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ESTIMATING RELATIVE ABUNDANCE FROM CATCH AND EFFORT DATA, USING NEURAL NETWORKS

by

Mark N. Maunder and Michael G. Hinton

La Jolla, California

2006

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ABSTRACT

We develop and test a method to estimate relative abundance from catch and effort data using neural networks. Most stock assessment models use time series of relative abundance as their major source of information on abundance levels. These time series of relative abundance are frequently derived from catch-per-unit-of-effort (CPUE) data, using general linearized models (GLMs). GLMs are used to attempt to remove variation in CPUE that is not related to the abundance of the population. However, GLMs are restricted in the types of relationships between the CPUE and the explanatory variables. An alternative approach is to use structural models based on scientific understanding to develop complex non-linear relationships between CPUE and the explanatory variables. Unfortunately, the scientific understanding required to develop these models may not be available. In contrast to structural models, neural networks uses the data to estimate the structure of the non-linear relationship between CPUE and the explanatory variables. Therefore neural networks may provide a better alternative when the structure of the relationship is uncertain. We use simulated data based on a habitat based-method to test the neural network approach and to compare it to the GLM approach. Cross validation and simulation tests show that the neural network performed better than nominal effort and the GLM approach. However, the improvement over GLMs is not substantial. We applied the neural network model to CPUE data for bigeye tuna (*Thunnus obesus*) in the Pacific Ocean.

INTRODUCTION

Catch per unit of effort (CPUE) from commercial vessels is often the main source of data for stock assessment models. Stock assessment models usually include the assumption that the population abundance is proportional to the CPUE. However, CPUE can vary due to factors other than abundance. These factors include those related to the environment and fishermen's behavior. Often factors related to the environment interact with those related to this behavior. For example, fishers control the depth of tuna longlines to target bigeye tuna, while the depth of the thermocline, which controls the vertical distribution of many species, changes with environmental conditions. Therefore, it is important to standardize CPUE by removing the factors that affect catchability that are not related to abundance.

There are numerous methods that have been used to standardize CPUE (Maunder and Punt, 2004). Standardization with generalized linear models (GLMs) is one of the most commonly used methods. In GLM analysis, which is limited to linear relationships between CPUE and the explanatory variables, the estimated year effect is used as a relative abundance index for input into stock assessment models. Polynomials and interaction terms can be used in GLMs to make the relationship between CPUE and the explanatory variables more flexible, but GLMs are still limited in the relationships they can describe.

An alternative to GLMs are mechanistic models based on our scientific understanding about the relationship between CPUE and the explanatory variables. These models may be complex and nonlinear. One such method that has been used for billfishes and tunas is the habitat-based standardization (HBS) method of Hinton and Nakano (1996). The HBS models the location of hooks in the water column, using gear models and the distribution of fish based on oceanographic data and habitat preference data for the species being modeled. Hooks that fish in habitat with a higher preference level are assigned higher effective effort.

GLMs and HBSs are two extremes of the possible methods used to standardize CPUE. The GLM models use little information about the structure of the relationships between CPUE and the explanatory variables, and use statistical methods to estimate parameters of the model. The traditional HBS includes the assumption that the relationships between CPUE and the explanatory variables are known without error, and use the current understanding and data to develop the HBS. A statistical HBS has been developed that allows the parameters of the sub-models used in the HBS to be updated, based on fitting to the observed catch and effort data (Hinton and Maunder 2003). The statistical HBS model also integrates the explanatory variables used in GLMs into the HBS. This is a much better approach because it combines powerful features of both the HBS and GLM models (Maunder *et al.* 2002).

One limitation of the statistical HBS is that the structural form of the HBS is fixed, based on scientific understanding. Often this understanding is based on other species or on the same species in different oceans. It is possible that the structure of the HBS model is incorrect, and may cause bias in the estimated year effects that are used in stock assessment models. Therefore, it would be beneficial to develop a model that has a flexible structure that can be estimated from the data.

A neural network allows a very flexible structure to the relationship between dependent and independent variables, and the data are used to estimate the relationship. Neural networks can be viewed as black boxes that take in explanatory variables and produce predictions, but do not provide the ability to easily interpret the relationship between them. If the year effect is all that is desired from the analysis, then as long as the neural network provides good estimates of the year effect, neural networks could be used to standardized CPUE data. Unfortunately, because of the difficulty of interpreting the explanatory variables, a standard neural network that takes the year as an input variable cannot be used. Therefore, the neural network must be modified to include a year effect.

We develop a method based on integrating a neural network with GLM-type categorical variables to standardize CPUE data. The year effect is included as a categorical variable, and can be used as an index of relative abundance. We use cross validation to determine the best neural network for the application. We test the neural network with simulated data based on the habitat model, and compare the results to a GLM. We apply this method to CPUE data for bigeye tuna in the Pacific Ocean.

ANALYTICAL METHODS

The method we describe is based on predicting the catch given the known level of fishing effort and choosing the values of the parameters of the model that produce predictions that are closest to the observed catch. Therefore, we must define a model that predicts catch and a measure of how close the predictions match the observations. A non-linear function optimizer is used to find those values of the parameters of the model that make the best predictions.

The model used to predict catch is divided into several components: the year effect, I; overall catchability, q; effort, E; continuous or discrete ordered explanatory variables, x; and categorical explanatory variables, p. The year effect is of interest to stock assessment scientists because it is used to represent the relative annual abundance of the population when doing stock assessments. The goal of the standardization process is to remove effects on CPUE that are not related to the abundance of the population, which is achieved through explanation of variance by the categorical variables and the neural network components. The methods can be viewed as integrating a GLM with a neural network.

The neural network component is used to include continuous variables or ordered discrete variables into the analysis. For example, continuous variables could include depth of the thermocline, sea-surface temperature, or vessel size; ordered discrete variables could include month or the number of hooks between floats for a longline. The neural network component is implemented, using a general equation to combine the explanatory variables. It has been shown that a single hidden layer in a neural network model can be used to approximate a variety of conditions (Funahashi 1989). We follow the general method of Chen and Ware (1999), which sums the weighted values of the explanatory variables, adds a bias term, and then passes them through a logistic function, with the logistic function serving as the neuron in the hidden layer. In our model (Figure 1) we simplify the network by having only a single hidden layer:

$$y_m = \phi_o \left\{ \beta_o + \sum_j w_j \phi_h \left(\beta_j + \sum_i w_{j,i} x_{i,m} \right) \right\}$$

where y_m is the output signal (dependent variable) at observation m; ϕ is the activation function [in our model logistic functions: $\phi(x) = (1+\exp(-x))^{-1}$] for the output layer; β_o is the bias for the output layer; $w_{j,i}$ is the weight between input signal i and hidden neuron j; ϕ_h is the activation function for the hidden layer; β_j is the bias for hidden neuron j; w_j is the weight of neuron j; and $x_{i,m}$ is the input signal (independent variable) i at observation m.

In this model, the neurons in the hidden layer are summed, a bias term is added, and then the sum is passed through a logistic function in the output layer. A single output layer represents the neural network contribution to the predicted catch. The number of neurons in the hidden layer determines the flexibility of the network, *i.e.* how well the model expresses the data, and can be modified to optimize performance of the model.

While it is normal to include explanatory variables in neural networks, and year may be included as an explanatory variable, it is not normal to obtain estimates of individual effects, *i.e.* parameter estimates, from networks, because the variables of interest generally have multiple significant interactions with other variables in the models, yet the estimate of the year effect is required as an index of relative abundance. To overcome this problem, we include the year effect as a separate set of categorical variables. Note that, in general, to prevent confounding of the categorical variables, in each variable the value in one category must be set to one. Predicted catch ($\hat{C}_m$) is equal to the product of the catchability standardized by the neural network, the overall catchability, the year effect and the effort: $\hat{C}_m = qI_t y_m E_m$, where q is the overall catchability, I_t is the year effect for year t, y_m is the neural network contribution to catchability for observation m, and E_m is the effort for observation m.

The neural network is not appropriate for explanatory variables that do not have a numerical order (many categorical variables, *e.g.* vessel). Therefore, using the method of Maunder (2001), we add additional terms for categorical explanatory variables that do not have a numerical order. Categorical explanatory variables that do have a numerical order (*e.g.* month) can either be added in this manner or included in the neural network component.

$$\hat{C}_m = qI_t y_m E_m p_a p_{b\ldots} p_n$$

where p_a represents the effect when the categorical variable *A* for observation *m* is in category *a*.

The type of interaction terms used in GLMs are incorporated in the neural network for ordered variables. Interaction terms with categorical variables can be implemented by having a different set of parameters for the neural network for each category of the categorical variable.

We use the likelihood function as a measure of how well the predicted catch from the neural network fits the observed catch. Since the level of catch differs significantly from observation to observation, a lognormal likelihood function which has a constant standard deviation is an appropriate choice. We also add a constant to the observed and predicted catch to avoid computational problems. The negative log-likelihood is minimized by simultaneously estimating the parameters of the neural network ($w_j, w_{j,i}, \beta_o, \beta_j$), the year effects (*I*), categorical variables (*p*), and the overall catchability (*q*). The likelihood equation is simplified in this case, because we are not estimating uncertainty or using the likelihood function for hypothesis testing. We use the function minimizer based on automatic differentiation in the AD Model Builder software package (Otter Research; http://otter-rsch.com/admodel.htm) to minimize the negative log-likelihood (ignoring constants):

$$-\ln L\left(data \mid parameters\right) = \left[\ln\left(C+1\right) - \ln\left(\hat{C}+1\right)\right]^2$$

Cross validation

There is the requirement to determine the number of neurons in the hidden layer. The objective of the analysis is to estimate the year effect. Therefore, it is not desirable to include a large number of parameters (neurons) so that the explanatory variables explain the year effect, but also it is not desirable to have two few parameters so that the year effect is influenced by factors other than the abundance. We use cross validation to determine how many neurons to include in the hidden layer. We randomly select 10 percent of the data as a test data set, and then fit the model to the remaining 90 percent of the data to obtain parameter estimates. These levels are consistent with levels for training sets and validation sets recommended by Amari *et al*. (1997) for the number of parameters and data sets used. We then use the parameter estimates to predict the catches for the test data set. We repeat this procedure for different numbers of neurons in the hidden layer. The model that gives the best prediction of the test data set, as determined by the negative log likelihood criteria, is selected as the best model. We note that cross validation can also be used to compare the results obtained from the neural network to results obtained from those obtained using more traditional methods, such as nominal effort and GLMs.

Starting values

The likelihood surface of the neural network often has multiple local optima. These local optima usually have similar prediction ability; however it is useful to investigate the different local minima to ensure that the analysis has not converged on a poor predictor. Therefore, it is important to investigate the estimates of the year effect with different random starting values for the neural network.

Simulation tests

We develop a simulation model based on the habitat model of Hinton and Nakano (1996). The model equations are given in the Appendix, and the following is a general description of the simulation. The fish are given a different preference level for each of 10 habitat strata, which are defined by depth. The fishing gear fishes at different depths, and the average depth fished has a trend toward greater depths over time. The depths are divided into 18 discrete categories to correspond to hooks per basket (HBP) used in tuna longlines (Hinton and Nakano 1996). The habitat strata change over time, based on a biased random walk, so that there is temporal correlation in the habitat. The population size also changes over time, based on a biased random walk with a declining trend. The data simulated are the catch, the month (the categorical variable), the depths of the 10 habitat strata, and the depth of each piece of fishing effort as one of the 18 categories. Ten observations are generated for each month, totaling 2400 data points.

We fit three models to the simulated data to estimate the year effect, (1) nominal effort, (2) GLM, and (3) neural network . The nominal effort model is implemented by simply estimating a year effect as a categorical variable. The GLM model is implemented by estimating a year effect while including month and depth of the fishing gear (18 categories) as categorical variables and the 10 depths of the habitat strata as 10 continuous quadratic variables. No interaction terms are used in the GLM, and all continuous variables are included in the analysis at the same time. The neural network is implemented with the depth of the fishing gear and the 10 depths of the habitat strata as variables of the neural network component and month as a categorical variable. For the neural network, we investigate the appropriate number of nodes in the hidden layer (3, 4, or 5) to use in the analysis.

The year effect from each of the models is normalized by the average, and then compared to the true year effect, which is also normalized. This is repeated 100 times. The median relative error, median absolute relative error, and median cross-validation scores are presented.

Application

We use the neural network to standardize CPUE and estimate the year effect for bigeye tuna in the Pacific Ocean from longline data in the area 20°S to 20°N and 140°E to 180°E. The catch (number of fish) and effort (number of hooks) data is summarized into 5° latitude by 5° longitude by month by HPB strata. A total of 23,870 records from 1975 to 2000 are used. The explanatory variables used are HPB, month, and temperature at depths of 40, 120, 200, 280, 360, and 440 meters. The objective function is weighted by $\ln(E_m)^2$, which is equivalent to weighting the standard deviation by $\ln(E_m)^{-1}$. We used the logarithm to reduce the influence of strata with extremely large effort (outliers). In the neural network application, month is used as a categorical variable, and HPB and depths are included in the neural network component. For the GLM application, month and HPB are used as categorical variables, and the depths are included as quadratics. For each neural network investigated (3, 4, and 5 hidden neurons) 5 different sets of starting values are used, and then the results for both the year effect and the cross validation score are averaged.

RESULTS

Simulations

The results are presented as medians, since for a few of the simulated data sets the neural network performed very poorly, inflating the mean (Table 1).

The estimated year effect from the nominal effort shows a significant bias, with a trend from negative bias in the early years to positive bias in the later years (Figure 2). This trend is due to the increasing depth of the fishing gear into habitat that has a greater abundance of fish over time. Therefore, using nominal effort would give the appearance of a population that is in a healthier state than is really the case (*e.g.* see Figure 3). The error in the estimate of the year effect from the nominal effort model is high for all years (Figure 4).

Both the GLM and neural network models do much better at estimating the year effect, with lower errors in the estimate of the year effect for all years (Figures 2 and 4). However, there is still a tendency to underestimate the year effect in the early years and overestimate it in the later years. The neural network does slightly better than the GLM method for all years (Figure 4). The neural network also produced smaller cross-validation scores (Table 1). The GLM performed better as more variables were included. It is interesting to note that including the continuous variables as quadratics substantially decreased the cross-validation score, but only slightly reduced the error in the estimate of the year effect (Table 1).

The neural network with three hidden neurons produced, on average, less error in the estimate of the year effect and lower cross-validation scores (Table 1). However, the neural network with four neurons produced a lower cross validation score 58 percent of the time. Using the cross-validation score to choose the number of neurons would choose three and four neurons about the same number of times. However, using the error in the estimated year effect, the neural network with three neurons would be chosen substantially more often. In fact, the cross-validation score would choose only the number of neurons (three, four or five) that gave the lowest error in estimated year effect 41 percent of the time.

When different random starting values were used with the neural network for one of the simulated data sets, the estimated year effect differed among the starting values (Figure 5). Starting values that gave lower cross validation scores in general gave less error in the estimates of the year effect (Figure 6).

Application

The cross-validation scores are improved for all models compared to the nominal effort (Table 3). The cross-validation scores for the GLM method are improved with the inclusion of the categorical variables and the continuous variables. The cross-validation scores suggest that a neural network with four hidden neurons is the optimal neural network, and is better than the GLM.

There is only a moderate difference in the year effect among all of the models (Figure 7). The biggest change from the nominal data is for the GLM that does not include the temperature data as continuous variables. This model estimates a greater decline in abundance than the other models. It is interesting to note that once the temperature data are included in the GLM the year effect moves back to being similar to the year effect from the nominal data. This suggests that the depth of the longline is not sufficient by itself, and that the environment that the longline is fishing in should also be considered.

The cross-validation scores differed enough among different starting values that some of the runs for the models with either three or five hidden neurons had lower cross-validation scores than some of the runs with four hidden neurons. However, the cross validation score from the GLM was never lower than the runs with four hidden neurons. The year effects from the different starting values were essentially identical, as were the year effects from the models with three, four, and five hidden neurons.

DISCUSSION

We have developed a neural network for standardizing CPUE data. This method works well at estimating the year effect, which can be used in stock assessment models. The neural network model was shown to perform better at estimating the year effect than nominal effort and a simple GLM model. We used cross validation as a method to choose the optimal neural network. Cross validation was shown to perform well at choosing a model with low average absolute relative error in the year effect, but did not always choose the model with the least error.

The performance of the neural network was not a substantial improvement over the simple GLM. Other formulations of the GLM (*e.g.* optimization by discarding some variables, including cubics or interaction terms) may have performed as well as the neural network. Wilson and Recknagel (2001) also found that the difference between multiple linear regression and a neural network was small for estimating algal abundance in freshwater lakes. However, the neural network shows promise, and simulations with different types of complex nonlinear relationships may indicate that, in some situations, the performance of the neural network is substantially better than a GLM. Modifications to the neural network, including additional hidden layers, constrained training, or different likelihood functions, may increase its performance.

One problem with the neural network model is that different estimates of the year effect can be obtained from different starting values. We have shown that starting values that give lower cross-validation scores also generally give less average absolute relative error in the year effect. Therefore, it is important that multiple starting values are used and that the estimates from those that give the least cross-validation score are used. It is also important to use multiple starting values when using cross validation to choose the number of neurons to use. Some form of model weighting based on the cross-validation scores may be a sensible way to combine results from multiple starting values, for example bagging (Wilson and Recknagel 2001).

The cross-validation test appears to be a reasonable method for selecting a model that has relatively low error. However, it may not always select the model with the least error. It is also possible that various randomly chosen training and test data sets will produce different results. It is also possible that choosing a different percentage of the data as a test set would also produce different results and high variance in predictions obtained from fitted models. Thus, it is important to determine how much of any data set should be devoted to training and how much to cross validation (Arami *et al*. 1997). If the neural network is used to predict observations that are underrepresented by the training data set, the method may not perform well. Therefore, for some applications, it is important to conduct tests that use groups of data (*e.g*. use all the data for a single year as the test data set), rather than using a random selection from all the data (Hilbert and Ostendorf, 2001). Note that our application is not used to predict observations that have yet to be recorded, and therefore a randomly selected test data set is appropriate.

The method we present is a black box for the neural network component. We did not attempt to determine which continuous variables had the most influence on the year effect. However, it is possible to some extent to investigate this influence. For example, Jeong *et al*. (2001) changed input values by ± 1 standard deviation and ± 2 standard deviations to determine the influence of each variable, and Reyjol *et al*. (2001) used a method based on the response of the partial derivative.

Other applications using neural networks are also applicable to fisheries research. Chen and Ware (1999) developed a neural network to predict recruitment of herring from several different explanatory variables. Neural networks could be used in place of population dynamics models to predict the abundance or catch in the next year. This method, termed recurrent neural networks, uses the predicted abundance in year t - 1 as an input in the model for year t. For example, Jeong *et al*. (2001) used neural networks to model the time series of phytoplankton abundance. Constrained training, where the results of the neural network are penalized by the predictions of a structural model (Scardi 2001) may be a way to combine neural networks with other models. The special issue of Ecological Modeling (Volume 146, issue 1-3) contains several other applications to ecological modeling.

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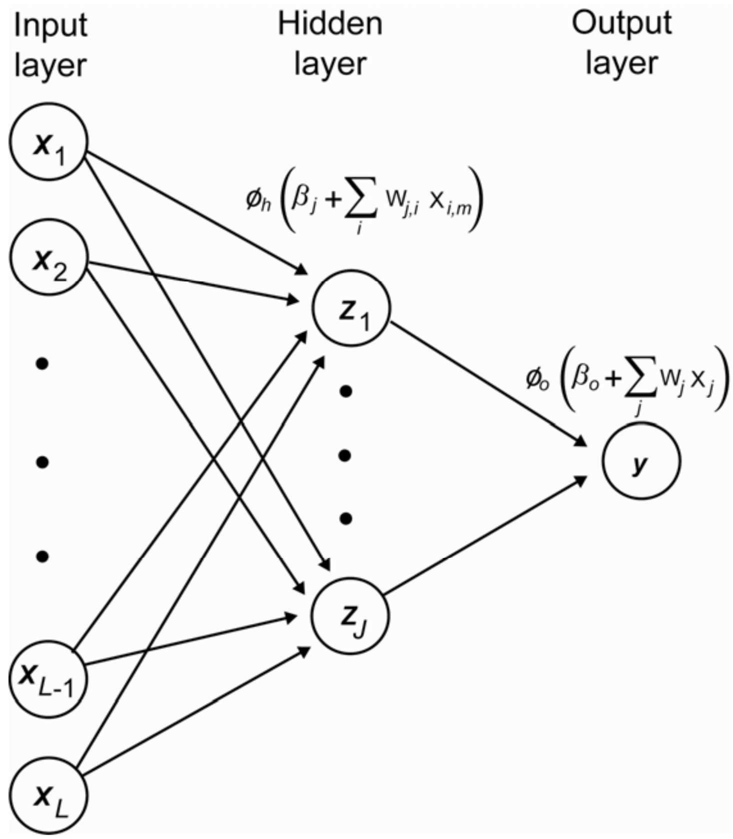

FIGURE 1. Structure of the neural network with a single hidden layer. *J* is the number of neurons in the hidden layer, *L* is the number of input variables, and z_j represents hidden node *j*.

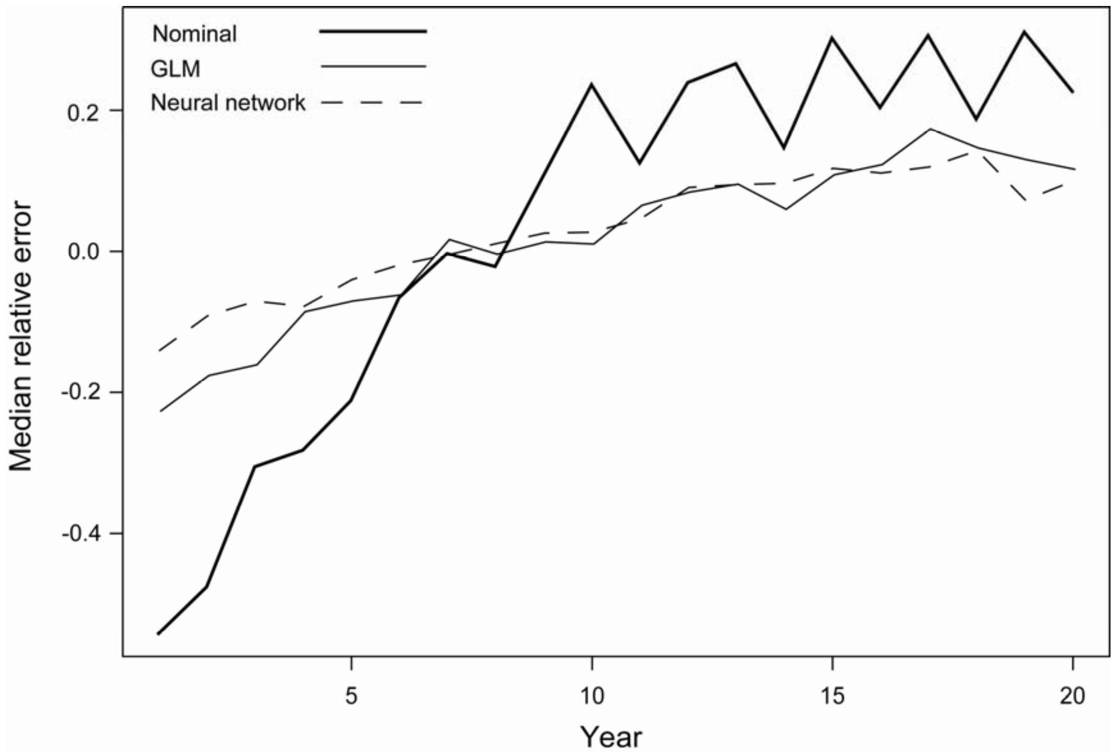

FIGURE 2. Median relative error for the three models tested over time.

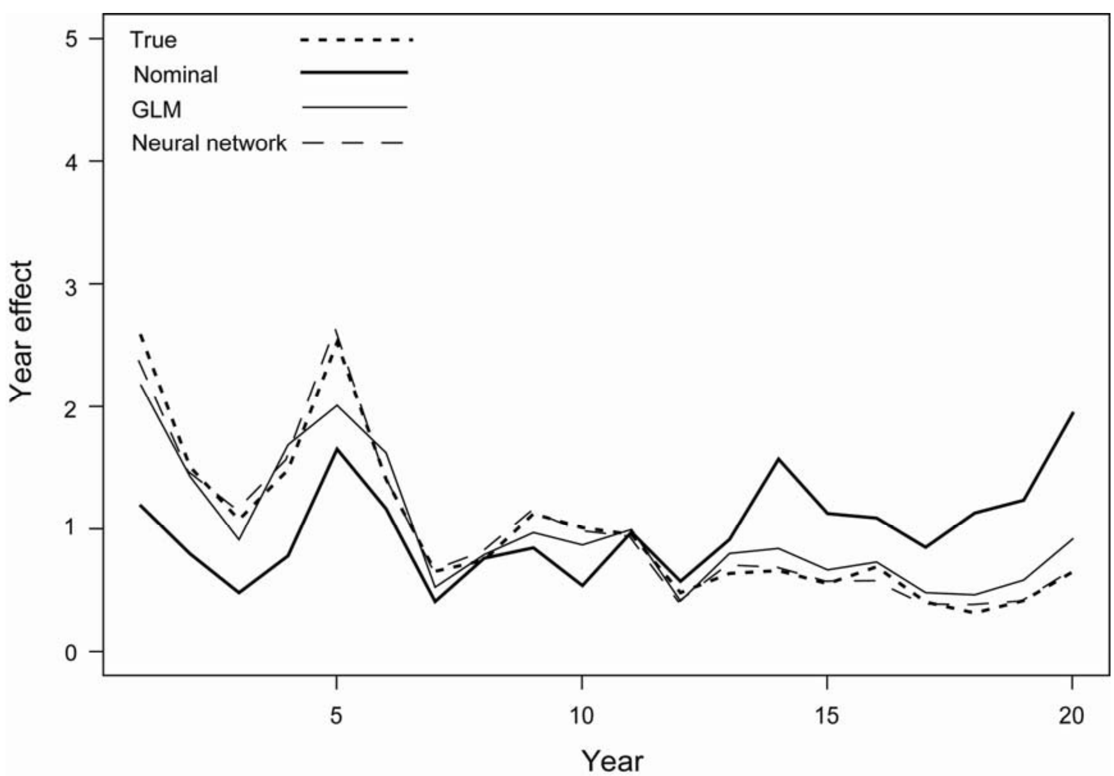

FIGURE 3. The estimated year effects from the three models compared to the true year effect for one realization of the simulated data.

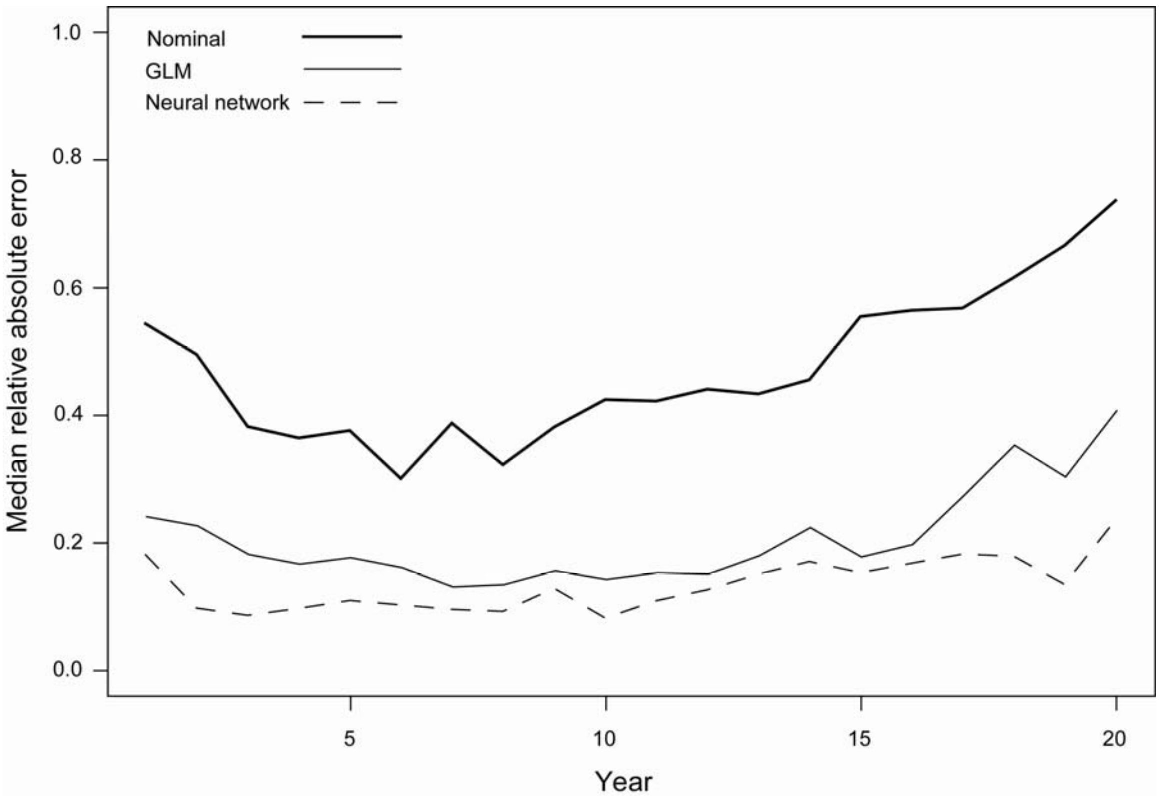

FIGURE 4. Median absolute relative error for the three models tested over time.

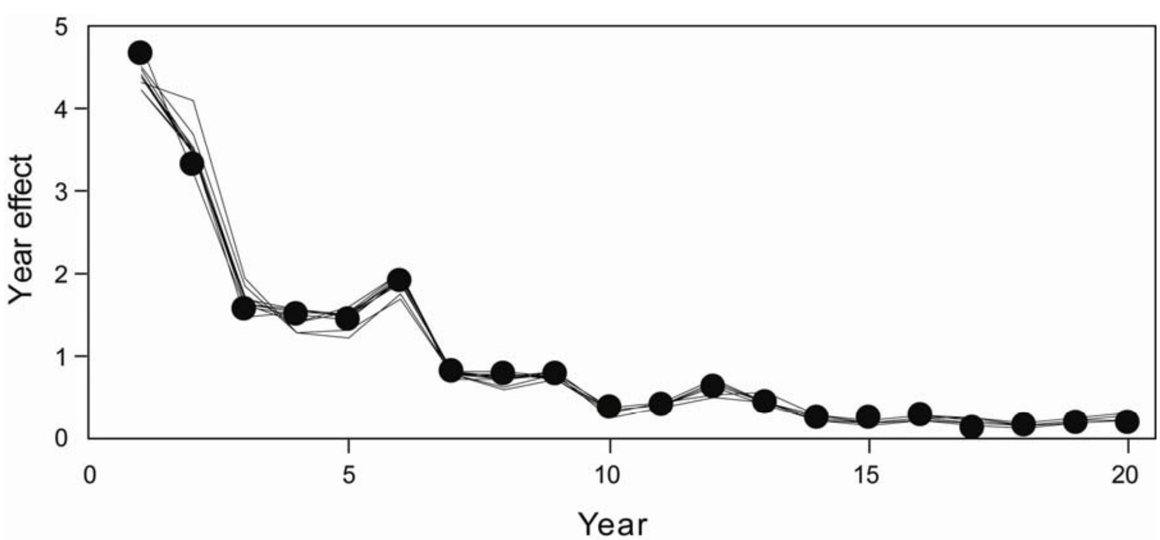

FIGURE 5. Estimates of the year effect from the neural network model with different starting values.

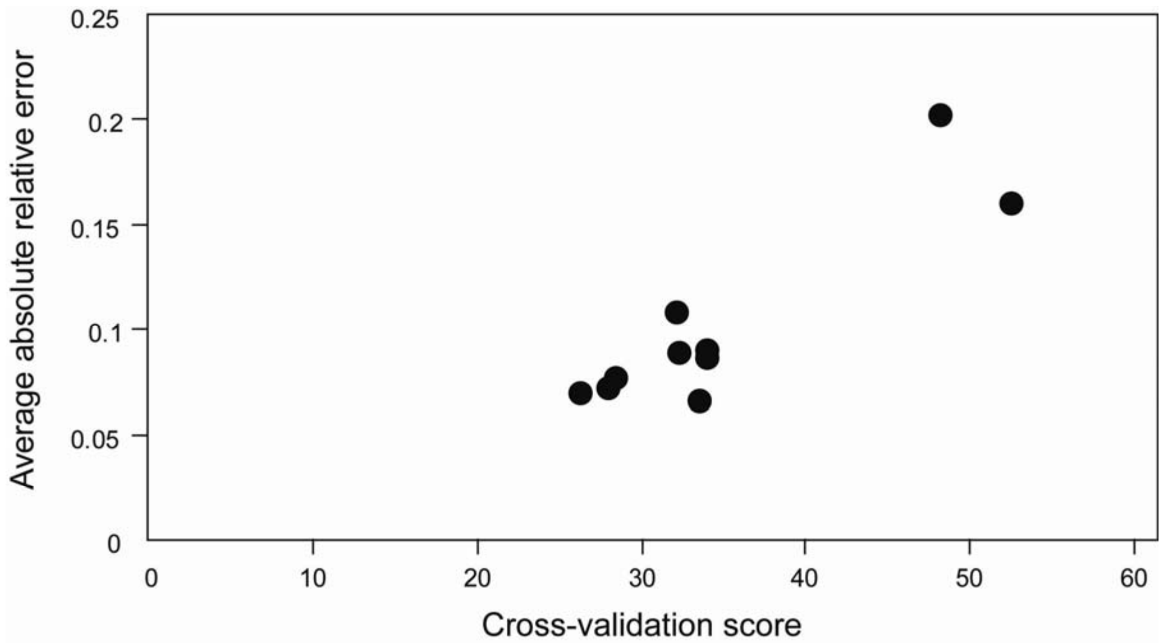

FIGURE 6. Comparison of the cross-validation score with the average absolute relative error for 10 different random starting values of the neural network.

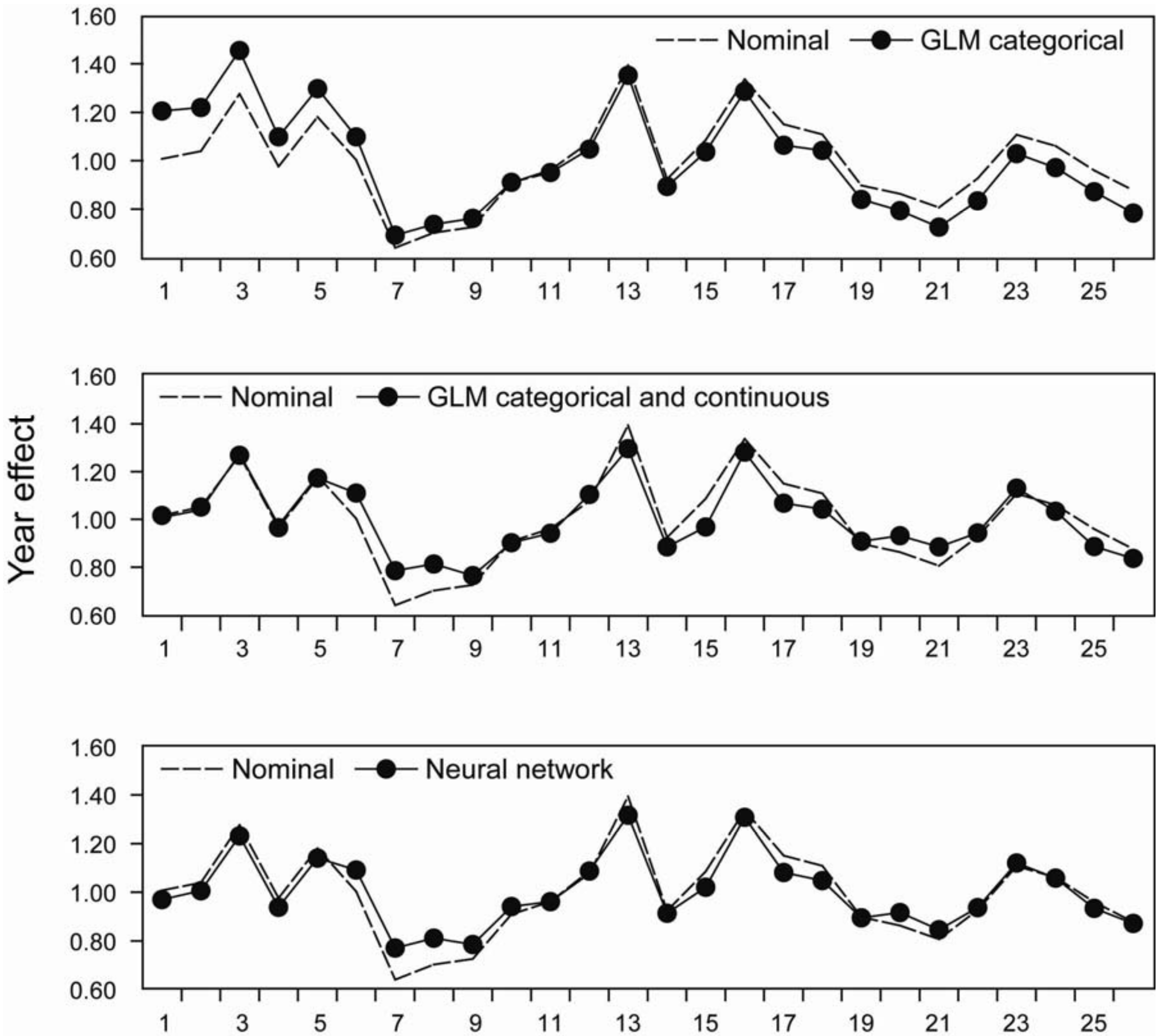

FIGURE 7. The year effect estimated by the GLM without including the depths as continuous variables (top panel), GLM including the depths as continuous variables (middle panel), and the neural network with four hidden neurons (bottom panel) compared to the year effect from nominal effort.

TABLE 1. Average cross-validation (cv) scores from the simulated data for several models. The cross-validation score is based on the negative log likelihood criteria.

Model	Variables	Number of parameters	Average absolute error	Median absolute error	Average cv score
Nominal	Year	20	0.62	0.46	482
GLM	Year, month	31	0.61	0.46	373
GLM	Year, month, depth	77	0.53	0.36	350
GLM	Year, month, depth, continuous	88	0.40	0.20	276
GLM	Year, month, depth, continuous as quadratic	99	0.39	0.19	229
Neural network	Year, month, 3 neurons	71	0.34	0.11	110
Neural network	Year, month, 4 neurons	84	0.55	0.13	126
Neural network	Year, month, 5 neurons	97	0.58	0.18	144

TABLE 2. The proportion of times that the neural networks with different numbers of neurons had the least average absolute error and cross-validation scores.

Number of neurons	Error	Cross validation
3	0.48	0.38
4	0.29	0.39
5	0.23	0.23

TABLE 3. Cross-validation (cv) scores for the different models applied to the bigeye tuna data.

Model	Number of parameters	cv score
Nominal	26	1803
GLM categorical	42	1751
GLM categorical and continuous linear	49	1491
GLM categorical and continuous quadratic	56	1447
Neural network with 3 hidden neurons	65	1428
Neural network with 4 hidden neurons	74	1407
Neural network with 5 hidden neurons	83	1411

APPENDIX

Simulated data

The following set of equations describes the model used to generate the simulated data. The parameter values used are presented in Table A1.

$$C_m = I_t p_s H_m q E_m \exp\left(\varepsilon_m\right)$$

$$\varepsilon_m \sim N\left(0, \sigma^2\right)$$

$$H_m = if \begin{cases} d_m \le 0 & = 0 \\ 0 < d_m \le D_1 & = h_1 \\ D_1 < d_m \le D_2 & = h_2 \\ . & . \\ . & . \\ . & . \\ D_{n-1} < d_m \le D_n & = h_n \\ D_n < d_m & = 0 \end{cases}$$

$$d_m = \left(1 + r_d\right)^{t-1} \exp\left(\varepsilon_d\right)$$

$$\varepsilon_d \sim N\left(0, \sigma_d^2\right)$$

$$D_1 = U\left(0, D_{\max}\right)$$
$$D_2 = D_1 + U\left(0, D_{\max}\right)$$
$$.$$
$$.$$
$$.$$
$$D_n = D_{n-1} + U\left(0, D_{\max}\right)$$

$$D_{\max} = \mu_t^D \exp\left(\varepsilon_D\right)$$

$$\varepsilon_D \sim N\left(0, \sigma_D^2\right)$$

$$\mu_t^D = \mu_{t-1}^D \left(1 + r_{\mu D}\right) \exp\left(\varepsilon_{\mu D}\right)$$

$$\varepsilon_{\mu D} \sim N\left(0, \sigma_{\mu D}^2\right)$$

$$I_t = I_{t-1}\left(1 + r_{year}\right)\exp\left(\varepsilon_I\right)$$

$$\varepsilon_I \sim N\left(0, \sigma_I^2\right)$$

where C_m is the catch for observation m, I_t is the year effect for year t, p_s is the month effect for month s, H_m is the habitat effect for observation m, q is the overall catchability, E_m is the effort for observation m, $D_{m,j}$ is the depth lower bound of habitat j for observation m, d_m is the depth of gear for observation m, r_d is the trend term for depth of gear, D_{max} is the maximum depth range within a habitat, $r_{\mu D}$ is the trend term for the mean of the maximum depth range of a habitat, r_{year} is the trend term for abundance, h_j is the habitat preference for habitat j.

TABLE A1. Parameter values used in the simulator.

Parameter	**Value**	**Parameter**	**Value**	**Parameter**	**Value**
σ	0.2	h_6	37	σ_d	0.2
h_1	1	h_7	40	σ_D	0.4
h_2	5	h_8	25	$r_{\mu D}$	0
h_3	10	h_9	8	$\sigma_{\mu D}$	0.2
h_4	20	h_{10}	2	r_I	-0.05
h_5	30	r_d	0.075	σ_I	0.5
h_5	30	r_d	0.075	σ_I	0.5

The IATTC's responsibilities are met with two programs, the Tuna-Billfish Program and the Tuna-Dolphin Program. The principal responsibilities of the Tuna-Billfish Program are (1) to study the biology of the tunas and related species of the eastern Pacific Ocean to estimate the effects that fishing and natural factors have on their abundance, (2) to recommend appropriate conservation measures so that the stocks of fish can be maintained at levels that will afford maximum sustainable catches, and (3) to collect information on compliance with Commission resolutions. The principal responsibilities of the Tuna-Dolphin Program are (1) to monitor the abundance of dolphins and their mortality incidental to purse-seine fishing in the eastern Pacific Ocean, (2) to study the causes of mortality of dolphins during fishing operations and promote the use of fishing techniques and equipment that minimize these mortalities, (3) to study the effects of different modes of fishing on the various fish and other animals of the pelagic ecosystem, and (4) to provide a Secretariat for the International Dolphin Conservation Program.

An important part of the work of the IATTC is the prompt publication and wide distribution of its research results. The Commission publishes its results in its Bulletin, Special Report, and Data Report series, all of which are issued on an irregular basis, and its Stock Assessment Reports and Fishery Status Reports, which are published annually.

The Commission also publishes Annual Reports and Quarterly Reports, which include policy actions of the Commission, information on the fishery, and reviews of the year's or quarter's work carried out by the staff. The Annual Reports also contain financial statements and a roster of the IATTC staff.

Additional information on the IATTC's publications can be found in its web site.

La CIAT cumple sus obligaciones mediante dos programas, el Programa Atún-Picudo y el Programa Atún-Delfín. Las responsabilidades principales del primero son (1) estudiar la biología de los atunes y especies afines en el Océano Pacífico oriental a fin de determinar los efectos de la pesca y los factores naturales sobre su abundancia, (2) recomendar medidas apropiadas de conservación para permitir mantener los stocks de peces a niveles que brinden las capturas máximas sostenibles, (3) reunir información sobre el cumplimiento de las resoluciones de la Comisión. Las responsabilidades principales del segundo son (1) dar seguimiento a la abundancia de los delfines y la mortalidad de los mismos incidental a la pesca con red de cerco en el Océano Pacífico oriental, (2) estudiar las causas de la mortalidad de delfines durante las operaciones de pesca y fomentar el uso de técnicas y aparejo de pesca que reduzcan dicha mortalidad al mínimo, (3) estudiar los efectos de distintas mortalidades de pesca sobre los varios peces y otros animales del ecosistema pelágico, (4) proporcionar la Secretaría para el Programa Internacional para la Conservación de los Delfines.

La pronta publicación y amplia distribución de los resultados de investigación forman un aspecto importante de las labores de la Comisión, la cual publica los resultados en su serie de Boletines, Informes Especiales, e Informes de Datos, publicados a intervalos irregulares, y sus Informes de Evaluación de Stocks y Informes de la Situación de la Pesquería, publicados anualmente.

La Comisión publica también Informes Anuales e Informes Trimestrales; éstos incluyen información sobre las labores de la Comisión, la pesquería, y las investigaciones realizadas en el año o trimestre correspondiente. Los Informes Anuales incluyen también un resumen financiero y una lista del personal de la CIAT.

En el sitio de internet de la CIAT se presenta información adicional sobre estas publicaciones.

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