Article title should be less than 15 words, no acronyms

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1. Introduction and first-level headings

Understanding and reporting ambient noise levels is a crucial part of all passive acoustic studies. Ambient noise levels can influence local marine life, sometimes adversely, and introduce bias into density, abundance, or occupancy estimates (Oedekoven et al. 2022, Palmer et al. 2022). Within the context of BOEMs wind energy areas (WEA), there is a concerted effort to understand whether and how ambient noise levels change between the baseline, construction, and operational phases of offshore wind farms and how this may affect different. These baseline data are critical to monitor changes in sound levels from anthropogenic sources in space and time as activities related to offshore wind development commence (Gabriel et al. 2018).

In creating sound level metrics, it is important to consider that levels vary as a function of three-dimensional location as well as time (Choelwiak et. al 2018). As the goal of many bioacoustics studies is to measure soundscape changes as they relate to species of interest, it is important to measure sound levels within the habitat they utilize or estimate it based on local measurements. For example, in deepwater environment measurements obtained from bottom mounted hydrophones my be representative of the foraging habitat of deep living, or diving, species but may not be representative of surface dwelling. Similarly, measurements from coastal locations are unlikely representative of offshore locations. While considerable efforts have been made to create spatial noise maps, they are often based on simulated sound sources (cite some of JASCO’s work and or that coming out of Arhus). While these approaches are hugely valuable, there is also a need to estimate or validate the spatial extent of noise by asking to what extent noise metrics in one location are representative levels in non-measured locations when sound source levels and positions are unknown.

In this preliminary work we lay out one approach for addressing these questions using a selection of data from the ADRIFT project. The ADRIFT project uses clusters of drifting buoys to produce snapshots of ambient noise levels and animal presence in wind energy areas. These short-term deployments are intended complement existing longitudinal studies from nearby seafloor hydrophones (cite sanct sound something from scripts). In this work we use correlation and Kriging and methods to document spatial variability in soundscapes and lay the groundwork for better understanding how well single sensors represent sound within the greater region.

* Understanding noise levels is challenging even with advanced technology and multiple instruments
* Noise varies in three spatial coordinates, time and frequency
* Received levels are defined by physics and propagation models but these models are difficult and costly to validate in the field
* Multiple drifting sensors provide an opportunity to investigate spatial and temporal variation at a relatively low cost.

1. Methods
   1. Data Collection and Processing

The ADRIFT project seeks to characterize soundscapes and habitat use around an wind lease area approximately 40km from Morro Bay, California, USA. Audio data were collected using custom drifting buoy (henceforth drifter) with attached SoundTrap ST640s and HTI microphones. Each drifter consisted of a surface suppression including a pole buoy with attached GPS unit which transmitted GPS coordinates ever 20 min, and a 0.5 m surface float.

Soundtrap ST640 attached to

Audio data were downloaded and decompressed after recovery. End-to-end calibration value was estimated as the sum of the soundtrap calibration value and the HTI hydrophone calibration values, both provided by the manufacturer(???).

Soundscape metrics were calculated using Triton Software (cite xxx), audio data were first decimated to 48 kHz and then long-term spectral averages (LTSAs) were calculated with 1 sec and 1 Hz resolution. From these LTSAs, several metrics including broadband and third octave band calculations were made. For the purpose of this analysis, median third octave levels per two-minute bin were used. Only levels from the lowest and highest third octave bands (cetner frequencies, XXX and YYY) were included to show contrast between the two frequency bands.

Polynomial interpolation was used to estimate the GPS receiver position for each 2-minute periods between subsequent pings. In doing so each noise level record was associated with a location

* 1. Spatial and Temporal Autocorrelation

As a preliminary analysis, spatial cohesion of ambient noise levels was investigated across the 7-drifter ensamble. Correlograms were used to measure similarity in trend in ambient noise levels between all seven instruments. Noise level correlation should be higher between more closely spaced instruments, lower frequencies (with less transmission loss), and in when the background noise comes from diffuse sources such as storm systems or distant shipping. Accordingly, lower correlation values are expected with widely spaced instruments and or/with local phenomena. The degree of the correlation in itself is valuable information as it indicates what proportion of the background noise is influenced by regional scale phenomena.

Noise levels recorded by the drifters are naturally correlated in space and time so care must be taken in the analysis in order to conflate these effects. This can be achieved in a variety of ways including using variograms to fit spatial/temporal models (CITE Fields, MRSEA) and or with spatial-temporal covariance structures (CITE gstat), each with their cost and benefits. However, teasing apart the spatial and temporal constrains in such a model typically involves multiple measurements at a fixed location which is not present in these data.

Instead, we evaluate the data from two perspectives, first we look at the temporal correlation in order to better understand how similar noise levels are between the units, as described above. We also use variograms with the raw to investigate the range at which we do no expect any correlation between units. The noise level data are then de-trended by subtracting the 60 min rolling median noise level across all instruments from each noise level observation. This removes the effects of large-scale phenomena and allow for a closer evaluation of regional and ephemeral sources of ambient noise. Kriging methods are then used with the variogram-derived range parameter to create a map of the variation in ambient noise levels across the hydrophone ensemble.

* 1. Spatial Variation in Ambient Noise Levels

Following normalization, the MRSEA package in r (Scott-Hayward et al, 2014) was used to investigate spatial variation in noise levels during the snapshot period. The approach couples spatially adaptive local smoothing algorithms (Walker et al 2010) with generalized estimating equations in order account for spatial and temporal autocorrelation associated with track lines.

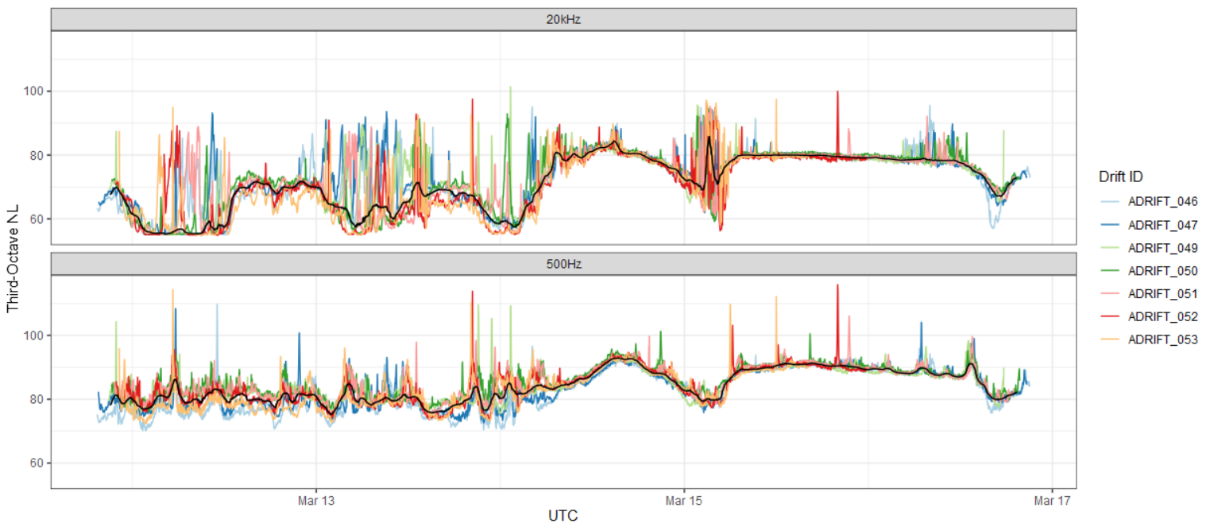
. Different covariance structures were investigated with a subset of the total dataset through the use of variograms. Through this process the Matern covariance structure was selected. This was then fit to the full, 2 minute dataset using the micro-Krig process which is optimized for large datasets which uses Monte Carlo simulations to estimate the compute the trace of the smoothing matrix in the case of large datasets.

The model summary is reported as well as the predictive power of the method through k-fold cross validation in which one drifter is held out, the model is recreated with the remaining drifts and the predications are compared to the observations at the held-out model.

1. Results
   1. Data Collection and Processing

All seven drifters were deployed on March 11th, 2023 in the Morro Bay WLA and recovered by the 16th of March. All drifters transited south with the prevailing currents and six of the seven drifters stayed roughly clumped together. The drifter nearest shore, ADRIFT\_53, travelled further and faster than the remaining units. Median speed across all drifters was 0.15 m/s with a standard deviation of ±0.08 m/s. The distance travelled from deployment to recovery, ranged from 40.6 km to 66.8 km. The total distance travelled by each instrument throughout the deployment ranged from 61.9 km to 77.3 km for ADRIFT\_53.

Figure 1 500 Hz and 20 kHz 1/3rd octave band timeseries of noise levels measured by ADRIFT. Black line indicates the 60-min rolling average noise level.



* 1. Spatial Cohesion

Figure 1shows the 2-minute median noise level in two third octave bins during an 8-day drift near the Morro Bay WEA. Increase in noise levels from two storms are march 14th and 15th that raised baseline noise levels approximately 10 and 20dB re 1µ Pa for the lower and upper third octave band respectively.

Correlations in raw noise levels between instruments were also high ranging from 0.64 to 0.83 in the 20 kHz band and 0.70 to 0.91 in the 500 Hz band (Figure). After normalization, these values were decreased to -0.16 to 0.46 in the 20 kHz band and -0.24-0.52 in the 500 Hz band.

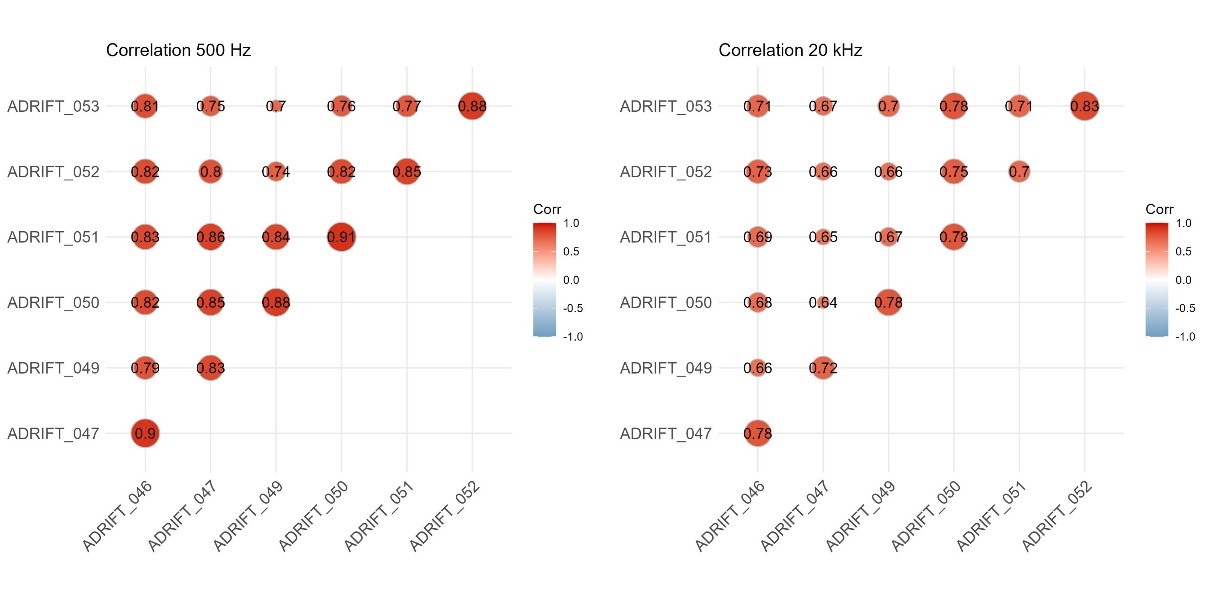


Figure 2 Raw collation scores between drifter data in the 500 hz (left) and 20 kHz (right) third-octave bins.

* 1. Spatial Cohesion

Model fitting resulted

4 Discussion

* Shown an approach for spatializing noise
* When used alone, can provide insights into
  + Propagation conditons
  + Spatial soundscape
* Can be combined with other analyses
  + Validate propagation models
  + Combine with windspeed to discriminate between environmental and anthropogenic inputs to the soundscape
  + Include spatialized noise levels in a predictor for habitat use for acoustically sentitive species

1. Conclusion

And in conclusion…

Supplementary Material

Acknowledgments

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The whale watch crew

Author Declarations

Conflict of Interest

A conflict-of-interest statement is required. If there are no conflicts to report, the authors must state that they have no conflicts to disclose.

Ethics Approval

Data Availability

A data availability statement is required. For the *Journal'*s data policy and suggested templates, please see the Information for Contributors: <https://pubs.aip.org/asa/jel/pages/manuscript>.

References and Links (BIBLIOGRAPHIC STYLE)

Cholewiak, D., C. W. Clark, D. Ponirakis, A. Frankel, L. T. Hatch, D. Risch, J. E. Stanistreet, M. Thompson, E. Vu, and S. M. Van Parijs (2018). Communicating amidst the noise: Modeling the aggregate influence of ambient and vessel noise on baleen whale communication space in a national marine sanctuary. Endangered Species Research 36:59–75.

Gabriele, C. M., D. W. Ponirakis, C. W. Clark, J. N. Womble, and P. Vanselow (2018). Underwater acoustic ecology metrics in an Alaska marine protected area reveal marine mammal communication masking and management alternatives. Frontiers in Marine Science 5:270.

Oedekoven, Cornelia S., Tiago A. Marques, Danielle Harris, Len Thomas, Aaron M. Thode, Susanna B. Blackwell, Alexander S. Conrad, and Katherine H. Kim. "A comparison of three methods for estimating call densities of migrating bowhead whales using passive acoustic monitoring."Environmental and Ecological Statistics 29, no. 1 (2022): 101-125. https://doi.org/10.1007/s10651-021-00506-3

K. J. Palmer, Gi-Mick Wu, Christopher Clark, Holger Klinck; Accounting for the Lombard effect in estimating the probability of detection in passive acoustic surveys: Applications for single sensor mitigation and monitoring. J. Acoust. Soc. Am. 1 January 2022; 151 (1): 67–79. <https://doi.org/10.1121/10.0009168>

Scott-Hayward, L.A.S., Mackenzie, M.L., Oedekoven, C.S. and Walker, C.G., 2014. Modelling impact assessment in renewables development areas using the new R package, MRSea v0. 1.1. Proc. EIMR, pp.2014-596.

Walker, C.G., Mackenzie, M.L., Donovan, C.R. and O'sullivan, M.J., 2011. SALSA–a spatially adaptive local smoothing algorithm. Journal of Statistical Computation and Simulation, 81(2), pp.179-191.

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