Listening to mangroves: Using Autonomous Recording Units and Machine Learning tools to assess avian biodiversity in the mangroves of coastal Suriname

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Abstract

This exploratory study investigates avian biodiversity in the mangroves of coastal Suriname, as part of an interdisciplinary project on flood risk management and coastline mapping. Automated Recording Units (ARUs) were deployed between December 2024–February 2025 and April–July 2025 across six focal sites representing the three species of mangroves found in the area: *Avicennia germinans* (Black), *Laguncularia racemosa* (White), and *Rhizophora mangle* (Red). Bird vocalisations were extracted from audio recordings and classified using the BirdNET algorithm. Acoustic Indices were calculated from the same audio and related to both mangrove composition and bird species richness. The results provide new information on the ecology of these mangrove habitats. By integrating non-invasive remote monitoring with machine-learning tools such as BirdNET, this study demonstrates how these state-of-the-art tools can aid our understanding of ecosystems in a data-driven world.

Contents

Acknowledgements

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Cover photo – Saheed Nabie on Google Maps ‘street view’ function, accessed August 2025.

1. Introduction

This report describes my work in a multi-disciplinary project that is looking at Mangroves and flood risk in Suriname by mapping erosion and changes in mangrove types and size. The mangrove ecosystems of coastal Suriname play a crucial ecological role, providing coastal protection and serving as critical habitats for diverse flora and fauna. This is a highly dynamic ecosystem, which experiences cyclical erosion and accretion as sediment is transported north-west up the coast from the mouth of the Amazon to the mouth of the Orinoco.

The major objective of the current study was to monitor avian biodiversity across diverse mangrove ecosystems, that were dominated by one of three key mangrove tree species in the region. To this end, we deployed Automatic Recording Units (ARUs) in mangroves at several sites along the coastline, collecting audio data containing bird vocalisations. We quantified the vocal activity with acoustic indices and used the machine learning algorithm BirdNET to detect and classify the vocalisations of specific species.

Passive acoustic monitoring has become a central tool for surveying avian communities, offering the ability to collect larger amounts of data than traditional methods. Recent advances in machine learning have accelerated the development of automated classifiers capable of detecting and identifying bird species from audio data. BirdNET is among the most widely used of these systems, and utilises the online bird audio dataset Xeno-Canto and the online repository of in-field recordings and logs, eBird. This report describes the methods we used, our findings, and provides discussion in light of wider research about using Acoustic Indices and classifying calls using the BirdNET algorithm.

2. The Ecology of Suriname

2.1 The role of Mangroves and Mudbanks

Suriname's 375-km coastline sits between mouths of the Amazon and Orinoco rivers. It is a low, muddy shore, uniquely shaped by west-migrating Amazon-derived mudbanks: Sediment is carried out to sea by the Amazon river and travels west up the coast. Suriname's tidal mudbanks dampen the force of waves and accrete sediment (bank phases), then leave high-energy gaps that erode the shore (inter-bank phases) (Anthony, 2015). Between 1986 and 2020, 6–8 subtidal mudbanks migrated in front of the coast, strongly influencing shoreline dynamics (de Vries et. al., 2022). Individual mudbanks are typically 10–60 km long and 20–30 km wide; up to around 5 m thick (Anthony et. al., 2019). They migrate around 1-3 km per year, causing multi-decadal cycles of erosion and accretion (typically around 15-30 years of erosion and 15-30 years of accretion) (Erftemeijer & Teunissen, 2009).

During 'bank' (accretion) phases, mangroves expand and colonise the mudbank. During 'inter-bank' (erosion) phases, wave energy increases, eroding the mangroves and washing away the sediment they grow on, so the mangroves die back, creating 'Mangrove Graveyards' of dead trunks (Anthony et. al., 2019). However, mangrove graveyards can also form when rapid sediment deposition or too much flooding prevents root respiration (Fromard, 1998), demonstrating the fragility of these ecosystems.

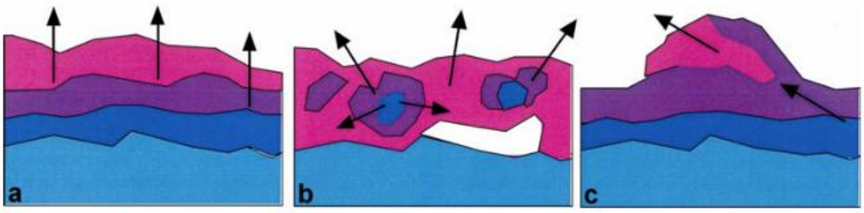

Figure 1: Process of mangrove colonization of mudbanks.

Figure 1 shows the process of mangrove colonisation of mudbanks. (Fromard et. al., 2004).
(a) Colonization by regular zonation, parallel to the coastline; (b) Colonization by expansion of patches, from residual mud patches not washed away in the previous erosion cycle; (c) Colonization by an arc of sediment in an east-west direction due to Amazon sediment movement. The colours show the sequential stages of the process.

2.2 Flood risk in Suriname and the role of mangroves in flood protection

Mangroves provide essential ecosystem services, including coastal protection, carbon storage, and habitats for fish and migratory birds (de Vries et. al., 2022). Protected areas such as the Multiple Use Management Areas (MUMAs) along the western side of the coast are particularly important. These wetlands support local livelihoods through fishing, hunting, agriculture, and tourism, while also serving as crucial feeding grounds for shorebirds and other coastal species (Djosetro & Behagel, 2024). Mangroves protect the coast against wave energy and provide habitats for wildlife, and are "more effective than concrete barriers [i.e., sea walls] in reducing erosion, trapping sediments, stabilizing shorelines, and dissipating the energy of breaking waves" (Erftemeijer & Teunissen, 2009). However, two areas of Suriname: Weg naar Zee (north of Paramaribo; one of our study sites) and Wanica, have experienced a combined 1200m of land loss in the period 1984-2014, with mangrove retreat of up to 450m at Weg naar Zee and up to 600m along Wanica. (World Bank Coastal Resilience Assessment, 2017).

Along the coast, particularly around the capital city of Paramaribo, there is an ongoing debate about whether to construct flood barriers or to promote mangrove ecosystems as natural coastal protection, which would reduce space for farming and other economic activities close to the coast (World Bank Coastal Resilience Assessment, 2017). The "Building with Nature" project at Weg naar Zee, by Anton de Kom University in collaboration with Conservation International, is an example of efforts to stimulate mangrove restoration and development in areas heavily affected by erosion (De Jong et al., 2020).
Local knowledge plays an integral role in sustainable management of these areas, and the most effective solutions will be those that integrate this within their scientific research (Djosetro & Behagel, 2024).

2.3 Mangrove Species

There are three species of Mangrove found on the Suriname coast, known as Black, White and Red:[1]

Black Mangrove ('Parwa') - *Avicennia germinans*

- Black Mangroves occur at the edge of the land, bordering the coastline to create 'fringing mangrove forest' (Erftemeijer & Teunissen, 2009). Black mangrove seedlings quickly colonise accreting mudbanks, using the processes in Figure 1 above, and have distinctive pneumatophore roots that grow upwards out of the mud/water to increase oxygen intake (Britanicca). They also occur further inland, where they can reach 12-15m tall and form mature mangrove forests.

Red mangrove ('Mangro') – *Rhizophora mangle*

- Red mangroves occur further inland, in monospecific forests alongside saline or brackish rivers and lakes, and alongside black and white mangroves in freshwater areas. Their prop roots (called rhizophores) are recognizable, and provide a nursery and habitat for fish. They are often 10-20m tall, but can grow up to 30m.

White Mangrove ('Akira') - *Laguncularia racemosa*

- White mangroves are usually found further inland than Black and Red, and grow to 9-12m. A distinguishing characteristic is the two glands on the petiole just below the leaf base, where excess salt is excreted.

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[1] The image of black mangroves is taken from the Living Oceans Foundation; https://www.livingoceansfoundation.org/ngg_tag/black-mangrove-pneumatophores/
The source of the other images and information is the Ask IFAS website, 'powered by' EDIS, University of Florida. https://edis.ifas.ufl.edu/

3. Methods

3.1 Sites of data collection

Autonomous Recording Units (ARUs) allow long-term non-invasive remote audio monitoring. We deployed 18 recorders across twelve sites in coastal Suriname. Figure 2 shows the different site locations and the species composition of the mangroves at that site. Figure 3 shows the two areas of the coastline where the ARUs were deployed, and Figures 4 & 5 'zoom in' on those sites to show specific locations and visualise mangrove composition at each site.

Unfortunately, a large number of the audio recorders were damaged by the environment (eg wind, animals), and/or only produced white noise. Figure 5 shows the sites where audio data was successfully obtained.

Table 2 – The List of locations that ARUs were deployed in, with each location's mangrove species composition

	Location	Black (%)	White (%)	Red (%)
	Totness (western site):			
1	Mozzie	52	48	0
2	West side of dike	69	31	0
3	East side of dike	62	38	0
4	Coronie Weather Station	100	0	0
	Weg naar Zee (WnZ) (eastern site):			
5	Crematory	50	47	3
6	Hindu Temple (west side)	9	86	5
7	Hindu Temple (east side)	7	93	0
8	WnZ, east of Ganpat	20	80	0
9	WnZ, end of the pier	88	12	0
10	Gummels Leonsberg (both sides of road)	25	75	0
11	West of sluice mouth	100	0	0
12	East of sluice mouth	81	0	19

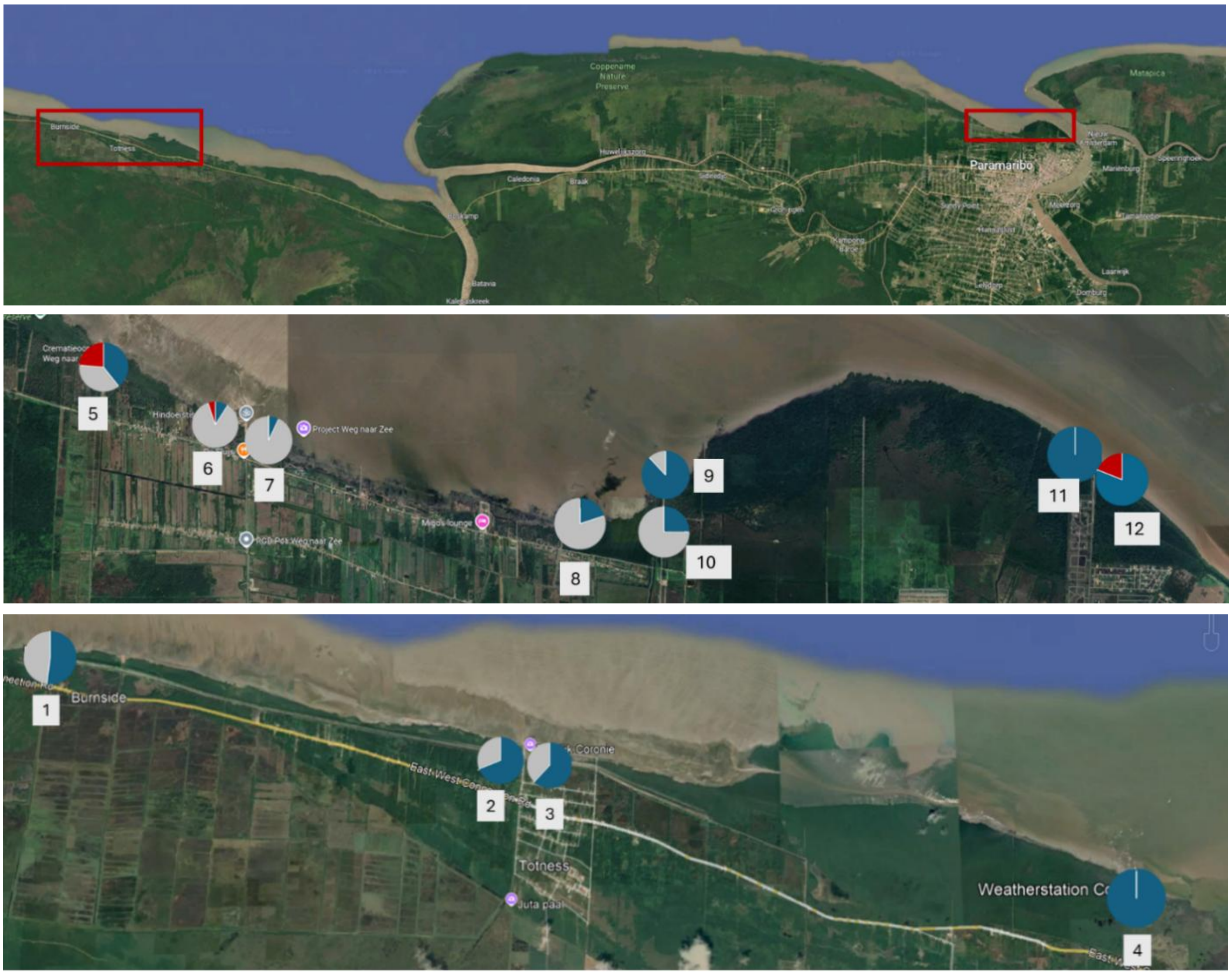
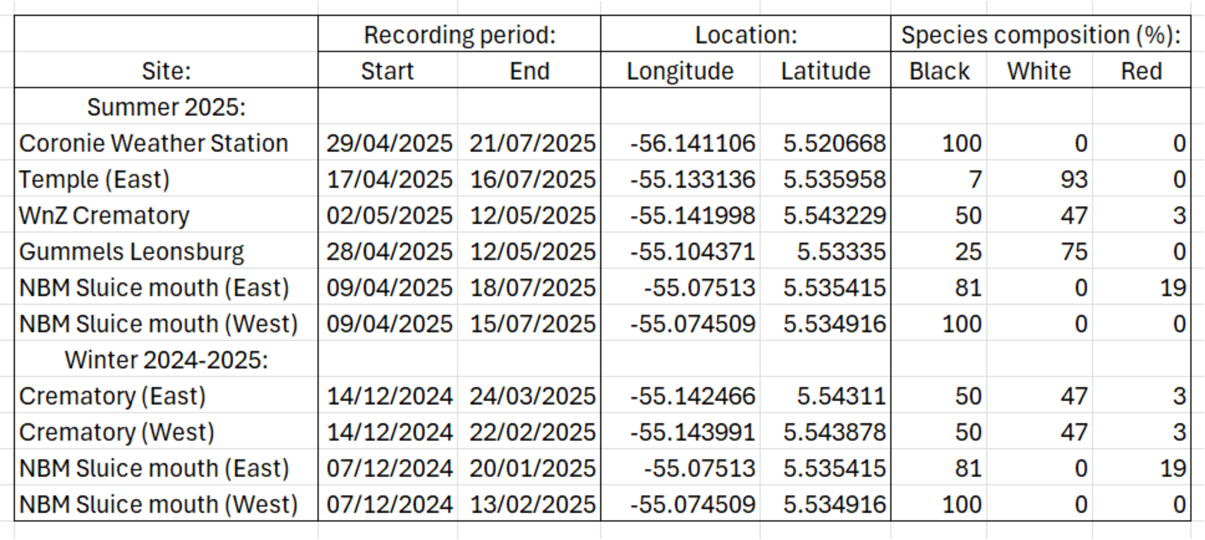


Figure 3 – The first image shows the two sites along the coast that recorders were deployed in, shown in red boxes. The second image shows the sites north of Paramaribo (right box) and the third shows the sites near Totness (left box). The pie charts show the mangrove composition of each site, with blue representing Black mangroves, grey representing white and red representing red.

Table 4 - Locations and time periods of successfully received audio, with the mangrove species composition of each location.



	Recording period:		Location:		Species composition (%):		
Site:	Start	End	Longitude	Latitude	Black	White	Red
Summer 2025:							
Coronie Weather Station	29/04/2025	21/07/2025	-56.141106	5.520668	100	0	0
Temple (East)	17/04/2025	16/07/2025	-55.133136	5.535958	7	93	0
WnZ Crematory	02/05/2025	12/05/2025	-55.141998	5.543229	50	47	3
Gummels Leonsburg	28/04/2025	12/05/2025	-55.104371	5.53335	25	75	0
NBM Sluice mouth (East)	09/04/2025	18/07/2025	-55.07513	5.535415	81	0	19
NBM Sluice mouth (West)	09/04/2025	15/07/2025	-55.074509	5.534916	100	0	0
Winter 2024-2025:							
Crematory (East)	14/12/2024	24/03/2025	-55.142466	5.54311	50	47	3
Crematory (West)	14/12/2024	22/02/2025	-55.143991	5.543878	50	47	3
NBM Sluice mouth (East)	07/12/2024	20/01/2025	-55.07513	5.535415	81	0	19
NBM Sluice mouth (West)	07/12/2024	13/02/2025	-55.074509	5.534916	100	0	0

Recorders
The two typers of recorders used were Songmeter Micro and Audiomoth. Specifications and further information can be found here: https://www.wildlifeacoustics.com/products/song-meter-micro-2; https://www.openacousticdevices.info/audiomoth.

Data
We received a large amount of data, so storing and moving data was time consuming. Spreadsheets were very large, so all data cleaning and analysis was done through the statistical programming tool 'R'. See Appendix (i) for information on where the audio data is currently stored.

3.2 Calculating Acoustic Indices

Acoustic indices are measures of the density of vocal activity, and provide a good overall estimate of the bird activity in an area. A comprehensive description of the different Acoustic Indices and their pros and cons for different data types can be found in the ‘Acoustic Index Users Guide’, published in Bradfer-Lawrence et. al., 2024: https://ecohack.shinyapps.io/Acoustic_Index_Users_Guide/

I have chosen the Acoustic Complexity Index for this study, due to its sensitivity to short changes in amplitude of noise. This means that bird calls that are distinct, repeated short bursts of noise will increase ACI, but constant insect noise will not, and therefore ACI can be used as a proxy for intensity and diversity of avian vocalization. McGrann et al., 2022 found positive associations between ACI and avian species richness.

I used the package ‘Soundecology’ in the statistical analysis tool ‘R’ to calculate ACI.
Arguments used: Function = "acoustic_complexity"; Minimum frequency = 0 kHz; maximum frequency = 15000 kHz; FFT = 512; j (i.e., cluster length) = 5 seconds.

Figure 4 shows the raw ACI values against date-time, illustrating that the raw data is difficult to interpret without modification:

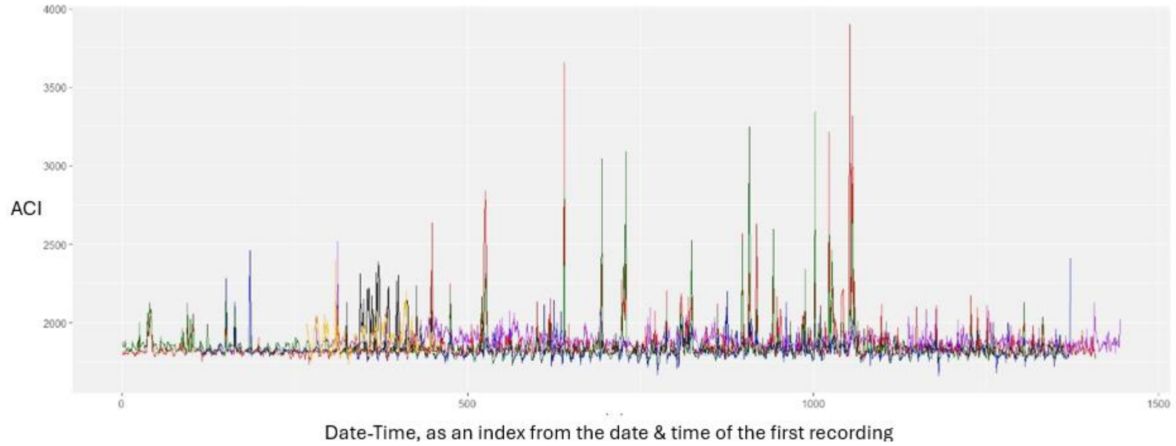


Figure 5 - raw ACI values

However, we can see diurnal patterns emerging by ‘zooming in’ on one section of the graph, shown in Figure 5.

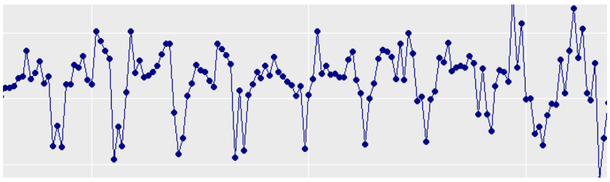


Figure 6 - Diurnal patterns found in the data. Each dot represents a recording clip, and we can see low points every 14 clips, which is once daily (14 clips were recorded per day).

To ‘clean’ the data, I removed the high anomalies (which were caused by animal scuffling activity near the recorders), by manually going through the audio clips with high ACI to check for non-bird noises. I checked all of the clips with ACI greater than 2,000. All of the audio clips with ACI greater than 2,400 had lots of non-bird noise, and negligible bird identifications, and were therefore removed. The smallest level of ACI removed was 2,410.63 in ‘Temple East’ at 10.35 on the 16th July.

3.3 Classifying Specific Species with BirdNET

3.3.1 Machine learning classifiers - background

Passive acoustic monitoring has become a central tool for surveying avian communities, offering the ability to collect large amounts of data, and provide a more complete picture of the ecology of an area than traditional methods like point counts and ‘capture-mark-recapture’. Recent advances in machine learning have accelerated the development of automated classifiers capable of identifying bird species from audio data, but also raise concerns regarding generalisability, bias, and interpretability (see Stowell, 2022 for a review of the ‘state of the art’). BirdNET (see Kahl et. al., 2021) is among the most widely used of these systems, and utilises the online bird audio dataset Xeno-Canto, and the online repository of in-field recordings and logs, eBird.

In 2018, initiatives like the Bird Audio Detection challenge (Stowell et al 2018) demonstrated the feasibility of ‘bird present/absent’ detection from audio using computational methods, and the review by Priydarhsani et. al (2018) highlighted the challenges of automated recognition in noisy, multi-species environments, where overlapping calls and background noises such as traffic and weather reduce the accuracy of models. However, there have been vast improvements to recognisers in the last seven years, and new software such as Kaleidescope (Wildlife Acoustics), BirdVox (Lostanlen et. al., 2022), and BirdNET (Kahl et., al., 2021) can be highly effective. New methodologies have been developed to mitigate against the issues raised in Priydarhsani 2018, such as band-pass filtering (to restrict audio to the pitches that birds vocalise in) and ‘de-noising’: classifying and removing anthropogenic noise from datasets (Er et. al., 2025). Our dataset had little of this noise, so I decided that this process would not add value. However, some non-bird noise which resulted in false classifications was manually removed post-classification (see ‘False positives’ in the results section below).

Recent practical guides explain the ways that BirdNET detector outputs can be interpreted (Wood & Kahl, 2024) and emphasise the importance of collaboration between ecologists and computer scientists (Kershenbaum et al., 2025). BirdNET provides an accessible and high-performing option for large audio datasets, but care must be taken when interpreting results to account for its limitations.

3.3.2 Optimising BirdNET settings for species detection

I used audio data from one location recorded over a 13-day period, to trial the BirdNET recogniser on our mangrove audio data. The data were passed through BirdNET repeatedly, adjusting settings to balance false positives and false negatives to maximise the true positive and true negative detections. Where settings are not specifically mentioned here, they were set at the recommended default settings. The three settings that were trialled were:

Sensitivity – set to default.
My original plan was to have very high sensitivity, which would generate false positives, and then go through all the classifications to verify them and remove them false positives. However, I got tens of thousands of classifications for just 13 days and one location of audio, so manual verification wasn’t

feasible. I took the sensitivity back down and increased it until I was getting more false positives than new identifications, and the outcome of this process was the default sensitivity setting.

Overlap – set to 0.5 seconds.
During the classification process, BirdNET splits the audio into 3-second chunks, called 'segments', and there is the option to allow these segments of audio to overlap. I used the same method as described above for overlap, increasing it until I was getting more false positives than new identifications, resulting in an optimum level of 0.5. The increase in overlap from default settings makes it more likely for the full call of birds with a longer call to be captured.

Time of year – set to 'year-round'.
BirdNET uses information about species on eBird to evaluate the likelihood of their presence in the audio, for example the area of the world and time of year they are found in. Some species with low information on eBird don't have their seasons specified. This means that they aren't on the 'list of options' of birds present in the specified week, and therefore don't get identified by BirdNET. I therefore used year-round time, as some of the potential species in the area had low levels of information on BirdNET. Further information about this issue can be found on GitHub: https://github.com/birdnet-team/BirdNET-Analyzer/issues/211#issuecomment-1849833360 It is worth noting that this issue does not occur with specifying the location of species, so the location filter was used and set to the longitude/latitude of each site.

4.Results

4.1 Acoustic Indicies

I have calculated the daily mean ACI to remove the ‘noise’ of the fluctuations due to diurnal bird vocalization patterns, shown in Figure 6.

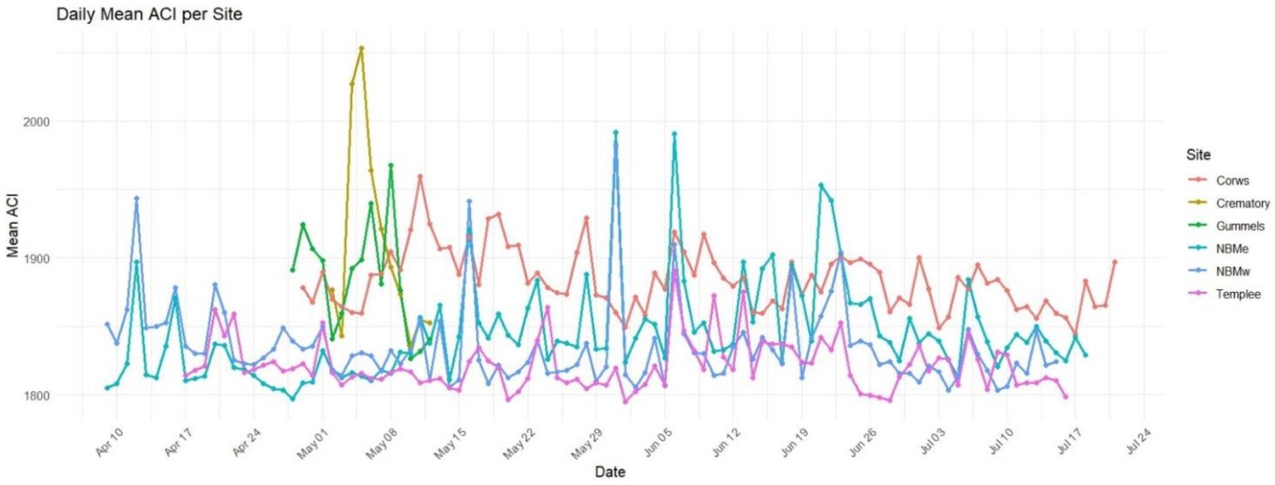


Figure 7 -Daily mean ACI, all sites

There are some times where we can see spikes in ACI at multiple sites, for example April 12th, May 16th, May 31st, and June 6th. The spikes of NBM East and NBM West are always correlated, often also with Temple East, but not with Coronie Weather Station. I therefore hypothesise that these spikes are due to weather events, as NBM East and West are very geographically close, with Temple East in a similar region, whereas Coronie is considerably further west along the coast. This could be where rain and wind noise have increased the ACI, or where the weather affects birds’ level of vocalisation.

Figure 7 shows the same data as Figure 6, but shown without the locations Gummels and Crematory (as these ARUs only collected data for a short time period) and the remaining locations colour-coded by species of mangrove present (black mangroves – black, white mangroves – yellow, red mangroves – red). Coronie WS is the higher black line; NBM west is the lower one.

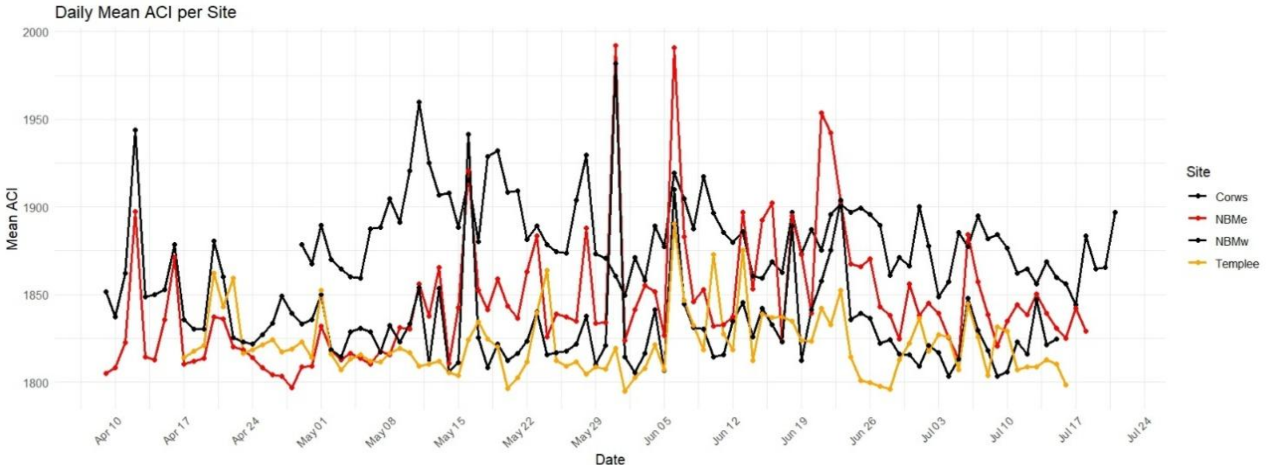
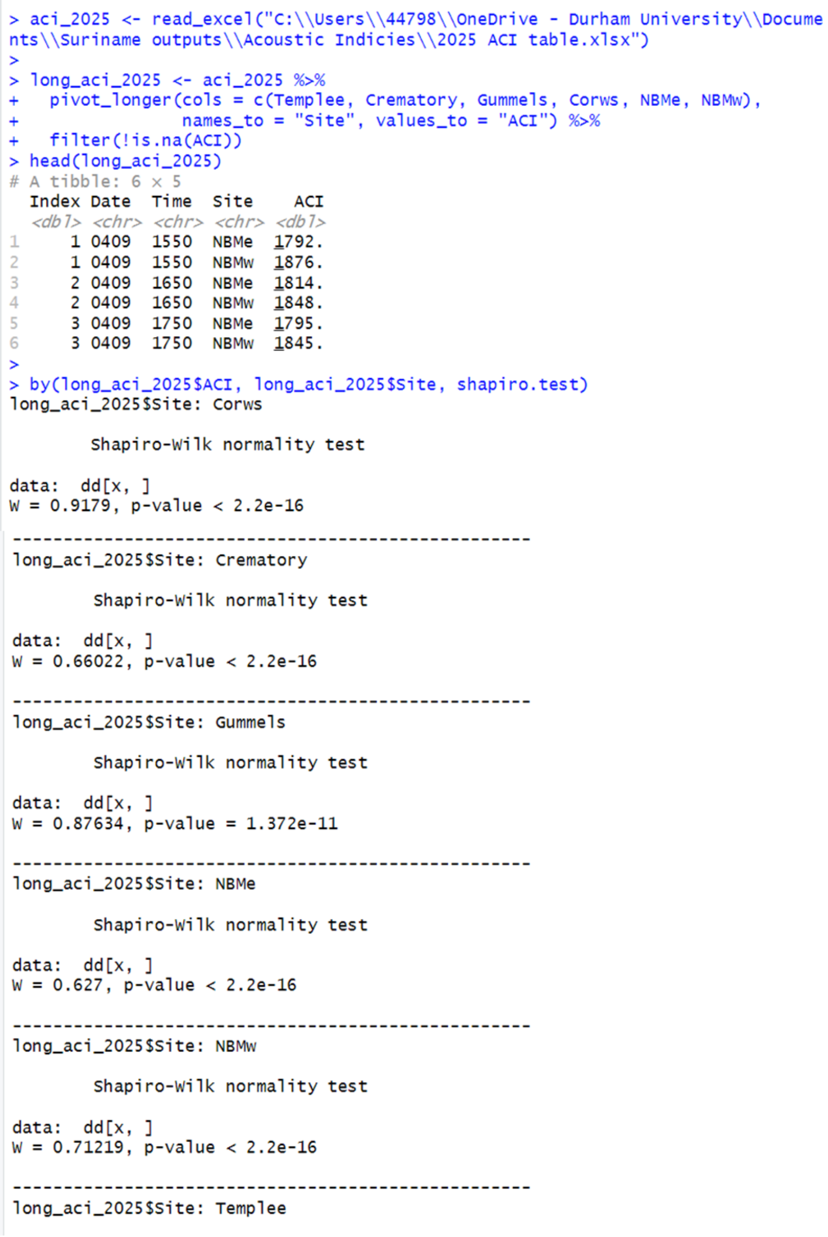


Figure 8 - ACI, four sites

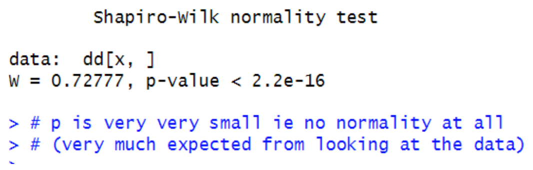
From both graphs, it would visually appear that there are differences between the acoustic complexity and therefore avian biodiversity (McGrann et al., 2022) at each site. I have statistically tested this (see next page) and found statistically significant differences between ACI at each site. One could hypothesize that there is less avian biodiversity in areas dominated by white mangroves (ie Temple east). However, due to the limited number of recording sites for each mangrove type, firm conclusions correlating mangrove type and avian biodiversity cannot be drawn.

4.1.1 Testing for statistically significant differences in ACI between sites

I used Shapiro-Wilk to test for normality (needed as normality is an assumption of the later used Kruksal-Wallace test). This was a formality – visually I could see that the data wasn't normal, and this was reflected in the very small p-values for the test (screenshot from RStudio console):

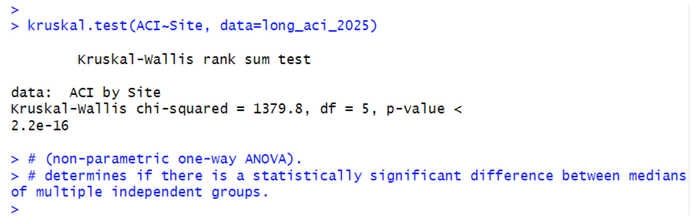


```
> aci_2025 <- read_excel("C:\\Users\\44798\\OneDrive - Durham University\\Docume
nts\\Suriname outputs\\Acoustic Indicies\\2025 ACI table.xlsx")
>
> long_aci_2025 <- aci_2025 %>%
+   pivot_longer(cols = c(Templee, Crematory, Gummels, Corws, NBMe, NBMw),
+                names_to = "Site", values_to = "ACI") %>%
+   filter(!is.na(ACI))
> head(long_aci_2025)
# A tibble: 6 × 5
  Index Date  Time  Site    ACI
  <dbl> <chr> <chr> <chr> <dbl>
1     1 0409  1550  NBMe  1792.
2     1 0409  1550  NBMw  1876.
3     2 0409  1650  NBMe  1814.
4     2 0409  1650  NBMw  1848.
5     3 0409  1750  NBMe  1795.
6     3 0409  1750  NBMw  1845.
>
> by(long_aci_2025$ACI, long_aci_2025$Site, shapiro.test)
long_aci_2025$Site: Corws

        Shapiro-Wilk normality test

data:  dd[x, ]
W = 0.9179, p-value < 2.2e-16

----------------------------------------------------
long_aci_2025$Site: Crematory

        Shapiro-Wilk normality test

data:  dd[x, ]
W = 0.66022, p-value < 2.2e-16

----------------------------------------------------
long_aci_2025$Site: Gummels

        Shapiro-Wilk normality test

data:  dd[x, ]
W = 0.87634, p-value = 1.372e-11

----------------------------------------------------
long_aci_2025$Site: NBMe

        Shapiro-Wilk normality test

data:  dd[x, ]
W = 0.627, p-value < 2.2e-16

----------------------------------------------------
long_aci_2025$Site: NBMw

        Shapiro-Wilk normality test

data:  dd[x, ]
W = 0.71219, p-value < 2.2e-16

----------------------------------------------------
long_aci_2025$Site: Templee
```



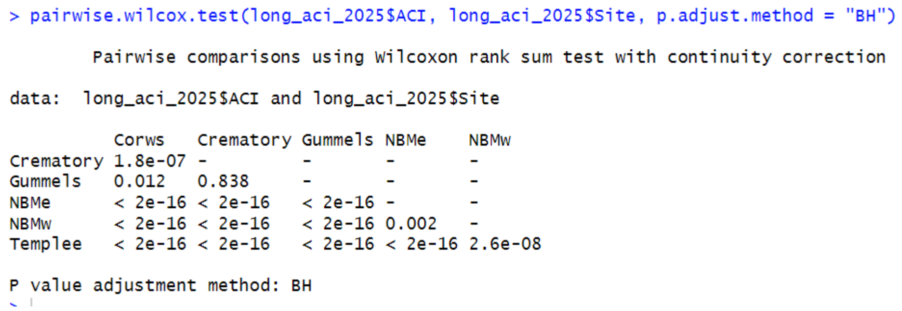
```
        Shapiro-Wilk normality test

data:  dd[x, ]
W = 0.72777, p-value < 2.2e-16

> # p is very very small ie no normality at all
> # (very much expected from looking at the data)
```

I then used a Kruksal-Wallace rank sum test, which determines if there is a statistically significant difference between medians of multiple independent groups. My p-values were all very small (p<<0.01 in all cases), so we can conclude that there are strong statistically significant differences between the Acoustic Complexity of the six focal sites.



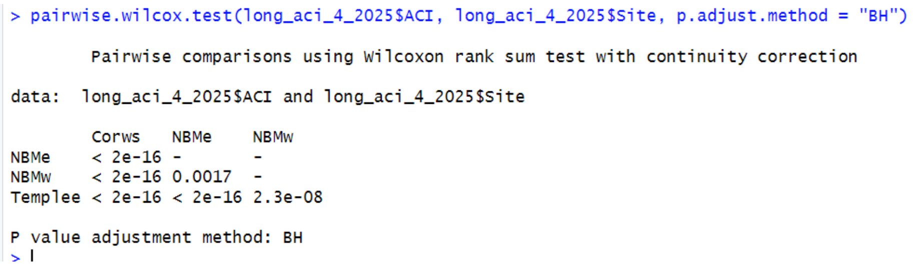
```
>
> kruskal.test(ACI~Site, data=long_aci_2025)

        Kruskal-Wallis rank sum test

data:  ACI by Site
Kruskal-Wallis chi-squared = 1379.8, df = 5, p-value <
2.2e-16

> # (non-parametric one-way ANOVA).
> # determines if there is a statistically significant difference between medians
of multiple independent groups.
>
```

The Kruskal-Wallis test shows that each site is different to the *others as a group*. However, there may be pairs of similar sites within the group. I then used the Wilcoxon rank sum test, which is used following a significant Kruksal-Wallis test result to check for significant differences between each individual pair of sites. The BH p-adjustment method references Benjamini & Hochberg (1995), and controls the false discovery rate (the expected proportion of false discoveries amongst the rejected hypotheses). The false discovery rate is a less stringent condition than the family-wise error rate used by Holm and Bofferoni corrections, making BH a more powerful and accurate correction method.



```
> pairwise.wilcox.test(long_aci_2025$ACI, long_aci_2025$Site, p.adjust.method = "BH")

        Pairwise comparisons using Wilcoxon rank sum test with continuity correction

data:  long_aci_2025$ACI and long_aci_2025$Site

          Corws   Crematory Gummels NBMe    NBMw
Crematory 1.8e-07 -         -       -       -
Gummels   0.012   0.838     -       -       -
NBMe      < 2e-16 < 2e-16   < 2e-16 -       -
NBMw      < 2e-16 < 2e-16   < 2e-16 0.002   -
Templee   < 2e-16 < 2e-16   < 2e-16 < 2e-16 2.6e-08

P value adjustment method: BH
```

Crematory and Gummels have artificially high p values (ie low difference between sites), because data for those sites was recorded for a similar, much smaller period of time than the other sites. Removing those from the table:



```
> pairwise.wilcox.test(long_aci_4_2025$ACI, long_aci_4_2025$Site, p.adjust.method = "BH")

        Pairwise comparisons using Wilcoxon rank sum test with continuity correction

data:  long_aci_4_2025$ACI and long_aci_4_2025$Site

        Corws   NBMe    NBMw
NBMe    < 2e-16 -       -
NBMw    < 2e-16 0.0017  -
Templee < 2e-16 < 2e-16 2.3e-08

P value adjustment method: BH
> |
```

We can see that the most similar sites are NBM Sluice (East) and NBM Sluice (West), which seems sensible as they are the closest geographically.

The method I have demonstrated here would allow for conclusions to be made about the relationship between mangrove species and avian biodiversity, if there was data available from a larger number of sites. An avenue for further research would be to repeat this methodology with some extra data from the area.

4.2 Classifying Specific Species with BirdNET

A total of 508 species were identified across all the sites, with 436 species identified across the 6 summer sites, and 404 across the 8 winter sites. Please see the spreadsheet linked in Appendix (ii) for the full lists of species present in each location, number of identifications of each species, and other summary information. The 'Read Me' tab in that spreadsheet contains a summary of the information below for easy reference. Tables of the 10 most frequently detected species at each site are presented below.

Frequency Index - I calculated a frequency index, which controls for varying amounts of audio data and allows species counts to be comparable across sites.

frequency index = (frequency /no of files) * 1000

I was able to use number of files rather than total audio time as all audio files are seven minutes long.

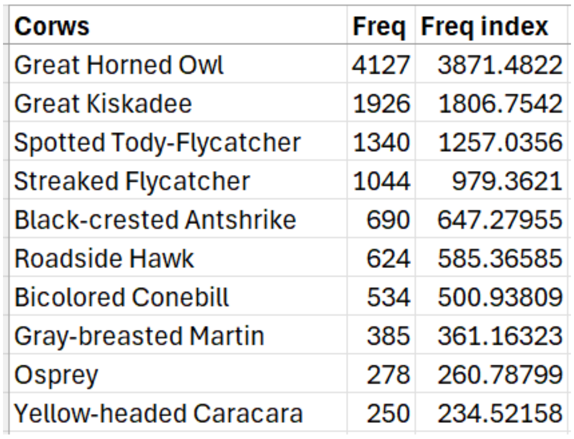
False positives - The identifications of Oilbird are false positives - BirdNET classified scuffling on the ground as a bird, as Oilbird, even though it is a cave-dwelling bird that would be very rare to see in the area. There may be other mistakes in the classifications – machine learning algorithms can only output likely classifications, nor certain ones. I have not undergone a systematic process to check for and remove other false positives, (due to the large amount of audio data and my lack of specialist knowledge in the bird calls of the area), so I have therefore not removed the Oilbird – I have instead highlighted it in red as a reminder that it is a false positive.

Segments - I have used BirdNET to extract all the 3-second clips of audio which contain classified species (the 'segments'), and stored them in folders by location, and within those by species. This will facilitate manual verification for a future researcher with more experience of birdsong. More information about where this data is stored can be found in the appendix 'data storage'.

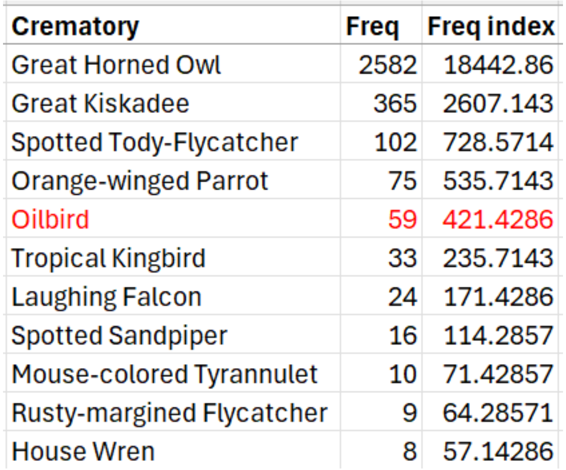
4.2.1 Species lists

Below are the 10 most frequently identified species for each site. The number of species identified per site ranged from 63 to 266 (see the spreadsheet linked in Appendix (ii) for full list).

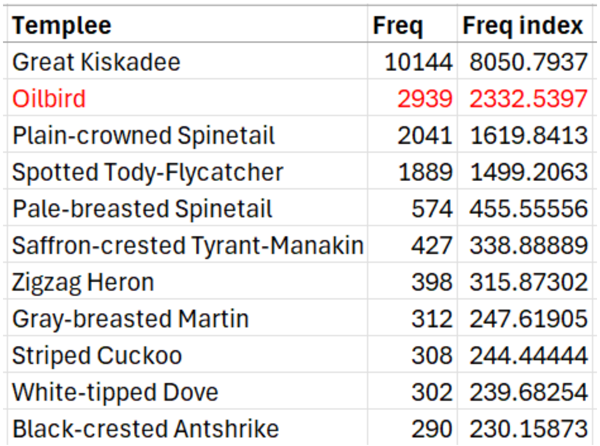
Summer Sites:



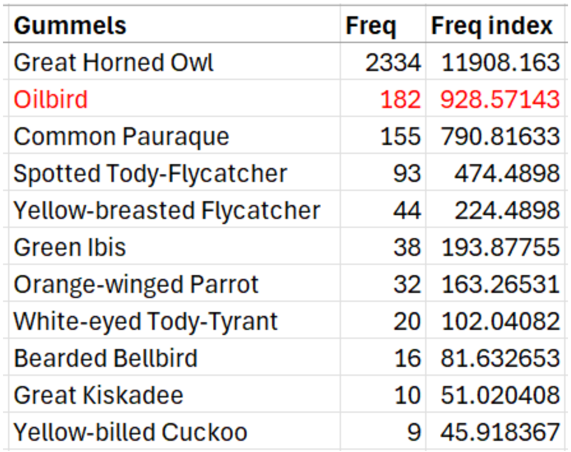
Corws	Freq	Freq index
Great Horned Owl	4127	3871.4822
Great Kiskadee	1926	1806.7542
Spotted Tody-Flycatcher	1340	1257.0356
Streaked Flycatcher	1044	979.3621
Black-crested Antshrike	690	647.27955
Roadside Hawk	624	585.36585
Bicolored Conebill	534	500.93809
Gray-breasted Martin	385	361.16323
Osprey	278	260.78799
Yellow-headed Caracara	250	234.52158



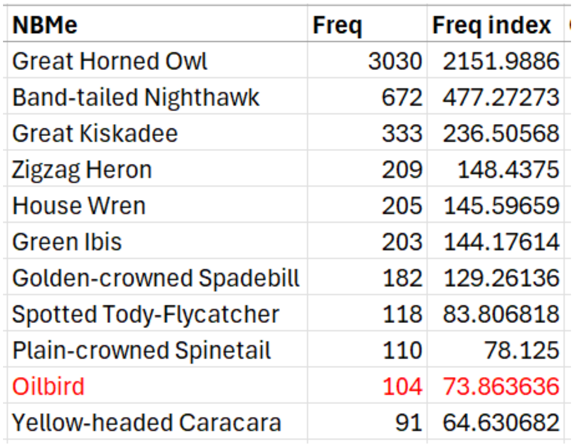
Crematory	Freq	Freq index
Great Horned Owl	2582	18442.86
Great Kiskadee	365	2607.143
Spotted Tody-Flycatcher	102	728.5714
Orange-winged Parrot	75	535.7143
Oilbird	59	421.4286
Tropical Kingbird	33	235.7143
Laughing Falcon	24	171.4286
Spotted Sandpiper	16	114.2857
Mouse-colored Tyrannulet	10	71.42857
Rusty-margined Flycatcher	9	64.28571
House Wren	8	57.14286



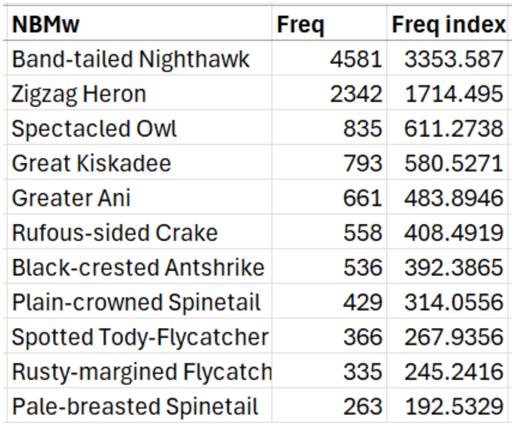
Templee	Freq	Freq index
Great Kiskadee	10144	8050.7937
Oilbird	2939	2332.5397
Plain-crowned Spinetail	2041	1619.8413
Spotted Tody-Flycatcher	1889	1499.2063
Pale-breasted Spinetail	574	455.55556
Saffron-crested Tyrant-Manakin	427	338.88889
Zigzag Heron	398	315.87302
Gray-breasted Martin	312	247.61905
Striped Cuckoo	308	244.44444
White-tipped Dove	302	239.68254
Black-crested Antshrike	290	230.15873



Gummels	Freq	Freq index
Great Horned Owl	2334	11908.163
Oilbird	182	928.57143
Common Pauraque	155	790.81633
Spotted Tody-Flycatcher	93	474.4898
Yellow-breasted Flycatcher	44	224.4898
Green Ibis	38	193.87755
Orange-winged Parrot	32	163.26531
White-eyed Tody-Tyrant	20	102.04082
Bearded Bellbird	16	81.632653
Great Kiskadee	10	51.020408
Yellow-billed Cuckoo	9	45.918367

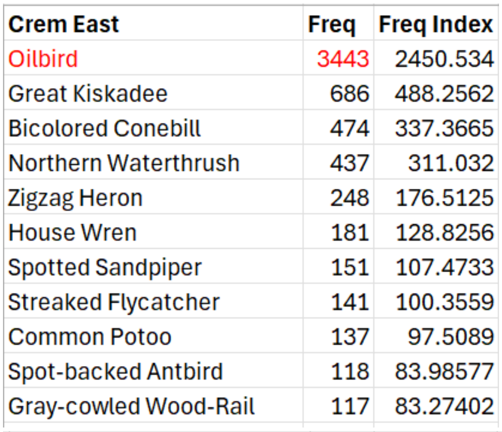


NBMe	Freq	Freq index
Great Horned Owl	3030	2151.9886
Band-tailed Nighthawk	672	477.27273
Great Kiskadee	333	236.50568
Zigzag Heron	209	148.4375
House Wren	205	145.59659
Green Ibis	203	144.17614
Golden-crowned Spadebill	182	129.26136
Spotted Tody-Flycatcher	118	83.806818
Plain-crowned Spinetail	110	78.125
Oilbird	104	73.863636
Yellow-headed Caracara	91	64.630682

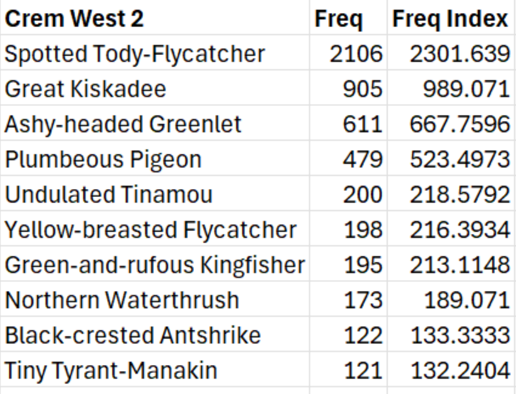


NBMw	Freq	Freq index
Band-tailed Nighthawk	4581	3353.587
Zigzag Heron	2342	1714.495
Spectacled Owl	835	611.2738
Great Kiskadee	793	580.5271
Greater Ani	661	483.8946
Rufous-sided Crake	558	408.4919
Black-crested Antshrike	536	392.3865
Plain-crowned Spinetail	429	314.0556
Spotted Tody-Flycatcher	366	267.9356
Rusty-margined Flycatch	335	245.2416
Pale-breasted Spinetail	263	192.5329

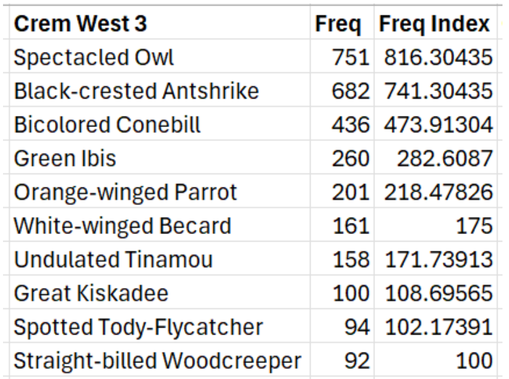
Winter sites:



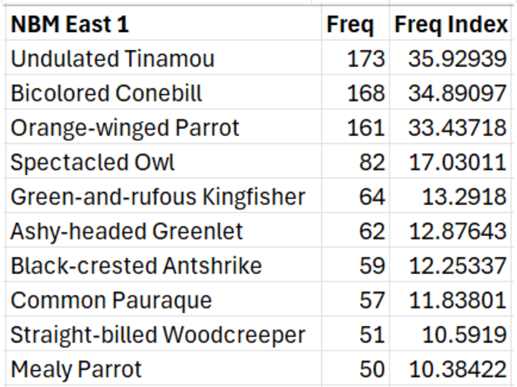
Crem East	Freq	Freq Index
Oilbird	3443	2450.534
Great Kiskadee	686	488.2562
Bicolored Conebill	474	337.3665
Northern Waterthrush	437	311.032
Zigzag Heron	248	176.5125
House Wren	181	128.8256
Spotted Sandpiper	151	107.4733
Streaked Flycatcher	141	100.3559
Common Potoo	137	97.5089
Spot-backed Antbird	118	83.98577
Gray-cowled Wood-Rail	117	83.27402



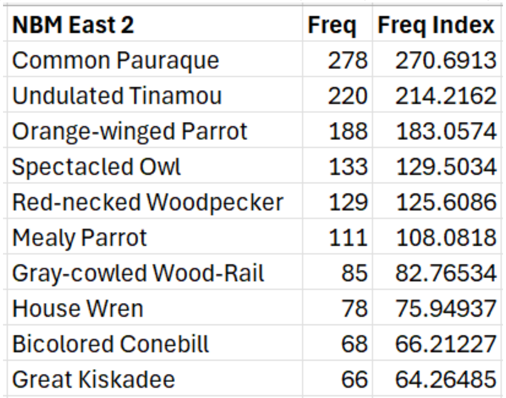
Crem West 2	Freq	Freq Index
Spotted Tody-Flycatcher	2106	2301.639
Great Kiskadee	905	989.071
Ashy-headed Greenlet	611	667.7596
Plumbeous Pigeon	479	523.4973
Undulated Tinamou	200	218.5792
Yellow-breasted Flycatcher	198	216.3934
Green-and-rufous Kingfisher	195	213.1148
Northern Waterthrush	173	189.071
Black-crested Antshrike	122	133.3333
Tiny Tyrant-Manakin	121	132.2404



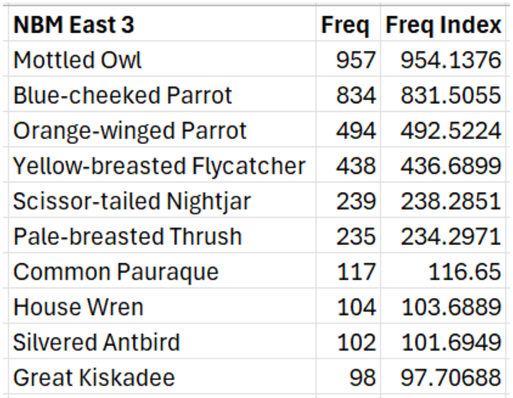
Crem West 3	Freq	Freq Index
Spectacled Owl	751	816.30435
Black-crested Antshrike	682	741.30435
Bicolored Conebill	436	473.91304
Green Ibis	260	282.6087
Orange-winged Parrot	201	218.47826
White-winged Becard	161	175
Undulated Tinamou	158	171.73913
Great Kiskadee	100	108.69565
Spotted Tody-Flycatcher	94	102.17391
Straight-billed Woodcreeper	92	100



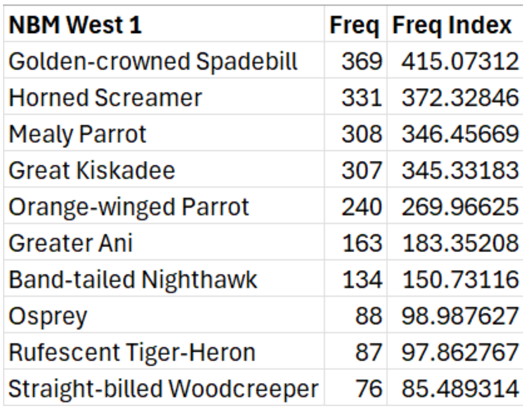
NBM East 1	Freq	Freq Index
Undulated Tinamou	173	35.92939
Bicolored Conebill	168	34.89097
Orange-winged Parrot	161	33.43718
Spectacled Owl	82	17.03011
Green-and-rufous Kingfisher	64	13.2918
Ashy-headed Greenlet	62	12.87643
Black-crested Antshrike	59	12.25337
Common Pauraque	57	11.83801
Straight-billed Woodcreeper	51	10.5919
Mealy Parrot	50	10.38422



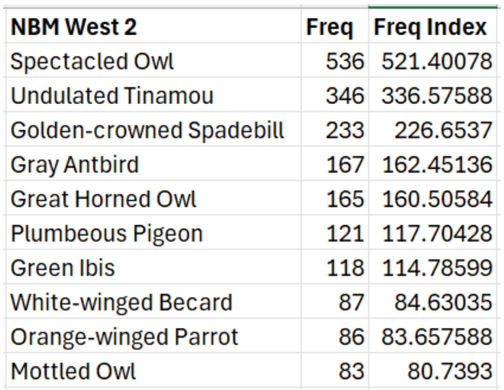
NBM East 2	Freq	Freq Index
Common Pauraque	278	270.6913
Undulated Tinamou	220	214.2162
Orange-winged Parrot	188	183.0574
Spectacled Owl	133	129.5034
Red-necked Woodpecker	129	125.6086
Mealy Parrot	111	108.0818
Gray-cowled Wood-Rail	85	82.76534
House Wren	78	75.94937
Bicolored Conebill	68	66.21227
Great Kiskadee	66	64.26485



NBM East 3	Freq	Freq Index
Mottled Owl	957	954.1376
Blue-cheeked Parrot	834	831.5055
Orange-winged Parrot	494	492.5224
Yellow-breasted Flycatcher	438	436.6899
Scissor-tailed Nightjar	239	238.2851
Pale-breasted Thrush	235	234.2971
Common Pauraque	117	116.65
House Wren	104	103.6889
Silvered Antbird	102	101.6949
Great Kiskadee	98	97.70688



NBM West 1	Freq	Freq Index
Golden-crowned Spadebill	369	415.07312
Horned Screamer	331	372.32846
Mealy Parrot	308	346.45669
Great Kiskadee	307	345.33183
Orange-winged Parrot	240	269.96625
Greater Ani	163	183.35208
Band-tailed Nighthawk	134	150.73116
Osprey	88	98.987627
Rufescent Tiger-Heron	87	97.862767
Straight-billed Woodcreeper	76	85.489314

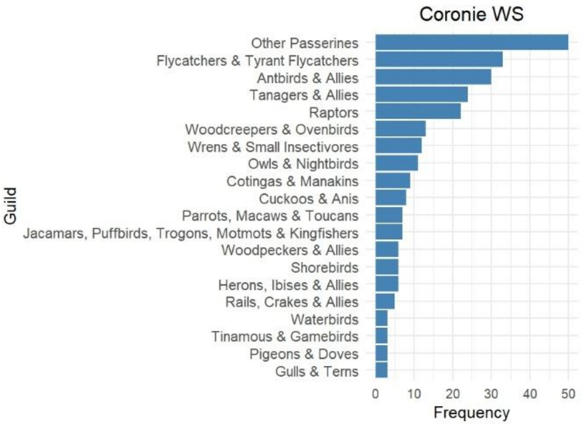


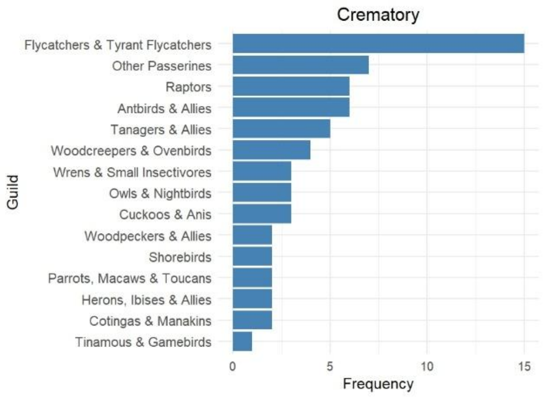
NBM West 2	Freq	Freq Index
Spectacled Owl	536	521.40078
Undulated Tinamou	346	336.57588
Golden-crowned Spadebill	233	226.6537
Gray Antbird	167	162.45136
Great Horned Owl	165	160.50584
Plumbeous Pigeon	121	117.70428
Green Ibis	118	114.78599
White-winged Becard	87	84.63035
Orange-winged Parrot	86	83.657588
Mottled Owl	83	80.7393

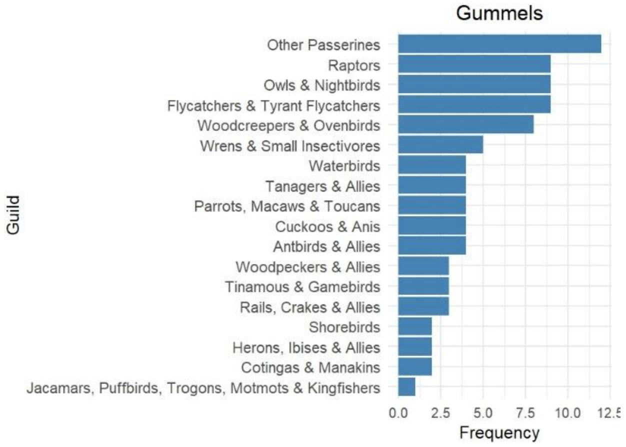
4.2.2 Species summaries by guild

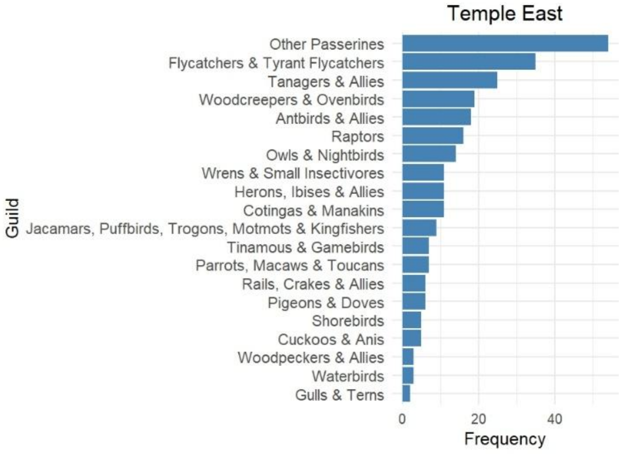
I have grouped the species into 20 rough taxonomic ‘guilds’ to allow for more readable summary conclusions to be created, which are listed in the ‘Read Me’ sheet of the spreadsheet. Below are bar charts showing the number of identifications of each guild per site.

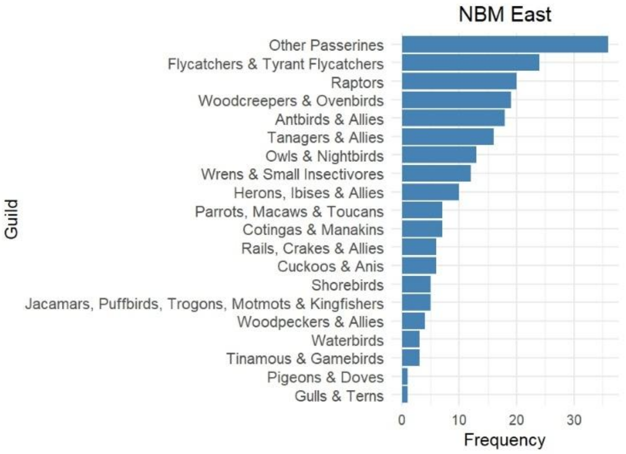
Summer 2025 sites:

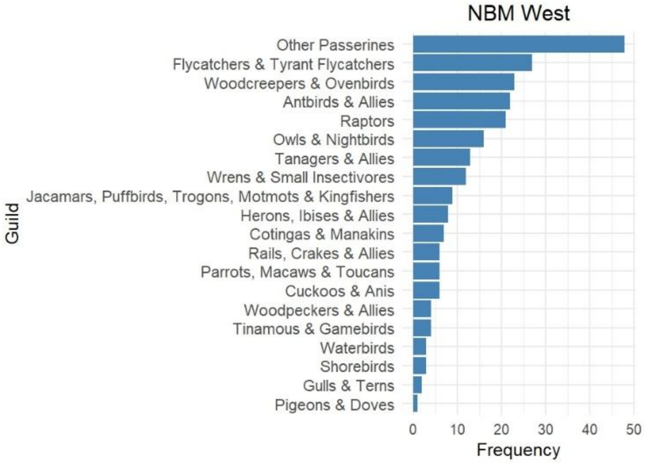




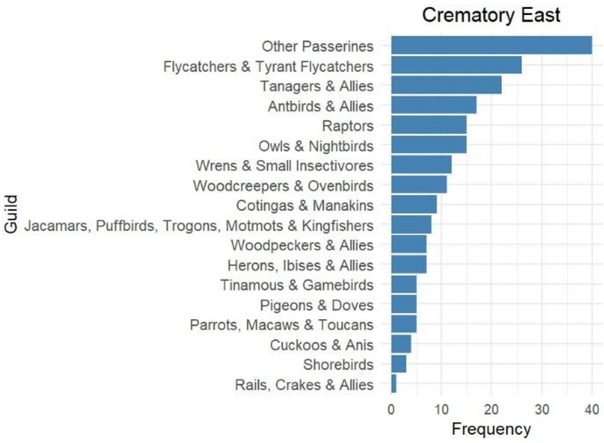


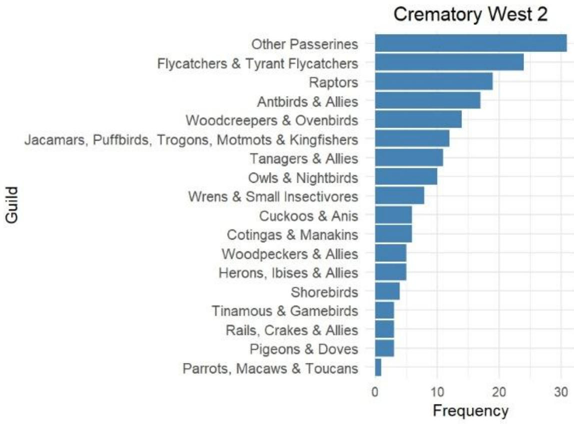


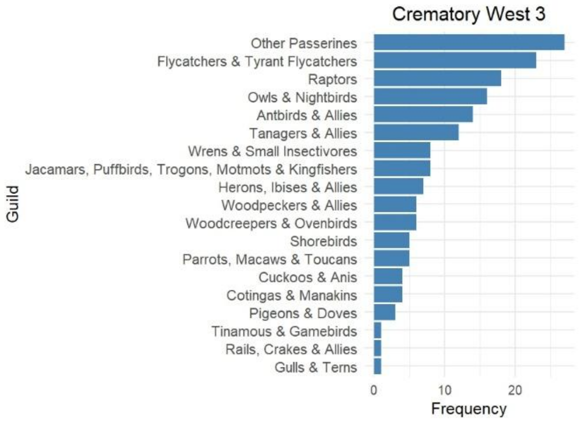


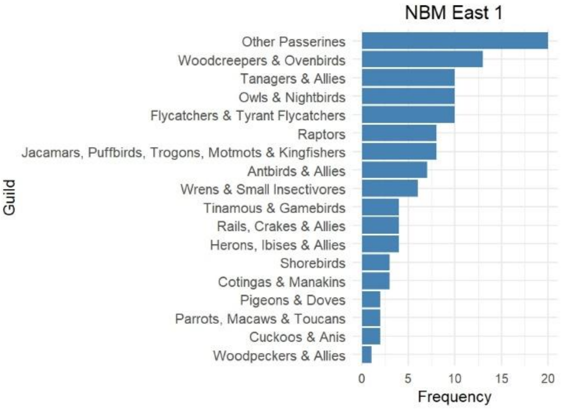


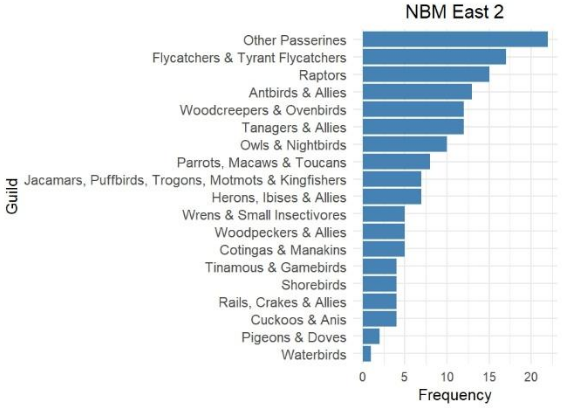
Winter 2024-25 sites:

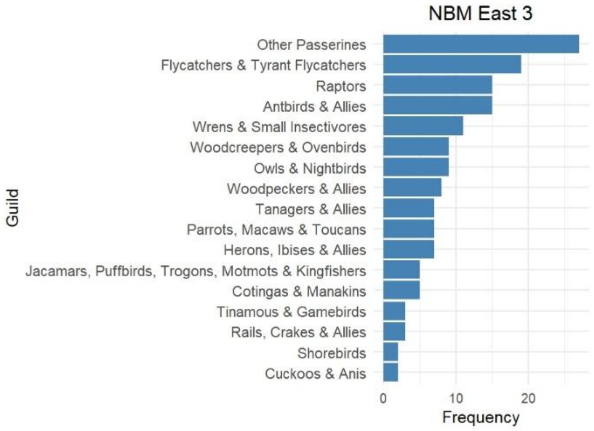

Crematory East


Crematory West 2


Crematory West 3


NBM East 1


NBM East 2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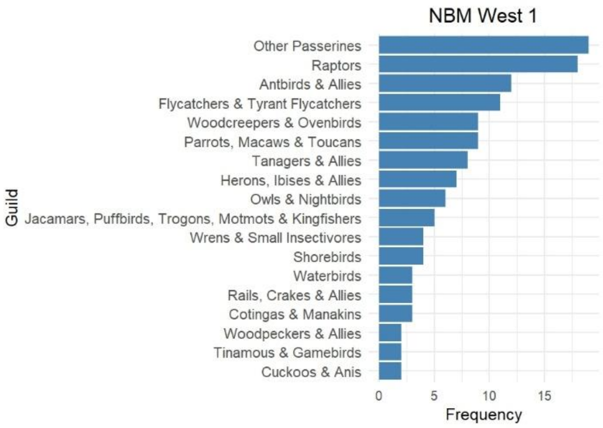
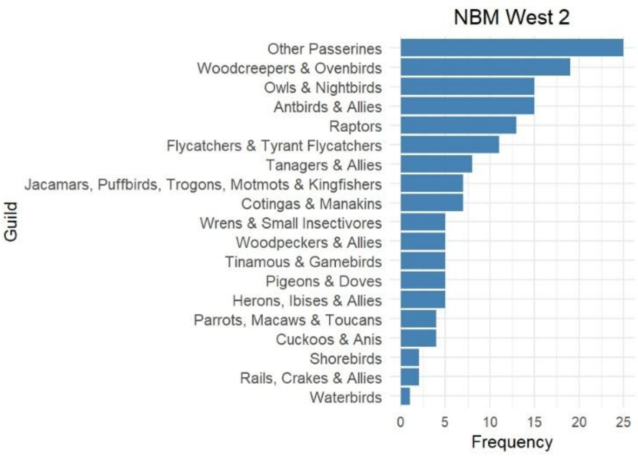

NBM West 1


NBM West 2

5. Discussion

5.1 Limitations of ACI

ACI calculations can be altered by weather (either where the addition of new weather sounds increases acoustic diversity and therefore ACI, or where loud weather sounds mask ecological sounds and cause ACI to be lower). Therefore consideration of how the weather impacted the ACI calculations, and data on the weather differences across the geographical and time period would help to control against this factor.

If different sounds create similar spectrogram patterns, the acoustic indices will be highly similar even if the sounds are from different sources (Bradfer-Lawrence at al, 2023). Therefore care must be taken when correlating acoustic indices to specific sounds.

ACI numbers can differ depending on the recording methods (Metcalf et al 2023), level of compression of the recording (Heath et al, 2021), and calculation software (Villanueva-Rivera 2015). For example, the sample rate of the recording affects the window length of the Fast Fourier Transform (FFT) and therefore the acoustic indices: (the FFT turns the vectors of values from the .wav recording into a spectrogram, from which the acoustic indices are calculated). Therefore sample rate can affect indices, so indices from recorders with large differences in sample rate are not comparable.

Even though two types of recorders were used during this study, the results are comparable as all recordings were taken at a 48,000 Hz sample rate. It is important to make sure to set sampling rates of recorders to be the same so that different recording sites and times are comparable within a study, and to exercise caution when comparing acoustic indie results across studies (Acoustic Index User's Guide, Bradfer-Lawrence et. al., 2024).

5.2 Options for analysis of BirdNET data post-classification

The BirdNET algorithm (and other automatic classifiers) can only output likely identifications, not certain ones. This means that the methods used to estimate occupancy and populations, are not the same as when using more traditional methods such as point counts or 'capture-mark-recapture'. When a species is identified, BirdNET outputs a 'confidence score': a numerical estimate of how likely the identification is to be correct. In this section, I explain how these confidence scores are calculated and the different ways they can be used. Due to time constraints, I was unable to model the populations of the birds, (which is complicated and depends on a wide range of factors affecting bird behaviour and vocalisation. Instead, I have calculated some cue densities, which are a metric used in population modelling. This section showcases different analysis techniques that can be applied to these kinds of datasets after species have been classified with a recogniser like BirdNET.

5.2.1 Interpreting Confidence Scores

Prediction uncertainty scores (ie BirdNET's 'confidence scores') resemble probabilities due to their range of 0-1, but are actually unitless prediction scores – they are "positively related to prediction accuracy in species-specific ways" (Wood & Kahl, 2024).
BirdNET confidence scores are not transferrable or comparable among species within a study, or among different studies of the same species. The score may have very different 'performance outcomes' (e.g., precision, recall, P(true positive)) for any two species or studies. This is because the scores depend on BirdNET's feature embeddings, which are affected by factors such as the microphone quality and sample rate, meaning that studies using audio recorded on different kinds or ARUs will result in incomparable confidence scores.

What is a BirdNET confidence score?

$$\text{Confidence score} = \frac{1}{1 + e^{\text{logit score} * \text{sensitivity}}}$$

The 'logit score' is the output of a linear classifier that uses feature embeddings to derive an unbounded linear class 'score' (ie BirdNET's output). The sensitivity is a setting determined by the user, and "determines the distribution of prediction scores" (Wood & Kahl, 2024) because it affects the sigmoid activation curve.[2]

There is a positive relationship between prediction accuracy and confidence score (a negative relationship is theoretically possible but has not been found), but the shape of this relationship varies between species and studies.

There are three key ways that these scores can be used:

1. The common signal classification metrics 'precision' and 'recall' can be calculated for any BirdNET score threshold:
   Precision is the proportion of predictions that are correct, [1 - false positive rate].
   Recall is the proportion of target signals that were correctly identified, [1 - false negative rate].
2. Scores can be used as they are, to allow researchers to manually verify only the 'least likely' identifications. However, care must be taken here – scores cannot be used as a likelihood threshold, as they vary in significance between species and recorders, as explained above.
3. Scores can be converted into probabilities by using logistic regression to relate prediction outcome to the probability that the prediction is correct. I was not able to do this due to time constraints, but would direct other researchers towards Wood & Kahl, 2024; Wood, Barceinas Cruz & Kahl, 2023; and Symes et. al., 2023.

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[2] The sigmoid activation curve determines how much neuron activation (ie how much 'signal' or 'evidence' of a species) is required to reach higher confidence scores. Lower sensitivity yields a steeper curve and increasingly binary outputs; higher sensitivity yields a shallower curve and a more uniform distribution of scores. (Wood & Kahl, 2024). High sensitivity and a more uniform distribution of scores means less very low scores that fall under the user's confidence threshold, so sensitivity can be increased to reduce false negatives at the expense of more false positives (and can be decreased for the inverse). Therefore the user can achieve the desired balance of false positives/negatives by either changing sensitivity or confidence score threshold, as the two are related. More information about the relationship between sensitivity and the sigmoid activation curve can be found here: https://github.com/mcguirepr89/BirdNET-Pi/discussions/507#discussioncomment-3437065

5.2.2 Occupancy and Population Modelling

Occupancy modelling

It is important to note that existing occupancy models use binary presence/absence data, whereas ARUs and ML models generate a new observation record that reflects the model's confidence that the species is present in a short time frame. This means that researchers are working with scores ranging continuously for 0 to 1, rather than a binary presence/absence. Rhinehart et al., (2022) describes a useful workflow to use detector scores in occupancy models to account for uncertainty.

Population Modelling

Species counts can be used to model bird density (Peres-Granados & Traba, 2021). Their study identified 8 approaches to estimating bird density, and gives descriptions of how to use each method. The method most relevant to our dataset is to use the Detected Vocal Activity Rate (DVAR):

Figure 9 - Table taken from Peres-Granados & Traba, (2021). Their paper showed a table with their 8 approaches to estimating bird denisty. Below is one row of their table, the Detected Vocal Activation Rate (DVAR).

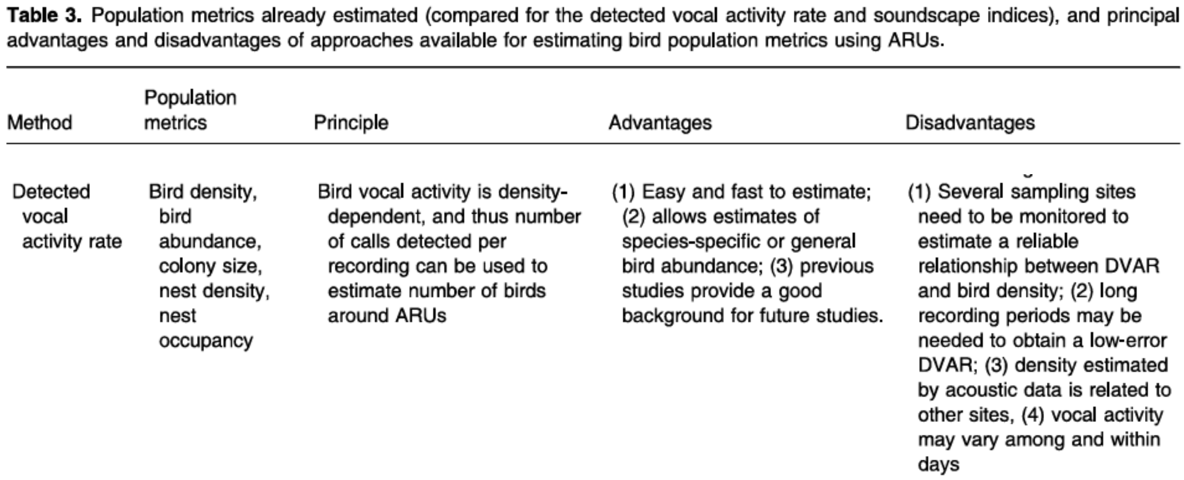

Table 3. Population metrics already estimated (compared for the detected vocal activity rate and soundscape indices), and principal advantages and disadvantages of approaches available for estimating bird population metrics using ARUs.

Method	Population metrics	Principle	Advantages	Disadvantages
Detected vocal activity rate	Bird density, bird abundance, colony size, nest density, nest occupancy	Bird vocal activity is density-dependent, and thus number of calls detected per recording can be used to estimate number of birds around ARUs	(1) Easy and fast to estimate; (2) allows estimates of species-specific or general bird abundance; (3) previous studies provide a good background for future studies.	(1) Several sampling sites need to be monitored to estimate a reliable relationship between DVAR and bird density; (2) long recording periods may be needed to obtain a low-error DVAR; (3) density estimated by acoustic data is related to other sites, (4) vocal activity may vary among and within days

If individuals can be differentiated from within recordings (such as using BirdNET embeddings – see next section), then population density can be easily determined by counting the number of individuals (Dawson & Efford, 2009). If not, then cue densities can be used:

A 'cue', or song burst, is one vocalisation of a bird, which may vocalise repeatedly within one recording interval.
'Cue density' is song bursts per hectare per minute, which is distinct from population density (individuals per hectare).
To calculate 'cue density', one must know the distance from which an ARU can 'hear' birdsong. This is the Effective Detection Radius (EDR) of the recorder, "defined as the radius at which as many vocalisations are undetected within that distance as are detected beyond that distance" (page 2).
Sound Pressure level (SPL) can be used instead, which allows the exclusion of far distances with very low probability of detecting a vocalisation.

To estimate population density from cue density, one needs to know the rate of cue production of the species, (ie song bursts per individual per minute). However, this is highly variable, and is affected by factors such as daily & seasonal patterns, mating, and the other species in the area. This information is difficult to quantify, so calculating cue production rates was beyond the scope of this report.

I have calculated the cue density for woodpeckers & piculets (the guild that we are most interested in) at each location in the dataset. Then if rate of cue production for a species was obtained, its population density could be calculated as follows:
Population density = cue density / rate of cue production; because:

$$\frac{\text{cue density}}{\text{rate of cue production}} = \frac{\frac{\text{song burst}}{\text{hectares * mins}}}{\frac{\text{song burst}}{\text{individuals * mins}}} = \frac{\text{individuals}}{\text{hectares}} = \text{population density}$$

Finding Effective Detection Radius:

There is no fixed radius of area that an ARU can ‘hear’ birds - it depends on the following factors:

1) The species call’s amplitude and frequency
2) Level of vegetation in the area
3) Other ambient noises, eg traffic and weather
4) The specifications of the individual recorders

I haven’t taken into account ambient noise, as this is difficult to numerically quantify, or variations in recorders, as the study only utilised two types of recorders (AudioMoth and Song Meter Micro-2) which have similar detection capabilities (see specification documentations).

I estimated the area that woodpeckers & piculets may be heard from by considering the frequency and amplitude of their calls and the typical habitat they would be occurring in, and by referring to the methods in the prior work on this topic (Yip et al., 2017; Winiarska et al., 2024; & Haupert et al., 2022). Their calls have medium amplitude, but are muted by the trees and bushes in their habitat, and I have therefore estimated their EDR at 100-120m. An EDR of 110m results in an area of 3.46 hectares (to 2 decimal places).

The cue densities for the woodpeckers & piculets can be found in the tab ‘Woodpeckers & Piculets’ in the spreadsheet linked in Appendix (ii).

6. Conclusion

This study uses passive acoustic monitoring to assess avian biodiversity in Suriname's mangroves, which are essential as a habitat for biodiversity and for coastal protection.

I have quantified vocal activity using Acoustic Indices, and found statistically significant differences between sites. The site Temple (East), an area of mainly white mangroves, had much lower acoustic complexity (and therefore avian biodiversity) than NBM Sluice (East) and NBM Sluice (West), which comprise mostly black. However, no conclusions of a relationship between mangrove type and avian biodiversity can be drawn, due to the small number of data sites.

Using BirdNET, a total of 508 species were identified across all the sites, with 436 species identified across the 6 summer sites, and 404 across the 8 winter sites. The types of birds most frequently detected were flycatchers and other passerines, with frequent detections of antbirds & allies, tanagers & allies, raptors and owls & nightbirds also. I have calculated frequency indexes to standardise data, and cue densities to provide a pathway to population modelling. I recommend ways to interpret BirdNET confidence scores, providing practical guidance and cautions on the limitations of this methodology.

This study contributes to the body of knowledge on remote acoustic monitoring and using BirdNET for species identification by applying it to a new area and ecosystem.

Appendix (i) – Data Storage

All audio data is in the folder labelled 'Audio' on Saidur Rahman's PRS drive. The folder contains:

- All of the raw audio data
- A logbook spreadsheet with all the information about recorders, sites and times of recording.
- A spreadsheet (also linked in Appendix (ii) with the BirdNET classifications for all sites, summaries by guild and cue densities for woodpecker species.
- 3-second clips ('segments') of audio where bird vocalisations were detected have been gathered in folders by site and then by species to facilitate manual verification. These are located in the folder 'Segments'.

Appendix (ii) – BirdNET results spreadsheet

Link TBC

Appendix (iii) – Bibliography

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