



# Vessel monitoring systems (VMS) reveal an increase in fishing efficiency following regulatory changes in a demersal longline fishery

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## ABSTRACT

A global expansion of satellite-based monitoring is making fisher behavioral responses to management actions increasingly observable. However, such data have been underutilized in evaluating the impacts of fishing on target and non-target fish stocks or the ramifications of management strategies on fishers. We demonstrate how vessel monitoring system (VMS) data can provide a suite of metrics (such as effort) for improving inputs to stock assessments, dynamic delineation of fishing grounds, and evaluation of regulatory or other (e.g., climatic) impacts on fisher performance. Using > 1 million VMS records from the Gulf of Mexico grouper-tilefish demersal longline fishery, we first develop a generalized additive modeling approach that predicts fishing duration with ~85% accuracy. We combine model predictions with logbook data to compare the fishery before and after implementation of a suite of regulatory changes (e.g., a shift to catch share management). We find a large-scale reduction in fleet size, accompanied by reduced fishing effort (duration \* number of hooks), shorter trips, lower operational expenses, higher catch rates, and more earnings for those vessels that remained in the fishery. We discuss how the combination of VMS and associated metrics can be expanded for use in management strategy evaluation, parameterizing economic models of fisher behavior, improving fishery-dependent stock assessment indices, and deriving socioeconomic indicators in fisheries worldwide.

## 1. Introduction

Many factors drive the dynamics of commercial fisheries and substantial effort is expended on understanding and predicting fisher responses to such drivers. As fishing fleets react to changing environments, markets, and governance, the ability of scientists and managers to quantify their behavior becomes increasingly critical for understanding not only the dynamics of exploited stocks but the economic sustainability of the fisheries themselves (van Putten et al., 2012; Fulton et al., 2011).

Vessel monitoring systems (VMS) have improved our ability to monitor fishing vessel movements and to evaluate fishing fleet behavior (e.g., fishing location) and spatially-explicit economic decision-making

(e.g., Watson and Haynie, 2018). VMS transmit vessel locations at regular intervals, and are required by dozens of national governments and regional fisheries management organizations. These systems facilitate monitoring of speeds, changes in bearing, locations, and other aspects of vessel behavior that can indicate when and where vessels are fishing.

VMS have been used to examine spatial fishing activities at higher temporal resolutions, leading to more precise estimates of effort (e.g., Mills et al., 2007; Peel and Good, 2011; Joo et al., 2013), validation of fisher-reported logbooks (e.g., Palmer and Wigley, 2009; Bastardie et al., 2010), delineation of fishing grounds (e.g., Stelzenmuller et al., 2008), assessment of benthic impacts from fishing (e.g., Lambert et al., 2011), and more. Some software packages now simplify and automate

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standard VMS analyses (Russo et al., 2014, or Hintzen et al., 2012), but specific case studies often still require customized modeling approaches. For example, Ducharme-Barth and Ahrens (2017) developed random forest algorithms with VMS data to assess changes in fishing effort as a result of closures associated with the Deepwater Horizon Oil Spill. O'Farrell et al. (2017) examined solutions for identifying fishing behavior when fishing events occurred over time intervals that were less than the VMS sampling frequency. Thus, while software can be used to automate some tasks, more general analytical approaches and metrics must be developed to address individual cases. As environments change and regulatory strategies shift, the ability to monitor impacts on fishers using VMS data will become increasingly important (Melnychuk et al., 2012; Clay et al., 2014).

Catch share systems are an example where managers may wish to quantify fisher responses to regulatory change. Catch shares seek to reduce the inefficiencies resulting from too many fishers competing for limited resources (Grafton, 1996) and evaluation of such systems can be enhanced through resolution of spatial dynamics in the fishery. With catch shares, individual fishers are allocated shares of the total catch, which enables them to seek fishing opportunities in locations that minimize costs and maximize expected revenue (e.g., Haynie and Layton, 2010; Birkenbach et al., 2017). VMS data provide the opportunity to monitor fishing locations and durations at the trip-, set-, or haul-levels. Through VMS-derived estimates of fishing duration, changes in the efficiency of fishing (e.g., catch or revenue per unit effort) can be quantified across time to monitor the effects of catch shares or other regulatory transitions.

The demersal longline fishery for reef fishes in the Gulf of Mexico is one fishery with VMS that has undergone a dramatic regulatory transition, providing an opportunity for quantifying the associated changes in fishing behavior (e.g., location and duration) and economic performance (e.g., catch, cost, and revenue). This fishery primarily targets gag grouper (*Mycteroperca microlepis*) and red grouper (*Epinephelus morio*) as well as tilefishes (*Caulolatilus* spp.) and a complex of other deep- and shallow-water groupers (Farmer et al., 2016; Supplementary material Appendix Table A.1), with 2015 ex-vessel revenue of \$28 million (NMFS, 2016). In 2010, an individual fishing quota (IFQ), or catch shares, system was implemented to avoid continuation of "... higher than necessary levels of capital investment, increased operating costs, increased likelihood of shortened-seasons, reduced safety at-sea, wide fluctuations in grouper supply, and depressed ex-vessel prices; leading to deteriorating working conditions and lower profitability for participants." (Amendment 29; Gulf of Mexico Fishery Management Council, 2008). The changes associated with the catch share transition came a year after sea turtle bycatch regulations were introduced, consisting of time-varying, area-specific depth restrictions and a reduction in the maximum number of hooks. The fleet was further impacted by a longline endorsement program that restricted fishing to vessels that had sustained average annual catches greater than 40 000 pounds from 1999 to 2007 (Amendment 31; Gulf of Mexico Fishery Management Council, 2010).

Our study makes several contributions to the literature on quantifying fisher behaviors (e.g., unobserved spatial fishing patterns) and exploring fisher responses to regulatory changes. First, we use VMS data to build a probabilistic model for estimating unobserved fishing duration (for our purposes, duration is longline set, soak, and retrieve time). Second, we combine the results from our VMS-based model with logbook data to derive fishing activity and performance metrics like trip distance, effort (fishing duration \* number of hooks), catch per unit effort, and revenue per unit effort. Finally, we test the hypothesis that regulatory changes increased fishing efficiency (i.e., increased revenue for less effort) in the Gulf of Mexico demersal longline fishery for reef fishes. Although we demonstrate our method by asking questions of fisher responses to regulatory changes, we stress that the approach could also be used to investigate fishing responses to a broad range of disturbances, including climatic regime shifts, catastrophic events (e.g.,

oil spills), or fishery collapse.

## 2. Data and methods

We integrated three data sources (observer, VMS, and logbook data) into our modeling approach. Observer data were used to train and validate models of VMS data for estimating fishing effort, as described below. VMS data were then merged with logbook data to derive and evaluate a suite of behavioral, performance and economic metrics to understand the impacts of regulatory changes. All analyses were performed using R Statistical Software Version 3.3.2 (R Core Team, 2016).

### 2.1. Data

An observer program was established in 2006 for all vessels federally permitted to target reef fish using demersal longlines in the Gulf of Mexico (Scott-Denton et al., 2011). The number of vessels in this program changed dramatically during our study period (discussed below). Trips in this fishery average ~10 days and on-board observers are assigned to vessels in the fleet to record operational and catch information (e.g., information on gear, set, catch and trip characteristics). In our case, 183 bottom longline trips (~4% of trips) were observed on 62 vessels from 2007 to 2012 for which we also had VMS and logbook data.

Since 1993, commercial vessels that were federally permitted in the Gulf of Mexico also had logbook reporting requirements. Logbook requirements have evolved since then and, for many years, longline soak times or other metrics of fishing duration were not consistently collected. Thus, no estimates of fishing duration other than trip days were available from logbooks for the pre- and post-regulatory transition (unless trip duration was considered as a proxy for fishing effort).

VMS programs have required the transmission of hourly vessel location information since 2007 (Amendment 18A; Gulf of Mexico Fishery Management Council, 2005). We used VMS-based vessel locations and time-stamps to calculate the distance between VMS records (using the Haversine formula [Sinnot, 1984; Charles et al., 2014]), vessel speed, and distance from port.

Speed calculations were based on the average time and distance travelled between records at times  $t$  and  $t-1$  and times  $t+1$  and  $t$ . Records with speeds over either of these time periods exceeding 20 knots were considered erroneous and were excluded.

### 2.2. Model-estimation of fishing duration from VMS data

VMS data for individual trips were combined with observer data and modeled to estimate fishing duration (see Supplementary material Appendix A for details on identification of trips from VMS data). When observers were present (~4% of trips during our study period), they reported the start and end times for each longline set, which allowed us to train models that predicted fishing duration based on VMS data. Observers reported an average of 27 ( $\pm 13.1$ ) sets per trip with an average duration of 4.2 h per set, so that the average set had 4–5 VMS records, depending on when a VMS ping occurred relative to observed start and stop times of fishing (see O'Farrell et al., 2017 for a discussion of VMS transmissions vs. fishing event duration). If a VMS record occurred between observer-reported set start and end times, we considered the VMS record to represent a fishing event. We fit logistic generalized additive models (GAMs; Hastie and Tibshirani, 1990; Wood, 2006) with a logit link to observed VMS records to estimate the probability that fishing occurred ( $p(\text{fishing})$ ) based on a suite of covariates (Table 1) that described fishing activities:

$$\text{logit}(p(\text{fishing})) = s_1(\text{Covariate}_1) + s_2(\text{Covariate}_2, \text{Covariate}_3) + \dots + s_j(\text{Covariate}_j), \quad (1)$$

where  $s_j(\cdot)$  represents an individual smoothing function for each

**Table 1**

Description of model covariates explored for predicting the probability of fishing for each VMS record, and the hypothesis of how they may affect model estimation of fishing. Values were included from original data or derived for each VMS record of each trip.

Variable name	Description	Expected relationship to fishing activity
Distance	Distance from nearest county line (proxy for distance from shore/port)	A proxy for fishing location; certain distances are more likely to be associated with fishing.
Depth	Depth (m) calculated using NOAA NGDC bathymetry data through the R Marmap package (Pante and Simon-Bouhet, 2013).	Depth restrictions and depth-specific fish habitat will affect chances of fishing.
Month	Month of VMS record (categorical)	Different regulations occur during certain months.
Year	Year of VMS record (categorical)	Accounts for changes in the fishery that may reflect regulatory dynamics.
Hour	Hour of the day, modeled using cyclic penalized regression splines (Wood, 2006)	Little fishing occurs in the middle of the night.
Speed <sub>t-1</sub>	Vessel speed calculated between the current and the previous VMS record	Indicative of what vessel speed was – certain speeds are not conducive to fishing.
Speed <sub>t+1</sub>	Vessel speed calculated between the current and subsequent VMS record	Indicative of new speeds, associated with transitions into or out of fishing operations.
Speed <sub>avg</sub>	Average of the forward and backward calculated speeds	When combined with above speed formulations, indicates slowing or speeding of vessel associated with fishing operations.
Speed <sub>15</sub>	Average of Speed <sub>avg</sub> over a 5 record moving window	Same as Speed <sub>avg</sub> but with a larger window
Δdistance	The change in the distance variable between the current and previous VMS record	Indicative of vessel direction to/from port versus along bathymetry lines
Δdistance <sub>p</sub>	Mean of the previous 5 values of Δdistance	Indicative of vessel direction during previous several hours
Δdistance <sub>s</sub>	Mean of the subsequent 5 values of Δdistance	Indicative of vessel direction during next few hours
Δdistance <sub>avg</sub>	Mean of Δdistance and the 2 previous and subsequent values of Δdistance	Similar to above with a different time window for transitions between directions
Latitude	Latitude	Identifies potential fishing grounds
Longitude	Longitude	Identifies potential fishing grounds

covariate, fit using thin plate regression splines (tensor splines were examined for bivariate terms but did not improve fits). All candidate models included univariate predictors, as illustrated by  $s_1(\text{Covariate}_1)$ , and some candidate models included bivariate terms allowing for interactions, as illustrated by  $s_2(\text{Covariate}_2, \text{Covariate}_3)$ . All covariates (Table 1) were continuous except for the categorical variables, month and year. Computational demands prevented examination of all possible covariate combinations but several dozen models were explored based on hypothesized relationships between fishing behaviors (e.g., preferred depths, times of day) and vessel movements (see Supplementary material Appendix Table A.2 for candidate models). Model selection is discussed below. We avoided covariate combinations (e.g., speed<sub>t-1</sub> and speed<sub>avg</sub> or speed<sub>t+1</sub> and speed<sub>avg</sub> [described in Table 1]) that led to collinearity as indicated by variance inflation factors > 3 (Zuur et al., 2010; R function *corvif* included in supplementary material of reference). Standard regression assumptions (e.g., normality, homoscedasticity) were checked via model diagnostics and residual plots.

Given the nature of VMS data, spatial autocorrelation may be a concern. We assumed that models including a spatial term (e.g.,  $s_j[\text{Longitude}, \text{Latitude}]$ ) accounted for such autocorrelation. For those models that did not include an explicit spatial term, we visually examined model outputs for spatial autocorrelation by mapping residuals.

Our primary interest was to develop the most accurate measure of fishing duration for unobserved trips so model selection proceeded by seeking the GAM that minimized prediction errors. We compared predictive ability for each of the models using leave-one-out cross validation (LOOCV) with the 183 observed fishing trips whereby models were fit to all but one trip and predictive accuracy was tested on the remaining holdout trip. This process was repeated for each of the 183 fishing trips, using parallel processing to reduce computation times (Knaus et al., 2009). We assessed prediction accuracy at the trip-level instead of set-level because our application of this model was more broadly focused on trip-level changes in fishing behaviors before and after the regulatory transition. To quantify prediction error at the trip-level we summed the predicted probabilities ( $p[\text{fishing}]$ ) for all VMS records within each trip and compared this to the number of VMS records that were observed to be fishing. To ensure that our best model was not over-predicting fishing, which would provide a low relative error rate for fishing and a high relative error rate for non-fishing, we

compared the predictions for non-fishing VMS records by comparing the sum of  $(1 - p(\text{fishing}))$  to the number of VMS records that were observed while not fishing. A simple percent error calculation  $(100 * [\text{observed} - \text{predicted}] / \text{observed})$  was performed for the comparisons. See Supplementary material Appendix A for further discussion and approaches on quantifying prediction errors.

We used the selected GAM to predict which VMS pings occurred while vessels were fishing during the remaining unobserved trips for which we had both VMS and logbook data ( $N = 2423$  trips, 62 vessels). We estimated trip-level effort by summing the predicted probabilities for all VMS records within each trip and multiplying the sum by the 60 min VMS transmission interval (see Supplementary material Appendix A for additional details on model selection and effort calculations). Gaps in VMS transmissions greater than expected did occur (6.5% of VMS records were transmitted at > 65 min intervals), but the median and mode of transmission frequencies were 60 min. We discuss the role of transmission gaps in a subsequent section.

### 2.3. Comparison of fishing behavior and performance before and after the regulatory transition period

Many vessels left the fishery after implementation of the catch share and longline endorsement programs (see Results). Vessels that remained in the fishery after catch share implementation were allocated initial shares based on their historic catches. To assess how regulations affected those vessels that remained in the fishery, all comparisons of pre- and post-regulation used only vessels that were present both before and after the transition.

To test the hypothesis that fishing efficiency increased following regulatory changes, we compared fishing performance and behavior before (2007–2008) and after (2011–2012) the regulatory transition. In addition to the January 1, 2010 switch to a catch share program, a series of depth restrictions, gear modifications, time-area closures, and the Deepwater Horizon Oil Spill (which yielded its own series of short-term time-area closures) all occurred during a transition period (2009–2010), leading to a protracted changeover from pre- to post-regulation behaviors. Thus, we excluded the transition years and focused only on the before and after periods. Our ideal situation would have included a control fishery to bolster our statistical comparison of the regulation effect, but even in a global meta-analysis of catch shares

**Table 2**

List of metrics evaluated as response variables for examination of the effects of regulation on the fishery. Some descriptions refer to metrics defined in previous rows of the table.

Metric	Description	Expectation
Trip distance <sup>a</sup>	Cumulative distance between all VMS records per trip	A proxy for fishing location; distance provides a simple indicator of changes in spatial behaviors.
Trip duration <sup>a</sup>	VMS-derived time between start and end of trip	Similar to trip distance but enables accounting for nearer to port trips (i.e., less time) that changed in duration. An increase in efficiency would generally lead to expected decreases in trip durations.
Fishing duration <sup>b</sup>	(GAM-derived probability of fishing per trip) * (median VMS transmission interval per trip [typically 60-min])	Intermediate calculation for effort metric (below)
Proportion of trip spent fishing	Fishing duration / Trip duration	Serves as a complementary indicator to fishing and trip durations to illustrate changes in fishing strategy.
Effort	(Logbook-reported number of hooks per trip) * (Fishing duration)	Intermediate value for catch per effort metric (below)
Catch <sup>a</sup>	Logbook-reported pounds per trip	Intermediate value for catch per effort metric (below)
Catch/Effort <sup>a</sup>	Catch / Effort	An increase in this metric suggests that the same amount of effort yielded greater catches following the transition, and thus an increase in fishing efficiency.
Earnings <sup>a</sup>	Logbook-reported gross earnings per trip (US dollars)	Intermediate value necessary for earnings/effort
Earnings/Effort <sup>a</sup>	Earnings/Effort	An increase in this metric suggests that the same amount of effort yielded greater revenue following the transition, and thus an increase in fishing efficiency.
Mean depth fished <sup>a</sup>	Average depth for each VMS record where p (fishing) > 0.5	Allows for characterization of targeting behavior (shallow- vs. deep-water species complexes).
Mean distance from shore <sup>a</sup>	Average distance from county line closest to each VMS record	Similar to depth, this may be an indicator of different targeting behavior or habitat use.
Bait expense <sup>a</sup>	Logbook-reported cost of bait per trip	Indicator of fishing costs; a decrease suggests an increase in efficiency.
Fuel <sup>a</sup>	Logbook-reported quantity of fuel per trip	Indicator of fishing costs; a decrease suggests an increase in efficiency.

<sup>a</sup> Terms that were log-transformed for model fitting.

<sup>b</sup> Terms that were used to derive other metrics but that are not included here as model response variables.

fisheries, Essington (2010) was unable to find controls for all before-after comparisons. Confounding factors or potential biases may exist in a before-after comparison, but we believe that our approach still provides a valuable comparison. In particular, by excluding the 2009–2010 transition years (i.e., removing so-called history threats to internal validity [Conrad et al., 1991]) and by using a full suite of fishing behavior and economic indicators, we have sought to remove and buffer against some potential biases.

We used linear mixed effects models (R *nlme* [Pinheiro et al., 2017]) to quantify the change in several fishery metrics (Table 2), or response variables ( $Y_{t,v}$ ) before and after the transition period. Several of these metrics are consistent with those explored by Brinson and Thunberg (2016) to evaluate changes in fishing performance (e.g., revenue), but most provide additional detail relevant to answering behavioral questions. One of the major regulatory changes included limitations on fishing depth as specified on a monthly basis, so we divided year into seasons A (Jan–Mar), B (Apr–Jun), C (July–Sep), and D (Oct–Dec) to allow for intra-annual variability in responses. We fit individual models by season to quantify the effect of regulatory changes on the responses. We explored the use of vessel and port as random effects within the full model (Eq. (2)) via restricted maximum likelihood (Zuur et al., 2009), yielding a random vessel intercept in all cases. For each response variable, we then used the AIC to select a model with (Eq. (2)) versus without (Eq. (3)) a continuous covariate for vessel length:

$$Y_{t,v} = (\beta_0 + b_{0v}) + \beta_1 * Regulation_{t,v} + \beta_2 * Vessel Length_v + \varepsilon_{t,v} \quad (2)$$

$$Y_{t,v} = (\beta_0 + b_{0v}) + \beta_1 * Regulation_{t,v} + \varepsilon_{t,v} \quad (3)$$

$$b_{0v} \sim \text{Normal}(0, \sigma_v^2)$$

$$\varepsilon_{t,v} \sim \text{Normal}(0, \sigma^2)$$

The subscripts  $t$  and  $v$  represent trip and vessel, respectively. *Regulation* was a dummy variable indicating whether a trip occurred during the pre- (0) or post-regulatory period (1). The effect of *Vessel Length* was treated as time-invariant, so we omitted the trip-level subscript from this term in (2). The random intercept for vessel ( $b_{0v}$ ) and the residuals ( $\varepsilon_{t,v}$ ) were assumed to be independent and normally distributed with means zero and variances  $\sigma_v^2$  and  $\sigma^2$ , respectively.

The term of primary interest was the fixed coefficient on *Regulation*, which measures the change in the response variable after regulatory transition. For log-transformed response variables (Table 2), the coefficient reflects percent change. For untransformed response variables, the coefficient was divided by the model intercept to obtain percent change.

### 3. Results

#### 3.1. Model-estimation of fishing effort from VMS data

We analyzed > 1 million VMS records to identify 4371 longline trips made by 150 vessels in the Gulf of Mexico from 2007–2013. Among these trips, 161 (3.5%) had onboard fishery observers, remained in the fishery after the regulatory transition, and were thus suitable for model development and validation. We present model estimation and comparison with the observer data, but logbooks typically did not include soak times so no comparison with logbook estimates on that metric was possible.

The final model (see Supplementary material Appendix A and Table A.2 for candidate model discussion) selected by LOOCV was:

$$p(\text{fishing}) = \text{month} + s(\text{distance}) + s(\text{hour}) + s(\text{depth}) + s(\text{speed}_{t-1}, \text{speed}_{t+1}) + s(\Delta \text{distance}_s, \Delta \text{distance}_p) \quad (3)$$

where all covariates were continuous (see Supplementary material Appendix Fig. A.1 for partial dependence plots) except for the factor, *month*. The covariates *distance* and *depth* provided spatial proxies for the locations of fishing grounds and the targeting of certain species complexes. Different speed formulations enabled the model to capture vessels speeding up and slowing down as they transitioned to different phases of gear setting and retrieval, consistent with other VMS-based estimates of fishing duration (e.g., Vermard et al., 2010; Joo et al., 2013; Gloaguen et al., 2015). The change in distance from port terms ( $\Delta \text{distance}_s$ ,  $\Delta \text{distance}_p$ ) allowed the model to capture vessel orientation along isobaths in two dimensions and, like the speed transitions, capture changes in vessel behaviors. For example, if a vessel was sequentially speeding up and slowing down while maintaining little change in the distance from shore (i.e.,  $\Delta \text{distance}$  was small), the vessel was likely



following an isobath, parallel to the coast, and more likely to be fishing. This rationale is consistent with targeting species at specific depths. Finally, most fishing occurred during daytime or early evening, with little fishing between midnight and early morning, explaining selection of *hour*. The *month* term was useful for estimating intra-annual differences in targeting behaviors, which may be associated with different distances from shore or depths. Residuals did not demonstrate an obvious spatial pattern and the selected model predicted better than spatially-explicit models, suggesting little effect from spatial autocorrelation.

The final model had an average trip-level prediction error ([observed – predicted]/observed) of  $-4.0\%$  (standard deviation  $24.1\%$ ) (Supplementary material Appendix Table A.2), with the negative sign indicating a propensity to predict more fishing than was observed. The average of the absolute percent error, was  $15.1\%$  and  $8.6\%$  for predicting fishing and non-fishing, respectively. It is counter-intuitive to have a greater percent error when predicting fishing than non-fishing given that our models tend to over-predict fishing. However, VMS records where fishing was occurring accounted for only two-thirds as many VMS records as non-fishing records. Thus, despite the slight over-prediction of fishing, it does not occur at such a rate that overwhelms the greater number of the non-fishing events. Prediction errors were not statistically different across years (ANOVA  $F(6,175) = 0.97$ ,  $p = 0.45$ ), which is consistent with similar operational behaviors (e.g., the speed at which gear is set and retrieved).

### 3.2. Comparison of fishing behavior and performance before and after regulatory transition

Regulatory changes in the fishery for reef fishes were associated with reduced fleet sizes; the fishery went from 129 and 120 vessels in 2007 and 2008, respectively, to 65 and 68 vessels in 2011 and 2012, respectively. The size composition of the fleet ( $\sim 14$  m average vessel length) did not change across our study period but vessels that left the fishery had, on average, landed only  $76\%$  as much fish per trip during the pre-regulatory period as those that remained. Additionally, these vessels earned only  $71\%$  as much gross revenue per trip during the pre-regulatory period. Those vessels that left the fishery landed on average only  $56\%$  as many pounds of fish per year as the vessels that remained in the fishery, and they earned only  $52\%$  as much gross revenue during the pre-regulatory period.

Vessels that remained in the fishery throughout the regulatory transition period increased their fishing efficiency, as determined by a series of fishing behavior and performance metrics (see Supplementary material Appendix Tables A.3 and A.4 for coefficients and standard deviation of random intercepts). We analyzed 2423 trips for which we could link VMS-derived metrics and logbook data, with comparable numbers of trips in the before ( $N = 1250$ ) and after ( $N = 1173$ ) periods. At the trip-level, the catch per unit effort (CPUE) nearly doubled while catch, gross revenue per unit effort, and gross revenue also increased substantially and across all four seasons while fishing effort decreased (Fig. 1). Much of the  $\sim 50\%$  decrease in effort (hooks \* hours) was attributable to the 2009 implementation of a maximum number of hooks per set, which reduced hook usage by  $\sim 60\%$  per trip. This effort reduction coupled with increased catches of  $\sim 50\%$  accounted for the doubling of CPUE. A notable difference occurred in several cases during C-season (July–September), when fishing was restricted to waters beyond the 35-fathom isobath to promote bycatch mitigation. During this period, the mean depth of fishing increased and there was a less marked decrease in effort than during other seasons, but catches shifted to valuable deep-water species complexes that facilitated an increase in gross revenues (ex-vessel prices have generally increased since the IFQ transition [NMFS, 2016]). During A and D-seasons, trip distances decreased slightly as fishing effort moved closer to shore (Fig. 2) (consistent with reduced trip distances and shallower fishing; Fig. 1).

In addition to examining fishing performance and economic metrics at the trip level, we also modeled aggregate levels, where response values were summed for each vessel (that remained in the fishery throughout the study period) and year over all trips per season during the before (2007–2008) and the after (2011–2012) regulatory periods (Fig. 3). The average number of trips per vessel per year was unchanged (Wilcoxon rank sum,  $P > 0.05$ ). Across all seasons, decreased bait costs, increased gross revenue, and decreased total effort were significant. During C-season, the number of trips decreased and there was a net reduction in the total distances and durations traveled at the vessel level. Maps suggested less notable movement in fishing locations during B and D-season (Fig. 2) so the increases in gross revenue and overall performance (though not in gross revenue variability) were likely more associated with the reduced fleet size than with shifts in behavior. Meanwhile, A-season effort moved slightly shoreward which was associated with a minor reduction in average travel distances. Less fuel was used each season (though not significantly in C-season) perhaps related not only to travel distances but to reductions in actual fishing time (vessels often use more fuel while engaged in fishing than transiting).

## 4. Discussion

By combining the spatial aspects of VMS data with fisher-reported logbook information on catch, costs, and gross revenue, we quantified an increase in fishing efficiency following a regulatory transition in the Gulf of Mexico bottom longline fishery. After the transition, there were fewer vessels. These vessels landed more fish and generated higher revenues in less time and with fewer hooks than before the transition. Our study required development of an accurate approach for estimating fishing duration in a longline fishery that had no prior reporting of trip-level fishing durations and for which many of the more ‘typical’ VMS-based approaches for estimating effort (e.g., speed thresholds [Deng et al., 2005]) yielded unreasonably large errors. This study also filled a gap in methods used to evaluate regulatory changes (e.g., catch shares [Clay et al., 2014; Brinson and Thunberg, 2016]), and other perturbations, by demonstrating *how* the relevant indicators of fishing performance could be derived, especially when valuable information like fishing duration was not available.

### 4.1. Model-estimation of fishing effort from VMS data

Many studies have used VMS data to resolve spatial dynamics and effort of fishing fleets but relatively few have done so for longlines (e.g., Chang and Yuan, 2014). This is likely due to the more complicated speed characteristics of vessels during the multiple phases of setting, retrieving, and repositioning associated with longline gears, as opposed to the relatively constant speeds of trawling. In contrast, our longline model included a combination of factors that served as proxies for not only what the vessel was doing (e.g., speeding up or slowing down) but also the time of day and vessel location (e.g., depth, and orientation to shore).

Our prediction of fishing was accurate, with an average absolute error of only  $15.1\%$  (standard deviation,  $19.2\%$ ). While our model failed to capture relevant vessel characteristics on some trips, a greater source of error may arise from aspects of the data themselves. First, the greatest errors occurred during trips with fewer numbers of observed fishing records (Fig. A.3), where smaller numbers of predictions could lead to larger percentage errors, and outliers were generally indicative of over-predictions of fishing. Examination of the individual VMS records associated with such trips suggested that behaviors on those trips were atypical compared to other observed trips. For example, in an extreme case, the model predicted a high probability of fishing when it was expected to do so; the vessel arrived at the fishing grounds, slowed to typical fishing speeds, and exhibited tortuous movement patterns consistent with other fishing sets, all at the time of day during which

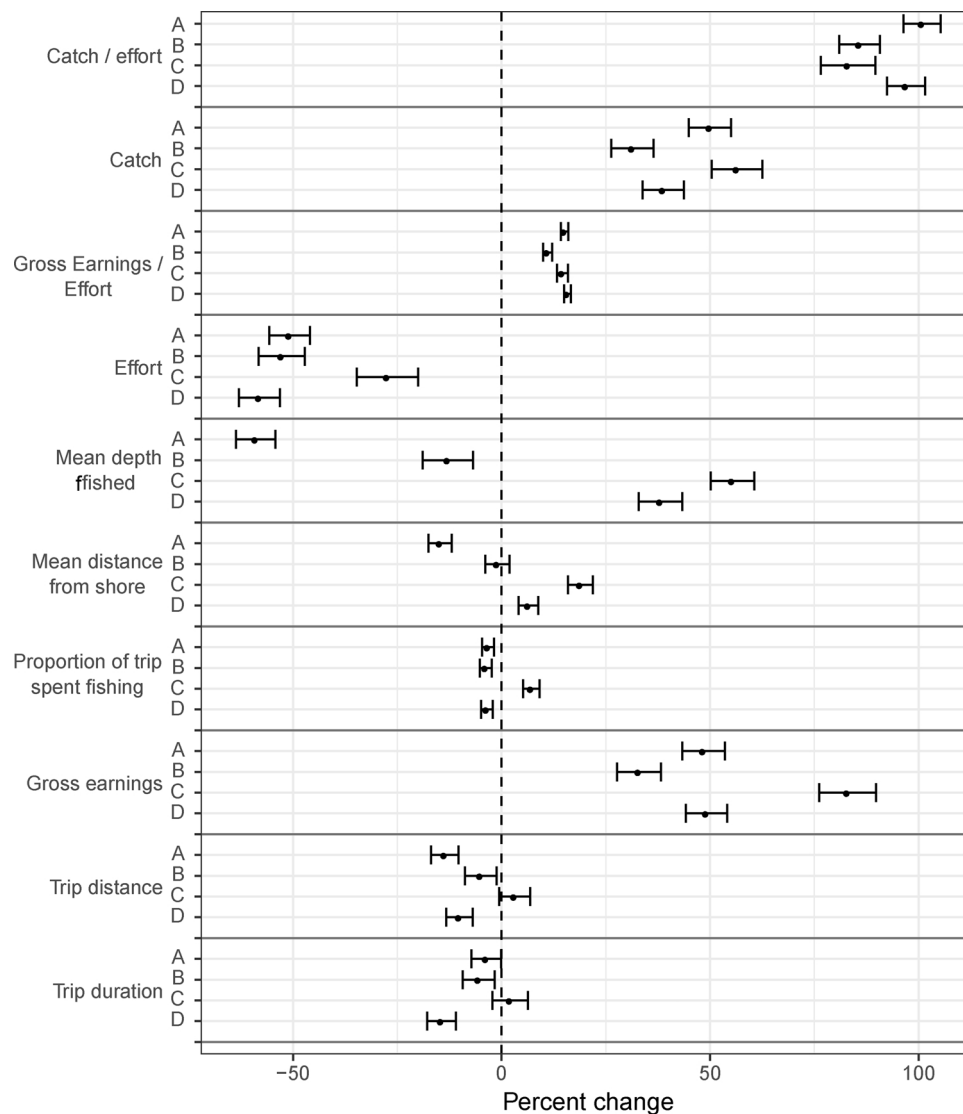


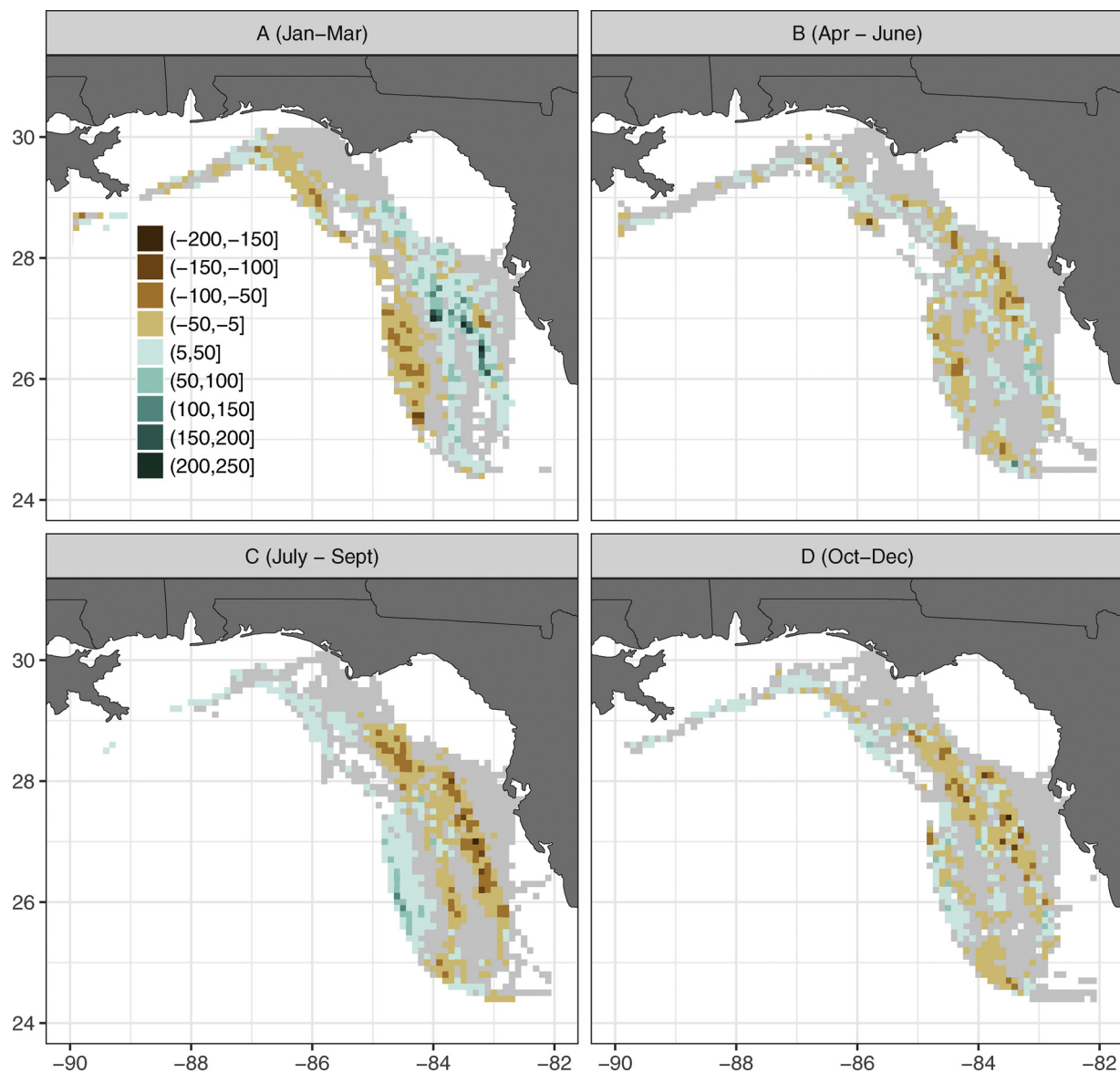
Fig. 1. Model estimates of the percent change in response variables after regulatory changes during the A–D seasons.

fishing generally occurred. However, the vessel was on the fishing grounds for more than 24 h before the observer data indicated that fishing occurred. In a second extreme case, a trip was observed to be nearly 20 days long but fishing was only reported during the first half of this period. However, the vessel behavior and the model predictions continued to suggest fishing activity was occurring, despite a lack of reported fishing. Such behaviors were difficult to account for with models, but, overall, the models fit well; trips with  $\leq 10\%$  absolute prediction errors accounted for 43% of trips, while 68.7% of trips had absolute prediction errors less than the standard deviation of prediction errors (19.2%). Additionally, errors associated with over-prediction of fishing often occurred for the VMS records that were adjacent to those observed to be fishing, suggesting that the transition to fishing behaviors often began before gear was set or continued slightly after gear was retrieved (i.e., times reported by observers to be the start and end times of fishing). A further source of error may be VMS transmission rates. Despite mandated transmission frequencies of 60-min, more than half of observed trips had at least one gap in VMS intervals greater than 60-min. Finally, as the time between VMS records increases, the accuracy of some model covariates decreased. Vessel speeds and changes in distance from port were calculated between consecutive VMS records, so as the time between records increased, the accuracy of derived fields decreased, as did the strength of their relationships with the modeled

response (see [Watson and Haynie, 2016](#); [Palmer, 2008](#) for further discussion).

Several candidate models yielded similar predictions, suggesting that while slight variations in model structure made a difference, certain aspects of vessel behaviors were more important than the nuances of how they were modeled. In some cases, including two speed formulations as univariate (i.e., fixed effects) versus bivariate (i.e., an interaction) terms yielded little difference in predictive success. Similarly, in one case, a model that included latitude and longitude reduced the AIC by more than 100 units, but the same model without the spatial component had a similar mean absolute percent error. The best predictive models included at least a single formulation for speed, distance from shore, time of day, depth, and change in distance from shore, and they suggest that future approaches may benefit from model averaging.

Several candidate models improved upon previous efforts to estimate fishing duration in a longline fishery (e.g., as compared with [Chang and Yuan, 2014](#)). For our application aimed at deriving socioeconomic indicators and evaluating a regulatory transition, several of our models would have yielded similar conclusions regarding fishery changes following regulation. However, for stock assessment or other management applications, we acknowledge that users may have different criteria that would prioritize covariate selection. For example,



**Fig. 2.** Difference in seasonal (A–D) fishing effort before versus after the regulatory transition period. Values are the difference between the predicted hours of fishing after the regulatory period minus the predicted hours of fishing before the regulatory transition, so positive numbers (blue-green colors) indicate more fishing after (2011–2012) and negative numbers (brown colors) indicate more fishing before (2007–2008). Grey pixels represent minimal difference in pre/post effort (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

instead of selecting a model by optimizing prediction accuracy at the trip-level, users may prefer an approach that optimizes prediction accuracy at the scale of individual VMS records to provide higher spatial resolution of fishing estimates.

#### 4.2. Comparison of fishing behavior and performance before and after regulatory transition

The objectives of the grouper-tilefish IFQ program were to reduce over-capacity, to increase fishing efficiency, and to mitigate derby-fishing conditions (NMFS, 2016). Over-capacity can be generally described as the difference between a fleet's potential and actual output (Kirkley et al., 2006). While only logbook and permit data are necessary to evaluate certain aspects of fleet capacity (e.g., number of vessels and trips) and derby conditions, our VMS-based approach provides a means to evaluate changes in fishing efficiency. We demonstrated large increases in catch rates and drastic reductions in fishing effort at both the trip- (Fig. 1) and aggregate-levels (Fig. 3). We have defined fishing

effort as longline soak time \* number of hooks, though it should be noted that entire papers have examined the complexities of selectivity, hook saturation and other aspects that can confound comparisons of effort metrics (e.g., Løkkeborg et al., 1989; Hovgaard and Lassen, 2000). For our purposes, we assume that fishers consistently seek to maximize the catch from their effort and that changes in effort are reflective of regulatory change (see below and Eigaard et al., 2011 for discussion of additional confounding possibilities). Bycatch regulations in the fishery reduced maximum hook numbers by ~60% per trip, dictating the majority of the observed effort reduction. For example, the greatest average trip-level reduction in effort was 48.7% (B-season) while the reduction in fishing duration during that season was only 9.3%. This suggests that bycatch mitigation (i.e., hook restrictions) played a greater role on effort reduction than the IFQ.

The effects of different regulations become confounded when describing fishery changes based on fishing efficiency alone. A longline endorsement program initiated a reduction in fleet size that further continued under the shift to IFQ. Vessels that left the fishery had

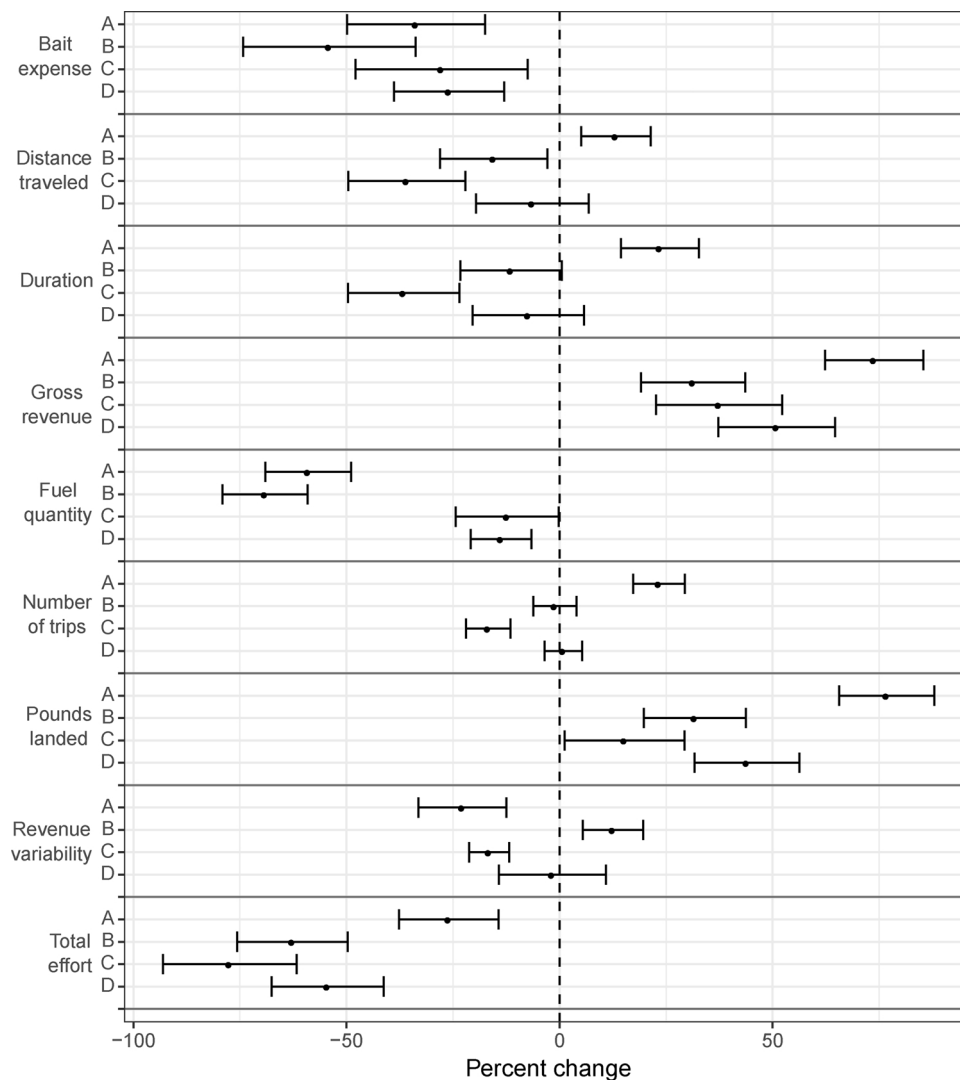


Fig. 3. Model estimated percent changes in average annual vessel metrics during the A–D-seasons.

historically only earned, on average, about half the annual gross revenue of vessels that remained, yet the reduction in fleet size still led to reduced competition that allowed fewer vessels with fewer hooks to catch more fish. So, while trip durations remained either similar or slightly shorter after the regulatory transition, there was an overall increase in fishing efficiency; attributing it to a single regulation, however, is difficult. Meanwhile, bycatch regulations during C-season restricted the fleet to deeper waters farther offshore where increased catch rates enabled them to meet their quotas for deep-water species faster, reducing the number of offshore trips and subsequently the overall days at sea during that period (Fig. 3).

We identified shifts in performance and spatial fishing behavior in two seasons, highlighting the differences in results that emerged from our method using VMS data. While C-season fishing moved offshore, there was an A-season shift to fishing nearshore, and both of these spatial redistributions were associated with higher catch rates, gross revenues, gross revenues per unit effort and lower revenue variability. To calculate how trip-level gross revenue per unit effort changed (Fig. 1), we divided the gross revenue per trip by our estimates of fishing effort. Gross revenue increased and effort decreased, leading to a slight overall increase in gross revenues.

Clay et al. (2014) proposed revenue-per-unit-effort as an indicator for evaluating social and economic performance of catch share programs but doing so using logbook data alone could have been

misleading in this fishery. If we had not used our VMS-derived effort metric but instead had used logbook-reported trip length, the estimated mean seasonal changes in gross revenues per unit effort would have approximately doubled because changes in trip duration (as reported by logbooks) were not as reflective of changes in fishing duration (as derived from VMS). Such findings would have over-estimated the effects of regulatory transition on this metric.

Our discussion of changes in fisher behavior and success has focused on regulatory drivers of behavior. However, productivity in a fishery is a function of fishermen's behavior, say  $B$ , and the (unobserved) stock characteristics,  $X$ . So the production function  $Y = f(B, X)$  changes over time due to changes in  $B$ , changes in  $X$  or both. Our paper suggests that the changes in  $Y = f(B, X)$  that we observed are all caused by changes in  $B$  (which are attributable to changes in regulations). However we do not control for changes in  $X$ , and we therefore have an identification problem. It would be preferable to include fishery independent stock estimates in our models of fisher responses but such estimates are not available and biomass estimates are only available for three of the more than a dozen species in the reef fish complex. While our treatment of behaviors at the seasonal level may account for some stock-specific targeting behaviors in each year, such complexities may not fully account for bias introduced by stock dynamics (e.g., Eigaard et al., 2011).



### 4.3. Implications for stock assessment

Our VMS-based approach is poised to improve both spatial and temporal aspects of estimating fishing effort for the purposes of stock assessment. In the Gulf of Mexico bottom longline fishery, scientists have used only number-of-hooks to calculate catch rates for groupers, snappers, and tilefishes because there was no reliable estimate for time spent actively fishing. Assessment of these stocks has been further complicated by the coarse spatial resolution of the logbook data; the entire fishery is divided into just a few statistical management grids, with single reporting areas stretching from the coastline to several hundred kilometers offshore and encompassing a depth range of more than 200 m. When trips include landings of both deep- and shallow-water stocks from a single management grid, there is no accounting for the proportions of effort that were allocated towards targeting deep species versus shallow species. Because the location of each VMS record can be associated with bottom depth, the spatial distribution of effort can be resolved to account for targeting of species complexes associated with distinct habitats and can better resolve catch rates. This finer resolution is particularly important for species like groupers, whose biology includes aggregating behavior that can lead to hyper-stable catch rates and subsequently, bias in stock abundance indices (Carruthers et al., 2015).

### 4.4. Broader implications and conclusions

While our study focused specifically on quantifying impacts from regulatory change, our approach also has broad applicability to understanding the spatial responses of fleets to environmental changes (e.g., Pinsky and Fogarty, 2012; Joo et al., 2014, 2015). A contemporary paradigm is that as waters warm, movement of fish to higher latitudes will be accompanied by similar shifts of fishing fleets (Pinsky and Fogarty, 2012). However, in cases like the Bering Sea pollock fishery, fisher spatial responses to climate dynamics do not support a simple northward shift; physical (e.g., Pfeiffer and Haynie, 2012), economic (Haynie and Pfeiffer, 2013), or a combination of factors (Watson and Haynie, 2018) have underscored the need for fine-scale spatial data to characterize the resiliency of fishing fleets to climatic change (Watson and Haynie, 2018) and to lay the foundation for adaptive management (Joo et al., 2015).

We have provided an example in which spatially-explicit fishery metrics were compared by examining the model coefficients of a binary dummy variable representing a regulatory change. However, this approach could be readily modified to examine continuous environmental covariates like water temperature or to account for events like an oil spill or implementation of a marine reserve. Similarly, intra-fleet dynamics could be compared using vessel groups: delivery to different processors, fishing in different areas, targeting different species complexes, or those associated with different levels of bycatch or discarding. The need for adaptive fisheries management has long been recognized (Walters, 1986), and with technological advances, we are now able to more accurately measure how fleets respond to such changes.

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### Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.fishres.2018.06.006>.

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