EVALUATION OF LONG-TERM TRENDS IN DEEP-OCEAN NOISE IN THE SOUTHERN OCEAN USING CTBTO HYDROACOUSTIC DATA

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Abstract: *The variation in the ambient sound levels in the deep ocean has been the subject of a number of recent studies, with particular interest in the identification of long term trends. This paper describes a statistical method for performing long term trend analysis and uncertainty evaluation of the estimated trends from deep-ocean noise data. The measured data used here originate from the Southern Ocean and span up to a maximum of 15 years, from 2003 to 2018. The data were obtained from the hydro-acoustic monitoring stations of the CTBTO. The analysis method uses a flexible discrete model that incorporates terms that capture seasonal variations in the data together with a moving-average statistical model to describe the serial correlation of residual deviations, with uncertainties validated using bootstrap resampling. The main features of the approach used include (a) using a model that includes terms to represent explicitly seasonal behaviour, (b) using daily aggregation intervals derived from 1 minute SPL averages, and (c) applying a non-parametric approach to validate the uncertainties of trend estimates that avoids the need to make an assumption about that distribution of those differences. The trend analysis is applied to time series representing monthly and daily aggregated statistical levels for five frequency bands to obtain estimates for the change in sound pressure level with associated coverage intervals. Statistically significant reductions in SPL are observed for all statistical percentiles for the different frequency bands as a result of negative trends in the examined time series. Strong seasonal variation is also observed, with a high degree of correlation with climatic factors such as sea surface temperature, Antarctic ice coverage and wind speed.*

Keywords: *ocean ambient noise; statistical trends, CTBTO monitoring*

BACKGROUND

Measurements of underwater ambient noise have been carried out since at least the 1960s [1]. Most of the studies demonstrating an increase in the levels of low frequency sound in the deep-ocean have been undertaken in the Pacific Ocean [2-4]. In part, the observed increasing trend has been attributed to increases in noise produced by shipping [5,6], but it is recognised that there is a variety of sound man-made and natural sources which contribute to the ambient sound field at frequencies below 100 Hz, including ice breaking [7,8]. The paucity of available data over the last 50 years has meant that attempts to determine trends have often been based on very few data points and relied on simple statistical techniques such as straight-line fits but in more recent studies covering the last 15 years, use has been made of much richer data sets where continuous monitoring has been undertaken [9-12].

This paper describes a statistical method for performing long term trend analysis and uncertainty evaluation of the estimated trends [13]. The method uses a flexible discrete model that incorporates terms capturing seasonal variations in the data together with a moving-average statistical model to describe the serial correlation of residual deviations, with uncertainties validated using bootstrap resampling. The measured data used in this study were obtained from the hydroacoustic stations of the Preparatory Commission for the Comprehensive Nuclear Test Ban Treaty Organization (CTBTO).

DATA PROCESSING

Each CTBTO hydroacoustic station consists of three hydrophones separated by approximately two kilometres that are typically placed in the deep ocean sound channel where the vertical sound speed profile exhibits a minimum. Although relatively sparse, the underwater network’s design is such that it allows very good spatial coverage of the world’s oceans by taking advantage of the physical principles governing the propagation of sound in water. The sampling frequency for the CTBTO sound pressure recordings is 250 Hz to provide information at acoustic frequencies up to 105 Hz. The selected bit depth of 24 bits yields a maximum possible dynamic range of approximately 144 dB.

The data analysed in this study come from the three hydrophones of CTBTO’s Cape Leeuwin (H01W) station located off the south west shore of Australia at a depth of about 1 km. For this study, recordings over 14 years, from January 1, 2003 to January 1, 2017, were examined. The data during this period was essentially complete with the total number of days of no data availability being approximately 2.5% of the overall duration of the recordings.

During the processing, the raw data were extracted, and the scaling factors were used to transform the data from A/D counts (outputs of the Analogue to Digital converter relative to the maximum range of the converter) to values of sound pressure. The scaled data were filtered using the inverse frequency responses of the hydrophone channels in order to eliminate artefacts introduced by the recording equipment and to obtain the true frequency content of the recorded signals. The filtered signals were then windowed into 1 minute long rectangular windows, and the data in each window were then filtered in the following five frequency bands to allow multiband analysis: 5–105 Hz (hereafter referred to as broadband), 10–30 Hz, 40–60 Hz, 56–70 Hz, and 85–105 Hz. The mean-squared sound pressure within each frequency band was calculated for each data window, and the resulting values were expressed as sound pressure levels (SPLs) in units of dB re 1 μPa^2. Though the choice of frequency bands is somewhat arbitrary, dividing the data into frequency sub-ranges does enable investigation of how the trends might vary with frequency, and the bands chosen match those used in several other studies of CTBTO noise data, thus enabling a degree of comparability [9].

The 1 minute averaged SPL values were aggregated to give daily, monthly, and annual average and percentile levels for the SPL distributions. The percentiles computed were the 1st, 10th, 50th, 90th, and 99th, hereafter referred to as P_1, P_{10}, P_{50}, P_{90}, and P_{99}. Use of percentiles allows thorough examination of various features of the time series associated with different aspects of the acoustic environment. The last step of the data reduction process was the removal of outliers from the aggregated time series. For this study, outliers were considered to be SPL values at least 20 dB greater than the arithmetic mean of the entire time series, but for this particular dataset, there was only a small number of such anomalously-high observations for each time series (most likely caused by electrical issues) so their removal was considered to have negligible impact on the analysis. An example of the resulting daily aggregated time series for the six statistical levels derived from the broadband values measured by hydrophone H01W1 is shown in Fig. 1. In the figure, the strong annual oscillations are clearly visible in all aggregated statistical levels.

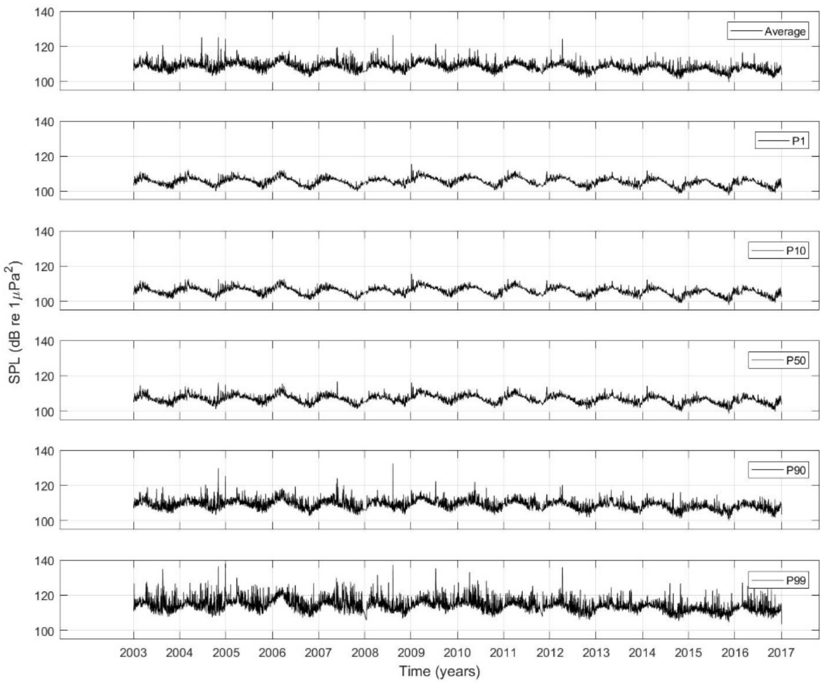

Fig. 1: Daily aggregated broadband SPL values for hydrophone H01W1 showing, from top to bottom, average, P_1, P_{10}, P_{50}, P_{90}, and P_{99} statistical levels.

ANALYSIS METHOD

The analysis method uses a flexible discrete model that incorporates terms that capture seasonal variations in the data together with a moving-average statistical model to describe the serial correlation of residual deviations, with uncertainties validated using bootstrap resampling. The main features of the approach used include (a) using a model that includes terms to represent explicitly seasonal behaviour, (b) using daily aggregation intervals derived from 1 minute SPL averages, and (c) applying a non-parametric approach to validate the uncertainties of trend estimates that avoids the need to make an assumption about that distribution of those differences.

Let $y_{i,j}, j = 1, \dots, n, i = 1, \dots, N$, denote the value of SPL at time $t_{i,j}$ corresponding to a chosen percentile (for example, P_1, P_{10}, P_{50}, P_{90} or P_{99}) of the distribution of SPLs for a chosen aggregation period (for example, daily, monthly or yearly). Here, n is the number of aggregation periods in a year and N is the number of years over which data are recorded. The data are modelled as:

$$y_{i,j} = at_{i,j} + s_j + e_k,\ k = (i-1)n + j,\ j = 1, \dots, n,\ i = 1, \dots, N, \tag{1}$$

where

$$e_k = \varepsilon_k + \theta_1 \varepsilon_{k-1} + \theta_2 \varepsilon_{k-2} + \cdots + \theta_q \varepsilon_{k-q}. \tag{2}$$

The parameter a describes the long-term trend and the terms $s_j, j = 1, \dots, n,$ are used to represent seasonal behaviour as departures from a long-term trend that are reproducible from year to year. A moving-average (MA) model of order q is used to account for possible serial correlation of the data-model differences e_k in which the ε_k are assumed to be random draws made independently from a normal distribution with expectation zero and variance, σ^2.

Estimates of the parameters $a, s_1, \dots, s_n$ of the seasonal regression model, of the parameters $\theta_1, \dots, \theta_q$ of the MA model and of the variance σ^2 are obtained by maximum-likelihood estimation. To select the order q of the MA model the estimation problem is solved for a sequence of models of increasing order, and selecting the value of q that minimises a measure of the quality of fit, such as the Bayesian Information Criterion. The uncertainty of the estimate of the trend a is calculated from a first-order sensitivity analysis of the maximum-likelihood estimator, and depends on the estimate of σ and the values of the derivatives of the model function with respect to the parameter estimates. A method of bootstrap resampling has been used to validate the calculated uncertainties.

A motivation for the model, and a comparison of its performance against simpler models (for example, without the MA model and without the seasonal terms), is given in Harris *et al*, 2019 [13].

RESULTS

Figure 2 illustrates a seasonal model fitted to the monthly aggregated data using a moving-average statistical model as well as the time series of the standardised residual deviations that estimate ε_k/σ. An analysis of these results show that there is no statistically significant serial correlation of the standardised residual deviations and that they can be considered as random draws made independently from a normal distribution.

Using daily aggregation of the SPL values, Figure 3 shows the results of the regression analysis using a seasonal model with a moving-average statistical model aggregated over the three hydrophones and for the six statistical metrics and each of the five frequency bands [13]. The aggregated trend estimates present some interesting characteristics. Perhaps the clearest observation is that the estimates for all metrics and all frequency bands show statistically significant SPL decrease corresponding to negative long term trends in the time series of the statistical noise levels, with the 85–105 Hz and 40–60 Hz frequency bands showing the slowest and fastest decrease with time, respectively. Another observation is that broadband trend estimates are very similar to the estimates for the lower end of the spectrum, indicating that the trends are dominated by the lower frequencies in the distribution of the spectral energy. Additionally, it is interesting that the distributions of the trend estimates for the different percentiles within each frequency band appear to be remarkably similar, with estimates for the lower percentiles indicating a negative trend that is smaller in absolute value than for higher percentiles. This indicates that apart from the overall reduction in SPL with time, the dynamic range of the recorded sound pressure decreases with time.

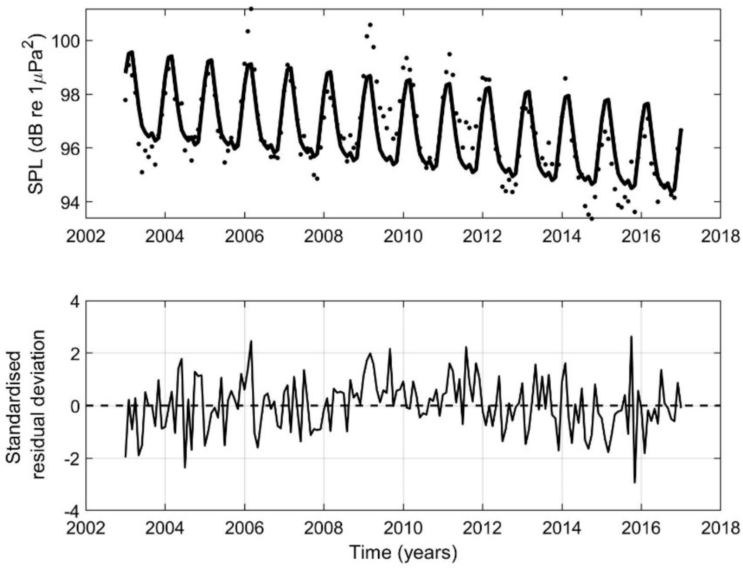

Fig. 2: Monthly aggregated P_{50} values for the 40-60 Hz frequency band from hydrophone H01W1 with fitted straight-line model including seasonal terms and a moving-average statistical model. The standardised residual deviations are also shown.

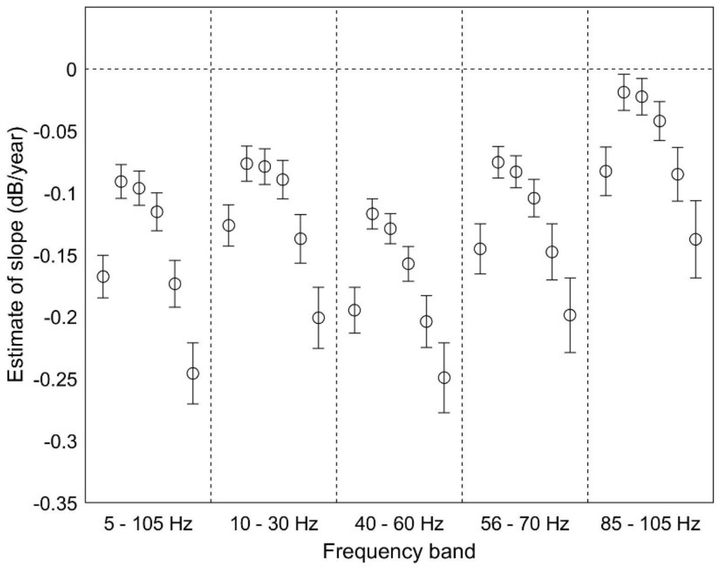

Fig.3: For daily aggregated data and each frequency band and each statistical level, estimates of the slope with associated 95 % coverage intervals obtained by aggregating the results for the three hydrophones. For each frequency band, results are presented for (left to right), average, P_1, P_{10}, P_{50}, P_{90} and P_{99} statistical levels.

These results are in accord with some of the outcomes from some recent studies performed on noise data from different locations [4, 9, 12], they contradict the understanding that noise in the oceans is in general increasing due to increasing human offshore activity. Shipping traffic, in particular, is believed to be one of the main man-made contributors to low-frequency ocean noise and it has been posited that a correlation should exist between trends in the international fleet size and ocean noise levels [6]. According to "Review of Maritime Transport 2016" issued by the United Nations [14], the trend in the international seaborne trade expressed in tonne-miles per year appears to monotonically increase from the mid-1980s until 2016 with only a small anomaly observed in 2009 because of the Great Recession. There is no evidence that the local volume of ship traffic in the region is decreasing, though no detailed information on ship movements derived from maritime Automated Identification System is available over the required time period to inform the work described here.

Another possible explanation is that there is a downward drift in the sensitivity of the hydrophones, but such a drift would have to affect all three hydrophones equally, and results of studies of the long-term stability of the CTBTO hydroacoustic stations suggest that this is an unlikely explanation, though hard to eliminate [15]. In addition to anthropogenic factors, there are also natural influences which could potentially be responsible for both the seasonal variation and long-term trends. Surface winds generate waves which are sources of sound on the ocean surface, and the sea surface temperature can influence the proportion of sound energy from surface sources which reaches the deep-ocean sound channel. In the latter case, the temperature-induced changes to the sound speed profile alter the propagation of sound due to refraction, a process sometimes called the “afternoon effect” [16.17]. Considering the location of Cape Leeuwin, the effect of low frequency noise generated by Antarctic ice breaking is also a possible influence, ice calving being known to be a source of low frequency sound and to influence the sound scape in the Southern ocean [7, 8].

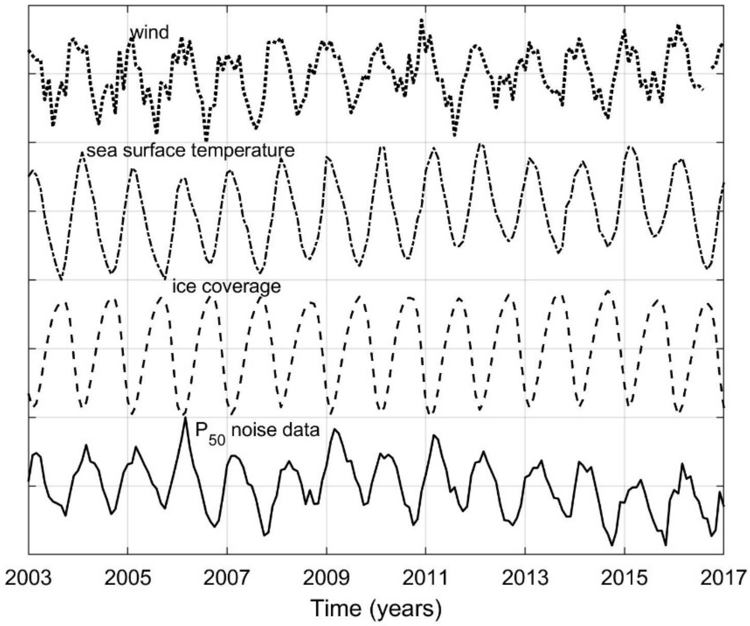

Fig. 4: Comparison (from bottom to top) of daily aggregated P_{50} values, Antarctic ice volume, sea surface temperature and wind speed. The time series for each effect is shifted to have the same mean, scaled to have the same amplitude, and then displayed with a different vertical offset.

To examine these effects, data for wind speed, sea surface temperature and ice coverage was obtained from public databases [18-20] and the data were examined for correlations with the acoustic noise data (see Figure 4). Data for wind speed shows only modest correlation, but there is strong correlation with sea surface temperature, and an even stronger correlation with Antarctic ice volume. This provides some empirical evidence that climatic factors such as ice coverage and sea surface temperature are influencing deep-ocean noise levels at seasonal timescales, and suggests the possibility that long-term gradual changes in these factors influence the noise trends over longer timescales.

CONCLUSION

The analysis demonstrated that it is possible to determine statistically significant trends in deep-ocean noise data over periods exceeding a decade. The results showed that statistically significant reductions in SPL are observed for all statistical percentiles for the different frequency bands as a result of negative trends in the examined time series for Cape Leeuwin. At this point, given the complexity of the acoustic environment and the fact that this is a purely observational study, it is difficult to be confident about the causes of the observed trends, which may be due to changes in anthropogenic sources, but could also be influenced by environmental factors such as seasonal and long-term variations in ice breaking noise and sea surface temperature.

ACKNOWLEDGEMENTS

The work described here was funded by the National Metrology Programme of the UK Department of Business, Energy and Industrial Strategy. The data was provided by the CTBTO, and the specialists at the virtual Data Exploitation Centre (vDEC) are gratefully acknowledged by the authors. The views expressed in the paper are those of the authors and do not necessarily represent those of the CTBTO.

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