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Research Article

Focused small-scale fisheries as complex systems using deep learning models

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ABSTRACT. Small-scale fishing (SSF) is a relevant economic activity worldwide, so sustainable development will be essential to assure its contributions to food security, poverty alleviation, and healthy ecosystems. However, the wide diversity of fisheries, their complexity, and the lack of information limit the ability to propose/evaluate management measures and plans and their effects on communities and other productive activities. The state of Baja California Sur, Mexico, our study case, ranks as the third place in national fisheries production, possesses SSF fleets, has a wide variety of fisheries that share fishing areas, fishing seasons, and operating units. In this work, assuming SSF as a complex system were proposed deep learning models (DLM) to forecast the catch volumes, evaluate each input variable's importance, and find interactions. Environmental variables and catch fisheries were tested in the DLM to estimate their predictive power. Different DLM structures and parameters to find the optimal model was used. The variables that presented higher predictive power are the environmental variables with R = 0.90. Moreover, when used in combination with the catches from other areas, the performance of R = 0.95 is obtained. Using only the catches, the model has an R = 0.81. This model allows the use of variables that indirectly affect the system and demonstrates a useful tool to assess a complex system's state in the face of disturbances in its variables.

Keywords: finfish; artisanal fisheries; artificial neural networks; complex systems; mathematical models.

INTRODUCTION

Small-scale fishing (SSF) contribute significantly to global and local food security, employment, and viable livelihoods (Stanford et al. 2017). The importance of SSF also extends to culture and heritage, and in many instances, they offer a livelihood for many people besides employment (Chuenpagdee et al. 2019, FAO 2020, Mendoza-Portillo et al. 2020).

Usually, SSF is controlled by fishing effort controls, calculated via forecasting biomass, spawning, recruitment, or volume of catch; this approach has been successful in some large-scale fisheries. Some efforts address single and multi-species reference points (Penaluna et al. 2017), ecosystem approach to fisheries (Serpetti et al. 2017, Wakamatsu & Wakamatsu 2017). However, SSF has not always been so successful, considering that their management is affected by poor data context, limited surveillance, or bad management decisions (Salas et al. 2007, Mahon et al. 2008, Leis et al. 2019).

In this way, SSF requires planned actions supported in predictive models that fit the disposition of existing information, which is usually insufficient, or low quality; but in the end, it is the only data generated in most developing countries (Salas et al. 2007, Hilborn & Ovando 2014, Pomeroy et al. 2016, de la Barra et al. 2019). Besides, this sector generally lacks economic

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resources for research, data collection, management, and surveillance.

SSF presents, among others, the following characteristics: multi-species, wide spatial distribution, a large number of operating units, decentralized operating systems, extensive and diverse market routes, administrative and ecosystem boundaries do not correspond at all (Fuller et al. 2017). Their management consists of multivariable non-linear problems and can be understood as complex adaptive systems (Mahon et al. 2008). For this case, it is proposed that the fisheries of Baja California Sur (BCS) as a complex adaptive system (CAS) whose elements are subsystems that correspond to the environmental, ecological, fishing, economic and social dimensions. Being a CAS, each layer or subsystem is interrelated at different levels (Mahon et al. 2008). If we consider the quality and availability of data and information from the BCS SSF, we face the impossibility of using traditional models, which require nonexistent data or expensive to obtain and will take time to collect.

In this context, developing those models' main problem is the lack of information and the statistical assumptions required to design them (Griffith & Fulton 2014).

The recent development of artificial intelligence has made it possible to open new inroads into models that allow time-series analyses from indirect perspectives. Artificial intelligence models, specifically deep learning models (DLM), are characterized by their ability to predict a variable's value concerning a specific scenario (Zhang et al. 2018). The DLM have been used to forecast the catches of different fisheries, like mackerel, cod, sardine or finfish (Kim et al. 2015, Naranjo et al. 2015, Kim et al. 2016, Cavieses-Núñez et al. 2018, Petatán-Ramírez et al. 2019). DLM has used as input variables of different data types, such as satellite images of sea spectrograph (e.g. sea surface temperature) or in situ measurements of the environment, fisheries biomass, and trip tickets of the fisheries catch (Yáñez et al. 2010, Fernandes et al. 2015, Kim et al. 2015). Considering the availability of the data and the characteristics of the DLM opens the opportunity to explore the possibilities of fisheries analysis from other perspectives.

DLM is robust enough for simulations of a fishery. However, if the previous points are considered, the following questions should be answered: Will it be feasible to use deep learning models to simulate complex systems such as SSFs in a region? Will they be able to identify relationships between fisheries? Will the predictive capacity be adequate, considering the insufficient data context of the fisheries?

This article seeks to better understand SSF from the complex adaptive system approach for decision-makers and others system participants. For this porpoise, the SSFs of BCS are proposed as a case study, using the available information and DLM, which have shown in recent studies the simulation capacity for fisheries. In this context, three DLMs are presented, each one raising different assumptions.

MATERIALS AND METHODS

Study area

BCS is in the northwest of Mexico above the 28ºN parallel, occupying the southern half of the Baja California Peninsula. Northern limits with Baja California State, eastern with the Sea of Cortés, southern, and western with the Pacific Ocean. Its capital is the city of La Paz. BCS covers 73,475 km², occupying 3.8% of the national territory (Fig. 1).

Administratively, the state has five municipalities: La Paz, Los Cabos, Loreto, Comondú and Mulegé. BCS has a population of 712,029 persons (INEGI 2015). The number of fishers registered is 6891, distributed in about 420 localities along the coastline (SPAyDA 2015).

The different fishing locations are related through the commercialization lines of fishing production. Besides, all neighboring localities integrate a complex interconnected system. The localities are distributed along both sides of the peninsula, the Pacific coast and the Sea of Cortés (Ramírez-Rodríguez et al. 2011, Díaz-Uribe et al. 2013).

The lagoon complex Bahía Magdalena-Almejas (BMA) is an essential fishing region in BCS; this zone produces almost 60% of the total catches volume. Several relevant fisheries developed there, such as shrimp, clams, crabs, lobsters, finfish, among others (Ojeda-Ruiz et al. 2018). In this region Puerto Adolfo López Mateos, Puerto Chale, Puerto San Carlos, Isla Margarita are some of the main localities.

The second region in importance is the Gulf of Ulloa; this corresponds to the Pacific's north shore of BCS, at the north of BMA, where the abalone, finfish, lobster, sharks, and clams are the most important fisheries (Ramírez-Rodríguez et al. 2010, Ramírez-Rodríguez & Ojeda-Ruiz 2012). In this zone can be highlight Las Barrancas or San Juanico as the most important localities.

As the third important region, the Cortés seaside of BCS. This zone integrates the communities of Mulegé, Loreto, La Paz, Los Barriles and Los Cabos; the principal fisheries identified are finfish and clams

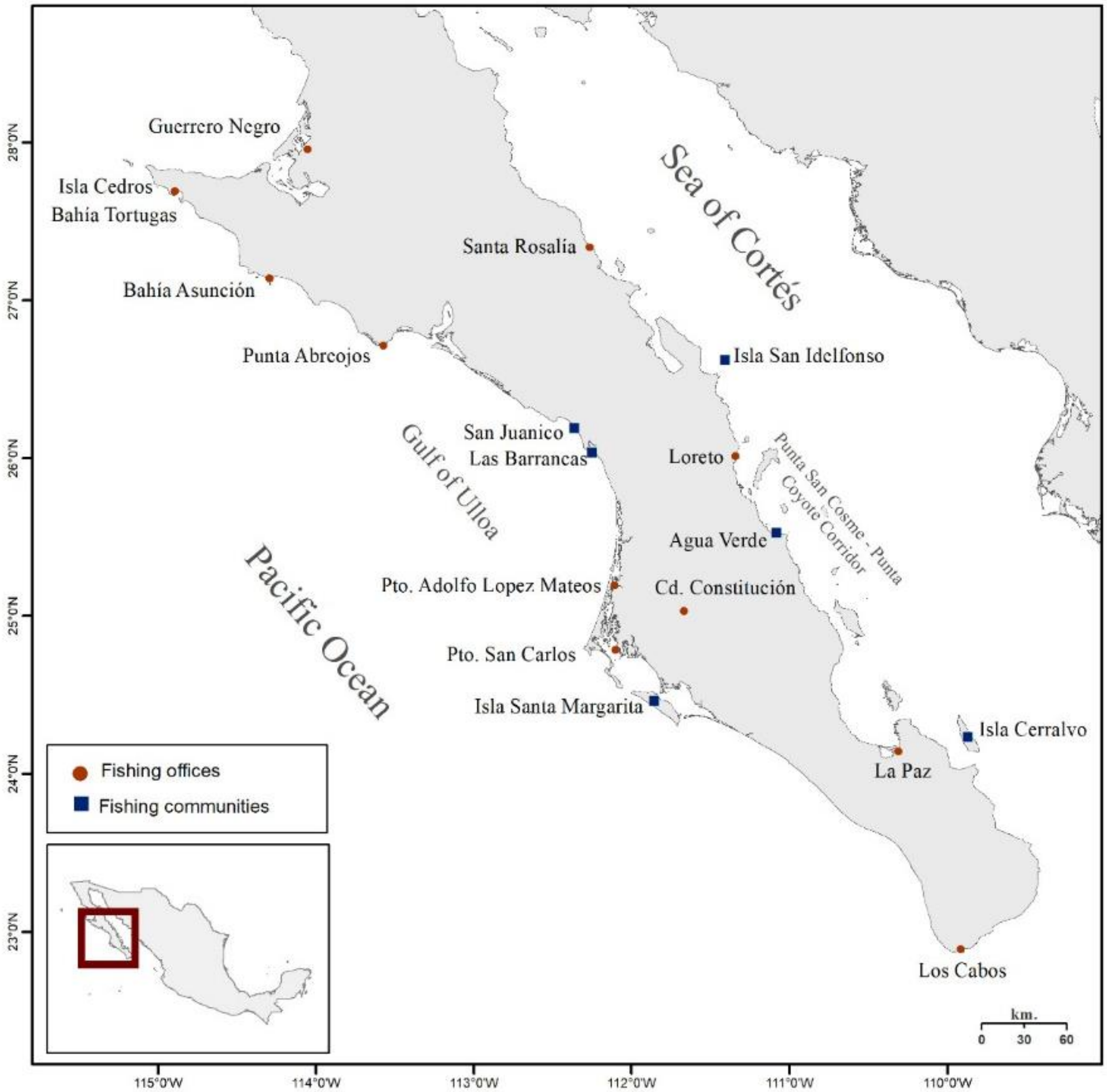

Figure 1. Study region: Baja California Sur, México.

(SAGARPA 2010, CONAPESCA 2018). In this region, San Cosme Corridor, Agua Verde, Isla San Idelfonso, Isla Cerralvo, among others.

BCS counts around 13 fisheries in almost all communities except for abalone and lobster fisheries operating in the north. The finfish fishery takes place throughout the year in all BCS zones. Due to seasonal temporality, the fisheries are the shrimp, warrior crab, clam, and shark fishery. BCS has 12 governmental offices (Table 1) where fishers from each locality report their catches in trip tickets.

The data

Trip tickets are the official Mexican document in which registered the catch data of each fisher. The data obtained by this document are the official catch landing reports (OCLR); among other fields of information OCLR provides the species caught, the national fishing register of the economic unit, landing zone, fishing locality, the volume catch, the date, and first-hand sale price "on the beach." This database is managed by the National Fisheries and Aquaculture Commission (CONAPESCA, acronym in Spanish).

The database consists of trip tickets from BCS from 2001 to 2017. The species reported by common name and the corresponding scientific name were assigned in the database, classified within any reported fisheries, the captured volume reported in kilograms, and its value in Mexican pesos.

The tickets in the database were classified by four zones proposed by Díaz-Uribe et al. (2013). Subse-

Table 1. Zoning of the catch landings reports offices.

Zone I	Zone II	Zone III	Zone IV
Loreto	Puerto Adolfo López Mateos	Bahía Tortugas	Guerrero Negro
La Paz	Ciudad Constitución	Bahía Asunción	
Santa Rosalía	Puerto San Carlos	Punta Abreojos	
Los Cabos		Isla de Cedros	

quently, a monthly average fishing catch time series was structured for each fishery. Table 1 shows the landing offices per zone.

The monthly average of sea surface temperature (SST) and chlorophyll-*a* concentration (Chl-*a*) was obtained through the GEOVANNI platform; those variables were selected due to the previous studies that used DLM for time series forecast in fisheries shown a good performance as a predictor (Kim et al. 2016, Cavieses-Núñez et al. 2018). In this case, SST is an indirect index of the environment temperature, even when the fishery target is not a superficial species. The CLA variable was used to evaluate the primary productivity in the zone. Those variables were spatially averaged for each zone every month to form the time series that would later be used in DLM. Also, time series of monthly rainfall for each zone were introduced to the model for a test, under the logic that higher rainfall at a given time, greater the probability that a meteorological phenomenon would occur, such as a hurricane that prevented the fisherman's tasks or modified the ecological environment of the fishery. Oceanographic indices like Pacific Decadal Oscillation or NIÑO3 have not been used because of the index's spatial resolution and the SST's autocorrelation.

Preprocessing data

The time series are ratio measurements and arranged as a Pandas Data-Frame, indexed by month intervals for each zone and fisheries. A maximum-minimum normalization method was applied to reduce the noise by the variables' magnitude, setting the variables in the 0 to 1 range (Kingma & Ba 2015).

Input variables were created from lagging the original time series; those were tested as input in the DLM to evaluate the importance of the previous state in the system; the ranges tested were three and six months, this concept is taken from the stock market analysis where it is stated that the slope of a Signal is an indicator of possible future values. In this way, the input tensioners' structure was as follows: (1, from 1 to 8 of delayed inputs, 173). The time series was divided into three groups, training 80% of data and 20% for tests and two years of data validation.

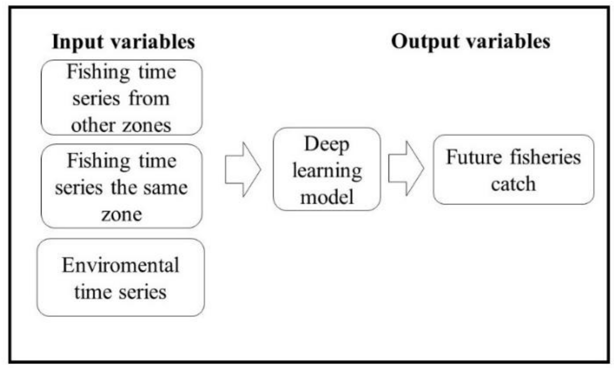

Figure 2. Conceptualization of the model for a node to the fisheries system proposed.

To determine autocorrelation and the delay between variables, linear correlation analysis and, a cross-correlation analysis was performed to finfish fisheries catch in different areas, and fisheries' catches in the study area. An exploratory analysis of the data was carried out to understand the catches' main characteristics in the BCS fishing system, with which trends, proportions, and seasons were obtained.

The system

A system can be understood as a conjunct of highly interactive elements or agents. In this case, the system is composed of the zones proposed by Uribe et al. (2013); each zone is interpreted as a subsystem where the fisheries are its elements. The links by the zones are conceptualized as the interaction done by the market or spatial-temporal fishing seasons. The neighborhood of a zone is the other element that composes the system.

The models

In this article, the ability of DLM to simulate elements of a complex adaptive system is evaluated; three DLM are implemented to simulate different elements of a subsystem in the fisheries dimension, which have as input variables catch data from the main SSF of BCS grouped by zones and catch as an output variable (Fig. 2).

A long short-term memory (LSTM) layer, Dense layer, MaxPooling layer, and Flatten layer was used (Ketkar 2017). Different hyper-parameter architectures

Table 2. Attribute setting options for the models.

Hyperparameter	Bach size	25, 50, 100, 150
	Epoch	100, 150, 250, 500, 1000, 1500
	Optimizer	Adamax, adam, rmsprop, sgd
	Loss	Mae, smae, mse
Parameter	Neurons	5,10,15,25,50,100,200
	Layers	1,2,3,4
	Dropout	0.2 0.4 0.6
	MaxPooling	yes / no
	Activation function	relu, linear, tansig, tanh

for training (number of iterations, batch size, error estimator) and model parameters (number of neurons, activation functions, number of layers, dropout ratio) were tested (Zela et al. 2018); these attributes are shown (Table 2).

The first model evaluates the ability of DLM to simulate the response of the catches of different SSF (abalone, seaweed, clams, squid, scallops, shrimp, warrior crabs, snails, sport-fishes, sea urchin, finfish, sharks, tuna, and others) in BCS using as input variables (Xi) SST, CLA, rain and historical data of catches. This model can be considered general for the complex adaptative system fisheries (CASF). The DLM has LSTM, rectified linear activation function (ReLu), MaxPooling, and Dense layers as presented in Figure 3a.

The second model evaluated simulates the catches of the finfish fisheries in one of the main areas of BCS. This proposed model as CAS element evaluates the interaction between catches of the finfish fishery and clams, warrior crabs, and sharks in zone II. Finfish fishery and zone II was chosen as the objective of this model due to its relevance to BCS´s fisheries (Ramírez-Rodríguez & Ojeda-Ruiz 2012, Cavieses-Núñez et al. 2018, Méndez-Espinoza et al. 2020). The second model's input variables were monthly SST data, CLA, and the finfish catches; this model comprises three layers, one LSTM, and two Dense layers, as shown in Figure 3b.

A third model simulates the possible interaction between captures of the essential SSF for BCS in different areas. For this case, it is stated that each BCS area is a node with its subsystems, for this model, the idea of that the nodes are connected by market demand, the target fishery of this model was finfish, the input data for the model are the monthly catches of each of the finfish fisheries in the other three zones, and the output data of the model are the captures of zone 2. This model is shown in Figure 3c; it has five neuron layers, combining LSTM and Dense layers. A *t*-student hypothesis test was carried out between each model's forecast and real data to evaluate the input variables' predictive power.

In the process of analysis of data and creation of the models, a virtual environment in the software anaconda with a version of Python 2.7 was used, with the following packages: Pandas 0.23.0, Tabulate 0.8.2, Matplotlib 2.2.2, Seaborn 0.8.1, Datetime, Sklearn, Numpy 1.13.3, Keras-GPU 2.2.2, Scipy 1.1.0, Tensorflow-GPU, Statsmodels 0.9.0, Tensorboard 1.10.0, JupyterLab 0.32.0. All the models and their python codes can be found on GitHub [https://github.com/rcavieses/fisheriesnode].

RESULTS

From the exploratory analysis of the data, the results of cross-correlation analysis of the input variables used in models 2 and 3 with the target variable can be seen in Figure 4. In Figure 4a, only the warrior crab and shark fisheries have high correlations ($R > 0.8$) for lags of -2.5 months, which corroborates that both fisheries are carried out in different seasons. The environmental variables present correlations with fisheries catch that indicate a relationship, which justifies their use in the DLM. Figure 4b presents the cross-correlations ($R > 0.75$) between the catches of the finfish fishery from different areas; this fishery is carried out most of the year and is made up of multiple target species, they also share intermediaries in the purchase of products, which contributes to a high correlation.

When comparing the proportions of catches by area and catch, we see that clam fishing contributes 51%, followed by finfish fishing with 31.4%, and it is found that the zones that contribute most of the production are the I and II (Fig. 5).

The results of the analysis of the predictive power of the input variables presented to Model 1 (Table 3) show which fisheries have a better forecast performan-

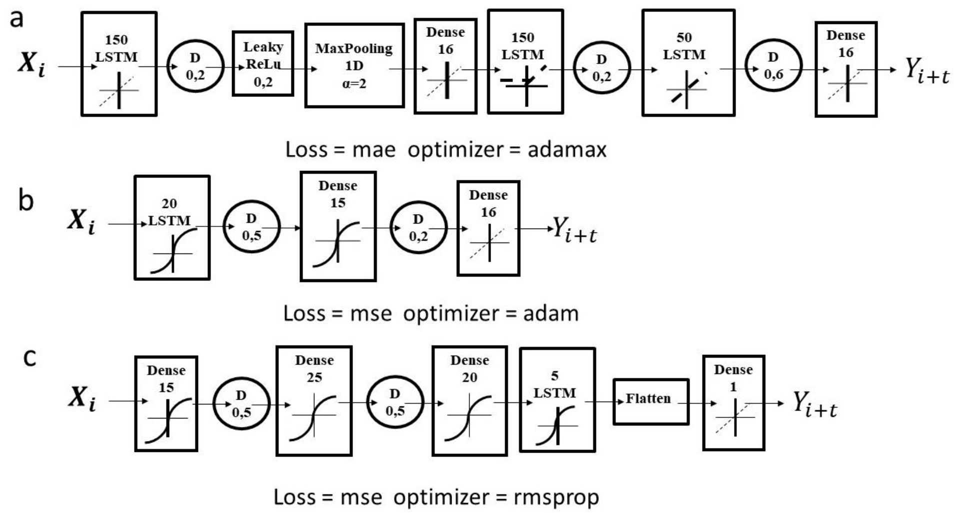

Figure 3. Deep learning models for small-scale fishing catches.

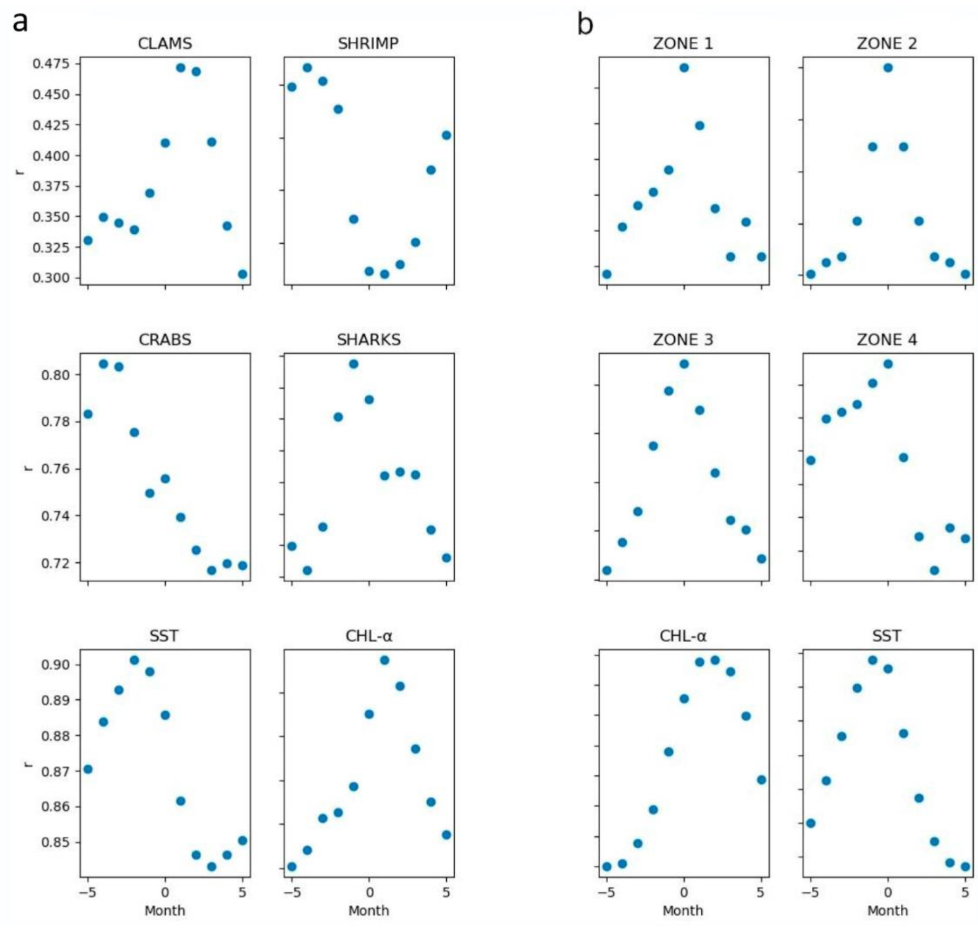

Figure 4. a) Cross-correlation analysis of input variables for Model 2, b) cross-correlation analysis for Model 3.

ce (marked in bold), and there is statistical evidence to affirm that the data from forecast and real data are not significantly different ($P > 0.05$). It should be noted that the model was not general enough since the predictive power for the scallop and warrior crab fishery has significant differences between the prognostic and actual value ($P < 0.05$).

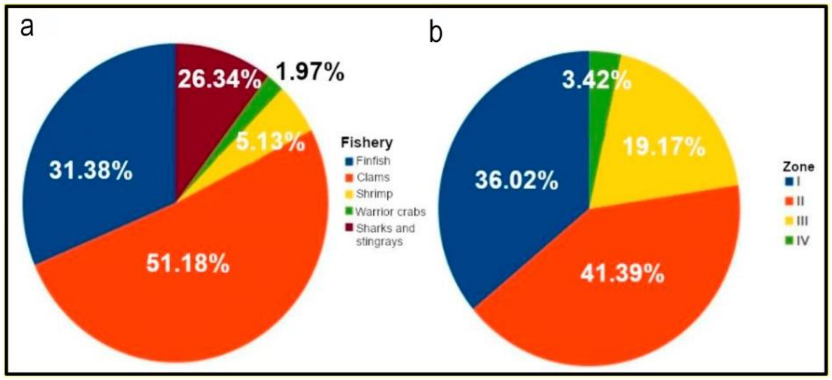

Figure 5. a) Proportion of total catches per fisheries in Zone 2, b) proportion of total catches per zone.

Table 3. Evaluation of predictive power for Model 1 (in bold means significant values). RMSE: root mean squared error, R: correlation coefficient, AIC: Akaike information criteria, BIC: Bayesian information criteria, *P*-value: probability value.

Fisheries	RMSE	R	AIC	BIC	*P*-value	*t*-statistic
Abalone	3669	**0.99461**	2501	2609	**0.347**	-0.2093
Seaweed	7	**0.98761**	630	738	**0.694**	-0.3949
Clams	416030	0.35734	3902	4010	0.0095	-2.6593
Squids	993428	0.86205	4159	4267	0.0001	-4.2532
Scallops	3001	**-**	2442	2550	0.0001	4.4438
Shrimp	5463	**0.64891**	2619	2727	**0.1098**	-1.6202
Crabs	14969	0.28563	2918	3026	0.0002	4.1427
Snails	145248	**0.87819**	3590	3698	**0.2588**	-1.1388
Sport-fishes	7435	**0.98186**	2711	2818	**0.8743**	-0.1589
Sea urchins	2117	-0.15749	2339	2447	**0.0908**	1.7337
Finfish	13757	0.70319	2893	3001	0.0048	2.9412
Warrior crab	5692	0.83997	2631	2739	0.0136	2.5499
Sharks	98946	0.93667	3477	3585	0.0273	2.2583
Tuna	112321	**0.91811**	3514	3622	**0.0826**	-1.7600
Others	23316	**0.41819**	3049	3157	**0.0626**	1.9091

The performance of each input variable's predictive power is affected by the delay applied to the inputs (Table 4). Except for SSF sharks catch, there have not found significant differences between the forecast and real data ($P > 0.05$).

If we consider the values of BIC and AIC, we can see that they do not have significant differences in terms of the number of variables that are entered into the model, on the other hand, there is a better correlation coefficient R = 0.982 when a delay equal to six months and as input variables we have TSS, Chl-*a*, clams, and shrimp. In Figure 6a, we can see that the model, using all the input variables and using a six-month lag, follows the real catch data trends in the finfish fishery; this observation confirms that there is no effect of the seasonality of data on the forecast. In this case, the bands from the standard error to the first standard deviation are presented.

Corresponding to the analysis of the predictive power of the input variables in Model 3 (Table 5) who considers the effect between zones, we can evaluate the effect between zones when only the fisheries catches are entered as input variables, in this case, the other zones have an R = 0.933 ($P > 0.05$) with a six-month lag of the variables. When all the input variables are tested, the AIC = 3779 and BIC = 3837 indices indicate a better model than only using the capture variables from other areas or only using the environmental variables. When the input variables are considered separately for the model, we can see a high relationship with zone 3 (R = 0.897, $P > 0.05$); this relationship is partly because both areas are located on the Pacific Ocean coast. On the other hand, the *t*-test for zone 1 has no significant relationship with zone 2 (R = 0.739, $P < 0.05$), this result indicates that there is not only a spatial relationship since these zones are in the Sea of Cortés.

Table 4. Evaluation of predictive power for input in Model 2. R: correlation coefficient, AIC: Akaike information criteria, BIC: Bayesian information criteria, SST: sea surface temperature, Chl-*a*: chlorophyll-*a* concentration in sea surface by MODIS-aqua.

Variables	Delay 3					Delay 6				
	R	AIC	BIC	*P*-value	*t*-student	R	AIC	BIC	*P*-value	*t*-student
SST, Chl-*a*, clams, shrimp, warrior crab, sharks	0.953	3857	3924	0.229	1.237	0.925	3868	3999	0.177	1.397
SST, Chl-*a*, clams, shrimp, warrior crabs	0.936	3825	3884	0.421	0.820	0.931	3851	3964	0.228	1.240
SST, Chl-*a*, clams, shrimp	0.915	3805	3854	0.461	0.750	0.982	3813	3907	0.176	1.400
SST, Chl-*a*, clams	0.894	3864	3904	0.258	1.163	0.920	3837	3913	0.188	1.359
SST, Chl-*a*	0.815	3966	3997	0.078	1.866	0.917	3842	3900	0.144	1.515
SST	0.839	3886	3907	0.339	0.977	0.949	3793	3833	0.188	1.358
Chl-*a*	0.832	3882	3903	0.348	0.959	0.885	3769	3808	0.398	0.862
Clams	0.685	3924	3946	0.357	0.943	0.727	3883	3922	0.306	1.048
Shrimp	0.848	3873	3894	0.280	1.110	0.882	3826	3866	0.515	0.663
Warrior crabs	0.484	3985	4007	0.321	1.018	0.172	3982	4021	0.427	0.766
Sharks	0.440	4029	4050	0.074	1.903	-0.047	4032	4071	0.022	2.564

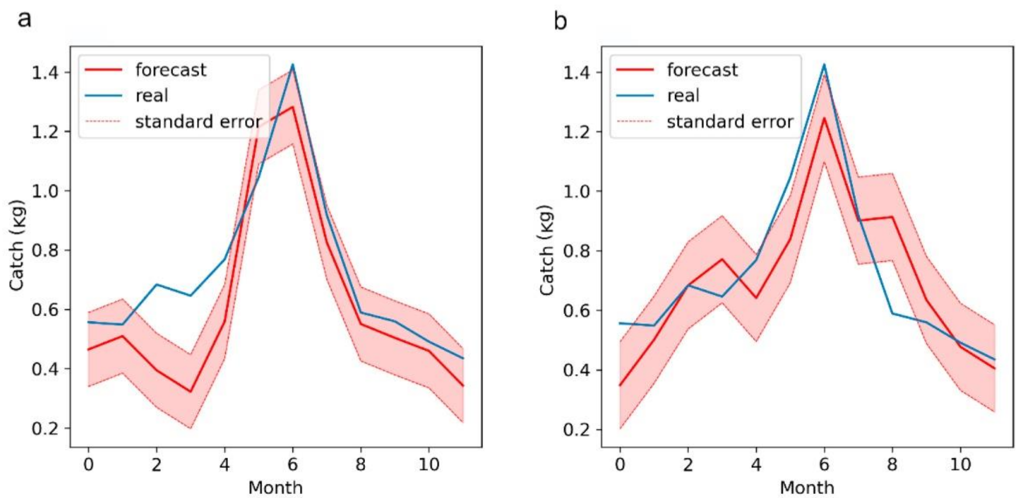

Figure 6. Forecast *vs*. real data of finfish catches in 2016. a) Model 1, b) Model 2.

Regarding the validation of the model presented (Fig. 6), it can be noted that the trend continues with a slight underestimation.

DISCUSSION

In this study, we proposed a deep neural network model that seeks relationships between the catches of SSF in BCS, and environmental variables, to provide a significant comprehension of the fisheries system and be an alternative method for analyzing the interaction between fisheries, zones, and the environment. A tool with the power to predict futures catches by using the available information on accessible databases and a low cost. It is important to mention that fisheries management in Mexico is done in a poor data context, as many others countries worldwide (Mendez-Espinoza et al. 2020).

Other authors such as Fuller et al. (2017) and Trifonova et al. (2017) have used the analysis of topological networks to describe the processes of interaction between various fisheries in multiple zones connected through markets. These analyses allow us to understand the degree of connectivity between the different factors within an environment; however, it does not simulate these topological networks' responses to external variables and changes.

Model 1, whose results are in Table 3, presents sufficient statistical evidence to consider that its predictive capacity is adequate and has the quality to make forecasts of the catch trends of different fisheries simultaneously.

Table 5. Evaluation of predictive power for inputs in Model 3. *R: coefficient correlation; AIC: Akaike information criteria;

BIC: Bayesian information criteria, ZN1: catches in Zone 1, ZN3: catches in Zone 3, ZN4, catches in Zone 4, Chl-*a*: Chlorophyll-*a* concentration in sea surface by MODIS-aqua.

Variables	Delay 3					Delay 6				
	R	AIC	BIC	*P*-value	*t*-student	R	AIC	BIC	*P*-value	*t*-student
SST, Chl-*a*, ZN1, ZN3, ZN4	0.906	3779	3837	0.629	0.49	0.927	3695	3808	0.783	0.279
SST, Chl-*a*, ZN1, ZN3	0.911	3756	3806	0.68	0.419	0.932	3755	3849	0.655	-0.453
SST, Chl-*a*, ZN1	0.908	3780	3820	0.527	0.643	0.964	3560	3636	0.92	-0.101
SST, Chl-*a*	0.726	3942	3973	0.205	1.314	0.767	3835	3893	0.448	0.775
SST	0.84	3878	3899	0.27	1.134	0.768	3828	3868	0.397	0.864
Chl-*a*	0.885	3894	3915	0.161	1.452	0.862	3741	3780	0.978	0.028
ZN4	0.631	3940	3962	0.361	0.936	0.81	3801	3841	0.514	0.666
ZN3	0.897	3771	3792	0.575	0.569	0.952	3572	3611	0.856	0.184
ZN1	0.739	3888	3910	0.517	0.661	0.656	3853	3892	0.783	0.279
ZN1, ZN3, ZN4	0.894	3782	3822	0.632	0.485	0.933	3703	3779	0.941	0.076

If we focus on the forecasting capacity of Model 1 for warrior crab and shark fisheries, we can see that it is accurate. These fisheries report catches throughout the year despite having temporary closures as a management tactic and protection of seasonal reproduction periods (Ramirez-Amaro et al. 2013, CONAPESCA 2018, Méndez-Espinoza et al. 2020). Also, they present their highest catches in different periods of the year. It has also been observed that they do not share operational units (Ramírez-Rodríguez & Ojeda-Ruiz 2012, Ramirez-Amaro et al. 2013, Méndez-Espinoza et al. 2020). Considering the above, the generalist model (Model 1) could simultaneously simulate both fisheries' catch trends.

Zones 2 and 3 are located at the Pacific shore, share similar fleets, and the finfish fisheries extract almost the same species (Cota-Nieto et al. 2018, Ojeda-Ruiz et al. 2018). These similitudes are supported by the statistical evidence shown in the correlation analysis and indicate that the differences are only administrative, as was observed by Díaz-Uribe et al. (2013).

The results of the DLM presented in this paper complement the interaction analysis techniques between fisheries, such as complex adaptive systems and or experts' agents in artificial intelligence. Those DLM could be used to simulate the environment (the CAS state in a specific frame of time) where the expert agents have to make decisions. Another technique used to describe the interaction between fisheries and their environment is the Bayesian probability networks (Trifonova et al. 2015), which explains fisheries' behavior in the face of changes in the environment. However, this technique uses preliminary fishery information, which requires *in situ* studies that describe the biology of the resource, as well as fishing techniques and effort, or the relationship of the target species with its ecosystem, among other data. This information is hardly available in small-scale fisheries in developing countries, such as Mexico. The models proposed by Kim et al. (2015), Naranjo et al. (2015) and Cavieses-Núñez et al. (2018) focused on time series forecasting, implementing deep neural networks with applied environmental variables as input, and catch as the target variable. These authors presented similar performances to those presented in this article, confirming that the deep learning techniques may solve fishing modeling problems considering different types of variables.

The model we proposed allows us to indirectly identify the interaction between the catches of the SSF occurring in the same zones or the interaction from zone to zones. The identification of interaction level occurs through the prediction power of an input variable. As an instance, the results present us evidence that clam fishery could be identified as a factor related to finfish fishery catch with an R = 0.685 (P = 0.357), but shrimp fisheries have a prediction power of R = 0.848 (P = 0.280), in this case, shrimp fisheries have more expectation of affecting the finfish fishery. When catches of finfish per zones are used as inputs, each zone's predictive power could be interpreted as the relationship between zones, and the model can simulate the responses to changes in the system.

Wilson (2006), collected the characteristics of the complex adaptive systems of fisheries, nature, and their interaction with humans, promoting that management strategies and policies should not only focus on controlling resources. This proposed deep learning model supports the idea that fishery resource management strategies cannot be specialized in a single species, metier, or community; on the contrary, they must be inter-fishery and inter-zone strategies. This complexity in fisheries may hinder the management as long the management meta-levels are not well defined, understanding the different fishery interactions, the actors, and the community's needs, as different levels of management. In this way, the management strategies' impact on a node would be predictable and adapted to the community's needs and the whole system.

CONCLUSIONS

DLM can simulate the response of the catch variable of the finfish fishery to changes in the environment, such as temperature or primary production, and catch volumes of other fisheries. DLM shows the feasibility of simulating the interaction between the different elements of a CAS and evaluating the level of interaction. The capacity to handle the poor data quality of those models is adequate to be recommended as a tool to simulates fisheries systems. However, it is highly recommended to explore these models' ability and capacity to perform analyses of complex adaptive fisheries systems.

According to our results and considering the use of other tools in this context, the deep learning ability to find not linear relationships between variables is one of the most significant advantages, mainly when a deep understanding of the operation of fishing systems is not required and prioritized the ability to simulate in scenarios posed due to immediate need.

It is essential to highlight that the development of artificial intelligence is advancing rapidly. We suggested investigating this technology's applicability to the different problems facing the fishing sector, such as expert agents' cases, to develop decision-making models that evaluate the actors' response to different management measures.

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