Non linear modelling for ecological tuna behaviour estimation based on remote sensing data

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EXTENDED ABSTRACT

Satellite remote sensing data and purse seining catch data are used to analyse the ecological behaviour of tuna in the Indian Ocean. A set of environmental parameters deduced from satellite data is extracted at the fishing points by using an interface developed at the "Institut de Recherche pour le Développement" (IRD). Statistical analysis were then carried out and some linear model and nonlinear models (neural networks) have been set and evaluated. A methodology based on genetic algorithms is used in order to avoid overfitting and to obtain suitable models.

This article addresses the problem of tuna location modelling by using means of remote sensing for fishing management purposes. Indeed, tuna tend to gather in the areas where the environmental conditions are suitable for their physiology and the probability of finding foods is high. Similar work using remote sensing products for estimating tuna positions have been partially studied, but here we describe a novel and methodical approach based on a wide variety of envionmental variables. Remote sensing data include sea surface temperatures (SST), chlorophyll–*a* concentrations (CHL) and sea level anomalies (SLA). SST is quite used since 1976 for fishing management (at least on experimental basis). CHL is known to be related to primary production (the food pyramid base). SLA is assumed relevant as an indicator of geostrophic currents and thermocline depth.

The data are structured in a database made up of two main tables: the Catch Data Table which includes the catches weight at some spatio-temporal coordinates and the Environment Table which consists of the values of environmental parameters inferred from the nearest pixels around the fishing locations. The Catch Data Table was created by Ifremer from information given by fishermen. The Environment Table is automatically filled by querying the Coverages Database. About 150000 data are referenced in the Catch Data Table. Unfortunately, due to a lack of available environment variables (some remote sensing data are very sensitive to cloud coverage), the number of useful data, may drastically drop down with respect to the diversity of model input.

First, we define some features of the oceanographic conditions (within the Indian Ocean) as a combination of environmental physical data (such as the temperature), a transform operator (such as a gradient), and a relative spatiotemporal position (such as 15 days back from the fishing day). Then, we estimate the most relevant features for our problem by computing the non-parametric correlation method called *Spearman* (a Pearson correlation applied on data ranks). Finally, we teach a model to be fed by the determined features and to yield as output a probability of *catchable tuna* presence or absence. Different models have been tested, from a basic linear regression to a neural network modelling.

When applying a neural network approach, we use *genetic algorithms* which has been successfully applied to evolve models for solving a variety of interesting problems. In this paper we apply the method to synthesis of *sigma-pi* neural networks. Unlike perceptron architectures, *sigma-pi* networks use product units as well as summation units to build higherorder terms.

The neural network synaptic weights (the parameters) are obtained by using a gradient descent method (conjugate gradient) and the structure is optimized by genetic algorithms.

The most promising model provides an 80% accurate rate (the model fails to predict the tuna absence or presence in 20% of the cases) versus 70% for the best linear regression and 50% for the actual fishing methodology. Our results show that the relationship between the environmental conditions and the tuna behaviour is quite non linear and that simultaneous use of both chlorophyll–*a* concentrations and sea level anomaly increase significantly the average accurate rate.

1 INTRODUCTION

About 40 years ago, the real life of tunas striked the scientific community with amazement when a bluefin tuna tagged in the Bahamas was caught less than 50 days later off the coast of Norway, 6700 km away (ref. Mather (1962)). This migratory lifestyle and the extraordinary anatomical and physiological features that permit it have interested observers since Aristotle. Their lives remain largely unknown nowadays but study of these creatures for their extreme biology is increasingly overshadowed by concern about their continued existence in robust and viable populations.

Since the majority of the world ocean is now visited more often by fishing vessels than by oceanographic expeditions, Sharp (2001) suggested encouraging the fishing vessels to participate in ocean monitoring and data sharing. Indeed, they provide greatly needed information on a lot more than just fisheries behaviour, for example, climate change and ocean dynamics. Seiners and tuna management in monitoring Indian Ocean fisheries have worked together in the frame of a regional collaboration as mentionned by Marsac and Hallier (1990). Fishing vessel crew measure and report a suit of relevant environmental observations every day they are at sea. These informations are archived in logbooks by the fishermen. The French Research Institute for Exploitation of the Sea (Ifremer) structured the informations given by the Indian Ocean fishermen in a database.

Tuna oceanography studies can provide useful information for those working to understand tuna fisheries and related tuna biology. One kind is to help understand the variations of catch statistics from various fisheries operating within similar or adjacent regions on one or more tuna species. Another kind is to help understand the general shifts in apparent population abundances over large and small areas in time. Others include learning more about the responses of tunas to ocean variability and production patterns so that forecasts of behaviours, catch potentials, and status of resource population might be improved.

Due to their global coverage, satellite remote sensing data provide a useful tool to describe tuna oceanography. They provide a continuum in scale observations for the oceanic structures and their dynamics. These data are more and more suitable to describe the oceanic landscape due to the development of efficient sensors and processing methods. Satellite remote sensing data and purse seining catch data are crossed to analyse the ecological behaviour of tunas in the Indian Ocean. In the first part of this paper, we will describe the catch data and the remote sensing data used in this study. Their design in the databases as well as the informations available will be explained. Then, we will present the methodology used to carry out the statistical analysis. To finish, the results will be analysed and discussed.

2 DATA

Catch data and remote sensing data are archived in two distinct databases: "Observations" and "Coverages". The remote sensing database is global for several projects whereas the catch data database can be replaced by a database of observations of cetaceans or of cholera cases for example. These databases have several utilities, they can be catalogues to make an inventory of the available data, search engines to quickly find images or catch data at arbitrary spatio-temporal coordinates, organizers to promptly construct crosstables between fisheries data and environmental data or recorders to archive results of costly or laborious calculations.

The Observations Database is made up of two main tables: the Catch Data Table which includes the catches weight at some spatio-temporal coordinates and the Environment Table which consists of the values of environmental parameters near the fishing points. The Catch Data Table was created by Ifremer from information given by fishermen. The Environment Table is automatically filled by querying the Coverages Database as will be explained in section 2.2. About 150000 data are referenced in the Catch Data Table. Unfortunately, due to a lack of available environment variables (some remote sensing data are very sensitive to the cloud coverage), the number of useful data, can drastically drop down with respect to diversity of the model input.

2.1 Catch Data

The Catch Data Table details the catches weights by specie and by category. Four species are considered here: ALB standing for Albacore tuna, BET for Bigeye tuna, SKJ for Skipjack, YFT for Yellowfin tuna. Two categories were proposed according to the weight of the fishes. Those less than ten kilograms weight were classified in the first category, c_1. Those more than ten kilograms weight were classified in the third category, c_3. Concerning our catch data, we had the following groups: YFT, $YFTc_1$, $YFTc_3$, SKJ, BET, $BETc_1$, $BETc_3$, ALB. The columns without indication of the category comprised the sum of the catches for all the categories (e.g., $YFT = YFTc_1 + YFTc_3$. The recording can refer to a day without fishing, a prospecting or an attempt of capture (successful or not). These cases were differentiated by the columns $hFishing$, $nSennes$ and $nHauls$ which can be interpreted as follows: $hFishing = 0$ means a day without fishing (less than 5% of the total recording), $hFishing > 0$ and $nSennes = 0$ means that the fisherman was prospecting (40% of the

fishing data), $nSennes > 0$ and $nHauls = 0$ means that the fisherman has made at least one attempt of capture but none succeeded (12% of the fishing data), $nHauls > 0$ means that at least one haul succeeded (48% of the fishing data). The schools caught by the fishermen can be associated to a fixed structure, a floating object or can be free. The free or associated character of the schools is specified in the table.

The main sources of information were the logbooks of the fishermen. They indicate their observations on the prospected areas and the catches weights. The quality of these data is variable in function of the individuals and is hard to determine for three main reasons. Firstly, the positions are quite rough even if most of the fishermen are equipped with a GPS positioning. Sometimes, the position mentioned in the logbook is not the position of the fishing point but rather the position noted the last time the fisherman took bearings (generally around twelve o'clock). Secondly, the species composition given by the skipper is usually approximate. Thirdly, the fishermen generally tend to underestimate the catches weight. We cannot make the catch data totally objective but we can try to reduce the differences originating from self interpretation. Two corrections were applied. Firstly, the probable proportion of the species was estimated by using the data of sampling campaigns and by taking into account the season. Secondly, a correction factor was calculated from the ratio of the landed weight to the declared weight. This correction was then applied to the weights declared at each haul.

The Environment Table includes a set of environmental parameters evaluated for each catch data. SST, CHL and SLA were considered at several dates –the day of fishing, (5, 10, 15, 20, 25 and 30) days before and 5 days after– at the location of the catch data. Those environmental indicators values are computed at the nearest geographical coordinate and the nearest date, interpolated spatially (bilinear interpolation) and temporally (linear interpolation). Spatial gradients calculations with various operators may be applied before interpolations.

In this paper, we attempt to model the presence or absence of *catchable* tuna in the indian ocean. In this context, the term *catchable* means fishes schools that can be visually observed by the fishermen and that are considered valuable to catch. It should be noted that the tuna may be present but unnoticed by the fishermen (e.g. they are too deep) or not economically viable to catch. When we use the term "probability of tuna presence", the reader should implictly understand "probability of catchable tuna presence".

2.2 Remote Sensing Data

Remote sensing data include SST, CHL and SLA. They are archived in the Coverages Database.

Ocean temperature is measured by using thermal-infrared wavelengths. The need for accurate global sea surface temperature fields has been receiving increasing attention, primarily due to its importance in understanding variability in the oceans' climate. Since 1981, the National Oceanographic and Atmospheric Administration (NOAA) series of polar-orbiting spacecraft have carried the Advanced Very High Resolution Radiometer (AVHRR), an instrument with three infrared (IR) channels suitable for estimating SST. AVHRR SST measurements, besides their reliability over more than twenty years, are attractive due to their global, repeated coverage and to their spatial resolution (1.1 kilometres at Nadir). Data are also widely used due to their low cost and possible access in real time thanks to an HRPT antenna. Multichannel SST estimates are computed from a combination of two ambient temperature channels by using the Multi-Channel Sea Surface Temperature (MCSST) algorithm (see Walton et al. (1998) and Kilpatrick et al. (2001)). Temperatures are available on weekly composites with a spatial resolution of 4 km at Nadir.

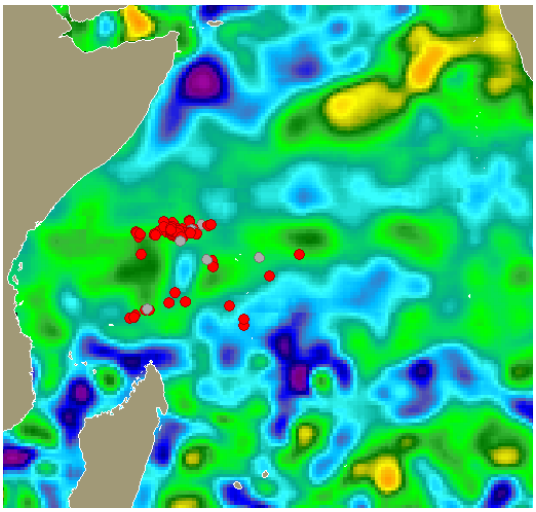

Figure 1. *Example of Sea Level Anomaly image.*

Chlorophyl–*a* concentration were determined by using visible wavelengths of the National Aeronautics and Space Administration's (NASA's) Sea-viewing Wide Field-of-view Sensor (SeaWiFS). Subtle changes in ocean color of deep sea waters signify various types and quantities of marine phytoplankton (microscopic marine plants), the knowledge of which has both scientific and practical applications. Since 1997, SeaWiFS data have provided quantitative data on global ocean bio-optical properties to the Earth science community. Blue and green channels of SeaWiFS were combined using the *OC4* algoritm (ref. OReilly et al. (1998)). CHL were calculated by doing a weighted mean of the chlorophyll concentrations over the previous eight days. They were available on weekly composites with a spatial resolution of 4 km at Nadir. SLA are gridded sea level anomalies,

computed with respect to a seven-year mean ocean surface [Aviso, `http://www-aviso.cls.fr/`]. Maps of sea level anomaly were obtained by merging *TOPEX/POSEIDON (T/P)* and *ERS-1/2* data. *T/P* has been measuring ocean topography with an unprecedented accuracy for more than 10 years while *ERS-1* and *ERS-2* have provided a very useful complementary sampling. The merging of *T/P* and *ERS-1/2* has provided, in particular, a description of the ocean circulation variability (mesoscale circulation, seasonal variation, El Niño...) with a resolution never achieved before. More details can be found in Ducet et al. (2000).

SST, CHL and SLA are known to be relevant as an indicator of tuna behaviour as indicated by Desruisseaux (2004). They were selected for their availability but some other data such as salinity and dissolved oxygen concentration would probably be pertinent for our objective.

3 NEURAL NETWORKS APPROACH

Most nonlinear models based on polynoms, wavelets or neural networks, have the universal approximation ability. Barron (1993) shows that this ability is particularly interesting in the case of the class of function defined by the neural networks. This ability allows the nonlinear models to outperform linear models when nonlinear relationship exist between variables. This could be a strong advantage, if this feature, plus the infinite variety of model structure, did not entail a problem called *overfitting*. Significant low results on the test set can occur when the generalization capacity of this model for the specific problem is poor and when the model overfits the learning set. Estimating the parameters of a model having a large degree of freedom (in general too many free parameters) for modeling an insufficient amount of noisy data, can yield an underestimation of the noise variance.

Another concern is called model selection. A model structure suited to the given problem, allows an easy parameter estimation and easily capture the underlying data dynamic. If you use nonlinear models, model selection becomes much more crucial since they are in general more flexible than linear models. In this application, we use an automatic method based on genetic algorithms for detecting the most suitable model in the class of nonlinear models.

In the frame of this application, we focus on a problem that can be viewed as a nonlinear regression with explicative variables.

$$Y_{i,j} = f(X^1_{i,j}, X^2_{i,j}, \ldots, X^n_{i,j}) + \varepsilon_{i,j} \qquad (3.1)$$

Where

- $Y_{i,j}$ denotes the probability of tuna presence at the coordinates (i, j),
- $(X^k_{i,j})_{1\leq k\leq P}$ denotes the P remote sensing data processed in order to extract the most pertinent spatio-temporal information (gradient...),
- $\varepsilon_{i,j}$ denotes some independant and identically distributed random variables with zero mean,
- f is the function that represents the underlying true relationship between the remote sensing data and the presence of tunas (possibly non-linear).

In practice, different kinds of neural networks (multilayer perceptrons, radial basis functions...) can be used for this purpose. They are all very efficient for nonlinear modeling and are actually used in many applications. Since we want to perform automatic model selection, we choose to select models in a large class of feedforward neural networks. This class, named general *sigma–pi* neural networks (see for example Rumelhart et al. (1986)) is composed of networks without layer structure (see an example figure 3) and includes the multilayer perceptron class.

This kind of neural net connects *sigma–pi* units (the neurons) composed of P input units, N hidden unit that include D *sigma* units and *pi* units and an output unit. To avoid feedback connection[1], we label the hidden units by h_1, $h_2, \ldots, h_N$, and we decide an arbitrary order relation: h_i can connect to h_j, only if $1 \leq i < j \leq N$. The input units receive no connection, but can connect to each hidden unit and to the output unit, and the output unit can be connected to any other units. The hidden units sum the values provided by the previous units, weighted by the synaptic coefficients (*sigma* unit processing), compute a product of their output (*pi* unit processing), and apply a transfer function. Because we perform regression, we associate linear transfer function to the input and output units, and a sigmoid transfer function (such as *tanh*) to the hidden units.

This network (see an example figure 3 with 2 *sigma* units per hidden unit), fully connected, can be defined by the following equation:

$$\begin{aligned} f_\theta(x_1, \ldots, x_P) &= \phi\left(\prod_{d=1}^{D} O_d^{N+1}\right) \qquad (3.2)\\ \text{with} \quad O_d^n &= \sum_{i=1}^{P} \theta_i^n X_i + \sum_{j=1}^{n-1} \theta_{P+j}\ \psi\left(\prod_{d=1}^{D} O_d^j\right) \end{aligned}$$

where:

[1]We actually deal with nets without loop. There is no feedback of information and this type of neural networks can not model recurrences

- $f_\theta(x_1, \ldots, x_P)$ stands as the neural network output (assumed here to be scalar),
- P is the number of inputs,
- D is the number of *sigma* unit dedicated to one hidden neuron,
- N is the number of hidden units,
- ψ is a sigmoid function such as *tanh*,
- ϕ is either a sigmoid function or the idendity function (depending on the problem),
- $(\theta_p^n)_{1\leq n\leq N+1,\, 1\leq p\leq P+N}$ denotes the set of parameters.

The example on figure 3 has 4 input units denoted $\{a, b, c, d\}$ and one output unit denoted h_3.

Commonly, the last input unit X_P denotes a constant equal to 1. Then the related weights $(\theta_P^n)_{1\leq n\leq N+1}$ denote the constants in the frame of the nonlinear regression. So far, we assume that there exists a set of parameters $(\theta_p^n)_{1\leq n\leq N+1,\, 1\leq p\leq P+N}$ such that f_θ matches up f from equation 3.1, and $\tilde{\theta}$, an estimation of θ, is found through optimization[2]:

$$\tilde{\theta} = \arg_\theta \sum_{i,j} \left(Y_{i,j} - f_\theta(X_{i,j}^1, X_{i,j}^2, \ldots, X_{i,j}^P)\right)^2 \tag{3.3}$$

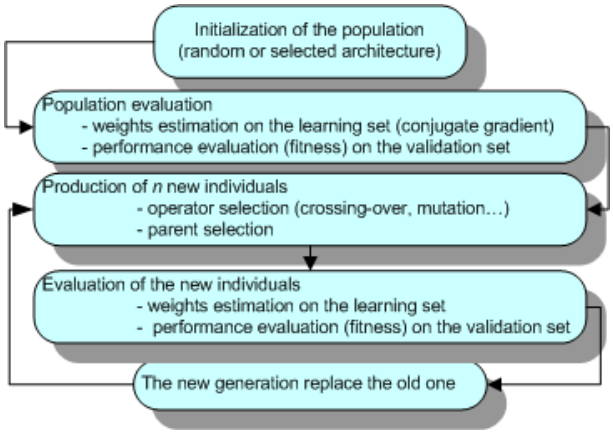

Figure 2. *Genetic algorithm principle.*

Of course, a fully connected architecture with a large number of hidden units is overparametrized, and this model can overfit the data. The goal is to find the most suitable architecture which can approximate the function f of the relation defined in equation 3.1, with the highest accuracy and the weakest overfitting. To search it within the class of sigma–pi feedforward neural networks, we use a genetic algorithm as described in Davis (1991) and Goldberg (1989).

Firstly the data is split into three subsets: a learning set, a validation set and a test set. To emphasize the ability of generalization, each architecture is evaluated following the same scheme:

[2]If we assume that the noise is gaussian, maximizing the likelihood of these i.i.d. random variables is equivalent to minimizing the sum of residual quadratic error.

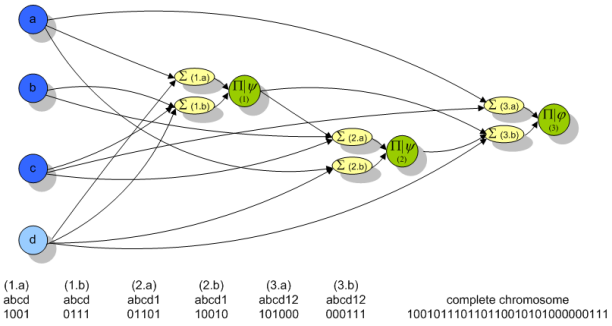

Figure 3. *Example of neural networks coding.*

- parameter estimation on the learning set,
- evaluation of the fitness (the sum of residual error (equation 3.3) on the validation set.

This way, the test set is totally independent of the parameter estimation and the architecture selection.

Secondly, we encode the neural network architecture into a chromosome, i.e. a sequence of bits. Considering the example on the figure 3, the first sigma unit is denoted (1.a) (hidden neuron (1), sigma unit (a)). The value 1 under a means that the unit (a) is connected to the sigma unit (1.a), and 0 under b means that there is no connection between unit b and (1.a). The complete chromosome appears at the very bottom of the figure. Each chromosome corresponds to a peculiar structure and a peculiar set of synaptic weights. Those neural network synaptic weights ($(\theta_p^n)_{1\leq n\leq N+1,\, 1\leq p\leq P+N}$ from equation 3.2) are obtained by using the gradient descent method (conjugate gradient).

At last, we genetically select the "best fit" model using the algorithm described on figure 2. For the model selection, we use the following operators :

- mutation to 0 (eliminating a synaptic weight),
- mutation to 1 (adding a new synapse),
- multiple random mutation,
- random operator (creating a new architecture),
- crossing over (merging parts of different architectures). See figure 4 for an example of crossing over.

Parent selection is made using the "fitness" (performance of accuracy on the validation set) of the architectures. The more accurate this fitness is, the higher is the probability of picking up the related architecture. Following the same scheme, the probability of choosing an operator depends on the performance accuracy of the neural models previously generated by it. The principle is to increase the probability of picking up an operator (and to decrease the others) if this one yields performant structures. This method is highly time consuming, because a

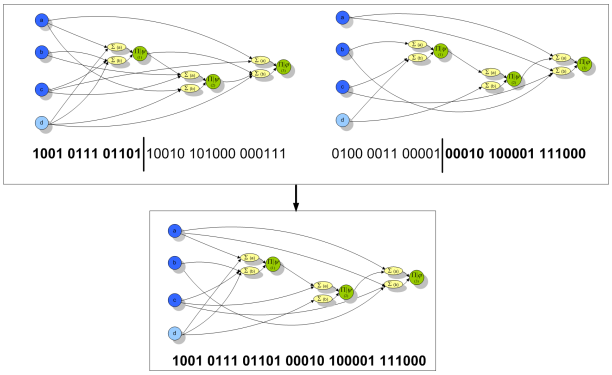

Figure 4. *Example crossing over.*

large amount of training is computed. In the field of previous applications described in Mangeas and Muller (1996) or Zhang and Mühlenbein (1994)) this algorithm yields very well suitable models.

4 TUNA PRESENCE PROBABILITY

The method consists of learning how to efficiently estimate the probability of tuna presence. For this task, the fish catch and the remote sensing data sets are split into 3 subsets. The first subset (70% samples randomly extracted) is used to compute the synaptic weights of the neural networks. Those data are included in the learning set. From the other data, 15% are used for evaluating the performance of the model on novel data (the validation set) and allow to compute the fitness in the frame of the genetic algorithms. The remaining (test set) is used for comparing the different models (linear and nonlinear).

We define some features of the oceanographic conditions (within the Indian Ocean) as a combination of environmental physical data (such as the temperature), a transform operator (such as a gradient), and a relative spatiotemporal position (such as 15 days prior to the fishing day). The most pertinent explanatory variables, determined by the means of spearman correlation, are used in the frame of the linear and nonlinear modelling. Here is a list of variables that have been computed to be significantly correlated to the tuna locating problem (for a location i, j, the fishing day is denoted d and ∇ stands for the spatial Sobel's gradient):

- SLA_d,SLA_{d-20},SST_d,SST_{d-20},CHL_{d-15}...
- ∇SLA_d,∇SLA_{d-20},∇SST_d,∇SST_{d-20}...
- other combinations (of order 2) of indicators

Due to the lack of available remote sensing data (CHL and SST can not be scanned if there are clouds on the specific location at the specific day) we have at our disposal around 12000 data for designing the models.

In order to find the most suitable structure of neural networks able to yield the best indicator of tuna presence, the first population of neural net architecture is made of 20 neural networks randomly set up. The optimization process on the 20 individuals is a highly consuming process (around one hour of computation on a 3Ghz PC). After 20 generations (around 20 hours later), any significant improvement concerning the fitness of the elite is observed and the process ends.

For this last process, the evolution of choosing the best operator during the convergence towards the best architecture is quite informative: we remark that, in a first phase, the probability of picking the "mutation to 1" opertor significantly increases (this operator yields more suitable architectures i.e. the set of structure, initially settled on, needed more connections). In a second phase, the probability of picking the "crossing over" operator increases (and so all others decrease). This behaviour indicates that the set of structures needed to be combined at some point.

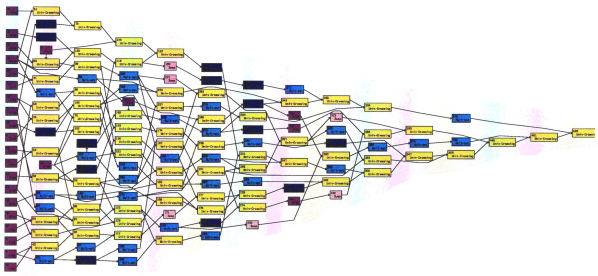

Figure 5. *example of family tree of the best neural net computed by genetic algorithms.*

Figure 5 reproduces an example of the family tree of the generated neural architectures. The different color variations are related to the operator used. The children are connected to their parents at each new generation. We can note that each architecture from the first generation is involved in the process and participate to produce the most suitable architecture (the one on the far right).

linear regression	Positive Actual	Negative Actual
Positive Predicted	40.96%	16.65%
Negative Predicted	11.68%	30.70%
neural network	**Positive Actual**	**Negative Actual**
Positive Predicted	50.80%	13.34%
Negative Predicted	6.08%	29.78%

Table 1. Confusion matrix – Linear and neural network models.

The results detailed table 1 show clearly that the neural network outperforms the standard linear regression with more than 80% of good estimations. This result can be compared with the performance of the fishermen that find tunas 50 per cent of the time when they use purse seining in the indian

ocean and with the linear model results that stands at around 70%. At this stage, it has to be remembered that only the location of the catch attempts are available. That means it is not quite the probability of tuna presence that the results denote but more a probability of catchable tunas presence with respect to the fishermen's criteria.

5 CONCLUSION AND FUTURE WORK

We have presented in this paper a real-world application of nonlinear regression by neural networks. The neural model is used to combine multiple remote sensing measurements into a single and precise estimate of the probability of tuna presence. Necessity and usefulness of higherorder neural networks have been wellknown. However the increasing number of terms has hampered the design and training of higherorder networks. Present work shows the potential effectiveness of genetic algorithms to handle this problem. In particular, we show how the *sigmapi* neural networks are able to simulate the underlying relationship between the tuna behaviour as a function of the data collected by remote sensing techniques.

The results show that the neural model is particularly efficient in comparison with standard linear regression and combine data more effectively in order to provide a good probability indicator.

We are currently attempting to apply a bayesian network technique to the problem of probability of tuna presence. The main advantage of such approach is to overcome the problem of missing data, in particular in the case of the SST and CHL remote sensing measurements that are very sensitive about cloud coverage. In particular, we hope to be able to estimate the missing data by using other available data. Indeed, most of the remote sensing data are highly correlated and can be deduced indirectly through the means of bayesian techniques.

A deep ecological analysis is also planned, using catch data from the indian, atlantic and pacific oceans in order to determine different tuna behaviours in relation to available remote sensing data.

6 ACKNOWLEDGEMENT

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