An automated approach to the detection and classification of fin whales in the California Current Ecosystem using open source software

Cory Ann Hom-Weaver[1], Taiki Sakai[1], Shannon Rankin[2]

1 Contractor with Environmental Assessment Services, LLC. in support of Southwest Fisheries Science Center (MMTD), NMFS/NOAA

2 Southwest Fisheries Science Center (MMTD), NMFS/NOAA

INTRO

- There is a current lack of knowledge of fin whale population structure and movement patterns in the eastern North Pacific.
- Use of passive acoustic methods have been suggested as a solution to help fill this gap.
- ***Goal: Develop an open-source approach to automatically detect and classify fin whales in short (2-minute) duty cycled data.***

METHODS

- 2-minute duty cycled recordings from autonomous drifting recorders.
- Drifts from 13 different locations in California Current Ecosystem (CCE).
- PAMGuard click detector used to detect 20Hz fin pulses.
- PAMpal (R package) used to create acoustic events and process data.
- BANTER (a hierarchical random forest acoustic event classifier) developed using validated data [1, 2].

RESULTS

- BANTER model correctly classified 80% of the fin whale events and 78% of non-fin whale events.
- Probability of assignment to inter-note-interval (INI) for the click detector was the most important predictor.
- Mode of INI (All_INI) for an event was ranked least important predictor.

LIMITATIONS

- We know INI is important in identifying fin whale song (previous studies).
- Our INI measurements were limited by 2-minute duty cycled recordings.

CONCLUSION

- This open source approach to automatically detecting and classifying fin whales is effective.
- We expect increased sample size of training data and increased duty cycle (>2-min) will improve accuracy.

BANTER correctly **classified 80% of fin whale events** in 2-minute duty cycled data.

Table 1. Confusion matrix for fin whale acoustic event model. Classification scores are shown as percent correct with 95% confidence intervals in parentheses.

	Fin Whale	Not Fin Whale	Correct (%)
Fin Whale	273	63	80.00 (73.94, 83.46)
Not Fin Whale	61	219	78.21 (72.91, 82.91)
Overall	--	--	78.62 (75.05, 81.89)

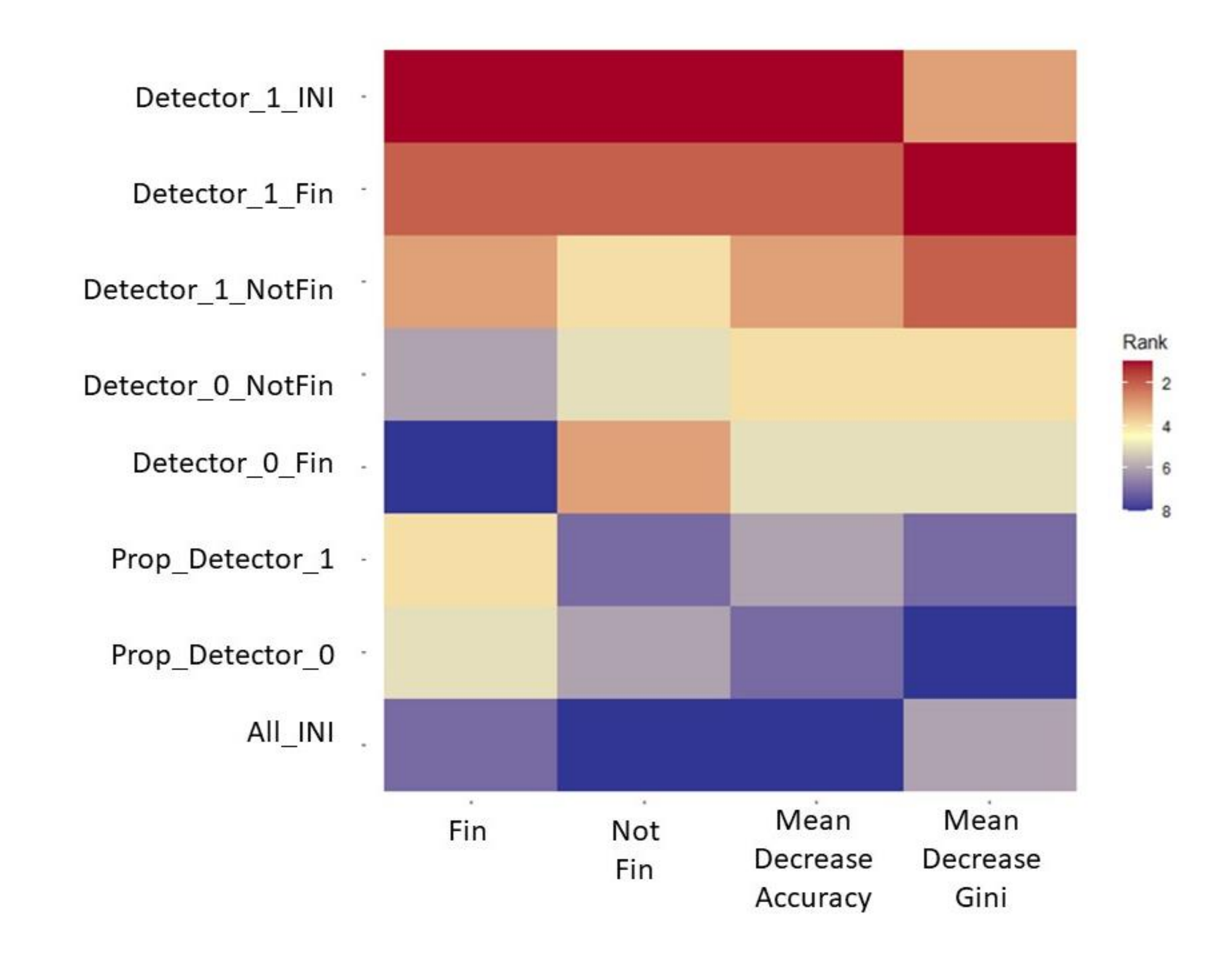

Figure 1. Rank of variable importance for BANTER classification model. Colors scale from most important (dark red) to least important (dark blue)

Increased duty cycle (>6 min) and increased sample size of training data will likely improve classification rates

Take a picture to learn more about BANTER

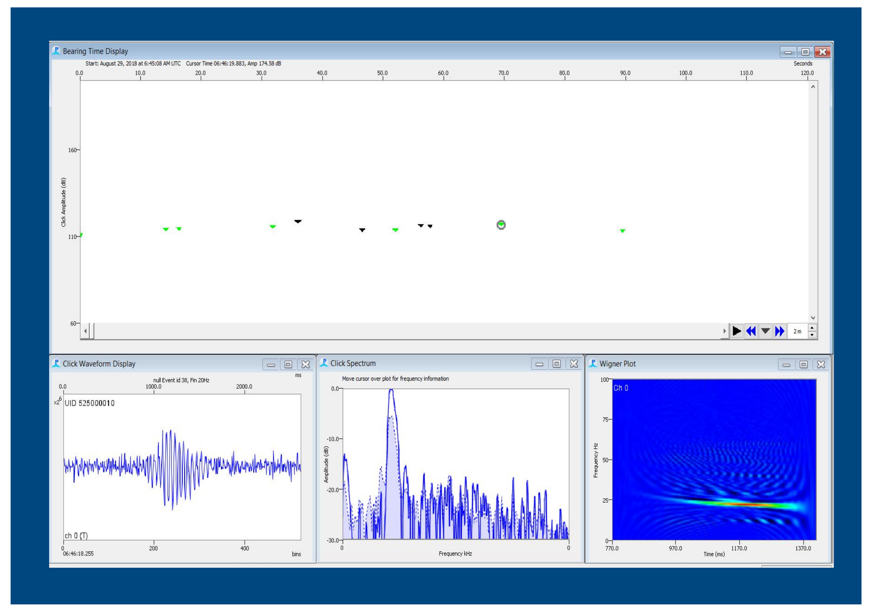

Figure 2. Click detector module in PAMGuard software. Upper window: Bearing vs. Time display. Lower windows: waveform of click, click spectrum and wigner plot (from left to right respectively).

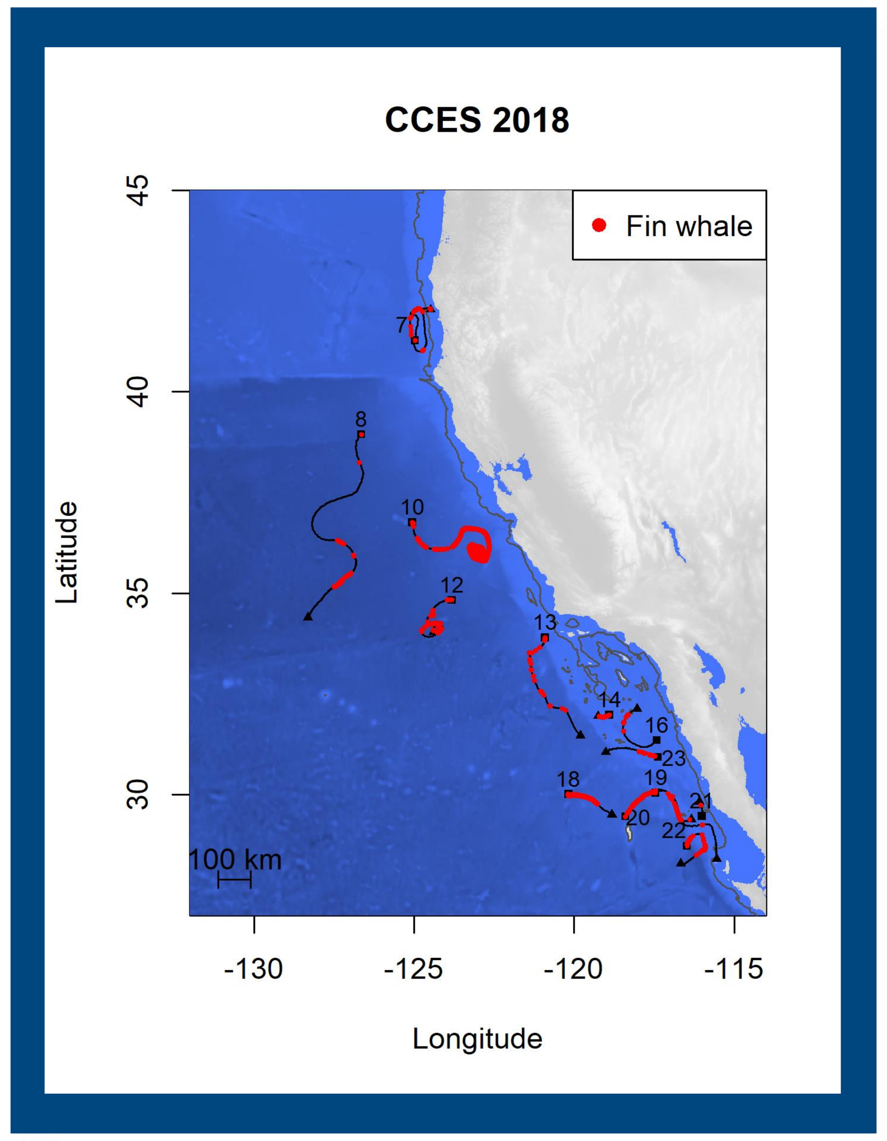

Figure 3. Acoustic detections of fin whales (red dots) along drifts in the CCES 2018 survey. Black square and triangles show drift deployment and recovery, respectively.

References Cited

[1]Archer, E. 2020. *Estimate permutation p-values for random forest importance metrics*, R package version 2.5, https://github.com/ EricArcher/rfPermute

[2]Rankin et al. 2017. https://doi.org/10.1111/mms.12381

Acknowledgments

I would like to thank Doug Gillespie and Madalina Matei at the University of St Andrews for sharing the click detector settings for the 20Hz fin whale pulses in PAMGuard. I would also like to thank Anne Simonis for creating the map used on this poster. This study was funded in part by the U.S. Department of the Interior, Bureau of Ocean Energy Management through Interagency Agreement M20PG00013 with the U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Marine Fisheries Service (NMFS), Southwest Fisheries Science Center (SWFSC)

BOEM Bureau of Ocean Energy Management