Relationships between satellite derived oceanic events and the albacore tuna (*Thunnus alalunga,* Bonaterre 1788) artisanal fishing grounds in the North East Atlantic.

J. Coca[*a], A. G. Ramos[a]

[a]Departamento de Biología Universidad de Las Palmas de Gran Canaria, Edificio de Ciencias Básicas, Campus Universitario de Tafira, Las Palmas de Gran Canaria, 35017 Spain

ABSTRACT

Satellite radiometers are widely used to detect oceanic structures which may allow for accumulations of pelagic fish. However, little information exists with respect to the possible use of spacecraft radar sensors in the detection and management of pelagic fisheries. This paper presents the satellite-derived ocenic events obtained from the Ekman Pumping (satellite wind scatterometer data derived), the Sea Level Anomaly, the Sea Surface Temperature and the Chlorophyll-a pigment images data sets, and how they relate to the albacore tuna fishing grounds distribution patterns in the North-East Atlantic. The statistical results show that catch per unit of effort (cpue) variability can be extensively explained by the satellite derived data base. The accumulation of CPUE records in specific zones is discussed too, in relation to the specific sensitivity of albacore due to the species' physiological thermo-conserving system. This paper emphasizes the importance of the combination of several satellite data sources in order to fully investigate mathematical relationships with the cpue.

Keywords: albacore tuna, remote sensing, fisheries

1. INTRODUCTION

The Basque artisan fishing fleet of albacore tuna is a long-standing tradition. Live bait and trolling are the two gears used by the fleet. This type of fishing is seasonal, usually taking place between June and September in line with the migration patterns of the species, which moves from the tropical waters to the area of convergence of the sub-tropical gyre and the Arctic gyre[1]. The zones fished by the fleet range from the Açores to the Bay of Biscay and the West Mediterranean.

To understand the use of satellite-derived oceanographic parameters and their relationship with the fishing of species of tuna, it is first necessary to understand the specific biological characteristics of the species. Said characteristics produce a response and patterns of behaviour with respect to the surrounding environment. The use of visible remote sensing (the concentration of pigments) and infra-red (sea surface temperature) in fishing has been amply researched and the commercial applications have been in place for some years. This article looks at the new remote sensing techniques applied to fishing, new not in that they are alternatives but rather that they exist as complementary to what is already available. The utility of the Ekman Pumping data is evaluated: these data are derived from the wind scatterometer data from SeaWinds on board QuikSCAT and anomalies in sea level as registered by the altimeter.

1.1. Catch data

The Institute of Research and Technology for Oceanography, Fishing and Agriculture at the Basque Government (AZTI) made available the catch data for low Basque fleet fishing albacore on an artisan scale. The data supplied corresponded to the fishing campaigns of 1999, 2000 and 2001. The database detailed date of catch, boat, latitude, longitude, tackle and nets used (whether by trolling or live bait) and total number of specimens caught. This was broken down into ranges by size for the same boat and day, thus offering a wide variety of data. The sizes were distributed in the following way over intervals with < 4 kg. as the first interval, between 4 and 7 kg. as the second and from 7 to 15 for size 3 (the categories of sizes make reference to commercial criteria rather than biological parameters).

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For the conversion of data to biomass, the marked quantities were taken by category as values of kilograms: 2, 5.5 and 11 for each category respectively and the biomass obtained was accumulated for the same boat and day. The fishing potential of these boats is similar and the catches were detailed by boat and day. This allowed us to calculate the catch per unit of effort (CPUE) using one day as the unit of time and the unit of the boat as the guiding parameter for effort thus allowing us to use the biomass per boat per day as the CPUE.

Remote sensing data

Four geophysical parameters obtained by satellite were used: Sea Surface Temperature (SST), concentration of chlorophyll-a (CHL), Ekman pumping and Sea Level Anomaly (SLA). For the SST and CHL there was daily data of 0,087890625° resolution in a cylindrical equidistant projection corresponding to Standard Mapped Image products (SMI). In order to minimise the problem of cloud, a five-day synthesis was carried out. Images were generated daily where the image of the day was used together with the two previous days and the following two. To obtain SST, the synthesis used the hottest pixel and obtained averages for the chlorophyll. The starting data for SST corresponded to the daily data for AVHRR available in the Jet Propulsion Laboratory (JPL) in the NASA and the best SST product was used for night controls. In the case of the chlorophyll, the available Seawifs data were used , as available in the Distributed Active Archive Center (DACC) of the NASA with the product corresponding to a daily chlorophyll concentration of level L3m selected. The time period of the data used comprised the months between June and October, 1999, 2000 and 2001. The data for sea level anomaly were supplied by the *Collect, Localisation, Satellite - Archiving, Validation and Interpretation of Satellite Oceanographic data* (CLS-AVISO) and correspond to data merged over 7 days. The original projection is mercator against which reprojections are made on an equidistant and cylindrical basis with a spatial resolution of 0.25° to homogenise the four remote sensing application parameters available.

Finally, Ekman pump data were obtained by applying the 1 Eq. to the available Quikscat data in the JPL. Each level L2B file (wind vectors given plus all the quality parameters and complementary information) contained a complete orbit around the Earth from South Pole to South Pole and rendered some 14 to 15 files per day. The daily images were generated and averaged out after five days. The average used the daily data plus the data for the four previous days. The projection, as in the previous parameters, is cylindrically equidistant but the resolution is much inferior (approximately 0.25°) The first available Quikscat data corresponded to the end of July, 1999.

$$(\nabla V_1 - \nabla V_2)h = \frac{1}{\rho f}\left(\frac{\partial \tau_y}{\partial x} - \frac{\partial \tau_x}{\partial y}\right) \tag{1}$$

A sub-window was extracted for the area of interest and for all the remote sensing parameters (50° N – 20° N, 30° W – 5° E). The time period for the available data comprised the months of June to October in 1999, 2000 and 2001.

1.2. Joint database

The aim of this study is to relate catches to the geo-physical parameters via remote sensing. The specific values in time were taken into account together with the spatial variation of the parameters and if there was ant time lag effect. The satellite images were taken for each specific catch point, defined by date, latitude and longitude, value of the geo-physical variables and another series of variables derived from the latter such as the sobel operator, the range in any one window, distance to the change in the signal etc. These variables attempt to define spatial variations of interest for the remote sensing parameters around the catch point. The value of the parameters and of these variables is extracted for the same point, 5, 10 and 15 days after catch in order to evaluate a possible time effect. Bearing in mind the time lapses and the variables extracted, the database contains 82 variables for each CPUE data.

The objective of this methodology consisted in reducing the dimensions of the problem. The extraction of values for different days eliminated the time dimension but allowed for evaluation of the possible effect of the derived parameters and variables alter a certain time elapsed. The definition of variables which evaluated the spatial variation of the parameters eliminated the dimensions of latitude and longitude but allowed for the effect of spatial structure around the place of catch to be considered. This generated a database with a high number of variables and yet simplified the spatial-temporal variation of the study. The selection of derived variables was carried out using visual analysis of temperature images, chlorophyll, Ekman pumping and sea level anomalies in the catches as the basis for observation.

1.3. Treatments

1.3.1. Visualisation

The available catch points are plotted according to the parameters of remote sensing and allow for a visual analysis of the relationship between point of catch and the parameters measured by satellite. The visual analysis of the catches over the images helps to define part of the variables to be extracted or derived from the remote sensing parameters which are included in the database of fishing – remote sensing.

1.3.2. Histograms and scatterometer derived data graphs

The histograms of all the variables extracted for latitude and longitude of where catches were produced 5, 10 and 15 days previous were plotted together with the catches for the five following days. This allowed us to see the distribution of the values of the variables for the catch points. The scatter diagrams were plotted for all the variables extracted for latitude and longitude where catches were produced 5, 10 and 15 days previous and 5 days following to compare the CPUEs obtained. This allowed us to see the relationship between the catch obtained and the value of the variable extracted. The ranges of groups for the discriminant analysis (see below) were fixed by CPUE values a certain accumulated percentages with range 1 fixed at above 70% (CPUE5=702), for range 2 for percentages between 35% (CPUE5=320) and 70% and, finally, for range 3, between 0% and 35%.

1.3.3. Multi-variable analysis

- Multiple linear regression: Selection by backward stepwise is used as the method for introduction of variables in the models. The variables which are introduced in the multiple linear regression treatments are variables that when dependent, depend upon the CPUE, and when independent, derive from the remote sensing parameters presented in the database.

- Discriminant analysis. The method of inclusion of variables is by steps. The method of selection used is based on the change in Wilks lambda. The variables which are introduced in the treatments via discriminant analysis are as variables that when dependent depend upon the CPUE grouped over three ranges and when independent as variables derived from the remote sensing parameters in the database described in Section 2.3. In both treatments, not all the available variables are introduced at the same time since the analysis of correlations is taken into account in order t o use variable groups where the difference in values of Spearman's *rho* between them was under 0.5.

1.3.4. Probability maps

Via the implementation of the models and functions obtained using multiple linear regression and discriminant analysis of the remote sensing parameters, maps of probability were generated for the fishing fleets. The real CPUE values were sketched on the same for the same date via circles , the sizes of which were proportionate to the amount of fish landed. The CPUEs obtained by applying the models of linear regression were used to generate maps on three levels: high, medium and low using the group ranges described previously for the discriminant analysis thus allowing for direct classification.

The enormous problem with these models is that they are generated by extracting the variables related in time and space with the points of catches and, thus, they do not contain the variability of the parameters of remote sensing for the total area studied. If the value of any of the four parameters of remote sensing for one pixel on the day of the forecast was outside the ranges captured in the histograms and scatter-grams described in section 2.4.2., the model was not applied and a value of outside the range or unevaluated was assigned. The generation of maps of probability assumed that the values of the remote sensing parameters (SST, SLA Ekman pumping and concentration of chlorophyll -a) outside these ranges were inadequate to the effects of the presence of albacore tuna. In order to check if there were differences between the distribution of variables as extracted at the points of catch with respect to the whole of the area of study, all the variables extracted with respect to each real catch over 5 positions chosen at random for the same day were extracted. This random extraction aimed at detecting whether differences existed between these variables and the variables extracted at the points of catch. To prove that the variances between the variables extracted at the points of catch and at random points was the same, Levene's test for homogeneity of variances was used. To compare the means, the Mann-Whitney U test was used.

2. DATA

2.1. Visualization

In the visualisation of the catches as reflected in the remote sensing parameters, we can see that these are basically distributed over areas of temperature gradient and that the range of temperatures at which catches are produced is fairly broad-ranging. Catches are not produced when values of chlorophyll are over mg*m^{-3} and often gradients of chlorophyll are to be detected. Catches are usually produced at positive SLA but with values close to zero and in areas where the gradient is not pronounced. Behaviour of Ekman's pumping is more variable and seems to be linked to the change of sign of the same.

2.2. Histograms and Scatterometer Derived Data graphs

These are shown in Fig. 1. The catches are produced over a range of temperatures between 15° and 24°C. No pronounced peaks are to be detected in the histograms which show a relatively uniform distribution. Greater catches are obtained at temperatures between 19° and 23°C. The histogram for chlorophyll on the day of the catch shows that no catches are produced at values below 0.1 mg*m^{-3} and very few at over 0.8 mg*m^{-3}, with practically all the catches accumulated at between 0.1 and 0.8. There is a peak on the histogram at around 0.15 with frequency falling as of this value. As for the scatterometer derived data graph, greater catches are also produced over the same range of values. In the case of the Ekman pumping, the greatest number of catches is produced around the value, -1*10^{-6} m*s^{-1} (slightly negative) with the frequency falling likewise on both sides of this value. The scatterometer derived data graph gives a similar picture with the highest catches around the same value. In the case of anomalous sea level, the distribution centres around a value which is slightly positive around 20 mm. The frequency of catch points diminishes on both sides of this value. Biggest catches are produced at ranges between –20 and 60 mm.

2.3. Multi-variable analysis

2.3.1. Multiple linear regression

Variables derived from different remote sensing parameters must be combined in order to achieve significant percentages for explanation. The levels of explanation which are obtained using one or two remote sensing device parameters and the derived variables are very low. To obtain models of linear regression which allow for levels of explanation of around 50% to be reached, and which do not include variables extracted over the 5 days after the catch, at least three remote sensing parameters and the derived variables from the same should be used. Various models can be obtained with similar levels of explanation of the variability. We are going to describe here two models of the results obtained, one of which uses one constant and three variables of three remote sensing device parameters which explains at 44% (R^2 corrected) the variability of the CPUE and which is outstanding for the simplicity of the variables used and the second which uses one constant and four variables, one derived from each parameter of the available remote sensing parameters and which explains 62% (R^2 corrected).

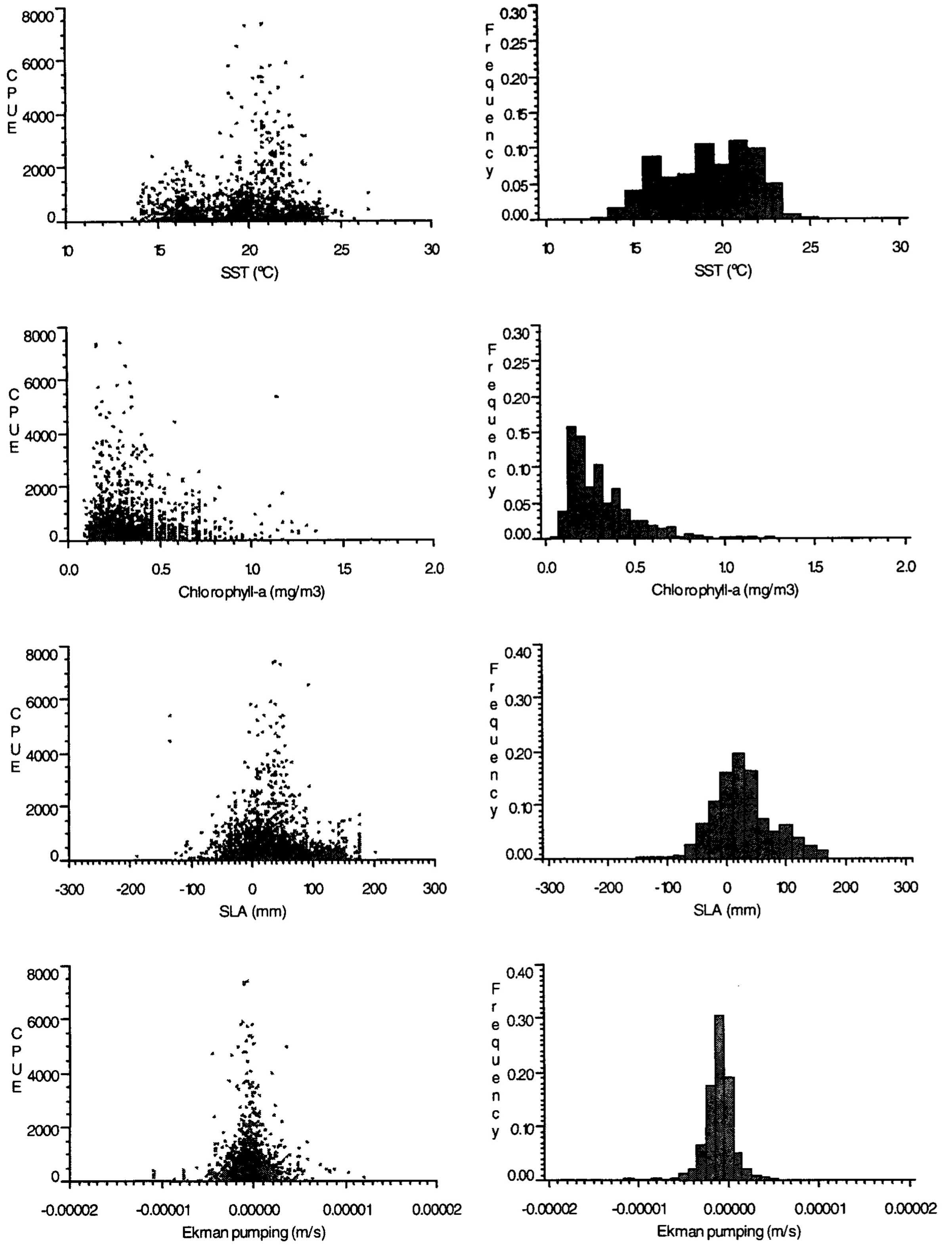

Fig. 1. CPUE scatterometer derived data graphs - remote sensing parameters and histogram of the same at the match points for SST, CHL, SLA and Ekman pumping.

The first model presents a standard error of estimation which is equal to 293.46. The resulting model is described by Eq. 2:

$$CPUE = -1410{,}531 - 6{,}462 * SLA0 + 96{,}710 * SST0 + 806{,}252 * CHL0 \qquad (2)$$

The simplicity of this model resides in the use of one constant and only three variables all of which are significant to a level inferior to 0.05, extracted for the days of catches and which correspond directly to the value of three remote sensing parameters without any derivation. The heaviest weighting of the three variables corresponds to the anomalous sea level, SLA0 (standardised coefficient –0,739), followed by the sea surface temperature, SST0 (standardised coefficient –0,458) and, in third place, the concentration of chlorophyll-a, CHL0 (standardised coefficient –0,254).

The second model presents a corrected R^2=0,623 with the Standard error of estimation at 305.70. The model estimates the CPUE using Eq. 3:

$$CPUE = -1363{,}914 - 6{,}637 * SLA15 + 648{,}815 * CHLs5 + 103{,}132 * SST0 - 2{,}9 * 10^7 * PUM\,\mathrm{Pr}10 \qquad (3)$$

This model is to be highlighted for the percentage of variability of the CPUE explained (62%). It is useful because it does not use variables extracted retrospective to the day of the catch. It is constructed with one constant and four variables, all of which are significant at under 0.05. Each of the four variables is derived from one of the four remote sensing parameters available. The variable with most weighting is the anomalous sea level fifteen days previous to the catch, SLA-15 (standardised coefficient –0.686). The second most significant variable in weighting is the temperature on the day of the catch, SST-0 (standardised coefficient 0.387). The third is the sobel operador on the chlorophyll five days previous to the catch, CHLs-5 which is, in weighting, similar to the SST-0 (standardised coefficient 0.307). The last variable of the model and of least weighting is the range of pumping in a five píxel window 10 days previous to the day of the catch, PUMPr-10 (standardised coefficient –0.198).

UIT respect to the previous model, the degree of explanation is increased by 17.9% by increasing the model by one variable. More important then the increase by one variable of the model is that this variable is derived from the remote sensing parameter not used in the previous model, that is, the Ekman pumping and that, to obtain this level of explanation, we need the four parameters of remote sensing. If we compare the first and the second model, the variable SST-0 is present in both and the anomalous sea level is kept as a direct variable but, in the second model, instead of using the value of that day, the value given 15 days previous is used. The variable derived from the chlorophyll in the second model is the sobel operator on the chlorophyll 5 days previous to the catch as opposed to the value of the chlorophyll on the day of the catch, as is used in the first model. The derived variable from the Ekman pumping which is introduced into the second model is the range of pumping in a 5 pixel window. In both models, the SLA is of greater weighting, with similar standardised coefficients (greater than in the case of the first model). In the first model, the variables relating to the SST and CHL have different weightings (greater for the temperature), whereas in the second model, the difference is reduced by decreasing the weighting of the SST and increasing that of the chlorophyll. The variable linked to pumping introduced in the second model has a clearly inferior weighting to the rest.

2.3.2. Discriminant analysis

The model obtained uses 6 variables and one constant. The variables are the temperature on the day of the catch (SST0), the distance to the change of the sign in the anomalous sea level 10 days previous (SLAd10), the sobel operator on temperatura for the same day (SSTs0), the sobel operator on the pumping on the same day (PUMPs0), the sobel operator on the SLA 5 days previous (SLAs5) and the distance to the change in sign for the pumping for the same day (PUMPd0). All the variables are significant below 0.001. The coefficients of the discriminant functions for this model are detailed in Table 1.

The Wilks lambda value for this model is 0.625 with a level of signification below 0.001 which indicates a high level of discrimination capacity. In general terms, the first model classifies 56.9% of the cases well and 56.4% for cross validation and, therefore, does not have a high capacity of global classification. This model is outstanding for its sensitivity in discriminating low CPUEs when the discriminant functions are applied. For cross-validation, it classifies as low CPUEs, 66.9% of the CPUEs which are, effectively, low. 25.4% of the low CPUEs are classified as medium and only 7.7% of the low CPUEs are classified as high. 72.3% of the high CPUEs are classified as high, 19.2% as average and only 8.5% as low. Therefore, it is possible to obtain discriminant functions which, from the derived variables extracted, allow us to classify satisfactorily the areas where, potentially, the catches obtained will be high or low. The number of variables which is used is somewhat high (which produces a number of lost values) and its main limitation resides in its poor classification of average values.

Tab. 1. Coefficients of the discriminant functions of Fisher.

CPUE	High	Medium	Low
PUMPd0	3,606	3,586	3,959
PUMPs0	768480,7	842854,5	815237,5
SLAd10	-1,020	-0,950	-0,788
SST0	6,990	6,670	6,318
SLAs5	0,052	0,052	0,056
SSTs0	2,486	2,312	2,258
Constant	-79,807	-73,920	-69,166

2.4. Maps of Probability

The two models of linear regression and the model of discriminant analysis were implemented to generate the maps of probability. In the comparison of the variances between the randomly extracted variables and the variables extracted at the point of the catch using the Levene test, the result obtained was that only 15 of the 82 variables extracted had equal variances in both cases. In the comparison of averages using the Mann-Whitney test, the result was that 21 of the 82 variables had equal averages. Of all the variables, only 8 shared equal variances and averages and none of these was included in the multi-variable models used. This supports the generation of maps of probability which exclude the ranges which remain outside the histograms for the match points. If we take the first model of linear regression as an example, we can see the problems which are derived from applying the model to all the pixels on the maps of probability. The model uses three variables all of which correspond to the day of the match or the day forecasted, the first of which is the temperature with a positive coefficient, the second, which is the anomalous sea level with a negative coefficient and, finally, the chlorophyll concentration with a positive coefficient. An increase in temperature produces an increase in the forecast catch which is reasonable given the values and situation of this study. The negative coefficient of the SLA indicates that an increase in the value of the same may decrease the forecast catch. The negative values of SLA produce an increase, on the contrary. The only problem is that catches are not produced at very negative SLAs although, should they be present in the whole of the area, the reverse is the case and the forecast of the model will be increased. The catches are produced at values of chlorophyll concentration which range between 0.1 and 0.8 $mg*m^{-3}$, with a positive coefficient for chlorophyll which means that in areas with high concentrations and upwelling, the forecasts are high and yet the levels of chlorophyll are inadequate for the presence of the albacore tuna. If not applied to the pixels with these values, the models will avoid offering forecasted catches which are high in areas which do not correspond to the distribution of the albacore tuna.

2.4.1. Multiple linear regression

In general, the results derived from the first model of linear regression described, produce areas of probability of high and medium catches which coincide adequately with the points of catch. We should remember that the level of explanation of this model does not reach 50%. When values outside the range are not included in the map, we avoid having high values for catches in periods where such are not given. In May, for example, there are high and medium probabilities of catches in the Mediterranean whereas, at the end of the month, there are nuclei of medium probability in the Bay of Biscay. In general, the forecasts coincide with the real catch points. In periods where catches are not given, this is due to the fact that a large number of values outside the range are included in the map.

The second model of linear regression which we have already described has a notable higher explanation of match than the first (62%) This model relates more accurately to the real catch points and, although the high and medium values are too frequent, nonetheless, they are less than given by the previous model. The change, by one variable, affects the number of lost values since the sobel operator for chlorophyll has been changed as this model demands a 3*3 pixel window without clouds, focusing on each pixel. The behaviour over periods in which no catches are given is similar to the previous model..

2.4.2. Discriminant analysis

The model described uses 6 variables and gives a high number of lost values. The problem of classification presented by this model resides in the medium values which are classified poorly and many of which are assigned to the category of high catches. In general, the values forecast by the first model derived from discriminant analysis produces excessive high and medium points of catches and few low regions. But the areas which are forecast as high, however, correspond in the main to the high and medium catches and, on very few occasions, to the low catches and, therefore, from the practical perspective, the model is considered to be worthwhile.

Figures 2a, 2b and 2c show that during the fishing campaign (from June to October) over the three years of the study, the proportion of pixels with high probability forecast in the Cantabrian window for all of the models described. In general, the graphs show that the relative frequency of high probabilities is greater in the months of July and August, falling off progressively in September and October. In the month of June, the frequencies are lower than for July and August but higher than for September and October. In the figures shown for the months of July and August 2001, the relative frequency of high probabilities is less than for the same months of the two previous years. The two situations are observed in the first model of linear regression (Fig. 2a), the second model of linear regression (Fig. 2b) and the discriminant analysis (Fig. 2c). These trends are coherent when compared with the real behaviour of catch movements with catches being produced, in the main, in the Cantabrian in the months of July and August whereas in June they move East and in the months of September and October, they progressively fall off in the area. The results given in the graphs are also coherent with the lower catches obtained in 2001 as compared with the previous fishing campaigns of 1999 and the year, 2000.

Figure 2d presents the proportion of values outside the range for the Cantabrian window which correspond to the first model of linear regresión. The proportion of values outside the range is lower in the months of July and August which corresponds to the time of the highest catches in this area (due to the better conditions for fishing albacore) and increases in the months of June, September and October, when so many catches are not accumulated (since the conditions for fishing albacore are less favourable). In spite of the fact that the number of values outside the range is the same for all the models, this is not the case for the relative frequency with respect to all the available values, thus varying the aspect. The number and location of the values obtained in the maps of probability depends upon the availability of the variables used for the extraction time lapses of the same. The use of a higher number of variables derived from the temperature and the concentration of chlorophyll, above all, when required at different time lapses, decreases the number of variables available in the maps of probability. The enormous variability of cloud coverage for the different models and/or day introduces noise in the graphs which present the results.

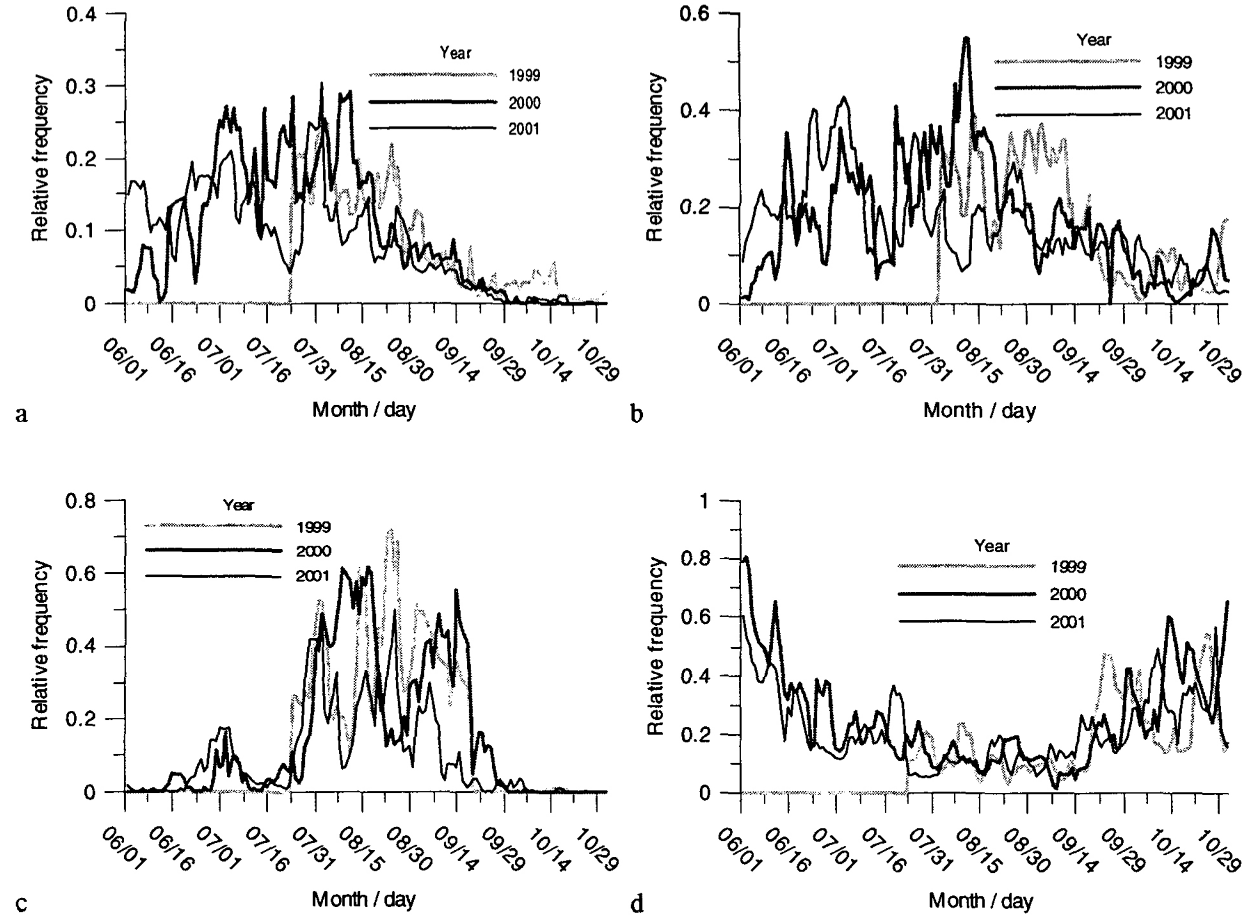

Fig. 2. Proportion of pixels on the map of probability calculated in correspondence with:: a highs on the first model of linear regression, b highs on the second model of linear regression, c highs for discriminant analysis, d outside the range for the first model of linear regression.

3. RESULTS

The divergence in the evolution of tunas, in general. and of the albacore tuna, in particular, with respect to other scombrids is due to their peculiar behaviour and reaction to their surrounding environment. The appearance of the *rete mirabilia* and the acquired capacity, therefore, for thermal regulation together with their constant search for prey to cover their substantial feeding requirements make them particularly sensitive to inconstant elements in the environment. The structures which produce a discontinuity of homogeneous conditions in the environment attract the albacore tuna in that these areas will probable offer conditions of accumulation of possible prey together with adequate environmental characteristics for their well-being which is what Petit[2] calls a coherent response.

The sea surface temperature, the chlorophyll concentration, the anomalous sea levels and Ekman pumping are four geo-physical variables obtained by satellite which allow us a closer look at the ocean surface. When this ocean is mapped into parameters using these variables. we can understand the distribution of the albacore tuna in the North-East Atlantic. The combination of the four geo-physical parameters allows us to make a deeper analysis since with one or two variables. little more than a descriptive analysis can be made.

The visual analysis of catches from the images generated by each parameter of the remote sensing is crucial in that it allows us to make a first approximation of the situation with respect to each variable. The catch points are most often than not situated in areas where there is an SST gradient of at least 0.5 degrees over a short distance and, then the absolute value is of less weighting. Many articles have underlined the importance of thermal fronts when fishing for albacore tuna in the Cantabrian Sea[3,4,5,6]. Santiago *et al.*[7] underline the importance of thermal discontinuities of various kinds and the association of the CPUE of the close shore Basque flee with the same, emphasizing likewise that the associations vary (sea floor upwelling or Galician upwelling, Pingree and Alborán gyres, warm pockets in the Bay of Biscay and filaments).

The sub-Artic zone of convergence is very intense at the beginning of the season with distinctly marked chlorophyll fronts. When the distinction between low and medium values of chlorophyll are most clearly marked, the catches relating to these fronts are poor. Polovina *et al.*[8] described the relationship between the boulter fishing of albacore tuna in the Pacific in the same area of convergence, where the cold, nutrient rich water is sunk below the poorer stratified warm water.

It is rare to find catches below 15°C or above $0.8mg*m^{-3}$, given that the albacore tuna is an optical predator. In some images, the catches can be seen occurring at these values but always in areas with lesser concentrations of chlorophyll and higher temperatures which are more to the liking of this species. Laurs[9] observed the presence of albacore tuna in warmer, clearer waters but closet o the colder and murkier water fronts when analysing the fishing performances on radiometric images of temperature and chlorophyll concentration. In relation to the chlorophyll concentration, it has been noted that there are pockets of highly concentrated chlorophyll at the beginning of the season at high sea with occasional upwelling in the Cantabrian. In general terms, the gradients of chlorophyll at the points of catches are not so intense. The points are mainly produced at fronts with medium to low values which explains the range of chlorophyll and the sobel operator in the histograms and scatterometer derived data graphs which show affinity by gradients and small ranges.

Catches are not usually produced at intense SLA and when this occurs, it coincides with the fact that the SLA in the whole of the area is intense and positive. In these situations, it is common to see association with the change of sign with small isolated nuclei of negative SLA in a predominantly positive area. Nel[10] related the accumulation of albatross on the rims of the positive anomalies with special preference for recently generated gyres due to biological processes relating to the same or because they have been less exploited by the competitors.

In general, catches occur in areas where the SLA variation is not great. There seems to be affinity with positive SLA but not at highly intense values. At the beginning of the season, the SLA is negative in the Cantabrian but as the season advances, it reaches positive values and the catches move further inwards into the Bay of Biscay. In September and October, the SLA values become extremely high and catches descend whereas the SST and the chlorophyll maintain adequate values for the species.

In the case of Ekman pumping, no clear relationship can be defined and behaviour is, at times, more variable. Sometimes, there is a relationship with the change in sign and, others, with predominantly negative values. It is, of all the parameters, the least conservative. The results show an increase in catches when these are produced in areas of intense convergence and divergence. Several authors have described the subsidiary implications of Ekman pumping at the beginning of the food chains[11,12,13,14]. Martin and Richards[15] studied the vertical transport mechanisms of nutrients in gyres at meso-scale in the North Atlantic and came to the conclusion that, although on a lesser scale, Ekman pumping also contributes to upwelling in deep waters.

Since the Ekman pumping variable is the variable of the tour which presents greatest variation, it may be affected by the praxeologic response which represents a reference to the time lapse between the creation of an anomaly of interest to the albacore tuna and the attraction of specimens to the same[15]. The behaviour of the tunid to pumping is conditioned by other parameters such as when the catches are situated over positive structures of extensive SLA which increases the relationship of the same with the change in sign of the pumping. On a larger scale, it would seem that the relationship between catches between frontal zones of positive and negative signs is to be appreciated when the pumping values are intense.

In the present study, 90% of the catches are accumulated between 15.4 and 23.2°C. This does not mean that this species limits its movements to waters at these temperatures. Laurs *et al.*[16]show that the albacore tuna spends most of its time at depths close to thermocline at temperatures between 10 and 19°C and spends little of its time in surface waters presumably when it is going to feed. The range of temperatures alone is not sufficient to define the area of distribution of the albacore tuna to lesser extensive regions. Abdon[17] used temperature data and data relating to catches of *Thunnus albacares, Thunnus alalunga* and *Thunnus obesus* in the waters of South and South-East Brazil to conclude that temperature alone is not indicative of the presence of this species.

In the report on boulter fishing of swordfish in the island of Reunion[18] there is a description of the relationship between the fishing and the satellite derived environmental variables (temperature, chlorophyll and SLA), although it also contains information corresponding to other species such as the albacore tuna. The histograms given for the variable of boulter fishing differ from these obtained here in that the SLA histogram is slightly shifted to the left which is the opposite of what occurred in this study where the results tend towards positive values. The temperatures are notably higher, 24-30° C and the chlorophyll is between 0.05 and 0.2 $mg*m^{-3}$ at surface values which are characteristic of the west Indian Ocean. The main difference is that the vector of extraction of the variables is boulter set whereas in the present study it is the point of catch. The data correspond to different types of fishing in different oceans but we are talking about the only study available with characteristics similar to what we are describing herein.

Andrade and Garcia[19] related fishing of tunids (CPUE) with fields of SST and worked with surface cross-net fishing. The SST at catch fluctuated between 17-30° C with a gaussian distribution and highest CPUEs at between 22-26° C. These authors found that the relationship between surface temperature and CPUE varied seasonally and that the highest catches were produced in the Summer independent of temperature. Temperature alone did not explain the CPUE but when the seasonal variation was eliminated from the data, however, a relationship could be traced between the inter-annual SST and the CPUE.

The only way of approaching the study, in spite of the limitations of the same, is to work with database of catches. The variable response is due to the fact. that catches are subject to immense variability which is difficult to capture in parameters. Catches are produced sporadically and do not cover the whole area which means that there are zones which are potentially good and which are not fished by any operator. It may also occur that poor catches are given in good areas with abundant fish due to factors which are outside the remote sensing derived parameters or that fish have momentarily accumulated there.

The models are generated using data with respect to the location of catches and whether these are high and low since there are no nil catch data available. This would also be complicated since these do not exist due to adverse environmental conditions or because fish has not been allowed to accumulate. It is patent that it is impossible to describe the relationship between the CPUE obtained and one sole parameter of remote sensing (and its derived variables). Power y May[20] using 6000 pieces of data with respect to boulter tail fishing and 109 images of SST found no relationship between the SST image derived statistics and the CPUE.

The multivariable analysis allows us to overcome the problem of visual empirical analysis of four parameters simultaneously. However, visual interpretation is crucial to multi-variable analysis in that it helps to define the variables to be extracted and which later will be introduced into the analysis. It is basic to have derived variables of more than one parameter when obtaining results.

With the models obtained via multiple linear regression, a high level of explanation is reached using a 'parameterised' ocean (four parameters) and, in spite of its limitations can be used to estimate the abundance of the CPUE. The weighting of the anomalous sea level is to be underlined in both models and the secondary importance of SST and chlorophyll-a concentration. Ekman pumping is of lesser importance but necessary to raise the degree of explanation in the second model. Another of the differences of the second model as opposed to the first is that, with the sole exception of sea surface temperature, the rest of the variables included correspond to periods previous to the day of catch.

The resulting model of discriminant analysis is to be highlighted for including values which correspond to 10 days before the match, with two variables linked to pumping although with lesser weighting than those linked to SLA and SST. The main problem of this model is its low capacity of classification of medium values which are distributed over high and low and, thus, which causes problems in the generation of the probability maps using this model.

In the analysis of boulter fishing of swordfish around the island of Reunion[18] the variable of effort number of hooks is included in the analysis and the models which explain 72% of the abundance of swordfish but the number of hooks and the distance from the coastline explained ten times more variability of the CPUE than the environmental parameters. In this study, the catches have been standardised with respect to the effort in order to relate the same solely to environmental variables as derived from satellite and the level of explanation of CPUE of albacore tuna achieved by the second model of linear regression is, thus, 62%.

The multi-variable models obtained use environmental variables extracted at the point of match given that they correspond to the data available in order to broach this subject. The probabilities make no reference to the possibility of catch or not but, rather, make reference to high, medium or low catches. But the distributions corresponding to these variables at the points of match are not the same as those which correspond to the whole fishing area. Of the 82 variables extracted, only eight can be saved from their average or variance being different at the point of catch and in the whole of the fishing area, none of the variables which are included in any of the models obtained. The models used in the generation of the maps give rise to incoherent results if they are applied over the whole window of study without previously having excluded details according to the ranges in which the catches are distributed. From a mathematical point of view, catches are not known of in these areas and there are no existing data which allow for these to be evaluated or compared with the variables. At the most, they may be considered to be unevaluated areas of probability. From an ecological and/or practical perspective, it would seem reasonable, in light of the results, to consider these areas to be difficult hosts to albacore tuna. The periods of time in which catches are produced outside the range fall mainly in the month of June when there are large fronts with values between high probability and outside the range (which are favourable to catching albacore tuna)

In general, the maps of probability excluding the values which are considered to be inadequate to the presence of albacore, give fairly coherent results with the catches available. The three levels of probability of the discriminant analysis and in which the results of the linear regression are grouped gain practical usefulness due to their 'buffer' effect on the medium values. The problem of the maps of probability derived from discriminant analysis resides in their scarce capacity to classify, above all, medium CPUEs. This means that only the areas classified as high can be considered to be useful since only 10% of the low catches will be considered amongst the high and those classified as medium contain high, medium and low in significant proportions. The maps generated via multiple linear regression give rise to coherent results both with the point of match and with the whole area. The second model gives rise to better results due to its greater level of explanation. The models which included a larger number of variables inevitably give rise to a larger number of lost values.

Using the combination of four parameters and variables derived from the same, it is possible to draw up maps of probability of fishing which go beyond a mere descriptive analysis. The inclusion of parameters with days' delay in the models take into account the importance of the praxeologic response. The appearance of probable zones and the accumulation of fish in these zones at the beginning of the season will depend upon the existence of corridors or communication with these zones through areas which are appropriate to the presence of the tuna. In other circumstances, the opposite may occur, that ism that the progressive disappearance of probable zones may make the tuna concentrate is isolated nuclei due to exclusion.

What happens as the result of a good or bad fishing harvest with respect to performances and the relationship of the same to the variables. The maps of probability contemplate these effects. If the maps corresponding to the year 2001 are observed, a year in which the catches were low as compared with the two previous years, the maps gave rise to lower probabilities. The graphs which represent the proportion of high probabilities for each day according to the campaigns with respect to the values presented in the images (that is, with respect to the sumo f the pixels outside the range plus those corresponding to all the values presented in the image) illustrate the coherence of the different models with the catches obtained in the different months and campaigns. The use of relative frequency of high probabilities is motivated by the large variability in the number of pixels calculated according to the model and day which makes it inadequate to use absolute frequency with respect to the whole image. Relative frequency to the pixels available is not a perfect parameter since we are unaware of the proportion which the probabilities obtain in the unavailable pixels but, nonetheless, it is an approximation to the proportions given the impossibility of having available values for the whole of the map.

4. CONCLUSIONS

One or two geo-physical parameters obtained by satellite are insufficient to quantify the relationships between the same and the CPUE. It is possible to quantify the relationships between parameters of remote sensing and the CPUE of albacore tuna using four parameters and the variables derived from the same. The levels of explanation which are reached are high, 62% in the case of multiple regression. In the case of discriminant analysis, there is a satisfactory rate of classification of high CPUEs at 72% and low at 63% with 8% of the highs quantified as low and 10% of the low as high. However, the classification of medium CPUEs is poor.

SLA is the most significant parameter both from the perspective of the direct relationship with the CPUE as for the relative importance of the same in the models.. This can be seen in the analyses carried out using multiple linear regression and discriminant analysis. The SST and the chlorophyll concentration have an intermediate weighting in the models. Variables linked to the SST are presented in all the models described. This is not the case for the concentration of chlorophyll nor for Ekman pumping which is of lesser individual importance but is basic to the levels of explanation.

The extraction of variables derived from the parameters of remote sensing is important when generating multi-variable models. These variables help to incorporate into the models the importance of spatial structure in the presence of the albacore tuna. This behaviour with respect to said variables is in coherence with the theory of coherent response[2]. The extraction of variables from the remote sensing derived parameters at different time lapses is important when generating multi-variable models. The time lapses help to incorporate the importance of delay between the generation of a structure and the capacity of accumulating specimen of albacore tuna into the model. This behaviour with respect to time lapses concords with the praxeologic response[15].

Maps of probability derived from models generated in multi-variable analysis are coherent with the periods and zones of fishing of albacore tuna. The excluded zones are also coherent when the ranges of extraction are taken into account.

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