

Utility of ocean wave parameters for improving predictions of ambient noise

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Abstract. This study is concerned with prediction of the “wind noise” component of ambient noise (AN) in the ocean. It builds on the seminal paper by Felizardo and Melville (1995), in which the authors quantified the correlation between AN and individual wind/wave parameters. Acoustic data are obtained from hydrophones deployed in the north and northeast Pacific Ocean, and wind/wave parameters are obtained from moored buoys and numerical models. We describe a procedure developed for this study which isolates the correlation of AN with wave parameters, independent of mutual correlation with wind speed (residual correlation). We then describe paired calibration/prediction experiments, whereby multiple wind/wave parameters are used simultaneously to estimate AN. We find that the improvement from inclusion of wave parameters is robust but modest. We interpret the latter outcome as suggesting that wave breaking responds to changes in local winds quickly, relative to, for example, total wave energy, which develops more slowly. This outcome is consistent with prior knowledge of the physics of wave breaking, e.g. Babanin (2011). We discuss this in context of the time/space response of various wave parameters to wind forcing.

I. INTRODUCTION

Ambient noise in the ocean is produced by shipping, biologics, weather, and other sources. The goal of this study is to improve prediction of the component of ocean ambient noise (AN) commonly referred to as “wind noise”. Important early work on this topic was performed by Knudsen et al. (1948) and Wenz (1962). In these works, it was recognized that the sea state (“surface agitation”) has a central role in the creation of this noise, while the underlying mechanisms were imprecisely ascribed to some combination of the action of bubbles in the water and/or the impact of sea spray on the surface. Wilson (1980) argued that the latter was a dominant mechanism, but by the end of the decade, there was general recognition that bubbles play the more important role (e.g., Prosperetti (1988), Medwin and Daniel (1990)). Prosperetti (1988) outlined three frequency regimes: 1) low frequencies, 100 to 200 Hz, where bubbles in the water act as amplifiers of “water turbulence noise”, 2) intermediate frequencies, 200 Hz to 1 or 2 kHz, where there is typically a broad maximum in the wind/wave noise, caused by “collective oscillation of bubble clouds”, and 3) high frequencies, 1 or 2 kHz to around 10 kHz, where individual bubble oscillation dominates. The last regime is the most well understood: this noise is emitted immediately (e.g. 10s of milliseconds, Manasseh et al. 2006) after the bubbles are formed, and the frequency of the emission is directly related to the bubble radius.

It is generally understood that wave breaking is the link between wind speed and bubble generation. Further, Farmer and Vagle (1988) established that the third noise mechanism above is a direct result of wave breaking. However, in the real ocean, wave breaking is not a simple function of wind speed. While wind speed is of primary importance, the frequency and intensity of wave breaking is affected by other environmental factors, e.g. see review by Babanin (2011). Consider, as

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illustration, an idealized case of 15 m/s wind speed over 100 m basin vs. the same wind over 100 km basin. The oceanographic difference (specifically, fetch) will result in different strength of breaking, and therefore different acoustic emissions for these two cases. Current AN models use wind speed, plus water depth (usually binary, i.e. deep vs. shallow, Wenz (1962)) and/or receiver depth Hildebrand et al. (2021) and predict AN as a function of frequency. Our hypothesis is that since the AN is more directly connected to wave breaking than to wind speed, then it should be possible to improve a prediction of wind noise by incorporating oceanographic information, particularly that associated with ocean waves.

The above hypothesis is not new. It was central to the landmark study of Felizardo and Melville (1995) (henceforth denoted “FM95”), who quantified the correlation between AN and several wind/wave parameters for a relatively short (10-day) field experiment, looking at three frequencies, from 4.3 to 14 kHz. They found that the AN correlation with predicted wave dissipation rate is equal to, or slightly higher, than the correlation with wind speed. In the present study, we perform similar analysis, though here we apply multiple input parameters simultaneously to predict AN, rather than one parameter at a time as in FM95. Further, we use a larger dataset: the cumulative duration of our dataset is 1291 days, making it more than 100 times larger than that of FM95, and a much broader range of frequencies are studied (127 Hz - 18 kHz, vs. 4.3 – 14 kHz). We employ wind and wave information at seven different hydrophone locations. At one location, wave characteristics are taken from observations, while at the other six locations, wave parameters are derived from numerical ocean wave models.

In Section II, we present an idealized example of wave growth, to illustrate the uncertainty around the behavior of emitted AN as a type of “wave parameter”. In Section III, we introduce the datasets used in the study. In Section IV, we present an analysis in which we study the correlation of AN with wave parameters, after the correlation with wind speed is removed. In Section V we perform multi-linear regression to predict AN using combined wind and wave parameters, and quantify the benefit of including wave parameters in terms of RMS error in dB, relative to the baseline performance, using wind information alone. In Section VI, we discuss limitations and future work, and in Section VII, we summarize our conclusions from this study.

In this study, we do not present a new predictive formula as was done, for example, by Wenz (1962), Hildebrand et al. (2021), and Pflug (2021). Also, bubbles are not explicitly part of the predictive models developed herein. The problem of noise from breaking waves in the surf zone, e.g. see Deane (1997) and Fabre and Wilson (1997), is not addressed here.

II. IDEALIZED CASE: FETCH-DEPENDENCE

As discussed in Section 1, it is self-evident that for an idealized fetch-limited case, AN should grow with fetch. However, this is merely a qualitative relation, and so it does not assist us in predicting AN. A numerical ocean wave model such as SWAN (Simulating WAVes Nearshore, Booij et al. (1999)) can be used to predict many different wave parameters, each of which is associated with wave breaking to a greater or lesser degree. Table 1 shows SWAN results for an idealized case with a 10-meter wind speed of 15 m/s.

TABLE I. Output from SWAN model for idealized case of wind speed of 15 m/s. Percentages shown are “percent relative to fetch of 300 km”.

fetch length	300 m	3 km	30 km	150 km
fetch (%)	0.1%	1.0%	10%	50%
$H_{sig}^{0.25}$	46%	61%	83%	95%
$H_{sig}^{0.5}$	21%	37%	69%	91%
H_{sig}	4.6%	14%	48%	83%
T_p	18%	35%	62%	91%
D_{tot}	15%	40%	96%	100%
m_{-1}	0.0%	0.6%	14%	60%
m_0	0.2%	1.9%	23%	69%
m_1	0.9%	5.7%	35%	78%
m_2	3.9%	15%	53%	86%
m_3	13%	35%	73%	94%
m_4	32%	61%	88%	98%
m_5	54%	84%	96%	99%
AN	unknown	unknown	unknown	unknown

Parameters given in Table 1 include moments of the wave energy density spectrum $E(f)$. They are computed as $m_n = \int_{f_1}^{f_2} E(f) f^n df$, where f_1 and f_2 are the upper and lower wave spectra frequency bounds, with 0.038 Hz and 1.0 Hz used here, respectively¹. Spectral moments typically have a physical relevance. For example, the significant waveheight H_{sig} is defined as $H_{sig} = 4\sqrt{m_0}$; m_2 is proportional to surface orbital velocity; m_3 is proportional to surface Stokes drift; m_4 is proportional to mean square slope of the sea surface; and m_5 is associated with the Phillips saturation level (Phillips 1966), sometimes taken as a basis for a breaking threshold (Babanin and Young 2005). D_{tot} is the integrated rate of dissipation of wave energy by whitecapping (deepwater breaking, defined in Section III), and T_p is peak period.

The wave parameters grow at a markedly different rate. For example, D_{tot} , m_4 and m_5 grow very quickly with fetch, while total energy (m_0) grows more slowly. For the “wave parameter” AN generated by breaking waves, the growth rate is unknown, though intuition would suggest a growth rate similar to D_{tot} , m_4 and m_5 . And of course, it must be recognized that even this unknown idealized growth rate of AN is likely dependent on the acoustic frequency.

III. DATASETS

This study relies on three datasets: 1) hydrophone observations of ambient noise, 2) observed wind/wave parameters, and 3) modeled wind/wave parameters. Each is described below.

¹ This is true for f_1 and f_2 throughout this manuscript, where SWAN is employed. However, where the moments are calculated from the Ocean Station Papa buoy (Section III), f_2 is determined by the buoy (0.58 Hz).

A. Hydrophones

1. NOAA/PMEL

The first hydrophone dataset is from a deployment by the National Oceanic and Atmospheric Administration (NOAA) Pacific Marine Environmental Laboratory (PMEL) at Ocean Station Papa (OSP), south of the Gulf of Alaska. The location is very remote, around 1000 km from the Alaska and Canada mainlands, and in deep water (4250 m depth), with the hydrophone at 500 m depth, which is above critical depth. Data were processed for October to December 2018. The processing of these data include eight analysis frequency bands, with center frequencies from 127 Hz to 1.7 kHz, with 5 kHz sample rate.

2. ONC

The second and third hydrophones are offshore of southwest Canada, deployed and managed by Ocean Networks Canada. Both are near the seafloor, and data were processed for October 2020 to December 2021. One hydrophone is the “Cascadia Basin” deployment, 202 km west of Vancouver Island. The more nearshore hydrophone is the “Clayoquot Slope” deployment, 78 km west of Vancouver Island. The wind climate for this region is primarily alongshore, so fetch-limited conditions are not common. These data include 18 analysis frequency bands, with center frequencies from 127 Hz to 18 kHz, with 64 kHz sample rate. At most frequencies, Cascadia is modestly quieter than Clayoquot, implying that at the latter, the impact of being within the sound channel is relatively more important than any suppression of sound by bottom interaction.

Most of the results herein from the OSP and ONC datasets were previously presented in the grey literature (Rogers et al. 2023).

3. HARP

The remaining four datasets are from hydrophone data provided directly by Dr. John Hildebrand (UCSD). These are the High-frequency Acoustic Recording Package (HARP) instruments described in Hildebrand et al. (2021).

4. Hydrophone summary

The instrument locations are shown in FIG. 1 and features of the hydrophone dataset are summarized in Table II. This table includes a simple metric for roughly estimating the fraction of each dataset which is fetch- or duration-limited based on the concept of separating between “forced conditions” (i.e. waves actively receiving energy from the wind) and “unforced conditions”². This is denoted as “% $C/U < 1$ ”, and here, U is the 10-m wind speed, C is the ocean wave phase velocity calculated using the deep-water relation, $C = gT/(2\pi)$ where g is gravitational acceleration, and T is calculated as $T = m_{-1}/m_0$, which is sometimes denoted $T_{m,-1,0}$.

² It must be emphasized that, in reality, a typical wave spectrum is composed of both forced and unforced components, with wind and wave direction playing an important role, implying that the metric C/U is imprecise and is used here only to roughly compare the wave climate at each site. This is discussed further in Section VI.C.

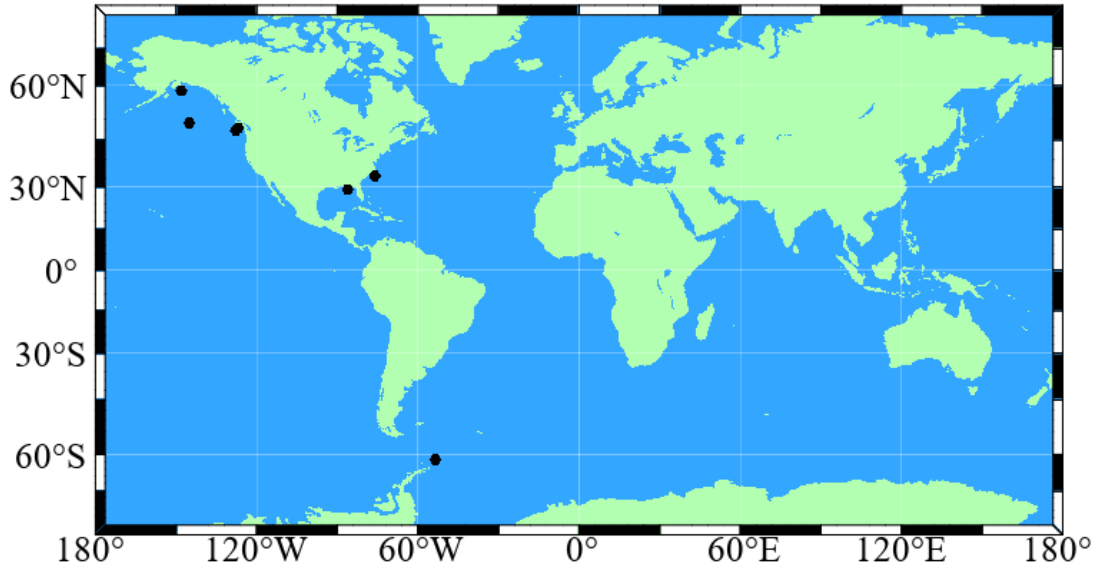


FIG. 1. Positions of hydrophones used in this study.

Table II. Summary of hydrophone data used in this study. “Long description” is, in the case of the HARP buoys, the designation in Hildebrand et al. (2021, Table V). Except for the OSP location, hydrophones are mounted near the seafloor (water depth is hydrophone depth). The last column, “% C/U<1”, is a rough measure for the fraction of records with waves that are actively forced by the local wind (see text).

Short-hand used herein	Long description	Start and end of data used herein	# of 30-minute co-locations	position	water depth (m)	hydro-phone rel. to critical depth (CD)	% C/U <1
OSP	NOAA/PMEL Station NRS02	2018/10/01 - 2019/01/01	4,403	214.87°E, 50.25°N	4250*	above CD	20
Cascadia	ONC-Cascadia Basin	2020/10/03 – 2021/12/17	13,311	232.23 °E, 47.77°N	2660	below CD	12
Clayoquot	ONC-Clayoquot Slope	2020/10/03 – 2021/12/17	10,946	233.15°E, 48.67°N	1260	no CD	16
GofAK	HARP GofAK_CB_09	2017/09/15 – 2017/12/31	5,147	211.97°E, 58.67°N	900	no CD or at CD**	20
WAT	HARP WAT_GS_02	2018/01/01 - 2018/04/01	4,292	284.00°E, 33.67°N	930	no CD	46
Antarc	HARP Antarc_EIE_01	2016/02/02 – 2016/11/30	13,775	306.52°E, 61.25°S	1033	below CD	35
GofMX	HARP GofMX_DC_11	2017/10/03 - 2018/04/30	10,079	273.90°E, 29.05°N	269	no CD	56

* OSP hydrophone is 500 m below surface

** This describes May through December only. At GofAK hydrophone location, there is no critical depth (CD) during May through November, and hydrophone is at CD in December.

5. *Acoustic data processing*

The procedure for wind noise estimation is similar for all data sets, with modifications to account for factors such as data bandwidth, hydrophone depth, and acoustic propagation characteristics. Raw hydrophone time series data were first processed using Welch’s method (Welch 1967) to produce spectral estimates over stationary time intervals. A Hann window was used to minimize off-frequency-bin energy leakage via spectral sidelobes (Harris 1978). Received sound levels were then estimated over analysis frequency bands spanning 100 Hz to 20 kHz with center frequencies and bin widths chosen to avoid redundancy. Analysis bin center frequencies for the 18 (eight in the case of OSP, due to lower sampling rate) ambient noise analysis bands are shown in Table III. For all data sets, lower frequencies (< 100 Hz) were not processed due to elevated ambient sound levels due to shipping activity. High frequency processing cutoffs were determined based on identified low pass filter roll-off and data acquisition system noise floor. Additional description of the quality control process used on the hydrophone data is given in the Appendix.

Table III. Acoustic center frequencies and bandwidths for analysis. Bins 1 – 8 were used for the PMEL data while bins 1 – 18 were used for all other hydrophone data used herein.

Bin #	1	2	3	4	5	6	7	8	9
Fc (Hz)	127	191	281	408	587	841	1199	1704	2260
ΔF (Hz)	53	75	105	149	210	297	419	592	520
Bin #	10	11	12	13	14	15	16	17	18
Fc (Hz)	2848	3588	4700	5875	7175	9040	11390	14350	18080
ΔF (Hz)	655	855	1400	950	1650	2080	2620	3300	4160

B. **Observed wind/wave parameters**

The OSP hydrophone is co-located with a PMEL buoy equipped with an anemometer at 4 m elevation (Ocean Climate Station (OCS) Project Office), and an Applied Physics Laboratory / University of Washington wave buoy (Thomson et al., 2015), which is Coastal Data Information Program (CDIP) Station 166³.

The ONC hydrophones are not co-located with wind/wave observations, but a number of U.S. and Canadian buoys are in the region, eight of which are used to validate input/output to/from the ‘SW (southwest) Canada’ wave model described in the next section. The HARP locations similarly have two to five buoys in each area which were used for wave model validation, with the exception of the ‘Antarc’ hydrophone, for which no contemporaneous/nearby in situ wave observations exist.

C. **Modeled wind/wave parameters**

For all locations other than the ‘GofMX’, we use a regional grid of the SWAN wave model (“Simulating WAVes Nearshore”, Booij et al. (1999)) nested within a global 1/4° hindcast with the wave model WAVEWATCH III® (“WW3”, Tolman (1991), WW3DG (2019)). The grid design of Rogers and Linzell (2018) is used for the global grid and resolutions from 1.8 to 2.8 km are used in the SWAN grids. As an example, the SW Canada (ONC) case, the resolution of the regional model

³ For further information on this buoy, see: <https://doi.org/10.18437/C7WC72> and www.apl.washington.edu/owsp.

is between 2.5 and 2.8 km and is illustrated in FIG. 2. For the ‘GofMX’ case, a global model was not needed; instead, a 2.1 km \times 2.2 km coastal SWAN grid was nested within a 11.9 km \times 13.9 km regional SWAN grid. The model settings and SWAN grid information are described in the Supplementary Material.

In the case of the two ONC locations, 10-m wind vector (and ice fraction, in the case of the global model) forcing fields for the models comes from the Navy’s operational global atmospheric model, NAVGEM (Hogan et al. 2014), given at 0.18° resolution. In the case of the HARP locations, wind and ice forcing is taken from the European Centre for Medium-Range Weather Forecast (ECMWF) Reanalysis v5 (“ERA5”, Hersbach et al., 2020), which are given hourly at 1/4° resolution, and the 10-m neutral winds are used⁴. Model results for the OSP location are not included in this manuscript⁵: only the observed wave parameters are used for OSP herein.

As mentioned in Section B above, with the exception of the ‘Antarc’ case, the SWAN implementations are validated using wave observations from moored buoys. These buoys are listed in the Supplemental Material.

WW3 and SWAN are both phase-averaged wave models which take inputs such as 10-m wind vectors and use them to predict directional wave spectral density, as a function of space, time, frequency, and direction. From the spectra, wave parameters such as the moments defined in Section II can be derived. They account for the effects of spatially and temporally varying winds (i.e. increasing, falling, turning) on wave growth, dissipation effects such as that by breaking, bottom friction, and interaction with sea ice, and advection in all dimensions. This makes them much more sophisticated (and complex) than a parametric model based on time/space averaged wind speed and approximated fetch. The model’s source terms can also be integrated to compute quantities such as energy fluxes and momentum fluxes. In this paper, we utilize the frequency- and direction-integrated dissipation by whitecapping, which is the primary component of energy flux from the waves to the ocean:

$$D_{tot} = \int_{f_1}^{f_2} \int_0^{2\pi} S_{ds}(f, \theta) df d\theta \quad (1)$$

For further information on the wave model governing equations, source terms, and methods, the reader is referred to Tolman (1991), Tolman and Booij (1998), Booij et al. (1999), WW3DG (2019), and SWAN (2019).

⁴ 10-m neutral winds are generally preferred over standard 10-m winds for forcing wave models, but are not available from some atmospheric models, such as NAVGEM.

⁵ Both models were, in fact, run for the OSP location, using both the NAVGEM and ERA5 forcing fields. The results are not presented here, for reasons explained in Section V. However, the uniquely co-located wave observations make the OSP case too valuable to exclude altogether.

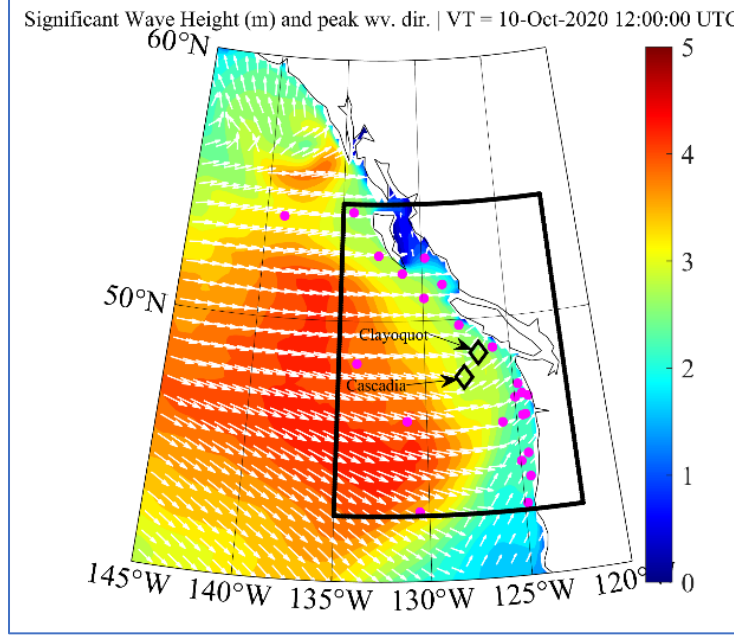


FIG. 2. Significant wave height (colors, in meters) and peak wave direction (white arrows), from the SW Canada SWAN model. Valid time is 2020 Oct. 10 12:00 UTC. The ONC hydrophones are indicated with black diamonds. Magenta dots indicate metocean buoys deployed by National Data Buoy Center (NDBC) of the National Oceanic and Atmospheric Agency (NOAA), and by ‘Environment and Climate Change Canada’ (ECCC). The open edges of the grid receive boundary forcing from WW3.

D. Co-locations

In the case of OSP observed wind/wave parameters, the hydrophone data is already geographically co-located. For other cases, i.e., those that employ *model* wind/wave parameters, bilinear interpolation is used for geographic co-location.

Temporal co-locations are made by taking the wind/wave parameters at 30-minute intervals, and for each temporal data point, averaging all valid AN data within ± 15 -minutes of the wind/wave time. From this, there are between 4000 and 14000 30-minute co-locations for each hydrophone, as listed in Table II. Across all locations, this results in a total of 1291 days of co-locations. Of the co-locations in this total, some include frequencies for which the AN data are marked as invalid by the quality control. The average fraction of valid AN data was 68% for the OSP case, 86-93% for the two ONC cases, and 95-98% for the four HARP cases.

E. Wind climatology at hydrophone locations

Waves that are not fully developed are either fetch-or duration-limited, which may be caused by non-uniformity and non-stationarity (respectively) of the winds. In the classic scenario, fetch is determined by the distance from a nearby coastline. Wind climatology can help us to understand how likely this scenario is, for each of our hydrophone locations, so here we briefly review this, using information taken from the “GLOSWAC” (GLObal Spectral WAVE Climate) database of Portilla-Yandún (2018). All else being equal, fetch- or duration-constrained (i.e. “young”) wave conditions are more likely to occur when wind speed is high; the “wave age” is typically defined as $C/(U \cos(\theta))$, where C is wave phase velocity (proportional to wave period if in deep water), U is the wind speed, and θ is the angle between wind and wave directions. Below, for brevity, we use shorthand notation for cardinal directions, e.g. “WSW” for winds from the west-southwest.

Ocean Station Papa (OSP, NOAA/PMEL): Westerly (especially WSW) winds are most common. Winds are often strong ($U_{10} > 12$ m/s), and occasionally reach 20 m/s.

Cascadia and Clayoquot (ONC): Winds are primarily along the coast, with winds from NW being most common but with the highest winds occurring more often from the SE.

Gulf of Alaska (“GofAK”): Winds from ESE and W are most common, and winds from north are least common. In the case of westerly winds, there is potential for limiting of wave conditions by fetch from the Alaska coastline, but since the distance is quite large (225 to 300 km), waves are expected to be fetch-constrained only for the strongest winds (e.g. $U_{10} > 15$ m/s).

Offshore of North Carolina (“WAT”): Similar to the ONC location, winds are often along the coast, with SW winds being most common.

Drake Passage (“Antarc”): Westerly winds are by far the most common. Winds are strong, occasionally reaching 20 m/s. Clarence Island is only 30 km west of the hydrophone, which strongly implies fetch-limitations, but the island is small, so it would have reduced effect on winds from NW and SW.

Gulf of Mexico (“GofMX”): Winds from E and SE are most common, though northerly winds are also common. Winds typically do not exceed 16 m/s. The coast is 120 to 150 km from this hydrophone. Waves are expected to be fetch-constrained only weakly, and only for the highest winds speeds.

Based on above, only the ‘Antarc’ location is likely to be fetch-constrained by topography for a significant fraction of the time series used. At other locations, the wave conditions may still be constrained (i.e., not fully-developed), but this would occur primarily as a result of non-uniformity and/or non-stationarity of the wind speed and direction.

IV. DE-CORRELATION ANALYSIS

Ambient noise is created by bubbles, which are created by breaking waves, and the wave energy is generated by wind action. Thus, the AN is strongly correlated with wind speed, and so models such as Wenz (1962) and Hildebrand et al. (2021) have had success. The direct correlation between AN and wave parameters (e.g. FM95) is difficult to interpret, because much of that AN-to-wave correlation is via mutual correlation with wind speed, which is already used in the AN predictive model. However, it is possible to anticipate the potential of wave parameters for improving the prediction by performing analysis while controlling for this mutual correlation. We have done this using two independent methods, which are described in the two sections following.

A. Band-normalized wave parameters

FIG. 3 shows examples from the (a) OSP observations and (b) Clayoquot (ONC) model output at a middle frequency, 841 Hz. The color scale here is the wave parameter m_3 , normalized by the mean m_3 in a wind speed bin of width 1 m/s. Horizontal black lines indicate these bins, and the mean AN in the bin, and thus these black lines are an example of an AN prediction that is based on wind speed alone.

These plots indicate that at higher wind speeds, there is little variation of AN from the black horizontal lines. This indicates that a “wind speed only” prediction of AN is already quite accurate, and little can be done to improve upon it. At lower wind speeds, there is much more scatter above and below the black lines, indicating that some improvement is possible over the “wind speed only” model. The colors indicate that where observed AN is higher than the “wind speed only” model, normalized m_3 tends to be higher (red and orange), and below the line, the opposite is true (blue colors). This indicates that some improvement can be made on the “wind speed only” model by incorporating m_3 into the prediction model.

A limitation of this type of diagram is that it only presents results for a single wave parameter and single acoustic frequency at a time.

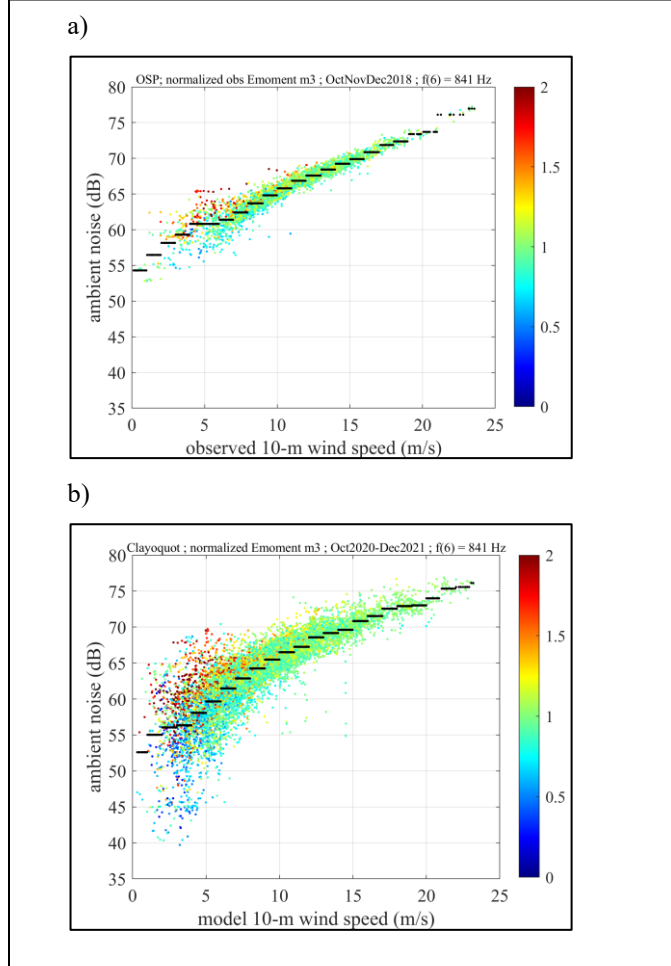


FIG. 3. AN at 841 Hz as a function of wind speed U_{10} ; colors indicate the value of normalized m_3 as described in the text. Panel (a) shows results for the OSP case. Panel (b) shows results for the Clayoquot case.

B. Correlation of residuals

Another method to anticipate the potential of wave parameters for improving the prediction is to remove the component of the AN signal that correlates with the wind. Any remaining correlation is the “residual correlation”.

First, we create a “wind speed only” prediction of AN for the dataset. Here, the population is split up into overlapping wind speed bins of width 1 m/s, and within each bin, a polynomial fit on frequency space is performed. Subsequently, the residual is computed as the misfit (or error) between the predicted and observed ambient noise. Having obtained the residuals, we are able to present all frequencies in the same plot: FIG. 4 shows the results for the wind speed band 4.2 to 5.2 m/s for the Clayoquot case. In panel (a) of FIG. 4, we see that the residual does not correlate with wind speed (the Pearson correlation, denoted R_P , is -0.01), i.e. the decorrelation is successful. In

panel (b), we find that correlation of the residual with the wave parameter m_4 is significant but not large, $R_p = -0.42$.

In FIG. 5, we plot the correlation vs. wind speed for several wind/wave parameters. This is the correlation with the wind speed correlation removed, and the result for wind speed is included as a thick blue line, both to indicate that the de-correlation has succeeded (low correlation), and to indicate the range in which correlation can be considered insignificant (equal to or smaller than thick blue line). A negative value indicates that a predictive model based on wind speed alone will have signed mismatch (error) that correlates negatively with the parameter in question (e.g. tendency for underprediction of AN for cases of larger m_3). Parameters are summarized here: 1) “BFI” is the “Benjamin-Feir Index” sometimes used to predict the probability of rogue waves (for this and other definitions, the reader is referred to SWAN (2019)); 2) “DSRP” is a metric for directional spread of the wave spectrum; 3) “FSPR” is a metric for frequency spread of the wave spectrum; 4) “PDIR” is peak wave direction (which may correlate with breaking due to proximity to coast line); 5) “QP” is associated with frequency width and wave groupiness ; 6) “STEEP” is the H_{sig}/L , where L is mean wavelength ; 7) “WnD” is wind direction; 8) “precip” is mean precipitation; 9) “mm1” is the spectral energy moment m_{-1} , 10) “m0” is the moment m_0 , etc.

This figure indicates that parameters such as m_2 , m_3 , m_4 , steepness, and integrated dissipation can help to improve the AN prediction, by a modest amount (correlation around 0.4), at lower wind speeds (3 to 6 m/s). At middle wind speeds (e.g. 6 to 10 m/s), this benefit is significant but smaller (correlation around 0.2). We find that despite the effort to remove precipitation during the acoustic data processing stage, there is significant correlation with precipitation, even at higher wind speeds.

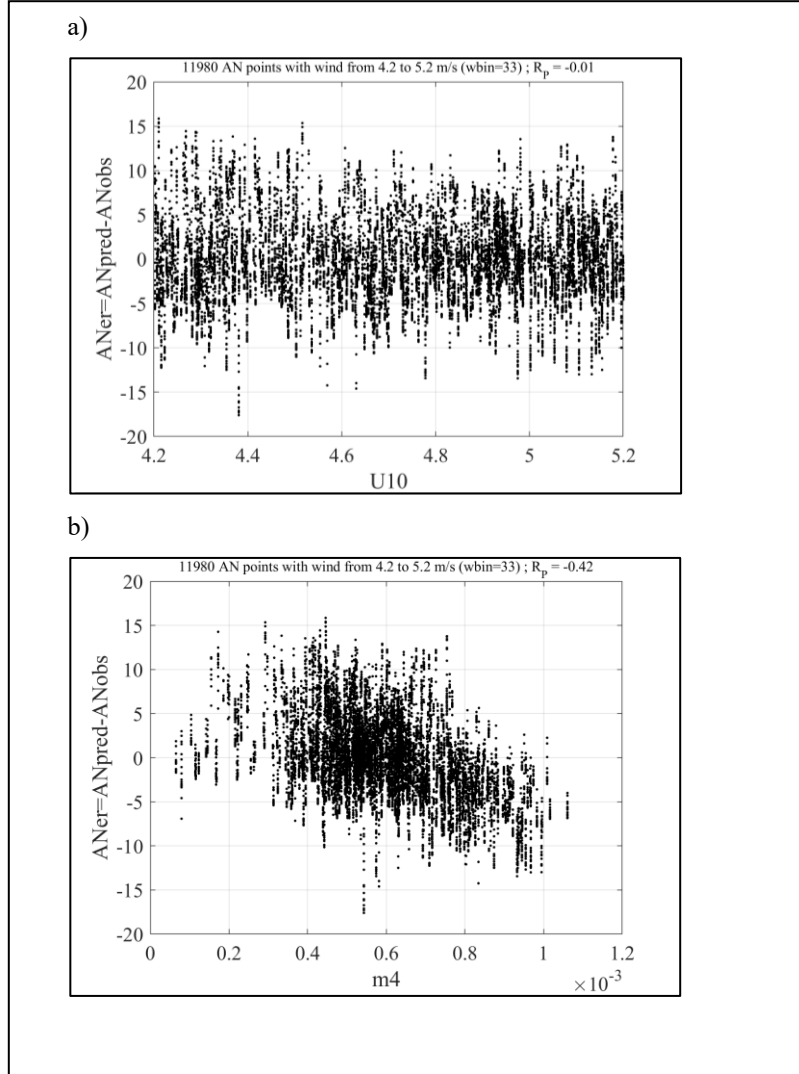


FIG. 4. Distribution of AN residual vs. wind/wave parameter for Clayoquot case, for the wind speed band of 4.2 to 5.2 m/s. In panel (a), dependency on wind speed U_{10} is shown. In panel (b), dependency on m_4 is shown.

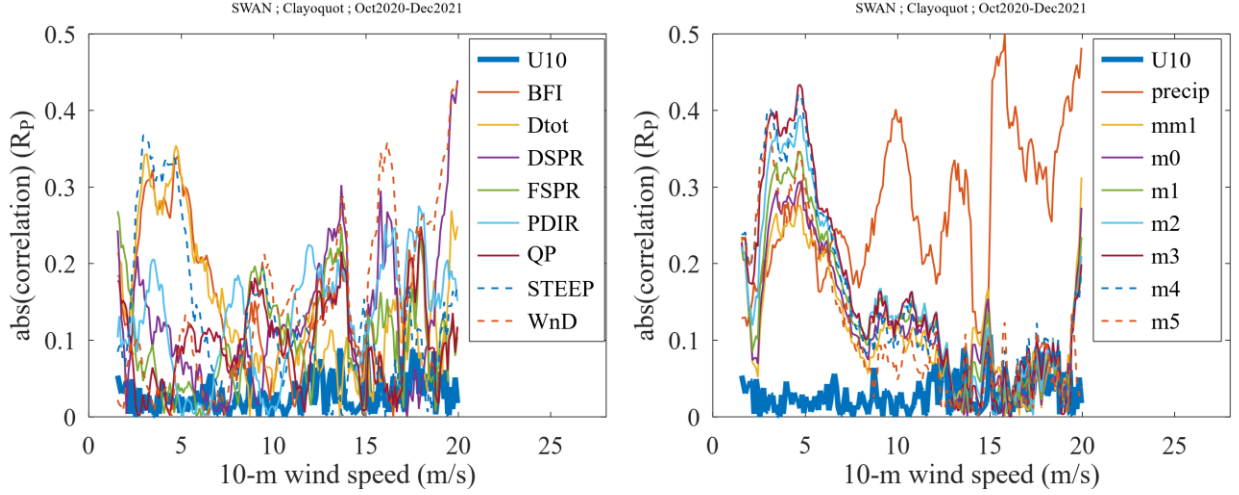


FIG. 5. Clayoquot case: Pearson correlation coefficient as a function of wind speed, for different wind/wave parameters. This is the correlation value after the correlation with wind speed has been removed (see text). The left and right panels show different lists of wave parameters for the same case, broken into two panels for readability.

V. MULTI-LINEAR REGRESSION

For each location, we perform linear regression to fit individual wind/wave parameters to AN and multi-linear regression to fit multiple parameters (e.g. wind speed plus one to five wave parameters). For each regression, we create both a linear fit, e.g. $AN = \text{coefficient1} \times \text{parameter1} + \text{coefficient2} \times \text{parameter2} + \dots$, and a log fit, e.g. $AN = \text{coefficient1} \times \log_{10}(\text{parameter1}) + \text{coefficient2} \times \log_{10}(\text{parameter2}) + \dots$, and select the one with higher skill. We also experimented with power fits, but those results are not presented here.

Multi-linear regression was performed for all seven locations, but the OSP results are excluded here. This is for two reasons. First: the frequency range (127 Hz to 1.7 kHz) is smaller than that from the other cases (127 Hz to 18 kHz), and second: AN levels at the lowest frequencies at the OSP location are inexplicably elevated relative to levels anticipated by models such as Wenz (1962). Both factors complicate the presentation of MLR results from OSP alongside the other cases, in particular the “cross-application” section below.

Below, we present results multilinear regression (MLR) using two broad approaches. In the first approach, that of “local application”, we calibrate using a data set from a location and then apply the MLR model to independent data from the same location. Each AN time series is segmented by “day of month”, with a separator at “day of month” equal to 21.0, so that roughly 2/3 of data are used for creating the regression, and 1/3 are used for prediction and evaluation.

In the second approach, that of “cross-application”, we calibrate MLR models for each location individually and apply the models at all six locations, including the location used for the calibration, resulting in 36 calibration/application pairs for each model type. No data are withheld. Since our prediction models do not control for sensor depth as in Hildebrand et al. (2021), or water depth as in Wenz (1962), we should anticipate that they suffer a penalty to overall accuracy. However, since the penalty applies to both the baseline model (using U_{10} alone) and the experimental models (using U_{10} plus wave—and in some cases precipitation—parameters), general conclusions about relative skill are still valid. Unlike those earlier works, our goal here is *not* to create a predictive model that

can be applied to other locations. In both cases (local application and cross-application) the goal is the same: to quantify the impact of inclusion of wave parameters on model predictive skill.

A. Local application

FIG. 6 shows evaluations of the multi-linear predictions, comparing the “wind speed only” model against six examples of experimental models. The vertical axis is the RMS error of the AN prediction, in dB. We find that there is modest but consistent improvement in the predictive skill, relative to the baseline model. The degree of improvement is mostly insensitive to the selection of wave parameters.

Some conclusions and conjecture can be made from the results shown in FIG. 6:

- The improvements vs. the baseline model are typically less than 0.3 dB RMSE.
- Improvements are typically small at the lowest and highest frequencies, and largest at the middle frequencies. This implies that our dataset is well-bounded for our problem, i.e., extending the experiment to lower or higher frequencies is not justified.
- The start and end of this mid-frequency range varies from one location to another.
- The selection of additional parameters has only minor impact, i.e., it appears that one set of wave parameters is as good as another.
- The ‘Antarc’ case is somewhat of an outlier: the baseline error is relatively high (over 4 dB at 2.5 to 6 kHz), as is the degree of improvement (more than 0.7 dB at 2 - 4 kHz). This result is not surprising given that the region of the hydrophone has sea ice present during some of the time period in question. While the baseline model does not account for the impact of sea ice on “wind noise”, the wave model does.

Though not shown here, we also compared the accuracy of models with just two input parameters, e.g. U_{10} and D_{tot} . As a general rule, these were slightly less accurate than the models shown in FIG. 6, which use four or more input parameters.

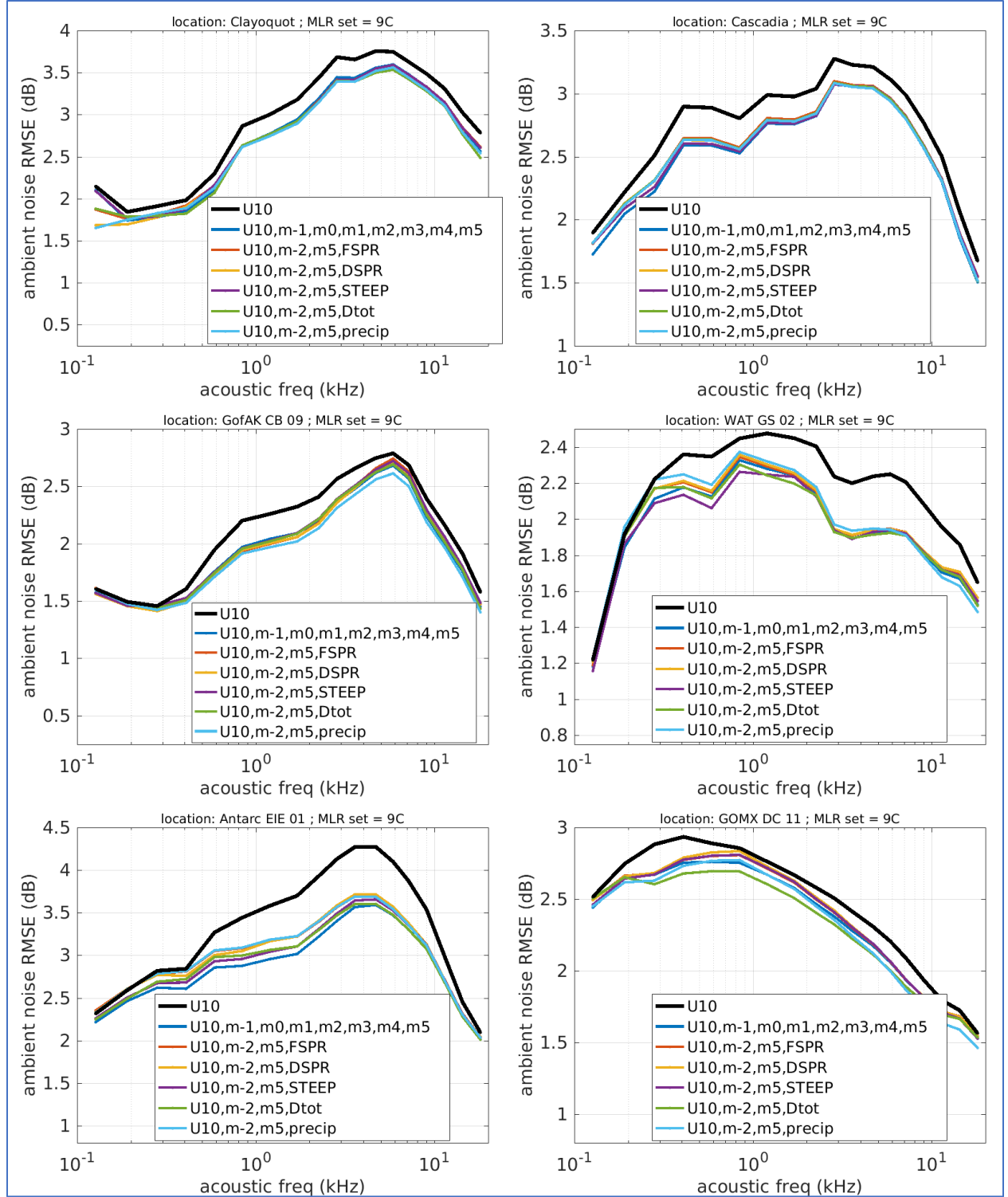


FIG. 6. RMS error in dB for prediction of AN for the six ONC and HARP locations, using different combinations of wind/wave parameters as inputs to the AN prediction, which is based on multi-linear regression.

B. Cross-application

With the cross-application experiments, there are 36 combinations per model, making it impractical to present in the format of FIG. 6. Instead, we will use tabulations of RMSE and RMSE summations. Table IV presents the RMSE for each combination for a single frequency bin near the middle of the frequencies used here, 2.85 kHz, and showing a single experimental model. (The experimental model which uses U_{10} and D_{tot} is selected for this, based on what we will show in Table VI.) The table indicates that the experimental model is an improvement over the baseline model which uses only U_{10} for 29 of the 36 combinations. In the case of the baseline model, the least successful calibration is that which was made using the ‘Antarc’ case, with a summed RMSE of 22.29 dB. This is unsurprising, since, as mentioned already, the baseline model does not take into account the effect of sea ice on ‘wind noise’. The experimental model calibrated to ‘Antarc’ outperforms the baseline model calibrated to ‘Antarc’ for all application cases successful (summed RMSE of 19.74 dB). Of the experimental model calibrations, the calibration to the ‘WAT’ case is most successful (summed RMSE of 18.86 dB).

Table V shows results for all frequencies, for the same two models (U_{10} baseline and $U_{10} + D_{tot}$ experimental). We see that the experimental model is more accurate than the baseline for 16 or 18 frequencies, and for all frequencies ≥ 408 Hz. In order to show results from several experimental models, we must further aggregate the outcomes. This is done, in Table VI, by indicating the number of frequency bins for which the experimental model outperforms the baseline model, using the summation across all 36 calibration-application combinations. Here we find that the model with only two inputs, U_{10} and D_{tot} , actually out-performs the same model with a third input parameter (m_3, m_4, m_5 , or DSPR), which is differs from our conclusions from the “local application” study. This implies that the models with several input parameters may be “over-tuned” to their specific locations.

Table IV. RMSE (in dB) when applying MLR calibrations to locations which include those different from the location of calibration (see “Formula from” and “Applied to”). Results for the 2.848 kHz band are shown. For each location, there are two rows: the first (lighter shading) shows the RMSE using the regression model with U_{10} as the only input (baseline model), and the second (darker shading) shows the RMSE using MLR with U_{10} and D_{tot} as input. The final column indicates the sum across the row. The “grand total” (sum of sum) for the baseline model (MLR using only U_{10}) is 125.62 dB and that of the $[U_{10}, D_{tot}]$ model is 117.81 dB.

-	Applied to:						
Formula from:	Clayo-quot	Cas-cadia	GofAK	WAT	Antarc	GofMX	summation
Clayoquot	3.71	3.36	2.98	2.47	4.78	3.02	20.32
	3.50	3.29	2.96	2.59	4.11	2.81	19.26
Cascadia	3.84	3.21	3.47	3.01	5.39	3.35	22.27
	3.67	3.11	3.49	3.13	4.72	3.22	21.34
GofAK	3.90	3.86	2.70	2.26	4.19	3.15	20.07
	3.83	4.03	2.47	2.13	3.56	2.94	18.97
WAT	3.83	3.70	2.72	2.24	4.30	3.13	19.92
	3.76	3.86	2.52	2.10	3.64	3.00	18.86
Antarc	4.40	4.65	2.97	2.77	3.98	3.50	22.29
	4.04	4.28	2.55	2.29	3.46	3.12	19.74
GofMX	3.80	3.55	3.10	2.59	4.82	2.90	20.76
	3.63	3.57	2.99	2.68	4.14	2.63	19.64

Table V. The “grand total” (sum of sum RMSE, in dB, for all locations), showing results from all 18 frequency bands, for the experiment of applying MLR calibrations to locations which include those different from the location of calibration. The frequency highlighted in gray is the frequency in Table IV (2.848 kHz). As with Table IV, the first model is the regression model which uses U_{10} as input, and the second is the MLR model which uses U_{10} and D_{tot} as input. The difference is the baseline model RMSE minus the experimental model RMSE.

freq. (kHz)	RMSE (dB) model= U_{10}	RMSE (dB) model= $[U_{10}, D_{tot}]$	difference (dB)
0.127	97.01	98.63	-1.62
0.191	99.29	99.12	0.18
0.281	107.36	107.56	-0.19
0.408	110.96	110.71	0.24
0.587	110.93	107.48	3.45
0.841	113.23	108.55	4.68
1.199	114.97	109.22	5.75
1.704	115.68	108.63	7.05
2.260	117.24	109.38	7.86
2.848	125.62	117.81	7.81
3.588	120.74	111.96	8.78
4.700	118.91	109.18	9.73
5.875	118.63	108.81	9.83
7.175	120.51	110.73	9.78
9.040	122.61	113.62	8.99
11.390	127.14	120.04	7.11
14.350	143.97	138.92	5.05
18.080	145.09	141.35	3.74

Table VI. Summary results of different models, for the experiment of applying MLR calibrations to locations which include those different from the location of calibration. The baseline model is the regression model which using U_{10} as input. Seven alternative models using MLR are shown, taking inputs as indicated in the second column. A “positive outcome” is a case where the “grand total” (sum of sum) RMSE is lower than that of the baseline model (model #1).

model #	parameter list (inputs to MLR model for prediction of AN)	# of frequencies with positive outcomes (out of 18)	range of frequencies w/ positive outcome
2	U_{10}, m_3, D_{tot}	7	2.26 - 9.04 kHz
3	U_{10}, m_4, D_{tot}	6	2.85 - 9.04 kHz
4	U_{10}, m_5, D_{tot}	13	0.84 - 18.08 kHz
5	U_{10}, D_{tot}	16	0.41 - 18.08 kHz
6	$U_{10}, D_{tot}, \text{precip}$	16	0.41 - 18.08 kHz
7	$U_{10}, \text{DSPR}, D_{tot}$	14	0.59 - 18.08 kHz
8	$U_{10}, m_3, m_5, \text{DSPR}, D_{tot}, \text{precip}$	9	1.20 - 7.18 kHz

VI. DISCUSSION

A. Limitations and future work

Non-local AN generation is not addressed here. All past studies have, to our knowledge, also omitted this. In principle, this can be addressed with an acoustic propagation model, but the calibration process would become prohibitively complex.

With the possible exception of the ‘Antarc’ case, datasets that we have used here are not severely fetch-constrained by proximity to land. We recommend that additional experiments be performed for cases where the hydrophone is less than 100 km from shore, and off-shore winds climatologically predominant.

We find here that the degree of improvement to model predictive skill by including wave parameters is increased in specific cases, e.g. when predicting AN a) for frequencies mostly falling in the middle of our frequency range, and b) for regions that are sometimes ice-covered, and c) for cases of lower winds. AN prediction tools using wave information which target these specific cases may be most fruitful.

Our MLR models treat the wave parameters as the independent variables, along with U_{10} . It may be useful to experiment with instead using the wind-normalized wave parameters, as was done in our correlation study (e.g., FIG. 3).

B. Omitted content

We make the following conclusions which are based on comparisons which are omitted from this manuscript for sake of brevity:

- The residual correlation with wave parameters is higher for lower acoustic frequencies. (This may be an indication of more remotely generated AN.)
- In our evaluations of RMSE for the OSP case (analogous to FIG. 6), we find significantly higher skill (up to around 0.5 dB) using input from observations (wind only or wind and waves) relative to using model values of the same. This indicates that accuracy (or lack thereof) of the winds is a primary determiner of AN predictive skill for all cases.

- We found that prediction of AN from wind/wave parameters using Machine Learning (ML) exhibits skill that is not significantly better than that using the simpler method of multilinear regression. However, since there is great variety in ML methods, this is an approach that should be explored further using our dataset.

C. Wave age

Herein, wave age is used for general description of climatology (Table II), and our thought experiment (Section II) centers on the issue of wave parameter development relative to a fully-developed condition. However, wave age is not included as an input parameter to our MLR models, which may seem counter-intuitive. There are two reasons for this. First, the actual wave age depends on both wave frequency and direction, i.e., it is a “wave age spectrum”, $C(f)/U\cos(\theta)$, where C is wave phase velocity and θ is the angle between the wind and the wave component. One can imagine a careful calculation as an energy-weighted integration of this spectrum, but we have not done this. Second, the dependence of ambient noise on wave age is non-monotonic, making any linear fitting problematic. This was first shown by Dragan-Gorska et al. (in press): they look at the trend for two datasets: one shows no trend ($R = -0.04$) and another shows negative trend ($R = -0.65$). Our assertion for non-monotonic dependence based on the following. At tiny fetch (or tiny wave age), the ambient noise generation will also be tiny, as the waves are mere ripples. On the other hand, when wave age is large, the waves are swell, which typically do not break in the open ocean, implying that they do not generate significant ambient noise.

VII. CONCLUSIONS

We conclude the following, based on results presented.:

- We used two methods of de-correlation analysis (removing the correlation of AN with wind speed, to leave only the component of correlation with wave parameters that is independent of mutual correlation with wind speed) and one method of AN prediction (multilinear regression (MLR) models). All three methods point to the same conclusion: that prediction of AN can be improved by including wave parameters, but that the degree of improvement is modest.
- A corollary to above: our experiments robustly indicate that information about AN exists in the ocean wave state that is not contained in the wind speed alone.
- Likely, the process which leads to ambient noise (wave breaking and bubbles) reaches a mature state more quickly than, for example, wave height. This implies that there is less penalty for using “wind only” prediction of AN than for using “wind only” prediction of wave height.
- The de-correlation analysis indicates that the potential for improving AN prediction using wave parameters is greatest for lower winds (e.g. 2.5-7.0 m/s).
- MLR models are calibrated to specific locations. The modest but consistent improvement via introduction of wave parameters is seen both when applying to the same location (local application) and applying to all locations (cross-application).
- In the local application of MLR, improvements via addition of wave parameters are typically small at the lowest and highest frequencies, and largest at the middle frequencies (e.g., 0.6 to 6 kHz for the ‘Antarc’ location).
- In the local application of MLR, RMSE of the baseline model (using U_{10} only) is especially high for the ‘Antarc’ case. We believe that this is because the baseline model does not account for the impact of sea ice on ‘wind noise’. Waves and wave breaking are, of course,

strongly affected by sea ice, and the improvement via introduction of wave information is therefore relatively high at this location.

- In the cross-application of MLR models, the models using only two or three input parameters are beneficial over a larger frequency interval than one which relies on six input parameters, which suggests a risk of “over-tuning”.

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AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts to disclose.

DATA AVAILABILITY

Data used here are available as “Ambient noise data processed by NRL, co-located with ocean wave data”, Mendeley Data, V1, doi: 10.17632/4v72pgswc6.1 . In the case of the HARP datasets, we are able to provide NRL-processed AN data if the requestor has explicit permission from Dr. John Hildebrand, UCSD, who was the provider of the original AN dataset.

APPENDIX

Acoustic data processing and quality control

Calibrated spectral estimates were formed from the raw spectra based on Transmission Voltage Response (TVR) curves which accompanied the data sets. The calibrated spectra were averaged over 1-min intervals and band levels were derived as the linear mean of the time averaged spectra for the analysis frequency bands (8 for OSP and 18 for ONC and HARP). For the PMEL data this averaging was done using 1s FFTs with 50% overlap (119 snapshots per minute, 1 Hz frequency resolution) while the ONC and HARP data were processed using 0.1s FFTs with no overlap (600 snapshots per minute, 10 Hz frequency resolution). Finally, an algorithm was developed for automated removal of wind noise contaminants based on statistical techniques for outlier removal. Outlier selection is based on signal normalization techniques and median-based statistical measures. These include a sliding split window normalizer (Summers 2018) combined with the Median Absolute Deviation (MAD) statistic (Rousseeuw and Croux 1993) and Mean-to-Median Ratio (MMR) statistic (Schwock and Abadi 2021a,b), utilized for threshold-based removal of time-frequency localized interference. For all site data, time domain transient detection was applied to each bin of normalized band averaged results. The MAD statistic was independently computed, in dB, across all relevant frequency bins of the averaged spectra, and the MMR statistic was formed as the ratio (dB difference) of the averaged power spectra and correspondingly computed median spectra. Thresholds applied for each detection criteria were empirically chosen to maximize interference removal while minimizing collateral damage due to the erroneous exclusion of valid wind noise data. FIG. 7. shows example spectra from the Clayoquot Slope site along with excluded points (dark blue and magenta bins/regions). Indicated regions of precipitation and shipping noise, along with other sources of interference, were largely removed across all data sets by automated pruning. FIG. 8 displays corresponding band wind noise estimates and coincident wind speed (magenta curves).

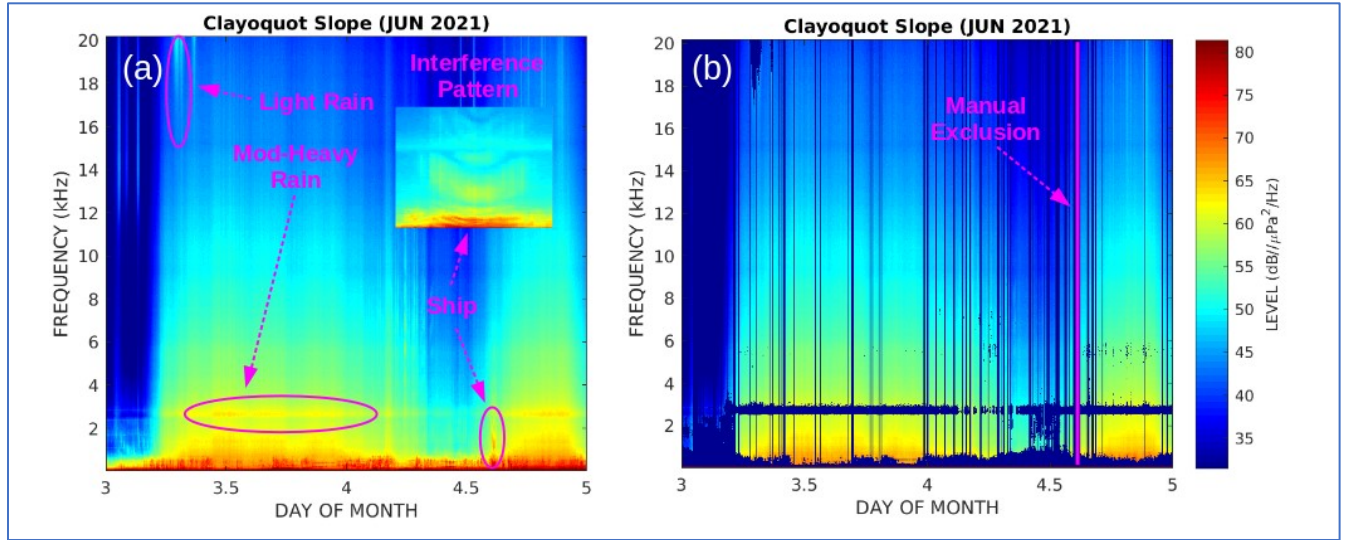


FIG. 7. (a) Clayoquot Slope averaged spectra for days 3 – 4 of June 2021 with indicated rain and shipping noise, and (b) edited spectra with bins excluded by automated pruning (dark blue) and manual editing (magenta).

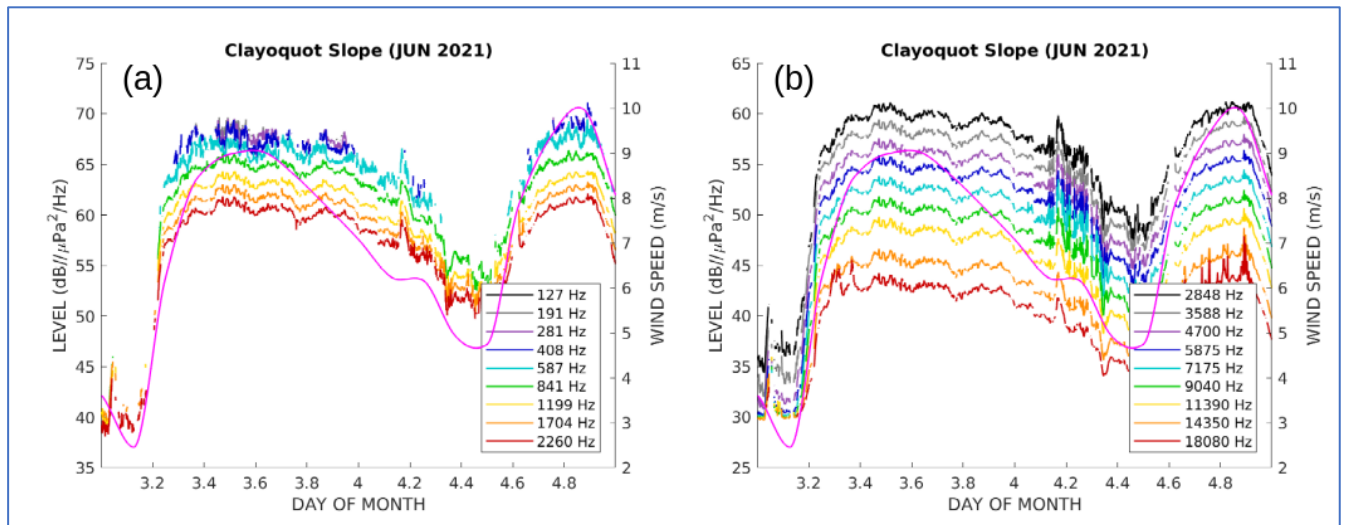


FIG. 8. Band levels derived from the edited spectra in Fig. 1-b overlaid with coincident wind speed (magenta curves) for (a) bins 1 – 9 , and (b) bins 10 - 18. Wind speed scale shown on the right of each plot.

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