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ARTICLE

Potential for a Simple GPS-Based Binary Logit Model to Predict Fishing Effort in a Vertical Hook-and-Line Reef Fish Fishery

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Abstract
Accurate fishing effort information is fundamental to the successful management of fisheries resources. Automated, independent, and reliable methods for quantifying fishing effort are needed. The use of vessel speed from Global Positioning System (GPS) data to identify fishing activity has worked well for trawl fisheries but has been less successful in stationary fisheries. Therefore, five trips on four vessels from a vertical hook-and-line reef fish fishery were used to examine the efficacy of GPS (speed and time) and electronic video monitoring (EVM) sensor (drum and video) data to corroborate an observer's account of effort using binary logistic regression classification (logit) models as well as a simple speed and time filter (filter). One minute was the minimum data collection interval examined that documented 100% of fishing events. As no fishing occurred at night, opportunistically defined as the 7 h between 2200 and 0500 hours, these records were excluded from analyses. During the day, vessels spent on average 45.2% of the time fishing. Classification success of the approaches examined ranged from 82.4% to 89.5%. Models that included both GPS and EVM sensor data outperformed the filter and GPS-only models. In general, the filter and most model results can be used as a proxy for observer effort data, at least for the trips examined here. The GPS-based speed + time logit model was chosen as the preferred approach because of its discriminatory power compared with the filter and the existing widespread use and lower costs of GPS data collection relative to EVM systems and sensors. The speed + time logit model outlined here may have broad utility in this and similar vertical-line fisheries, including the offshore marine recreational fishing sector.

Accurate fishing effort information is fundamental to the successful management of fisheries. High-resolution accounts of fishing effort, collected and interpreted with minimal subjectivity, are preferred because of their increased utility for use in fisheries and ecosystem management (Kracker 1999; Witt and Godley 2007; Hamel and Andrefouet 2010).

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More recently, autonomously collected fishing effort data coupled with catch information has served as the basis for both theoretical (Hiddink et al. 2006; Bastardie et al. 2014; Russo et al. 2014b) and management applications (Chang 2011; Gerritsen and Lordan 2011; Russo et al. 2014a).

While there are numerous approaches for collecting fishing effort information, those discussed in this study are listed and defined in Table 1. At-sea observers have long been considered the highest standard in data collection (Liggins et al. 1997). However, observer coverage can be prohibitively expensive for many fisheries (NMFS 2011). Logbooks completed by fishermen are the most economical and problematic collection method for effort data (Fox and Starr 1996; McCluskey and Lewison 2008; Roman et al. 2011). Video-based electronic monitoring (EVM) has recently emerged as an effective alternative for observer coverage in some fisheries (Ames et al. 2007; Stanley et al. 2009). The cost of EVM implementation can be less than equivalent observer coverage (Stanley et al. 2011). Electronic video monitoring is perhaps most cost effective when it is used as a tool to audit self-reported logbook data (Stanley et al. 2011). Satellite-based vessel monitoring systems (VMSs) (Deng et al. 2005; Harrington et al. 2007; Witt and Godley 2007; Lee et al. 2010; Hintzen et al. 2012; Jennings and Lee 2012; Russo et al. 2014a) and even simple GPS data loggers (GPSDLs) (Marrs et al. 2002; Gallaway et al. 2003a, 2003b) are also capable of effort accounting. The raw, unfiltered data produced from these two systems are also useful for general enforcement and compliance (Chang 2011; Enguehard et al. 2013; Porter et al. 2013). The costs associated with VMSs can be significant and impractical for use on very small vessels (NMFS 2013). In general, GPSDLs can perform the same functions as VMSs but at lower costs and with reduced at-sea reporting capabilities (NMFS 2015). Two additional, but less studied approaches, include the use of the fishery observing system (Falco et al. 2007) and the automated identification system (Natale et al. 2015). In general, the fishery observing system combines environmental and oceanographic data to assist in the analysis of catch and effort data (Carpi et al. 2015). The automated identification system appears to offer the same data as a VMS but with an improvement in terms of temporal resolution (Natale et al. 2015). Regardless of the approach, there is a need to continue exploratory electronic effort data collection and validation in fisheries, such as with simple GPS data.

A growing body of literature supports the use of a vessel speed rule to predict fishing and nonfishing activity (Lee et al. 2010; Gerritsen and Lordan 2011; Natale et al. 2015). However, most studies to date have analyzed gear types that require substantial vessel movement to actively harvest fish, such as trawls. Investigators that previously examined more stationary gear types, such as hook and line (longline) (Lee et al. 2010), pot gear (Mullowney and Dawe 2009), and purse seines (Walker and Bez 2010; Bez et al. 2011; Joo et al. 2011, 2015), all described some degree of difficulty with regard to identifying fishing activity based on vessel speed alone. To date, no one has attempted to analyze a stationary, vertical hook-and-line reef fish fishery. In addition, little emphasis has been placed on logit modeling to classify fishing activity from GPS data. In order to document and model fishing activity in relation to vessel speed and potentially other variables, observers and high-frequency electronic data collection are required.

Several factors make the commercial fishery in the U.S. southern Atlantic Ocean for snappers (family Lutjanidae) and groupers (family Polyprionidae) a suitable candidate for an effort characterization pilot study. First, the fishery relies on industry self-reported logbook data for catch and effort information (SEDAR 2003; SAFMC 2006). No dedicated funding exists for observer coverage (NMFS 2011) and electronic devices (VMSs and GPSDLs) are not utilized for management or enforcement. Researchers have recently implemented short-term projects in attempts to characterize the fishery with both observers (GSAFF 2010) and EVM (Baker and Von Harten 2009). Second, many of the 61 species in the fishery exhibit aggregation behaviors and life history traits that may lead to overexploitation (Coleman et al. 2000; SAFMC 2010). In order to protect some of the deepwater species within the fishery, a series of eight marine protected areas (MPAs) were created in 2009 that range in size from 21 km^2 to 388 km^2 (SAFMC 2009). Most of the MPAs are located far offshore from land, which makes enforcement of prohibited fishing activity difficult (SAFMC 2009). Utilization of an approach to independently estimate effort, or perhaps validate logbook accounts of effort, could serve as both a fisheries management and enforcement tool.

Perhaps of broader interest would be the potential application of effort characterization in the marine charter (for hire) and private recreational vertical-line reef fish sector. Here there is the potential to collect GPS data from more common personal devices, like smartphones. As of April 2015, 64% of Americans own and use a smartphone of some kind (Smith 2015). Therefore, the likelihood of having at least one smartphone among a group of offshore fishermen aboard a vessel should be quite high. Dedicated smartphone applications (apps) like “iSnapper” have been developed and successfully utilized to self-report angler catch in a spatial context and are deliverable in near real time (M. Johnson, G. Stunz, and D. Yoskowitz, paper presented at the 141st annual meeting of American Fisheries Society, 2011).Even standard cell phones have been used to communicate self-reported accounts of catch and effort data for fisheries through manual data entry and text messaging (Baker and Oeschger 2009). Native smartphone apps can be run while the vessel is at sea providing a virtual track log for inspection and management purposes (Johnson, Stunz, and Yoskowitz, unpublished). Just as importantly, this type of location data can be collected

TABLE 1. List of the methods for collecting fishing effort data that are discussed in this study.

Method	Meaning	Definition
Observer		Trained professional onboard a fishing vessel that collects information about fishing activity. Could be tasked with other duties as required.
EVM	Electronic video monitoring	An integrated system that includes a GPS, video cameras, and possibly other sensors designed to passively monitor fishing operations through observing and/or tracking. Also referred to as video monitoring or simply EM.
VMS	Vessel monitoring system	A satellite-based system that tracks fishing vessel movement, including its position, time at position, course, and speed. Data is often reported at set intervals (e.g., every 60 min) during normal fishing operations.
GPSDL	Global Positioning System data logger	A simple electronic data logger that can be configured to record GPS data (position, time, speed) at set, predetermined intervals. Some simply store data onboard the unit until retrieved, whereas others transmit data over cellular networks when in range.
Logbook		A paper logbook in which fishermen self-report landings, discards, and effort data after trip completion.
AIS	Automatic identification system	A system that allows ships to view marine traffic in their immediate area as well as be seen by other ships or receiving stations. Data transmitted is similar to that of VMS and GPSDL systems.
FOS	Fishery observing system	An approach in which environmental and/or oceanographic conditions at the time and location of capture are coupled with high-resolution fishing effort information.

passively by participating anglers (Martin et al. 2014; Papenfuss et al. 2015). The possibility of a legal requirement to have a smartphone app or GPSDL onboard to record vessel position, speed, and time of day is conceivable. Requirements and standards for data collection, data use, privacy, and confidentiality would all have to be carefully considered (Hinz et al. 2013); however, the technology exists to collect such data with smartphones and certainly with small, inexpensive cellular GPSDLs like that currently used in the U.S. Gulf of Mexico shrimp (order Decapoda) fishery (NMFS 2015).

The goal of this study was to determine the potential for GPS and select EVM sensor data to match observer-documented fishing effort in a stationary, vertical-line reef fish fishery. Specifically, the study objectives were as follows: (1) determine the minimum data collection interval required to record the locations of all the fishing events in this type of fishery, (2) describe the variables collected by GPS units and EVM sensors in relation to fishing and nonfishing activity, and (3) examine the effectiveness of a simple data filter and four nested binary logit models to predict fishing and nonfishing activity as confirmed by observer data.

METHODS

Description of fishery and study area.—The United States southern Atlantic Ocean snapper–grouper commercial fishery is geographically widespread, covering the area of the United States East Coast, ranging from Cape Hatteras, North Carolina, to Key West, Florida, and includes both nearshore and offshore waters (Figure 1). In 2013, the fishery consisted of 10,054 trips and 18,431 d away from port and accounted for 2,490 metric tons of landed catch comprised of over 61 fish species (National Marine Fisheries Service [NMFS] Southeast Fishery Science Center Logbook Program). The fishing fleet is composed of over 500 small (mostly < 12 m) vessels (SAFMC 2006). Although not well described, vessel characteristics of the greater fleet are thought to be similar to those vessels that operate in the Gulf of Mexico reef fish fishery described in Scott-Denton et al. 2011. Bycatch and mortality associated with regulatory discards is a primary concern in this fishery as many species have low annual catch limits (SAFMC 2010). The majority of fishing activity is thought to occur in midshelf and shelf-break waters (Stephen and Harris 2010). While nighttime fishing is allowed, most fishing is reported to occur between sunrise and sunset (Rudershausen et al. 2007; Stephen and Harris 2010). The area of interest for this study is the northern portion of the management area off the coasts of North Carolina, South Carolina, and Georgia. This area accounts for approximately 56% of the total annual landings (SAFMC 2006) for the fishery.

Descriptions of trips and gear.—This paper examines the potential for GPS and EVM variables to independently classify vessel activity at sea as fishing or not fishing based on observer documentation from actual fishing trips. Therefore, an EVM system and an observer were placed onboard four different vessels for a total of five trips (26 sea days) from June to September 2010. Details regarding the participating vessels and fishing activity as characterized by

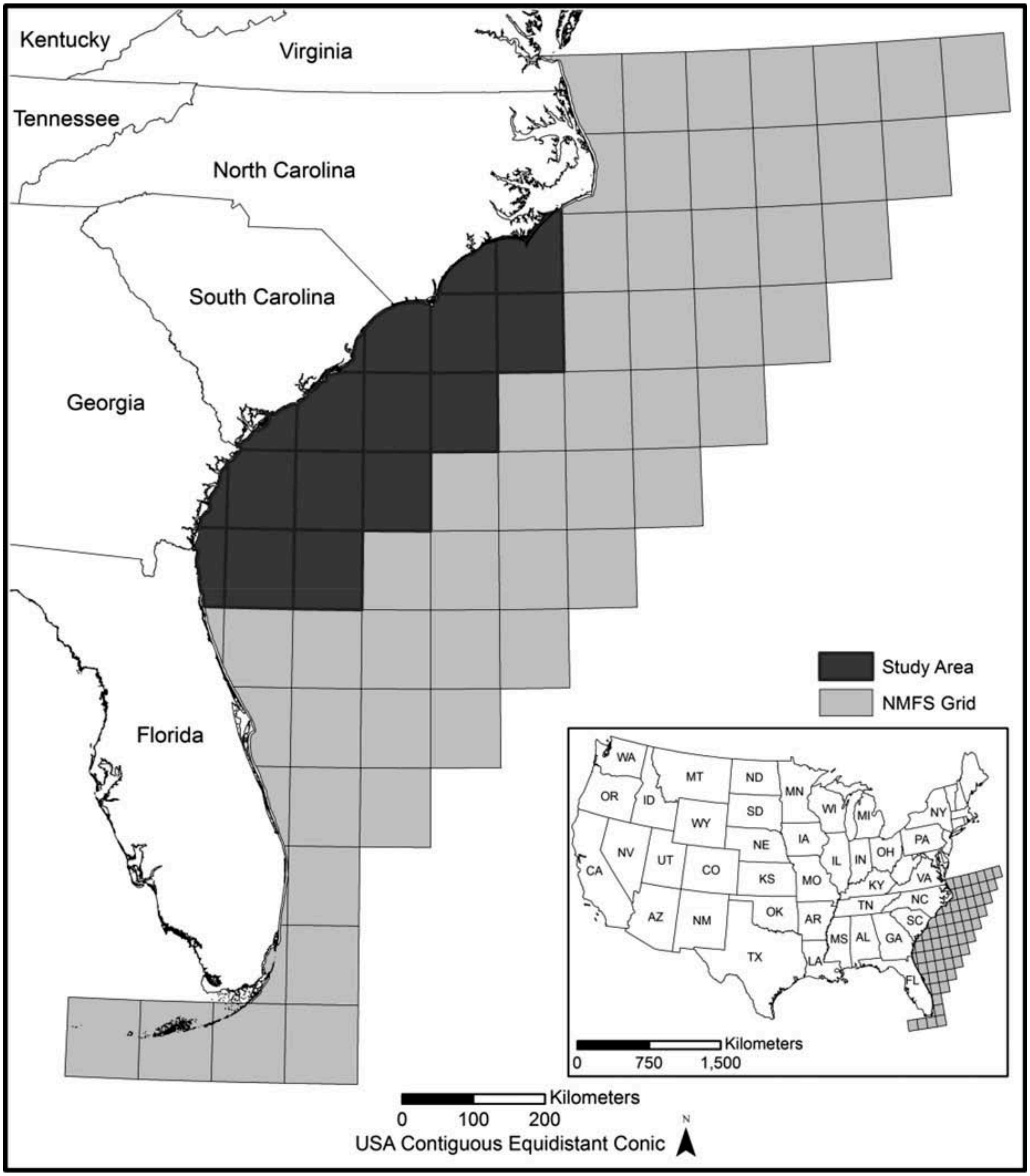

FIGURE 1. Map of the study area. Each grid, designated by the National Marine Fisheries Service (NMFS), represents 1° latitude by 1° longitude and is the unit by which fishing activity is reported and/or accounted for in the commercial snapper–grouper fishery. The dark grids encapsulate the study area.

an onboard observer are provided in Table 2. Trips 3 and 4 were completed by the same vessel. Fishing occurred 32–160 km offshore in water depths ranging from 21 to 148 m. The fishing practices and terminal tackle used by fishermen were similar to that described in Rudershausen et al. (2007), Stephen and Harris (2010), and Scott-Denton et al. (2011). Briefly, fishing vessels were equipped with three to four electrically powered bandit reels (Figure 2) equipped with mostly two-hook gear fished vertically in the water column on or near the bottom. Unlike horizontal longline gear that is left in the water to passively fish for an extended length of time, bandit gear is actively deployed and retrieved multiple

TABLE 2. Description of trip details as documented by an observer.

Level	Item	Results as documented by an observer
Study	Time period	Jun 2010 to Sep 2010
	Sea days	26
	Participation	Five trips aboard four vessels
	Sets or fishing events	487
Vessels	Length	Mean (SD) = 12.3 m (1.4); range = 10.4–14.6 m
Trip	Duration	Mean (SD) = 5.1 d (2.9); range = 1–13 d
	Hours fished	Mean (SD) = 37.8 h (24.7); range = 12–77 h
Fishing event	Number of fishing events per day	Mean (SD) = 15.9 (4.7); range = 9–25
	Soak time	Mean (SD) = 0.5 h (0.5); range = 0.02–5.80 h
	Number of reels fished	Mean (SD) = 3.0 (0.6); range = 1–4
	Number of times gear deployed	Mean (SD) = 8.7 (12.0); range = 1–101
	Time each hook spent in the water	Mean (SD) = 0.09 h (0.09); range = 0.01–0.73 h
	Number of hooks fished	Mean (SD) = 51.1 hooks (67.5); range = 2–404
	Number of hooks per reel	Mostly two hooks per reel; range = 2–4
	Water depth	Mean (SD) = 47 m (12); range = 21–148
	Fishing state	On anchor = 98%; drifting = 2%
Harvest	Landings, ranked by species percent occurrence. Top five species (shown) represent 82% of landings.	1. Vermilion Snapper *Rhomboplites aurorubens* (46%)
		2. Gray Triggerfish *Balistes capriscus* (16%)
		3. Red Porgy *Pagrus pagrus* (10%)
		4. Black Sea Bass *Centropristis striata* (7%)
		5. White Grunt *Haemulon plumierii* (3%)
	Discards, ranked by species percent occurrence. Top five species (shown) represent 78% of discards.	1. Vermilion Snapper (36%)
		2. Red Porgy (20%)
		3. Black Sea Bass (13%)
		4. Tomtate *Haemulon aurolineatum* (6%)
		5. Scamp *Mycteroperca phenax* (3%)

times while the vessel is held stationary by anchor or motoring in place at a fishing location (Table 2).

Logbooks.—Self-reported logbooks are required for all fishing trips and contain catch and effort information that includes the general fishing location, date of departure, and date of return as well as total hours fished per trip (SEDAR 2003). Fishing locations for each species landed and discarded are reported to the NMFS statistical grid (1° latitude × 1° longitude), indicating where the majority of fishing activity or catch took place (SEDAR 2003) (Figure 1). Logbooks were completed by fishermen after each trip.

Observers.—A single observer collected detailed accounts of fishing activity throughout the entirety of each trip (Table 2). Fishing events, defined as a unique geographic location fished each day of the trip, were documented. Hours fished was defined by the observer as the period of time when hooks were being either deployed from the surface, fished in the water, or retrieved back to the surface using a bandit reel. For the purposes of this analysis, all other activities (e.g., anchoring or positioning the vessel prior to the start of fishing events, transiting to and from the fishing grounds, etc.) were not considered fishing. As vessels in this study hosted either three or four bandit reels and typically the observer was only able to document fishing activity on a subsample of those reels during the course of a fishing event (Scott-Denton et al. 2011), for this study it was assumed that all fishing reels operated at similar times, unless noted.

Electronic video monitoring system.—The EVM systems used for this project were custom manufactured by Archipelago Marine Research in Victoria, British Columbia. The EVM system components included a single optical rotational drum sensor mounted to one of the vessel's bandit reels, a GPS unit, three to four video cameras, and a control box in the wheelhouse (Ames et al. 2007). Therefore, for this study, the EVM systems recorded both GPS (speed, time, and location) as well as EVM-specific (drum and video) data at 10-s intervals. The single drum sensor was attached to the primary bandit reel (Figure 2), defined simply as a reel that would be fished during every fishing event regardless of other fishing activity. The drum sensor documented each revolution of the primary bandit reel. A strip of reflective tape, affixed to the inside of the bandit wheel, activated the

FIGURE 2. Bandit reels attached to the stern deck of a typical commercial snapper–grouper fishing vessel.

drum sensor with each revolution. To meet vessel power criteria, the EVM system was to be powered continuously by a 12-V battery (connected to the vessel alternator for recharging) while at sea. Data were recorded onto a 500-GB hard drive in the control box.

Time was recorded by the EVM system in the hhmmss (hours, minutes, and seconds) format. Specific latitude and longitude locations were recorded by the EVM system's GPS unit. The purpose of the drum sensor in this study was to activate the video cameras in order to document all fishing activity. Video, once activated, remained on for a minimum of 10 min unless a subsequent drum rotation caused the 10-min period to restart, thus extending the video-recording period. Both video and drum data were converted to a binary response (on = fishing, off = nonfishing) in order to aid in logit model analyses.

The electronic dataset utilized in this study has been repurposed from a previously completed but unpublished study (Baker and Von Harten 2009). Using the observer-documented fishing events as a guide, the EVM viewer used vessel location (GPS), sensor and video imagery, and proprietary EVM system event codes (power failure, manual shutdown, etc.) to estimate fishing effort (hours fished) for each trip. Those data will be presented in the results for comparison purposes. The proprietary event codes collected by the EVM system were not utilized in this study as this information would not be available from common GPS units, such as with a simple GPSDL (Marrs et al. 2002; Gallaway et al. 2003a, 2003b). We simply analyzed the selected variables as they were recorded as raw text files by the EVM system. The authors did not use the accompanying video or the software from Archipelago Marine Research to define or annotate the database for fishing activity, only the observer's account of fishing activity.

Datasets.—All records from trips were first combined into one dataset and then sorted by trip in chronological order. The combined dataset consisted on the following columns: vessel, date, time, location, speed, heading, voltage, video, drum, observed activity (fishing, not fishing), and set number (if fishing). Records collected while the vessels were in port were removed from the database. Next, the electronic records collected by the EVM system were analyzed for completeness. Trips 3 and 4 were both 100% complete, meaning that all the variables that should have been collected were collected. Trips 1, 2, and 5 had completeness rates of 61%, 76%, and 60%, respectively. On the trips with incomplete data, the observer indicated that EVM systems were periodically and manually powered down during prolonged periods of nonfishing activity, usually during the night. During this time, captains often turned off the engine while at anchor and did not want the possibility of the EVM system draining the vessel power supply. The observer verified that no fishing occurred during the periods when the EVM was turned off. No fishing activity occurred between 2200 and 0500 hours on any trip, regardless of whether the EVM system was on or off. For this study, this period of time was opportunistically defined as night.

Given the missing data for three trips, it was not feasible to document vessel activity electronically over the full 24-h period. Seventy-two percent of the missing nonfishing records occurred between 2200 and 0500 hours. Missing records observed during the day were mostly due to vessels starting fishing activity after 0500 hours or finishing fishing activity prior to 2200 hours. As no fishing activity occurred during the night and this part of the dataset was incomplete, these records were excluded from analyses.

Data analysis.—To determine what impact the interval of electronic data collection would have on fishing effort documentation success, the dataset was analyzed at full resolution (10 s) and then at intervals of 1, 2, 4, 8, 15, 30, 60 and 120 min, beginning with the first record in the combined dataset. Fishing event documentation success was defined as the number of fishing events documented divided by the total number of fishing events. If the chosen interval documented at least one record during the course of a fishing event, the fishing event was considered documented at that time interval. The percentage of the dataset denoted as fishing was also documented for each data collection interval evaluated. The goal was to choose the coarsest interval capable of documenting 100% of the fishing events for use in simple filters and logit models.

Next, the dataset associated with the chosen interval was compared against the original dataset. Chi-square tests of independence (χ^2) and two-sample *t*-tests with equal variance were used to compare dataset attributes (Table 3).

The combined dataset was first subjected to a combination speed and time filter (filter) in an attempt to identify fishing activity. The speed cutoff associated with fishing was based on the distribution of vessel speeds associated with fishing and nonfishing activity as identified by the observer. By default,

TABLE 3. Comparison of native resolution EVM data (10-s intervals) to the minimum resolution (1-min intervals) required to account for all fishing events in the study. Speed is reported in knots as mean ± SD. Time is reported in hhmm (hours, minutes) as mean ± SD. All variables are reported as individual data points collected ordering to Status. Records between 2200 and 0500 hours have been excluded because of lack of fishing activity during this period.

Variable	Status	EVM resolution		Test
		10 s	1 min	
Activity	Fishing	67,600	11,267	χ^2 = 0.00016, df = 1, P = 0.999
	Nonfishing	82,044	13,672	
Speed	Fishing	0.22 ± 0.40	0.22 ± 0.39	t = 0.168, df = 78,865, P = 0.433
	Nonfishing	4.54 ± 3.12	4.54 ± 3.54	t = 0.003, df = 95,714, P = 0.498
Time	Fishing	13.3 ± 4.0	13.3 ± 3.9	t = 0.007, df = 78,865, P = 0.497
	Nonfishing	13.2 ± 4.8	13.2 ± 4.8	t = 0.046, df = 95,714, P = 0.481
Drum	Fishing, drum = off	45,387	7,590	χ^2 = 0.221, df = 3, P = 0.974
	Fishing, drum = on	22,213	3,677	
	Nonfishing, drum = off	80,596	13,431	
	Nonfishing, drum = on	1,448	241	
Video	Fishing, video = off	4,582	756	χ^2 = 0.079, df = 3, P = 0.994
	Fishing, video = on	63,018	10,511	
	Nonfishing, video = off	53,547	8,918	
	Nonfishing, video = on	28,497	4,754	

the variable time was automatically included in this filter considering that night records had to be excluded from the dataset because of missing EVM records.

Logit analyses were performed in an attempt to predict fishing status with classification success rates significantly greater than would be achieved by chance alone. Classification success was defined simply as the sum of the number of observations classified correctly (both fishing and not fishing) divided by the total number of observations. Chance was defined as the binomial distribution of fishing (45.2%) and nonfishing activity (54.8%) in the combined dataset. A total of four nested logit models using one to four variables were analyzed: (1) speed (S), (2) speed + time (ST), (3) speed + time + drum (STD), and (4) speed + time + drum + video (STDV). For this study, models S and ST were based solely on GPS data, whereas models STD and STDV utilized both GPS and EVM sensor data. Trip was originally included as a covariate but was excluded from model runs because it did not significantly affect model classification success. Generalized adjusted coefficients of determination were calculated for each model using the RSQ option of the PROC LOGISTIC procedure in SAS software version 9.2. Predicted probability values were obtained from each logit model run, and the classification success of those predictions was tested against known fishing status.

Classification success was considered the primary tool to determine filter and model fit as classification was the intended use (Peng et al. 2002). Classification success was based on calculations of sensitivity, specificity, and false positive or false negative scores (Hosmer and Lemeshow 1980; Peng et al. 2002). No additional tools were used to assess the performance of the filter. Secondary tools used to assess the fit of models included the receiver operating characteristic (ROC) and the Akaike information criterion (AIC), both produced using SAS software. Briefly, the ROC provides a performance value (0–1) of a binary classifier system as its discrimination threshold is varied. Comparisons of ROC scores between different models applied to the same dataset were compared using χ^2 tests and thus used to select the best models (Landriault et al. 2009; Weber and McClatchie 2010; Palialexis et al. 2011). The AIC is a widely accepted measure of model fit and rewards goodness of fit but assesses a moderate penalty that increases as the number of model predictors increases (Akaike 1974).

A leave-one-out cross-validation procedure (similar to a jackknife) was used to check the fit of each model (Arlot and Celisse 2010). This was done by first fitting each model to the dataset to generate a ROC score and then using the cross-validated predicted probabilities to provide a new ROC score for comparison using a Mann–Whitney U-test. If a model and its predicted model ROC scores were significantly different from each other, then the model was excluded from further consideration.

Next, observer, EVM viewer, logbook, filter, and model accounts of hours fished by trip were compared. To accomplish this, predicted fishing activity for the filter and models was converted to hours fished for each trip. Next, one logit model was chosen as the preferred model, with preference given to classification success, simplicity, and cost of data collection. Finally, the preferred model was then applied to each individual trip so that model fit in relation to vessel- and trip-specific characteristics could be further explored and potentially improved. Like with the combined dataset, the filter approach was applied to each trip individually as well for comparison purposes.

RESULTS

Fishing Event Documentation

The landings, discards, and overall fishing practices observed in this study (Table 2) were similar to previous examinations of this fishery (Rudershausen et al. 2007; GSAFF 2010; Stephen and Harris 2010). On average, each trip in this study had 15.9 fishing events per day, with each event lasting approximately 30 min (Table 2). Mean fishing event documentation success by electronic data collection interval ranged from 100% at 10 s to 24% at 120 min (Figure 3) and was best fit using a three-order polynomial curve (R^2 = 99%). The percentage of the dataset documented as fishing remained relatively unchanged at each interval examined (Figure 3). One minute was the coarsest interval examined that documented at least a portion of all 487 fishing events.

Electronic Video Monitoring Dataset

As the 1-min-interval dataset was not significantly different from the original dataset collected at 10-s intervals (Table 3), the truncated dataset was used from this point forward. Descriptive statistics of the variables speed, time, drum, and video associated with fishing and nonfishing are provided in Table 3. Analysis of speed while fishing indicated an unrealistic value (> 3.5 knots, consistent with Lee et al. 2010) for a small segment (< 1%) of fishing activity. This speed cutoff exceeded the maximum speed associated with drifting fishing (Table 2) (mean = 0.8 knots, range 0.2–3.1 knots, < 2% of fishing activity). The outliers are likely nonfishing records incorrectly coded as fishing activity, an unfortunate consequence of manually merging a high-resolution EVM dataset with observer records over the course of five combined trips. Like Lee et al. 2010, we considered these records outliers. However, we included them in our analyses as they did not have a significant impact on the model results. Vessel speed followed a bimodal distribution with peaks at less than 1 knot and at 6 knots (Figure 4). A total of 95% of fishing activity and 53% of nonfishing activity occurred at vessel speeds ≤ 0.4 knots (Figure 4, inset). All fishing activity occurred between 0500 and 2200 hours (Figure 5). Outside these hours, vessels sat at anchor, moved to other fishing locations in the study area, or transited between their home port and the fishing grounds. The drum sensor was activated during 33% and < 1% of records denoted as fishing and nonfishing, respectively. The video

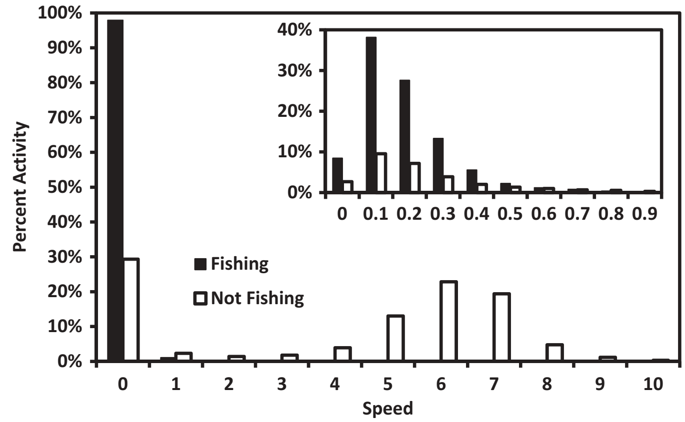

FIGURE 4. Percent fishing and nonfishing activity by speed category (in knots) and (inset) speeds between 0.0 and 0.9 knots over five combined trips as documented by the electronic monitoring system's GPS unit and an observer.

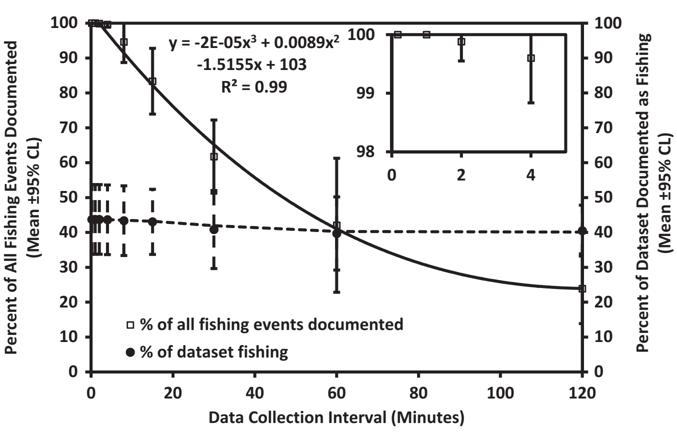

FIGURE 3. Percent of unique fishing events (open squares) and percent fishing activity (closed circles) by all data collection intervals and (inset) intervals of 10 s to 4 min for all five observed trips combined. Values are given as means; error bars indicate the 95% CI. One minute was the minimum data collection interval tested that documented 100% of fishing events.

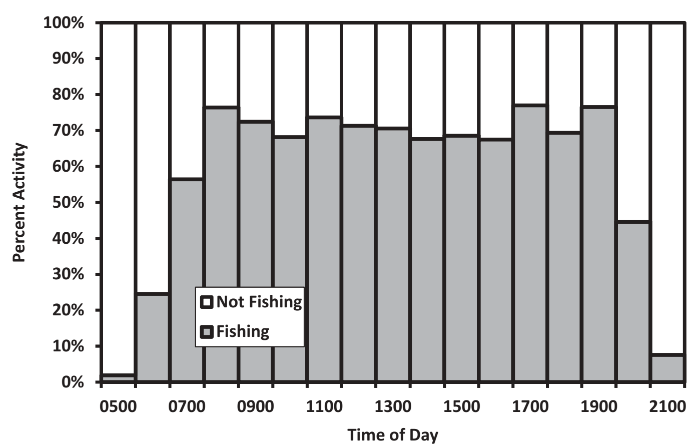

FIGURE 5. Percent fishing and nonfishing activity by the time of day for five combined trips. Data was provided by an electronic monitoring system's GPS unit and an observer. Note that no fishing activity occurred between 2200 and 0500 hours.

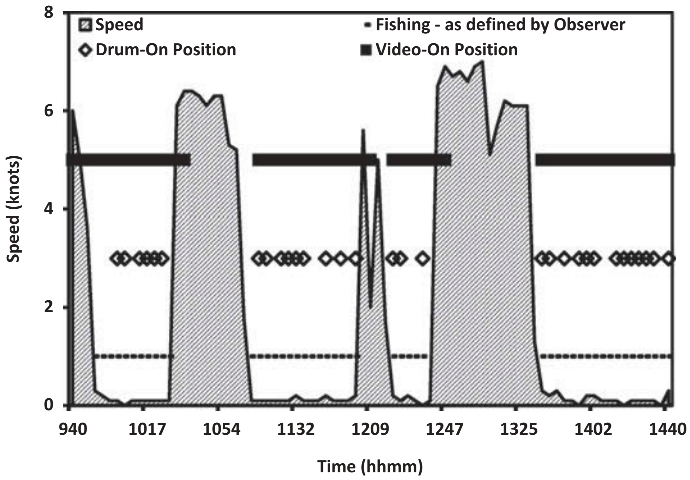

FIGURE 6. Snapshot from a fishing trip on vessel 1 that demonstrates how vessel speed, time, video (on or off), and drum (on or off) relate to fishing and nonfishing activity as documented by an observer. For the drum and video, the on position indicates fishing. Time was recorded by the EVM system in the hhmm (hours, minutes) format. From left to right, four fishing events (complete, complete, complete, and partial) are shown. Note that in general, drum response underestimates fishing and video response overestimates fishing.

sensor was activated during 93% and 35% of records denoted as fishing and nonfishing, respectively. A visual example of the relationship between vessel speed, time, drum, and video relative to fishing status is shown in Figure 6.

Filter and Logit Models

The classification success of this filter approach was 82.4% (Table 4). Specifically, the filter eliminated 6.8% of fishing activity and 73.4% of nonfishing activity. For this analysis, only records with speed values ≤ 0.4 knots and/or consistent with daytime (between 0500 and 2200 hours) were categorized as fishing.

The results of the four nested logit models applied to the combined dataset are also presented in Table 4. The classification success of the GPS logit models was similar to the results obtained by the filter. Classification success was lowest but identical in the S and ST models, intermediate in the STD model, and highest in the STDV model. Note that despite having identical rates of classification success, the ST logit model performed significantly better than the *S* model as dictated by ROC scores. Overall, the ROC scores indicate that model fit improved significantly as the variables were added to each nested model. The AIC values support the differences identified by the ROC scores. In general, the model classification success was 1.8–2.0 times more effective than classification success by chance alone (45.2%). Leave-one-out cross-validation results indicated that all models except the S model were acceptable (Table 4).

Accounts of effort by method controlling for trip (length) are shown in Figure 7. Results are shown for the filter as well as the best performing models based on GPS (ST) and GPS + EVM sensor (STDV). Logbook effort was in excess of that reported by the observer in three out of five trips. The EVM viewer produced effort estimates in close agreement to that of the observer and the STDV model, as would be expected given that observer data were used as a reference. Filter and model results appeared to align closer with the observer in short (≤ 3 d) as opposed to longer trips. When the results of the two logit models and the filter were compared to the observer record, the slopes ($F_{3,\ 16}$ = 0.19, P = 0.904) and intercepts ($F_{3,\ 16}$ = 0.08, P = 0.972) of the four regression lines were not significantly different (Figure 7). A Tukey

TABLE 4. Results of a simple filter and four binary logistic regression models applied to the dataset of all trips combined. Records between 2200 and 0500 hours were excluded from analyses because of missing records and because no fishing activity occurred during this time. An asterisk indicates that model coefficients are significant at $P < 0.05$. Different letters indicate significant differences ($P < 0.5$) between ROC scores.

	Filter	GPS models		GPS + EVM sensor models	
Item	ST	S	ST	STD	STDV
Intercept		1.223*	0.991*	0.711*	–0.616*
Speed (*S*)		–1.135*	–1.232*	–1.444*	–1.203*
Time (*T*)			0.018*	0.012*	–0.029*
Drum (*D*)				2.195*	1.351*
Video (*V*)					2.76*
Classification success (%)	82.4[a]	82.5	82.5	82.8	89.5
AIC		18,757	18,739	17,213	13,589
ROC		0.861 z	0.866 y	0.897 x	0.945 w
Leave-one-out cross-validation ROC		0.827*[b]	0.864	0.896	0.945

[a]It was not possible to examine a simple speed filter alone due to nighttime activity already being removed from the dataset.

[b]Significant difference between the model ROC and the leave-one-out cross-validation ROC at $P < 0.05$.

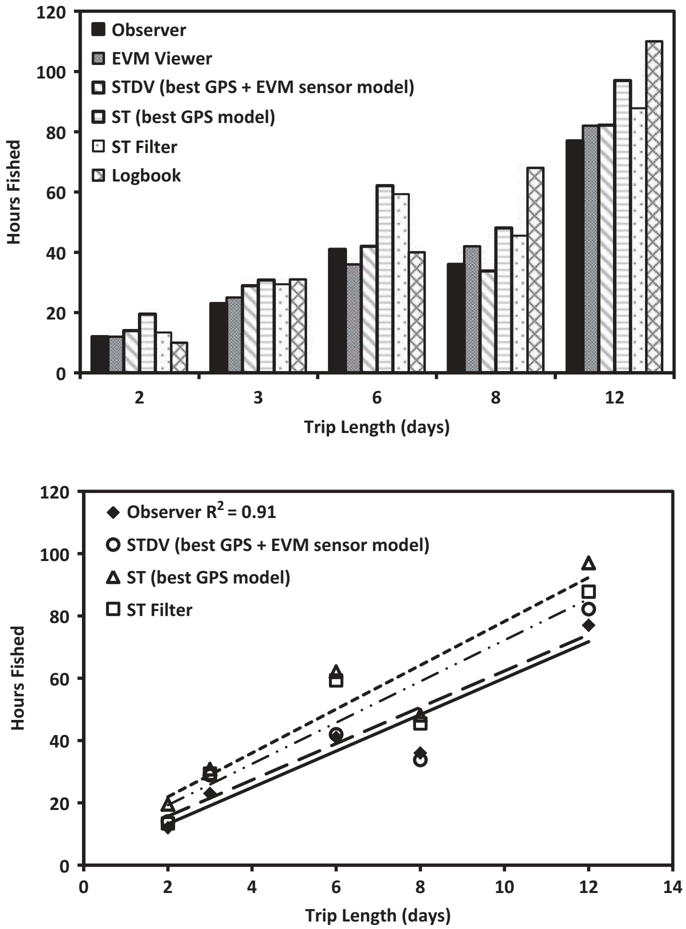

FIGURE 7. Comparison of all the effort (hours fished) methods by trip (top panel) and a comparison of the filter, GPS (ST), and GPS + EVM sensor model (STDV) estimates of effort relative to the observer record (bottom panel). Trips 3 and 4 (6 and 2 d, respectively) were conducted by the same vessel.

comparison of least square means revealed no significant differences between the observer (37.8 h), ST (51.5), STDV (40.2), and filter (47.1) accounts of mean hours fished ($P > 0.05$). These results indicate that output from the filter and models examined can be used as proxies for observer effort, at least for the trips examined here.

The GPS-based ST model was selected as the preferred approach because of its discriminatory power compared with the filter and the existing widespread use and lower costs of GPS data collection relative to EVM systems and sensors. The application of the filter and ST model to each of the five individual trips is shown in Table 5. The classification success scores and ROC values indicate that the filter and ST model both fit the data well despite the variation in trip length (Table 2) and percentage of fishing activity by trip (Table 5).

DISCUSSION

Filter and Logit Model Performance

The datasets available for this analysis allowed for a limited comparison of nested logit models to a simple combination speed and time filter to determine fishing activity. While the filter produced equivalent rates of classification success as that of the S, ST, and STD models, the logit approach proved to be more flexible and informative than the filter for our exploratory purposes. For example, model fit diagnostics indicated that the ST model significantly outperformed the S model. This is likely because of the lack of fishing activity during 0500–0700 and 1900–2200 hours relative to other times of the day (Figure 5). The binary filter as examined could not detect any such differences. In addition, the filter approach relies on expert knowledge, or in this case observer data, in order to assign practical speed and time parameters. Moving forward, the filter approach might be useful now that typical fishing practices have been characterized for this fishery.

Vessel speed clearly contributed to the classification success of both approaches. The range of vessel speed associated

TABLE 5. Results of a simple combination speed and time filter and the binary logistic regression model speed + time (ST) applied to five different trips individually. Records between 2200 and 0500 hours were excluded from the analyses because no fishing activity occurred during this time. Trips 3 and 4 were conducted by the same vessel. An asterisk indicates that model coefficients are significant at $P < 0.05$.

	Trip identity (trip length in days)				
Item	1 (3)	2 (12)	3 (6)	4 (2)	5 (8)
Fishing activity (%)	50	53	45	36	35
ST logit model					
Intercept	2.344*	2.260*	–0.314*	1.455*	0.863*
Speed (*S*)	–1.954*	–1.666*	–1.023*	–0.672*	–1.614*
Time (*T*)	0.045*	–0.041*	0.076*	–0.076*	0.041*
Classification success (%)	87.7	86.1	73.9	71.9	88.0
ROC	0.899	0.896	0.803	0.804	0.936
ST combination filter					
Classification success (%)	86.4	84.7	72.2	68.0	90.3

with fishing activity was similar to other studies that examined stationary gear. Unfortunately, it was not possible to truly examine speed as a stand-alone predictor given that the exclusion of night records was built into the dataset.

Multiple data sources suggest that the temporal fishing preferences observed in this study (Figure 4) are similar to general patterns observed elsewhere in the study area (Rudershausen et al. 2007; Stephen and Harris 2010) and the region. Analysis of an additional unobserved 87 EVM monitored trips by some of the same vessels used in this study revealed that the fishing activity occurring between 2200 and 0500 hours only accounted for 2% of the total hours fished (M. S. Baker Jr., unpublished data). A query of the NMFS reef fish observer database consisting of both southern Atlantic Ocean trips (2006–2011, n = 3,089 observed fishing sets) and Gulf of Mexico trips (2006–2013, n = 28,606 observed sets) indicated that, in general, 99% and 97% of observed fishing activity, respectively, occurred during daylight hours, which is defined as the period between sunrise and sunset (Liz Scott-Denton, NMFS, personal communication).

The addition of EVM sensor data clearly improved the classification success of logit models. However, the drum sensor alone failed to capture a large percentage of fishing activity (mean = 33%) because the bandit reels did not spin while terminal tackle was positioned on or near the seafloor. This is the case with any vertical fishing reel operation, including rod and reel. However, the use of the drum sensor alone practically insures that all activity recorded is fishing activity, which may be useful in identifying specific fishing locations. Video provided an overestimate of fishing activity because the 10-min run-on period caused the video to remain on even at times when fishing activity had ceased (Figure 6). The EVM video run-on period was set at 10 min prior to the start of the study but can be adjusted as needed.

The small increase in classification success through the addition of drum and video sensors came at a substantial cost considering the price differences alone for data collection equipment. For example, at the time of this study, the EVM system cost approximately US$10,000, whereas a GPS or GPSDL costs less than $500. These figures are for equipment alone and do not include other costs associated with data retrieval and analysis.

Future studies could build on this work by evaluating the use of a new algorithm to combine and replace the effect of actual drum and video sensor data in the logit model. Specifically, an algorithm should be considered that maintains the predicted status “fishing” for subsequent records for an ideal run-on period after fishing has been predicted based on speed and time. Considering that a 10-min run-on period led, in part, to overestimated fishing activity, the run-on period could be set initially to 1 min to coincide with the coarsest data collection interval determined to document all observed fishing activity (Figure 3). Using this approach, it may be possible to achieve classification success at levels greater than the full model (STDV) but without the use of actual EVM sensors.

While the filters and logit models examined here performed well, no approach achieved the 100% classification success that is typically assumed for observer data. This study relied on a single observer to define vessel activity as fishing or nonfishing, among other duties. A key problem with observer data, however, is that it too can contain errors (Liggins et al. 1997; Karp and McElderry 1999; Ames et al. 2007). Any difference in classification success between filters, models, and observers can be partly attributed to human error by the observer.

Had EVM data been collected over the full 24-h period for all trips, the classification success scores obtained from both the filter and model approaches could have been higher. For example, the incorporation of night records (all records between 2200 and 0500 hours) would have effectively increased classification success by an average of 6.3% (Table 4). The impact of this addition would have been greater still when considering that fishing activity on average dropped to 29.4% over the 24-h period versus 45.2% over the 17-h period (this study). The combination of increased classification success and lower fishing activity would have made the filter or logit model approach 3.0–3.2 times more effective at designating fishing activity in the dataset than chance alone, much closer to the 100% classification success assumed for the observer.

It is not uncommon to encounter a substantial portion of missing records in EVM pilot studies. An EVM pilot study conducted on the Gulf of Mexico longline reef fish fishery (M. J. Pría, H. McElderry, M. Dyas, and P. Wesley, Archipelago Marine Research, unpublished report) produced average EVM dataset completeness values of 65%, similar to that observed in this study. In both studies, manual shutdown of the EVM system by the captains accounted for > 90% of incomplete sensor data. The fact that two of the five trips (one of four vessels) had 100% EVM dataset completeness suggests that EVM systems would have functioned as designed had they not been manually powered down.

Implications for U.S. Reef Fish Fisheries

Multiple lines of evidence support that the small dataset of vessels and trips analyzed here is representative of the greater fleet in the study area as well as perhaps the region (e.g., Gulf of Mexico reef fish fishery). From a regional perspective, the southern Atlantic Ocean snapper–grouper fishery (Table 2) and the Gulf of Mexico reef fish fishery fishing practices (GSAFF 2010; Scott-Denton et al. 2011) are also quite similar. Given the high classification success in this study, the use of the models or even the filter developed here should be considered for evaluation in other similarly prosecuted commercial fisheries, such the Gulf of Mexico reef fish fishery.

The relatively low percentage of unique fishing events documented by common intervals of electronic data collection (e.g., every 60 min, such as with VMSs in the similarly prosecuted U.S. Gulf of Mexico reef fish fishery) provides further evidence that the snapper–grouper fishery may be difficult to characterize fully without observers or a combination of GPS and higher resolution self-reported logbook data. If the management objective is to document the locations of 100% of fishing events during trips, then a data collection interval of 1 min would be required based on this study. Logbooks would also need to be redesigned to collect data at the fishing event level as opposed to the trip-level data currently collected. If the objective is to simply corroborate hours fished and the general location (e.g., 1° × 1° NMFS logbook grid) of fishing activity as reported by fishermen, the results suggest that the coarsest resolution examined (120-min intervals) would suffice.

If vessel position data could be captured uniformly from a representative number of vessels over an extended period time, it may be possible to begin to identify the general area of fishing operations and provide perspective on the overlap or repeat visitation patterns of unique vessels to specific fishing areas. For example, Murawski et al. 2005 used VMS, observer, and log book data to examine spatial trends in fishing activity before and after the implementation of MPAs and determined that fishing patterns shifted after the MPAs were put in place. This approach would be useful to the snapper–grouper fishery as a series of MPAs are currently in place and more may be under consideration in the future.

Conclusions

Our results suggest that vessel speed and time of day collected from a simple GPS unit can serve as a powerful predictor of fishing activity in this stationary, vertical-line reef fish fishery. For fisheries that do not have dedicated and continuous sources of funding available for traditional at-sea monitoring programs, self-reported logbooks in either paper or digital format will likely continue to be the preferred effort reporting method. The addition of GPS data capture and integration with or in comparison to logbook records could add value for industry and management. Given the recent advances in GPS data collection technology, some form of automated, spatial effort accounting tool might provide the most accurate effort data for this and similar fisheries.

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