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ARTICLE

On the precision of predicting fishing location using data from the vessel monitoring system (VMS)

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Abstract: Defining fishing grounds based on data from vessel monitoring systems (VMS) has been a widely researched topic in recent years. Much of the research has focused on filtering algorithms for identifying fishing locations from VMS point data, most often supplemented with either imputed or reported vessel speed information. This study compared the precision of categorizing fishing locations from VMS data either by the most wide-spread "speed rule" approach or by a probability model. Using data from Northeast U.S. Fisheries for fishing years 2010–2014, we showed that the traditional representation of fishing activities as derived by speed rules leads to a severe misrepresentation of fishing grounds for gears other than bottom otter trawl. Predictions based on probability models outperformed gear-specific speed rules in classifying VMS polls for sink gillnet and scallop dredge trips, without adding substantial computational effort. The probability models thus provide the largest improvements in gears with complicated fishing patterns, while controlling for issues such as fleet dynamics that historically have not been dealt with in the static speed rules but which can have significant impacts on the quality of predictions.

Résumé : La délimitation des régions de pêche à la lumière de données de systèmes de surveillance des navires (SSN) est un sujet qui a fait l'objet de nombreux travaux de recherche ces dernières années. Une bonne partie de ces travaux s'intéressait aux algorithmes de filtrage permettant de cerner les lieux de pêche à partir de données de SSN ponctuelles, le plus souvent complétées par de l'information sur la vitesse imputée au navire ou rapportée pour celui-ci. L'étude compare la précision de la catégorisation des lieux de pêche à partir de données de SSN par l'approche la plus répandue des « règles de vitesse » et avec un modèle de probabilité. En utilisant des données sur les pêches dans le nord-est des États-Unis pour les années de pêche de 2010 à 2014, nous démontrons que la représentation traditionnelle des activités de pêche établie à partir de règles de vitesse produit une caractérisation très imparfaite des zones de pêche pour les engins autres que les chaluts à panneaux de fond. Les prédictions basées sur les modèles de probabilité donnent de meilleurs résultats que les règles de vitesse pour des engins précis pour la classification des données de SSN pour les sorties de pêche au filet maillant de fond et au pétoncle à la drague, sans nécessiter d'importants efforts computationnels supplémentaires. Les modèles de probabilité produisent donc les plus grandes améliorations pour les engins associés à des motifs de pêche compliqués, tout en tenant compte de questions, comme la dynamique des flottes, qui, par le passé, n'étaient pas intégrées dans les règles de vitesse statiques, mais qui peuvent avoir une importante incidence sur la qualité des prédictions. [Traduit par la Rédaction]

Introduction

Vessel monitoring systems (VMS) are satellite-based surveillance systems that send vessel identification and location (the VMS poll) information at pre-specified time intervals, often for fishery enforcement. In the Northeastern U.S., VMS is used in part because the use of human observers is cost prohibitive and they are impractical to deploy on every trip. Globally, there is a desire to use VMS data for fine-scale fishing location information. Likewise, in the Northeastern U.S., fine-scale fishing location data from VMS units may augment self-reported fishing location data, where fishermen are only required to report one fishing latitude–longitude per logbook entry. For example, a bottom trawler in our data reported a single latitude–longitude for a 13 day trip of length of roughly 1 300 km, including 50 hauls. The spatial coarseness of the logbook data creates substantial imprecision in determining relevant spatial metrics (e.g., biomass removals, habitat impacts, etc.), and this underlies the need for VMS-based analysis.

The most common method to classify VMS polls as fishing, as the data itself do not directly indicate this, is the speed rule. This method classifies VMS as fishing if the vessel speed falls within a specific range. VMS-based speed rules have been used to evaluate the seabed impact of demersal fishing (Diesing et al. 2013; Gerritsen et al. 2013), assess the impact of closures on cod in Scotland (Needle and Catarino 2011), calculate stock allocations in the Northeastern U.S. fisheries (Palmer and Wigley 2009), and identify spawning areas of blue ling in the UK (Large et al. 2010). Depending on the fishery and the specific thresholds employed, speed rules have demonstrated that high rates of true positives are often connected to high rates of false positives. So, for example, Skaar et al. (2011) obtained for their small sample of demersal stern trawlers in the Barents Sea a true positive rate of 75%–80% and a false positive rate of only 10%–15%. In contrast, Gerritsen and Lordan (2011) correctly predicted 88% of fishing polls for the Irish otter trawl fleet, while at the same time, a false positive rate of 68% was generated. More strikingly, O'Farrell et al. (2017) attained a

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true positive rate of only 49% but a false positive rate of 95% when employing speed rules in the Gulf of Mexico bandit-reel fishery.

The appropriate speed rule depends on the characteristics of the fleet of interest, including size and horsepower of the vessels, gear employed, species targeted, depth of fishing, current strength, and wave size. These characteristics obviously vary greatly across management regions. Furthermore, the elapsed time between polls may range from at least once an hour in the Northeastern U.S. to 2 h in much of Europe (EC 2009; Murray et al. 2011) and to every 6 h in certain Taiwanese fleets (Chang and Yuan 2014). These differences lead to data variation that hinders the simple transfer of speed rules across fleets or regions.

This study developed a probability model for VMS polls applicable across gear groups and robust to variable polling frequencies. Although not the first statistical approach employed (e.g., Vermard et al. 2010; Walker and Bez 2010; de Souza et al. 2016), the generalized linear model (GLM) framework presented here is amenable to large datasets and varying polling frequencies that can prove problematic to Bayesian techniques (Peel and Good 2011; Banerjee and Fuentes 2012), with only a small increase in implementation complexity over speed rules. We assess probability models for three fishing gear types with a focus on their ability to correctly predict both fishing and nonfishing activity and find that these models provide substantial performance gains relative to speed rules for two of three gears.

Materials and methods

Data

This study used data from the Northeast U.S. Fisheries for the fishing years 2010–2014. The analysis was restricted to the three main gear groups employed in the region: (*i*) scallop dredges, (*ii*) sink gillnet, and (*iii*) bottom otter trawl. VMS data were merged with logbook data (vessel trip reports, VTR) to assign the fishing gear employed to each VMS poll in the dataset. The data was also linked to the Northeast Fisheries Observer Program (NEFOP) and the At-Sea-Monitoring Program (ASM) datasets, which were compiled by on-board human monitors that identify the start and end times of the fishing hauls.

Vessels were required to have a VMS on board if their commercial fishing activity was subject to a Fishery Management Plan with a VMS requirement. Relevant for federal management and for this study was only the fishing activity within the exclusive economic zone (EEZ) and conducted after the vessel crossed the VMS demarcation line (approximately three nautical miles from shore). Although there were some exceptions (e.g., scallop rotational area trips and groundfish trips exploiting the shared U.S.–Canada resource), most vessels were obliged to send their positions once an hour and at increased intervals when the vessel approached fishing closures.

This research focused on VMS signals that could be temporally linked to an active commercial fishing trip according to the VTR (Bastardie et al. 2010). Due to the time gap between VMS signals, the VTR–observer data were merged with the VMS data by date and time, with a deviation of 1 h to capture VMS signals shortly before and after the self-declared start and end of the trip, as defined in the vessel's VTR. According to the VTR records, in total, more than 108 000 bottom otter trawl, ca. 73 000 sink gillnet, and 44 000 scallop dredge trips occurred in the period under consideration. However, not all of these trips were required to have a VMS transponder on board. Furthermore, only a fraction of the trips was required to take a human observer on board (ca. 15%, but varies widely between fisheries). Our final dataset, the combined logbook, VMS, and observer data, represents ca. 8% of all commercial bottom otter trawl trips, 10% of all commercial sink gillnet trips, and 5% of all commercial scallop dredge trips for the given period — coverage that was driven primarily by observer coverage requirements and, importantly, not by failure to match trips across data sets. Although this coverage of commercial fishing trips may seem low, the bottom otter trawl dataset consisted of about 930 000 VMS polls, the sink gillnet dataset consisted of about 147 000 VMS polls and the scallop dredge dataset consisted of about 550 000 VMS polls, presenting an abundance of data. Furthermore, the probability model was based predominantly on the physical characteristics of fishing activities that are mechanistic in nature and unlikely to be affected by fisherman's strategic behavior when observed. All VMS polls of trips with data inconsistencies (e.g., new trip starts before last trip ends, or VMS signals generating imputed speeds above 40 km/h) or of trips that did not have enough data for reliable estimation (e.g., only one VMS poll per trip, trip duration is less than 1 h, or no observed fishing activity was captured by any of the VMS polls within the trip) were excluded. VMS polls were also removed from the dataset if there was less than 1 m movement between two consecutive polls belonging to the same trip or if all polls belonging to one trip were only located between shore and VMS demarcation line, to focus on federal fishing activities. Cleaned VMS data included duplicates in coordinates (i.e., ca. 7% of the bottom otter trawl VMS polls, 4% of the scallop dredge VMS polls, and 3.5% of the sink gillnet VMS polls) that were sent with different timestamps but likely overlap due to imprecision in the transmitted location. These duplicated coordinates were excluded from the analysis.

VMS polls were identified as observed fishing polls if their timestamp fell within the time range of an observed fishing haul according to the onboard observer. The observed VMS fishing polls were the baseline for the comparison between the speed rule and probability models conducted in this study. It should be noted that the ratio of fishing polls to nonfishing polls in the observed VMS data differed substantially between gear groups. For bottom otter trawlers, the ratio of fishing to nonfishing VMS polls averaged 1.3 across the study period, whereas the same ratio was about 0.9 for scallop dredges and 0.5 for sink gillnetters. These differences were driven by differences in fishing practices, particularly with regards to the duration of fishing hauls and length of trips (predominantly 1 day trips for sink gillnetters vs. multi-day trips for bottom otter trawlers or scallop dredges). Moreover, bottom otter trawlers tended to fish over long periods of time (averaging 3.3 h) following relatively linear depth contour lines (Thomas-Smyth et al. 2015). In contrast, scallop dredges often followed a zig-zag course with shorter tow durations (averaging 1 h), before circling back to their starting point. After the haul, scallop fishermen would sometimes stop the vessel to shuck (i.e., process) scallops and clear the deck (Hart and Rago 2006; Palmer and Wigley 2009). This created very different speed patterns of fishing in the data between the two gears. In comparison, sink gillnetters are considered a fixed gear, which means the vessels stop to haul anchored nets on board, empty the catch, and reset the nets. This fishing activity averaged less than 1 h, meaning that VMS polls fall within observed fishing activities less frequently than the other gears studied, an issue previously raised by O'Farrell et al. (2017).

Unlike other systems, VMS in the Northeastern U.S. did not transmit the instantaneous speed or the bearing angle of the vessel, necessitating the calculation of imputed speeds and angles. Speed at the VMS poll was calculated as the mean vessel speed (distance/time) from the lagged VMS poll assuming the vessel traveled in a straight line between consecutive polls. The difference in speed between the imputed speed of the current and lagged VMS polls was also derived for the analysis. The bearing angle of the current VMS poll heading towards the next VMS poll was estimated assuming a straight line between polls. The bearing angle was included in the analysis following the argument of Mills et al. (2007) that vessel bearing angle may help to characterize the activity of the vessel at a point in time and has been used in numerous studies (Vermard et al. 2010; Bez et al. 2011; O'Farrell et al. 2017).

To more precisely differentiate between fishing, anchoring, and steaming activities, an indicator variable called speed range was computed, which took on a value of 1 if the imputed speed of the current VMS poll deviated less than 1 km/h from the mean speed of the lag, current, and lead VMS polls (O'Farrell et al. 2017). Given that speed was an imputed average at a point in time, the "speed range" indicator sought to capture the probability that a shift in activity occurred shortly before or after the current poll, while the continuous variable of "difference in speed" captured the probability that the shift in activity occurred shortly after the proceeding poll.

Fishing is more likely to be observed in the middle of the fishing trip, as both the beginning and end of a trip tends to represent travel to and from port. To capture this nonlinearity, a position weight and the squared accumulated distance of the trip were included. The position weight (p_i) was an inverse U-shaped function based on the position of the VMS poll within the trip, with a maximum of 1 and taking the following form:

$$p_i = \frac{1}{(n_i - (N/2 + 1))^2} \text{ if } (n_i - (N/2 + 1)) \neq 0, \text{ otherwise } p_i = 1 \tag{1}$$

where n_i is an integer indicating the position of the VMS poll within a sub-trip and N denotes the total number of VMS polls belonging to the sub-trip. A trip was broken up into sub-trips if consecutive VMS polls had a deviation of less than 1 m. As an example, if a sub-trip included 40 VMS polls, the first and last VMS poll received a position weight close to 0 whereas VMS poll 21 received a position weight of 1. Sub-trips were defined following similar logic to that employed when developing the indicators for abrupt speed changes. This weight only accounted for the VMS poll's relative position within the trip but did not account for the distance or the time lag between VMS polls. Scheduled VMS polls were sometimes missing due to issues such as poor weather conditions. Additionally, VMS systems were used for ship to ship communications, and a VMS poll was sent each time the vessel used the VMS system as a communication tool. This generated polls at higher frequency than would otherwise be expected. To account for the nonstandard time frequency between the VMS polls, the accumulated distance between the VMS polls based on the geodetic distance was included (similar to O'Farrell et al. (2017)). Assuming, as above, that the earlier and latter parts of the trips were steaming rather than fishing activities and noting that substantial travel was necessary to reach certain fishing locations, any nonlinearity of the likelihood of the fishing activity with respect to distance traveled was captured by including the squared accumulated distance in addition to the position weight, without accounting for sub-trips.

To capture the depth of the seabed at the vessel's location, the VMS poll was linked to its closest coastal bathymetric contour line, measured in metres and based on data originating from the U.S. Coastal Relief Model made available by the NOAA National Geophysical Data Center. The depth of the seabed was included to capture target species ranges (NEFMC 2016). For example, scallop dredges primarily target Atlantic sea scallops (*Placopecten magellanicus* (Gmelin, 1791)), which are commercially harvested predominantly at depths between 35 and 100 m. Similar general rules regarding the depth of species target by sink gillnets and bottom otter trawls apply. For example, black sea bass (*Centropristis striata* (Linnaeus, 1758)) is most often found at less than 36 m, monkfish (*Lophius americanus* Valenciennes in Cuvier and Valenciennes, 1837) occurs primarily between 25 and 200 m, and summer flounder (*Paralichthys dentatus* (Linnaeus, 1766)) range in depths up to 152 m during the spring but, in fall, tend to occur at depths less than 61 m. Hence, the depth variable helped to distinguish between areas in which fishing was likely due to target species abundance (in a similar manner to O'Farrell et al. (2017)). A variable for the difference in depth (depth – depth$_{t-1}$) captured the fact that mobile fishing gears tend to follow depth contours while actively fishing (Thomas-Smyth et al. 2015). Hence, large differences in seabed depth were more likely to be associated with steaming instead of fishing.

Time-specific characteristics were captured by indicator variables denoting fishing year, month, and day of the week and whether the VMS poll occurred during the day or night. Moon phases were also included, as they can correlate to activity levels and other fish behavior (Henderson and Fabrizio 2011), which in turn could change optimal targeting and fishing behavior or the tide might influence fishing location (e.g., Damalas et al. 2007). Because of this, the moon phases of the night before and the night of the VMS poll were controlled for through another set of indicator variables. Although moon phase dummies looked to capture cyclical changes in target species behavior that might in turn have affected fishing behavior, day of the week dummies identified cyclical market dynamics that might explain the probability of steaming versus fishing activity. For example, Lee (2014) indicates that demand for groundfish in New England is lower on Fridays, as processors tend to close over the weekend. This would suggest that groundfish fishermen were less likely to be steaming to shore on Fridays, when compared with other days of the week, changing the overall probability of a poll being associated with fishing activity.

Fishing speed is determined not only by the vessel gear and its size, but also by the vessel's power. We controlled for this by incorporating the ratio of the vessel's horse power to its length (VHP/length). An interaction term between the vessel characteristic and imputed speed captured the interdependence between these characteristics for fishing activities.

To avoid scaling issues, continuous variables were z standardized (subtracting the mean and dividing by the standard deviation of the respective variable) before entering the regression models. The descriptive statistics of the data in raw format can be found in Appendix Tables A1 and A2. The geographic distribution of the data by gear group is shown in Figs. 1–3.

Fishing activity prediction based on VMS data

Speed rule method

To separate VMS polls into fishing and nonfishing activities, Palmer and Wigley (2009) developed a gear-specific speed rule for the same fleet as the present study using a different period (i.e., calendar year 2005). We used their study as a point of departure for our analysis. Palmer and Wigley (2009) argue that VMS polls with an imputed speed in the range of 3.7–7.4 km/h for otter trawls, 4.6–11.1 km/h for scallop dredges, and 0.2–2.4 km/h for sink gillnet generally represent fishing activity. Lee et al. (2010) claim that a speed range of 1–8 knots (i.e., 1.852–14.816 km/h), irrespective of the gear employed, reliably identifies fishing polls and corresponding fishing locations. We compared the two speed rules to assess the predictive quality of these simple rules (i.e., true positive and false positive rates) compared with actual observed fishing locations (i.e., VMS polls related to fishing activities according to the human observer on board of the vessel).

Probability model

Instead of using speed rules, D. Records and C. Demarest (2013, unpublished manuscript) proposed the use of a GLM, specifically a logistic regression model, to estimate the probability a VMS poll corresponds to fishing activity based on observer data. The logistic regression estimates the log odds of the probability of "fishing", which depends on a set of p explanatory variables $X = (X_1, X_2, ..., X_p)$. The dependent variable y_i equals 1 if the VMS poll occurs during a known fishing period and equals 0 otherwise. More formally, this relationship is modeled as follows, based on Greene (2008):

Fig. 1. Spatial distribution of VMS polls that belong to a fishing haul according to observer data (left) and according to GLM prediction using the Youden's *J* statistic as threshold (right) for scallop dredge trips (fishing years 2010–2014).

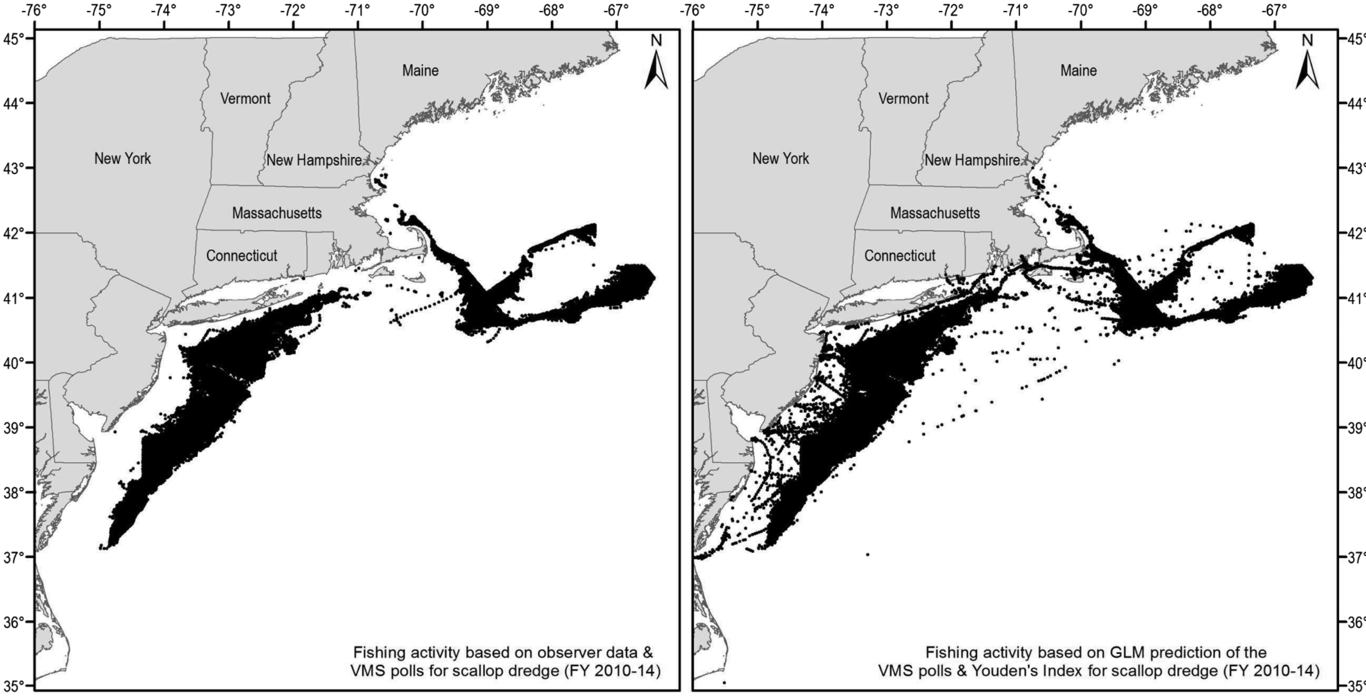
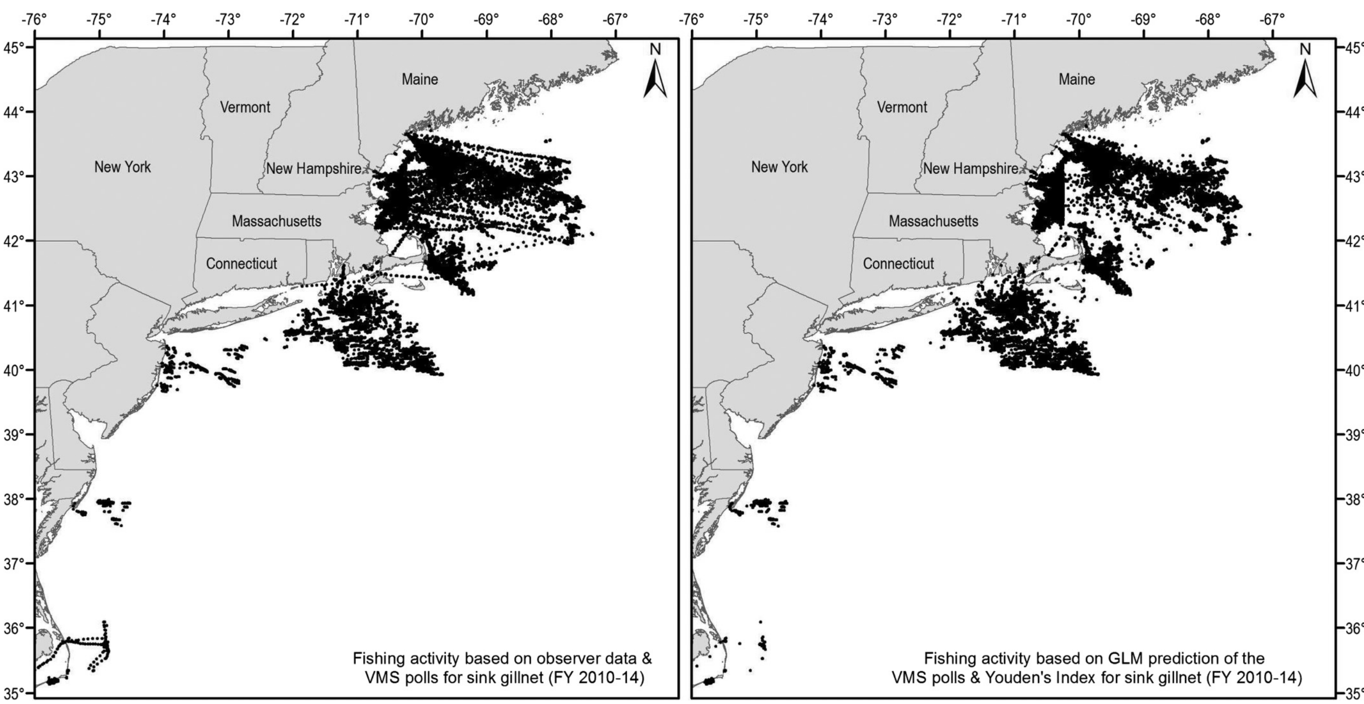


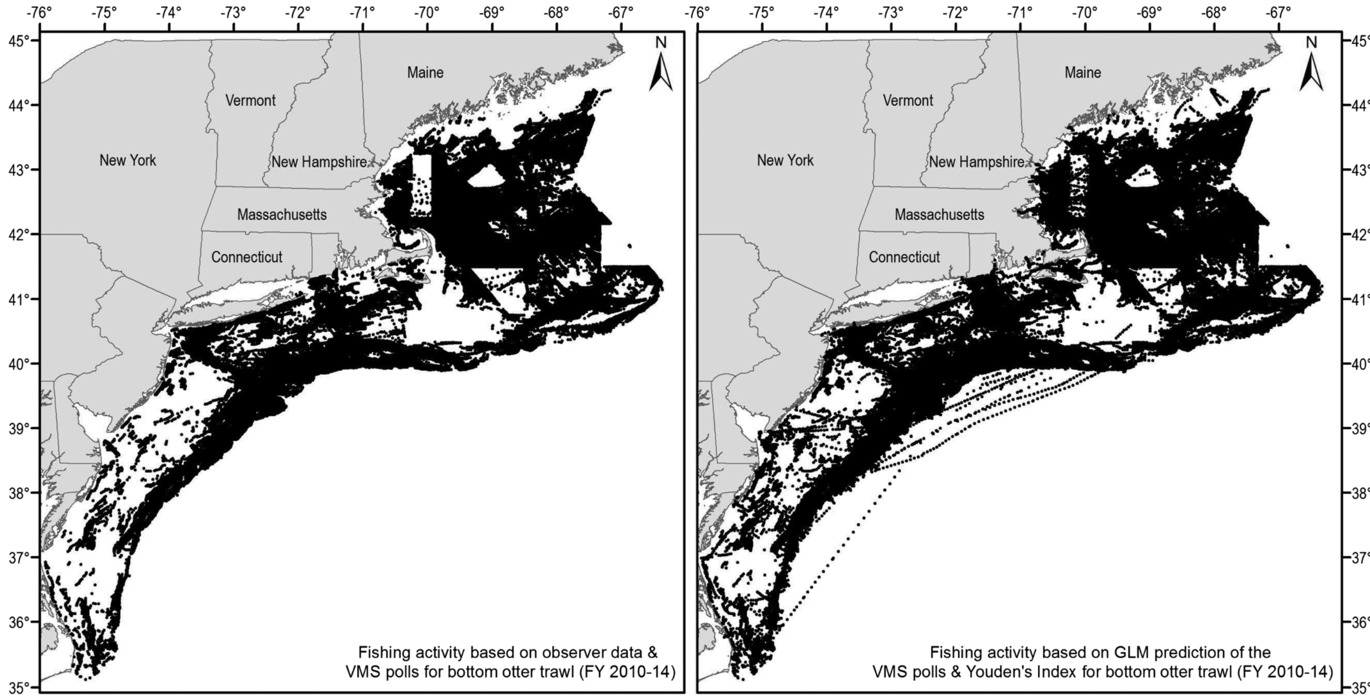
Fig. 2. Spatial distribution of VMS polls that belong to a fishing haul according to observer data (left) and according to GLM prediction using the Youden's *J* statistic as threshold (right) for sink gillnet trips (fishing years 2010–2014).



$$\text{(2)} \qquad \Pr(Y = 1|X = x_i) = F(x, \beta) = \frac{e^{X'\beta}}{1 + e^{X'\beta}}$$

In this formulation, $Y = (y_1, y_2, \ldots, y_n)$, which took the value of 1 if poll $i \in (1, \ldots, n)$ occurred during a known fishing event and equaled 0 otherwise, x_i were observed characteristics of poll i, and β were the parameters to be estimated. We estimated the probability of a VMS poll being a fishing poll based on the following explanatory variables (X): speed, its square (speed^2), difference in speed (speed – speed$_{t-1}$), deviation in speed (speed range), ocean depth (depth), difference in ocean depth (depth -- depth$_{t-1}$), turning angle (angle), position weight, the accumulated distance (distance), its square (distance^2), the vessel characteristic (VHP/length), an interaction term between vessel power characteristic and speed (VHP/length × speed), and temporal dummies (for ex-

Fig. 3. Spatial distribution of VMS polls that belong to a fishing haul according to observer data (left) and according to GLM prediction using the Youden's *J* statistic as threshold (right) for bottom otter trawl trips (fishing years 2010–2014).



ample, fishing year, month, day of the week, time of the day, and moon phase). The model stability, quality, and convergence characteristics were assessed by calculating the variance inflation factor for the matrix of independent variables, as well as the gradients and the condition number of the estimation models, following McCullough and Vinod (2003) and Greene (2008). The estimation results were thus investigated for potential biases and convergence issues due to multicollinearity and overspecification. We tested the residuals of the estimation for spatial and serial correlation. Spatial correlation in the residuals were assessed by calculating Moran's I (assessing global spatial correlation) and Geary's *C* (assessing local spatial correlation) for the 15 nearest neighbors. Results were robust to changes in the number of neighbors used. We tested for serial autocorrelation by calculating and assessing Durbin–Watson statistics, following Baltagi (2011) who notes that serial correlation does not bias the coefficient estimation but inflates the standard error in a similar manner to multicollinearity. To guard generally against biased standard errors, we calculated the standard error based on a heteroscedasticity and autocorrelation consistent covariance matrix (i.e., sandwich method as described in Greene (2008)). The models were further estimated separately for each gear group to allow for difference in the coefficients of the explanatory variables between gears.

We randomly drew 50% of trips for each fishing year and reserved their corresponding VMS data to fit the GLM. The remaining data was used to generate out-of-sample predictions to validate our estimates. To avoid potential sampling bias, we repeated the random draw of trips 20 times. According to Greene (2008), the difference in the predicted probability should be small if the variation in the sample data are low. Hence, if sampling bias or outliers (i.e., high leverage) were an issue, both the coefficient and the predicted values should deviate significantly. This process (including the number of repeats) was similar to the iterative bootstrap approach used by O'Farrell et al. (2017) to assess the prediction quality of their training data approach. We chose 20 draws, a number sufficient to detect sampling bias if it existed.

Comparing speed rule approach with probability model prediction quality

The predictions of the deterministic speed rule approaches were compared with the predictions of the probability models using receiver operating characteristics (ROC) graphs and the area under its curve (AUC) following Fawcett (2006). The ROC is a two-dimensional graph, which plots the sensitivity (true positive rate) and specificity (1 – false positive rate) of different prediction methods against each other while continuously increasing the cutoff threshold. This method allows a direct comparison of the predictive quality of differing methods. However, the speed rule methods provided only one true positive and false positive rate for each approach. To compare the speed rule approaches with the probability model, this one point was connected by a direct line with the (0, 100) and (100, 0) point of the graph to create comparable ROC curves, as well as to calculate the AUCs. The approach with the best predictive quality is the one with the most upper-left extent in the ROC graph. However, as curves may overlap and the direction "top left" is a rather flexible definition, the AUC provided a more precise measure of the prediction quality. The method that generates the largest AUC delivers the highest predictive quality.

As each observation was predicted anywhere from 1 to 20 times, we randomly drew a single predicted value for each observation. These randomly selected observation predictions formed the basis for constructing the ROC curve to which each corresponding speed rule's curve was compared. The 95% confidence intervals for the GLM predictions were used as lower and upper bounds of the ROC curve (GLM-ROC). The cutoff threshold was determined by the Youden's *J* statistic (Youden 1950) based on the predicted GLM-ROC. The threshold was fixed for the ROC created by the speed rule approaches to assess the true positive and false positive rates at this cutoff point for these approaches (Table 4). Maps were drawn using the Youden's *J* statistic as the cutoff point, based on the GLM predictions (Figs. 1–3). We did not include similar maps for speed rule determined fishing locations, as on this scale, the differences between maps were not observable.

Table 1. Results of the general and parsimonious GLM estimations for the scallop dredge VMS polls based on 50% of the trips resampled (with replacement) randomly 20 times.

	Full model		Parsimonious model	
Variable	Coefficient	Robust standard error	Coefficient	Robust standard error
Speed	−0.719*** [−0.763; −0.688]	0.009 [0.008; 0.009]	−0.724*** [−0.775; −0.693]	0.008 [0.008; 0.009]
VHP/length	0.051*** [0.022; 0.084]	0.005 [0.005; 0.006]	0.055*** [0.033; 0.090]	0.005 [0.005; 0.006]
VHP/length × speed	0.104*** [0.087; 0.123]	0.007 [0.006; 0.007]	0.102*** [0.067; 0.139]	0.007 [0.006; 0.007]
Speed^2	−1.092*** [−1.120; −1.059]	0.011 [0.010; 0.012]	−1.089*** [−1.118; −1.062]	0.010 [0.009; 0.011]
Speed – speed$_{t-1}$	0.006 [−0.007; 0.025]	0.006 [0.006; 0.006]	—	—
Angle	0.016* [0.004; 0.027]	0.005 [0.005; 0.005]	0.014** [0.004; 0.029]	0.005 [0.005; 0.005]
Position weight	0.008 [−0.018; 0.039]	0.013 [0.012; 0.013]	—	—
Depth	−0.003 [−0.079; 0.041]	0.006 [0.004; 0.010]	—	—
Depth – depth$_{t-1}$	−0.024* [−0.034; −0.011]	0.006 [0.006; 0.007]	−0.022** [−0.036; −0.009]	0.007 [0.005; 0.009]
Speed range	−0.613*** [−0.632; −0.579]	0.010 [0.009; 0.010]	−0.606*** [−0.649; −0.560]	0.010 [0.009; 0.010]
Distance	0.020* [−0.013; 0.044]	0.006 [0.006; 0.006]	—	—
Distance^2	−0.006 [−0.030; 0.022]	0.004 [0.004; 0.005]	—	—
4–7 o'clock	0.085*** [0.055; 0.135]	0.019 [0.018; 0.019]	—	—
7–10 o'clock	0.332*** [0.270; 0.370]	0.019 [0.018; 0.019]	—	—
10–13 o'clock	0.468*** [0.392; 0.527]	0.019 [0.019; 0.020]	—	—
13–16 o'clock	0.529*** [0.481; 0.582]	0.019 [0.019; 0.020]	—	—
16–19 o'clock	0.439*** [0.387; 0.493]	0.019 [0.019; 0.019]	—	—
19–22 o'clock	0.289*** [0.240; 0.322]	0.019 [0.019; 0.019]	—	—
22–1 o'clock	0.093*** [0.043; 0.140]	0.019 [0.018; 0.019]	—	—
New moon	0.050 [−0.090; 0.142]	0.037 [0.035; 0.040]	0.061 [−0.024; 0.161]	0.037 [0.035; 0.039]
First quarter	−0.120* [−0.223; −0.041]	0.036 [0.034; 0.038]	−0.131* [−0.240; −0.021]	0.037 [0.034; 0.039]
Full moon	0.071 [−0.056; −0.194]	0.037 [0.035; 0.039]	0.095 [−0.046; 0.234]	0.037 [0.035; 0.039]
Last quarter	0.010 [−0.109; 0.122]	0.039 [0.036; 0.042]	−0.013 [−0.134; 0.087]	0.038 [0.036; 0.040]
Monday	−0.039 [−0.065; −0.002]	0.018 [0.018; 0.018]	—	—
Tuesday	0.001 [−0.031; −0.048]	0.018 [0.018; 0.018]	—	—
Wednesday	−0.034 [−0.082; 0.021]	0.018 [0.018; 0.018]	—	—
Thursday	−0.045 [−0.089; −0.002]	0.018 [0.017; 0.018]	—	—
Friday	−0.029 [−0.065; 0.011]	0.018 [0.017; 0.018]	—	—
Saturday	−0.020 [−0.059; 0.017]	0.018 [0.017; 0.018]	—	—
Monthly dummies	Yes		Yes	
Yearly dummies	Yes		Yes	
Constant	0.973*** [0.772; 1.203]	0.035 [0.032; 0.037]	1.220*** [0.862; 1.562]	0.030 [0.027; 0.034]
No. of observations	549 674		549 674	
AIC	253 534 [246 951; 266 960]		255 194 [247 183; 262 152]	
Condition no.	1085.64 [878.46; 1266.84]		361.17 [283.89; 453.91]	
VIF [minimum; maximum]	[1.004; 3.980]		[1.000; 3.732]	
Gradient [minimum; maximum]	[-8.64×10^{-10}; 1.63×10^{-9}]		[-6.46×10^{-11}; 7.37×10^{-11}]	
DW test	1.031*** [1.002; 1.064]		1.028*** [1.003; 1.051]	
Moran's *I*	0.000 [0.000; 0.000]		0.000 [0.000; 0.000]	
Geary's *C*	1.043 [0.900; 1.233]		1.036 [0.867; 1.196]	
LogLik	−143 442		—	
LR test χ^2 (degrees of freedom) [LogLik]	84 107*** (44) [−185 495]		1 879.4*** (18) [−144 381]	

Note: Reported are the mean [minimum; maximum] coefficients, robust standard errors, and indicators for the regression estimation. Significance: ***, 0.001; **, 0.05; *, 0.1.

Apart from calculating a threshold on the fitted value with the help of the Youden *J* statistic, another way of using the derived fitted values from the probability model was to use a trip-specific threshold (e.g., trip-specific mean of predicted values). Generating a trip-specific threshold provided control for trip-level unobserved characteristics that, due to the sheer number of trips, cannot directly be controlled for in the GLM estimation. For example, weather and other environmental effects may lead to variation in haul characteristics, even if hauls were conducted by the same crew, gear, and vessel and targeting the same species. A trip-specific threshold was a theoretically simple way to capture trip-individual effects, which should improve prediction quality noting that similar approaches were not possible using the speed rule approach. In the following, we implemented a trip-specific threshold defined as the trip mean probability value for bottom otter trawl and scallop dredges and the 45th percentile for sink gillnet trips. This difference in threshold was designed to create true positive rates above 80% without raising the false positive rate above 50%, an implicit goal of the co-authors. Although the trip mean met this goal for scallop dredge and bottom otter trawl trips, the sink gillnet trip threshold needed to be adapted slightly to increase predictive performance, highlighting the complexity in creating a single approach that performs well across different fisheries.

Robustness check: daytime and parsimonious models

Beyond investigating potential sampling bias through resampling, the stability of the probability model was further assessed by excluding insignificant variables if they were not part of an interaction term (Brambor et al. 2006). The parsimonious scallop dredge model was assessed through iterative bootstrapping in the same manner as the full model, excluding the difference in speed, depth, position weight, distance, and weekday variables. The parsimonious model for sink gillnet trips excluded the explanatory variables weekday, difference in depth, position weight, and the interaction term of VHP/length × speed, whereas the estimation

Table 2. Results of the general and parsimonious GLM estimations for the sink gillnet VMS polls based on 50% of the trips resampled randomly 20 times.

	Full model		Parsimonious model	
Variable	Coefficient	Robust standard error	Coefficient	Robust standard error
Speed	−0.744*** [−0.788; −0.690]	0.014 [0.013;0.016]	−0.800*** [−0.851; −0.749]	0.013 [0.012; 0.013]
VHP/length	0.072** [0.008; 0.167]	0.012 [0.009; 0.019]	0.072*** [0.033; 0.122]	0.010 [0.009; 0.014]
VHP/length × speed	−0.008 [−0.056; 0.028]	0.011 [0.008; 0.015]	—	—
Speed^2	−0.284*** [−0.381; −0.204]	0.022 [0.021; 0.025]	−0.371*** [−0.445; −0.312]	0.023 [0.021; 0.024]
Speed − speed$_{t-1}$	−0.277*** [−0.297; −0.255]	0.012 [0.012; 0.012]	−0.264*** [−0.281; −0.249]	0.011 [0.011; 0.012]
Angle	0.024* [0.008; 0.044]	0.009 [0.009; 0.010]	0.032** [0.006; 0.059]	0.009 [0.009; 0.009]
Position weight	0.021 [−0.008; 0.040]	0.010 [0.010; 0.011]	—	—
Depth	−0.230*** [−0.278; −0.133]	0.016 [0.012; 0.024]	−0.125*** [−0.217; −0.074]	0.010 [0.009; 0.010]
Depth − depth$_{t-1}$	0.008 [−0.013; 0.028]	0.012 [0.011; 0.013]	—	—
Speed range	0.196*** [0.112; 0.250]	0.020 [0.020; 0.021]	0.052* [0.003; 0.101]	0.019 [0.019; 0.020]
Distance	−0.071 [−0.252; 0.124]	0.046 [0.017; 0.088]	—	—
Distance^2	0.066 [0.007; 0.139]	0.023 [0.005; 0.044]	—	—
4–7 o'clock	0.550*** [0.466; 0.678]	0.046 [0.045; 0.050]	—	—
7–10 o'clock	1.410*** [1.265; 1.567]	0.045 [0.043; 0.051]	—	—
10–13 o'clock	1.078*** [0.932; 1.213]	0.043 [0.042; 0.047]	—	—
13–16 o'clock	0.917*** [0.793; 1.029]	0.044 [0.043; 0.047]	—	—
16–19 o'clock	0.907*** [0.741; 1.006]	0.049 [0.047; 0.052]	—	—
19–22 o'clock	0.459*** [0.364; 0.525]	0.051 [0.049; 0.054]	—	—
22–1 o'clock	0.164*** [0.100; 0.230]	0.051 [0.049; 0.054]	—	—
New moon	0.066 [−0.075; 0.242]	0.070 [0.065; 0.075]	0.127 [−0.060; 0.350]	0.067 [0.061; 0.075]
First quarter	−0.413*** [−0.692; −0.107]	0.078 [0.072; 0.088]	−0.406*** [−0.689; −0.172]	0.078 [0.070; 0.087]
Full moon	−0.179* [−0.374; 0.057]	0.065 [0.060; 0.070]	−0.132 [−0.331; 0.067]	0.063 [0.058; 0.071]
Last quarter	0.122 [−0.052; 0.374]	0.072 [0.068; 0.079]	0.115 [−0.090; 0.357]	0.070 [0.066; 0.075]
Monday	−0.039 [−0.102; 0.039]	0.036 [0.035; 0.037]	—	—
Tuesday	−0.020 [−0.119; 0.145]	0.035 [0.035; 0.037]	—	—
Wednesday	−0.044 [−0.189; 0.071]	0.036 [0.035; 0.037]	—	—
Thursday	−0.017 [−0.155; 0.098]	0.035 [0.034; 0.037]	—	—
Friday	0.028 [−0.079; 0.133]	0.035 [0.034; 0.036]	—	—
Saturday	0.016 [−0.060; 0.109]	0.035 [0.035; 0.037]	—	—
Monthly dummies	Yes		Yes	
Yearly dummies	Yes		Yes	
Constant	−1.967*** [−2.536; −1.594]	0.070 [0.065; 0.078]	−0.861*** [−1.186; −0.553]	0.047 [0.044; 0.052]
No. of observations	147 042		147 042	
AIC	72 121 [67 500; 74 594]		73 871 [70 988; 77 920]	
Condition no.	1375.81 [837.19; 1735.88]		521.27 [371.44; 663.12]	
VIF [minimum; maximum]	[1.005; 4.700]		[1.004; 3.887]	
Gradient [minimum; maximum]	[-8.35×10^{-9}; 1.34×10^{-10}]		[-9.75×10^{-12}; 8.92×10^{-12}]	
DW test	1.222*** [1.187; 1.283]		1.199*** [1.152; 1.250]	
Moran's *I*	0.008 [0.000; 0.028]		0.001 [0.000; 0.003]	
Geary's *C*	1.007 [0.867; 1.216]		1.016 [0.744; 1.263]	
LogLik	−36 393		—	
LR test χ^2 (degrees of freedom) [LogLik]	15 986*** (44) [−44 386]		2419.8*** (12) [−37 603]	

Note: Reported are the mean [minimum; maximum] coefficients, robust standard errors, and indicators for the regression estimation. Significance: ***, 0.001; **, 0.05; *, 0.1.

for the parsimonious model for bottom otter trawl data did not include the variables weekday and bearing angle.

Although the explanatory variable daytime was significant in all three probability models, as a further robustness check, it was removed from the regression because human observers may observe less hauls at nighttime, a time they normally sleep. Using time of day as an explanatory variable might bias the results.

Results

Probability models

For bottom otter trawl and scallop dredges, the speed variable and its nonlinear formation (speed^2) dominated the probability prediction of the estimation models (Tables 1 and 3). However, for sink gillnet trips, the daytime variable was the major driver in the estimation model (Table 2). Nevertheless, the parsimonious sink gillnet estimation model, which excluded the daytime variable, provided similar estimation results. In general, the coefficients and the predictive performance deviated only slightly between the full and parsimonious estimation models. Although the weekday variable for "Thursday" was still significant for bottom otter trawl in the full model, it was insignificant in the parsimonious model; hence, all weekdays variables were taken out of the parsimonious model regression. However, a likelihood ratio test comparing the parsimonious against the full model indicated that the individually insignificant variables excluded in the parsimonious model significantly improved the explanatory power of the full model. We used the predicted probability of the full models in the following comparisons and noted that we found no indication of heteroscedasticity in the results (see diagnostics in Tables 1–3).

Comparison of probability models and deterministic speed rules

The ROC curves (Figs. 4 and 5) indicated that the GLMs for the scallop dredge and sink gillnets outperformed the speed rules by up to 30% considering the difference in AUC values (Table 4). Specifically for sink gillnets, the speed rule of Lee et al. (2010)

Table 3. Results of the general and parsimonious GLM estimations for the bottom otter trawl VMS polls based on 50% of the trips resampled randomly 20 times.

	Full model		Parsimonious model	
Variable	Coefficient	Robust standard error	Coefficient	Robust standard error
Speed	–1.215*** [–1.258; –1.160]	0.013 [0.012; 0.013]	–1.223*** [–1.255; –1.198]	0.013 [0.012; 0.013]
VHP/length	–0.032** [–0.052; –0.005]	0.005 [0.005; 0.006]	–0.031** [–0.059; –0.005]	0.005 [0.005; 0.006]
VHP/length × speed	0.177*** [0.156; 0.204]	0.008 [0.007; 0.009]	0.181*** [0.149; 0.208]	0.008 [0.007; 0.009]
Speed^2	–1.760*** [–1.811; –1.717]	0.018 [0.017; 0.019]	–1.812*** [–1.853; –1.769]	0.018 [0.017; 0.020]
Speed – speed$_{t\text{-}1}$	–0.033*** [–0.042; –0.024]	0.006 [0.006; 0.006]	–0.039*** [–0.047; –0.030]	0.006 [0.006; 0.006]
Angle	–0.001 [–0.010; 0.007]	0.004 [0.004; 0.004]	—	—
Position weight	0.027** [0.007; 0.040]	0.010 [0.009; 0.010]	0.061*** [0.049; 0.086]	0.010 [0.010; 0.010]
Depth	–0.248*** [–0.304; –0.196]	0.007 [0.006; 0.008]	–0.237*** [–0.275; –0.208]	0.007 [0.006; 0.008]
Depth – depth$_{t-1}$	0.035*** [0.027; 0.048]	0.007 [0.006; 0.008]	0.036*** [0.028; 0.046]	0.007 [0.007; 0.008]
Speed range	0.164*** [0.144; 0.186]	0.009 [0.009; 0.010]	0.116*** [0.095; 0.141]	0.009 [0.009; 0.010]
Distance	–0.005 [–0.029; 0.024]	0.006 [0.005; 0.007]	–0.037*** [–0.061; –0.009]	0.006 [0.005; 0.006]
Distance^2	–0.052 *** [–0.076; –0.017]	0.004 [0.003; 0.006]	–0.041 *** [–0.061; –0.015]	0.004 [0.003; 0.005]
4–7 o'clock	0.291 *** [0.264; 0.308]	0.016 [0.016; 0.016]	—	—
7–10 o'clock	0.789 *** [0.757; 0.829]	0.016 [0.016; 0.017]	—	—
10–13 o'clock	0.716 *** [0.660; 0.764]	0.016 [0.016; 0.017]	—	—
13–16 o'clock	0.622 *** [0.570; 0.678]	0.016 [0.016; 0.017]	—	—
16–19 o'clock	0.589 *** [0.563; 0.620]	0.017 [0.016; 0.017]	—	—
19–22 o'clock	0.249 *** [0.215; 0.287]	0.016 [0.016; 0.016]	—	—
22–1 o'clock	0.103 *** [0.081; 0.131]	0.016 [0.015; 0.016]	—	—
New moon	–0.010 [–0.089; 0.078]	0.032 [0.030; 0.033]	—	—
First quarter	0.050 [–0.056; 0.128]	0.032 [0.030; 0.034]	—	—
Full moon	–0.020 [–0.116; 0.072]	0.031 [0.029; 0.032]	—	—
Last quarter	0.031 [–0.041; 0.109]	0.033 [0.031; 0.036]	—	—
Monday	–0.007 [–0.061; 0.024]	0.015 [0.015; 0.016]	—	—
Tuesday	0.002 [–0.040; 0.067]	0.015 [0.015; 0.016]	—	—
Wednesday	–0.017 [–0.050; 0.019]	0.015 [0.015; 0.016]	—	—
Thursday	–0.043* [–0.090; 0.012]	0.016 [0.015; 0.016]	—	—
Friday	0.021 [–0.030; 0.059]	0.016 [0.015; 0.016]	—	—
Saturday	0.020 [–0.008; 0.052]	0.015 [0.015; 0.015]	—	—
Monthly dummies	Yes		Yes	
Yearly dummies	Yes		Yes	
Constant	0.558*** [0.452; 0.628]	0.024 [0.024; 0.025]	1.027*** [0.909; 1.103]	0.019 [0.018; 0.020]
No. of observations	933 896		933 896	
AIC	343 446 [335 533; 353 580]		346 314 [337 680; 358 646]	
Condition no.	600.01 [514.90; 711.68]		398.24 [171.45; 484.74]	
VIF [minimum; maximum]	[1.002; 2.216]		[1.026; 2.135]	
Gradient [minimum; maximum]	[–2.00×10^{-9}; 2.02×10^{-9}]		[–1.78×10^{-10}; 1.84×10^{-10}]	
DW test	0.951*** [0.934; 0.963]		0.934*** [0.911; 0.945]	
Moran's *I*	0.001 [0.000; 0.004]		0.000 [0.000; 0.004]	
Geary's *C*	1.023 [0.995; 1.062]		1.028 [0.995; 1.069]	
LogLik	–187 608			
LR test χ^2 (degrees of freedom) [LogLik]	240 584*** (44) [–307 901]		4553.9*** (18) [–189 885]	

Note: Reported are the mean [minimum; maximum] coefficients, robust standard errors, and indicators for the regression estimation. Significance: ***, 0.001; **, 0.05; *, 0.1.

performed worse than a random equal probability classification of polls, with a ROC curve below the 45° line (Fig. 5). Conversely, for bottom otter trawl, a comparison of ROC curves created by the speed rule of Palmer and Wigley (2009) and GLM indicated that there were a small number of cutoff thresholds in which the two approaches had a similar predictive performance (Fig. 6). However, the AUC of the GLM-ROC was about 6% higher than the one of the ROC based on the speed rule of Palmer and Wigley (2009). In general, the GLM generated the maximum AUC for all three gear groups (Table 4), meaning it is the most accurate prediction method. Although the Palmer and Wigley (2009) gear-specific speed rule for bottom otter trawl performed well, the probability model resulted in more stable results overall.

Visual comparison of the maps of observed fishing locations with the GLM predicted fishing locations (Figs. 1–3) indicated that the GLM overpredicted fishing activities in closed areas (in particular for the otter bottom trawl) or closer to the shore (in particular for the scallop dredges).

A comparison of predictions using ROC curves at the optimal cutoff point identified by the Youden's *J* statistic, we found for scallop dredges that the GLM generated a 15.8% higher true positive rate than the speed rule of Palmer and Wigley (2009) and only increased the false positive rate by 2.25% (Table 4). The GLM approach generated the highest accuracy for the sink gillnetters and resulted in a 39% higher true positive rate and 7.8% lower false positive rate compared with the rates determined by the speed rule from Lee et al. (2010). For bottom otter trawl, however, both the true positive rate and false positive rate were increased by a comparable magnitude using the GLM approach instead of the speed rule approach of Palmer and Wigley (2009).

Employing trip-specific thresholds led to similar results to those obtained using Youden's *J* statistic as the cutoff (Table 4). Although for the scallop dredge and sink gillnet estimations, the false positive rate increased slightly, the trip-specific threshold raised the true positive rate for bottom otter trawlers. The speed

Fig. 4. ROC graph for scallop dredge prediction vs. speed rules. The ROC based on a random sample of one prediction for each observation are plotted next to the ROC curves based on the classification of the speed rule by Palmer and Wigley (2009) and Lee et al. (2010). The 95% confidence interval of the GLM prediction is plotted as the grey dashed line; however, due to the low variation, the curve of the prediction overlays the curves on the upper and lower boundaries of the predictions. The solid, grey line is the 45° line.

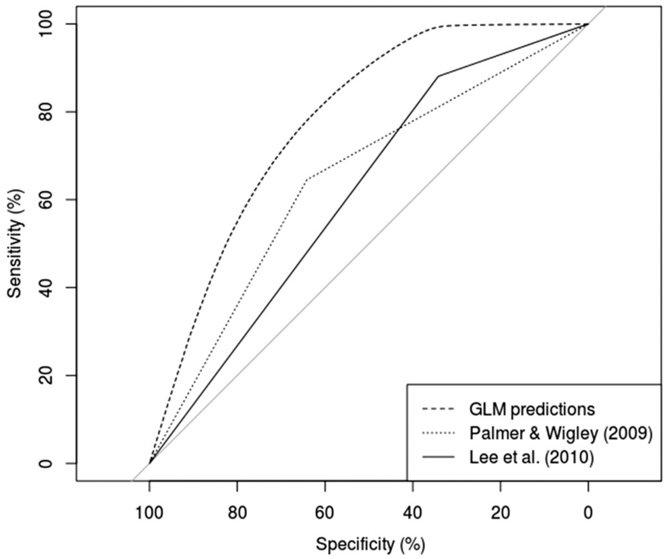
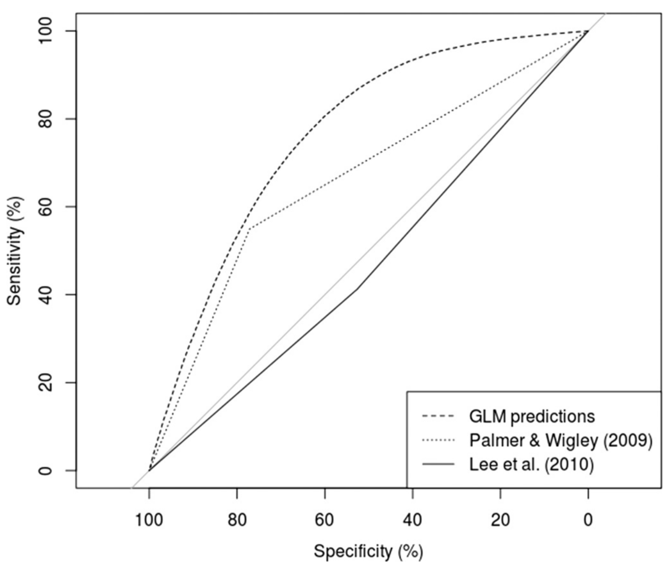


Fig. 5. ROC graph for sink gillnet prediction vs. speed rules. The ROC based on a random sample of one prediction for each observation are plotted next to the ROC curves based on the classification of the speed rule by Palmer and Wigley (2009) and Lee et al. (2010). The 95% confidence interval of the GLM prediction is plotted as the grey dashed line grey; however, due to the low variation, the curve of the prediction overlays the curves of the upper and lower boundaries of the predictions. The solid, grey line is the 45° line.



rule of Lee et al. (2010) remained to perform worst of all approaches, in particular with regards to sink gillnetters.

Discussion

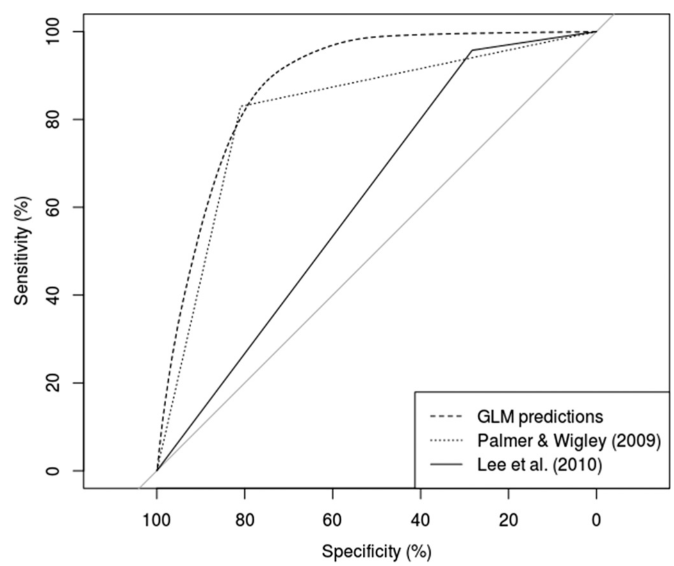
This paper investigated the ability of a GLM to accurately predict observed fishing activity, while guarding against misclassification of nonfishing as fishing, for VMS data. The GLM prediction results were compared with the most widely used alternative approach, the VMS speed rule, for the same datasets and gear groups. For all three gears studied, the GLM outperformed a ge-

Table 4. Indicators on the classification quality following the speed rule approaches of Palmer and Wigley (2009) and Lee et al. (2010) compared with the GLM predictions.

	Palmer and Wigley (2009)	Lee et al. (2010)	GLM
Scallop dredge			
Youden's *J* statistic: 0.623			
True positive (%)	64.55	88.07	80.34
False positive (%)	35.86	65.80	38.11
AUC (%)	64.34	61.13	77.90 [77.89; 77.90]
Trip-specific threshold			
True positive (%)	63.02	86.61	81.07
False positive (%)	36.08	64.87	45.84
Sink gillnet			
Youden's *J* statistic: 0.590			
True positive (%)	54.96	41.23	80.26
False positive (%)	22.86	47.34	39.55
AUC (%)	66.05	46.94	76.23 [76.22; 76.24]
Trip-specific threshold			
True positive (%)	52.34	39.63	78.22
False positive (%)	21.90	45.90	45.26
Bottom otter trawl			
Youden's *J* statistic: 0.659			
True positive (%)	82.98	95.74	88.93
False positive (%)	19.06	71.71	25.18
AUC (%)	81.96	62.02	88.14 [88.11; 88.16]
Trip-specific threshold			
True positive (%)	82.77	86.61	92.33
False positive (%)	18.41	64.87	31.14

Note: Comparison is conducted by either using the gear group specific calculated Youden's *J* statistic or by trip-specific thresholds to classify the fitted values. For the GLM AUC values, [minimum; maximum] values are also given.

Fig. 6. ROC graph for bottom otter trawl prediction vs. speed rule. The ROC based on a random sample of one prediction for each observation are plotted next to the ROC curves based on the classification of the speed rule by Palmer and Wigley (2009) and Lee et al. (2010). The 95% confidence interval of the GLM prediction is plotted as the grey dashed line grey; however, due to the low variation, the curve of the prediction overlays the curves of the upper and lower boundaries of the predictions. The solid, grey line is the 45° line.



neric speed rule.

neric speed rule when predicting fishing activity of individual VMS polls. For bottom otter trawlers, the gear-specific speed rule can outperform the GLM in some instances. However, the GLM substantially outperformed the gear-specific speed rules for gears fishing in more complex patterns or for shorter durations such as the zig-zag course of the scallop dredge vessels and the more stationary practices employed when fishing with fixed gear (e.g., sink gillnet).

The GLM described in this research performed well in predicting fishing locations both in and out of sample for the analyzed gear groups, without the computational burden of the Markovian process models based on Bayesian inferences. An increase in the VMS frequency is likely to facilitate improved VMS analysis generally, as previously argued by e.g., Deng et al. (2005) or O'Farrell et al. (2017). It is unclear whether there is political will to implement such a management measure in the Northeastern U.S. due to the increased costs associated with additional polling. The GLM, nevertheless, has been shown to effectively estimate and predict fishing activity for extremely large datasets, a challenge that may prove problematic for alternative techniques including engineering training and Bayesian approaches like Markovian process models. Moreover, the GLM is not dependent on a constant VMS poll transmission frequency, in contrast to the Markovian process models. The simple speed rule tends to heavily misclassify activities for gear groups employing complex fishing patterns. Given the tractability and the relative ease of implementation of the GLM, there is no strong reason to choose the speed rule. A major caveat is that the GLM, like all statistical approaches, depends on observer data for the region and fishery under research to derive the estimation parameters, which could limit its global application.

Furthermore, as evidenced by our comparison of the Palmer and Wigley (2009) analysis, which was based on calendar year 2005 data, and the same rule applied to data for fishing year 2010–2014, static speed rules are likely to need temporal updating to reflect changes in fleet dynamics, reporting requirements, and management measures and other causes likely to induce shifts in fishing behavior. In their study, Palmer and Wigley (2009) found that their speed rule classified 99.2% of the fishing VMS polls correctly and reported a false positive rate of 31.8% for bottom otter trawl trips. However, for the fishing years 2010–2014, the true positive rates decreased to 82.8% and the false positive rate decreased to 19.0%. Similar changes in prediction quality over time can be noted for scallop dredge vessels. Palmer and Wigley (2009) reported a true positive rate of 98.3% and false positive rate of 69.3; we noted that using the same speed range with our more recent dataset reduced the true positive rate to 63.0% and false positive rate to 36.1%. Hence, the speed rule seems to have lost validity over time. Changes in the composition of the fisheries and vessels monitored by VMS can induce shifts in the distribution of speeds surrounding fishing activity, which may not be adequately captured by a static speed rule.

In future research, this analysis should be extended to other gears, as it would lend additional insight into the general practicability of the approach for gear types with lower VMS coverage or for fisheries with fishing behavior that often falls in-between VMS polls (e.g., Gulf of Mexico bandit-reel fishery). Moreover, exploring the heterogeneity of fishing activity within gear groups seems a necessary further step to fully understand fishing activity and location choices. As we demonstrated, the GLM mildly outperformed the gear-specific speed rule for bottom otter trawls and substantially outperformed the speed rule for sink gillnet and scallop dredge gears. For other fisheries using gears such as the purse seiner, hidden Markov models may better classify activities, given the movement patterns of the vessel while actively fishing (Vermard et al. 2010; Bez et al. 2011; de Souza et al. 2016). Nevertheless, for the gears studied in this paper, the GLM provided a better understanding of fishing activities and improved the prediction of fishing locations for purposes such as impact assessments.

Although not explicitly used in this paper, the probability model provides additional information — specifically, the estimated probability values themselves — that is not available from the simpler speed rules traditionally applied to VMS. These probability values can be used to spatially attribute fishing effort, catch, and revenue metrics in a manner that explicitly considers the uncertainty inherent in the data. Future research should more fully consider this added information.

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Appendix A

Table A1. General structure of the data.

Fishing year	2010	2011	2012	2013	2014	All
Scallop dredge						
No. of trips	306	375	411	456	445	1.993
No. of VMS polls	100 014	119 042	154 320	116 853	109 826	600 055
Ratio of observed fishing to nonfishing VMS polls	1.163	1.096	1.347	0.647	0.628	0.953
Mean time between polls (h)	0.478	0.477	0.472	0.483	0.477	0.477
Sink gillnet						
No. of trips	1886	2029	1335	896	1165	7311
No. of VMS polls	37 779	45 633	29 974	25 548	32 329	171 263
Ratio of observed fishing to nonfishing VMS polls	0.442	0.611	0.453	0.628	0.597	0.542
Mean time between polls (h)	0.707	0.658	0.673	0.661	0.666	0.673
Bottom otter trawl						
No. of trips	1888	2230	1702	1465	1449	8734
No. of VMS polls	220 595	284 773	171 262	173 948	172 233	1 022 811
Ratio of observed fishing to nonfishing VMS polls	1.197	1.411	1.426	1.317	1.171	1.306
Mean time between polls (h)	0.560	0.530	0.538	0.540	0.532	0.540

Table A2. Descriptive statistics.

Variable	*N*	Mean	Standard deviation	Minimum	Maximum
Scallop dredge					
Speed (km/h)	549 674	7.167	4.678	0	39.723
Speed – speed$_{t\text{-}1}$	549 674	0.015	3.514	−32.970	37.335
Angle (rad)	549 674	2.877	1.893	0	6.283
Position weight	549 674	0.054	0.37	0	4
Depth (m)	549 674	−57.706	74.821	−3163	−1
Depth – depth$_{t\text{-}1}$	549 674	0.006	9.904	−1022	875
Speed range	549 674	0.480	0.5	0	1
Distance (km)	549 674	733.37	481.22	0.027	3721.37
Month (date landed)	549 674	6.343	2.752	1	12
Daytime (3 h interval)	549 674	4.527	2.282	1	8
Weekday	549 674	3.023	1.994	0	6
Moon phase	549 674	0.167	0.684	0	4
VHP/length	549 674	9.492	2.949	4.280	29.172
Trip duration (h)	549 674	217.521	81.383	5	406.667
Time between VMS polls (h)	549 674	0.469	0.146	0.0003	3
Observed VMS fishing polls	549 674	0.491	0.500	0	1
Sink gillnet					
Speed (km/h)	147 042	6.853	6.552	0	37.363
Speed – speed$_{t\text{-}1}$	147 042	0.206	5.414	−34.861	35.471
Angle (rad)	147 042	3.110	1.840	0	6.283
Position weight	147 042	0.355	0.907	0	4
Depth (m)	147 042	−93.381	60.234	−306	−1

Table A2 (*concluded*).

Variable	N	Mean	Standard deviation	Minimum	Maximum
Depth – depth$_{t-1}$	147 042	–0.074	21.836	–173	171
Speed range	147 042	0.469	0.499	0	1
Distance (km)	147 042	135.40	136.31	0.008	2519.87
Month (date landed)	147 042	7.077	3.027	1	12
Daytime (3 h interval)	147 042	4.012	1.898	1	8
Weekday	147 042	3.057	1.946	0	6
Moon phase	147 042	0.175	0.708	0	4
VHP/length	147 042	7.556	3.137	0.028	62.5
Trip duration (h)	147 042	55.870	60.966	1	306.5
Time between VMS polls (h)	147 042	0.678	0.333	0.001	3
Observed VMS fishing polls	147 042	0.375	0.484	0	1
Bottom otter trawl					
Speed (km/h)	933 896	7.093	4.462	0	39.681
Speed – speed$_{t-1}$	933 896	0.016	2.835	–35.487	36.759
Angle (rad)	933 896	2.944	1.884	0	6.283
Position weight	933 896	0.073	0.427	0	4
Depth (m)	933 896	–122.251	96.458	–2658	–1
Depth – depth$_{t-1}$	933 896	–0.001	28.972	–1158	1076
Speed range	933 896	0.679	0.467	0	1
Distance (km)	933 896	501.500	384.440	0.006	4874.64
Month (date landed)	933 896	6.556	3.557	1	12
Daytime (3 h interval)	933 896	4.446	2.234	1	8
Weekday	933 896	2.990	2.004	0	6
Moon phase	933 896	0.170	0.693	0	4
VHP/length	933 896	8.702	3.111	0	29.172
Trip duration (h)	933 896	145.970	75.803	2	606.667
Time between VMS polls (h)	933 896	0.540	0.247	0.001	3
Observed VMS fishing polls	933 896	0.575	0.494	0	1