Evaluating forest restoration effects on timing of avian dawn chorus in Ranomafana National Park, Madagascar

Marjolein Pijper

Evaluating forest restoration effects on timing of avian dawn chorus in Ranomafana National Park, Madagascar

Marjolein Pijper

Abstract

Monitoring of forest restoration efforts is essential to ensure healthy, self-sustaining tropical rainforests. Passive acoustic monitoring is used to monitor vocal activity of birds, which play a key role in forest ecosystems as seed dispersers. Communication between birds seems most profitable during a peak of bird singing in the morning, known as the dawn chorus. Anthropogenic disturbances leading to increased light levels affect the timing of this chorus in individual species. This research sheds a light on the effect of forest restoration on the dawn chorus using automatic detection methods to identify bird sounds from acoustic data. Machine learning methods like clustering and pattern matching were used alongside a manual analysis to describe the dawn chorus in protected forests as well as restoration sites around Ranomafana National Park, Madagascar.

Restoration sites were found to have lower species richness and increased interference from insect sounds. No difference was found between timing of the dawn chorus in both forest habitats. This can possibly be assigned to changes in community composition and decreased detectability of species in insect-dominated landscapes. Future research could further disentangle these effects, by filtering of acoustic data, development of workflow pathways and the use of stronger machine learning methods that allow for more reliable species-specific detection. In the current state of automatic acoustic methods, close cooperation with local experts is recommended to achieve effective monitoring in tropical rainforests.

Keywords: Acoustic monitoring, forest restoration, dawn chorus, avian singing, bird monitoring, automatic recognition

Table of contents

List of figures

1. Introduction

1.1 Problem statement

In our effort to mitigate the effects of climate change, the International Panel of Climate Change (2022) underlines the importance of conservation and restoration of forests. Not only do they play a crucial role in removing carbon dioxide from our atmosphere, but they also provide essential ecosystem services for the 880 million people living in and around forests that depend on them for their livelihood (FAO, 2020). Especially the poorest populations rely on forest resources such as firewood (K. A. Brown et al., 2013), and its conversion to agricultural land (Klanderud et al., 2010), drives intense deforestation and dramatic loss of biodiversity. This leads to loss of species-specific functional traits and ecosystem services, generating less resilient environments that leave its population even more vulnerable to further environmental change (K. A. Brown et al., 2013).

With its large tropical rainforests, Madagascar is one of the richest countries in terms of biodiversity, with about 90% of all animal and plant species being endemic to the country (Hobbs & Dolan, 2008). At the same time its human population ranks amongst the poorest in the world (Belghith et al., 2016), with over 90% living on less than $2 a day (UNIDO, 2021). The dependence of these people on forest resources and land for agriculture (K. A. Brown et al., 2013), has led to alarming deforestation rates (Klanderud et al., 2010) threatening the endemic biodiversity, and the livelihood of the Madagascar human population. Forest restoration practices are implemented (Klanderud et al., 2010), but adequate monitoring of the diversity of species in the forest environment is needed to assess their success in terms of recovery of functional traits and ecosystem services (Le et al., 2012).

Bird species provide important functions in the restoration of disturbed forests, such as the dispersion of seeds and pollination, thereby promoting the growth of vegetation and enhancing the forests carbon storing capacity (Pejchar et al., 2008). Traditional bird monitoring methods rely on manual observations often depending on volunteers and funding (Stowell et al., 2019). Additionally, forests are not easily accessible and in the face of extreme poverty, conservation is often not a priority (Razafindravony et al., 2023). This makes such knowledge, funding and manpower scarce resources.

Remote acoustic monitoring devices can be part of the solution for low-cost bird monitoring by providing 24-hour data in remote areas, providing comparative information about the vocal behaviour of bird species in forests with different levels of disturbance (Stowell et al., 2019; Toenies & Rich, 2021). For effective acoustic monitoring, it is important to know more about variation in, and drivers of, bird vocal activity.

1.2   Bird vocal activity

Birds, and species of the songbird family Passeriformes in particular, are dependent on vocal communications for their survival and reproduction (Chen et al., 2015; Huang et al., 2022). They use singing to attract partners, to defend territory, to communicate about potential predators, and for many other functions (Cuthill & Macdonald, 1990; Slagsvold, 1996). This singing turns out to be especially advantageous in the morning (Huang et al., 2022; Puswal et al., 2021), resulting in a peak of bird singing known as the dawn chorus. To detect calls from their own species in noisy environments, like a tropical rainforest dawn chorus, species differentiate using distinct melodies, pitch and through temporal separation (Francis et al., 2009; Kempenaers et al., 2010; Luther, 2009; Slabbekoorn & Peet, 2003). Species with higher ability to distinguish themselves from other species consequently have more effective communication, positively affecting their fitness and survival rates (Francis et al., 2009; Slabbekoorn & den Boer-Visser, 2006). Temporal separation of the acoustic spectrum has led to a predictable sequence at which different species start singing (Kempenaers et al., 2010; Thomas et al., 2002), but the exact timing can be influenced by different climatic variables such as ambient temperature, cloud cover and ambient light (Bruni et al., 2014; Da Silva et al., 2014; Hutchinson, 2002; Puswal et al., 2021).

1.3   Ambient light levels

As mature tropical rainforests are biodiverse systems with a high vegetation density consisting of many different layers, the microclimatic conditions within it are highly variable. The upper layer can receive up to 100 times as much light as the lowest layer, the forest floor (M. L. Berg et al., 2005; Engelbrecht & Herz, 2001; and see D. W. Lee, 1987). Recently reforested tropical rainforest is often characterized by a single layer of seedlings or saplings, so although its composition is highly variable depending on its restoration phase and initial position, its vegetation density is much lower than mature forest (Le et al., 2012). This dramatically increases the penetration of light all the way down to the ground layer,

potentially affecting the vocal behaviour of bird species living in these disturbed forests.

Earlier studies into anthropogenic light pollution show that increased ambient light levels lead to earlier singing times (Kempenaers et al., 2010). However, the size of this effect is not similar across all species, and it depends strongly on their sensitivity to light (Thomas et al., 2002), with more sensitive species singing earlier relative to their normal starting time. Thomas et al. (2002) found that this sensitivity is related to eye size, suggesting evolutionary adaptation to the species' foraging height, corresponding with light availability. In forests, canopy species are adapted to high light conditions with smaller eyes and lower sensitivity, while ground species adapted to low light conditions have larger eyes and higher sensitivity (Ausprey et al., 2021). Species inhabiting different foraging layers are, therefore, expected to exhibit different responses to light levels and to drivers that affect light levels in forests, such as deforestation or reforestation.

Another species characteristic that influences the response to changing light levels in forests is related to the generalist-specialist concept, as described by Devictor et al. (2008). Generalist species can survive in many different habitats, while specialists are adapted to a particular type of habitat. Generalists are thought to be more plastic in their behaviour, adapting on non-evolutionary timescales. Anthropogenic changes inducing higher light levels are therefore expected to have larger fitness consequences for specialists, who will have a lower ability to adapt their behaviour. Generalists species, on the other hand, will likely adapt their behaviour and singing time to be more synchronous with the surrounding ecosystem.

1.4 Research gap

The response of tropical songbirds timing to light pollution and habitat disturbance has been studied before. However, we do not yet know to what extent reforestation affects the timing of singing. In Madagascar in particular, assessments of the effects of reforestation on animal activity is important to support and maintain its vulnerable endemic biodiversity. In the long-term process of reforestation, bird community compositions are likely to shift as more and more of the original forest layers return (Devictor et al., 2008; Le et al., 2012). The different responses amongst generalist and specialists are especially important in conservation, as specialist species are known to be under the greatest threat of habitat conversion (Devictor et al., 2008). More knowledge on the timing of singing activity as a response to reforestation leads to more accurate estimation of sampling strategies and therefore to more effective monitoring and conservation. This will eventually contribute to improved reforestation results and a better livelihood for the community living in Madagascar's rainforests.

1.5 Research objectives

This research has focused on forest restoration sites around Ranomafana National Park (RNP) in Madagascar and aimed to determine differences in the timing of vocal activity at dawn amongst bird species in and around RNP and between mature forest protected by the National Park (NP) and forest restoration sites (RS). I have used acoustic data from these forest treatment habitats to test how the start time of the dawn chorus differs between these habitats. The research focusses on three objectives.

I set out to evaluate whether the timing of dawn singing is different in restoration sites compared to mature forest, for different tropical bird species and whether this response can be related to species-specific traits (*objective 1*).

I have analysed this using acoustic software developed to identify and classify different sounds. This method is still quite new and under development, so I expected that methodological challenges would arise during the process. I considered it valuable to support the development of these methods. Therefore, I also aimed to identify these methodological challenges and determine which factors could influence the identification of bird sounds in audio recordings from tropical rainforests (*objective 2*). Two of the factors I suspected would impact the identification result are ambient sound levels and overall species abundance and diversity. These factors are therefore also considered in the analysis.

Given the large insecurity of identification results, I formulated a third objective in case species-specific identification proved to be infeasible. This was to examine whether bird communities, irrespective of species, in restoration areas exhibit an earlier dawn chorus compared to those in mature forests (*objective 3*).

Figure 1: Souimanga Sunbird, Cinnyris Sovimanga, one of Ranomafana National Park's most common bird species. Jean-Sébastien Guénette / Macaulay Library at the Cornell Lab (ML119864591)

2. Theory

2.1 Dawn chorus

Singing is used by bird species as an important part of communication to defend their territory, attract mates and to communicate about foraging locations, possible predators and mate localization (Chen et al., 2015; Huang et al., 2022). Many species show a diurnal singing pattern, characterized by two peaks in singing activity near both sunrise and sunset. The first peak, known as the dawn chorus, is often the most pronounced, and three non-mutually exclusive hypotheses are often discussed to explain its occurrence (K. S. Berg et al., 2006). The *acoustic transmission hypothesis* postulates that singing is most effective at the coolest time of the day because sound travels further at lower temperatures (K. S. Berg et al., 2006; T. J. Brown & Handford, 2003). The *efficient foraging hypothesis* explains how the low morning light availability prohibits the possibility of many day-time activities like foraging, making mornings a more profitable time to spend their energy on singing (Chen et al., 2015; Hutchinson, 2002; Kacelnik, 1979). Lastly, the *energy stochasticity hypothesis* relies on the notion that birds store high reserves in the evening to prepare for unpredictable nightly conditions, and use singing at dawn to get rid of excess reserves (Hutchinson, 2002; Reid, 1987; Thomas, 1999).

All though all three of these mechanisms are likely to influence the general onset of dawn chorus in singing birds, individual differences remain between species (K. S. Berg et al., 2006; Kempenaers et al., 2010). One explanation for these differences among species is the threshold hypothesis, which states that birds start singing at dawn after a certain threshold level of light is reached (Da Silva et al., 2014). This threshold level differs per species and is dependent on the light sensitivity of their visual system, leading to species-specific timing of dawn song, as empirically shown by Kempenaers et al. (2010) and Da Silva et al. (2014).

2.2 Adaptations to light intensity

In altered light conditions, such as through anthropogenic light pollution, the species with high sensitivity respond with earlier singing as soon as the artificial

light level rises above their threshold (Da Silva et al., 2014, 2014; Miller, 2006). This threshold is often not reached in species with lower light sensitivity, causing the timing of their first song to be unaffected by the increased light conditions (Kempenaers et al., 2010).

In tropical rainforests, these variations in light conditions are naturally present throughout different layers of vegetation. Greater canopy density alters the solar radiation reaching the understory, as it blocks direct sunlight, thereby altering the light spectral composition and intensity (D. W. Lee, 1987). Average light conditions in understory of dense tropical forests are often below 1% of the light reaching the canopy (Engelbrecht & Herz, 2001). However, great variation (70%) is found in different understory light conditions in distinct types of tropical forests. Figure 2 illustrates this dense tropical rainforest in Ranomafana National Park.

Figure 2: Tropical rainforest of Ranomafana National Park, with dense vegetation existing of many layers, blocking direct sunlight to the lowest levels. Sipa, 2013.

2.3   Species-specific variations in dawn singing

Bird species are found in all different layers of tropical forests, with all these different light conditions, thereby leading to the prediction that they have evolved different sensitivity to light. By studying dawn chorus in a neo-tropical forest, Berg et al. (K. S. Berg et al., 2006), found that time of first song is related to specific species characteristics related to ambient light level and visual sensitivity. For passerine birds included in the study, timing of bird singing is earlier in species with bigger eye size. They also found that timing of singing is earlier in species with a higher foraging height. This supports the *efficient foraging hypothesis,* as the higher light availability in the higher foraging heights leads to earlier foraging possibilities and therefore to earlier singing, as explained by Thomas et al. (2002). These

findings suggest an evolutionary adaptation towards increased visual sensitivity to lower light conditions (McNeil et al., 2005).

Interestingly, the opposite results have been found by Chen et al. (2015), who found that in East-Asian tropical montane forest, lower-layer species initiated singing earlier than upper-layer species. They suggest, however, that this relationship is highly dependent on the habitat type, and this pattern is more likely to occur in forests lacking sufficient canopy height. Visual ability is therefore likely a more dominant factor in a study area like theirs, with less-structured vegetation and low canopy (10-12m), while foraging height is found to be most dominant in forests with tall trees (25m or more) and distinctive inter-layer vegetation that leads to significant variations in light availability (K. S. Berg et al., 2006; T. J. Brown & Handford, 2003).

2.4   Light levels change in forests

Habitat disturbance such as land conversion affects the microclimatic variables in tropical forests (Ausprey et al., 2021). While in undisturbed forests the changes from canopy to the floor are gradual due to the many vegetation layers, disturbed forests have a more simplified structure due to lower plant diversity. This causes abrupt changes in microclimatic conditions like light levels and temperature (Fontúrbel et al., 2021). Species adapted to dark environments (such as forest floors), do not respond well to these changes, showing lower abundances in more open areas (Ausprey et al., 2021). The fast dynamics of habitat conversion do not allow species to adapt evolutionary, thereby favouring species that have a high adaptability to more diverse environments, known as generalists (Devictor et al., 2008). While other environmental variables like temperature and food availability also affect the song rate, song length and the abundance of certain species (see e.g. K. S. Berg et al., 2006; Huang et al., 2022; Johnson & Rashotte, 2002), the timing is most strongly affected by a change in light levels.

3. Methods

3.1 Research area
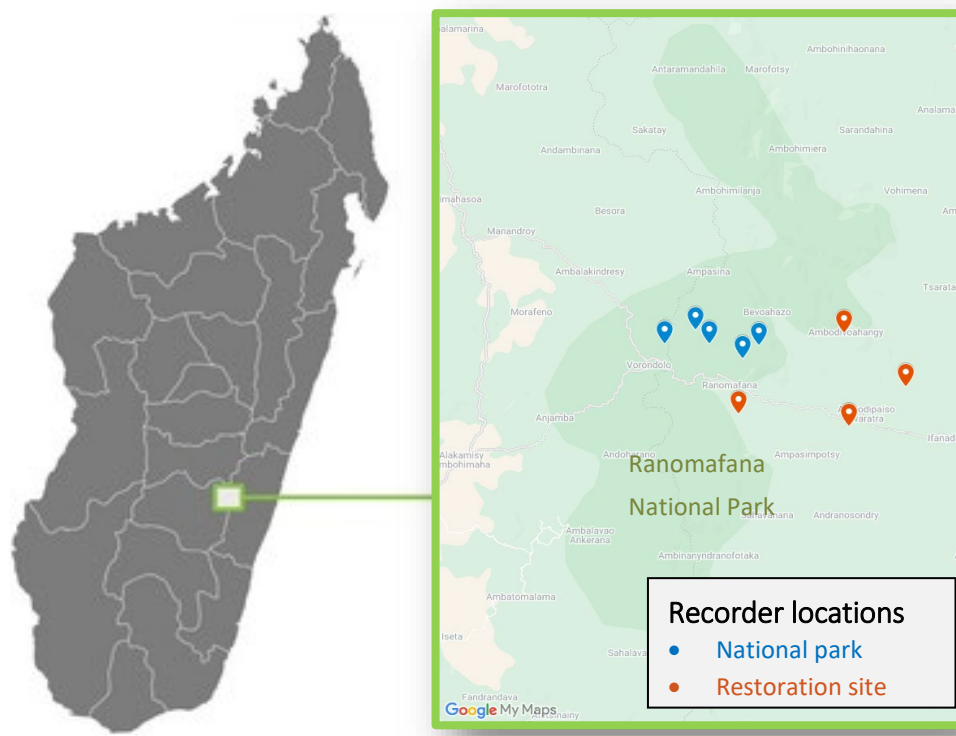
Figure 3: Map of Ranomafana National Park, Madagascar. Pointers represent the recorder deployment points within the park (blue) and at the restoration sites (red). Adapted from Razafindravony et al. (2023).

Ranomafana National Park (RNP) is a montane rainforest in Eastern Madagascar, with elevations ranging from 400-1417 m altitude, spanning an area of 416 square kilometres (WildMadagascar, n.d.). The park is home to 115 bird species, of which 30 endemics to the area (Hobbs & Dolan, 2008). The park is one of the field sites of the program Rewilding Madagascar, a multi-year research program, run by SLU with Dr. Sheila Holmes as program leader, looking into the role of seed dispersal for reforestation success. RNP hosts a research station, and it is used in this program to test monitoring techniques, such as camera traps and acoustic devices. Because

this research program focusses on reforestation success, it evaluates forests with various stages of reforestation as well as mature forests within RNP, providing an excellent opportunity to examine the effect of restoration on bird behaviour.

3.2 Data

The continuous acoustic data of the Rewilding Madagascar project has been collected using AudioMoth acoustic recording devices (Hill et al., 2018; Open Acoustic Devices, n.d.) at different restoration sites (RS) outside the national park (n=4) and multiple locations within RNP (NP) as control treatment (n=5) (see Figure 3 and Appendix 3). Each acoustic device performed 24-hour recordings on five consecutive days with a time schedule of 1 min on and 1 min off to save memory and battery life. The recorders were deployed in the field between February 22nd and May 3rd 2022 (unpublished data, Andriamavosoloarisoa, 2023). For this research, I used recordings from 5 A.M. to 6 A.M., which includes the onset of nautical twilight up until or just before sunrise for all recorded sites and dates. Mornings with excessive rain were excluded from the dataset because bird calls could not be identified. This led me to discard three mornings, two of which were the only ones of one of the NP sites (AND13#1), so that site was removed from the dataset. Thereby the final dataset came down to four sites for both treatments, both with thirteen mornings to analyse, resulting in a total length of 2 * 13 * 30 recorded minutes = 13 h.

The data was obtained from the 'Rewilding Madagascar' project through the RFCx-ARBIMON platform (Aide et al., 2013), an online audio processing software further referred to as Arbimon.

3.3 Species identification

3.3.1 Species selection

My analysis started with the first objective of this research, to find a species-specific response in singing times to the different forest habitats. For this, I identified species that were present in the recorded data and showed different characteristics with regards to foraging height and level of specialisation.

Mahefa Andriamavosoloarisoa, PhD researcher in the Rewilding Madagascar project responsible for collecting the data, provided a list of thirteen most-occurring species in the area based on his local experience and his preliminary assessment of the dataset (M. Andriamavosoloarisoa, personal communication, April 28th 2023). I also extracted a list of Ranomafana's most common species and their characteristics and observation counts within the area of Ranomafana from the

eBird Database (Sullivan et al., 2009). The complete list of species that I used in my analysis consisted of the thirteen from Andriamavosoloarisoa and thirteen more of the remaining species with the highest observations from eBird. The full list of analysed species can be found in Appendix 1.

3.3.2 Arbimon software

I chose the Arbimon software to process and analyse the audio data for its three key features: sharing data, visualizing data, and its incorporation of machine learning models. Firstly, the fact that Arbimon runs online allows data (once uploaded) to be accessible for collaborators all over the world, allowing validation of results and facilitating the data to be used in more distinct research projects. Secondly, Arbimon's immediate conversion of audio files into visual representations that can be filtered by frequency and time makes a scan of the recording faster and more efficient. Lastly, Arbimon's built-in machine learning methods makes them accessible for researchers across all fields of expertise.

3.3.3 Machine learning methods

Audio processing relies on the use of spectrograms. Spectrograms are a visual representation of sound with time on the x-axis, frequency on the y-axis and the amplitude of the signal is illustrated by the darkness of the pixels. An example of a bird call represented by a spectrogram is seen in Figure 4. By converting sound to a visual spectrogram, it can be analysed by machine learning methods such as audio event-detection (AED), clustering and pattern matching (PM). I will expand upon these methods below.
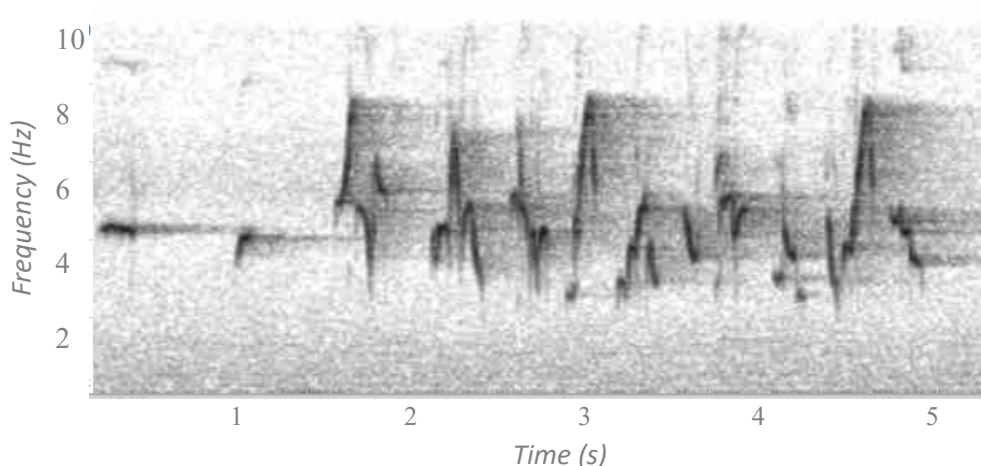
Figure 4: Spectrogram of the song of bird species Cinnyris sovimanga. eBird, 2023.

Audio event-detection and clustering

AED detects sound events in audio files based on threshold values it receives as an input, such as minimum amplitude, duration or bandwidth. A frequency range can also be specified. It can be used to filter the amount of data to search through during identification. An example of resulting detections is shown in Figure 5. When combined with a clustering analysis, the detected audio events can be categorized, after which they can be identified to species using visual inspection and audio playback (Rainforest Connection, 2022a). This clustering analysis will group the found audio events according to how similar the pixels of the spectrograms are. This will thus create groups of audio events that have similar features.

Audio event detection (AED)
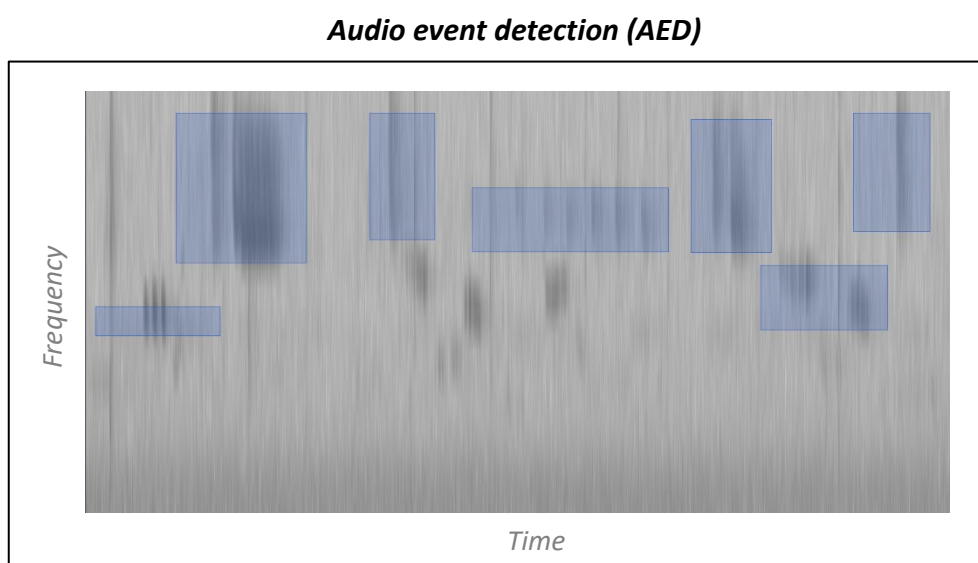
Figure 5: Example of audio event detection on a spectrogram. Blue boxes are sound events detected by the algorithm.

This feature can be used to search for examples of desired calls, without the need for existing examples and could therefore be used to start the analysis. I used these examples of calls in the PM analysis to efficiently detect more examples of the pre-determined sounds. I stored the best sound patterns of each selected sound as a template within Arbimon, and because Arbimon requires them to be assigned to a species, I assigned them to 'unknown species' codes (sp1, sp2, etc.) that are available within the software.

I ran multiple AED's with different parameter-settings (Min. frequency 0-1.6 kHz, Max. frequency 8-10 kHz, Min. amplitude 0.5-1 (in number of standard deviations from the mean of the spectrogram), Min. duration 0.2 s, Min. bandwidth 0.5-1 kHz), resulting in different amounts of detected sound events and clusters. This method was only used as an exploratory way to start to understand patterns in the data and to find examples of clear bird calls. Following this approach, I stored only those call templates that were clearly distinctive of a bird species and of which

I found multiple others, in order to improve the chance of success of their PM analysis.

Pattern matching
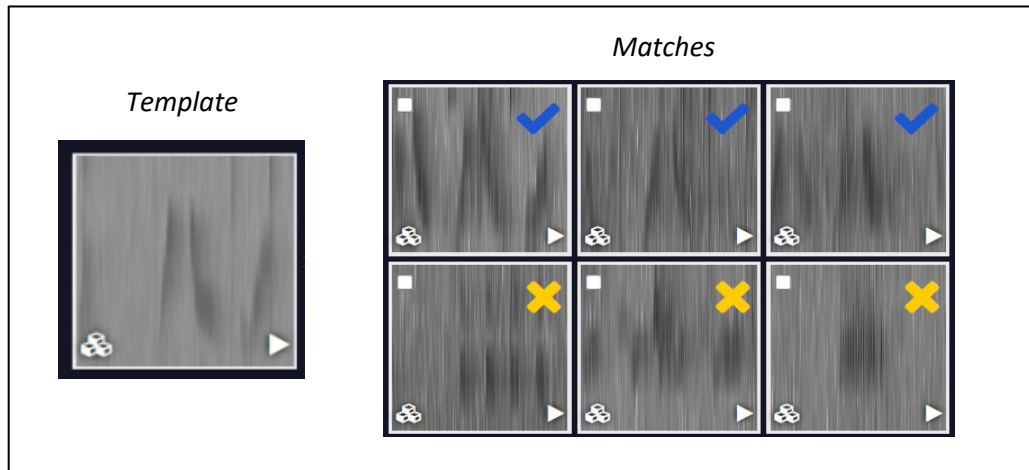
Figure 6: An illustration of how pattern matching works. The desired vocalization is given as a template spectrogram. The algorithm then returns instances where the recordings resemble this template. Manual validation is then required to mark true matches as present (blue tick) and false matches as absent (yellow cross).

Pattern matching

Pattern matching is a semi-automatic sound classification algorithm implemented in the Arbimon software for which an example, or template, of a sound (spectrogram) is compared to other spectrograms within the recording (Rainforest Connection, 2022b). This process returns correlation scores per match that describes the similarity of pixels within the spectrograms. All matches with a correlation score above a given value are then presented to the user. It is semi-automatic because the resulting matches can then be manually evaluated both by visual comparison and auditory playback. This is visualized in Figure 6. In conclusion, PM is useful if you have a known call and you want to find more instances of that call within your dataset.

The templates that I used were from three different sources. I started with the three unidentified species from the above-explained AED/c analysis. Then, I added those templates from species on my list, which were already identified in other public Arbimon projects and were therefore publicly available. Finally, I created templates myself from the first thirteen species of my species lists. This was done with the help of recordings from the Macaulay Library at the Cornell Lab of Ornithology, as explained in the following section.

Creating the templates

For each species on the list, I requested a few (two to four) recordings from the Macaulay Library in which a clear, distinctive call or song could be heard,

preferably recorded in Madagascar, because location-specific templates are found to improve selection results (LeBien et al., 2020). See Appendix 2 for a full list of recordings used. I imported these recordings into a public Arbimon project called 'Madagascar Bird Templates'. I used Arbimon's software to cut out call templates from these recordings that could be used to identify these calls in other recordings. Per species I selected three different templates with different calls or different qualities. For example, some calls were repeated with a couple of seconds in between them, in which case I selected one template with the single call and one template with three or four times that same call to provide more context. All of these templates were added to the Rewilding Madagascar Project.

Consequently, I performed PM analyses on each of these templates (with parameters: min. correlation score = 0.2; max. nr. of matches per recording = 2; max. nr. of matches per site = no limit). Then I verified the results visually by comparing spectrograms, and audibly through playback (see Figure 9 in the results for clarification). When the number of matches was lower than 20, I lowered the correlation threshold from 0.20 to 0.15 to increase the chance of true matches. When more than 600 matches were found, only the 600 with the highest score were validated and others were automatically discarded.

These machine learning methods did not provide observations of all the species of interest, and a visual scan through the data revealed that many bird calls were missed using this method. The evaluation of this method, as described in objective two, will be performed in more detail in the results and discussion section. To accurately define dawn singing behaviour, the focus was therefore switched to objective three, in which the dawn singing behaviour of the complete bird community was assessed.

3.4 Manual detection of bird sounds

A manual analysis was required to capture the complete behavioural pattern of bird vocalizations in the dawn choruses of the test sites. This analysis was performed in Raven Lite (K. Lisa Yang Center for Conservation Bioacoustics at the Cornell Lab of Ornithology, 2023).

3.4.1 Raven Lite Software
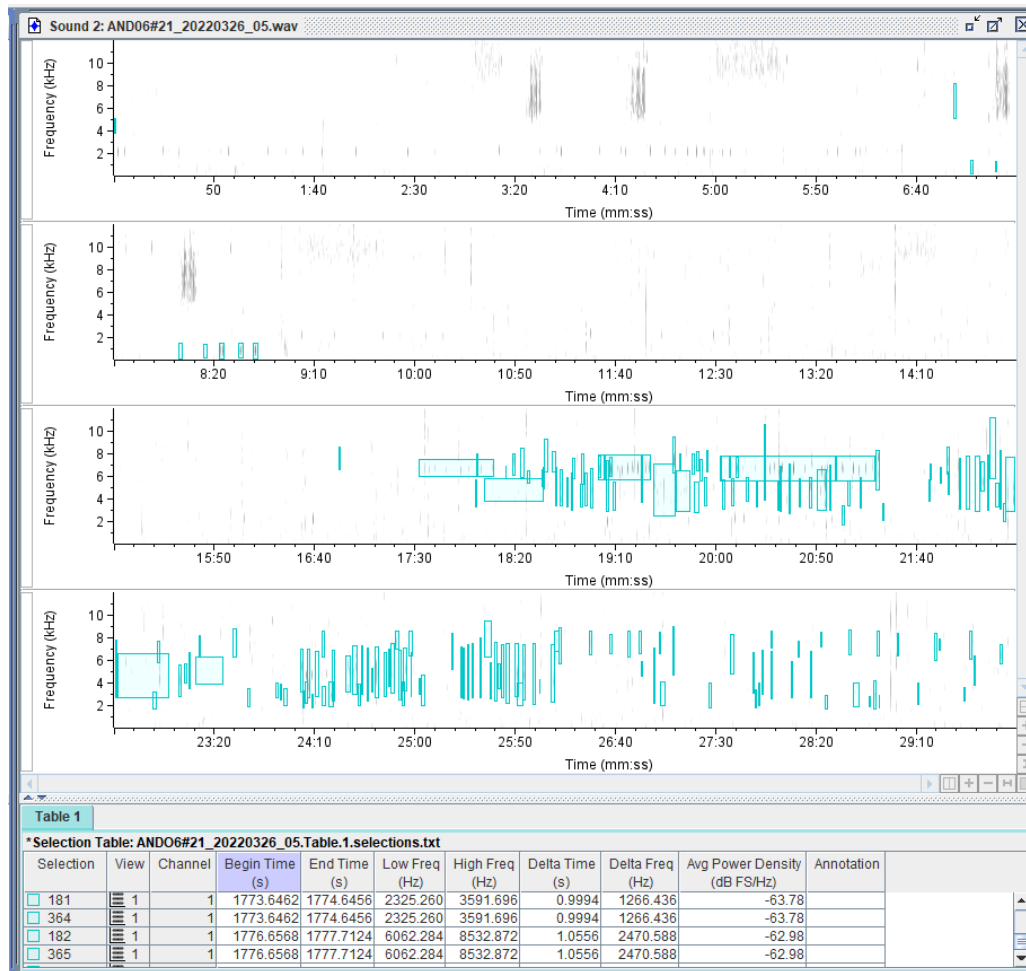
Figure 7: Example of a selection result for site AND06#21, day 2. All recordings have been placed after each other and can be processed as one recording.

I chose Raven Lite for the manual assessment because it has a couple of advantages over Arbimon for the task of manually scanning and annotating large datasets (see Markolf et al., 2022). Namely, it allows you to treat consecutive recordings as one to scan through it more efficiently, it allows you to adjust the brightness and contrast to adapt to various levels of ambient sounds, and it provides intuitive annotation methods.

For each recorded morning, I visualized all 30 recorded minutes as one l, and I adjusted the visible frequency range to 0-10 kHz, the typical frequency range of bird sounds (Slabbekoorn & den Boer-Visser, 2006). Thereafter, I adjusted the brightness and contrast to values between 55 and 68 % by choosing those values in which bird calls had a good contrast with the ambient sounds, which differed per recording. Within this view I scrolled through each recorded morning and selected and marked spectrograms that were bird vocalizations. I did this both by recognizing spectrograms and by listening to the call to be sure that I was not

selecting sounds from other animals. The most challenging part was to distinguish bird sounds from insect sounds. I was able to identify insect sounds because of the continuous and repetitive nature, mostly spanning complete recorded minutes and often even more than one.

3.4.2 Call type annotation

A species might have two or more calls that sound different and also look different on the spectrogram, two different call types. However, since I did not have the expertise to assign calls to specific species, I was also unable to identify when two calls types were from the same species. Instead of counting the number of species, I therefore counted the number of different call types that were observed within each minute. Instead of defining the number of species (the species richness), I thus defined the number of different calls (the call richness) per minute.

By defining the call richness per minute, I could use this to evaluate the pattern of activity over the morning. The start of the dawn chorus is usually determined by the first call of the morning when looking at specific dawn-singing species (see e.g. Thomas et al., 2002), but here I examined the full spectrum of bird calls irrespective of species and species characteristics. It was therefore possible that I also detected a rare call of a nocturnal species. To increase robustness of the result, I therefore defined the start of the dawn chorus by the first time that the call richness was higher than 0 for at least three consecutive minutes (see Figure 8). To account for differences in sunrise times, I converted the recorded times of the found species calls to time relative to sunrise, according to the Astronomical Applications website of the US Naval Observatory (as in K. S. Berg et al., 2006). This procedure resulted in an annotated spectrogram like the one shown in Figure 8.

Other variables that were determined per morning were the ambient sound level and the maximum call richness. The ambient sound level is given in Raven Lite as the average power density. The unit they use is in decibel full-scale per Hertz (dB * FS / Hz), where the full scale is defined by zero as the highest sound amplitude that can be recorded with the recording system. The maximum call richness was defined as the highest call richness value detected in the morning.
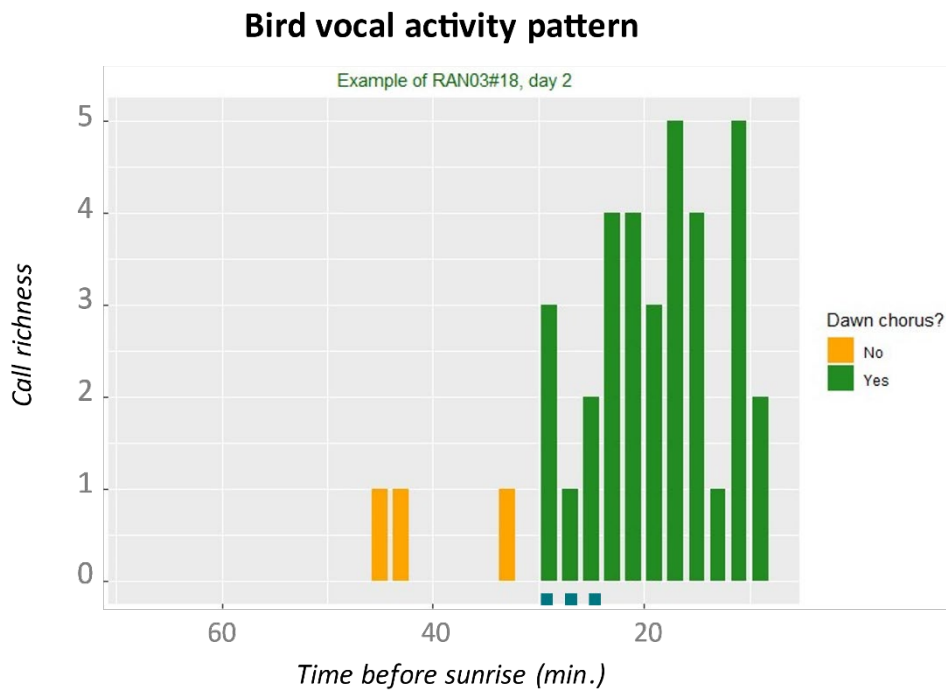
Figure 8: Example of how the start time of the dawn chorus is determined. The first time after which call richness > 0 for three or more consecutive minutes.

3.5 Statistical analysis

The measured response variables were the maximum call richness, the start time of the dawn chorus and the ambient sound level. These variables are used to compare the two forest treatment groups NP and RS. I used R software for the statistical analyses (R Core Team, 2023). The distance between pairs of recorders was large enough to avoid the same individuals being recorded at multiple sites. Therefore, the observations among sites can be seen as independent observations. However, recordings from different days at the same site cannot. Hence, I used a linear mixed model to test if the response variables were different among treatments, while including a random intercept per site to correct for multiple measurements.

4. Results

4.1 Audio event detection and clustering

The range of detected audio events was 800 to 1600 per site (10-20 per minute), with clusters ranging from 20 to 100 events. From these, I selected three calls to create a template from, because they were clear bird vocalizations, they were repeated throughout multiple recordings and they were distinctive enough to be used in a pattern matching analysis.

4.2 Pattern Matching

The results from the pattern matching analyses varied strongly depending on how the call sounded and how the spectrogram looked. The amount of (unvalidated) matches found per template ranged between 4 (Coua Caerulea t1) and 973 (for Dicrurus fortificatus t1). After validation, calls of only one species (*Copsychus albospecularis*) were eventually found with certainty in six different sites. Other species were found in four (*Cinnyris sovimanga*), three (*Terpsiphone mutata*), or two different sites (*Cuculus rochii*, *Neomixis tenella* and *Nesillas typica*), but these could not be verified.

Of the unknown species templates, four unknown species calls were found in two other sites than where the templates were originally found, and one was found back in one other site.

Two examples of pattern matching results are presented here to exemplify the range of different outcomes. Figure 9 shows pattern matching results after validation of an unknown species 'sp13', whose template was taken from one of the recordings in the dataset. Twenty-seven matches were found that had sufficient correlation with the example template. Of them, fifteen were then classified as true matches, or present, by verifying them audibly and visibly. Figure 10 shows the result of known species *Cinnyris sovimanga*, whose template was imported from a Macaulay Library recording. In this case 103 matches were found, of which only one was validated as present. Finding one, zero, or very little true matches was exemplary for patterns used from imported templates.
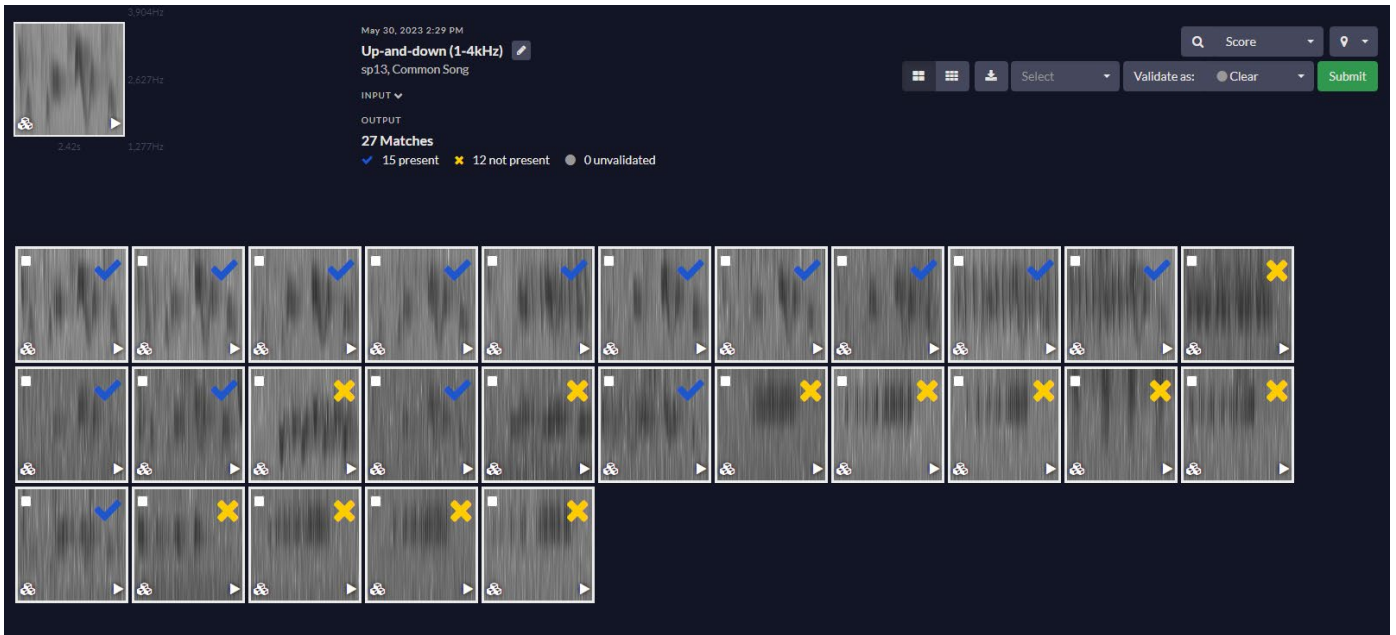
Figure 9: Pattern Matching result for a template of unknown species 'sp13' that was selected from an event detection analysis. In this successful case, 15 of 27 matches were validated as present (blue tick), the other 12 as not present (yellow cross).
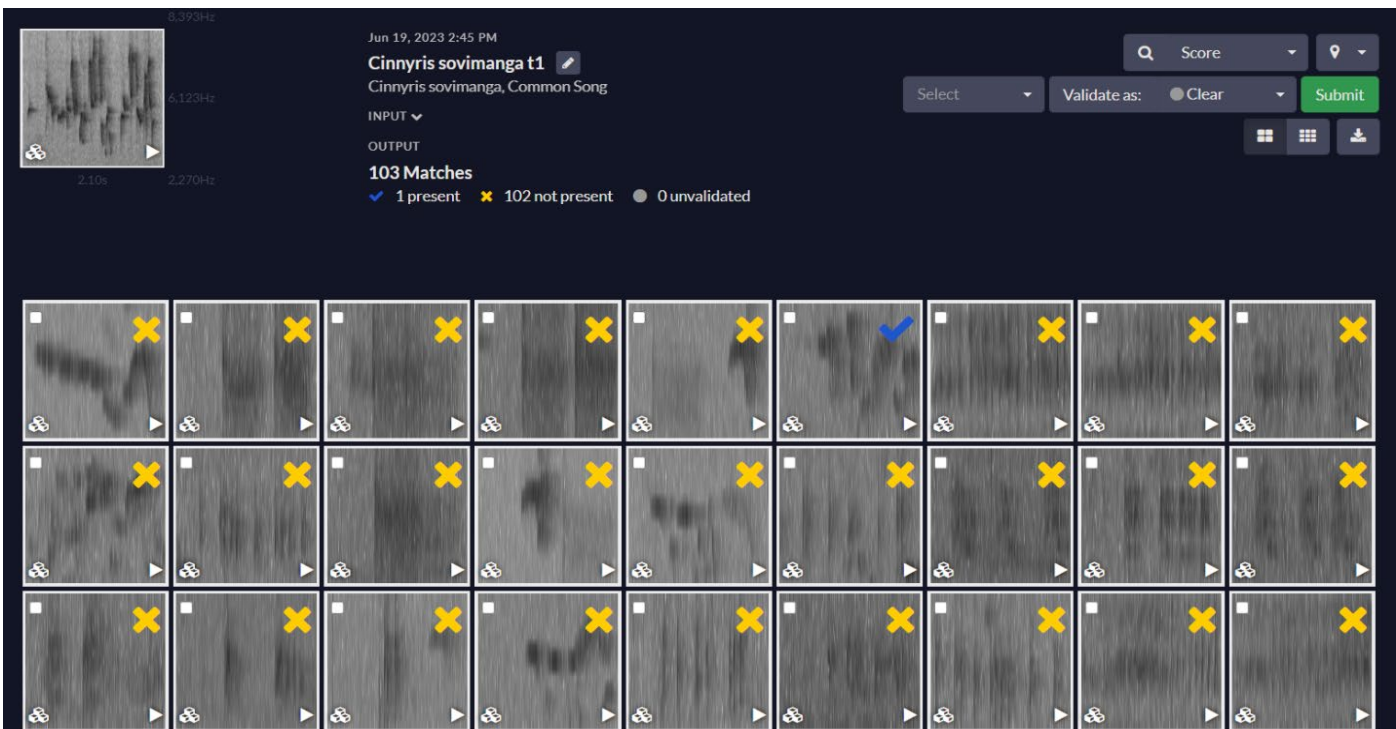
Figure 10: Pattern Matching result for a template of Cinnyris sovimanga that was obtained from a Macaulay Library recording. In this case, one of the 103 matches was validated as present (blue tick), the other 102 as not present (yellow cross).

4.3 Manual analysis

During the analysis it proved much more difficult to identify bird sounds in some of the restoration sites because of the high level of insect noise that was present. This noise often completely blocked out other sound in the frequency range of 3 to 5 kHz and sometimes also 6 to 9 kHz.

4.3.1 Activity pattern

The call richness was visualised in activity patterns across time for each recorded morning, as seen in Figure 11 (NP) and Figure 12 (RS).
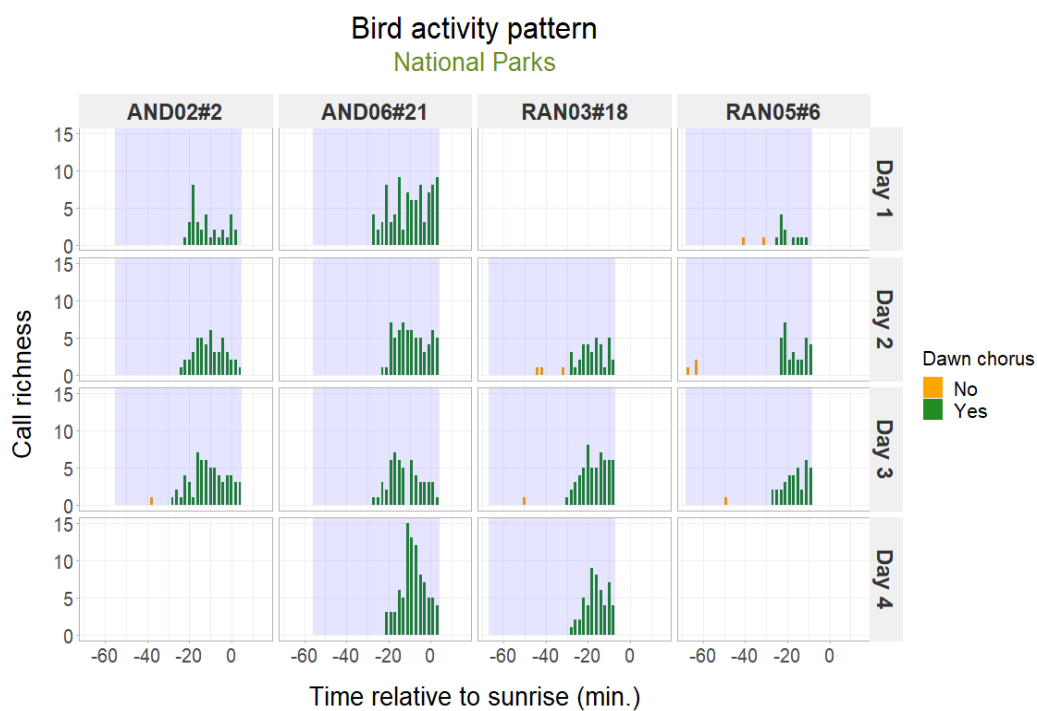
Figure 11: Richness of bird vocalizations per minute during the start of dawn chorus for National Parks. The measured window (blue area) displays the activity pattern per recorded day, per site. Sampling frequency of measurements is 30 per hour. Time = 0 corresponds to sunrise.
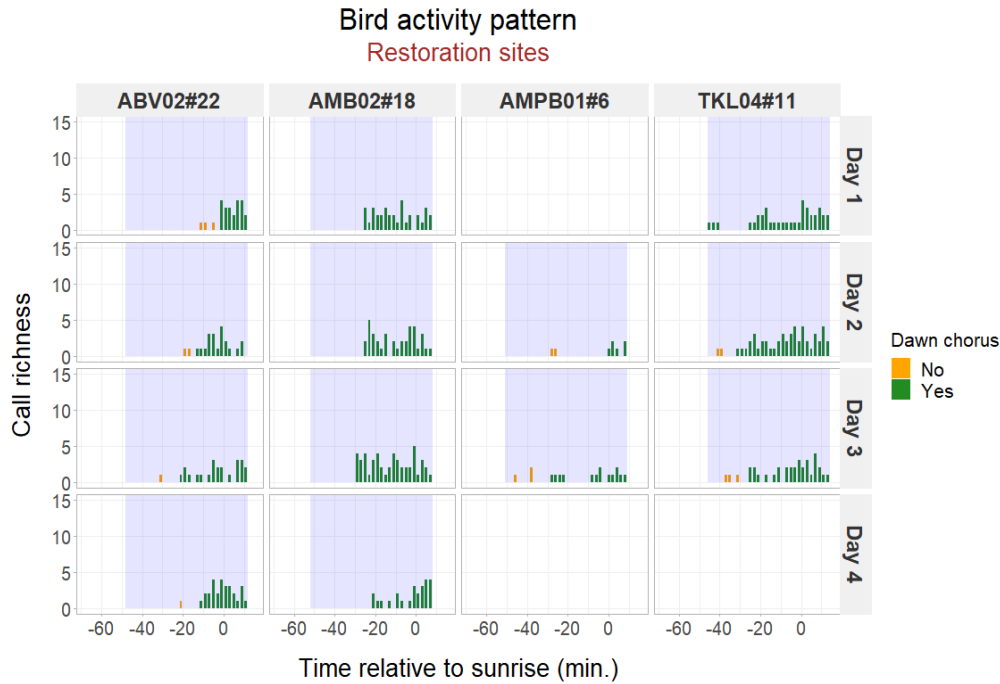
Figure 12: Richness of bird vocalizations per minute during the start of dawn chorus for restoration sites. The measured window (blue area) displays the activity pattern per recorded day, per site. Sampling frequency of measurements is 30 per hour

4.4 Dawn chorus characteristics

The maximum call richness was higher in the national parks, with numbers reaching up to 15 in the national parks, and only 5 in the restoration sites (estimated difference: -3.92, 95% CI: -6.04 to -1.81, p=0.001, Figure 13A). No difference could be found between the two treatments for the start time of dawn chorus (estimated difference: 4.53 min., 95% CI: -6.26 to 15.32, p=0.394, Figure 13B). The ambient sound level was higher in the restoration sites than in the national parks (estimated difference: 7.51, 95% CI: 3.55 to 11.47, p=0.001, Figure 13C).
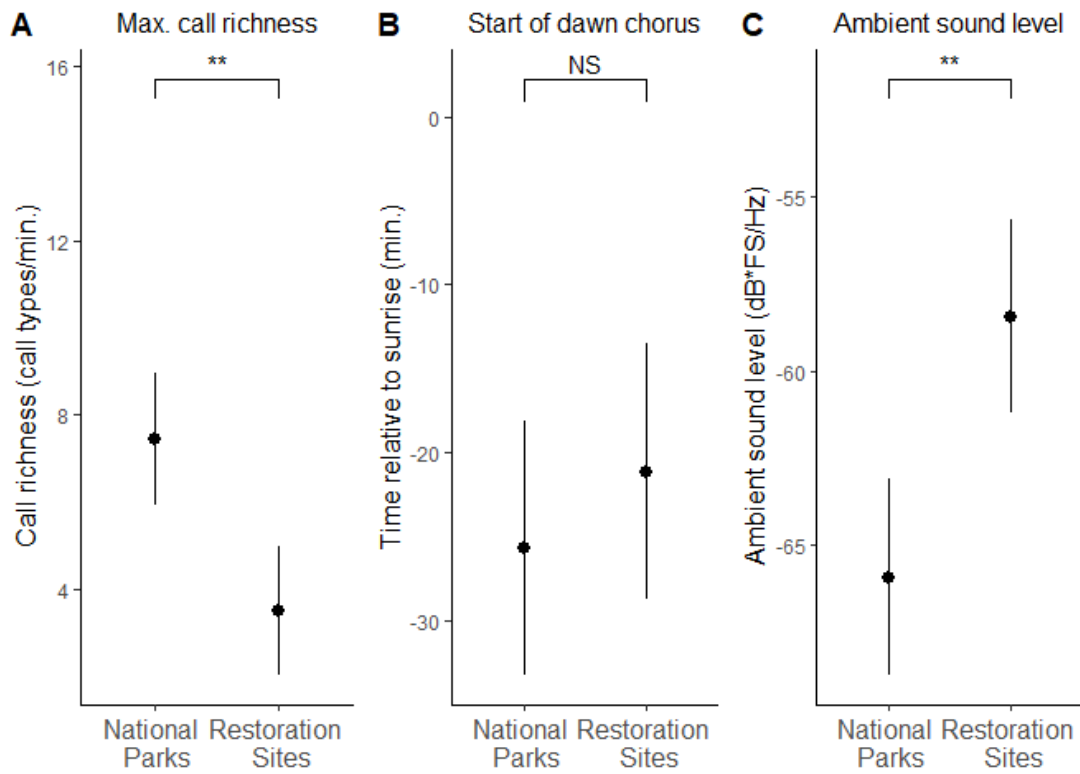
Figure 13: Linear mixed model results comparing treatments for A) max. call richness per minute, B) start time of the dawn chorus and C) ambient sound level of the recordings. Black bars represent model estimates with upper and lower limits of the 95% confidence interval.

5. Discussion

In this research, I have aimed to define the effect of forest restoration on the start time of the dawn chorus in tropical forests in Madagascar. To analyse this effect, I used audio recordings from test sites that were located both in mature forests of Ranomafana National Park and surrounding areas with forest restoration. I will first discuss the results and their implications, and will later describe the challenges that need to be taken into account for acoustic monitoring in tropical forest ecosystems.

5.1 Summary of results

The analysis was first focussed on species-specific identification through the use of machine learning methods (objective 1). The automatic pattern matching and cluster analysis method was not accurate enough to facilitate species recognition.

The challenges faced in this analysis (objective 2) were mostly connected to high variability in interfering insect sound sources, and the current reliability of recognition software on validation by local expert knowledge.

By focussing the objective to differentiating all bird calls from the surrounding soundscape I could detect the communal dawn chorus (objective 3). I found that there was no difference between the start time of the dawn chorus in mature forests and forest restoration areas (Figure 13B). I also found that restoration areas showed a lower maximum call richness and a higher ambient sound level (resp. Figure 13 A and C).

5.2 Reduced species richness in restoration areas

The call richness during the dawn chorus was higher in mature forests, as also illustrated by Figure 11 and Figure 12. The results therefore show a higher species richness in the national parks than in the restoration sites, which adds supporting evidence to the knowledge that protected forests have higher species richness than anthropogenically disturbed forests (Barlow et al., 2016; IPCC, 2022).

The call richness was used as a proxy for species richness, and I will expand upon some of the considerations of this. As explained, two different calls may correspond to the same species, as they use different vocalizations to communicate

different messages (Clay et al., 2012). To compare species richness by call richness, two things have to be assumed. First, the detected species in both forest treatments use an equal number of different vocalizations. This is accounted for in this study by selection of study sites close enough to exhibit comparable bird communities. Second, all species should have equal chances of detection. All detection methods (e.g. camera traps, point counts) have a sampling bias towards species with specific habitats, behaviour or body size (Fontúrbel et al., 2020; Manu & Cresswell, 2007). Acoustic monitoring is found to be comparable to point counts in detection of call activity and is therefore considered a suitable alternative (Digby et al., 2013). In order to improve the accuracy of this prediction, local expert knowledge is needed. This entails excellent knowledge of bird vocalizations of species local to the study area. This knowledge is scarce, and it is precisely where and why automatic detection algorithms can aid research in this field.

5.3 Dawn chorus timing not affected

The hypothesis that the dawn chorus in restoration sites would start earlier because of increased light levels, cannot be supported by this study. It should first be excluded that the differences between light availability were too small in this study. Although I did not perform a formal analysis on the vegetation at both treatment sites, the researchers collecting the data have confirmed that vegetation structure in the restoration sites is indeed much less diverse, leading to much higher light levels. This lack of difference in timing can therefore not be ascribed to the lack of differences in light levels.

Even though studies on individual bird species found that species started singing earlier when exposed to higher light-levels (see Kempenaers et al., 2010), opposing results have also been found when studying the chorus of the complete bird community. Lee et al. (2017) found that environments with increased light counter-intuitively exhibited even later dawn choruses. They argue that other aspects, such as the adaptation of species communities to these environments, possibly play a role in this. Species with lower sensitivity could then be expected to inhabit the areas with higher light availability, as shown earlier by Kempenaers et al. (2010).

Caterall et al. (2012), show that species composition takes considerable time to recover towards a rainforest-like bird community. They estimate that most forest bird communities will need more than 150 years to recover, even if rainforest-requirements like closed canopy-cover, high stem-density and ground litter layer are met within 10 years. In the studied restoration sites, none of these parameters are met. It is therefore possible that the bird community that now inhabits the restoration sites consists of more species with low sensitivity. This would then lead to later dawn singing than expected from the environmental conditions.

5.4 Interference from insects in restoration sites

Insects in audio recordings
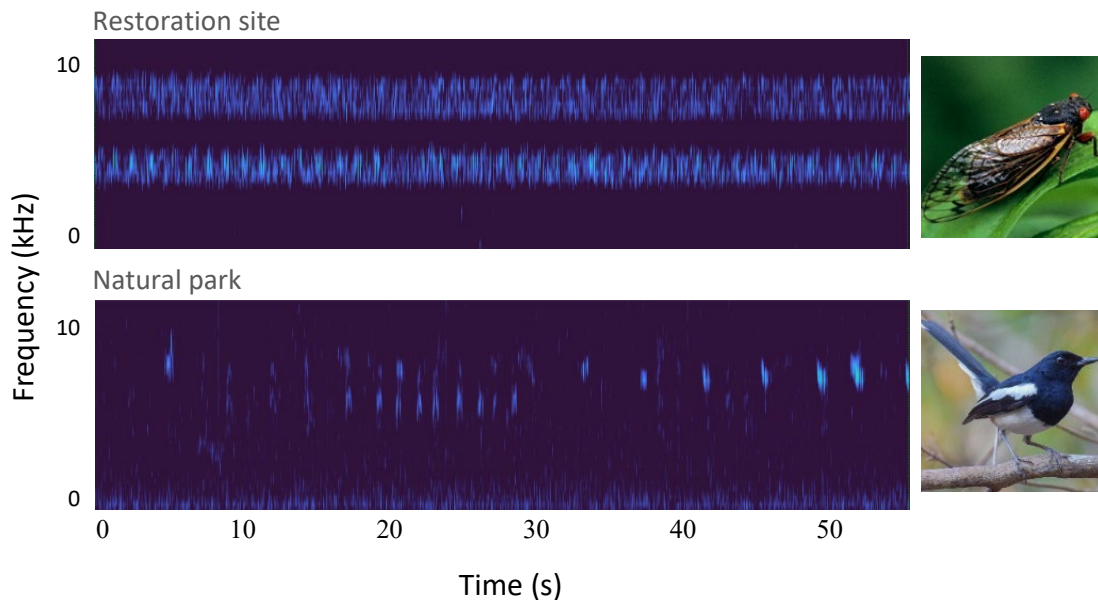
Figure 14: Spectrograms of a restoration site (above) with many insect sounds and of a national park (below) with bird vocalizations. These species groups often interfere, where the louder, continuous sound of insects often masks the sound of birds.

Another explanation for why this study was not able to detect differences in timing of the dawn chorus could have been because detectability of birds was decreased in restoration areas. It was found that insect sounds are predominant in most restoration sites, as also illustrated by the increased ambient sound level. Their dominance in the soundscape often masks large parts of the frequency range that are used by birds in their vocalizations, impeding their detection (see Figure 14).

In bioacoustics, environmental noise is a frequently encountered problem (see Aide et al., 2017; Burivalova et al., 2022). Studies have focussed on de-noising recordings by filtering out rain and wind (Juodakis & Marsland, 2022). Brown et al. (2019) have even developed a method to not only detect cicadas in acoustic recordings, but to also filter them from the data. However, these studies have only been able to achieve effective filtering through band pass filtering, where the frequency band used by insects is detected and deleted, thereby also removing the masked bird vocalizations. More studies into insect filtering are therefore required to more effectively detect birds from acoustic landscapes dominated by insects.

The research method should therefore be adjusted to be workable in restoration areas with high insect populations. It should not be ruled out that in those research sites, audio recorders might not be the best monitoring tool for bird species evaluations. Other remote monitoring tools, like camera traps, should also be considered.

5.5 Recommendations on the use of machine learning methods

Automatic acoustic detection is under continuous development. This was illustrated in this research by its reduced effectiveness in noisy environments and by minor but time-consuming issues like data-corruption. I hope to aid future research into detection of birds in tropical rainforests, by addressing strengths and limitations of the used analyses.

5.5.1 Cluster analysis

The main difficulty in the clustering analysis, was choosing the right parameters for both the audio event detection and the clustering itself. Because there is a high diversity in the soundscape of the data (with diverse ambient sound levels), the optimal parameters may not be equal for every recorded day because of the high variability in environmental parameters. The resulting clusters were not necessarily homogeneous, with different call types appearing in the same cluster, and, conversely, similar calls ending up in different clusters. The few calls that could be distinguished led to what I defined before as 'unknown species'.

Therefore, clustering analysis cannot be used to identify occurrences of species without additional knowledge of bird vocalizations; information often only accessible through local experts. In this study, I tried to surpass this by taking existing recordings from common species in the research area and use them in a pattern matching analysis.

5.5.2 Pattern matching analysis

In the pattern matching method I tried identifying the twenty-six most common species by importing their templates from the Macaulay Library. LeBien et al. (2020) have shown before that using a local context greatly improves selection results. Therefore, all of the recordings I used were from Madagascar, and even from the Ranomafana region if they were available for the given species. However, imported templates from outside the dataset still did not work as well as templates that were created within the same dataset (see Figure 9 and Figure 10). The context therefore was thus still not close enough to the recordings, and surrounding factors like weather conditions, time of year, or simply individual variations were too high to find successful matches.

Another factor that could possibly improve selection results is the selection of suitable templates. Bird vocalizations encountered during the selection varied in terms of pitch, rhythm, tone and repetition (The Cornell Lab, 2009). Especially if calls were repeated, it made it difficult to determine the right number of repetitions to choose for the template. Templates of short calls were often not suitable, but

adding more repetitions also increased the disturbance by surrounding sounds, thereby decreasing suitability again. Other questions are how to deal with individual variations in song pattern, or what the minimum length of a template should be. An analysis into the characteristics of template suitability would greatly enhance workflow in pattern matching and increase its overall efficiency.

5.5.3 Alternative analyses

Automated bird species identification from audio recordings is a challenging problem, and stronger methods are probably needed than pattern matching and clustering analysis. Such stronger methods, like neural network applications have been developed for the general public to use in the Northern Hemisphere (see application apps Merlin (Chu, 2012) or BirdNet (Kahl et al., 2021)). Unfortunately, the identification of birds from tropical areas is not that far developed. Templates of tropical species are not yet available in different environmental contexts to make species identification robust. However, recent studies show potential of animal sound detection networks requiring only a few examples, referred to as few-shot learning (Nolasco et al., 2023). In this study pattern matching, or template matching, was evaluated with an F-score of 12.35%, while state of the art neural network solutions were able to get an F-score of 61.83% with just 5 templates. The potential of these developments is promising, and more research can reveal its potential for a variety of environmental contexts and species groups.

At this stage of the developments, however, it is still essential for species identification to work in close cooperation with an expert knowledgeable of local species and their sounds. I was able to conduct this study in cooperation with an expert in the field, PhD candidate Mahefa Andriamavosoloarisoa, who collected all the data and provided me with knowledge about common species in the area. However, this type of research requires the experts to be out in the field for long stretches of time, in remote areas with limited access to internet, making cooperation difficult and slow. This highlights the need for development of stand-alone detection algorithms, to reduce dependence on local expertise.

5.6 Future of rainforest restoration monitoring

Although my results shed a light on the diversity of the acoustic landscape among forest treatments, the multitude of interactions between insects, birds and restoration status are still unclear. For example, it is suspected that the interference of sounds can have potential fitness consequences for birds (e.g. decreased communication, higher risk of predation (J. Lee et al., 2017), increased food availability, etc.), and it is unclear how insect communities respond to restoration

(e.g. species richness, volume of sound, etc. (Schmidt & Balakrishnan, 2015)) and what the underlying mechanisms are (e.g. microclimatic variations). These interactions could be further studied through enhanced insect filtering mechanisms, but species-specific recognition is also required for more detailed response patterns.

Simultaneously, this research clearly shows the challenges faced in bird call recognition from acoustic data in the tropical rainforests of Madagascar. Although automatic detection methods are being developed and made available to the public, they still come with many limitations and the handbooks to use them have yet to be developed. The rapid advances and possibilities of machine learning methods being used in other areas of the world do give hope that these will also become available for those areas in the world where they are needed most urgently. Development of reliable machine learning algorithms for species recognition will decrease our dependence on the knowledge of local experts. With a continuation of data collection and annotation through strong cooperation with local experts, these methods can be extended towards more and more similar habitats. This will eventually lead to a better understanding of rainforest restoration and behavioural response of those species vital to re-establish healthy, self-sustaining forests.

References

Aide, T. M., Corrada-Bravo, C., Campos-Cerqueira, M., Milan, C., Vega, G., & Alvarez, R. (2013). Real-time bioacoustics monitoring and automated species identification. *PeerJ*, *2013*(1), e103. https://doi.org/10.7717/PEERJ.103/FIG-4

Aide, T. M., Hernández-Serna, A., Campos-Cerqueira, M., Acevedo-Charry, O., & Deichmann, J. L. (2017). Species Richness (of Insects) Drives the Use of Acoustic Space in the Tropics. *Remote Sensing*, *9*(11), Article 11. https://doi.org/10.3390/rs9111096

Ausprey, I. J., Newell, F. L., & Robinson, S. K. (2021). Adaptations to light predict the foraging niche and disassembly of avian communities in tropical countrysides. *Ecology*, *102*(1), e03213. https://doi.org/10.1002/ECY.3213

Barlow, J., Lennox, G. D., Ferreira, J., Berenguer, E., Lees, A. C., Nally, R. M., Thomson, J. R., Ferraz, S. F. de B., Louzada, J., Oliveira, V. H. F., Parry, L., Ribeiro de Castro Solar, R., Vieira, I. C. G., Aragão, L. E. O. C., Begotti, R. A., Braga, R. F., Cardoso, T. M., de Oliveira, R. C., Souza Jr, C. M., … Gardner, T. A. (2016). Anthropogenic disturbance in tropical forests can double biodiversity loss from deforestation. *Nature*, *535*(7610), Article 7610. https://doi.org/10.1038/nature18326

Belghith, N. B. H., Randriankolona, P. L., & Osborne, T. (2016). *Madagascar poverty and inequality update: Recent trends in welfare, employment, and vulnerability.* International Bank for Reconstruction and Develpoment / The World Bank.

Berg, K. S., Brumfield, R. T., & Apanius, V. (2006). Phylogenetic and ecological determinants of the neotropical dawn chorus. *Proceedings of the Royal Society B: Biological Sciences*, *273*(1589), 999–1005. https://doi.org/10.1098/RSPB.2005.3410

Berg, M. L., Beintema, N. H., Welbergen, J. A., Berg, J. K., Beintema, M. L., And Komdeur, J. A., Berg, M. L., Beintema, N. H., Welbergen, J. A., & Komdeur, J. (2005). Singing as a handicap: The effects of food availability and weather on song output in the Australian reed warbler Acrocephalus australis. *Journal of Avian Biology*, *36*(2), 102–109. https://doi.org/10.1111/J.0908-8857.2005.03285.X

Brown, A., Garg, S., & Montgomery, J. (2019). Automatic rain and cicada chorus filtering of bird acoustic data. *Applied Soft Computing*, *81*, 105501. https://doi.org/10.1016/j.asoc.2019.105501

Brown, K. A., Johnson, S. E., Parks, K. E., Holmes, S. M., Ivoandry, T., Abram, N. K., Delmore, K. E., Ludovic, R., Andriamaharoa, H. E., Wyman, T. M., & Wright, P. C. (2013). Use of provisioning ecosystem services drives loss of functional traits across land use intensification gradients in tropical forests in Madagascar. *Biological Conservation*, *161*, 118–127. https://doi.org/10.1016/J.BIOCON.2013.03.014

Brown, T. J., & Handford, P. (2003). Why birds sing at dawn: The role of consistent song transmission. *Ibis*, *145*(1), 120–129. https://doi.org/10.1046/J.1474-919X.2003.00130.X

Bruni, A., Mennill, D. J., & Foote, J. R. (2014). Dawn chorus start time variation in a temperate bird community: Relationships with seasonality, weather, and ambient light. *Journal of Ornithology*, *155*(4), 877–890. https://doi.org/10.1007/S10336-014-1071-7/FIGURES/5

Burivalova, Z., Maeda, T. M., Purnomo, Rayadin, Y., Boucher, T., Choksi, P., Roe, P., Truskinger, A., & Game, E. T. (2022). Loss of temporal structure of tropical soundscapes with intensifying land use in Borneo. *Science of The Total Environment*, *852*, 158268. https://doi.org/10.1016/j.scitotenv.2022.158268

Catterall, C. P., Freeman, A. N. D., Kanowski, J., & Freebody, K. (2012). Can active restoration of tropical rainforest rescue biodiversity? A case with bird community indicators. *Biological Conservation*, *146*(1), 53–61. https://doi.org/10.1016/j.biocon.2011.10.033

Chen, W. M., Lee, Y. F., Tsai, C. F., Yao, C. T., Chen, Y. H., Li, S. H., & Kuo, Y. M. (2015). Dawn chorus variation in East-Asian tropical montane forest birds and its ecological and morphological correlates. *Contributions to Zoology*, *84*(3), 255–265. https://doi.org/10.1163/18759866-08403005

Chu, M. (2012, August 9). *Merlin: Online bird identification with human learning and machine learning*.

Clay, Z., Smith, C. L., & Blumstein, D. T. (2012). Food-associated vocalizations in mammals and birds: What do these calls really mean? *Animal Behaviour*, *83*(2), 323–330. https://doi.org/10.1016/j.anbehav.2011.12.008

Cuthill, I. C., & Macdonald, W. A. (1990). Experimental manipulation of the dawn and dusk chorus in the blackbird Turdus merula. *Behavioral Ecology and Sociobiology*, *26*(3), 209–216. https://doi.org/10.1007/BF00172088/METRICS

Da Silva, A., Samplonius, J. M., Schlicht, E., Valcu, M., & Kempenaers, B. (2014). Artificial night lighting rather than traffic noise affects the daily timing of dawn and dusk singing in common European songbirds. *Behavioral Ecology*, *25*(5), 1037–1047. https://doi.org/10.1093/BEHECO/ARU103

Devictor, V., Julliard, R., & Jiguet, F. (2008). Distribution of specialist and generalist species along spatial gradients of habitat disturbance and fragmentation. *Oikos*, *117*(4), 507–514. https://doi.org/10.1111/J.0030-1299.2008.16215.X

Digby, A., Towsey, M., Bell, B. D., & Teal, P. D. (2013). A practical comparison of manual and autonomous methods for acoustic monitoring. *Methods in Ecology and Evolution*, *4*(7), 675–683. https://doi.org/10.1111/2041-210X.12060

Engelbrecht, B. M. J., & Herz, H. M. (2001). Evaluation of different methods to estimate understorey light conditions in tropical forests. *Journal of Tropical Ecology*, *17*, 207–224.

FAO. (2020). The State of the World's Forests 2020. Forests, biodiversity and people. In *The State of the World's Forests 2020*. FAO and UNEP. https://doi.org/10.4060/CA8642EN

Fontúrbel, F. E., Orellana, J. I., Rodríguez-Gómez, G. B., Tabilo, C. A., & Castaño-Villa, G. J. (2021). Habitat disturbance can alter forest understory bird activity patterns: A regional-scale assessment with camera-traps. *Forest Ecology and Management*, *479*, 118618. https://doi.org/10.1016/J.FORECO.2020.118618

Fontúrbel, F. E., Rodríguez-Gómez, G. B., Fernández, N., García, B., Orellana, J. I., & Castaño-Villa, G. J. (2020). Sampling understory birds in different habitat types using point counts and camera traps. *Ecological Indicators*, *119*, 106863. https://doi.org/10.1016/j.ecolind.2020.106863

Francis, C. D., Ortega, C. P., & Cruz, A. (2009). Noise Pollution Changes Avian Communities and Species Interactions. *Current Biology*, *19*(16), 1415–1419. https://doi.org/10.1016/J.CUB.2009.06.052

Hill, A. P., Prince, P., Piña Covarrubias, E., Doncaster, C. P., Snaddon, J. L., & Rogers, A. (2018). AudioMoth: Evaluation of a smart open acoustic device for monitoring biodiversity and the environment. *Methods in Ecology and Evolution*, *9*(5), 1199–1211. https://doi.org/10.1111/2041-210X.12955

Hobbs, J. J., & Dolan, A. (2008). *World Regional Geography*. Cengage Learning.

Huang, S. Y., Schaening-Lopez, D., Halterman, V., Pravosudov, V. V., & Branch, C. L. (2022). Differences in daily singing routines reflect male condition along a montane gradient. *Behavioral Ecology and Sociobiology*, *76*(10), 1–9. https://doi.org/10.1007/S00265-022-03246-X/TABLES/1

Hutchinson, J. M. C. (2002). Two explanations of the dawn chorus compared: How monotonically changing light levels favour a short break from singing. *Animal Behaviour*, *64*(4), 527–539. https://doi.org/10.1006/ANBE.2002.3091

International Panel on Climate Change (IPCC). (2022). Summary for Policymakers. In H.-O. Pörtner, D. C. Roberts, E. S. Poloczanska, K. Mintenbeck, M. Tignor, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, & A. Okem (Eds.), *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 3–33). Cambridge University Press. https://doi.org/10.1017/9781009325844.001

Johnson, F., & Rashotte, M. E. (2002). Food availability but not cold ambient temperature affects undirected singing in adult male zebra finches. *Physiology & Behavior*, *76*(1), 9–20. https://doi.org/10.1016/S0031-9384(02)00685-6

Juodakis, J., & Marsland, S. (2022). Wind-robust sound event detection and denoising for bioacoustics. *Methods in Ecology and Evolution*, *13*(9), 2005–2017. https://doi.org/10.1111/2041-210X.13928

K. Lisa Yang Center for Conservation Bioacoustics at the Cornell Lab of Ornithology. (2023). *Raven Lite: Interactive Sound Analysis Software* (2.0.4) [Computer software]. The Cornell Lab of Ornithology. https://ravensoundsoftware.com/

Kacelnik, A. (1979). The foraging efficiency of great tits (Parus major L.) in relation to light intensity. *Animal Behaviour*, *27*(PART 1), 237–241. https://doi.org/10.1016/0003-3472(79)90143-X

Kahl, S., Wood, C. M., Eibl, M., & Klinck, H. (2021). BirdNET: A deep learning solution for avian diversity monitoring. *Ecological Informatics*, *61*, 101236. https://doi.org/10.1016/J.ECOINF.2021.101236

Kempenaers, B., Borgström, P., Loës, P., Schlicht, E., & Valcu, M. (2010). Artificial Night Lighting Affects Dawn Song, Extra-Pair Siring Success, and Lay Date in Songbirds. *Current Biology*, *20*(19), 1735–1739. https://doi.org/10.1016/J.CUB.2010.08.028

Klanderud, K., Mbolatiana, H. Z. H., Vololomboahangy, M. N., Radimbison, M. A., Roger, E., Totland, Ø., & Rajeriarison, C. (2010). Recovery of plant species richness and composition after slash-and-burn agriculture in a tropical rainforest in Madagascar. *Biodiversity and Conservation*, *19*(1), 187–204. https://doi.org/10.1007/S10531-009-9714-3/TABLES/2

Le, H. D., Smith, C., Herbohn, J., & Harrison, S. (2012). More than just trees: Assessing reforestation success in tropical developing countries. *Journal of Rural Studies*, *28*(1), 5–19. https://doi.org/10.1016/J.JRURSTUD.2011.07.006

LeBien, J., Zhong, M., Campos-Cerqueira, M., Velev, J. P., Dodhia, R., Ferres, J. L., & Aide, T. M. (2020). A pipeline for identification of bird and frog species in tropical soundscape recordings using a convolutional neural

network. *Ecological Informatics*, *59*, 101113. https://doi.org/10.1016/J.ECOINF.2020.101113

Lee, D. W. (1987). The Spectral Distribution of Radiation in Two Neotropical Rainforests. *Biotropica*, *19*(2), 161. https://doi.org/10.2307/2388739

Lee, J., MacGregor-Fors, I., & Yeh, P. (2017). Sunrise in the city: Disentangling drivers of the avian dawn chorus onset in urban greenspaces. *Journal of Avian Biology*, *48*. https://doi.org/10.1111/jav.01042

Luther, D. (2009). The influence of the acoustic community on songs of birds in a neotropical rain forest. *Behavioral Ecology*, *20*(4), 864–871. https://doi.org/10.1093/BEHECO/ARP074

Manu, S., & Cresswell, W. R. (2007). Addressing sampling bias in counting forest birds: A West African case study. *Ostrich*, *78*(2), 281–286. https://doi.org/10.2989/OSTRICH.2007.78.2.25.105

Markolf, M., Zinowsky, M., Keller, J. K., Borys, J., Cillov, A., & Schülke, O. (2022). Toward Passive Acoustic Monitoring of Lemurs: Using an Affordable Open-Source System to Monitor Phaner Vocal Activity and Density. *International Journal of Primatology*, *43*(3), 409–433. https://doi.org/10.1007/S10764-022-00285-Z

McNeil, R., McSween, A., & Lachapelle, P. (2005). Comparison of the retinal structure and function in four bird species as a function of the time they start singing in the morning. *Brain, Behavior and Evolution*, *65*(3), 202–214. https://doi.org/10.1159/000083881

Miller, M. W. (2006). Apparent effects of light pollution on singing behavior of American Robins. *The Condor*, *108*, 130–139.

Nolasco, I., Singh, S., Morfi, V., Lostanlen, V., Strandburg-Peshkin, A., Vidaña-Vila, E., Gill, L., Pamuła, H., Whitehead, H., Kiskin, I., Jensen, F. H., Morford, J., Emmerson, M. G., Versace, E., Grout, E., Liu, H., Ghani, B.,

& Stowell, D. (2023). Learning to detect an animal sound from five examples. *Ecological Informatics*, 102258. https://doi.org/10.1016/j.ecoinf.2023.102258

Open Acoustic Devices. (n.d.). *AudioMoth*. Retrieved March 28, 2023, from https://www.openacousticdevices.info/audiomoth

Pejchar, L., Pringle, R. M., Ranganathan, J., Zook, J. R., Duran, G., Oviedo, F., & Daily, G. C. (2008). Birds as agents of seed dispersal in a human-dominated landscape in southern Costa Rica. *Biological Conservation*, *141*(2), 536–544. https://doi.org/10.1016/J.BIOCON.2007.11.008

Puswal, S. M., Jinjun, M., & Liu, F. (2021). Effects of temperature and season on birds' dawn singing behavior in a forest of eastern China. *Journal of Ornithology*, *162*(2), 447–459. https://doi.org/10.1007/S10336-020-01848-8/FIGURES/5

R Core Team. (2023). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Rainforest Connection. (2022a). *Audio Event Detection (AED) and Clustering Analysis*. https://support.rfcx.org/article/157-aed-and-clustering

Rainforest Connection. (2022b). *What is Pattern Matching (PM) in Arbimon?* https://support.rfcx.org/article/99-what-is-pattern-matching-pm-in-arbimon

Razafindravony, L. E., Donohue, M. E., Docherty, M. A., Maggy, A. M., Lazasoa, R. S., Rafanomezantsoa, O. J. S., Ramarjaona, R. A., Randriarimanana, J. N. M., Rafanambinantsoa, A. O., Randrianarivelo, H., & Wright, P. C. (2023). Evaluating the impact of environmental education around Ranomafana National Park. *American Journal of Primatology*, e23477. https://doi.org/10.1002/AJP.23477

Reid, M. L. (1987). Costliness and reliability in the singing vigour of Ipswich sparrows. *Animal Behaviour*, *35*(6), 1735–1743. https://doi.org/10.1016/S0003-3472(87)80066-0

Schmidt, A. K. D., & Balakrishnan, R. (2015). Ecology of acoustic signalling and the problem of masking interference in insects. *Journal of Comparative Physiology A*, *201*(1), 133–142. https://doi.org/10.1007/s00359-014-0955-6

Slabbekoorn, H., & den Boer-Visser, A. (2006). Cities Change the Songs of Birds. *Current Biology*, *16*(23), 2326–2331. https://doi.org/10.1016/J.CUB.2006.10.008

Slabbekoorn, H., & Peet, M. (2003). Birds sing at a higher pitch in urban noise. *Nature 2003 424:6946*, *424*(6946), 267–267. https://doi.org/10.1038/424267a

Slagsvold, T. (1996). Dawn and Dusk Singing of Male American Robins in Relation to Female Behavior. *The Wilson Bulletin*, *108*(3), 507–515.

Stowell, D., Wood, M. D., Pamuła, H., Stylianou, Y., & Glotin, H. (2019). Automatic acoustic detection of birds through deep learning: The first Bird Audio Detection challenge. *Methods in Ecology and Evolution*, *10*(3), 368–380. https://doi.org/10.1111/2041-210X.13103

Sullivan, B. L., Wood, C. L., Iliff, M. J., Bonney, R. E., Fink, D., & Kelling, S. (2009). eBird: A citizen-based bird observation network in the biological sciences. *Biological Conservation*, *142*(10), 2282–2292. https://doi.org/10.1016/j.biocon.2009.05.006

The Cornell Lab. (2009, April 20). *Bird ID Skills: How to Learn Bird Songs and Calls*. All About Birds. https://www.allaboutbirds.org/news/how-to-learn-bird-songs-and-calls/

Thomas, R. J. (1999). Two tests of a stochastic dynamic programming model of daily singing routines in birds. *Animal Behaviour*, *57*(2), 277–284. https://doi.org/10.1006/ANBE.1998.0956

Thomas, R. J., Székely, T., Cuthill, I. C., Harper, D. G. C., Newson, S. E., Frayling, T. D., & Wallis, P. D. (2002). Eye size in birds and the timing of song at dawn. *Proceedings of the Royal Society B: Biological Sciences*, *269*(1493), 831. https://doi.org/10.1098/RSPB.2001.1941

Toenies, M., & Rich, L. N. (2021). Advancing bird survey efforts through novel recorder technology and automated species identification. *California Fish and Wildlife*, *107*(2), 56–70. https://doi.org/10.51492/cfwj.107.5

UNIDO. (2021). *Madagascar: Country context.* https://www.unido.org/who-we-are/unido-worldwide/africa/offices/ madagascar/country-context

WildMadagascar. (n.d.). *Ranomafana*. Retrieved April 5, 2023, from https://www.wildmadagascar.org/conservation/parks/Ranomafana.html

Popular science summary

The restoration of forest plays a large role in our efforts to mitigate climate change, but they are also crucial for the 880 million people who depend on forests for their livelihood. Restoration of tropical rainforests is urgent in a country like Madagascar, in which many species are endemic. Birds play a large role in the restoration of forests because of the key role they play in seed dispersal. In order to monitor and evaluate the restoration of forests, monitoring of birds is therefore crucial. Acoustic monitoring devices can used as a low-cost solution.

Mature tropical rainforests provide a typical habitat of dense vegetation and low light conditions to which birds have adapted their behaviour. Restoration areas, however, are much less dense in vegetation and are characterised by much higher light levels. Typically, birds show a peak of singing behaviour in the morning, triggered by the onset of day. This is known as the dawn chorus. A change in light levels is expected to influence the timing of singing in bird species depending on their sensitivity to light. The relative disturbance of singing times can possibly influence fitness of individual species.

This research aimed to identify differences in dawn singing time of individual species and the complete community, by comparing mature protected forests by forest restoration sites in and around Ranomafana National Park, Madagascar. The analysis was performed using novel automated machine learning methods, which are still under continuous development.

The challenge of analysing acoustic data from rich tropical soundscapes was revealed here. Template matching and audio event detection did not provide species-specific identification without close collaboration of local experts. However, manual analysis of the data revealed that species richness was lower in restoration sites, but no difference in timing of the dawn chorus could be found. The restoration sites were also characterized by higher insect sound in the recorded data, increasing the challenge of identification of birds. Further research into the underlying mechanisms of insect abundance, its potential fitness consequences for birds and methodological advancements are needed to further distangle the effect of restoration on the dawn chorus. With more efforts and energy directed towards species-identification in tropical areas, for which the needs for effective monitoring are much more urgent, we can decrease our dependence on local knowledge and expand insights into the most effective ways to perform and monitor restoration.

Acknowledgements

Appendix 1

Species list Ranomafana National Park.

Table 1: Bird species occurring in and around Ranomafana National Park, according to *mad PhD-candidate Mahefa Andriamavosoloarisoa (2023) or ** eBird (2021). Observations, foraging height and main diet were also taken from eBird (2021).

English name	Latin name	Observations	Foraging height	Main diet	Source
Malagasy Bulbul	Hypsipetes madagascariensis	589	Upper	Fruits, insects	*
Souimanga Sunbird	Cinnyris sovimanga	543	Upper	Nectar	*
Madagascar Magpie-Robin	Copsychus albospecularis	500	Undergrowth	Insects, fruit	*
Madagascar Wagtail	Motacilla flaviventris	490	Undergrowth	Invertebrates, insects	*
Malagasy Paradise-Flycatcher	Terpsiphone mutata	478	Middle	Insects	*
Crested Drongo	Dicrurus forficatus	460	Upper	Invertebrates, fruits	*
Blue Coua	Coua caerulea	427	Middle	Insects, invertebrates, fruits	*
Malagasy Brush-Warbler	Nesillas typica	396	Undergrowth	Insects and spiders	*
Common Jery	Neomixis tenella	297	Upper	Insects	*
Lesser Vasa Parrot	Coracopsis nigra	263	Upper	Fruits	*
Malagasy Coucal	Centropus toulou	247	Undergrowth	Insects, invertebrates, small vertebrates	*
Forest Fody	Foudia omissa	204	Upper	Seeds, insects, nectar	*
Red Fody	Foudia madagascariensis	179	Lower	Seeds, insects, nectar	*
Malagasy White-eye	Zosterops maderaspatanus	528	All	Insects, seeds, fruit	**
Pitta-like Ground-Roller	Atelornis pittoides	450	Undergrowth	Invertebrates, fruits	**
Nelicourvi Weaver	Ploceus nelicourvi	402	All	Insects	**
Velvet Asity	Philepitta castanea	396	Undergrowth	Fruits	**
Madagascar Cuckoo	Cuculus rochii	386	Middle	Insects	**
Common Newtonia	Newtonian brunneicauda	383	Middle	Insects	**
Tylas Vanga	Tylas eduardi	376	Middle	Insects	**
Red-tailed Vanga	Calicalicus madagascariensis	370	Upper	Insects	**
Mascarene Martin	Phedina borbonica	362	Lower	Insects	**
Spectacled Tetraka	Xanthomixis zosterops	355	Undergrowth	Insects	**
Madagascar Cuckooshrike	Coracina cinerea	323	Upper	Invertebrates	**
Cuckoo-roller	Leptosomus discolor	314	Middle	Invertebrates, reptiles	**

Appendix 2

Macaulay Library recordings. The following recordings were provided by the Macaulay Library of the Cornell Lab of Ornithology.

Table 2: Recording numbers of recordings from the Macaulay Library of the Cornell Lab of Ornithology (2023) used in creating templates for the Pattern Matching analysis.

ML 73397	ML 85852	ML 85867	ML 85872	ML 85888	ML 86416
ML 87958	ML 87974	ML 91642	ML 92888	ML 92974	ML 92989
ML 93111	ML 93555	ML 93609	ML 93632	ML 93824	ML 93844
ML 93895	ML 94017	ML 95336	ML 95355	ML 95623	ML 95638
ML 95784	ML 95821	ML 95832	ML 95839	ML 95842	ML 95851
ML 95893	ML 95914	ML 95918	ML 95921	ML 95942	ML 95944
ML 95951	ML 95969	ML 95982	ML 95995	ML 95998	ML 97427
ML 97455	ML 97456	ML 97458	ML 97480	ML 97485	ML 97488
ML 97489	ML 97500	ML 97501	ML 97521	ML 97537	ML 97564
ML 97597	ML 97597	ML 97963	ML 97965	ML 98778	ML 100007
ML 101983	ML 141911811	ML 503918061	ML 503918061	ML 504227001	ML 504227021

Appendix 3

AudioMoth Deployment Sites.

Table 3: Deployment sites of the AudioMoth recorders are used in this study.

ID	Site	Treatment	Latitude	Longitude	Altitude	Height	Direction	Date deployed
AND02#2	Andranofady	NP	21.226223	47.395664	1143	7	10	22/03/2022
AND06#21	Andranofady	NP	21.214359	47.421957	1205	13.5	142	24/03/2022
AND13#1	Andranofady	NP	21.226253	47.433634	1078	14	70	30/03/2022
RAN03#18	Ranomena	NP	21.227459	47.475265	1082	15	11	28/04/2022
RAN05#6	Ranomena	NP	21.238254	47.46181	1057	15	30	29/04/2022
ABV02#22	Ambatovory	RS	21.283594	47.458088	803	2.8	252	01/03/2022
AMB02#18	Ambodivoahangy	RS	21.217104	47.547612	671	4	32	13/03/2022
AMPB01#6	Ampitambe	RS	21.261109	47.599323	569	2	0	09/03/2022
TKL04#11	Tanambao Kelilalina	RS	21.294172	47.551847	733	1.8	118	25/02/2022

Publishing and archiving

Approved students' theses at SLU are published electronically. As a student, you have the copyright to your own work and need to approve the electronic publishing. If you check the box for **YES**, the full text (pdf file) and metadata will be visible and searchable online. If you check the box for **NO**, only the metadata and the abstract will be visible and searchable online. Nevertheless, when the document is uploaded it will still be archived as a digital file. If you are more than one author, the checked box will be applied to all authors. You will find a link to SLU's publishing agreement here:

- https://libanswers.slu.se/en/faq/228318.

☒ YES, I/we hereby give permission to publish the present thesis in accordance with the SLU agreement regarding the transfer of the right to publish a work.

☐ NO, I/we do not give permission to publish the present work. The work will still be archived and its metadata and abstract will be visible and searchable.