# FORECASTING PELAGIC FISH IN MALAYSIA USING ETS STATE SPACE APPROACH

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# ABSTRACT

Modelling and forecasting fish catch has been undertaken for a long time over the world. However, From time to time, researchers are always looking for a new model that can predict more accurately the number of fish catch. The objective of this study is to propose the Error Trend and Seasonal (ETS) state space approach.In this study, two techniques of time series analysis were used to forecast fish catch of three commercial fish species found in the Malaysian waters. One of such techniques is the Box-Jenkins method which concerns the building of linear and stochastic dynamic models with minimum data requirements. The second technique is the Error Trend and Seasonal (ETS) state space exponential method which requires no assumptions about the correlations between successive values of the time series. The two class models were used to model and forecast two years monthly catches of the three fish species based on the collected data for the period 2007 – 2011. The SARIMA(1,1,1)(0,0,1)[12], SARIMA(1,1,4)(0,0,1)[12], SARIMA(2,1,1)(0,0,1)[12] and ETS (M, A, M), ETS (M, N, M), ETS (M, A, M) for *Dussumiera acuta* (tamban buloh), *Rastrelliger kanagurta* (kembong) and *Thunnus tonggol* (Tongkol hitam) were proposed respectively. The diagnostic checking for all the fitted models confirmed the adequacy of the models. Results based on the root mean square error (RMSE) and mean absolute error (MAE) demonstrated that the ETS models performed better for *Thunnus tonggol* and *Rastrelliger kanagurta,* while SARIMA model performed better for *Dussumiera acuta*. This shows that ETS model which has so far not been used in fisheries in Malaysia is our main contribution in this research. Nevertheless, both models have proven successful in describing and forecasting the monthly fishery dynamics. These forecasts proves helpful in formulating the needed strategies for sustainable management and conservation of the stocks, and can also help the decision makers to establish priorities in terms of fisheries management.

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# ABSTRAK

Permodelan dan ramalan tangkapan ikan telah dijalankan untuk masa yang lama di seluruh dunia. Namun, terdapat masalah dalam mencari model yang sesuai yang boleh memperoleh dinamik data tang sebagai atribut kepada data tangkapan ikan. Dari masa ke semasa, penyelidik sentiasa mencari model baru yang boleh meramal lebih tepat lagi beberapa tangkapan ikan. Dalam kajian ini, dua teknik analisis siri masa telah digunakan untuk meramal hasil tangkapan ikan daripada tiga spesies ikan komersial yang terdapat di perairan Malaysia. Salah satu teknik itu adalah kaedah Box-Jenkins yang berkaitan dengan pembinaan model dinamik linear dan stokastik dengan keperluan data minimum. Teknik yang kedua ialah ETS keadaan ruang kaedah eksponen yang tidak memerlukan andaian tentang hubungan antara nilai-nilai berturut-turut siri masa. Kedua-dua kelas model digunakan untuk dimodelkan dan meramal dua tahun tangkapan bulanan daripada tiga spesies ikan berdasarkan data yang dikumpul bagi tempoh 2007 - 2011. SARIMA (1,1,1) (0,0,1)[12], SARIMA (1,1,4) (0,0,1)[12], SARIMA (2,1,1) (0,0,1)[12] dan ETS (M, A, M), ETS (M, N, M) , ETS (M, A, M) untuk *Dussumiera acuta* (tamban Buloh), *Rastrelliger kanagurta* (Kembong) dan *Thunnus tonggol* (Tongkol hitam), telah dibangunkan. Semakan diagnostik untuk semua model dipasang mengesahkan kecukupan model. Keputusan berdasarkan punca min ralat kuasa dua (RMSE) dan bermakna ralat mutlak (MAE) menunjukkan prestasi model ETS lebih baik untuk *Thunnus tonggol* dan *Rastrelliger kanagurta*, manakala prestasi model SARIMA lebih baik untuk *Dussumiera acuta*.Ini menunjukkan model ETS yang belum pernah digunakan di perikanan Malaysia ialah penyumbang utama dalam kajian ini. Walau bagaimanapun, kedua-dua model telah terbukti berjaya dalam menerangkan dan meramal dinamik perikanan bulanan. Ramalan boleh membantu dalam merangka strategi yang diperlukan untuk pengurusan dan pemuliharaan stok yang berterusan, malah membantu pembuat keputusan untuk menubuhkan keutamaan dari segi pengurusan perikanan.

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| | |
|---|---|
| ARIMA | Autoregressive Integrated Moving Average |
| SARIMA | Seasonal Autoregressive Moving Average |
| AIC | Akaike Information Criteria |
| ACF | Autocorrelation Function |
| PACF | Partial Autocorrelation Function |
| RMSE | Root Mean Square Error |
| ETS | Error Trend Seasonal |
| FAD | Fish Aggregation Device |
| MAE | Mean Absolute Error |

**APPENDIX**

# CHAPTER 1

# INTRODUCTION

## 1.0 Introduction

Fisheries management appeals on fisheries science in order to find ways to protect fishery resources for a possible sustainable exploitation. Modern fisheries management often referred to as a governmental system of appropriate management rules based on defined objectives and a mix of management means to implement the rules, which are to put in place by a system of monitoring, control and surveillance. The integrated process of information gathering, analysis, planning, consultation, decision making, and allocation of resources, formulation and implementation, with enforcement is necessary as regulations or rules which govern fisheries activities in order to ensure the continued productivity of the resources are among other fisheries objectives.

Effective management is essential if marine resources are to be utilized in a sustainable and a responsible manner. Sustainable and responsible fisheries management is of a fundamental importance as fisheries are one of the main pillars of the Malaysian economy. Given this fact, this work studied the fisheries dynamics of some selected fishes commonly found in Malaysian waters using two time series analysis techniques. Time series analysis is an economical method for forecasting fish catches which are essential for fisheries management. It describes the time structure of the catch data (Noble and Sathianandan, 1991). Many fields like agriculture, environmental, economics, tourism, meteorology and fisheries have been forecasted using time series models (Mahendran et al., 2008). This study evaluated, modeled and forecasted the Malaysian fish catches for some selected fish species using SARIMA and ETS state space approach. SARIMA is a common model used by many researchers e.g, Hae-hoon park (1998), Geogakarakos et al. (2012) whereas ETS state space approach has never been used in fisheries research in Malaysia

## 1.1 Background of the study

The fisheries sector plays an important role in the Malaysian national economy. It contributes to the national Gross Domestic Product (GDP), it is also a source of employment, foreign exchange and source of chief protein supply for the urban and rural population in the country. Fish constitutes 60-70% of the national animal protein intake, with per capita consumption of 47.8 kg per year (Che Ayub, 2012).

The rate of demand for fish as the main source of protein is expected to increase from the current population of 26,330 000 with a per capita consumption of 60 kg/year. In 1997, the fisheries sector contributed 1.57% to GDP, and it provides employment for more than 79,000 fishermen and 20,000 fish farmers. In 2003, the total fish production amounts to 1,483,958 tons valued at RM5.22 billion (US$ 1.36 billion). This contributed to about 1.37% of Gross Domestic Product (GDP) and provided direct employment to 89,433 fishers and 21,114 fish aqua culturists (Annual Fisheries Statistic, 2003), and also production of 1.71 million tons valued at RM 8.546 billion in 2009 (Che Ayub, 2012).

Malaysia has one of the highest intakes of fish in the world with estimated consumption in excess of 50kg per person, per year and accounting for approximately 60% of total animal protein intake (Azam-Ali et al. 2012).Approximately 75% of the fish harvested in Malaysia are wild, and caught from the marine environment. The Malaysian fisheries sector is divided into two: the capture fisheries (marine and inland) and the aquaculture. The marine capture fisheries cover a total area of 547,200 km$^2$ and categorized into coastal fisheries and deep-sea fisheries. In 2003, the coastal fisheries and deep-sea fisheries contributed about 1,084,802 tons (73.1%) and 198,453 tons (13.4%) respectively, to the total marine landings. There are more than 100 commercial fish species found in the Malaysian waters. The Malacca Straits and the South China Sea are the two main fishing areas which contribute most to Malaysian marine fishery and the rest are Sulu and Sulawesi seas in the east coast of Sabah.

Pelagic fishes are among the important contributor of deep sea catch. Pelagic fish refers to those fish that spend most of their life swimming in the water column (seas, oceans or open waters which associated with the surface or middle depths of a water body) with little contact with or dependency on the bottom of the sea floor. Many pelagic fish feed on plankton. The important pelagic fishes found in Malaysian waters include mackerel, tuna and sardines. Since fisheries resources are renewable, proper management issues should be taken to manage these fisheries resources. One of the issues is to forecast the upcoming fish catch. Fish forecasting is a very important tool for fisheries managers and scientists to enable them to decide on sustainable management issues.

## 1.2 Common fish species found in Malaysian waters

Tuna, mackerel, and sardines are some of the common fish species distributed over warmer oceans in the world (Campbell, 2008), and they are found to be common in Malaysian waters (Table 1.1; Noraish and Raja 2009; Samsudin 2012).

### 1.2.1 The Tuna Fish

The tuna fish are fast growing species with a catch size ranging from 1.8kg - 684kg depending on the type of species. Tuna spawn once a year and they are broadcast spawners, that is, they scatter their eggs into open water and fertilize externally. Tuna are known to make seasonal excursions to higher latitudes as water temperatures increase with season. A spawning female may release as many as 100,000 eggs per 2.2 pounds (1 kg) of body weight. The age of tuna at sexual maturity ranges from three to five years, depending on the species. Several popular species of tuna are being over fished, while others are sustainable. Other species are either already endangered or may soon become so (Langley et al. 2002). The majority of tuna are caught using one of the following methods; hook and line, purse seine, or gill net. Table 1.1 gives the most common tuna species found in Malaysian waters (Samsudin et al. 2012).

Table 1.1**:** Tuna fish species found in Malaysian waters

| Fish | Scientific Name | English Name | Local Name | Plate |
|---|---|---|---|---|
| **Tuna** | *Thunnus tonggol* | Longtail tuna | Tongkol hitam | 1.1 |
| | *Thunnus albacores* | Frigate tuna | Tongkol selasih | 1.2 |

Plate 1.1**:** *Thunnus tonggol* (Bleeker, 1851) or commonly called tongkol hitam

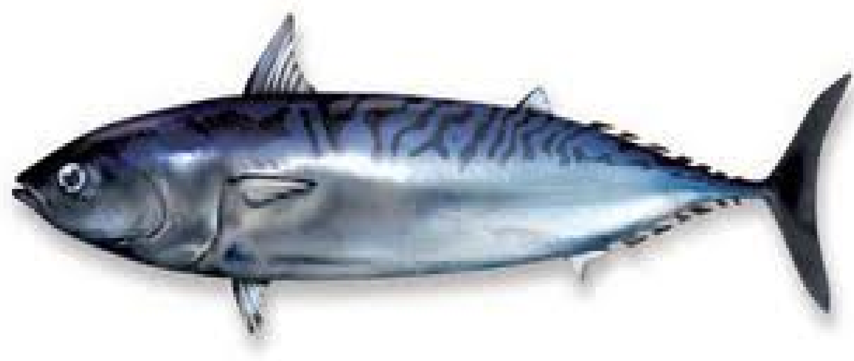

Plate 1.2**:** Thunnus albacores (Bonnaterre, 1788) or commonly called tongkol selasih

### 1.2.2 The Mackerel

Similar to the tuna family, mackerels share a family with the many species of tuna. Like tuna, they live in saltwater environments, usually in warm or temperate regions. Mackerel are typically an open ocean fish with greedy feeding habits, and may grow as large as 7.5 lb with maximum age of 20 years depending on the species; most species reach maturity at the age of two (Shuman, 2013). Although over fishing has started to be a problem it is expected that mackerel stock remain stable for few more year. Mackerel spawn near the surface and the eggs float in the water. Some methods used in catching mackerel are: spinning, floating, hook and line. Some mackerel species found Malaysian in waters (Samsudin et al. 2012) are displayed in table 1.2.

Table 1.2**:** Mackerel fish species found in Malaysian waters

| **Fish** | **Scientific Name** | **English Name** | **Local Name** | **Plate** |
|---|---|---|---|---|
| **Mackerel** | *Rastrelliger kanagurta* | Indian mackerel | Kembong | 1.3 |
| | *Rastrelliger brachysoma* | Short mackerel | Pelaling | 1.4 |
| | *Scrobemorus gattatus* | King mackerel | Tenggiri papan | 1.5 |
| | *Scrobemorus commerson* | Spanish mackerel | Tenggiri batan | 1.6 |

Plate 1.3: *Rastrelliger kanagurta* (Cuvier, 1817) or commonly called Kembong

Plate1.4**:** *Rastrelliger brachysoma* (Bleeker, 1851) or commonly called pelaling

Plate1.5: *Scombemorus gattatus* (Bloch & Schneider, 1801) or commonly called tenggiri papan

Plate1.6: *Scrobemorus commerson* (Lacepede, 1800) or commonly called tenggiri batan

### 1.2.3 The Sardines

Sardines are also among the most abundant and commercially important fish species in many countries around the world and are soft-boned fish that travel in schools. This fish range from 2.5 - 8.5 inches and weigh less than 1.0 lb. The sardine is a batch spawner and water temperature is very important environmental factor for their spawning dynamics (Ana et al. 2010). Some methods of catching sardine include; purse seine, hook and line. Sardine species found Malaysian in waters (Samsudin et al. 2012) are given in Table 1.3.

Table 1.3: Sardine fish species found in Malaysian waters

| Fish | Scientific Name | English Name | Local Name | Plate |
|---|---|---|---|---|
| **Sardine** | *Sardinella fimbriata* | Fringe Scale | Tamban Sisek | 1.7 |
| | *Dussumiera acuta* | Rainbow Sardine | Tamban buloh | 1.8 |
| | *Amblygaster leiogaster* | Smoothbelly Sardine | Tamban Beluru | 1.9 |

Plate1.7: *Sardinella fimbriata* (Valenciennes, 1847) or commonly called tamban sisek

Plate1.8: *Dussumiera acuta* (Valaenciennes, 1847), or commonly called Tamban buloh

Plate1.9: *Amblygaster leiogaster* (Valenciennes, 1847) or commonly called tamban beluru

## 1.3 Fishing Methods

In Malaysia; different fishing methods are practiced which include spinning, floating purse seining, gill netting, and hook and line. However, among all these methods, only purse seine, gill net and hook and line are the most commonly used. Samsudin et al. (2012) says Malaysian fishery are of multi-species and multi-gears fishery and the catches are dominated by two commercial fishing gears namely trawlers (Gill-netting) and purse seines. The trawlers and purse seines contribute more than 75% of total marine catch and the rest of the catches are from traditional gears. For example, in tuna fishery, the purse seines and trawlers catches 95% of neritic tuna and the rest by traditional gears such as trolling, hook and lines.

### 1.3.1 Purse seining method

Schools of fish are caught by means of a large net which surrounds the school. The net is then ‘pursed’ when the purse line closes the bottom of the net, after which the net is gradually brought aboard. The fish are then lifted out of the net using mechanical grabs, the purse seine fisheries use drifting Fish Aggregation Devices (FADs). Typically these are bamboo rafts of about 3.0 x 1.5m under where the fish tend to congregate; and they may be monitored remotely from the fishing vessel (Plate1.10), the purse seine is shot around the FAD, which increases capture. Fish including skipjack tuna, and other species, may congregate under the FAD. Dolphins are not usually found in association with FADs, but catches of undersize tuna and other pelagic can be higher using FADs. The purse-seine method is used primarily to catch fish for processing that is canning process (Aherne, 2011).

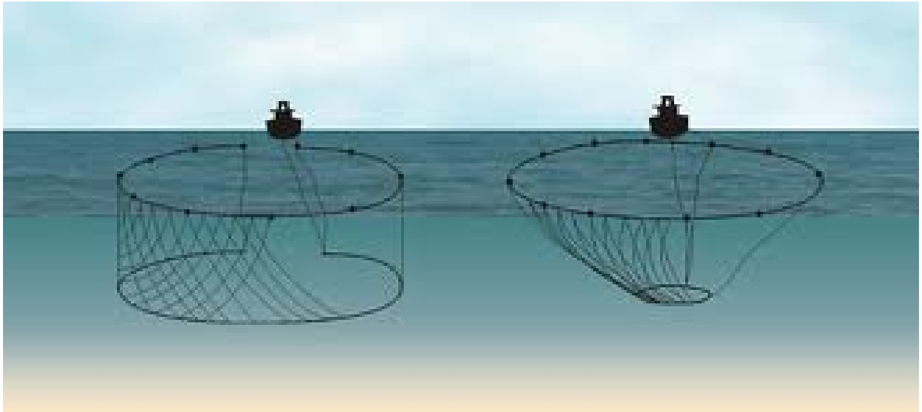

Plate 1.10: Purse seining method

### 1.3.2 Gill-netting

Gill-netting is a common fishing method used by commercial and artisanal fishermen of all the oceans and in some freshwater and estuary areas. Gill nets are vertical panels of netting normally set in a straight line (Plate 1.11). Fish may be caught by gill nets in 3 ways: (1) wedged – held by the mesh around the body (2) gilled– held by mesh slipping behind the opercula, and (3) tangled – held by teeth, spines, maxillaries, or other protrusions without the body penetrating the mesh. In most cases fish caught by gilled as can be seen in Plate 1.11. Where the fish swims into a net and passes only part way through the mesh, when it struggles to free itself, the twine slips behind the gill cover and prevents escape (Murphy and Willis, 1996). Gillnets are so effective that their use is closely monitored and regulated by fisheries management and enforcement agencies. Mesh size, twine strength, as well as net length and depth are all closely regulated to reduce by catch of non-target species. Gillnets have a high degree of size selectivity. This method in particular has an extremely low incidence of catching non-target species.

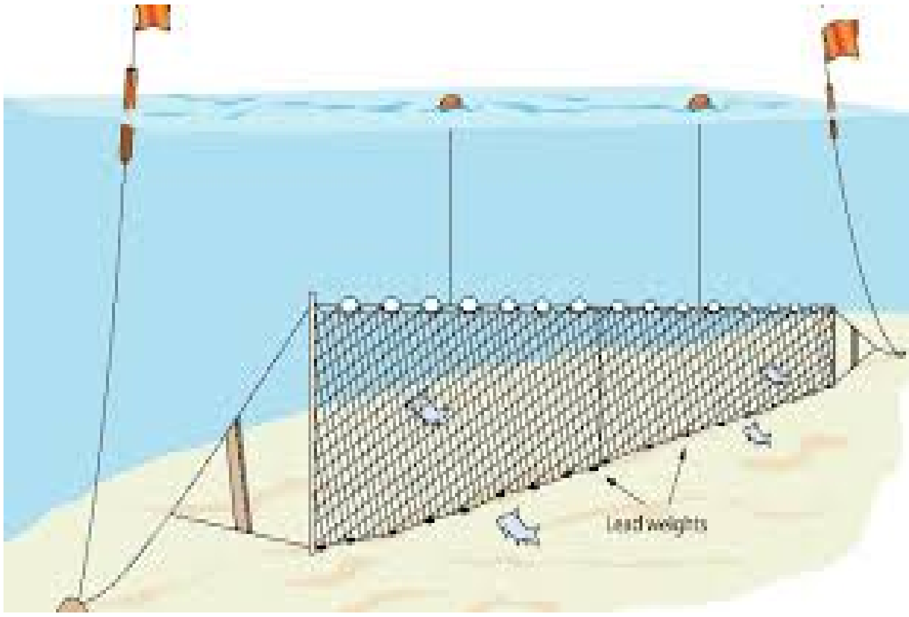


Plate 1.11: Gill-netting method

### 1.3.3 Hook and Line

A fishing line is a cord used or made for angling (method of fishing by means of an "angle" or fish hook). The hook is usually attached to a fishing line and the line is often attached to a fishing rod as shown in Plate1.12. Fishing rods are usually fitted with a fishing reel that functions as a mechanism for storing, retrieving and paying out the line. The hook itself can be dressed with bait which is designed to attract fish’s attention; a bite indicator such as a float is sometimes used. Angling is the principal method of sport fishing, but commercial fisheries also use angling methods. In many parts of the world, size limit apply to certain species, meaning fish below or above a certain size must, by law, be released. Important parameters of a fishing line are its length, material, and weight (thicker lines are more visible to fish). Some important factors that may determine what line an angler chooses for a given fishing environment include breaking strength, knot strength, UV resistance, cast ability, limpness, stretch, abrasion resistance, and visibility. Fish are caught with a fishing line by encouraging a fish to bite on a fish hook. A fish hook will pierce the mouthparts of a fish and is normally barbed to make escape less likely.


Plate 1.12: Hook and line method

## 1.4 Fishing seasons in Malaysia

The two main monsoon seasons in Malaysia are the Northeast Monsoon and the Southwest Monsoon Season. The monsoon that affects the living of the Peninsular Malaysia east coast, particularly those in the fishing industry is mainly the Northeast Monsoon which brings strong wind and rainfall from November to January. The northeast monsoon season is characterized by constant winds that blow from the northeast. It is associated with the development of the Siberian High which is a massive collection of cold dry air on the Eurasian terrain and the movement of the heating maxima from the Northern Hemisphere to the Southern Hemisphere. Northeasterly winds flow down Southeast Asia with wind speeds reaching as high as 30 to 40 km/hr. During the season, the states on the east coast of Peninsular Malaysia, coastal areas of Sarawak and Sabah will experience episodes of continuous heavy rain normally for a total of two to three days due to monsoon surge. In the case of extreme weather, the whole episode of heavy rain can last for three to eight days, and may cause flooding. There are some days that strong wind and thunderstorm will disrupt the fishing routine but the fishermen can still be able to fish during that season.

The monsoon seasons affects the species of fish caught by the fishermen on the east coast. During the beginning of the season, fish species from the mackerel and threadfin family will be abundant.
(https://sites.google.com/site/southeastasiafish/fishing-weather).

Policy makers establish goals and objectives to forecast uncontrollable events, then select appropriate actions which hopefully will result to the realization of the goals and objectives. Forecasting is very important because it plays a central role in management; it precedes planning which in turn precedes decision making (Makridakis et al. 2000).

## 1.5 Status of Pelagic fisheries

Although the fish catch of Tuna, Sardines and Mackerel are still sustainable, over fishing might still be an upcoming problem that is why since fisheries resources are renewable, proper management issues should be taken to manage these fisheries resources. Fish forecasting is a very important tool for managers and scientist to enable them to decide on sustainable management issues. Statistical modelling fundamentally consists of developing a model to sufficiently represent the relevant features of the problem under study. Subsequently, it is used to forecast future values of the underlying phenomenon which may be for example, commercial landings of some important fish species.

## 1.6 Problem Statement

Forecasting has become increasingly useful and important in formulating educated estimates of things to come. As previously noted, strategists, policy makers, business executives, project managers, investors, and foremen resort to forecasting for help in strategic planning, investment, policy planning, resource procurement, scheduling, inventory maintenance, quality assurance, and resource mobilization in the short run. Nonetheless, the strategists and planners are aware that the basic and ultimate purpose of forecasting is to predict in the near term what will happen in order to avoid substantial cost or loss.

Modeling and forecasting fish catch has been undertaken in a long time over the globe, but the problem that exists is finding a suitable model that can capture both the dynamics attributed to fish catch data. From time to time, researchers are always looking for new models that can predict more accurately the number of fish catch. However, Malaysia being one of the countries with high intakes of fish in the world has received less concern in knowing the dynamics of future fish catches in the country. To the best of our knowledge only few studies concerned about modeling and forecasting fish catches in the Malaysian waters.

## 1.7 Objective of the research

The objectives of the research are to:

1. Propose a suitable model for forecasting fish catches in Malaysian waters using ETS state space approach.
2. Compare the forecast ability of ETS and SARIMA model using tuna, sardine, and mackerel fish catch data to see which model forecast better.

## 1.8 Scope of the research

In this research, the Box-Jenkins time series methodology and the ETS are used to analyze and forecast the monthly fish catch of Tuna, Sardines and Mackerel fishes based on the monthly data from 2007-2011. The data were collected mainly in Peninsular Malaysia.

## 1.9 Significance of the Study

The contribution of this research was in proposing the ETS model which has not been used in fisheries in Malaysia, and the ETS model was compared with SARIMA model to see which one forecast better. These then can help managers in the line of pelagic fish production and fisheries management in general. Another gap that was bridged was extending the forecasting years from 2012 - 2013.

The next chapters of the dissertation are organized as follows: Chapter 2 provides an overview of the related works. Chapter 3 discusses the statistical methods used in this study for modeling and forecasting fish catch. Chapter 4 presents the result and discussion of the study and Chapter 5 summarizes the dissertation, draws the appropriate conclusions, recommendations and outlines some potential directions for further research work.

# CHAPTER 2

# LITERATURE REVIEW

## 2.1 Introduction

This chapter first glances on time series analysis. The chapter also provides through selective reference a clearer understanding of the contributions of Box-Jenkins methodology and ETS state space exponential smoothing models in time series modeling and forecasting.

## 2.2 Time Series Analysis

A time series is a sequence of data points measured at successive time intervals. Understanding the mechanism that generated a time series data or making predictions are among the main goals of time series analysis. The modelling of univariate time series is a subject of great importance in a variety of fields, e.g. astronomy, meteorology, hydrology, economics, and many others. It is worth emphasizing that to talk about the time series suggests that there is some type of randomness. A time series is really a stochastic procedure that describes the evolution of the random variable. It units of time will vary with the application. They could be years, quarters, months, days, hours, minutes or even microseconds, depending on the situation to be modelled. The unit of time is not important, what is important is that; the observations are equally spaced in time (Iffat, 2009). In time series studies, the interest is on time delay or time lag (or time step), not actual time. If the observations are not equally spaced, everything gets much more complicated. The aim of time series temporal analysis would be to predict future values of the given variable according to its past behavior. In other words, it is to develop a model that signifies time series after which make use of the model to forecast the near future values.

## 2.3 Modelling and Forecasting Fisheries Time Series

Time series analysis comprises methods for analysing time series data in order to extract meaningful statistics and other characteristics of the data. Time series data have a natural temporal ordering. This makes time series analysis different from other common data analysis problems, in which the ordering of the observations doesn't matter. Modelling and Forecasting are one of the main aims of time series analysis. Different approaches may be used for modelling and forecasting time series. There are forecasts from exponential smoothing. There are also the X-11 (or X-12) forecasts, which predict fairly well over a 12-month period or so. The Box–Jenkins methodology which is generally very good for short-term forecasting, regression analysis which can be used with moving average models or series with deterministic trends may also serve to predict over the longer run. Modeling and forecasting Fisheries dynamic have been undertaken for a long period of time, for example, Micheal (1983) applied time series methods to predict daily data of tripe and average catch per tripe (effort and CPUE) for anchovy and mackerel fishing in San Pedro, California, purse-seine fishery. The study shows that high fishing effort leads to a slight increase in CPUE.

Grant et al. (1988) applied Markov model to forecast total annual commercial harvest of brown shrimp in the northwestern Gulf of Mexico and the results showed good predictions can be made by June or July and some predictive capabilities present as early as April.

Stretta (1991) reported that tropical tuna movement can be observed from space, but must be deduced by models based on tuna behavior. In finding the highest concentration of tunas, he found an area with a high density of tuna forage. The knowledge of the surface thermal signature of the fertilizing process of water masses is possible using satellite infrared radiometers, he estimated forage production and thereby predicted tuna distribution.

Sterigou (1991) described and forecasted the sardine- anchovy complex in the eastern Mediterranean Greece using the vector autoregression model. The model explained 93% variability of anchovy and 72% of the variability of sardine catches and they produced an accurate and unbiased fits and forecasts. The result showed model predicted persistence, a 3-year periodicity of catches, and a negative relationship between anchovy and sardine catches.

Sterigiou and Christou (1996) used eight forecasting techniques to model and provide operational forecasts of annual landings of 16 species in the Hellenic marine waters. The operational forecast was based on four general categories of forecasting techniques which are multiple regression models using different variables, univariate time series models, multivariate time series techniques; and the biological exponential surplus-yield model. The result of their study showed that the annual catches of all the 16 species displayed long term trends.

Walia and Jain (1998) used nonlinear statistical models to forecast fish weight at the time of harvest after 12 months of stocking fish. The results revealed that forecasting of fish weight can be made three months before harvest for the species of fish studied.

Stroyer and Mccomish (1998) used time series analysis method to analyze the annual index trawl of yellow percaflavascens in the southern Lake Michigan from 1975-1996, and the model predicted that the relative abundance of quality size yellow perch in the lake Michigan remain low in 1997 and 1998.

Venogopal and Srinath (1998) used univariate time series and multivariate time series modeling approaches to evaluate efficiency with a view to modelling and providing accurate operational forecasts of quarterly commercial landings of seven species of marine fishes along with the total landings for Tamil Nadu.

Raymond et al. (1999) predicted fish yield of 59 African lakes using neural network. The result showed the advantages of the back propagation procedure of the neural network in stochastic approaches to fisheries ecology.

Anne et al. (2000) evaluated the impact of fishing on marine communities by applying four multispecies models which are descriptive multispecies, dynamic multispecies, aggregate system, and dynamic system models they concluded that these models provide a basis for assessing the benefit in the marine ecosystem.

Monterro (2002) developed a growth model for a fish population in the coastal ecosystem. The growth model provides the basis to build a model of the movement of fish in marine environment according to their environmental preference.

Borges (2003) used time series analysis to investigate the effect of wind condition and North Atlantic oscillation (NAO) on the sardine catches. Recruitment is forced to a lower level when wind exceeds a certain limit in winter and the time series analysis shows evidence of climatic driven regime-shift.

Premwadee (2006) developed statistical models for forecasting the quantity of various types of marine fish landing at the Pattani fishery port, allowing for trend and seasonality. The data comprised of daily and monthly totals by weight for eight types of fish. The results shows that mackerels and other food fish and squid catches tend to decrease, whereas the catches of scads tend to increase and trash fish catches have no detectable trend up or down, shrimp and lobster tend to decrease exponentially and the trend of crab is constant.

Leathwick et al. (2006) used two statistical techniques which are generalized additive models (GAM) and multivariate adaptive regression splines (MARS) to analyze the relationship between the distributions of 15 freshwater species and their environments. The result indicated little difference between the performance of GAM and MARS models.

Goodwin et al. (2007) applied a new technology known as the numerical fish surrogate who helps in designing a fish bypass and guidance structures at hydro facilities by combing three types of modelling to forecast fish behavior and trajectories.

Sathianandan (2007) forecasted the relationship between eight commercially important marine fish species in Kerala from 1960-2005 using vector autoregressive models. The result was the production of 16 individual models consisting of different landing time series and the behavior of each time series was examined.

Guitierrez-Estrada et al. (2007) used the hybrid of computational neural networks (CNN) and ARIMA models to forecast one month ahead of anchovy catches in the north area of Chile. The results obtained from individual models shows strong correlation amongst models. However, the calibrated CNN+ARIMA models captured the general trend of the historical data.

Sarawuth and Apiradee (2008) developed a statistical model to forecast the quantity of fish catches in Songhla lake basin in southern Thailand. The model had seasonal effect and time lagged terms for the preceding two months. The result showed that catches has decreased substantially in the last ten years and no long-term trend is evident.

Xinjun et al. (2008) applied the catch data and satellite derived environmental variables to determine habitat suitability indices for Chub mackerel during July to September in the East China Sea. More than 90% of the total catch were found to come from the areas with sea surface temperature of (28.0°C- 29.4°C), sea surface salinity of (33.6- 34.2) psi, chlorophyll-*a* concentration of (0.15 - 0.50 mg/m$^3$) and sea surface height anomaly of (0.1 - 1.1 m). Of the four conventional models of HSI, the Arithmetic Mean Model (AMM) was found to be most suitable according to Akaike Information Criterion. Based on the estimation of AMM in 2004, the monthly HSIs in the waters of 123°- 125°E and 27°30´ - 28°00´N were more than 0.6 during July to September, which coincides with the catch distribution in the same time period. This implies that AMM can yield a reliable prediction of the Chub mackerel's habitat in the East China Sea.

Nibaldo and Orlando (2009) forecasted a 1-month ahead monthly sardines catches using a multivariate polynomial model combined with multi-scale stationary wavelet decomposition. The observed monthly sardine catches were decomposed into various sub-series employing wavelet decomposition techniques and then appropriate sub-series were used as an inputs to the autoregressive forecasting model. The forecasting strategy parameters were estimated using the least squares method and found that the method achieves 99% of the explained variance with a mean absolute percentage error (MAPE) below 7.6%. They also employed a functional autoregressive (FAR) model combined with multi-scale stationary wavelet decomposition technique for one-month-ahead monthly sardine catches forecasting in the northern area of Chile.

Albanez-Lucero and Arregun-Sanchez (2009) used artificial neural network (ANN) tools to model red grouper (*Epinephelus morio*) distribution. ANN was used to relate discrete relative abundance data to differentiate substrate within and between defined areas in order to provide a reliable distribution map. The result showed a significant relationship between the types of substrate and the three stages of distribution.

Samanthan and Ghosh (2011) reported to the fishery biologists about the existence of a very versatile self-exciting threshold autoregressive moving average

(SETARMA). This model is capable of describing cyclic fluctuations in modelling mackerel landings in Karnataka, India.

Sarawuth and Chamnein (2011) studied the monthly catch weight in the Songhkla Lake from the period Jan 2003 – Dec 2006 with a regression model containing three species. Catch weight was first aggregated by species and a combination of the bi-monthly season of the year and catching gear. The first component was represented by the most species of estuarine and marine vertebrates. The second component mainly represented freshwater fish and some marine invertebrates and reflected the fact that most of these species were caught by gill nets. The third component focused on the seasonal fluctuations in catch weight. They concluded that the patterns indicated increasing freshwater catch weights, while marine invertebrate catches decreased.

Table 2.1: Summary on Modelling and Forecasting Fisheries Time Series

| **S/no** | **Names of authors** | **Method employed** | **Work** | **Conclusion** |
|---|---|---|---|---|
| 1 | Micheal (1983) | Time series methods. | Predicted the daily data of tripe and average catch per tripe (effort and CPUE) for anchovy and mackerel fishing. | High fishing effort leads to a slight increase in CPUE. |
| 2 | Grant et al. (1988) | Markov model | To forecast total annual commercial harvest of brown shrimp. | Good predictions were made. |
| 3 | Stretta (1991) | Satellite infrared radiometers | Finding the highest concentration of tunas. | Predicted tuna distribution. |
| 4 | Sterigou (1991) | Vector autoregression model. | Described and forecasted the sardine- anchovy. | The model produced an accurate and unbiased fits and forecasts. |
| 5 | Sterigiou and Christou (1996) | Univariate time series models, multivariate techniques; and the biological exponential surplus-yield model. | To model and provide operational forecasts of annual landings of 16 fish species. | The study showed that the annual catches of all the 16 species displayed long term trends. |

Table 2.1: (Continued)

| | | | | |
|---|---|---|---|---|
| 6 | Walia and Jain (1998) | Nonlinear statistical models. | To forecast fish weight at the time of harvest after 12 months of stocking fish. | Forecasting of fish weight can be made three months before harvest for the species of fish studied. |
| 7 | Stroyer and Mccomish (1998) | Time series analysis method. | To analyze the annual index trawl of yellow percaflavascens | The model predicted that the relative abundance of quality size yellow perch in the lake Michigan remain low in 1997 and 1998 |
| 8 | Venogopal and Srinath, (1998) | Univariate time series and multivariate time series modeling approaches. | To model and providing accurate operational forecasts of quarterly and the total landings of seven species of marine fishes. | The models produced fits and forecasts. |
| 9 | Raymond et al. (1999) | Neural network. | Predicted fish yield of 59 African lakes. | The result showed the advantages of the back propagation procedure of the neural network in stochastic approaches to fisheries ecology. |
| 10 | Anne et al. (2000) | Descriptive multispecies, dynamic multispecies, aggregate system and dynamic system models. | Evaluated the impact of fishing on marine communities. | Concluded that these models provide a basis for assessing the benefit in the marine ecosystem |

Table 2.1: (Continued)

| | | | | |
|---|---|---|---|---|
| 11 | Monterro (2002) | Growth model. | To study fish population in the coastal ecosystem. | The growth model provides the basis to build a model of the movement of fish in marine environment according to their environmental preference. |
| 12 | Borges (2003) | Time series analysis. | To investigate the effect of wind condition and North Atlantic oscillation on the sardine catches. | The time series analysis shows evidence of climatic driven regime-shift. |
| 13 | Premwadee (2006) | Statistical models. | Forecasting the quantity of various types of marine fish landing, allowing for trend and seasonality. | The result shows that mackerel's catches tend to decrease. |
| 14 | Leathwick et al. (2006) | Generalized additive models (GAM) and multivariate adaptive regression splines (MARS). | To analyze the relationship between the distributions of 15 freshwater species and their environments. | The result indicated little difference between the performance of GAM and MARS models. |
| 15 | Goodwin et al (2007) | Numerical fish surrogate. | Designed a fish bypass and guidance structures at hydro facilities by combing three types of modeling. | Forecasted fish behavior and trajectories. |
| 16 | Sathianandan (2007) | Vector autoregressive models. | Modelling and forecasting. | Forecasted the relationship between eight commercially important marine fish species. |
| 17 | Guitierrez-Estrada et al. (2007) | Computational neural networks and ARIMA. | Forecast anchovy catches in the north area of Chile. | Calibrated CNN+ARIMA models captured the general trend of the historical data. |

Table 2.1 :(Continued)

| | | | | |
|---|---|---|---|---|
| 18 | Sarawuth and Apiradee (2008) | Statistical model | To forecast the quantity of fish catches in Songhla lake basin in southern Thailand. | The result showed that catches has decreased substantially in the last ten years and no long-term trend is evident. |
| 19 | Nibaldo and Orlando (2009) | Multivariate polynomial model combined with Multi-scale stationary wavelet decomposition. | Modelling and forecasting. | Forecasted 1-month ahead monthly sardines catches. |
| 20 | Albanez-Lucero and Arregun-Sanchez (2009) | Artificial neural network (ANN) tools. | To model red grouper (*Epinephelus morio*) distribution. | The result showed a significant relationship between the types of substrate and the three stages of distribution. |
| 21 | Xinjun et al. (2008) | Satellite derived environmental variables and Arithmetic Mean Model (AMM). | To determine habitat suitability indices for Chub mackerel during July to September in the East China Sea. | AMM was found to be most suitable according to Akaike Information Criterion |
| 22 | Samanthan and Ghosh (2011) | Self-exciting threshold autoregressive moving average (SETARMA). | Modelling mackerel landings in Karnataka, India. | The model is capable of describing cyclic fluctuations in modelling mackerel landings. |
| 23 | Sarawuth and Chamnein (2011) | Regression model. | To model three monthly catch weight in the Songhkla Lake. | They concluded that the patterns indicated increasing freshwater catch weights, while marine invertebrate catches decreased. |

# REFERENCES

Aherne, D. (2011). Seafish Guidance Note. The tuna supply chain. http://www.seafish.org/upload/b2b/file/resource_sustainability/SeafishResponsibleSourcingGuide_Tuna_201006.pdf.

Akaike, H. (1974). A new look at the statistical model identification, IEEE Transactions on Automatic Control 19 (6): 716–723

Albanez-Lucero, M.O. and Arreguín-Sánchez, F. (2009). Modelling the spatial distribution of red grouper (Epinephelus morio) at Campeche Bank, México, with respect substrate Ecological Modeling, 220, 2744–2750.

Alex, C., Wertheimer, J. A., Orsi, E. A. and Molly V. S. (2010). Forecasting pink salmon harvest in south Alaska from juvenile salmon abundance and associated parameters: 2011 returns and 2012 forecast. NPAFC Doc.1414, 20pp.

Ana, P., Mirko, D., Aleksandar, J., Slovbodon, R., Predrag, S. and Branko, G. (2010). Some reproductive patterns of the sardine, Sardina Pilchardus. ACTA ADRIAT, 51(2):159-168.

Anne, B. H., Nicholas, Bax., Richard, B., Jeremy, C., Micheal, F., Patricia, L., John, P. and Jake, C. R. (2000). Are multispecies model an improvement on single-species model for measuring fishing impact on marine ecosystem? ICES, Journal of marine science, 57, 707-719.

Azam-Ali, S., McCullough, F. and Mitra, S. (2012). The role of fish and other aquatic animal species in the Malaysian diet: Barriers to increasing consumption of farmed-species. Project, University of Nottingham, Malaysia. www.nottingham.edu.my › CFFRC.

Azami, Z., Ahmad, M. R., Tee, P. G. and Kamaruzzaman, S. (2009). Time series analysis of solar radiation data in the tropics. European Journal of Scientific Research, 25(4), 672-678.

Baran, E. and Myschowoda, C. (2008). Have fish catches been declining in the mekong river basin?. Modern Myths of the Mekong, Water & Development Publications - Helsinki University of Technology, pp. 55-64, ISBN 978-951-22-9102-1.

Borges, M.F., Santos, A.M.P., Crato, N., Mendes, H., Mola, B. (2003). Sardine regime shift off Portugal: A time series analysis of catches and wind conditions. Sci.mar, 67, 235-244.

Box, G.E.P. and Jenkins, G.M. (1976). Time Series Analysis: Forecasting and Control. Holden-Day, Boca Raton, Fla., USA.

Campbell, R.A. (2008). Summary of Catch and Effort Information pertaining to Australian Longline Fishing Operations in the Eastern Tuna and Billfish Fishery. Background paper to ETBF Resource Assessment Group meeting, 29-30 July 2008, Hobart.

Chatfield, C. (2001). Time-Series Forecasting. Chapman & Hall/CRC, Florida.

Christou, E.D. and Sterigou, K.I. (1998). Modelling and Forecasting the Forth nightly Cladoceran Abundance in the Soronikos Gulf (Aegean Sea), Journal of Plankton Research, 20, 7, 1313-1320.

Department of Fisheries Malaysia (2005). Malaysia National Plan Of Action For The Conservation And Management Of Shark. Kuala Lumpur: Department of Fisheries Malaysia, Ministry of Agriculture and Agro-Based Industry Malaysia.

Dıaz-Robles, L. A., Juan, C. O., Joshua, S. F., Gregory, D. R., Judith, C. C., John, G. W. and Juan, A.M.H. (2008). A hybrid ARIMA and artificial neural networks model to forecast particulate matter in urban areas: The case of Temuco, Chile. Atmospheric Environment, 42, 8331–8340.

Dyer, T.G.J. and Gillooly, J.F. (1979). Simulating fish production using exponential smoothing. Ecol. Modeling, 6,77-87.

Efthymia, V.T., Christos, D.M. and John, H. (2007). Modelling and Forecasting Pelagic Fish Production Using Multivariate and Univariate ARIMA Models. Fisheries Science, 73, 5, 979-988.

El Tatawy, N. (2012). Economic impact of lake edku pollution. International conference on applied life science, 10-12 September, 2012.

Fadhilah, Y. and Ibrahim, L. K. (2012). Modeling Monthly Rainfall Time Series Using ETS State Space and SARIMA Models. International Journal of Current Research, 4, 09, 195-200.

Fadhilah, Y. and Ibrahim, L. K. (2013).Volatility modeling of rainfall time series". Theor Appl Climatol, 113, 247–258.

Floros, C. and Pierre, F. (2006). Forecasting monthly fisheries prices: Model comparison using data from Cornwall (UK). European Journal of Scientific Research, 14, 2, 613-624.

Gardner, Jr. E.S. (1985). Exponential Smoothing: The State of the art. Journal of Forecasting, 4, 1-28.

Geogakarakos, S., Koutsoubas, D. and Valavanus, V. (2006). Time Series Analysis and Forecasting Techniques Applied on Lolignid and Ommastrelhid Landings in greek waters. Fisheries Research, 78:55-71.

Giraitis, L., Leipus, R. and Philippe, A. (2002). The Test for Stationarity versus Trends and Unit Roots for a wide class of Dependent Errors. Department of Economics, London School of Economics, Houghton Street, London WC2A 2AE, United Kingdom, 2-3.

Goodwin, A. R., John, M., Nestler, J., Anderson, J. and Larry, W. J. (2007). Anew tool to forecast fish movement and passage. The magazine of the North American Hydroelectric Industry, Hydro-Review. 26, 4.

Grant, W,E., Matis, J.H. and Miller, W. (1988). Forecasting commercial harvest of marine shrimp using markov chain model. Ecological Modeling, 43:183-193.

Guitierrez-Estrada, J. C., Claudio, S., Eleuterio, Y., Nibaldo, R., Inmaculado, P. C. (2007). Monthly Catch Forcasting of Anchovy Engraculis ringens in the North Area of Chile: Nonlinear Univariate Approach. Fisheries Research, 86, 188-200.

Gujarati, D.N. (2003). Basic econometrics, 4th ed., Boston, McGraw–Hil.

Hae-Hoon, P. (1998). Analysis and prediction of walleye pollock (Theragra chalcogramma) landings in Korea by time series analysis. Fisheries Research, 38, 1, 1-7.

Hanson, P.J., Vaughan, D.S. and Narayan, S. (2006). Forecasting Annual Harvests of Atlantic and Gulf Menhaden. North American Journal of Fisheries Management, 26, 753–764.

Huusko, L. (2011). Developing a forecasting model for doctor´s appointments in healthcare business, Helsinki Metropolia University of Applied Sciences Master’s Degree in Industrial Management. Master’s Thesis.

Hyndman, R. J. (2002). Forecasting based on state space models for exponential smoothing.

Hyndman, R.J., Koehler, A.B., Ord, J.K. and Snyder, R.D. (2005). Prediction intervals for exponential smoothing using two new classes of state space models. Journal of Forecasting 24: 17– 37.

Hyndman, R.J. and Khandakar, Y. (2008). Automatic Time Series Forecasting: The forecast Package for R. Journal of statistical software. http://www.jstatsoft.org/.

Iffat A. G. (2009). Novel Computationally Intelligent Machine Learning Algorithms for Data Mining and Knowledge Discovery. PhD thesis, submitted to Department of Computing Science and Mathematics, University of Stirling, Scotland, UK.

Jabatan Perikanan Malaysia (2003). Annual Fisheries Statistics 2003, Jilid 1, Jabatan Perikanan Malaysia.

John, M. (1988). Forecasting with adaptive exponential smoothing. Journal of the academy of marketing science, 16, 3&4, 062-070.

Koutromanidis, T., Lazaros, I. and Geogios, K. S. (2006). Time Series Modelling of Fishery Landings Using ARIMA Models and Fuzzy Expected Intervals Software. Environmental Modelling and Software, 21, 1711-1721.

Langley, A., Hampton, J. and Willians, P. (2002). The Western and Central Pacific Tuna Fishery: 2002 Overview and Status of Stocks. Report to the Secretariat of the Pacific. Available at: http://www.spc.org.nc/OceanFish/html/sctb/index.htm.

Lazim, A. (2012). ARIMA Model for Gold Bullion Coin Selling Prices Forecasting, International Journal of Advances in Applied Sciences (IJAAS), 1, 4, 153-158.

Leathwick, J.R., Elith, J. and Hastie, T. (2006). Comparative Performance of Generalised Additive Models and Multivariate Adaptive Regression Slines for Statistical Modelling of Species Distribution. Ecological Modeling, 199, 188-196.

Ljung, G.M. and Box, G.E.P. (1978). On a Measure of a Lack of Fit in Time Series Models. Biometrika, 65, 2, 297–303.

Lloret, J., Jordi, L. and Ignasi, S. (2000). Time Series Modelling of Landings in Northwest Mediterranean Sea. ICES Journal of Marine Science, 57, 171-184.

Luis, M.M., Juan C.G.E. and Julio, M.G. (2010). Seasonal Patterns of Three Fish Species in a Caribbean Coastal Gill-net Fishery: Biologically Induced or Climate Related Aggregation?. Fisheries Research, 106, 358-367.

Medina, D. C., Findley, S. E. and Seydou, D. (2008). State–Space Forecasting of Schistosoma haematobium Time-Series in Niono, Mali". www.plosntds.org. 2(8).

Mahendran, S., Pauline, M., Lim, Y.C. and Lim, Y.S. (2008). ARIMA and ARFIMA Models for forecasting Annual Demersal and Pelagic Marine fish Production in Malaysia. Malaysian Journal of Mathematical sciences, 2, 2, 41-54.

Makridakis, S. and Hibon, M. (2000). The M3-Competition: results, conclusions and implications. International Journal of Forecasting, 16, 451–476.

Micheal, J. F. (2011). Time Series Model of Maine Lobster Fishery: The effect of Temperature. Canadian Journal of Fisheries and Acquatic Science. 4, 7, 1145 - 1153.

Monteiro, R.S.O. (2002). Fish Growth Modelling: Growth of the European anchovy (Engraulis encrasicolus) in the Tagus Estuary, Portugal. DEA Modelling of the Marine Environment, 01/02, 1 – 56.

Murphy, B. and Willis, D. (1996). Fisheries Techniques: Second edition. Bethesda, MD: American Fisheries Society.

Nibaldo, R., Orlando, D., Broderick, K. (2009). Multiscale Functional Autoregressive Model for monthly sardines catches forecasting. Journal of Oceanography, 65, 1, 93-102.

Noble, A. and Sathianandan, T.V. (1991). Trend analysis in all Indian mackerel catches using ARIMA models. Indian journal of fisheries, 38, 2, 119-122.

Noraisyah, A. and Raja Bidin, H. (2009). Tuna Fisheries in Malaysia. WP09_final Overview of Tuna Fisheries and National Stock Assessment_5.pdf.

Pegels, C.C. (1969). Exponential Forecasting: Some New Variations. Management Science, 15, 5, 311-315.

Pottier, M. and Drapeau, L. (2000). Modelling and Forecasting the Catch of the Scads (Decapterus macrosoma, Decapterus russelli) in the Javanese Purse Seine Models. Asian fishery society, 13, 75-85.

Premwadee, K., Phattrawan, TK. and Wanchamai, K. (2006). Trends in Marine Fish Catches at Pattani Fishery port (1999-2003) Songklanakarin. Journal of science and Technology, 28, 4, 887- 895.

Raymond, L., Sovan, L., Jacques, M. (1999). Predicting fish yield of African lakes using neural networks. Ecological Modeling, 120, 325–335.

Sallehuddin, R., Siti Mariyam, Hj. S., Siti Zaiton, M. H., and Ajith, A. (2007). Forecasting Time Series Data Using Hybrid Grey Relational Artificial Neural Network and Auto Regressive Integrated Moving Average Mode". Neural Network World, 573-605.

Samsudin, B., Noraisyah, A.B. and Sallehudin, J. (2012). Information on fisheries, research and statistics. Malaysia National Report to the Scientific Committee of the Indian Ocean Tuna Commission for 2012. IOTC-2012-SC15-NR16 Rev_1.

Sathianandan, T.V (2007). Vector Time Series Modelling of Marine Fish Landings n Kerala. J. Mar. Biol. Ass. India, 49, 2, 197-205.

Stretta, J.M. (1991). Forecasting Models for Tuna Fishery with Aero spatial Remote Sensing. Int .J. Remote Sensing, 12, 4, 771-779.

Sarawuth, C. and Chamnein, C.P. (2011). A model for Clustering Fish Community Structure with Application to Songkla Lake Bi-Monthly Catches 2003-2006. Turkish Journal of Fisheries and Aquatic Sciences, 11, 177-184.

Sterigou, K.I. and Christou, E.D. (1996). Modelling and Forecasting annual fisheries catches: Comparison of Regression, Univariate and Multivariate Time Series Method Fisheries Research 25:105-138.

Stroyer, S. M. and Mccomish, T. S. (1998). Forecasting Abundance of Quality-Sized Yellow Perch in Indiana Waters of Lake Michigan. North American Journal of Fisheries Management, 18, 19-24.

Samantha, S. P., and Ghosh, H. (2011). Modelling and Forecasting Cyclic Fish Landings: SETERMA Non Linear Time Series Approach. Indian J. Fish, 58, 3, 39-43.

Sarawuth, C., and Apiradee, L. (2008). Forecasting fish catches in the Songkhla Lake basin. Science Asia, 34, 335-340.

Shuman, C. (2013). Marine Sport fish Identification: Tuna & Mackerels. http://www.dfg.ca.gov/marine/mspcont1.asp.

Singini, W., Kaunda, E., Kasulo, V. and Jere, W. (2012). Modelling And Forecasting Small Haplochromine Species (Kambuzi) Production In Malaŵi – A Stochastic Model Approach. International Journal of Scientific and Technology Research, 1, 9, 69 – 73.

Stat 510; (2013). Applied time series, Department of statistics, Eberly college of science.

Taylor, J.W. (2003). Exponential smoothing with a damped multiplicative trend. International Journal of Forecasting 19, 715–725.

Venugopalan, R. and Srinath, M. (1998). Modelling and forecasting fish catches : Comparison of regression, univariate an d multivariate time series methods. Indian J. Fish., 45, 3, 227-237.

Walia, S.S., and Jain, R.C. (1998). Non-linear Statistical Models for Pre harvest Forecasting of Fish Production from Inland Ponds. Indian journal of fisheries 45, 1, 75-78.

Wang, W., Van Gelder, P. H. A. J. M., Vrijling, J. K., and Ma, J. (2005). Testing and modelling autoregressive conditional heteroskedasticity of streamflow processes. Nonlin. Processes Geophys, 12, 55 – 66.

Xinjun, C. Li, G., Feng B. and Tian, S. (2008). Suitability Index of Chub Mackerel, Scomber japonicas from July to September in the east china sea. Journal of oceanography.

# APPENDIX A

1. Predictive Modeling of Pelagic Fish Catch Using Seasonal ARIMA Models. Agriculture, Forestry and Fisheries. Vol. 2, No. 3, 2013, pp. 136-140.

2. Pelagic Fish Catch Modeling and Forecasting using Seasonal ARIMA and Triple Exponential Smoothing. (Seminar Kembangsan Aplikasi Sains dan Matematik, (SKASM 2013, 29-30, October 2013).

APPENDIX B