# Using Vessel Monitoring System Data to Estimate Spatial Effort in Bering Sea Fisheries for Unobserved Trips

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## *Abstract*

*Vessel monitoring system (VMS) technology records the time, location, bearing, and speed for fishing vessels that have the technology on board. VMS equipment has been put in place on all vessels in a number of fisheries, including all trawling vessels that fish for pollock, cod, and Atka mackerel in the United States Eastern Bering. VMS technology has been used in enforcement but a limited amount of work has been done utilizing VMS data to improve estimates of fishing activity. This paper integrates VMS data and National Marine Fisheries Service (NMFS) observer data from the United States Eastern Bering Sea pollock fishery to predict whether or not fishing is occurring for unobserved fishing trips. While there is 100 percent observer coverage for all catcher-processors and motherships in the fishery and some of the vessels that deliver to shoreside processors, approximately 2/3s of catcher vessels that deliver to shoreside processors have coverage for only 30 percent of their fishing days. The primary goals of this paper are to determine how accurately we can predict fishing for observed vessels and to estimate where and when fishing occurs for the unobserved trips of the vessels with partial observer coverage.*

*We employ a variety of techniques and data specifications to improve model performance and out-of-sample predictive success, but finally settle upon a generalized additive model (GAM) as the best formulation for predicting fishing. Assessing the probability of fishing in any location begins with a consideration of contemporaneous observable information: speed, change in direction, and location and we utilize these predictors in developing the model. We assess spatial correlation in the residuals of the* *chosen model, but find no correlation after taking into consideration other VMS predictors. We compare maps of fishing effort to predictions for vessels with 100 percent observer coverage and compare the results to observed data for 2004. We assess the effectiveness of these methods for fisheries with lower observer coverage and conclude with a discussion of a variety of policy considerations.*

## Introduction

Vessel monitoring system (VMS) technology records the time, location, bearing, and speed for monitored vessels. Fisheries that have 100% VMS coverage include all trawling fleets that fish for pollock, cod, and Atka mackerel in the United States Eastern Bering Sea. But while VMS technology has been used extensively in the enforcement of area closures, a limited amount of research has been conducted utilizing VMS data to improve our estimates of fishing activity. For example, Rijnsdorp et al. (1998) used VMS to examine trawling effect on benthic organisms in the North Sea and later Rijnsdorp et al. (2001) examined the redistribution of the cod fleet in the North Sea after the institution of a marine protected area. Deng et al. (2005) explored the use of VMS to examine trawling intensity and stock depletion due to trawling in Australia's northern prawn fishery. Murawski et al. (2005) documented the spatial distribution of fishing effort adjacent to marine protected areas using VMS. Mills et al. (2006) mapped the spatial extent of trawling effort using VMS data gathered from trawlers in the North Sea. Seemens et al. (2007) and Okeeffe et al. (2007) used VMS to estimate fishing effort applied to scallop fisheries off the Tasmanian coast and in the Irish and Celtic Seas respectively.

Over this same time period other researchers were developing methods for modeling vessel fishing behavior. Dorn (2001), for example, used a hierarchical model to characterize factory trawler behavior while vessels fished for Pacific hake and Bertrand et al. (2007) made use of VMS data to characterize the foraging strategies of fishermen fishing on Peruvian anchovy. Each of these studies shows the promise that remotely sensed data coupled with sophisticated modeling techniques can have for expanding our understanding of fishing behavior as well as adding to the body information available for fisheries stock assessment and management.

This paper employs VMS data and NOAA Fisheries North Pacific Observer Program data from the United States Eastern Bering Sea to predict whether or not fishing is occurring for vessel trips with VMS data but without observer data. Because the North Pacific Observer Program database provides us with a large number of vessel trips for which we know whether or not fishing is occurring from information recorded by on-board observers, we are able to compare our predictions with the observed data to develop a reasonable and validated model and to determine how accurate our predictions can be.

Assessing the probability of fishing in any location begins with a consideration of contemporaneous observable information: speed, change in direction, and location. To achieve this goal, we utilize a variety of modeling techniques and data specifications. The chosen model can then be evaluated for interpretability, predictive success, and consistency over time. Once judged adequate the model can be used for mapping fishing effort over a region to aid management. This will be the approach we will take in this paper.

## *Methods*

### Description of Bering Sea pollock fishery

The Bering Sea pollock fishery is the largest fishery in the United States. Total Allowable Catch (TAC) was 1.5 million tons per year from 2003-2006. The fishery was rationalized by the American Fisheries Act (AFA) in 1998 and today slightly more than 100 vessels do all of the fishing in the fishery. The fishery's TAC is divided into several allocations. Community Development Quota (CDQ) groups receive 10 percent of the TAC, after which the remaining TAC is divided between the Catcher Processor (40 percent), Mothership (10%) and Inshore (50%) sectors. Most of the fishery returns to Seattle in the off-season, but the vast majority of landings in the fishery occur in the port of Dutch Harbor/Akutan on the southern edge of the Bering Sea.

Figure 1 displays Alaska including the Bering Sea. The grids in the figure are the Alaska Department of Fish and Game (ADF&G) Statistical Areas (Areas) that are a common means of summarizing spatial effort in the fishery. These areas are 1 degree in longitude by ½ degree in latitude, although they can be less regular near land.

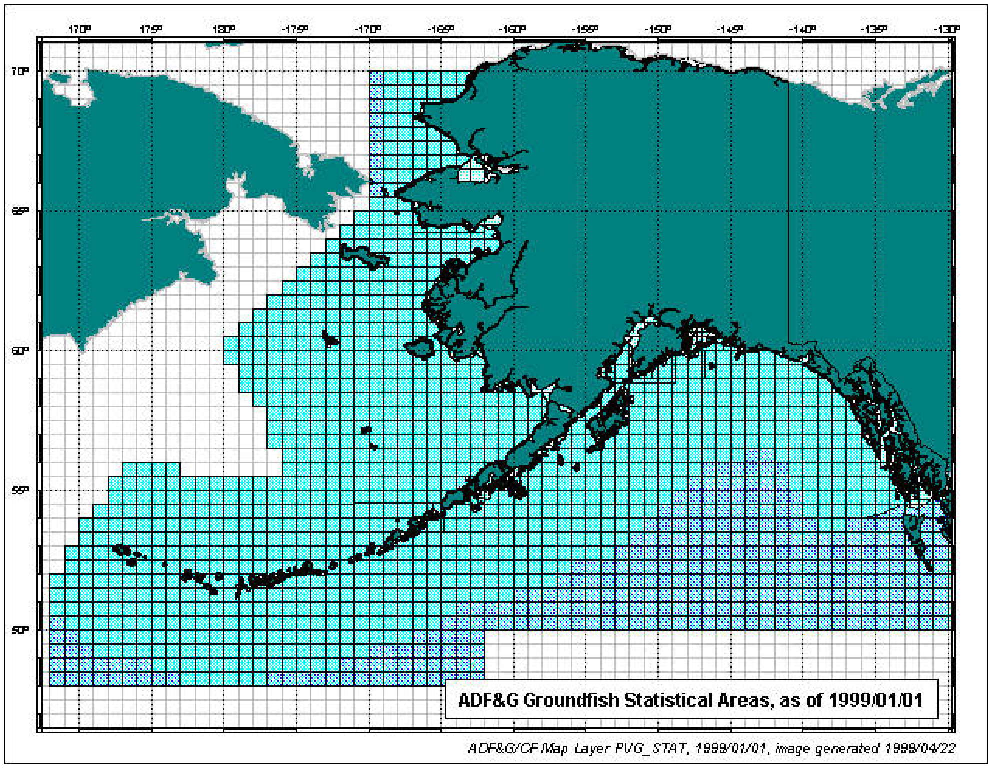


**Figure 1: ADF&G Statistical Areas in the Bering Sea and Gulf of Alaska**

## Description of VMS and Observer Program data

VMS data are available for all vessels from the directed pollock fishery in the Bering Sea since October 1, 2002. In this paper, we utilize data from all pollock trips in the Bering Sea by catcher vessels. We obtained the VMS data from the Alaska Division of NOAA Fisheries Office of Law Enforcement for the complete years 2003-2006. The data contain a vessel identifier, a time stamp, latitude, longitude, bearing, and speed. Observations from vessels are sent to NMFS Enforcement slightly more than 2 times per hour. Limiting the data to complete records for the Eastern Bering Sea resulted in the total number of vessels and total number of records shown in Table 1 providing a good sample size for model training, cross-validation and prediction.

**Table 1.** Number of vessels and number of VMS records associated with each component of the analysis for each year

| | 100% Observer Coverage | | 30% Coverage |
|---|---|---|---|
| | Training | Crossvalidation | Prediction |
| No. Vessels | 14 | 13 | 69 |
| 2003 | 36894 | 40891 | 169174 |
| 2004 | 40614 | 35182 | 145232 |
| 2005 | 49475 | 43957 | 153132 |
| 2006 | 58328 | 43345 | 159078 |

The North Pacific Observer Program at the NOAA Fisheries Alaska Fisheries Science Center places observers on vessels 60-124 feet (18-38 meters) for 30% of their days at sea while vessels 125 feet (38 meters) and larger have observers on board for 100 percent of days at sea. Vessels smaller than 60 feet do not carry observers. All of the vessels in the Bering Sea pollock fishery are larger than 60 feet, so all vessels have some observer records. The Observer Program began this wide-spread coverage in 1990 in response to concerns that the fishery may have been impacting endangered Steller sea lions. Importantly, the partial-coverage vessels choose when they are observed, so there is no guarantee that the observed trips for these vessels are representative of their total effort.

In the Bering Sea pollock fishery, more than 80 percent of all catch is observed. For the inshore sector, however, this number is much lower, with just over half of all trips being observed.

## Model Formulation

To characterize the nonlinear fluctuations in the probability of fishing as a function of vessel speed and bearing a logistic version of a generalized additive model (GAM) was employed (Hastie and Tibshirani 1990, Wood 2008):

**Equation 1**

$$\log\left\{\frac{\pi}{1-\pi}\right\} = \alpha + s(S_t) + s(S_{t-1}) + s(\Delta B_{(t-2,t+2)})$$

$$\begin{aligned} &\text{where} \\ \pi &= \text{Probability of fishing} \\ \alpha &= \text{Intercept} \\ s(S_t) &= \text{Smooth function of speed at time } t \\ s(S_{t-1}) &= \text{Smooth function of speed at time } t-1 \\ s(\Delta B_{(t-2,t+2)}) &= \text{Smooth function of change in bearing} \\ &\quad \text{over times } t-2 \text{ to } t+2 \end{aligned}$$

The smoothing functions s() represent penalized regression splines (Wood 2003, 2008). Speed is computed as the difference in location over time and bearing, in degrees, is computed as the arctangent of the change in latitude divided by the change in longitude. The change-in-bearing predictor used by the smoothing spline function is the mean of the changes in bearing taken at five time periods:

**Equation 2**

$$\Delta B_{(t-2,t+2)} = \frac{1}{5}\left(\Delta\theta_{t-2} + \Delta\theta_{t-1} + \Delta\theta_{t} + \Delta\theta_{t+1} + \Delta\theta_{t+2}\right)$$

This modeling approach was selected from a wide variety of methods and formulations estimated as part of this research process. The modeling techniques explored included classification regression trees (Breiman et al. 1984), neural network analysis (Bishop 1995), generalized additive models (Hastie and Tibshirani 1990), intensity kernel smoothers (Bowman and Azzalini 1997), and geostatistical methods (Rivoirard et al. 2000). Once the final modeling approach was settled upon model comparisons were made using analysis of deviance (Hastie and Tibshirani 1990). A number of lags for speed and change in bearing were explored under the GAM formulation in an attempt to make use of information available on adjacent VMS intervals.

The estimated percentage of effort per area $i$ is calculated by summing the GAM predicted probability of fishing for each of the VMS observations in an area and dividing this by the total probabilistic effort for all areas in a given time period $t$.

**Equation 3**

$$\%Effort_{Est} / Area = \frac{\sum \mathrm{Prob}(Fishing)_{i,t}}{\sum \mathrm{Prob}(Fishing)_{t}}$$

This estimated percentage effort is then compared to the observed percentage effort-per-area *i*, which is calculated by summing over the actual fishing activity where a value of one represents "fishing" and a zero represents "not fishing". As above, this is divided by the total number of ones (total number of observed fishing events) for all areas in a given time period *t*.

**Equation 4**

$$\%Effort_{Obs} / Area = \frac{\sum 1(Fishing)_{i,t}}{\sum 1(Fishing)_{t}}$$

In order to calculate confidence intervals for effort predictions given in Eq. 3, we used a binomial random number generator in R to generate realizations of fishing activity based on the predicted probabilities of fishing estimated from the GAM applied to the 2004 data. A zero or one was generated for each VMS location recorded in the region  The ones were then summed for each statistical area for each realization as in Eq. 4 to get different realizations of percent effort. One thousand such realizations were simulated. We then select the 2.5% and 97.5% observations from these draws to estimate the 95% confidence intervals for area predictions.

## *Results*

A number of model formulations and analyses techniques were explored before the final version of the model outlined above was settled upon. The continuous nature of the predictor functions used in the GAM and the parsimony of the model aided interpretation over the types of predictors used in classification and regression tree analysis and neural network analysis although the predictions were fairly consistent across analysis methods. Intensity kernel smoothers were adequate for spatial classification of fishing activity but made no use of the VMS information on speed and bearing and thus were found lacking as an estimation technique. Factor representations of latitude and longitude were also explored as predictor variables in the GAM, but provided little explanatory value after speed and bearing had been included. The residuals from the model fit were examined for spatial autocorrelation using variogram analysis, but no spatial correlation remained. The results of the selected model fitting are summarized in Table 2.

**Table 2.** Fitted parameters and approximate significance of smoothing functions of GAM approach (eqn. 1).

| | | | | |
|---|---|---|---|---|
| Parametric coefficient: | | | | |
| | Estimate | Std. Error | z value | Pr(>\|z\|) |
| (Intercept) | -3.17007 | 0.04147 | -76.44 | <0.0001 |
| | | | | |
| Approximate significance of smooth terms: | | | | |
| | Effective df | Chi.square | p-value | |
| $s(S_t)$ | 7.446 | 1583.9 | <0.0001 | |
| $s(S_{t-1})$ | 7.421 | 338.5 | <0.0001 | |
| s(ΔBearing) | 8.921 | 124.1 | <0.0001 | |

The shape of the resulting model can be examined for each of the years 2003-2006 by plotting model predictions of the probability of fishing for each predictor while holding the other predictors constant at their mean levels (Figures 2a,b and 3). The predictions indicate that fishing is most likely to take place at speeds of 3-4 knots and at average changes in bearing above 45$^o$. The predictions also show consistency across years.

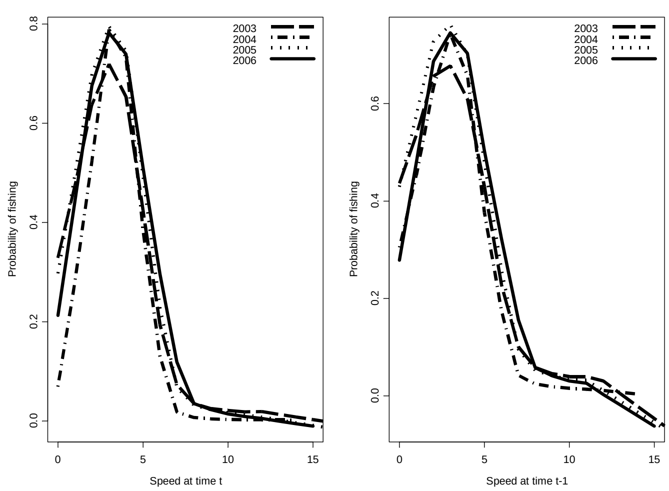

**Figure 2a.** Predicted probability of fishing given speed at time t and **2b** given speed at time t-1 while all other predictors are held constant at their mean value for 100% coverage vessels for years 2003-2006

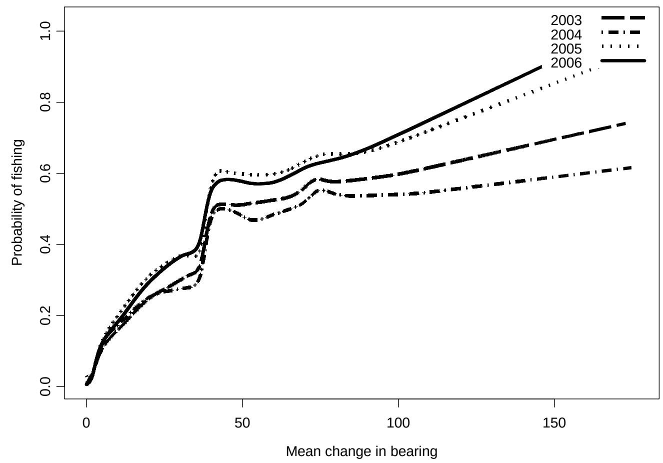


**Figure 3.** Predicted probability of fishing given mean change in bearing while all other predictors are held constant at their mean value for 100% coverage vessels for years 2003-2006.

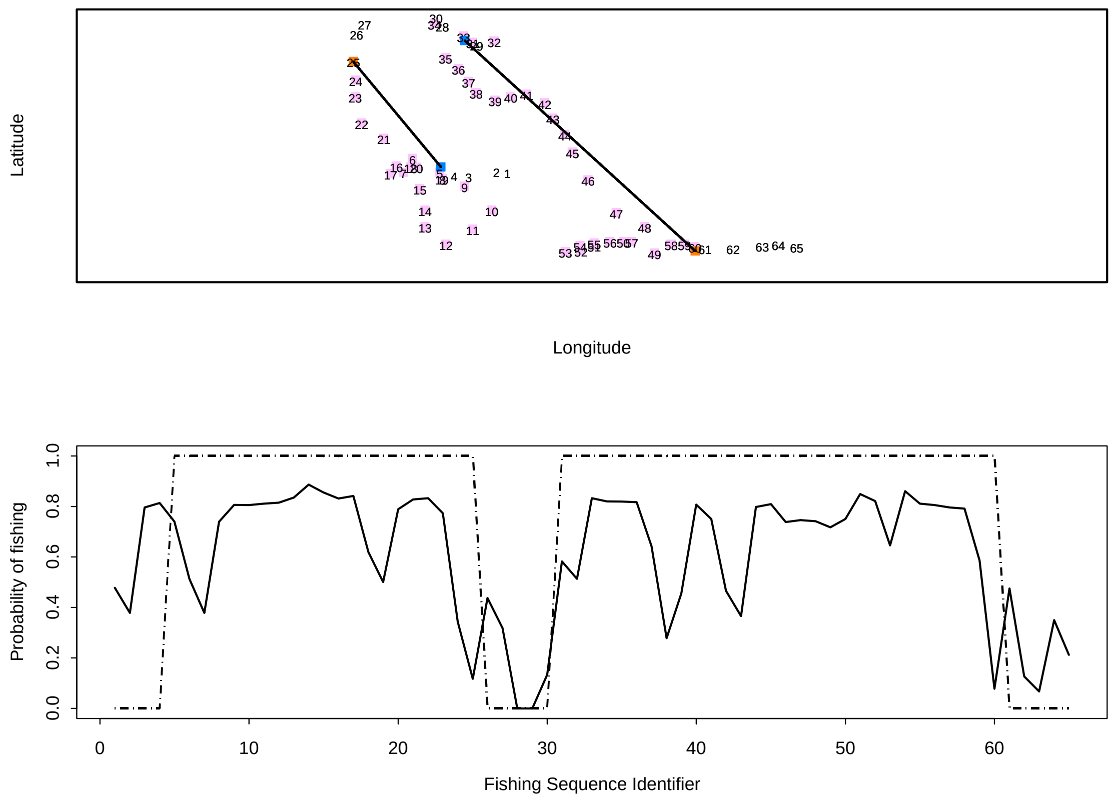


Figure 4. Sample tracks of fishing activity for a single vessel. Numbers in top figure are in time order and correspond to fishing sequence identifier provided in bottom figure. Pink squares in the top portion of the figure correspond to fishing. Segment lines connect starting (blue) and ending (orange) times.

To explore the model diagnostically one can examine the sensitivity of the prediction (sensitivity=Prob(Pred=1|Obs=1)) relative to the specificity of the prediction (specificity=Prob(Pred=0|Obs=0). Plotting sensitivity against 1-specificity creates a receiver-operator characteristic (ROC) curve that serves as a tool for judging the quality of the prediction rule. Ideally we would like to have high sensitivity with low false positives (high specificity). Figure 5 shows the cross-validated ROC curve for the 2004 VMS vessels with 100% observer coverage. The data were split with data from half the vessels used to fit the model and the other half used for validation and creation of the ROC curve shown. The 0.94 area under the curve indicates that the model performs well.

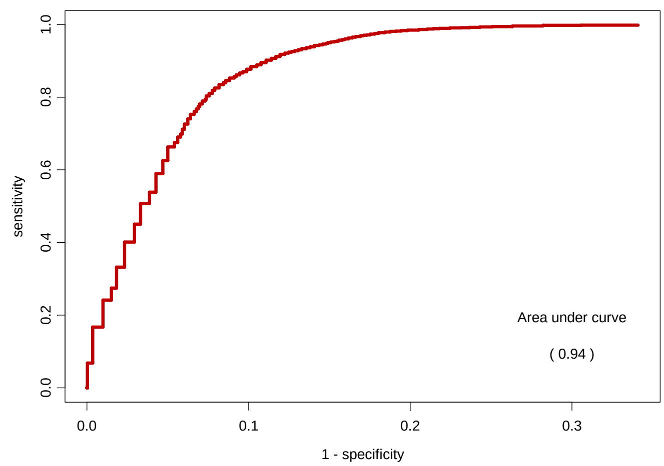


**Figure 5.** ROC plot of sensitivity (Prob(Prediction=1|Observation=1)) relative to 1 – specificity (Prob(Prediction=1|Observation=0)) for prediction given speed and change in direction for three vessel classes. The area under curve, in parenthesis, indicates poor performance if near 0.50, with better performance if near 1.00.

## Model performance

Table 3 displays the results of Equations 3 and 4 for the 100-percent coverage vessels and the 30% coverage vessels.  The first column shows the ADF&G statistical area number, followed by the number of VMS observations (Obs), the percent of predicted effort in each area (Prob%), the percentage of observed effort in the area (Obs%), and the difference between the predicted and observed percentages. This information is displayed for the 100% coverage vessels and the 30% coverage vessels.

In order to assess the effectiveness of the model, we first compare the observed fishing that occurs in each statistical area with the predicted amount of fishing for the 100-percent coverage vessels. We then calculate the difference in proportion of effort predicted from observed. If the model were error-free, assuming the observer data is completely accurate, we would expect to see observed percentages closely fit predicted percentages for the 100% coverage vessels. We see that the maximum difference in terms of fishing effort is 1.1%, with the median absolute error per statistical area (the difference over the observed) equal to 0.092. Importantly, while these are 100% coverage vessels, they are from a holdout sample so this prediction represents out-of-sample prediction, so all other things being equal we would expect to achieve a similar level of predictive accuracy with the 30%-coverage vessels.

After evaluating the error for 100% coverage vessels, we now compare the observed fishing that occurs in each statistical area for the 30% coverage vessels with the predicted amount of fishing and calculate the difference in proportion of effort predicted versus observed. Here we see that in some cases the deviation is much larger, implying that observed fishing effort is not completely representative of all fishing effort. Most dramatically, the second most frequently visited area, 645501, is predicted to have 6.5% less effort than appears in the observed trips, with 14.3% of effort predicted versus 20.8% observed. The top 3 zones, in terms of both predicted and observed effort appear to be substantially over-represented in the observed trips, with 52.3% of observed effort occurring in these areas versus 40.0% predicted. For the 100% vessels, we predict 30.4 percent of the effort to occur in these three zones and we observe 30.5 percent.

**Table 3: Comparison of observed and predicted fishing in the top 50 statistical areas for 100% and 30% vessels (2004)**

| | 100 percent Vessels | | | | 30 percent Vessels | | | |
|---|---|---|---|---|---|---|---|---|
| **AREA** | **Obs** | **Prob%** | **Obs%** | **Dif%** | **Obs** | **Prob%** | **Obs%** | **Dif%** |
| 655430 | 2511 | 16.9 | 17.9 | 0.98 | 1785 | 18.0 | 21.1 | 3.11 |
| 645501 | 1415 | 10.8 | 10.1 | 0.67 | 1761 | 14.3 | 20.8 | 6.53 |
| 645434 | 360 | 2.8 | 2.6 | 0.21 | 878 | 7.7 | 10.4 | 2.74 |
| 655500 | 778 | 5.9 | 5.5 | 0.39 | 445 | 5.1 | 5.3 | 0.21 |
| 665530 | 637 | 4.0 | 4.5 | 0.53 | 274 | 3.9 | 3.2 | 0.68 |
| 665430 | 700 | 4.9 | 5.0 | 0.04 | 359 | 3.7 | 4.2 | 0.53 |
| 675500 | 1181 | 7.3 | 8.4 | 1.15 | 347 | 3.7 | 4.1 | 0.45 |
| 675530 | 855 | 5.5 | 6.1 | 0.60 | 224 | 3.4 | 2.7 | 0.78 |
| 665600 | 206 | 1.3 | 1.5 | 0.14 | 136 | 2.5 | 1.6 | 0.94 |
| 665500 | 511 | 3.5 | 3.6 | 0.12 | 151 | 2.5 | 1.8 | 0.76 |
| 645600 | 262 | 2.1 | 1.9 | 0.24 | 208 | 2.4 | 2.5 | 0.03 |
| 755900 | 64 | 0.4 | 0.5 | 0.04 | 0 | 2.2 | 0.0 | 2.16 |
| 655409 | 1228 | 8.1 | 8.8 | 0.68 | 160 | 2.2 | 1.9 | 0.26 |
| 635530 | 64 | 0.5 | 0.5 | 0.08 | 70 | 1.6 | 0.8 | 0.81 |
| 745900 | 47 | 0.3 | 0.3 | 0.05 | 2 | 1.6 | 0.0 | 1.56 |
| 685630 | 127 | 0.9 | 0.9 | 0.02 | 52 | 1.5 | 0.6 | 0.93 |
| 675600 | 489 | 2.9 | 3.5 | 0.57 | 141 | 1.5 | 1.7 | 0.17 |
| 645530 | 293 | 2.1 | 2.1 | 0.05 | 67 | 1.4 | 0.8 | 0.56 |
| 645433 | 8 | 0.1 | 0.1 | 0.02 | 232 | 1.3 | 2.7 | 1.43 |
| 705630 | 153 | 1.2 | 1.1 | 0.11 | 39 | 1.2 | 0.5 | 0.69 |
| 705600 | 272 | 1.8 | 1.9 | 0.18 | 132 | 1.1 | 1.6 | 0.45 |
| 745830 | 0 | 0.1 | 0.0 | 0.07 | 0 | 1.0 | 0.0 | 0.99 |
| 735900 | 0 | 0.0 | 0.0 | 0.01 | 27 | 1.0 | 0.3 | 0.63 |
| 685530 | 318 | 1.9 | 2.3 | 0.38 | 205 | 0.9 | 2.4 | 1.48 |
| 745930 | 0 | 0.0 | 0.0 | 0.00 | 0 | 0.9 | 0.0 | 0.91 |
| 655600 | 249 | 1.7 | 1.8 | 0.03 | 37 | 0.9 | 0.4 | 0.45 |
| 765930 | 57 | 0.4 | 0.4 | 0.01 | 30 | 0.9 | 0.4 | 0.53 |
| 655410 | 36 | 0.3 | 0.3 | 0.04 | 56 | 0.9 | 0.7 | 0.22 |
| 675630 | 130 | 1.0 | 0.9 | 0.06 | 45 | 0.8 | 0.5 | 0.29 |
| 655530 | 151 | 1.0 | 1.1 | 0.07 | 98 | 0.8 | 1.2 | 0.38 |
| 765900 | 16 | 0.1 | 0.1 | 0.00 | 0 | 0.7 | 0.0 | 0.73 |
| 735830 | 0 | 0.0 | 0.0 | 0.01 | 0 | 0.7 | 0.0 | 0.66 |
| 635600 | 28 | 0.5 | 0.2 | 0.33 | 0 | 0.7 | 0.0 | 0.66 |
| 635504 | 81 | 0.7 | 0.6 | 0.14 | 54 | 0.6 | 0.6 | 0.02 |
| 665630 | 28 | 0.4 | 0.2 | 0.22 | 33 | 0.5 | 0.4 | 0.15 |
| 625531 | 2 | 0.1 | 0.0 | 0.05 | 18 | 0.5 | 0.2 | 0.31 |
| 635630 | 9 | 0.3 | 0.1 | 0.20 | 0 | 0.5 | 0.0 | 0.49 |
| 705701 | 49 | 0.3 | 0.3 | 0.06 | 69 | 0.5 | 0.8 | 0.33 |
| 755930 | 7 | 0.1 | 0.0 | 0.01 | 0 | 0.5 | 0.0 | 0.46 |
| 655630 | 49 | 0.3 | 0.3 | 0.03 | 48 | 0.4 | 0.6 | 0.16 |
| 695600 | 125 | 0.9 | 0.9 | 0.00 | 49 | 0.4 | 0.6 | 0.21 |
| 755830 | 43 | 0.3 | 0.3 | 0.01 | 0 | 0.4 | 0.0 | 0.35 |
| 715700 | 6 | 0.0 | 0.0 | 0.02 | 8 | 0.3 | 0.1 | 0.23 |
| 625600 | 0 | 0.0 | 0.0 | 0.01 | 0 | 0.3 | 0.0 | 0.33 |
| 645630 | 11 | 0.2 | 0.1 | 0.16 | 7 | 0.3 | 0.1 | 0.24 |
| 665401 | 2 | 0.7 | 0.0 | 0.68 | 11 | 0.3 | 0.1 | 0.15 |
| 685600 | 92 | 0.7 | 0.7 | 0.07 | 39 | 0.3 | 0.5 | 0.21 |
| 675430 | 119 | 0.9 | 0.8 | 0.05 | 7 | 0.3 | 0.1 | 0.17 |
| 695631 | 29 | 0.2 | 0.2 | 0.03 | 19 | 0.1 | 0.2 | 0.08 |
| 625630 | 0 | 0.3 | 0.0 | 0.31 | 0 | 0.1 | 0.0 | 0.12 |

Figure 6 displays the difference by statistical area of the percentage fishing per area between the predicted and observed values for partial coverage vessels for 2004.

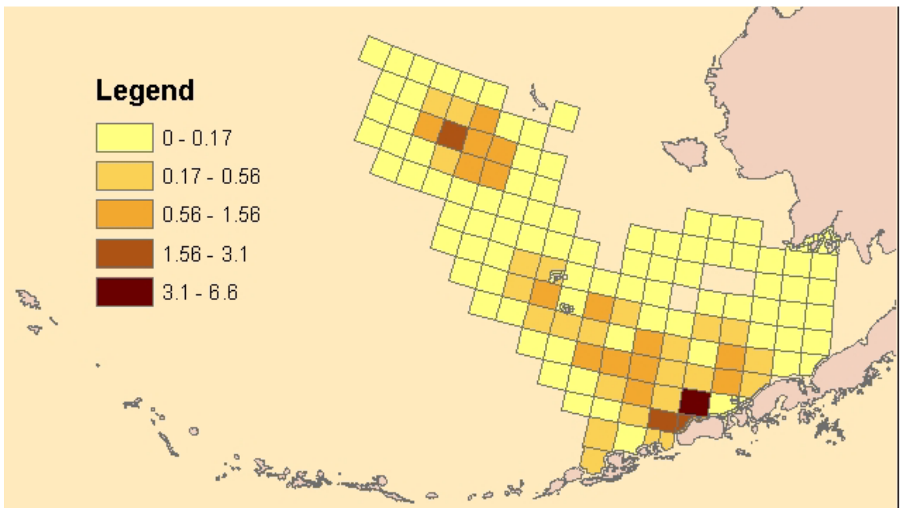


**Figure 6: Differnce in Percent of Total Effort between Observed and Predicted for Partial Coverage Vessels by ADF&G Statistical Area, 2004**

## ***Discussion***

This paper illustrates how VMS data can be used to estimate where fishing occurs for unobserved trips in the Bering Sea pollock fishery.  We consider a number of different model specifications and find that lagged functions of speed and bearing work well within a logistic GAM to predict fishing activity. The model was not improved by controlling for spatial correlation in effort after smooth functions of speed, lagged-speed, and mean change in bearing were included.  The predictions here indicate that using the observed trips for the partial coverage vessels is not completely representative of their overall fishing activity, with some of the most frequently fished zones being substantially over-reported in the observer data.

The measure of variability in percent effort per area is conditioned on the location, speed, and bearing being known, but seems to be an adequate representation of the uncertainty in the area effort predictions. The binomial simulations do not take into account uncertainty in the estimation of the probability of fishing at each location, but the large sample sizes resulted in very tight errors on the mean prediction levels so that ignoring that error was not seen as serious.

We have found that with a relatively high probability, repeated changes in speed and bearing lasting for 2-5 VMS time stamps imply that fishing is occurring. It is a rare event in this fishery where vessels slow down and change direction several times over 1-2 hours when they are not fishing. However, this may occur randomly at times, which would cause us to predict fishing when it is not occurring. A much more likely source of variance between predicted and observed behavior for 100% coverage vessels is that the VMS time-stamps are random in relation to when fishing starts, so fishing behavior may or may not always be captured at the start or the end of a haul.

Why does observed and predicted effort differ so significantly for 30 percent coverage vessels? There may be several explanations for this. First, it may be the result of vessels having observers on board for the most accessible trips that occur at certain times of year.

Because the requirement for observer coverage is for “days at sea” an over-night trip gives credit for 2 days.  Thus the apparent bias may be due to the response to observer regulations.  Alternatively, vessels may choose to avoid being observed for trips to high-salmon bycatch areas.  Salmon bycatch has been a significant problem in this fishery during the years covered by this analysis.  However, it should be noted that bycatch is attributed to the fleet based on the areas where the vessels report fishing based on 3-week moving averages, so the ability of fishers to successfully lower recorded bycatch through the observer process is less straightforward than simply avoiding being observed in high-bycatch periods.

We chose to conduct this research on the Bering Sea pollock fishery because of its high level of observer coverage, but more important gains in understanding of fisheries are likely to be had in applying this methodology to fisheries with lower observer coverage. The effectiveness of this method – using changes in speed in bearing to determine fishing – may vary across different gear types.  Future research will investigate predictive accuracy in cod fisheries that use longline, pot, and pelagic trawl gear and in flatfish fisheries that use bottom trawl gear.

The effectiveness of this type of methodology combined with the wide-spread distribution of VMS technology provides new opportunities for fisheries managers to understand the fisheries that they manage and how they respond to regulation, changing fish stock and environmental conditions.  The cost of the technology continues to decline so that it may become economically feasible even for artisanal fisheries in developing countries to employ. Significant fisheries management problems, such as illegal, unreported, and unregulated (IUU) fishing, ghost gear, and marine reserve violations can all be greatly minimized with this technology.

The method developed in this paper was necessary in the case of unobserved trips because the VMS technology itself does not monitor gear deployment. Affordable technology is now available that allows direct monitoring of whether or not gear is deployed. There seems little reason not to implement this type of monitoring, but in instances like the Bering Sea where this technology is not in place but we have VMS records for past fishing activity, the method developed in this paper provides the ability to predict fishing effort with considerable precision for most applications.

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## *References*


Bertrand, S., Bertrand, A., Guevara-Carrasco, R., Gerlotto, F. 2007. Scale-invariant movements of fishermen: the same foraging strategy as natural predators. Ecological Applications, 17(2):331-337.

Bishop, C. M. 1995. Neural Networks for Pattern Recognition. Oxford University Press.

Breiman, L., J. H. Friedman, R. A. Olshen, and C. J. Stone. 1984. Classification and Regression Trees. Wadsworth International Group, Belmont, California.

Bowman, A. W., and A. Azzalini. 1997. Applied Smoothing Techniques for Data Analysis: The Kernal Approach with S-Plus Illustrations. Oxford University Press.

Deng, R..,Dichmont, C., Milton, D., Haywood, M., Vance, D., Hall, N., Die, David. 2005. “Can vessel monitoring system data also be used to study trawling intensity and population depletion? The example of Australia's northern prawn fishery,” *Canadian Journal of Fisheries and Aquatic Sciences*, 62(3): 611-622.

Dorn, M. W. 2001. Fishing behavior of factory trawlers: a hierarchical model of information processing and decision-making. ICES Journal of Marine Science **58**:238–252.

Hastie, T. J., and R. J. Tibshirani. 1990. Generalized Additive Models. Chapman and Hall, New York.

Mills et al.  2006. “Estimating high resolution trawl fishing effort from satellite-based vessel monitoring system data,” ICES Journal of Marine Science Advance Access published December 14, 2006.

Murawski, S. A., Wigley, S. E., Fogarty, M. J., Rago, P. J., and Mountain, D. G. 2005. Effort distribution and catch patterns adjacent to temperate MPAs. ICES Journal of Marine Science, 62: 1150–1167.

Okeeffe, E; Hervas, A; Tully, O; Hickey, J; Sutton, G; Berry, A; Hartnett, M; Monteys, X. 2007**.** Utilization of geographic information systems in scallop stock assessment. Journal of Shellfish Research 26(4):1329-1330.

Rijnsdorp, A.D., Buys, A.M., Storbeck, F., and Visser, E.G. 1998. Micro-scale distribution of beam trawl effort in the southern North Sea between 1993 and 1996 in relation to the trawling frequency on the sea bed and the impact on benthic organisms. ICES J. Mar. Sci. **55**: 403–419.

Rijnsdorp, A.D., Piet, G.J., Poos, J.J. 2001. Effort allocation of the Dutch beam trawl fleet in response to a temporarily closed area in the North Sea, ICES Document CM 2001/N: 01. 17 pp.

Rivoirard, J., Simmonds, J., Foote, K.G., Fernandes, P., and Bez, N. 2000. Geostatistics for Estimating Fish Abundance. Blackwell Science, London, U.K.

Semmens, J M; Harrington, J J; Haddon, M 2007. Assessing the spatial distribution of scallop dredge fishing and the use of industry conducted surveys as the data collection method in the Tasmanian commerical scallop, Pecten fumatus, fishery, Australia. Journal of Shellfish Research, 26(4):1344.

Wood, S.N. 2003. Thin plate regression splines. J.R.Statist.Soc.B 65(1):95-114

Wood, S.N. 2008. Fast stable direct fitting and smoothness selection for generalized additive models. J.R.Statist.Soc.B 70(3):495-518