1 hardRain: an R package for quick, automated rainfall detection in ecoacoustic datasets using a
2 threshold-based approach.

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13 Abstract

14 The increasing demand for cost-efficient biodiversity data at large spatiotemporal scales has led to
15 an increase in the collection of large ecoacoustic datasets. Whilst the ease of collection and storage
16 of audio data has rapidly increased and costs fallen, methods for robust analysis of the data have not
17 developed so quickly. Identification and classification of audio signals to species level is extremely
18 desirable, but reliability can be highly affected by non-target noise, especially rainfall. Despite this
19 demand, there are few easily applicable pre-processing methods available for rainfall detection for
20 conservation practitioners and ecologists. Here, we use threshold values of two simple measures,
21 Power Spectrum Density (amplitude) and Signal-to-Noise Ratio at two frequency bands, to
22 differentiate between the presence and absence of heavy rainfall. We assess the effect of using
23 different threshold values on Accuracy and Specificity. We apply the method to four datasets from
24 both tropical and temperate regions, and find that it has up to 99% accuracy on tropical datasets
25 (e.g. from the Brazilian Amazon), but performs less well in temperate environments. This is likely due
26 to the intensity of rainfall in tropical forests and its falling on dense, broadleaf vegetation amplifying
27 the sound. We show that by choosing between different threshold values, informed trade-offs can
28 be made between Accuracy and Specificity, thus allowing the exclusion of large amounts of audio
29 data containing rainfall in all locations without the loss of data not containing rain. We assess the
30 impact of using different sample sizes of audio data to set threshold values, and find that 200 15s
31 audio files represents an optimal trade-off between effort, accuracy and specificity in most
32 scenarios. This methodology and accompanying R package 'hardRain' is the first automated rainfall
33 detection tool for pre-processing large acoustic datasets without the need for any additional rain
34 gauge data.

35 Keywords: Ecoacoustics, Environmental monitoring, Bioacoustics, Soundscape ecology, Rain
36 detection, Acoustic pre-processing

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38   1.Introduction

39   Ecological questions are increasingly being answered using large datasets (Hampton et al., 2013;
40   McCallen et al., 2019; Villanueva-Rosales et al., 2014), and faced with an ongoing biodiversity crisis,
41   cost-effective collection of ecological data to address conservation challenges is vital (Gardner et al.,
42   2008). The recent rapid development of cost-effective ecoacoustic sampling methods has facilitated
43   collection of acoustic big data (Burivalova et al., 2019; Deichmann et al., 2018) and catalysed an
44   increase in ecoacoustic monitoring. Despite the cost-effective nature of this sampling method
45   (Deichmann et al., 2018; Hill et al., 2018), there are still significant challenges associated with the
46   analysis of large acoustic datasets,. Automated detection and classification using machine or deep-
47   learning techniques has been widely touted as one answer to this challenge (Priyadarshani et al.,
48   2018). However, large datasets often require initial data cleaning to remove 'noise' (sounds which
49   are not of interest, such as engines, wind and even electrical noises produced by the recorder
50   (Stowell et al., 2016). The presence of hard rainfall (HR) is a significant contributor to noise as it can
51   entirely mask all signals of interest or hinder their identification, and it can be especially problematic
52   in both biodiverse and pluviose ecosystems such as tropical forests where our knowledge of
53   biodiversity is most limited and acoustic data may be most useful. The use of acoustic indices, a
54   common technique for quantifying biodiversity in large datasets without recourse to species level
55   identification (Sueur et al., 2014; Towsey et al., 2014), have also been shown to be biased by the
56   presence of heavy rainfall (Depraetere et al., 2012; Fairbrass et al., 2017; Towsey et al., 2014).
57   Automated detection and excision of audio data at times of high rainfall is therefore often desirable
58   before further analyses are undertaken, especially when using automated classifiers for detection of
59   ecological sounds, as it reduces the potential for false identifications and increases processing time.

60   Despite the need for effective tools to identify and remove audio segments containing heavy rain,
61   little research currently exists on the topic. Other published methods have different objectives;
62   focussing on detection of rainfall as an objective in its own right (Brown et al., 2019), finding a proxy
63   variable for quantification of total rainfall, or being designed to function in specific geographic areas
64   to study the effect of rainfall within a wider soundscape (Bedoya et al., 2017). This has resulted in
65   prioritising optimisation of accuracy of detection over ease of use and specificity. Other methods,
66   such as the ecoacoustic event detection approach (Farina et al., 2018) allow a holistic approach to
67   identification of all acoustic events, in which rainfall identification becomes a secondary benefit. We
68   argue that many ecologists and conservation practitioners will primarily be interested in quickly
69   identifying the majority of rain files rather than ascertaining the presence or absence of rain, to
70   allow for better classification of ecological sounds and unbiased indices. For these users, the priority
71   will be minimizing effort and maximising specificity –e.g. ensuring that false positive rates are very
72   low so that ecological data are not removed from a dataset to achieve a higher overall accuracy of
73   rainfall detection. Therefore, the most successful reported method of automated rainfall
74   classification Brown et al. (2019), which involves a complex machine-learning approach and an
75   extensive feature set, could be prohibitive for non-specialists. Many users may be willing to trade-off
76   a small amount of accuracy in return for much lower analytical effort and greater ease of
77   comprehension.

78   A simpler, quicker approach to classification has been proposed by Bedoya et al. (2017). This utilizes
79   two acoustic measures indicative of rainfall taken at a single frequency band to set a decision
80   threshold above which rainfall is determined to be present. However, this method uses minimum
81   values over a period of acoustic data with rain of known intensity (using a rain gauge) to set the
82   decision threshold. Obtaining verified rainfall data may not be possible in many cases, and requires
83   additional cost and effort – especially in closed canopy ecosystems. Additionally the use of minimum
84   values to set thresholds prioritizes accuracy over specificity, potentially leading to avoidably high

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85 false positive rates for relatively small gains in accuracy and the exclusion of potentially informative
86 audio files. Setting threshold values from the second quartile of the interquartile range (Q2) may
87 give more conservative predictions for the presence of HR, enabling a trade-off between higher
88 specificity scores at the expense of accuracy. Furthermore, the amplitude of rainfall increases most
89 noticeably at two frequency bands, 0.6-1.2 kHz and 4.4-5.6 kHz where the impact of raindrops
90 hitting vegetation is most noticeable. Bedoya measures the indices at 0.6-1.2 kHz as light intensity
91 rainfall is more noticeable, and it contains less biophony than the higher frequencies. However, it is
92 unclear if the use of both of the frequency bands would produce better results when classifying only
93 heavy rain, or in locations with higher levels of anthropophony (man-made noise).

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95 Here we present a user-friendly methodology and associated R package (R Studio Team, 2015)
96 'hardRain', for automated rainfall detection that maintains high specificity and accuracy for use with
97 new datasets. We build on the thresholding approach of Bedoya, developing a method to remove
98 the need for any additional data from rain gauges to set threshold values. We investigate, at
99 multiple tropical and temperate sites, whether using both 0.6-1.2 kHz and 4.4-5.6 kHz frequency
100 bands provide greater accuracy and specificity than using only the lower frequency band, and assess
101 the optimal number of files containing rainfall to use as training data from which to obtain threshold
102 values. We also explore how differences in location affect classification results, and the trade-offs in
103 accuracy and specificity when using minimum or Q2 values for setting decision thresholds.

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105 ## 2. Methods

106 ### 2.1. Definition of rainfall

107 Identifying audio files containing rain without rain gauge data is not straightforward, as light rainfall
108 can be indistinguishable from background noise (Bedoya et al., 2017). However, in these cases,
109 rainfall is less likely to be less disruptive for the automated classification of ecological sounds. Here,
110 we focus on the detection of heavy rainfall, here defined as rainfall that visually masks or
111 significantly degrades other sound events (see Figure 1 for examples). Audio files were manually
112 assigned as either 'Hard Rain (HR)' or 'Clear' through visual inspection of spectrograms in Raven Pro
113 (Cornell Bioacoustics Research Program, 2010). For consistency, a single observer (OM) undertook all
114 manual classifications in this paper.

115
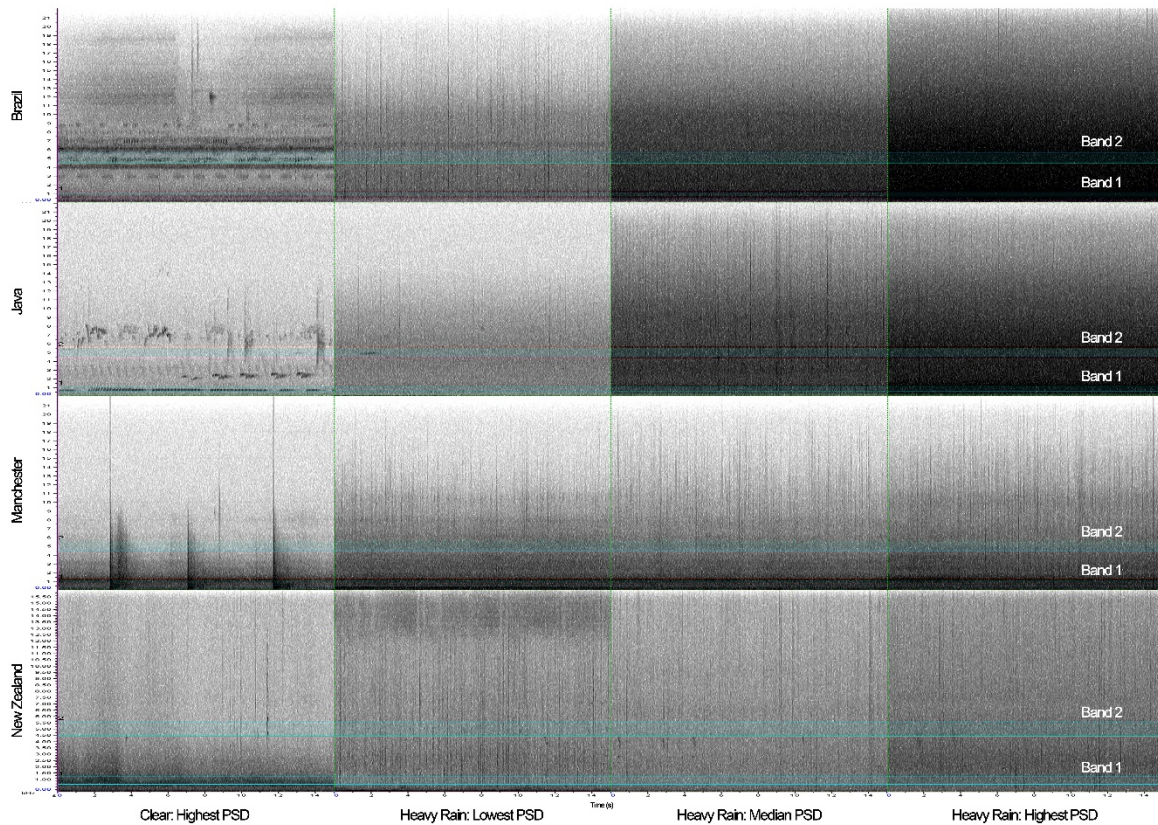
Figure 1. Examples of spectrograms assigned to rainfall present and absent taken from the combined training and test dataset of each country, ranked by power spectral density (PSD).

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118   2.2 Data

119   This paper uses four primary datasets; two were collected in tropical rain forest; Santarém, Pará
120   state, Brazil (-3.046, -54.947) and West Java, Indonesia (-6.181, 106.827), and two from temperate
121   climates; one from temperate forests in Taranaki, New Zealand (-39.448, 174.414) and one from an
122   urban balcony in Manchester, United Kingdom (53.485, -2.228). All include periods of time when
123   both rainfall and clear weather were prevalent. The Brazil dataset comprises more than 10,000 hrs
124   of data from 29 sites, the Java data set consists of more than 10,000 hours of data from 11 sites in
125   montane forests in West Java with 12 recorders per site, Manchester over 600 hrs from one site and
126   New Zealand over 3,900 hrs from 31 recorders at one site. For further information on data collection
127   locations and durations at each of the sites see supplementary online material (SOM Table 1). Data
128   were collected using Frontier Labs Bioacoustic Audio recorders (Frontier Labs, 2015), with the
129   exception of the New Zealand dataset which used NZ Department of Conservation recorders (see
130   Metcalf et al., 2019 for more information). All audio data were recorded at a sampling rate of 44.1
131   kHz except the New Zealand data set recorded at 32 kHz. All audio data were subdivided into 15 s
132   sound files.

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134   2.3 Threshold Setting and Optimisation

135   From each primary dataset, a training and test dataset were selected. The test and training datasets
136   comprised 1000 files each. We manually selected 1,500 files that were then randomly split into
137   1,000 training files and 500 test files. A further 500 files that had been manually selected as being

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138 Clear (of Heavy Rainfall) were included in the test dataset, so that both the training and test dataset
139 are composed of 1000 files. The Brazilian training dataset comprised 13 sites including both
140 undisturbed primary and heavily degraded primary forests. The test dataset comprised eight sites
141 and three sites for HR and Clear files respectively. Java training data came from 11 sites, whilst the
142 test dataset used data from eights sites for HR and one site for Clear data. Manchester HR data were
143 collected between 25th-28th April 2019, whilst Clear data was from 4th November 2018. The New
144 Zealand training data were from 18 sites, whilst HR test data came from 16 sites and Clear from 18
145 sites.

146 We followed Bedoya et al., (2017) in using power spectral density (PSD) and signal-to-noise ratio
147 (StN) as acoustic indices. The PSD of an acoustic file increases with rainfall intensity, while StN is
148 useful to differentiate files that have high PSD because of continuous rainfall versus those that have
149 high PSD because of non-continuous loud sound sources, such as biophony (e.g. animal
150 vocalisations) or anthropophony. The PSD values in both 0.6-1.2 kHz and 4.4-5.6 kHz frequency
151 bands were calculated for every file with the 'spectro' function from the seewave package in R
152 (Sueur et al., 2008). The window length used to calculate PSD values was set to equal the duration of
153 the audio file (typically 15 s segments – see package documentation; Figure 2 shows these values
154 from the test datasets). We used mean divided by standard deviation of the PSD for the Signal-to-
155 Noise ratio, following Bedoya et al., (2017), although we note a typographical error in point 3 of
156 Algorithm 2.1 as the deviation of the mean is not squared in the standard deviation formula. See
157 SOM Table 2 for all PSD and StN values for all training and test datasets.
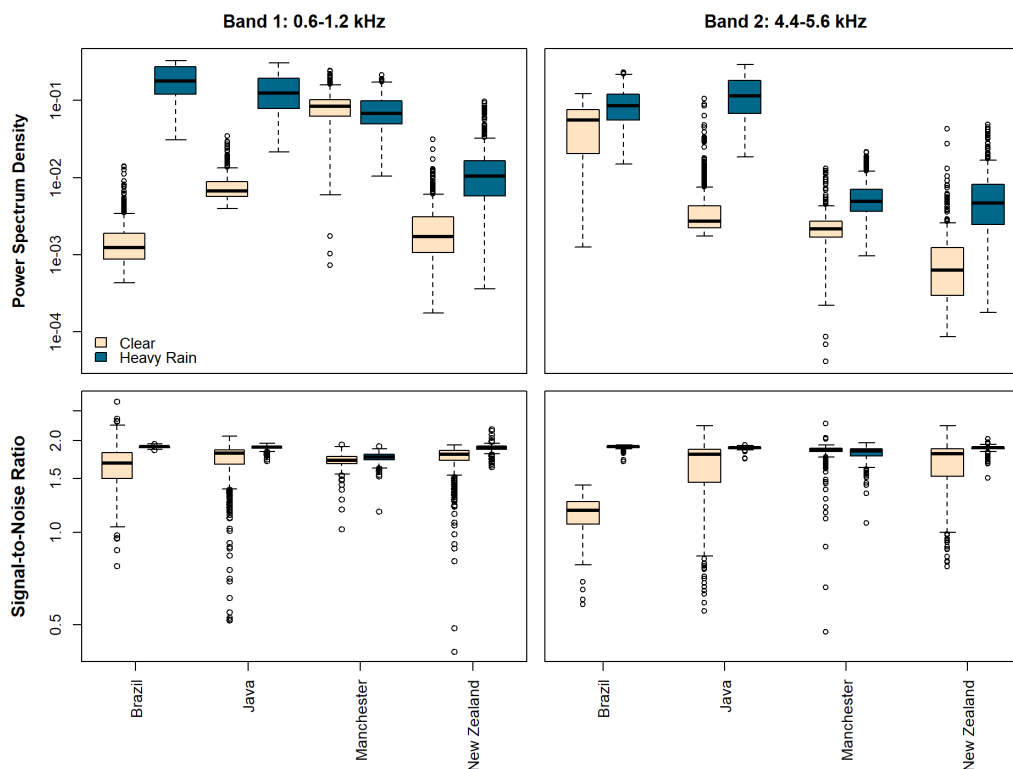
159 *Figure 2 Power Spectral Density and Signal-to-Noise Ratio values for audio files containing heavy rain*
160 *and clear files from the test datasets. The y-axes are presented on a log scale.*

161 In predicting the presence of heavy rain, we followed Bedoya et al., (2017) in using thresholds for
162 PSD and StN, so that if any of the measured values from an audio file exceed the threshold, they
163 were predicted to contain heavy rain. We used mean balanced accuracy (Accuracy) and specificity

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164 (Specificity) (Velez et al., 2007) to assess the performance of classifier models. Although accuracy is
165 the primary objective of classification, in some uses the penalty for the rejection of useable data
166 (false-positives) may be far higher than the consequences of keeping files containing rain in the
167 dataset (false-negatives), and specificity is the best measure for that circumstance (Fielding and Bell,
168 1997).

169 We tested classification performance using thresholds of PSD and StN from frequency band 1 (e.g.
170 values had to exceed two thresholds to be classified as HR) against classification using PSD and StN
171 from frequency bands 1 and 2 (e.g. values have to exceed four thresholds to be classified as HR)
172 using a paired Wilcoxon rank test. To assess the effect, we took 100 subsamples of n=500 from each
173 of the four countries' training datasets. Minimum and Q2 threshold values were then obtained and
174 used to classify the applicable test dataset. Accuracy and specificity values were calculated by
175 country, threshold choice and the mean of all countries combined.

176 To optimise the number of training samples required, we assessed the relationship between the
177 number of training samples and accuracy/specificity with the aim of balancing the effort of manually
178 selecting training data and the susceptibility of threshold values to outliers and variation in data sets.
179 For each training dataset, 100 subsamples of size n= 10, 20, 30, 40, 50, 75, 100, then increasing
180 increments of 50 to 1000, were taken and threshold values obtained using both frequency band 1
181 and 2 and these used to classify the applicable test dataset. Mean accuracy, specificity and their
182 standard deviations were then calculated for each sample size by country and threshold choice. The
183 sample size of n=500 was tested for significant differences in classification Accuracy and Specificity
184 between the countries using Kruskal-Wallis and pairwise Wilcoxon tests, significant at <0.05.

185 In order to assess if there was overtraining between the test and training datasets, we conducted a
186 case study using the Brazilian primary data. A random sample set of 6,960 files (1 hour from each
187 transect), independent from the test and training data, was taken from the Brazilian primary dataset
188 and manually labelled. A further subsample of 500 files was taken from the Brazilian training dataset
189 to obtain threshold values, and these were used to predict the presence and absence of rainfall in
190 the Brazilian random sample.

191

192 3.Results

193 The results produced by using both frequency bands were on average significantly better than those
194 using just the 0.6-1.2 kHz band across both Specificity and Accuracy, with the exception of Accuracy
195 when using the Q2 threshold, although results varied somewhat by country (Table 1). As Accuracy is
196 not likely to be as important a consideration as Specificity for those choosing to use a Q2 threshold,
197 using two frequency bands was deemed the better choice, and all further results discussed here are
198 for classification with measurements taken from both frequency bands.

199
200 *Table 1: Accuracy and Specificity scores by country, threshold choice, and number of frequency bands measured. 500*
201 *samples were used to set the thresholds.*

Country	Mean Accuracy (%)				Mean Specificity (%)			
	Minimum threshold		Q2 Threshold		Minimum threshold		Q2 Threshold	
	1 band	2 bands	1 band	2 bands	1 band	2 bands	1 band	2 bands
Brazil	**99.69±0.00**	**99.67±0.00**	**83.10±0.01**	**69.36±0.01**	100±0.00	100±0.00	100±0.00	100±0.00
Java	99.76±0.00	99.75±0.00	**87.13±0.01**	**71.31±0.01**	**99.80±0.00**	**100±0.00**	100±0.00	100±0.00

Manchester	54.81±0.01	55.73±0.01	79.39±0.01	67.77±0.00	10.15±0.01	12.60±0.01	91.05±0.01	97.39±0.00
New Zealand	51.75±0.03	60.14±0.03	82.65±0.01	72.61±0.01	3.66±0.05	20.49±0.06	98.00±0.00	100±0.00
Mean	76.50±0.01	78.83±0.01	83.07±0.01	70.26±0.01	53.40±0.02	58.27±0.02	97.27±0.00	99.35±0.00

Results with significant differences (corrected p-value <0.05) between one and two bands are in bold. All differences in which two bands performed better than one band are shaded. A table of the p-values can be found in supplementary online material (SOM Table 3).

Detection responses to sample size varied both by country and by the choice of threshold value, but were consistent across Specificity and Accuracy metrics. When using minimum threshold values, Accuracy showed rapid increases until an asymptote at 200 samples for Brazil and Java, but declines for Manchester and New Zealand (Figure 3a). Specificity reaches 100% for all samples sizes in the Brazil and Java datasets, but follows a similar, but steeper trend to Accuracy for Manchester and New Zealand (not shown in Fig 3). Using the Q2 threshold, Specificity is at 100% for all sample sizes for Brazil and Java and New Zealand and around 97% for Manchester (Fig 3b), whilst Accuracy reaches stable scores for all countries between 100 and 200 samples (Fig 3c). Full tables of results are available in SOM Tables 4 and 5.
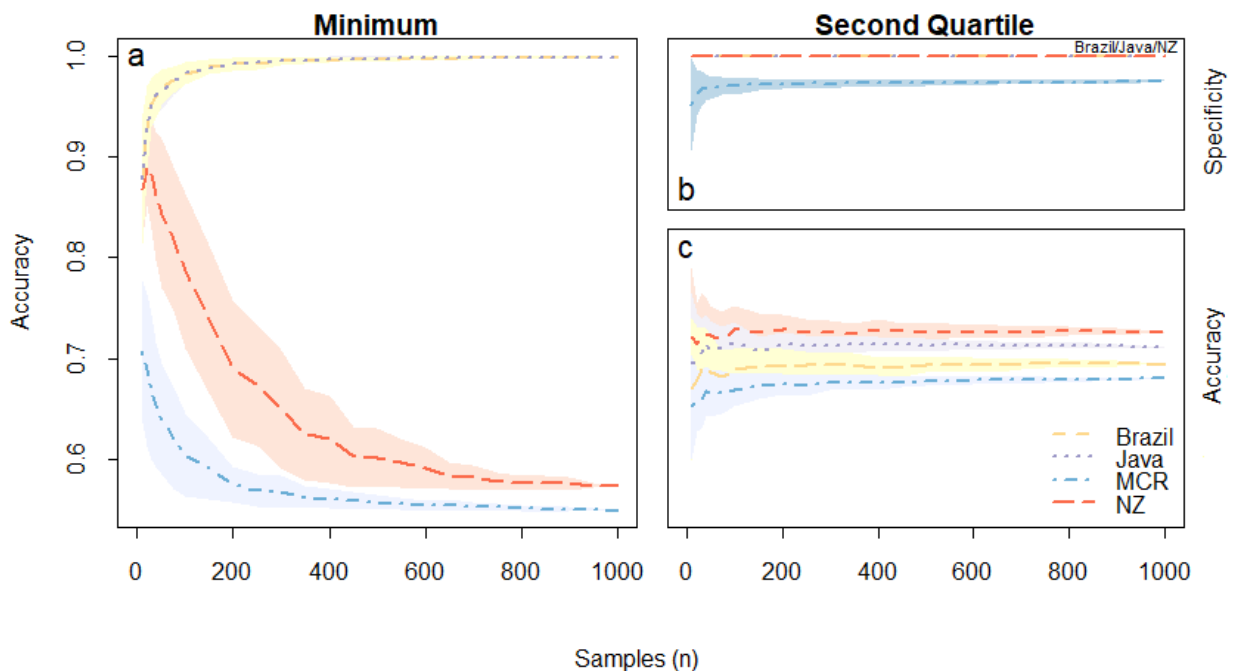
Figure 3 Selected Accuracy and Specificity scores by sample size (n), country and threshold selection method. Specificity scores for minimum threshold method not shown as Specificity=1 for all sample sizes in Brazil and Java data, and below 0.5 for almost all sample sizes in Manchester and New Zealand datasets. The shading represents standard deviation of 100 repetitions. NZ= New Zealand, MCR=Manchester.

Comparison between country scores showed that there were significant pairwise differences between all countries for both threshold choices in Accuracy and Specificity, except where Specificity was at 100% (Table 1; also see SOM Table 3). As expected, there was no clear threshold value choice to maximise both Specificity and Accuracy across all countries. The best Accuracy scores were achieved using Minimum threshold values, >99% for all training sample sizes over 200 for both Brazil and Java but this performed poorly for Manchester and New Zealand (Table 1, Fig 3). This suggests

227   that in some countries, the differentiation is not enough to achieve high levels of Accuracy even
228   when excellent Accuracy scores are achieved with the same method in other locations. Using the Q2
229   threshold, Accuracy was low for all countries (between 65% and 73%). Despite this, high Specificity
230   scores can be achieved for all countries using the Q2 threshold (Table 1, Fig 3). This highlights that
231   even in datasets where there may be poor distinction between Clear and HR data using PSD and StN
232   indices, 35-50% of all HR files can be identified with loss of less than 5% of data containing no rain.
233   Confusion matrices are provided in Table 2 for the mean scores of a sample size of 500 training files
234   applied to the Manchester and New Zealand test datasets using second quartile thresholds.

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236   *Table 2. Confusion matrices with 500 samples of training data using second quartile threshold values.*

		Manchester - testing dataset		New Zealand – testing dataset	
		Second Quartile Threshold		Second Quartile Threshold	
		Actual Class			
Predicted Class		TRUE	FALSE	TRUE	FALSE
	TRUE	185	15	230	0
	FALSE	315	485	270	500
	Sensitivity=38.15%, Specificity=97.39%, Accuracy=67.77%			Sensitivity=45.22%, Specificity=100%, Accuracy=72.61%	

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238   The results for classification of the case study using 6,960 files of the Brazilian dataset remained
239   good, although lower than the test scores suggesting a small amount of overtraining between the
240   test and training datasets (Table 3). To read in, measure and classify all 6960 files took 15 min 16 s
241   using a Dell EliteBook laptop with a 4-core Intel Core i7-7600U CPU and 16 GB RAM running
242   Windows 10.

243   *Table 3. Matrix of the Brazilian case study*

		Brazil - 6960 randomly selected audio files			
		Minimum Threshold		Second Quartile Threshold	
		Actual Class			
Predicted Class		TRUE	FALSE	TRUE	FALSE
	TRUE	88	14	33	0
	FALSE	22	6836	69	6858
	Sensitivity=86.27%, Specificity=99.68%, Accuracy=92.98%			Sensitivity=32.35%, Specificity=100%, Accuracy=66.18%	

244   *Data are a random sample of the entire audio dataset (n=6960, HR n=102) with threshold values*
245   *taken from 500 randomly selected audio files from the Brazilian training dataset.*

246   4.Conclusions

247   We have shown that it is possible to fully automate rainfall identification within audio data from
248   tropical environments using only two simple measurements at two frequency bands, and requiring
249   only a relatively small set of files containing known rainfall to extract threshold values. We also
250   demonstrate that by using different thresholds, minimum and second quartile, the technique can be
251   adjusted for use even in cases where there is poor differentiation between rain presence and

252 absence with a reasonably high level of success. This means that users of hardRain can make
253 informed trade-offs between effort, accuracy and specificity.

254 The effectiveness of the method is clearly dependent on sample sizes, with standard deviations
255 declining with increasing samples, but divergent impact on Accuracy by site and threshold selection
256 method. Whilst it is possible to devise various stopping rules to optimise the sample number, the
257 optimal solution will vary with the ease of obtaining training files containing rain and the objectives
258 of individual research projects. The standard deviation of Accuracy and Specificity is relatively low
259 for almost all measures at 200 samples (Fig.3, SOM Table 5), with corresponding accuracy and
260 specificity scores close to their maximum for the tropical datasets when using minimum threshold
261 values, and for all datasets when using second quartile values.

262 Using only PSD and StN as measurements to differentiate between rain presence and absence has
263 clear advantages in minimising effort and ease of understanding. Along with Brown et al., (2019), we
264 did not find StN to be a useful index for classification when we initially analysed our data using the
265 printed formula in Bedoya et al., (2017). However, when we used the standard formula for standard
266 deviation, the use of both PSD and StN was better than just PSD. In some circumstances, even the
267 use of both indices resulted in poor differentiation. This is especially the case for datasets from
268 temperate climates, with Manchester and New Zealand performing worse, presumably due to
269 poorer distinction between PSD scores (Fig 2). This is possibly because rainfall is less intense at these
270 locations, or because rain falling on to predominately concrete (Manchester) and more open
271 temperate forest canopies (New Zealand), results in less amplification than in tropical forests (Java
272 and Brazil). Despite this shortcoming, by using second quartile thresholds between 40-50% of rain
273 data was identified even in Manchester and New Zealand, with no or only a very small percentages
274 of rain-free data misidentified (Table 2).

275 Although not herein directly compared, our methodology is unlikely to match the AUC scores of the
276 method proposed by Brown et al., (2019) or the accuracy and quantification of Bedoya et al., (2017).
277 For those scholars studying rain through audio data, or requiring extremely precise cleaning, these
278 would be better methods to use. However, our methodology provides a quick and effective
279 classification method that can be applied to audio data, and is especially suited to tropical forests
280 where the need for reliable acoustic data on biodiversity is greatest and rainfall is frequent. For
281 researchers wishing to quickly remove rain files from large datasets prior to classification, this
282 method will often represent the most time-effective way to do so. Additionally for research in which
283 the penalty of false-negatives is far lower than that of false positives, this method of rain detection
284 allows for informed trade-offs between Accuracy and Specificity which previous methods of rain
285 detection do not.

286

287 **Package description**
288 To facilitate the use of this rain detection method, we have developed the R package 'hardRain'. The
289 package will i) set thresholds (based on training data consisting of short segments of known rain
290 audio recordings), ii) apply the thresholds to audio data and identify presence of rain in each input
291 file, or subdivisions therein, iii) cut audio segments with rain and save the remaining segments, and
292 optionally, create a label file view in Audacity or Raven software. It can also be used to test the
293 accuracy of the classification using known testing and training data. The package consists of
294 four main functions (Table 4).
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298 *Table 4. Functions in the R package 'hardRain'.*

Function	Description	Main inputs
getThreshold	This function measures PSD and Signal-to-Noise Ratio on all input training files at two frequency bands (defaults to 0.6-1.2 kHz and 4.4-5.6 kHz) and calculates minimum and 2nd quartile thresholds over these.	wav filenames (and locations where these are stored) of audio segments of known rain, i.e. training data (see above for discussion on how many files are needed), but typically 200 wav files of about 15 s duration
classifyRain	This function takes the testing data, calculates the PSD and Signal-to-Noise Ratio and applies the thresholds produced by getThreshold function and classifies each input file (or subdivision thereof) for the presence / absence of rain. Optionally, if the function is used for accuracy testing, a label can be included denoting which files have presence of rain or not.	wav filenames (and locations) of testing data files may be of short duration already (typically, 15-30 s segments) or may be provided as much longer files (e.g. 2-3 hours) and split into segments within the function, using the t.step argument (division size, in seconds); thresholds from getThreshold()
cutRain	This function takes the output from classifyRain() and cuts out the segments identified as rain in the input wav files and saves the remaining contiguous audio in a new folder and writes a label file for the original length audio file, marking segments with no rain (either or both of these options are available). Optionally, the new start time of each file can be recorded in the filename.	output from classifyRain() -only when longer files are classified in subdivisions; output location for new wav files.
getMetrics	This function does not generally need to be called directly. It is the workhorse function that reads wav files, extracts PSD and Signal-to-Noise for specified frequency bands using seewave function spectro(). This function is called by getThreshold() and classifyRain() which will generally be used directly.	wav filenames (and locations); time division (in seconds) to subdivide wav input files for analysis (optional)

299 *The package can be downloaded from: https://github.com/Cdevenish/hardRain*

300

301 Before using the classify function it is necessary to decide which threshold values to use. If it is
302 reasonable to make assumptions about the distinction between rain presence and absence, for

303 instance if the data is collected in tropical rain forest, then the threshold can be selected and the
304 results checked after. However, if it is unclear whether there will be a good distinction, accuracy can
305 be tested using the classifyRain function with known testing and training data (i.e. labelled audio
306 segments of heavy rain or clear) and confusion matrices and accuracy metrics produced (see
307 example in vignette).
308
309 See vignettes included in the package for further details on functionality.
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