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Effects of environmental conditions and fishing operations on the performance of a bottom trawl

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Trawl performance was studied based on net spread and variability in the contact of the footrope with the seabed and their relationship with vessel operations, catch weight, and environmental conditions. Artificial neural networks (ANNs) and generalized additive models (GAMs) were used to model the response of each variable. For the variables net spread and variability in footrope contact (VFC), the ANN models were more accurate than the GAMs, with greater generalization capacity in the validation phase. In the best ANN model for net spread, all variables were significant. The relationship between tow direction and wind direction (tactic) was most important in the sensitivity analysis. Net spread increased with increasing towing speed and windspeed, and decreased with increasing wave height. In the ANN model for VFC, there were differences among vessels, and both scope ratio and catch size were not significant. VFC increased with increasing depth and decreased with increasing towing speed and windspeed. The results demonstrate that both operational variables and environmental conditions affect trawl performance, and suggest that survey protocols designed based on this information might help to improve the precision of biomass estimates.

Keywords: catch weight, crustacean trawl, environmental conditions, fishing operations, footrope contact, net spread.

Introduction

There have been crustacean fisheries for nylon shrimp (*Heterocarpus reedi*), yellow squat lobster (*Cervimunida johni*), and red squat lobster (*Pleuroncodes monodon*) off the Chilean coast (26–38°S) since the 1950s (Acuña *et al.*, 2003). Economic interest in these species and massive reductions in biomass have made it necessary to regulate the catch through annual catch quotas, which are based on the results of surveys performed on board chartered trawlers, each using its own bottom trawl. These trawls are similar in construction and, for stock assessments, are assumed to have equal catching efficiency. However, they are not certified as identical or standardized sampling trawls, and in all likelihood the results challenge the primary assumption of equal catching efficiency. The difference in the objectives of commercial fishing (i.e. to maximize the catch) and scientific sampling (i.e. to maintain a constant trawl efficiency) and its concomitant effects on trawl design and repair are rarely appreciated by commercial fishers (ICES, 2009), so cannot be overlooked by researchers.

A major area of uncertainty in trawl surveys is the effect of changes in catchability on estimates of abundance attributable to changes in trawl geometry and performance (Carrothers, 1981). Minimizing these errors to an acceptable level needs to be the focus in any survey operation (Walsh and McCallum, 1997). Standardization is important to keep the performance and the efficiency of the survey trawl gear consistent between stations and over time, thereby ensuring that differences in survey catch per unit effort reflect real changes in stock distribution and abundance (ICES, 2009; Kotwicki *et al.*, 2011). Some of the key standardization aspects of trawl surveys include the vigilant control and monitoring of trawl deployment in the field, the subsequent screening and analyses of trawl geometry data that may enter into tow validation decisions, and the careful observation of other variables related to vessel operations and the environment

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that may affect trawl performance and hence capture efficiency (Koeller, 1991; Zimmermann *et al.*, 2003; ICES, 2009). Fishing protocols need also be standardized to reduce the number of invalid hauls and to improve the consistency of trawl surveys (Walsh and McCallum, 1997; Zimmermann *et al.*, 2003; von Szalay, 2004).

In the past decade, some improvements have been incorporated into crustacean trawl surveys in Chile. Among these, the use of net-spread sensors from 2002 and the use of bottom-contact sensors (BCSs) from 2004, to determine the real start and endpoint of hauls, have been particularly valuable. However, the records from both instruments exhibit significant differences between hauls by the same vessel, which may be associated with the topography of the seabed, operational conditions of the vessel, or environmental conditions of the sea (Melo *et al.*, 2004). In this respect, Weinberg and Kotwicki (2008) demonstrated that differences in trawl performance, in terms of net spread and bottom contact, depend on several variables related to a vessel's operation, the catch weight, and the environmental conditions. For example, the contact of a light footrope with the seabed can decrease with increasing net speed through the water, such as may be caused by variable bottom currents or vessel operation (Somerton and Weinberg, 2001), reducing the capture efficiency for some species in trawl surveys (Weinberg *et al.*, 2002). Trawl performance may also be influenced by other environmental conditions such as depth, windspeed, wave height, and sea state, thus affecting catch rates (Maynou and Sardà, 2001; Poulard and Trenkel, 2007; Stewart *et al.*, 2010; Wieland *et al.*, 2011).

In Chile, a new trawl is currently undergoing evaluation for crustacean fisheries and could be used in future surveys. The transition to new trawl gear offers an opportunity also to make changes to survey practice. Therefore, this study focused on determining whether vessel operations, catch weight, and environmental conditions affect the performance of trawl gear. Relationships between these variables could be complex, so we applied two techniques of high capacity to fit linear and non-linear relationships between dependent and independent variables. Understanding the effects on trawl performance will contribute to the development and improvement of sampling protocols for future trawl surveys.

Material and methods

Vessels and trawl gear

During the evaluation of the new trawl for Chilean crustacean fisheries, several hauls were made to acquaint the skippers with the gear and to test the operational performance of the trawl under different operating conditions. To study trawl performance, we analysed a set of 34 hauls made on traditional fishing grounds (29°30–33°00′S) with muddy and sandy substrata. The hauls were made by four fishing vessels with overall lengths and engine powers ranging from 18 to 21 m and from 350 to 450 hp, respectively. All vessels used the same net design, consisting of a two-panel crustacean trawl of 28.8-m headrope and 32.9-m footrope. The nets were made of knotted polyethylene with mesh sizes of 80 mm for the upper panel, 54 mm for the lower panel, and 56 mm for the codend. The footropes were in two sections: (i) a 3.9-m central section with a diameter of 150 mm (ø), consisting of a chain (ø = 13 mm) protected by a wrapping of polyamide (PA) netting and mixed (PA–polypropylene) rope, and (ii) a 14.5-m section in each wing consisting of a steel wire (ø = 19 mm) with rubber discs (ø = 100–150 mm). Trawl configuration was standardized where possible, using sweep and bridle lengths of 1 and 5 m, respectively, and the otter boards used were V-style weighing between 280 and 350 kg each.

Variables and instrumentation

Trawl performance was determined from measurements of two variables. The first was net spread, which was measured from wing tip to wing tip (± 0.1 m) with an acoustic sensor (Trawlmaster, Notus Electronics) at intervals of 15–20 s. The second was the contact between the footrope and the seabed. In this case, a calibrated BCS (Mac Marine Instruments) was used to measure the tilt-angle of the central section of the footrope (Weinberg and Somerton, 2006). The sensor registered data at 1-s intervals and recorded the average value every 5 s. To avoid irregularities in the seabed, especially the effect of slope, the variability of the tilt-angle was calculated at 60-s intervals (corresponding to the s.d. of 12 consecutive records) and used as a proxy for footrope performance. Variability in footrope contact (VFC) with the seabed was related to the average value of the acoustic records of net spread over the same time-interval (corresponding to 3–4 records). Although tow duration varied between 15 and 35 min, we discarded the first ca. 5 min of data from data analysis to allow for stabilization of the trawl. Similarly, the analyses did not consider data recorded at the end of the tow during wire retrieval.

The variables that might explain changes in trawl performance were classified into three categories, according to Weinberg and Kotwicki (2008): (i) vessel operation, (ii) catch weight, and (iii) environmental conditions. The first category included trawl speed, scope ratio, towing direction, and vessel. The last variable was included to incorporate the variation attributable to the unique characteristics and skippers of each vessel. Trawl speed was expressed as the average values of the records obtained from a Global Positioning System (GPS). Somerton and Weinberg (2001) demonstrated that speed through water is a better indicator than speed estimated from positional data, but the latter measurement was used owing to its ease of recording. The length of trawl wire used during a tow was determined by the skippers as a function of depth. The relationship between the length of wire and the average depth defines the scope ratio, which is a fixed value throughout the tow. Tow direction was obtained directly from the gyrocompass, using the mean value of the start and the end readings of the tow for analysis. The second category consisted of catch weight, which was ln-transformed. As the trawls lacked catch sensors, we assumed that the catch entered the net in a homogeneous and proportional manner during each haul. The third category included towing depth, wave height, wind direction, and windspeed. Depth was expressed as an average value of the records obtained from the echosounder. To obtain more-representative data, all vessels carried out the same number of hauls below and above a depth of 300 m. Moreover, wave and wind data were estimated by the skippers (who each had more than 15 years of fishing experience) and were compared with the sea states on the Beaufort scale.

During previous surveys, skippers changed their fishing tactics in response to wind direction and speed. In central Chile, the fishing area is characterized by winds mainly from the south and southwest, whereas the isobaths of the fishing grounds run in a north–south direction. Taking advantage of these characteristics, the tow direction (operational) and wind direction

(environmental) were incorporated as dummy variables referred to as the "tactic". The possible values of tactic were 0 if the trawl was made in the same direction as the wind, or 1 if the trawl was made against the direction of the wind. In all, eight independent variables were used in the analyses.

Modelling techniques and data analyses

Trawl performance, expressed in terms of net spread and VFC, was modelled using generalized additive models (GAMs) and artificial neural networks (ANNs). These techniques were selected because both have a good capacity to fit linear and non-linear relationships between dependent and independent variables.

A GAM is a generalization of a multiple linear regression. Specifically, in a linear regression, a linear least-squares fit is computed for a set of predictors or q variables to predict a dependent variable. The generalization of the multiple regression models implies maintaining the additive nature of the model, but replacing the simple terms of the linear equation by a non-parametric function. Therefore, instead of a single coefficient for each variable (additive term) in the model, in GAMs, an unspecified (non-parametric) function is estimated for each predictor to achieve the best prediction of the dependent variable values (Hastie and Tibshirani, 1990). In this study, Gamma distribution models were fitted to the data with logit link functions and cubic spline smoothing function in the GAMs. To avoid the use of an overly complex model and overfitting the data, we used a conservative view, so only models with 3 degrees of freedom were calibrated. The effects of the variables on net spread and VFC were modelled using the R package mgcv (Wood, 2006).

ANNs are heuristic models inspired by the neural architecture of biological nervous systems. The most widely studied and used ANN models involve multilayer feed-forward networks or multilayer perceptrons (Rumelhart *et al.*, 1986). These models "learn" in an iterative way, whereby the data are introduced a number of times to the neural network until a predetermined level of error is reached. ANNs are faster than other statistical techniques when the problem is complex and do not require *a priori* knowledge of the underlying process or assumptions of the structure of the target function (Aertsen *et al.*, 2010). Detailed descriptions of the performance of multilayer perceptron ANNs have been published by several authors (e.g. Hsu *et al.*, 1995; ASCE, 2000a, b; Shrestha *et al.*, 2005; Gutiérrez-Estrada *et al.*, 2007; Pulido-Calvo and Portela, 2007).

Before model calibration, the dataset was randomly divided into calibration (CS), selection (SS), and validation (VS) subsets. The first two (CS and SS) were used during the training process; specifically, CS was used for ANN calibration or learning, and SS for internal validation, allowing the ANN training process to stop avoiding over-learning effects. These subsets were composed of 70 and 15% of the data, respectively. The validation subset, 15% of the remaining data, was not used during the training process, but the trained network was applied to this subset to test the final performance of the model. To obtain valid comparisons, we used the same data subsets for GAM and ANN. The subset used for the ANN calibration and selection stage (CS and SS) was used to fit the GAM, and the subset used for the ANN testing stage (VS) was used for the GAM prediction.

In relation to the ANN analysis, the process included three stages: (i) exploratory analysis, (ii) calibration and selection, and (iii) testing. The exploratory analysis was performed using the Intelligent Problem Solver (IPS) function of the software Statistica 7, and it consisted of identifying the appropriate net architecture using the highest coefficients of determination (r^2). For this procedure, we used a multilayer perceptron structure (Rumelhart *et al.*, 1986), testing 200 networks with 1 or 2 hidden layers, using between 5 and 20 neurons in each layer. The best neural configurations were used in the second stage, in which a learning process based on the Levenberg–Marquardt algorithm (Shepherd, 1997) was applied. This process consists of a second-order, non-linear optimization algorithm that guarantees local convergence. In the final two stages, 30 neural networks were calibrated for each neural configuration identified during the exploratory analysis using the Custom Network Designer (CND) function of the software Statistica 7.

The contribution of each variable was verified through a sensitivity analysis based on the approach of the missing-value problem. The analysis was carried out by replacing each selected input variable with missing values and assessing the effect of this on the output error. The newly calculated error was compared with the original error to obtain a ratio (error of the model with an input variable with missing values/error of the model with all selected input variables). Hence, for any input variable x, a ratio equal to or very close to 1 indicated that the variable had a very low weight in the general structure of the model (Hunter *et al.*, 2000).

The error measurements used for each model were the coefficient of determination (r^2), root mean square error (RMSE), standard error of prediction (%SEP), mean absolute error (MAE), average relative variance (ARV), and coefficient of efficiency (E_2; Nash and Sutcliffe, 1970; Kitanidis and Bras, 1980; Ventura *et al.*, 1995; Legates and McCabe, 1999). The estimated error measurements for each neuronal configuration were compared using analysis of variance (ANOVA; $\alpha = 0.05$). A Tukey *post hoc* analysis (HSD) was performed to identify the best configuration during the calibration and selection stages. In both GAM and ANN modelling methods, non-significant variables based on highest p-values ($p > 0.05$) were removed to obtain the final model.

Results

Hauls were made at depths of 140.5–393.5 m at an average trawl speed of 1.9 knots (Table 1). Wire length used in the hauls depended basically on depth and varied from 350 to 850 m. The wire scope ratio averaged 2.2-fold the depth, ranging from 1.8- to 2.6-fold. Average catch was 272.6 kg, and single catches ranged from 72 to 570 kg. More than 80% of the total catch

Table 1. Summary statistics for each dependent and independent variable.

Variable	Mean	Minimum	Maximum
Wave height (m)	0.9	0.1	4.0
Windspeed (knots)	9.0	1.0	27.0
Wind direction (°)	220.8	45.0	270.0
Depth of tow (m)	271.7	140.5	393.5
Towing speed (knots)	1.9	1.3	2.2
Tow direction (°)	166.0	0.0	355.0
Wire length (m)	585.3	350.0	850.0
Scope ratio (wire length/depth)	2.2	1.8	2.6
Net spread (m)	15.7	11.8	18.8
Tilt-angle of the footrope (°)	9.4	0.1	46.7
Total catch (kg)	272.6	72.0	570.0

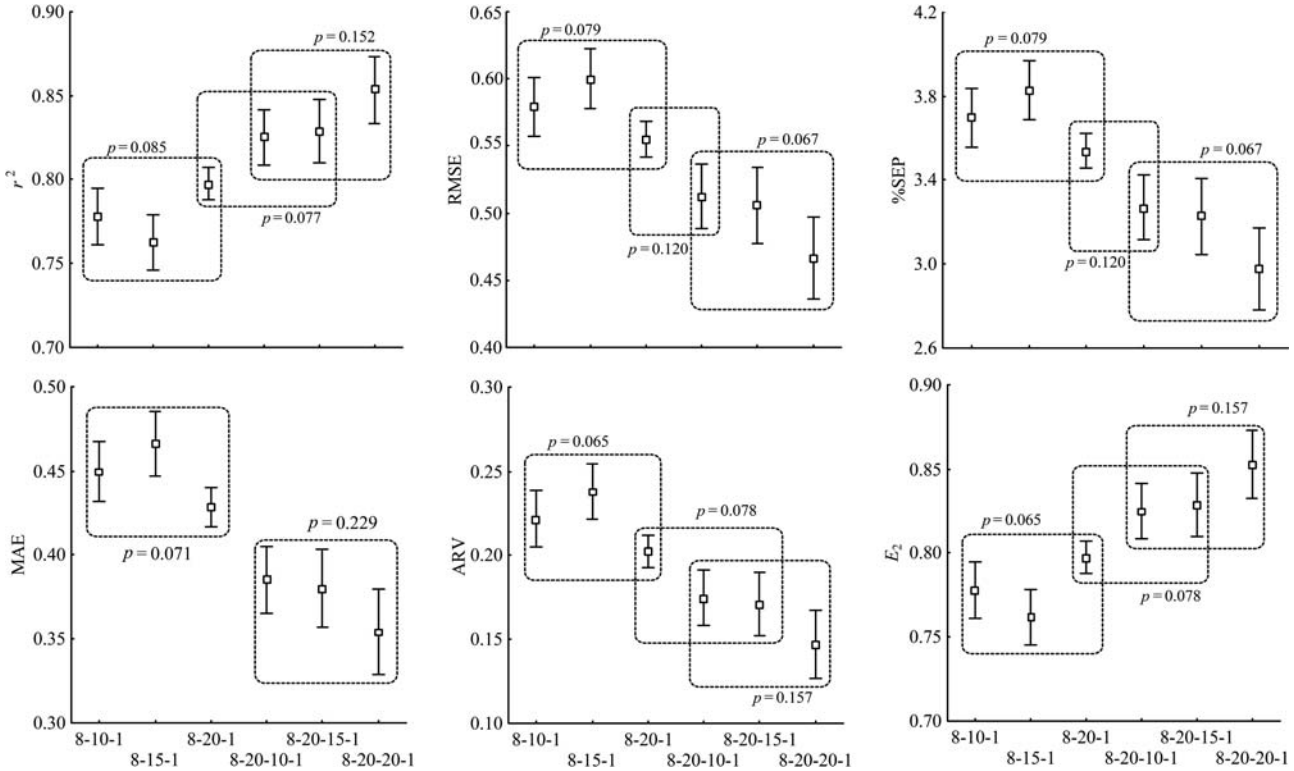

Figure 1. Error terms for ANN models of net spread during the calibration phase. The groups surrounded by dashed lines indicate models that do not differ significantly according to Tukey's test ($p > 0.05$).

consisted of nylon shrimp and yellow squat lobster. In terms of environmental conditions, average wave height was 0.9 m, ranging from 0.1 to 4.0 m. Average windspeed was 9 knots, ranging from 1 to 27 knots. Southwesterly winds dominated during the hauls.

Net spread

In the IPS exploratory analysis, we determined that the best network architecture could include one or two hidden layers. In the former case, the number of neurons ranged from 10 to 20, but in the latter case, the first hidden layer was made up of 20 neurons, and the second of 10–20. Based on these parameters, six architectures with eight variables input and one output were trained: three architectures with one hidden layer (8-10-1, 8-15-1, and 8-20-1) and three with two hidden layers (8-20-10-1, 8-20-15-1, and 8-20-20-1).

During the calibration and selection stage, the ANOVA of the error terms (r^2, RMSE, %SEP, MAE, ARV, and E_2) showed significant differences among networks ($p < 0.05$). In general, the best mean absolute results were obtained with two hidden layers of ANN. However, a *post hoc* analysis (Tukey's HSD test) did not show significant differences ($p > 0.05$) between the neural configurations 8-20-1 and 8-20-10-1 (Figure 1). Therefore, the ANN with two hidden layers and the least complexity (8-20-10-1) was selected.

In the ANN sensitivity analysis, all predictive variables exhibited significant ratios. Among them, tactic was the most important variable (ratio = 2.37), and the scope ratio the least important (ratio = 1.60; Table 2). No variables were removed from the analysis. Net spread increased with increasing towing speed and windspeed and decreased as a function of increasing wave height, catch, and scope ratio. Net spread also increased with increasing depth, but only from 250 m (Figure 2).

Table 2. Sensitivity analysis of the selected ANN model (8-20-10-1) and GAM results for net spread.

Variable	ANN		GAM (linear terms)		
	Ratio	Ranking	Estimate	*t*-value	*p*-value
Intercept	–	–	2.71	108.82	<0.001
Tactic	2.37	1	0.03	2.36	0.019
Vessel	1.83	5	0.01	0.06	0.956
			GAM (smoothing terms)		
			EDF	*F*	*p*-value
Depth of tow	1.91	2	1.99	15.48	<0.001
Wave height	1.88	3	2.57	44.32	<0.001
Towing speed	1.85	4	2.74	2.80	0.041
Windspeed	1.81	6	2.00	28.40	<0.001
Catch	1.65	7	2.26	4.73	0.004
Scope ratio	1.60	8	2.73	5.98	<0.001

EDF, estimated degrees of freedom.

The GAM of net spread was expressed as: net spread ~ vessel + s(depth) + s(wave height) + s(towing speed) + s(windspeed) + tactic + s(ln catch) + s(scope ratio). In the fitted model, all variables were significant ($p < 0.05$), except for vessel ($p = 0.956$; Table 2). The explained variance (r^2) of the model was 0.58 when excluding the vessel variable. Figure 3 shows the effect of each continuous variable on net spread. The curves show tendencies similar to those shown by the selected ANN model,

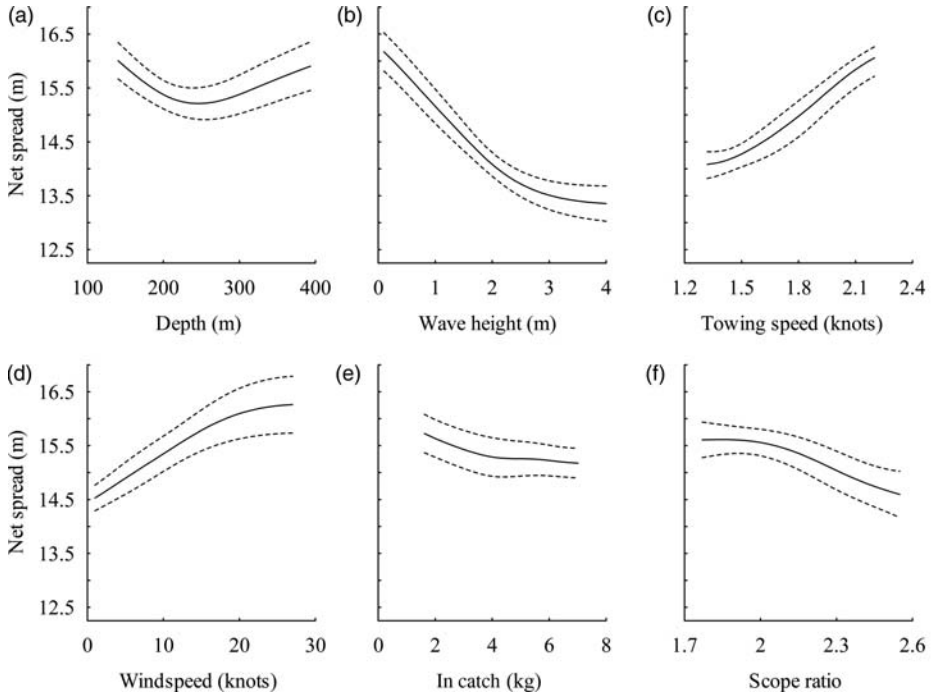

Figure 2. Mean response (solid lines) and 95% confidence intervals (dashed lines) of net spread to significant terms in the best neural network model (8-20-10-1). (a) Depth; (b) wave height; (c) towing speed; (d) windspeed; (e) ln catch; (f) scope ratio.

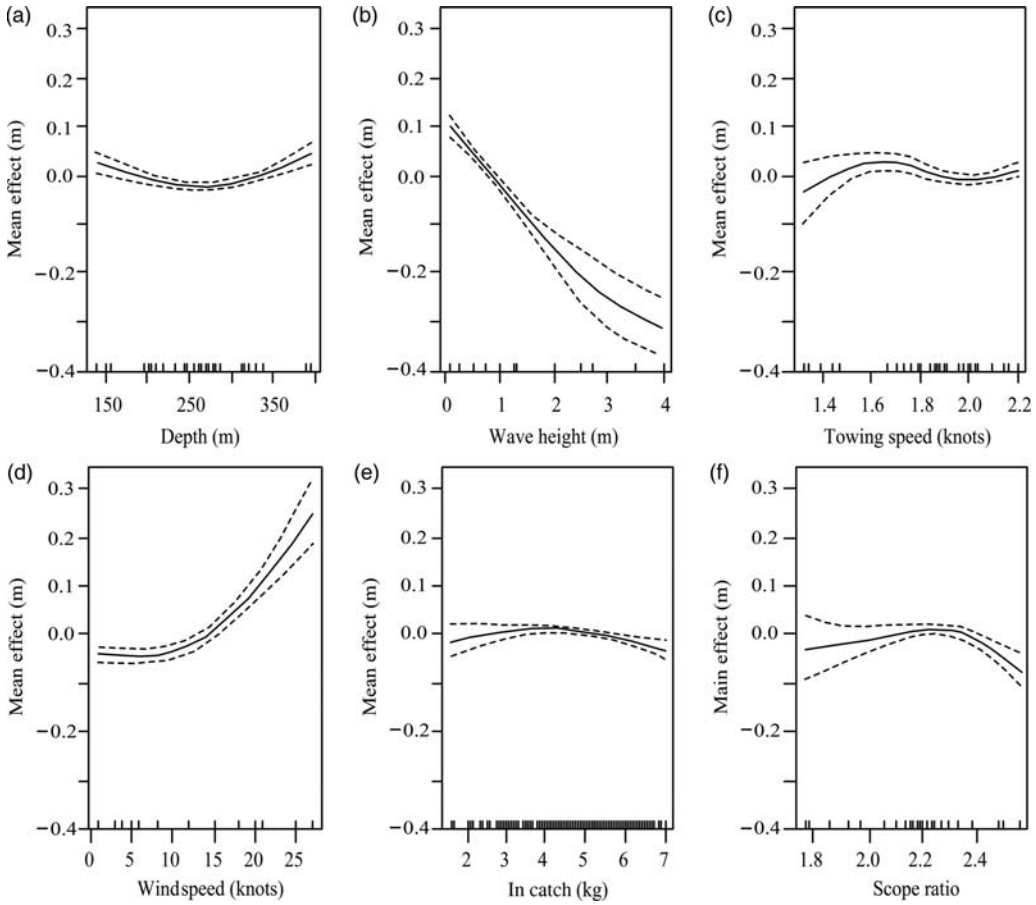

Figure 3. Mean effects (solid lines) and 95% confidence intervals (dashed lines) of significant terms on net spread in the GAM. (a) Depth; (b) wave height; (c) towing speed; (d) windspeed; (e) ln catch; (f) scope ratio.

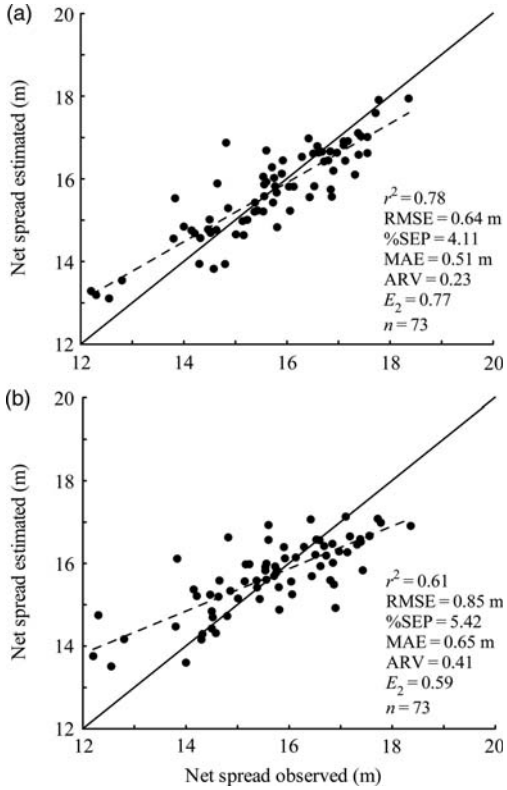

Figure 4. Linear regression between observed and estimated net spread from the (a) ANN model, and (b) the GAM during the testing phase (external validation). The error terms of each model are also shown.

Table 3. Sensitivity analysis of the selected ANN model (6-10-1) and GAM results for VFC, both excluding the catch and scope-ratio variables.

Variable	ANN		GAM (linear terms)		
	Ratio	Ranking	Estimate	*t*-value	*p*-value
Intercept	–	–	−0.52	−2.88	0.004
Vessel	1.79	1	0.40	6.57	<0.001
Tactic	1.42	4	0.01	0.21	0.835
			GAM (smoothing terms)		
			EDF	*F*	*p*-value
Depth of tow	1.67	2	2.00	96.19	<0.001
Windspeed	1.45	3	2.00	14.61	<0.001
Towing speed	1.26	5	1.58	7.12	0.001
Wave height	1.24	6	2.93	5.58	<0.001

EDF, estimated degrees of freedom.

especially with respect to the behaviour of depth, wave height, and windspeed, whereas scope ratio and towing speed show different patterns between models.

When the two approaches were compared, both models (ANN and GAM) showed a highly significant relationship ($p < 0.001$) between the observed values of net spread and those predicted in the external validation. The average net-spread values predicted by the ANN model and GAMs were 15.70 and 15.72 m, respectively. The error terms (r^2, RMSE, %SEP, MAE, ARV, and E_2) of the ANN model were consistently better than those from the GAM (Figure 4).

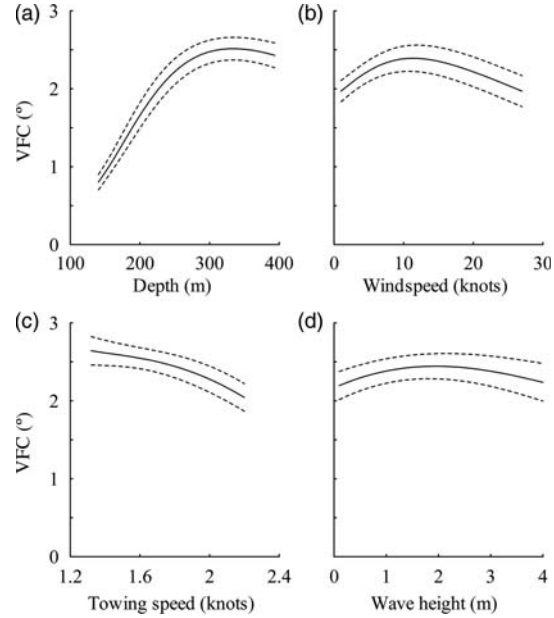

Figure 5. Mean responses (solid line) and 95% confidence intervals (dashed lines) of VFC to significant terms in the best neural network model (6-10-1). (a) Depth; (b) windspeed; (c) towing speed; (d) wave height.

VFC with the seabed

In the IPS, the catch and scope ratio variables had ratios close to 1 in the sensitivity analysis, so these variables were excluded from subsequent analysis. The network architecture could consist of one or two hidden layers. For one hidden layer, the number of neurons ranged between 5 and 15, and for two hidden layers, between 10 and 15 neurons made up each layer. Therefore, six architectures with six variables input and one output were trained: three architectures with one hidden layer (6-5-1, 6-10-1, and 6-15-1), and three with two hidden layers (6-10-10-1, 6-15-10-1, and 6-15-15-1).

During the calibration and selection stage, the ANOVA of the error terms (r^2, RMSE, %SEP, MAE, ARV, and E_2) revealed significant differences among networks ($p < 0.05$). In all error terms, the 6-5-1 model showed significant differences (HSD; $p < 0.05$) and worse performance than the other models. Among the models with similar performance, the least complex architecture with ten neurons in the hidden layer (6-10-1) was selected.

In the sensitivity analysis, all predictive variables had significant ratios. The most important variable was vessel (ratio = 1.79), and wave height was the least important variable (ratio = 1.24; Table 3). VFC gradually increased with increasing depth, especially between 140 and 320 m and decreased with increasing windspeed and towing speed (Figure 5).

The GAM for VFC was expressed as: VFC ~ vessel + s(depth) + s(wave height) + s(towing speed) + s(windspeed) + tactic. In the fitted model, the only non-significant variable was tactic ($p = 0.835$; Table 3). Excluding this last variable of the final model, the explained variance (r^2) was 0.49. Figure 6 shows the effects of the continuous variables on the VFC. The curves

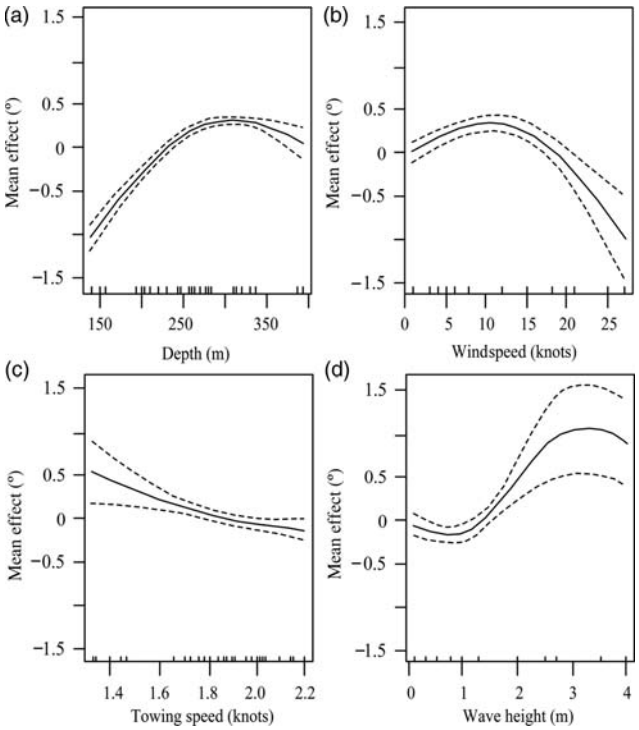

Figure 6. Mean effects (solid lines) and 95% confidence intervals (dashed lines) of significant terms on VFC in the GAM. (a) Depth; (b) windspeed; (c) towing speed; (d) wave height.

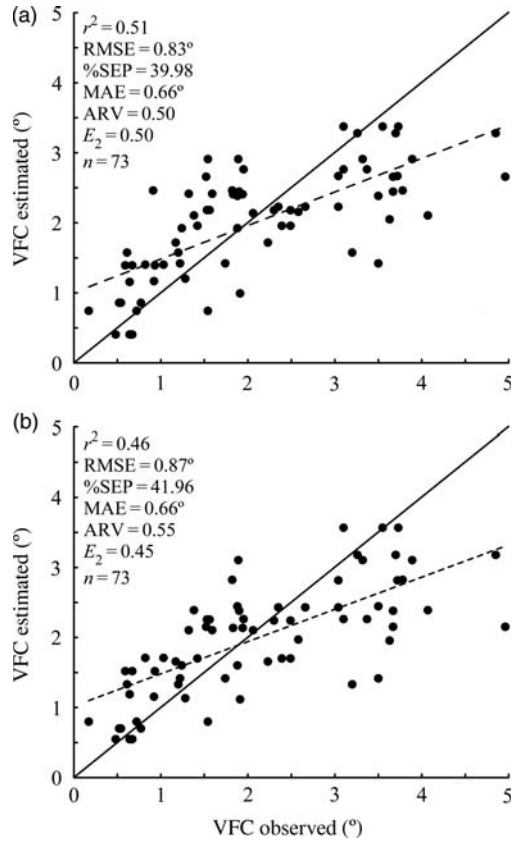

Figure 7. Linear regression between observed and estimated VFC from (a) the ANN model and (b) the GAM during the testing phase (external validation). Error terms of each model are also shown.

show tendencies similar to those shown by the ANN model, especially with respect to the behaviour of depth, windspeed, and towing speed.

The external validation showed that both the ANN model and GAMs produced significant relationships ($p < 0.01$) between predicted and observed VFC values. The error terms (r^2, RMSE, %SEP, MAE, ARV, and E_2) of both models were similar, although the variance explained by the ANN model was slightly greater than that explained by the GAM (ANN, $r^2 = 0.51$; GAM, $r^2 = 0.46$; Figure 7).

Discussion

In this study, the effects of different variables on trawl performance were analysed using ANNs and GAMs. Both non-linear methods allowed modelling of data and were appropriate and consistent in analysing the relationship between variables. In both cases, the results show that net spread depends on the operational characteristics of the vessel, catch weight, and environmental conditions. The ANN analysis showed that all variables considered contributed to explaining the variation in net spread. The 8-20-10-1 ANN model explained 78% of the variance during the external validation stage. Although the GAM explained a smaller percentage of the variance (61%), the tendencies in the responses of net spread to each continuous variable were similar, confirming the results obtained from the ANN model. For the footrope-contact variable, a simpler model was obtained using the ANN (6-10-1 architecture). The explained variance was similar for both models (ANN and GAM), ~50%.

Swept-area is an important parameter for abundance estimation from bottom-trawl surveys (Godø and Engås, 1989), which is defined by the geometry of the gear (e.g. net spread) and the distance actually travelled by the gear in contact with the bottom (Bertrand *et al.*, 2002). In terms of the geometry of the trawl used in this study, the average spread from the total number of records (2568 measurements in 34 hauls) was 15.7 m. This value is similar to that obtained by Queirolo *et al.* (2009) using a scale model and a dynamic simulation (15.8 and 16.5 m, respectively, for a speed of 1.9 knots), indicating consistency between our direct measurements and other estimates. In this study, net spread increased as a function of increasing trawl speed, a predictable response to the increase in lift force with door spread. However, higher speeds may generate undesirable effects on trawl performance owing to the relative increase in the resistive component (net drag) in relation to the lift forces (Fridman, 1986), which tends to reduce the net spread (Somerton and Weinberg, 2001) and hence negatively affects the potential catch (Godø, 1994).

In both the ANN model and GAMs, depth of tow significantly influenced net spread and VFC. For net spread, a consistent pattern was demonstrated, with greater net spread in deeper waters (Godø and Engås, 1989; Rose and Walters, 1990), as observed here. Lower variability of the tilt-angle in shallower waters could be explained by the higher scope ratios used in this case. In deeper waters, lower scope ratios were used, and VFC was increased. However, the scope ratio did not explain the performance of the footrope significantly, probably because of the high correlation with depth of tow, the latter being more important in the modelling. Depth could also be correlated with the

seabed type (Scott, 1982; Lamy *et al.*, 1998), although in this work, the seabed type was not sampled. This variable needs to be incorporated in future studies because it has been shown to affect not only net spread (Godø and Engås, 1989), but also bottom contact (Weinberg and Kotwicki, 2008) and catch efficiency (Dawe *et al.*, 2010).

Although the sensitivity analysis of the ANN model demonstrated that an increasing scope ratio tends to reduce net spread, the scope ratio had low relative importance. Moreover, this variable had no significant effect on variability of footrope contact. Although these results seem inconsistent, we note that the narrow range of this variable (with most values falling between 1.9:1 and 2.4:1) may have been insufficient to detect significant effects, so trawl performance would be relatively insensitive to small variations in the scope ratio, as indicated by Stauffer (2004). In general, the relationship between wire length (scope) and depth affects not only net spread, but also bottom contact (Weinberg and Kotwicki, 2008). Scope can affect the upward vector of warp tension on the doors, which can affect door behaviour and trawl performance (Carrothers, 1981). Therefore, we believe that the contribution of both scope and scope ratio needs to be studied experimentally in future, in the latter case considering a wider range of the variable (e.g. between 1.8:1 and 3.5:1).

The captains often navigated against the wind when windspeed exceeded 15 knots. Although this tactic helped to keep the vessels stable during trawling in adverse conditions, it also increased net spread and reduced VFC as the windspeed increased. There was a strong inverse relationship between wave height and net spread. Vertical movement of the vessels, low trawl speeds, and low scope ratios could influence the interactions of these forces, producing pulsing motions of the trawl (O'Neill *et al.*, 2003). Similarly, wave height was the most relevant variable for footrope performance in the GAM. With waves >2 m, variability in net contact with the bottom increased, probably reducing catch efficiency. Some studies have found that reduced bottom contact increases fish escape possibility, especially for benthic species that might escape under the footrope (Engås and Godø, 1989; Dremière *et al.*, 1999; Weinberg *et al.*, 2002), so this variable needs to be monitored systematically during each evaluation haul.

Although the trawl used was the same for all vessels, we would have expected a significant effect of the vessel for both net spread and VFC, mainly as a result of differences in vessel dimension, engine power, and trawl doors. Nevertheless, the effect of the vessel was not consistent for both GAMs, probably because the tactic variable is correlated with the vessel variable, in particular in terms of the decision of how to make the tow depending on environmental conditions. Therefore, there may be some substitution between the variables tactic and vessel in the models, although we cannot exclude the possibility that the small number of hauls influenced the results. Certainly, a specific experimental design would be better in detecting the individual contribution of each variable on trawl performance.

In surveys of crustacean stocks performed in Chile between 1999 and 2006, between 7 and 23% of hauls were taken in sea states Beaufort 5 or higher, corresponding to wave heights of 1.5 m or more. Stewart *et al.* (2010) analysed the effects of adverse conditions on survey trips and discussed the possibility of suspending sampling to avoid increased estimation bias when wave heights exceeded certain limits. Several other studies have shown that sea conditions may affect trawl efficiency through partial or combined effects on trawl performance (Maynou and Sardà, 2001; Weinberg and Kotwicki, 2008) or on target species behaviour under different wind and current conditions (Perry *et al.*, 2000; Wieland *et al.*, 2011).

The models developed here show that increasing catch weight, mainly crustaceans, was related to reduced net spread, although this effect was smaller than that of other variables. Although drag resistance tends to increase with increasing catch (O'Neill *et al.*, 2005), recorded catches in this study (72–570 kg) were not large enough to produce a pronounced effect. For example, Weinberg and Kotwicki (2008) recorded larger catches (average, 1.5 t; maximum, 13.3 t) and showed a clear reduction effect on net spread with increasing catch.

In Chile, BCSs have been used only to define the start and endpoints of hauls in trawl surveys. Nevertheless, variation in contact within the haul can help discard certain hauls whose catches are questionable or to increase the precision of the effective swept area based on actual contact time between the trawl and the seabed. Although efforts have been made to incorporate acoustic devices in nets and to standardize sampling procedures (e.g. sampling design; Acuña *et al.*, 2008), the protocol used to conduct fishing operations during trawl surveys is incomplete, because it does not consider some relevant material and variables, such as standard sampling net, trawl speed, and environmental conditions. However, changes to survey procedures and practices should be considered carefully and applied only after a method to calibrate intersurvey results has been developed. For this reason, it is generally agreed that changes in survey strategy, methodology, practice, and equipment should be avoided until a full calibration study can be performed (Kingsley *et al.*, 2008; K. L. Weinberg, pers. comm.).

To summarize, we have demonstrated that trawl performance is influenced by environmental conditions and fishing operations. Non-linear models, particularly the ANN models for net spread and VFC, contributed to understanding better the relationship between these parameters and the environmental and operational variables during hauls. Although the calibration phase of GAMs is significantly less complex than that of ANN models, it seems clear that the generalization capacity of ANNs is better in the validation phase, so we propose their use for similar studies. Survey estimates from swept-area methods could be improved if survey protocols were developed to consider the effect of operational variables and environmental conditions on trawl efficiency.

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References

Acuña, E., Alarcón, R., Cid, L., Cortés, A., Cubillos, L., Godø, O., León, R., *et al.* 2008. Estandardización de procedimientos metodológicos para la evaluación de crustáceos demersales a través del método de área barrida. Informe Técnico FIP-IT/2006-19. 326 pp.

Acuña, E., González, M. T., and González, Y. 2003. Pesquerías de langostinos y camarón nailon en el norte de Chile. *In* Actividad

Pesquera y de Acuicultura en Chile, pp. 263–287. Ed. by E. Yáñez. Ediciones Universitarias de Valparaíso, Valparaíso. 444 pp.

Aertsen, W., Kint, V., van Orshoven, J., Özkan, K., and Muys, B. 2010. Comparison and ranking of different modelling techniques for prediction of site index in Mediterranean mountain forests. Ecological Modelling, 221: 1119–1130.

ASCE (Task Committee on Application of Artificial Neural Networks in Hydrology). 2000a. Artificial neural networks in hydrology. 1. Preliminary concepts. Journal of Hydrologic Engineering, 5: 115–123.

ASCE (Task Committee on Application of Artificial Neural Networks in Hydrology). 2000b. Artificial neural networks in hydrology. 2. Hydrologic applications. Journal of Hydrologic Engineering, 5: 124–137.

Bertrand, J. A., Leonori, I., Dremière, P-Y., and Cosimi, G. 2002. Depth trajectory and performance of a trawl used for an international bottom trawl survey in the Mediterranean. Scientia Marina, 66(Suppl. 2): 169–182.

Carrothers, P. J. G. 1981. Catch variability due to variations in groundfish otter trawl behavior and possibilities to reduce it through instrumented fishing gear studies and improved fishing procedures. *In* Bottom Trawl Surveys, pp. 247–257. Ed. by W. G. Doubleday, and D. Rivard. Canadian Special Publication of Fisheries and Aquatic Sciences, 58. 273 pp.

Dawe, E. G., Walsh, S. J., and Hynick, E. M. 2010. Capture efficiency of a multi-species survey trawl for snow crab (*Chionoecetes opilio*) in the Newfoundland region. Fisheries Research, 101: 70–79.

Dremière, P-Y., Fiorentini, L., Cosimi, G., Leonori, I., Sala, A., and Spagnolo, A. 1999. Escapement from the main body of the bottom trawl used for the Mediterranean international trawl survey (MEDITS). Aquatic Living Resources, 12: 207–217.

Engås, A., and Godø, O. R. 1989. Escape of fish under the fishing line of a Norwegian sampling trawl and its influence on survey results. ICES Journal of Marine Science, 45: 269–276.

Fridman, A. L. 1986. Calculations for Fishing Gear Designs. Fishing News Books. Farnham, Surrey, England. 264 pp.

Godø, O. R. 1994. Factors affecting the reliability of groundfish abundance estimates from bottom trawl surveys. *In* Marine Fish Behaviour in Capture and Abundance Estimation, pp. 166–199. Ed. by A. Fernö, and S. Olsen. Fishing New Books, Oxford. 240 pp.

Godø, O. R., and Engås, A. 1989. Swept area variation with depth and its influence on abundance indices of groundfish from trawl surveys. Journal of Northwest Atlantic Fishery Science, 9: 133–139.

Gutiérrez-Estrada, J. C., Silva, C., Yáñez, E., Rodríguez, N., and Pulido-Calvo, I. 2007. Monthly catch forecasting of anchovy *Engraulis ringens* in the north area of Chile: non–linear univariate approach. Fisheries Research, 86: 188–200.

Hastie, T. J., and Tibshirani, R. J. 1990. Generalized Additive Models. Monographs on Statistics and Applied Probability, 43. Chapman and Hall/CRC, New York. 335 pp.

Hsu, K., Gupta, H. V., and Sorooshian, S. 1995. Artificial neural network modeling of the rainfall-runoff process. Water Resources Research, 31: 2517–2530.

Hunter, A., Kennedy, L., Henry, J., and Ferguson, I. 2000. Application of neural networks and sensibility analysis to improved prediction of trauma survival. Computer Methods and Programs in Biomedicine, 62: 11–19.

ICES. 2009. Report of the Study Group on Survey Trawl Standardization (SGSTS), by Correspondence. ICES Document CM 2009/FTC: 09. 127 pp.

Kingsley, M. C. S., Wieland, K., Bergström, B., and Rosing, M. 2008. Calibration of bottom trawls for northern shrimp. ICES Journal of Marine Science, 65: 873–881.

Kitanidis, P. K., and Bras, R. L. 1980. Real time forecasting with a conceptual hydrological model. 2. Applications and results. Water Resources Research, 16: 1034–1044.

Koeller, P. A. 1991. Approaches to improving groundfish survey abundance estimates by controlling the variability of survey gear geometry and performance. Journal of Northwest Atlantic Fishery Science, 11: 51–58.

Kotwicki, S., Martin, M. H., and Laman, E. A. 2011. Improving area swept estimates from bottom trawl surveys. Fisheries Research, 110: 198–206.

Lamy, F., Hebbeln, D., and Wefer, G. 1998. Terrigenous sediment supply along the Chilean continental margin: modern regional patterns of texture and composition. Geologische Rundschau, 87: 477–494.

Legates, D. R., and McCabe, G. J. 1999. Evaluating the use of goodness-of-fit measures in hydrologic and hydroclimatic model validation. Water Resources Research, 35: 233–241.

Maynou, F., and Sardà, F. 2001. Influence of environmental factors on commercial trawl catches of *Nephrops norvegicus* (L.). ICES Journal of Marine Science, 58: 1318–1325.

Melo, T., Queirolo, D., Hurtado, C., and Gaete, E. 2004. Determinación *in situ* del contacto de redes de arrastre de fondo. Investigaciones Marinas (Valparaíso), 32: 91–97.

Nash, J. E., and Sutcliffe, J. V. 1970. River flow forecasting through conceptual models. 1. A discussion of principles. Journal of Hydrology, 10: 282–290.

O'Neill, F. G., Knudsen, L. H., Wileman, D. A., and McKay, S. J. 2005. Cod-end drag as a function of catch size and towing speed. Fisheries Research, 72: 163–171.

O'Neill, F. G., McKay, S. J., Ward, J. N., Strickland, A., Kynoch, R. J., and Zuur, A. F. 2003. An investigation of the relationship between sea state induced vessel motion and cod-end selection. Fisheries Research, 60: 107–130.

Perry, R. I., Boutillier, J. A., and Foreman, M. G. G. 2000. Environmental influences on the availability of smooth pink shrimp, *Pandalus jordani*, to commercial fishing gear off Vancouver Island, Canada. Fisheries Oceanography, 9: 50–61.

Poulard, J-C., and Trenkel, V. M. 2007. Do survey design and wind conditions influence survey indices? Canadian Journal of Fisheries and Aquatic Sciences, 64: 1551–1562.

Pulido-Calvo, I., and Portela, M. M. 2007. Application of neural approaches to one-step daily flow forecasting in Portuguese watersheds. Journal of Hydrology, 332: 1–15.

Queirolo, D., DeLouche, H., and Hurtado, C. 2009. Comparison between dynamic simulation and physical model testing of new trawl design for Chilean crustacean fisheries. Fisheries Research, 97: 86–94.

Rose, C. S., and Walters, G. E. 1990. Trawl spread variation during bottom trawl surveys: causes and consequences. *In* Proceedings of the Symposium on Applications of Stock Assessment Techniques to Gadids, pp. 57–67. Ed. by L-L. Low. Bulletin of the International North Pacific Fisheries Commission, 50.

Rumelhart, D. E., Hinton, G. E., and Williams, R. J. 1986. Learning representations by back propagation errors. Nature, 323: 533–536.

Scott, J. S. 1982. Selection of bottom type by groundfishes of the Scotian Shelf. Canadian Journal of Fisheries and Aquatic Sciences, 39: 943–947.

Shepherd, A. J. 1997. Second-Order Methods for Neural Networks. Springer, New York. 145 pp.

Shrestha, R. R., Theobald, S., and Nestmann, F. 2005. Simulation of flood flow in a river system using artificial neural networks. Hydrology and Earth System Sciences, 9: 313–321.

Somerton, D. A., and Weinberg, K. L. 2001. The affect of speed through the water on footrope contact of a survey trawl. Fisheries Research, 53: 17–24.

Stauffer, G. (Compiler). 2004. NOAA Protocols for Groundfish Bottom Trawl Surveys of the Nation's Fishery Resources. US Department of Commerce, NOAA Technical Memorandum, NMFS-F/SPO-65. 205 pp.

Stewart, I. J., Keller, A. A., Fruh, E. L., Simon, V. H., and Horness, B. H. 2010. Throwing in the towel: when do adverse conditions dictate a weather day during a bottom trawl survey? Fisheries Research, 102: 130–140.

Ventura, S., Silva, M., Pérez-Bendito, D., and Hervás, C. 1995. Artificial neural networks for estimation of kinetic analytical parameters. Analytical Chemistry, 67: 1521–1525.

von Szalay, P. G. 2004. The effect of improved footrope contact measurements on trawl area swept estimates. Fisheries Research, 69: 389–398.

Walsh, S. J., and McCallum, B. R. 1997. Performance of the Campelen 1800 shrimp trawl during the 1995 Northwest Atlantic Fisheries Centre autumn groundfish survey. NAFO Scientific Council Studies, 29: 105–116.

Weinberg, K. L., and Kotwicki, S. 2008. Factors influencing net spread and sea floor contact of a survey bottom trawl. Fisheries Research, 93: 265–279.

Weinberg, K. L., and Somerton, D. A. 2006. Variation in trawl geometry due to unequal warp length. Fishery Bulletin US, 104: 21–34.

Weinberg, K. L., Somerton, D. A., and Munro, P. T. 2002. The effect of trawl speed on the footrope capture efficiency of a survey trawl. Fisheries Research, 58: 303–313.

Wieland, K., Olesen, H. J., Pedersen, E. M. F., and Beyer, J. E. 2011. Potential bias in estimates of abundance and distribution of North Sea cod (*Gadus morhua*) due to strong winds prevailing prior or during a survey. Fisheries Research, 110: 325–330.

Wood, S. N. 2006. Generalized Additive Models: an Introduction with R. Chapman and Hall/CRC. Press, Boca Raton, FA 391 pp.

Zimmermann, M., Wilkins, M. E., Weinberg, K. L., Lauth, R. R., and Shaw, F. R. 2003. Influence of improved performance monitoring on the consistency of a bottom trawl survey. ICES Journal of Marine Science, 60: 818–826.

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