Prediction of global sea cucumber capture production based on the exponential smoothing and ARIMA models

Yugui Z.H.U.[1]; Hongbing L.V.[1]; Jiansong C.H.U. [2*]

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Abstract

Sea cucumber catch has followed "boom-and-bust" patterns over the period of 60 years from 1950-2010, and sea cucumber fisheries have had important ecological, economic and societal roles. However, sea cucumber fisheries have not been explored systematically, especially in terms of catch change trends. Sea cucumbers are relatively sedentary species. An attempt was made to explore whether the time series analysis approach (exponential smoothing models and autoregressive integrated moving average (ARIMA) models) is also applicable to relatively sedentary species. This study was conducted to develop exponential smoothing and ARIMA models to predict the short-term change trends (2011-2020), according to the time series data for 1950-2010 collected from the FAO Fishstat Plus database. The study results show that the single exponential smoothing and ARIMA (1, 1, 1) models are best for predicting sea cucumber short-term catches, and the predictive powers of both models are good. However, the accuracies of the models would be better if the data quality was resolved and the variables influencing sea cucumber capture production were fully considered.

Keywords: Sea cucumber, Capture production,Prediction, Time series analysis, Exponential smoothing, ARIMA

1- College of Fisheries, Ocean University of China, Qingdao 266003, P. R. China
2- College of Marine Life Sciences, Ocean University of China, Qingdao 266003, P. R. China
* Corresponding author's E-mail: oucjs@ouc.edu.cn

Introduction

Sea cucumber catch trends, according to the FAO Fishstat Plus database, have followed "boom-and-bust" patterns since the 1950s, declining nearly as quickly as they expanded (Bruckner, 2005; Conand and Muthiga, 2007; Toral-Granda *et al.*, 2008). Besides, sea cucumbers are important ecologically as suspension feeders, detritivores and prey (Uthicke, 2001; Bruckner *et al*., 2003; Pouget, 2004). In addition to the ecological importance of sea cucumbers, the long-term sustainability of sea cucumber fisheries is of great importance to many coastal communities, in terms of both social and economic aspects (Nash and Ramofafia, 2006; Kinch *et al*., 2008; Dissanayake *et al*., 2010).

Considering the importance of these fisheries, in order to achieve the sustainable development of sea cucumber fisheries, it is necessary and essential to know as much as possible about the short-term catch change trends of sea cucumber populations. More often than not, the commercial fishing of sea cucumber leads to many changes in sea cucumbers rather than ecosystem changes, including changes in abundance, total biomass, size frequency distributions, age-structure and spatial distributions (Uthicke, 2004; Uthicke and Conand, 2005; Al-Rashdi *et al.*, 2010). There is generally a lack of abundance data, catch statistics are often incomplete, market demand is ever-increasing, and exploitation has not been effectively controlled (Baine, 2004; FAO, 2004, 2008). The references listed reveal that there has been much discussion regarding country-specific sea cucumber fisheries, or insight into the dynamics of the global sea cucumber trade (Clarke, 2004; Uthicke and Conand, 2005; FAO, 2008). However, quantitative analyses, especially predictive analysis, are currently limited globally to the capture production of sea cucumber fisheries.

For efficient forecasting, adequate mathematical models are necessary. To date, there are no models which have being developed for forecasting sea cucumber capture production. In general, there are two categories of univariate time series models which can be used for forecasting, namely exponential smoothing models and autoregressive integrated moving average (ARIMA) models. In this study, an attempt has been made to develop the exponential smoothing and ARIMA models for forecasting available sea cucumber capture production time series data. This methodology has been successful in forecasting the fishery dynamics of a wide variety of species (Dyer and Gillooly, 1979; Saila *et al.*, 1980; Stocker and Hilborn, 1981; Noakes, 1986; Stergiou and Christou, 1996; Lloret, *et al.*, 2000; Georgakarakos *et al.*, 2002; Punzón *et al.*, 2004; Georgakarakos *et al.*, 2006). Stergiou *et al.* (1997) suggested ARIMA models as the most appropriate method to forecast fishery landings in the Hellenic marine waters, due to the fact that systematic biological time series data sets from explanatory variables are unavailable. Consequently, the specific purpose of this study is to develop appropriate ARIMA models for the time series of global sea cucumber capture production during the period 1950-2010. In addition, exponential smoothing models are also used to predict the sea cucumber production changes, in order to compare the efficiency of the two models.

Material and methods

Smoothing model forecasts are based on the future projection of the basic pattern after eliminating randomness with smoothing. Exponential smoothing models apply unequal and exponentially decreasing weights to average past observations. In this study we used single exponential smoothing, second exponential smoothing and triple exponential smoothing, to determine the best-fit model according to the principles of minimization of mean square error (MSE) and relative error %, as well as the maximization of the coefficient of determination (R^2).

Although ARIMA models are similar to smoothing models in that forecasts are developed from historical time series data analysis, ARIMA models are based on well-articulated statistical theory. They capture the historic autocorrelations of the data and extrapolate them into the future.

Data source

The sea cucumber capture production statistics obtained from the Food and Agriculture Organization of the United Nations (FAO) Fishstat Plus database are recorded in terms of wet weight. On the basis of these data, sets of the discrete time series of annual capture production were determined for the period of 1950-2010 (Fig. 1).

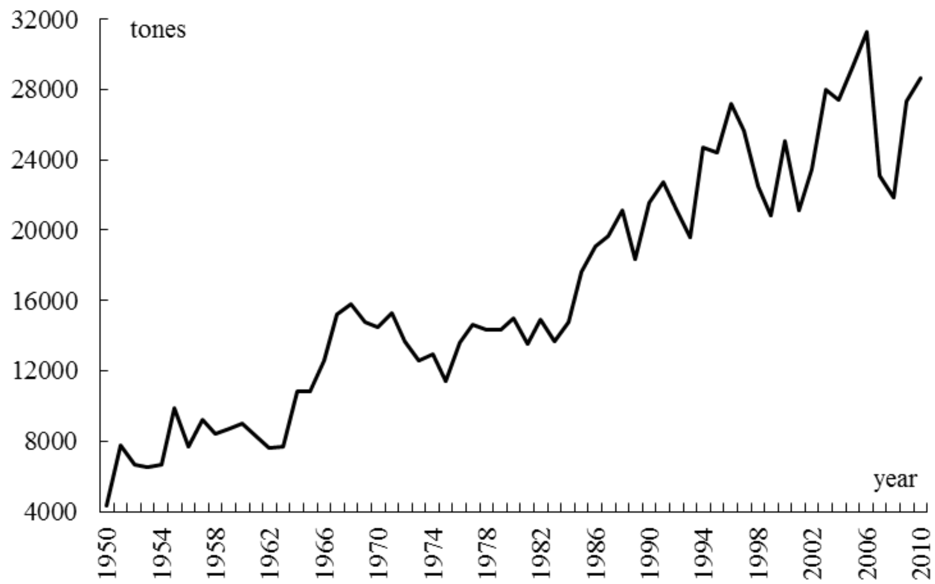


Figure 1: The changes of global sea cucumber capture production over the period of 1950-2010. Data source: Fishstat Plus, 2012.

According to Fig. 1, the sea cucumber capture production trends upward overall during the period 1950-2010, for the following reasons. First of all, the continued strong market demand, abundant natural resources of sea cucumber as well as large and widespread sea cucumber fishing resulted in an increase in capture production (Baine, 2004; Chen, 2004; Toral-Granda *et al.*, 2008). Secondly, new low-value species are exploited to supplement the decline in production of high-value species caused by overfishing (Uthicke and Conand, 2005; Purcell *et al.*, 2009; Al-Rashdi and Claereboudt, 2010). Thirdly, fishing activities have been expanded from intertidal zones to the deep-sea with the advances in fishing techniques (Akamine, 2004; Choo, 2008; Skewes *et al.*, 2010).

Exponential smoothing models

In single exponential smoothing, the future values e_{t+1} of a variable d for each instant of time $t+1$ are computed as the weighted average of their actual values d_t in instant time t. η_d is a smoothing constant/ weight between 0 and 1, and the value of η_d has considerable impact on the forecast. A large value of (say 0.99) gives very little smoothing in the forecast, whereas a small value of η_d (say 0.01) gives considerable smoothing. In this manner, the smoothed variable $S_t^{(1)}$ for each instant of time t is obtained (forecast) by the following equation (Brown, 1963; Kalekar, 2004):

$$S_t^{(1)} = \eta_d d_t + (1 - \eta_d) S_{t-1}^{(1)} \quad (1)$$

$$e_{t+1} = S_t^{(1)} \quad (2)$$

Therefore, in effect, each smoothed value is the weighted average of the previous observations, where the weights decrease exponentially depends on the value of parameter η_d (0< η_d <1).

The second exponential smoothing method is smoothed once more on the basis of the linear exponential smoothing. The formula is as follows:

$$\mathrm{S}_{t+1}^{(2)} = \eta_{\mathrm{d}} S_t^{(1)} + (1 - \eta_d) S_t^{(2)} \quad (3)$$

$$e_{t+1} = S_t^{(2)} \quad (4)$$

Where the second exponential smoothing value $S_t^{(2)}$ for each instant of time t is equal to the future values e_{t+1} of variable d for each instant of time $t+1$.

Similarly, the triple exponential smoothing method is smoothed once again on the basis of the second exponential smoothing, which is calculated as follows:

$$\mathrm{S}_{t+1}^{(3)} = \eta_{\mathrm{d}} S_t^{(2)} + (1 - \eta_d) S_t^{(3)} \quad (5)$$

$$e_{t+1} = S_t^{(3)} \quad (6)$$

where the triple exponential smoothing value $S_t^{(3)}$ for each instant of time t is equal to the future values e_{t+1} of a variable d for each instant of time $t+1$.

ARIMA models

The ARIMA models represent a stochastic process which captures the correlation structures of a discrete, stationary time series (Box and Jenkins, 1976; Keller, *et al.*, 1987). ARIMA model data are assumed to be the output of a stochastic process, generated by unknown causes, from which future values can be predicted as a linear combination of past observations, as well as estimates of current and past random shocks to the system (Box *et al.*, 2008).

For a stationary time series, DX_t, an ARIMA (*p*, *d*, *q*) model which considers the last p-known values of the series and *q* of the past modeling errors was developed (Box and Jenkins, 1976; Vandaele, 1983; Bowerman and O'Connell, 1993; Chatfield, 2003). The model is as follows:

$$\mathrm{DX}_t = C + \sum_{i=1}^{p} \varphi_i DX_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad (7)$$

Parameters *p* and *q* denote the order of autoregressive (AR) and moving average (MA), while *d* denotes the degree of differentiation in the series to obtain stationarity. In addition, DX_t is the observation at time t, C is the constant term, φ and θ are coefficients and ε is an error term. The autocorrelation (ACF) and partial autocorrelation functions (PACF) of a series together are the most powerful tool usually applied to reveal the correct values of the parameters. The ACF gives the autocorrelations calculated at lags 1, 2, and so on, while PACF gives the corresponding partial autocorrelations, controlling for autocorrelations at intervening lags.

Due to the fact that the above method is subjective, various statistics such as the minimum Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) were used in order to identify the ARIMA model objectively. Furthermore, the estimation of model coefficients (φ, θ) was achieved by means of the maximum likelihood method, using SPSS 20.0 software. Verification of the model was performed through diagnostic checks of the residuals.

Evaluation of forecasting accuracy

The ability of the above described models to forecast the global sea cucumber capture production on a yearly basis was tested by applying each fitted model to all of the available data, excluding the annual data of the final stage (2000-2010), which were used to compare with the forecasts obtained for that stage. For the purpose of comparing forecasting procedures, many measures of forecasting accuracy can be used (Makridakis *et al.*, 1983). To evaluate the accuracy of the exponential smoothing and ARIMA processes, in this study we used (a) the coefficient of determination (R^2); (b) two relative statistical measures (relative error %, RE %; mean absolute percentage error, MAPE); and (c) a standard statistical measure (mean square error, MSE).

Results

Exponential smoothing models

Table 1 show the results of the single, second and triple exponential smoothing models with a level of acceptable statistical significance ($\alpha < 0.05$). In this case, although the coefficient of determination (R^2) of the single exponential smoothing model was less than the second exponential smoothing and greater than the triple exponential smoothing model and the mean square error (MSE), relative error % (RE %) and mean absolute percentage error (MAPE) of the single exponential smoothing model were minor in comparison to the other models. Therefore, the single exponential smoothing model was used to predict the sea cucumber capture production from 2000-2010, in terms of the corresponding time series data over the period of 1950-1999. The predicted results show clearly that the actual and predicted values based on an application of the single exponential smoothing model over the period 2000-2010 are very similar (Fig. 2).

In order to further confirm whether the single exponential smoothing model is more predictive than the second and triple exponential smoothing models, these smoothing models were used to simultaneously predict the sea cucumber capture production over the period of 2011-2020 according to the corresponding time series data over the period of 1950-2010. The statistic results reveal that the R^2 value of the single exponential smoothing model (R^2=0.949) was less than the second exponential smoothing (R^2=0.953), and greater than the triple exponential smoothing model (R^2=0.940). In addition, the MSE and RE % of the single exponential smoothing model were minor in comparison to the other models (Table 2).

Consequently, the single exponential smoothing model was statistically the preferred model compared to the second exponential smoothing and triple exponential smoothing model in terms of predictive power. Therefore, the actual values over the period 1950-2010 were used to draw the fitted curve of single exponential smoothing model, and accordingly predict the sea cucumber capture production from 2011-2020 (Figs. 3 and 7). In conclusion, the results of the parameter test reveal that the MAPE of the single exponential smoothing model is 11.725% from 2000-2010 (Table 2). Therefore, according to Table 3, 10%<11.725% < 20%, thus the predictive power of the single smoothing model is good.

ARIMA models

According to Fig.1, the changes of global sea cucumber capture production over the period 1950-2010 are not stable, and hence a hypothesis is made that the time series data must be a non-stationary time series data. The ADF test is used to verify whether the hypothesis is valid. The unit root test results of ADF indicate that the critical values of the 1% level, 5% level and 10% level are -3.560019, -2.917650 and -2.596689, respectively (Table 4). Due to the fact that the ADF test statistics is 0.209672, and 0.209672 is less than the above three absolute values (i.e. -3.560019, -2.917650 and -2.596689), the above hypothesis is rejected.

Therefore, the difference of the first order (d=1) for the original time series data is made. Subsequently, the differential time series data is tested by the ADF method once again.

Table 1: The exponential smoothing models of sea cucumber capture production over the period of 1950-1999.

Exponential smoothing model	Coefficient of determination (R^2)	Mean square error (MSE)	Relative error % (RE %)	Mean absolute percentage error (MAPE)	η_d
Single exponential smoothing	0.954	1771.761	10.255	11.725	0.880
Second exponential smoothing	0.995	1917.324	10.727	26.471	0.400
Triple exponential smoothing	0.944	2006.798	11.397	47.600	0.286

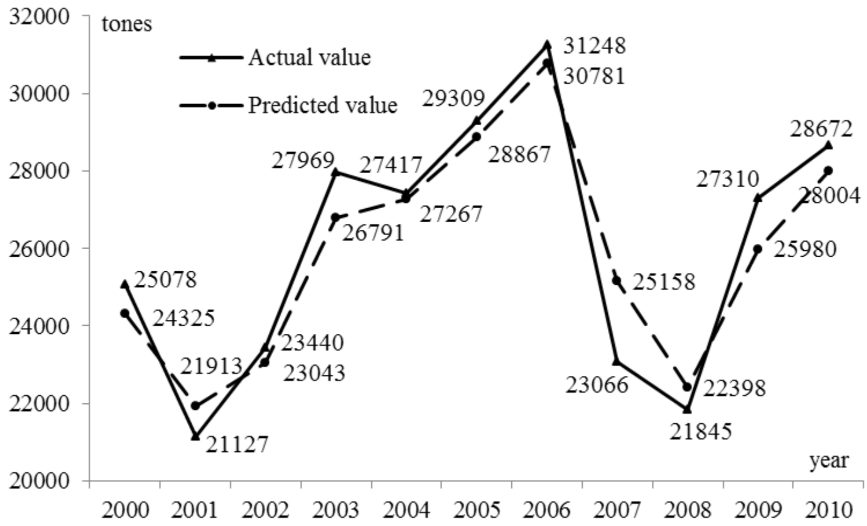


Figure 2: The actual and predicted values based on an application of a single exponential smoothing model over the period of 2000-2010.
Data source: FAO Fishstat Plus, 2012.

Table 2: The exponential smoothing models of sea cucumber capture production over the period of 1950-2010.

Exponential smoothing model	Coefficient of determination (R^2)	Mean square error (MSE)	Relative error % (RE %)	η_d
Single exponential smoothing	0.949	2269.826	10.742	0.740
Second exponential smoothing	0.953	2319.620	11.366	0.050
Triple exponential smoothing	0.940	2426.513	11.970	0.107

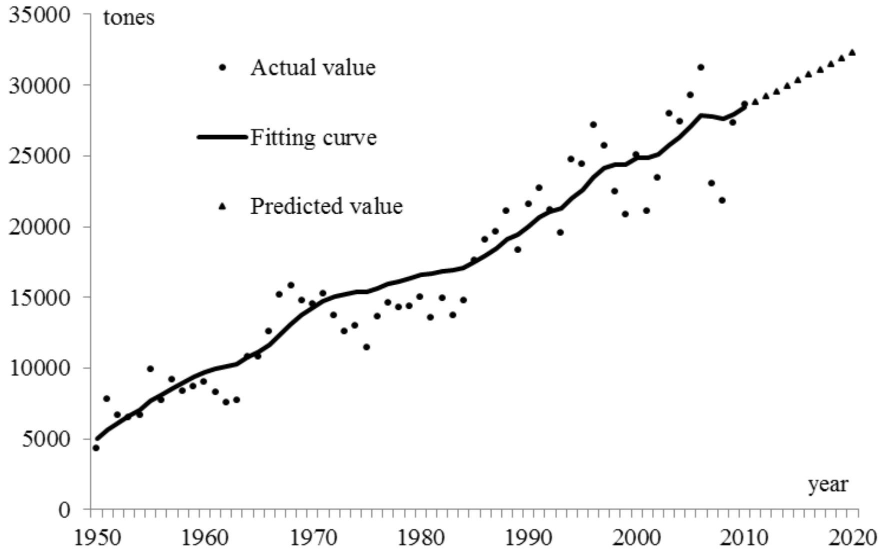


Figure 3: The fitted curve and predicted values based on an application of a single exponential smoothing model over the period of 1950-2010 and in 2011-2020, respectively. Data source: FAO Fishstat Plus, 2012.

Table 3: Predictive power level of MAPE and RMSPE.

MAPE & RMSPE	Predictive power
<10%	Highly accurate
10~20%	Good
20~50%	Reasonable
>50%	Incorrect

Data source: Delurgio, 1998.

Table 4: The ADF Test Results of the Global Sea Cucumber Capture Production Time-series Data over the period of 1950~2010.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.209672	0.9708
Test critical values:	1% level	-3.560019	
	5% level	-2.917650	
	10% level	-2.596689	

* Mackinnon (1996) one-sided *p*-values.

The ADF test results show that the critical value of 1% level, 5% level and 10% level are -3.560019, -2.917650 and -2.596689, respectively, while the ADF test statistics is -4.979052 (Table 5). Because the absolute value of -4.979052 is more than any absolute value (including -3.560019, -2.917650 and -2.596689), the null hypothesis is rejected. In other words, the new time series data after the difference of first order are stationary time series data.

The coefficient figure of ACF and PACF is drawn based on the above new time series data (Fig. 4). Subsequently, the identification of the models is developed. The autocorrelation coefficients are not equal to 0 when the respective lag orders are 1, 5 and 7 on the basis of the coefficient figure of ACF. In other words, the parameter *p* of AR(p) can be assigned to 1, 5 and 7, respectively. Meanwhile, the parameter *q* of MA(q) can be assigned to 0 and 1 according to the coefficient figure of PACF, respectively. Therefore, the following models are constructed initially, after which the estimation of the parameters is developed.

Model 1: ARIMA (1, 1, 1) $DX_t = C + \varphi_1 DX_{t\text{-}1} + \theta_1 \varepsilon_{t\text{-}1} + \varepsilon_t$ (8)

Model 2: ARIMA (5, 1, 1) $DX_t = C + \varphi_1 DX_{t\text{-}1} + \varphi_2 DX_{t\text{-}5} + \theta_1 \varepsilon_{t\text{-}1} + \varepsilon_t$ (9)

Model 3: ARIMA (5, 1, 0) $DX_t = C + \varphi_1 DX_{t\text{-}1} + \varphi_2 DX_{t\text{-}5} + \varepsilon_t$ (10)

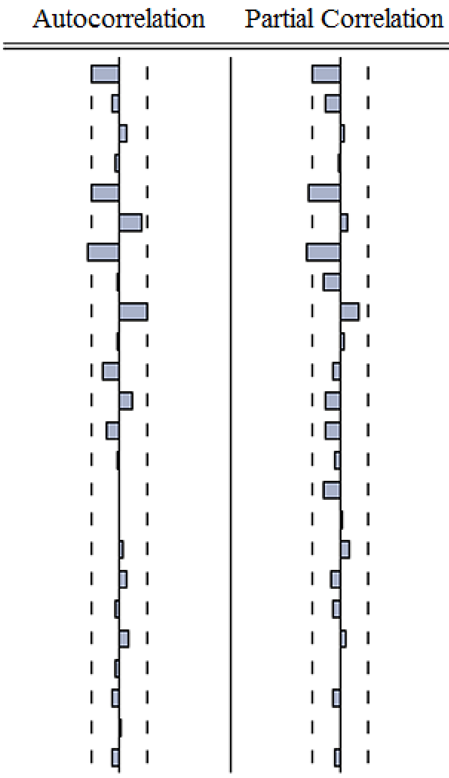
Model 4: ARIMA (7, 1, 0) $DX_t = C + \varphi_1 DX_{t\text{-}1} + \varphi_2 DX_{t\text{-}5} + \varphi_3 DX_{t\text{-}7} + \varepsilon_t$ (11)

Model 5: ARIMA (7, 1, 1) $DX_t = C + \varphi_1 DX_{t\text{-}1} + \varphi_2 DX_{t\text{-}5} + \varphi_3 DX_{t\text{-}7} + \theta_1 \varepsilon_{t\text{-}1} + \varepsilon_t$ (12)

Table 5 : The ADF test results of the global sea cucumber capture production time-series data of the first order difference over the period of 1950~2010.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.979052	0.0001
Test critical values:	1% level	-3.560019	
	5% level	-2.917650	
	10% level	-2.596689	

* Mackinnon (1996) one-sided *p*-values.



	AC	PAC	Q-Stat	Prob
1	-0.264	-0.264	4.0408	0.044
2	-0.062	-0.142	4.2702	0.118
3	0.080	0.026	4.6515	0.199
4	-0.031	-0.010	4.7101	0.318
5	-0.269	-0.295	9.2438	0.100
6	0.221	0.065	12.377	0.054
7	-0.292	-0.310	17.964	0.012
8	-0.014	-0.157	17.977	0.021
9	0.267	0.169	22.822	0.007
10	-0.013	0.040	22.834	0.011
11	-0.148	-0.078	24.401	0.011
12	0.121	-0.137	25.474	0.013
13	-0.124	-0.143	26.623	0.014
14	-0.019	-0.041	26.650	0.021
15	-0.007	-0.152	26.654	0.032
16	-0.005	0.017	26.656	0.045
17	0.030	0.082	26.727	0.062
18	0.080	-0.089	27.275	0.074
19	-0.033	-0.078	27.368	0.096
20	0.092	0.049	28.127	0.106
21	-0.039	0.002	28.264	0.133
22	-0.067	-0.069	28.692	0.154
23	0.024	-0.006	28.748	0.189
24	-0.066	-0.049	29.193	0.213

Figure 4: The coefficient figure ACF and PACF of the global sea cucumber capture production time-series data of the first difference over the period of 1950-2010.

The parameters of the above models are estimated and the results are shown in Table 6. The minor values of MAPE are Model 1 and Model 5, according to Table 6. Eventually, Model 1 is selected as the prediction model based on the comprehensive consideration of AIC and SBC. According to the results of the parameter estimation, the final construction of the prediction model is as follows:

$$DX_t = -0.0273 - 0.2799 DX_{t-1} - 0.1287\varepsilon_{t-1} + \varepsilon_t \quad (13)$$

Based on the above prediction model, the time series data of global sea cucumber capture production over the period 1950-1999 is used to predict the changes of global sea cucumber capture production from 2000-2010. The results are shown in Fig. 5. The results of the parameter test reveal that the MAPE of the prediction model for 2000-2010 is 13.472%. Therefore, according to the evaluation standard in Table 3 the predictive power of the constructed model is good.

Consequently, the time series data of global sea cucumber capture production over the period 1950-2010 is used to predict the changes of the global production from 2011-2020 in terms of the ARIMA (1, 1, 1) model, and the results are shown in Figs. 6 and 7.

Table 6: The vales of model parameter test on the basis of time series data of sea cucumber capture production over the period of 1950-1999.

Model	R^2	AIC	SBC	p-Q	MSE	RE %	MAPE
Model 1	0.175	17.891	18.002	0.100	4461.352	14.819	13.472
Model 2	0.183	17.950	18.107	0.062	4053.734	16.789	17.539
Model 3	0.171	17.929	18.043	0.079	4042.025	16.711	17.283
Model 4	0.259	17.861	18.017	0.556	4219.434	14.797	13.937
Model 5	0.277	17.879	18.074	0.417	4247.364	14.998	13.690

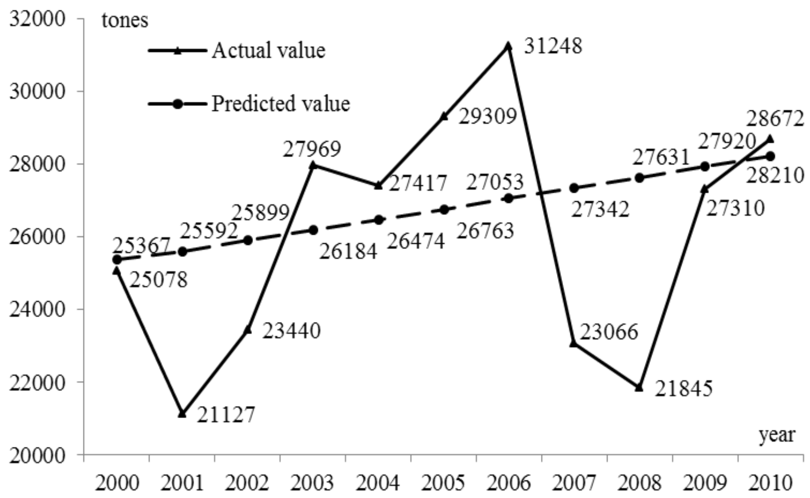


Figure 5: The actual and predicted values based on an application of ARIMA(1,1,1) model over the period of 2000-2010.

$$DX_t = -0.0322 + 0.3678 DX_{t-1} + 0.8310\varepsilon_{t-1} + \varepsilon_t \quad (14)$$

Overall assessment of the models' forecasting performances

Tables 1 and 6 summarize the measurements of forecasting accuracy for the capture production examined and the two types of models applied. According to the measures of forecasting accuracy used, the best forecasting performance for sea cucumber was shown by the single exponential smoothing model (R^2=0.954, MSE=1771.761, RE %=10.255%, MAPE=11.725%). The optimal forecasting technique of genetic modeling (Yang, 2004; Theodoros, *et al.*, 2006) significantly improved the forecasting values obtained by the selected ARIMA (1, 1, 1) model (R^2=0.175, MSE=4461.352, RE%=14.819%, MAPE=13.472%), because its value of MAPE is the least one compared to any other ARIMA models.

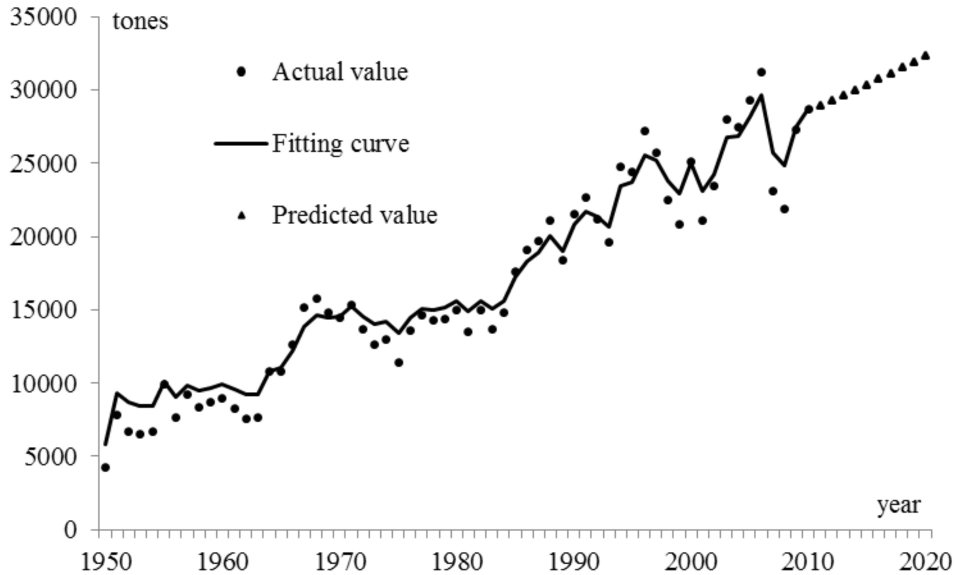


Figure 6: The fitted curve and prediced values based on an application of ARIMA(1,1,1) over the period of 1950-2010 and in 2011-2020, respectively.
Data source: FAO Fishstat Plus, 2012.

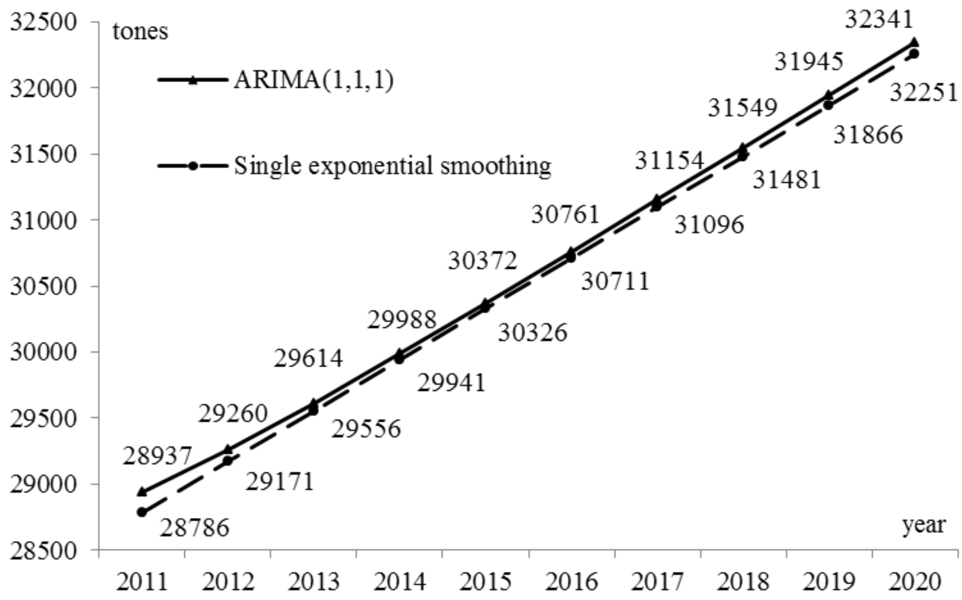


Figure 7: Comparison on the predicted values between the ARIMA(1,1,1) model and single exponential smoothing model regarding sea cucumber capture production in 2011-2020.

Discussion

Data quality

We expected that we would encounter problems involving the quantity, quality, consistency and availability of the data related to sea cucumber fisheries. The reasons for these inaccuracies are manifold. First of all, some national governments pay little attention to sea cucumber capture production, due to its low volume compared to other fisheries (Choo, 2008). Secondly, sea cucumber catches are severely underestimated and/or under-reported in some countries, such as parts of Southeast Asian countries, Papua New Guinea, Mozambique and the Solomon Islands (Baine, 2004; Clarke, 2004; Choo, 2008). Finally, sea cucumber capture production has not been reported exclusively in some countries such as Malaysia (Baine, 2004), China (Choo, 2008) and Canada (Hamel and Mercier, 2008). Therefore, predicting the future capture production of global sea cucumber based on the time series data in the FAO Fishstat Plus database is quite challenging. In other words, if the production data quality problem of the sea cucumber capture fisheries could be resolved, then the predictive power of the models would be better. In addition, it may promote the statistical standardization of the sea cucumber capture production data in the FAO Fishstat Plus database (Skewes *et al.*, 2004; Purcell *et al.*, 2009).

Model fitting

As suggested by Legates and McCabe (1999), a multicriteria performance assessment based on different accuracy measures was developed to select the best models. In some cases, the explained variances such as coefficient of determination (R^2) were significantly high/low fitted towards the good/bad performance of the model, but the values of MSE, RE % and/or MAPE were significantly worse/better than those obtained with the other models. For example, the numerical values of statistics R^2, MSE, RE % and/or MAPE of the different models were not exactly the same size (Tables 1, 2 and 6). In this way, high correlations can be achieved by relatively good models on the basis of the comprehensive consideration of R^2, MSE and RE %, as well as MAPE. Similar conclusions were obtained in the forecasting of different types of time variables (Stergiou *et al.*, 1997; Pulido-Calvo and Portela, 2007; Velo-Suárez and Gutiérrez-Estrada, 2007).

The exponential smoothing and ARIMA models are constructed to describe the data sets. For all the models built in this study, the coefficients are computed based on the minimization of MSE, RE % and MAPE, as well as the maximization of R^2. The final values of the smoothing coefficients are presented in Tables 1 and 6, along with the goodness-of-fit statistics. The R^2 values due to model fitting ranged from 0.944 to 0.995 and 0.171 to 0.277, showing that the exponential smoothing models fit the datasets quite well, while the ARIMA models do not, due to the non-stationarity of the time series of the data. However, the single exponential smoothing model and ARIMA (1, 1, 1) model are selected on the basis of an overall consideration of the above minimization and maximization (R^2).

Forecasting power

An attempt has been made to examine the accuracy of the selected model by comparing the final data observations (the time series data of sea cucumber capture production over the period 1950-1999) with the values obtained by fitting the selected model in all of the data sets after ignoring the final data values (the time series data of sea cucumber capture production from 2000-2010). These values, along with the forecast of sea cucumber capture production for the past 11 years (2000-2010), are presented in Figs. 2 and 7. It is observed from the predicted values that all the data sets are quite near the actual values during 2000-2010. This further strengthens the appropriateness of the selected models.

The biological features (late maturity, high longevity, low or infrequent recruitment, density-dependent reproduction and low survival of larvae) can be implicit in the configuration of the model. In this manner, sea cucumber recruitment is highly non-linearly dependent on the survival of the larvae (Conand and Byrne, 1993). On the other hand, the variance explained by the linear component of the ARIMA (1, 1, 1) model, can be associated to the spawning secondary process (Juan *et al.*, 2007).

The good results obtained in this study indicate that, from the point of view of the univariate approach, a *quasi*-complete characterization of sea cucumber capture production has been reached. However, it is also necessary to point out the model's limitations (i.e. forecasting capacity and/or biological significance) in the context of a short-medium term time period. To assume that there is either a linear or non-linear relationship between the time series data of the sea cucumber capture production over the period 1950-2010, each observation can be explained as a linear/non-linear function of its past values. This implies that the variance of data series is equivalent to the variances sum of any external variable that has an influence on the sea cucumber capture production. Therefore, the univariate model that explains shifts of historical data has the capacity to detect the external variables influence implicit in the variance of time series data. However, if new external variables such as some biological factors (abundance, total biomass, size frequency distributions, age-structure and spatial distributions) intervene with the system, then as a result the forecasting accuracy of the constructed model will be better.

Research significance

The time series analysis approach to forecast short term catches has been widely applied, and the application results have shown that its applicability in economics and accuracy has been well recognized. However, the available existing case studies usually pay close attention to single species fisheries short term capture production forecasting, which commonly are more mobile species (Georgakarakos *et al.*, 2006; Célia and Henrique, 2009; Santana and Freitas, 2013).

Therefore, this study has attempted to explore whether the time series analysis approach is also applicable to relatively sedentary species. The research results indicate that the predictive power of the time series approach (exponential smoothing models and ARIMA models) is good. In short, this study demonstrates that the time series approach (exponential smoothing models and ARIMA models) is also applicable to relatively sedentary species.

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