MONITORING FARMLAND AVIAN BIODIVERSITY USING ACOUSTIC INDICES IN GÖDENCE, İZMİR

by

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MONITORING FARMLAND AVIAN BIODIVERSITY USING ACOUSTIC INDICES IN GÖDENCE, İZMİR

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To all the inspiring creatures that coexist in harmony in nature, especially birds...

...and to all procrastinating perfectionists who relentlessly doubt the value of their efforts along the journey until they exhaust themselves and others...

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ABSTRACT

MONITORING FARMLAND AVIAN BIODIVERSITY USING ACOUSTIC INDICES IN GÖDENCE, İZMİR

Acoustic indices are emerging, cost-effective tools for monitoring biodiversity. However, recent studies in this field led to inconclusive results regarding their effectiveness, suggesting that further studies are needed to evaluate their performance across different regions and habitats. This study focuses on one of the relatively understudied regions and habitats, namely, agricultural lands in the Mediterranean, via acoustic data collected in two agroecological orchards in the Gödence Village, İzmir, Türkiye. Passive acoustic recorders (Audiomoths) were employed at five recording points each season in 2022-2023, recording the entire soundscape continuously from two hours before sunrise to two hours after sunset, delivering over 350 hours of sound data per recording point. Five widely-used acoustic indices (BI, NDSI, ACI, AEI, ADI) were calculated for each five-minute file. Two expert ornithologists listened to a subsample of 183 five-minute files and identified the bird species vocalizing in each file. The same files were uploaded to an automated tool for species identification, Merlin Bird ID, and detections were compared with those of the experts. Correlations were calculated for bird species richness and acoustic indices. In addition, the sensitivity of acoustic indices to seasonal variations and different sound compositions were evaluated. BI and ACI were positively correlated with bird species richness, however, acoustic indices were sensitive to different types of sonic conditions (e.g. cicadas and wind). The present study suggests that if cautions are taken for their effective use, acoustic indices are promising tools for monitoring farmland avian biodiversity in Mediterranean farmlands.

ÖZET

GÖDENCE, İZMİR'DE TARIM ARAZİSİ KUŞ BİYOÇEŞİTLİLİĞİNİN AKUSTİK ENDEKSLER KULLANILARAK İZLENMESİ

Akustik endeksler, kuş biyoçeşitliliğinin izlenmesi için ortaya çıkan, uygun maliyetli araçlardır. Bununla birlikte, bu alanda yapılan son çalışmalar, endekslerin etkinliği konusunda uzlaşılamamış sonuçlara işaret etmiş ve farklı bölgelerle habitatlardaki performanslarını değerlendirmek için daha fazla çalışmaya ihtiyaç duyulduğunu ortaya koymuştur. Bu çalışma, Gödence Köyü, İzmir, Türkiye'deki iki agroekolojik meyve bahçesinden toplanan akustik veriler aracılığıyla görece az çalışılmış habitatlardan biri olan Akdeniz bölgesindeki tarım arazilerine odaklanmaktadır. Pasif akustik kayıt cihazları olan Audiomoth'lar, 2022-2023 yıllarında her mevsim beş kayıt noktasında kullanılmış, gün doğumundan iki saat öncesinden gün batımından iki saat sonrasına kadar kesintisiz olarak ses manzarası kaydedilmiştir. Böylece kayıt noktası başına 350 saatten fazla ses verisi elde edilmiştir. Kayıtlardan elde edilen beş dakikalık dosyaların her biri için beş yaygın akustik endeks (BI, NDSI, ACI, AEI, ADI) hesaplanmıştır. Ardından, 183 ses dosyasından oluşan bir örneklem iki uzman ornitolog tarafından dinlenilerek, her dosyada duyulan kuş türleri belirlenmiştir. Aynı dosyalar, otomatik tür tespiti yapan Merlin Bird ID uygulamasına da yüklenmiş, tespit edilen türler uzmanların bulguları ile karşılaştırılmıştır. Akustik endekslerin performansını değerlendirmek üzere, kuş türü zenginliği ve akustik endeks değerleri arasındaki korelasyonlar da hesaplanmıştır. Ayrıca, bu beş akustik endeksin mevsimsel değişimlere ve farklı ses kompozisyonlarına duyarlılığı da değerlendirilmiştir. Bulgular, BI ve ACI endekslerinin kuş türü zenginliği ile olumlu yönde ilişkili olduğunu gösterirken, akustik endekslerin farklı ses koşullarına (örneğin ağustos böcekleri ve rüzgar seslerinin varlığına) duyarlı olduğunu ortaya koymuştur. Sonuç olarak bu çalışma, akustik endeksleri kullanırken dikkat edilmesi gerekenler olduğuna işaret etmekle birlikte, bu endekslerin Akdeniz tarım alanlarındaki kuş biyoçeşitliliğinin izlenmesi için umut verici araçlar olduğunu göstermiştir.

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LIST OF ABBREVIATIONS

Abbreviation	Explanation
ACI	Acoustic Complexity Index
ADI	Acoustic Diversity Index
AEI	Acoustic Evenness Index
App / app	Application (software)
BIO	Bioacoustic Index
dB	Decibel
FFT	Fast Fourier Transform
g	Gram(s)
ha	Hectare (10.000 meters-square)
IUCN	International Union for Conservation of Nature
microSD card	Micro Secure Digital Memory Card
n	Sample size
kHz	Kilo-Hertz
NDSI	Normalized Soundscape Index
PC	Personal Computer

1. INTRODUCTION

Birds are among the most studied taxonomic groups, with over 11,000 identified species(BirdLife International, 2023). They inhabit various environments, from extreme habitats of polar zones to dense tropical forests (Birdlife International, 2022). Some also dwell in locations near humans, such as farmlands or bustling cities. Due to their proximity to people and broad geographical dispersal, birds have been observed and studied extensively in many regions (Birkhead & Charmantier, 2009). Therefore, historically, avian species influenced societies in numerous ways (Anderson, 2010). Today, they are still embedded in some socio-cultural values of human communities (Cocker & Tipling, 2013), used as inspiration in artistic works (Lederer, 2019) and emulated by technological advancements (Sreeramagiri, 2021). More crucially, birds are at the core of fundamental ecological processes that directly or indirectly affect many organisms, including humans.

Due to their crucial roles in ecosystems, birds are often considered as indicator species for ecosystem health in general and in farmlands in Europe, in particular (European Commission, 2023). However, farmland bird species indicators have been strongly declining by 61% from 1980 to 2022 in Europe (PanEuropean Common Bird Monitoring Scheme, 2023). This period strongly coincides with the intensification of agriculture in Europe and in other developed countries such as the U.S. Indeed, a recent IUCN report (2024) titled "Agriculture and Conservation" suggested that agriculture is a threat for at least 34% of the species evaluated in the Red List. Agriculture affects 72% of globally threatened birds, amounting to 1,026 species (Birdlife International, 2022). On the other hand, agriculture can also constitute crucial opportunities for birds and other wildlife species by offering suitable habitats for them. Accordingly, at least 17% of all species in the Red List of the IUCN benefit from agriculture (IUCN, 2024). Hence, effective conservation measures and agricultural policy favoring wildlife and biodiversity require monitoring of bird populations in different habitats, including farmlands.

Acoustic monitoring is a relatively new, emerging method for following population changes in vocalizing animals such as birds and bats. The field has been growing and becoming more popular in recent years, thanks to advancements in low-cost equipment technologies and data storage possibilities. In particular, Passive Acoustic Monitoring (PAM) has received increased attention in the last years (Budka et al., 2023; Sugai et al., 2019). PAM requires the deployment of acoustic

recorders in a selected environment, often programmed for recording the entire soundscape on a pre-programmed schedule, and after this designated duration, recorders are collected, and acoustic data are stored and used for further analysis, used as an alternative to traditional methods of assessment and monitoring biodiversity.

More recently, PAM studies have been utilizing acoustic indices as proxies for species richness and abundance, especially of bat and bird species. Acoustic indices are statistical tools that return numerical values calculated from the properties of sound, such as decibels and frequencies, in a sound recording. To date, there are over 60 acoustic indices, yet, in practice, only a handful have been investigated so far for different habitats and daily and seasonal conditions (Bradfer-Lawrence et al., 2019) . Even though tracking biodiversity involves several other aspects than just the number of species (such as functionality), with the current accelerated rates of extinction, acoustic indices could be quick and beneficial tools. They can facilitate evaluation of the ecosystem health and impacts of land use changes in different habitats including forests, protected areas, and agricultural production, among others (Abrahams, 2021). In particular, monitoring and evaluation of agri-environmental policies such as Nature Restoration Law (European Commission, 2024) and agri-environment schemes in Europe, could be undertaken quickly and cost-effectively using acoustic indices, if scientific studies can establish clear standards for applying them. However, the literature suggests that both their performance (are they related with species richness?) and sensitivity (how do they respond to different sonic compositions?) need to be evaluated carefully for different habitats, regions, land use characteristics, and temporal properties such as daily patterns and seasons (Ross et al., 2021).

Mediterranean farmlands are one of these understudied habitats for assessing the performance of acoustic indices in the temperate regions. To the best of my knowledge, no specific scientific study has used acoustic indices to evaluate farmland biodiversity so far in Türkiye. The present study will therefore be the first one to adopt acoustic indices for evaluating farmland avian biodiversity in the country. More specifically, the thesis assesses acoustic indices' performance as well as their sensitivity in the presence of geophony (mild and moderate wind) and non-focal biophony (such as insects and cicadas) to track bird species richness in an under-studied habitat of Mediterranean agroecological farmland in Gödence, İzmir. In this context, the specific research questions of the present study were as follows:

- How can acoustic indices be employed for evaluating farmland biodiversity in Mediterranean farmlands effectively?

- How do **acoustic indices** perform in a **Mediterranean agro-ecological farmland** soundscape for assessing **bird species richness**?
- How do **non-focal sounds** (geophony such as winds, and non-focal biophony such as cicadas) affect their performance (i.e. how sensitive are they towards non-focal sounds in the study area?)

To answer these questions, I collected acoustic data in two agroecological mixed orchards in the Gödence Village, İzmir, Türkiye. I employed passive acoustic recorders, Audiomoths, at five points for recording the soundscape for at least six days each season in 2022-2023, from two hours before sunrise to two hours after sunset, continuously for at least 15 hours each day. This delivered over 350 hours of sound data per each of the five recording sites, which were then divided into 5-minute files, and five widely-used acoustic indices (BI, NDSI, ACI, AEI, ADI) were calculated for each file. Afterward, two expert ornithologists manually listened to a subsample of 183 sound files and identified the bird species vocalizing in each file. The same files were also uploaded to an automated tool for species identification, Merlin Bird ID, and detections were compared with those of the experts. Correlations were calculated for bird species richness and acoustic indices. In addition, the sensitivity of these five acoustic indices to seasonal variations, and different sound compositions (in the presence of other non-focal sounds) were also evaluated.

The findings of the study were generally in line with the literature indicating that acoustic indices can serve as effective proxies to represent bird species richness, if specific daily and seasonal patterns of the investigated taxa and ecological specifics of habitats are taken into account. More specifically, BI and ACI were positively correlated with bird species richness, however, ACI was more robust in the presence of wind and non-focal cicada/insect vocalizations. The present study therefore confirms the main finding in the literature that if cautions are taken for their effective use, acoustic indices are promising tools for tracking changes in bird biodiversity across time and for different agricultural practices and conservation policies in Mediterranean farmlands. The study also aims to provide practical guidelines and general recommendations for future studies in the region and for similar habitats. The next section discusses the relevant empirical literature applying passive acoustic monitoring and acoustic indices in different habitats for different land use characteristics.

2. LITERATURE REVIEW

This chapter will first provide a brief overview of the overlaps between agriculture and biodiversity conservation. Then it will continue with introducing acoustic monitoring for biodiversity, focusing on passive acoustic monitoring (PAM). This will be followed by a brief introduction to acoustic indices for evaluating biodiversity in general, and the last subsection will discuss the findings of the most recent empirical studies on acoustic indices.

2.1. Agricultural Production and Biodiversity

The IUCN (International Union for the Conservation of Nature) describes agriculture-nature relationships as follows: “Agriculture is a vital human activity that deeply impacts, but also deeply relies on nature.” (IUCN, n.d.). Indeed, farmlands provide habitats for many species of high conservation value, and at the same time, intensive agriculture puts pressure on many more species under the threat of extinction (IUCN, 2024). Moreover, biodiversity is declining at an unprecedented pace where one in every four species is threatened by extinction, and agriculture is the leading contributor to the land use change, a crucial driving factor of this extinction (IPBES, 2019).

In this context, biodiversity conservation in farmlands has received increased scientific and public attention internationally, which renders the long-term monitoring of farmland biodiversity crucial for evaluating different agri-environmental policies such as agri-environment schemes and new EU regulations such as Nature Restoration Law (European Commission, 2024), a key element of the EU Biodiversity Strategy, proposing the restoration of degraded ecosystems in Europe, including agricultural lands. However, the concept of farmland biodiversity has so far not received much attention in Türkiye. Moreover, currently, a commonly agreed list of farmland bird species for the country does not exist. Scientific studies are quite limited on this subject as well, apart from a few invaluable ones (Karaçetin et al., 2017; Pekin, 2013, 2016). Yet, civil society and conservation organizations have initiated some conservation projects on farmland areas recently. For instance, Doğa Koruma Merkezi, Buğday Derneği, Doğa Araştırmaları Derneği are among the few conservation organizations working with farmers for the implementation of biodiversity-friendly farming methods (such as wind breaks, direct drilling, etc.) and for documenting traditional agroecological farming practices in Anatolia. Government-initiated agri-environment projects and support for farmers doing biodiversity-friendly farming are also relatively rare. One important pilot

project in this context was the ÇATAK Project (Environmentally-based Agricultural Land Protection), as part of the IPARD (Instrument for Pre-Accession Assistance Rural Development) program of the EU for pre-accession countries, between 2006-2022, which provided economic support for farmers implementing conservation measures such as reduction of tillage and soil erosion (Delikkaya & Ataseven, 2021). Yet, the program was discontinued in 2022, suggesting that the government does not prioritize biodiversity conservation in farmlands anymore.

In this context, this thesis proposes a cost-effective and quick method for monitoring farmland avian biodiversity via passive acoustic monitoring and the use of acoustic indices as proxies for bird species richness. The next subsections explain in more detail how these methods can be utilized in practice for monitoring farmland biodiversity.

2.2. Acoustic Monitoring

Recording and analysis of animal sounds has come a long way in its history of over 100 years. Early studies mainly collected sound data for species identification. More recently, more precise information, such as age, sex, behavior, mating status, or even the health of a single individual in a population, can be extracted from vocalizations (Erbe & Thomas, 2022). It is even possible to detect the dialects of different individuals of the same species to track the geographical dispersions of populations (Oñate-Casado et al., 2023). Thus, long-term acoustic monitoring has been employed in various ecosystems to estimate population density or to track environmental pressures leading to habitat loss, such as anthropogenic impacts.

Acoustic monitoring efforts have boomed with the improvements in recording technologies in the last few decades (Sugai et al., 2019). Digitalization has reduced the equipment size and weight, improving their portability on-site. With the help of smaller recording devices and directional microphones, field researchers could collect data as specialized as the vocalizations of a single individual. This significantly increased the depth and authenticity of the findings. Within acoustic monitoring, one can differentiate between active and passive acoustic monitoring methods (Melo et al., 2021). Active acoustic monitoring requires a surveyor on site which limits the duration of recordings. In contrast, passive acoustic monitoring (PAM) allows recording for longer intervals, without the need for an expert on-site at all times. It emerged after technological advances enabled the use of programmable recorders widespread and has revolutionized the field of acoustic monitoring. As a result, passive acoustic monitoring has become popular in recent years and is used by many experts in fields such as ecology and conservation biology as an easy, fast, non-invasive and

cost-effective method of biodiversity monitoring. However, it has to be noted that for a reliable interpretation of population dynamics, it is essential to employ multiple recorders and better understand the sound characteristics of the study area (Blumstein et al., 2011).

One key advantage of PAM is that human presence, hence the environmental disturbance, is minimal when recording the soundscape. Therefore, it increases the possibility of capturing more vocalizations from some species that tend to move away or become silent when a surveyor is around (Thomas & Marques, 2012). Another advantage of this method is that it allows recording for extended periods thanks to its programmable nature. This overcomes the challenge of finding a sufficient number of experts to record the soundscape for long hours (Pérez-Granados & Traba, 2021). In addition, budgeting for trips, arranging accommodations, and planning work schedules are still challenging in traditional acoustic monitoring schemes, even if the number of experts would be sufficient. For these reasons, PAM is seen as a promising alternative with cost- and time-efficiency in acoustic and biodiversity monitoring studies.

There are two main approaches when it comes to analyzing the bioacoustics recordings. The first and more common method focuses on detecting the species or individuals in the area of interest (Laiolo, 2010). The second one assesses the environment as a whole to capture a soundscape (Pijanowski et al., 2011). In this second approach, acoustic indices are used as a metric to extract meaning from the soundscapes. Acoustic indices have the potential to serve as proxies for species diversity and abundance for the monitored region and may be utilized to estimate the biomass and human impact on the given environment, as well as specific land uses and agricultural measures (Bradfer-Lawrence et al., 2019; Budka et al., 2023; Metcalf et al., 2021; Ross et al., 2021). The next subsection introduces acoustic indices in more depth.

2.3. Acoustic Indices

Acoustic indices may be used to investigate soundscapes for two different purposes. While within-group (alpha) indices mainly focus on the abundance or richness of a single species in a given environment, between-group (beta) indices are used to investigate inter-site diversity (Sueur et al., 2014). Both the weaknesses and strengths of the acoustic indices originate from the same root: simplification. They aim to compress broad and abstract concepts like biodiversity or abundance into a single number. However, deducing information only from a single acoustic index is almost impossible, so studies typically use and compare multiple acoustic indices in combination (Bradfer-Lawrence et al., 2019). While simplification is the main advantage of the acoustic indices, not having

a single universally accepted index as a proxy for monitoring biodiversity is one of the main challenges for their usage (Ross et al., 2021). However, combining the findings of several acoustic indices could suggest specific ecological patterns and point out a well-informed direction for the conservation measures in practice.

Acoustic indices do not provide any opportunities for the identification of individual species or a single taxonomic group. However, they offer a rapid summarization of a massive amount of data, including biophony and other non-focal sounds in the environment. Therefore, acoustic indices can be used in multiple habitats, from terrestrial to marine and freshwater environments. This flexibility makes acoustic indices excellent proxies for quick assessment of large-scale landscapes for monitoring long-term changes in ecological integrity or impacts of different land use practices. Their potential for scalability makes them valuable tools for rewilding studies and agri-environment schemes (Abrahams, 2021).

In essence, an acoustic index is a numerical reduction of significant ecological properties with the help of statistical calculations based on the energy and frequencies of the sound (Towsey et al., 2014). Currently, there are over 60 acoustic indices (Bradfer-Lawrence et al., 2019) used in biodiversity assessment studies by using the different parameters of the sound to serve as a proxy for a particular ecological characteristic of the recordings. Despite this diversification, acoustic indices measure some common features about a soundscape. Species richness and abundance are one of the most common metrics that acoustic indices represent for vocalized species such as birds (Alcocer et al., 2022; Shamon et al., 2021). By recording these vocalized species in a time series, daily and seasonal changes in the soundscape can be tracked (Buxton et al., 2016). In addition, long-term monitoring entailing acoustic indices could highlight the land use changes since vocalizing species are indicators of the habitat dynamics based on their vocalization frequencies. Also, if they are applied to the recordings of the same species from different habitats, population characteristics across different habitats for the (Atemasov & Atemasova, 2019; Shaw et al., 2021). Therefore, acoustic indices can give both spatial and temporal understandings about soundscapes.

Acoustic indices have several advantages, yet they also have some limitations. For instance, acoustic indices can only capture the diversity of vocalizing species. Therefore, it should be noted that for a comprehensive ecosystem assessment additional monitoring methods for “silent” species may also be required (Budka et al., 2023). However, acoustic indices can still give fast and powerful insights into the general trends of ecosystem health based on the vocalizing indicator species. Another drawback is that there is not a single acoustic index which could accurately represent species richness

on its own. Since acoustic indices represent different aspects of the soundscape, they should be evaluated in combination to enhance their substitution potential for the traditional (more costly and time-consuming) biodiversity measurements (Sueur et al., 2014). Lastly, acoustic indices are relatively new tools for which specific standards have yet to be established by scientists. Even though recent scientific articles try to create guidelines and best practices for applying them reliably, to date, there is no widely agreed standard procedure to which all scientists and conservation practitioners should adhere. Moreover, the field of acoustic indices is an evolving field where findings may contradict each other for different habitats, for different employment and recording practices (Bradfer-Lawrence et al., 2020) and under the presence of other aural sources in the soundscape than just the biophony (Ross et al., 2021).

When it comes to the performance of acoustic indices for representing bird species richness, there are still some inconsistencies in the literature. The correlations between one specific acoustic index and bird species richness may be positive in some studies, while other studies may find negative correlations for the same index (Bradfer-Lawrence et al., 2020; Shamon et al., 2021). In addition, it is stated that hourly and seasonal variations may affect the significance of these correlations (Atemasov & Atemasova, 2019; Dröge et al., 2021). Furthermore, recent studies reported that the performance of acoustic indices is sensitive to different sonic (Ross et al., 2021) and ecological conditions (Eldridge et al., 2018).

Since their performance and sensitivity are still under debate, it is important to test the effectiveness of acoustic indices for different geographical regions, habitats, seasons, and time of the day (Budka et al., 2023). Agricultural lands have so far been understudied habitats for this kind of evaluation; therefore, it is even more critical to assess fluctuations in the performance of acoustic indices when various sonic conditions are present in the farmland soundscapes (Ross et al., 2021).

Below I present the definitions and explanations for the most widely used five acoustic indices in the literature, that were also utilized in the present study. For a deeper understanding of acoustic indices, Appendix A provides some details regarding the properties of sound in general.

2.3.1. **Bioacoustic Index (BI)** (Boelman et al., 2007)

It is calculated by measuring the area under the power curve (dB vs Hz). Two parameters are used in the calculation and therefore affect the output index value. The first of them is FFT size, according to which spectrogram resolution and therefore the power curve and total area under the

curve can change. A larger total area will yield a higher index value. Second parameter is the frequency range used in the calculation. If a narrower frequency band is chosen, it will exclude some sounds and therefore amplitudes represented under the power curve. Thus, narrower frequency bands would result in a lower index value compared to broader ranges.

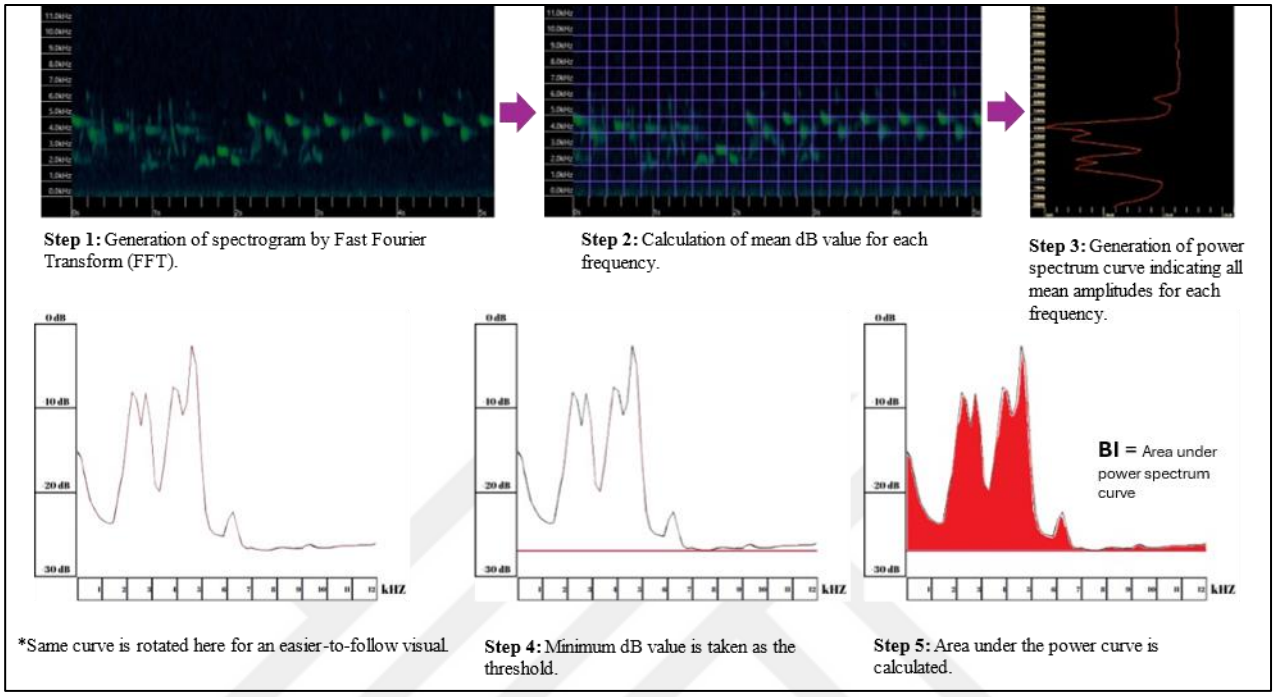


Figure 2.1. Summary of calculation steps for Bioacoustic Index (BIO).

Interpretation: It assumes that diverse environments will have more acoustic activity among different frequency ranges due to more sounds propagated by the organisms trying to optimize their share in the acoustic niche. Therefore, this will result in a larger area under the power curve and hence higher calculated index value. Low values indicate no acoustic activity in the environment.

2.3.2. Normalized Difference Soundscape Index (NDSI) (Gage & Axel, 2014; Kasten et al., 2012)

Similar to BI, NDSI calculates the area under the power curve. However, NDSI divides the soundscape into two specific frequency ranges, and delivers a ratio by comparing the areas under the power curves for these frequency ranges. These two frequency ranges correspond to anthropophonic (usually selected as to be below 2 kHz) and biophonic sounds (usually above 2 kHz). Therefore, NDSI checks how much disturbance is in a soundscape affecting the biophony by calculating the ratio of anthrophony to biophony. The frequency ranges for both sound types can be defined by the researcher. Hence, the index values are again subject to change according to the FFT size (effect on

the power curve) and the selected frequency ranges (frequency range will change the calculated are, in addition the ratio between the two ranges).

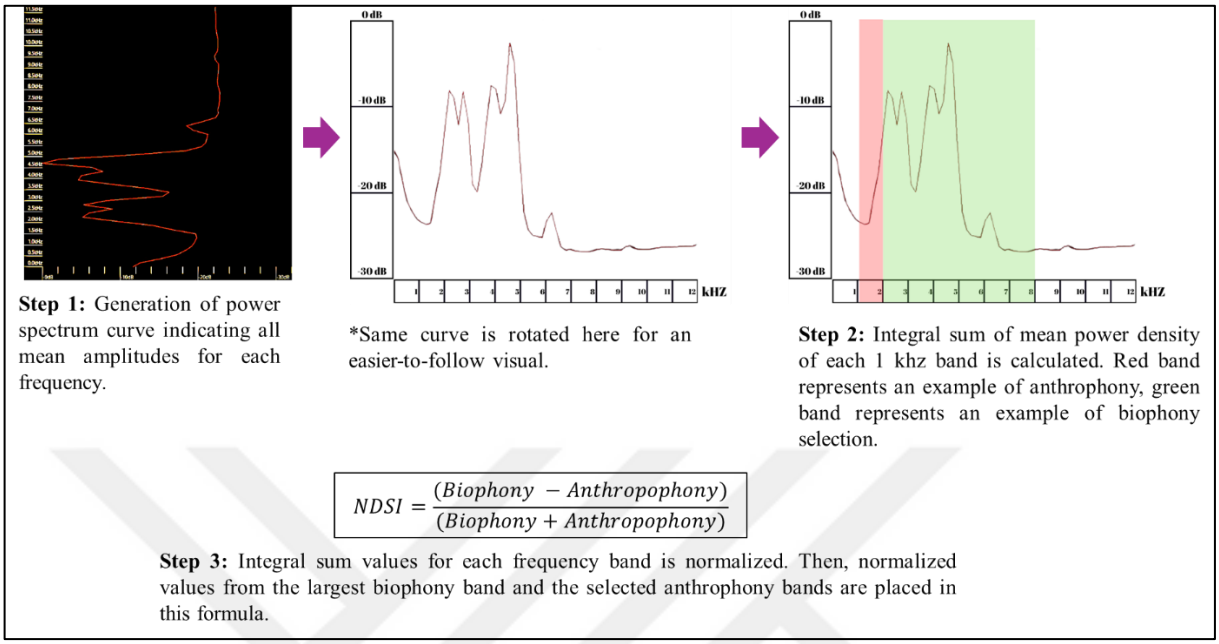


Figure 2.2. Summary of calculation steps for Normalized Difference Soundscape Index (NDSI).

Interpretation: Since it gives a ratio by comparing the two sound categories (anthropophony versus biophony), the index values range between -1 and +1. The values close to -1 imply that the anthrophony is dominant in the environment, while the values close to +1 mean biological sounds are the main acoustic sources in the recorded soundscape.

2.3.3. Acoustic Complexity Index (ACI) (Farina et al., 2016; Pieretti et al., 2011)

For the calculation of the ACI, the spectrogram is divided into equal frequency bins, corresponding to equal durational pieces of the recording. The differences in the amplitude relative to the total amplitude in a frequency band is calculated from one bin to the next one. Then all the values obtained are summed up, which yields a single index value for the recording. It reflects how complex dominant sounds are, based on the assumption that diversified environments will have more unrepeated patterns. Since the soundscapes of these kinds of environments will have rapid acoustic variations both in frequency and amplitude, more complexity is considered as higher biophony (especially bird song). ACI typically is insensitive to constantly repeating sounds such as stridulating insects or noisy machinery.

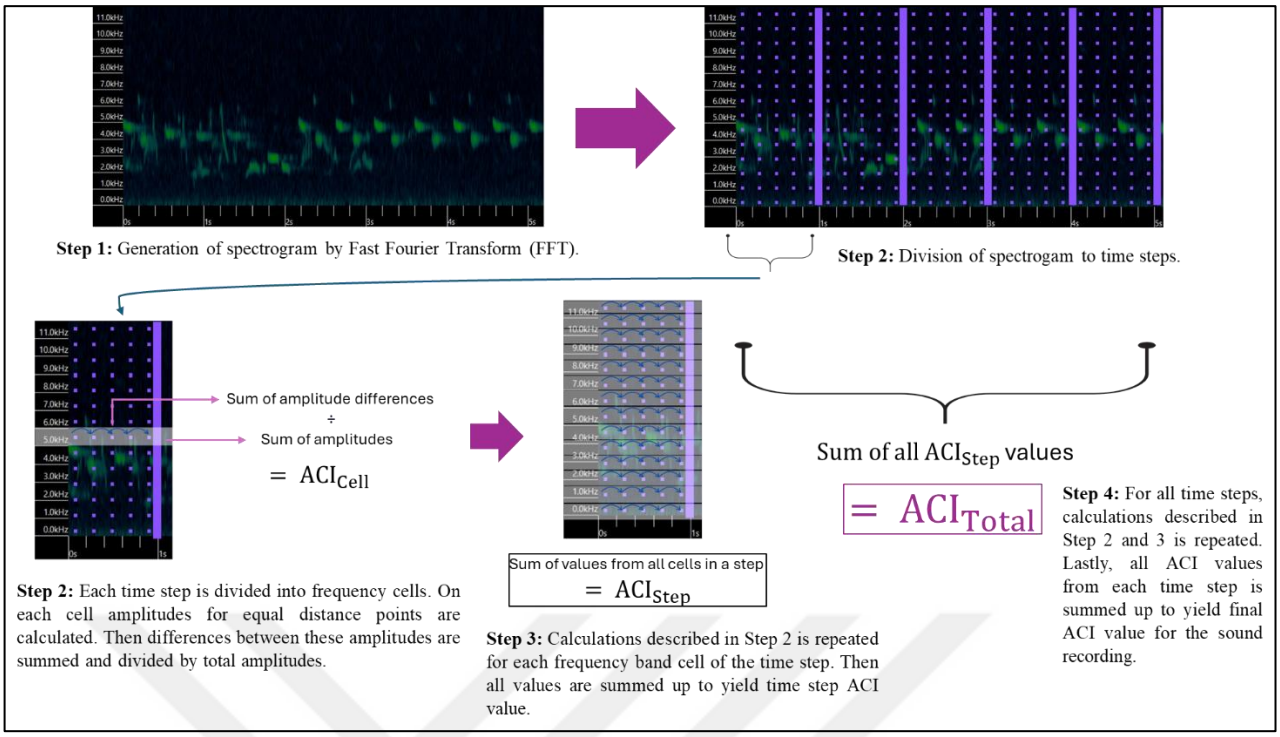


Figure 2.3. Summary of calculation steps for Acoustic Complexity Index (ACI).

Interpretation: The index values are positive real numbers. Higher index values correspond to more biophonic activity, especially for birds. However, they could also indicate irregularly distributed acoustic events such as storm, rain or volatile wind or communicating insects. On the contrary, lower values are generally associated with more regularly propagated sounds such as stridulating cicadas.

2.3.4. **Acoustic Diversity Index (ADI)** (Villanueva-Rivera et al., 2011)

ADI divides the spectrograms into frequency bands and applies the Shannon Index to each band, but only to the signals above a specific dB threshold in order to check how many diverse sounds are present in the environment.

Interpretation: The ADI values will be positive real numbers. It assumes that more biophony in the environment will result in more distinct patterns in the frequency bands, and frequency bands will be different from each other, leading to a higher value.

2.3.5. **Acoustic Evenness Index (AEI)** (Villanueva-Rivera et al., 2011)

AEI utilizes the same calculation parameters as ADI. It also uses the frequency bands, but applies the Gini index to those bands instead of the Shannon Index. Again, only the signals above a chosen

amplitude are considered for the calculation of the index. The Gini coefficient is calculated proportional to the sounds, and the evenness between the sounds in the frequency bands is compared.

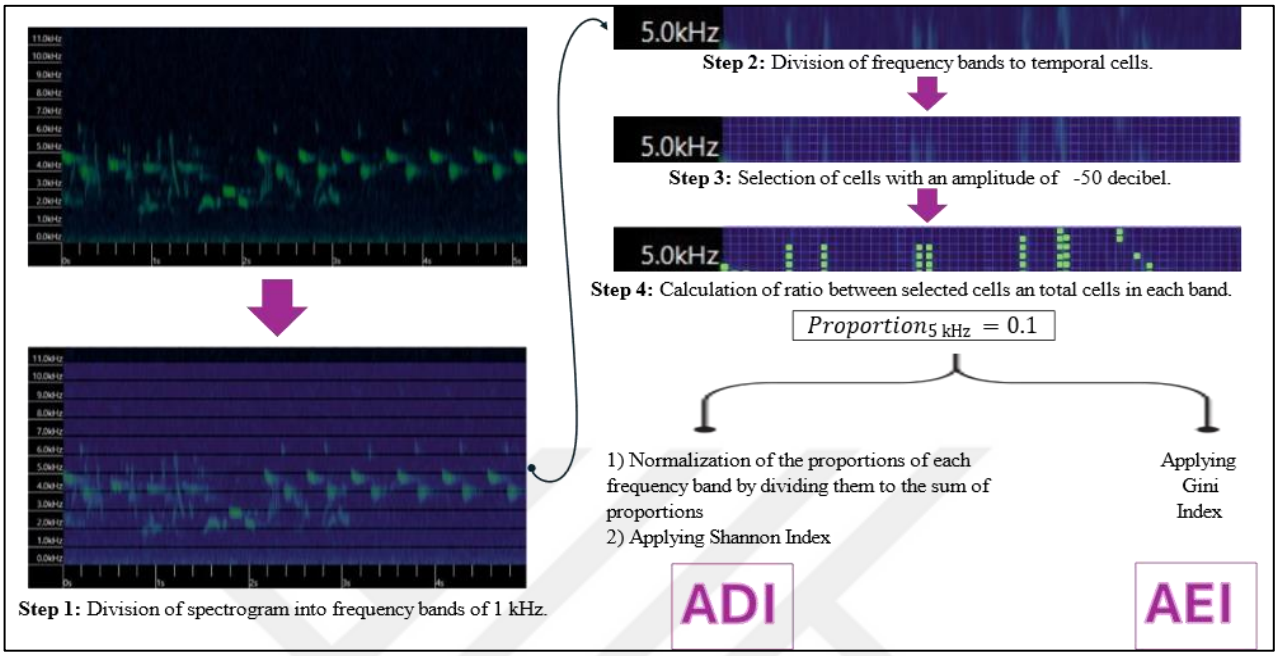


Figure 2.4. Summary of calculation steps for Acoustic Diversity Index (ADI) and Acoustic Evenness Index (AEI).

Interpretation: AEI values range between 0 and 1 where 0 means perfect evenness and 1 means perfect unevenness. If the value indicates perfect evenness, then there is either no sound or the same repeated sounds are present. Therefore, more even sounds indicate less biophony. However, if there is only a single dominant bird species with a simple song, then the frequency bands will be pretty even, resulting in a higher AEI value. Of course, the species richness is low in that case, but the sounds which can be categorized as biophony are actually high. This could lead to confusion if one assumes that lower values will always indicate less biophony.

2.4. Recent Empirical Studies on Acoustic Indices for Different Land Uses

Empirical studies utilizing acoustic indices for evaluating land use change impacts and different land uses are growing. However, scientific articles specifically targeting agricultural land use are still very limited. Below is a list of recent empirical studies investigating the acoustic indices and their performance and sensitivity in different habitats, including agricultural landscapes. While some of those specifically or partially focus on agricultural land use (Dröge et al., 2021; Eldridge et al., 2018; Galappaththi et al., 2024; Myers et al., 2019), others scan a range of different land uses including

forests (Atemasov & Atemasova, 2019; Budka et al., 2023; Hilje et al., 2017; Shaw et al., 2021), grasslands (Shamon et al., 2021) and protected areas (Buxton et al., 2016).

Overall, the majority of these empirical studies pointed out that the acoustic indices BI and ACI were better performing indices representing the patterns of bird species richness better. Galappaththi et al. (2024) in Southern China, for instance, compared seven different acoustic indices and they found weak to moderate correlations between bird species richness and for some of the indices used in the study. Accordingly, only BI and ACI had positive and consistent relationships with bird species richness, even though the correlations were rather weak. A recent study from the temperate biodiversity rich forests of Poland (Budka et al., 2023) compared BI, ACI and ADI and also found moderate correlations for bird species richness, but they noted fluctuations pertaining to the effectiveness of indices regarding daily and seasonal patterns. In their study, BI was found to be the best performing index across seasons, yet, BI still did not represent daily and seasonal changes effectively. Ross et al. (2021), carried a similar study on an island habitat of Japan to compare the sensitivity of 11 acoustic indices. Their study revealed that BI and ACI were not sensitive to the presence of insect noises in the environment, which is the most common biophonic competitor of bird vocalizations.

The study conducted in Greece on olive groves was particularly relevant for the present study, as it has been carried out in the Mediterranean olive groves (Myers et al., 2019) In this study, the researchers calculated a set of acoustic indices but did not investigate their relationship with any bird species richness data for ground-truthing their findings. In their study, BI, ACI and ADI values were compared for the soundscapes of organic and conventional olive groves. While all three indices yielded higher values in organic farmlands, only values of BI and ACI were found to be significantly higher.

Overall, past studies have shown that there is much value in using acoustic indices for assessing the effectiveness of agri-environment schemes and for comparing different agricultural land use categories (Bobryk et al., 2016; Eldridge et al., 2018; Villanueva-Rivera et al., 2011), as they are logistically easy to implement, detection of species in a radius of 50-100 meters fits the evaluation at the field scale well, and they are able to capture changes in the environments due to land use (Abrahams, 2021). Relying on the analysis on bird species (as well as bats) makes also sense from the perspective of farmland biodiversity monitoring (ibid). Table 2.1 summarizes some of these empirical studies using acoustic indices.

Table 2.1. Recent empirical studies on acoustic indices and different land uses including agricultural production.

Author	Year	Country	Land use	Point Count or Manual listening	Acoustic indices
Ross et al.	2021	Japan	Island	Manual Listening	NDSI, BIO, ADI, H, ARI, AEI, ACI, M
Galappaththi et al.	2024	China	Forest and Surrounding Agricultural Lands	Point Counts	ACI, ADI, AEI, AR, BIO, H, NDSI
Myers et al.	2019	Greece	Olive Grooves	None	ACI, ADI, BIO
Bradfer-Lawrence	2019	Panama	Mix (Mainly Forest with Some Plantations and Pastures)	-	ACI, ADI, AEI, BIO, H, M, NDSI
Bradfer-Lawrence	2020	Panama	Mix (Mainly Forest with Some Plantations and Pastures)	Point counts	ACI, ADI, AEI, BIO, H, M, NDSI
Budka et al.	2023	Poland	Temperate Forest	Manual Inspection	BIO, ACI, ADI
Shamon et al.	2021	USA	Grassland	Manual Inspection	BIO, ACI, ADI, AEI
Buxton et al.	2016	USA	Glacier Bay National Park	Automated detection (Raven Pro) + Manual validation	ACI
Atemasov and Atemasova	2019	Ukraine	Forest	Manual Inspection	ACI, ADI, AEI, BIO, H, NDSI
Shaw et al.	2021	Sweden	Boreal Forest	Point counts + Manual Inspection	ACI, ADI, AEI, BIO, H, NDSI
Dröge et al.	2021	Madagascar	Forests, Agroforests and Rice Paddies	Point counts	ACI, ADI, AEI, H
Eldridge et al.	2018	England and Ecuador (comparative study)	Forests, Regenerative Forests and Agricultural Land	Manual Inspection	ADI, AEI, BIO, H, NDSI
Hilje et al.	2017	Costa Rica	Tropical Dry Forest	None	ACI

3. STUDY AREA

This section provides a general overview of the study area. Below, I summarized its characteristics regarding its geographical location and climate, as well as the main agricultural production methods adopted in the mixed orchards in the Gödence Village, as these are some of the essential features affecting bird populations and species richness.

3.1. Location and Climate Profile

Gödence is a mountain village at 440 meters altitude, located on the Aegean coast of Türkiye in İzmir province, in the district of Seferihisar (highlighted in Figure 3.1). It is in the temperate zone characterized by the Mediterranean climate. Local vegetation surrounds the village, and agricultural lands are mainly surrounded by Turkish red pine forests (*Pinus brutia Ten.*).

In the Seferihisar region, the average precipitation is about 620 mm, and average humidity is about 64%. Thus, irrigation is necessary in the dry season in the summer for olive production (Akça Uçkun et al., 2021)

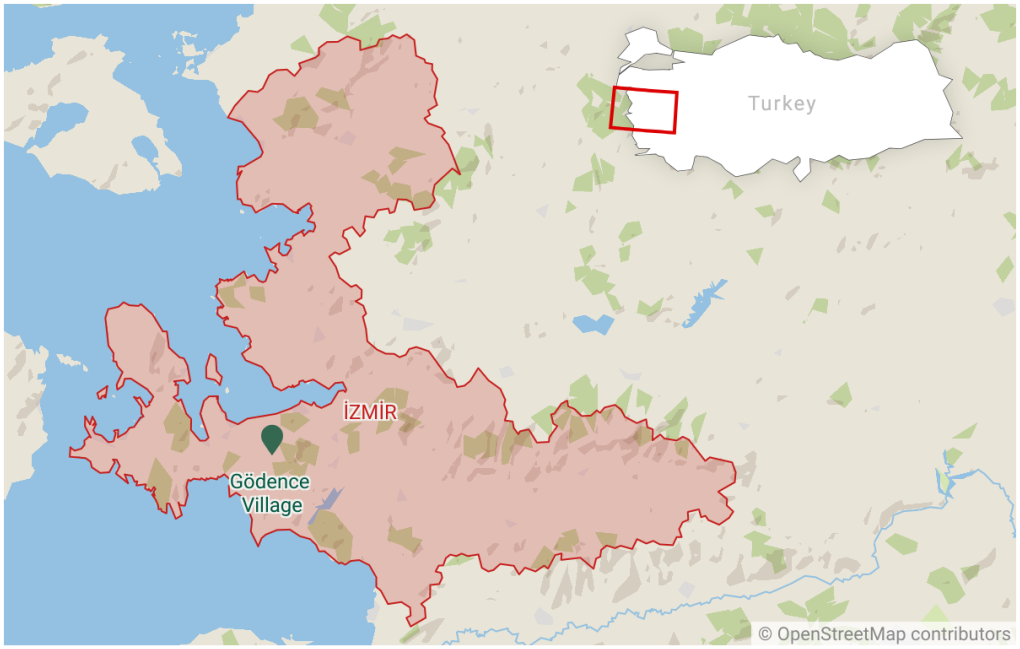


Figure 3.1. Location of Gödence Village in İzmir (Created with Datawrapper).

3.2. Agricultural Production

The rather warm climate of Seferihisar (yearly average temperature 16.4 degrees Celsius according to the (Akça Uçkun et al., 2021)) creates suitable conditions for many typical Mediterranean agricultural products. Olives, figs, grapes, pears, mastic, almonds, and walnuts are leading products grown in the region. Olive oil production has been carried out in the Gödence Village since 1974 and the village cooperative registered its own brand in 1992 through the Gödence Agricultural Production Cooperative (Pehlivan-Gürkan, 2021). Other products marketized by the cooperative are almonds, dried fruits such as figs and plums, as well as mastic.

According to the Head of the Gödence Cooperative, high altitudes and the micro-climate of the Gödence Village limits the presence of olive fruit flies (*Bactrocera oleae*), the primary pest of cultivated olives, in Gödence, which enables agroecological production of olives without much extra effort for pest management. Century-old olive trees local to this mountainous habitat are still kept in most of the orchards. Accordingly, these do not require irrigation under normal climatic conditions since they store water during winter on their roots below the soil. Therefore, farmers follow low-intensity agricultural practices with minimal (or no) pesticide and water use, for growing olives. In addition to these, other agroecological farming practices, such as planting sister species, are employed in these farmlands.

We selected two mixed orchards for assessing avian farmland biodiversity in the Gödence Village of Izmir, Turkey (38°16'11.8"N, 26°55'06.1"E). The owners of these two farms have been contacted based on our knowledge that they are cooperative and value wildlife and biodiversity in their farmlands. This was crucial because frequently farmers are having economic priorities and well-justified concerns about their livelihoods and do not want to collaborate with scientists whenever it interferes with their main farming activities.

The first orchard selected covers an area of 10 ha in the hills of Gödence Village and is owned by the head of the agricultural cooperative of the village. The average farm size is around 3-3.5 ha in Gödence, smaller than the average farmland size in Turkey. The orchard has seven different types of fruit trees in it, as well as some small forest patches (red pine trees). The fruits grown in the field include olives, grapes, mastic/gum, figs, almonds, pears, and walnut. The farm is extensively managed, without any use of synthetic inputs such as pesticides and fertilizers. Stone walls ensure that the soil is kept intact for agricultural production at different parts of the orchard, as the farmland is located in a rather steep area. There are two big irrigation ponds (the largest one shown in Figure

3.2 below) excavated by the owner in 1985, one with a capacity of 40 tons of rainwater, and the other one 80 tons of rainwater. They are natural substratum pools, as the base of these pools is naturally covered by clay, which retains water quite well and releases it only gradually. The ponds are filled with rainwater without any additional effort on the side of the farmer (there is no need to redirect the rainwater, as it fills the pond naturally due to the steep slope around them). Irrigation ponds are very important artefacts at farmlands to support wildlife and biodiversity, especially for the agricultural production in regions with Mediterranean climate (Fuentes-Rodríguez et al., 2013). Eight additional smaller ponds were made by the owner of this farmland of concrete. They were later built by the farmer, each with a capacity of keeping 10 tons of rainwater.



Figure 3.2. Irrigation pond in the study area.

The second orchard we selected covers an area of around 5 ha, and is in the same village, at a similar altitude. This orchard has mainly younger olive trees and almond trees. There is no irrigation pond in this fruit orchard, yet a small stream is flowing (with a seasonally dry waterbed in the summer) at the field margin. This orchard is extensively managed as well, the soil is tilled once in a year, either at the end of the winter or beginning of the spring season. The farmland borders consist of stone walls. Rainwater is harvested and collected in a metal container. Synthetic pesticides and fertilizers are not used in this orchard, either.

Below, in Table 3.1, a summary of the agricultural practices adopted in the mixed orchard, owned

by the Head of the Gödence Village Agricultural Cooperative is given. This land was one of the two mixed orchards where Audiomoths were deployed in the study area.

Table 3.1. General agricultural practices of the mixed orchard covering three recording points (table content adopted from Karaçetin et al., 2017).

How many years have as a producer?	30 years (Gödence Cooperative is operating for 52 years)
Main production methods	Organic production (olives are certified organic, not the other fruits) & agroecological production
Land size	100 acres
Number of trees	1,600-1,700 olive trees (300 of them are old trees), 250 fig trees, over 1,000 almond trees
Labor needs	For harvesting, planting, and cleaning of the surface area
Fertilizer Use	None
Irrigation	They do supportive irrigation especially to cope with dry seasons due to climate change and to increase the yield (Both for olives and other fruit trees.) Daily temperature cycles are considered, evening irrigation is preferred to make the water reach in depth. Irrigation is not carried out very frequently so as to allow trees to root deeper so that they can reach more water resources themselves. Rain harvest-through natural irrigation ponds. There are 2 natural irrigation ponds, and 8 irrigation reservoirs.
Pest control	No pesticide use (organic certification) Only Bordeaux mixture (copper II sulfate) is used against fungus. (Against "*dal kanseri*")
Weed control	Plucking, tilling, cutting. Wild berry bushes are the main plant species they are trying to remove.
Stone sets	Yes
Use of agricultural machinery	A tractor is used for tilling
Pruning	Young trees are pruned to shape them ("şekil budaması"). Yearly pruning to open the space between the branches ("ürün budaması"). In addition, pruning to obtain young twigs ("gençleştirme budaması")
Harvesting	Depending on the length of the tree, brushing with rakes manually or using automated branch shakers.

4. METHODOLOGY

This chapter summarizes the particular steps followed in the present study. First, details will be provided regarding how passive acoustic monitoring has been conducted in the study area, including the recording schedule that was used. Next step was the calculation of acoustic indices for the entire data set. Then a subsample was created from the entire dataset, and manual filtering was implemented for this subsample. Bird species richness was evaluated by two expert ornithologists for the same subsample, and data analysis was done for the identification of correlations between the acoustic indices and bird species richness detected from this subsample. Lastly, Merlin Bird ID was used for some more ground-truthing of the findings.

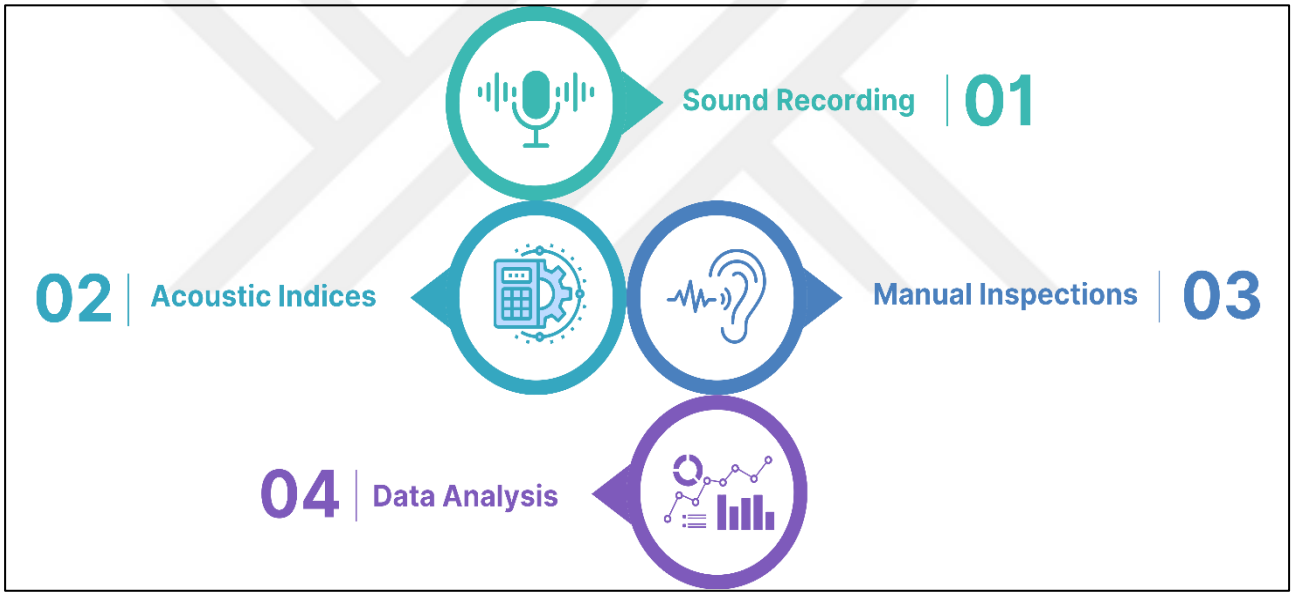


Figure 4.1. General steps of this study.

4.1. Sound Recording via Passive Acoustic Monitoring (PAM) and Recording Schedule

Passive Acoustic Monitoring (PAM) is a cost-effective, non-invasive method for monitoring biodiversity (Sugai et al., 2019), and recommended for the evaluation of land use changes, including agricultural land use (Abrahams, 2021). In this study, I carried out PAM to collect sound data using five AudioMoth sound recorders. Three official complementary apps (two for desktop and one for mobile) were used for PAM in this study. These apps enabled me to add the recording schedule to the devices, to update the installed firmware, to trigger the recorders before their placement on the field, and to split the long recordings into shorter files once the data had been collected. Further details

regarding the sound recorder, additional components, and complementary apps are given in Appendix B. These five AudioMoth devices were employed at five recording points in the two agroecological farmlands of Gödence Village in Seferihisar, Izmir for each of the four seasons in the 2022-2023 period, as described in Section 3.

In this study, we aimed to record the entire soundscape, with a specific focus on the vocalizations of bird species in the study area. I also wanted to identify daily and seasonal patterns of bird vocalizations in the soundscape, with respect to bird species richness. As recommended in the literature (Bradfer-Lawrence et al., 2019), the Audiomoth devices were programmed to record continuously for at least 120 hours per each recording location (rather than subsampling on a schedule, for instance, five minutes each hour). The recordings started two hours before sunrise and continued until two hours after sunset for each day of recording.[1]

As the study area was located in a temperate region, sunset and sunrise times varied between seasons. Therefore, given the recording schedule, winter and spring recordings lasted for 15 hours per day, while the summer and fall recordings lasted for 17 hours. Table 4.1 below summarizes the recording schedule and specific dates of recording employed in the study.

Table 4.1. Recording schedule of each season.

Season	Recording Dates	Sunrise – Sunset	Recording Hours
Fall	8th – 13th September 2022 (6 days)	~ 6:50 - 19:27	04:30 – 21:30 (17 hours)
Winter	31st January – 6th February 2023 (7 days)	~ 8:15 - 18:36	06:00 – 21:00 (15 hours)
Spring	30th March – 3rd April 2023 (5 days)	~ 6:57 - 19:34	06:00 – 21:00 (15 hours)
Summer	30th July – 8th August 2023 (11 days)	~ 6:16 - 20:19	05:00 – 22:00 (17 hours)

Eight field visits were made in total to the study area, two for each season. On the first visit of each season, I deployed the AudioMoths at the five recording points. I left the recorders unattended

[1]This was the case for fall and winter seasons. However, for spring and summer, to save energy and memory space, the devices recorded starting one hour before sunrise and continuing until 1 hour after the sunset, as we realized that adding two extra hours delivered silent files only, and did not contribute to the study.

during the deployment period and then paid another visit to collect the recorders after the recording period was over. The devices recorded the entire soundscape for at least five days in each season. I specifically tried to deploy the recorders on dates with minimal human presence in the study area in order to minimize the non-focal human-made (anthropogenic) sounds. Therefore, I avoided labor-intensive periods in agricultural land, such as harvesting fruits, for instance.

Since the target taxa were birds, 48 kHz was chosen as the sampling rate, as it is the usual practice in the literature (Budka et al., 2023; Metcalf et al., 2021). This sampling rate allows recording of all sound up to 24 kHz in the soundscape. This covers the entire audible frequency range for humans, comparable to a traditional surveyor present on the field. In the study area, the expected frequencies from local bird species were between 0.5 and 10 kHz, so our sampling rate covered this range. We chose the Medium Gain option on the AudioMoth Configuration App to keep an optimal frequency response. This gave enough amplification for the intensity of the sound while keeping the distortion relatively low. Recordings were saved in files with .wav format, as is standard for acoustic monitoring recorders.[2]

The five recording points in the study area are shown below in Figure 4.2 and the coordinates of all recording points are given in Table 4.*2*.

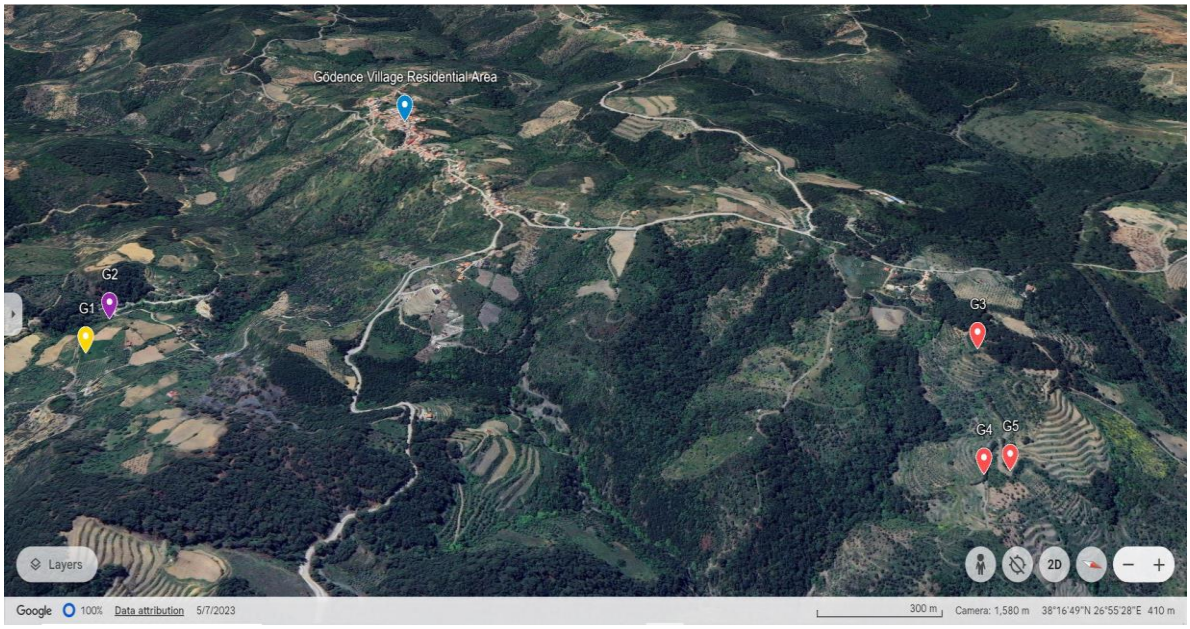


Figure 4.2. Five recording points and the center of Gödence Village.

[2] The size of the WAV files is bound to 4 GB in maximum size due to their 32-bit nature, which limited the maximum length of each file to 12.5 hours based on our chosen sample rate.

Two AudioMoths (G1 and G2) were placed in the first mixed orchard including mainly olive and almond trees. An almond tree on the elevated part of the orchard was chosen strategically to have better coverage of the soundscape for G1. The second device (G2) was employed at the field margins of the same orchard. The other three devices (G3, G4 and G5) were employed in the second mixed orchard (including olives, almonds, figs, and grapes), partially also covered by pine tree forest patches. One of them (G3) was placed in the upper section of the orchard close to the natural irrigation pond surrounded by olive trees and pine forest patches. The second one (G4) was attached to the top tree in the middle-lower section where almond and grape trees were present. The last one (G5) was placed on the lower section of the farmland mainly covered by fig trees. Agricultural production in both of these mixed orchards is carried out extensively with minimal human interference, as is usual in the mountainous villages of Seferihisar, like the Gödence Village.

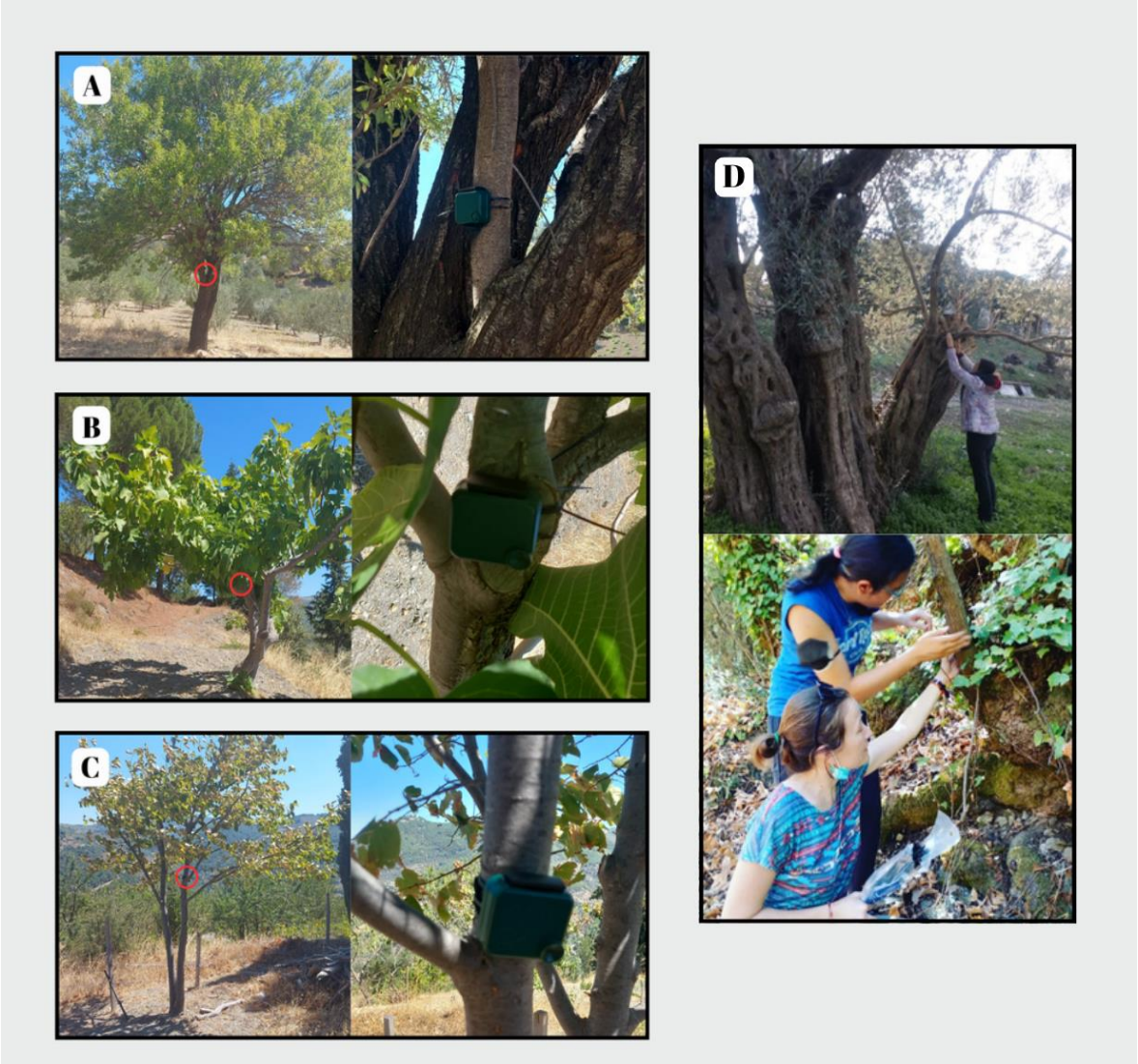


Figure 4.3. Photos of some deployed AudioMoths: (A) on an almond tree at G2, (B) on a fig tree at G5, (C) on a pear tree at G4. (D) Deployment on an olive tree (top) and at a forest patch (bottom).

Table 4.2. The coordinates of the five recording points in the two agroecological orchards.

Recorder Label	Latitude	Longitude
G1	38.269822	26.932366
G2	38.268974	26.930834
G3	38.286129	26.923265
G4	38.286595	26.926539
G5	38.286995	26.926262

Some cautionary measures were taken while deploying AudioMoths in line with the recommendations for similar projects employing PAM (Rhinehart, 2019). Distances from the ground, water sources, vegetation, and roads were considered, as well as the trunk size of the trees, exposure to the sun, and dominant wind direction. I deployed the devices at least one meter above the ground but placed them even higher in general (see Figure 4.*1*3), to increase the radius of sounds captured. Deployment close to running waters, dense vegetation, and busy roads are generally not preferred, and these were absent in the study area. I chose the opposite direction to the dominant wind for employing devices to reduce wind noise. I attached the devices to the trees with medium-sized trunks to keep them sturdy enough while minimizing blocked sounds. Shaded parts of a tree were preferred to prevent the devices from overheating. Lastly, AudioMoths were secured with triple plastic zip ties to avoid getting loose with strong wind.

The recording schedule described above delivered more than 350 hours of sound data for each of the five recording points such that the entire dataset amounted to more than 1,750 hours. This was equivalent to more than 4,000 five-minute files in .wav format for each of the recording points. This was in line with the recent recommendations in the literature which suggest that in total at least 120 hours of continuous recordings need to be conducted for each recording site (Bradfer-Lawrence et al., 2019) in order to be able to characterize the study area using acoustic indices. This also minimizes the standard error variance of the acoustic indices (ibid).

4.2. Calculation of Acoustic Indices

Five widely used acoustic indices were calculated for 5-minute .wav files in the entire dataset to evaluate their performance as proxies for bird species richness at the five recording points. The selected indices were the Bioacoustic Index (BI), Normalized Difference Soundscape Index (NDSI), Acoustic Complexity Index (ACI), Acoustic Evenness Index (AEI), and Acoustic Diversity Index (ADI). These are five of the most commonly used acoustic indices in the literature (e.g. Bradfer-

Lawrence et al., 2020a; Budka et al., 2023a; Metcalf et al., 2021a; Myers et al., 2019) and are readily available for calculation in Kaleidoscope Pro software. The literature on acoustic indices recommends that multiple acoustic indices should be used in combination for each study (instead of using just one acoustic index) in order to capture soundscape characteristics better (Bradfer-Lawrence et al., 2019). This also helps with the identification of diel and seasonal patterns (ibid).

The Kaleidoscope Pro software offers several (in total 25) acoustic indices, and the user can choose calculation parameters such as maximum and minimum frequencies, FFT size, frequency step, and dB threshold. We used the default parameters of the software as follows: FFT Size was 512 for all indices, except for the NDSI for which 1,024 FFT Size was chosen. For BI 2 kHz was the minimum frequency, and 8 kHz was the maximum frequency. For NDSI minimum and maximum frequencies for the anthrophony were selected as 1-2 kHz, and for biophony, it was selected as 2-8 kHz. For ACI, the minimum frequency was taken as 0, and Nyquist frequency was chosen for the maximum frequency. Additionally, "continuous" option was selected for the number of frequency bins (denoted by J), while no dB threshold was set. Lastly, for AEI and ADI, minimum-maximum frequency were 0-10 kHz and the step for frequency bands was 1 kHz. The threshold for dB was set as -50. These selected parameters were mainly in line with the widely used default parameters for calculating acoustic indices.

One advantage of using Kaleidoscope Pro (rather than other alternatives for calculating acoustic indices, such as the R studio package *soundecology* (Pieretti et al., 2011)) was availability of inspection for the corresponding index values for each five-minute file simultaneously with the associated spectrogram as shown in Figure 4.4 without a need for going back and forth between different windows. This was particularly useful for the inspection of the highest and lowest values for each acoustic index. For each acoustic index, I inspected the 50 highest and lowest values for each recorder manually in order to identify some general sound composition patterns. These general patterns were mainly in line with the previous studies (e.g. Bradfer-Lawrence et al., 2019a) and are summarized in the Results Chapter of the present study.

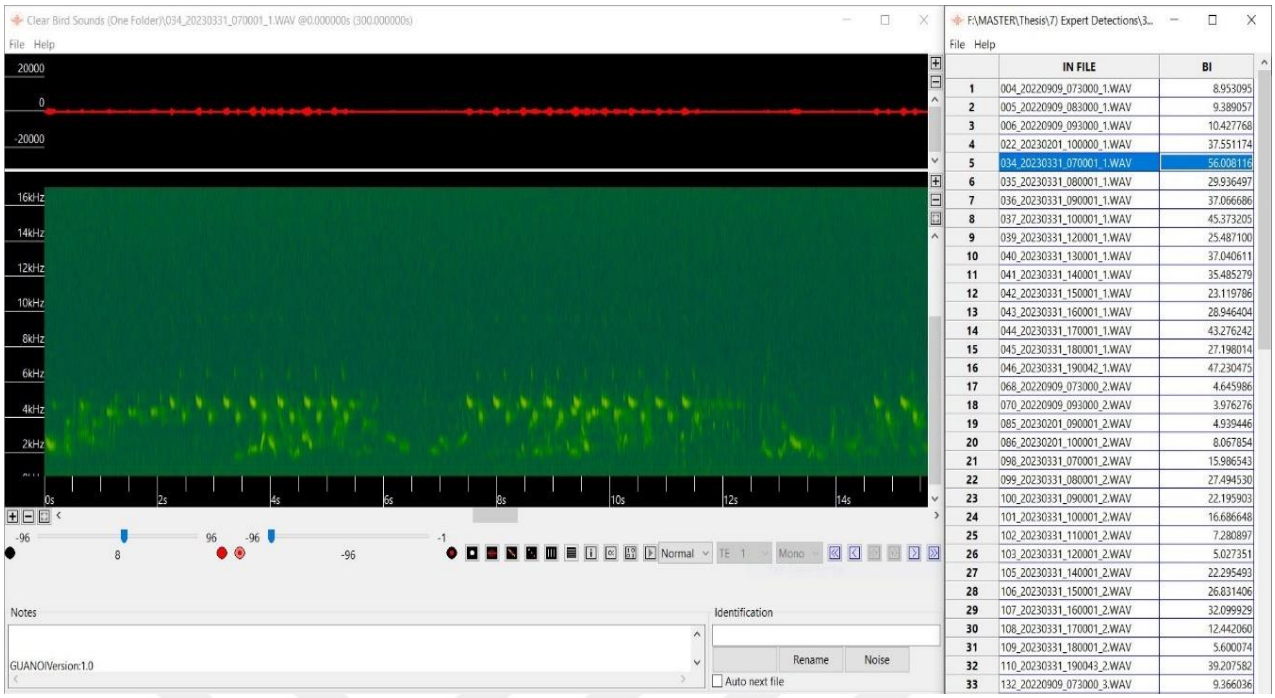


Figure 4.4. A spectrogram of a dawn chorus file on the Kaleidoscope Pro. Corresponding acoustic index value for the given spectrogram is highlighted at the list, on the right.

4.3. Manual Listening by Two Expert Ornithologists for Bird Species Richness

A subsample was selected from the entire dataset so that two expert ornithologists could further analyze the selected recordings for bird species richness by manually listening to the five-minute recordings. To do this, I selected each season's first day of deployment for each recording point and the first five-minute file of each hour on that selected day. This sampling delivered 303 files in total.[1] Afterward, I manually filtered these 303 files: the silent files (without any biophony, geophony or anthropophony) and the files with only non-focal sounds, such as other sources of biophony (e.g., only cicadas without any bird vocalizations) and geophony (e.g., only heavy wind or rain without bird vocalizations) were removed. After this manual filtering, 183 five-minute files remained in the dataset to be inspected by the experts. These 183 files included mainly bird vocalizations, some in the presence of mild and moderate wind, and others in the presence of cicada vocalizations. These 183 files amounted to about 15 hours of sound data. Each expert listened manually to one half of the recordings and noted the bird species that they identified for each five-minute sound file. The experts also noted the unidentified species, in case there were any. The total count of identified and unidentified bird species for each five-minute subsample file delivered the bird species richness variable for our dataset. The two experts (Ergün Bacak and Sercan Bilgin) who evaluated bird species richness for the present study are well-known ornithologists in Türkiye with about 20 years of experience, having worked as experts at different national and international projects for the socio-

environmental impact assessments of windfarms, airports and natural gas pipelines, as well as conservation and monitoring of birds.

Appendix C provides a comparison of the expert findings with the bird species lists in eBird for each season in the region in close proximity to Gödence. The list is encompassing the eBird observation points Orhanlı, Eski Orhanlı, Orhanlı Vadisi, Kavakçay Deresi, Kavacık, Menderes, and the Turkish Breeding Bird Atlas square 35SMC92. The selected eBird points are shown in Figure 4.5 below. Among those points, Orhanlı Village was especially significant because here prominent bird watchers frequently enter their observations into eBird. Overall, the experts could identify a relatively large share of those birds in the eBird lists (64 out of the 200 bird species in the eBird over 4 seasons), and identified an extra 27 bird species previously not listed in eBird for the same season.



Figure 4.5. Locations for species checklists from eBird.

4.4. Data Analysis

4.4.1. Correlations Between Acoustic Indices and Bird Species Richness

R Studio was used for the identification of correlations (Spearman's rho and Kendall's tau) between the bird species richness and each of the five acoustic indices used in this study, for the subsample of 183 five-minute files. This provided insights regarding the performance of each acoustic index for capturing bird species richness in the study area. Kendall's tau was added as an additional

measure of correlation as Spearman's rho requires monotonicity in the dataset. In our dataset, the assumption of monotonicity was violated because for the same number of bird species, the acoustic indices could deliver smaller or bigger values. Correlations were also calculated separately for each season and for the presence of some of the important non-focal sound categories (e.g., cicadas/insects, wind) to evaluate seasonal variation and sensitivity of acoustic indices to non-focal sounds, respectively.

4.4.2. Automated Identification of Bird Species Richness via Merlin Bird ID App

In addition to the calculation of the correlations between the acoustic indices and bird species richness via experts' manual listening to the 5-minute files, the same subsample of 183 files were also uploaded to Merlin Bird ID for the automated identification of bird species. Then the species detections from Merlin Bird ID were compared with the findings of the experts. The insights regarding this comparison are described in the Results Chapter of the present study. Indeed, automated tools are an emerging tool for species identification, however, their reliability is still subject to improvement in the near future. That is why complementing the analysis with experts' bird species identification was crucial for the present study.

5. RESULTS

On average, 342.7 hours of sound data were collected per recording point. The cumulative sum of all the files obtained from five recorders corresponds to 1,713 hours of sound data from the study area. The soundscape was recorded continuously (without pre-scheduled sampling), and then they were split into five-minute .wav files for further analysis. That means, the entire dataset consisted of, on average, 4,170 five-minute files in .wav format. Acoustic indices were calculated for this entire dataset, but manual bird species identifications were carried out for the subsample consisting of 183 five-minute files, as described in the Methodology Chapter.

5.1. Analysis of General Patterns for the Acoustic Indices in the Entire Dataset

Once the acoustic indices had been calculated, recordings from the complete dataset were sorted for each index separately from highest to the lowest values. Then, corresponding files for the highest and lowest 50 values were inspected manually for each acoustic index, by checking each spectrogram. This gave us general soundscape patterns as they are reflected by different acoustic indices (Bradfer-Lawrence et al., 2019).

Files with the highest BI, ACI and ADI values were the ones where clear bird vocalizations were present without any other sonic disturbance, mainly from the dawn and dusk chorus periods. The lowest index values for BI and ACI were mainly from silent files, and for ADI the lowest index values were from the recordings with constant insect sounds or strong dominant wind.

For NDSI, the highest values (positive values close to one) originated from clean (without non-focal sounds) dawn and dusk files. However, the lowest 50 values (all close to negative 1) originated from files with the presence of strong wind, especially dominating the frequencies below 2,000 Hz, but also strong wind spanning the entire frequency range that has been recorded. Normally, negative values are expected to indicate anthropophony for the specific case of the NDSI, but in our recordings, this was associated with strong wind.

Table 5.1. Overlaps between findings and expectations based on the literature (mainly based on Bradfer-Lawrence et al., 2019).

Acoustic Index	Expectation	Findings in the present study		In line with the general patterns in the literature?
NDSI **Range:** (-1) to (+1)	- Biophony dominant soundscape if the value close to +1 - Anthrophony dominant soundscape if the value is close to -1	Highest	Clear bird sounds (dawn and dusk)	Yes
		Lowest	Strong wind below 2 kHz	Yes
			Strong wind filling the entire spectrogram	Yes
BI **Range:** 0+ (positive real numbers)	Higher values are expected in case there are large differences between loudest and quietest frequency bands	Highest	Clear bird sounds (dawn and dusk)	Yes
		Lowest	No sound	Yes
ACI **Range:** 0+ (positive real numbers)	Values increase for increased Biophony, as this increases irregularity in the soundscape; values not affected by persistent, constant-intensity sounds	Highest	Clear bird sounds (dawn and dusk)	Yes
			Dominant geophony especially rain, or irregular discrete vocalizations of cicadas spanning all frequency bands	Yes
		Lowest	Silent files or regular continuous repetitive sounds in a narrow frequency band without any other sound	Yes
ADI **Range:** 0+ (positive real numbers)	Values increase when evenness increases; an even signal (either noisy across all frequency bands or no sound at all) gives a higher value; a pure tone (all energy in one frequency band) gives 0.	Highest	Clear bird sounds (dawn and dusk)	Yes, if bird vocalizations dispersed in many frequency bands, increasing the evenness
			Bird sounds in the presence of strong geophony	Yes, if noisy across all frequency bands
		Lowest	Constant insect sounds	Yes, if in a limited narrow frequency band
			Dominant wind	Yes, if in a limited narrow frequency band
AEI **Range:** 0 to 1	Values increase when unevenness increases (as it uses the Gini coefficient); lower values are expected for increased evenness. It is the reverse of ADI.	Highest	Constant mild wind in the low frequencies without any other sound presence	Yes
		Lowest	Clear bird sounds (dawn and dusk)	Yes, if bird vocalizations dispersed in many frequency bands, increasing the evenness
			No sound	Yes

Regarding the AEI, the highest values (close to +1) originated from the recordings where constant mild wind was present in the low frequencies without any other sound presence. Recordings with dominant bird vocalizations yielded the lowest AEI values (close to 0), as expected. However, some of these lowest numerical values for AEI were also from the files with no sound at all. Overall, the patterns observed for each index were parallel to the patterns described by Bradfer-Lawrence et al. (2019), as described in Table 5.1.

5.2. Bird Species Richness (via Manual Listening to the Recordings)

Next, we analyzed the subsample of 183 five-minute files. Selection criteria and procedures have already been described in the Methodology Section. These 183 five-minute files, corresponding to 15 hours in total duration, were submitted to the two experts for manual listening and inspection. Their analysis gave the following results:

- In total, in these 15 hours of recording for 4 seasons, 36 species were detected by manual listening, and the Common Chaffinch (*Fringilla coelebs*) was the most frequent species with presence in 123 out of 183 files. The number of occurrences for each species detected are given in Figure 5.1. Appendix D provides the abbreviations used for each bird species.

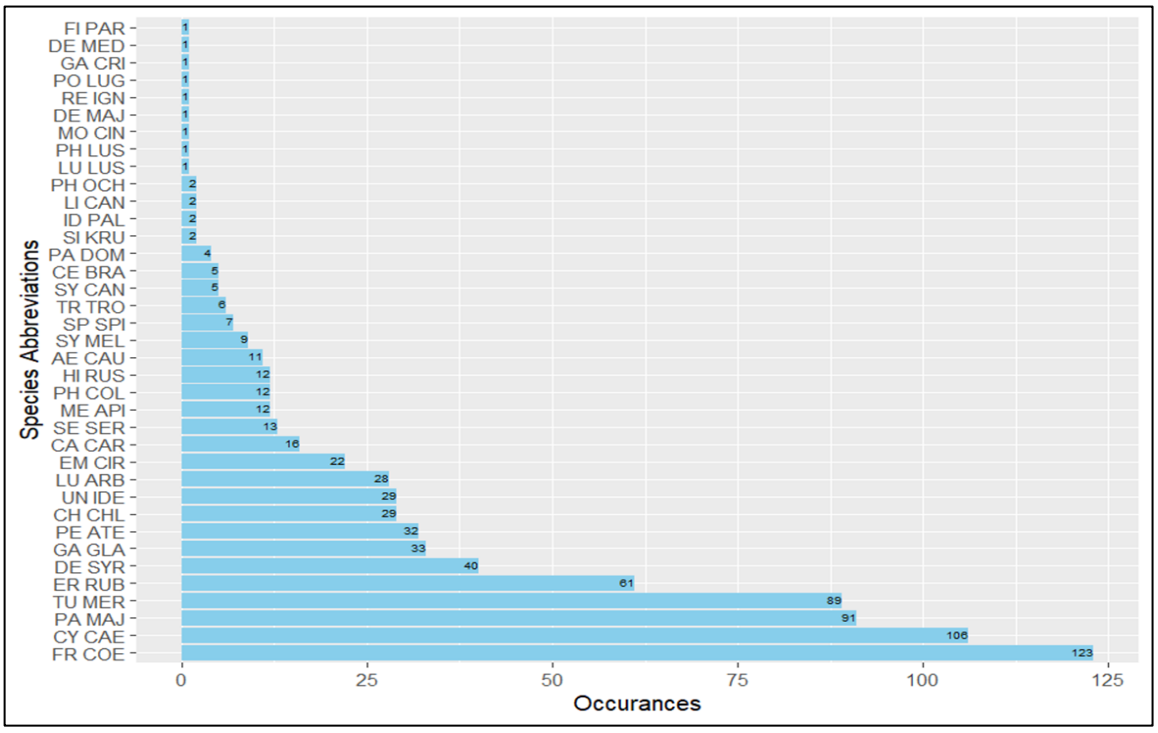


Figure 5.1. Number of occurrences for each detected bird species.

- Common Chaffinch was followed by some other abundant species of Mediterranean coastal farmlands, such as Eurasian Blue Tit (*Cyanistes caeruleus*), Great Tit (*Parus Major*), Common Blackbird (*Turdus merula*), European Robin (*Erithacus rubecula*) and Syrian Woodpecker (*Dendrocopos syriacus*) (they were present in 106, 91, 89, 61 and 40 files, respectively). Those were dominantly vocalizing species in the study area, so high detections were notable but not unexpected.

- Nine of these 36 species were only present in a single file each. Species detected only in a single file were Red-breasted Flycatcher (*Ficedula parva*), Middle Spotted Woodpecker (*Dendrocoptes medius*), Great Spotted Woodpecker (*Dendrocopos major*), Crested Lark (*Galerida cristata*), Sombre Tit (*Poecile lugubris*), Common Firecrest (*Regulus ignicapilla*), Grey Wagtail (*Motacilla cinerea*), Willow Warbler (*Phylloscopus trochilus*), Thrush Nightingale (*Luscinia luscinia*).

- Eastern Olivaceous Warbler (*Iduna pallida*), Common Linnet (*Linaria cannabina*), Black Redstart *(Phoenicurus ochruros*), Krüper`s Nuthatch (*Sitta krueperi*), Subalpine Warbler (*Sylvia cantillans*) and Sardinian Warbler (*Sylvia melanocephala*) were some other species worth noting even though their vocalizations were detected in a lower number of files.

5.3. Hourly Distribution of Detected Bird Species Richness for Each Season

Next, the hourly distribution of the number of identified bird species for each season was checked to see whether the detections followed the anticipated ecological temporal patterns. It was expected to see an increase in the detected number of species around sunset and sunrise (dawn and dusk choruses). We also expected higher bird species richness for spring and fall than the winter and summer. The results were coherent with those expectations. For each season, the peak number of identified bird species occurred during the dawn chorus. Spring had more bird species richness than all other seasons. It had the highest average bird count for the dawn chorus with 8 species, while all the other seasons had 6. The distribution of hourly average detected bird species for each season is shown in Figure 5.2. The pattern for summer was skewed for two reasons: First, one of the recorders malfunctioned in summer, so no data could be collected from one of the recording points in summer. Due to that, the number of recordings from summer was already lower in the subsample than all other seasons. Secondly, there were dominant daytime cicada vocalizations in the majority of the recordings in the summer. Therefore, several summer recordings, except for the files from dawn and dusk

choruses, had to me removed during manual filtering prior to the analysis of bird species richness by experts due to the lack of bird vocalizations. The number of identified species increased at the dusk choruses before the sunset, especially in fall and spring.

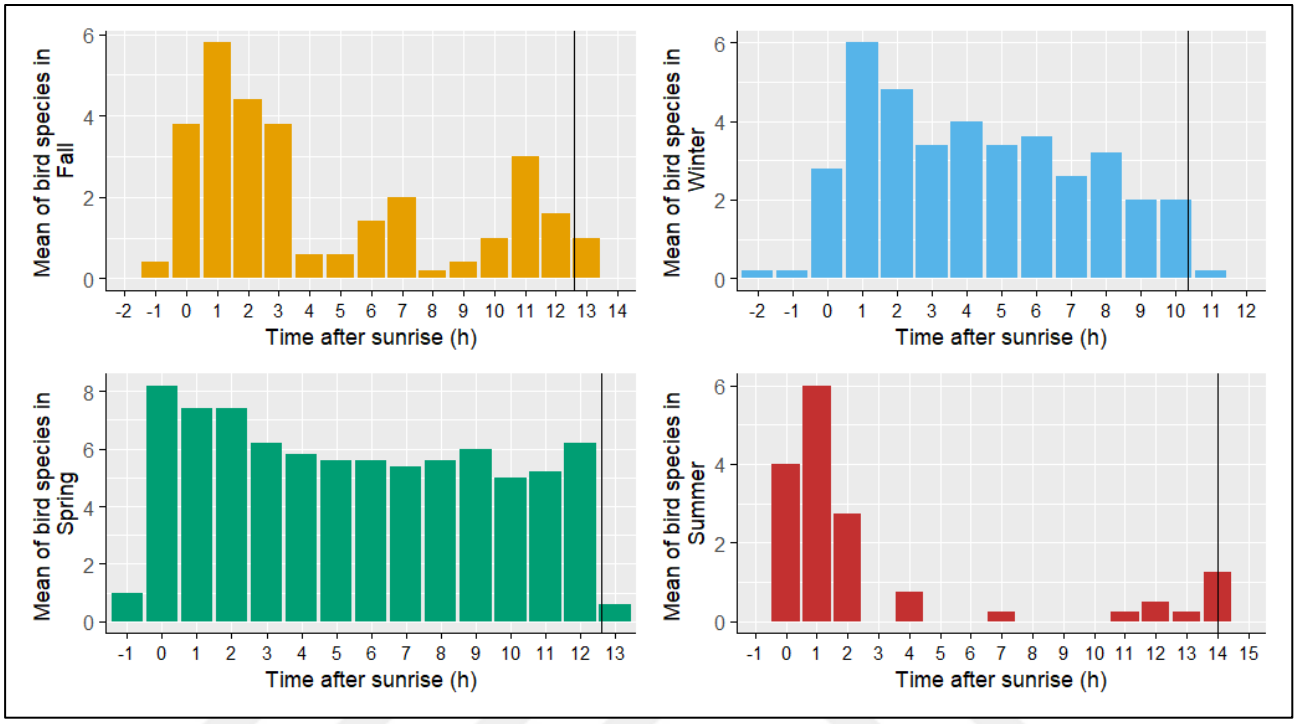


Figure 5.2. Hourly distribution of average bird species in every season (black vertical lines representing sunset time).

5.4. General Patterns for Bird Species Richness and Acoustic Indices

Next, I attempted to visualize the general patterns for bird species richness and each acoustic index. Based on the specific statistical properties of the acoustic indices, I expected a positive relationship between bird species richness and BI, ACI and ADI values, because an increase in biophony should affect values calculated for these indices positively. I also expected the NDSI values to converge towards +1 as bird species richness increased, because by design, NDSI values close to +1 indicate that biophony dominates the soundscape. Lastly, a higher number of identified bird species would mean less evenness in a soundscape, that is expected to lead to higher values for the AEI. AEI and ADI values are expected to provide values opposite to each other, as AEI is designed to measure evenness in the soundscape whereas ADI is designed to measure the opposite, the increased diversity.

For the BI, these expected patterns were observed for the winter and spring seasons, but lesser so for the other two seasons. The ACI values were in line with the expectations for the spring, summer, and winter seasons, but not so much for fall. Values of ADI and AEI did not change much with the increasing bird species richness, except for a few spikes in winter and spring. Yet, these deviations did not affect overall patterns. As expected, opposing trends were observed for ADI and AEI. For the NDSI, overall, all seasons yielded positive values in average, which indicates the dominance by biophony rather than anthrophony in the soundscape for every season. This is in line with the characteristics of the soundscape of the study area where humans were mostly absent during the recording periods. However, NDSI values did not increase when the number of bird species identified in a file increased. These patterns are visualized in Figure 5.3 cumulatively for all seasons and in Figure 5.4 specific to each season.

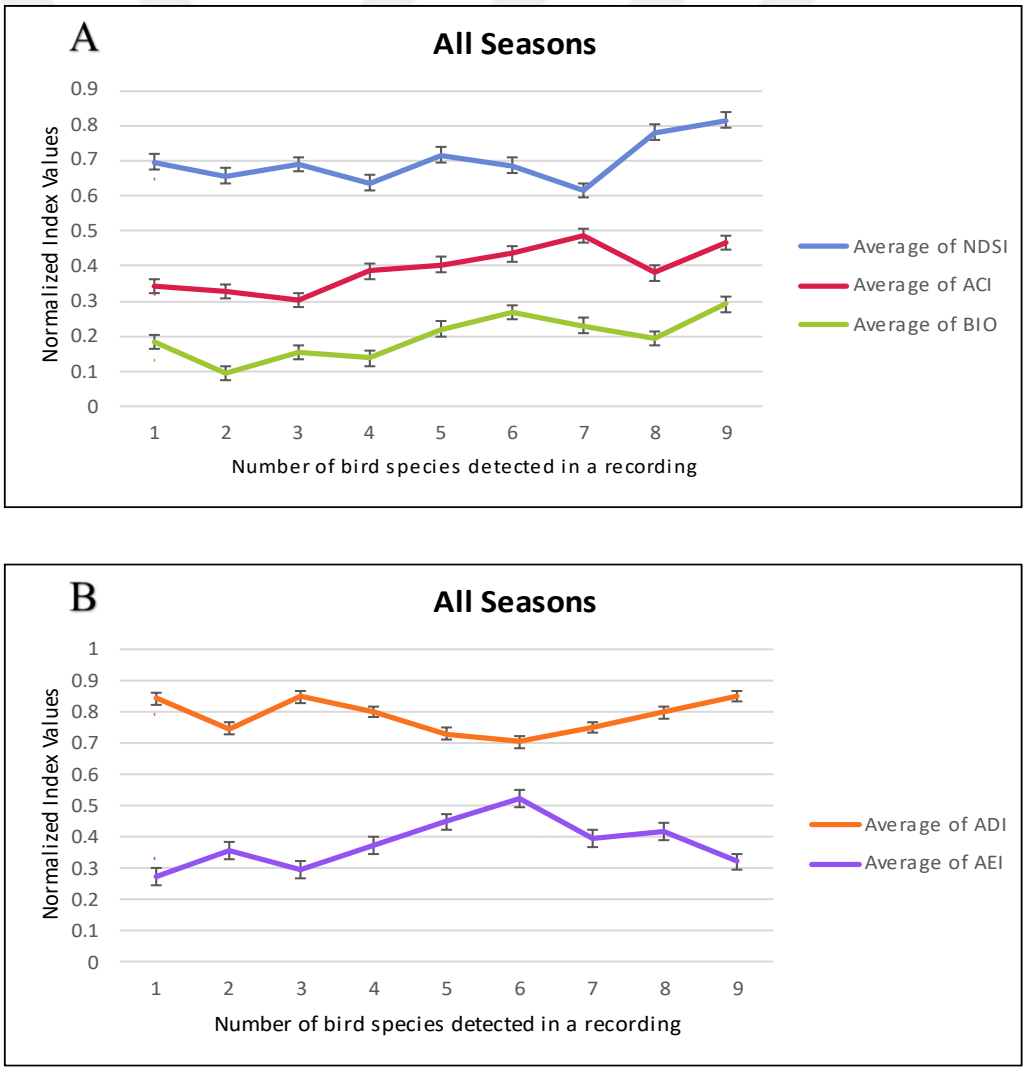


Figure 5.3. Patterns between acoustic index values and increasing bird species richness. BIO, ACI and NDSI patterns are given in Graph A, while ADI and AEI patterns are given in Graph B.

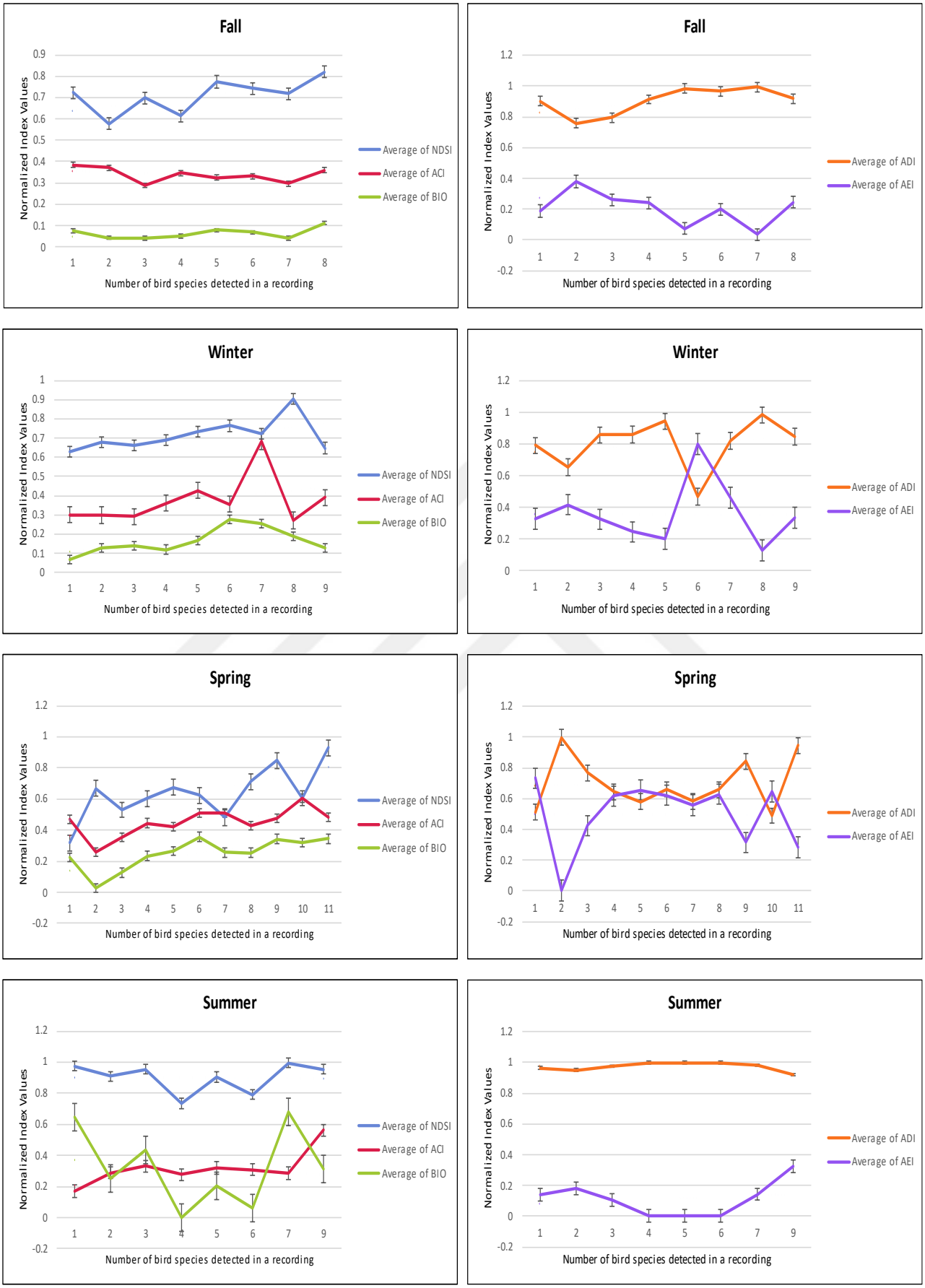


Figure 5.4. Seasonal patterns between acoustic index values and increasing bird species richness. Patterns for BIO, NDSI and ACI are given on the left graphs, while for ADI and AEI on the right.

5.5. Statistical Analysis: Correlations Between Bird Species Richness and Acoustic Indices

General trends between bird species richness and acoustic indices gave some initial insights, however, checking their statistical significance was needed. Hence, correlations between the number of identified bird species in a file and the acoustic index value for the same file were examined. The subsample size was small and did not have a normal distribution, so Spearmen's rho and Kendall's tau were the suitable correlation tests for the data at hand. First, correlations for all 183 files in the subsample were checked. Statistically significant positive correlations were found between the number of bird species and the index values of BI and ACI.

Table 5.2. Correlations between bird species richness and acoustic index values for the complete subsample (yellow highlights on the significant ones).

	BIO	NDSI	ACI	AEI	ADI
Spearman's rho	0.35***	0.09	0.44***	-0.15*	-0.14
Kendall's Tau	0.25***	0.07	0.32***	-0.11	-0.10
Significance	* = p < 0.05	*** = p < 0.001			

Afterward, the files were divided into seasonal categories for studying the temporal variations. There was no statistically significant correlation in fall for any of the acoustic indices. However, BI and ACI exhibited statistically significant positive correlations for winter and spring. In summer, there was a very strong positive correlation between the ACI and bird species richness, despite the small sample size for this season. NDSI, ADI and AEI values were not significant for any of the seasons.

Table 5.3. Correlations between bird species richness and acoustic index values for seasonal categories (yellow highlights on the significant ones).

		BIO	NDSI	ACI	AEI	ADI
Fall	Spearman's rho	0.13	0.09	0.04	0.09	0.09
n=46	Kendall's Tau	0.10	0.08	0.02	0.08	0.08
Winter	Spearman's rho	0.34*	0.20	0.36*	-0.04	-0.06
n=49	Kendall's Tau	0.24*	0.14	0.26*	-0.04	-0.05
Spring	Spearman's rho	0.32**	0.22	0.27*	0.08	0.07
n=70	Kendall's Tau	0.23**	0.17	0.19*	0.06	0.05
Summer	Spearman's rho	-0.44	-0.44	0.70**	0.31	0.36
n=18	Kendall's Tau	-0.34	-0.32	0.53**	0.24	0.27
Significance	* = p < 0.05	** = p < 0.01	*** = p < 0.001			

Lastly, recordings were categorized according to different sonic compositions (presence of non-focal sounds) in order to check the sensitivity of each acoustic index to distinct acoustic sources while species richness was considered. There were four main sound groups: (1) clear bird vocalizations without any interference from other sound sources, (2) bird vocalizations in the presence of cicadas/insects, (3) bird vocalizations in the presence of mild wind, and finally, (4) bird vocalizations under moderate wind. Seven recordings did not fall under any of these categories; therefore, they were grouped separately. Figure 5.5 below provides typical samples of spectrograms for each sound category (dawn chorus, the presence of cicadas, mild wind, and moderate wind) that were analyzed in the present study.

In the figure below, one can observe how clear bird vocalizations were visible in a spectrogram without any interference from different non-focal sounds. Mild wind was usually below 2 kHz, thus rarely masking bird vocalizations which were typically above 2 kHz. However, moderate wind often spanned the entire spectrogram in terms of different frequencies and overlapped more strongly with bird vocalizations, in contrast to mild wind. When cicada vocalizations were dominant in the recordings, they were often masking the bird vocalizations, as these were mostly overlapping with the frequency ranges where birds vocalized. These spectrograms will be useful for the further analysis and interpretation of the relationships/correlations between the acoustic indices and bird species richness, presented in the following paragraphs.

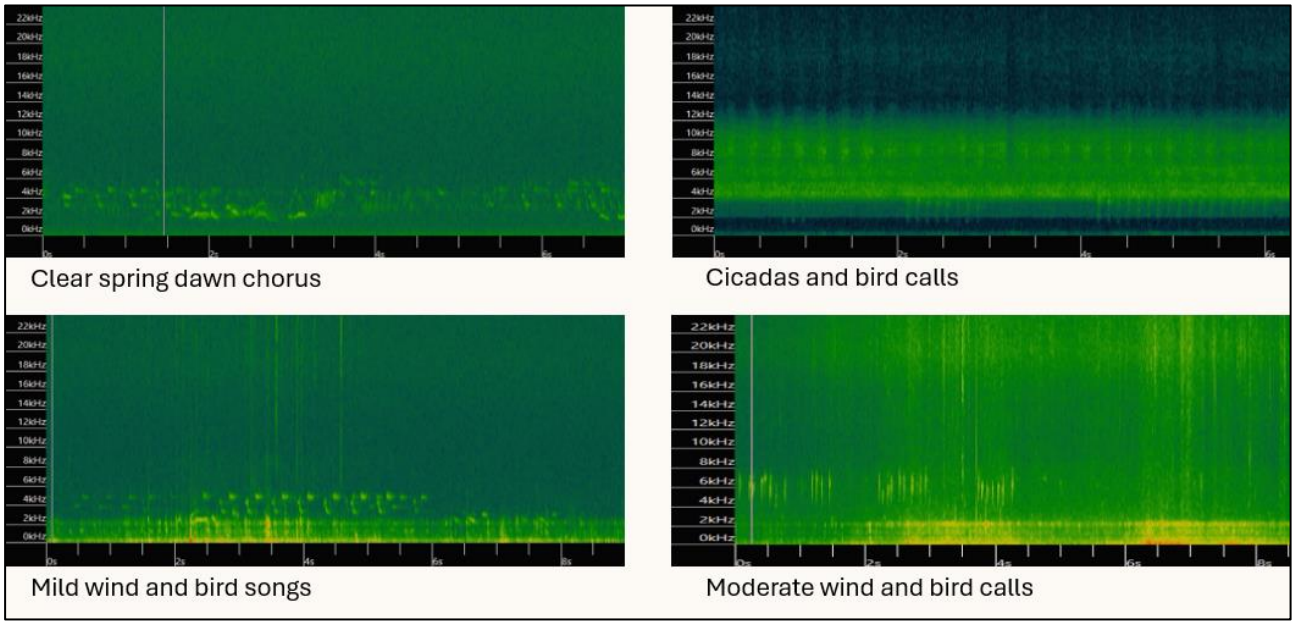


Figure 5.5. Examples for spectrograms of different sound categories.

Overall, clear bird vocalizations positively correlated with BI, NDSI, and ACI. In addition, all the other sound groups (excluding the Others group) positively correlated with the ACI. For the recordings with bird vocalizations accompanied by some mild wind, BI also exhibited statistically significant positive correlation. ADI and AEI were not related with any of the distinct sound categories investigated. Similarly, the NDSI was not significant for any other sonic composition despite having a high correlation for clear bird sounds.

Table 5.4. Correlations between bird species richness and acoustic index values for sound categories (yellow highlights on the significant ones).

		BIO	NDSI	ACI	AEI	ADI
Only Birds	Spearman's rho	0.54***	0.42***	0.54***	-0.21	-0.21
n=84	Kendall's Tau	0.39***	0.29***	0.39***	-0.16	-0.15
Cicadas + Birds	Spearman's rho	-0.39	-0.46	0.73***	0.35	0.43
n=13	Kendall's Tau	-0.30	-0.36	0.55*	0.21	0.3
Mild Wind + Birds	Spearman's rho	0.61***	-0.12	0.51***	-0.17	-0.17
n=33	Kendall's Tau	0.47***	-0.11	0.42***	-0.12	-0.12
Moderate Wind + Birds	Spearman's rho	0.29	-0.05	0.39*	-0.20	-0.20
n=46	Kendall's Tau	0.18	-0.02	0.28*	-0.17	-0.16
Others + Birds	Spearman's rho	-0.29	0.44	0.60	-0.02	-0.02
n=7	Kendall's Tau	-0.25	0.35	0.35	-0.05	-0.05
Significance	* = p < 0.05	*** = p < 0.001				

In addition, pairwise correlations between the five different acoustic indices used in the present study were also calculated. The results are provided in Table 5.5 below. The findings confirmed the inverse pattern between the ADI and AEI, as suggested by the literature. Similarly, ACI had positive correlation with ADI and negative correlation with AEI.

Table 5.5. Pairwise correlations between acoustic indices used in the study.

	BIO				**NDSI**			**ACI**		**ADI**
	NDSI	ACI	AEI	ADI	ACI	ADI	AEI	ADI	AEI	AEI
Spearman's rho	0.18*	0.63	0.35	-0.34	-0.17*	-0.39	0.38	0.47	-0.45	-1
Kendall's Tau	0.14	0.48	0.23	-0.23	-0.13	-0.28	0.27	0.34	-0.33	-0.98
* For the marked ones, p-value for statistical significance is less than 0.05, for the others it is less than 0.01.										
Positive correlation										
Negative correlation										

5.6. Further Investigation of Bird Species Richness via Merlin Bird ID and eBird Lists

Acoustic indices are useful tools, but their effectiveness for representing species richness still needs more in-depth evaluation. Traditional methods such as point counts or manual listening of the recordings are often used in the literature to obtain species detections to check the correlations with acoustic index values. These are accepted as reliable practices for species detections from a study area. However, both of these methods require highly trained individuals, and it is often difficult to find experienced experts. Furthermore, the required time for expert reviews increases with the amount of data gathered. Thus, employing automated tools such as Merlin Bird ID could be beneficial and quick to enlarge the sample size of recordings, if they are reliable enough. Their performance is also constantly improving; however, those are also far from being perfect for the identification of bird species. To gather some first-hand insights regarding their potential for bird species identification, the same 183 files used for expert detection were also reviewed by Merlin Bird ID app. Obtained detections by this app on each recording file were compared to the manual listening detection results by the experts.

Overall, the total number of unique detections by experts (E) and by Merlin Bird ID (M) (17 and 14, respectively), the maximum number of species detected in a single file (E:11, M:8) and the mean number of species detected in each file (E:4.41, M:3.28) were similar. However, Merlin Bird ID returned a drastically higher number of files where no detections were made. Experts had only a single file without any detection, but there were additionally four more files for which experts couldn't identify the exact species of bird that they listened to. Detailed comparisons are given in Appendix E, but a summary is also provided in Figure 5.6. Reviewing the 14 bird species that were only identified by Merlin Bird ID (but not by the experts) revealed that only one species (Eurasian Magpie – *Pica pica*) could be relevant for the study area. The remaining 13 species are most likely false positives, but a further expert investigation could not be carried out for confirmation.

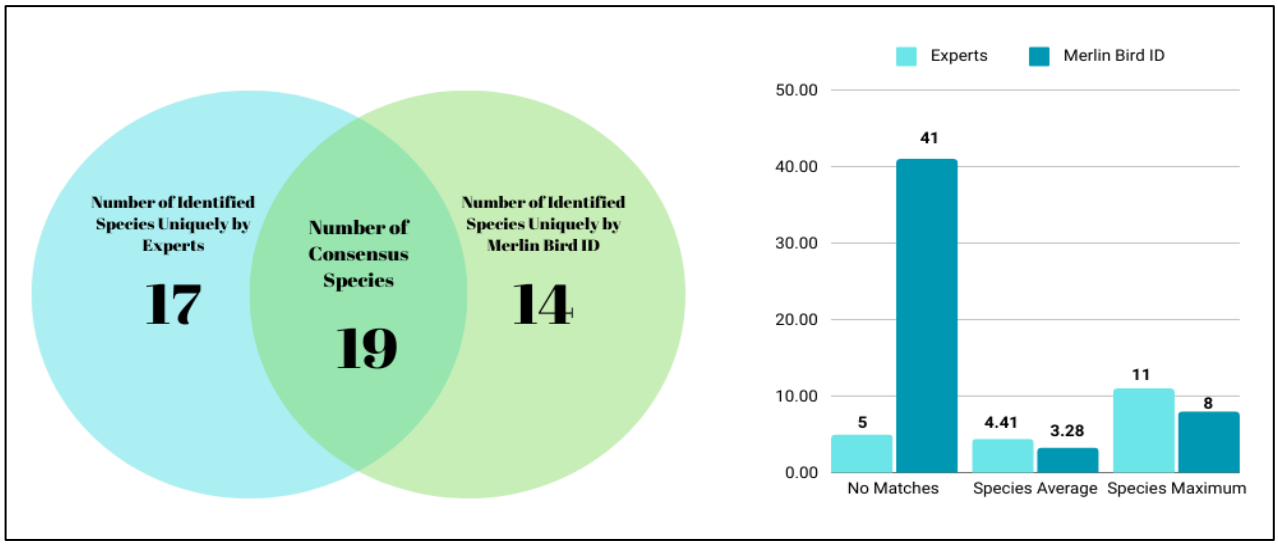


Figure 5.6. Comparison of detection performance of experts versus Merlin Bird ID.

Additionally, bird species detected by two expert ornithologists were compared with the previous eBird records from the close proximity (in 5-12 km radius) to Gödence Village. This confirmed that experts were able to identify almost 50 percent of the species recorded in the eBird lists, by only listening and inspecting sound recordings, especially in summer and fall seasons. Eliminating the mostly "silent" species that rarely vocalize in the eBird lists would most likely increase the identifying percentages of the experts in comparison to eBird lists, however this kind of classification was not performed in this study due to time constraints. Numerical comparison is provided in Table 5.6 below.

Table 5.6. Comparison of the number of identified species by experts with the eBird records.

Season	Number of bird species from eBird entries	Number of species identifed by experts that was matched on eBird lists	Match percentage	Number of identified species only by the experts that were not listed in eBird
Fall	36	17	47.2	9
Winter	52	18	34.6	2
Spring	95	22	23.2	6
Summer	14	7	50	10

6. DISCUSSION

Acoustic indices are emerging tools with considerable potential for tracking changes in ecosystems and biodiversity. However, there is still a need for the evaluation of their performance and sensitivity in different habitats and under different acoustic conditions (Ross et al., 2021). The present study aimed to evaluate the performance of the five commonly used acoustic indices for representing bird species richness in an understudied Mediterranean agroecological farmland context.

Manual inspections of recordings by the experts were the main reference for ground-truthing our findings with respect to the bird species richness in this study. Two experts with substantial experience and expertise in the identification of bird species evaluated about 15 hours of "cleaner" recordings. Their findings were checked to evaluate whether detected bird species were in line with the ecologically expected daily and seasonal patterns of bird vocalizations in temperate regions (Bruni et al., 2014): Identified bird species richness was higher a few hours before and after sunrise and sunset, i.e. in dawn and dusk choruses, especially for spring. We observed that the peak number of detected species was always around sunrise and high numbers of species continued for a few hours during the dawn chorus in line with the literature (Budka et al., 2023). The number of species generally decreased until a few hours before sunset and drastically dropped for the hours after sunset. In addition, comparison of the expert detections with eBird lists showed that the experts were able to identify up to 50 percent of the bird species in a soundscape by just listening to the acoustic data recorded. In fact, if rarely vocalizing "silent" bird species were excluded from the eBird lists, detection percentage would most probably go up substantially.

For seasonal changes, spring is the season for the temperate regions to have the highest number of distinct species since migratory birds pass through or breed in these regions at this season. This was also reflected in our data where the maximum number of species detected by the experts for this season in different hours was eight, while it was six for all other seasons. Similarly, due to constant cicada vocalizations in summer, the number of recordings during the day with clear bird vocalizations were relatively low. There were either none or a few species that could have been detected except dawn and dusk choruses in the summer. Those findings seem to support our expectations that the recordings were good enough to detect various species and experts were qualified enough to detect them through the recordings.

The findings revealed that the acoustic indices performed better when the vocalizations of the focal taxa in the recordings had minimal disturbance from other (non-focal) acoustic sources. For instance, dawn and dusk chorus recordings when weather conditions were favorable delivered index values that were closely associated with higher species richness. This was in line with the findings of Budka et al., (2023) who reported that in the temperate regions, bird species richness correlates positively with the acoustic indices in habitats with low anthropogenic noise and where birds are the main vocalizing species.

When general patterns were investigated for the entire dataset in terms of the highest and lowest acoustic index values, the following patterns emerged, in line with the literature: i) ADI and AEI were inversely related to each other, as expected. ii) Positive NDSI values close to +1 were indicative of dominant biophony in the study area in line with the expectations. iii) Both ACI and BI had increasing trends in winter and spring with respect to bird species richness, and ACI also had an increasing trend in summer. These general trends in data were matching with the general patterns described by (Bradfer-Lawrence et al., 2019) suggesting that ACI and BI may be good proxies for bird species richness. I carried out further statistical analyses to confirm these preliminary observations statistically.

When correlations were investigated between acoustic indices and bird species richness, I found that BI and ACI performed better than the other indices under investigation in this study: Index values of BI and ACI exhibited significantly positive correlations with the bird species richness when the recordings were not grouped. Furthermore, these two were still positively correlated with bird species richness when the files were grouped according to the different seasons and according to the presence of the different non-focal sound categories. ACI was performing relatively well, even if different non-focal acoustic sources were present. Indeed, the relative insensitivity of the ACI to constant noises was reported in the literature (Ross et al., 2021). ACI was found to have a strong positive correlation with bird species richness even under cicada interference. Positive correlations between bird species richness and BI and ACI had been reported in several studies so far such as Boelman et al. (2007), Eldridge et al. (2018), Galappaththi et al. (2024), Hilje et al. (2017), and our findings were in parallel to them. The strength of the correlations in the present study was in general moderate, around 0.3 in line with the literature for temperate regions (Alcocer et al., 2022; Budka et al., 2023), except for the summer recordings where correlations were relatively higher at about 0.5-0.7. Whether this is related to the small sample size (several files were removed from the subsample because of the heavy

presence of cicada vocalizations) and/or the higher quality of the remaining files in terms of bird vocalizations needs to be further investigated.

Interestingly, the fall season did not exhibit significant correlations with any of the acoustic indices. To understand the ecological foundation behind this pattern, the subsample of files for the fall season were manually inspected. This inspection revealed that bird vocalizations were often only present in a designated limited time frame of the recordings (e.g. the first few seconds of the 5-min recording or a few seconds in the middle of the 5-min recording, etc.) leaving the rest of the spectrogram quite silent. In addition, most of the vocalizations were calls rather than songs of the birds, which is often equivalent to only a short duration in a soundscape, which was enough to detect the species by manual listening, yet not intense enough to increase the calculated acoustic index values dramatically. Therefore, when the correlations between bird species richness and acoustic index values were checked for the fall season, increasing number of bird species was not found to be significantly correlated with a higher acoustic index value.

ADI and AEI were not correlated with bird species richness, neither with respect to different seasons, nor to other sonic categories. Similarly, NDSI was not found to be correlated with bird species richness in general, nor did it exhibit any significant correlations for different seasons. Yet, when the data were manually filtered to include only clear bird vocalization without any disturbance from non-focal sounds, NDSI exhibited a significant positive correlation. However, it has to be noted that expanding the sample size (the number of observations in the subsample) could still change the performance of NDSI, ADI and AEI.

The findings suggest that BI and ACI are better-performing acoustic indices as proxies for bird species richness in Mediterranean farmlands and, therefore, could be helpful in similar habitats. However, BI was more sensitive to the presence of cicada vocalizations in the summer and moderate wind, while ACI was relatively insensitive to non-focal sounds such as cicadas/insects, and mild and moderate wind. Yet, this does not suggest that ACI is to be preferred over BI; as the literature recommends, utilizing multiple acoustic indices for the same habitat should be prioritized (Bradfer-Lawrence et al., 2020). Researchers need to use them in combination in order to better characterize the different daily and seasonal patterns as well as to be able to interpret the impacts of different non-focal sounds. For instance, the inspection of the entire dataset for the highest and lowest values in our dataset was very illuminating. BI values were high during dawn and dusk chorus; however, higher values were also achieved when only cicadas were present in the environment. Negative NDSI values

were yielded when there was strong geophonic noise even though no anthrophony was present. Therefore, it is very important to caution that applying acoustic indices without ground-truthing through manual inspection and listening and perhaps also through automated tools of bird identification may deliver inconsistent findings. Moreover, in line with (Ross et al., 2021), we found it valuable to evaluate both performance (how do they perform for capturing bird species richness in general?) and sensitivity (how do they perform in the presence of different non-focal sound categories?) of acoustic indices.

In this context, automated identification tools seem to be practical tools to quickly detect the species in a recording. In fact, Merlin Bird ID had similar patterns with the experts both in the identity and the average number of detected species. However, in comparison with the expert ornithologists' findings, the number of files returning no matches by Merlin Bird ID was relatively high. This indicated that performance of the automated detection tools is good enough for a quick inspection, but there is still room for further improvement before relying on them as perfect measures of species diversity.

Overall, the present study was one of the first attempts of utilizing acoustic indices for monitoring farmland avian biodiversity in Türkiye. I tested about 15 hours of recordings for their performance and sensitivity and found that there was value of using them, especially the indices BI and ACI, as cost-effective and quick proxies of bird species richness in a Mediterranean agroecological farmland context where human interference is minimal due to the extensive agricultural practices adopted. I contributed to the growing field of acoustic indices by studying an under-investigated region and habitat so far in the literature, adopting state-of-the-art, best-practice recommendations in passive acoustic monitoring. However, it has to be noted that the field of acoustic indices is relatively young and still developing, hence, specific standards of applying them are still being developed by researchers and practitioners worldwide. Further studies are therefore needed to evaluate them in different habitats and land use contexts worldwide.

Moreover, acoustic indices are potent and relatively inexpensive tools to evaluate agricultural policy (such as agri-environment schemes, rewilding and restoration of agricultural areas) and different farming practices (conventional, organic, agroecological, etc.), yet this potential has not been utilized widely so far (Abrahams, 2021). Farmland biodiversity monitoring can also be carried out, via passive acoustic monitoring and acoustic indices, relatively easily for long-term projects of conservation organizations for evaluating the ecological impacts of their conservation measures (e.g. biodiversity- and wildlife-friendly farming practices) in farmlands, such as the impacts of

windbreaks, direct-drilling, live fences, etc. on biodiversity in and around farmlands. These may be used for convincing the policy-makers to support farmers for more biodiversity-friendly practices through agri-environment schemes and subsidies. Farmland bird species are still not extensively documented in Türkiye, yet alone to develop tailor- made conservation schemes for them. Therefore, acoustic monitoring in farmlands could both contribute and benefit from a clear documentation of farmland avian species to monitor these species in the long term. In the future, species listed in the present study could be used for the Mediterranean farmland bird species.

7. CONCLUSION

This study was, to the best of my knowledge, one of the first studies in Türkiye, using the novel method of acoustic indices for evaluating farmland avian biodiversity. Most of the findings were in parallel with the general empirical results of the acoustic indices in the literature. As such, the study confirmed that acoustic indices, emerging tools for biodiversity monitoring, can provide quick assessments for the diversity of vocalizing species in a soundscape. Given the accelerating pace of climate crisis, biodiversity loss and increasing international regulations on nature conservation, more and more biodiversity tracking tools will be needed, and acoustic indices may fill in that gap with their potential on long-term monitoring applications. However, their effectiveness in different habitats and sonic compositions are still far from well-understood. Therefore, the study confirmed that it is important to evaluate their performance and sensitivity under different conditions, and carried out these analyses for an agroecological farmland in Izmir, Seferihisar.

The present study focused on the evaluation of five widely-used acoustic indices in an agroecological farmland in the Mediterranean region, one of the 36 global biodiversity hotpots, and as such very valuable in terms of conservation of biodiversity. Farmlands are so far understudied habitats for acoustic indices (Abrahams, 2021). Utilizing and evaluating acoustic indices in farmlands is especially important to reveal how agricultural production is impacting or interacting with the biodiversity around them. The present study found that BI and ACI may perform better for bird species richness in this given habitat under investigation in this study, while NDSI, ADI and AEI were relatively less useful for understanding the distinct patters in the study area. The findings of the present study can also support evaluations regarding different types of agricultural practices (such as conventional versus organic versus agroecological), and biodiversity before and after a specific change in the agri-environmental practice (such as direct drilling, wind breaks, live fences, no tilling, etc.).

When different time frames and sonic compositions were considered, it can be concluded that dawn and dusk chorus recordings, especially in the spring season, and recordings with minimal disturbances from geophony and non-focal biophony made acoustic indices perform better. Employing multiple indices proved that evaluation of the performance of acoustic indices should not solely depend on a single index. Hence, based on the best performing indices, the most suitable acoustic indices for a given study area can be chosen for long-term studies. Similarly, as suggested

in the literature (Bradfer-Lawrence et al., 2019), continuous recording was useful in this study (rather than recording via a pre-defined sampling schedule), as this expands the opportunities for further in-depth analyses of the recordings, at least for the exploratory studies in a soundscape to understand the sonic characteristics better. Subsampling can always be done after continuous recording, based on the research questions and specific needs of the study area.

Ground-truthing of the findings via manual listening to the recordings (as well as through automated identification app) proved to be a valuable practice . While manual identification requires substantial expertise and is a very time-consuming process, automated species identification tools seemed like good complementary practice for overcoming these issues in the manual inspection. However, our results show that the number of files where the automated tool missed specific bird vocalizations was relatively high. Thus, the use of automated species identification tools should also be carried out with caution. However, there is very rapid technological development potential for these automated tools in the future which may improve the reliability of these tools quite quickly.

In this study, evaluation of acoustic indies in a farmland habitat delivered important insights for the use and performance of the acoustic indices. However, many research possibilities are still available that were beyond the scope of the present study. New analysis perspectives could expand the knowledge gained from this study with the same data. Even further, several different directions and approaches could be taken for acoustic monitoring and acoustic indices analysis, especially in the understudied Mediterranean farmlands. Below I provide some more ideas for further studies in the region. These recommendations also highlight the limitations in the present study:

- The analysis may be complemented with point counts, and the two methods (point counts and acoustic monitoring) can be compared in the same habitat/study area.
- Another alternative is to compare different landscape properties. Additional data on environmental, topographic, ecological, and farmland specific variables could be considered in the analysis, and their impact on acoustic index values could be assessed (Similar to Myers et al., 2019).
- Enlarging the sample size (the bottleneck here is the time and effort for manual listening to recording) could enable the researcher to employ more statistical tools, such as ANCOVA and GLMM models (Galappaththi et al., 2024; Myers et al., 2019).
- Different parameters may be compared for the performance of each acoustic index (such as the FFT size and chosen frequency range)

- The set of acoustic indices chosen can be widened; studies can be carried out at more recording points and locations; or time series data (long-term monitoring over several years) could be collected and analyzed.

In conclusion, acoustic indices are potent tools for tracking changes in ecosystems such as farmlands through vocalizing bird species. However, their performance and sensitivity in the chosen habitat should be considered to understand suitable acoustic indices for the study area. This can enable researchers and conservation practitioners to use acoustic indices effectively for conservation decisions.

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APPENDIX A: SOME PROPERTIES OF SOUND RELEVANT TO CALCULATON OF ACOUSTIC INDICES

The sound itself is basically a wave signal traveling over time. It is represented as a sinusoidal wave, so it has **peak** and **trough** points in oscillations. The length between two peaks (or two troughs) of a sinus wave is the **wavelength**, whereas the height of the peaks in the wave is the **amplitude**. All these terms are visualized in Figure A.1 below.

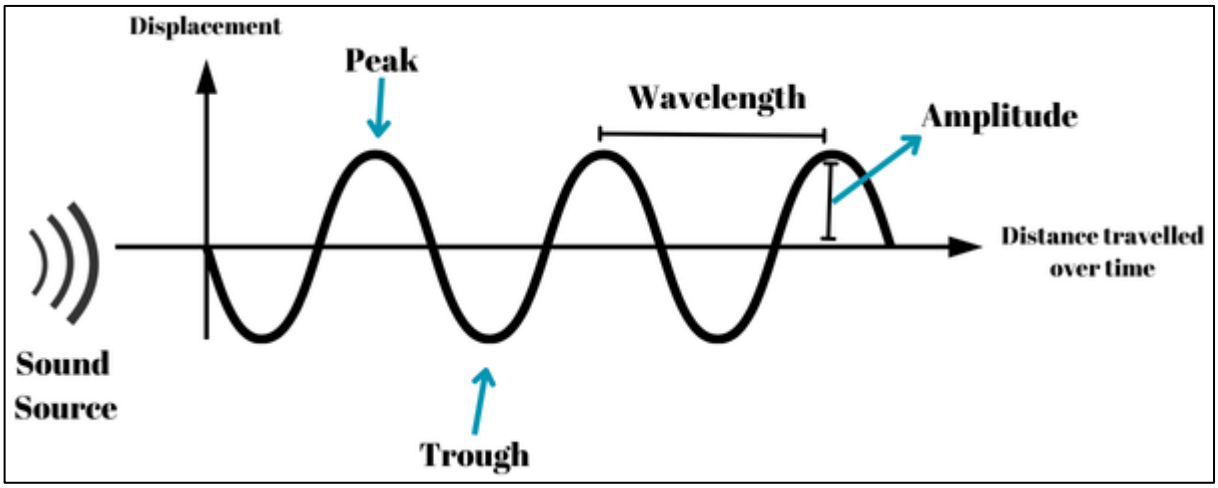


Figure A.1. Representation of a sinusoidal sound wave.

The measure of the amplitude gives the **intensity** of the sound. The intensity of the sound measured in **decibels** (**dB** in short). Decibel scale is determined based on a reference point which corresponds to the minimum amplitude of sound waves in a recording. Reference point is equivalent to the 0 dB while all the other intensities, would have minus dB values based on the relative difference between the reference point. Decibel is a log10 function of the amplitude value. The higher the decibel value means the louder the acoustic source gets.

The amplitude of a sound wave decreases further than the source due to **attenuation** in the medium. Attenuation is also dependent on frequency of the sound wave while high frequency sounds are absorbed more in the environment. The low frequency sounds therefore can travel a longer distance. **Frequency** which is measured in **Hertz** (**Hz** in short) is the number of waves repeated (see Figure A.2) on the environment where sound is propagated. Frequency can also be defined as the inverse of the **period** which is defined as the time passed for the wave to complete one oscillation.

Based on the frequency in acoustics, sounds can be categorized by **pitch**. Low-pitched sounds are deeper whereas high-pitched sounds are sharper or more treble. The pitch of the sound is more of a perceptual concept but in general the higher the frequency will result in a higher experienced the pitch.

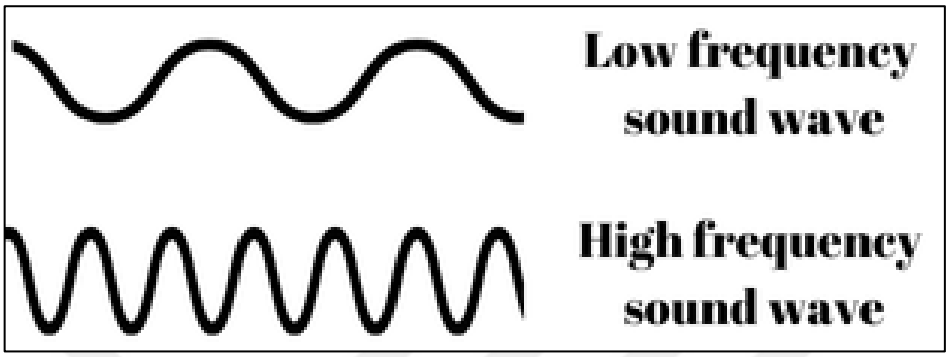


Figure A.2. Representation of low and high frequencies.

The **spectrogram** is a visual representation of sound recordings. It shows the frequency of sound over time. Louder sounds will have more intensity; therefore, they will be represented with a brighter color. The sounds with lower amplitude, thus the lower intensity, will be captured as quieter signals. Hence, they will be represented by darker colors. In a spectrogram, lower frequency sounds are placed at the bottom, while higher frequency sounds are at the top. Spectrograms are visual aids to see the sound and to understand how it is divided along different axis and used in the calculations of the acoustic indices. The horizontal grouping in a spectrogram would be considered as a **frequency band**, while the vertical section in a spectrogram is called **frequency bins** (**temporal steps**). These categorizations are visualized in Figure A.3 below.

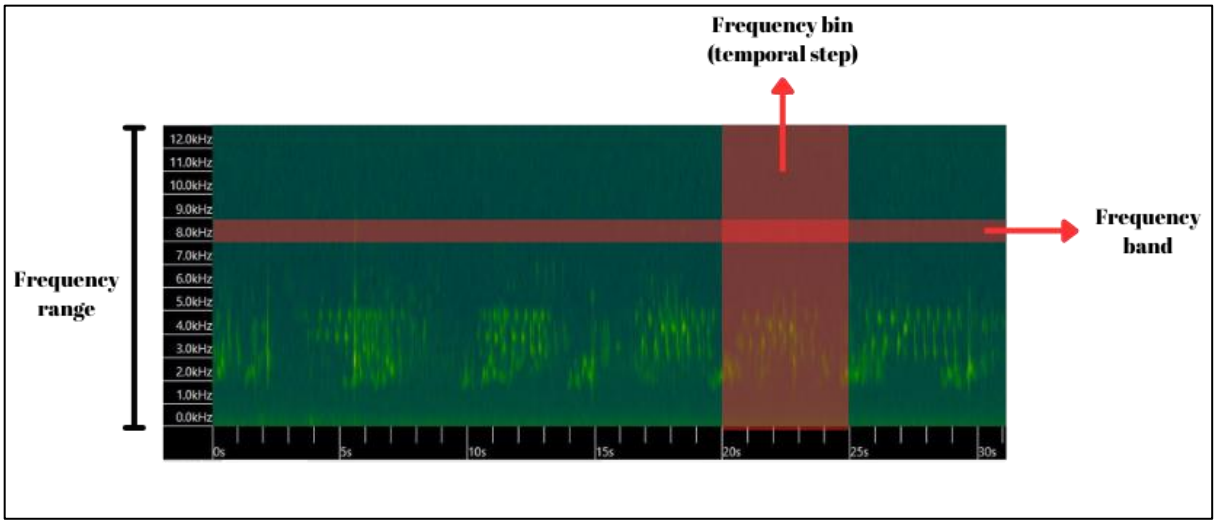


Figure A.3. A spectrogram with frequency range, band and bin.

To convert sound waves to images a transformation function is required. **Fast Fourier Transform (FFT)** is the set of mathematical equations. FFT basically looks for how many peaks are in a frequency versus amplitude graph. If there is a peak in this graph there will be a mark for that sound propagated in that frequency. The higher the peak the more intense the sound will be shown in the graph. **FFT size** determines how many sample points will be analyzed at a time to decide the representation of the sound during this transformation. Therefore, FFT size is a compromise between **frequency resolution** and **time resolution**. The larger FFT size gives a more precise frequency value, but it takes longer to execute which could be a drawback in the data analysis process or especially in real time applications it could result in a delay.

Since the sound signals have peak and through points in a cycle, the sample rate should be twice as the peak amplitude of a sound wave to capture the full signal. Therefore, frequencies only up to half of the sample rate can be captured in a sound recording. The maximum frequency that can be captured by the chosen sample rate is called **Nyquist frequency**.

Lastly, a **power curve** shows the frequencies against the amplitudes of the sound waves as represented in Figure A.4. This is a representation of the energy carried by the sound wave or the power of the sound in the environment. Decibel values correspond with the sounds on each frequency band represented in this curve, but the decibel values are minus since they are based on the amplitude difference between the signal with the minimum peak. Therefore, to exclude some louder sounds a dB threshold can be chosen.

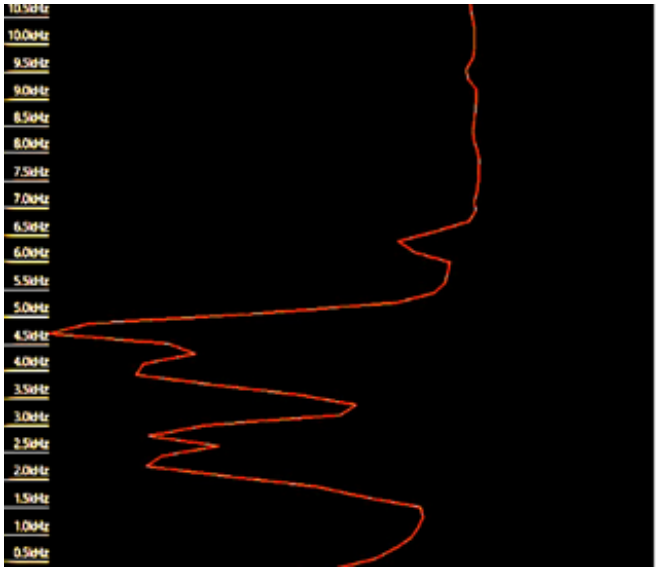


Figure A.4. A power curve based on a spectrogram.

APPENDIX B: RECORDING DEVICE, ADDITIONAL COMPONENTS AND COMPLEMENTARY APPS

AudioMoth is a pocket-size, lightweight sound recorder, as represented and compared with a smartphone in Figure B.1. It is suitable for many acoustic monitoring schemes in terrestrial environments and has a variant (Hydromoth) for marine applications. Each AudioMoth requires three AA batteries for the power supply and one microSD card to save the sound recordings. Detailed technical features of AudioMoth are given in Table B.1.



Figure B.1. AudioMoth Recorder (top-left), waterproof case (bottom-left), and a smartphone (right) for the size comparison with a ruler in centimeters at the left edge.

The recorders themselves are not waterproof. Therefore, we additionally ordered the original protective cases (also shown in Figure B.1) to protect the devices against rain, dust, and other sources of damage from the environment. Since we recorded in different seasons, the waterproof cases were beneficial in multiple ways. They partially masked the noise from strong winds in fall, protected electronic components against rainwater leakage in winter, provided a better camouflage between leaves in spring, and covered the recorders from direct sunlight to some extent in summer. There are also some alternatives to original waterproof cases with a varying degree of protection. In similar applications basic zip lock bags are also used where deployment periods were shorter. There were also more advanced solutions such as 3D printing custom cases, however those tailored solutions were beyond our expertise and budget of the current study. Hence, the original waterproof cases gave us reliable enough protection with minimal additional work.

Table B.1. Technical details of AudioMoth.

Sample rate options	8-16-32-48-96-192-250-384 kHz
Recording file type	Uncompressed .wav format
Data Saving	On microSD card
Power	3 AA batteries (suitable for rechargeable batteries as well)
Microphone	Analog MEMS
Processor	EFM32 Gecko
Size	58 x 48 x 15 mm
Weight	~23 gr (without accessories, batteries, and microSD card)
Configuration	On Free PC App via Micro-USB connection
Amplification and filtering	Analog pre-amplifier with adjustable gain
Time registry	The onboard real-time clock keeps track of time in UTC
Additional microphone	Exposed header for 3.5 mm jack microphone (from version 1.2.0 onwards)

We used rechargeable AA batteries to minimize battery waste. The highest-capacity (2,500 mAh) rechargeable batteries available on the consumer market of Türkiye at the time of this study were chosen to maximize the number of recording days. Batteries were discharged and stored between the deployments. Before each field visit, batteries are charged, and each battery's charge percentage is inspected to ensure they are working correctly. This minimized any malfunctioning risk due to the faulty batteries. Batteries and chargers are shown below in Figure B.2.



Figure B.2. Rechargeable batteries and the charger with the charge percentage indication.

Higher data writing speed was an essential criterion for selecting the memory cards. In the user manual of AudioMoth faster cards are recommended for higher sampling rates than 48 kHz (Open Acoustic Devices, 2022). Yet, our sampling rate was 48 kHz, therefore Class 10 type microSD cards were sufficient for our study. We chose SanDisk Ultra (Red-Grey variant) microSD cards as shown in Figure B.3 to have a balance between the limits of our study budget and reliable performance. We recorded the soundscape in 4 different seasons, where Fall was our first deployment. For Fall, we used 32 GB cards. However, we needed more storage for our deployment duration, so we replaced them with 64 GB cards.



Figure B.3. The chosen microSD card model.

During deployments, a sturdy point should be selected to attach the recorders. For this reason, the additional weight of accessories should also be considered. Therefore, the weight of five AudioMoths was measured separately, with and without all these accessories. Then, the average values were taken from each combination of the device and its accessories. These values are given below in Table B.2.

Table B.2. Average weight measurements of five AudioMoths with and without accessories.

Weighted Items (n:5)	**Mean Weight ± Standard Deviation (g)**
AudioMoth	22.6 ± 0.4
Waterproof Case	59.1 ± 0.2
Memory Card (microSD)	0.3 ± 0.1
Rechargeable AA Batteries (x3)	88.9 ± 0.1
AudioMoth + Batteries + microSD Card	111.8 ± 0.5
AudioMoth + Batteries + microSD Card + Waterproof Case	170.9 ± 0.4

Several complementary apps were used for programming AudioMoths, for their maintenance for configuring them during deployments and for splitting the recordings afterwards. The first of these is the AudioMoth Flash App on PC. This app was used for updating our devices to the latest possible

firmware. New updates generally offered more flexibility in recording settings or solved some frequent recording issues. Therefore, we kept our devices up-to-date to benefit from the full potential of the recorders. Before every deployment, we connected them via micro-USB cable to the PC to update the firmware to the latest version available on the AudioMoth Flash App. We used firmware 1.8.1 (shown in Figure B.4), which was the highest version available during our data collection year. Newer versions are released frequently with more capabilities. Currently (November 2024), the latest version is 1.10.1, and it has additional features such as adding location to metadata with the help of the AudioMoth Chime mobile app or setting relative sunrise and sunset times. However, these features were not available during our data collection period, hence, not employed in this study.

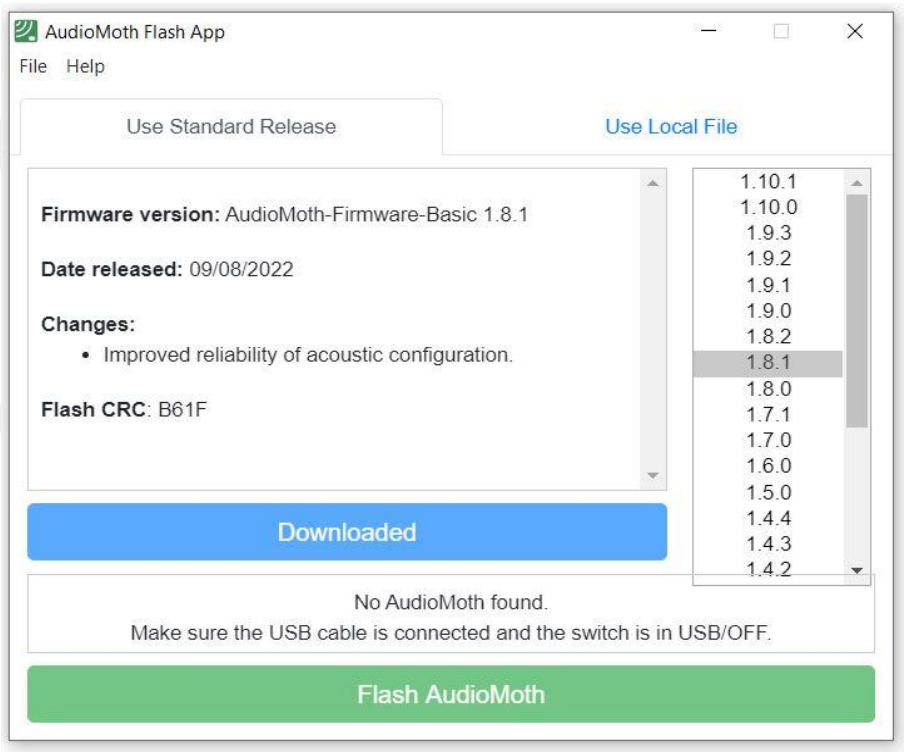


Figure B.4. The interface of the AudioMoth Flash App shows version 1.8.1.

AudioMoth has two recording modes: (1) the CUSTOM mode, which operates on a predetermined manually uploaded recording schedule, or (2) the DEFAULT mode, which records right after switching the recorder on. In our study, all recordings are taken in CUSTOM mode, which requires configuration. The second and maybe the most detailed app employed in this study was served for this purpose: the AudioMoth Configuration App on PC. We used this one to set up the following recording properties: sampling rate, gain, and daily recording schedule. We also chose two additional options in the advanced settings given in Figure B.5: (1) NiMH battery indication due to the use of rechargeable batteries and (2) the requirement for an acoustic chime in CUSTOM mode,

so we could start recording by playing an encoded chime from the mobile app on the field. According to the selected recording properties and schedule, this app estimates the daily energy consumption, number of generated files, and approximate daily total size of the files. This feature helped us to decide how many days we could deploy the recorders on the field without running out of battery or memory. When a device is connected to the PC while the configuration app is running, it is also possible to see the current configurations of the device, local time and date settings, unique device ID, firmware version, and battery level. This app also provides more possibilities for recording settings, such as adding sleep-start cycles, frequency triggers or band-pass filters, and other advanced options for several applications. However, we did not need to apply these options in our study. Last but not least, the Configuration App also has the feature to split long AudioMoth recordings into shorter files. We used this feature to split our one-hour or longer recordings into 5-minute files.

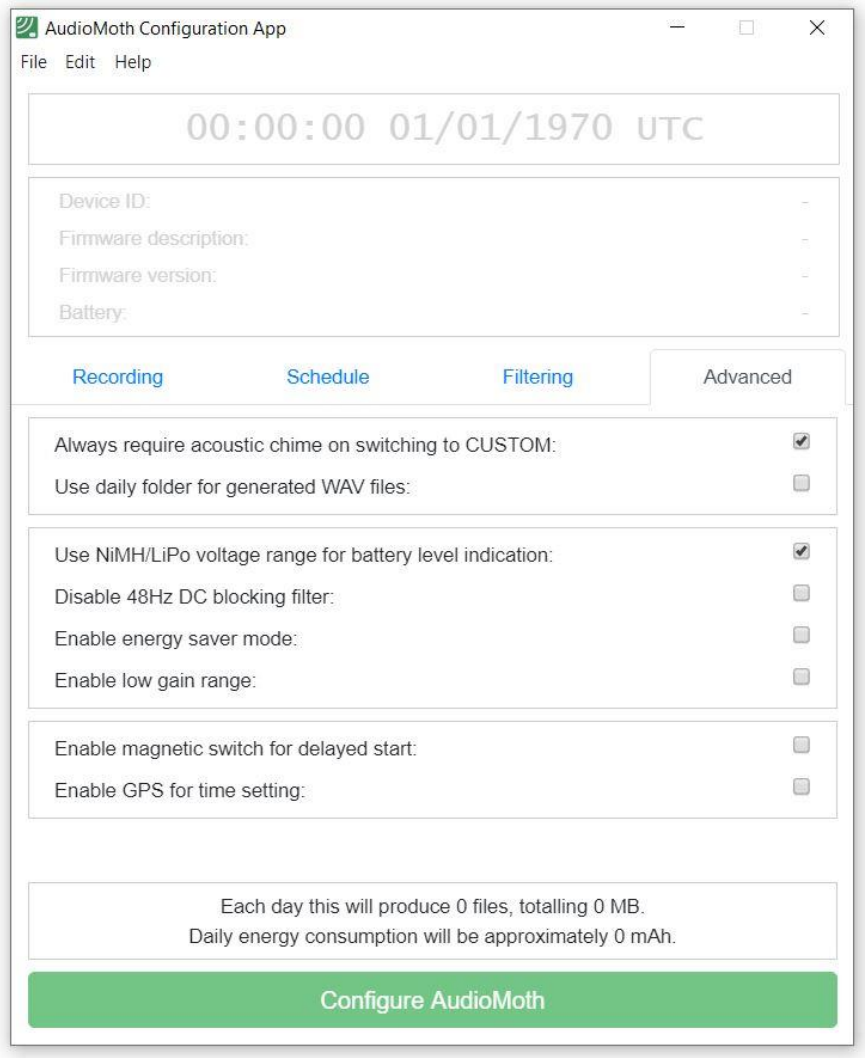


Figure B.5. The Advanced Pane of the AudioMoth Configuration App with additional settings.

Once the configurations were done, the devices were ready to record in CUSTOM mode. However, we preferred to activate the recorders with an acoustic chime option to ensure they record in local time. The mobile AudioMoth Chime App is used via a smartphone for this purpose. When devices were set to CUSTOM mode, the LED light under the power-off switch started to blink. This indicated that the recorder was expecting an audio trigger to start recording. The specific local-time-encoded melody can be played via the mobile app (interface is shown in Figure B.6) or on the browser if downloading the app is not preferred. This chime trigger was a secondary caution to ensure that devices were recorded according to the correct time zone. Even if the local time would set wrong on configuration app by mistake, the issue would be fixed on the field via the Chime app. Also, in the app's current version, the location data from the phone could be optionally sent in the encoded chime. Unfortunately, this feature wasn't available during our study, so we manually noted the GPS locations.



Figure B.6. The interface of the AudioMoth Chime mobile app.

APPENDIX C: BIRD SPECIES AROUND THE STUDY AREA LISTED FROM EBIRD

In these lists, all the bird species entered in eBird from the data points around Gödence Village was collected. Detected species on this study cross-checked with the eBird lists for each season. Species detected by manual inspections in this study without a prior record on eBird for the corresponding season were noted in a separate table below the checklists of each season.

Table C.1. Fall checklist comparing eBird records with the identified species by the experts.

Scientific Name	**English Name**	**Turkish Name**	**Check**
Accipiter nisus	Eurasian Sparrowhawk	Atmaca	
Aegithalos caudatus	Long-tailed Tit	Uzunkuyruklu baştankara	x
Buteo buteo	Common Buzzard	Şahin	
Carduelis carduelis	European Goldfinch	Saka	x
Certhia brachydactyla	Short-toed Treecreeper	Bahçe tırmaşıkkuşu	x
Chloris chloris	European Greenfinch	Florya	x
Circaetus gallicus	Short-toed Snake-Eagle	Yılan kartalı	
Columba livia	Rock Pigeon (*)	Kaya güvercini	
Corvus corax	Common Raven	Kuzgun	
Corvus cornix	Hooded Crow	Leş kargası	
Curruca melanocephala	Sardinian Warbler	Maskeli ötleğen	x
Cyanistes caeruleus	Eurasian Blue Tit	Mavi baştankara	x
Dendrocopos syriacus	Syrian Woodpecker	Alaca ağaçkakan	x
Dryobates minor	Lesser Spotted Woodpecker	Küçük ağaçkakan	
Emberiza calandra	Corn Bunting	Tarla kirazkuşu (çintesi)	
Emberiza cia	Rock Bunting	Kaya kirazkuşu (çintesi)	
Emberiza cirlus	Cirl Bunting	Bahçe kirazkuşu (çintesi)	x
Erithacus rubecula	European Robin	Kızılgerdan	x
Fringilla coelebs	Common Chaffinch	İspinoz	x
Garrulus glandarius	Eurasian Jay	Alakarga	x
Motacilla alba	White Wagtail	Ak kuyruksallayan	
Motacilla cinerea	Gray Wagtail	Dağ kuyruksallayanı	
Muscicapa striata	Spotted Flycatcher	Benekli sinekkapan	
Parus major	Great Tit	Büyük baştankara	x
Passer domesticus	House Sparrow	Serçe	
Periparus ater	Coal Tit	Çam baştankarası	x
Phoenicurus ochruros	Black Redstart	Kara kızılkuyruk	x
Phylloscopus collybita	Common Chiffchaff	Çıvgın	x
Phylloscopus trochilus	Willow Warbler	Söğütbülbülü	x
Sitta krueperi	Krüper's Nuthatch	Anadolu sıvacısı	
Sitta neumayer	Western Rock Nuthatch	Kaya sıvacısı	

Table C.1. Continued.

Streptopelia decaocto	Eurasian Collared-Dove	Kumru	
Sturnus vulgaris	European Starling	Sığırcık	
Sylvia atricapilla	Eurasian Blackcap	Karabaşlı ötleğen	
Turdus merula	Eurasian Blackbird	Karatavuk	x
Turdus philomelos	Song Thrush	Öter ardıç	
TOTAL:		36	17

Table C.2. Additional species identified by the experts in Fall.

Scientific Name	**English Name**	**Turkish Name**
Dendrocopos major	Great Spotted Woodpecker	Orman alaca ağaçkakanı
Dendrocoptes medius	Middle Spotted Woodpecker	Ortanca ağaçkakan
Ficedula parva	Red-breasted Flycatcher	Küçük sinekkapan
Hirundo rustica	Barn Swallow	Kır kırlangıcı
Lullula arborea	Woodlark	Orman toygarı
Luscinia luscinia	Thrush Nightingale	Benekli bülbül
Merops apiaster	European Bee-eater	Arıkuşu
Serinus serinus	European Serin	Küçük iskete
Periparus ater	Coal Tit	Çam baştankarası
TOTAL:		9

Table C.3. Winter checklist comparing eBird records with the identified species by the experts.

Scientific Name	**English Name**	**Turkish Name**	**Check**
Accipiter nisus	Eurasian Sparrowhawk	Atmaca	
Aegithalos caudatus	Long-tailed Tit	Uzunkuyruklu baştankara	x
Asio otus	Long-eared Owl	Kulaklı orman baykuşu	
Athene noctua	Little Owl	Kukumav	
Buteo buteo	Common Buzzard	Şahin	
Carduelis carduelis	European Goldfinch	Saka	x
Certhia brachydactyla	Short-toed Treecreeper	Bahçe tırmaşıkkuşu	x
Chloris chloris	European Greenfinch	Florya	x
Circus cyaneus	Hen Harrier	Gökçe delice	
Coccothraustes coccothraustes	Hawfinch	Kocabaş	
Columba livia	Rock Pigeon	Kaya güvercini	
Columba palumbus	Common Wood-Pigeon	Tahtalı	
Corvus corax	Common Raven	Kuzgun	
Corvus cornix	Hooded Crow	Leş kargası	
Curruca melanocephala	Sardinian Warbler	Maskeli ötleğen	
Cyanistes caeruleus	Eurasian Blue Tit	Mavi baştankara	x
Delichon urbicum	Western House-Martin	Ev kırlangıcı	
Dendrocopos syriacus	Syrian Woodpecker	Alaca ağaçkakan	x
Dendrocoptes medius	Middle Spotted Woodpecker	Ortanca ağaçkakan	
Dryobates minor	Lesser Spotted Woodpecker	Küçük ağaçkakan	
Emberiza calandra	Corn Bunting	Tarla kirazkuşu (çintesi)	
Emberiza cirlus	Cirl Bunting	Bahçe kirazkuşu (çintesi)	x
Erithacus rubecula	European Robin	Kızılgerdan	x

Table C.3. Continued.

Falco tinnunculus	Eurasian Kestrel	Kerkenez	
Fringilla coelebs	Common Chaffinch	İspinoz	x
Fringilla montifringilla	Brambling	Dağ ispinozu	
Galerida cristata	Crested Lark	Tepeli toygar	
Garrulus glandarius	Eurasian Jay	Alakarga	x
Hirundo rustica	Barn Swallow	Kır kırlangıcı	x
Lullula arborea	Wood Lark	Orman toygarı	x
Motacilla alba	White Wagtail	Ak kuyruksallayan	
Motacilla cinerea	Gray Wagtail	Dağ kuyruksallayanı	
Parus major	Great Tit	Büyük baştankara	x
Passer domesticus	House Sparrow	Serçe	
Passer montanus	Eurasian Tree Sparrow	Ağaç serçesi	
Periparus ater	Coal Tit	Çam baştankarası	x
Phoenicurus ochruros	Black Redstart	Kara kızılkuyruk	
Phylloscopus collybita	Common Chiffchaff	Çıvgın	x
Pica pica	Eurasian Magpie	Saksağan	
Poecile lugubris	Sombre Tit	Akyanaklı baştankara	
Saxicola rubicola	European Stonechat	Taşkuşu	
Scolopax rusticola	Eurasian Woodcock	Çulluk	
Serinus serinus	European Serin	Küçük iskete	x
Sitta europaea	Eurasian Nuthatch	Sıvacı	
Sitta krueperi	Krüper's Nuthatch	Anadolu sıvacısı	x
Streptopelia decaocto	Eurasian Collared-Dove	Kumru	
Strix aluco	Tawny owl	Alaca baykuş	
Sturnus vulgaris	European Starling	Sığırcık	
Sylvia atricapilla	Eurasian Blackcap	Karabaşlı ötleğen	
Turdus merula	Eurasian Blackbird	Karatavuk	x
Turdus philomelos	Song Thrush	Öter ardıç	
Tyto alba	Barn Owl	Peçeli baykuş	
TOTAL		52	18

Table C.4. Additional species identified by the experts in Winter.

Scientific Name	**English Name**	**Turkish Name**
Linaria cannabina	Common Linnet	Ketenkuşu
Spinus spinus	Eurasian Siskin	Karabaşlı iskete
TOTAL:		2

Table C.5. Spring checklist comparing eBird records with identified species by the experts.

Scientific Name	**English Name**	**Turkish Name**	**Check**
Accipiter nisus	Eurasian Sparrowhawk	Atmaca	
Aegithalos caudatus	Long-tailed Tit	Uzunkuyruklu baştankara	
Alectoris chukar	Chukar	Kınalı keklik	
Anthus trivialis	Tree Pipit	Ağaç incirkuşu	
Apus apus	Common Swift	Ebabil	

Table C.5. Continued.

Ardea cinerea	Gray Heron	Gri balıkçıl	
Asio otus	Long-eared Owl	Kulaklı orman baykuşu	
Athene noctua	Little Owl	Kukumav	
Bubo bubo	Eurasian Eagle-Owl	Puhu	
Buteo buteo	Common Buzzard	Şahin	
Caprimulgus europaeus	Eurasian Nightjar	Çobanaldatan	
Carduelis carduelis	European Goldfinch	Saka	x
Cecropis daurica	Red-rumped Swallow	Kızıl kırlangıç	
Cercotrichas galactotes	Rufous-tailed Scrub-Robin	Çalı bülbülü	
Certhia brachydactyla	Short-toed Treecreeper	Bahçe tırmaşıkkuşu	x
Chloris chloris	European Greenfinch	Florya	x
Ciconia nigra	Black Stork	Kara leylek	
Circaetus gallicus	Short-toed Snake-Eagle	Yılan kartalı	
Circus aeruginosus	Western Marsh Harrier	Saz delicesi	
Coccothraustes coccothraustes	Hawfinch	Kocabaş	
Columba livia (Feral Pigeon)	Rock Pigeon (Feral Pigeon) (*)	Kaya güvercini	
Columba palumbus	Common Wood-Pigeon	Tahtalı	
Corvus corax	Common Raven	Kuzgun	
Corvus cornix	Hooded Crow	Leş kargası	
Corvus monedula	Eurasian Jackdaw	Küçük karga	
Cuculus canorus	Common Cuckoo	Guguk	
Curruca cantillans	Eastern Subalpine Warbler	Bıyıklı ötleğen	
Curruca communis	Greater Whitethroat	Akgerdanlı ötleğen	
Curruca crassirostris	Eastern Orphean Warbler	Akgözlü ötleğen	
Curruca curruca	Lesser Whitethroat	Küçük akgerdanlı ötleğen	
Curruca melanocephala	Sardinian Warbler	Maskeli ötleğen	x
Curruca ruppeli	Rüppell's Warbler	Karaboğazlı ötleğen	
Cyanistes caeruleus	Eurasian Blue Tit	Mavi baştankara	x
Delichon urbicum	Western House-Martin	Ev kırlangıcı	
Dendrocopos syriacus	Syrian Woodpecker	Alaca ağaçkakan	x
Dendrocoptes medius	Middle Spotted Woodpecker	Ortanca ağaçkakan	
Egretta garzetta	Little Egret	Küçük ak balıkçıl	
Emberiza caesia	Cretzschmar's Bunting	Kızıl kirazkuşu	
Emberiza calandra	Corn Bunting	Tarla kirazkuşu (çintesi)	
Emberiza cia	Rock Bunting	Kaya kirazkuşu (çintesi)	
Emberiza cirlus	Cirl Bunting	Bahçe kirazkuşu (çintesi)	x
Erithacus rubecula	European Robin	Kızılgerdan	x
Falco eleonorae	Eleonora's Falcon	Ada doğanı	
Falco tinnunculus	Eurasian Kestrel	Kerkenez	
Ficedula albicollis	Collared Flycatcher	Halkalı sinekkapan	
Fringilla coelebs	Common Chaffinch	İspinoz	x
Garrulus glandarius	Eurasian Jay	Alakarga	x
Hippolais olivetorum	Olive-tree Warbler	Zeytin mukallidi	
Hirundo rustica	Barn Swallow	Kır kırlangıcı	x
Iduna pallida	Eastern Olivaceous Warbler	Ak mukallit	x
Lanius collurio	Red-backed Shrike	Kızılsırtlı örümcekkuşu	

Table C.5. Continued.

Lanius minor	Lesser Gray Shrike	Karaalınlı örümcekkuşu	
Lanius nubicus	Masked Shrike	Maskeli örümcekkuşu	
Lanius senator	Woodchat Shrike	Kızılbaşlı örümcekkuşu	
Larus michahellis	Yellow-legged Gull	Gümüş martı	
Linaria cannabina	Eurasian Linnet	Ketenkuşu	x
Lullula arborea	Wood Lark	Orman toygarı	x
Luscinia megarhynchos	Common Nightingale	Bülbül	
Merops apiaster	European Bee-eater	Arıkuşu	
Monticola solitarius	Blue Rock-Thrush	Gökardıç	
Motacilla alba	White Wagtail	Ak kuyruksallayan	
Motacilla flava	Western Yellow Wagtail	Sarı kuyruksallayan	
Muscicapa striata	Spotted Flycatcher	Benekli sinekkapan	
Oenanthe finschii	Finsch's Wheatear	Aksırtlı kuyrukkakan	
Oenanthe melanoleuca	Eastern Black-eared Wheatear	Karakulaklı kuyrukkakan	
Oenanthe oenanthe	Northern Wheatear	Kuyrukkakan	
Oriolus oriolus	Eurasian Golden Oriole	Sarıasma	
Otus scops	Eurasian Scops-Owl	İshakkuşu	
Parus major	Great Tit	Büyük baştankara	x
Passer domesticus	House Sparrow	Serçe	x
Periparus ater	Coal Tit	Çam baştankarası	x
Phalacrocorax carbo	Great Cormorant	Karabatak	
Phoenicurus ochruros	Black Redstart	Kara kızılkuyruk	
Phylloscopus collybita	Common Chiffchaff	Çıvgın	x
Phylloscopus trochilus	Willow Warbler	Söğütbülbülü	
Pica pica	Eurasian Magpie	Saksağan	
Poecile lugubris	Sombre Tit	Akyanaklı baştankara	x
Saxicola rubicola	European Stonechat	Taşkuşu	
Serinus serinus	European Serin	Küçük iskete	x
Sitta neumayer	Western Rock Nuthatch	Kaya sıvacısı	
Spilopelia senegalensis	Laughing Dove	Küçük kumru	
Streptopelia decaocto	Eurasian Collared-Dove	Kumru	
Streptopelia turtur	European Turtle-Dove	Üveyik	
Strix aluco	Tawny Owl	Alaca baykuş	
Sylvia atricapilla	Eurasian Blackcap	Karabaşlı ötleğen	
Sylvia borin	Garden Warbler	Boz ötleğen	
Tachymarptis melba	Alpine Swift	Akkarınlı ebabil	
Tadorna ferruginea	Ruddy Shelduck	Angıt	
Troglodytes troglodytes	Eurasian Wren	Çitkuşu	x
Turdus merula	Eurasian Blackbird	Karatavuk	x
Turdus philomelos	Song Thrush	Öter ardıç	
Turdus torquatus	Ring Ouzel	Boğmaklı ardıç	
Turdus viscivorus	Mistle Thrush	Ökse ardıcı	
Tyto alba	Barn Owl	Peçeli baykuş	
Upupa epops	Eurasian Hoopoe	İbibik	
TOTAL		95	22

Table C.6. Additional species identified by the experts in Spring.

Scientific Name	**English Name**	**Turkish Name**
Galerida cristata	Crested Lark	Tepeli toygar
Phoenicurus ochruros	Black Redstart	Kara kızılkuyruk
Regulus ignicapilla	Common Firecrest	Sürmeli çalıkuşu
Sitta krueperi	Krüper`s Nuthatch	Anadolu sıvacısı
Spinus spinus	Eurasian Siskin	Karabaşlı iskete
Sylvia cantillans	Subalpine Warbler	Bıyıklı ötleğen
TOTAL		6

Table C.7. Summer checklist comparing eBird records with the identified species by the experts.

Scientific Name	**English Name**	**Turkish Name**	**Check**
Apus apus	Common Swift	Ebabil	
Carduelis carduelis	European Goldfinch	Saka	x
Cecropis daurica	Red-rumped Swallow	Kızıl kırlangıç	
Curruca melanocephala	Sardinian Warbler	Maskeli ötleğen	x
Cyanistes caeruleus	Eurasian Blue Tit	Mavi baştankara	x
Dendrocopos syriacus	Syrian Woodpecker	Alaca ağaçkakan	x
Erithacus rubecula	European Robin	Kızılgerdan	
Garrulus glandarius	Eurasian Jay	Alakarga	x
Hirundo rustica	Barn Swallow	Kır kırlangıcı	x
Passer domesticus	House Sparrow	Serçe	
Passer hispaniolensis	Spanish Sparrow	Söğüt serçesi	
Poecile lugubris	Sombre Tit	Akyanaklı baştankara	
Streptopelia decaocto	Eurasian Collared-Dove	Kumru	
Turdus merula	Eurasian Blackbird	Karatavuk	x
TOTAL	14		7

Table C.8. Additional species identified by the experts in Summer.

Scientific Name	**English Name**	**Turkish Name**
Aegithalos caudatus	Long-tailed Tit	Uzunkuyruklu baştankara
Chloris chloris	European Greenfinch	Florya
Emberiza cirlus	Cirl Bunting	Bahçe kirazkuşu
Fringilla coelebs	Common Chaffinch	İspinoz
Iduna pallida	Eastern Olivaceous Warbler	Ak mukallit
Lullula arborea	Woodlark	Orman toygarı
Parus major	Great Tit	Büyük baştankara
Periparus ater	Coal Tit	Çam baştankarası
Serinus serinus	European Serin	Küçük iskete
Troglodytes troglodytes	Eurasian Wren	Çitkuşu
TOTAL		10

APPENDIX D: SPECIES NAME ABBREVIATIONS ON THE EXPERT DETECTIONS

Table D.1. Abbreviation list for the identified species by the experts.

ABBREVIATION	SCIENTIFIC NAME	ENGLISH NAME	TURKISH NAME
AE CAU	*Aegithalos caudatus*	Long-tailed Tit	Uzunkuyruklu baştankara
CA CAR	*Carduelis carduelis*	European Goldfinch	Saka
CE BRA	*Certhia brachydactyla*	Short-toed Treecreeper	Bahçe tırmaşıkkuşu
CH CHL	*Chloris chloris*	European Greenfinch	Florya
CY CAE	*Cyanistes caeruleus*	Eurasian Blue Tit	Mavi baştankara
DE MAJ	*Dendrocopos major*	Great Spotted Woodpecker	Orman alaca ağaçkakanı
DE MED	*Dendrocoptes medius*	Middle Spotted Woodpecker	Ortanca ağaçkakan
DE SYR	*Dendrocopos syriacus*	Syrian Woodpecker	Alaca ağaçkakan
EM CIR	*Emberiza cirlus*	Cirl Bunting	Bahçe kirazkuşu
ER RUB	*Erithacus rubecula*	European Robin	Kızılgerdan
FI PAR	*Ficedula parva*	Red-breasted Flycatcher	Küçük sinekkapan
FR COE	*Fringilla coelebs*	Common Chaffinch	İspinoz
GA CRI	*Galerida cristata*	Crested Lark	Tepeli toygar
GA GLA	*Garrulus glandarius*	Eurasian Jay	Alakarga
HI RUS	*Hirundo rustica*	Barn Swallow	Kır kırlangıcı
ID PAL	*Iduna pallida*	Eastern Olivaceous Warbler	Ak mukallit
LI CAN	*Linaria cannabina*	Common Linnet	Ketenkuşu
LU ARB	*Lullula arborea*	Woodlark	Orman toygarı
LU LUS	*Luscinia luscinia*	Thrush Nightingale	Benekli bülbül
ME API	*Merops apiaster*	European Bee-eater	Arıkuşu
MO CIN	*Motacilla cinerea*	Grey Wagtail	Dağ kuyruksallayanı
PA DOM	*Passer domesticus*	House Sparrow	Serçe
PA MAJ	*Parus major*	Great Tit	Büyük baştankara
PE ATE	*Periparus ater*	Coal Tit	Çam baştankarası
PH COL	*Phylloscopus collybita*	Common Chiffchaff	Çıvgın
PH LUS	*Phylloscopus trochilus*	Willow Warbler	Söğütbülbülü
PH OCH	*Phoenicurus ochruros*	Black Redstart	Kara kızılkuyruk
PO LUG	*Poecile lugubris*	Sombre Tit	Akyanaklı baştankara
RE IGN	*Regulus ignicapilla*	Common Firecrest	Sürmeli çalıkuşu
SE SER	*Serinus serinus*	European Serin	Küçük iskete
SI KRU	*Sitta krueperi*	Krüper`s Nuthatch	Anadolu sıvacısı
SP SPI	*Spinus spinus*	Eurasian Siskin	Karabaşlı iskete
SY CAN	*Sylvia cantillans*	Subalpine Warbler	Bıyıklı ötleğen
SY MEL	*Sylvia melanocephala*	Sardinian Warbler	Maskeli ötleğen
TR TRO	*Troglodytes troglodytes*	Eurasian Wren	Çıtkuşu
TU MER	*Turdus merula*	Common Blackbird	Karatavuk
UN IDE	*Unidentified*	Unidentified	Tanımsız

APPENDIX E: COMPARISONS OF EXPERT DETECTIONS WITH MERLIN BIRD ID DETECTIONS

Table E.1. Numerical comparison between species identified by the experts and Merlin Bird ID.

Total number of inspected files	183
The number of files that experts detect species (including unidentified)	182
The number of files that experts detect species (excluding unidentified)	178
The number of files that Merlin detects species (including rare and uncommon)	142
The number of files that Merlin detects species (excluding rare and uncommon)	138
The number of files that Merlin detects rare or uncommon species	29 (12 rare, 15 uncommon, two both rare and uncommon)
The number of files where Merlin detected a species that experts on the whole dataset never detected	10 (One of the files also had a unique species where experts are not detected)
The number of files where Merlin detected species that were not annotated by experts on that file	26 (One of the files also had a unique species where experts are not detected on the whole dataset)
The number of "consensus" files (excluding rare and uncommon)	148
The number of "consensus" files where Merlin has at least one detected species (excluding no match) (excluding rare and uncommon)	103
Number of species identified by experts	36 (19 consensus + 17 unique) (excl. un-ide)
Number of species identified by Merlin	33 (19 consensus + 14 unique (7 rare or uncommon))