

Evaluating the impact of the grouper-tilefish individual fishing quotas (IFQ) program on the fishing capacity of the US Gulf of Mexico reef-fish fishery: 2005-2014.

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Abstract

This study measure changes in fishing capacity, capacity utilization (CU) and overcapacity (OC) brought about the implementation of the grouper-tilefish individual fishing quotas (G-T IFQ) program in the US Gulf of Mexico reef-fish fishery. This study adds to the literature by evaluating the impact of a multiple quotas structure on a multi-species fishery. To do so, we implement stochastic distance frontier analysis which allows us to account for the multi-species and random nature of the fishery. Our findings show that fleet capacity decreased after the implementation of the G-T IFQ program, primarily due to the exit of fishing vessels. CU increased marginally indicating modest decreases in Excess Capacity. OC decreased significantly for all species but Tilefish, but remains at high levels. Lastly, our results show a great variation on the optimum size of the feet depending on the targeted species. On average, 40% of the current fleet could harvest the overall quota.

Keywords: Individual Fishing Quotas, Fishing Capacity, Stochastic Production Frontier, Distance Function,

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METHODS

The methodology used in this study is built on the framework presented in Solís et al. (2015). Specifically, we implement an output distance function (ODF) model, which has been described as one of the preferable stochastic methodologies to study fishing operations (Orea *et al.* 2005). Following Coelli and Perelman (1999) a translog (TL) multi-output production frontier is used to estimate the proposed ODF model. This model can be depicted as:

$$\begin{aligned} \ln D_{oi} = & \beta_0 + \sum_{m=1}^M \beta_m \ln y_{mi} + 0.5 \sum_{m=1}^M \sum_{n=1}^M \beta_{mn} \ln y_{mi} \ln y_{ni} + \sum_{m=1}^M \beta_{tm} t \ln y_{mi} + \sum_{k=1}^K \beta_k \ln x_{ki} + \\ & 0.5 \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^K \beta_{tk} t \ln x_{ki} + \sum_{k=1}^K \sum_{m=1}^M \beta_{km} \ln x_{ki} \ln y_{mi} \end{aligned} \quad [1]$$

where D_{oi} is the output distance, and y_{mi} and x_{ki} are, respectively, the production level of output m and the quantity of input k used by vessel i . To allow the rate of technical change to be non-constant and non-neutral we interact time, t , with the first-order factors for inputs and outputs.

From an analytical point of view, a well behaved ODF is homogeneous of degree 1 in outputs and is symmetric in parameters. We impose homogeneity by normalizing the function by an arbitrary output, and impose for symmetry by imposing the following restrictions: $\beta_{mn} = \beta_{nm}$ and $\beta_{kl} = \beta_{lk}$. Thus, equation 1 is now transformed into:

$$\begin{aligned} \ln \left(\frac{D_{oi}}{y_{1i}} \right) = & \beta_0 + \sum_{m=2}^M \beta_m \ln \left(\frac{y_{mi}}{y_{1i}} \right) + 0.5 \sum_{m=2}^M \sum_{n=2}^M \beta_{mn} \ln \left(\frac{y_{mi}}{y_{1i}} \right) \ln \left(\frac{y_{ni}}{y_{1i}} \right) + \sum_{m=2}^M \beta_{tm} t \ln \left(\frac{y_{mi}}{y_{1i}} \right) \\ & + \sum_{k=1}^K \beta_k \ln x_{ki} + 0.5 \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^K \beta_{tk} t \ln x_{ki} + \sum_{k=1}^K \sum_{m=2}^M \beta_{km} \ln x_{ki} \ln \left(\frac{y_{mi}}{y_{1i}} \right) \end{aligned} \quad [2]$$

With some arithmetic transformation, equation 2 can be written as:

$$\begin{aligned}
-\ln y_{li} &= \beta_0 + \sum_{m=2}^M \beta_m \ln \left(\frac{y_{mi}}{y_{li}} \right) + 0.5 \sum_{m=2}^M \sum_{n=2}^M \beta_{mn} \ln \left(\frac{y_{mi}}{y_{li}} \right) \ln \left(\frac{y_{ni}}{y_{li}} \right) + \sum_{m=2}^M \beta_{tm} t \ln \left(\frac{y_{mi}}{y_{li}} \right) \\
&+ \sum_{k=1}^K \beta_k \ln x_{ki} + 0.5 \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^K \beta_{tk} t \ln x_{ki} + \sum_{k=1}^K \sum_{m=2}^M \beta_{km} \ln x_{ki} \ln \left(\frac{y_{mi}}{y_{li}} \right) - \ln D_{oi}
\end{aligned} \quad [3]$$

To introduce the concept of stochastic frontier in our model, the distance between each observation is defined as the inefficiency term, i.e., $\ln D_{oi} = -u_i$, and a random noise term (v_i) is also include into equation 3. Therefore, our empirical model can now be represented as:

$$\begin{aligned}
-\ln y_{li} &= \beta_0 + \sum_{m=2}^M \beta_m \ln \left(\frac{y_{mi}}{y_{li}} \right) + 0.5 \sum_{m=2}^M \sum_{n=2}^M \beta_{mn} \ln \left(\frac{y_{mi}}{y_{li}} \right) \ln \left(\frac{y_{ni}}{y_{li}} \right) + \sum_{m=2}^M \beta_{tm} t \ln \left(\frac{y_{mi}}{y_{li}} \right) + \\
&\sum_{k=1}^K \beta_k \ln x_{ki} + 0.5 \sum_{k=1}^K \sum_{l=1}^K \beta_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^K \beta_{tk} t \ln x_{ki} + \sum_{k=1}^K \sum_{m=2}^M \beta_{km} \ln x_{ki} \ln \left(\frac{y_{mi}}{y_{li}} \right) + v_i + u_i
\end{aligned} \quad [4]$$

where v_i , is the random variable and its variance, σ_v^2 , is a measure of the importance of random shocks in determining variation in output. u_i , the inefficiency term and is intended to capture differences in skill or efficiency across vessels. To facilitate the interpretation of the parameters and make them comparable to those from standard production function model, we transformed the left side of the equation to be $\ln y_l$ rather than $-\ln y_l$ as suggested by Coelli and Perelman (1999).

Vessel-levels of TE can be estimated using Jondrow *et al.* (1982):

$$\hat{TE}_i = \hat{TE}_{i|v} = \hat{TE}_{i|v} (\hat{TE}_i - \hat{TE}_i) \quad [5]$$

TE scores are bounded between 0 and 1. TE achieves its upper bound when a vessel is producing the maximum feasible output, given the available inputs and stock abundance.

Finally, to estimate capacity measurements at the vessel level, it is necessary to calculate $\hat{TE}_i - \hat{TE}_i$ assuming that the variable inputs are fully utilized. In other words, output levels and the fixed input usage are observed from the fishing activity of the fleet while variable input usage is increased to maximum potential levels. Thus,

$$\begin{aligned}
v_i - u_i = & \ln y_{li} + \hat{\beta}_0 + \sum_{m=2}^M \hat{\beta}_m \ln \left(\frac{y_{mi}}{y_{li}} \right) + 0.5 \sum_{m=2}^M \sum_{n=2}^M \hat{\beta}_{mn} \ln \left(\frac{y_{mi}}{y_{li}} \right) \ln \left(\frac{y_{ni}}{y_{li}} \right) + \sum_{m=2}^M \hat{\beta}_{tm} t \ln \left(\frac{y_{mi}}{y_{li}} \right) + \\
& \sum_{k=1}^K \hat{\beta}_k \ln x_{ki} + 0.5 \sum_{k=1}^K \sum_{l=1}^K \hat{\beta}_{kl} \ln x_{ki} \ln x_{li} + \sum_{k=1}^K \hat{\beta}_{tk} t \ln x_{ki} + \sum_{k=1}^K \sum_{m=2}^M \hat{\beta}_{km} \ln x_{ki} \ln \left(\frac{y_{mi}}{y_{li}} \right)
\end{aligned} \tag{6}$$

The capacity TE (TE^C) is the distance from the observed outputs to the maximum attainable production level assuming full utilization of variable inputs and is calculated by $\frac{y_{li}^*}{y_{li}} = \frac{y_{li}^*}{y_{li}} \frac{y_{li}}{y_{li}^*}$. TE^C is bounded between zero and one. To obtain a capacity measure for each vessel, the observed outputs have to be multiplied by the inverse of TE^C .

DATA AND EMPIRICAL MODEL

To estimate the empirical model we used primary data from the National Marine Fisheries Service (NMFS) Southeast Coastal Fisheries Logbook Program and the Permits Information Management Systems (PIMS) databases. The NMFS logbook data contains detailed trip-level information on landings and fishing effort, and the PIMS dataset includes information on vessel characteristics.¹ The empirical analysis is conducted independently for vessel using Vertical Lines and Bottom Longline (the two main technologies used in reef-fish fishery) to avoid biases due to heterogeneous production. Aggregate fishery estimates are computed by adding the capacity measurements of the two subgroups of vessels within the fishery.

In this study we bounded our analysis to five years before (2005-2009) and after (2010 and 2014) the implementation of the Grouper-Tilefish IFQ in 2009. Observations with missing or incomplete input and/or output data were also excluded from the analysis resulting in an unbalanced panel data of 83,207 observations on 695 distinct vessels. Following Felthoven and Morrison Paul (2004) we aggregated our trip-level data into seasonal vessel-level observations (each year was divided into four equally distributed seasons). The final data set contained 18,869 (seasonal vessel-level) observations.

Figures 1 and 2 present the evolution of the fleet size and the average vessel-level trip characteristics, respectively. Specifically, Table 1 shows that during the studied period the fleet contracted approximately 30%. Two distinct shocks in fleet size can be observed in Table 1. The

¹ More information on these datasets can be found at <http://www.sefsc.noaa.gov/fisheries>.

first shock can be explained by the implementation of the Red Snapper IFQ program in 2007, and the second one with the implementation of the Grouper-Tilefish IFQ program in 2009. After the Grouper-Tilefish IFQ program the fleet stabilized at approximately 600 vessels. Figure 2 shows that after implementation of Grouper-Tilefish IFQ fishers began, on average, to take longer but fewer trips. The number of trips and days at sea stabilized after 2012.

As indicated, translog functional form is used to estimate our ODF (equation [6]). The variables included in the model comprise included seven outputs, three conventional inputs, biomass shock for the main species and a set of geographical dummies. The seven outputs were specified as total quarterly landings of gag grouper (y_1), red grouper (y_2), other shallow-water grouper (OSWG; y_3), deep-water grouper (DWG; y_4), tilefish (y_5), red snapper (y_6), and other species (y_7). Output levels are measured in pounds (gutted weight, g.w.) and y_1 was used to normalize the OSDF and to impose linear homogeneity in outputs. The conventional inputs included vessel length (x_1), number of fishing days (x_2), and crew size (x_3). Fishing days and crew size were measured as total counts for each season.

The model also controls for changes in stock levels, technical change, and seasonal and regional variability in production. Following Felthoven and Morrison Paul (2004) spawning biomass indexes (stock) were used as proxies of abundance to capture the influence of variations in stock size on catch rates. Specifically, our model included stock levels for gag grouper, red grouper and red snapper. This information was provided by the NMFS. Quarterly dummy variables (Q_1 , Q_2 and Q_3 ; Q_4 is the base quarter) were included to control for seasonal changes in fishing conditions and fishing areas dummies were added to account for productivity differences across the different fishing grounds in the Gulf region (Figure 1). Linear and quadratic time trends (t and t^2) were included to account for technical change. Table 2 presents key summary statistics of the variables included in the empirical model.

RESULTS AND DISCUSSION

CONCLUSIONS

References

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Table 1. Descriptive statistics.

Variable	Unit	Parameter	Vertical Line		Bottom Longline	
			Mean	S.D.	Mean	S.D.
Gag grouper landings	<i>lbs /trip</i>	y ₁	70.52	236.55	205.13	454.64
Red grouper landings	<i>lbs/trip</i>	y ₂	226.94	511.07	1971.89	2621.29
OSWG landings	<i>lbs/trip</i>	y ₃	30.89	128.76	134.04	345.55
DWG landings	<i>lbs/trip</i>	y ₄	19.81	148.43	642.82	1531.50
Tile landings	<i>lbs/trip</i>	y ₅	2.99	56.98	345.62	1910.22
Red snapper	<i>lbs/trip</i>	y ₆	445.49	1236.31	110.33	476.17
Other species landings	<i>lbs/trip</i>	y ₇	617.35	1158.95	667.22	1126.33
Vessel Length	<i>feet</i>	x ₁	36.10	9.14	43.63	9.92
Days away	<i>days</i>	x ₂	3.40	2.85	7.47	4.75
Crew size	<i>count</i>	x ₃	2.47	1.12	3.09	0.90
Texas (base dummy)	<i>dummy</i>	TX	0.07	0.26	0.04	0.20
Louisiana	<i>dummy</i>	LA	0.10	0.30	0.13	0.34
Alabama-Mississippi	<i>dummy</i>	ALM	0.07	0.25	0.04	0.20
South Florida	<i>dummy</i>	SFL	0.21	0.41	0.08	0.28
Center Florida	<i>dummy</i>	CFL	0.20	0.40	0.53	0.50
North Florida	<i>dummy</i>	NFL	0.35	0.48	0.16	0.37
Stock gag grouper	<i>Biomass</i>	stock _{y1}	11,113	4,222	10,990	4,424
Stock red grouper	<i>Biomass</i>	stock _{y2}	33,390	2,516	33,869	2,257
Stock red snapper	<i>Biomass</i>	stock _{y6}	43,947	13,925	42,735	14,595
<i>N. Observations</i>			70,776		12,431	

Table 2 Parameter estimates of the OSDF model

Parameter ^a	Handline		Longline	
	Coefficient	SE	Coefficient	SE
Constant	-6.011**	(2.659)	-33.171***	(7.130)
Y_2	-0.165***	(0.005)	-0.488***	(0.012)
Y_3	0.001	(0.005)	-0.028**	(0.012)
Y_4	-0.143***	(0.007)	-0.103***	(0.009)
Y_5	-0.380***	(0.009)	-0.051***	(0.009)
Y_6	-0.060***	(0.003)	-0.077***	(0.008)
Y_7	-0.219***	(0.005)	-0.262***	(0.009)
$Y_2 * Y_2$	-0.040***	(0.001)	-0.074***	(0.002)
$Y_3 * Y_3$	-0.021***	(0.002)	-0.001	(0.004)
$Y_4 * Y_4$	0.044***	(0.002)	-0.031***	(0.003)
$Y_5 * Y_5$	0.088***	(0.003)	-0.038***	(0.002)
$Y_6 * Y_6$	-0.032***	(0.001)	-0.003	(0.002)
$Y_7 * Y_7$	-0.046***	(0.001)	-0.072***	(0.003)
$Y_2 * Y_3$	0.005***	(0.001)	-0.002	(0.002)
$Y_2 * Y_4$	-0.001	(0.001)	0.016***	(0.002)
$Y_2 * Y_5$	-0.012***	(0.001)	0.019***	(0.002)
$Y_2 * Y_6$	0.009***	(0.001)	0.001	(0.001)
$Y_2 * Y_7$	0.030***	(0.001)	0.040***	(0.002)
$Y_3 * Y_4$	-0.001	(0.001)	-0.004*	(0.002)
$Y_3 * Y_5$	0.004**	(0.002)	-0.001	(0.002)
$Y_3 * Y_6$	0.004***	(0.001)	0.005***	(0.002)
$Y_3 * Y_7$	0.008***	(0.001)	0.007***	(0.002)
$Y_4 * Y_5$	-0.037***	(0.002)	0.009***	(0.002)

$Y_4^* Y_6$	-0.000	(0.001)	-0.001	(0.001)
$Y_4^* Y_7$	-0.004***	(0.001)	0.010***	(0.002)
$Y_5^* Y_6$	-0.009***	(0.001)	-0.002	(0.001)
$Y_5^* Y_7$	-0.018***	(0.002)	0.015***	(0.002)
$Y_6^* Y_7$	0.024***	(0.001)	-0.000	(0.002)
x_1	-0.125**	(0.052)	0.714***	(0.158)
x_2	0.995***	(0.012)	1.382***	(0.040)
x_3	0.400***	(0.031)	0.076	(0.112)
$x_1^* x_1$	-0.437***	(0.164)	0.480	(0.632)
$x_2^* x_2$	0.160***	(0.010)	0.045	(0.032)
$x_3^* x_3$	-0.092	(0.057)	-1.151***	(0.208)
$x_1^* x_2$	0.105***	(0.026)	-0.014	(0.091)
$x_1^* x_3$	0.012	(0.074)	0.547*	(0.313)
$x_2^* x_3$	0.126***	(0.015)	0.102*	(0.057)
$Y_2^* x_1$	-0.101***	(0.010)	0.012	(0.031)
$Y_2^* x_2$	-0.068***	(0.002)	-0.033***	(0.006)
$Y_2^* x_3$	-0.007	(0.006)	-0.040**	(0.020)
$Y_3^* x_1$	0.070***	(0.012)	-0.060	(0.040)
$Y_3^* x_2$	0.000	(0.003)	-0.002	(0.008)
$Y_3^* x_3$	0.007	(0.007)	0.043*	(0.024)
$Y_4^* x_1$	0.002	(0.015)	-0.006	(0.033)
$Y_4^* x_2$	0.023***	(0.004)	0.001	(0.008)
$Y_4^* x_3$	0.007	(0.009)	-0.023	(0.023)
$Y_5^* x_1$	0.141***	(0.019)	0.021	(0.032)
$Y_5^* x_2$	0.153***	(0.005)	0.026***	(0.008)
$Y_5^* x_3$	0.033***	(0.012)	0.042*	(0.022)

$Y_6^* x_1$	-0.023***	(0.007)	-0.022	(0.025)
$Y_6^* x_2$	-0.019***	(0.002)	0.024***	(0.006)
$Y_6^* x_3$	-0.011***	(0.004)	-0.035*	(0.020)
$Y_7^* x_1$	-0.071***	(0.010)	0.042	(0.029)
$Y_7^* x_2$	-0.089***	(0.002)	-0.023***	(0.006)
$Y_7^* x_3$	-0.031***	(0.006)	-0.033*	(0.017)
$Y_2^* t$	0.001	(0.001)	0.000	(0.002)
$Y_3^* t$	-0.002**	(0.001)	0.002	(0.002)
$Y_4^* t$	0.002**	(0.001)	0.007***	(0.002)
$Y_5^* t$	0.002*	(0.001)	-0.005***	(0.002)
$Y_6^* t$	0.004***	(0.001)	0.007***	(0.001)
$Y_7^* t$	-0.007***	(0.001)	-0.009***	(0.002)
$x_1^* t$	-0.001	(0.009)	0.004	(0.029)
$x_2^* t$	0.004**	(0.002)	-0.027***	(0.006)
$x_3^* t$	-0.003	(0.005)	0.059***	(0.020)
LA	0.420***	(0.028)	-0.648***	(0.110)
$AL\&MS$	0.186***	(0.033)	-0.351***	(0.134)
SFL	0.149***	(0.032)	-0.089	(0.117)
CFL	0.152***	(0.033)	-0.260**	(0.111)
NFL	0.361***	(0.030)	-0.330***	(0.110)
Q_1	0.066***	(0.015)	0.084**	(0.037)
Q_2	0.055***	(0.014)	0.047	(0.037)
Q_3	-0.000	(0.014)	-0.014	(0.036)
$Stock y_1$	0.074**	(0.034)	0.200***	(0.072)
$Stock y_2$	0.161	(0.100)	0.645**	(0.270)
$Stock y_6$	0.656***	(0.206)	3.082***	(0.508)

t	-0.040	(0.025)	-0.333***	(0.058)
t^2	-0.003**	(0.001)	0.004	(0.003)
σ_u	0.327***		0.895	
σ_v	0.591***		0.411	
$\lambda = \sigma_u / \sigma_v$	0.553***		2.178	
Log-Likelihood	-14,954		-3,065	
N	15,816		3,053	

* $P < 0.10$; ** $P < 0.05$; *** $P < 0.01$

^a To impose linear homogeneity in outputs the right hand side outputs are normalized by gag grouper (e.g., $Y_2 = y_2/y_1$).

Table 3. Partial distance input and output elasticities and return to scale (RTS).[†]

	Vertical Line				Bottom Longline			
	Whole Period	2005-2009	2010-2014	Test of means	Whole Period	2005-2009	2010-2014	Test of means
y₁	-0.04	-0.06	-0.01	0.00	0.00	0.00	0.01	0.84
y₂	-0.16	-0.18	-0.15	0.00	-0.49	-0.49	-0.49	0.79
y₃	0.00	-0.01	0.01	0.00	-0.03	-0.03	-0.02	0.00
y₄	-0.14	-0.15	-0.13	0.00	-0.10	-0.09	-0.11	0.00
y₅	-0.38	-0.37	-0.38	0.00	-0.06	-0.06	-0.05	0.00
y₆	-0.06	-0.02	-0.10	0.00	-0.07	-0.07	-0.07	0.00
y₇	-0.23	-0.22	-0.23	0.00	-0.27	-0.28	-0.25	0.01
x₁	-0.13	-0.11	-0.17	0.00	0.73	0.75	0.71	0.00
x₂	1.02	1.02	1.02	0.88	1.26	1.29	1.19	0.00
x₃	0.38	0.40	0.36	0.00	0.35	0.28	0.48	0.00
RTS	1.27	1.31	1.21	0.00	2.34	2.32	2.38	0.00

[†] Partial distance input elasticities: $\epsilon_{y_j} = \frac{\partial \ln Q}{\partial \ln y_j} = \alpha_j + \sum_{i=1}^n \alpha_i \cdot \frac{\partial \ln Q}{\partial \ln y_j} + \sum_{i=1}^n \alpha_i \cdot \frac{\partial \ln Q}{\partial \ln y_i} + \sum_{i=2}^n \alpha_i \cdot \frac{\partial \ln Q}{\partial \ln y_i}$; Partial distance output elasticities: $\epsilon_{x_j} = \frac{\partial \ln Q}{\partial \ln x_j} = \alpha_j + \sum_{i=1}^n \alpha_i \cdot \frac{\partial \ln Q}{\partial \ln x_j} + \sum_{i=1}^n \alpha_i \cdot \frac{\partial \ln Q}{\partial \ln x_i} + \sum_{i=1}^n \alpha_i \cdot \frac{\partial \ln Q}{\partial \ln x_i}$; and return to scale: $\epsilon_{Q} = \sum_{i=1}^n \frac{\partial \ln Q}{\partial \ln x_i}$.

^a Test (P-values) before and after the implementation of the IFQs.

Table 6 Fleet average CU measures.

Period*	Vertical Line			Bottom Longline		
	CU ^{TE,MAX}	CU ^{TE,25}	CU ^{TE,50}	CU ^{TE,MAX}	CU ^{TE,25}	CU ^{TE,50}
Entire period	0.568	0.966	0.935	0.459	0.828	0.718
Pre-IFQ	0.558	0.966	0.934	0.450	0.825	0.713
Post-IFQ	0.581	0.967	0.936	0.475	0.834	0.727
<i>% change</i>	<i>4.0</i>	<i>0.1</i>	<i>0.2</i>	<i>5.5</i>	<i>1.2</i>	<i>2.1</i>

* Average CU measures during the time period.

Table ## Fleet Overcapacity by species (1,000's lbs. g.w.). Annual

Period*	GAG*	Red Grouper	OSW G	DW G	Tilefish
Whole period	--	1,676	1,150	1,290	1,104
2005-2009	--	1,998	1,754	1,625	1,019
2010-2014	71	1,355	547	956	1,190
<i>% change</i>	<i>--</i>	<i>-32.2</i>	<i>-68.8</i>	<i>-41.2</i>	<i>16.8</i>

* Annual average capacity measures during the time period.

** Prior to 2009 Gag grouper and Red grouper were part of the OSWG

Table. Optimum Fleet size in 2014 (currently 595 vessels)

Period*	GAG	Red Grouper	OSWG	DWG	Tilefish
No. of Vessels	241	136	160	365	270
% of the Fleet	40.5	22.8	27.9	61.5	45.4

** Prior to 2009 Gag grouper and Red grouper were part of the OSWG

Figure 1. Evolution fleet size

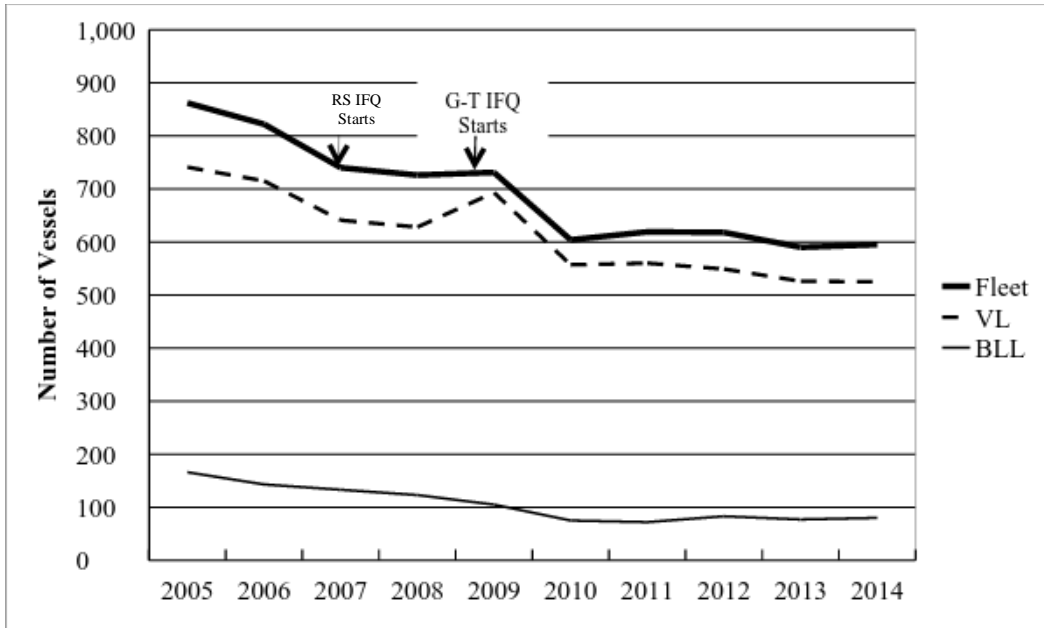


Figure 2. Average vessel-level trip characteristics (whole fleet)

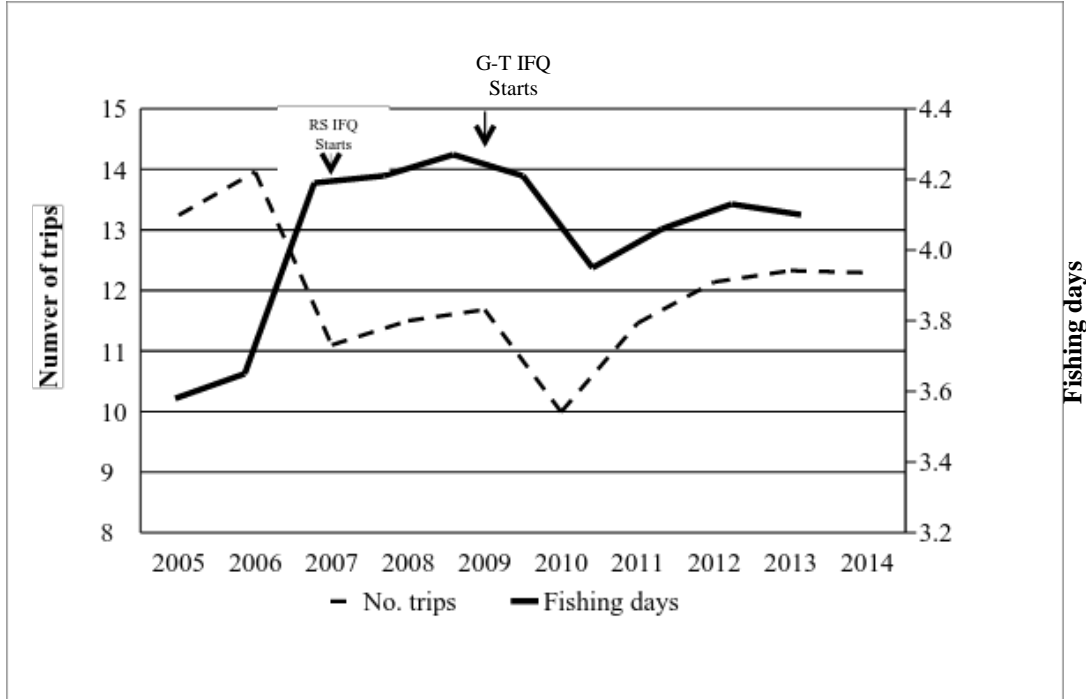


Figure 3. Studied Area

