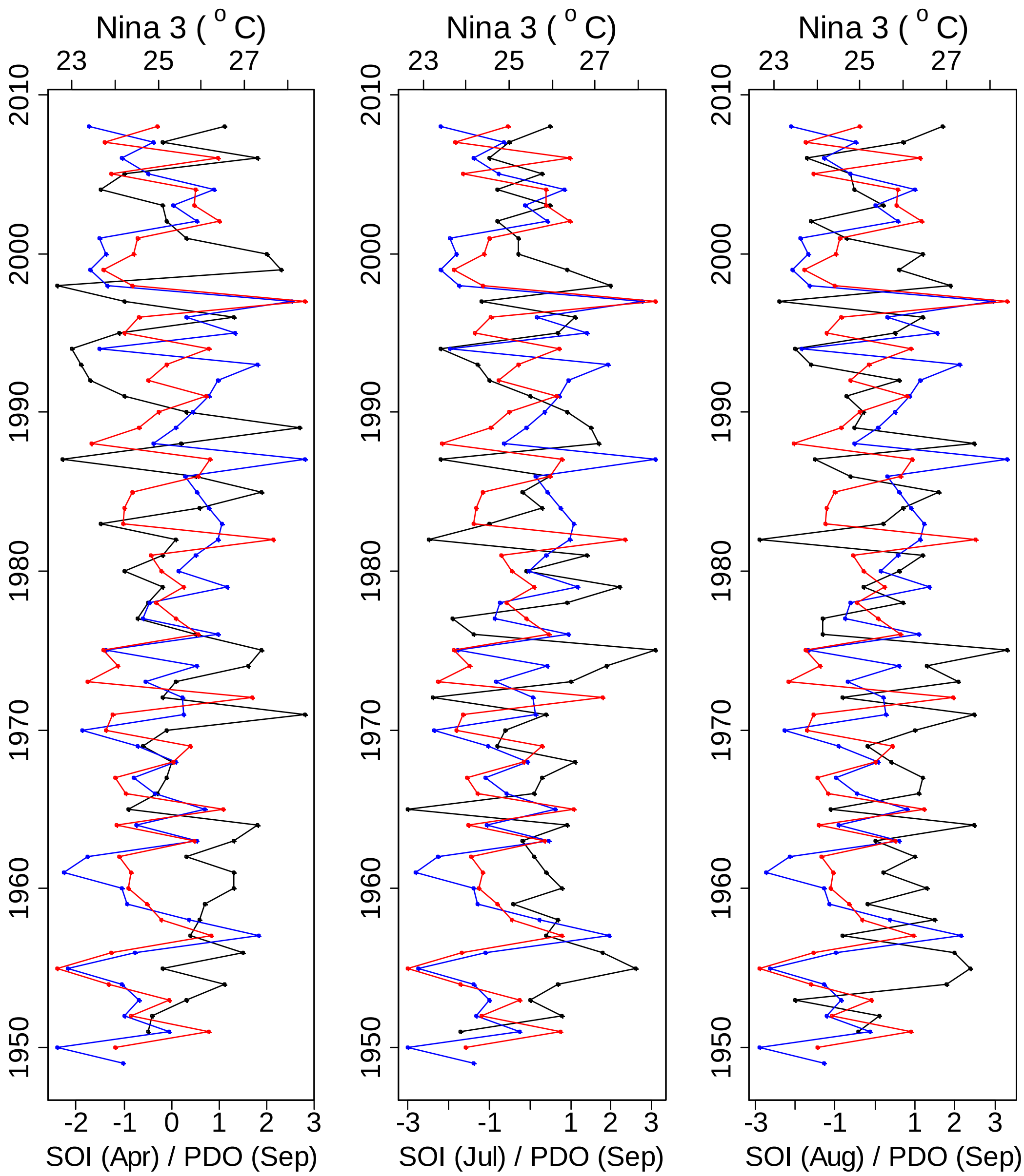

Figure 4-12. Relationship of the SOI incorporated into the models for Zone 1 (I_a), Zone 2 (I_j) and Zone 3 (I_g) (black line) with the climatic conditions of the Pacific Decadal Oscillation (PDO) for the month of September (blue line) and Niña 3 (red line) which is the Eastern Tropical Pacific sea surface temperature (5ºN-5ºS 150ºW-90ºW). SOI exhibits negative relationship with both PDO and Niña 3. La niña episodes occur during positive SOI while El niño events happen during negative SOI.

CHAPTER 5

Impact of Climatic factors on albacore tuna *Thunnus alalunga* in the South Pacific Ocean

Keywords: Albacore tuna, *Thunnus alalunga*, global mean land and ocean temperature index, Pacific warm pool index, Pacific decadal oscillation, catch per unit effort

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5.1. ABSTRACT

Over the years there has been growing interest on the effects of climatic variations on marine biodiversity. The exclusive economic zones of South Pacific Islands and territories are home to major international exploitable stocks of albacore tuna (*Thunnus alalunga*), however the impact of climatic variations on these stocks is not fully understood. This study was aimed at determining the climatic variables which have impact on the time series stock fluctuation pattern of albacore tuna stock in the Eastern and Western South Pacific Ocean which was divided into three zones. The relationship of the climatic variables of the global mean land and ocean temperature index (LOTI), the Pacific warm pool index (PWI) and the Pacific decadal oscillation (PDO) were investigated against the albacore tuna catch per unit effort (CPUE) time series in Zone 1, Zone 2 and Zone 3 of the South Pacific Ocean from 1957-2008. From the results it was observed that LOTI, PWI and PDO at different lag periods exhibited significant correlation with albacore tuna CPUE for all three areas. LOTI, PWI and PDO were used as independent variables to develop suitable stock reproduction models for the trajectory of albacore tuna CPUE in Zone 1, Zone 2 and Zone 3. Model selection was based on Akaike Information Criterion (AIC), R^2 values and significant parameter estimates at p<0.05. The final models for albacore tuna CPUE all three zones incorporated all three independent variables of LOTI, PWI and PDO. From the findings it can be said that the climatic conditions of LOTI, PWI and PDO play significant roles in structuring the stock dynamics of the albacore tuna in the Eastern and Western South Pacific Ocean. It is imperative to take these factors into account when making management decisions for albacore tuna in these areas.

5.2. INTRODUCTION

In the Pacific Ocean, the most dominant fishery can be said to be tuna fisheries for albacore (*Thunnus alalunga*), yellowfin (*Thunnus albacares*), bigeye (*Thunnus obesus*) and skipjack (*Katsuwonus pelamis*) which represent around >90% of the total global tuna harvests (Lehodey *et al.*, 2011). The exclusive economic zone (EEZ) of the Pacific Island countries and territories (PICTs) within the Western and Central Pacific Convention Area Fish (WCPCA) between ~25ºN to 25ºS and 130ºE to 130^{o}W have a coverage area of >27 million km^2 and the economy and food security of most of these PICTs are heavily dependent on oceanic fisheries activities (SPC, 2012a; Bell *et al.*, 2009; Gillett, 2009). Albacore tuna is substantially distributed within the WCPCA and contribute to ~6% of the global tuna catch in recent years (ISSF, 2011; Miyake *et al.*, 2004; Collette and Nauen, 1983). In the Western and Central Pacific Ocean in recent years the total annual catch of albacore tuna has been ~126,000 tonnes with a value of ~USD 342 million. About 50% of these catches originate from the EEZs of PICTs (SPC, 2012a).

Albacore tuna (*Thunnus alalunga*) is a commercially important species of tuna to the economy of various countries in the WCPCA in the South Pacific (Amoe, 2005; Aaheim and Signa, 2000). They are also highly migratory with sexual maturity, age, seasonally and their catch varies both seasonally and spatially (Langley and Hoyle, 2008; Polovina *et al.*, 2001; Jones, 1991). Albacore tuna fisheries has expanded considerably in the South Pacific Ocean with almost three fold increase in catch in the past two decades from 1990 to 2010 (Harley *et al.*, 2011). Even though there has been long history of albacore tuna fisheries in the Pacific Ocean, their ecological characteristics are not sufficiently understood.

The significant role of climatic conditions in structuring the time series trajectory, spatial distribution and biological processes relating to tuna species has been shown previously in (Lehodey *et al.*, 2013). In the Pacific Ocean the projected distribution of yellowfin, skipjack and bigeye tuna within the 21st century is likely shift towards the East in response to alterations in the warm pool and the Pacific Equatorial Divergence (Ganachaud *et al.*, 2013; Lehodey *et al.*, 2013; Le Borgne *et al.*, 2011). Singh *et al.*, (2015) showed that the time series stock trajectory of yellowfin tuna in the Eastern and Western South Pacific was significantly influenced by the climatic conditions of Pacific warm pool index (PWI), global mean land and ocean temperature index (LOTI) and Southern oscillation index (SOI). Polovina *et al.*, (2001) studied the movement of albacore tuna in relation to the movement of the transition zone chlorophyll front in the North Pacific. Albacore tuna stock was shown to follow this chlorophyll front movement which was substantially correlated with El Niño and La Niña events. The relationship of albacore tuna to El Niño and La Niña events has also been shown in Lehodey *et al.*, (2003) and Zainuddin *et al.*, (2004) where albacore shows low recruitment during El Niño and high during La Niña events. Albacore tuna recruitment in the Pacific has been shown to be correlated to the climatic indices of El Niño Southern Oscillation (ENSO) and Pacific Decadal Oscillation (Lehodey *et al.*, 2003). Dufour *et al.*, (2010) studied the feeding migration of the albacore tuna from 1967 to 2005 in the Bay of Biscay in relation to climatic variables. Results showed significant relationship of the albacore tuna to the climatic variables of North Atlantic Oscillation and Northern Hemisphere Temperature Anomaly. It was also shown that long time scales are necessary to detect relationships with environmental and climatic variables.

In the Pacific Ocean the albacore spawning stock and fishing effort are still within sustainable levels, however during the lifespan of the recorded fishery, the stock by weight has gradually declined and in recent years catches have continued to increase with increasing effort (SPC, 2012b). In many cases fisheries management decisions for most fisheries are primarily based on implementing adjustment to the fishing pressure. While this may work for some fisheries and over short periods of time, the concept cannot be generalized across different species and different areas of the globe. Each fishery by species and location are affected by biotic and abiotic factors in different ways. The extent to which these factors impact a fishery differs significantly which makes it fundamental to understand the role of the intrinsic and extrinsic factors affecting the underlying trajectory of a fish stock in order to effectively manage the fishery. The objective of this study is to elucidate which climatic conditions are related to the stock trajectory of the albacore tuna in the Eastern and Western South Pacific Ocean and to which degree. To incorporate these climatic conditions into models and attempt to reconstruct the stock dynamics of albacore tuna in the designated areas.

5.3. MATERIALS AND METHODS

5.3.1. Data

The commission members and cooperating non-members of the Western and Central Pacific Fisheries Commission (WCPFC) provide aggregate, operational and annual tuna catch and effort estimates which the WCPFC uses to compile a public domain version (https://www.wcpfc.int/) of the aggregated catch and effort data. The catch and effort data on albacore tuna (*T. alalunga*) in the Eastern and Western South Pacific from 1957 to 2008 was obtained from the WCPFC public domain data. The stock distribution of albacore tuna data used for this study is shown in **Figure 5-1**.

The albacore tuna data from longline was selected over pole and line and purse seine data as the longline data was most extensive (SPC, 2012b) by time series and the effort was available as the number of hooks which reduced the possibility and extent of observation errors. Also, due to the difference in the type of effort data, pole and line and purse seine data could not be used together with longline data. Monthly summaries of catch numbers, total weights and total number of hooks were georeferenced in 5º longitude and latitude grids and separated into three areas; Zone 1 (2.5ºN – 47.5ºS, 162.5ºW – 152.5ºW, 7.5ºS – 47.5ºS, 152.5ºW – 132.5ºW), Zone 2 (2.5ºN – 47.5ºS, 172.5ºE – 162.5ºW) and Zone 3 (2.5ºN – 47.5ºS, 147.5ºE – 172.5ºE) (**Figure 5-1)**. Annual albacore tuna catch and effort was calculated from aggregated longline monthly data by geographical coordinates for Zone 1, Zone 2 and Zone 3. The catch per unit effort (CPUE) was calculated from the catch and effort data for the three areas with the catch data being in tonnes and effort as the number of hooks (**Figure 5-2A**, **Figure 5-2B** and **Figure 5-2C**). It was important to treat albacore tuna data for Zone 1, Zone 2 and Zone 3 as three different stocks as the total area was too large for any one stock and exploratory analysis showed differences in catch and CPUE patterns and magnitudes and catch and effort relationships for the three areas.

In **Figure 5-2A** the fluctuation pattern for the albacore tuna CPUE time series in Zone 1 for the years 1957 to 2008 can be seen. There is an increasing trend for the years 1957-1960, 1964-1966, 1972-1974 1975-1978, 1981-1983, 1984-1986, 1990-1992, 1995-1998, and 2000-2002 and from 1960-1964, 1966-1969, 1970-1972, 1986-1990, 1992-1995, 1998-2000 and 2002-2004 a decreasing trend can be observed with the highest peak in 1960 and the lowest point in 1995. CPUE is distinctively high from 1958-1962 with a sharp decline from 1960-1964. For Zone 2 (**Figure 5-2B**) the trajectory of albacore tuna has an increasing trend for the years 1965-1967, 1974-1976, 1979-1981, 1984-1986, 1989-1991, 1995-1997 and 2004-2006 with a decreasing trend for the years 1967-1974, 1991-1993, 1997-2000, 2001-2004 and 2006-2008. The CPUE is at its highest peak in 1962 with sharp declines from 1960-1963 and 1967-1974 with the lowest values in 1974, 1979, 1982, 1984 and 1989. **Figure 5-2C** shows the trajectory of albacore tuna in Zone 3 where an increasing trend can be observed from 1957-1959, 1968-1970, 1976-1978, 1996-1998, 2003-2006 with a decreasing trend from 1961-1964, 1970-1972, 1978-1982, 1983-1985 and 1986-1990. The highest peaks can be observed in 1959 and 1970 with sharp declines from 1959 to 1964 and 1970 to 1974. Zone 1 and Zone 2 CPUE trajectory for albacore tuna have more similarities compared with Zone 3 which is more chaotic in contrast.

The climatic data for the global mean land and ocean temperature index (LOTI) for the latitude band 44ºS to 64ºS was obtained from the National Aeronautics and Space Administration (NASA), Goddard Institute for Space studies, Goddard Space Flight Center, Science and Exploration Directorate, Earth Science Division (http://data.giss.nasa.gov/gistemp) from 1952 to 2008. The LOTI data was calculated on monthly basis by combining and using data files from National Oceanic and Atmospheric Administration (NOAA) Global Historical Climatology Network v3 for meteorological stations, Extended Reconstructed Sea Surface Temperature for ocean areas and Scientific Committee on Antarctic Research for Antarctic stations as outlined in Hansen *et al.*, (2010). The calculated monthly data on Pacific warm pool index (PWI) and Pacific decadal oscillation (PDO) was obtained from the NOAA, Earth System Research Laboratory, Physical Sciences Division (http://www.esrl.noaa.gov) from 1952 to 2008.

5.3.2. Exploratory analysis and unit root test

Regression analysis was applied to identify if relationships existed between the dependent variables of albacore tuna CPUE in Zone 1 (Y_{z1}), Zone 2 (Y_{z2}) and Zone 3 (Y_{z3}) against the climatic independent variables of LOTI (L), PWI (P) and PDO (O). Monthly and annual L, P and O were tested against Y_{z1}, Y_{z2}, and Y_{z3} at t-n years where n=0, 1,…,5 since the age of most of the stock harvested in the Pacific Ocean ranges between 2-4 years old (Wells *et al.*, 2013; Chen *et al.*, 2012; ALBWG, 2011). Results with $p<0.05$ were considered as significant relationships. To avoid violations of assumptions from the statistical techniques utilized, the protocol for data exploration was followed as in Zurr *et al.*, (2010). As outlined in Zurr *et al.*, (2010), all selected variables were tested for the presence of outliers using scatterplots and boxplots and as well as for correlations among independent variables. Results with coefficient of correlation with $R>0.500$ were considered as significant.

When certain variations in a time series have transient effects and do not permanently alter the trend of the time series, the trend is classified as being stationary. When variations or shocks permanently alter the time series, the trend is classified as stochastic and having a unit root. The presence of a unit root in a time series can result in specious correlations among variables (Kwiatkowski *et al.*, 1992; Dickey and Fuller, 1979). The independent variables which exhibited significance correlation with the dependent variables as well as the albacore tuna CPUE in Zone 1, Zone 2 and Zone 3 were analyzed to confirm whether any of the time series data were a non-stationary process with the Augmented Dickey-Fuller and MacKinnons unit root test (MacKinnon, 1996; Kwiatkowski *et al.*, 1992; Dickey and Fuller, 1979).

5.3.3. Stock reproduction model

Independent variables which exhibited significant relationship at $p<0.05$ and lowest AIC values with albacore tuna CPUE from exploratory analysis for each climatic condition were incorporated in the development of stock reproduction models of the albacore tuna CPUE in the South Pacific Zone 1, Zone 2 and Zone 3. The objective was to construct a stock reproduction model which can reconstruct the albacore tuna CPUE trajectory using climatic data as independent variables at $p<0.05$. The Generalized Linear Model (GLM) was used as parent formula for the stock reproduction model for Y_{z1}, Y_{z2} and Y_{z3} as shown in Equation (1)

$$\ln\left(Y_{zi,t}\right) = \ln(\alpha_0) + \alpha_{1,n}s_{1,t-n} + \alpha_{2,n}s_{2,t-n} + \cdots + \alpha_{k,n}s_{k,t-n} + \varepsilon_{zi,t} \qquad (1)$$

where $Y_{zi,t}$ is the CPUE of albacore tuna in the South Pacific region, z is the distribution zone with i = 1, 2, 3, α_0 is the parameter for the intercept, $\alpha_1, \alpha_2, \ldots, \alpha_k$ are parameter estimates, $s_1, s_2, \ldots, s_k$ are the independent climatic variables with k = 1, 2 and 3, t is the year with n= 0, 1,…,5 and $\varepsilon_{zi,t}$ is an unsolved normally distributed random variable.

The response surface methodology (RSM) is a set of statistical and mathematical techniques which uses linear and polynomial functions to incorporate independent variables into mathematical and statistical models to describe a system or data which is under study (Myers *et al.*, 2009; Bezerra *et al.*, 2008; Buchanan and Phillips, 1990; Box and Behnken, 1960). RSM was used to transform Equation (1) by incorporation of second and third order polynomials to determine if variables could be better fit with this technique (Equation 2).

$$\ln\left(Y_{zi,t}\right) = \ln(\alpha_0) + \alpha_{1,q,n}s_{1,t-n}^{q} + \alpha_{2,q,n}s_{2,t-n}^{q} + \cdots + \alpha_{k,q,n}s_{k,t-n}^{q} + \varepsilon_{zi,t} \qquad (2)$$

where q =1, 2 and 3. Log transformation of the dependent variable and y-intercept were done to reduce the effects of outliers and skewness. For Equation (1) and Equation (2), independent variables were investigated in various combinations by successive elimination to identify suitable models for reconstructing the trajectory of the albacore tuna stock in Zone 1, Zone 2 and Zone 3. Tests for the homogeneity of variance of the residuals of the model against the fitted values were performed. The least square estimators would be significantly degraded if the range of variance were ≥4.00 (Fox, 2008). Akaike Information Criterion (AIC) and R^2 values at $p<0.05$ were used for model selection criteria (Akaike, 1981). The predicted and referred trajectory of the albacore tuna CPUE in Zone 1, Zone 2 and Zone 3 were plotted. The statistical software "R", version 3.0.1 was used to perform all statistical analysis for this study (R Core Team, 2014).

5.4. RESULTS

5.4.1. Catch and effort trajectory

From **Figure 5-3** the catch and effort for albacore tuna in the South Pacific Zone 1, Zone 2 and Zone 3 show similar trajectory patterns. The linear relationship of the albacore tuna catch and effort in all three areas are shown in **Figure 5-4**. The points below the slope mostly refer to the years where the CPUE was low and the points above the slope mostly refer to the years where the CPUE high. In **Figure 5-4**, the further (closer) the points disperse from the slope, the lower (higher) the correlation between the catch and effort. For Zone 2 and Zone 3 the catch and effort correlate strongly with most of the points lying close to the slope line. For Zone 1, the relationship of the effort although significant, is much weaker in comparison to Zone 2 and Zone 3. The determination coefficients for Zone 1, Zone 2 and Zone 3 are 0.544, 0.786 and 0.884 respectively which makes it evident that the catch dynamics of albacore tuna in Zone 1, Zone 2 and Zone 3 are influenced significantly at varying degrees by the fishing effort which makes the catch trend unsuitable for trend analysis. For this study we decided to use the CPUE as it standardizes the effort with reference to catch and is a more suitable representative of the albacore tuna stock dynamics which will enable better trend analysis and determination of relationships with independent variables.

In **Figure 5-5** the differences and similarities between the catch and CPUE of albacore tuna in Zone 1, Zone 2 and Zone 3 can be observed. The catch levels fluctuate around similar magnitudes from 1957 to around 2000 and from around 2000 the catch levels begin to diverge and by 2008 there is significantly large difference in catch among the three zones with Zone 3 being the largest followed by Zone 2 and the least being for Zone 1. Between 1958 to 1962 significantly large differences can be observed in the CPUE magnitudes for the three areas with Zone 1 being the largest followed by Zone 2 and the lowest being for Zone 3. From around 1970 the CPUE for the three zones becomes synonimous until 2008.

Although the catch magnitudes are quite different from around the year 2000 the CPUE for the three zones remains constant.

5.4.2. Exploratory analysis and unit root test

The results for regression analysis of the albacore tuna CPUE in the South Pacific Zone 1, Zone 2 and Zone 3 against independent variables of climatic conditions for the years t-n (n=0, 1,…,5) are presented in **Table 5-1**. The results only include the variables which exhibited highest correlations according to the R^2 and AIC values at p<0.05. LOTI for the latitude band 44ºS to 64ºS (L), PWI for the month of February (P_f) and November (P_n) and PDO for the month of February (O_f) and March (O_m) had significant correlations with the dependent variables of Y_{z1}, Y_{z2} and Y_{z3}. LOTI exhibited strongest correlation with a lag of t-1 year for all three zones with PWI exhibiting most significant correlations at t-2 in all three cases with P_n for Y_{z1} and Y_{z2} and at P_f for Y_{z3}. PDO had most significant correlation at t-4 for all three zones with O_f for Y_{z1} and Y_{z3} and O_m for Y_{z2}. These independent variables made ecological sense as they geographically relate to the data coverage area for Zone 1, Zone 2 and Zone 3.

In **Figure 5-6** the boxplots show the spread of the albacore tuna CPUE for Zone 1, Zone 2 and Zone 3 and the climatic variables from **Table 5-1**. Some relatively high values can be observed for the CPUE in the three Zones, especially for Zone 1 where a single high value is way outside the range of the rest of the data. However, these values should not be labeled as outliers without further exploration (Zurr *et al.*, 2010). To identify whether outliers are present in the CPUE data, scatter plots of the catch and effort data used in the calculation of the CPUE were presented. It can be seen from **Figure 5-6** that the catch and effort values are not unusually large or small. Due to this and the large sets of data that were used to calculate the annual catch and effort, the likelihood of observation and process errors are greatly minimized and it is safe to assume that the CPUE values which extend outside the boxplot range are not outliers but authentic values.

Spurious correlations may sometimes arise when regression analysis is used. Unit root test which is a statistical method to identify cases of unauthentic correlations (MacKinnon, 1996; Kwiatkowski *et al.*, 1992; Dickey and Fuller, 1979) was performed for all the time series the data used in this study. **Table 5-2** shows the results for MacKinnon's test (M-test) and Augmented Dickey-Fuller test (ADF-test). Time-series have a stationary process if they exhibit t-test value (t-value) <0 at $p<0.05$. The tests showed that all the variables showed stationarity and did not have a unit root process and the relationships presented in **Table 5-1** are non-spurious.

5.4.3. Stock reproduction model

Table 5-3 shows the results of incorporating the independent climatic variables from **Table 5-1** into stock reproduction models for the CPUE of the albacore tuna in the South Pacific Zone 1, Zone 2 and Zone 3. Models with highest R^2 and lowest AIC values at $p<0.05$ are shown for each zone. Model (i) had the highest R^2 and lowest AIC value for albacore tuna in Zone 1 which incorporates the variables $L_{t\text{-}1}$, $P_{n,t\text{-}2}$ and $O_{f,t\text{-}4}$. For the albacore tuna in Zone 2 model (iv) was the most suitable according to the highest R^2 and lowest AIC value which incorporated the variables $L_{t\text{-}1}$, $P_{n,t\text{-}2}$ and $O_{m,t\text{-}4}$. For Zone 3, model (vii) is the most suitable and it incorporates the independent variables $L_{t\text{-}1}$, $P_{f,t\text{-}2}$ and $O_{f,t\text{-}4}$ (**Table 5-3**).

There were no significantly high correlations observed for the collinearity tests among the independent variables incorporated into the models in **Table 5-3**. According to the results of homogeneity tests all model residuals shown in **Tables 5-3** have a variance of <0.09 as shown in **Figure 5-7** which fulfilled the requirements of homogeneity where in order for the least square estimators to be reliable the variance needs to be <4.00 (Fox, 2008).

The plot of Zone 1 albacore tuna CPUE and the estimated CPUE trajectory from model **5-i** (**Table 5-3**) can be seen in **Figure 5-8**. Similarly the plot of the referred and forecasted CPUE of the albacore tuna in Zone 2 from model **5-iv** can be seen in **Figure 5-9**. For Zone 3 the albacore predicted CPUE from model **5-vii** and referred CPUE can be seen in **Figure 5-10**. For Zone 1 and Zone 2 the referred CPUE has strong fitness with the predicted CPUE compared to Zone 3 where although significant, the predicted CPUE has much weaker fitness with referred CPUE. **Figure 5-11** shows the linear correlations of the referred and predicted albacore tuna CPUE in Zone 1, Zone 2 and Zone 3 from the models presented in **Table 5-3**. For models **5-i**, **5-iv** and **5-vii** the determination coefficients of the referred CPUE to the CPUE predicted (**Table 5-3**, **Figure 5-11**) are 0.889, 0.884 and 0.453 respectively. For **Figure 5-11**(i) the slope is 1.431 with 95% confidence interval of (1.222, 1.641), for **Figure 5-11**(iv) the slope is 1.027 with 95% confidence interval of (0.873, 1.182) and for **Figure 5-11**(vii) the slope is 1.123 with 95% confidence interval of (0.494, 1.752). These values show that the slopes in all three cases are either close to or not significantly different from unity which as indication of significant impact of the independent variables on the albacore tuna stock trajectory in the South Pacific Ocean.

The fluctuation patterns for the independent variables *L*, *P* and *O* time series which showed significant relationships with the dependent variable from **Table 5-1** and resulted in statistically significant models for the albacore tuna in the South Pacific Zone 1, Zone 2 and Zone 3 from **Table 5-3** are shown in **Figure 5-12**. While LOTI exhibits a gradually increasing pattern from 1952 to 1977 from which point it fluctuates approximately parallel to the x-axis up to 2008. PWI shows a gradual increasing pattern throughout the time series while PDO on average seems to run parallel to the x-axis with different averages between 1952 to 1976 and 1977 to 2008. PDO is a climatic condition which is related to the climatic condition of Southern Oscillation Index (SOI) and El Niño and La Niña events. Indeed exploratory analysis showed the correlation of the PDO incorporated into the final models for albacore tuna in Zone 1 , Zone 2 and Zone 3 (O_f and O_m) with SOI for the month of March and February and Niña 3 which is the Eastern Tropical Pacific sea surface temperature for the area (5ºN-5ºS, 150ºW-90ºW) (**Figure 5-13**). From the three climatic conditions only PDO was used for modeling as it was interrelated to SOI and Niña 3 and was the most significant among the three variables.

5.5. DISCUSSION

This study was undertaken to determine the impact of climatic variables on the stock trajectory of the albacore tuna (*T. alalunga*) in the Eastern and Western South Pacific Ocean Zone 1, Zone 2 and Zone 3 (**Figure 5-1**). From **Figure 5-2A** and **Figure 5-2B** it can be seen that the CPUE in Zone 1 and Zone 2 was significantly higher in the early 1960s for Zone 1 and up to late 1960s for Zone 2 compared to the later decades where the CPUE has remained somewhat stable at lower levels. For Zone 3, (**Figure 5-2C**) the CPUE has more chaotic behavior in comparison to Zone 2 and Zone 3 but does not show significant change over the time series. From **Figure 5-5** it can be observed that although the catch magnitudes among the three zones are quite different after the year 2000 the CPUE remains constant and synonymous which can be an indication that the stock levels in the South Pacific are still within sustainable limits which has also been stated in SPC, (2012b). However, this does not guarantee sustainable albacore harvests for the future. From **Figure 5-3** it can be observed that from the early 1990s the catch and effort have increased at an explosive rate for albacore tuna in all three zones. This behavior combined with the significant impact of the climatic conditions (**Table 5-3**) shown in this study poses a significant threat to the sustainability of the stock which can cause reduced CPUE of albacore tuna fishery where progressively higher efforts will be needed to maintain certain levels of catch which may not be economically viable leading to low supplies and higher prices of the catch.

We used CPUE for analysis in this study as it is a more suitable representative of albacore tuna stock time series compared to catch which we have shown to be significantly correlated to effort levels (**Figure 5-4**). For CPUE the effort is standardized with the underlying assumption that the strength of each unit of effort remains constant over the time series which is reasonable as the effort for the time series utilized in this study has been recorded as the number of hooks. There can be some argument regarding this that even though the efforts are recorded as the number of hooks, technological development such as fish finders, better navigation, better hooks and lines might have increased the effort efficiency over time (Bigelow *et al.*, 2002). However, due to unavailability of such information we will accept the underlying assumption of albacore tuna effort for this study.

The results show that the climatic conditions of LOTI, PWI and PDO influence the albacore tuna stock trajectory in the South Pacific Zone 1, Zone 2 and Zone 3 and the models incorporating these variables exhibit significant fitness to the response variables (**Table 5-3**, **Figure 5-8**, **Figure 5-9**, **Figure 5-10**). LOTI is the index of the global land and sea surface air temperature with the latitude band of 44ºS to 64ºS (*L*) incorporated into the final models. This latitude band is of ecological significance as it cuts across and overlaps with the data coverage area, however their impact on albacore tuna stock is probably indirect in nature affecting intrinsic factors which more directly relate to the stock. LOTI has most significant fitness with albacore tuna stock trajectory in Zone 1, Zone 2 and Zone 3 with a lag of *t*-1 year (**Table 5-3**). Albacore tuna in the Pacific Ocean recruit to surface fisheries when they are about 2 years old and while age at catch range from 1 to 15 years most of the stock is harvested when the stock is between 2-4 years old (Wells *et al.*, 2013; Chen *et al.*, 2012; ALBWG, 2011). Ramon and Bailey, (1996) have shown that spawning by mature albacore tuna takes place in the South Pacific tropical and subtropical latitude band of 10ºS to 25ºS and the recruitment of the juveniles occurs after one year at around 40ºS in New Zealand waters. Chen *et al.*, (2005) showed that the SST, chlorophyll concentration and surface salinity requirement differed between the different developmental stages of the albacore tuna in the Indian Ocean from 1979 to 1985. From this it can be inferred that LOTI has indirect impact at the post-recruitment life stages of albacore tuna affecting factors such as prey stock levels, distribution as well as other factors relating to the ecological requirements of albacore tuna.

PWI is the water temperature index of a certain oceanic area in the Pacific Ocean which tends to be warmer than the rest of the ocean area. PWI for the month of November has most significant fit with albacore tuna trajectory in Zone 1 and Zone 2 and the month of February for Zone 3 with a lag of *t*-2 years in all three cases (**Table 5-3**). Zainuddin *et al.*, (2006) studied the relationship of the albacore tuna catch data from 1998 to 2003 in the North Pacific Ocean (30ºN to 40ºN) with sea surface temperature (SST) using remote sensing satellite images and chlorophyll-a concentration. Results showed that high albacore CPUE occurred in areas with high chlorophyll-a concentrations which was related to warm SST and catches were highest for the month of November from 1998 to 2003. Dufour *et al.*, (2010) showed that the feeding migration of the offshore longitudinal distribution of albacore tuna in the Bay of Biscay was related the warmer 17ºC isotherm longitude from 1967 to 2005. Farley *et al.*, (2012) showed that the peak spawning of albacore tuna in the South Pacific Ocean occurred from October to December from 2006 to 2011. Tuna has been projected to relocate from the West of 170ºE to the East of 170ºW of the Pacific Ocean within the 21st century following the more productive and preferred water temperatures of the Warm pool and Pacific Equatorial Divergence Province (Bell *et al.*, 2013; Ganachaud *et al.*, 2013; SPC, 2012a; Le Borgne *et al.*, 2011; Ganachaud *et al.*, 2011; Lehodey *et al.*, 2011). PWI most likely affects the prey abundance and distribution as well as the spawning stages for the younger portion of the albacore tuna stock harvests in the South Pacific Ocean where major part of the harvested stock ranges between 2-4 years olds (ALBWG, 2011).

The PDO has been described as the El Niño like pattern of the North Pacific SST variability North of 20ºN (Deser *et al.*, 2004; Mantua *et al.*, 1997; Zhang *et al.*, 1997). The effect of the PDO is spread Pacific wide where during the positive phase the South Pacific and central North Pacific gyres cool and the equatorial region and Eastern margin become warm and *vice versa* over decadal time scales (Linsley *et al.*, 2015). Linsley *et al.*, (2015) showed the strong association of the PDO with alterations in the upper oceanic heat of the South Pacific Ocean between 0.5ºS – 89.5ºS and 64ºW – 147ºE which falls within the albacore tuna distribution for Zone 1, Zone 2 and Zone 3 (**Figure 5-1**). Also, the spawning zone for the albacore tuna between 10ºS and 25ºS in the South Pacific Ocean is geolocated within the coverage area of Zone 1, Zone 2 and Zone 3 (Farley *et al.*, 2012; Ramon and Bailey, 1996). Lehodey *et al.*, (2015) showed a significant link between the changes in the Oceanic temperature and albacore tuna spawning in the Eastern and Western South Pacific between 5ºN – 55ºS and 140ºE – 80ºW. PDO for the month of February fits most significantly with albacore tuna CPUE in Zone 1 and Zone 3 and in the month of March for Zone 2 with a lag of *t*-4 year for all three zones. Since most of the albacore tuna harvests in the Pacific Ocean are 2-4 years olds (ALBWG, 2011), it can be assumed that PDO affects the spawning and early life stages of the albacore tuna in the Eastern and Western South Pacific Ocean. Lehodey *et al.*, (2003) showed that the time series pattern for the South Pacific albacore tuna from the early 1960s to 2000 was related to the PDO time series trajectory. The relationship of El Niño and La Niña events and the related ENSO and SOI have been shown to be correlated to tuna stocks in the Pacific Oceans previously (Zainuddin *et al.*, 2004; Lehodey *et al.*, 2003; Polovina *et al.*, 2001). Indeed, exploratory analysis did show significant relationship between PDO, SOI and Niña 3 with El Niño events dominating during high Niña 3 SST and La Niña events dominating during low Niña 3 SST (**Figure 5-13**).

When comparing the correlation of the referred CPUE to the predicted CPUE for Zone 1, Zone 2 and Zone 3 from **Figure 5-11**, the slopes are either close to or not significantly different from unity, which accentuates that the climatic variables of LOTI, PWI and PDO incorporated into the models can reproduce a significant proportion of the albacore tuna stock trajectory in the three zones and that these climatic variables are responsible for a considerable portion of the fluctuation pattern of albacore tuna stock. The equation below represents the time series trajectory of albacore tuna in the South Pacific Zone 1, Zone 2 and Zone 3 written as

$$Y_{zi,t} = f(a_{1,t-n}, a_{2,t-n}, \cdots, a_{k,t-n}) \tag{3}$$

where $Y_{zi,t}$ is the CPUE in the coverage zone zi with i = 1, 2 and 3, in year t and f () is the function determined by the abiotic climatic factors a_i (i = 1, 2,…, k) with lag period of n where n= (0, 1,…,5). Equation (3) shows the relationship which is followed for the albacore tuna stock through the climatic factors in the South Pacific Zone 1, Zone 2 and Zone 3.

For albacore tuna in Zone 1 the fitted models with climatic condition of LOTI, PWI and PDO were most significant, followed closely by the fitted models for Zone 2 (**Table 5-3** and **Figure 5-11**). For Zone 3, although the fitted models were significant, their fitness was much lower in comparison to Zone 1 and Zone 2 models. When we compare the relationship of the catch and effort from **Figure 5-3** and **Figure 5-4**, it is noted the relationship gets higher in significance from Zone 1 to Zone 2 with Zone 3 having the highest correlation. From **Figure 5-4** and **Figure 5-11** the further (closer) the points disperse from the slope the higher (lower) the bias between the predicted and referred CPUE and the catch and effort relationship. From this phenomenon it can be stated that the better proportion of the albacore tuna time series trajectory for Zone 1 is influenced by the climatic conditions of LOTI, PWI and PDO followed closely by Zone 2 and at a much lower level by Zone 3. This harmonizes with the catch and effort relationship where the catch trajectory for Zone 3 is determined to a great extent by the effort followed by Zone 2 with the catch and effort relationship in Zone 1 being much lower in comparison to Zone 2 and Zone 3. With this argument it can be said that the stock characteristics of albacore tuna in Zone 1 is markedly different from Zone 2 and Zone 3. As we move from the Eastern to the Western South Pacific Ocean the influence of LOTI, PWI and PDO on albacore tuna stock gets more prominent.

Tuna stocks in the tropical Pacific Ocean is presently seen as healthy, however continuous increase in fishing effort and can present challenges for sustainable management (SPC, 2012b; Rice and Garcia, 2011). A common misconception in many fisheries management is that the stock trajectory of a fish is mainly due to the applied fishing pressure, however as the results of this study shows that there may be a variety of biotic and abiotic factors acting together resulting in the stock dynamics of a fish species. Although fishing pressure probably does influence the stock trajectory of a given fishery, it should not be used as the only factor for the management of fisheries populations. Unavailability of data on various biotic and abiotic factors relating to the complex food web of tuna species in the Pacific Ocean poses challenges and creates gaps in knowledge (Ganachaud *et al.*, 2013; Le Borgne *et al.*, 2011) for deducing and understanding the mechanisms by which climatic conditions affect these populations. In some cases the structure such as observer programs for collection of such data are already in place and offer an opportunity to collect such data as explained in Nicol *et al.*, (2013). For the albacore tuna stock in the Eastern and Western South Pacific Ocean Zone 1, Zone 2 and Zone 3, it is recommended that when management decisions are made for albacore tuna fishery in these areas, the influence of the climatic conditions of LOTI, PWI and PDO should be taken into consideration and further research should be directed at understanding the mechanism by which these climatic conditions influence the stock of albacore tuna for better management of the fishery.

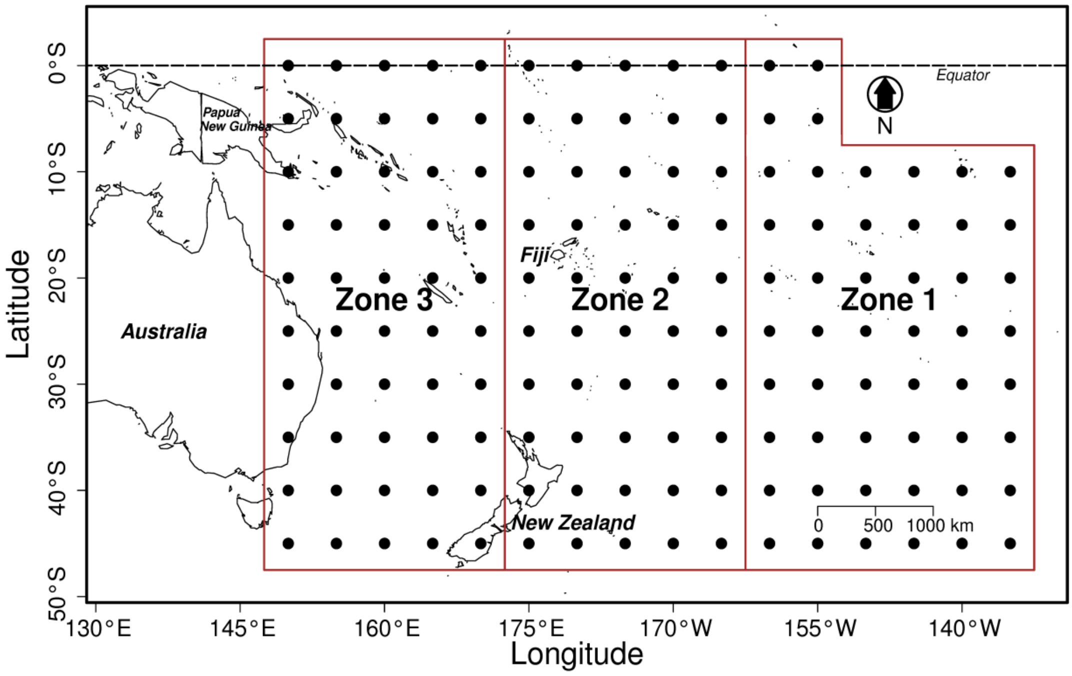

Figure 5-1. Map showing the stock distribution of the albacore tuna (*T. alalunga*) in the Eastern and Western South Pacific Ocean. The study area was divided into Zone 1, Zone 2 and Zone 3 shown by the enclosure polygons and the black circles represent the data distribution in 5º by 5º geographical grids.

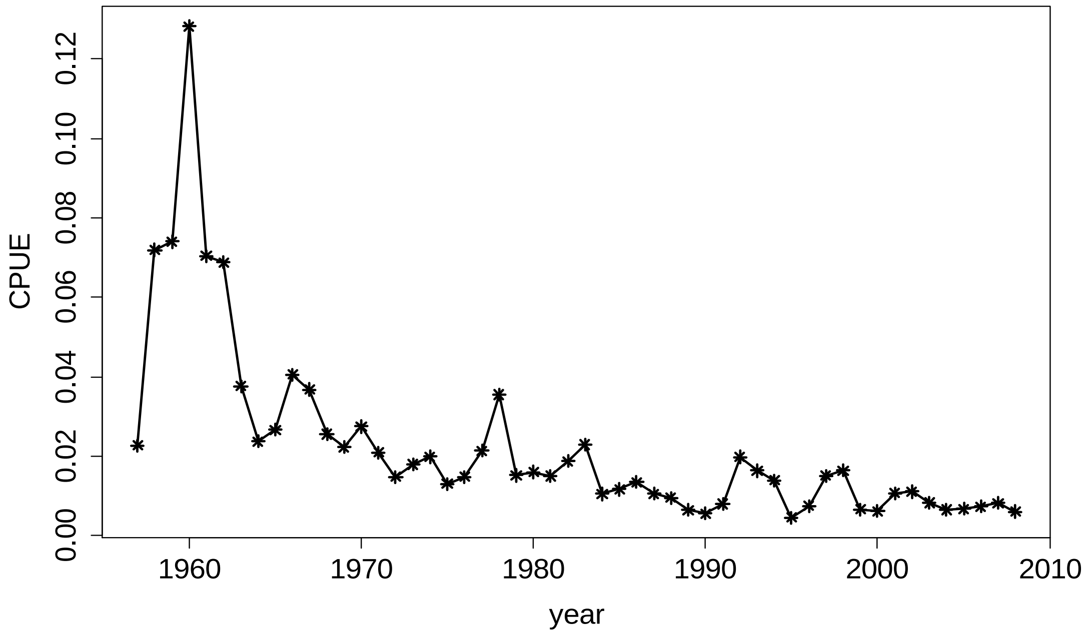

Figure 5-2A. The CPUE time series trajectory of the albacore tuna (*T. alalunga*) stock in Zone 1 for the years ranging from 1957-2008.

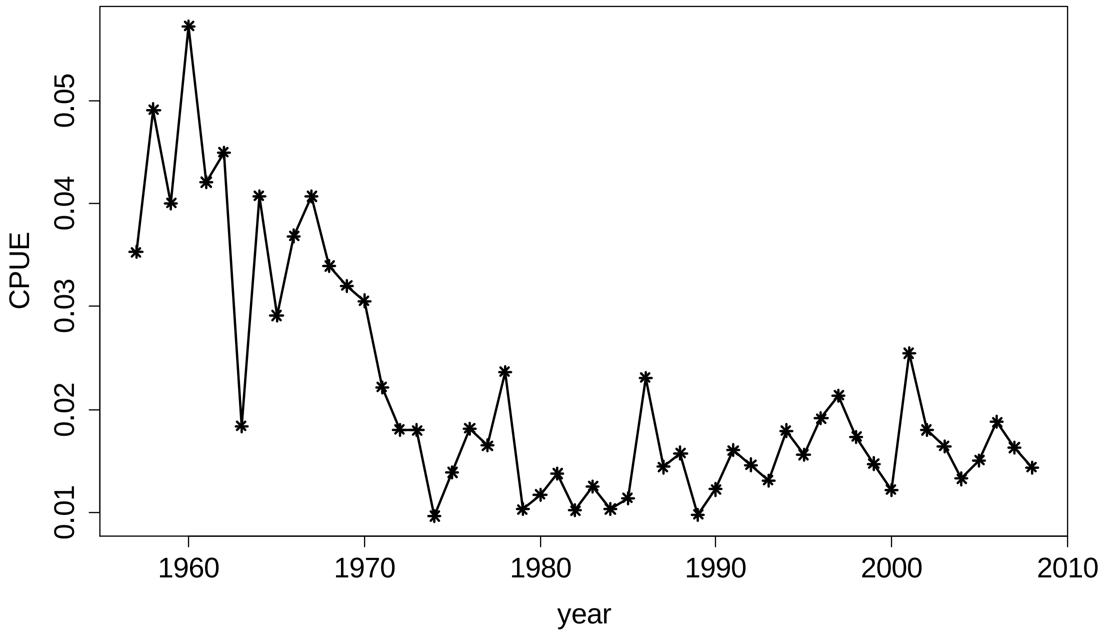

Figure 5-2B. The CPUE time series trajectory of the albacore tuna (*T. alalunga*) stock in Zone 2 for the years ranging from 1957-2008.

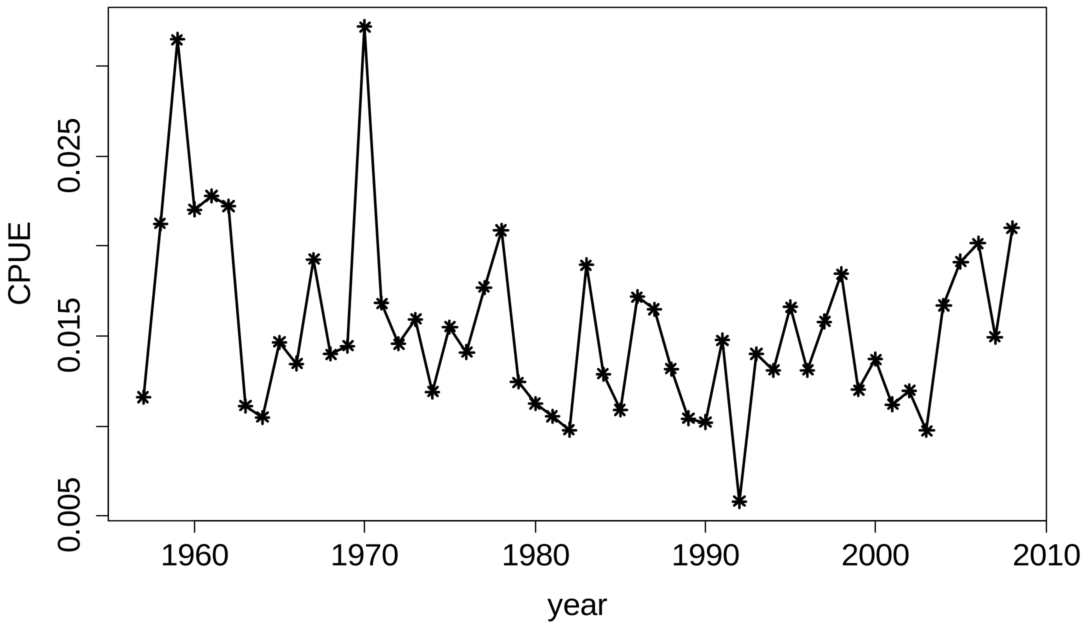

Figure 5-2C. The CPUE time series trajectory of the albacore tuna (*T. alalunga*) stock in Zone 3 for the years ranging from 1957-2008.

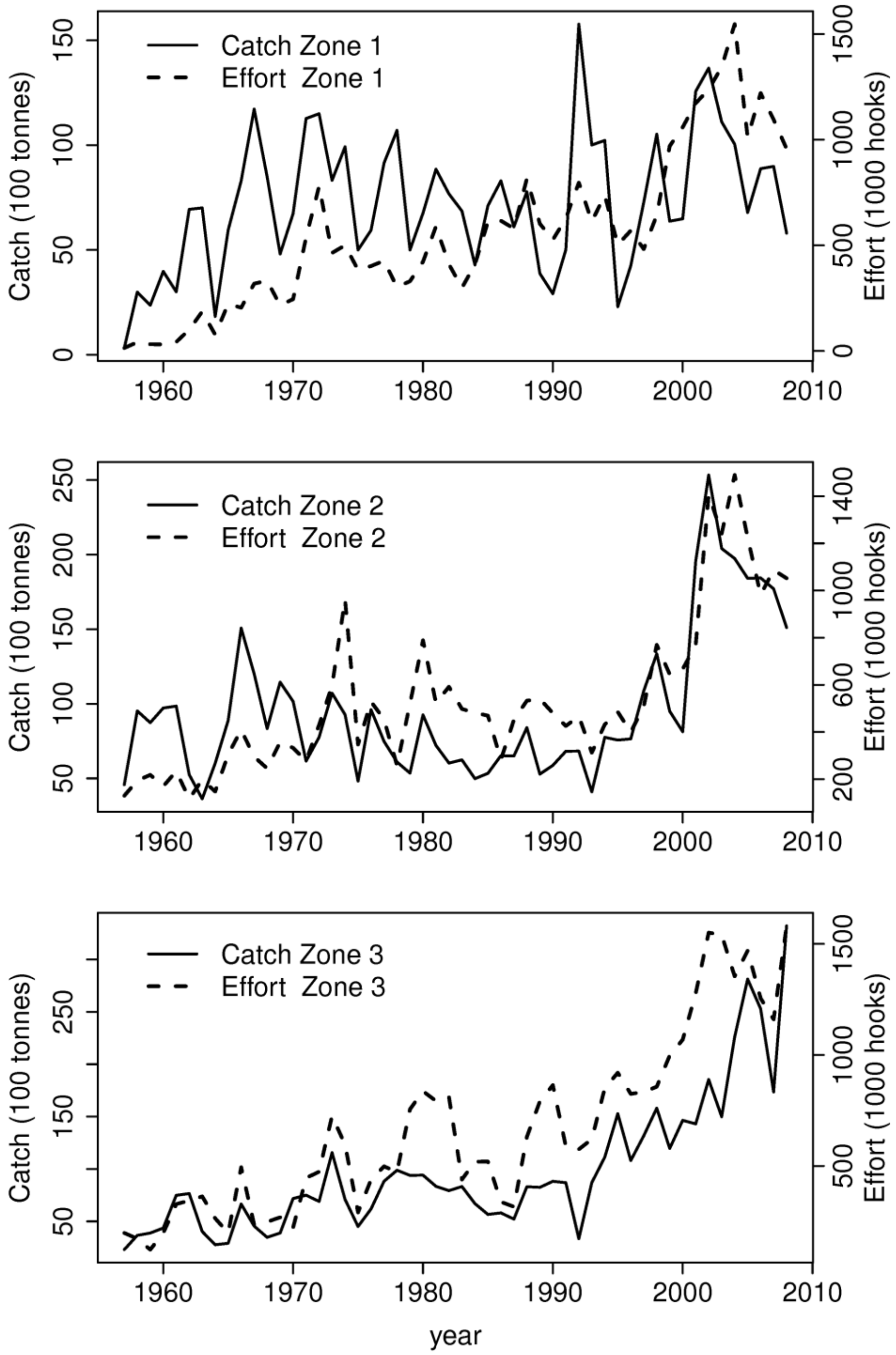

Figure 5-3. The catch and effort time series trajectory of the albacore tuna (*T. alalunga*) stock in Zone 1, Zone 2 and Zone 3 from 1957-2008. The similarities and differences in the time series patterns can be observed.

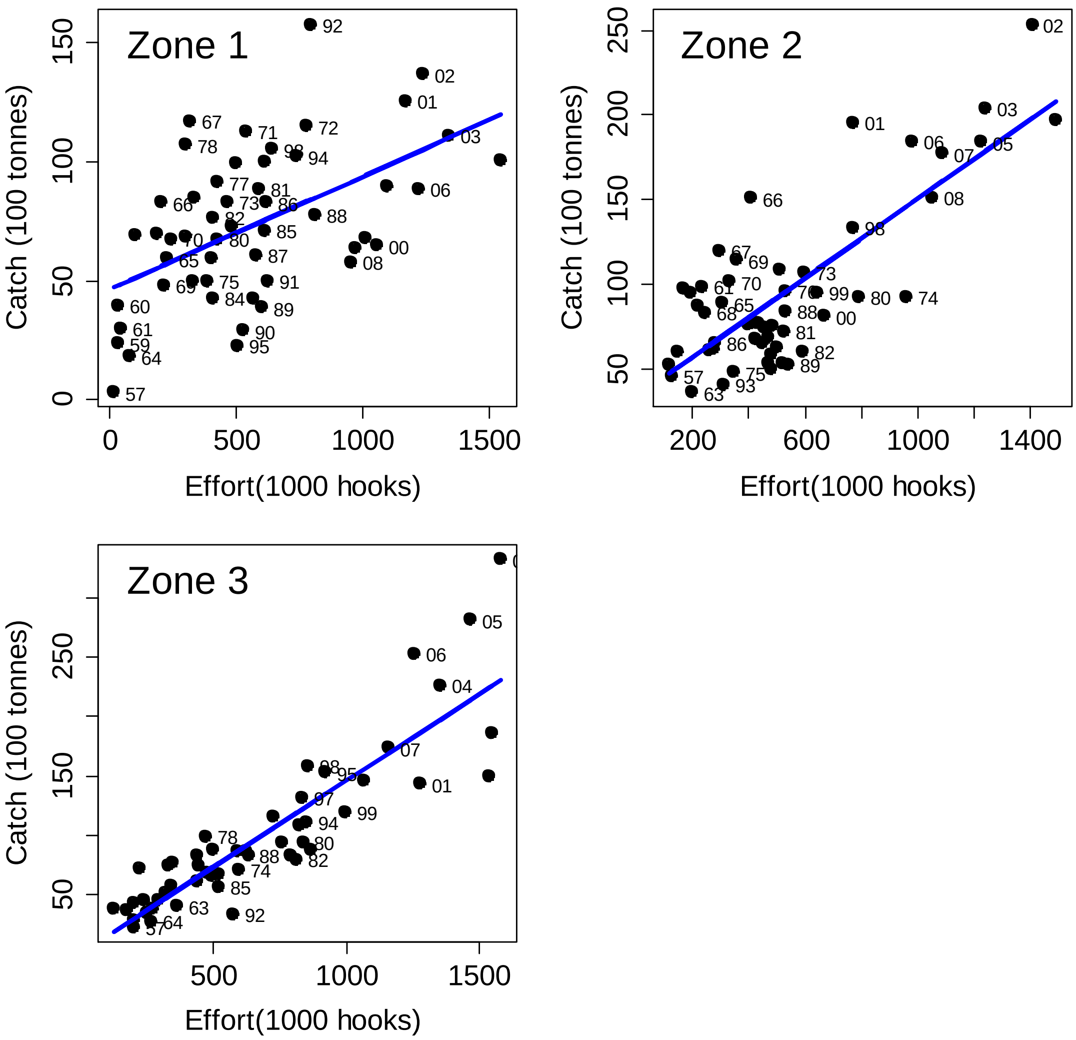

Figure 5-4. The relationship between the catch and effort for the albacore tuna (*T. alalunga*) stock in Zone 1, Zone 2 and Zone 3 from 1957-2008. The determination coefficients are 0.544, 0.786 and 0.884 respectively.

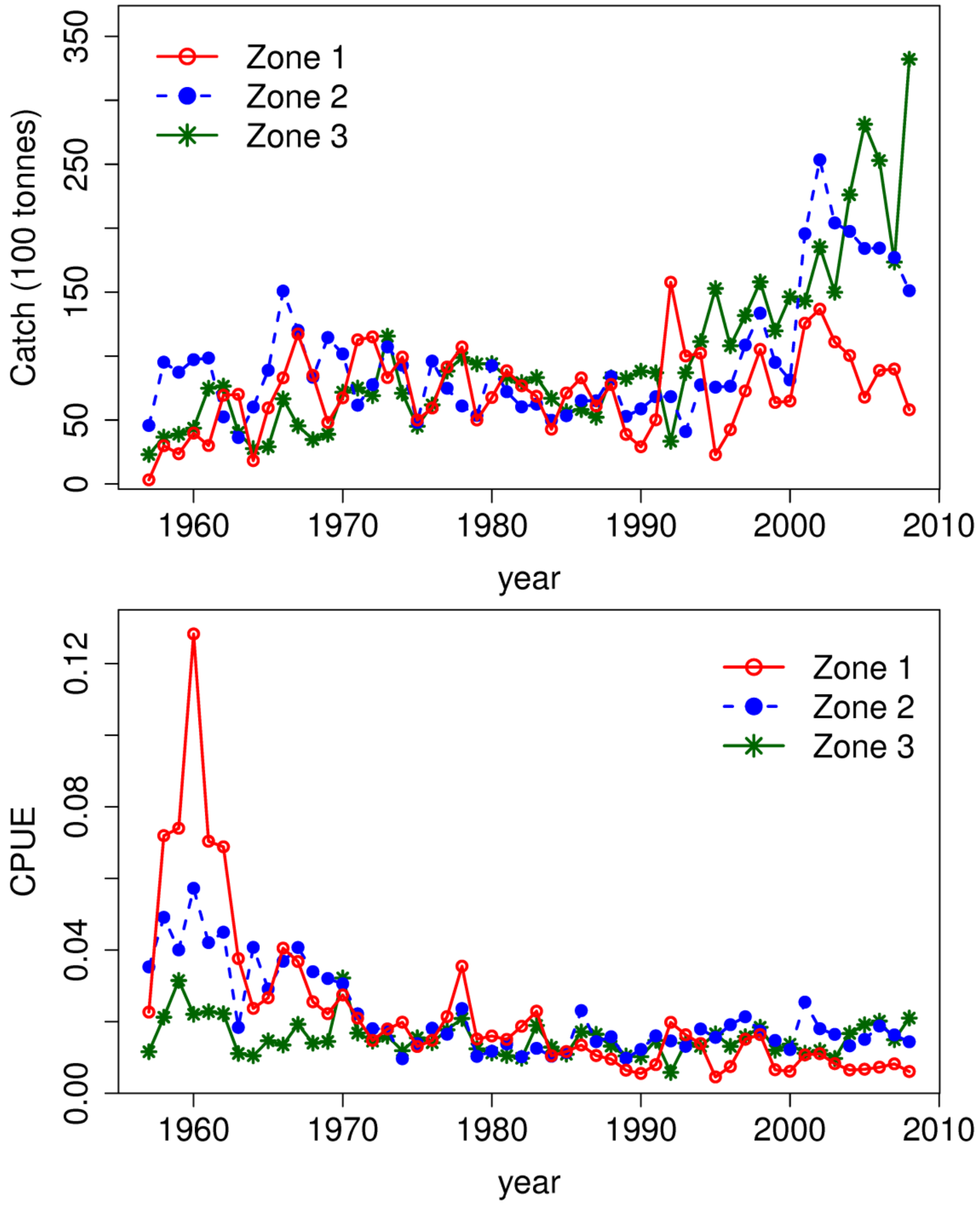

Figure 5-5. The catch and CPUE time series trajectory of the albacore tuna (*T. alalunga*) stock in Zone 1, Zone 2 and Zone 3 from 1957 to 2008. Differences can be seen in the recent years for catch and in earlier years for CPUE magnitudes for each zone.

Table 5-1. Results for regression analysis of albacore tuna (*T. alalunga*) stock in the South Pacific Ocean Zone 1, Zone 2 and Zone 3 against independent climate variables. Variables exhibiting values with p<0.05 are significant.

				Zone 1					
	Y_{z1}, L			Y_{z1}, P_n			Y_{z1}, O_f		
Year	R^2	p-value	AIC	R^2	p-value	AIC	R^2	p-value	AIC
t	0.388	8.08×10^{-7}	-266	0.258	1.23×10^{-4}	-256	9.19×10^{-5}	9.46×10^{-1}	-241
t-1	0.434	1.08×10^{-7}	-270	0.283	4.89×10^{-5}	-258	0.016	3.75×10^{-1}	-242
t-2	0.376	1.32×10^{-6}	-265	0.307	2.07×10^{-5}	-260	0.054	9.78×10^{-2}	-244
t-3	0.365	2.15×10^{-6}	-264	0.278	5.99×10^{-5}	-258	0.118	1.26×10^{-2}	-247
t-4	0.290	3.89×10^{-5}	-259	0.287	4.31×10^{-5}	-258	0.230	3.26×10^{-4}	-254
t-5	0.331	8.02×10^{-6}	-262	0.301	2.59×10^{-5}	-259	0.148	4.86×10^{-3}	-249
				Zone 2					
	Y_{z2}, L			Y_{z2}, P_n			Y_{z2}, O_m		
t	0.518	2.05×10^{-9}	-349	0.234	2.83×10^{-4}	-325	0.095	2.65×10^{-2}	-316
t-1	0.566	1.30×10^{-10}	-355	0.232	3.00×10^{-4}	-325	0.140	6.40×10^{-3}	-319
t-2	0.524	1.30×10^{-9}	-350	0.275	6.56×10^{-5}	-328	0.216	5.16×10^{-4}	-324
t-3	0.547	3.71×10^{-10}	-352	0.253	1.43×10^{-4}	-326	0.134	7.65×10^{-3}	-319
t-4	0.459	3.41×10^{-8}	-343	0.253	1.46×10^{-4}	-326	0.226	3.67×10^{-4}	-325
t-5	0.450	5.27×10^{-8}	-342	0.208	6.87×10^{-4}	-323	0.213	5.72×10^{-4}	-324
				Zone 3					
	Y_{z3}, L			Y_{z3}, P_f			Y_{z3}, O_f		
t	0.118	1.27×10^{-2}	-404	0.002	7.28×10^{-1}	-398	0.006	5.81×10^{-1}	-398
t-1	0.144	5.53×10^{-3}	-406	0.005	6.31×10^{-1}	-398	0.004	6.49×10^{-1}	-398
t-2	0.095	2.60×10^{-2}	-403	0.094	2.69×10^{-2}	-403	0.015	3.85×10^{-1}	-398
t-3	0.085	3.62×10^{-2}	-402	0.042	1.45×10^{-1}	-400	0.028	2.39×10^{-1}	-399
t-4	0.117	1.29×10^{-2}	-404	0.031	2.11×10^{-1}	-399	0.152	4.35×10^{-3}	-406
t-5	0.109	1.71×10^{-2}	-404	0.011	4.55×10^{-1}	-398	0.141	6.01×10^{-3}	-406

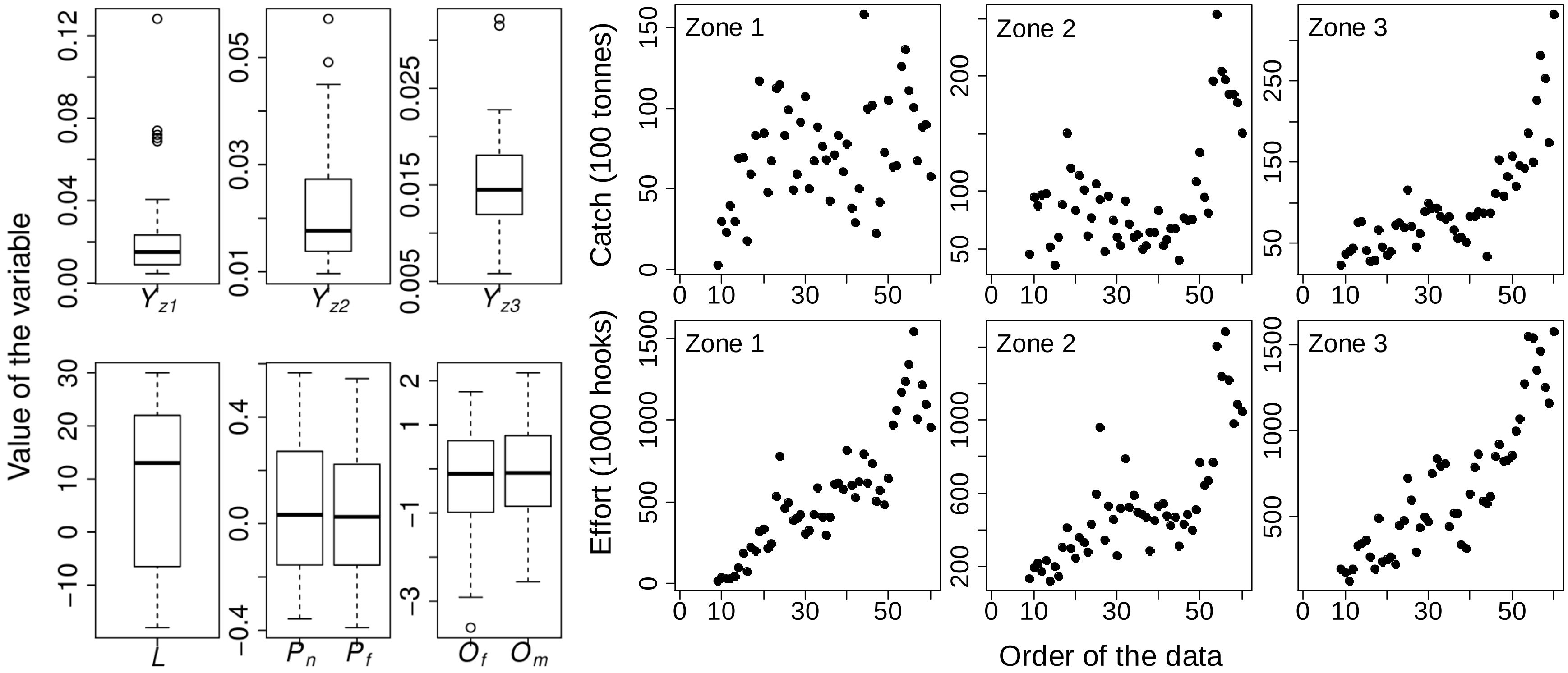

Figure 5-6. The boxplots for the dependent and independent variables showing the spread of the data with the line in the middle of the boxes representing the median. Scatter plots show the distribution for the catch and effort data for Zone1, Zone 2 and Zone 3.

Table 5-2. Results of unit root tests for dependent and independent variables used in regression analysis from **Table 5-1**.

Series	M-test		ADF-test	
	t-value	*p*-value	t-value	*p*-value
Y_{z1} 1957-2008	-7.698	6.32×10^{-10}	-7.698	$<1.00\times10^{-2}$
Y_{z2} 1957-2008	-11.795	8.69×10^{-16}	-11.795	$<1.00\times10^{-2}$
Y_{z3} 1957-2008	-10.531	4.53×10^{-14}	-10.531	$<1.00\times10^{-2}$
L 1949-2008	-10.655	4.37×10^{-15}	-10.655	$<1.00\times10^{-2}$
P_n 1949-2008	-10.750	3.12×10^{-15}	-10.750	$<1.00\times10^{-2}$
P_f 1949-2008	-13.030	$<2.20\times10^{-16}$	-13.025	$<1.00\times10^{-2}$
O_f 1949-2008	-11.161	7.36×10^{-16}	-11.161	$<1.00\times10^{-2}$
O_m 1949-2008	-11.345	3.88×10^{-16}	-11.345	$<1.00\times10^{-2}$

Table 5-3. Stock reproduction models and some parameters using the independent variables *L*, *P* and *O* from **Table 5-1** for the albacore tuna (*T. alalunga*) stock in the South Pacific Ocean Zone 1, Zone 2 and Zone 3. Values are only shown for statistically most significant models at *p*<0.05.

	Model	R^2	t-value	*p*-value	AIC
	Zone 1				
5-i)	$\ln(Y_{z1,t}) = -3.83 - 2.25 \times 10^{-2} \times L_{t-1} - 1.50 \times P_{n,t-2} + 8.03 \times 10^{-2} \times O_{f,t-4}^{2}$	0.791	13.748	$<2.20\times10^{-16}$	-322
5-ii)	$\ln(Y_{z1,t}) = -3.78 - 2.06 \times 10^{-2} \times L_{t-1} - 1.37 \times P_{n,t-2} - 3.49 \times 10^{-2} \times O_{f,t-4}^{3}$	0.787	13.580	$<2.20\times10^{-16}$	-321
5-iii)	$\ln(Y_{z1,t}) = -3.97 - 5.06 \times 10^{-2} \times L_{t-1} + 1.56 \times 10^{-3} \times L_{t-1}^{2} - 4.26 \times P_{n,t-2}^{3} - 0.129 \times O_{f,t-4}$	0.751	12.287	$<2.20\times10^{-16}$	-313
	Zone 2				
5-iv)	$\ln(Y_{z2,t}) = -3.89 - 3.17 \times 10^{-2} \times L_{t-1} + 7.82 \times 10^{-4} \times L_{t-1}^{2} - 0.754 \times O_{m,t-4} + 1.69 \times P_{n,t-2}^{2}$	0.781	13.358	$<2.20\times10^{-16}$	-390
5-v)	$\ln(Y_{z2,t}) = -3.79 - 3.58 \times 10^{-2} \times L_{t-1} + 2.86 \times 10^{-5} \times L_{t-1}^{3} - 0.669 \times O_{m,t-4} + 1.76 \times P_{n,t-2}^{2}$	0.766	12.779	$<2.20\times10^{-16}$	-387
5-vi)	$\ln(Y_{z2,t}) = -3.86 - 2.89 \times 10^{-2} \times L_{t-1} + 6.35 \times 10^{-4} \times L_{t-1}^{2} - 1.012 \times O_{m,t-4} + 4.41 \times 10^{-2} \times (L_{t-1} \times P_{n,t-2})$	0.764	12.731	$<2.20\times10^{-16}$	-386
	Zone 3				
5-vii)	$\ln(Y_{z3,t}) = -4.15 - 6.94 \times 10^{-3} \times L_{t-1} + 0.983 \times O_{f,t-4}^{2} - 2.38 \times\times 10^{-2} \times (L_{t-1} \times P_{f,t-2})$	0.205	3.588	7.57×10^{-4}	-410
5-viii)	$\ln(Y_{z3,t}) = -4.19 - 7.00 \times 10^{-3} \times L_{t-1} - 2.46 \times O_{f,t-4}^{3} + 1.34 \times P_{f,t-2}^{2}$	0.190	3.429	1.22×10^{-3}	-409
5-ix)	$\ln(Y_{z3,t}) = -4.166 - 5.25 \times 10^{-3} \times L_{t-1} - 2.17 \times 10^{-2} \times O_{f,t-4}^{3}$	0.155	3.028	3.89×10^{-3}	-406

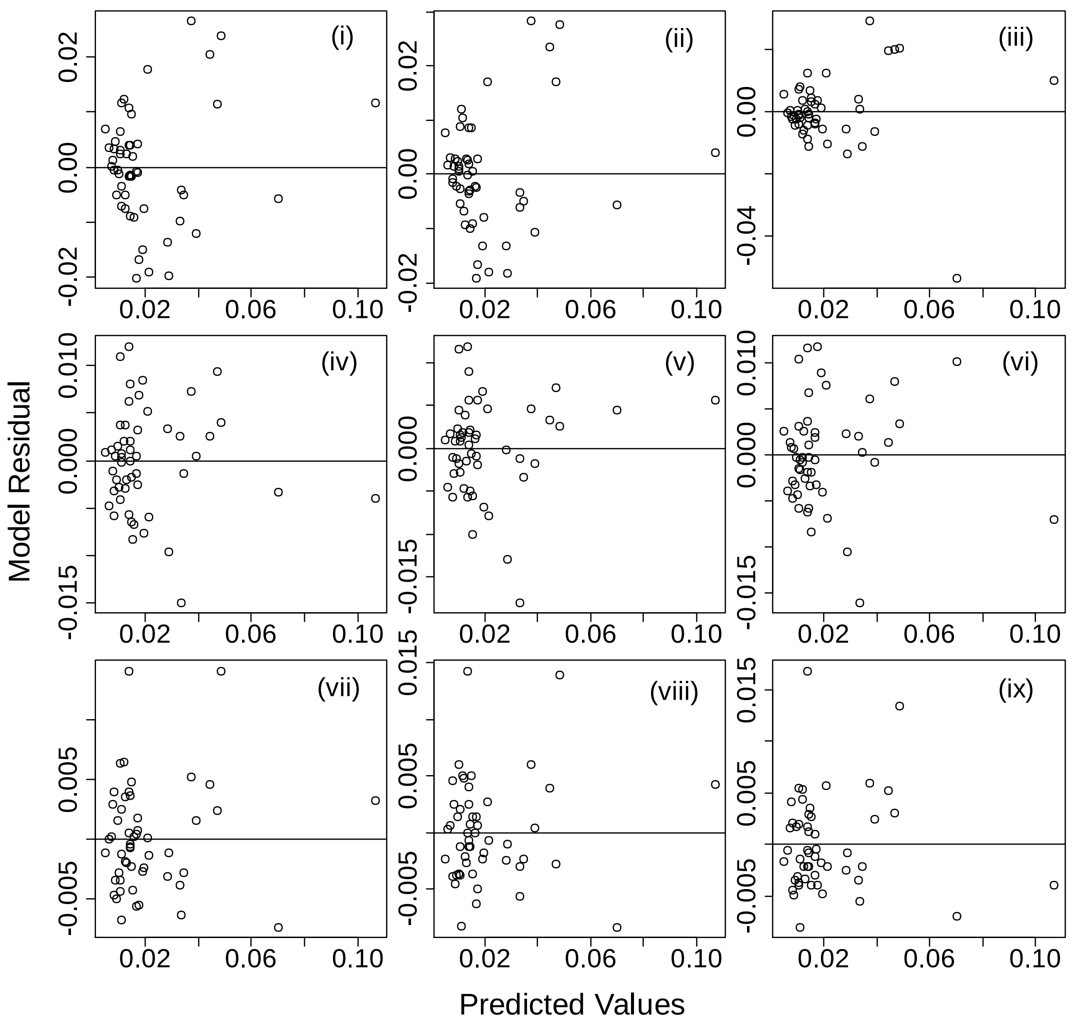

Figure 5-7. The residuals of models from **Table 5-3** against the predicted values. The top panel is for Zone 1, middle panel for Zone 2 and the bottom panel for Zone 3. The roman numerals refer to the model numbers in **Table 5-3**. The residual variance in all cases is <0.09.

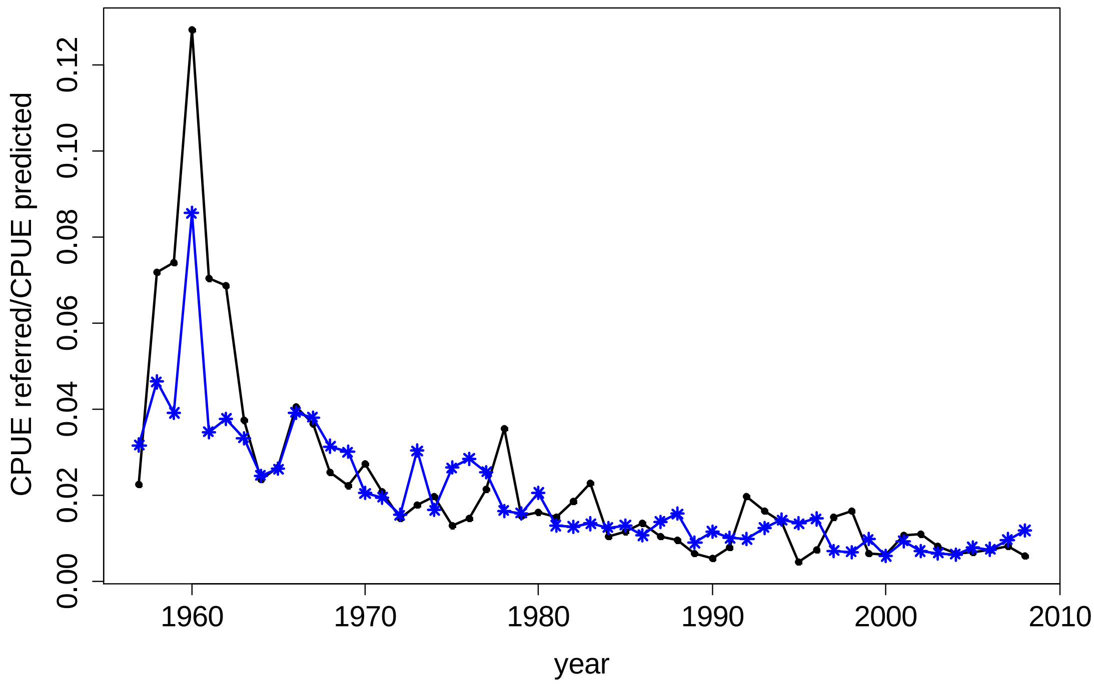

Figure 5-8. Graph showing the actual CPUE time series trajectory of the albacore tuna (*T. alalunga*) stock in Zone 1 in black and the trajectory which resulted from model 5-**i** (**Table 5-3**) in blue for the years 1957-2008.

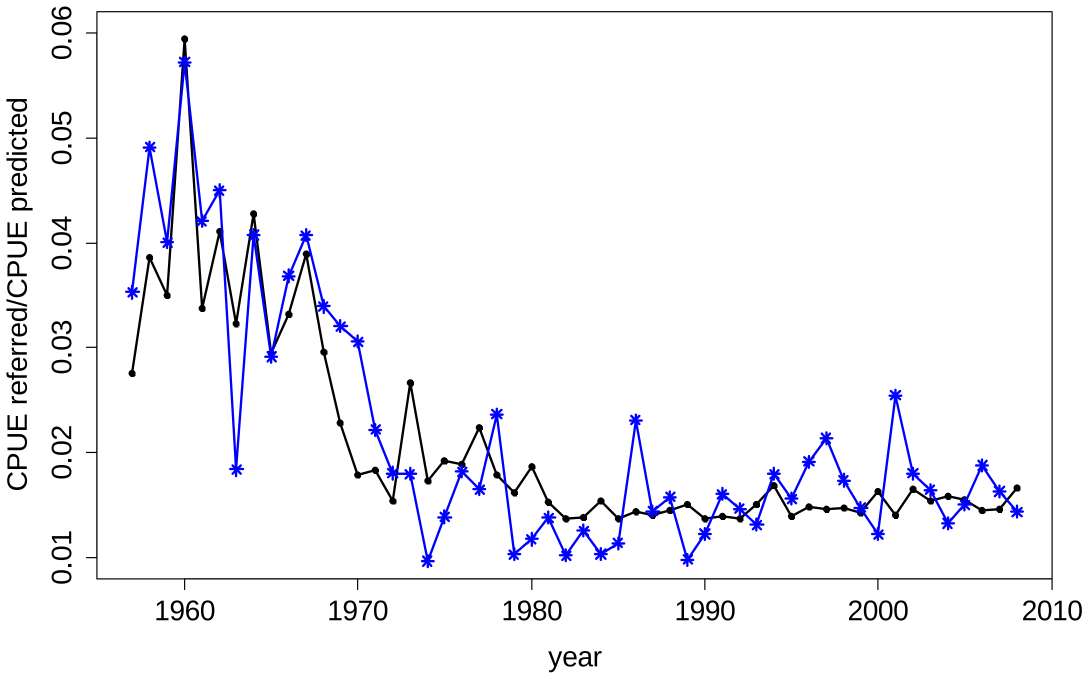

Figure 5-9. Graph showing the actual CPUE time series trajectory of the albacore tuna (*T. alalunga*) stock in Zone 2 in black and the trajectory which resulted from model 5-**iv** (**Table 5-3**) in blue for the years 1957-2008.

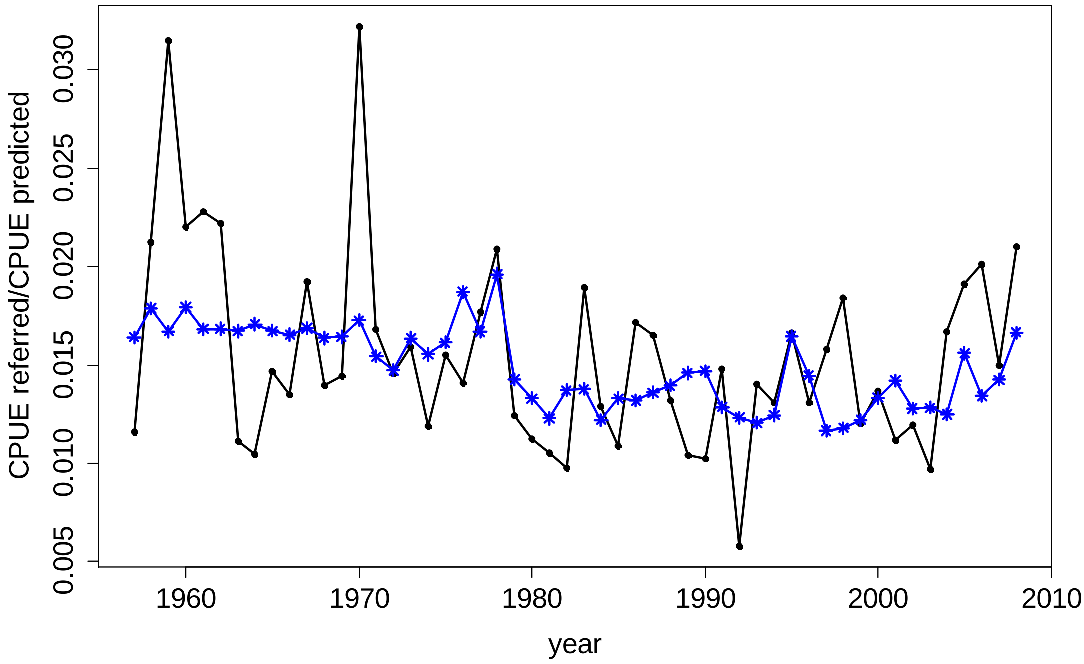

Figure 5-10. Graph showing the actual CPUE time series trajectory of the albacore tuna (*T. alalunga*) stock in Zone 3 in black and the trajectory which resulted from model 5-**vii** (**Table 5-3**) in blue for the years 1957-2008.

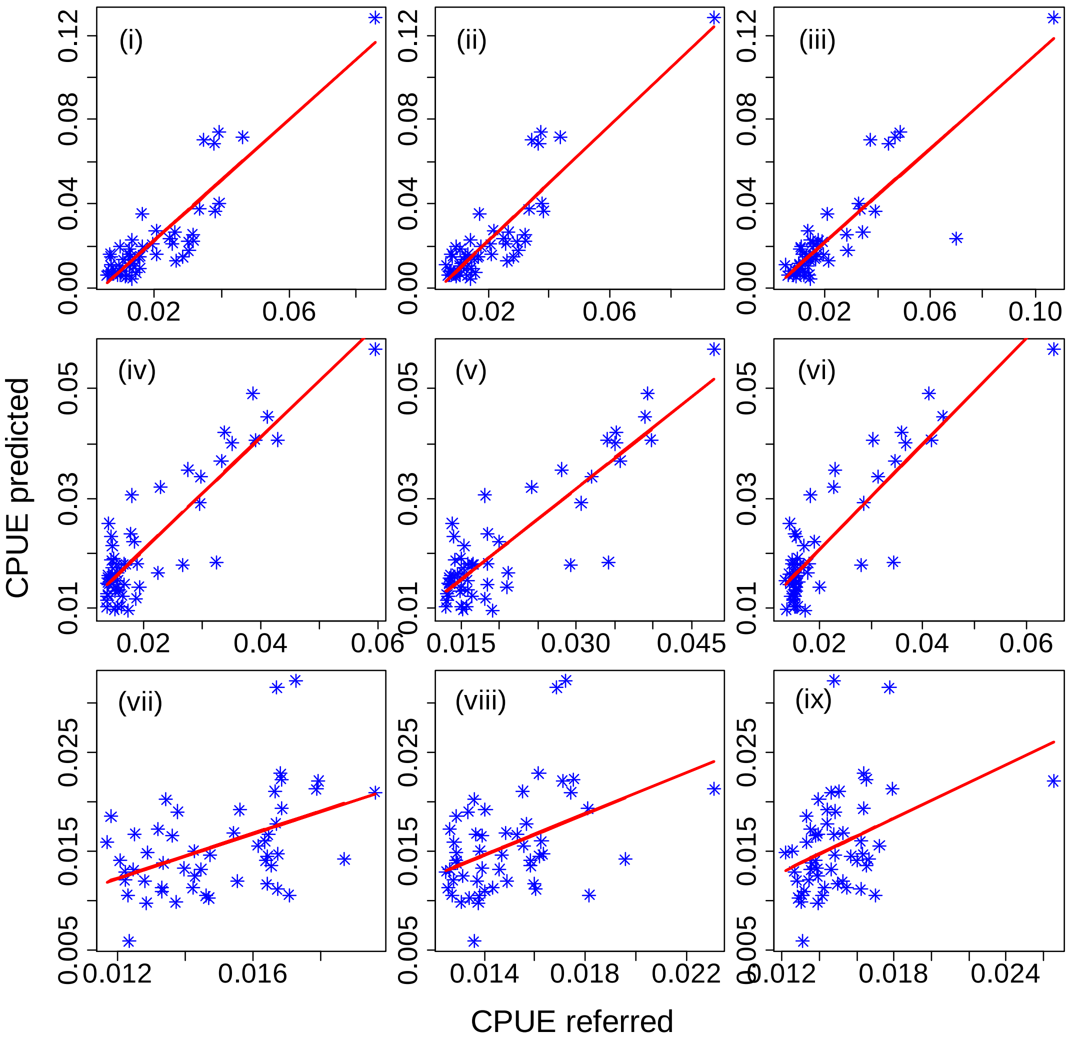

Figure 5-11. The linear relationship between the CPUE predicted and CPUE referred for the albacore tuna (*T. alalunga*) stock in the South Pacific Ocean Zone 1 (top panel), 2 (middle panel) and 3 (bottom panel). The numbers refer to the model number presented in **Table 5-3**.

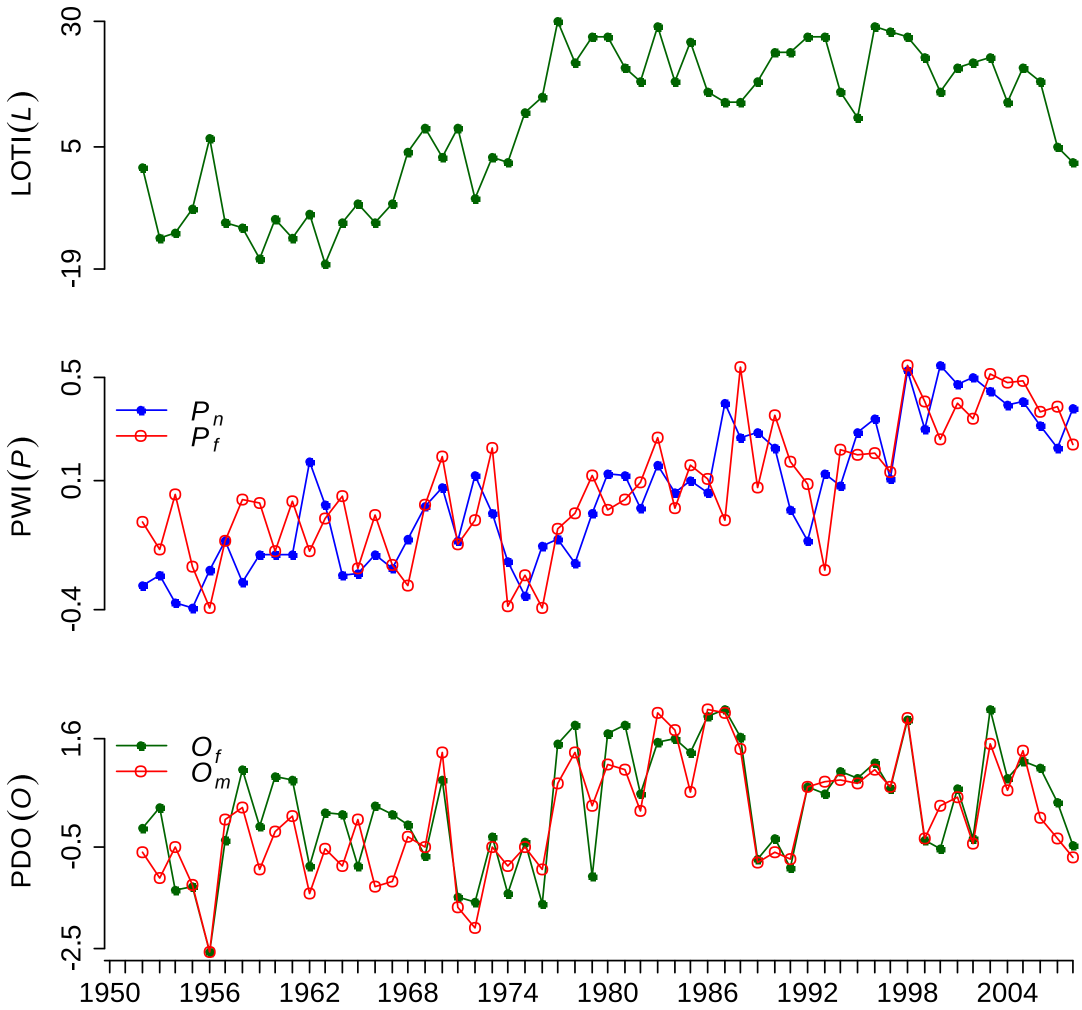

Figure 5-12. Time series pattern of the climatic conditions from 1952 to 2008. Graphs from top; the global mean land and ocean temperature index (LOTI) for the latitude band 44ºS to 64ºS (L), Pacific warm pool index (PWI) for the month of February (P_f) and November (P_n) and Pacific decadal oscillation (PDO) for the month of February (O_f) and March (O_m).

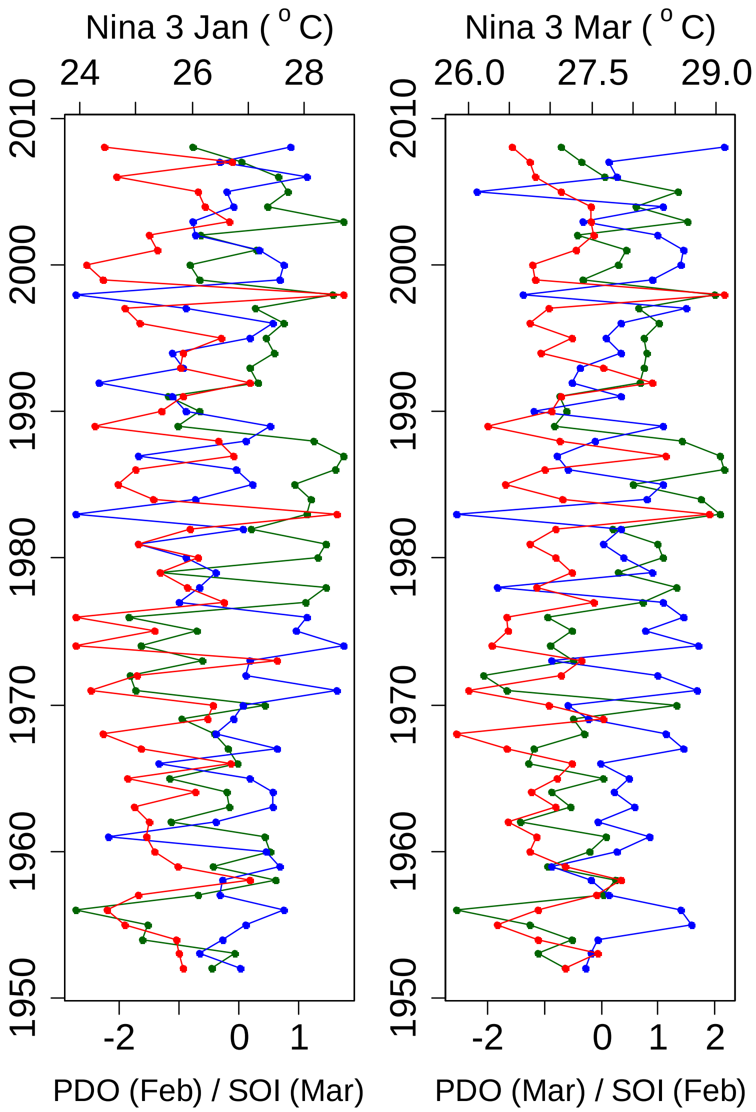

Figure 5-13. Relationship of the PDO incorporated into the models for Zone 1 (O_f), Zone 2 (O_m) and Zone 3 (O_f) (green line) with the climatic conditions of the Southern Oscillation Index (SOI) for the month of March and February (blue line) and Niña 3 (red line) which is the Eastern Tropical Pacific sea surface temperature for the area (5ºN-5ºS 150ºW-90ºW) from 1952-2008. PDO exhibits negative relationship with SOI and positive relationship with Niña 3. During negative PDO La Niña episodes dominate while El Niño events dominate during positive PDO. SOI and Niña 3 time series data were obtained from NOAA, Earth System Research Laboratory, Physical Sciences Division (http://www.esrl.noaa.gov).

CHAPTER 6

General discussion and closing remarks

6.1. GENERAL DISCUSSION AND CONCLUDING STATEMENTS

The theme of the work presented here was to determine the link between ecological and environmental conditions and the stock behavior of four commercially important fish species over a time series. The findings and arguments presented act as valuable information for fishery managers to incorporate in their decision making for the sustainability of their individual fishery industries.

In this study we were able to elucidate the effect of different ecological and climatic conditions on the time series trajectories of four different commercially important fish species; the Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura and Kitaura, Peruvian anchoveta (*E. ringens*) off Peru, yellowfin tuna (*T. albacares*) and albacore tuna (*T. alalunga*) in the Eastern and Western South Pacific Ocean and develop suitable stock reproduction models for each stock. We were also able to reanalyze and verify the presence of different regimes and density dependent effect within each regime in the time series of the Peruvian anchoveta.

6.1.1. Key Points and Concluding statements

1. Long time-series are preferable over short time series for comparing trends and identifying linkages among dependent and independent variables as shorter time series may identify relationships which do not persist over long periods of time.
2. In order for regimes to exist and different density dependent effects within regimes to be present, sustained alternate trends should be present in all time series components of a stock including the recruitment (R), spawning stock biomass (SSB) and recruitment per spawning stock biomass or recruitment success (RPS).
3. Sea surface temperature (SST) and the southern oscillation index (SOI) can effectively determine a significant proportion of the recruitment time-series trajectory for the Peruvian anchoveta (*E. ringens*) off Peru from 1963 to 2004.
4. Independent variables, dependent variables and results obtained from correlation analysis and modeling need to go through sufficient exploration for verification and avoiding violations of assumptions from the statistical

techniques used and detection for the presence of possible errors.

5. A significant proportion of the stock trajectory of the Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura and Kitaura, Ibaraki prefecture, Japan can be determined by the variables of phosphorus and global mean land and ocean temperature index (LOTI) for the latitude band of 24ºN to 90ºN from 1972 to 2008.
6. Anthropogenic activities influence the stock abundance of the Japanese pond smelt in Lake Kasumigaura and Kitaura. While abatement programmes may increase the stock abundance of Japanese pond smelt, the affect of such actions cannot be predicted without considerable understanding of the functioning of the Lake ecosystems.
7. Yellowfin tuna stock dynamics in the Eastern and Western South Pacific are significantly determined in proportion by the climatic variables of Pacific warm pool index (PWI), LOTI for the latitude band 0ºN to 24ºS and the southern oscillation index (SOI) from 1957 to 2008.
8. The stock trajectory of the albacore tuna from 1957 to 2008 in the Eastern and Western south Pacific Ocean are effectively determined in proportion to the climatic variables of PWI, LOTI for the latitude band 44ºS to 64ºS and the Pacific Decadal Oscillation.
9. The climatic conditions of SOI, PDO and El Niño and La Niña events are interrelated and they all affect the time series trajectory of yellowfin tuna and albacore tuna in the Eastern and Western South Pacific Ocean from 1957 to 2008.
10. The larger proportion of the stock time series pattern for yellowfin tuna in the South Pacific Zone 3 is due to the alterations in the climatic conditions of LOTI, PWI and SOI with the trajectory for Zone 2 being affected less than Zone 3 and Zone 1 although significant, being the least affected by the three climatic conditions. This coincides with the catch and effort relationship where the catch trajectory in Zone 1 is mostly determined by the effort level followed by Zone 2 with the lowest being Zone 3.
11. The better proportion of the albacore tuna time series trajectory for Zone 1 is influenced by the climatic conditions of LOTI, PWI and PDO followed closely

by Zone 2 and at a much lower level by Zone 3. This harmonizes with the catch and effort relationship where the catch trajectory for Zone 3 is determined to a great extent by the effort followed by Zone 2 with the catch and effort relationship in Zone 1 being much lower in comparison to Zone 2 and Zone 3.

12. Stock behavior, catch and effort relationships, relationship to the climatic variables and model significance levels differ for the yellowfin tuna and the albacore tuna from 1957 to 2008 as we move from the Eastern to the Western South Pacific.
13. As we move from the Eastern to the Western South Pacific Ocean the influence of LOTI, PWI and PDO on albacore tuna stock gets more prominent.
14. As we move from the Western to the Eastern South Pacific Ocean the influence of LOTI, PWI and SOI on yellowfin tuna stock gets more prominent.
15. Alterations in climatic conditions play a key role in structuring the stock dynamics of the Peruvian anchoveta off Peru, Japanese pond smelt in Lake Kasumigaura and Kitaura, yellowfin tuna and albacore tuna in the Eastern and Western South Pacific Ocean.

6.2. FINAL VIEWS AND RECOMMENDATIONS

At the beginning, when commercial industrial fisheries rose, there was little or no control exercised for harvesting of fisheries resources. These practices were quite devastating to the fisheries resources and led to the collapse of numerous fisheries industries around the globe which made fisheries managers realize that in order for their fishery industries to be sustained, they need to gain a better understanding of their fishery resources. It was becoming more evident that in order for fisheries industries to survive there was a need to strike a balance between economical and biological sustainability.

Fisheries management plans initially were targeted towards the regulating fishing effort by using concepts like maximum sustainable yield (MSY), total allowable catch (TAC) among others. While such practices may have worked for some fisheries or for some period of time and slowed down the rate of resource decline, it was not a permanent solution as various resources continued to see declines. Better understanding of the spawning behavior, recruitments and prey species led to management by restrictions applied to the fishing season, size of catch, etc. As research progressed and stock assessment techniques improved, it came to light that fisheries resources abundance and distribution behavior are more complex than initially assumed and are governed by the interaction of numerous intrinsic and extrinsic factors.

Biotic, abiotic and climatic conditions play a significant role in structuring the abundance and distribution of fisheries resources over a time series. Research over the past three decades has indentified significant links between different fisheries stocks and various climatic conditions. While fishing pressure does affect the abundance, fisheries resources are also affected significantly by ecological and environmental conditions. The extent of availability and sustainability of a fisheries resource is a sum of the effects of the fishing pressure, ecological conditions, anthropogenic influence (for example, various forms of pollution), and climatic conditions. Among these factors, fishing effort is the easiest to control and manage, followed by anthropogenic activities, and finally climatic conditions which are highly improbable to control and regulate and even less without international cooperation. Fisheries managers need to take the effects of ecological, anthropogenic and environmental factors into account for making management decisions and plans by striking a suitable balance between the biological and economical sustainability for the survival of their fishery.

The Pacific Island nations EEZ and territories are home to major stocks of tuna in the Pacific Ocean which are still within sustainable limits. Most of the Island nations and territories in the Pacific depend heavily on the economic gains from tuna fisheries industry and although tuna is of global commercial importance there are limitations in the data availability on tuna species. This is especially true for developing Pacific Island nations where although some structures for data collection are already in place such as fisheries observers, very little data is collected in regards to the ecosystem of the tuna species as the focus of these nations is on the economic sustainability and gains and little attention is given to research and understanding of the tuna stocks. It is recommended that the Pacific Island nations increase their efforts to collect as much data as possible on tuna stocks and their biological, physiochemical and other ecosystem variables. Availability of quality data on various variables will enable better stock assessments and understanding of tuna stocks in the Pacific which will enable fisheries managers and decision makers to make better decisions and mitigation procedures to ensure both the biological and economical sustainability of tuna stocks in the Pacific.

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SUMMARY

The theme of this work was to determine the link between ecological and environmental conditions and the stock behavior of four commercially important fish species over a time series. The work also aimed to determine if the stock trajectory of the four species could be determined in proportion by the climatic variables using a Generalized Linear Model. The findings and arguments presented act as valuable information for fishery managers to incorporate in their decision making for the sustainability of their individual fishery industries. We were able to elucidate the effect of different ecological and climatic conditions on the time series trajectories of four different commercially important fish species; Japanese pond smelt (*H. nipponensis*) in Lake Kasumigaura and Kitaura, Peruvian anchoveta (*E. ringens*) off Peru, yellowfin tuna (*T. albacares*) and albacore tuna (*T. alalunga*) in the Eastern and Western South Pacific Ocean and develop suitable stock reproduction models for each stock. We were also able to reanalyze and verify the presence of different regimes and density dependent effect within each regime in the time series of the Peruvian anchoveta.

Chapter 2: The Japanese pond smelt (*Hypomesus nipponensis*) stock has been observed to fluctuate quite rigorously over the years with sustained periods of low catch in Lake Kasumigaura and Kitaura of the Ibaraki prefecture, Japan which would adversely affect the socioeconomic livelihood of the local fishermen and fisheries industry. Through exploratory analysis it was found that the pond smelt had significant relationship with total phosphorus (TP) level in both lakes. The global mean land and ocean temperature index (LOTI) was also found to be indirectly related to the pond smelt stock in Lake Kasumigaura and Kitaura at the latitude band of 24°N to 90°N. Both TP and LOTI had inverse relationship with pond smelt trajectory in both lakes. For both Lake Kasumigaura and Kitaura, TP for the individual lakes and LOTI were used as independent variables using generalized linear model and response surface methods for modeling the stock dynamics of the pond smelt in the two lakes. Model selection was based on significant parameter estimates (p<0.05), Akaikes Information Criterion and R^2 values. Phosphorus loading is an indication of increasing anthropogenic activities in the surrounding

area having negative impact on the pond smelt population. When management decisions are being made regarding pond smelt fishery and sustainability plans in the Ibaraki prefecture, the effects of TP and LOTI should be taken into account.

Chapter 3: This study was aimed at re-examining the validity of the results from Cahuin *et al.*, (2009) and identify a model to describe the stock-recruitment relationship of the Peruvian anchoveta (*Engraulis ringens*). Regression analysis was used to determine if density-dependent effects were present. The analysis did not show the existence of any density dependent effects. It is important to use environmental factors and take observational and process errors into account when attempting to identify density-dependent effects in fish populations. Sea surface temperature (SST) and Southern Oscillation Index (SOI) were used as independent variables to fit the recruitment dynamics of the anchoveta. Both SST and SOI were found to be significantly important parameters in structuring anchoveta dynamics. The results of this study do not correlate with the findings of Cahuin *et al.*, (2009), where density-dependent effects and the presence of regimes were detected. In conclusion, the recruitment R_t is essentially determined in proportion to spawning stock biomass S_t, and the environmental factors in year t further change the recruitments. This mechanism is completely same with that for Japanese sardine proposed by Sakuramoto, (2012).

Chapter 4: Yellowfin tuna (*Thunnus albacares*) is a commercially important fish species for South Pacific island nations and territories and for effective conservation efforts it is important to understand the factors which affect their time series pattern. We utilized various climatic factors for the years t-n with n=0, 1,…,8 and investigated their statistical relationship to the catch per unit effort (CPUE) of yellowfin tuna stock from 1957-2008 for three South Pacific zones ranging from the East to the West Pacific Ocean within the coverage area of the Western and Central Pacific Convention Area. Results showed that the climatic conditions of; (i) the global mean land and ocean temperature index (LOTI), (ii) the Pacific warm pool index (PWI) and (iii) Southern Oscillation Index (SOI) had significant relationship with the CPUE of yellowfin tuna in all three zones. LOTI, PWI and

SOI were used as independent variables and fitted through modeling to replicate the CPUE trajectory of the yellowfin tuna in Zone 1, Zone 2 and Zone 3. Models selected for all three zones had LOTI, PWI and SOI as the independent variables. This study showed that LOTI, PWI and SOI are climatic conditions which have significant impact on the fluctuation pattern of the yellowfin tuna CPUE in the Eastern and Western South Pacific Ocean. From the findings of this study it can be recommended that when management decisions are being made for yellowfin tuna fishery conservation and sustainability in the Eastern and Western South Pacific, it is imperative to take the effect of climatic factors into account.

Chapter 5: Over the years there has been growing interest on the effects of climatic variations on marine biodiversity. The exclusive economic zones of South Pacific Islands and territories are home to major international exploitable stocks of albacore tuna (*Thunnus alalunga*), however the impact of climatic variations on these stocks is not fully understood. This study was aimed at determining the climatic variables which have impact on the time series stock fluctuation pattern of albacore tuna stock in the Eastern and Western South Pacific Ocean which was divided into three zones. The relationship of the climatic variables of the global mean land and ocean temperature index (LOTI), the Pacific warm pool index (PWI) and the Pacific decadal oscillation (PDO) were investigated against the albacore tuna catch per unit effort (CPUE) time series in Zone 1, Zone 2 and Zone 3 of the South Pacific Ocean from 1957-2008. From the results it was observed that LOTI, PWI and PDO at different lag periods exhibited significant correlation with albacore tuna CPUE for all three areas. LOTI, PWI and PDO were used as independent variables to develop suitable stock reproduction models for the trajectory of albacore tuna CPUE in Zone 1, Zone 2 and Zone 3. The final models for albacore tuna CPUE all three zones incorporated all three independent variables of LOTI, PWI and PDO. From the findings it can be said that the climatic conditions of LOTI, PWI and PDO play significant roles in structuring the stock dynamics of the albacore tuna in the Eastern and Western South Pacific Ocean. It is imperative to take these factors into account when making management decisions for albacore tuna in these areas.

Biotic, abiotic and climatic conditions play a significant role in structuring the abundance and distribution of fisheries resources over a time series. Research over the past three decades has indentified significant links between different fisheries stocks and various climatic conditions. While fishing pressure does affect the abundance, fisheries resources are also affected significantly by ecological and environmental conditions. The extent of availability and sustainability of a fisheries resource is a sum of the effects of the fishing pressure, ecological conditions, anthropogenic influence (for example, various forms of pollution), and climatic conditions. Among these factors, fishing effort is the easiest to control and manage, followed by anthropogenic activities, and finally climatic conditions which are highly improbable to control and regulate and even less without international cooperation. Fisheries managers need to take the effects of ecological, anthropogenic and environmental factors into account for making management decisions and plans by striking a suitable balance between the biological and economical sustainability for the survival of their fishery.

The stock trajectory of all four species in this research can be determined in proportion by the ecological and environmental variables using a Generalized Linear Model (GLM).