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TRAINING AN A.I. CMP FOR ATLANTIC BLUEFIN TUNA

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SUMMARY

Two artificial neural networks that estimate biomass in the West and East Atlantic areas respectively, were trained on simulated projected data from the 96 stochastic reference set operating models. Simulated projected data were sampled from nine exploratory CMPs, the combination of three levels of fixed harvest rate in the West area and three levels of fixed harvest rate in the East area. For each stochastic simulation, operating model and CMP, a future year was sampled at random and the simulated index and catch data were used to derive 57 independent input variables including trend in indices, index levels and total catches taken in the projection up to that point. The East area and West area neural networks were each trained to the perfectly known biomass of age 3+ fish in the corresponding area. The biomass estimation performance of the neural networks was evaluated with independent validation and testing datasets. The performance of a fixed harvest rate CMP using those estimates was evaluated in the current ABT MSE framework. The neural networks provided good to very good estimation accuracy using only catch and index data. The A.I CMP was better than conventional CMPs at tailoring catch recommendations to available biomass, providing better yield performance in productive OMs and better biological performance in less productive OMs. The use of neural networks raises important issues of CMP overparameterization, omniscience and robustness which are briefly discussed.

RÉSUMÉ

Deux réseaux neuronaux artificiels qui estiment la biomasse dans les zones de l'Atlantique Ouest et de l'Atlantique Est respectivement, ont été entraînés sur des données projetées simulées à partir des 96 modèles opérationnels du jeu de référence stochastique. Les données projetées simulées ont été échantillonnées à partir de neuf CMP exploratoires, soit la combinaison de trois niveaux de taux de capture fixe dans la zone Ouest et de trois niveaux de taux de capture fixe dans la zone Est. Pour chaque simulation stochastique, modèle opérationnel et CMP, une année future a été échantillonnée au hasard et les données d'indice et de capture simulées ont été utilisées pour dériver 57 variables d'entrée indépendantes, y compris la tendance des indices, les niveaux d'indice et les captures totales considérées dans la projection jusqu'à ce point. Les réseaux neuronaux de la zone Est et de la zone Ouest ont chacun été entraînés à la biomasse parfaitement connue de poissons d'âge 3+ dans la zone correspondante. Les performances des réseaux neuronaux en matière d'estimation de la biomasse ont été évaluées à l'aide de jeux de données de validation et de test indépendants. La performance d'une CMP à taux de capture fixe utilisant ces estimations a été évaluée dans le cadre actuel de la MSE pour l'ABT. Les réseaux neuronaux ont fourni une précision d'estimation bonne à très bonne en utilisant uniquement les données de capture et d'indice. La CMP A.I. était meilleure que les CMP conventionnelles pour adapter les recommandations de capture à la biomasse disponible, offrant un meilleur rendement dans les OM productifs et un meilleur rendement biologique dans les OM moins productifs. L'utilisation de réseaux neuronaux soulève toutefois d'importantes questions de surparamétrage, d'omniscience et de robustesse des CMP, qui sont brièvement examinées.

RESUMEN

Dos redes neuronales artificiales que estiman la biomasa en las zonas del Atlántico occidental y oriental, respectivamente, se entrenaron con datos proyectados simulados a partir de los 96 modelos operativos del conjunto de referencia estocástico. Los datos proyectados simulados se muestrearon a partir de nueve CMP exploratorios; la combinación de tres niveles de tasa de captura fija en la zona oeste y tres niveles de tasa de captura fija en la zona este. Para cada

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simulación estocástica, modelo operativo y CMP, se muestreó un año futuro de forma aleatoria y los datos de índices y capturas simulados se utilizaron para derivar 57 variables de entrada independientes, que incluían la tendencia de los índices, los niveles de los índices y las capturas totales consideradas en la proyección hasta ese momento. Las redes neuronales de la zona este y de la zona oeste se entrenaron con la biomasa perfectamente conocida de peces de edad 3+ en la zona correspondiente. El desempeño de la estimación de la biomasa de las redes neuronales se evaluó con conjuntos de datos independientes de validación y prueba. Se evaluó el desempeño de un CMP de tasa de captura fija que utiliza esas estimaciones en el marco actual de la MSE de ABT. Las redes neuronales proporcionaron una precisión de estimación entre buena y muy buena utilizando únicamente datos de capturas e índices. El CMP A.I fue mejor que los CMP convencionales a la hora de adaptar las recomendaciones de captura a la biomasa disponible, proporcionando un mejor desempeño en los OM productivos y un mejor desempeño biológico en los OM menos productivos. El uso de redes neuronales plantea importantes problemas de sobreparametrización, omnipresencia y robustez del CMP que se discuten brevemente.

KEYWORDS

Management Strategy Evaluation, bluefin tuna, operating model, management procedure, artificial neural network

Introduction

Artificial neural networks ('neural networks') are computing systems designed to 'learn' tasks without task-specific programming. Analogous to the biological neural network of an animal brain, they are a network of artificial neurons organized in layers from which all neurons in consecutive layers are connected. These 'synapses' pass signals, typically a real number, between the artificial neurons which process the signal via a log-linear function of the inputs and then send on the processed signal. The neural network learns (is trained, fitted) by altering the weights of the various signals that enter each artificial neuron.

Neural networks maybe trained on both input data (i.e. an independent variable - the 'input layer') and output data (a dependent variable – the output layer) to minimize a cost function in a process referred to as supervised learning (i.e. model fitting). This differs from unsupervised learning where only input data are provided and the neural net characterizes these data (e.g. clustering). There are two classes of supervised learning that either provide a discrete classification of input data (pattern recognition; is this a photograph of a fish?) or a regression analysis of data (a.k.a. function approximation: what size is the fish in that photograph?). The process of training neural networks is commonly referred to as 'machine learning' and when the neural network has more than one hidden layer of neurons between the input layer and the output layer, this is referred to as 'deep learning'.

Driven by the development of learning algorithms, the availability of computing power and the increasing digitization of information, there has been a recent explosion in the application of machine learning. Use of neural networks and artificial intelligence (A.I.) is now prevalent in everyday life, amongst many other things, supporting internet search engines, targeted advertising, voice recognition, language translation, image recognition and self-driving vehicles. The use of machine learning in the management of renewable resources is comparatively rare. In fisheries science, machine learning has focused on classification problems such as species identification (Haralabous and Georgakarakos 1996; Cabreira et al. 2009) and to a lesser extent regression problems such as forecasting recruitment dynamics (Chen and Ware 2011), approximating spatial dynamics (Adam and Sibert 2004), estimation of fishery reference points (Hillary 2007) and data-weighting (Neville et al. 2004). Thus far, machine learning has not been investigated for the provision of management advice (e.g. a total allowable catch) using fishery data.

It has long been recognised that the correct interpretation of fishery data in the formulation of robust management advice can be complex (Hilborn and Walters 1992, Quinn and Deriso 1999). This is reflected in ongoing research and discussion over the correct weighting of various data, the functional form of stock assessment model, the type of harvest control rules, use of precautionary buffers, the inclusion/exclusion of data types and the most appropriate statistical measures of assessment model fit.

The interpretation of fishery data includes complex conditionalities and interdependencies. Given the current configuration of the Atlantic bluefin tuna MSE framework, candidate management procedures must work from only catch and relative abundance index data. Currently, CMPs are using the level and in some cases slope of relative abundance indices. There is evidence that existing CMPs may not be as responsive as they could be to available vulnerable biomass, chronically underfishing Eastern and Western stocks in some recruitment scenarios and overfishing in others. It may be hypothesized that the various indices and catch data contain sufficient information to support responsive and robust management decisions if those CMPs allow for more complex hierarchical interpretations of those data. These may be represented by statements such as: "if catches have been high in the East Atlantic and indices are also high there, a large fraction of fish in the West may be of Eastern origin" or "western stock specific indices are relatively high but east area indices are relatively low indicating that a low fraction of fish in the West may be of Eastern origin". The approximation of complex, non-linear, hierarchical systems is a problem for which neural networks are ideally suited.

It was recently observed (N. Duprey comm.) that the existing CMPs - that are still in development - do not appear to be as responsive as they could be, substantially underfishing in some OMs and overfishing in others. The objective of this paper is to investigate the potential of neural networks as (1) a tool for informing CMP design to improve management performance of any index-based CMP but also (2) as the algorithm for an A.I. CMP for Atlantic bluefin tuna.

Methods

Details of the neural network configuration are available in Table 1.

Simulated datasets were generated by projecting nine constant fishing mortality rate CMPs for all 96 stochastic reference set operating models. These nine CMPs comprised high, medium and low harvest rates in the West area crossed with high, medium and low harvest rates in the East area. These simulations created a range of simulated outcomes for both stocks. The stochastic operating models include 48 simulations each. Over 9 CMPs this leads to 41,472 simulated projections (96 x 48 x 9). In each of these projections a single projection year was sampled, and for this year eight types of data were recorded:

(1) current index level of all 13 indices subject after Loess smoothing (13 data points);
(2) the mean level of the index in the projection to date (13 data points);
(3) the slope in the index in the first 4 projection years (13 data points);
(4) the slope in the index in the first 6 projection years (13 data points);
(5) mean catches over the last three years in both ocean areas (2 data points);
(6) mean catches in both ocean areas to date (2 data points);
(7) the projection year;
(8) the total simulated biomass in each ocean area of fish age 3 or older (2 data points).

This results in 57 independent variables (input layer features) and 1 dependent variable (the output layer - area biomass of fish age 3+) for training two neural networks, one for predicting total biomass of 3+ fish in the East area and another for predicting total biomass of age 3+ fish in the West area. Only one projection year was sampled per simulation to ensure all data points originate from independent time series. Random seeds were generated to ensure that the projected simulated data and dynamics were not the same as those used in MSE testing.

The wider dataset of 41,472 'observations' was split into three component datasets, a training set, a validation set and a testing set. The training set was used to fit the neural network using the backpropagation algorithm. The validation set was used to monitor training and where possible adjust meta parameters of the fitting and network design to improve accuracy. The testing set remained completely independent of the process of fitting or the selection of training hyperparameters that controlled the network fitting process. The split of these data was approximately 75% training, 20% validation, 5% testing.

Prior to fitting, data were all normalized to have mean 0 and standard deviation 1. The parameters of this data normalization was saved in the neural network design to ensure it was preserved when predictions are made from the new datasets provided to a CMP. To focus estimation on smaller stock sizes where CMP performance is most critical, the highest 10% of simulated biomasses were removed from the fitting (include many optimistically high outliers) and fit was conducted by minimizing mean squared error on log area biomass.

It has been shown that two hidden layers are sufficient to characterize the structure of any non-linear problem, and that at least two are required to capture complex hierarchical interactions. It follows that a three-layer (two hidden layers) neural network was investigated allowing for deep learning. As is typically the case in the design of neural networks, the width (number of nodes) and depth (number of hidden layers) was decided by ad-hoc experimentation as it is specific to each problem. In both East and West neural networks, relatively high accuracy was achieved with two hidden layers comprising 24 in the first layer and 24 in the second (Figures 1 and 2). This leads to 2,017 parameters per neural network which are the weights among the layers (the coloured lines of Figure 1), in addition to the biases in the hidden and output layers (one for each of the nodes in the lower three layers of nodes in Figure 1) (2,017 = 57 x 24 + 24 x 24 + 24 x 1 + 24 + 24 + 1). In general, the validation loss rate (the mean squared error in log total biomass of age 3+ fish) stopped improving after 350 epochs (iterations of fitting) (see Figure 2 for mean absolute error plots).

The neural networks were used in fixed harvest rate CMPs. The TACs in each area were set by the 3+ biomass estimate from the corresponding neural network multiplied by a tuning parameter that is the fixed harvest rate in each area. CMPs AI1, AI2 and AI3 were tuned to an eastern stock Br30 (spawning stock biomass, SSB relative to dynamic SSB MSY after 30 projected years) of approximately 1.55 and western stock Br30 of 1.00, 1.25 and 1.50, respectively. Similarly to other CMPs, the TAC advice arising from the A.I. CMPs were constrained by minimum (10kt East, 0.5kt West) and maximum (50kt East, 4kt West) levels in addition to maximum percentage increases (25%) and decreases (35%). If the new TAC is less than a 5% different from the previous TAC no change is implemented.

The performance of the AIx CMPs was evaluated alongside the most recent mixed stock (MPx, TC10, TC11, TC12) and Butterworth-Rademeyer (BR10, BR11, BR12) CMPs that are tuned to comparable western stock Br30 values.

Contrary to popular belief, neural networks are not 'black boxes' in the sense that their parameters can be plotted and similarly to other non-linear models (e.g. stock assessment models) their sensitivity to input data can be evaluated and visualized. This provides a basis for using neural networks to learn about potential improvements to CMP design (the original motivation behind this research). The marginal sensitivity of the neural networks to marginal changes in data inputs was calculated and is presented in Figures 4 and 5.

Results

When evaluated by the testing dataset the neural networks provided good to very good estimation performance with log normal error CVs of approximately 13% and 18% for the East area and West area biomass, respectively (Figure 3). There was some evidence for underestimation of East area biomass at high biomass levels (Figure 3), but as a basis for setting TACs this is substantially less of an issue than if the converse were true and there was overestimation at low biomass levels.

Calculating the sensitivity of biomass estimates to marginal changes in input data reveals considerable complexity in the way the neural networks interpret such data. For example, depending on the other data available, there were often varying responses in the biomass estimate (hence TAC advice) and in some cases even increasing / decreasing East area biomass estimates as indices increased (e.g. Portugese Trap index panel Figure 4 panel f). Depending on the simulation in question, increasing total projected catches could strongly or weakly reduce estimates of current West area biomass in either a linear or non-linear relationship (Figure 5 panel bb). Overall, the neural networks provide biomass estimates reliant on complex conditionalities among the data, which can be expected where biomass is the product of mixing among more than one stock of widely varying magnitude and trajectory.

Conventional index-based CMPs such as the BR and TC types, express their responsiveness and obtain robustness by varying the magnitude of TACs depending on the magnitude of available biomass and productivity of the various operating models. Violin plots of yield outcomes show strong bimodality in catches in response to the productivity of the operating models (the left-hand panels of Figure 6). In general, this is seen most distinctly among the varying scenarios for recruitment. In comparison to the conventional index-based CMPs of type TC and BR, the A.I. CMPs exhibit greater responsiveness and more divergent TAC setting high productivity (e.g. recruitment level 1) and low productivity (e.g. recruitment level 2) operating models (Figure 7). The product is much less variability in biomass outcomes among operating models (right hand panels of Figure 6).

Discussion

Compared with conventional index based CMPs, the A.I. CMPs were better able to adapt TAC advice relative to available biomass, providing higher catches in high-productivity OM scenarios and obtaining higher biomass outcomes in low-productivity OM scenarios.

The design of the A.I. CMPs is fundamentally based on the idea of constant harvest rates applied to estimates of area biomass. It is however possible to train A.I. CMPs to other quantities such as the TAC recommendations arising from a 40-10 harvest control rule. Further experiments in A.I. output layers (dependent variables) and CMP design could provide additional performance gains.

It was demonstrated that the neural networks presented in this paper were not overparameterized for the simulated datasets generated from the reference set of operating models. However, there is another form of overparameterization that occurs at a higher level and relates to the intention of the reference set OMs as a representation of plausible states of nature. The concern is that any CMP that is highly specialized to the specific conditions of the operating models may not be robust to other plausible states of nature including those that may persist in reality. This concern increases as CMP algorithms increase in flexibility and number of parameters. If operating models are intended as *archetypes* of possible system dynamics (e.g. a recruitment shift in projection year 10 is intended to represent *a recruitment shift*) and OMs cannot be considered to be an exhaustive set of plausible states of nature (e.g. recruitment shifts could occur in any projected year), the A.I. CMP of this paper has an unfair advantage: it is trained on projected outcomes of the complete range of projected conditions. The CMP therefore may not be robust to equally plausible but substantively different archetypes of system dynamics (e.g. as a shift in recruitment in projection year 20). The undesirable result would be a CMP that performs substantially better in the MSE test than it would given the real system dynamics that are unlikely to be exactly represented by any one reference set OM.

Although of less concern for simpler CMPs with fewer parameters, in principle this problem could apply to any CMP that has been developed iteratively to optimize performance over the entire set of reference OMs. Should it matter whether the neural network used to learn and optimize CMPs is the natural one in the CMP developers brain or artificial one in the computer code of the CMP? Similarly to the iterative tweaking of other CMPs, the A.I. CMP has 'seen' many future data sets and these are the same types of data (index and catches) available to all CMPs. Unlike other CMPs the A.I. CMP does not attempt to identify the specific OM (the particular test) and then assume comparable dynamics – this so-called 'omniscience' was at the heart of the VW 'diesel gate' scandal. In that legal case, it was shown that the car's computer could identify when it was being tested for emissions, allowing the car to obtain fuel efficiency that would not be achievable in reality. By analogy, the A.I. CMP is similar to legal engine management systems that attempt to identify driving requirements and adjust engine management settings accordingly. Fundamentally it is the same algorithm applied to all simulations and operating models applied without prior and codified knowledge of system dynamics. The A.I. CMP also has no codified knowledge of the projection specifications of the OMs. For example, unlike other CMPs it does not use any caps on TAC that could relate to the regime shift that occurs in projection year 10 for recruitment level 3 operating models. The most omniscient aspect of the A.I. CMPs is arguably their design as a constant harvest rate control rule – fundamentally little about sustainable rates of exploitation changes substantially among the various operating models, but this knowledge is also leveraged by index-based CMPs such as TC. Furthermore, the A.I. CMP is tuned to projected data from only 9 fixed harvest rate MPs, and those training data are the product of stochastic simulations arising from a different random seed than the simulations used to evaluate the CMPs. While other CMPs have been developed to achieve good management performance across the projections of the reference set OMs, the A.I. CMP is optimized only to accurately estimate regional biomass and has just two performance tuning parameters relating to regional harvest rates.

If it is acceptable to tune the parameters of CMPs to obtain better performance across the reference OMs, then the issue is not fitting of CMPs but more specifically overfitting, a quantitative problem requiring quantitative evaluation. It is perhaps the case that establishing a flexible and relatively complex A.I. CMP simply reveals the need for an independent set of OMs for testing overparameterization of CMPs. For example, a recruitment shift in projection year 20 or an intermediate natural mortality rate scenario.

Regardless of whether A.I. CMPs are accepted as viable basis for the provision of management advice they suggest that the data available contain sufficient information to support better performance than is currently obtained by conventional index-based CMPs such as TC.

Acknowledgments

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Table 1. Neural network configuration.

Configuration	Used in this analysis	Alternatives
1. Software	KERAS R package (Falbel et al. 2021) + Tensorflow (2021) + NVIDIA CUDA (NVIDIA 2021)	neuralnet R package (Fritsch et al. 2016) nnet R package (Ripley 2016) (and many others)
2. Network type	Simple recurrent	Fully recurrent, Recursive, Multilayer perceptron, Convoluted, Bi-directional, Hierarchical, Stochastic, Long short-term memory, Sequence to sequence, Shallow, Echo state
3. Training algorithm (optimizer)	'rmsprop'	'adam', 'sgd', 'adamax', 'adadelta', 'adagrad'
4. Cost function	Mean squared error	Mean absolute error, mean squared, logarithmic error, mean absolute percentage error
5. Intensiveness of training	500 epochs (sufficient for stabilization of cost function, Figure 2)	-
6. Input data types	• Current index level (13 indices, each loess smoothed) • Index slope: first 4 yr. of projection • Index slope first 6 yrs of projection • Index • Mean index level in projection • Projection year number • Mean catch levels in projection (both East and West area)	
7. Output data	East / West Area specific biomass (age 3+)	Stock biomass, stock biomass x exploitation rate
8. Size of training / validation / testing data sets	31,519 / 7,880 / 2,074 (approx.. 75% / 20% / 5%)	-
9. Network design (number of neurons in consecutive layers demarked by ':') and Activation functions	**Input layer**: 57 (data types) **Hidden layers**: 24:24 (2,401 parameters) **Output layer**: 1 **Activation functions:** rectified linear unit	Linear, sigmoid, hyperbolic, tangent
10. Neural net performance evaluation	**Validation**: cross-validation **Estimation performance**: mean squared error / mean absolute error **Management performance**: MSE testing with ABT-MSE package	

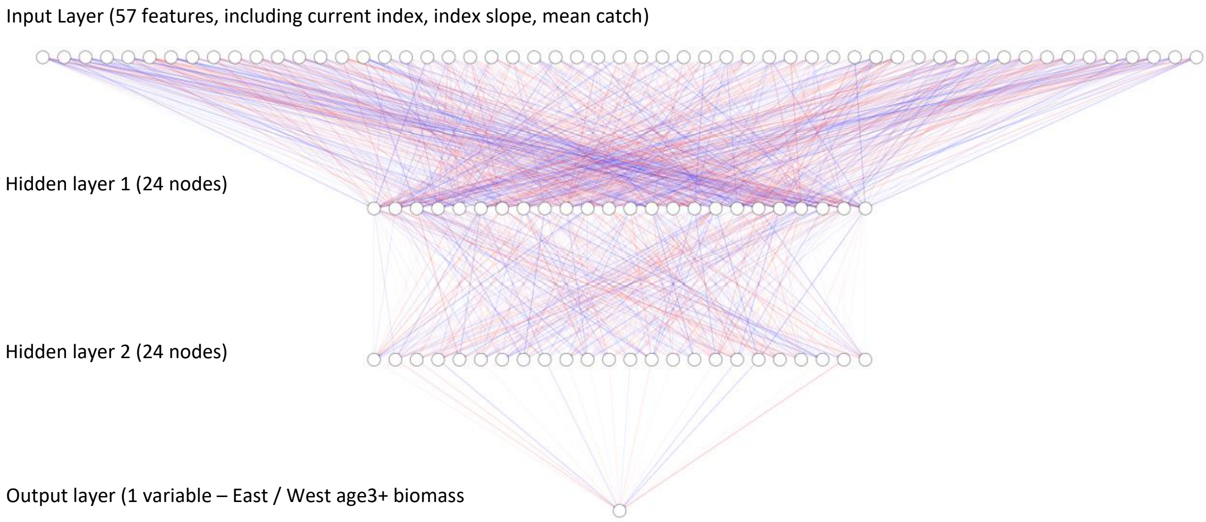

Figure 1. Neural network design. Lines represent estimated weights, circles represent nodes for which a bias is estimated per node for each hidden layer and the output layer.

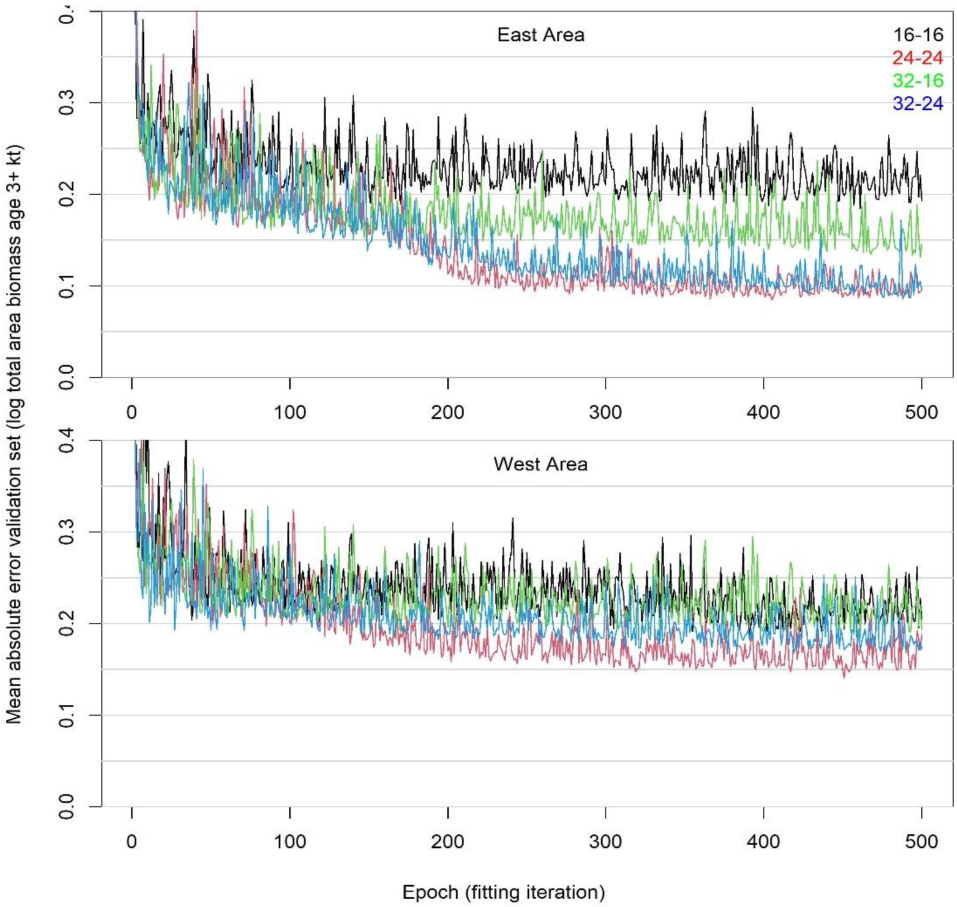

Figure 2. Comparison of validation data fit given alternative neural network designs. Each line represents a neural network design. For example, '32-16' is a neural network with 32 nodes in the first hidden layer and 16 nodes in the second hidden layer.

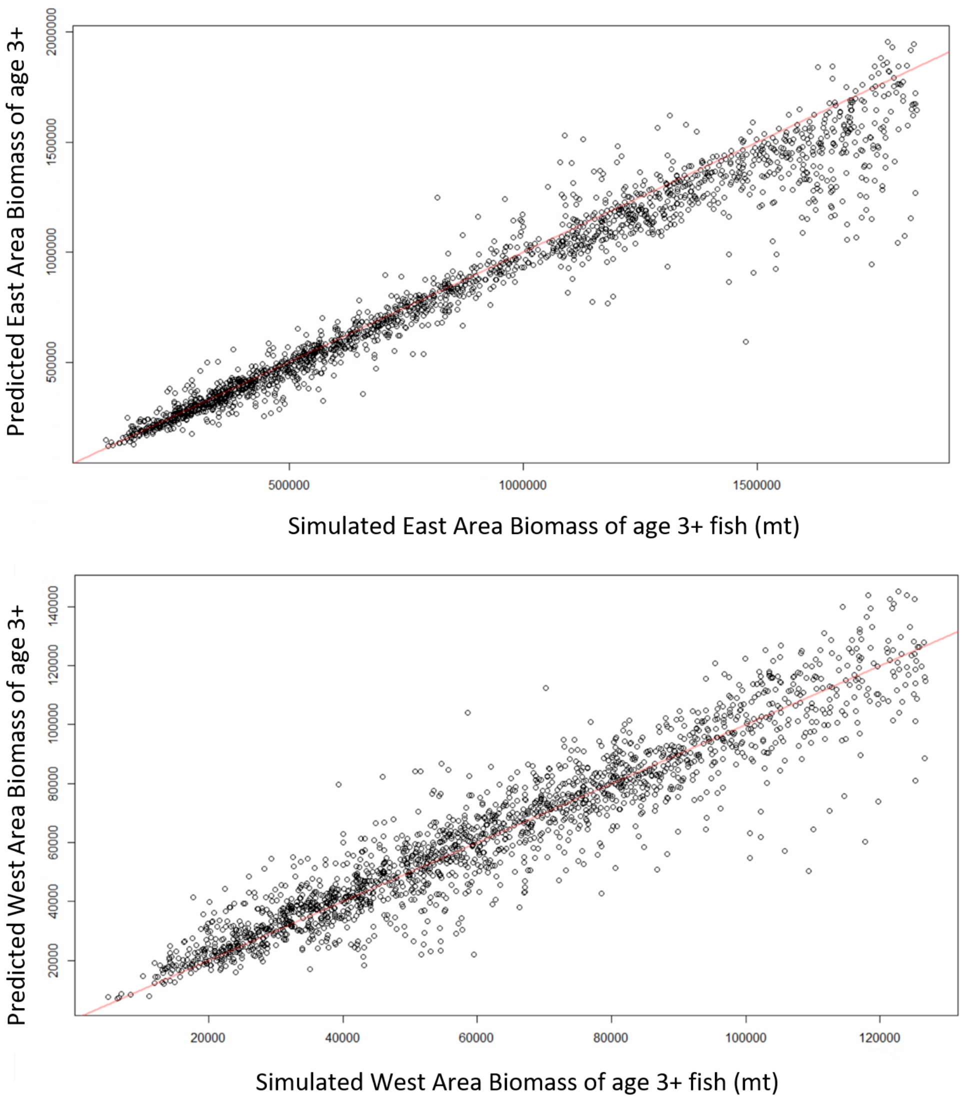

Figure 3. Estimation performance of the East and West neural networks evaluated by the independent testing dataset. Each point is a projection year (of projection years 1-50) pulled from a unique projection arising from the 96 stochastic operating models and a collection of nine fixed fishing mortality rate scenarios (a cross of high, medium and low for both East and West areas). Each plotted point represents a biomass estimate from the neural network given 57 covariate data points including the level and early projection trends of all 13 indices and the east and west area catch levels.

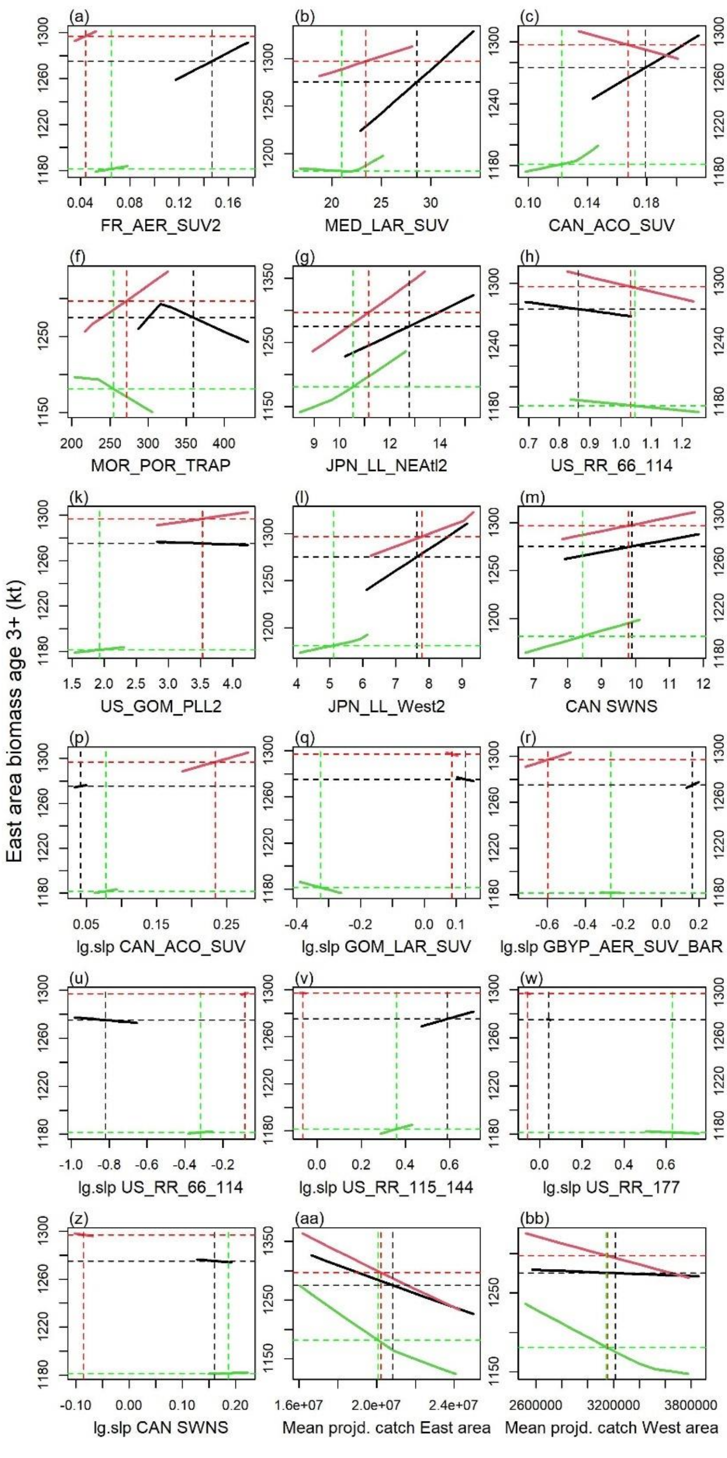

Figure 4. Sensitivity of neural network estimates of biomass of East area age 3+ fish with respect to marginal changes in various input data. In each plot the results for three randomly selected simulated datasets are presented (the black, red and green lines). Each dataset was from projection year 10. The horizontal and vertical lines show the original value of the data input and the estimated biomass level at this point. The bold lines show how the neural network prediction varies with marginal changes (+/- 20%) in each input data point in turn.

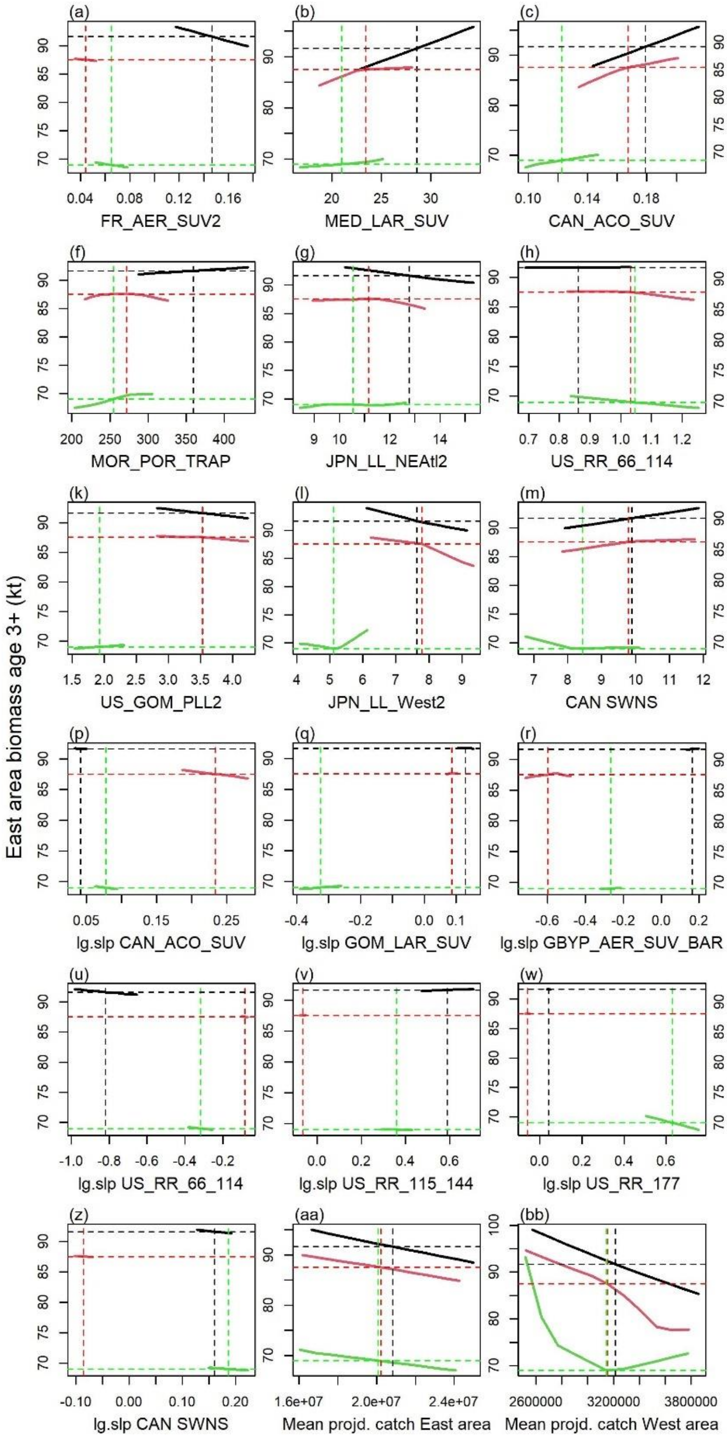

Figure 5. Sensitivity of neural network estimates of biomass of West area age 3+ fish with respect to marginal changes in various input data. In each plot the results for three randomly selected simulated datasets are presented (the black, red and green lines). Each dataset was from projection year 10. The horizontal and vertical lines show the original value of the data input and the estimated biomass level at this point. The bold lines show how the neural network prediction varies with marginal changes (+/- 20%) in each input data point in turn.

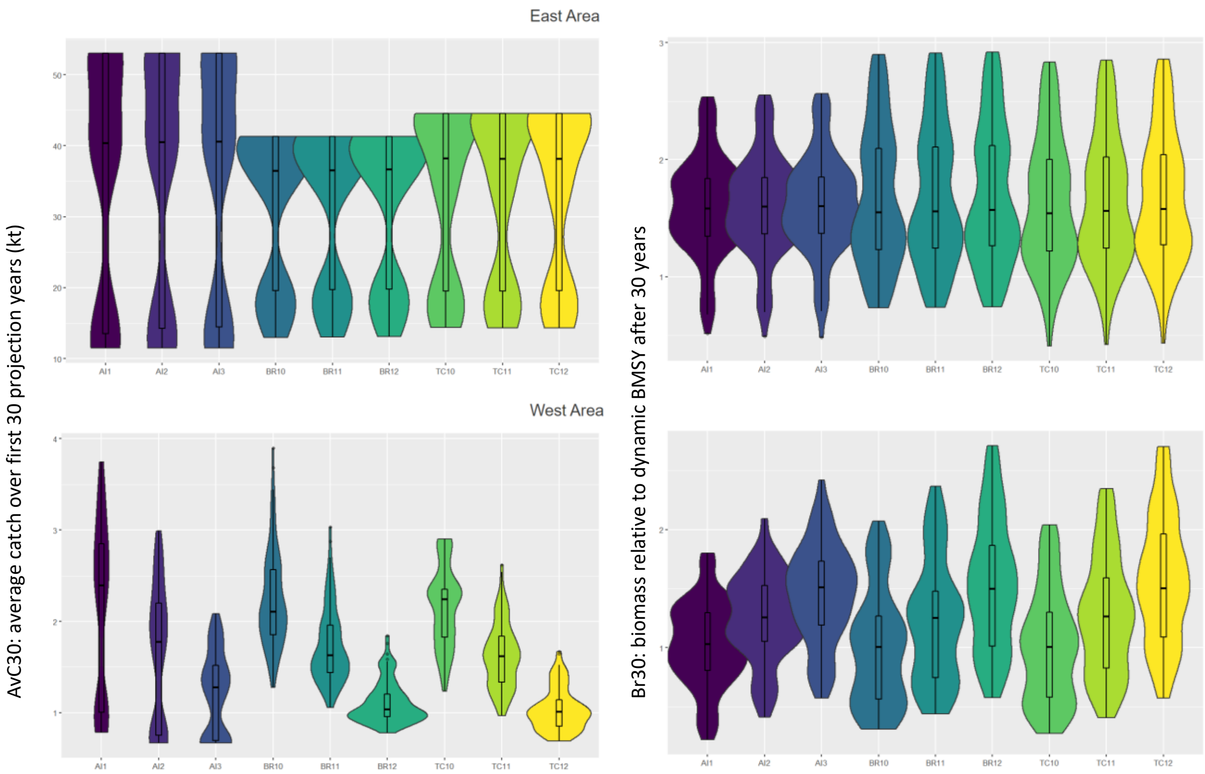

Figure 6. Comparison of CMP performance integrated over all reference set OMs for the AI, BR and TC CMPs tuned to 1.00, 1.25 and 1.50, respectively.

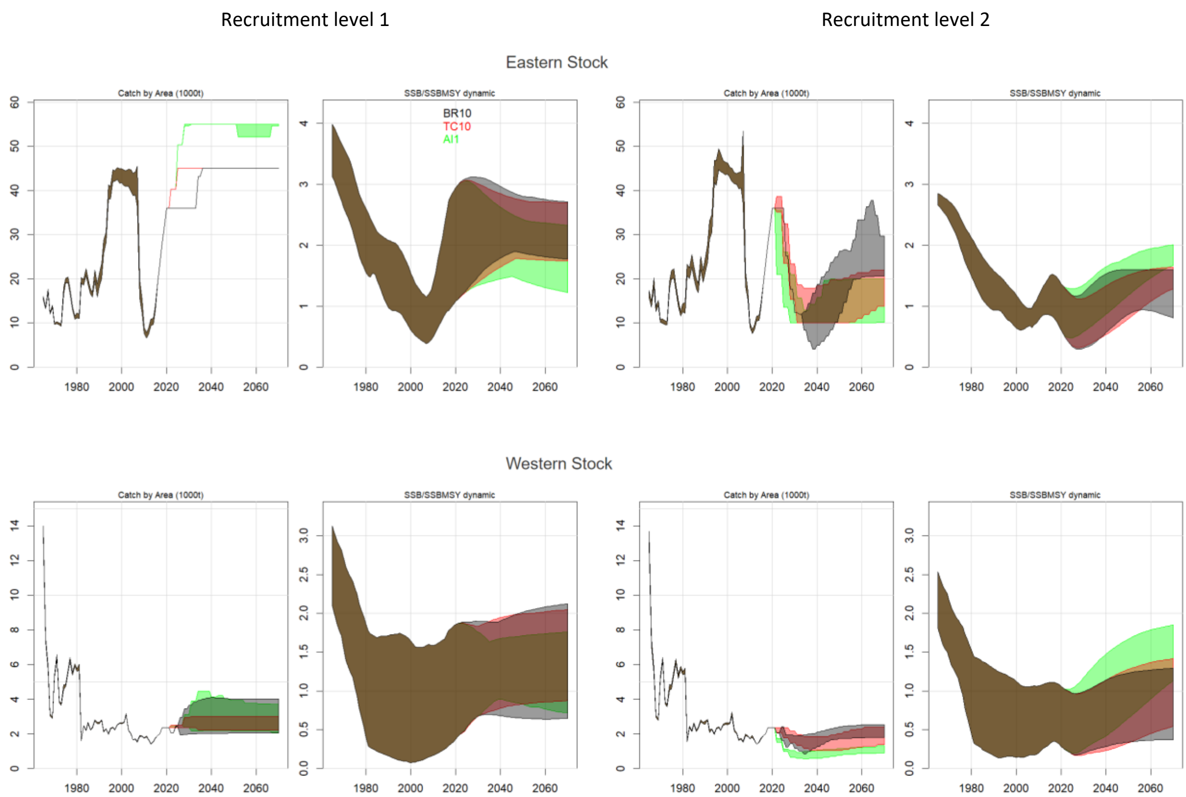

Figure 7. Comparison of CMP performance integrated over all reference set OMs for the AI, BR and TC CMPs tuned to 1.00, 1.25 and 1.50, respectively.