Combining forecasts to enhance fish production prediction: the Case of Coastal Fish Production in Morocco

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Abstract

This paper seeks to enhance forecast accuracy by combining three individual forecasting models. These models include: the Autoregressive Integrated Moving Average model (ARIMA), the Generalized Autoregressive Conditional Heteroscedastic model (GARCH), and the Census X11 model. Applied to the Moroccan coastal fish production, the empirical results show that in terms of predictive ability the composite model outperforms the individual forecasting models. In addition, the results reveal that the forecast accuracy gains arising from combining the individual forecasts range from nearly 8% to over 95%.

Resumen

Este documento pretende mejorar la precisión del pronóstico mediante la combinación de tres modelos de pronóstico individuales. Estos modelos incluyen: el Modelo Autorregresivo Integrado de Media Móvil (ARIMA), el Modelo Generalizado Autorregresivo Condicional Heterocedástico (GARCH) y el Modelo de Censo X 11. Aplicado a la producción pesquera costera marroquí, los resultados empíricos muestran que, en términos de capacidad predictiva, el modelo compuesto supera a los modelos de pronósticos individuales. Además, los resultados revelan que las ganancias de la exactitud del pronóstico que surgen de la combinación de las predicciones individuales varían desde casi el 8 % a más del 95 %.

Key words: forecasting, composite model, fish production,

Jel Codes: C53, C59, Q22.

1. Introduction

In an attempt to enhance prediction of coastal fish production in Morocco, this paper develops a composite forecasting model. Towards this end, the paper first develops individual forecasting models, including notably the Autoregressive Integrated Moving Average (ARIMA), the Generalized Autoregressive Conditional Heteroskedastic (GARCH), and the Census X11 models. The paper then combines these individual models into a composite forecasting model.

In a seminal article, Bates and Granger (1969) found that combining individual forecasts can significantly improve forecast accuracy. This finding is subsequently confirmed by the literature review in Clemen (1989). Since then combing forecasts has gained popularity among forecasters and academicians. Combining individual forecasts as a way of enhancing forecast accuracy has been used in a myriad of studies and fields. These include, among others, economics (e.g., Engle et al., 1984), accounting and finance (e.g., Newbold et al., 1987; Fan et al., 1996; Pemman, 1998), and psychology (e.g., Einhorn and Hogarth, 1975; Einhor et al., 1977), just to mention a few. This paper extends this line of literature to fisheries by developing a composite forecasting model to improve the prediction of coastal fish production in Morocco particularly pelagic and benthic fish production.

The coastal fish production in Morocco is primarily dominated by pelagic and benthic fish production. Taken together, pelagic and benthic fish production account for 79% of Morocco's total seafood production and generate nearly 4 billion MAD in revenues (MAPM, 2010). [1] Seafood production has increased markedly over the past three decades reaching nearly 1.14 million metric tons in 2010 and amounting to over 6.6 billion MAD (MAPM, 2010).

In fisheries and aquaculture, forecasting analysis has been the subject of a wide range of papers. These papers used a variety of models ranging from simple to more complex forecasting models. These forecasting models include: multivariate regression model (Wolff et al., 2007); artificial neutral networks model (Zhou et al., 2003); empirical Bayes method (Whiting et al., 2000); vector autoregressive model (Stergiou, 1991); classical additive decomposition, Holt Winters Exponential Smoothing, Auto Regressive

[1] MAD refers to Moroccan Dirham. 1 US dollar is equivalent to 9.67 MAD.

Moving Average, Vector Auto Regression, and naïve models (Guttormsen, 1999). Univariate and multivariate autoregressive integrated moving average models (Tsitsika et al., 2007); and Bayesian hierarchical model (Yu and Leung, 2010).

The remainder of this paper proceeds as follows. The first section provides an overview about the Moroccan fish industry. The second section describes the data. The third section outlines the methodology. The fourth section tests the predictive ability of each forecasting model. The last section concludes the paper.

2. An Overview about the Moroccan Fishery Industry

Morocco has a coastline of nearly 3500 km stretching along the Atlantic Ocean and the Mediterranean Sea, and a maritime area of about one million square kilometer. Notwithstanding these natural attributes, fishing industry has a modest contribution to the Moroccan gross domestic product, ranging between 2% and 3% (MAPM, [2008]). In terms of employment, fishery industry accounts for 170, 000 jobs from direct employment and generates 4900, 000 jobs from indirect employment (MAPM, [2008]).

2.1. The structure of the fishery industry

The Moroccan fishery industry is composed of three sectors: aquaculture, sea fishing, and fish processing sectors. Aquaculture has a marginal contribution to the fish production in Morocco, accounting for less than 2% of total national fish production. According to a study by the Food and Agriculture Organization (FAO, 2004), aquaculture in Morocco consists of two components: inland aquaculture, and maritime aquaculture. While the former component is dominated by the production of European sea bass and gilthead sea bream, the latter component is dominated by the production of common carp (FAO, 2004). Fishing sector, on the other hand, is a key contributor to fish production, accounting for over 98%

of total fish production. Fishing sector consists of three major segments: artisanal and small-scale fishing, coastal fishing, and high-sea fishing (FAO, 2004).

The fish processing sector consists of 406 processing plants. These plants process fish into different forms, primarily frozen fish, fresh fish, and canned fish, accounting for 49%, 16% and 12% of total processed fish, respectively (MAPM, 2008). According to a report by the Ministry of Agriculture and Sea Fishing (2008), the processing industry is still grappling with inherent challenges, particularly capacity under-utilization; e.g., the rate of capacity utilization is less than 50%.

2.2. Seafood consumption and trade

In Morocco, fish is one of the key sources of protein, with a per capita consumption ranging from 10 to 12 Kg (MAPM, 2008). Per capita fish consumption is, however, characterized by wide regional variations. For example, per capita consumption in rural areas is 6.2 kg compared with 13.2 kg in urban areas (El Basri, 1998). The consumption of seafood products, however, is still lagging compared to that of other meats, particularly poultry and red meat. According to a study conducted by El Basri (1998), seafood products account for 29.2% of total meat consumption, compared with 37.5% and 33.3% for poultry and red meat, respectively.

Morocco is a net exporter of seafood products. According to the Ministry of Agriculture and Sea Fishing [2008], 70% of total fish production is exported, generating nearly 11.4 billion MAD in revenues. Fish exports consist primarily of frozen fish (36%), canned fish (31%), and fresh fish (12%). Although Morocco has free trade agreements with a range of countries, including the United States, Turkey, Egypt and Tunisia, its seafood exports are exclusively destined to the European Union Market, which accounts for over 65% of Morocco's total seafood exports (MAPM, 2010). The concentration of seafood exports on the European Union market can be attributed, in part, to its proximity and the implementation of trade association agreement.

Although the Moroccan fishery industry has experienced a significant growth and expansion in the last decades, it is still facing numerous challenges, including especially poor resource management; stiff competition and increasingly stringent foreign market requirements in terms of quality standards;

inefficient distribution networks; poor performance of sea ports; and outdated legal, regulatory and sanitary frameworks (MAPM, 2007).

3. Data

In order to forecast pelagic and benthic fish production we use monthly data from December 2000 to December 2010. The data were collected from the Ministry of Agriculture and Sea Fishing (MAPM, 2010). Summary statistics for both benthic and pelagic fish production is provided in Table 1.

Table 1: Summary Statistics for Pelagic and Benthic Fish Production

	Mean	CV[1]	Median	Max	Min
Benthic Fish Production (Metric Ton)	10026.3	29.9	9775	25490	3393
Pelagic Fish Production (Metric Ton)	57990.7	45.6	53784.5	138026	16831

[1]Coefficient of variation (%).

4. Methodology

In this paper, we use a tow-step procedure consisting of developing individual forecasting models and then combining them into a composite forecasting model. These individual forecasting models include: the Autoregressive Integrated Moving Average model (ARIMA), the Generalized Autoregressive Conditional Heteroskedastic model (GARCH), and the Census X11 model.

4.1. Individual Forecasting Models

This section develops and estimates three individual forecasting models, which include the GARCH model, the ARIMA model, and the Census X-11 model.

4.1.1. GARCH Model

The Generalized Autoregressive Conditional Heteroskedastic model, commonly known as GARCH model, was introduced by Bollerslev (1986). The GARCH model, which is an extension of the ARCH model developed by Engle (1982), combines both autoregressive lags (i.e., ARCH terms) and moving average lags (i.e., GARCH terms). Subsequently hybrid GARCH and ARCH models were developed and used. These include, among others, the Exponential GARCH model (Nelson, 1991); the Threshold ARCH and the Threshold GARCH models (Glosten et al., 1993; Zakoian, 1994). In this paper, the choice of the appropriate GARCH model for both benthic and pelagic fish production is made on the basis of statistical criteria. These include the Akaike information criterion; and the forecasting accuracy criteria which include the mean absolute percentage error (MAPE), the mean square error (MSE), and the R-squared.[2] The empirical results show that while the GARCH (1, 1) is the most appropriate model for pelagic fish production, the Symmetric EGARCH (1, 1) is the most appropriate model for benthic fish production. Specifically, the GARCH (1, 1) model can be written as,

(1)
$$\begin{cases} Q_t^P = \beta_0 + \sum_{i=1}^{12} \beta_i Q_{t-i}^P + \varepsilon_t, \\ \varepsilon_t \sim N\left(0,\ \sigma_t^2\right), \text{ and} \\ \sigma_t^2 = \alpha_0 + \gamma_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2 \end{cases}$$

Where, Q_t^P is pelagic fish production.

[2] The mean square error (MSE) is computed as the sum of square of forecast errors divided by the number of periods; the mean absolute percentage error (MAPE) is computed as the sum of the absolute percentage forecast errors divided by the number of periods; and the R-squared is the coefficient of determination, which is obtained by regressing the actual value on the forecasted value.

The symmetric EGARCH (1, 1), on the other hand, can be written as

$$\textbf{(2)} \quad \begin{cases} Q_t^B = \beta_0 + \sum_{i=1}^{12} \beta_i Q_{t-i}^B + \varepsilon_t, \\ \varepsilon_t \sim N\left(0,\ \sigma_t^2\right), \text{ and} \\ \log\left(\sigma_t^2\right) = \lambda_0 + \delta_1 \log\left(\sigma_{t-1}^2\right) + \lambda_1 \left|\dfrac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \end{cases}$$

Where, Q_t^B is benthic fish production. Parameter estimates for the GARCH and the EGARCH models are provided in table 2.

Table 2: Parameter Estimates for GARCH and EGARCH Models

	GARCH (1, 1)		Symmetric EGARCH(1, 1)	
Parameter	Estimate	S.E.[1]	Estimate	S.E.[1]
β_0	17815.500	10102.930***	8668.275	4530.644***
β_1	0.235	0.051*	0.008	0.068
β_2	0.378	0.076*	-0.031	0.111
β_3	-0.049	0.049	-0.009	0.091
β_4	-0.256	0.072*	-0.022	0.082
β_5	-0.063	0.071	-0.061	0.066
β_6	0.054	0.069	0.193	0.095**
β_7	-0.119	0.066***	0.051	0.109
β_8	-0.081	0.067	-0.092	0.131
β_9	0.185	0.056*	-0.061	0.088
β_{10}	0.180	0.065*	-0.066	0.090
β_{11}	-0.129	0.054**	0.060	0.092
β_{12}	0.385	0.053*	0.160	0.066**
α_0	1.840E8	4.846E6*	–	–
γ_1	0.820	0.224*	–	–
α_1	-0.233	0.091**	–	–
λ_0	–	–	11.278	5.163**
δ_1	–	–	-0.142	0.185**
λ_1	–	–	0.299	0.329
R^2	57.19%		14.44%	
Log likelihood	-1467.845		-1223.133	
AIC[2]	22.482		18.774	

[1]Standard Error
[2]Akaike Information Criterion
Level of statistical significance: *, **, *** represents 1%, 5%, and 10%, respectively.

4.1.2. ARIMA Model

The Auto Regressive Integrated Moving Average model, commonly referred to as ARIMA, was developed by Box and Jenkins (1970). The ARIMA models have been extensively used in fisheries and aquaculture. For instance, the ARIMA models have been used in Tsitsika et al., (2007) to predict anchovy, sardine, and horse mackerel catches in the Mediterranean Sea. In order to select the appropriate ARIMA models, we use the Akaike information criterion; and the forecasting accuracy criteria which include the mean absolute percentage error, the mean square error, and R-squared. The results reveal that the most appropriate ARIMA model for both pelagic and benthic fish production is ARMA (12, 11). Formally, the ARMA model for pelagic fish production can be expressed as

(3) $$Q_t^P = \gamma_0 + \sum_{i=1}^{12} \gamma_i Q_{t-i}^P + \sum_{j=1}^{11} \theta_j \varepsilon_{t-j} + \varepsilon_t,$$

Similarly the ARMA model for benthic fish production is given by

(4) $$Q_t^B = \gamma_0 + \sum_{i=1}^{12} \gamma_i Q_{t-i}^B + \sum_{j=1}^{11} \theta_j \varepsilon_{t-j} + \varepsilon_t,$$

Where, Q_t^B and Q_t^P are benthic fish production and pelagic fish production, respectively. Table 3 contains parameter estimates for the ARMA models for pelagic and benthic fish production.

Table 3: Parameter Estimates for ARMA Models

	Pelagic Fish Production ARMA (12, 11)		Benthic Fish Production ARMA (12,11)	
Parameter	Estimate	S.E.[1]	Estimate	S.E.[1]
γ_0	59438.280	1852.422*	9754.695	656.963*
γ_1	-0.786	0.179*	0.281	0.125**
γ_2	-0.641	0.142*	-0.121	0.075
γ_3	-0.416	0.170**	-0.128	0.068***
γ_4	-0.349	0.141**	0.067	0.070
γ_5	-0.269	0.149***	-0.015	0.067
γ_6	-0.446	0.109*	0.048	0.0645
γ_7	-0.531	0.139*	-0.112	0.058**
γ_8	-0.727	0.146*	0.214	0.065*
γ_9	-0.493	0.184*	0.050	0.059
γ_{10}	-0.416	0.134*	-0.163	0.067
γ_{11}	0.076	0.148	0.503	0.081
γ_{12}	0.432	0.085*	0.113	0.116
θ_1	0.997	0.217*	-0.212	0.086
θ_2	1.176	0.181*	0.071	0.091
θ_3	0.923	0.235*	0.152	0.094
θ_4	0.772	0.220*	-0.078	0.091
θ_5	0.526	0.226**	0.008	0.094
θ_6	0.684	0.183*	0.124	0.085
θ_7	0.758	0.198*	0.119	0.084
θ_8	1.042	0.187*	-0.317	0.095*
θ_9	0.890	0.225*	-0.228	0.079*
θ_{10}	1.086	0.149*	0.317	0.078*
θ_{11}	0.214	0.182	-0.809	0.097*
R^2	74.04%		51.52%	
Log likelihood	-1442.950		-1188.581	
AIC[2]	22.227		18.372	

[1]Standard Error
[2]Akaike Information Criterion
Level of statistical significance: *, **, *** represents 1%, 5%, and 10%, respectively.

4.1.3. Census X11 Model

The Census II X-11 model is an improved seasonal decomposition method, which consists of separating the trend-cycle component from the seasonal and irregular components of an economic time series. This method has several positive features compared with earlier seasonal decomposition methods (see, Shiskin et al., 1967).

4.2. Composite Forecasting Model

Having estimated the individual forecasting models, the next step is to use these models to construct a composite forecasting model. The composite forecasting model is a linear combination of the GARCH model, the ARIMA model, and the Census X11 model. Formally, the composite forecasting model can be expressed as:

(5) $$F_C = \omega_1 F_{GA} + \omega_2 F_{AR} + \omega_3 F_{CX} ,$$

where, F_C is the composite forecast; F_{AR} is the ARIMA model forecast; F_{GA} is the GARCH model forecast; F_{CX} is the Census X11 model forecast; and ω_1, ω_2 and ω_3 are weights associated with each individual forecasting model.

There is an extensive literature regarding the selection of the weights associated with each individual forecasting model. For instance, Makridakis and Winkler (1983), and Zou et al., (2007) used a simple average. Winkler and Makridakis (1983) used a variety of variance-covariance combination techniques. Clemen (1986), on the other hand, used a multiple linear regression consisting of the actual value, as the dependent variable, and the forecasted values of each individual forecasting model as the independent variables. The estimates of the weights are the Ordinary Least Squares estimates of the coefficients associated with each individual forecasting model in the multiple linear regression model. In addition, Clemen (1986) looked at different scenarios including restricting the coefficients associated with each individual forecasting model to add up to one; and including an intercept with and without restricting the coefficients to sum up to one. Lastly, Bayesian procedure has been used in Walz and Walz (1989), and in Min and Zellner (1993).

Because there is no a priori theoretical or empirical background concerning the selection of the weights, our strategy is to use different techniques and then choose the technique that yields the lowest root-mean-square error (RMSE); i.e., the technique with the highest forecast accuracy. To estimate the coefficients associated with each individual forecasting model (equation 5); that is, ω_1, ω_2 and ω_3, we use simple average, constrained minimization and unconstrained minimization. The constrained minimization consists of minimizing the mean square error of the composite forecast such that the weights add up to one; the unconstrained minimization, on the other hand, consists of minimizing the mean square error without imposing any constraint on the weights (a detailed formulation of the constrained and unconstrained minimization problem is provided in the Appendix). The weight estimates for the composite forecasting models for pelagic and benthic fish production are reported in Table 4.

Table 4: Weight Estimates for the Composite Models

Method	Weight Estimate			RMSE[1]
	ω_1	ω_2	ω_3	
		Pelagic Fish Production		
Simple Average	1/3	1/3	1/3	12371.34
Constrained Minimization	-0.3867	1.0396	0.3471	8891.24
Unconstrained Minimization	-0.3904	1.0405	0.3608	8864.74
		Benthic Fish Production		
Simple Average	1/3	1/3	1/3	1780.02
Constrained Minimization	-0.1420	0.4260	0.7160	1471.44
Unconstrained Minimization	-0.1342	0.4423	0.7082	1462.29

[1]Root Mean Square Error is defined as the square root of the Mean Square Error (MSE).

Because the unconstrained minimization has the lowest root mean square error, we choose this technique to estimate the weights associated with each individual forecasting model and thus construct composite forecasting models for both pelagic and benthic fish production. Monthly pelagic fish production for 2010 from the composite forecasting model, the GARCH model, the ARIMA model and the CensusX11are shown in Table 5 and figure 1.

Table 5: Actual and Forecasted Monthly Value for Pelagic Fish Production for 2010

		Forecasted Value			
Month	Actual Value	GARCH	ARIMA	Census X11	Composite
January	63367	44407.28	55588.14	58,171.43	63246.98
February	42675	33739.45	34895.21	41,732.71	42841.20
March	49891	42812.84	48554.25	45,172.27	47805.98
April	50338	42445.16	42941.70	47,638.18	48490.31
May	44153	51512.13	46926.26	50,653.74	49525.87
June	69785	60978.57	62750.36	72,291.96	74054.08
July	92734	77059.45	70172.41	92,033.98	90995.55
August	118246	96366.33	103671.70	107,130.73	111252.8
September	70616	91877.59	73452.01	85,744.90	79850.04
October	103257	111788.30	108810.20	111,414.36	111543.20
November	33013	62483.50	55164.79	62,047.47	60070.29
December	54127	55783.97	58811.92	50,028.66	51496.10

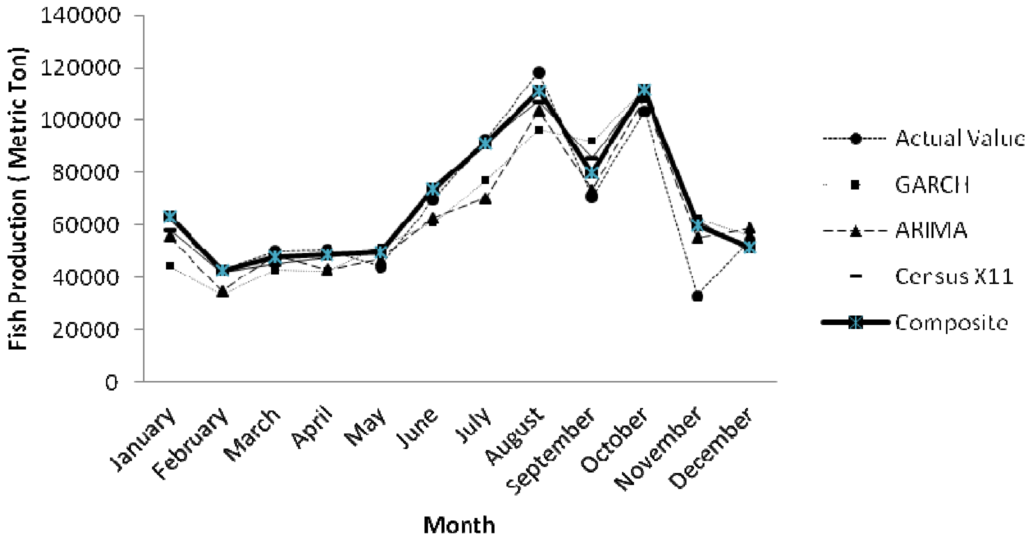

Fig. 1: Actual and Forecasted Monthly Values for Pelagic Fish Production for 2010

Monthly benthic fish production for 2010 from the composite forecasting model, the EGARCH model, the ARIMA model, and the CensusX11 model are shown in Table 5 and figure 2.

Table 5: Actual and Forecasted Monthly Values for Benthic Fish Production for 2010

		Forecasted Value			
Month	Actual Value	EGARCH	ARIMA	Census X11	Composite
January	13381	10645.81	9067.31	13,056.25	12,699.71
February	9070	11267.92	10940.29	11,932.06	11,522.01
March	11322	9442.53	10261.55	11,150.85	10,726.71
April	10007	9686.49	9175.32	10,220.44	10,806.81
May	6941	9739.45	10930.76	5,699.26	6,215.59
June	7973	10379.21	7807.36	9,229.25	9,637.94
July	9204	10441.53	10078.33	9,860.10	10,050.71
August	9361	9734.54	10016.90	8,326.84	8,936.52
September	6863	10355.22	9749.91	7,070.19	7,416.71
October	8324	10548.69	8506.94	7,617.54	8,536.82
November	3393	8430.49	10226.59	3,958.13	5,056.68
December	7286	10909.69	7596.30	6,543.75	7,124.56

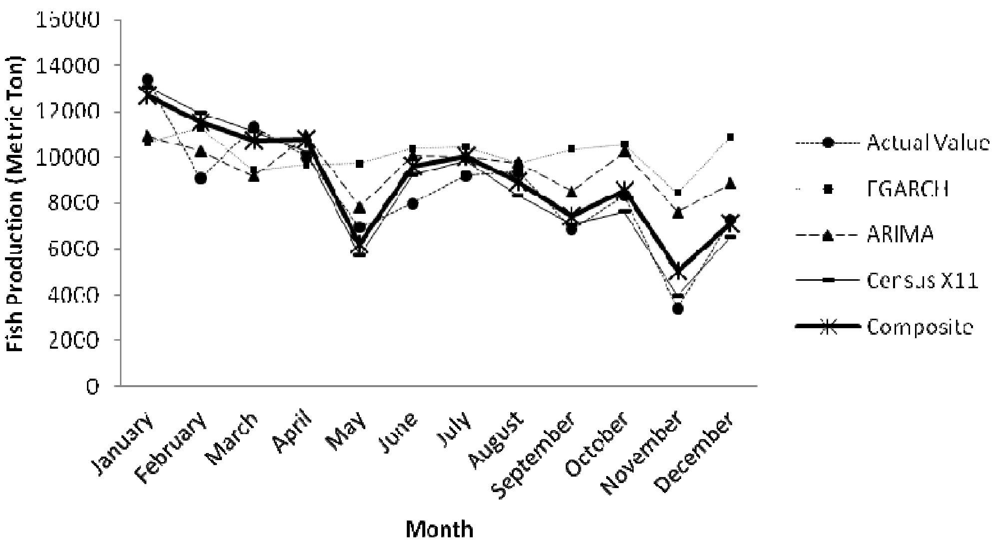

Fig. 2: Actual and Forecasted Monthly Values for Benthic Fish Production for 2010

5. Predictive Ability Assessment

To gauge the predictive ability of each model, we use forecasting accuracy measures. These measures include: the root-mean-square error (RMSE), the mean absolute percentage error (MAPE), and R-squared (R^2). Table 6 contains accuracy measures for each forecasting model. A mere glance at the results clearly indicates that the composite model outperforms the individual forecasting models regardless of the accuracy measure used both for pelagic and benthic fish production. The Census X11 model has the best predictive ability both for pelagic and benthic fish production compared with the remaining individual forecasting models. The GARCH and the EGARCH models have the least predictive ability.

Table 6: Predictive Ability Assessment

	Accuracy Measure		
Forecasting Model	RMSE	MAPE (%)	R^2 (%)
		Pelagic Fish Production	
GARCH Model	17372.30	27.60	58.68
ARMA Model	13527.77	21.13	74.22
Census X11 Model	9540.97	13.71	86.87
Composite Model	8864.74	13.53	88.89
		Benthic Fish Production	
EGARCH Model	2616.00	19.34	10.51
ARMA Model	1969.35	16.04	52.24
Census X11 Model	1747.30	12.09	66.67
Composite Model	1462.44	11.34	73.43

To compute forecast accuracy gains arising from combining forecasts, we use the root mean square error for the composite model as a benchmark. As such the forecasting accuracy gain is defined as the difference between the root mean square error of each individual forecasting model and that of the composite model scaled by the root mean square error of the composite model. A comparative analysis of forecasting accuracy gains arising from using the composite forecasting model compared to using individual forecasting models is reported in Table 7. A casual look at the results shows that the forecast accuracy gains due to combining forecasts range from 7.6% to 96% for pelagic fish production, and from 19.5% to nearly 79% for benthic fish production.

Table 7: Comparative analysis

	Forecast Accuracy Gain (%)
Pelagic Fish Production	
GARCH vs Composite Model	95.97
ARMA vs Composite Model	52.60
Census X11 vs Composite Model	7.63
Benthic Fish Production	
EGARCH vs Composite Model	78.88
ARMA vs Composite Model	34.66
Census X11 vs Composite Model	19.48

6. Conclusion

The major objective of this paper is to develop a composite forecasting model in order to improve the prediction of the Moroccan coastal fish production particularly pelagic and benthic fish production. To this end, the paper combines three individual forecasting models, including the Autoregressive Integrated Moving Average model (ARIMA), the Generalized Autoregressive Conditional Heteroskedastic model (GARCH), and the Census X11 model in such a way as to enhance forecast accuracy. The empirical results show that the composite forecasting model outperforms the individual forecasting models. The results also reveal that forecast accuracy gains arising from combining forecasts range from 7.6% to 96% for pelagic fish production, and from 19.5% to nearly 79% for benthic fish production.

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Appendix

1. Constrained minimization

The mean square error criterion for the composite forecast; i.e., MSE, is given by:

$$\mathrm{MSE} = \frac{\sum_{t=1}^{n}\left(A_t - F_{ct}\right)^2}{n} = \frac{\sum_{t=1}^{n}\left(A_t - \omega_1 F_{AR} - \omega_2 F_{GA} - \omega_3 F_{CX}\right)^2}{n},$$

where, MSE is the mean square error; *n* is the number of periods; A_t is the actual value in period *t*; Fc_t is the composite forecast value for period *t*; F_{AR} is the ARIMA model forecast; F_{GA} is the GARCH model forecast; F_{CX} is the Census X11 model forecast; ω_1, ω_2 and ω_3 are weights associated with each individual forecasting model; and *t* is the time period. Constrained minimization amounts to minimizing the MSE subject to the constraint that all the weights add-up to one. Formally, constrained minimization problem can be formulated as:

$$\begin{cases} \underset{\omega_1\,\omega_2\,\omega_3}{\mathrm{Min}}\ \mathrm{MSE} = \underset{\omega_1\,\omega_2\,\omega_3}{\mathrm{Min}} \left[\dfrac{\sum_{t=1}^{n}\left(A_t - \omega_1 F_{RA} - \omega_2 F_{GA} - \omega_3 F_{CX}\right)^2}{n}\right] \\ \text{Subject to:} \\ \qquad \omega_1 + \omega_2 + \omega_3 = 1 \end{cases}$$

2. Unconstrained minimization

Unconstrained minimization amounts to minimizing the MSE without imposing any constraints on the weight. Formally, unconstrained minimization problem can be formulated as:

$$\underset{\omega_1\,\omega_2\,\omega_3}{\mathrm{Min}}\ \mathrm{MSE} = \underset{\omega_1\,\omega_2\,\omega_3}{\mathrm{Min}} \left[\frac{\sum_{t=1}^{n}\left(A_t - \omega_1 F_{AR} - \omega_2 F_{GA} - \omega_3 F_{CX}\right)^2}{n}\right]$$

All the variables and parameters are as previously defined.