Mukti Zainuddin

Prediction of Albacore Tuna Habitat Hot Spots

A Satellite Remote Sensing and GIS Perspective

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CHAPTER I
INTRODUCTION

1.1 The historical aspect of the application of remote sensing and GIS to fisheries

A combined remote sensing (RS) and geographic information system (GIS) approach is playing an increasingly important role in marine fisheries research and fish harvesting. Satellite sensors make synoptic measurements of sea surface temperature (SST), surface chlorophyll-a concentration or ocean color, surface winds, ice cover, sea surface height and surface currents over large areas of the ocean with short time periods. Variations in these ocean environmental conditions play key roles in natural fluctuation of fish stock (fish distribution and abundance) and in their vulnerability to harvesting. While, GIS technology allows the display, spatial modeling and analysis, prediction and overlay of real-time or near real-time historical data from many sources (ESRI, 2001). The core of marine fisheries RS and GIS is the ability to derive and incorporate biological and physical data into many spatial and temporal scales (Simpson, 1992, 1994). Therefore, an integration of RS and GIS provide some insight into detection, identification and prediction of high productive tuna habitat in the expansive ocean environment.

The promise of satellite RS and GIS techniques for fisheries research, management and exploitation has been widely recognized. It is well known that there are significant progresses and expansions in the utilization of satellite RS data for meeting the need of fisheries researcher and managers for marine oceanographic information. The reasons for the advance of using RS as follows (Laurs and Polovina, 2000): (1) increases in the availability and improvements in the access to satellite data, (2) the development of easy to use satellite data processing and display software packages combined with low cost computer hardware systems, and (3) the increasing awareness of the successes in demonstrating the application of the technology to marine fisheries problems. The major benefits of using GIS are the ability to display, overlay and analyze the RS data from statistical framework to look for spatial patterns of the oceanographic processes affecting fish distribution and abundance

(Wright, 2002; Fisher and Rahel, 2004). The spatio-temporal distribution and patterns of oceanographic processes that are playing significant role to the biological productivity can be handled efficiently and effectively using GIS (Valavanis, 2002).

From historical point of view, satellite RS and GIS has proved an important source of information to marine science and fisheries oceanography research. Yentsch (1973) pointed out that distribution pattern of chlorophyll-a concentrations corresponds to distribution of tuna abundance and this variable can be easily detected by satellite remote sensing. In the sea around Japan, migration routes of Pacific saury in response to the dynamics of warm-core rings observed from thermal images of SST have been described (Saitoh et al., 1986). In the Gulf of Mexico, the SST variability observed from satellite imagery in relation to the CPUE of yellowfin tuna has been investigated (Power and May, 1991).

Using remotely sensed satellite SST data (NOAA/AVHRR) in the western North Atlantic, swordfish CPUE were found to associate with distance to the nearest thermal front, where very high CPUEs occurred more frequently in the vicinity of the front (Podesta et al., 1993). Humston et al. (2000) explored the relationship between bluefin tuna distributions and specific SST isotherm derived from NOAA/AVHRR as the stimulus on the simulation model. Polovina et al. (2000) discussed the use of multi-spectrum remotely sensed satellite data in explaining the loggerhead turtles movement along the oceanic fronts and found that the largest catch rates of loggerhead associate with a specific combination of synoptic environmental conditions of SST, chlorophyll-a and geostrophic current. Integrating of RS and GIS approaches, spatial distributions of *Illex argentinus* have been shown to correspond to mesoscale oceanographic features (thermal fronts) calculated from NOAA/AVHRR SST in the south Atlantic (Waluda et al., 2001). Inagake et al. (2001) discussed the seasonal migration pattern of bluefin tuna in relation to environmental conditions of western North Pacific derived multi-sensor satellite data of SST (AVHRR), chlorophyll-a concentration (SeaWiFS) and SSHA (Topex/Poseidon and ERS-2).

In the similar methods (using RS and GIS), skipjack tuna schools have been correlated with seasonal variation of the SST derived from NOAA/AVHRR in the south-western Atlantic (Andrade, 2003). In the western Mediteranian sea, Royer et al. (2004) investigated the relationship between bluefin tuna schools and bio-optical and thermal properties of the sea surface obtained from high-resolution sensors (AVHRR and SeaWiFS). Using AVHRR SST data and GIS techniques, persistent pelagic habitat (high density of thermal gradients) for some pelagic species (i.g. Swordfish, striped marlin and blue whales) have been demonstrated in the Baja California to Bering Sea (Etnoyer et al., 2004). In the sea of Japan, the spatial pattern of common squid fishing fleets and their north-south migration route using nighttime visible images (DMSP/OLS) have been clearly demonstrated (Kiyofuji and Saitoh, 2004).

Despite a lot of remarkable findings have been proved by remote sensing and GIS techniques in improving capability of fish exploitation and marine management strategies, some investigations have also found weaker statistically relationship between CPUE and oceanographic conditions. The relationship between bluefin tuna and SST front observed from satellite imagery was inconsistent in the Gulf of Maine (Schick et al., 2004). Zagaglia et al. (2004) found that the largest CPUE of yellowfin tuna strongly associate with the large oceanic phenomena of the Intertropical Convergence Zone (ITCZ) in the equatorial Atlantic, but it could not be linked with environmental conditions of SST, chlorophyll-a and SSHA. Certainly, the nature of relationship between marine fish and environments are not only depends on the precision and availability of the data but also depends on the effectiveness, accuracy and capability for selecting appropriate analyses in many different spatial and temporal scales using RS and GIS.

1.2 Characteristics of study area

The northwestern North Pacific Ocean is one of the world's most biologically productive regions, it is also a region where two predominant currents meet, the warm Kuroshio Current and the cold Oyashio Current (Figure 1). The interaction of these currents between the subtropical front (approximately 30-32°N) and subarctic boundary (about 42-45°N) forms the transition region or perturbed area (Kawai, 1972; Roden, 1991). Using satellite-derived environmental chlorophyll data, the location of transition zone occurring between 30 and 40°N has been clearly demonstrated (Glover et al., 1994).

The dynamics of the physical oceanographic structures in this region, including warm or cold core rings, the Kuroshio and Oyashio currents, the Kuroshio Extension, meandering eddies and frontal zones, results in a highly productive habitat, which serves as a feeding ground for various commercially and ecologically important species, such as tuna, anchovy (*Engraulis japonicus*) and sardine (*Sardinops melanostictus*), Pacific saury (*Cololabis saira*) and small squid (*Berryteuthis sp.*) (Uda, 1973; Pearcy, 1991; Laurs and Lynn, 1991; Sassa et al., 2002). Inagake et al. (2001) and Komatsu et al. (2002) have exhibited that the oceanic current circulations, environmental conditions and topographic characteristics of study area such as the Shatsky Rise and the Emperor Seamount Chain play an important role for aggregating mechanisms of marine pelagic species.

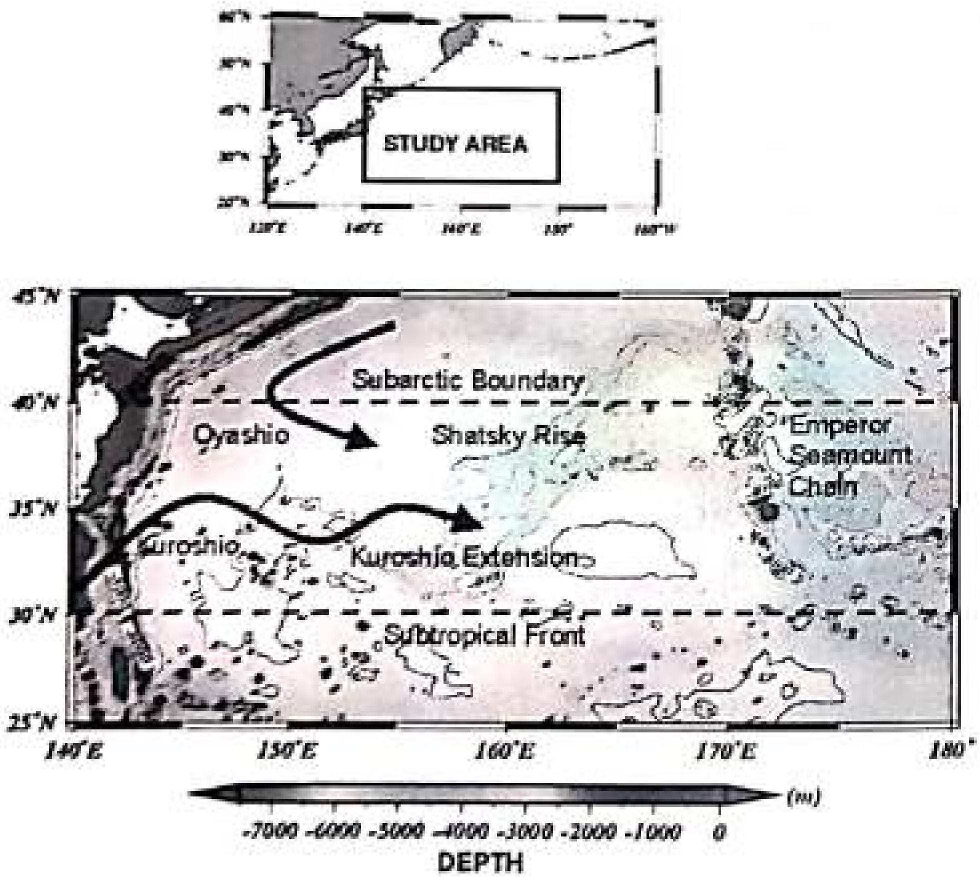

Figure 1. Location and topography of the study area selected in the northwestern Pacific Ocean.

1.3 Albacore tuna (*Thunnus alalunga*)

Albacore, *Thunnus alalunga*, is an important target species of the Japanese longline fishery in the northwestern North Pacific. Albacore occur between 10° and 50°N in the North Pacific (Laurs and Lynn, 1991) and appear to migrate widely from an area surrounding the Japanese Islands to the west coast of the United States (Otsu and Uchida, 1962). This species spawns in summer near the North Equatorial Counter Current region between 10 and 20°N, south of the subtropical convergence (Laurs and Lynn, 1991; Kimura et al., 1997). Albacore are also believed to perform transpacific migration no more than one within a 1-year period (Otsu and Uchida, 1962; Laurs and Lynn, 1977). Albacore is known as a visual predator like all tuna (Laurs et al., 1984). The albacore are opportunistic carnivores that forage in the Transition Zone on smaller pelagic predators including cephalopods, crustaceans, and especially the Japanese anchovy (*Engraulis japonicus*), small squid (*Berryteuthis sp.*) and Pacific saury (*Cololabis saira*) (Laurs and Lynn, 1991; Pearcy, 1991; Polovina et al., 2001, Watanabe et al., 2004).

Albacore are amongst the most highly specialized tuna in regard to sustained, high levels of locomotive activity. These species swim continuously to counterbalance their negative buoyancy and migrate long distance for searching high densities of food organisms to satisfy their high energetic requirements. This strategy has resulted in morphological and physiological adaptation particularly for thermoregulation mechanisms (Holland et al., 1992; Lehodey, 2001). Consequently, albacore distribution and migration have a strong relationship with environmental conditions such as SST and chlorophyll-a concentrations, which can be used as proxies for albacore forage habitat (Laurs et al., 1984; Polovina et al., 2001; Zainuddin et al., 2004).

1.4 Consideration and hypothesis

Albacore is a commercially and ecologically important fish stock in the North Pacific. This species has a high economic value and wide market acceptance. In term of ecological sense, several investigators found that the migration and distribution of albacore have been linked to specialized oceanographic features such as oceanic fronts and eddies (eg. Uda, 1973; Laurs et al., 1984; Fiedler and Bernard, 1987; Ramos et al., 1996; Polovina et al., 2001). In the western North Pacific, Kimura et al. (1997) and Sugimoto et al. (2001) described the effect of the large oceanic phenomena such as the Kuroshio Extension and ENSO events on albacore migration, distribution and abundance.

Remotely sensed satellite observations of sea surface may provide significant information to assess and improve the potential yield of fishing ground (Butler et al., 1988). Spatial distributions of albacore catches are found to associate with ocean color and thermal fronts observed from satellite images of chlorophyll-a concentration Nimbus/CZCS and SST NOAA/AVHRR (Laurs et al., 1984) (Figure 2). Polovina et al. (2001) concluded that ocean color feature is a good indicator of seasonal variations of oceanic fronts indicated by 0.2 mg m^{-3} surface chlorophyll-a density (known as Transition Zone Chlorophyll Front, TZCF) estimated from SeaWiFS in the central-eastern North Pacific where albacore were using the front as a migration route and as a forage habitat (Figure 3). However, recent studies stated that the spatial relationship between bluefin tuna distribution and SST fronts is inconsistent in the Gulf of Maine (Schick et al., 2004) and spatial distribution patterns of yellowfin tuna CPUE are not related to satellite derived SST conditions (Montañez et al., 2004). Most investigations dealing with oceanographic factors related to catch data are concerned with the correlation of a single parameter with spatial and temporal tuna distributions.

Despite the study area is one of the most productive fishing grounds in the world, little is known about underlying oceanographic features affecting the spatial dynamics of albacore habitat, and understanding of the dynamics of high productive habitat is of interest. Tuna distribution and abundance are known to be sensitive to variability of their environments and are believed to associate strongly with the high density of forage (Sund et al., 1981; Stretta, 1991; Lehodey et al., 1997). It is most likely that albacore tuna respond to a number of environmental variables. Thus, it is important to combine several environmental factors, which might provide new insight into detection of the high-density tuna forage areas. Synoptic data of SST and chlorophyll-a concentration derived satellite imageries are found to have a good association with albacore distribution and abundance (e.g. Laurs et al., 1984; Zainuddin et al., 2004).

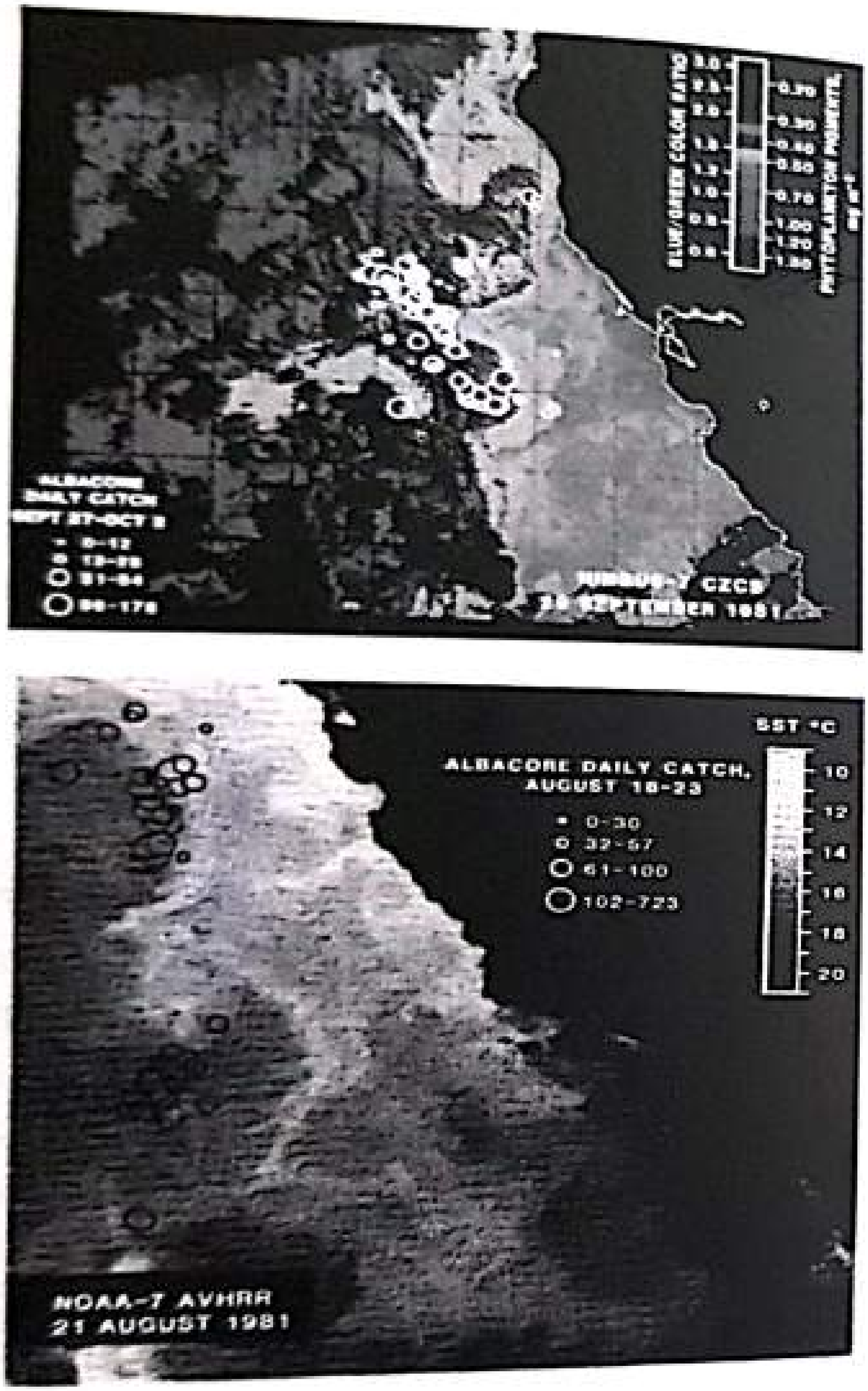

Figure 2. Spatial distribution of daily albacore catch (fish number) sup satellite images of Nimbus/CZCS surface chlorophyll-a con September 29, 1981 (top) and NOAA/AVHRR SST on Aug (bottom) (Laurs et al., 1984).

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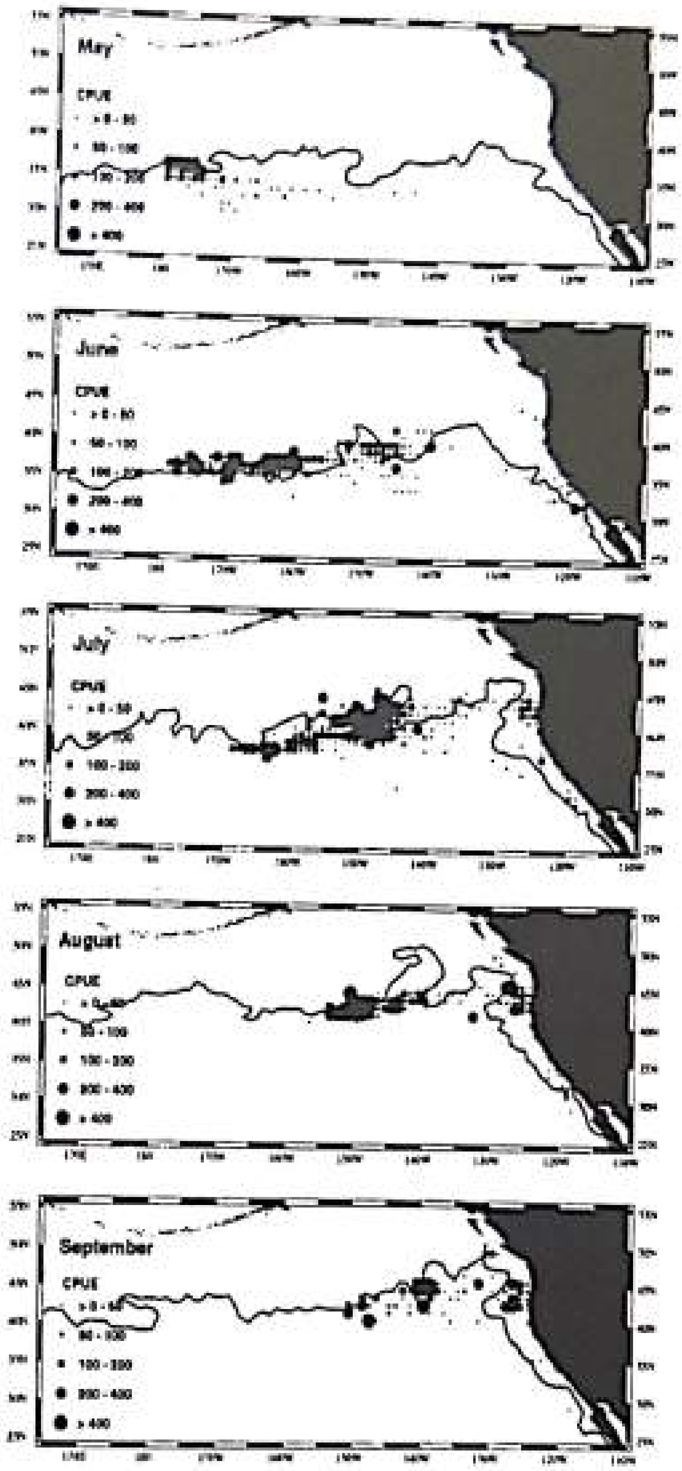

Figure 3. The spatial distribution of albacore CPUE (albacore/boat-days) from the US troll fishery shown as dots for May–September, 1998 overlain with the TZCF indicated by the 0.2 mg m^{-3} surface chlorophyll isopleth (Polovina et al., 2001).

SST and chlorophyll-a concentrations are important oceanic parameters in explaining the dynamics of tuna fishing ground in the northwestern North pacific. Thermal features of sea surface provide reliable proxy indicators of the spatial and temporal distribution of prey abundance, which subsequently affects tuna distribution (Lehodey et al., 1997; Hunston et al., 2000). Ocean color feature is a good indicator of seasonal variations of chlorophyll fronts (TZCF), which are linked to albacore forage habitat (Polovina et al., 2001) (Figure 4). Here the SST and chlorophyll-a concentration were combined with altimetry data, which might be used to locate another important fish habitat, such as eddy fields. The altimetry data (SSHA) have been shown to be important factor in locating ocean hot spots for albacore in the northwestern North Pacific (Zainuddin et al., 2006). Considering all these points, this study hypothesizes that favorable oceanographic conditions are linked to albacore habitats, and thereby these habitats are detectable and predictable. In this study, the detection, identification and prediction of the potential habitat hot spots and migration route for albacore using a combined satellite remote sensing and GIS are discussed.

1.5 Objectives

The goals of this study are: (1) to investigate the relationship between albacore fishing ground formation and environmental conditions; (2) to explore potential habitat hot spots for albacore; (3) to predict spatial pattern of high productive habitat hot spots; and (4) to analyze migration pattern for albacore tuna using an integration of remotely sensed satellite data and GIS techniques.

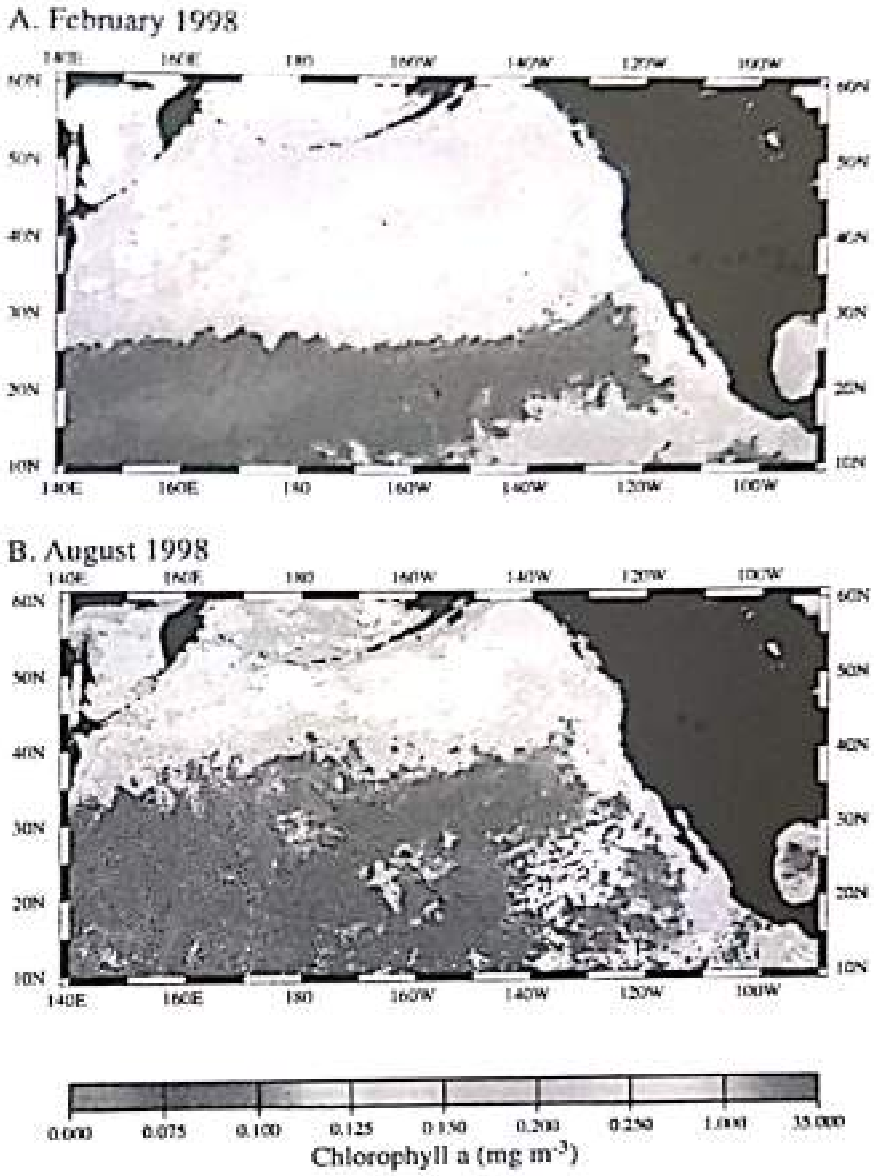

Figure 4. Surface chlorophyll-a density estimated from SeaWiFS ocean color for the North Pacific, A) February and B) August 1998. The TZCF position is clearly indicated from the SeaWiFS images (Polovina et al., 2001).

CHAPTER II

DATA AND PROCESSING METHODS

Two types of data sets were used in this work, fishery and satellite data from 1998 to 2003. These data were combined to gain some insight into detection, identification and prediction of potential habitat hot spots for albacore, and their migration pattern in the study area of northwestern North Pacific (Figure 5).

2.1 Remotely sensed satellite data used for analysis

Physical and biological environmental data used to describe the oceanographic conditions around the fishing locations are sea surface temperature (SST), surface chlorophyll-a concentration (chl-a), primary production (PP), sea surface height anomaly (SSHA), eddy kinetic energy (EKE) and geostrophic currents. All the satellite data used for analyses are summarized in Table 1.

Tabel 1. A description of satellite data sets used in this study

Satellite	Sensor	Parameter	Spatial resolution	Temporal resolution	Period
TRMM	TMI	SST	25 km x 25 km	Monthly and Daily	1998-2003
NOAA	AVHRR	SST	9 km x 9 km	Monthly	1998-2003
Orbview-2	SeaWiFS	Chl-a	9 km x 9 km	Monthly and eight days	1998-2003
Orbview-2	SeaWiFS	PAR	9 km x 9 km	Monthly	1998-2003
T/P - (Jason) and ERS2 (Envisat)		SSHA & EKE	1/3° x 1/3°	Weekly	1998-2003

2.1.1 Sea surface temperature (SST)

Tropical Rainfall Measuring Mission (TRMM)/TRMM Microwave Imager (TMI) was used to study sea surface temperature (SST). This study used monthly mean and eight days (composite images from the original daily data) TRMM/TMI

SST data sets version 3a, extending from approximately 40°S to 40°N at a pixel resolution of 0.25° (about 25 km) for both latitude and longitude obtained from the Remote Sensing System database (http://www.remss.com) and JAXA/EORC database (TMI SST version 2.0) (http://www.eorc.nasda.go.jp). The TMI SSTs have been shown to agree well with SSTs measured with buoys and ships observation in the mean difference of about less than 0.1 °C (Bhat et al., 2004) and the rms difference is about 0.6°C (Wentz et al., 2000; Bhat et al., 2004). This sensor has a full suite of channels ranging from 10.7 to 85 GHz and represents a satellite microwave sensor that is capable of accurately measuring SST under nearly all weather conditions (Wentz, et al., 2000). The TMI data are suitable for studying tuna distribution and migration, since it has a high accuracy with large number of data available and cover mostly the distribution range of albacore in northwestern North Pacific Ocean. Since the spatial resolution of TRMM/TMI is 25 km, the SST images were resampled onto 9 km grid to match with the SeaWiFS chlorophyll-a data using the Interactive Data Language (IDL) software package.

SST data derived from NOAA/AVHRR Pathfinder Version 5.0 were used to generate predictions of albacore occurrence and abundance during 1998-2003. The global monthly data sets were obtained from http://podaac.jpl.nasa.gov/ (the NASA/JPL PO-DAAC Pathfinder database) with a spatial resolution of 4 km for both latitude and longitude. These data were also resampled to a lower spatial resolution (9 km x 9 km) using the IDL. These data have been selected to perform predicted occurrence and CPUE over the entire range of the study area, since TMI SST data cover the area only through 40°N.

2.1.2 Chlorophyll-a concentration

The Orbview-2/Sea-viewing Wide Field-of-view Sensor (SeaWiFS) sensor has provided high spatial and temporal data resolutions with the accuracy of chlorophyll estimations approximately 30-50% of ship-based observations (McClain et al., 1998). This sensor has proved the key source of information to recent studies on fisheries oceanography research in the eastern and central North Pacific (Polovina et al., 2001).

These data were obtained from the NASA GSFC's Distributed Active Archive Center (DAAC). Global Area Coverage (GAC), eight days and monthly composite SeaWiFS level 3 standard mapped images (SMI) with a spatial resolution of about 9 km x 9 km on equidistant cylindrical projection for the period from January 1998 to December 2003 were used.

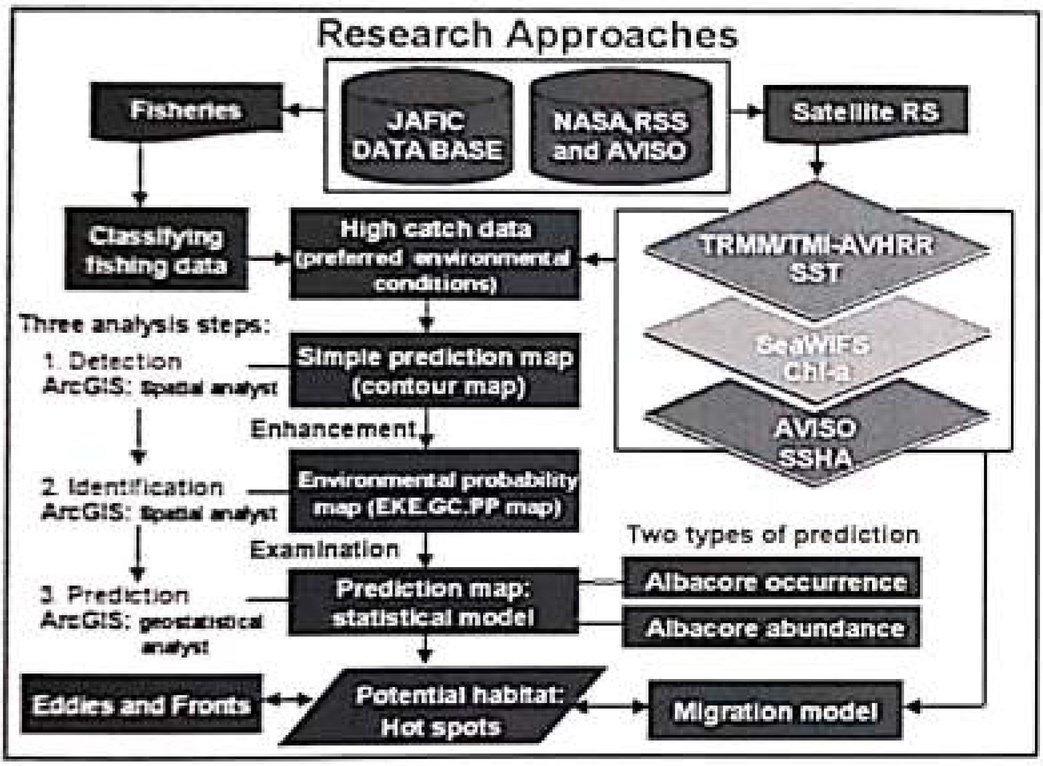

Figure 5. Analysis flow of research approaches developed in investigating potential habitat hot spots and migration pattern for albacore tuna. RS: Remote sensing; SST: Sea surface temperature; SSHA: Sea surface height anomaly; EKE: Eddy kinetic energy; GC: Geostrophic currents; and PP: Primary production.

2.1.3 Primary production (PP)

Monthly primary production (PP) during January 1998 - December 2003 was estimated using the vertically generalized production model (VGPM) developed by Behrenfeld and Falkowski (1997). The VGPM estimates the PP from the relationship between surface chlorophyll-a and depth-integrated euphotic depth primary production. The input data for this model are TRMM/TMI sea surface temperature (SST), SeaWiFS surface chlorophyll-a concentration and SeaWiFS photosynthetically active radiation (PAR) level 3 (three). All satellite data sets used to estimate the PP have a 9 km x 9 km spatial resolution.

2.1.4 Sea surface height anomaly (SSHA)

The SSHA data were obtained from the Maps of Sea Level Anomalies (MSLA/Archiving, Validation and Interpretation of Satellite Oceanographic Data (AVISO) scientific team of Collecte, Localisation, Satellite (CLS/ Centre National d'Etudes Spatiales (CNES) data center (http://www.jason.oceanobs.com/). The gridded data are calculated by combining Topex/Poseidon or Jason-1 and ERS or ENVISAT altimeter data. The data from different altimeter missions are merged into a single map using optimal interpolation method between tracks (Le Traon et al., 1998). The accuracy of these maps can be reduced to about 3 cm RMS in average since it has the very efficient correction of orbit errors on along track data (Testut et al., 2003). In this study, weekly high resolution SSHA data were used and were also used to made monthly composite map from the weekly data during 1998 to 2003 to identify eddy-like features by considering the estimation of current magnitude and direction, eddy kinetic energy (EKE) and sea level anomaly. The *u* and *v* geostrophic components were averaged to obtain more realistic estimates. Geostrophic velocities were calculated with 0.5° latitude and longitude resolution. The SSHA and EKE images were made and were resampled into 9 km x 9 km resolution to match with the SeaWiFS data.

2.2 Fishery data

The Japanese longline fishery, which extends from near the coast of Japan eastward to near 180° longitude, catches albacore mostly in winter (November-March) (Laurs and Lynn, 1991; Kimura et al., 1997). The fishery database indicates that albacore are distributed by latitude mainly between the subtropical front and subarctic front (about 30-40°N), and that tuna abundance is high in winter. In this study, fishery data were compiled from daily into eight days and monthly temporal resolutions during 1998-2003. The data, including albacore catch numbers per unit effort and fishing position, were georeferenced in 0.088° grid (about 9 km x 9 km) latitude and longitude resolution. This is an operational data approach for adjusting to temporal and spatial scales of satellite remote sensing data. The CPUE was defined as a number of albacore captured per fishing-boat days. For example, monthly CPUE means all albacore fished for all fishing-boats operating daily during one month. These data were obtained from the Japan Fisheries Information Service Center (JAFIC) database.

CHAPTER III
ANALYSIS METHODS

3.1 Relationship between albacore tuna and environmental conditions

According to Andrade and Garcia (1999), the catch data were divided into three categories, null catches, positive catches and high catches. For this study, albacore CPUE were divided into three cases: (1) cases with CPUE equal to zero – 'null catches'; (2) cases with CPUE greater than zero but lower than 17 (albacore/fishing-boat days) – 'positive catches'; and (3) cases with CPUE greater than 17 – 'high catches' for all fishery data set during winter period 1998-2003. The value 17 represents the lower limit of the upper quartile of CPUEs greater than zero. In the present study, the high catch data were used to estimate optimum ranges of three oceanographic variables, SST, chlorophyll-a concentration and SSHA during the winter period. For the high catch data, the preliminary study found a significant difference between the high data distribution and the other distributions (positive and null catches) using t-test.

The high catch data during the winter period (November-March) 1998-2003 were used to calculate preferred oceanographic conditions using histogram graphs and confidence range (mean ± one standard deviation). Using empirical cumulative distribution function (ECDF), the significant associations between the three oceanographic variables (SST, SSC and SSHA) and albacore CPUE during the period were analyzed to test the reliable environmental ranges for the analysis using three equations (Perry and Smith, 1994; Andrade and Garcia, 1999) as follows:

$$f(t)=\frac{1}{n}\sum_{i=1}^{n} l(x_i) \quad (1)$$

where,

$$l(x_i)=\begin{cases}1, & \text{if } x_i \le t \\ 0, & \text{otherwise}\end{cases}$$

$$g(t)=\frac{1}{n}\sum_{i=1}^{n}\frac{y_i}{\bar{y}}\, l(x_i) \quad (2)$$

$$D(t)=\max|f(t)-g(t)| \quad (3)$$

where, $f(t)$: empirical cumulative distribution function, $g(t)$: catch-weighted cumulative distribution function, $l(x_i)$: indication function and $D(t)$: absolute value of the difference between two curves $f(t)$ and $g(t)$ at any point t, and assessed by standard Kolmogorov-Smirnov test, n : the number of fishing trips, x_i : the measurement for satellite-derived oceanographic variables in a fishing trip i, t : the ordered observations from lowest to highest value of the variables, y_i: the CPUE obtained in a fishing trip i, and $\bar{y}$: the estimated mean CPUE of all fishing trips during winter period. $Max|f(t)-g(t)|$ denotes the specific value of the variables indicated the strongest association with albacore catch.

3.2 Detection of habitat hot spots

To detect potential hot spots for albacore, this study generated simple prediction map as the first step analysis and highlighted the main hot spot using contour map. A detailed description of these approaches can be found in appendix A.

3.2.1 Generating simple prediction map

Prediction map was constructed from the significant and favorable ranges of the three environmental variables (SST, chlorophyll-a and SSHA) calculating from the confidence range (mean ± one standard deviation) of histogram high catch data and the ECDF. The map consisted of binary output in which the yellow color represents the predicted area (locations of high productive habitat) known also as fishing ground formation (FGF) or potential albacore habitat, and the blue color denotes low probability area of finding albacore. The prediction map was computed by combining the two preferred oceanographic conditions of satellite images (SST and chlorophyll-a concentration into a single map with the same spatial and temporal scale for each grid satellite data using an algorithm of the IDL. The prediction map was then classified and was visualized using ArcGIS Spatial Analyst (ESRI, 2001). The fisheries data were superimposed on the map and the potential CPUEs were compared with the simple predicted potential habitat hot spots.

3.2.2 Generating contour map

Contour lines of specific surface chlorophyll-a and SST isotherm (the mean value of the preferred ranges) were computed to make monthly and eight days fishing ground contour maps during 1998-2003. The center chlorophyll value was considered to represent the optimum value of the preferred chlorophyll-a concentration range (high catch SeaWiFS chlorophyll-a data). The mean SST value was selected since it was considered to be the center value of the favorable SST range (high catch TRMM/TMI SST data). The fisheries data were plotted on the contour map to describe relationship between the specific chlorophyll-a and SST signatures and potential albacore fishing areas. The relationship between the latitudinal distance of the SST and SSC contour lines and CPUE was examined and was used to detect the possible occurrence of the enhanced fronts (the confluence of the chlorophyll front and warm water SST). The contour line maps presented were created using the Generic Mapping Tool (GMT) software package.

3.3 Identification of habitat hot spots

Habitat hot spots for albacore were identified using the environmental probability map. This second step analysis was used to enhance the degree of importance of albacore habitat that has performed generally using the simple prediction map. This study also used primary production, EKE and geostrophic current velocity maps to investigate more detail aspects of the high productive habitat for tuna. Further detail for this step can be seen in appendix B.

3.3.1 Generating environmental probability map

In an attempt to understand and locate biological hot spots in the northwestern North Pacific Ocean, an environmental probability map was applied. Habitat hot spots are areas of high biologically activity where linkages occur between physical forcing, primary production, secondary consumer and higher tropic level predators including albacore. Pelagic hot spots for tuna were visualized using a probability map generated from satellite-derived environmental SST, ocean color images. To accurately identify ocean hot spots, this study took into account both CPUE and frequency of fishing effort in relation to the biophysical environmental variables (SST and chlorophyll-a). CPUE was considered as an index of fish abundance (Bertrand et al., 2002), and fishing effort was considered as an index of fish occurrence or fish availability (Andrade and Garcia, 1999). These factors are critical points for studying dynamic aspects of the ecology of marine pelagic species.

The probability was calculated from the relationships between total CPUE and environmental variables, and between fishing frequency and the variables by histogram graphs. Firstly, probability indices were created based on total CPUE at a given interval of histogram divided by the maximum total CPUE, and fishing frequencies were also computed with the same rule for each variable. Secondly, the average of probability indices from interval ranges of ocean environmental variables was calculated. The highest probability value indicates the highest histogram frequency of a fishing set and total CPUE in relation to a given interval of the variables. This represents the most favorable environmental factors (hot spots). Thirdly, the SST and chlorophyll-a images were combined to generate a probability map (9 km x 9 km resolution) for all interval ranges of the oceanographic conditions. Catch data were then superimposed on the map, and the probability of the joint environmental variables was extracted around the fishing locations. Then the relationship between total catches of albacore and the rates of probability around fishing locations were examined. Here this attempt focused an analysis of the pelagic hot spots on the seasons of highest albacore abundance 1998-2003. The probability area was classified and was visualized using ArcGIS Spatial Analyst (ESRI, 2001) and GMT software package.

3.3.2 Estimation of geostrophic currents and Eddy Kinetic Energy (EKE)

The merged SSHA grid data derived from AVISO were converted to binary data format using the IDL. The grid data of absolute altimetry values (z) was then evaluated in the IDL algorithm, which calculated the east-west and north-south gradients. The variables, x, y and z are all in centimeters. The geostrophic current components (u and v) and the EKE were computed using the main equations as follows (Polovina et al., 1999; Robinson, 2004):

$$u = -(g/f)\frac{\partial z}{\partial y} \tag{4}$$

$$v = (g/f)\frac{\partial z}{\partial x} \tag{5}$$

$$EKE = \frac{1}{2}(u^2 + v^2) \tag{6}$$

where $g = 980$ cm s^{-2};

$f = 2\Omega \sin\Phi$;

$\Omega = 7.29 \times 10^{-5}$ radians per second;

Φ = latitude;

$\frac{\partial z}{\partial y}$ = north-south gradient of geostrophic current; and

$\frac{\partial z}{\partial x}$ = east-west gradient of geostrophic current.

3.3.3 Estimation of primary production

The primary production (PP) was calculated from TRMM/TMI SST, SeaWiFS level 3 chlorophyll-a and SeaWiFS level 3 PAR using the VGPM with two main equations (Behrenfeld and Falkowski, 1997):

$$PP = 0.66125 \times P^B_{opt} \times Z \times C_{opt} \times D_{irr} \left[\frac{E_0}{E_0 + 4.1} \right] \tag{7}$$

$$\begin{aligned} P^{B*}_{opt} = {} & 1.2956 + 0.2749T + 0.0617T^2 - 2.05 \times 10^{-2}T^3 + 2.462 \times 10^{-3}T^4 \\ & - 1.348 \times 10^{-4}T^5 + 3.4132 \times 10^{-6}T^6 - 3.27 \times 10^{-8}T^7 \end{aligned} \tag{8}$$

$$P^B_{opt} = \begin{cases} 1.13 & if \quad T < -1.0 \\ 4.0 & if \quad T > 28.5 \\ P^{B*}_{opt} & otherwise \end{cases}$$

where C_{opt} is chlorophyll-a concentration derived satellite data (SeaWiFS), D_{irr} is photoperiod (daily length) in decimal hours, Z is the physical depth of the euphotic zone receiving 1% of surface irradiance (E_0) in meter, E_0 is PAR data derived from SeaWiFS level 3, P^B_{opt} is the maximum rate of carbon fixation within water column [mg C (mg Chl-a)$^{-1}$ hour^{-1}], and T is satellite SST data in degree centigrade (°C).

3.4 Prediction of habitat hot spots for tuna using statistical models

To develop spatial prediction of tuna habitat using statistical modeling, this study developed two types of models: (1) model for prediction of tuna occurrence, and (2) model for prediction of tuna abundance. The systematic description of spatial prediction for both tuna occurrence and abundance using statistical models are shown in appendix C.

To predict spatial pattern of habitat hot spots and to examine simple prediction map and environmental probability map for albacore in November 1998-2003, a combination of a generalized additive model (GAM) and a generalized linear model

(GLM) were applied. These models were used to assess the nature of trend of albacore in relation to the three covariates (SST, chlorophyll-a and SSHA). A GAM represents a nonparametric method of estimating a smooth relationship between predictor variables and response. The GAM can identify the nature of the relationship between the response (i.e. albacore CPUE) and the covariates (i.e. environmental variables) with less restrictive in assumption of the underlying statistical data distribution (Hastie and Tibshirani, 1990). A GAM has form (Hastie and Tibshirani, 1990):

$$g(\mu(x)) = \eta(x) = \alpha + \sum_{i=1}^{p} f_i(x_i) \tag{9}$$

where g is the link function, x_i is a set of predictor variables, $\eta(x)$ is the additive predictor, μ is the mean response, α is a constant intercept term and f_i corresponds to the nonparametric function describing the relationship between the transformed mean response and the *i*th predictor.

Despite the GAM may explain variance of CPUE more effective and flexible than the GLM, the model has no analytical form (Mathsoft, 1999). A GLM provides a way to estimate a function of mean response (dependent variable) as a linear function of some set of covariates (predictors). This study considered that the GAM and the GLM could complement one another to investigate relationship between response and some set of predictors in more realistic prediction. The general form of a GLM is expressed as (McCullagh and Nelder, 1989):

$$g(\mu(x)) = \eta(x) = \beta_0 + \sum_{i=1}^{p} \beta_i x_i \tag{10}$$

Where β_0 and β_i are constants, $\eta(x)$ is referred to as the linear predictor and is analogous to the additive predictor of a GAM defined in equation (9). Using the integration of GAMs and GLMs, two dynamic aspects of tuna ecology, distribution and abundance, were predicted for evidence of correlation with specific oceanographic conditions, and forage availability that may modulate fish occurrence and abundance in the study area. In the present study, two types of modeling were integrated to predict the probability of finding potential habitat hot spots for albacore.

3.4.1 Prediction of tuna occurrence

A GAM with logit link, binomial model was implemented to investigate the high probability of finding tuna occurrence (albacore availability). The binomial family uses logit link defined by (Hasti and Tibshirani, 1990):

$$log\left(\frac{p(x)}{1-p(x)}\right) = \alpha + s(SST) + s(Chl-a) + s(SSHA) + e \tag{11}$$

where s(.) is a cubic spline smoothing function of the variables (SST, Chl-a and SSHA) and e is a random error term. *p(x)* is the probability of detection of albacore. This parameter corresponds to the mean response of a binary (0 or 1) variable (presence/absence of high albacore abundance). From the equation (11), a GLM was constructed based on the trend of the previous model to predict fish availability as follow:

$$log\left(\frac{p(x)}{1-p(x)}\right) = \beta + \beta_1(SST) + \beta_2 Log(Chl-a) + \beta_3(SSHA) + e \tag{12}$$

Where β is constant, β_1, β_2 and β_3 is the vector of model coefficients and e is a random error term.

3.4.2 Prediction of tuna abundance

To estimate the mean abundance of albacore, three independent environmental variables were included in the analysis using GAMs fitting in the following form:

$$Ln(CPUE+1) = \alpha + s(SST) + s(Chl-a) + s(SSHA) + e \tag{13}$$

The GLM was constructed based on the trend of albacore CPUE in relation to the predictors resulting from a generalized additive model (GAM) with the least different of residual deviance (Mathsoft, 1999). So, in the present study, the GLM fit was used to predict a spatial pattern of albacore CPUE by investigating the relationship between CPUE and three predictor variables using the following approach:

$$Ln(CPUE+1) = \beta + \beta_1(SST) + \beta_2 Log(Chl-a) + \beta_3(SSHA) + e \tag{14}$$

Albacore CPUEs follows a continuous distribution, the GLM was fit using a Normal distribution as the family associated with identity link function (McCullagh and Nelder 1989). The data distribution and the link function in the GLM were exactly same as those used in the GAM in this section. A logarithmic transformation of the CPUE was used to normalize asymmetrical frequency distribution, and a value of 1 was added to all CPUE values to account for zero CPUE data. The number of zero catches was small in this month (November) and hence the value was still considered in this analysis.

3.4.3 Selection of best model

The model selection process for the best predictive model of both predicted albacore occurrence and abundance in explaining CPUE data was based on the analysis of deviance table through stepwise GLM. The predictors were considered significant for explaining of the variance of CPUE, if the residual deviance and Akaike Information Criteria (AIC) decrease with each addition of the variables and the probability of final set of variables was lower than 0.05 ($P<0.05$). Then, the significant GLM fits were used to predict spatial pattern of both tuna occurrence and tuna abundance (CPUE) from satellite derived environmental variables. Statistical analyses were carried out using S-PLUS software package (Mathsoft, Inc., Seattle, USA). Mean abundance and probability of finding tuna were interpolated using ordinary kriging interpolation in ArcGIS Geostatistical Analyst (ESRI, 2001).

3.5 Simulation of albacore migration pattern using kinesis model

A kinesis model driven by high-accuracy TRMM/TMI SST was used to simulate albacore tuna movement (migration) in the study area during winter (November-March 1998-1999). The results of this simulation will compare with fishing data and environmental features. Monthly (November-March) and eight days (early November - late December) SST data were used to generate simulation using the following algorithms (Humston et al., 2000):

$$|\varepsilon| = \sqrt{(\phi^2 / 2)} \qquad (15)$$

$$V(t) = f(V_{t-1}) + g(\varepsilon) \tag{16}$$

$$S_t = V(t) \times \delta \tag{17}$$

$$f(V_{t-1}) = V_{t-1} \times H_1 \left[e^{(-0.5)((T-T_0)/\sigma)^2} \right] \tag{18}$$

$$g(\varepsilon) = \varepsilon \times \left[1 - \left(H_2 e^{(-0.5)((T-T_0)/\sigma)^2} \right) \right] \tag{19}$$

where Φ is maximum swimming velocity; ε is distributed normally random component; $V(t)$ is total velocity of an individual fish at time t; V_{t-1} is total velocity of an individual fish at time t-1; S_t is the distance of an individual fish movement at time t; H_1 is height of Gaussian curve in $f(V_{t-1})$; H_2 is height of Gaussian curve in $g(\varepsilon)$; σ is width of Gausian curves; T is ambient temperature during time step; T_0 is an optimal temperature for albacore in the study area; and δ is time step length.

To examine the performance of model simulation and investigate the potential mechanisms affecting spatio-temporal distributions of albacore, two types of simulations were run using the series algorithms (Appendix D). The first was to test the model sensitivity using a simple method in a single dimension. The model was run in Cartesian plane, using position along the X-axis (X_o=0 km as a target) as the stimulus parameter. Maximum swimming speed of albacore was set to 6.6 km h^{-1} (Laurs et al., 1977) for two model runs, indicating the search velocity of this species outside the preferred range. Following Humston et al.(2000), model run was initialized by uniformly distribution of fish along the X-axis (-50,50). Each fish was assigned a random velocity for initial time step and then run by 1000 individuals for the periods of 30-50 days using the IDL.

The second model run was generated to simulate dynamic movements of 500 albacore in the study area using TRMM/TMI SST maps as the stimulus. One different from Humston's approach that used static condition of SST map (only a single map), this study attempted to simulate spatial movement and migration of albacore using dynamic maps of SST with monthly and eight days temporal resolutions during winter period. In all simulations, T_o was set at 20° with σ=1.6, reflecting the optimum SST for albacore in the study area (Zainuddin et al., 2004). The widths of Gaussian functions for deterministic (H_1) and stochastic (random) components (H_2) were set at 0.7 and 0.9, respectively. Albacore movements were simulated for 5 months (winter period) of monthly data and for two months of eight days data using the IDL. The starting position of fish on the SST map in November for monthly simulation and early November for eight days simulation was determined using random function in the IDL, and the model was run up to 82 days, allowing fish to disperse preferentially throughout the model domain. The next step simulation was run up to one month, in each month from December to March using each monthly images of SST as the stimulus. For eight days data, the simulation was run every eight days in the next step after completing starting model run in early November. Final positions of fish in each period (monthly and eight days) were visualized using the GMT and were compared with positions of albacore fishing ground obtained from the JAFIC database. The dynamics of fish movement resulting from the simulation will also compare to the oceanic features.

CHAPTER IV

HABITAT HOT SPOTS AND MIGRATION PATTERN

4.1 Temporal variation of albacore CPUE and environmental conditions

Temporal variability of albacore CPUE during 1998-2003 showed a similar pattern, particularly during 1998-2000 (Figure 6: Top). Albacore CPUEs are significantly high in winter, especially in November-December. The mean CPUE and GAM fit also exhibited a similar trend (Figure 6: Bottom). The highest CPUEs were found in November based on actual fishery data and were predicted by the GAM near this month. In this month, fishing sets were carried out in relatively warm SST varying from 18.09°C to 21.47°C (19.78 ± 1.69°C) (Figure 7a) and relatively high chlorophyll-a concentration ranging from 0.18 mg m^{-3} to 0.44 mg m^{-3} (0.31 ± 0.13 mg m^{-3}) (Figure 7b). Albacore were obtained in substantial numbers in November corresponding to the relatively high positive SSHA of 13.4 – 29.0 cm (21.2 ± 7.8 cm) (Figure 7c). Primary production was observed to have three main peaks, in March, July and November. The largest numbers of albacore obtained in November occupied areas with primary production levels of 15.65-20.61 g C m^{-2} $month^{-1}$ (18.13 ± 2.48 g C m^{-2} $month^{-1}$) (Figure 7d). The temporal prediction by the GAM indicated that the high CPUEs mostly coincided significantly with areas of warm water SST of about 20°C, relatively high SSC near 0.3 mg m^{-3} and positive SSHA of approximately 18 cm (Figure 7). At the same time, primary production (PP) tended to increase about 18.13 g C m^{-2} $month^{-1}$. The significant decline of CPUE occurred in summer in areas of relatively high SST and PP, lower chlorophyll-a and SSHA.

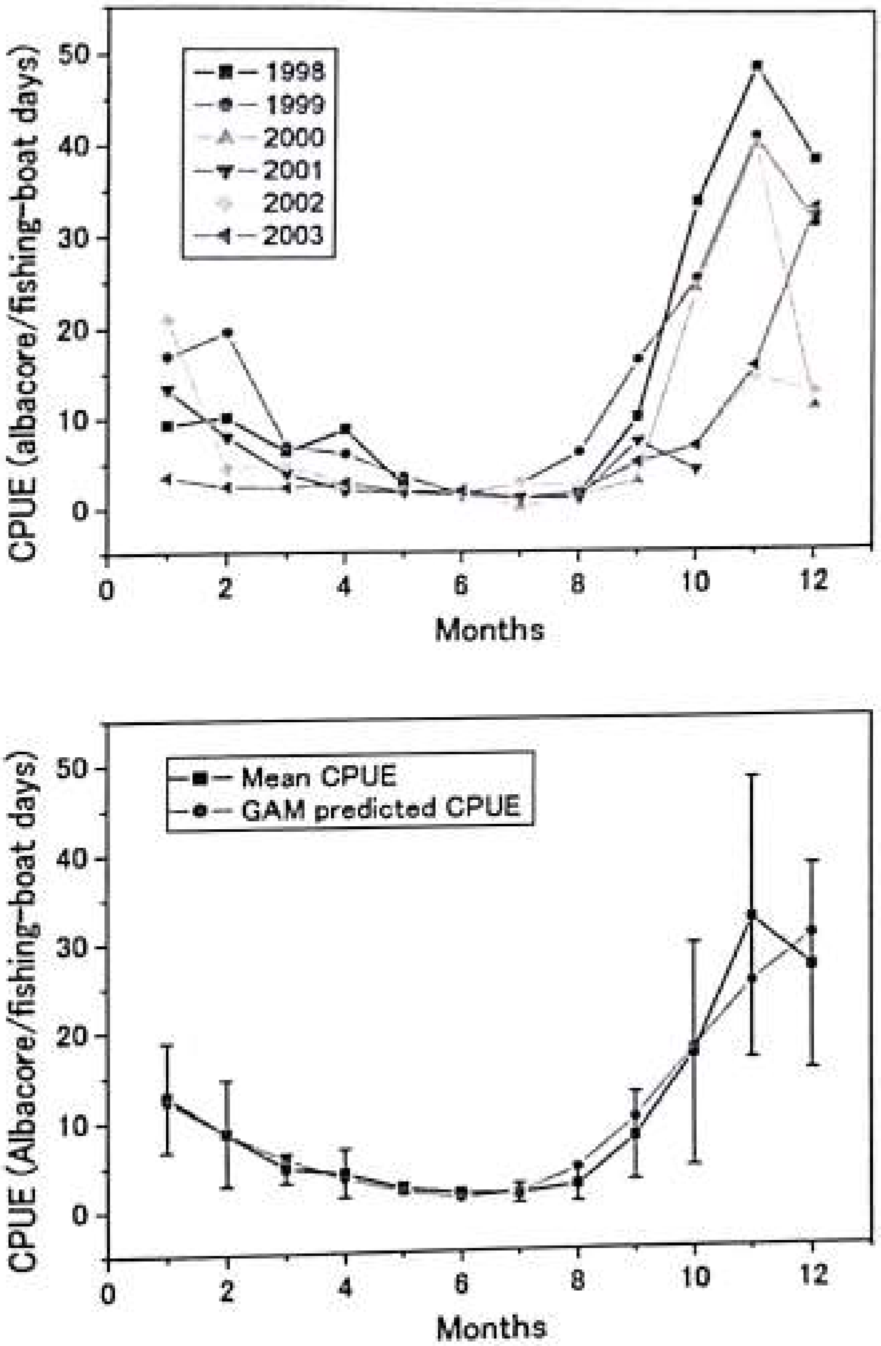

Figure 6. Temporal variability of CPUE of albacore fishery from the Japanese longline fishery (top) during 1998-2003 and the mean observed CPUE (black line) and fitted CPUE by GAM (red line) (Bottom).

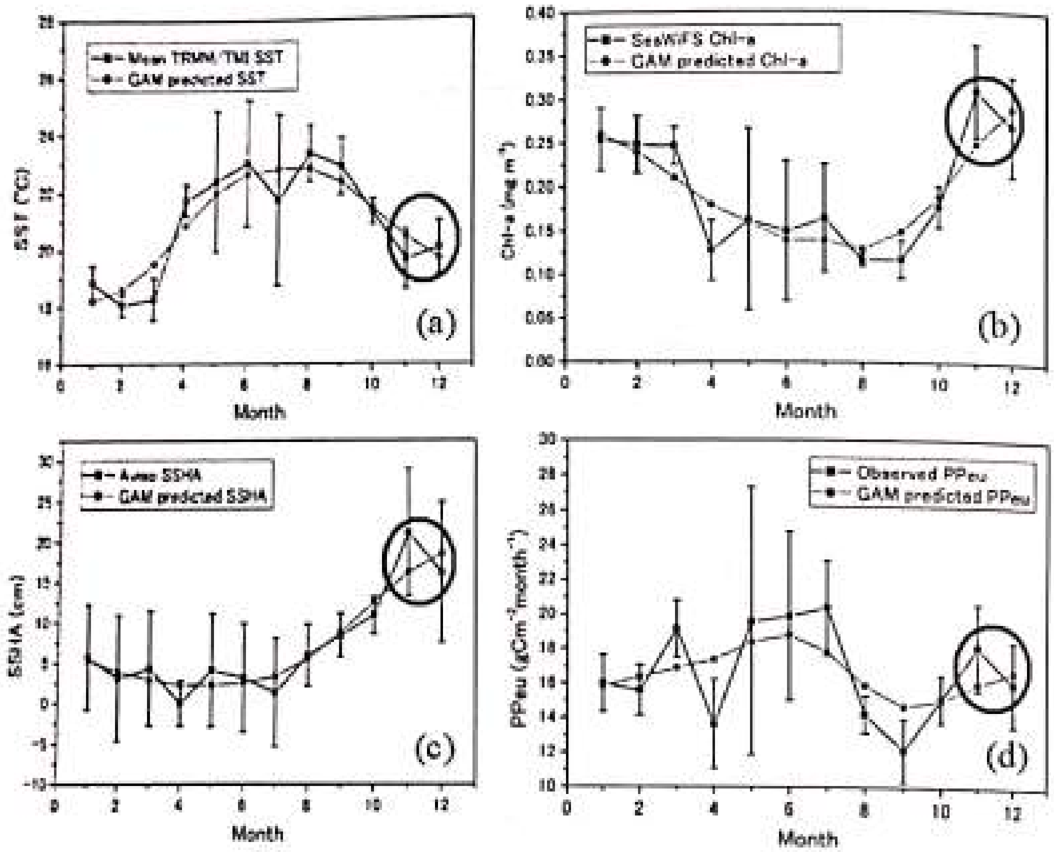

Figure 7. Temporal variability of environment conditions of TRMM/TMI SST (a), chlorophyll-a concentration (b), SSHA (c) and primary production (d) from fishing grounds of longline fishery during 1998-2003.

4.2 Preferred oceanographic conditions for albacore tuna

The largest albacore CPUE associated with a certain combination of preferred environmental factors during the winter period, warm water SST of about 17.5-21.5°C, relatively high chlorophyll-a concentrations near 0.2-0.4 mg m^{-3} and positive SSHA (5-40 cm) (Figure 8). Using empirical cumulative distribution function (ECDF), the relationship between albacore CPUE and the three environmental variables reinforced the result obtained above (Figure 9). The cumulative distribution curves of the variables are different and the degrees of the difference between two curves (*Dt*) are highly significant ($P<0.01$). The results indicated that the stronger association between CPUE and the variables, SSC ranging from 0.2 to 0.4 mg m^{-3} (Figure 9a), SST ranging from 17.5 to 20.5°C (Figure 9b) and SSHA ranging from –5 to 40 cm (Figure 9c). The peaks of the differences occurred near 20°C SST, 0.3 mg

m^{-3} SSC and 18 cm SSHA. CPUEs tended to decrease in areas of outside those favorable ranges.

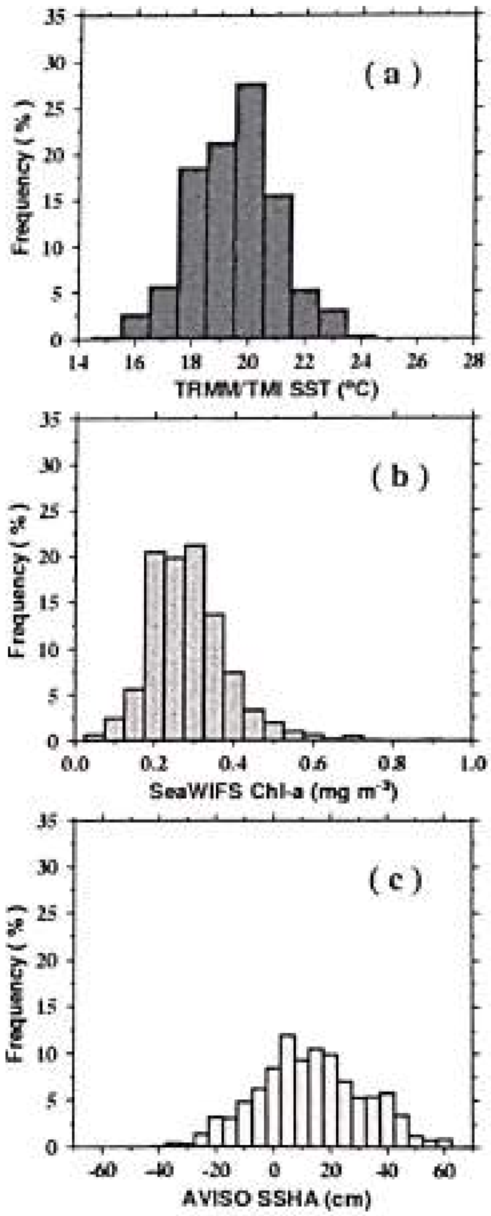

Figure 8. Relationship between environmental variables of TRMM/TMI SST (Top), SeaWiFS chlorophyll-a (middle) and AVISO SSHA (Bottom), and fishing frequencies of high catch data for albacore during winter period 1998-2003.

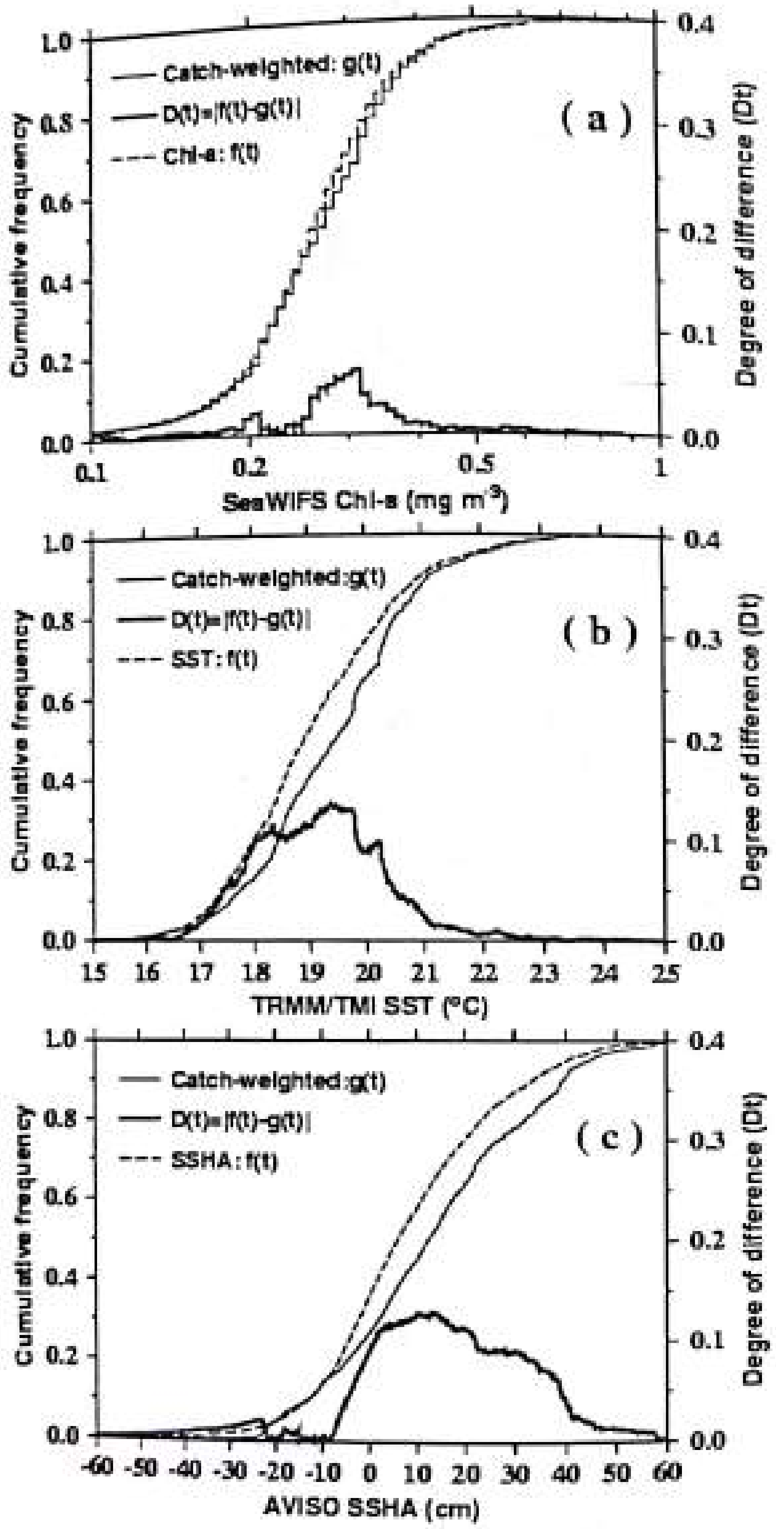

Figure 9. Empirical cumulative distribution frequencies for (a) SeaWiFS surface chlorophyll-a concentration, (b) TRMM/TMI SST, and (c) AVISO SSHA, and SST, chlorophyll-a and SSHA as weighted by albacore catch during the winter period 1998-2003.

4.3 Detection of habitat hot spots for albacore tuna

4.3.1 Simple prediction map

The preferred ranges of the three oceanographic conditions, chlorophyll-a 0.2 - 0.4 mg m^{-3}, SST 17.5 - 20.5°C and SSHA –5 - 40 cm were considered as a reliable oceanographic indicator to detect albacore habitat (Figures 8 and 9). Since SSHA has a wide range (large standard deviation, but significant), this study focuses an analysis of potential habitat on the favorable SST and chlorophyll-a ranges. Therefore, the statistically significant environmental ranges of these variables were used to generate simple prediction map where albacore are most likely occurred (Figure 10). Both these ranges were synoptically indicated by yellow area as the predicted location with binary value of 1. Conversely, non-predicted areas (outside of the favorable ranges) were shown by blue area with zero binary value.

In November 1998, potential habitat for albacore (known also as fishing ground formation/FGF) occurred in the areas of near 34°N-38°N and 164°E-170°E (Figure 10a). The predicted area of occurrence was wider in November 1999 than in 1998 and was mainly associated with the productive albacore fishery in the location of 160-172°E and that of 35-38°N. While in November 2000, albacore habitat was primarily concentrated between 35°N and 37°N, and 162°E and 166°E. There is no catch data in November 2001. In November 2002, albacore fishery occurred in the southern part of the main predicted area and appeared to associate with the Kuroshio Extension (32-35°N and 160E-166E°) (Figure 10b). Albacore seemed to experience remarkable fishing ground displacement in November 2003. In this year, the high productive habitat hot spots were found nearly western dateline (35-38°N and 175E-180°).

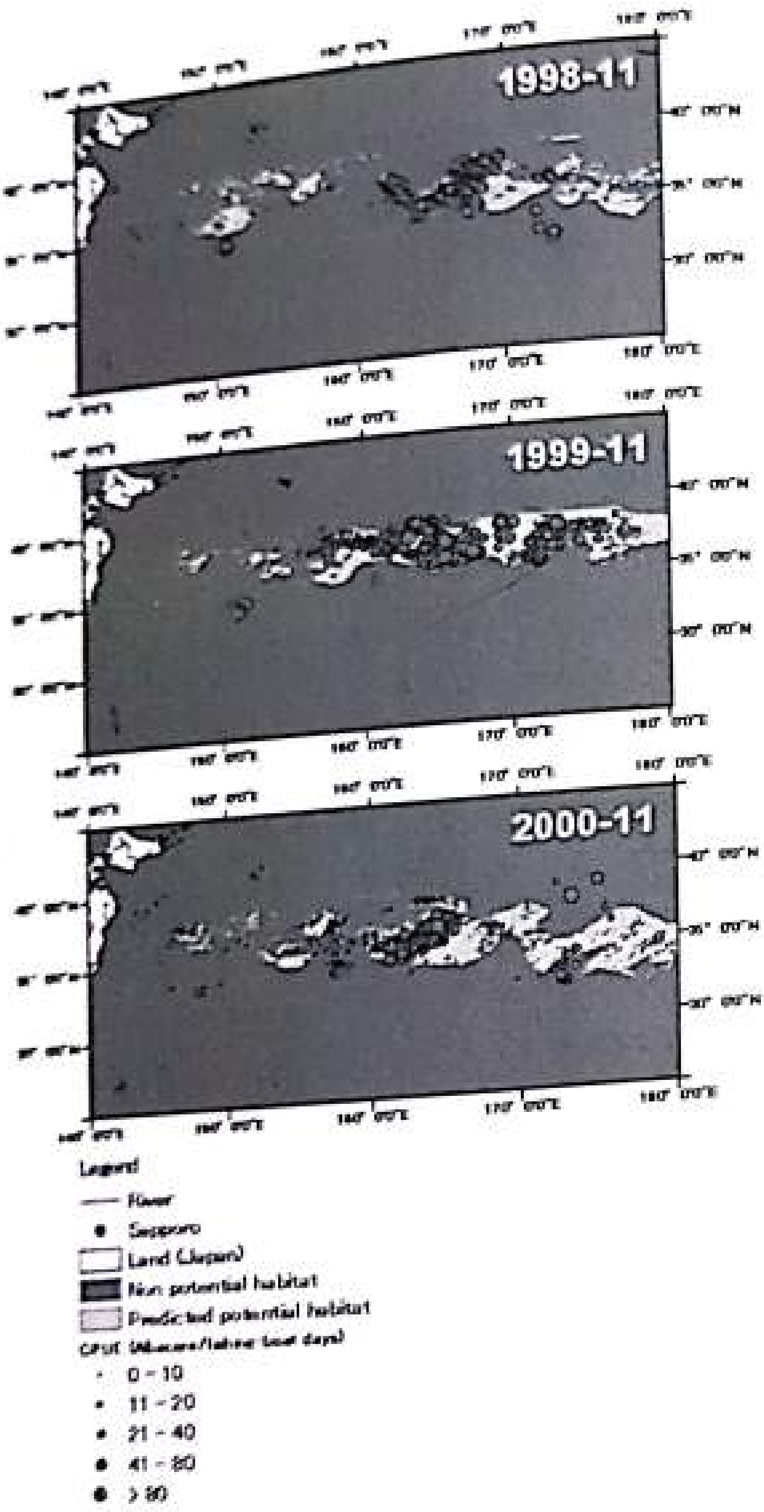

Figure 10a. The spatial pattern of potential habitat on simple prediction map generated from combination of TRMM/TMI SST, SeaWiFS chlorophyll-a satellite data, and spatial distributions of albacore CPUE (albacore/fishing-boat days) from longline fishery in November from 1998 to 2000 were overlain on the map.

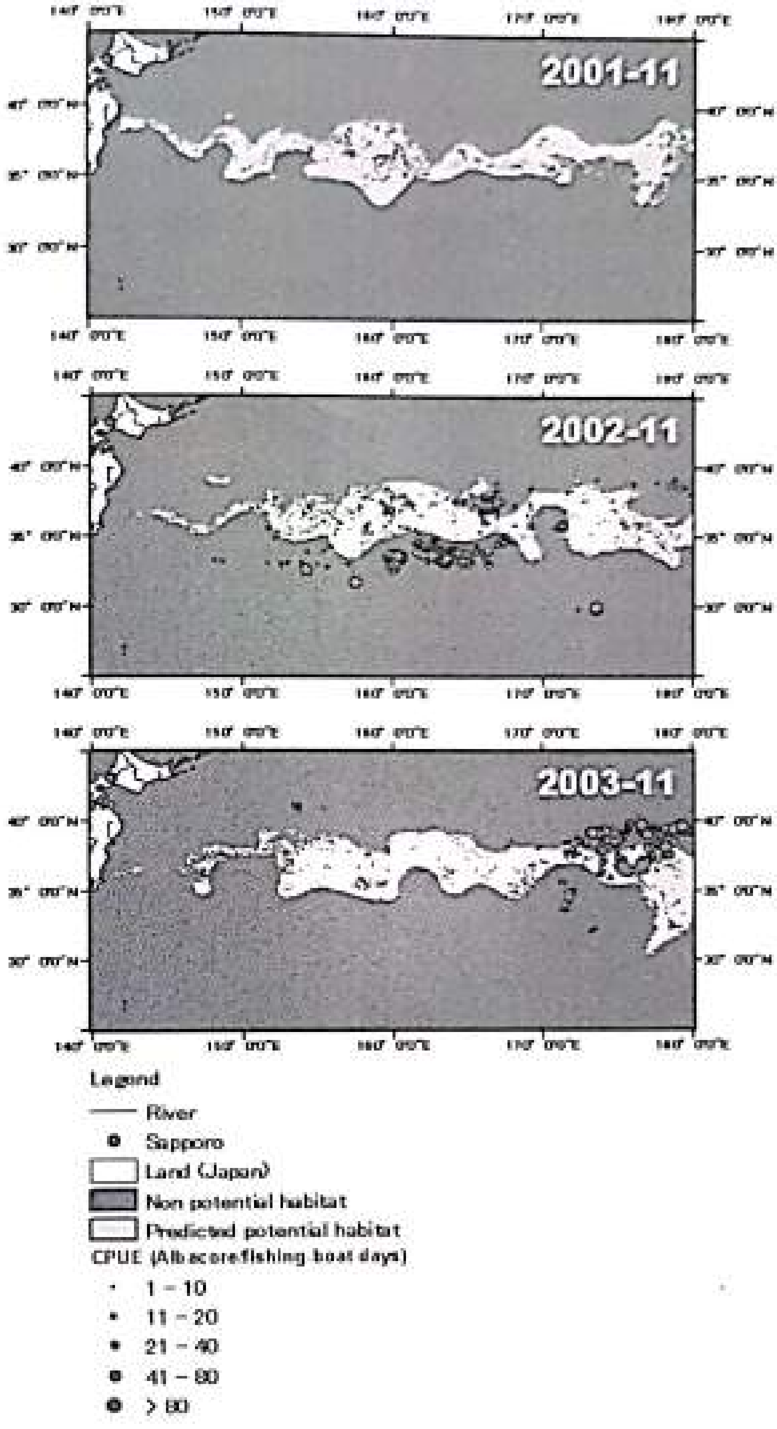

Figure 10b. The spatial pattern of potential habitat on simple prediction map generated from combination of TRMM/TMI SST, SeaWiFS chlorophyll-a satellite data, and spatial distributions of albacore CPUE (albacore/fishing-boat days) from longline fishery in November from 2001 to 2003 were overlain on the map.

4.3.2 Contour map

The mean values of the preferred ranges of oceanographic variables were the 0.3 mg m^{-3} chlorophyll-a concentration and the 20°C SST isotherm. The high albacore CPUEs were detected in area where warm water SST indicated by the 20°C SST isotherm was in close proximity to the chlorophyll front identified by 0.3 mg m^{-3} chlorophyll-a concentration. The relationship between CPUE and the mean latitudinal distance of the specific values of both variables was highly significant (CPUE = 39.39 – 3.9078x, R= -0.76, $P < 0.0001$, N=29) (Figure 11).

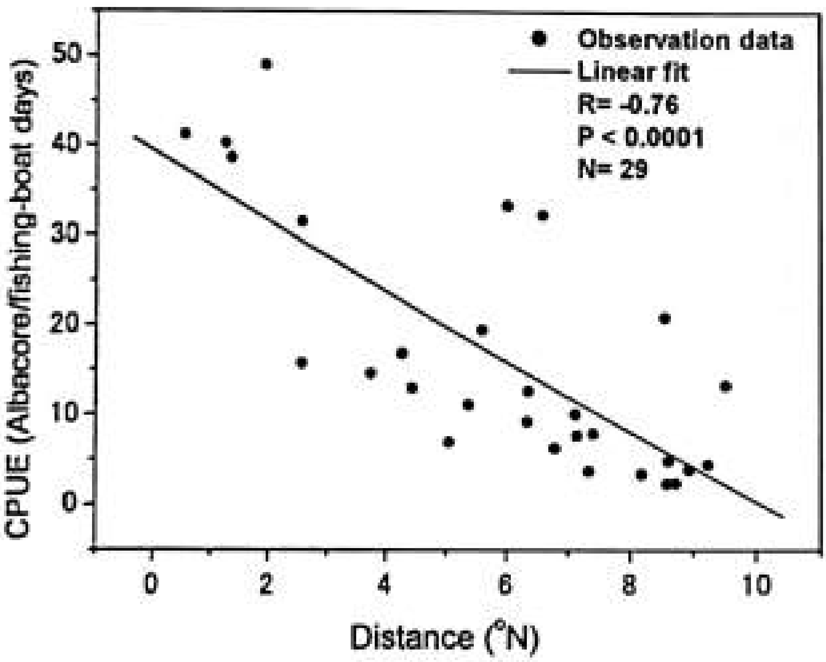

Figure 11. The relationship between Albacore CPUE and the distance of mean position between the 20°C SST isotherm and the 0.3 mg m^{-3} chlorophyll-a isopleth contour lines by latitude (°N) from 160°E to 180° in winter period during 1998-2003.

The high productive area (small distance between two indicator contour lines) for albacore occurred near 35-36°N and 160-170°E and seemed to associate with formation of albacore fishery during November 1998-2000 (Figure 12). In 2002, the main albacore fishery concentrations occurred southward of the potential fishing area that located approximately 34-35°N and 150-160°E. Potential fishing grounds in 2003 were again detected near the dateline (35-36°N and 172-178°E) corresponding with the area of small distance between 20°C SST isotherm and 0.3 mg m^{-3} chlorophyll-a concentration. There is no fishery data in 2001 and the contour lines estimated the productive area in the location near 35°N along 163-170°E and near the Honshu Island (Japan).

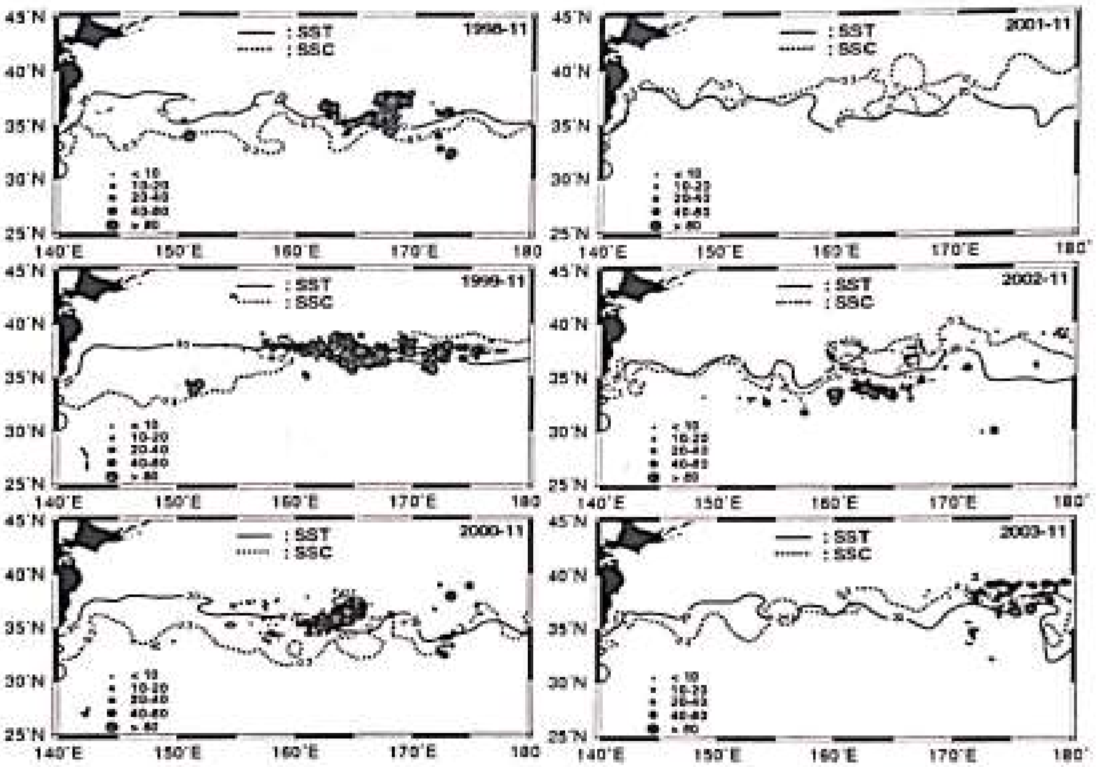

Figure 12. Spatial pattern of the optimal contour lines of the 20°C SST (TRMM/TMI) and the 0.3 mg m^{-3} chlorophyll-a concentration (SeaWiFS) known as habitat hot spots, and spatial distributions of albacore CPUE from Japanese longline fishery shown as dots in November from 1998 to 2003 were overlain on the map.

4.4 Identification of habitat hot spots for albacore tuna

4.4.1 Environmental probability map

Habitat hot spots were effectively identified with more specific preferred environmental ranges of both SST and chlorophyll-a using each interval of histogram graphs (Figure 13). Monthly distribution of albacore CPUE showed that both the fishing sets and the highest CPUEs were concentrated mostly near the areas of high probability greater than 80 % (the main ocean hot spots) during November of 1998-2003, particularly during 1998-2000 (Figure 14).

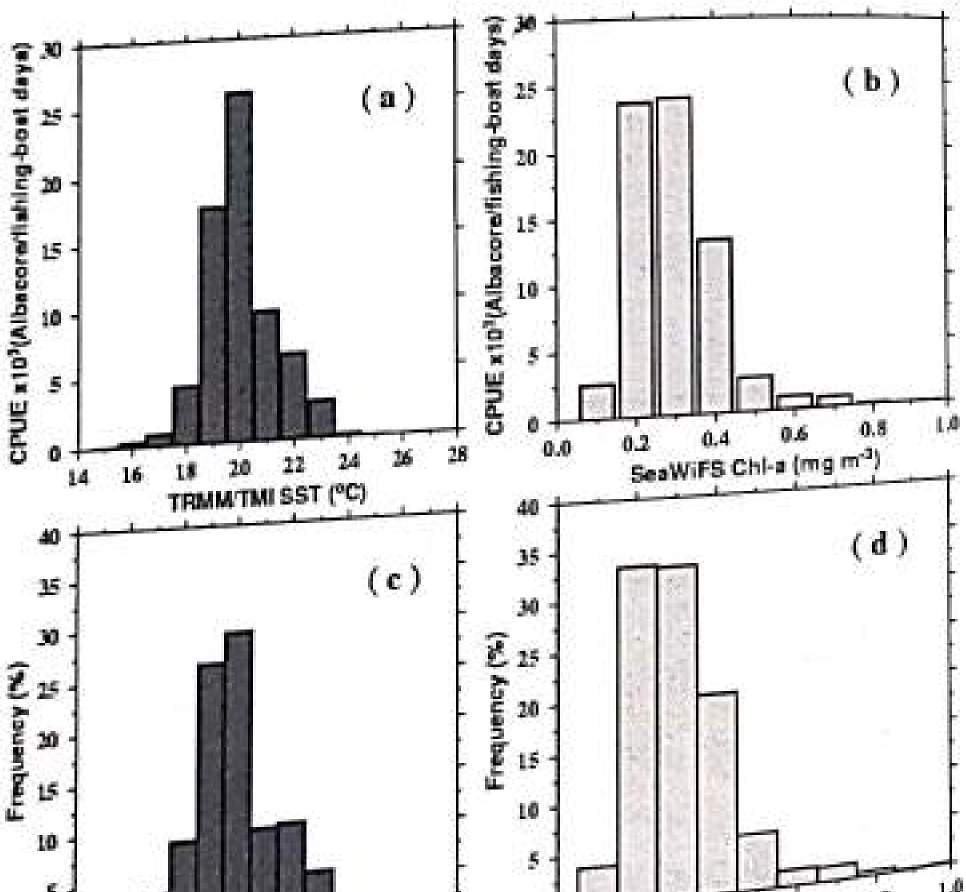

Figure 13. Total albacore CPUE in relation to TRMM/TMI SST (a) and SeaWiFS chlorophyll-a (b), and albacore fishing frequency in relation to TRMM/TMI SST (c) and SeaWiFS chlorophyll-a (d) during November 1998-2003.

In 2002, albacore tended to aggregate in waters of lower probability rates of about 60-70%. In this period, the high probability areas (red area) occurred in a narrow latitudinal band. In 2003, albacore concentrations occurred near 180° longitude in areas of increased probability, but some fish were distributed widely outside this area.

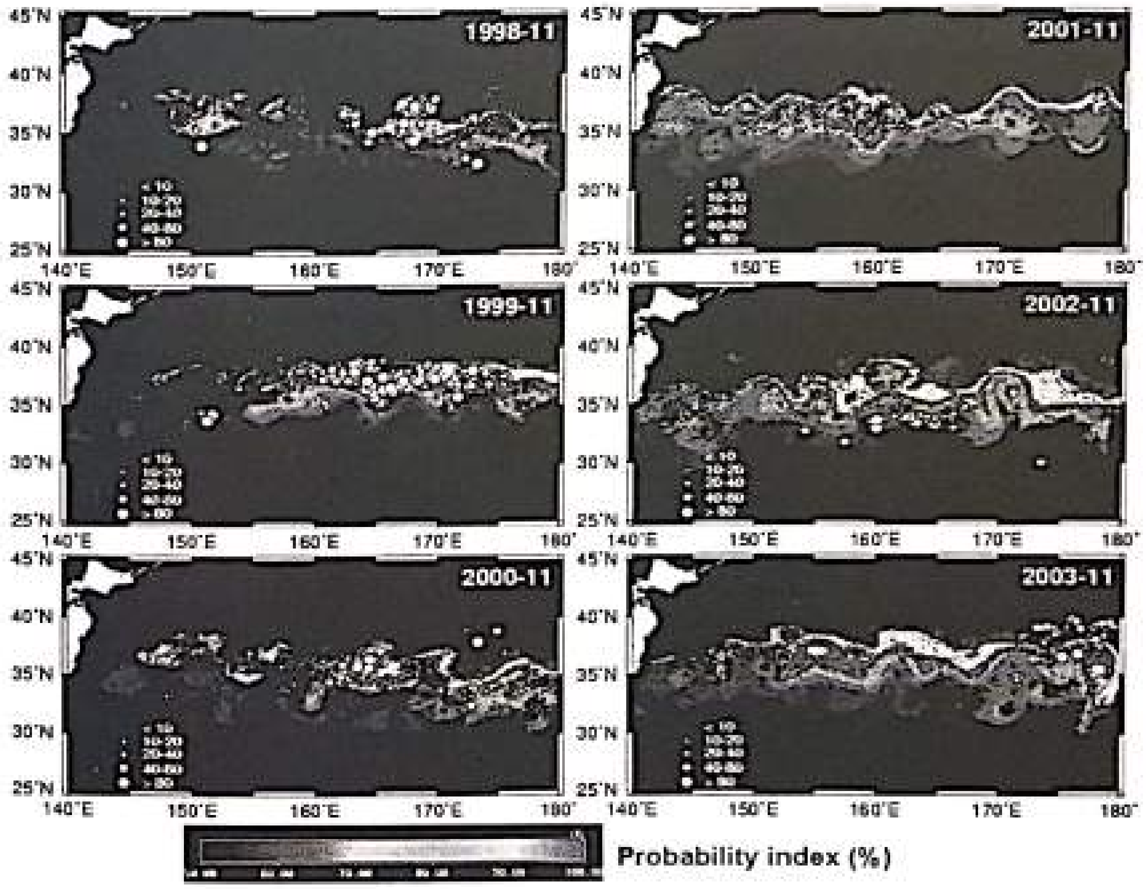

Figure 14. The spatial pattern of potential habitat hot spots on an environmental probability map generated from TRMM/TMI SST and SeaWiFS chlorophyll-a images, and spatial distributions of albacore CPUE (albacore/fishing-boat days) from the longline fishery in November from 1998 to 2003 were depicted on the map (Zainuddin et al., 2006).

In all years, the total CPUEs tended to increase with the increasing probability values of the joint environmental variables. This relationship was statistically significant using piecewise linear regression (R^2= 0.79, P<0.0001, N=67) (Figure 15). The first equation of the regression lines was $E(Y) = b_0 + b_1X_1$, when $X_1 \leq 55$ (X=55 means the point where the slopes change), and the second equation was $E(Y) = (b_0 - 55b_2) + (b_2+b_1)X_1$, when $X_1 > 55$. From these results, potential tuna habitats were classified into four types: excellent, good, fair and poor habitats based on the significant relationship between albacore CPUE and the probability index. Poor habitat was defined as an area where the probability of environmental index was less than 55%.

The point of 55% was selected since the model has a higher accuracy (higher R^2) when the slope changes at that point. The probability of greater than 55 was defined as fair habitat for the probability of 55-75%, good habitat for the probability of 75-90% and excellent habitats for the probability of greater than 90%. The value of 75% represents the lower limit of upper quartile (Q3) that explain the location of high catch data. While, the 90% value was set to indicate the lower limit of excellent probability (the most potential hot spots).

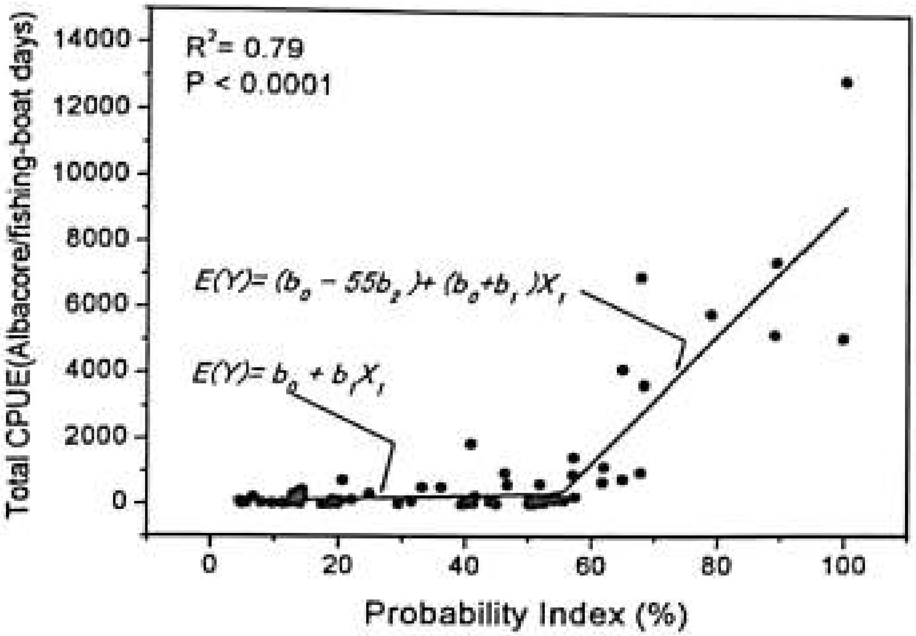

Figure 15. The relationship between total Albacore CPUE and the probability index of environments around fishing ground using piecewise linear regression during November 1998-2003 (Zainuddin et al., 2006).

The potential habitat hot spots were easily identified using the classifying habitat based on the probability index in ArcGIS Spatial Analyst. The main ocean hot spot (excellent habitat) for albacore in 1998 concentrated in a narrow area near 36-37°N and 167-170°E and covered only 1.1% of study area (Figure 16a). The fair and good habitats occurred about 35°N and 162-168°E and located in area of 13.8% and 2.6.1% of northwestern North Pacific, respectively. In 1999, the potential tuna habitats (excellent and good habitats) accounted for 3.5% and 4.2% of study area, respectively and associated with albacore fishery with straight path formation approximately 36°N along 160-175°E. The fair habitat accounted for 13.8 %. The major congregating spot (excellent habitat) in 2000 coincided perfectly with large albacore concentration in a specific area of 35°N and between 162-165°E, and covered only 3.26% of study area. In this year, the good habitat was 3.9% of study area and fair habitat was 18.52%. The fair habitat appeared to be more scatter than the previous years and occupied a wider longitudinal and latitudinal band.

During 2001-2003, the areas of albacore habitats were wider than during 1998-2000, particularly fair habitat (Figure 16b). In 2002, albacore seemed to inhabit the fair habitat that covered study area of about 29.65% in area near 33°N along 160-165°E. The excellent and good habitats in this year covered about 3.68% and 5.6%, respectively. The ocean hot spots developed near the dateline in 2003 and tended to associate with albacore fishery. For this year, the excellent habitat spanned from 155°E to the dateline and propagated around 35°N. The main habitat hot spot occupied about 6.07% of the study area. For 2001, the excellent habitats were primarily found in the central (around 35°N and 160°E) and in the eastern part of the study area (near the dateline).

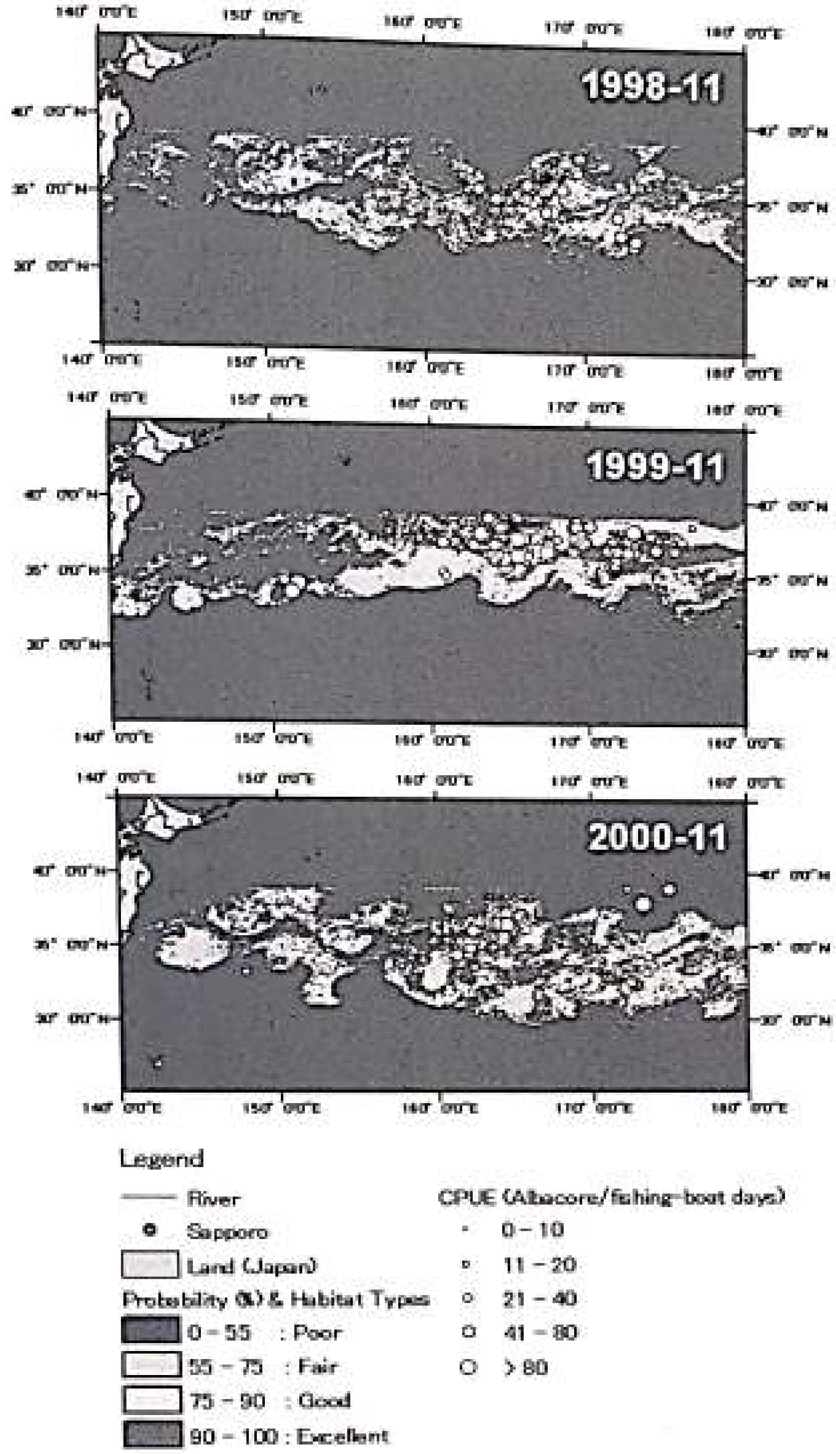

Figure 16a. The spatial distribution pattern of albacore habitats hot spots on an environmental probability generated from TRMM/TMI SST and SeaWiFS chlorophyll-a images, and spatial distribution of albacore CPUE (albacore/fishing-boat days) from the longline fishery in November from 1998 to 2000 were superimposed on the map.

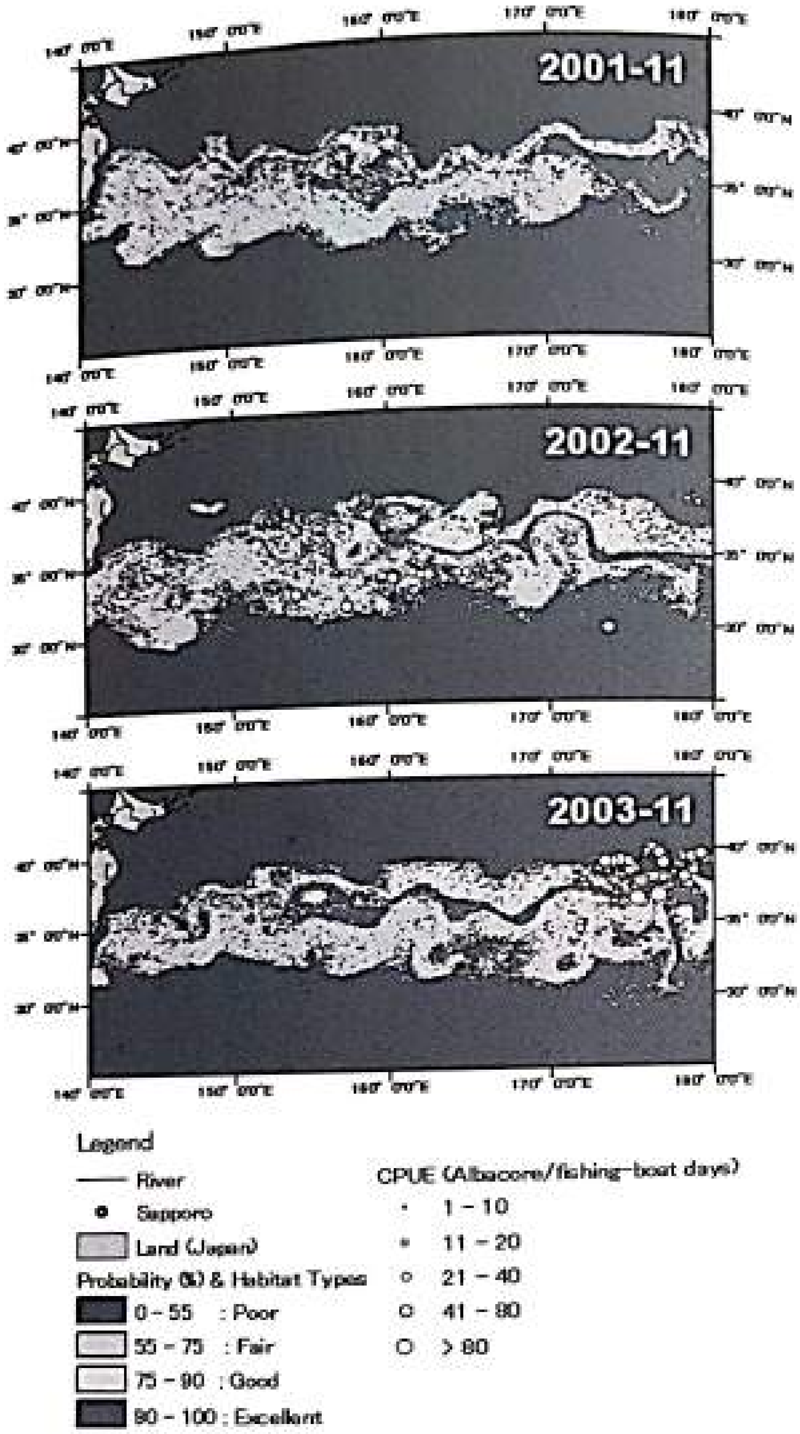

Figure 16b. The spatial pattern of albacore habitats hot spots on an environmental probability map generated from TRMM/TMI SST and SeaWiFS chlorophyll-a images, and spatial distribution of albacore CPUE (albacore/fishing-boat days) from the longline fishery in November from 1998 to 2000 were superimposed on the map.

4.4.2 Primary production and altimetry map

It is clearly apparent that the transition zone of northwestern North Pacific extending from 30°N to 40°N has a higher primary production (PP) than surrounding areas (Figure 17). From November 1998 to 2000, the relatively high PP occurred near coastal region, and in 2001 and 2002 PP was found to be lower in that area. In 2003, the PP was again high near that location. Catch rates during November 1998-2000 were clearly higher than in November 2002-2003 (Figure 18a). In that period, the high CPUEs have relatively higher probability indices and primary productivity rates than those during November 2002 -2003 (Figure 18b-c).

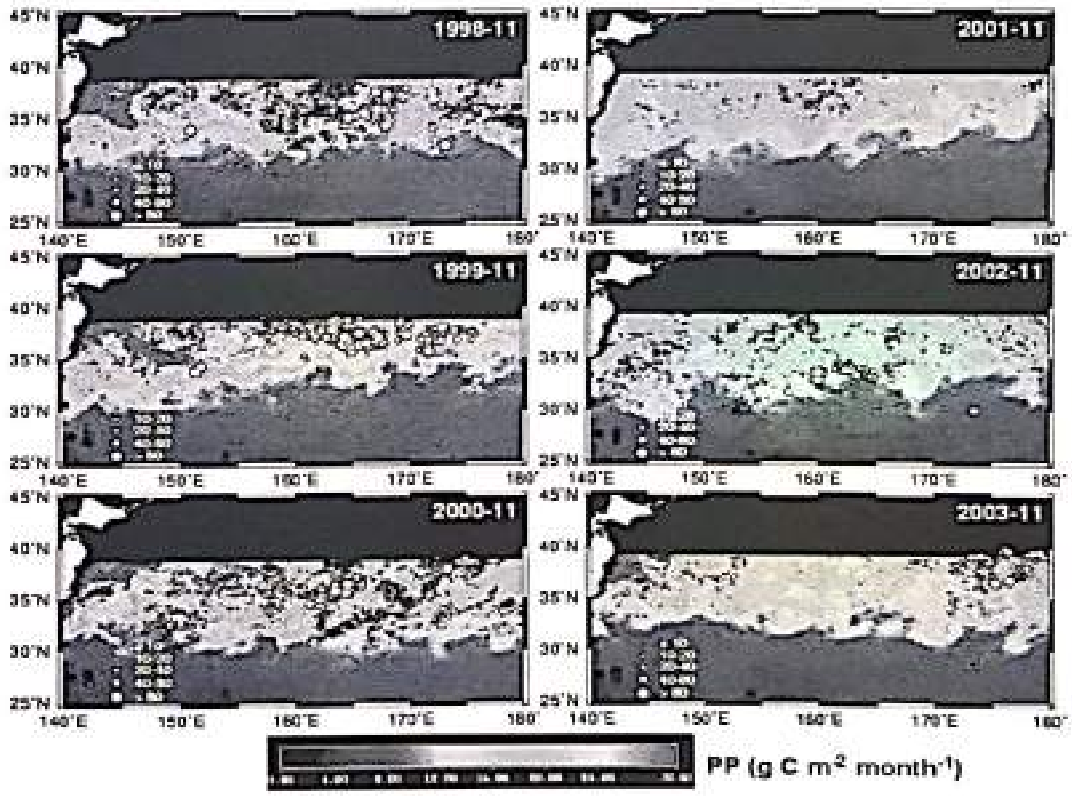

Figure 17. The spatial distribution of primary production and albacore CPUE (albacore/fishing-boat days) from the longline fishery during November 1998-2003 were overlain on the map (Zainuddin et al., 2006).

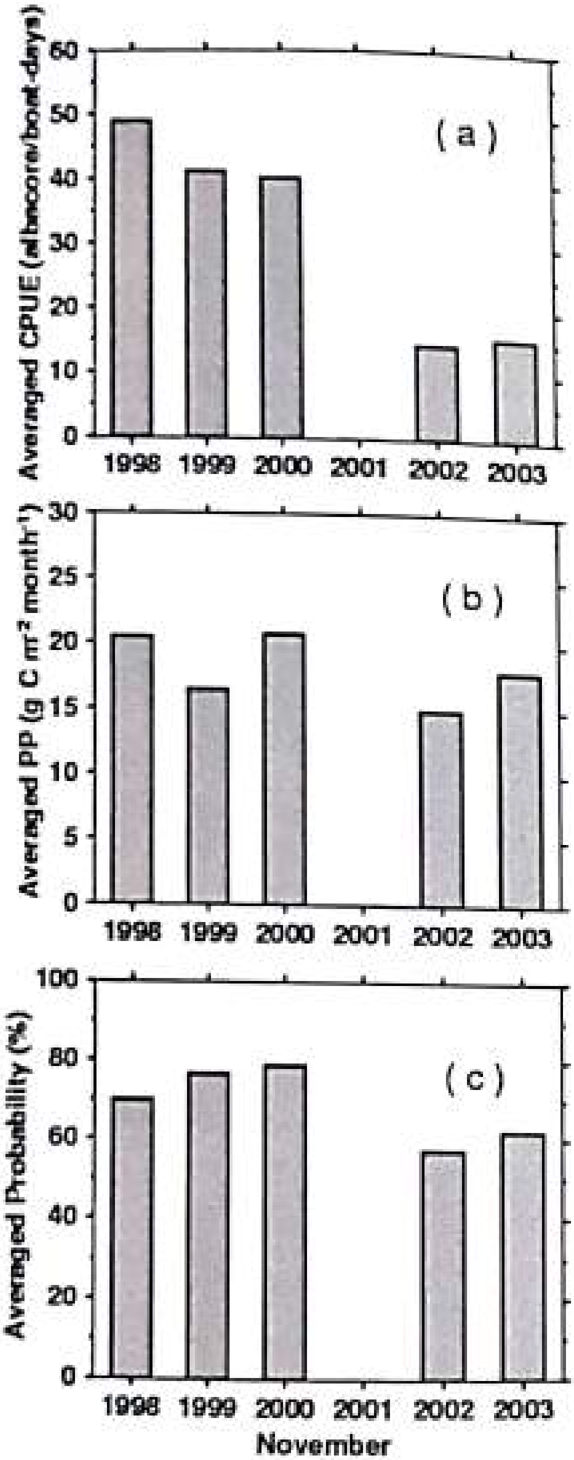

Figure 18. Interannual variation of averaged CPUE (albacore/fishing-boat days) (a), primary production (b), and probability of joint environmental variables of the albacore fishing ground (c) during November 1998-2003. No catch data in 2001 (Zainuddin et al., 2006).

Satellite altimetry images showed that ocean hot spots for albacore have specific signatures, positive SSHA and relatively high eddy kinetic energy (EKE) associated with geostrophic currents. The ocean hot spots occurred near 36-37°N and 167-170°E for November 1998 and located near 35-37°N for November 2000 linking with positive SSHA, relative high EKE and anticyclonic meander like eddy fields (Figures 19 and 20). The other hot spot sites were found in November 2002 near 34°N corresponding with positive SSHA, relative high EKE and geostrophic current velocities around the Kuroshio Extension Current. In November 1999, the high CPUEs developed without any specific signatures of altimetry data. The potential habitat hot spot in November 2003 was found near the dateline and was associated with anticyclonic meandering eddy filed, positive SSHA and slightly high EKE. Figure 20 clearly shows the Kuroshio Extension Current signature that seems to have different patterns annually during November 1998-2003.

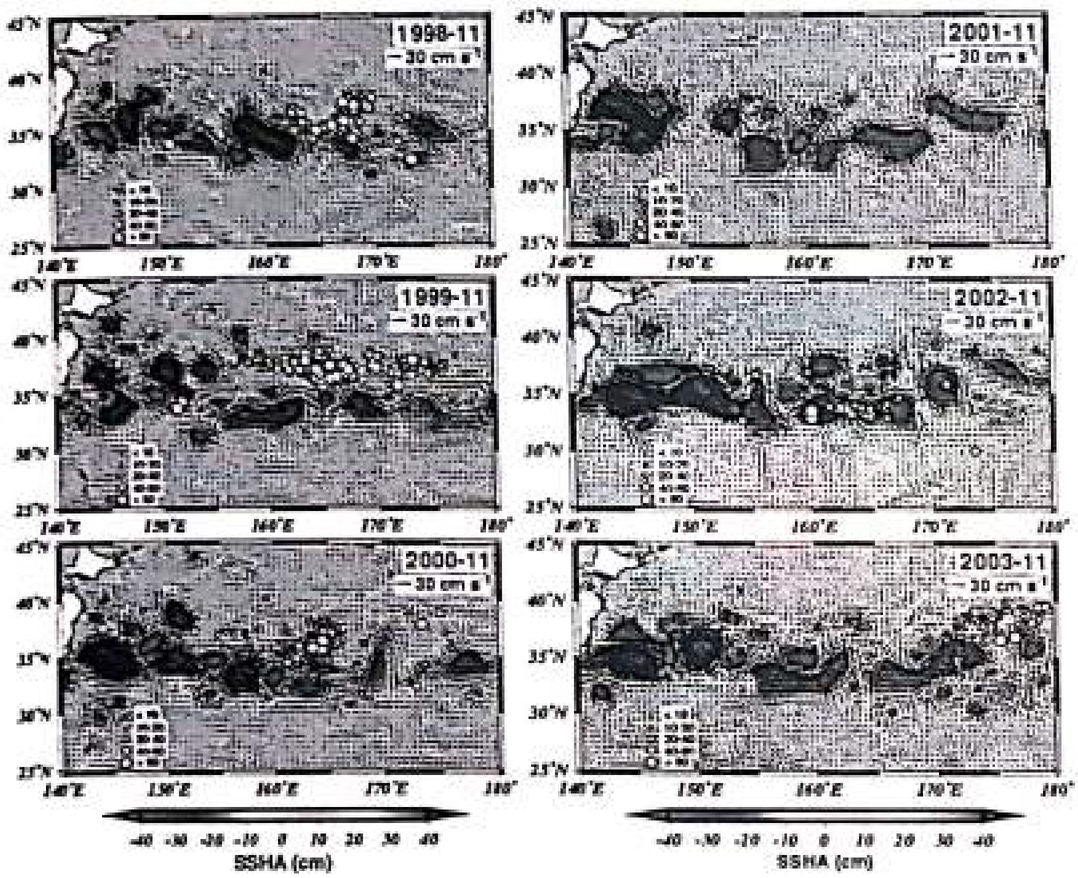

Figure 19. The SSHA images with geostrophic velocities, and spatial distributions of albacore CPUE (albacore/fishing-boat days) from the longline fishery during November 1998-2003 were superimposed on the map.

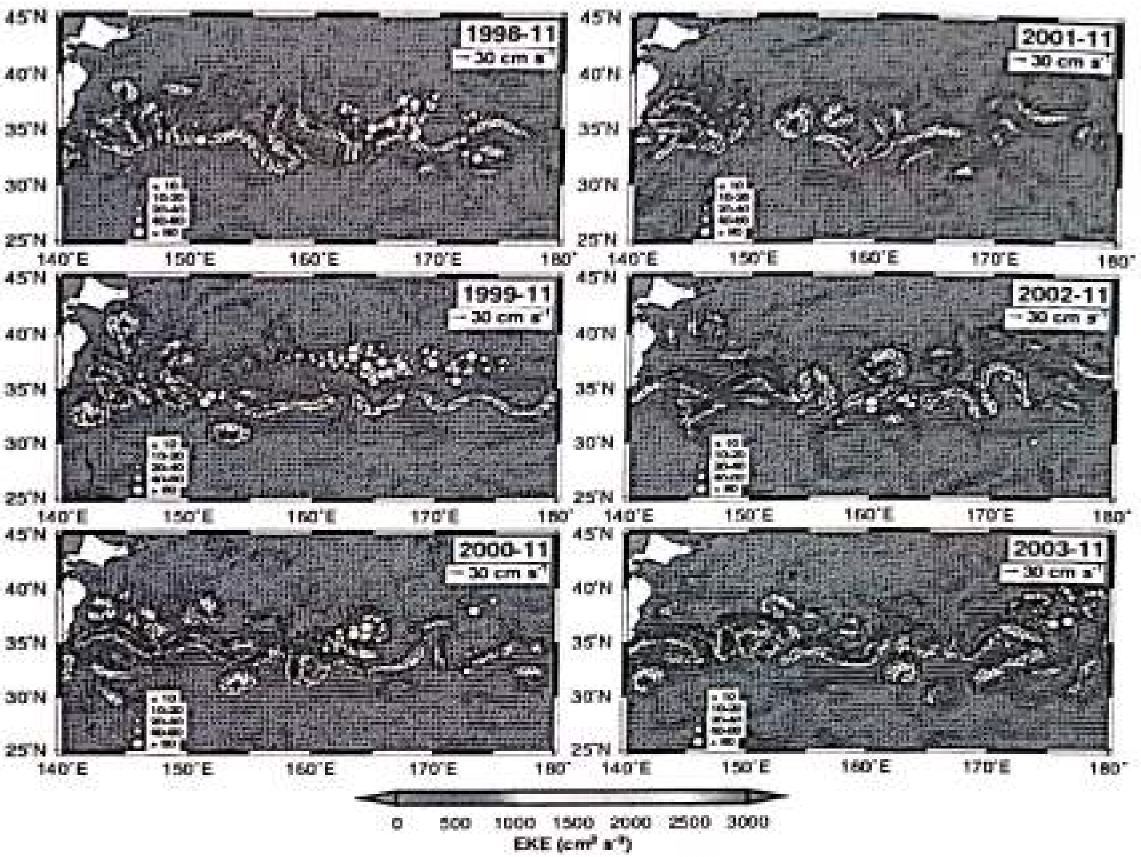

Figure 20. The Eddy Kinetic Energy (EKE) images with geostrophic velocities, and spatial distributions of albacore CPUE (albacore/fishing-boat days) from the longline fishery during November 1998-2003 were superimposed on the map (Zainuddin et al., 2006).

4.5 Prediction of potential habitat hot spots for albacore tuna

4.5.1 Prediction of habitat hot spots for tuna occurrence

To find a systematic description of prediction procedure for tuna availability, the analysis flow has been constructed (Figure 21). The final goal of this approach was to determine spatial pattern of habitat hot spots, the high probability areas of finding albacore. It is clearly shown that the probability of finding albacore in the study area during the highest season has a specific trend (Figure 22). The relationship between fishing frequency of high catch data and oceanographic variables (SST and SSHA) were statistically significant ($P < 0.001$) using the GAM. The variable of chlorophyll-a was less significant. It has probability more than 0.001. It means that using the GAM, SST and SSHA have a contribution for explaining albacore better than chlorophyll-a. Figure 22 showed that SST and SSHA have significant ranges approximately between 18 and 22°C and between 5 and 40 cm, respectively. The shape of SST trend indicated a quadratic form and the strongest relationship between fish occurrence and SST occurred near 20°C SST. The linear shape of SSHA at the specific interval indicated that the probability of finding albacore increased linearly at the certain positive SSHA range. Whilst, chlorophyll-a seemed to have smaller favorable range, occurring from 0.2 to 0.3 mg m^{-3}. The chlorophyll-a has an exponential trend and the probability of obtaining albacore tended to decrease when the variable value was greater than 0.3 mg m^{-3} and less than 0.2 mg m^{-3}.

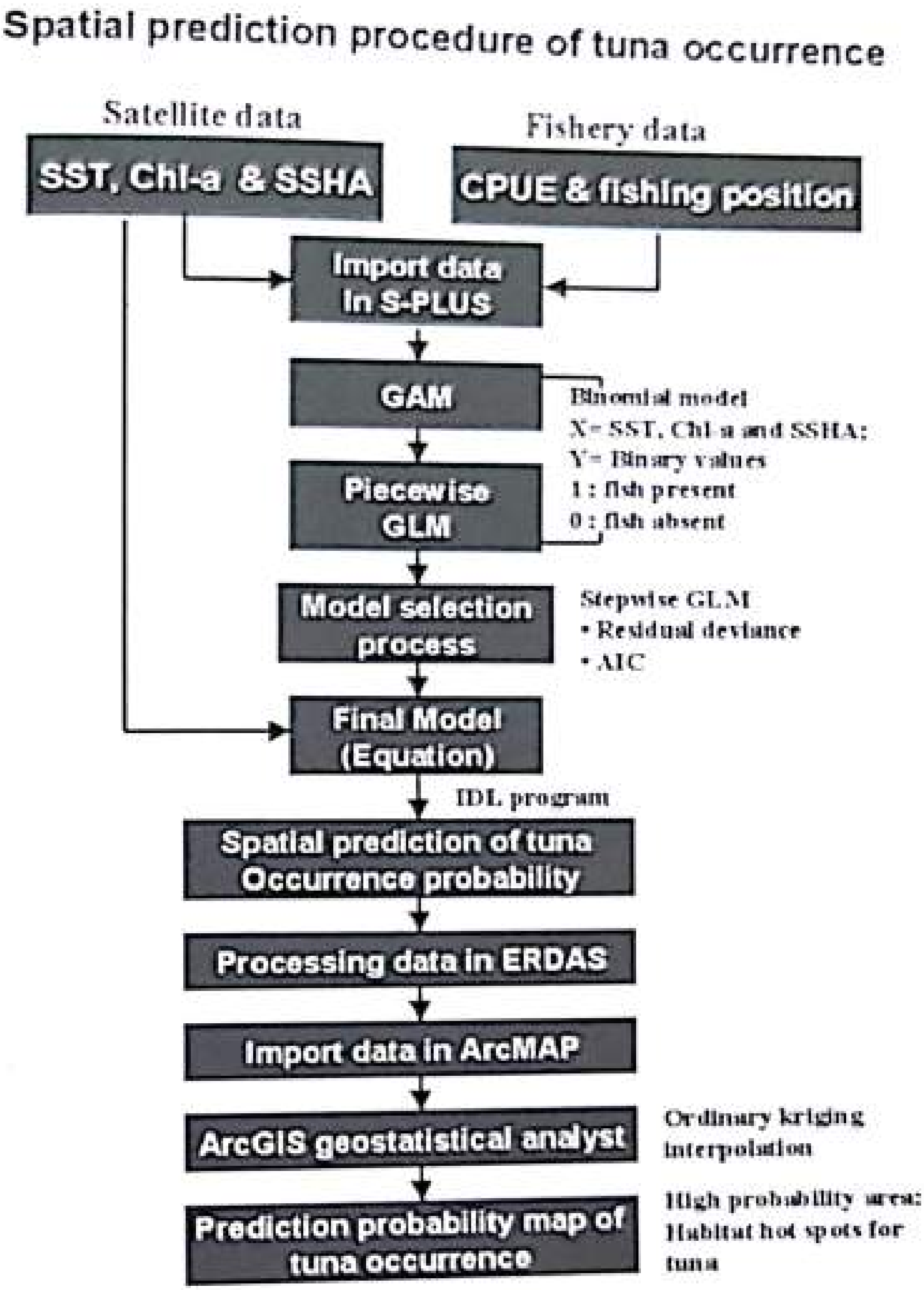

Figure 21. The analysis flow of spatial prediction procedure of tuna occurrence probability using statistical model (a combined GAM/GLM).

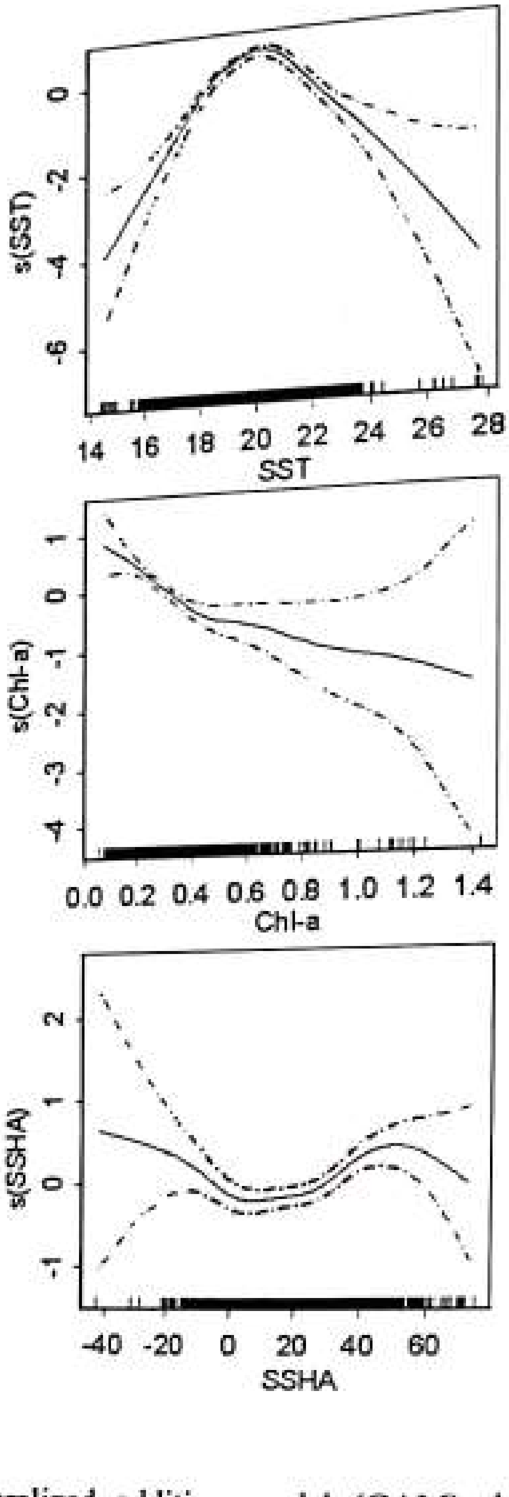

Figure 22. Generalized additive model (GAM) derived effect of oceanographic variables (top) TRMM/TMI SST (middle) SeaWiFS chlorophyll-a and (bottom) AVISO SSHA on albacore presence/absence. Dashed lines indicate 95 % confidence intervals. The relative density of data points is shown by the rug plot on the x-axis.

The relationship between albacore occurrence and the three covariates (SST, chlorophyll-a and SSHA) using piecewise GLM was highly significant ($P < 0.001$, Table 2). It means that all variables have a significant contribution for explaining tuna availability and abundance, and thereby the probability of finding albacore can be predicted accurately using the three variables as input data of the models. For this model, with each addition of the variables selected to represent subsequent periods, the residual deviance decreased, the AIC statistic decreased, and probability was very significant, suggesting that all variables contributed significantly to increasingly better model fit and parsimony using the three oceanographic variables (Table 2). Hence, the final GLM sets for predicting the probability of albacore occurrence consisted of three oceanographic variables, SST, chlorophyll-a and SSHA.

Table 2. Construction of the GLM for prediction of tuna occurrence. As each variable is added, residual deviance, AIC and probability are examined to find significantly predictors.

Variable	Resid. d.f.	Resid. deviance	AIC	P(Chi)
NULL	1934	2661.978	2663.978	
Poly(sst, 2)	1932	2478.392	2484.392	0.000
Log(chl-a)	1931	2435.651	2443.651	0.000
I((ssha-(-15)*(-15< ssha ≤ 30)*(ssha>30))	1930	2419.600	2429.600	6.1e-05

The probability of finding albacore generating from statistical model was primarily found in the transition region of study area extending from 30 to 40°N (Figure 23). Specifically, in November 1998, the high probability areas (hot spots) occurred between 32 and 38°N along 165-175°E corresponding to the fishing ground formation of albacore fishery (Figure 23a). The hot spot areas in 1999 moved northward occupying latitude of 35-40°N along the study area. In 2000, the potential habitat hot spots again occurred in a wider latitudinal band (30-40°N), but three main hot spots appeared in the western, central and eastern part of study area. In this year, the high CPUEs of albacore fishery concentrated in the central hot spots of study area with probability more than 76%. During 1998-2000, albacore tuna tended to locate the areas of probability greater than 70%.

During November 2001, the major hot spot occupied the center of the transition zone, especially in the central and eastern area of study (Figure 23b). In 2002, the potential habitats were more scatter, and the fishery data tended to occur in a wide area both latitude and longitude. In this year, albacore fishery occupied lower probability than that of during 1998-2000. The high probability areas in 2003 were found in the central and eastern transition region. Large abundance of albacore fishery associated with the main hot spot in the eastern side of study area near the dateline with the probability of about 70%.

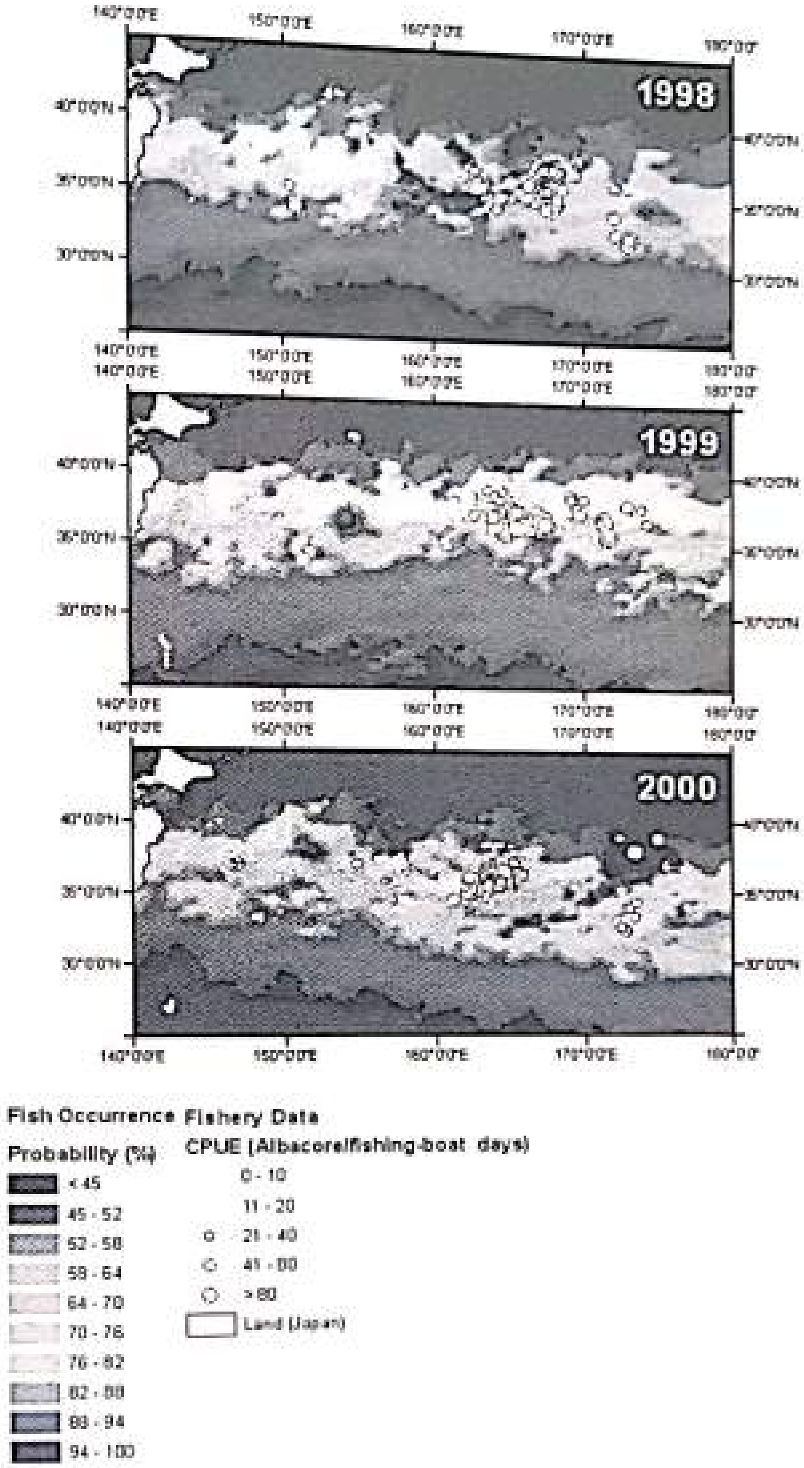

Figure 23a. The spatial pattern of habitat hot spots on predicted probability map by the GLM using the three predictors (NOAA/AVHRR SST, SeaWiFS chlorophyll-a and AVISO SSHA), and the distributions of albacore CPUE (albacore/fishing-boat days) from longline fishery in November from 1998 to 2000 were overlain on the map.

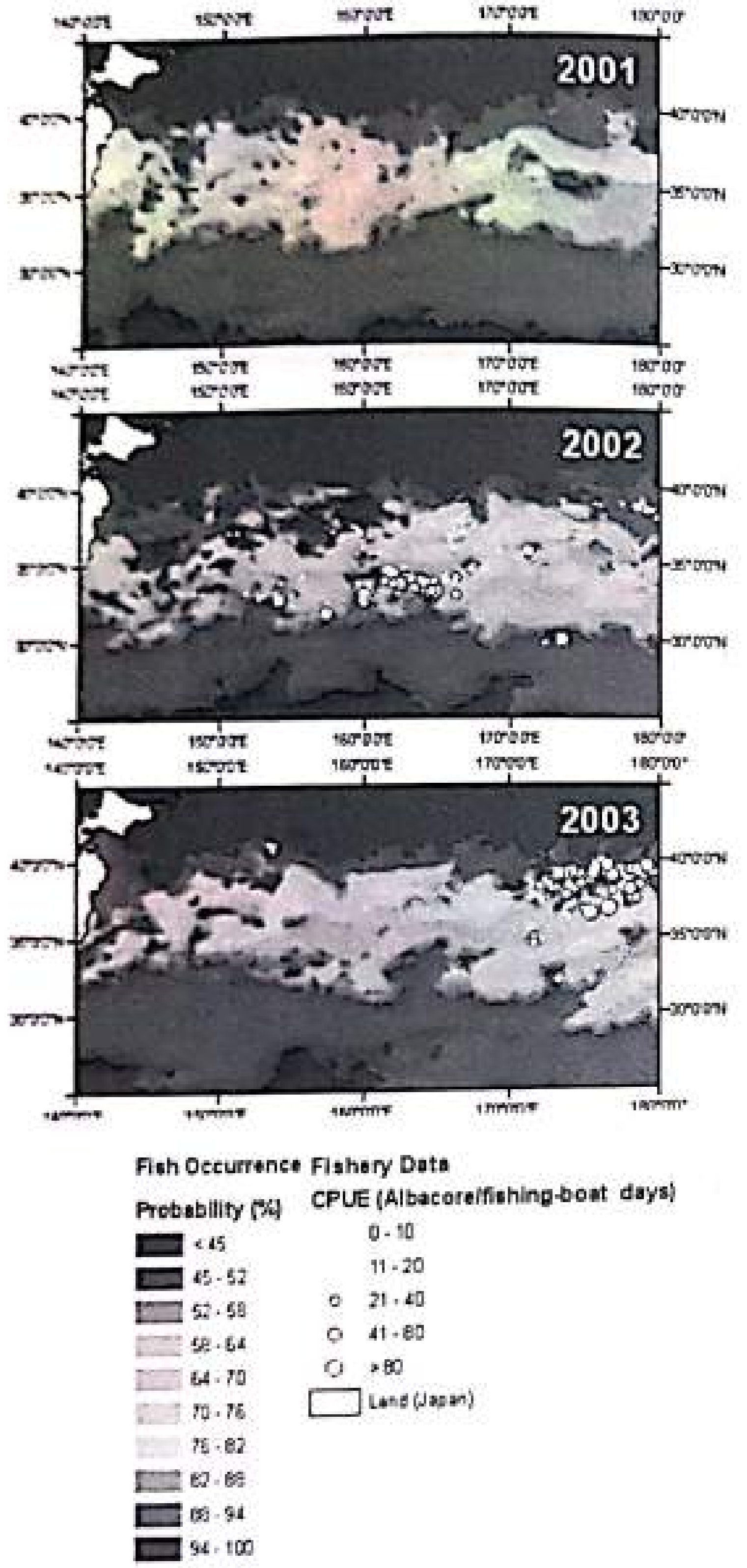

Figure 23b. The spatial patterns of habitat hot spots on predicted probability map by the GLM using the three predictors (NOAA/AVHRR SST, SeaWiFS chlorophyll-a and AVISO SSHA), and the distributions of albacore CPUE (albacore/fishing-boat days) from longline fishery in November from 2001 to 2003 were overlain on the map.

4.5.2 Prediction of habitat hot spots for tuna abundance

The flow chart analysis has been generated to describe systematically the spatial prediction procedure of tuna abundance in the study area (Figure 24). The final objective of this approach was to predict spatial pattern of habitat hot spots, the high productive areas where albacore are most probably abundant.

Tuna abundance in relation to environmental variables showed that all covariates (SST, chlorophyll-a and SSHA) were highly significant ($P< 0.001$) using the GAM. Albacore CPUEs were found in significant association with environments of SST ranging from 18.0 to 22°C, SSC from 0.2 to 0.4 mg m^{-3} and SSHA from –5 to 40 cm (Figure 25). The shape of SST pattern (quadratic trend) indicated that the strongest relationship between SST and fish abundance also occurred near 20°C. Albacore CPUE tended to decrease with quadratic pattern at the levels of SST less than 18°C and greater than 22°C. The chlorophyll-a with the exponential trend tended to be strongest at the point of 0.3 mg m^{-3} chlorophyll concentration. Farther below the value of 0.2 and above 0.4 mg m^{-3}, the CPUEs tended to decrease in accordance with the trend. For the SSHA, the shape of trend was linearly positive at the interval value above. The CPUE tended to increase linearly at the certain range of positive SSHA. These results reinforced the evidence obtained from the ECDF and histogram graphs. A comparison of Figure 22 and 25 shows the similarity between the model patterns. The model trend of tuna abundance in relation to their environments using the GAM was sharper than the probability of tuna availability in relation to the environments.

Using piecewise GLM, albacore abundance in relation to the three oceanographic variables also showed highly significant ($P < 0.001$, Table 3). It infers that all variables have a significant contribution for explaining tuna abundance, and thereby albacore abundance can be predicted accurately using the three variables as input data on the final model. For this model, with each addition of the variables selected to represent subsequent periods, the residual deviance decreased, the AIC statistic decreased, and probability was also very significant, reflecting that all variables contributed significantly to increasingly better model prediction (Table 3).

Hence, the final GLM model for predicting albacore abundance consisted of three oceanographic predictors, SST, chlorophyll-a and SSHA.

Table 3. Construction of the GLM for prediction of tuna abundance. As each variable is added, residual deviance, AIC and probability are examined to find significantly predictors.

Variable	Resid. d.f.	Resid. deviance	AIC	P(F)
NULL	1929	3663.509	3667.307	
Poly(sst, 2)	1927	3438.443	3449.838	0.000
Log(chl-a)	1926	3286.795	3301.988	0.000
I((ssha-(-15)*(-15< ssha ≤ 30)*(ssha>30))	1925	3216.803	3225.795	0.000

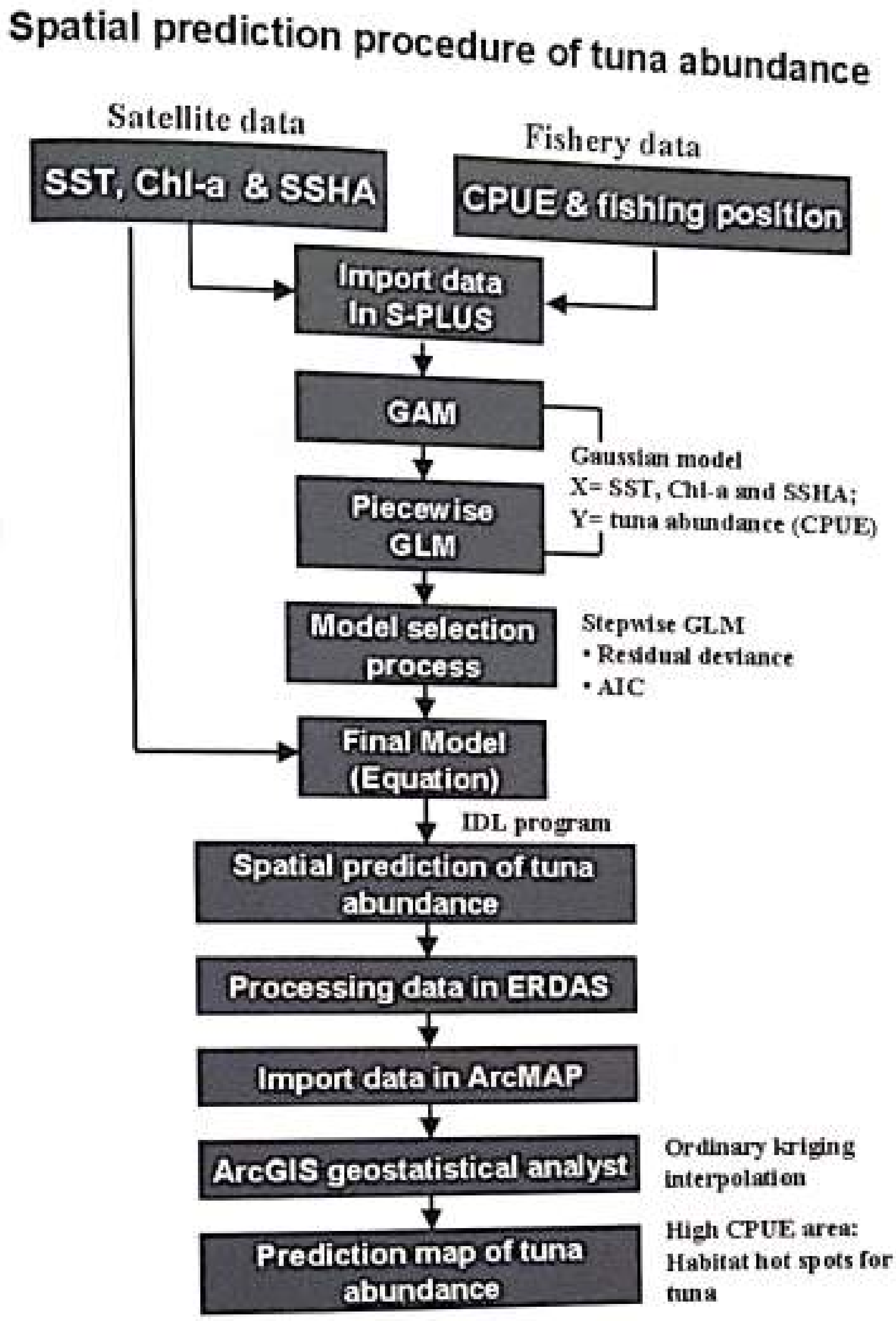

Figure 24. The flow chart analysis of spatial prediction procedure of tuna abundance (CPUE) using statistical model (a combined GAM/GLM).

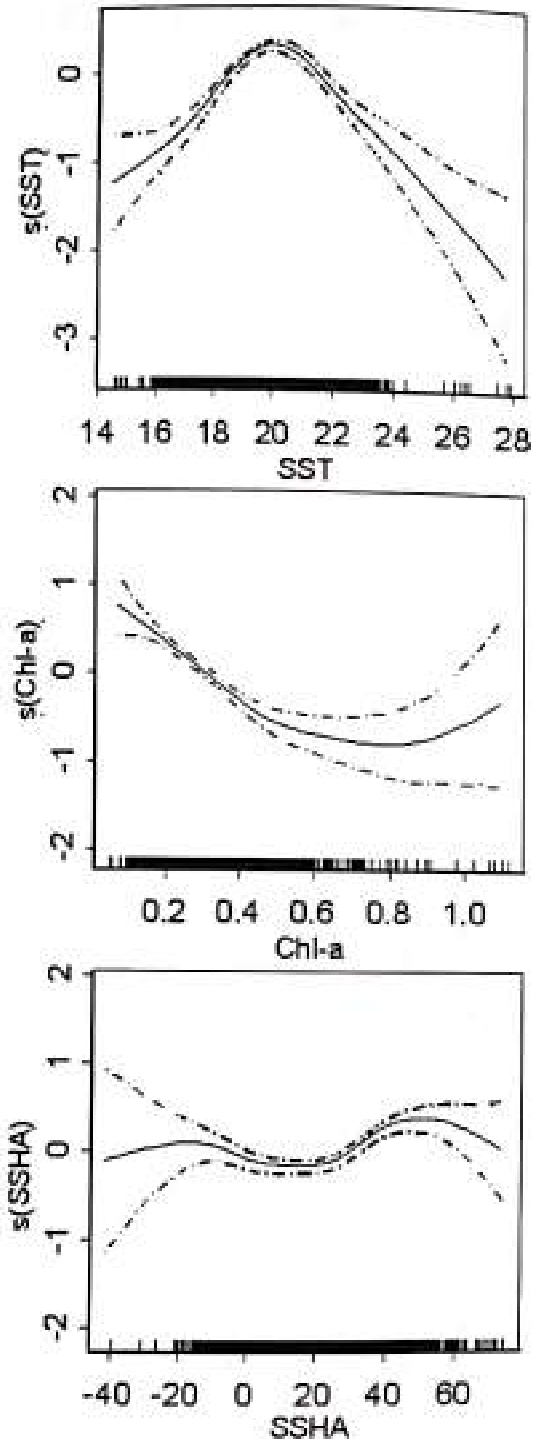

Figure 25. Generalized additive model (GAM) derived effect of oceanographic variables (top) TRMM/TMI SST (middle) SeaWiFS chlorophyll-a and (bottom) AVISO SSHA on albacore CPUE (log transformed). Dashed lines indicate 95 % confidence intervals. The relative density of data points is shown by the rug plot on the x-axis.

Spatial pattern of predicted tuna abundance (CPUE) showed that there were specific locations of habitat hot spots where albacore are abundant (Figure 26). This pattern was similar to the predicted of tuna occurrence. Predicted tuna CPUE was clearly enhanced from the probability map produced by the combined GAM/GLM. The prediction of high CPUEs coincided with the higher probability area using statistical models. The highest catch rates of actual fishery occurred in areas of higher CPUEs and probability predicted by the model.

During 1998-2000, the high productive fishing grounds were more developed than during 2001-2003. Habitat hot spots developed near 34-37°N along 165-175°E in a good association with high productive albacore fishing grounds in November 1998 (Figure 26a). In November 1999, albacore habitats formed approximately 35-38°N along 150E-180° corresponding with formation of albacore fishery. In November 2000, hot spots well developed in the northern part of the Kuroshio Extension linking with high concentration of albacore fishery. During November 2001-2003, potential habitats for tuna occupied wider areas about 30-40°N and hot spots seemed to be more scatter than the proceeding years (Figure 26b).

Albacore fishery in 2002 and 2003 appeared to distribute widely following the formation of predicted tuna abundance. However, the areas of high estimated abundance that developed near the dateline in 2003 were consistent with the high aggregation of albacore fishery. The potential tuna habitat occurred mostly within the transition zone of northwestern North Pacific. Albacore catches tended to be lower in around the colder subarctic region (northern part of 40°N) and the warmer subtropical area (southern side of 30°N).

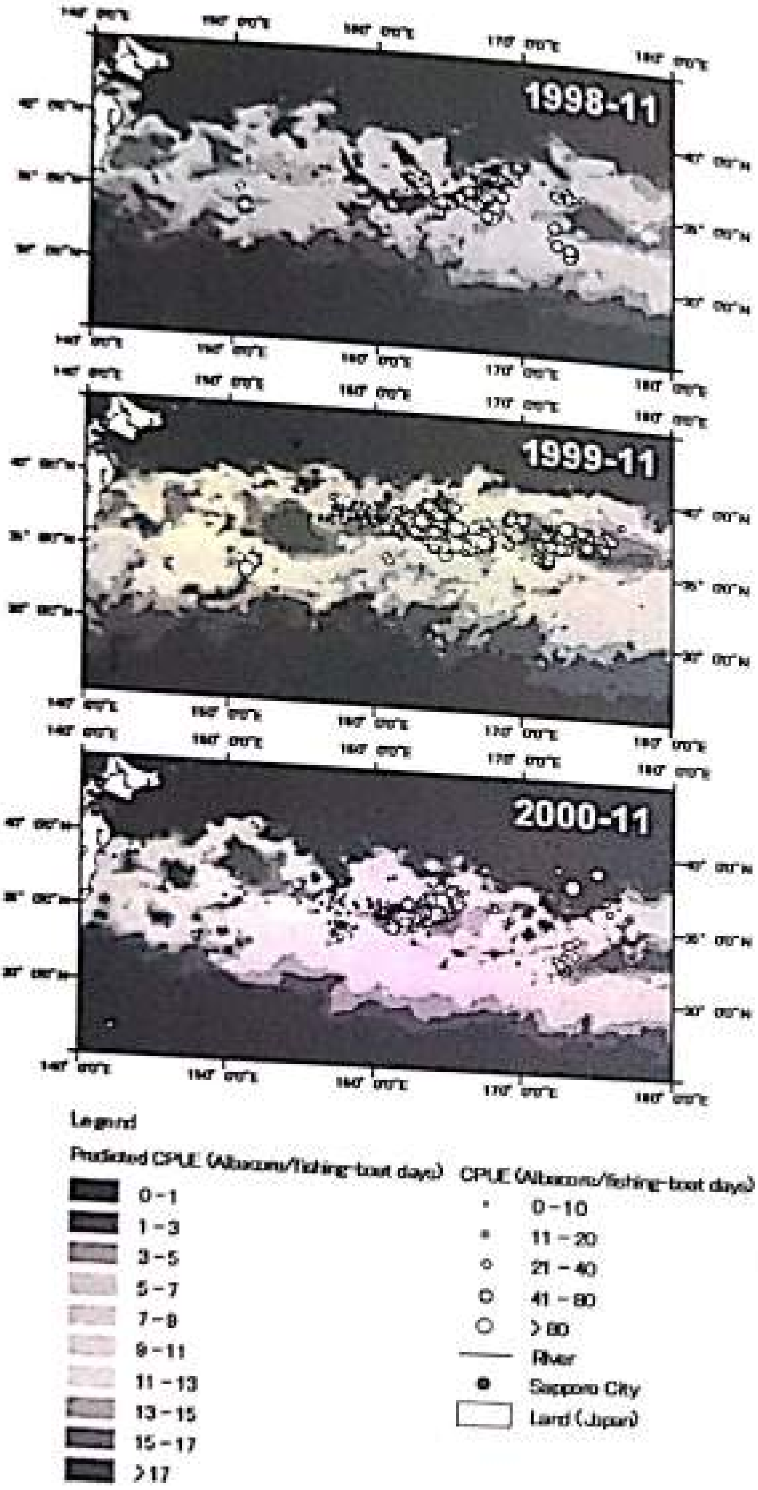

Figure 26a. The spatial patterns of habitat hot spots on predicted CPUE map by the GLM using the three predictors (NOAA/AVHRR SST, SeaWiFS chlorophyll-a and AVISO SSHA), and the distributions of albacore CPUE (albacore/fishing-boat days) from longline fishery in November from 1998 to 2000 were overlain on the map.

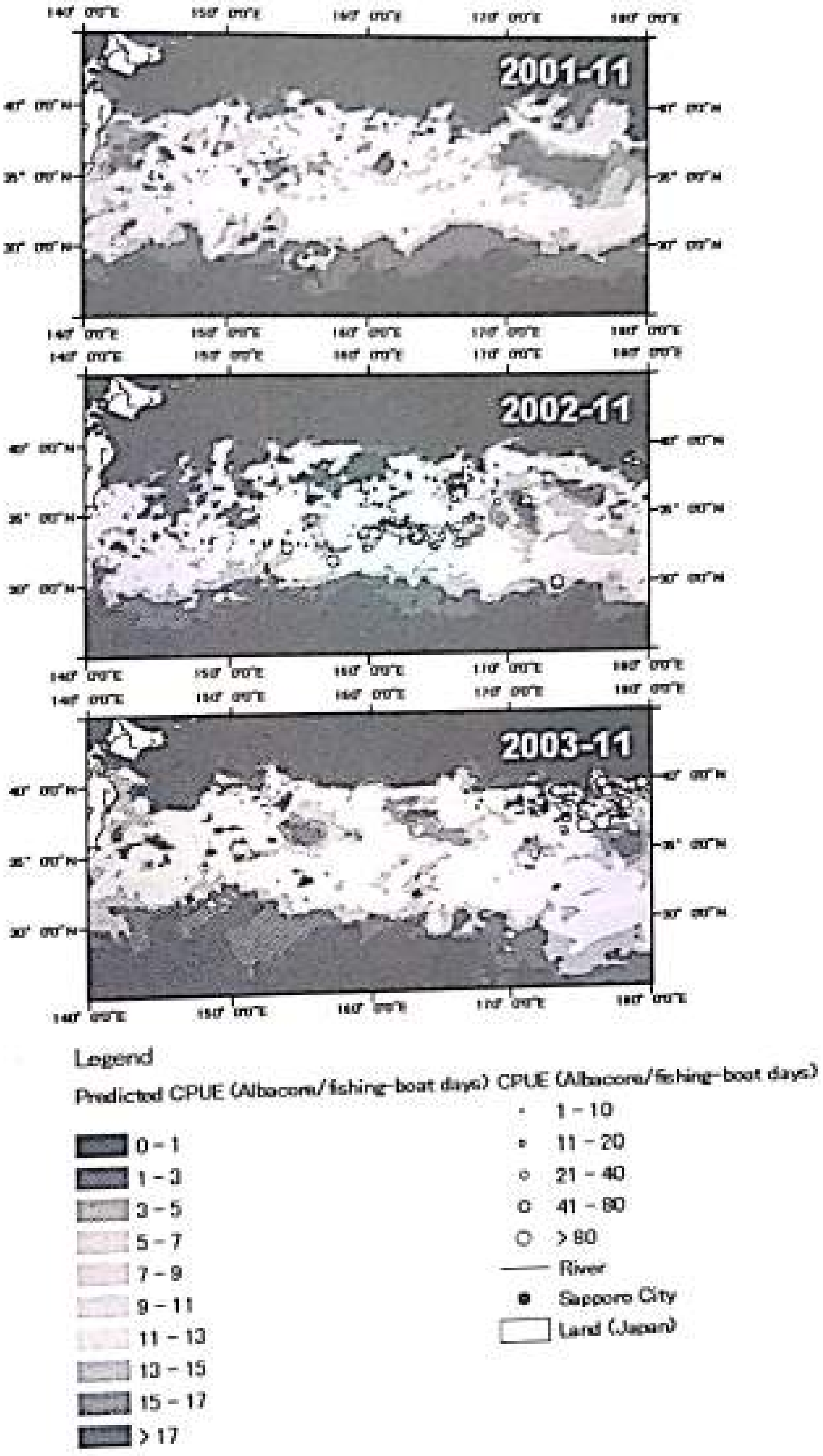

Figure 26b. The spatial patterns of habitat hot spots on predicted CPUE map by the GLM using the three predictors (NOAA/AVHRR SST, SeaWiFS chlorophyll-a and AVISO SSHA), and the distributions of albacore CPUE (albacore/fishing-boat days) from longline fishery in November from 2001 to 2003 were overlain on the map.

Predicted CPUE and occurrence for albacore again confirmed the results produced by the simple prediction map and probability map. The results of statistical model showed that potential habitat hot spots for albacore have a good association with the preferred oceanographic conditions, for example in November 2000 (Figure 27). Potential habitat hot spots (Figures 23a and 26a) were predicted to correspond with the high probability index of environments (Figure 27a). At the same time, the habitat hot spots defined by the models tended to form in areas of SST 18 - 21°C (Figure 27e) and surface chlorophyll-a 0.2 - 0.4 mg m^{-3} (Figure 27d). Observing from satellite altimetry, the ocean hot spots formed in waters of positive SSHA (Figure 27c) and relatively high EKE (Figure 27b). The ocean rich-environmental hot spot was clearly occurred in the specific location of approximately from 35 to 36 °N and from 162 to 166°E near the Shatsky Rise area, northern part of the Kuroshio Extension. Using multi-environmental parameters, it is clearly exhibited that each parameter has a specific signature, which could form high productive albacore habitat.

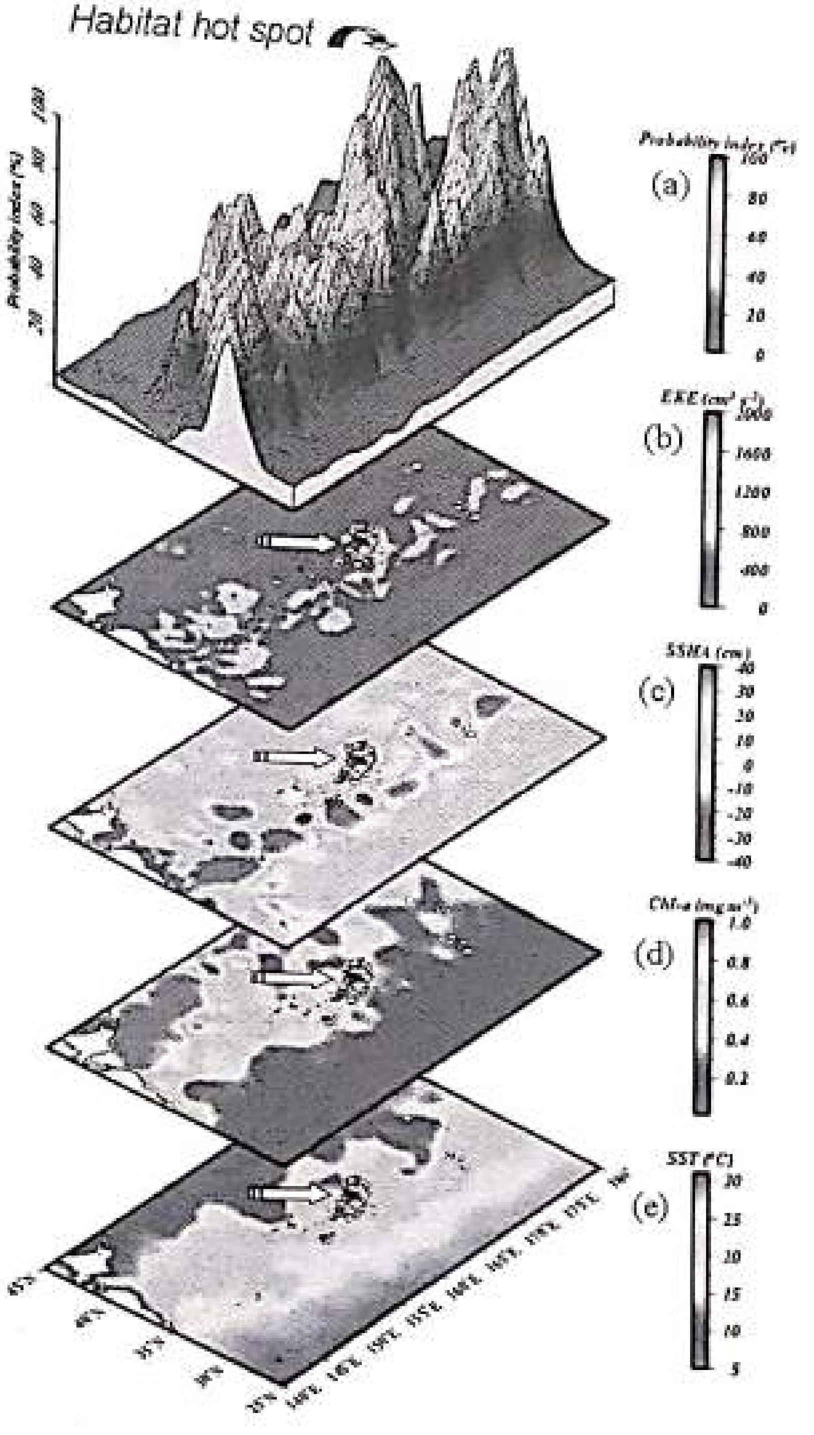

Figure 27. Potential habitat hot spot in November 2000 corresponding with probability index of environments (a) with specific signatures of eddy kinetic energy (EKE) (b), AVISO SSHA (c), SeaWiFS chlorophyll-a (d), and NOAA/AVHRR SST. Albacore CPUEs (albacore/fishing-boat days) were overlain on each map.

4.5.3 Spatial and temporal variation of habitat hot spot prediction

The high productive habitat hot spot experienced space-time dynamics linking with variations in oceanographic conditions of study area. Figure 28 showed that the predicted high CPUEs moved gradually to the south during winter period November 1998 - March 1999. In particular, in November 1998 the main hot spots occurred in three locations: first, about 38°N and 149°E; second, near 35-38°N and 167-170°E; and third, approximately 34-36°N and 173°E-180°. Formation of albacore fishery developed in the second zone. The major hot spots in December 1998 shifted southward in areas: (1) from 148 to 158°E, and (2) from 162-173°E, along the latitude of 32-25°N. Albacore fishing ground well developed and coincided perfectly with the hot spots habitat in the second region.

In 1999, the potential habitat hot spots occurred and dispersed in wide areas latitudinally and longitudinally. In January 1999, two major hot spots formed particularly in areas of about 33-36°N and 152-158°E, and 32-35°N and 168°E-180°. Fishing ground formation of albacore fishery developed in area of relatively higher productive habitat hot spots near 31-34°N along 161°E-174°E. The ocean rich-areas were formed in a wider longitudinal and latitudinal band from 30 to 35°N and between 152°E and 180° in February 1999, which were mainly associated with albacore fishery in areas of about 33°N and 173°E, and about 32°N and 173°E. In these locations, albacore were obtained in substantial numbers. The strongest hot spots were found in March 1999, which were located in widest areas from eastern coast of Japan to the dateline and from 30 to 37°N during winter period. In this month, albacore fishery dispersed widely and as a result CPUEs decreased considerably.

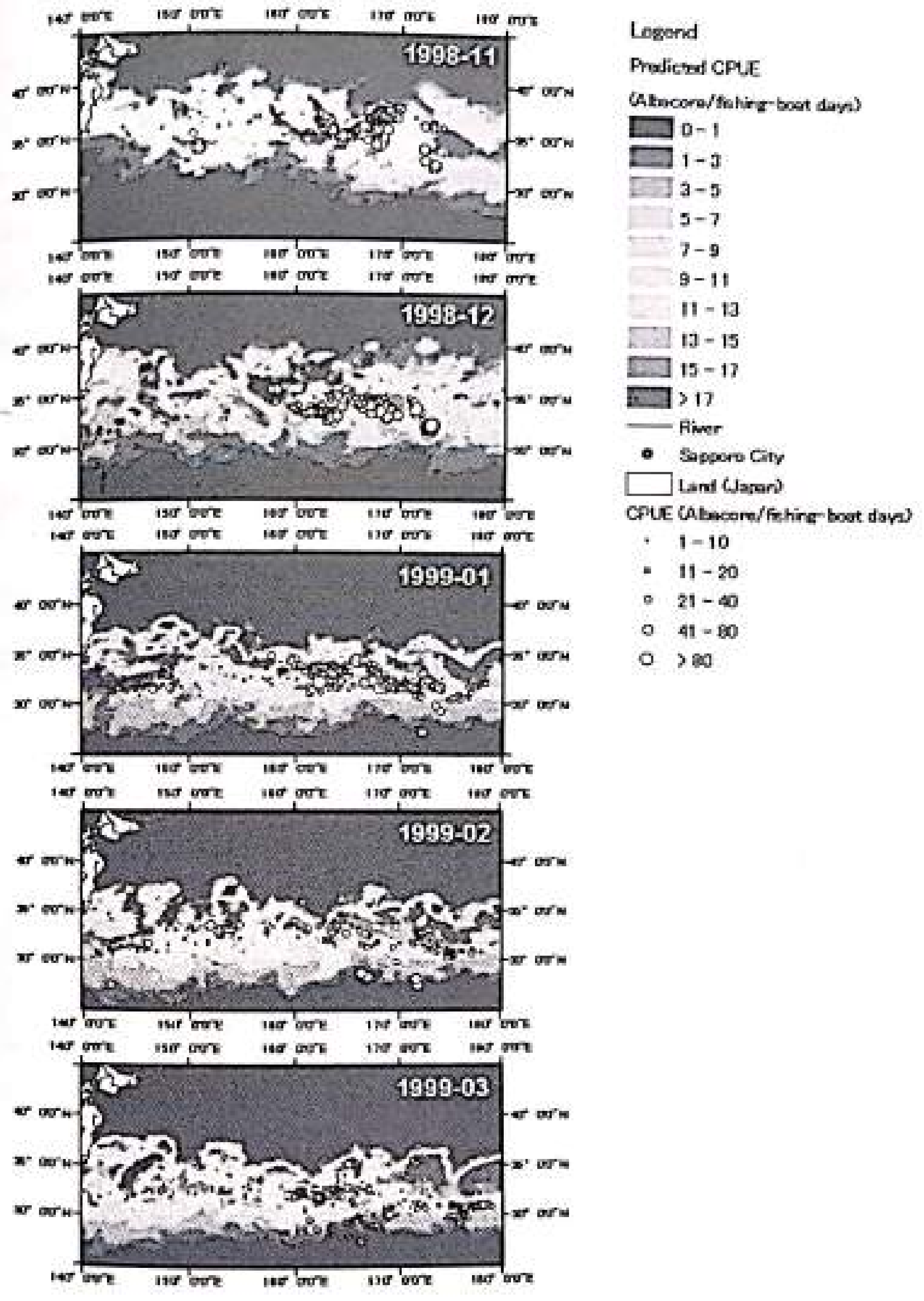

Figure 28. The spatial patterns of habitat hot spots on predicted CPUE map by the GLM using the three predictors (NOAA/AVHRR SST, SeaWiFS chlorophyll-a and AVISO SSHA), and the distributions of albacore CPUE (albacore/fishing-boat days) from longline fishery from November 1998 to March 1999 were depicted on the map.

4.6 Albacore tuna migration pattern

Model results from sensitivity analysis are shown in Figure 29. Using a time step of 0.25 h, the model produced excellent aggregation over the specified range of target area. Number of fish around the target position increased with the shorter time step. As time step increased, the effectiveness of the kinesis model was reduced. Using longer time step, the model resulted no significant aggregation of fish near the target position. All parameter values of albacore spatial movement model are shown in Table 4.

Table 4. Parameter values of albacore tuna spatial movements model used for running simulation (Zainuddin et al., 2011)

Symbol	Description	Value	Unit	Reference
T	Ambient SST during timestep	Spatially variable	°C	TRMM/TMI
To	Optimal SST	20	°C	Zainuddin et al. (2004)
σ	wide of Gaussian curve	1.6	Dimensionless	Zainuddin et al. (2004)
Φ	Maximum sustained swimming speed	6.6	Km h^{-1}	Laurs et al. (1977)
δ	timestep length	0.25	h	
H_1	Height of Gaussian curve in $f(V_{t+1})$	0.9	Dimensionless	
H_2	Height of Gaussian curve in $g(\varepsilon)$	0.7	Dimensionless	

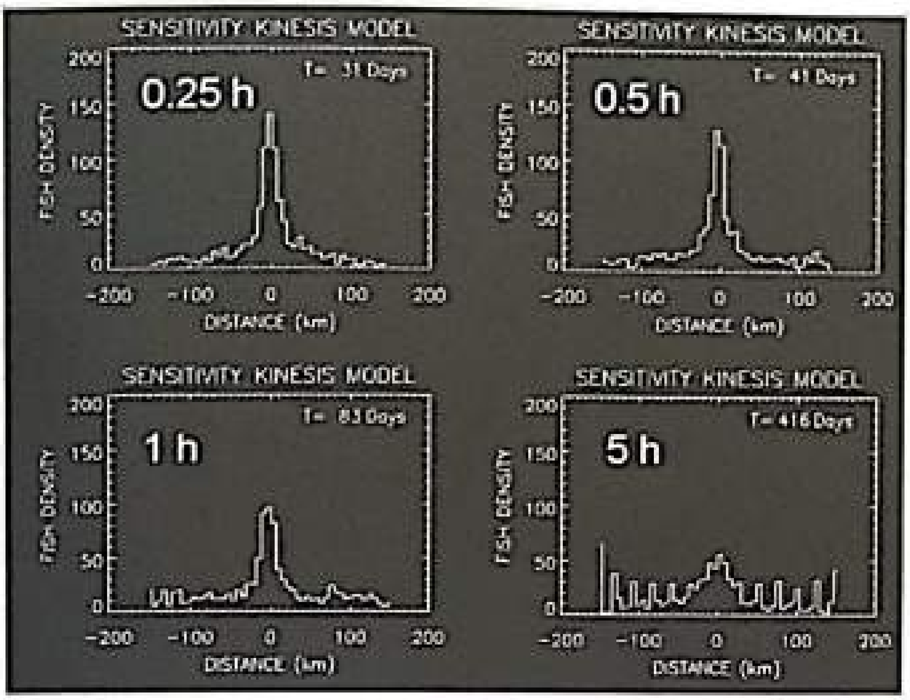

Figure 29. Results of sensitivity analysis of kinesis model using different time steps parametrized to $\delta = 0.25$, 0.5, 1 and 5 h. (h=hour) (Zainuddin et al., 2011).

Simulation model of albacore movement in the northwestern North Pacific at starting position are shown in Figure 30. The temperatures occupied by albacore at the start of model run generally ranging from 17°C to 28°C. The spatial fish distributions tend to distribute randomly. At the end model run (more than 44 days) fish appeared to aggregate from 20 to 24°C SST (fish density greater than 10%) with the highest concentration near 20°C SST isotherm. At the final position, the fish clearly aggregated in the specific zone around 35°N.

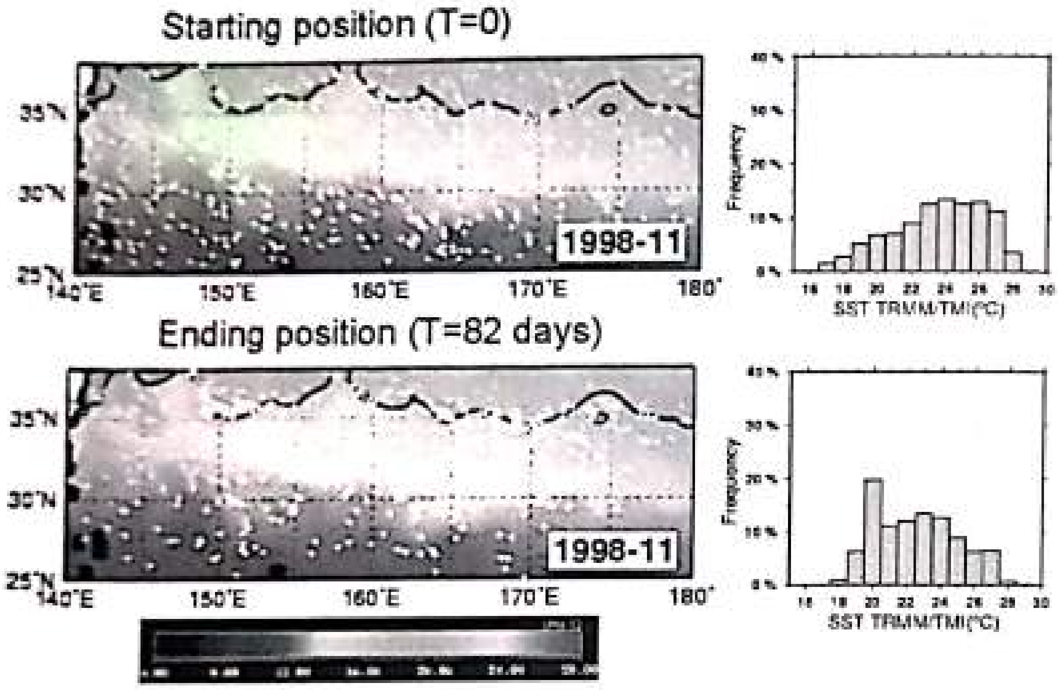

Figure 30. Spatial distribution of albacore at starting position (random distribution) (top) and at the ending position (first model run) (bottom) with each histogram frequency of TRMM/TMI SST around the fish distribution in November 1998 (Zainuddin et al., 2011).

Simulations of albacore tuna movement produced spatial distributions with similar to those observed in longline fishery data (Figure 31). At the running model monthly from November 1998 to March 1999 (a single winter period), fish tended to concentrate near the center of the thermal front indicated by 20°C SST. The fishing data occupied near the location of high fish concentration resulting from model run, particularly in November-December. During January-March, fish occurred in areas of SST 18 - 20°C, northern part of optimum temperature model. In this period, fish resulted from the model consistently occurred near the target temperature.

The histograms of SST occupied by fish at the model runs in all months indicated that the highest concentrations of fish were found in water of SST 18.5 - 21.5°C and tended to be centered at 20°C SST (Figure 32: left). These are very similar to SST in the high catch of fishing ground (Figure 32: right). Both these histograms are consistent with the favorable range of SST as illustrated in the preferred oceanographic condition for albacore produced by the ECDF and histogram of high catch data.

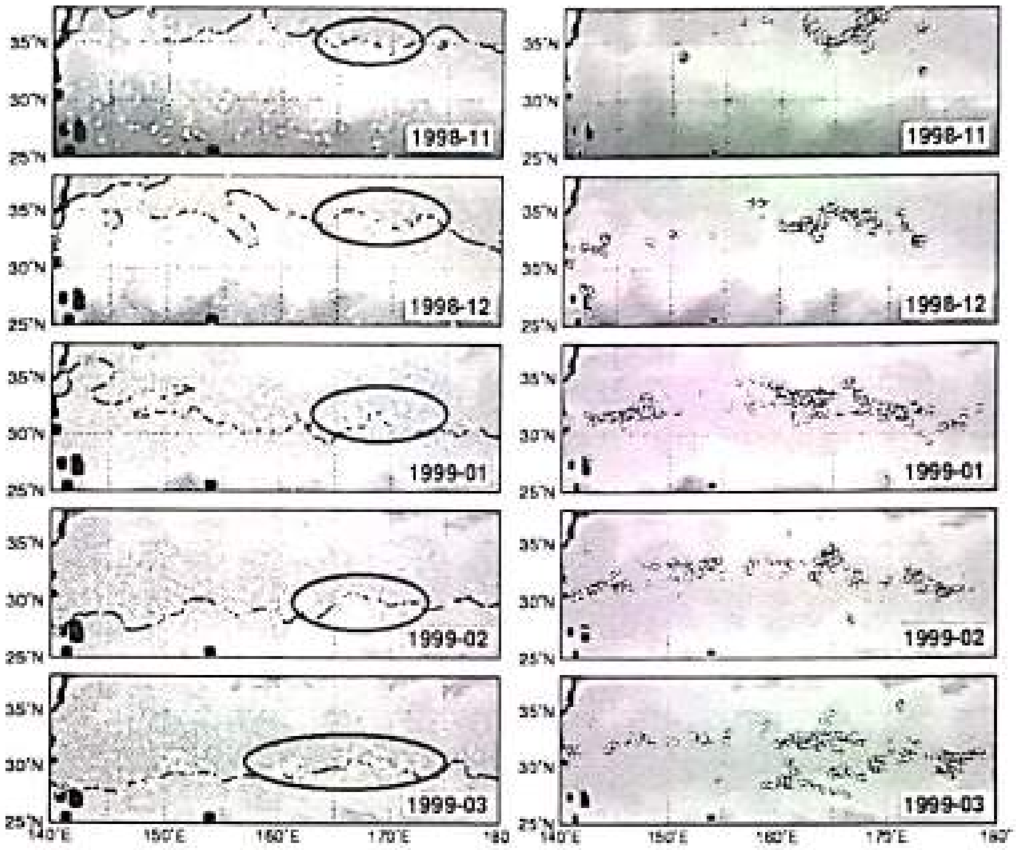

Figure 31. Spatial distribution of albacore displayed as observation data (right) and the result of kinesis model (left) for tracking migration pattern of albacore in winter period (November 1998-March 1999) ((Zainuddin et al., 2011).

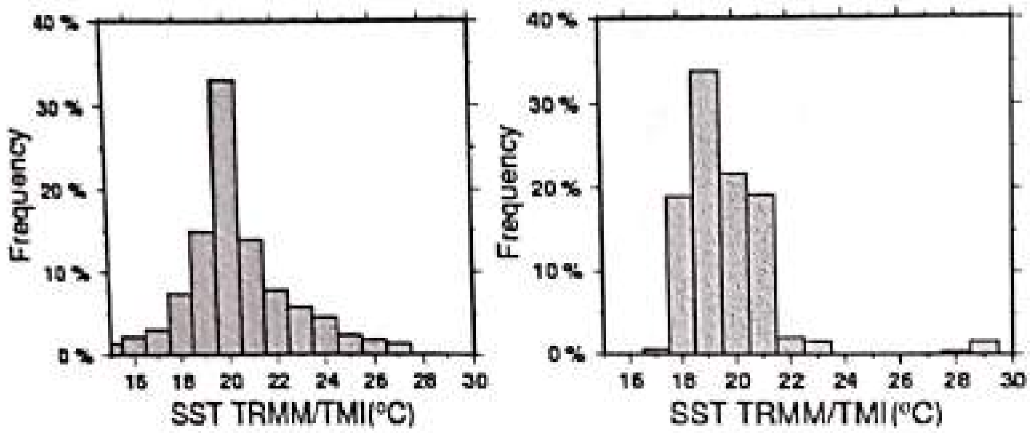

Figure 32. Sea surface temperature in relation to frequency of fish distribution produced by kinesis model (left) and fishing area (right) during winter term (November 1998-March 1999) (Zainuddin et al., 2011).

Using finer temporal scale (eight days), it is clearly apparent that spatial distribution pattern of fish produced by simulation model tended to aggregate near optimum SST isotherm (Figure 33). In the first week of November, individual fish dispersed randomly tried to search the location of optimum temperature, and the density of fish appeared to start to accumulate near the target temperature (Figure 33a). During the second and the third periods, the numbers of fish considerably increased near the optimum location about 18-22°C SST especially near 35°N along 165-170°E (Figure 34:left). When the specific isotherm again moved back slightly to the north in the last November, individual fish again distributed randomly particularly in the middle and southern part of the study area. As a result, fish density tended to be uniform and spatial distribution pattern of the fish disappeared.

In the first week of December, fish aggregation again formed near the isotherm as a consequence of southward shifting of the isotherm (Figure 33b). In next period, when the 20°C SST isotherm constantly moved down to the south, fish aggregation formed well around the optimal temperature. Consequently, the fish density increased significantly near the target area of 20°C SST isotherm (Figure 34:right).

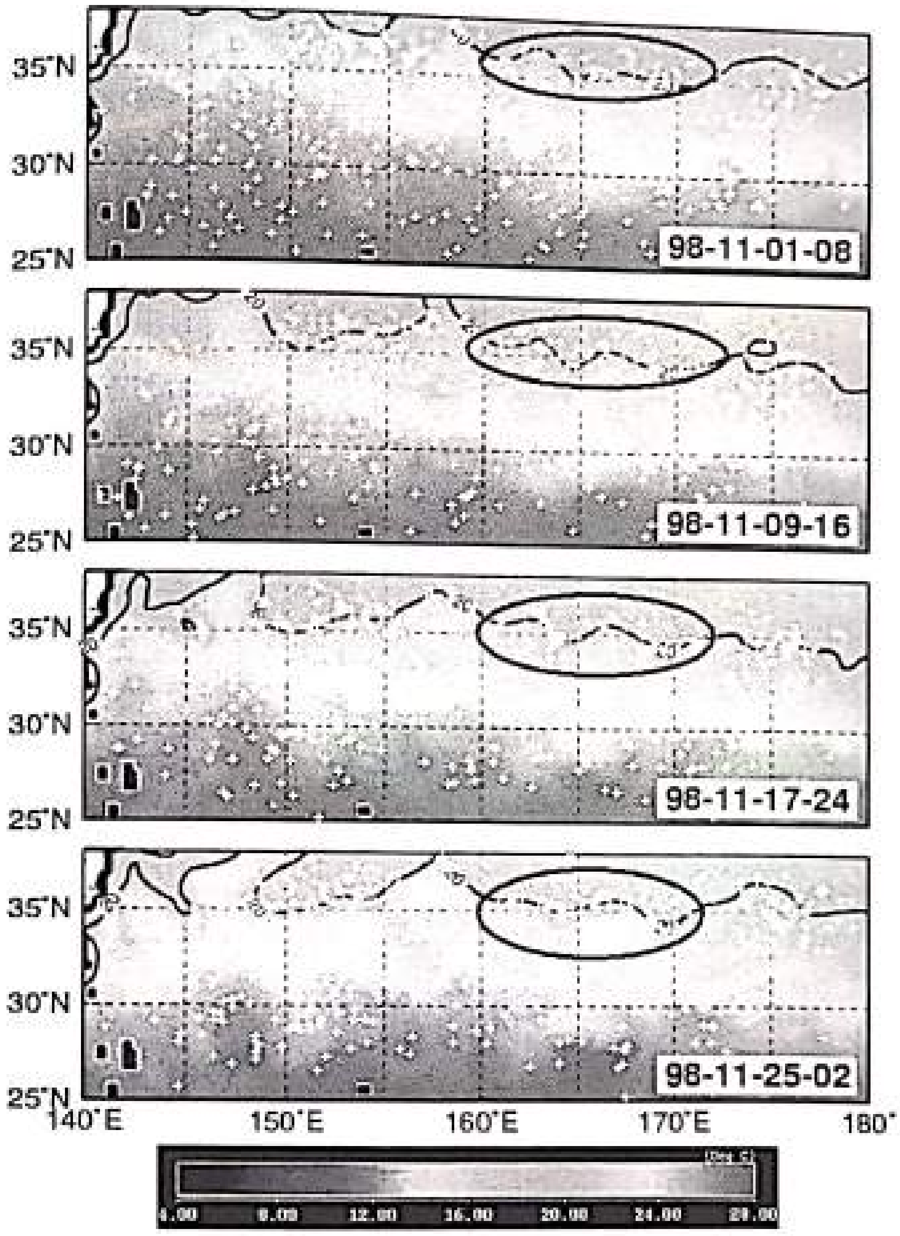

Figure 33a. Spatial migration pattern of albacore from early to late November 1998 driven by high accuracy eight days TMI SST data using simulation of kinesis model and the optimum 20°C SST isotherm contour line was indicated by black line.

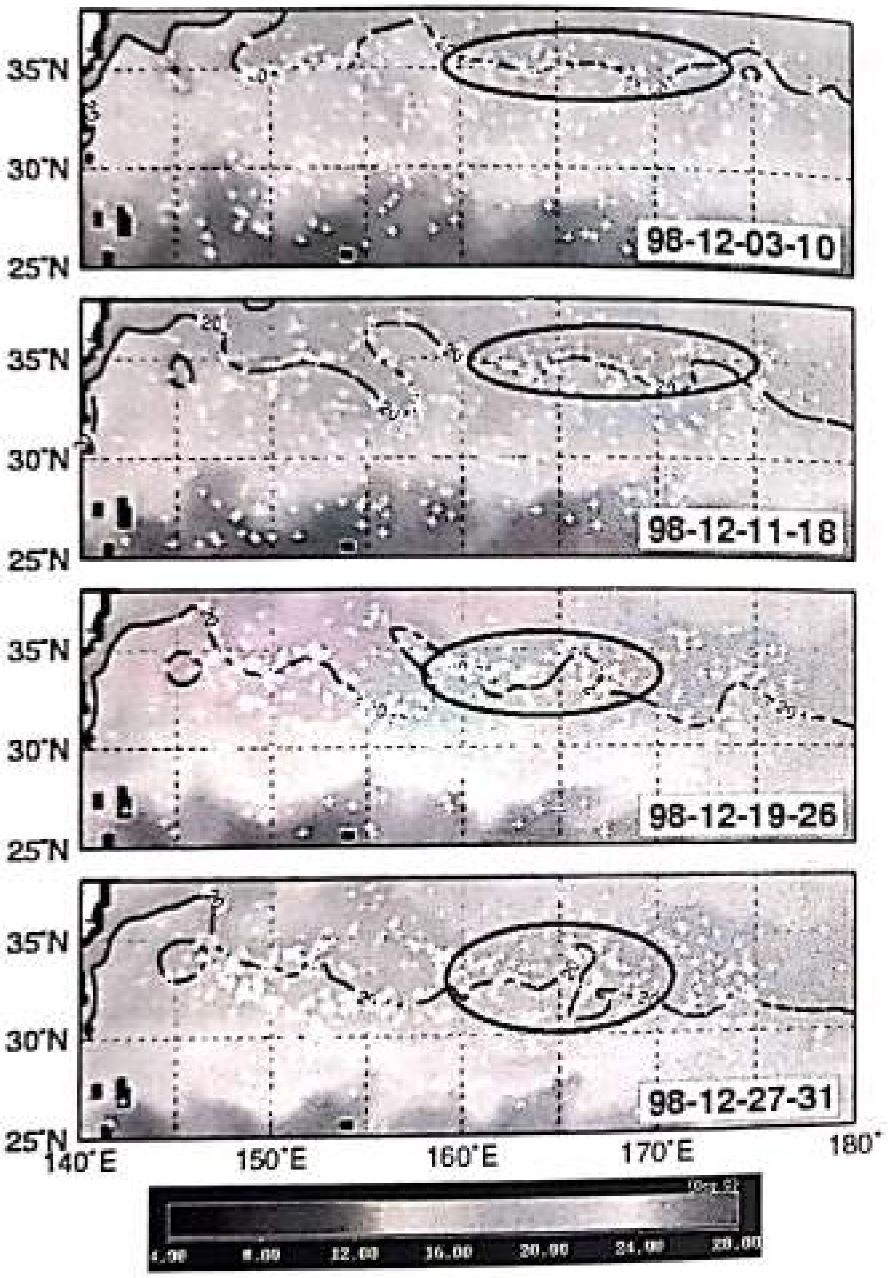

Figure 33b. Spatial migration pattern of albacore from early to late December 1998 driven by high accuracy eight days TMI SST data using simulation of kinesis model and the optimum 20°C SST isotherm contour line was indicated by black line.

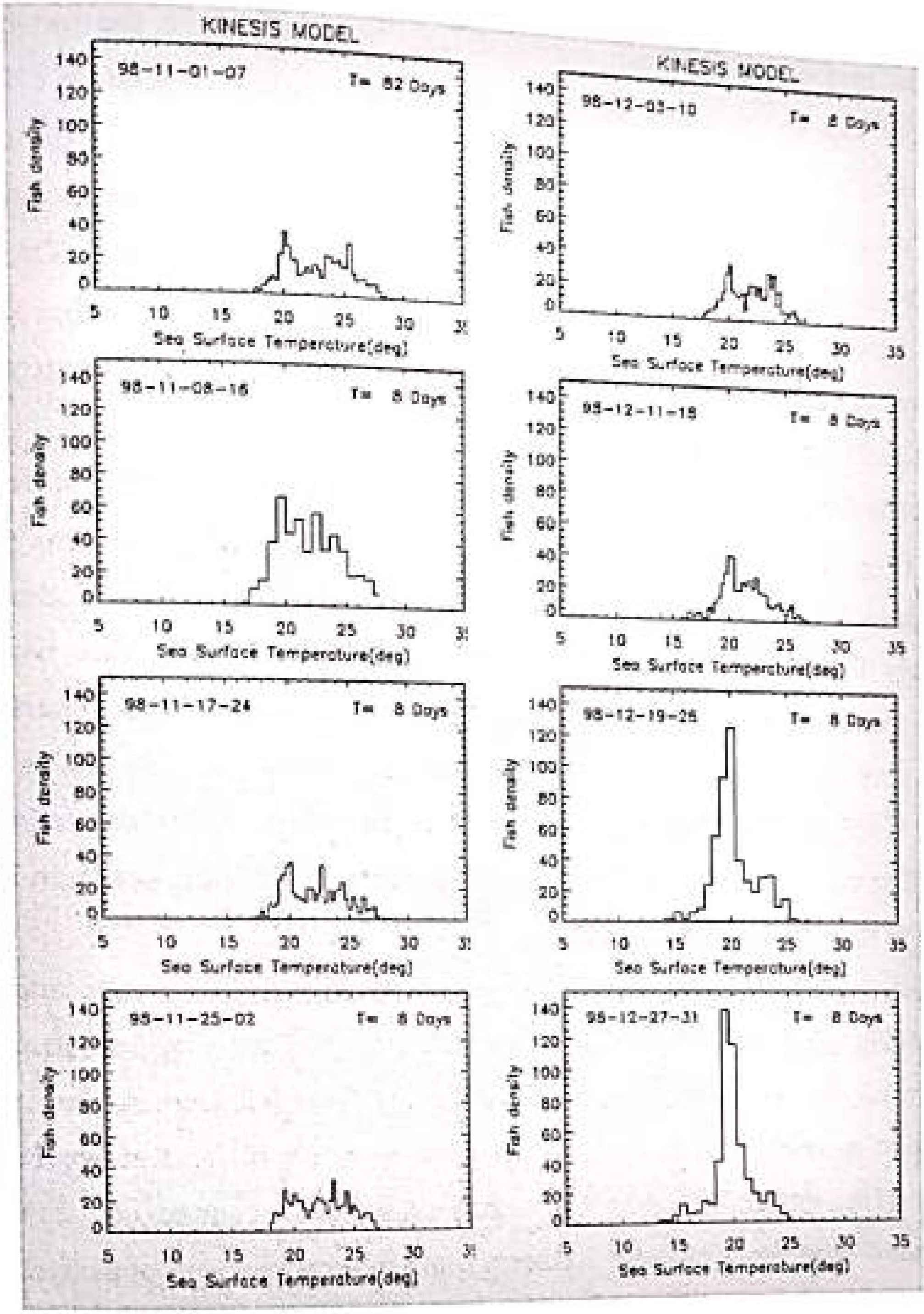

Figure 34. Histogram of fish density in relation to SST produced by the simulation model from early to late November (left) and from early to late December (right) 1998 using eight days data.

It is interesting to note that the migration pattern of albacore during the simulation period using a finer temporal scale associated with the movement of habitat hot spot to the south, the area where warm water temperature (20°C SST contour line) is in close proximity to the chlorophyll front (0.3 mg m^{-3} chlorophyll-a concentration contour line) (Figure 35). Figure 35 indicates that albacore tended to migrate to the south during November-December from 38°N to 34°N. This species moved eastward from approximately 162°E to 172°E from late November to middle December. In this period, actual albacore fishing ground formation mostly formed near the small distance between the two indicator contour lines.

At the first week of November 1998, some of fish occupied areas of near target position (Figure 33a). Albacore fishery occurred faintly north of the proxy contour lines (Figure 35). At the same time, EKE and geostrophic currents map indicated that the fishery formed near anticyclonic eddy field (Figure 36a). One week later, albacore started to shift to the south toward probable enhanced fronts observed from contour map and associated with EKE and geostrophic currents along the KE between 165°E to 170°E when the eddy field began to decay. The simulation model showed that the individual fish consistently concentrated near the optimum isotherm about 35°N through late November.

The albacore migrated toward the cyclonic eddy field when this oceanic feature was evolving (Figure 36b). Formation of albacore fishery was persistent in that location until the eddy field experienced decaying. Then albacore moved up to the KE Current in late December since ocean hot spots (fronts and eddies) were not formed. The model indicated that spatial distribution pattern of fish mostly concentrated near the 20°C SST isotherm during December and appeared to have similar pattern with albacore fishery.

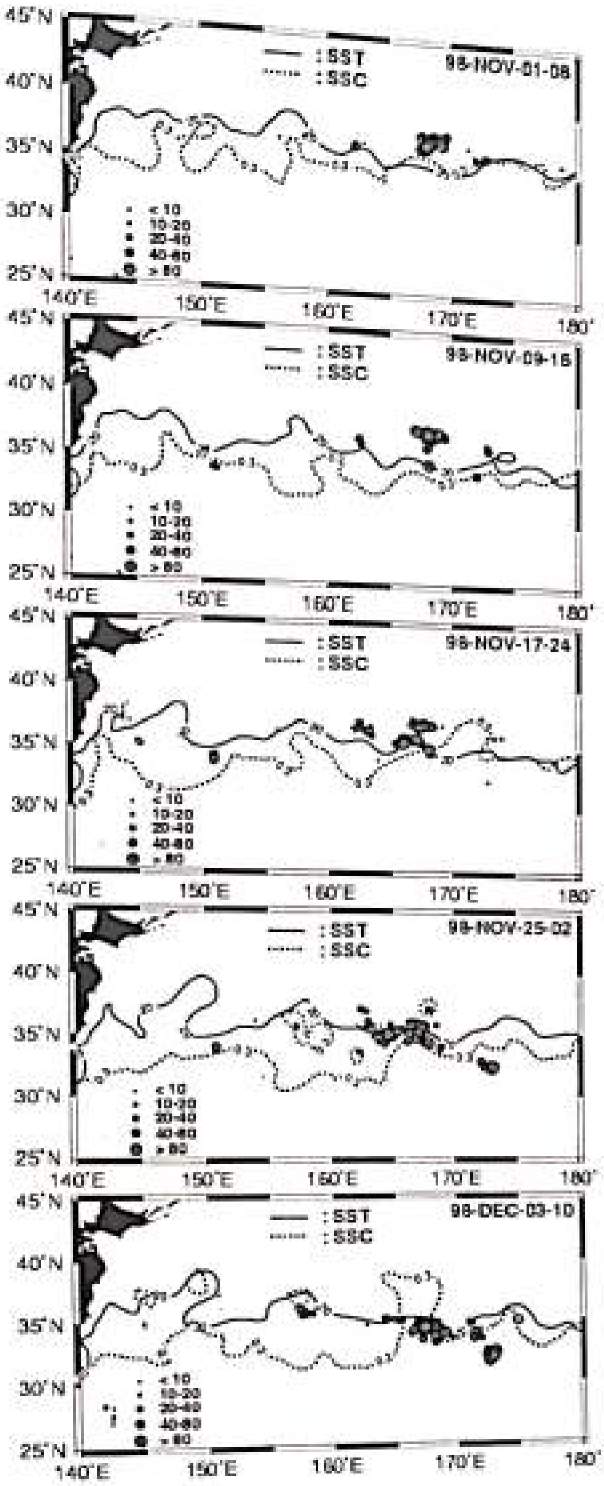

Figure 35. Spatial pattern of albacore hot spots movement identified from small distance between contour lines of 20°C TRMM/TMI SST and 0.3 mg m^{-3} SeaWiFS chlorophyll-a concentration early November to early December 1998 using eight days data, and albacore fishery distributions were superimposed on the map.

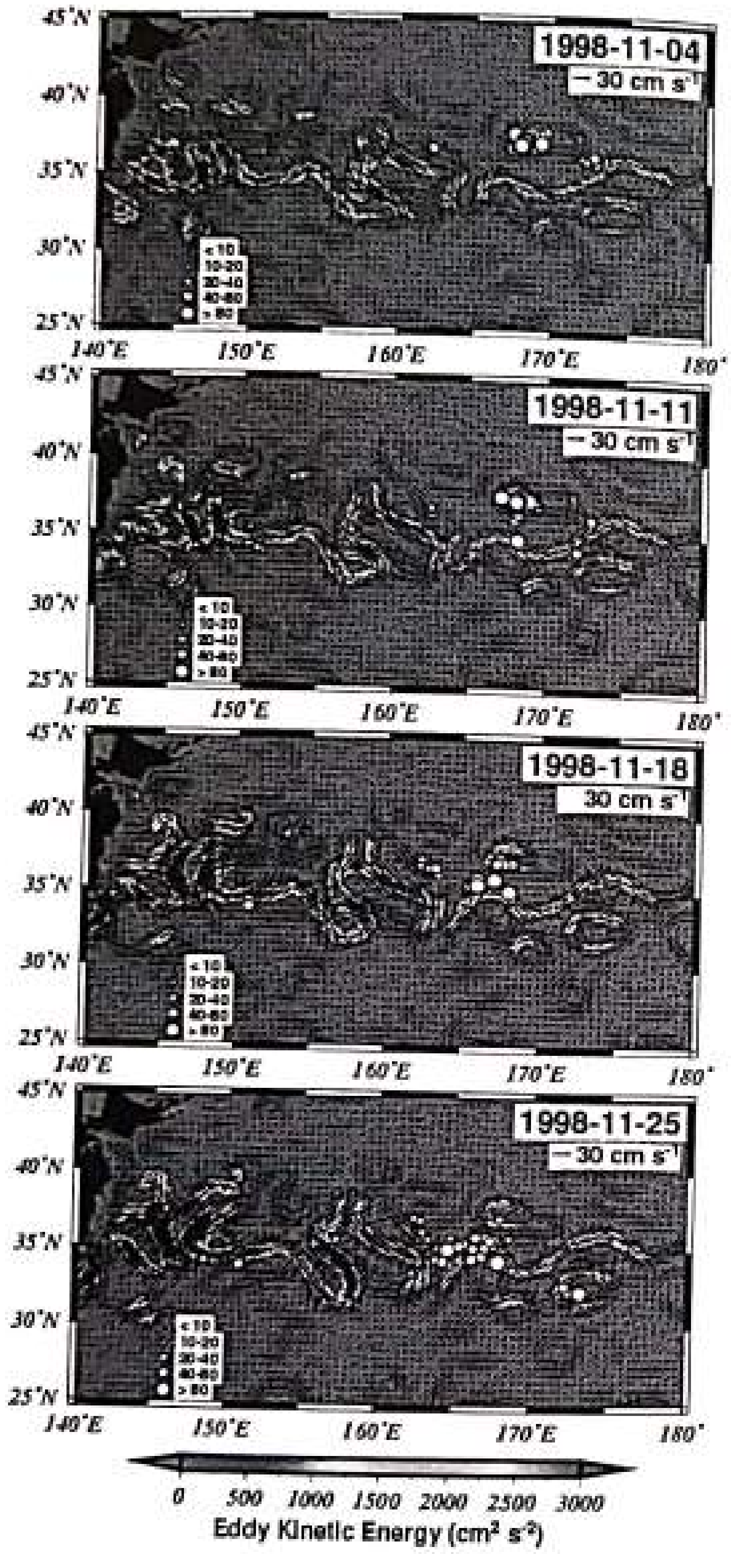

Figure 36a. Spatial pattern of albacore hot spots movement identified eddy kinetic energy (EKE) images with geostrophic currents during November 1998 using eight days data, and albacore fishery distributions were overlain on the map.

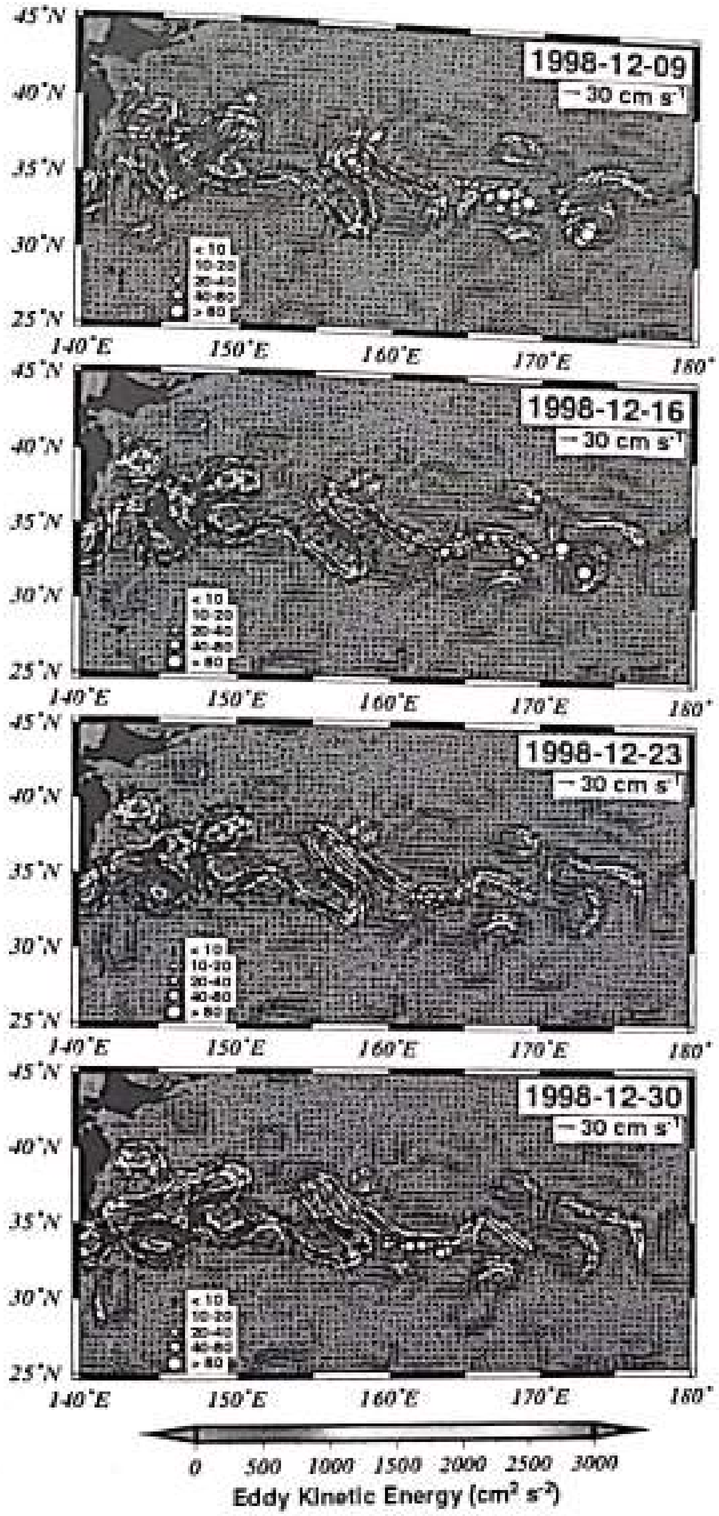

Figure 36b. Spatial pattern of albacore hot spots movement identified from eddy kinetic energy (EKE) images with geostrophic currents during December 1998 using eight days data, and albacore fishery distributions were overlain on the map.

CHAPTER 5
DISCUSSION

The hydrography and topography in the northwestern North Pacific Ocean, act together to produce biologically rich areas ("hot spots") for commercially important pelagic species such as tuna. The physical structures of this region, such as the Kuroshio and Oyashio Currents, Kuroshio Extension, fronts, and eddies, and topographic features (i.e. Shatsky Rise) seem to influence the migration, distribution and abundance of albacore tuna (Uda, 1973; Kimura et al., 1997; Sugimoto et al., 2001). Based on satellite derived-measurements, the transition zone of this study area has high primary productivity rates. The spots where albacore were abundant appear to be linked with the physical features, which probably control the productivity levels. The most productive albacore habitats, which likely represent the frontal zones and eddy fields, can be identified using proxy environmental variables such as SST, sea surface level and surface chlorophyll-a concentrations (Polovina et al., 2001; Zainuddin et al., 2004; Zainuddin et al., 2006). Integrating remotely sensed satellite data from multi-sensors and GIS provide a powerful tool to examine systematically basin-wide coverage of the dynamic nature of environmental conditions.

This study developed three primary analysis methods in investigating habitat hot spot for albacore: (1) detection of potential ocean rich habitat; (2) identification of the ocean hot spot and; (3) prediction of spatial pattern of the habitat hot spot. Each analysis has strength and weakness (advantage and probably disadvantage) to meet the purposes of study. For example, the simple prediction map can be easily used to detect potential habitat hot spots. However, it is still roughly to define more specific location where hot spot is more enhanced. To find the appropriate approach, this study combined the prediction map with the contour map, which can detect ocean hot spots in more specific location. It is worth noting that this study combined an integrated analysis that complements one another to meet the main objectives of this research. The analysis methods used in this study are described in Table 5.

5.1 Potential habitat hot spots for albacore tuna

In the present study, the detection, identification and prediction of potentially important habitat hot spots for albacore were explored using remote sensing and GIS techniques. In an attempt to map out the ocean hot spots for tuna, this study considers the underlying environmental variables of SST, chlorophyll-a and SSHA using the three main analysis methods (Zainuddin et al., 2007). In respect to tuna ecology, SST is an important variable for thermoregulation process and physiological adaptation for tuna, while chlorophyll-a concentration is an important indicator for tuna forage habitat (Gower, 1972; Polovina et al., 2001). SSHA data provide a useful signature for locating meandering eddy fields, which may associate with albacore distribution (Zainuddin et al., 2006). All these environmental variables are important factors in determining spatial patterns of tuna habitat.

It is clear that potential albacore habitats referred to as "habitat hot spots", the sites where albacore are most probably abundance, associate with specific environmental conditions. The fact that there is specific time period like in winter period particularly in November, when the highest catches occurred, correspond with certain level of environmental conditions. This evidence can be confirmed in this paper (Figures 6,7 and 8). There were synoptic ranges (joint environmental conditions of SST, chlorophyll-a and SSHA) where albacore were mostly abundant and it can simply be predicted. These ranges are found to be statistically significant (Figure 9), reflecting that these preferred oceanographic ranges are consistent for analysis of potential albacore habitats. The oceanographic indicators are similar to the findings of previous investigations of chlorophyll-a (Polovina et al., 2001; Zainuddin et al., 2002) and SST signatures (Uda, 1973; Zainuddin et al., 2002) for albacore distribution.

Potential habitat hot spots for tuna have been detected to have a significant association with the distribution of albacore fishery. During November 1998-2000 albacore coincide well with formations of the simple predicted habitat and this indicates that the favorable environmental ranges are more developed during the period than that of during 2001-2003 (Figure 10). It is probably that these ranges provide cues for specialized oceanographic features operating near the Shatsky Rise area around the northern side of the Kuroshio Extension, which can enhance prey distribution and abundance for albacore (Komatsu et al., 2002). The SST and chlorophyll signatures have been used to demonstrate a clear indication of high productive tuna habitat (Lehodey et al., 1997; Laurs and Lynn, 1984; Polovina et al., 2001; Zainuddin et al., 2004). Specifically, the oceanographic features such as ocean color and thermal fronts encourage high albacore concentration when the warm water SST indicated by 20°C is in close proximity with chlorophyll front identified with 0.3 mg m^{-3} chlorophyll-a concentration (Figures 11 and 12).

It is clearly apparent that from 1998 to 2000, the number of albacore that greater than 40 associated strongly with those oceanographic indicators. The oceanographic features are probably less developed during 2001- 2003, hence the predicted locations are wider longitudinally and latitudinally than during 1998-2000. It is inferred that in this period, prey abundance driven by the environmental feature are less enhanced. So, the catch rates in the period of 2001-2003 are lower that that of 1998-2000. It is interesting to note that in 2003 the high tuna aggregations around the dateline are again detected near the small distance between the two proxy environmental indicators. Therefore, the simple predicted habitat provide useful indicator for detecting potential habitat, which may represent a region of elevated biological activity in term of ecological sense.

To explore ocean hot spots more detail, a probability map of environmental variables was constructed. This map visualizes the degree of importance of entire regions over the study area relative to environmental conditions. The highest CPUEs correspond significantly with areas of high probability index of environments (Figures 14 and 15), suggesting that the specific ranges of both SST and surface chlorophyll-a provide reasonable indicators for detection and visualization of tuna hot spots in the study area (Zainuddin et al., 2006). These factors appear to play a key role in controlling the distribution and abundance of albacore. It is likely that the high probability regions account for most of the ocean color and thermal fronts operating effectively within transition zone over the study area.

Using environmental probability map to enhance the simple predicted habitat, this study have identified four types of habitats: excellent, good, fair and poor (Figure 16). It is interesting to note that the highest CPUEs were correlated with the high probability of environmental conditions. It suggests that locations of excellent habitat have stronger affinity for aggregating albacore than the other habitats. This also indicates that the high productive habitats may attract larger quantities of tuna than less productive habitats.

During November 1998-2000, probable albacore concentrations occurred consistently high near the Kuroshio Extension and the eastern Shatsky Rise area. In 1998 (fish schools in the southern side) and 1999, the high probability areas coincided well with large tuna abundance, reflecting that the frontal zones may well be enhanced without any significant contribution from the eddy field (Figures 16,19 and 20). This suggests that the preferred environmental ranges (high probability index) of frontal areas can sustain secondary consumers such as zooplankton and attract higher trophic level including forage preyed upon by albacore such as Pacific saury, squid and crustaceans (Laurs and Lynn, 1991; Kimura et al., 1997), which then lead to high concentrations of albacore. The association of tuna with the frontal systems could be explained as a consequence of forage concentrations (Sund et al., 1981; Laurs et al., 1984; Fiedler and Bernard, 1987; Stretta, 1991). The elevated probability zones might provide not only enhanced food abundance (with preferred chlorophyll-a range) but also suitable for physiological adaptations within a favorable SST range.

Large catches of albacore fishery in 1998 (fish schools in the southern area) and 2000 were concentrated in areas with relatively high EKE and geostrophic velocities. This suggests that albacore are associated with eddy fields (particularly anticyclonic eddies) around the Kuroshio Extension and the Shatsky Rise area. The presence of meandering eddies likely trapped albacore prey transported by the Kuroshio Extension to near the Shatsky Rise area (Komatsu et al., 2002). Eddies generated from the Shatsky Rise presumably localize tuna forage and then create a good feeding opportunity for albacore. Another possible reason for the congregation of these species is the intrusion of the Oyashio Current, which may transport albacore prey such as Pacific saury and squid in the late fall (Sinclair, 1991; Kimura et al., 1997).

The eddy habitat produces locally elevated chlorophyll and zooplankton abundance, and mechanically affects local aggregation of prey organisms (Owen, 1981), and thereby stimulates a good feeding condition (Logerwell and Smith, 2001). In November 1998 and 2000, this study found that the primary production levels were higher than in other years, reflecting that the intensity eddy-rich environments increased in 1998 and 2000 (Figures 17 and 18). Hence, high nutrient supply generated by the oceanographic features developed in the fishing locations. These results suggest that relatively high primary production during the period can drive effectively secondary producer subsequently attract higher trophic level predator such as albacore. It is likely that the proxy indicators for SST and chlorophyll-a concentration confirmed that the probability indices of areas where eddies might have evolved are high (Figures 14, 16, 19 and 20). These findings led to hypothesize that the frontal zones and eddy fields represent important physical features generating habitat hot spots for tuna aggregation in this area.

In November 2002, when the PP was lower, CPUEs were also lower than in other years, suggesting that the physical features (i.e. fronts and eddies) controlling hot spots in this period were poorly developed. In this period, some albacore tended to concentrate in the lower primary production, EKE and probability area, indicating that other environmental and biological features affect their distribution pattern such as the environmental preferences of different life stages, spawning grounds and impact of ENSO events (Kimura et al., 1997; Chen et al., 2005). Certainly, these subjects warrant future investigation. In 2003, the high catch rates seemed to have been associated with the increased probability near the dateline, reflecting that the front and eddy account for high tuna concentrations. The contour map and altimetry map (EKE and geostrophic currents) provide a clear indication of the physical features generating habitat hot spots (Figures 12, 19 and 20). These results indicate that the area of high probability index corresponds to the strong affinity of habitat hot spot. Therefore, the environmental probability map provides plausible explanation for marine habitat hot spots for albacore.

The probabilities of fishing ground environments were clearly higher during November 1998-2000 than in November 2002-2003. As a result, CPUEs in 1998-2000 were higher than in the following years. In this period albacore habitat, especially excellent habitat was well developed.

Statistical models effectively confirm that habitat hot spots for albacore are consistent with the predicted area, probability map and observation data (Zainuddin et al., 2006; 2008). The GAM captured the significant trend of albacore availability and abundance relative to their environments (Figures 22 and 25). In the first modeling (prediction of tuna occurrence), the probability of finding albacore were mostly driven by warm water SST and positive SSHA. For the second modeling (prediction of tuna abundance), albacore CPUEs were strongly influenced by the three environmental factors. Using the piecewise GLM, this study indicates that the predictions of spatial patterns of fish occurrence and abundance were controlled by the variables of SST, chlorophyll-a and SSHA. The three proxy variables have demonstrated that distribution patterns of the probability of tuna occurrence are similar to that of fish abundance (Figures 23 and 26). This evidence suggests frequency of fishing effort influences albacore abundance. These results also recommend that tuna management system can be developed from spatial modeling using statistical analysis. Certainly, the application of these results will be an important step toward improving pelagic habitat protection and tuna fishing management (Hyrenbach et al., 2000).

The models developed here can generate effectively potential predicted habitat from statistical framework where a combination of environmental conditions are preferred by albacore. This study clearly expressed that favorable environmental conditions observed from multi-sensor satellite data constructed habitat hot spots for albacore in the specific space-time. The potential habitat is successfully predicted by the model that corresponds with positive SSHA anomaly, SST near 20°C and chlorophyll-a 0.3 mg m^{-3}, for example in 2000 (Figure 27). It is interesting that the models can be used to estimate high productive tuna fishing grounds such as eddy files and frontal regions corresponding the favorable environmental conditions. Despite the statistical models produce the underestimate CPUEs, results suggest that a combined GAM/GLM is an effective mechanism for describing predictions of potential habitat hot spots of tuna in the study area. Therefore, using multi-sensor satellite remote sensing and GIS techniques, the detection, identification and prediction of potential habitat can be developed based on the interconnection of tuna fishery-related environmental data.

5.2 Migration pattern for albacore tuna

This study selected the TMI SST data for generating simulation of migration route, since the microwave sensor is capable of measuring SST through clouds. Considering this point, it has been assumed that the SST data set represents the real variability of temperature in fishing ground in relation to the availability of albacore tuna. Therefore, the accuracy of this research has been improved. Applying the optimum SST for albacore aggregation, i.e. 20°C SST isotherm as a target indicator, some patterns of migration route were illuminated using the kinesis model in winter period. The different point from the Humston et al. (2000) model is that this study used the dynamic map of serial SST images as the stimulus. As a result, the modifying model can be used to track migration route for the fish with monthly and eight days temporal resolutions. After examining sensitivity analysis, the best time step for migration model is 0.25 h (the shortest one) (Figure 29). This finding is consistent with the result obtained by Humston et al. (2000). The short time steps are needed since stimulus levels are only considered at the starting and ending positions of a fish movement during a time step (Humston et al., 2000). Therefore, it becomes more realistic that fish would respond the changes in stimulus over their environment even small spatial and temporal scales.

The north and south tuna migrations for albacore are important bio-ecological phenomena in the study area. This study has demonstrated on how albacore migrate from northern to southern area during November-March using a kinesis model. The movement of albacore to the southward during the period can be tracked clearly by the model (Figure 31). It is most likely that this species respond to the progression of seasonal warming during their southward migration. The fish tend to occupy the favorable SST range of approximately 18 - 21°C, which might be linked to the movement of forage fish. The serial maps suggest that the fish tend to search for optimum temperature (thermal front) during their north-south migration. This result is very similar to the SST in fishing ground (fishing data) (Figure 32). This study found that the high CPUEs appear to be obtained in substantial number in November-December when the fish seem to concentrate in close proximity to the front. However, during January-March, albacore fishery tends to occur in water of SST about 18-19°C and the fish aggregations produced by the model consistently occurs near the 20°C SST isotherm. As a consequence, albacore fisheries were found mainly in northern part of the fish concentrations resulting from the model. To resolve this problem, this study recommends the use of multi-parameter environmental stimulus such as SST and chlorophyll-a combining together into the simulation model using monthly basis data.

Overall, the model can illustrate the southward migration pattern for albacore, which probably corresponds to the movement of albacore prey such as Pacific saury and squid to the south during summer-fall (Sinclair, 1991; Kimura et al., 1997). The movements of prey abundance influence the behavior of tuna migration (Polovina, 1996). Some aspects of the dynamic albacore forage have been illuminated using the movement of the 20°C SST isotherm as a hot spot surrogate for simulation model.

Using SST satellite data as stimulus, this model performed reasonable spatial distribution of albacore around the optimum temperature. During five months of simulation (November-March), this model produced SST with no significant difference of the two modes when compared to SST fishing data using one sample Kolmogorov-Smirnov test ($P < 0.05$). Albacore appear to track the preferred SST in all series of images indicating by the solid contour line during their migration to the south. The sensitivity of model in explaining spatial pattern of fish migration depends strongly on the location of target area such as thermal front. The individual fish tend to disperse randomly when the optimal stimulus is not encountered. This fact is clearly found at the starting simulation, fish densities near the target location do not increase significantly.

It is worth noting that using finer temporal resolution of SST data, migration pattern of albacore associate clearly with the preferred SST in all series of images indicating by contour line (Figure 35). It takes sometime for albacore to find optimum SST where the fish use this condition for optimum thermoregulation and physiological adaptation. The model can track effectively the movement of optimum SST indicator, when it has regular movement and not far away from the fish location. At the first stage simulation, the numbers of fish concentration around the target area are not remarkable increased. This fact is due to the position of contour line farther northern side of the study area, so only the fish near that location approach. In next stage simulation, the dynamics of fish migration to the south associate with the contour SST isotherm.

The fish concentrations increase significantly near the target area. It suggests that migration pattern of albacore to the south can be tracked and predicted using the optimum isotherm. This seems to correspond well with the southward dynamics of ocean hot spots for albacore during the high season abundance (Figure 33). The consistency of dynamic movement of fish distribution produced by simulation model with the habitat hot spots (fronts identified by contour map) suggesting that the ocean hot spots for tuna can be simulated by developing the kinesis model (Figures 33 and 35). Indeed, the migration routes for albacore are also strongly related to the dynamics of eddy field (Figure 36). Albacore tend to concentrate when the eddy well forms and disperse widely when the eddy decays. Therefore, the understanding of dynamic ocean hot spots plays a key role to investigate behavioral migration pattern for tuna (Etnoyer et al., 2004; Zainuddin et al., 2006).

Despite this simulation model could not explain completely north-south migration of albacore, the model can track effectively the dynamics of the optimum SST isotherm. This environmental indicator probably corresponds to the high productive tuna habitat (hot spots). Albacore appeared to utilize some part of the isotherm for north-south migration and most likely the species respond to many environmental cues including directional orientation such as searching food within favorable habitat. To produce the innovative and more realistic approach, this study suggests the development of simulation model using a number of optimum oceanographic conditions as stimulus factors and the use of input data (serial satellite images) with finer spatial and temporal resolution.

5.3 Future aspects of prediction on albacore tuna fishing ground

Understanding and ultimately predicting how albacore respond to natural ocean environments of study area is an important challenge for integrating remote sensing and GIS into fisheries management and exploitation. This study has developed three important analysis methods: (1) detection, (2) identification, and (3) prediction of habitat hot spots for albacore. Then, a simulation model for assessing migration pattern for tuna has also been attempted using one of ocean hot spot indicators.

This study found that the distribution, abundance and migration of albacore are linked to specific oceanographic conditions. It has been demonstrated that albacore have preferred SST, chlorophyll-a and SSHA. The oceanographic conditions preferred by albacore can be plotted out on the map, so that the spatial pattern of albacore habitat can be effectively described using RS and GIS. This study confirmed that there are specific areas linking with the favorable oceanographic conditions where albacore are abundant referred to 'habitat hot spots'. These habitats have been explained using the simple prediction map (Zainuddin et al., 2008). To look for the main hot spot area, the contour map is an effective and innovative approach that can detect the potential habitat in more specific location (Zainuddin et al., 2004). Then this study has enhanced the habitat hot spots using the environmental probability map that can evaluate the degree of importance of the habitat around hot spots (Zainuddin et al., 2006). Finally, this paper has developed the habitat hot spot prediction using statistical models (a combined GAM and GLM) (Zainuddin et al., 2008) to examine the potential habitat produced by the simple prediction map and the environmental probability map. The results indicated that all integrated analysis methods used in this study is highly consistent to estimate where the ocean hot spots for albacore are most likely occurred.

This study realized that the research approaches developed here rely on the underlying oceanographic conditions i.e. SST, chlorophyll-a and SSHA together with catch data. The three oceanographic parameters were expected to explain important oceanic habitat features, such as eddies and fronts. This study hypothesize that the habitat hot spots have links to these oceanic features, when several evidences have confirmed. Certainly, the analyses used here could not explain some parts of migration, distribution and abundance of albacore. In particular, the simulation model has only explained the dynamics of the optimum temperature (20°C SST isotherm). The migration of albacore in response to biological interest such as spawning could not be explained in this study, since the spawning ground occurs outside the preferred oceanographic conditions (warmer SST near tropical region). Therefore, this study describes mostly the feeding ground for tuna, as a result albacore fishing ground formation in response to preferred oceanographic condition of feeding ground could be the main target of this investigation.

To develop future prediction for albacore fishing ground, it is interesting to combine this study with the idea of habitat index using biogeochemical model, which can be used to predict tuna forage (Lehodey et al., 1998). The habitat index can be estimated using satellite data as input variables and it can be used to predict tuna abundance (Bertignac et al., 1998). Another important points are the use of another parameters such as bathymetric feature (depth), fishing position in latitude and longitude into the statistical modeling for future prediction. In analyzing migration route for albacore, it would be more appropriate to apply multi-parameters of environmental conditions as stimulus factors into the simulation model.

It is a great challenge to see the application of scientific findings in the real fishery environment. This study has been developed through analysis-synthesis interconnections, where the linkage from environment to the top level of predator (fishermen activity) has been illustrated. Therefore, this study may give a great scientific contribution in elucidating important mechanisms in response to the classical questions by fishermen, where and where the fish occur over the large area in the ocean. To respond the recent need by fishermen, fishing company and fishery scientist, in near future, ubiquitous fisheries information system will be applied on the ground for providing synoptic fisheries oceanographic information in near real time based on satellite remote sensing and GIS technologies (Kiyofuji et al., 2007). The system will integrate underlying oceanographic parameters to improve future spatio-temporal prediction of pelagic fishing ground including tuna. This study will assist and open on developing of satellite and operational fisheries oceanography in near future. It will be an important challenge and frontier to apply research findings by fishing company, fishermen and fishery scientists.

Table 5. A summary of the main analysis methods used for exploring potential habitat hot spots and migration pattern for albacore tuna

Methods	Input variables	Output	Purpose	Advantage	Disadvantage
Histogram graph	SST, Chl-a and SSHA	Graph of oceanographic range	Describe preferred oceanographic conditions	Simple	No assessment of significant level
ECDF	SST, Chl-a and SSHA	Graph of oceanographic range	Describe preferred oceanographic level	Allows assessment of significant level	None
Contour analysis	SST and Chl-a	Contour map	Detect potential habitat hot spots and migration pattern	Easily to find more specific habitat	Low accuracy for large number of no data value
Simple prediction habitat	SST and Chl-a	Prediction map	Detect high productive area (habitat Hot spots)	Simple, effective and easy to visualize	No assessment of degree of importance of habitat
Environmental probability index	SST and Chl-a	Environmental probability map	Identify potential habitat Hot spots	Can identify the degree of habitat	None
Statistical model : (GAM-GLM)					
1. Prediction of probability	SST, Chl-a and SSHA	Probability map	Predict potential habitat Hot spots	Allows assessment of significant level for each variable	Less useful for small number of zero data
2. Prediction of abundance	SST, Chl-a and SSHA	CPUE map	Predict potential habitat Hot spots	Allows assessment of significant level for each variable	Any possibility to underestimate
Kinesis model	SST	Fish distribution map	Assess migration pattern	Simple, flexible and effective	Useful only for normally data distribution

CHAPTER 6

SUMMARY AND CONSLUSIONS

This study indicated that migration, distribution and abundance of albacore in the northwestern North Pacific were linked with the specific level of joint environmental factors. The ECDF and the GAM/GLM analyses reinforced that the high tuna catches were significantly related to the preferred oceanographic conditions of SST, chlorophyll-a concentration and SSHA. The prediction map can detect habitat hot spots where albacore are most likely abundant.

The main hot spots have a good association with a small distance between 20°C SST isotherm and 0.3 mg m^{-3} chlorophyll-a concentration on the contour map. To enhance the prediction map, a better approach has been developed to identify potential habitat hot spots for albacore using environmental probability map that consider more detail the degree of preferred oceanographic conditions. To predict spatial pattern of potential habitat hot spots in stronger and more accepted statistical framework, the statistical models (GAM and GLM) have been applied. In summary, the models can describe the dynamics of the ocean rich habitat for tuna which is fairly consistent with the prediction map, probability map and fishery observation data. In particular, these models effectively discover high probability of fish occurrence and fish abundance and seem better to explain potential habitat hot spots for albacore.

The main findings of this study are presentation methods on how to detect, identify and predict potential habitat hot spots for albacore tuna. Using one of hot spot indicators, migration pattern for albacore tuna can be tracked effectively using kinesis model driven by high accuracy of TRMM/TMI SST data. Certainly, this study can provide an important step toward the improvement of management fishery system for albacore using multi-spectrum satellite imageries combined with GIS in the northwestern North Pacific in particular and North Pacific in general.

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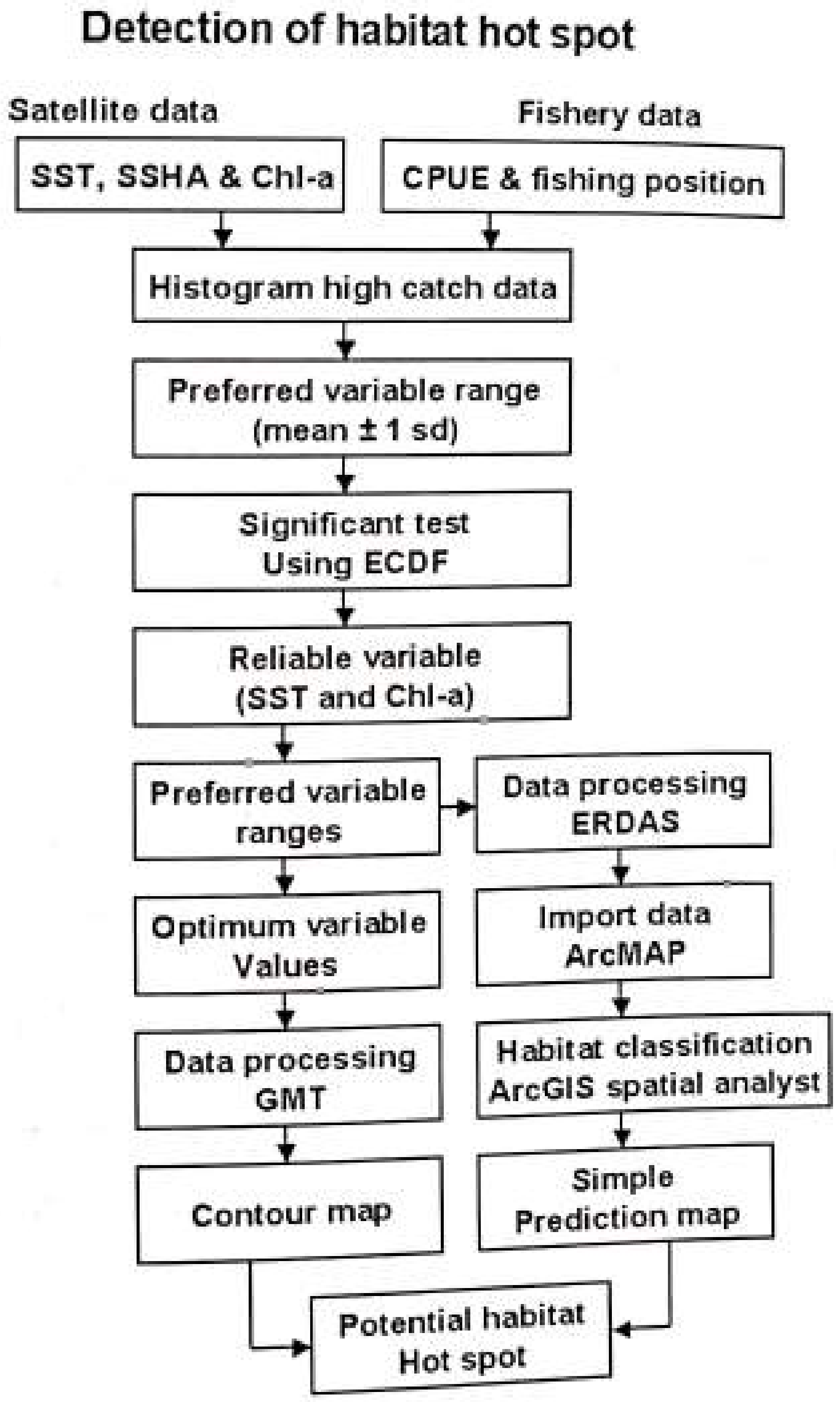
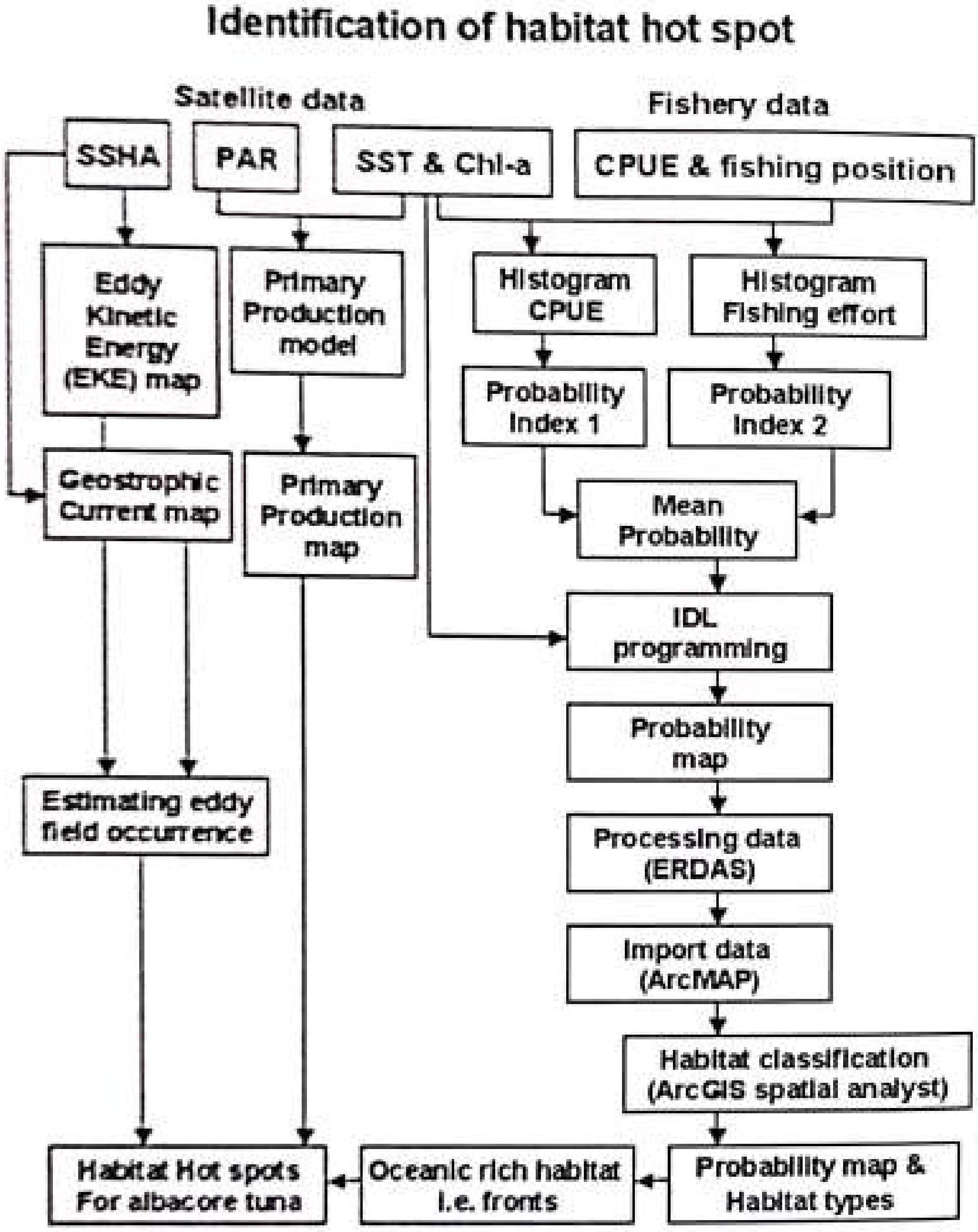
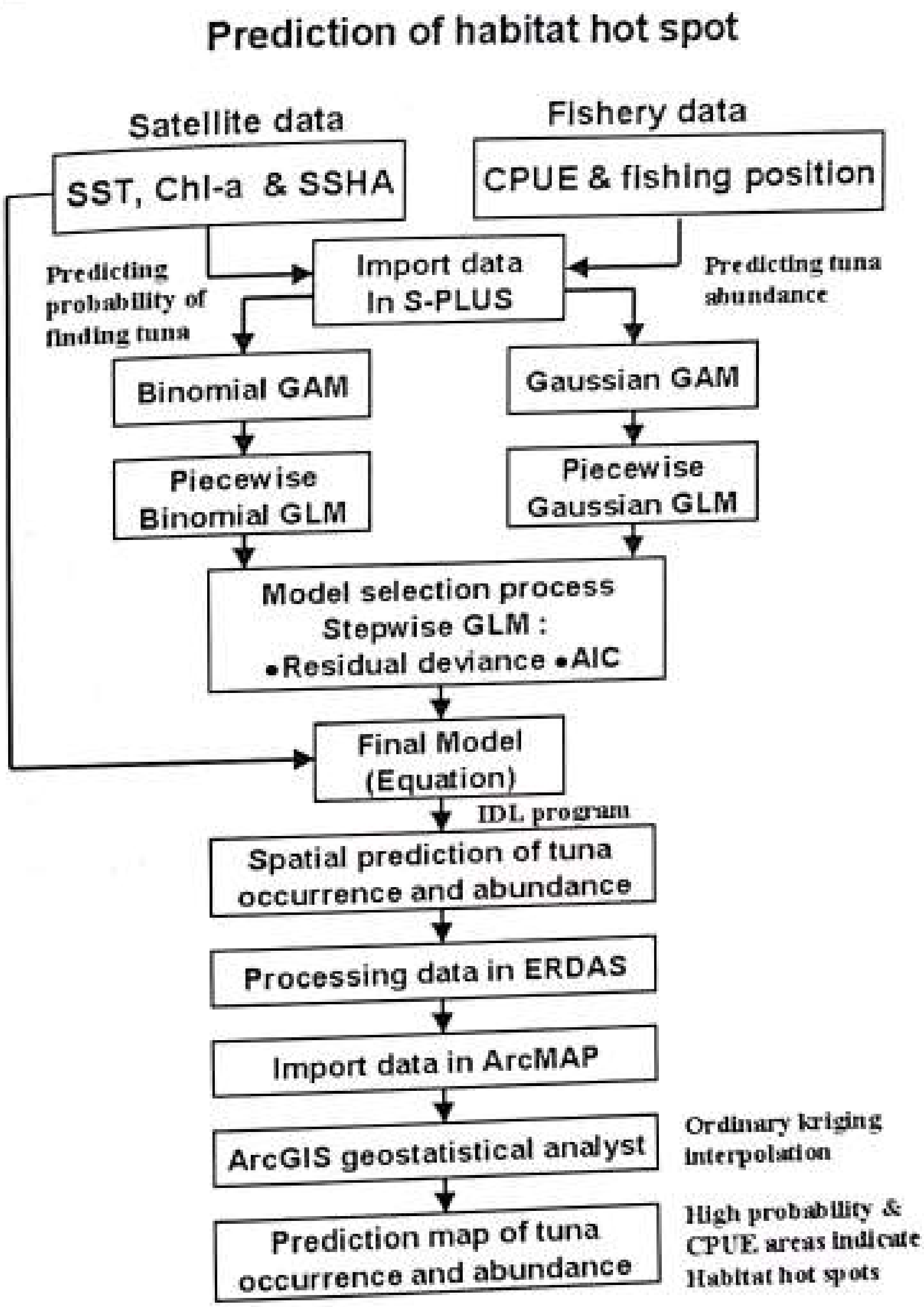
APPENDIX A


Detection of habitat hot spot
Satellite data
Fishery data
SST, SSHA & Chl-a
CPUE & fishing position
Histogram high catch data
Preferred variable range (mean ± 1 sd)
Significant test Using ECDF
Reliable variable (SST and Chl-a)
Preferred variable ranges
Data processing ERDAS
Optimum variable Values
Import data ArcMAP
Data processing GMT
Habitat classification ArcGIS spatial analyst
Contour map
Simple Prediction map
Potential habitat Hot spot

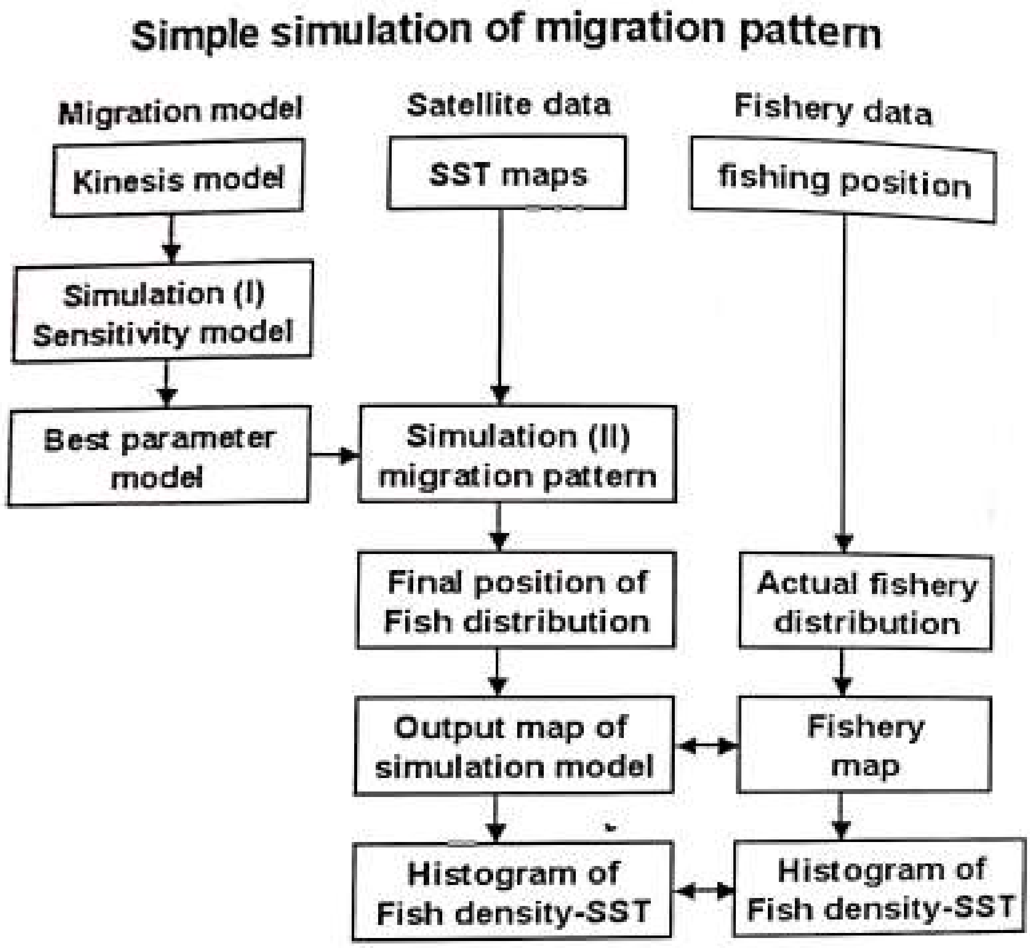
APPENDIX B


Identification of habitat hot spot
Satellite data
Fishery data
SSHA
PAR
SST & Chl-a
CPUE & fishing position
Eddy Kinetic Energy (EKE) map
Primary Production model
Histogram CPUE
Histogram Fishing effort
Probability Index 1
Probability Index 2
Geostrophic Current map
Primary Production map
Mean Probability
IDL programming
Probability map
Estimating eddy field occurrence
Processing data (ERDAS)
Import data (ArcMAP)
Habitat classification (ArcGIS spatial analyst)
Habitat Hot spots For albacore tuna
Oceanic rich habitat i.e. fronts
Probability map & Habitat types

APPENDIX C


Prediction of habitat hot spot
Satellite data
Fishery data
SST, Chl-a & SSHA
CPUE & fishing position
Import data
In S-PLUS
Predicting probability of finding tuna
Predicting tuna abundance
Binomial GAM
Gaussian GAM
Piecewise
Binomial GLM
Piecewise
Gaussian GLM
Model selection process
Stepwise GLM :
•Residual deviance •AIC
Final Model
(Equation)
IDL program
Spatial prediction of tuna occurrence and abundance
Processing data in ERDAS
Import data in ArcMAP
ArcGIS geostatistical analyst
Ordinary kriging interpolation
Prediction map of tuna occurrence and abundance
High probability & CPUE areas indicate Habitat hot spots

APPENDIX D


Simple simulation of migration pattern
Migration model
Satellite data
Fishery data
Kinesis model
SST maps
fishing position
Simulation (I)
Sensitivity model
Best parameter
model
Simulation (II)
migration pattern
Final position of
Fish distribution
Actual fishery
distribution
Output map of
simulation model
Fishery
map
Histogram of
Fish density-SST
Histogram of
Fish density-SST

Ocean hot spots are key pelagic habitats for tuna. A better understanding of these biologically rich areas leads to one important step in better tuna management. The main scientific findings of this study are presentation methods on how to detect, identify and predict potential habitat hot spots for albacore tuna from satellite remote sensing and geographic information system perspective. It is important to note that the pelagic habitats correspond synoptically to a number of environmental factors such as SST, chlorophyll-a and sea surface height anomaly (geostrophic currents). Statistical models and spatial analyses developed in this book to predict the spatial and temporal dynamics of the ocean rich habitats for tuna are significantly consistent with fishery observation data. In particular, these models effectively discover high probability of tuna occurrence and abundance and seem better to explain potential habitat hot spots and migration pattern for albacore tuna.

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