Supplementary Information for

A machine learning approach for detecting wind farm noise amplitude modulation

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This PDF file includes:

Figs. S1 to S5
Tables S1 to S4
SI References

Supplementary Methods

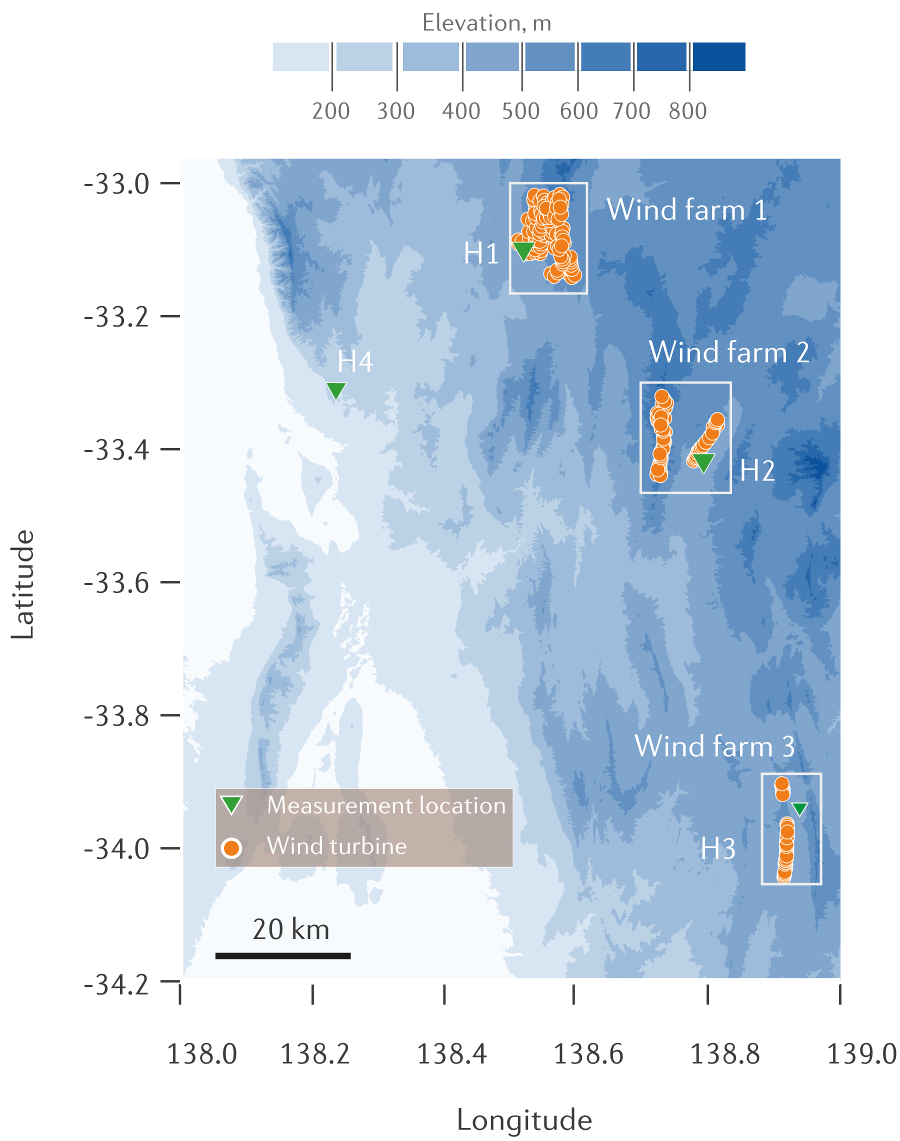

Fig. S1. (Color online). Three measurements (H1-H3) located near South Australian wind farms. The data measured at wind farm 1 and 2 were used for training and validating the algorithm. The data measured at wind farm 3 when the wind farm was not operating and at unoccupied residence H4 were used for false positive rate validation. Wind farm 1 comprised 99 Siemens 3.2 MW turbines at the time of the measurements. Wind farm 2 comprised 70 Suzlon 2.1 MW wind turbines. Wind farm 3 was made up of 37 Vestas V90-3.0MW wind turbines. Typical measurement setup: the microphone was positioned at ground level and protected using a hemispherical secondary windshield with a diameter of 450 mm (See Hansen et al. (1) for details). The microphone was typically positioned at least 10 m away from the residence and surrounding vegetation to minimize façade reflections and wind-induced vegetation noise.

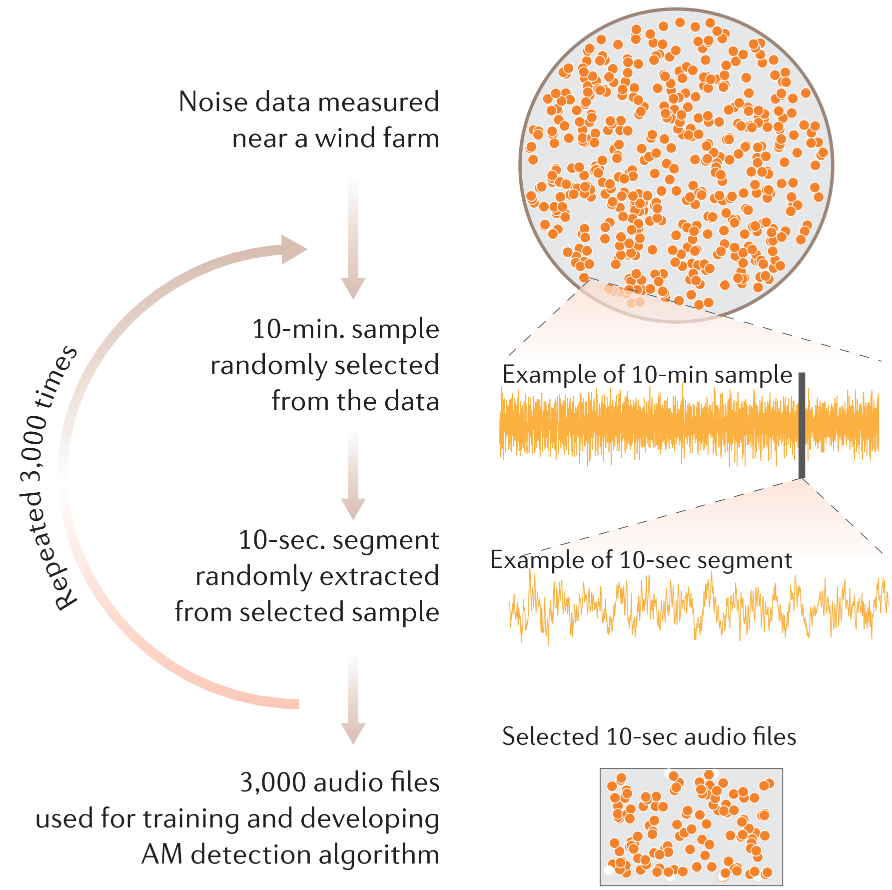

Fig. S2. (Color online). For illustration purposes, each orange dot inside the top circle represents a 10-minute sample in a measured data set. To extract 10-second audio files, we randomly selected 3,000 10-minute samples from each data set (data measured at each locations See Fig. S1) using the resampling without replacement technique (i.e., each 10-minute sample has only one chance to be selected in the data set). From each selected sample, a 10-second duration segment was randomly selected then extracted. The segments were then converted to audio files (.wav). Exclusion criteria were not specified for the data extraction (i.e., raining, dogs barking, farming machinery noise etc.)

Fig. S3. (Color online). MATLAB GUI for rating the presence of amplitude modulation audio files. The chosen example shows the characteristics of an audio sample with broadband amplitude modulation at 250 – 1000 Hz. The octave-band 100 ms fast-weighted SPL in the time and frequency domains was shown during audio presentations as the visual presence of noise characteristics was expected to improve the scorer's sensitivity. It should be noted that the amplitude (y-axis) as shown in the left figure has been normalised for visual inspection purposes. The frequency resolution of the signals in the right figure was 0.1 Hz. Scorers could listen to the audio files multiple times before rating. The experiment required a high concentration on the noise all the time, and thus to mitigate wrong classifications, the scorer was instructed to have break if they could not focus on the noise. To evaluate the inter-scorer agreement, Scorer 2 also listened and rated 100 audio samples, which were selected randomly from the 6,000 audio files. These results were compared with those of Scorer 1 based on the Matthews correlation coefficient metric. It took more than two weeks for Scorer 1 and nearly two days for Scorer 2 to listen and rate the audio files.

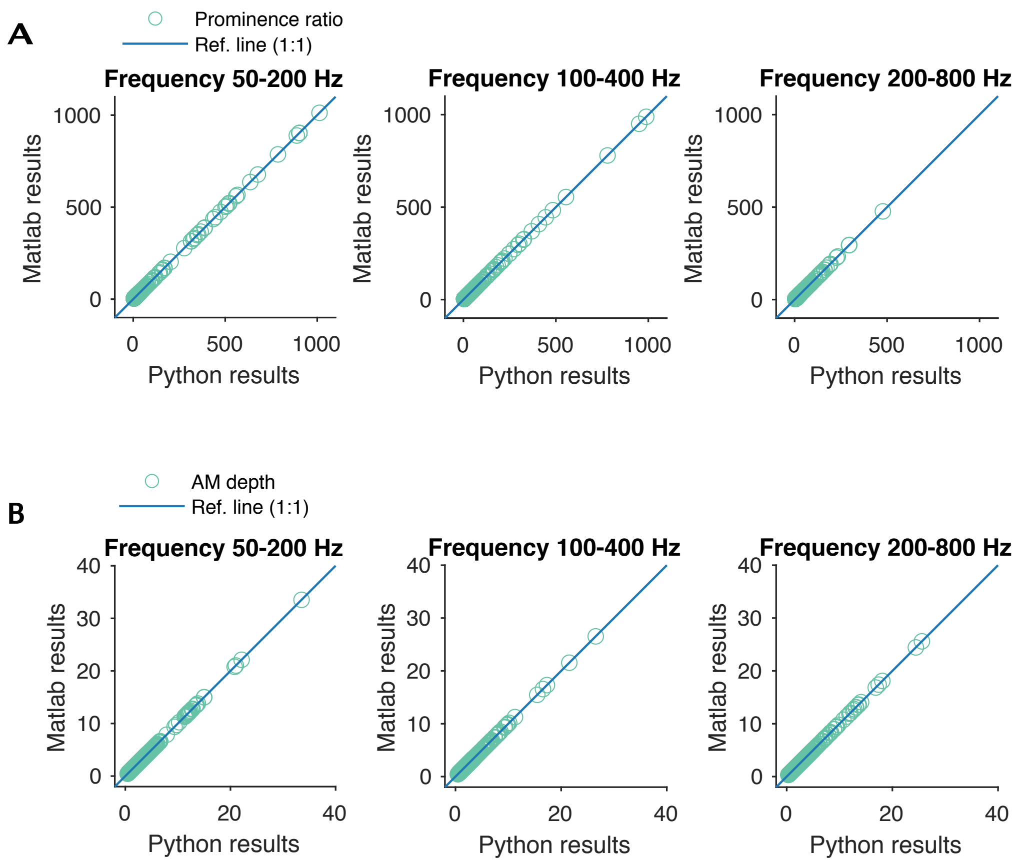

Fig. S4. (Color online). Comparison between MATLAB and Python (2) results. **A**, Comparison of prominence ratio (PR) between MATLAB and Python results. **B**, Comparison of AM depth between MATLAB and Python results

Algorithm 1: Hybrid AM detection algorithm (3)

Data: 10-second audio files

Result: Prominence ratio, present or absent AM

for *band-pass filter between ([50-200Hz],[100-400Hz],[100-800Hz])* **do**

> Apply band-pass filter to the input signals;
> Apply the A-weighting filter to the obtained signal;
> Calculate the fast (100 ms) time-weighted SPL, $L_{Aeq}(fast)$;
> Detrend the SPL signal using a third order polynomial curve fit, resulting in ΔLA;
> Transform the detrended SPL (ΔLA) to the frequency domain;
> Find spectral peaks located in the range of 0.4 to 1.0 Hz;
> A = max (peaks) in the range [0.4 to 1 Hz];
> B = mean (4 spectral lines) which are closest to the max peak location (except the two peaks closet to the max peak);
> Calculate the prominence ratio, $PR = A/B$;

if $PR \geq 4$ **then**

AM present, and the AM depth is calculated ;

else

AM absent;

Go to the end of the loop;

Algorithm 2: Frequency-domain AM detection algorithm (4)

Data: 10-second audio files

Result: AM factor, present or absent AM

> Apply low-pass filter at 1kHz;

> Apply the A-weighting filter;

> Calculate the fast (100ms) time-weighted SPLs, $L_{Aeq}(fast)$;

> Detrend the SPL signal using a third-order polynomial curve fit;

> Transform the detrended SPL to the frequency domain using an FFT;

> Calculate the amplitude modulation spectrum;

$AMS = \sqrt{2} * |FFT(detrendedLA(fast)|/N$;

> Calculate the AM factor ;

$AMfactor = max(AMS(f)) \quad with \quad [0.6 \quad 1Hz]$;

if $AMfactor \geq 0.4$ **then**

  AM present ;

else

  AM absent;

Algorithm 3: Time-domain AM detection algorithm (5)

Data: 10-second audio files

Result: DAM

$>$ Apply low-pass filter at 1kHz;

$>$ Apply the A-weighting filter;

$>$ Calculate slow (1s) and fast (100ms) time-weighted SPLs, $L_{Aeq}(slow)$ and $L_{Aeq}(fast)$;

$>$ Detrend the SPL signal:$\Delta LA = L_{Aeq}(fast) - L_{Aeq}(slow)$;

$>$ Calculate the 95$^{\text{th}}$ and 5$^{\text{th}}$ percentiles of ΔLA ;

$>$ $DAM = \Delta LA5 - \Delta LA95$;

No.	Type	$Feature$ (description)	Ref.
1-11	Spectrum shape-based features	$spectralCentroid$ $spectralCrest$ $spectralDecrease$ $spectralEntropy$ $spectralFlatness$ $SpectralFlux$ $spectralKurtosis$ $spectralRollofPoint$ $spectralSkewness$ $spectralSlope$ $spectralSpread$	(6, 7)
12-13	Tonality based-features	$pitch$ $harmonicratio$	(6, 7)
14-17	Overall noise features	LA (LAeq) $ratioLGLA$ (LGeq/LAeq $ratioLCLA$ (LCeq/LAeq) $diffLCLA$ (LCeq-LAeq)	(8)
18-27	Time domain features	$peakLoc$ (Peak location) $peakVal$ (Peak value) $posSlope$ (Mean positive slope) $negSlope$ (Mean negative slope) $peakloc\_unweightedSPL$ $L1000$ (Var. octave-band SPL at 1000 Hz) $L500$ (Var. octave-band SPL at 500 Hz) $L250$ (Var. octave-band SPL at 250 Hz) $L125$ (Var. octave-band SPL at 125 Hz) $L63$ (Var. octave-band SPL at 63 Hz)	proposed
28-31	Automated methods	LA (LAeq) PR (Prominence ratio) Fo (Fundamental frequency) $AMfactor$ DAM	(3–5)

Table S1. Feature descriptions

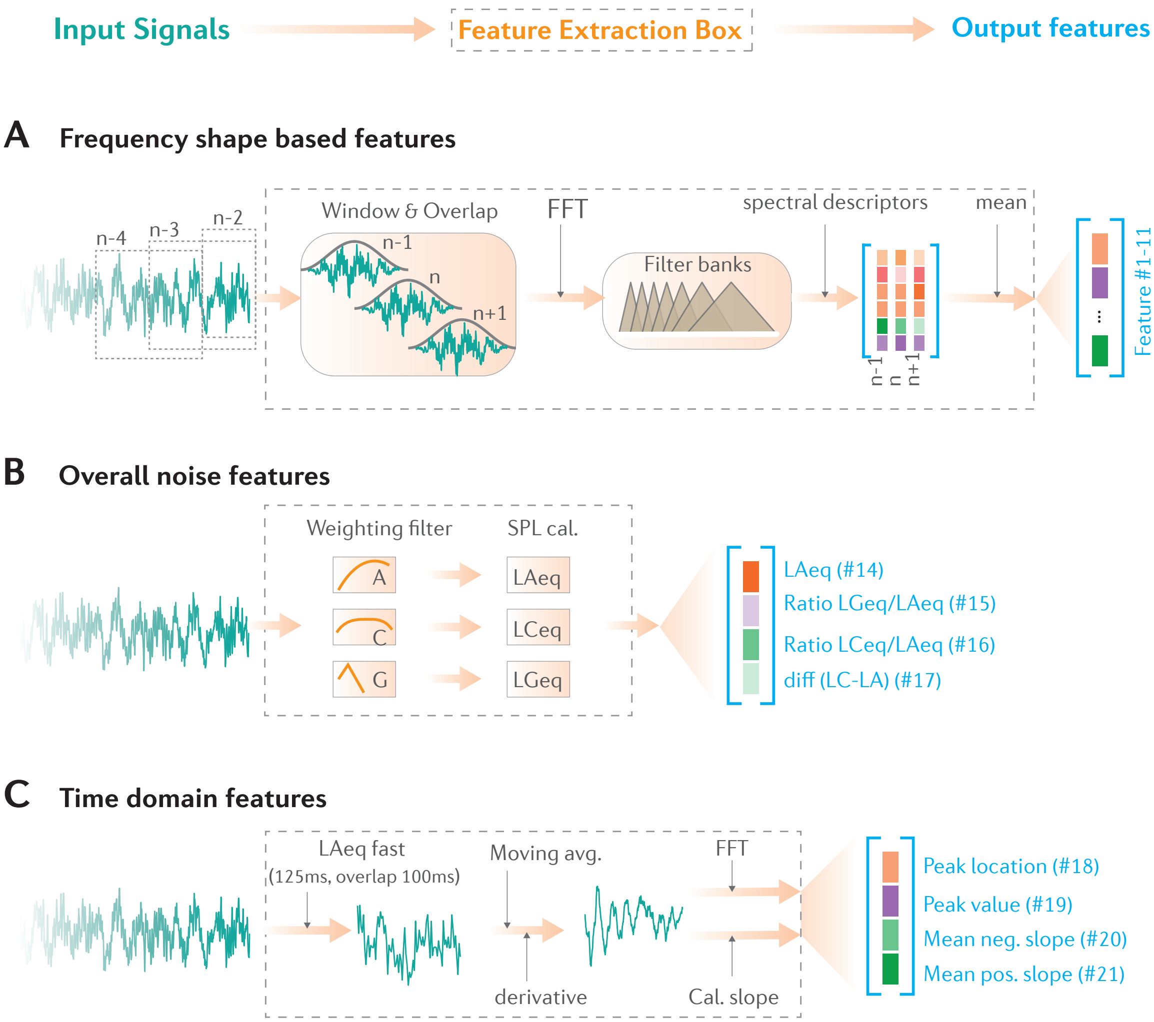

Fig. S5. (Color online). The spectrum shape and tonality based-feature categories (Feature 1 to feature 13) have been explained in detail in previous reviews (6, 7) and the pseudo code for extracting these features can be also found in (7). Figure (**A**) shows the process to extract these audio features. A hamming window of 125 ms (50% overlap) is applied to the input signals which are then transformed to the frequency domain using an FFT. The signals are then filtered using bark scale filter banks and the spectral shape features are calculated for each hamming window. The outcome of the process is a matrix (no. of features x no. of windows). The mean values of the rows in this matrix were calculated, resulting in a single value for each feature. The overall noise feature category (Feature 14 to feature 17) such as A, C and G-weighted SPLs were also extracted as shown in Figure (**B**). The selected features were $LGeq/LAeq$, $LCeq/LAeq$, and $LCeq - LAeq$, as these measures are expected to be indicative of wind farm noise presence (9–11). The $LAeq$ was selected as it has been used as a metric for analyzing AM in previous studies (4, 12). The time-domain feature category (Feature 18 to feature 27) was extracted as shown in Figure (**C**). The fast-time weighted (125 ms) SPL was calculated by sampling at time intervals of 25 ms. This process is similar to the method for calculating the prominence of impulsive sounds outlined in Nordtest (13). We further modified the process by smoothing the SPL using a moving average window of 5 samples. To estimate the rate of change of the smoothed SPL, the first derivative of the signal was calculated. The derivative signal was then transformed to the frequency domain using an FFT. The highest peak (Feature 19) and its corresponding frequency (Feature 18) of the derivative in the frequency domain were obtained. Also, the mean values of positive (rising slope) and negative slope (decay slope) of the derivative signals were estimated (Feature 20 and 21, respectively). This modification is advantageous because the fluctuation rate of the derivative signal is similar to the smoothed SPL, while its amplitude is less variant compared to the smoothed SPL. As a result, the blade-pass frequency peaks were clearer in the frequency domain. Feature 22 was calculated in a similar way to feature 18, except using the unweighted SPL. Features 23-27 are variations (calculated as L5-L95) of the octave-band unweighted SPL centered at 63 Hz to 1000 Hz. The automated methods (a1, a3 and a3) were also used as noise features (Feature 28 to 31).

Definitions:	
True positive (TP):	Correct detection of AM
False positive (FP):	Incorrect detection of AM
True negative (TN):	Correct detection of no AM
False negative (FN):	Incorrect detection of no AM
Fundamental equations:	
Recall (Sensitivity):	$recall = \frac{TP}{TP + FN}$
Precision:	$precision = \frac{TP}{TP + FP}$
F1-score:	$F1score = 2\frac{precision \times recall}{precision + recall}$
Specificity:	$Specificity = \frac{TN}{TN + FP}$
Accuracy:	$Accuracy = \frac{TP + TN}{N}$ where $N = TP + TN + FP + FN$
Cohen's kappa:	$k = \frac{\frac{TP + TN}{TP + TN + FP + FN} - Pr(e)}{1 - Pr(e)}$ where
	$Pr(e) = \frac{TP + FN}{N}\frac{TP + FP}{N} + (1 - \frac{TP + FN}{N})(1 - \frac{TP+FP}{N})$
Matthews Correlation Coefficient (MCC):	$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FN)(TP + FP)(TN + FP)(TN + FN)}}$

Table S2. Evaluation metrics: Definitions and equations

Metric	Mean [95%CI]
Recall	0.79 [0.66 0.92]
FPR	0.14 [0.06 0.23]
FNR	0.21 [0.008 0.34]
Specificity	0.86 [0.77 0.94]
Precision	0.75 [0.6 0.89]
FDR	0.25 [0.12 0.4]
FOR	0.11 [0.03 0.19]
NPV	0.89 [0.81 0.96]
Accuracy	0.84 [0.76 0.91]
F1-score	0.77 [0.66 0.87]
MCC	0.65 [0.49 0.8]
Cohen's kappa	0.64 [0.48 0.8]

Table S3. Inter-scorer agreement

Metric	Out-of-bag validation value= mean [95%CI]
Recall	0.81 [0.8 0.82]
FPR	0.17 [0.17 0.18]
FNR	0.19 [0.18 0.20]
Specificity	0.83 [0.82 0.83]
Precision	0.7 [0.69 0.72]
FDR	0.3 [0.28 0.31]
FOR	0.11 [0.1 0.11]
NPV	0.89 [0.89 0.90]
Accuracy	0.82 [0.81 0.83]
F1-score	0.75 [0.74 0.76]
MCC	0.62 [0.60 0.63]
Cohen's kappa	0.61 [0.60 0.63]
AUC	0.88 [0.88 0.89]
AUPRC	0.85 [0.84 0.86]

Table S4. Performance of the best classifier on the out-of-bag samples

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