SEFSC
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Rock Shrimp

Case study of Gulf ~~reef fish~~ VMS data inputted into the Gulf shrimp effort algorithm for illustration of compatibility

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Commercial reef fish (vertical line) effort from VMS

A common approach to identifying effort involves marking pings as either 'fishing' or 'not fishing' whenever an onboard observer has recorded, respectively, that gears were or were not deployed at that moment in time.

This point-labelling method works well with long-set fisheries such as <u>pelagic longline or otter trawl </u>where multiple pings are usually transmitted during each set.

However, for short-set fisheries such as bandit reel, point labelling can reduce classifier performance because vessels are usually engaged in 'fishing behaviour' for a period before and after the gear is deployed.

Hence, it is more complicated to identify fishing effort for bandit gear

Table 2. Ranked importance of predictor variables in constructing each forest.

Point-labelled random forest		Window-labelled random forest	
Features	**Mean decrease in Gini index**	**Features**	**Mean decrease in Gini index**
Hour of day*	2013	Velocity mean*	3381
Velocity mean*	1899	Hour of day*	3282
Depth*	1746	Depth*	3031
Velocity prior	1534	Leg distance prior*	2487
Leg distance prior	1450	Velocity prior*	2442
Velocity post	1346	Velocity post	1964
Turn angle	1052	Turn angle	1162
Heading	997	Heading	989

Variables that contributed significantly to each forest are indicated with an asterisk.

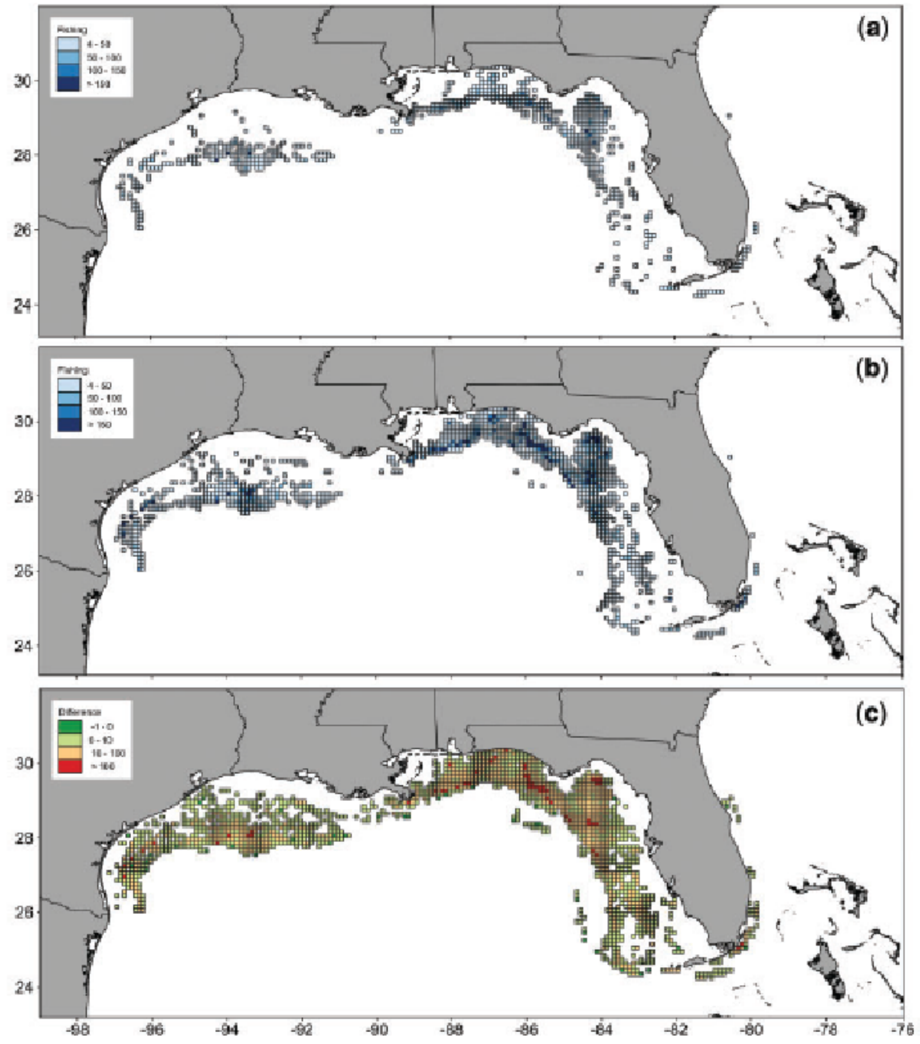

Figure 5. (a and b) Extent and intensity maps of US Gulf of Mexico bandit-reel fishing produced by training a random forest classifier to identify fishing behaviour in VMS data using two methods, point labelling (a) and window labelling (b). Shading shows the count of VMS pings classified as fishing behaviour in each 0.1° grid cell. (c) This shows the difference between the methods in the number of VMS pings identified as fishing behaviour in each cell.

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Original Article

Improving detection of short-duration fishing behaviour in vessel tracks by feature engineering of training data

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Big data, such as vessel monitoring system (VMS) data, can provide valuable information on fishing behaviours. However, conventional methods of detecting behaviours in movement data are challenged when behaviours are briefer than signal resolution. We investigate options for improving detection accuracy for short-set fisheries using 581 648 position records from 181 vessels in the Gulf of Mexico bandit-reel fishery. We first investigate the effects of increasing VMS temporal resolution and find that detection accuracy improves with fishing-set duration. We then assess whether a *feature engineering* approach—in our case, changing the way pings are labelled when training a classifier—could improve detection accuracy. From a dataset of 12 184 observed sets, we find that the conventional point-labelling method results in only 49% of pings being correctly labelled as 'fishing', whereas a novel window-labelling method results in 88% of records being labelled as 'fishing'. When the labelled data are used to train classifiers, point labelling attains true-positive/balanced-accuracy rates of only 37%/66%, whereas window labelling achieves 68%/83%. Finally, we map fishing distribution using the two methods, and show that point labelling underestimates the extent of fishing grounds by ~33%, highlighting the benefits of window labelling in particular, and feature engineering approaches in general.

The simple shrimp algorithm that uses the point labeling method works great for shrimp but would not work well for reef fish (bandit gear)

Hence, as we have better methods, we did not apply the shrimp algorithms

NOAA FISHERIES

We evaluated VMS data from one rock shrimp vessel

LAT	LON	MM	DD	YY	HH	MI	SS	TIME
[redacted]		1	1	11	0	36	0	2011.01.01 00:36
		1	1	11	1	36	0	2011.01.01 01:36
		1	1	11	2	36	0	2011.01.01 02:36
		1	1	11	3	36	0	2011.01.01 03:36
		1	1	11	4	36	0	2011.01.01 04:36
		1	1	11	5	36	0	2011.01.01 05:36
		1	1	11	6	36	0	2011.01.01 06:36
		1	1	11	7	36	0	2011.01.01 07:36
		1	1	11	8	36	0	2011.01.01 08:36
		1	1	11	9	36	0	2011.01.01 09:36
		1	1	11	10	36	0	2011.01.01 10:36
		1	1	11	11	36	0	2011.01.01 11:36
		1	1	11	12	34	0	2011.01.01 12:34
		1	1	11	13	34	0	2011.01.01 13:34
		1	1	11	14	34	0	2011.01.01 14:34
		1	1	11	15	34	0	2011.01.01 15:34
		1	1	11	16	34	0	2011.01.01 16:34

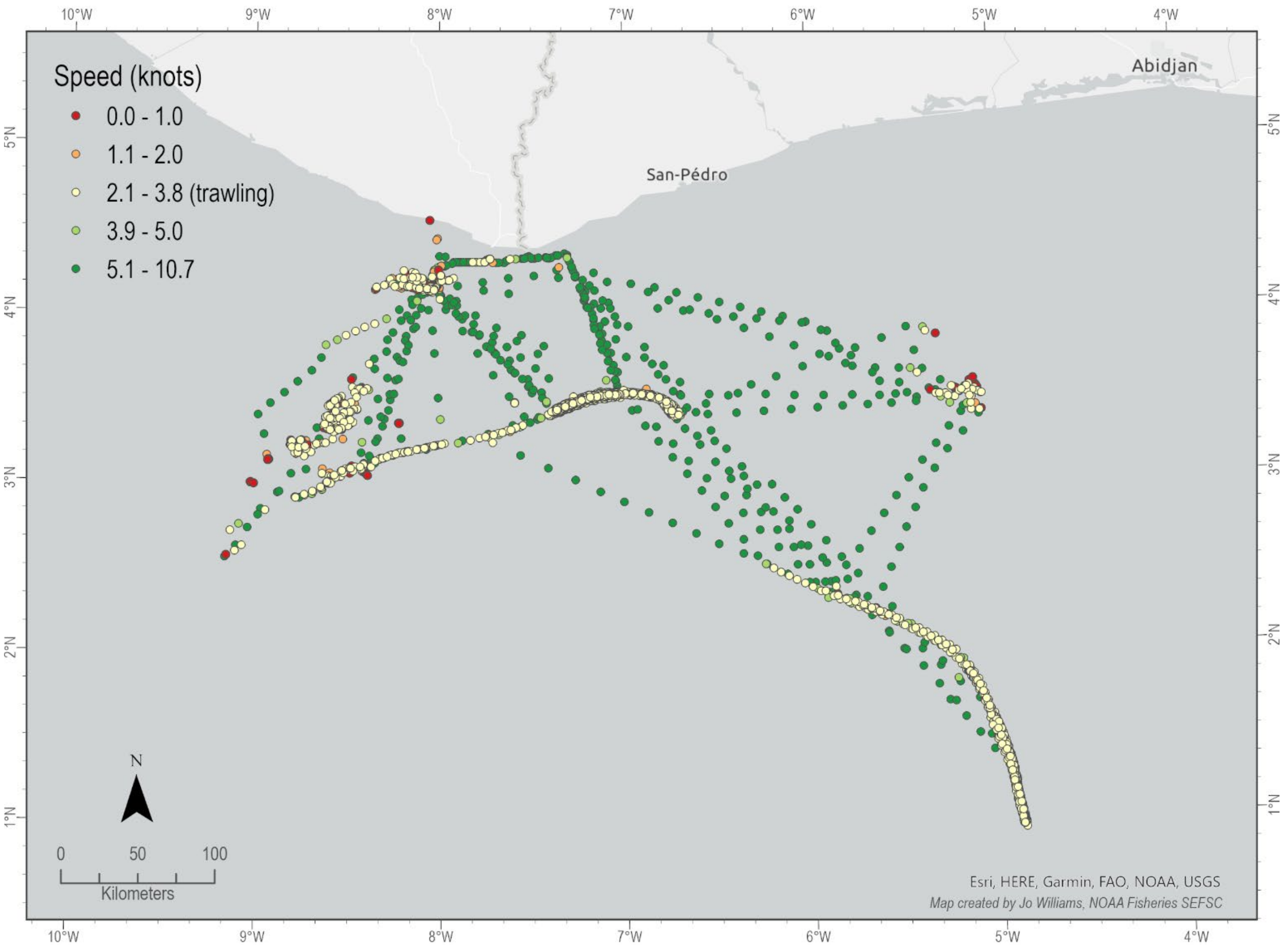
The basic VMS data is very similar to the eLB data

The downloaded VMS data we tested was at 1 hour resolution

We did not run it through the eLB algorithm but it would be rather simple to do so if we had 10 minute resolution

NOAA FISHERIES

One ‘test’ rock shrimp vessel in a disguised location



Note altered spatial location (e.g. we do not have any shrimp fishing in Liberia, but we’ve scrambled it to avoid confidentiality concerns).

The key here is that we can used the inferred speed to identify trawling vs steaming

Conclusions

It will be straightforward to use VMS data (provided it is collected at 10 minute intervals) to run through the shrimp ELB algorithm to estimate effort

Also possible to link to trip ticket landings, in same manner as the eLB program