Article title should be less than 15 words, no acronyms

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1　Understanding the spatial and temporal extent and context of sound levels is of

2　increasing interest in the bioacoustics field. Spatial analysis of ambient noise is

3　usually done using costly large scale arrays or through a combination of single

4　sensors and propagation models. This work presents a method for mapping sound

5　variation in environmental sound level using drifting hydrophones within the MRSea

6　framework. This method is well suited for low frequency analysis relative to the

7　ensemble aperture. We present the findings and limitations of this work and propose

8　analysis and deployment modifications to meet a variety of needs.

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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 the Bureau of Ocean Energy Management's (BOEM) 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, ZoBell et al 2024). 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 deep-water environment measurements obtained from bottom mounted hydrophones may be representative of the foraging habitat of deep diving, species but may not be representative of the habitat occupied by mesopelagic or epipelagic species. Similarly, measurements from coastal locations are only somewhat representative of offshore locations. While considerable efforts have been made to create spatial noise maps (Pirotta et al. 2014, ZoBell et al 2024,), they are often based on simulated sound sources (cite some of JASCO's work and or that

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34   coming out of Arhus). While these approaches are hugely valuable, there is also a

35   need to estimate or validate the spatial extent of noise by asking to what extent noise

36   metrics in one location are representative levels in non-measured locations when

37   sound source levels and positions are unknown.

38   This work showcases a method for tackling these questions through short-

39   term ensembles of drifting acoustic recorders. These cost-effective devices,

40   compared to bottom-moored instruments, ~~and~~ with their brief deployments,

41   complement ongoing longitudinal studies using nearby seafloor hydrophones (cite

42   sanct sound something from scripts). They serve as a platform for assessing acoustic

43   activity in the epipelagic zone where many of the animals of research concern reside.

44   These deployments also provide an opportunity for validation of acoustic models of

45   vessel activity, which has become an~~d~~ important aspect of managing and monitoring

46   marine protected areas.

47   Noise levels recorded by the drifters are naturally correlated in space and

48   time so care must be taken in the analysis in order to conflate these effects. This can

49   be achieved in a variety of ways, including using variograms to fit spatial/temporal

50   models (CITE Fields, MRSEA) and or with spatial-temporal covariance structures

51   (CITE gstat), each with their cost and benefits. However, teasing apart the spatial

52   and temporal constrains in such a model typically involves multiple measurements at

53   a fixed location which is not present in these data.

54   Instead, we evaluate the data from two perspectives, first we look at the

55   temporal correlation in order to better understand how similar noise levels are

56   between the units, as described above. The noise level data are then de-trended to

57   account for regional-scale phenomena subtracting the 90 min rolling average noise

58 level from each noise level observation. This allows for a closer evaluation of

59 regional and ephemeral sources of ambient noise. Kriging methods are then used to

60 map noise level variation hydrophone ensemble.

61

62 **2. Methods**

63 *2.1 Data Collection and Processing*

64   Audio data were collected using eight custom drifting buoys (henceforth

65 "drifters"). Each drifter is composed of a deep hydrophone array (cable with two

66 HTI hydrohpones, a SoundTrap 640 recorder, depth sensors and 30lb anchor), a

67 weighted High Flyer pole buoy (containing a solar GPS and a radar reflector), and a

68 floating line/surface float to facilitate retrieval. The hydrophone array and High Flyer

69 are connected by 100m ¼" line with two hard trawl floats (one at the surface and a

70 subsurface float at depth), a dampener plate and an in-line bungee for vertical

71 movement, and a drogue for horizontal movement (Fig x.). consisted of a pole buoy

72 with attached GPS, 0.5m diameter surface float, 100m of nylon line, sea anchor,

73 black plate thingine, and 20lb weight. SoundTrap ST640s and with HTI

74 hydrophones were attached to each drifter assembly and recorded continuously at

75 100m depth. GPS units were scheduled to send coordinates every 20 min and, with
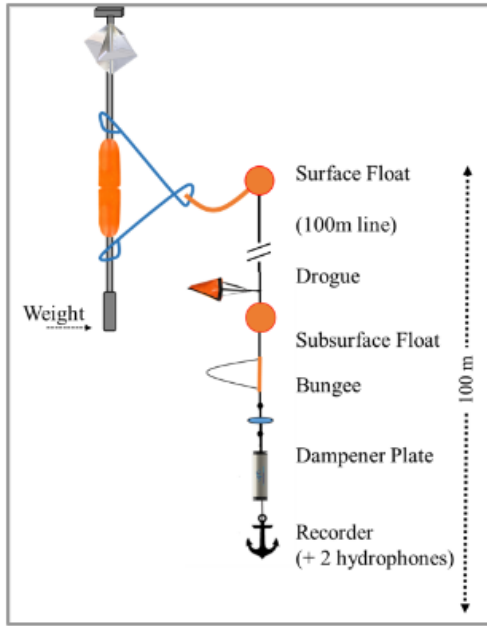
76 few exceptions did so.

Figure X. Diagram of a drifter

~~Audio data were downloaded and decompressed after recovery.~~

Following recovery of the drifters, compressed SUD files were downloaded from the SoundTrap 640 recorders. Using the SoundTrap host software, audio data were decompressed, pre-processed, and several quality checks were run to look for recording gaps or inconsistent file sizes. ~~Data were restricted to periods when all seven buoys were between 35.3 and 35.6° Latitude to ensure reasonable spatial by multiple instruments.~~ Full bandwidth long-term spectral averages were created to visually scan data ~~Audio data were also evaluated~~ for the presence of persistent self-noise (e.g. cable strumming) that would bias the analysis. No obvious signs of this were found on these drifters. End-to-end calibration value was estimated as the sum of the soundtrap calibration value and the HTI hydrophone calibration values, both

90   provided by the manufacturer(???). Data were restricted to periods when all seven

91   buoys were between 35.3 and 35.6° Latitude to ensure reasonable spatial by multiple

92   instruments.

93   Soundscape metrics were calculated using Triton Software (cite xxx), audio data were

94   first decimated to 48 kHz and then long-term spectral averages (LTSAs) were

95   calculated with 1 sec and 1 Hz resolution. From these LTSAs, several metrics

96   including broadband and third octave band calculations were made. For the purpose

97   of this analysis, median third octave levels per two-minute bin were used. Only levels

98   from the lowest and highest third octave bands (cetner frequencies, XXX and YYY)

99   were included to show contrast between the two frequency bands.

100   Polynomial interpolation was used to estimate the GPS receiver position for

101   each 2-minute periods between subsequent pings. In doing so each noise level record

102   was associated with a location

103

104   *2.2 Temporal trends*

105   As a preliminary analysis, spatial cohesion of ambient noise levels was

106   investigated across the 7-drifter ensemble. Correlograms were used to measure

107   similarity in trend in ambient noise levels between all seven instruments. Noise level

108   correlation should be higher between more closely spaced instruments, lower

109   frequencies (with less transmission loss), and in when the background noise comes

110   from diffuse sources such as storm systems or distant shipping. Accordingly, lower

111   correlation values are expected with widely spaced instruments and or/with local

112   phenomena. The degree of the correlation in itself is valuable information as it

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113   indicates what proportion of the background noise is influenced by regional scale

114   phenomena.

115   *2.3 Spatial Variation in Ambient Noise Levels*

116   Following detrending, noise level variations across the survey area were

117   evaluated using the MRSEA package (Scott-Hayward et al, 2014). The approach

118   couples spatially adaptive local smoothing algorithms (Walker et al 2010) with

119   generalized estimating equations to account for spatial and temporal autocorrelation

120   associated with line surveys. Some functions in the package modified to calculate

121   distances using haversine rather than Pythagorean which is a better distance

122   approximation across larger scales. These changes are available on the ~~github~~GitHub

123   repository associated with this work

124   (https://github.com/JPalmerK/SpatializeNoise).

125   For both low and high frequency analysis 250 knots were chosen from the

126   drifter tracks from which to fit the smoothed model. Gaussian basis functions were

127   selected to estimate variance as a function of spacing between the units. SALSA 2d

128   models were run and allowed to automatically select the number of knots.

129   Concordance and marginal r2 are reported for the resulting models.

130   **3. Results**

131   *3.1 Data Collection and Processing*

132   Eight drifters were deployed on March 11th, 2023 in the Morro Bay WLA and

133   recovered by the 16th of March with approximately 5km spacing between units

134   (Figure 1). One SoundTrap failed to record and was therefore excluded from the

135   analysis.

136   Instruments drifted primarily southward with the prevailing currents with six of

137   seven roughly maintaining their spacing throughout the deployment period. The

138   Northeastern most drifter travelled further and faster than the remaining units.

139   Median speed across all drifters was 0.15 m/s with a standard deviation of ±0.08

140   m/s. The distance travelled from deployment to recovery, ranged from 40.6 km to

141   66.8 km. The total distance travelled by each instrument throughout the deployment

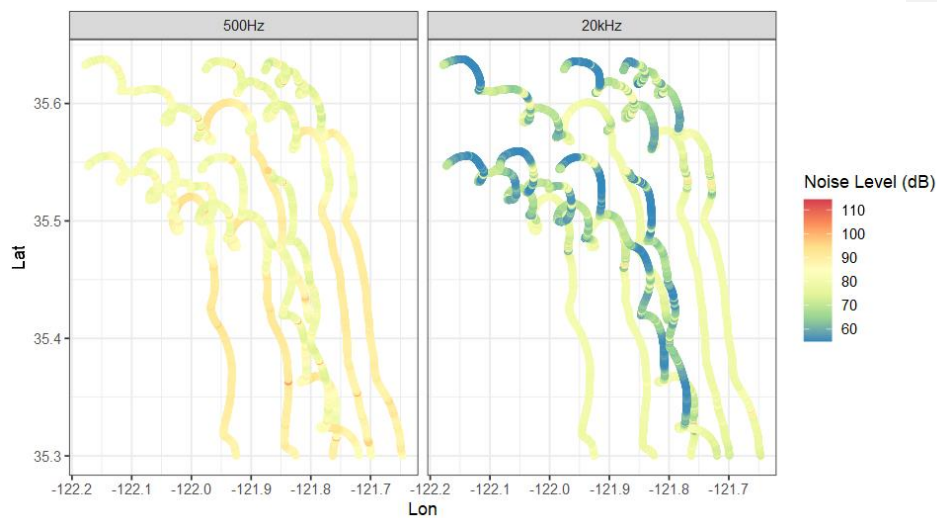142   ranged from 61.9 km to 77.3 km for ADRIFT_53.

143   *Figure 1 GPS tracks and aAverage 2-min Noise levels recorded by the seven drifters in the study in the lowest*
144   *(500 Hz; left) and highest (20 khz; right) 1/3rd octave frequency bands.*

145

146   *3.2 Temporal Trends*

147   Two storm events (atmospheric rivers) occurred during the second half of

148   the deployment with the first starting on March 14th and second on the 15th. Noise

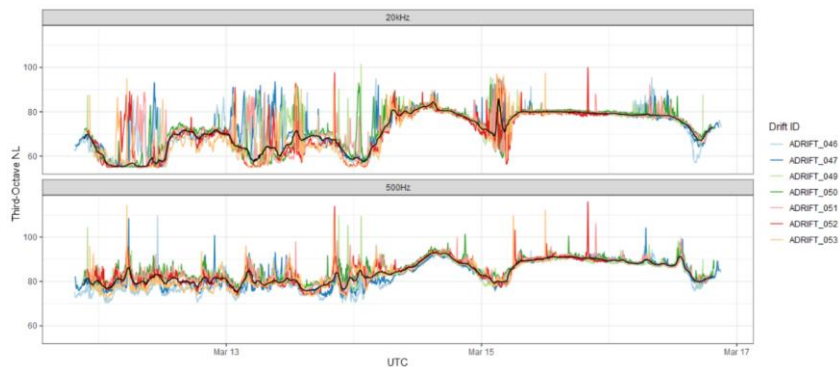149   levels in both 500 hz and 20 khz bins were elevated during these periods.

Figure 2 Two-minute timeseries of 1/3rd octave band levels for the 500 Hz and 20 kHz band. Black line indicates the 60-min rolling median noise level across all instruments.

150   Figure 1 shows the 2-minute median noise level in two third octave bins

151   during an 8-day drift near the Morro Bay WEA. Increase in noise levels from two

152   storms are march 14th and 15th that raised baseline noise levels approximately 10 and

153   20dB re 1μ Pa for the lower and upper third octave band respectively. Between the

154   storms there was a period of increased variation in the 20khz bin. Visual inspection

155   of this time period indicated the presence of persistent humpback whale song and

156   dolphin whistles.

157   Correlations in raw noise levels between instruments were also high ranging

158   from 0.64 to 0.83 in the 20 kHz band and 0.70 to 0.91 in the 500 Hz band (Figure).

159   After normalization, these values were decreased to -0.16 to 0.46 in the 20 kHz band

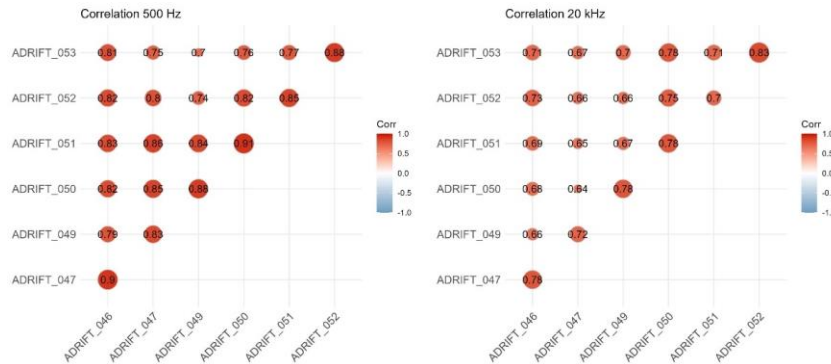160   and -0.24-0.52 in the 500 Hz band.

Figure 3 Raw collation scores between drifter data in the 500 hz (left) and 20 kHz (right) third-octave bins.

3.3 Spatial Trends

The best fitting model for the 20kHz model had 43 spline terms, a concordance value of 0.4372 and a marginal r6 value of 0.2797. Scaled Pearson's residuals showed only minimal trend in relationship with the fitted values indicating that the model was reasonable estimate of the physical properties in the area. Variogram fitting resulted in estimated range parameter of 2531 m, beyond which variation in noise levels are not considered correlated. K-fold cross validation without replication resulted in average prediction error of 4.7 dB using this modelling approach.

The modelling approach for the high frequency data was much less successful. The best fitting model for the 500 Hz data had a concordance score of 0.1671 and a marginal r2 of 0.0912. Investigation of the scaled Pearson's residuals indicated a linear decrease in the relationship between the observed and fitted values indicating that the estimation model was not a good representation of the

10

177 underlaying processes. Average k-fold cross validation (n=5) prediction error for the

178 high frequency model was 22.92 dB.

179 Figure 3 shows the predicted variation in ambient noise levels above the 90

180 min median for the 500 hz and 20khz Bands within the range estimates. Spatial

181 patterns in variations. In the low frequency band, noise level trends over the survey

182 period were lower northeast as compared to the northwest and southern part of the

183 survey area. In contrast, high frequency predictions indicated two areas of high

184 activity in the norther part of the study area and other areas of potential interest on

185 the eastern part of the survey area. However, given the low value of the model and

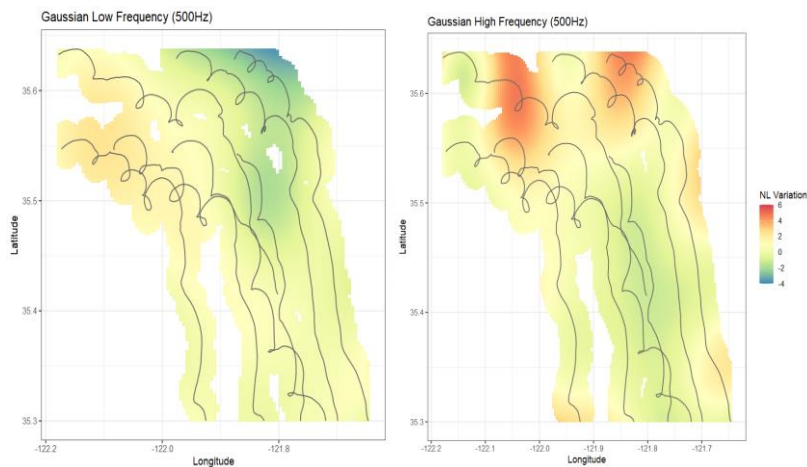186 with consideration of edge effects, these values should be considered indicative at

187 best.

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190 *Figure 4 Predicted variation in noise levels across the study area and within the variogram estimated range*
191 *of each of the sensors.*

192

193   *4 Discussion*

194

195   Sound in the ocean is complex. The sound received at any given location is a

196   combination of the physical environment as well the combination of the

197   environmental, biological, and anthropogenic sound sources in the area. All such

198   sources vary in time, frequency, and amplitude. Storm systems can raise noise levels

199   across multiple frequency bands and can act over hundreds of kilometers. Similarly,

200   in the shallow Alaskan North Slope, the reverberation from seismic air guns can raise

201   the background sound levels over 100 km from the source (Guerra et al. 2013). In

202   contrast, dolphin clicks and whistles are generally detectable out to XXX km.

203   The analysis presented here outlines some of the benefits and limitations of

204   using a kriging smoothing approach with generalized estimating equations to evaluate

205   spatial trends in sound. This approach worked reasonably well for the 500hz band

206   and considerably less well in for the 20 kHz band. Causes for the poor model

207   performance are well understood. First, the attenuation is greater for higher

208   frequency sounds than lower. Second, and more important, in this case the 20khz

209   band was dominated by wind/wave action and bioacoustics signals including dolphin

210   whistles and humpback whale song. This was particularly true during the early hours

211   of March 15th coinciding with the period of largest variation. The source levels from

212   these animals and subsequent propagation distances of these sounds varies

213   considerably. While it would be reasonable to expect humpback whale song to be

214   detected by multiple instruments in the ensemble, the same is not the case for

215   dolphin whistles. The combination of these disparate sources means that some

216   signals will result in high concordance while others will not, lending to poor model

217 fit. Thus, future studies seeking to use these methodologies should take this into

218 consideration if they are seeking to map higher frequency components, a smaller

219 aperture array is required. In contrast if the primary goal of the deployment is to

220 investigate concordance among low (<1khz) sounds, a larger aperture ensemble may

221 justified.

222   It is also worth nothing that there was little vessel activity noted on either

223 deployment or recovery days and given the offshore sea conditions during the

224 deployment, it is unlikely that vessel activity dominated the local soundscape.

225 Investigation of the LTSAs did indicate the presence of ship noise across many of

226 the instruments but vessel noise was not otherwise common in these data.

227   Variogram range estimates were similar between both frequency bands and

228 lower than would be expected for the low-frequency analysis. This is because the

229 study sought to investigate spatial variation within the survey area. Doing so required

230 removing the dominant signals acting across the array which would have had higher

231 concordance values. The remaining signals were those that differed from the average

232 background noise and, by definition, ensonified smaller regions of the study area.

233   The variability in concordance between different sources, again, points to the

234 value in of considering aperture spacing, as much as is possible in the California

235 Current and carefully considering the scope of the analysis. In this case data were

236 collected as part of exploratory surveys of an offshore wind lease area. The

237 overarching goals were to 1) measure soundscapes in the wind lease area 2) evaluate

238 the presence of cetaceans in the habitat. As such, an initial ensemble spacing of 5km

239 was chosen to maximize spatial coverage while trying to maintain the recoverability

240 of the drifting buoys. Increasing the array spacing would have allowed for a better

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241 understanding of the spatial extent of low frequency noise without the need to

242 normalize the recorded levels. Conversely a more directed survey with smaller >1km

243 spacing would have allowed for detailed high frequency analysis over a smaller area.

244   This work highlights some of the inherent values of using multiple drifting

245 sensors as compliments to bottom-moored arrays. These instruments are much more

246 orders of magnitude more affordable than other offshore equipment and can be

247 deployed in a variety of configurations. Because the units drift with the prevailing

248 currents they are also capable of covering large distances at a fraction of the expense

249 of towed arrays and without the noise of the towing vessel.

250   As offshore wind construction begins on the US West coast, there will be a

251 need to study the impacts of construction on marine life. The most popular

252 methodology for large scale studies of ambient noise levels within restricted region

253 involves combining AIS ship density with propagation models in order to estimate

254 sound levels on larger scales. These are usually validated with single bottom moored

255 single sensors (Joy et al. 2017, Farcas et al. 2020). When applied for sound

256 management these approaches are best used when the validating hydrophone

257 occupies the same habitat as the species of interest.

258 **4. Conclusion**

259   In conclusion, this study demonstrates the feasibility of using drifting

260 acoustic recorders to monitor ambient noise levels in offshore wind energy areas.

261 The results highlight the complexity of ambient noise dynamics and the challenges in

262 modeling high-frequency noise sources. Despite these challenges, drifting sensors

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263 offer valuable insights into spatial and temporal variations in noise levels,

264 complementing long-term studies using fixed sensors.

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267 **Supplementary Material**

268 All data and models are available on github

269 **Acknowledgments**

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271 The Fulmar crew

272 The whale watch crew

273 **Author Declarations**

274 *Conflict of Interest*

275 A conflict-of-interest statement is required. If there are no conflicts to report,

276 the authors must state that they have no conflicts to disclose.

277 *Ethics Approval*

278 **Data Availability**

279 A data availability statement is required. For the *Journal*'s data policy and

280 suggested templates, please see the Information for Contributors:

281 https://pubs.aip.org/asa/jel/pages/manuscript.

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