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Management-relevant applications of acoustic monitoring for Norwegian nature

The Sound of Norway

Sarab S. Sethi, Frode Fossøy, Benjamin Cretois & Carolyn M. Rosten

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Bugg device and solar panel in the field © Sarab S. Sethi

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Abstract

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High quality, large scale, and long-term field data is required as a foundation for any successful evidence-based nature management scheme. Whilst traditionally this data has been painstakingly collected by hand, breakthroughs in microelectronics and machine learning have opened the door for fully automated methods of ecosystem monitoring. Acoustic monitoring has shown particular promise as an affordable means to obtaining high quality ecological data on vast scales, and an array of sophisticated methods for data collection and analysis have been developed in the past decade.

In this report, we first survey existing literature in ecological acoustic monitoring through the lens of four Norwegian nature management priority areas: ecological base maps, green infrastructure, ecological condition, and species action plans. In each case, we detail the type of data needed for effective management, how acoustic monitoring can contribute to the desired goals, and identify the areas in which further research is required for acoustic monitoring to contribute to these priority areas. We find straightforward opportunities for automated vocalisation detection approaches to contribute species occurrence, abundance, and behavioural data at high resolutions and large scales to ecological base maps, green infrastructure, and species action plans. Additionally, we note that soundscape level analyses can provide new, holistic measures of ecosystem health which may improve measures of ecological condition.

We then cover the design, implementation, and results from the Sound of Norway project; a fully autonomous acoustic monitoring network deployed across the nation. Using the first large scale deployment of Bugg, a state-of-the-art ecological acoustic monitoring system, we surveyed 41 sites across forest, semi-natural grasslands, and urban settings between July and November 2021. 58 355 hours of audio data were uploaded directly from the field over a mobile internet link and analysed in real-time using a bird vocalisation detection model (BirdNET) and a soundscape fingerprinting approach. Once the analyses had been processed in the cloud, results were delivered through an intuitive and interactive web dashboard and the full dataset was exported in a machine-readable format for more in-depth analyses.

From expert annotations, we derived precision and recall metrics for the BirdNET model. The model had over 60% precision for 44 species (of which 21 species had 100% precision) and failed to identify any true calls for 5 species. Quantifying accuracy in this way gave us insight into strengths and weaknesses of the model and allowed us to control for potential misclassifications in downstream analyses. We used the filtered BirdNET detections to map species communities and changes in species richness across the full monitoring network, and to demonstrate that important phenological patterns could be derived from continuous acoustic monitoring data.

We also demonstrated that high level soundscape fingerprints could be used to discern spatial and temporal patterns across our monitoring network, without the need for vocalisation detection models. Spatially, we showed that soundscape features differed across different land-use types through our network, and temporally, we showed that changes in the community driven by the seasons were represented in a similar way.

Finally, we provide clear recommendations for how acoustic monitoring can best contribute to Norwegian nature management today. We identify existing monitoring programs which can, (i) benefit from the fine temporal resolution of acoustic data (e.g., TOVe, SEAPOP), (ii) integrate soundscape analyses to measure overall ecosystem health (e.g., ANO), and (iii) make use of audio based continuous measures of human disturbance (e.g., the national insect monitoring project). We then conclude by suggesting the most impactful directions for further methodological

development to fine tune existing acoustic monitoring solutions to best serve the needs of Norwegian nature management.

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Sammendrag

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Høykvalitets, storskala og langsiktige feltdata er et viktig grunnlag for å sikre en vellykket empirisk basert naturforvaltning. Tradisjonelt sett har disse dataene blitt innsamlet for hånd, men gjennombrudd innen mikroelektronikk og maskinlæring har nå muliggjort helautomatiserte metoder for overvåkig av økosystemer. Akustisk overvåking er en lovende og kostnadseffektiv metode for å samle inn økologiske data på stor skala, og det har blitt utviklet en rekke sofistikerte metoder for datainnsamling og analyse det siste tiåret.

I denne rapporten starter vi med å kartlegge eksisterende litteratur innenfor økologisk akustikk med fokus på fire norske naturforvaltningsområder: økologiske grunnkart, grønn infrastruktur, økologisk tilstand og handlingsplaner for trua arter. I hvert tilfelle diskuterer vi hvilken type data som trengs for en effektiv forvaltning, hvordan akustisk overvåking kan bidra til å nå de ønskede målene, og identifiserer områder der ytterligere forskning er nødvendig for at akustisk overvåking skal kunne bidra til disse prioriterte områdene. Vi viser hvordan enkle automatiserte deteksjonsmetoder for lyd kan bidra med høyoppløselige data på artsforekomst, bestandsstørrelse og atferd på en stor skala til økologiske grunnkart, grønn infrastruktur og handlingsplaner for trua arter. I tillegg kan analyser av lydbilder gi nye, helhetlige mål på økosystemhelse og forbedre mål på økologisk tilstand.

Vi rapporterer deretter oppsett, implementering og resultater fra Lyden av Norge-prosjektet; et helautonomt akustisk overvåkingsnettverk fordelt over store deler av landet. Vi presenterer den første storskala testen av BUGG, et toppmoderne økologisk akustisk overvåkingssystem, der vi overvåket 41 lokaliteter på tvers av skog, semi-naturlig mark og mer urbane habitater mellom juli og november 2021. Totalt ble 58 355 timer med lyddata lastet opp direkte fra felt over en mobil internett-kobling og analysert i sanntid ved hjelp av en deteksjonsmodell for fuglelyd (BirdNET) og en lydbilde-fingeravtrykkstilnærming. Når analysene var behandlet i skyen, ble resultatene levert gjennom et intuitivt og interaktivt online dashbord, og hele datasettet ble til slutt eksportert i et maskinlesbart format for mer dyptgående analyser.

Vi utledet presisjons- og gjenkallingsmålinger for modellen ved hjelp av ekspertvurderinger. Modellen hadde over 60 % presisjon for 44 arter (hvorav 21 arter hadde 100 % presisjon) og identifiserte 5 arter der modellen gav falske positiver, altså at disse artene ikke fantes på lokaliteten. Å kvantifisere nøyaktighet på denne måten ga oss innsikt i styrker og svakheter ved modellen og tillot oss å kontrollere for potensielle feilklassifiseringer i videre analyser. Vi brukte de filtrerte BirdNET-deteksjonene for å kartlegge artssamfunn og endringer i artsrikdom på tvers av hele overvåkingsnettverket, og for å demonstrere at viktige fenologiske mønstre kan utledes fra kontinuerlige akustiske overvåkingsdata.

I tillegg demonstrerte vi at lydbilder kan brukes til å beskrive mønstre i tid og rom på tvers av overvåkingsnettverket vårt. Fra disse analysene har vi vist at automatisert akustisk overvåking kan gi kontinuerlige økologiske data både for enkeltarter og på et overordnet samfunnsnivå, inkludert informasjon om biodiversitet, samfunnsendringer og migrasjonstidspunkt.

Til slutt gir vi anbefalinger for hvordan akustisk overvåking kan benyttes av norsk naturforvaltning i dag. Vi identifiserer eksisterende overvåkingsprogrammer som kan, (i) dra nytte av den høye tidsmessige oppløsningen til akustiske data (f.eks. TOVe, SEAPOP), (ii) integrere lydbildeanalyser for å måle generell økosystemhelse (f.eks. ANO), og (iii) integrere lydbaserte kontinuerlige mål på menneskelig påvirkning (f.eks. nasjonal overvåking av insekter). Vi avslutter med å peke på de mest effektive løsningene for videre metodeutvikling som kan finjustere eksisterende akustiske overvåkingsløsninger og ivareta behovene til norsk naturforvaltning.

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Contents

Foreword

Understanding the full effects of anthropogenic pressures on ecosystems is one of the major challenges of our times. As we learn more about the subtle and complex ways in which nature is changing, we can implement evidence-based management and policy measures to ensure human development can go hand in hand with a sustainable and thriving natural world.

Whilst best known for its relaxing properties, recording and listening to the sounds of nature also provides a uniquely rich ecological data source. Monitoring ecosystems using audio can provide us with incredibly high-resolution datasets at both the species and community levels. Crucially, acoustic monitoring can be fully automated, allowing data to be collected on vast spatial and temporal scales. The pace of methodological development in the field of automated acoustic monitoring has been rapid – and shows no sign of slowing.

In this study, we took a step back from pure methodological development and asked how acoustic monitoring could best contribute to the effective management of Norwegian nature. We explored the existing literature in four priority management themes and deployed a first-of-its-kind nationwide real-time acoustic monitoring network. Having analysed almost 60 000 hours of audio, we gained intuition for the practical strengths and weaknesses of acoustic monitoring and integrated these into clear recommendations for Norwegian management authorities.

The undertaking of the work contained within this report been a truly interdisciplinary effort which has benefited from the contributions and expertise of numerous people throughout the year.

To begin, we would like to thank John Gunnar Dokk and Torbjørn Havnås for coordinating and carrying out the bulk of the fieldwork for the Sound of Norway project. Additionally, we would like to thank Anders Endrestøl, Arne Laugsand, Julia Wiel, and Jørgen Rosvold for their assistance in deploying and retrieving recording equipment when extra hands were needed.

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Finally, thank you to Tomas Holmern for his continued input and guidance, ensuring this work remained of maximum relevance to real Norwegian nature management goals.

01.12.2021 Sarab S. Sethi, Frode Fossøy, Benjamin Cretois, Carolyn M. Rosten

1 Introduction

1.1 Overview

With biodiversity in worldwide decline and global ecosystems under pressure from human activities, high quality data upon which to base management decisions is vital. Sustainable nature management and ecosystem conservation depends critically on cost-effective, scientifically sound, and management-relevant methods for monitoring and assessing biodiversity, ecological status, drivers of change, and impacts of mitigation measures.

Present state-of-the-art monitoring has led to a bias towards monitoring of specific habitats and species, while more holistic evaluation of ecosystem structure and function is more limited. Novel autonomous cost-efficient tools, such as passive acoustic monitoring, can provide new and complementary data to fill existing data gaps for evidence-based management. In particular, passive acoustic monitoring provides a tractable means to obtaining a holistic picture of ecosystem health. Continuous, autonomous monitoring is already possible with low-cost devices (Hill et al., 2018; Sethi et al., 2020a) enabling long-term monitoring of whole ecosystem soundscapes. Automated acoustic recording devices can run continuously for months and years and accumulate data containing a long list of ecological information, such as: species absence/presence, population structure, community structure, species interactions, animal phenology, reproduction period, migration period, and ecosystem functions, in addition to records of human activity (Rosten and Fossøy, 2020). After decades of development and refinement, passive acoustic monitoring is now ready to be applied as an ecosystem-level monitoring tool for evidence-based nature management.

Here, we present four key nature management priorities identified by the Norwegian Environmental Agency: ecological base maps, green infrastructure, ecological condition, and species action plans. For each priority, we identify the specific ways in which acoustic monitoring can contribute solutions and fill information gaps that are left with current approaches.

1.2 **Ecological base maps**

Ecological base maps are used by Norwegian nature management authorities to gather data on how habitat types, species, and environmental variables are distributed spatially. Examples of applications include mapping of key habitats (e.g., spawning grounds), threatened habitats (e.g., those at risk of exposure to development pressures), and invasive or threatened species. Traditional ecological survey approaches tend to scale poorly across large scales, often leading to sparse datasets with key areas of interest under-represented.

Acoustic recorders can monitor continuously and be deployed in inaccessible areas, thus increasing the spatial and temporal coverage of existing monitoring programs. Automated analyses which detect species vocalisations in acoustic recordings have been explored for decades, so methods here are well developed. Prior work has demonstrated how acoustic monitoring can provide insight into both the distribution of rare, cryptic species at fine scales (Bobay et al., 2018; Campos-Cerqueira and Aide, 2016) and the population growth of invasive species at broad scales (Juanes, 2018; Rountree and Juanes, 2010). Whilst information on a single species can be gathered from soundscape recordings, the same dataset can be used to monitor multiple species simultaneously. Further research such as developing automated detection models which cover a broader range of species and expanding data collection to target area-representative and key habitats on a nationwide scale will greatly increase the potential for passive acoustic monitoring to contribute to ecological base maps.

1.3 **Green infrastructure**

The objective for green infrastructure is to preserve biodiversity and important ecological functions by providing a connected network of natural and semi-natural areas. By connecting high value habitats (e.g., those inhabited by threatened species or providing essential ecological functions) with dispersal corridors, the resilience and ecological value of all habitats is increased (Fahrig, 2003; Saunders et al., 1991). Practical ecosystem management is challenging since the adaptations, habitat requirements, and dispersal abilities of species vary on different spatial and temporal scales. Monitoring approaches which provide both high level overview and in detail species data simultaneously are necessary for effective management of such complex environments.

Acoustic monitoring provides near-continuous data on a large range of sound-producing species in any given ecosystem. Networks of acoustic detectors can provide insight on behaviour (Pirotta et al., 2014) and movement (Bateman et al., 2021; Wrege et al., 2017) of organisms within and between green infrastructure components. This can help verify whether the green infrastructure and corridors are functioning as expected, or whether they need upgrading or restoring. Analysis of the overall soundscape, either with entropy based indices or machine learning methods, can identify biodiversity hotspots in and around green infrastructure areas enabling prioritisation of management actions (Dixon et al., 2020; Holgate et al., 2021).

1.4 **Ecological condition**

Ecological condition seeks to measure the overall “health” of an ecosystem by integrating ecological structure with measures of ecosystem functioning (Jakobsson et al., 2021). Measuring ecological structure is traditionally done by collating data from taxonomically specific surveys to get an overview of community composition. Ecosystem functions (also called ecosystem processes) are defined as the biological, geochemical, and physical processes that occur within an ecosystem. Key examples of biological processes are energy flow between (e.g., distribution and migration) and within (e.g., food web dynamics, trophic interactions) systems. These dynamic processes are challenging to measure, and a number of knowledge gaps still exist. Being able to track ecological condition accurately allows early identification of high level breakdowns in an ecosystem, potentially aiding intervention and mitigation efforts (Jakobsson et al., 2021).

Through the use of vocalisation detection models, acoustic monitoring can provide us with the full community composition of sound producing species. From this, one can derive a picture of community structure and its dynamics over time (Chhaya et al., 2021). Ecosystem processes reflecting energy flow within systems such as reproduction phenology (Schackwitz et al., 2020) and success (Ulloa et al., 2019), intra-or inter-species competition (Wood et al., 2021, 2019), hibernation (Blomberg et al., 2021) and variation in trophic interactions (Buxton et al., 2018) can also be captured by species specific acoustic monitoring. The necessary technology and data pipelines are already available to achieve the desired scale of monitoring (Hill et al., 2018; Sethi et al., 2020a), though automated detection and classification models for a broader range of species is currently the limiting factor to this approach (Aide et al., 2013; Blumstein et al., 2011).

Soundscape ecology (Pijanowski et al., 2011; Sueur and Farina, 2015) is a whole soundscape approach which has become popular for its ability to assess whole ecosystem features without individual species identification. Soundscape features, obtained through indices or machine learning, can be used to decipher between good or poor ecosystem condition in a variety of terrestrial and aquatic systems (Campos-Cerqueira and Aide, 2016; Desjonquères et al., 2018; Do Nascimento et al., 2020; Gottesman et al., 2020; Harris et al., 2016; Sánchez-Giraldo et al., 2021; Shaw et al., 2021). One elegant study combining acoustics, cameras, and biomass measurements found that acoustic indices reflected biomass of grazer, planktivore and tertiary consumer functional groups (Elise et al., 2019). Once calibrated against other measures of ecological condition, soundscape ecology can be a powerful tool in the toolbox for holistic ecosystem monitoring.

1.5 Species action plans

Species action plans are used to develop and implement conservation measures for key species of interest. Commonly, these plans include monitoring of target species as one of the measures. Monitoring is directed at population size, distribution, and health (e.g. recruitment, survival, genetic composition, age structure) as well as key habitat characteristics and responses to human disturbance (Framstad, 2013). Monitoring for species action plans often begins with systematic, repeated monitoring to document the status and changes over space and time. The follow up phase is then more directed monitoring to test specific hypotheses or evaluate management measures or achievement of management goals (Framstad, 2013). A challenge, however, is that the species of interest tend to be rare or have low detectability, so collecting sufficient data using traditional survey methods is difficult (Manne and Pimm, 2001).

Acoustic monitoring has enormous potential to add value to species action plans for species which vocalise. Deploying acoustic sensor networks with vocalisation detection models can allow us to track occurrence and occupancy over long time periods and in real-time (Balantic and Donovan, 2019; Campos-Cerqueira and Aide, 2016; Sethi et al., 2020a; Shaw et al., 2021). The use of microphone arrays can enable 3D positioning of individuals in the landscape, opening up the potential for estimates of species abundance (Mennill et al., 2012; Verreycken et al., 2021). Acoustic monitoring, often in combination with existing methods, can additionally improve the detectability of rare species. For example, it has been used to increase detections of bats (Tuneu-Corral et al., 2020), nocturnal birds such as nightjars (Raymond et al., 2020) and marine cetaceans (Gillespie et al., 2020; Miller et al., 2015). The same acoustic dataset used for population information can also be applied to assessment of key habitat characteristics of the population under evaluation, in particular features and extent of human disturbance (Buxton et al., 2018; Wrege et al., 2017).

There are a number of prioritised animal species in Norway which have action plans which are either active, under development, or recently finished. Of these, the vocal species include mammals (Arctic foxes and many bats), birds (horned grebe, corn crake, eagle owl, lesser white-fronted goose, black-tailed godwit and ortolan bunting), amphibia (pool frog and great crested newt), and insects (mountain cicada). However, while precedents exist for the inclusion of acoustic data in action plan monitoring, with integration of acoustics in bat monitoring plans abroad (Barlow et al., 2015; Barova and Streit, 2018), it remains uncommon in the Norwegian management context.

2 The Sound of Norway project

2.1 Project design

To provide a direct demonstration of how acoustic monitoring can provide actionable insight into the state and health of Norwegian ecosystems, NINA carried out the “Sound of Norway” project in 2021.

The Sound of Norway project builds upon on the pilot project testing AudioMoth acoustic loggers in association with the Norwegian insect monitoring project in 2020 (Rosten & Fossøy 2020). The pilot project concluded that future studies should include real-time autonomous loggers to provide a better and more rigorous platform for recording and storing acoustic data. In 2021, we have tested a newly developed real-time acoustic logger (Bugg, https://www.bugg.xyz/) connected to a battery and solar panel to make a fully autonomous system. We chose to overlap with the Norwegian insect monitoring project in 2021, and further included sites used by the project “Early detection and warning of new alien species in Norway” (Jacobsen et al., 2020). Both of these projects use Malaise traps to capture flying insects in combination with DNA-metabarcoding for taxonomic classification, providing comprehensive species lists covering a broad taxonomical range (Åström et al., 2020; Jacobsen et al., 2020). The Norwegian insect monitoring project is a recently started program for assessing spatial and temporal trends in insect biodiversity. The project is currently limited to eastern and middle Norway and two distinct habitats: forest and semi-natural grassland. The early detection project focuses on invasive species hotspots located around the Oslo fjord area. It aims to discover door-knocker species and early settlement of invasive species in time to implement proper mitigations. The inclusion of the early detection project expands the range of habitats, but most importantly this expansion included many sites where human sounds are dominating, in strong contrast to the sites in the Norwegian insect monitoring project. The Malaise traps were emptied every two weeks in the insect monitoring program and every fourth week in the early detection project, providing lists of insect diversity at each location and time point.

Overlapping with existing monitoring projects was done for two primary reasons; (i) ongoing surveys and historical data at each site could be used as ground truth data for our acoustic surveys, and (ii) this would allow us to demonstrate how acoustics can complement alternative ecological survey methods and help to build a more cohesive overview of biodiversity and ecosystem health.

We succeeded with installing real-time acoustic monitoring devices (Buggs, Section 4.2) at 41 locations; 16 on the early detection project and 25 on the insect monitoring project (9 in forests, 16 in semi-natural grasslands) (Fig. 1). Data was transmitted in real-time to remote servers from 37 sites, and from 4 sites, without mobile internet coverage, data was manually collected from SD cards. In this report we will summarise data from the 37 sites with real-time data transmission, but in the future integrating the remaining data into the same pipeline will be a straightforward process.

Devices were deployed between the 9th and the 30th of July 2021, and collection of devices from the field begun in early October 2021. Five recorders in the Trøndelag region remain deployed in the field until 23rd November but we imposed a cut-off of 6th November 2021 for data analysis used in this report. Overall, 700 260 five-minute audio files (58 355 hours) were uploaded to the server and analysed using the Bugg platform during the survey period.

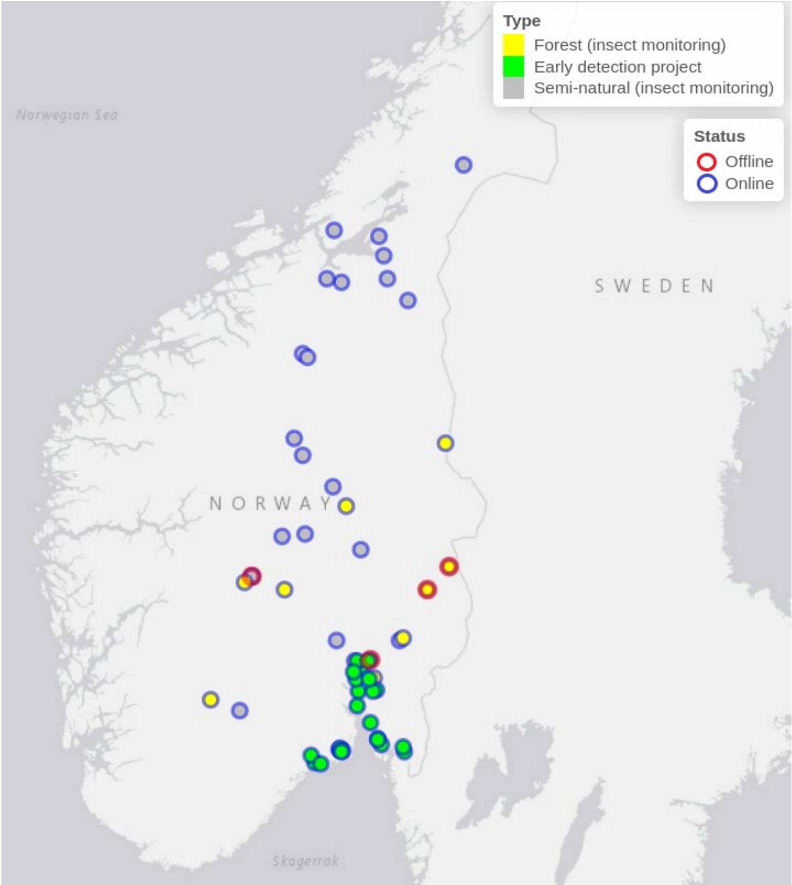

Figure 1: *We deployed autonomous acoustic monitoring devices at 41 locations across the country for the Sound of Norway project. 16 locations overlapped with the early detection project and 25 with the insect monitoring project, representing a range of land use types and across a broad latitudinal gradient.*

2.2 Infrastructure

2.2.1 Data collection, analysis, and presentation

At its core, the task of recording acoustic data does not require a very sophisticated setup. For example, a smartphone can be taken into a forest and a simple voice recorder application can be used to capture audio to a file. However, challenges arise when long-duration audio recordings are to be made from a large number of sites, and the collected data must be organised, analysed, and stored for longevity.

Semi-autonomous acoustic recording devices such as the Audiomoth or Solo recorders attempt to tackle the data acquisition part of the problem (Hill et al., 2018; Whytock and Christie, 2017). However, these devices record data locally to an SD card, and then this data must be manually retrieved, sorted, and analysed before ecological insight can be derived from the acoustic survey. This step is laborious (and therefore expensive), prone to error, and means that often results are only seen months or years after data is collected – a delay that limits the ability for acoustics to be used in active management scenarios (Rosten and Fossøy, 2020).

In the Sound of Norway project, we carried out the first scale deployment of the Bugg platform (https://www.bugg.xyz/). Bugg is a system based on open-source research developing methods for fully autonomous acoustic monitoring, but is built to a higher production quality than earlier prototypes (Sethi et al., 2018, 2020a). The recording devices used in the Bugg system (Fig. 2) are small weatherproof units based on a Raspberry Pi Compute Module 4 with a high-quality MEMS microphone and a 3G/4G mobile network connection. Data can be recorded continuously by these devices in five-minute files at a sample rate of up to 80 kHz (44.1 kHz was used in this study). Each file was compressed to MP3 format using the variable bit rate 0 compression scheme before being uploaded to a cloud-based server hosted on Google Cloud Services. In instances where an internet connection could not be secured (e.g., due to lack of coverage) audio data was saved locally to a removable microSD card for manual retrieval.

To facilitate uninterrupted 24-hour data collection, recording devices were powered using an off-grid solar power set up. A 100 W solar panel was connected to a 24 Ah LiFePo4 12 V deep cycle lithium battery through a 10 A solar charge controller. The Bugg device was connected to the load terminal of the solar charge controller, and the charge controller and battery were sealed in a waterproof box. During daylight hours the battery was charged by the solar panel, and during the night the battery reserve was used to continue operation of the recording device. The full setup, mounted on plastic fence posts, is shown in Fig. 2.

***Figure 2**: The Bugg recording devices and solar panels were mounted as illustrated at each of the 41 locations throughout Norway. The lithium battery and solar charge controller were placed on the ground nearby and sealed in a waterproof box (with an opening for cables in and out).*

Once data was uploaded to the central server, the audio was immediately indexed, interpreted using a range of automated analyses, and the results were stored in databases. The original audio files were also stored so data can be reanalysed at a later date with new or updated analytical techniques. The analyses were computed using an elastic computing structure that automatically scales to the volume of incoming data. In this way the same infrastructure can be used for either small (<10 devices) or large (100s of devices) projects. The analysis platform was designed such that extra analyses can be inserted or removed easily using a modular set up. In this project we implemented three cutting-edge machine learning based analyses: (i) automated bird identification using BirdNET (Kahl et al., 2021), (ii) soundscape fingerprinting using VGGish features, and (iii) unsupervised anomaly detection for picking out the most unusual sounds (which may, for example, be used to detect illegal hunting or logging behaviour) (Sethi et al., 2020b).

Finally, the Bugg system provides an intuitive web dashboard (Fig. 3). This is intended to present easily digestible summaries from the acoustic monitoring network in a format that can be understood and actioned upon by non-technical users. Devices can be configured through this dashboard to record at different sampling rates or to collect data only at specific hours of the day. Automated detections from species identification models can be listened to for verification purposes, and graphs of changing calling activity are displayed over configurable time periods.

Additionally, the web dashboard provides a means to downloading the raw audio or the results of the automated analyses in a machine-readable format (CSV files) for further analysis purposes.

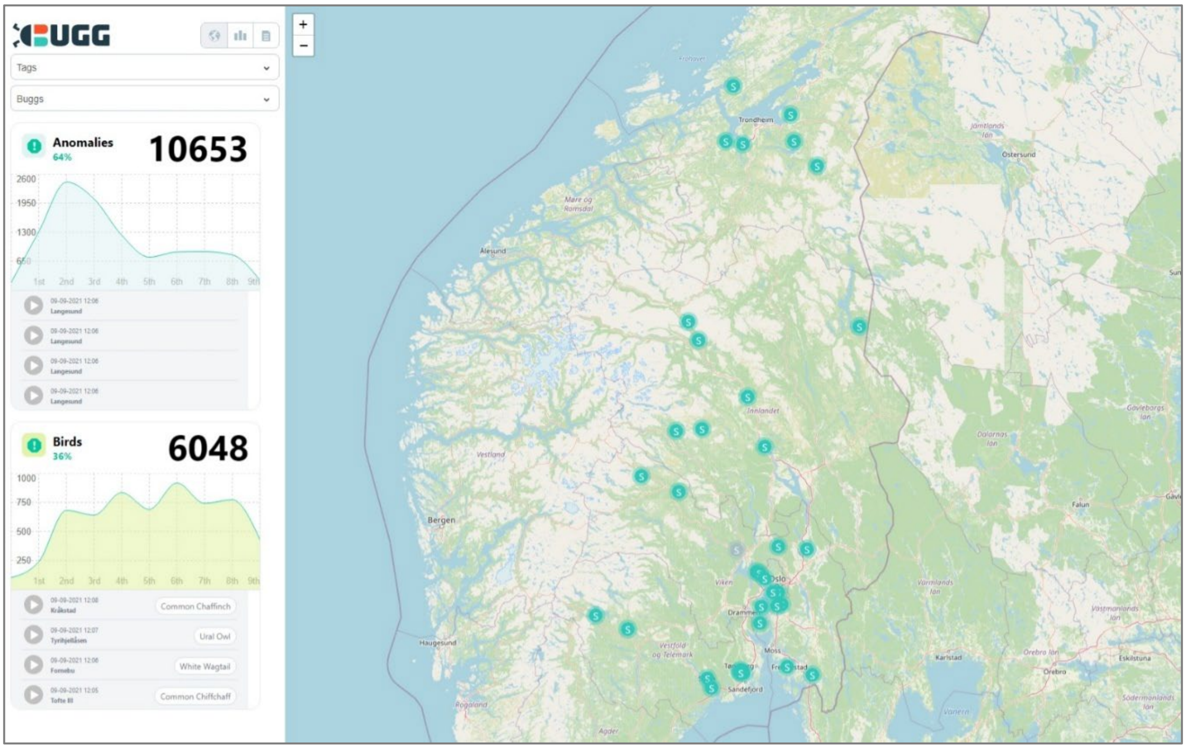

***Figure 3**: The Bugg autonomous acoustic monitoring system presents its results in an intuitive web dashboard. Functionality includes monitoring of device uptime, verification of outputs from automated species detections model, and exporting of raw data in machine readable formats for downstream analyses*

2.2.2 Range testing of recording devices

Every acoustic monitoring device has a slightly different sensitivity due to the use of different microphones, enclosures, or simply natural variation in the manufacturing process. Since Bugg recording devices use MEMS microphones which are manufactured using a highly controlled process, we can safely assume that the variation between devices was negligible. Consequently, since the enclosures are the same, we could assume each of the 41 deployed devices had similar audio recording properties. However, real world tests were still needed to determine how far key sounds of interest can travel in actual ecosystems with complex and varying topologies, vegetation structures, and background sound profiles.

We performed controlled playback experiments at two locations which were representative of our survey sites; one in a forest and one in semi-natural grassland. At each location a calibrated handheld speaker was used to play the sound of two people having a conversation (a man and woman), the call of a Eurasian eagle-owl, and a truck driving. Each sound was played as close to realistic sound pressure levels as possible; people talking at 70 dB SPL, owl call at 75 dB SPL, and truck driving at 80 dB SPL. These sounds were played at 1m, 5m, 10m, 20m, 30m, 50m, 70m, 80m, 90m, and 100m from a Bugg recording device which was fixed to a tree 1m from the ground.

We listened to the recorded audio data and determined the furthest distance we could hear each of the three sound samples used. The results are summarised in the below table:

Sound type	Last distance audible (forest)	Last distance audible (grassland)
People talking (70 dB SPL)	20m (intelligible at 10m)	50m (intelligible at 30m)
Owl call (75 dB SPL)	30m	70m
Truck driving (80 dB SPL)	30m	30m

As expected, sounds travelled further in the semi-natural grassland than in the forest. This is because the denser vegetation in the forest absorbs sound energy, whereas in the grassland there was a line-of-sight view between the speaker and the recorder. Despite having a lower absolute sound pressure level than the truck, the owl call travelled the furthest since it covers a broad spectrum of frequencies and is therefore less likely to be masked. The truck sound, in contrast, covered only relatively low frequencies and this was completely masked by the intrinsic microphone noise at distances beyond 30m. Real sound detection ranges might exceed those measured using playback experiments due to the speaker's limited frequency output range. However, these experiments provide valuable indicative figures and more intricate experiments using real sound events could follow for cases where detection range was of critical importance.

2.3 Continuous monitoring of focus species

2.3.1 Implementation and evaluation of a species detection model

Perhaps the most well-known use of acoustic monitoring in ecology is to infer species occurrence data by listening for identifiable individual sounds in the soundscape. It is possible to generate occurrence data using this principle through visual inspection of a spectrogram (an image representation of audio data) by a trained expert. However, when dealing with large amounts of data it is simply not feasible to manually annotate every recording. Over just a few months of pilot deployments carried out as part of the Sound of Norway project we collected over 58,000 hours of audio data, so finding an automated model to identify vocalisations in the audio was essential.

Many animals across diverse taxonomic groups make sounds, either through vocalisations (wolves howling, birds singing), stridulations (crickets or grasshoppers chirping), as a by-product of typical behaviours (bats echolocating), or through passive interactions with their environments (bees buzzing or mosquitos whining). In theory, if a sound is uniquely identifiable and loud enough to be recorded, a machine learning model can be trained to detect and identify it. Despite this, a major practical barrier is the scarcity of libraries of recorded calls for most of these examples – a resource that is essential when training an automated sound detection model.

Birds, however, are an exception to this rule. Bird species, especially those of Europe and North America, have been studied intensively for centuries and there exist relatively comprehensive libraries of calls for most common species. Consequently, the reliable automated identification of many bird vocalisations has been possible for many years. In this study we used BirdNET, a state-of-the-art bird detection model developed by the Cornell Lab of Ornithology (Kahl et al., 2021).

BirdNET is a deep neural network model that is trained on thousands of hours of manually labelled vocalisation data and can identify the vocalisations of over 900 bird species. As well as a processed spectrogram of a three-second audio clip, BirdNET takes GPS co-ordinates as an additional input parameter to filter out species that are impossible to find at a given location from the predictions it returns. For each audio clip run through the model, BirdNET returns a confidence score for how likely it believes each species to be present in the recording. We used a fixed threshold of 0.8 for classifying a species as present, however future studies could investigate the optimal value to use based on the desired balance between precision and recall for each species.

We implemented the BirdNET model in the Bugg monitoring pipeline, and so the analysis was run in real-time on all 700,260 audio files that were transmitted from the field. In total there were 148,793 individual detections from the model, across 185 unique species. However, the distribution of detections per species was highly skewed, with most species having very few detections. Machine learning models generally perform better on classes with more training data, and it is likely that many of the predictions for the least common species were misclassifications. Therefore, we filtered our results to only include species for which there were at least 50 detections each (up to the 27th September 2021), giving us a final set of 51 unique species.

For each of these 51 species we exported 50 detections at random and sent the associated audio clips to a trained ornithologist. The ornithologist labelled each detection as either correct, incorrect, or inconclusive (e.g., if the call was too far away). This data allowed us to assess the precision of BirdNET for each of the 51 species – i.e. how likely a detection is to truly be the stated species rather than a misclassification (Fig. 4).

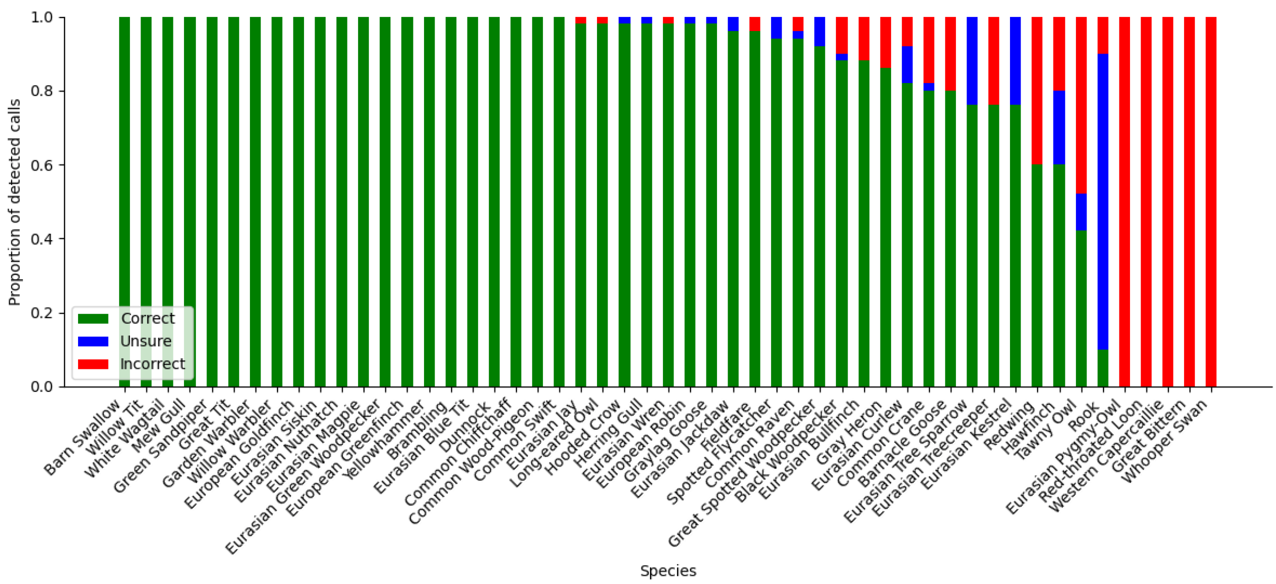

***Figure 4**: A trained ornithologist listened to 50 automated BirdNET detections of 51 species and classified each as correct, incorrect, or unsure. This provided us with precision metrics for each species, which can be used as a filter to control the number of potential misclassifications in downstream analyses using BirdNET.*

The results from this verification step were extremely encouraging. For 21 species every prediction BirdNET made was correct and so the precision was 100%. This would indicate that for targeted monitoring of any of these 21 species, BirdNET could be used for highly accurate data on its presence or absence at a given location or time.

For 44 species the precision was above 60%, and for 39 species the precision was above 80%. When considering species community level analyses (e.g., species richness metrics, or species community turnover), these lower levels of accuracy may be sufficient to gain an ecosystem level picture of biodiversity. The exact threshold used will depend on the trade-off between breadth of community coverage and acceptable error or the ability to control for uncertainty in downstream analyses.

For 5 species, every BirdNET prediction was a false positive, corresponding to a precision of 0%. For most of these, the sounds were in fact made by anthropogenic noise sources (e.g., motors or drills) but the BirdNET model incorrectly identified them as birds which have mechanical sounding calls. Any downstream analysis should simply ignore data from BirdNET which is classified as any of these species as it is highly likely to be a misclassification and add noise to derived results. The existence of these species demonstrates the critical importance of manually verifying outputs from automated detection algorithms. Without expert annotations, detections of these species would be treated equally, adding significant noise and potentially masking interesting community level patterns in the overall dataset.

Whilst the above analysis gave us insight into the precision of the BirdNET model when deployed in a Norwegian monitoring scenario, it does not tell us anything of its recall – i.e., how sensitive the model is and how many calls of interest are completely missed. For each site with more than 50 BirdNET detections, we exported 7 five-minute audio files stratified by how many detections BirdNET found in each file (at percentiles 5, 10, 15, 50, 85, 90, and 95 – excluding files with 0 detections). We sent the resulting 182 five-minute audio files to a trained ornithologist and asked them to identify every bird species they heard vocalising in each file. For each file we compared these manual annotations to the automated detections from BirdNET. Each file was scored on the proportion of expert annotated species that BirdNET successfully identified (Fig. 5)

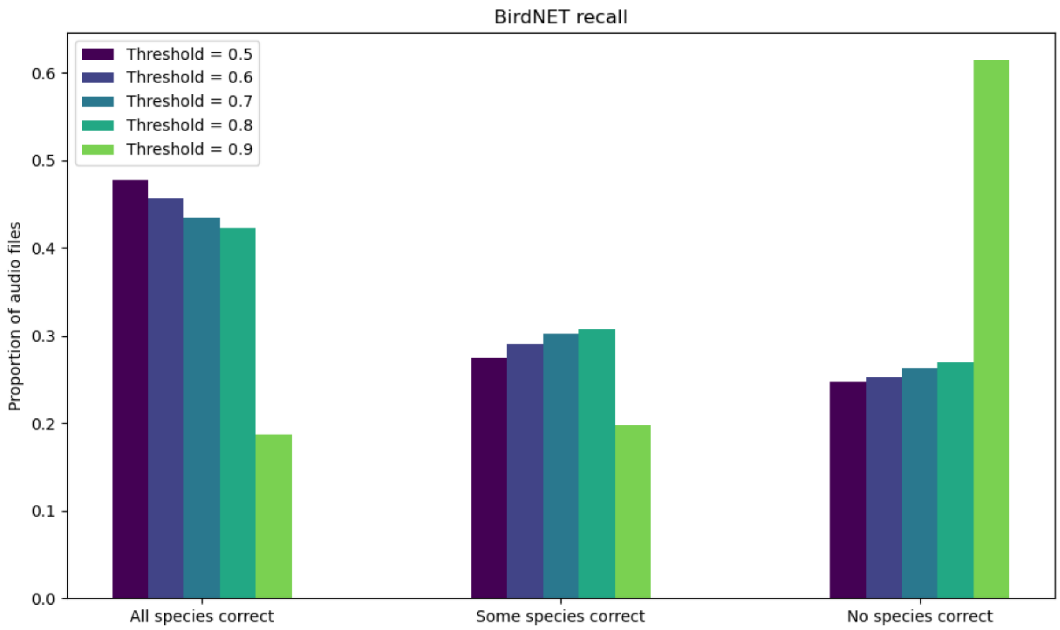

***Figure 5**: A trained ornithologist labelled bird vocalisations in 182 five-minute audio files from the Sound of Norway project. After running BirdNET on the same data, we evaluated the proportion of expert annotated species that BirdNET successfully identified within each file, and how this varied with confidence threshold used. Bars show the proportion of files for which there was total agreement, partial agreement, and no agreement between BirdNET and the trained ornithologist. Lower confidence thresholds resulted in more files with total agreement, though differences were relatively small up to a threshold of 0.9, after which there was a large reduction in performance.*

The results from this analysis give us an idea of how many species vocalisations the BirdNET model may be missing. As expected, using a higher confidence threshold on the output of the BirdNET model resulted in lower recall. Using a classification threshold of 0.5 (e.g., considering a species is present even if BirdNET is not very confident of the prediction) there is a higher level of agreement between the trained ornithologist's labels and the automated labels. Between the ranges of 0.5 to 0.8 the differences were small but using a confidence threshold of 0.9 resulted in a large reduction in agreement between the automated species detection algorithm and the labels from the ornithologist. Lower confidence thresholds, however, will come at the expense of higher false positive rates, and therefore there is a balance to be struck. From these results we suggest that a confidence threshold of 0.7-0.8 (as used in the precision analysis) is in the appropriate range.

Further targeted annotations would be required to derive a per-species recall metric, although this should be considered a necessary step if acoustic monitoring is to be deployed in highly specific projects focussed on just one or two species. When modelling community dynamics using this data it is important to remember that absence of an automated detection does not necessarily mean absence of the species. This goes beyond inaccuracies in the BirdNET model – the species may be present but simply not vocalising. Such shortcomings exist for any survey method (e.g., camera traps will never find a hibernating species) and this emphasises the need for a multi-pronged approach to ecosystem monitoring at a high level.

2.3.2 Species community changes

Having evaluated BirdNET's precision and recall on the Sound of Norway data, we can now confidently use it as a tool to track species communities with better knowledge of its strengths and weaknesses.

At each site across the Sound of Norway project with at least 50 detections, we measured the avian species richness on each day (Fig. 6). For this analysis we used a BirdNET confidence threshold of 0.8, and we discounted any detections from species with under 60% precision. This allowed us to capture overall community level trends for a large number of species, whilst minimising the number of false detections in our dataset.

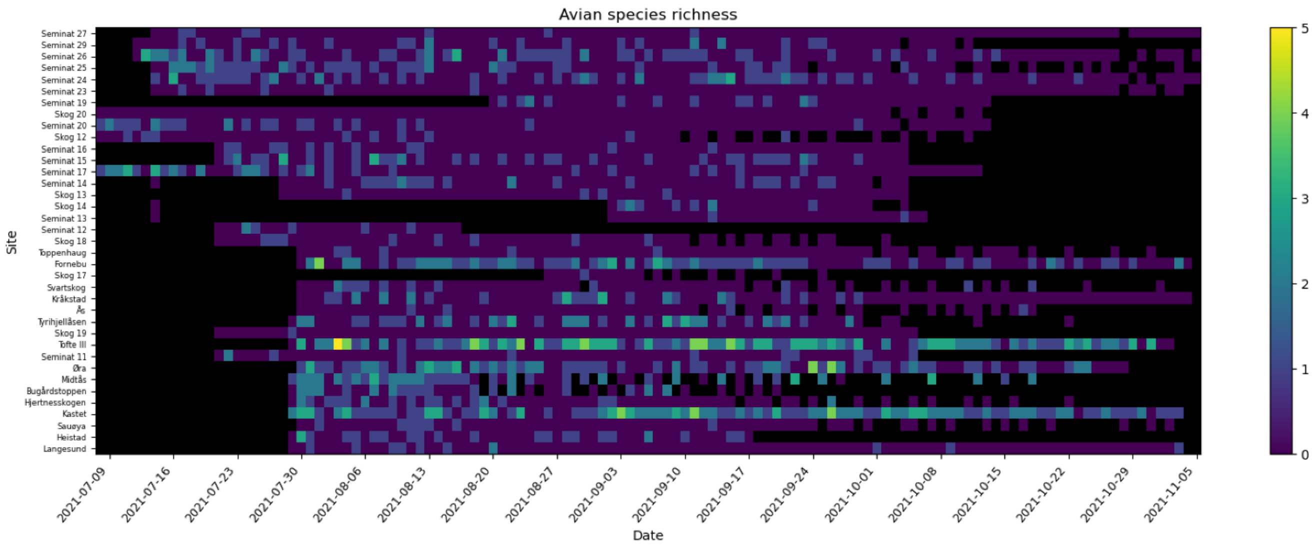

***Figure 6**: Using a BirdNET confidence threshold of 0.8 and only considering species with precision metrics of over 60%, we mapped avian species richness (number of unique species) per day across the Sound of Norway project. Sites are ordered by latitude, with the northernmost points at the top and southernmost at the bottom. Days on which no data was collected from a given site are shown as black. A clear trend can be seen in many sites where diversity decreases over the sampling period as the summer months give way to winter.*

Mapping avian richness in this way demonstrates how autonomous acoustic monitoring can provide extremely high-resolution biodiversity metrics over large spatial and temporal scales.

Assessing daily avian diversity at 41 sites simultaneously over 3 months using traditional methods such as point counts would be impossible due to logistics, expense, labour availability, and a range of other factors. Clear expected community trends are visible in the data, as diversity reduces from the end of the summer (July) to the fall and winter months (November). The exact timing and manner in which biodiversity reduces would be of great interest to those studying migration or phenology of bird species.

In addition to community level biodiversity metrics, autonomous acoustic monitoring also provides high resolution species presence and absence data. Below, we show how species communities at specific sites change over the seasons at two sites located in the insect monitoring project (Fig. 7).

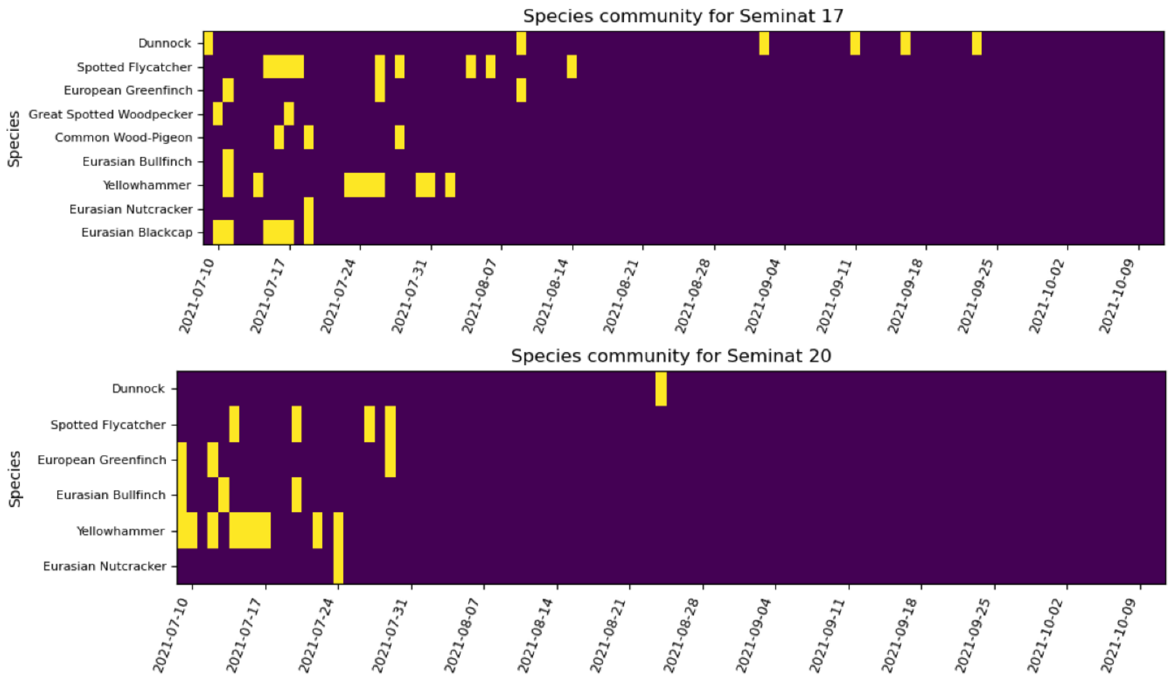

***Figure 7**: Running BirdNET on the Sound of Norway data allowed us to autonomously map presence and absence data for a number of species at every site. Here data is shown for two sites in semi-natural grasslands in the insect monitoring project. For this visualisation a BirdNET confidence threshold of 0.8 was used and only species with precision metrics of over 60% were used. As before, it is evident that diversity decreases from the summer to the winter, however, here we can see the exact species level patterns on a finer scale.*

Having access to fine-grained occurrence data for a wide range of species opens up a wide range of possibilities. In contrast to taxonomically narrowly focused datasets, from the co-existence data here we can start to investigate potentially how competition amongst species may be affecting their population distributions. Additionally, we can see how certain species persist later into the winter and can investigate how their date of departure relates to the local climate or resource availability (e.g., insect diversity, or vegetation coverage) at each given site.

From our earlier validations of the BirdNET model, one might expect that a point count at a given date and site might contain the same species as we observe here. However, this data shows that the species that would be found at the same site a day earlier or later could differ significantly. Monitoring continuously over long time periods gives us a more reliable image of the species community that is less affected by natural temporal variation in community composition.

2.3.3 Tracking phenology on a national scale

Understanding phenology, i.e., how species move within and across landscapes or change their behaviour across seasons, can help us to understand the potential impact of anthropogenic pressures on nature. Since acoustic monitoring provides long-term data with high temporal resolution, it provides an ideal method to track phenology. In Figs. 6 and 7 we have already seen how community diversity and individual species presence and absence can be charted as summer moves to winter. Additionally, we investigated whether the last date that a species occurred at a given site was correlated with latitude across the Sound of Norway project. We found for two migratory species, the common chaffinch and common wood-pigeon, there was a significant negative Spearman's correlation between last date of detection and site latitude (Fig. 8). This follows expectations, as the northernmost sites are likely to experience colder climates, leading to earlier emigration of species compared to the southern locations. The start-up of the Sound of Norway project in June and July was unfortunately too late for assessing arrival times of migrating birds. But future studies should deploy the loggers already in March, in order to track arrival dates and potential future changes caused by climate change.

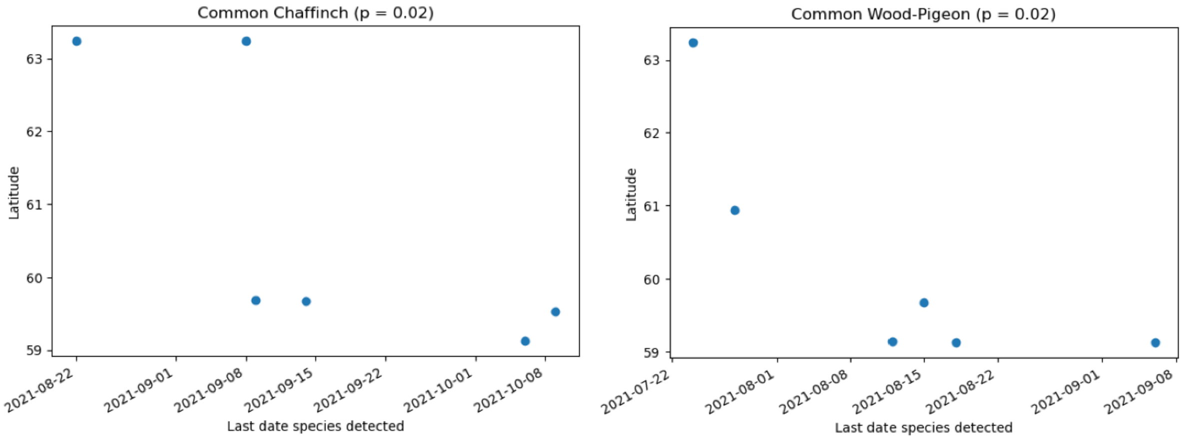

Figure 8: *The date at which two migratory species, the common chaffinch and common wood-pigeon, were last detected by the BirdNET model at each site correlated negatively with latitude (Spearman's correlation, $p < 0.05$). This agrees with intuition as populations based in the northern sites experiencing colder climates are likely to emigrate earlier than those in the south with comparatively milder conditions.*

Species population declines across taxonomic groups have been well documented by several long-term monitoring programs across Norway. However, the exact reasons why populations are declining is a source of much debate and low-resolution traditional survey data often struggles to shed light on this issue. Continuous and long-term acoustic monitoring provides us with a unique opportunity to start to understand the cause of these declines in a way that has not been explored before. For example, the match-mismatch hypothesis suggests that as climate warming in temperate regions leads to earlier springs, bird species which migrate from tropical climes may miss the peak of food-availability and hence experience reduced breeding success and potential populations declines in the future.

In the Sound of Norway project, we have demonstrated that avian communities can be monitored on fine time scales, down to the species level, over long time periods, and in a fully automated manner. Investigating this long-term species community data together with fine resolution climate data (e.g., from satellites) can allow us to test hypotheses on what may be driving species declines. From this understanding we will be able to design policies and management best-practices that manage biodiversity in a more nuanced and well informed manner.

Changing phenology also presents a practical challenge to ongoing long-term monitoring projects. For example, the Miljødirektoratet funded TOV-E project has been surveying avian communities at over 500 locations throughout Norway annually since 2005. However, as climate change causes warmer temperatures, specifically in the northern parts of Norway, migration dates have been changing from year to year. The TOV-E project is co-ordinated nationally so data is collected on a pre-defined schedule each year. With changing dates of migration, though, there is a real possibility that species may be missed as they breed and sing earlier in the year in ways that can't exactly be predicted ahead of time. Further to this there is simply natural variation in which species will be detectable by a given observer from day to day or week to week. It is important to note that TOV-E provides invaluable data such as abundance and breeding pair counts that would not be possible to derive from acoustic monitoring. However, deploying a complimentary continuous acoustic monitoring network alongside TOV-E would allow more in depth understanding of avian community dynamics, and could better inform when the detailed in-person surveys should be carried out each year.

2.4 Ecosystem condition using soundscapes

In the previous section we explored how species-specific vocalisations can be used to track community dynamics using a bottom-up approach. However, soundscapes can also be analysed from the top-down, by tracking how an ecosystem's overall acoustic fingerprint varies with time and location. This approach gives a more holistic view of the ecosystem's state as it does not disregard any aspects of the acoustic environment.

Within the Bugg analysis infrastructure, we calculated soundscape features using the VGGish deep neural network (Gemmeke et al., 2017; Hershey et al., 2017). The VGGish network provided us with 128 features for every 0.96 s of audio, serving as a fingerprint of the ecosystem's soundscape. Prior research has shown that these features correlate very closely with real temporal and spatial patterns in ecosystem dynamics and activity, and that they can be used to predict ecosystem health accurately (Sethi et al., 2020b). Furthermore, fitting a probability density function to these features can allow us to extract anomalous sounds from long-duration recordings in an unsupervised manner. This anomaly detection algorithm has also been implemented within the Bugg system, though we do not present analysis of the data in this report.

Applying a Linear Discriminant Analysis to our data, we showed that soundscapes in different land-use types across our network separated in feature space (Fig. 9). The early detection project represented a wide variety of land-use types, but one core difference was that sites tended to be in more population dense areas than the semi-natural or forest land uses in the insect monitoring project. This will have resulted in a higher number of anthropogenic sounds recorded at these locations, most likely explaining the broader spread in acoustic features.

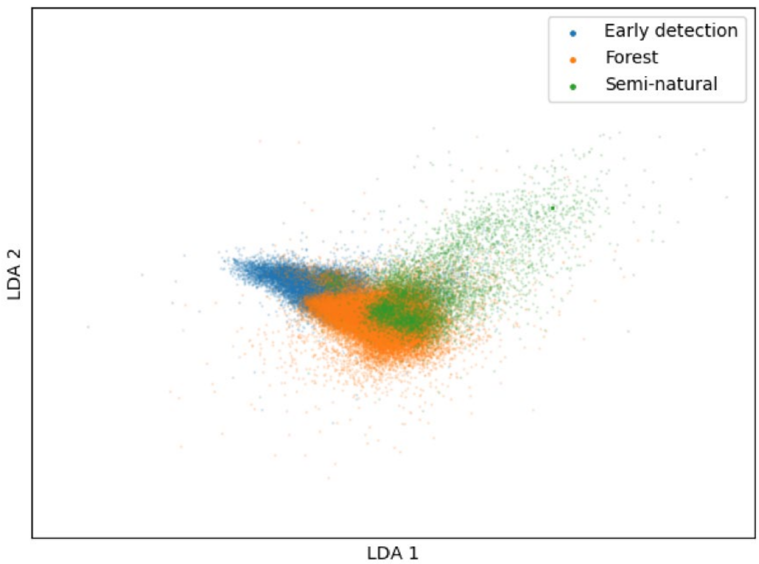

***Figure 9**: Soundscape features differ in different subsets of sites across the Sound of Norway project; those in the early detection project, the semi-natural grassland sites, and the forest sites. Here, the soundscape feature corresponding to each 5-minute audio file across the monitoring network was projected into a 2D space (from the full 128-dimensional VGGish features). The 2D space shown was derived using a Linear Discriminant Analysis. There are clear differences in the regions of feature space populated by the different site types, implying that the soundscape approach allows us to detect community level differences in ecosystem types across space.*

Tracking soundscape fingerprints also allows monitoring of temporal changes in ecosystems on a per site basis. We embedded the VGGish audio features from two sites in a 2D space using a PCA projection, to show how natural temporal trajectories are represented in the soundscape (Fig. 10).

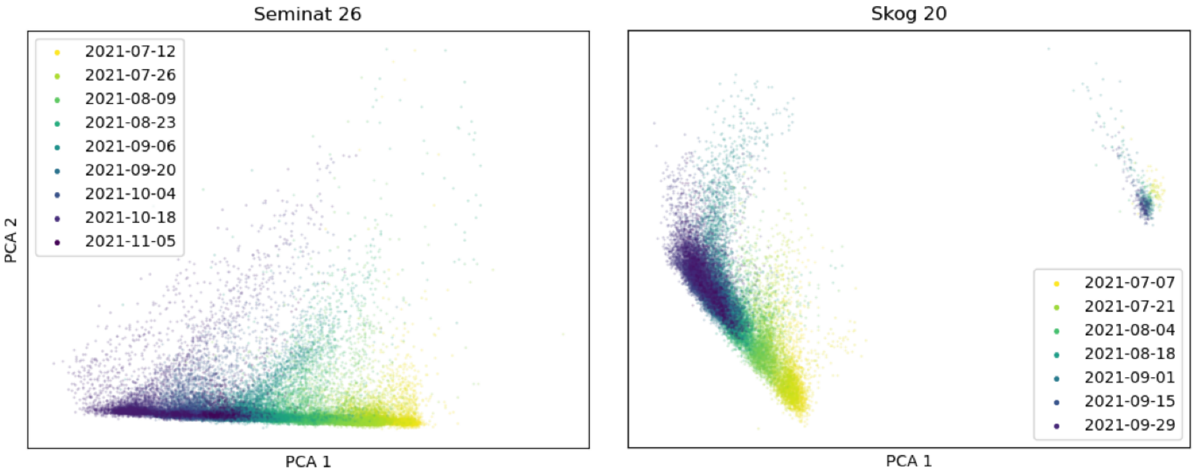

***Figure 10**: Soundscape features change smoothly over months, tracking expected changes in species community. Here, a Principal Component Analysis was used to project the 128-dimensional features into a 2D space. As above, each point represents the soundscape features of a 5-minute audio file uploaded from the given site. At both a semi-natural site and a forest site, the trajectory in soundscapes from the summer months (yellow) to winter months (dark blue) is apparent, indicating that the soundscape approach allows us to track the evolution of species communities across time.*

These preliminary analyses show that soundscape features vary in the same ways that we expect the species community to change – across spatial and temporal gradients. The key strength to this method, though, is that collecting the audio and deriving the acoustic fingerprints required no taxonomically specific classifiers to be trained, and the community patterns fall out from a fully automated and unsupervised approach. This approach can be applied to new locations without modification, providing a very efficient method to both qualitatively and quantitively (with more sophisticated statistical approaches) compare ecosystems in a way that captures information across a wide range of species – all those that contribute to the soundscape in some form.

2.5 Anonymisation and measurement of human disturbance

Collecting acoustic data on such vast scales raises important privacy issues. Whilst we attempted to place recording devices not immediately adjacent to houses or settlements, capturing some human speech was inevitable within a dataset of almost 60,000 hours of audio.

We evaluated two existing state-of-the-art methods for the automated removal of audio speech which were developed for use in outdoor or urban settings. However, due to the high diversity of ecosystem soundscapes compared to these environments (e.g., from rain, wind, and animal calls) there was a good chance that they would not perform well for our purposes. Therefore, we also developed our own model using a convolutional neural network that was purpose made for detecting speech within acoustic datasets collected from natural ecosystems.

Having developed these speech detection models, we performed playback experiments in a forest landscape and a semi-natural grassland. At each location we played speech samples from a man, woman, and child at varying distances from a recording device. We then applied our speech detection model to the recorded audio to evaluate our ability to detect human speech in representative environments from the Sound of Norway project. From these experiments we determined that our model was able to successfully detect speech in acoustic data, without triggering too many false positive detections (Fig. 11). Speech was reliably detected at distances of up to 10m. At 20m the model identified parts of speech, though at this distance the voices were barely audible and unintelligible to a human listener, so the privacy implications were less serious.

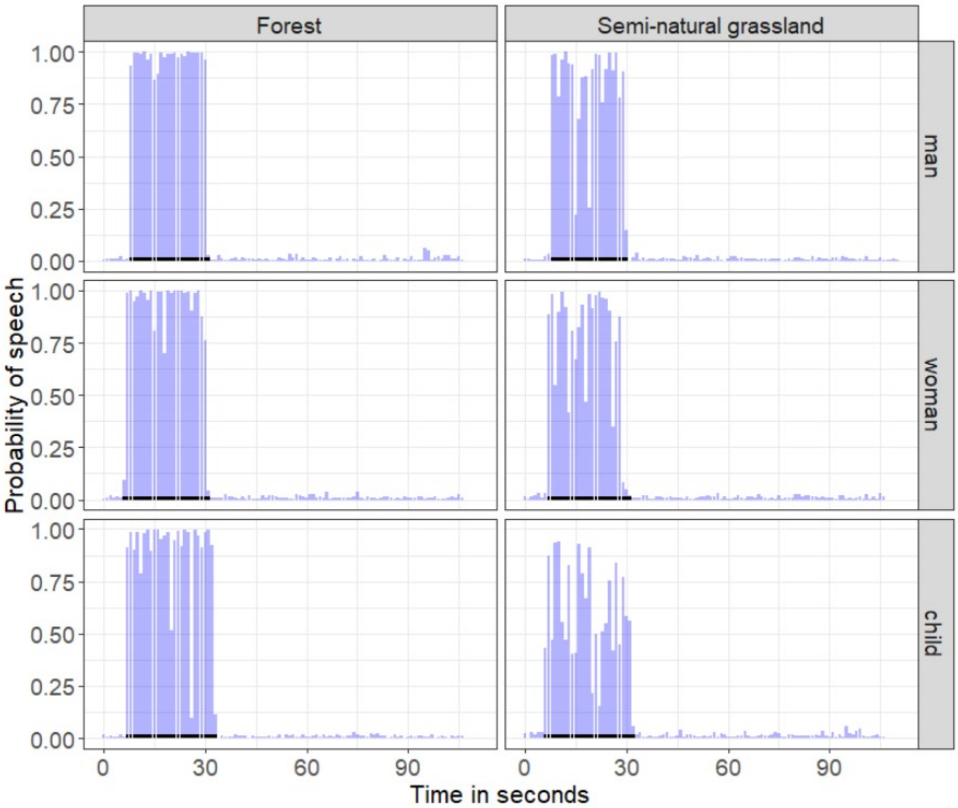

***Figure 11**: We built a model to detect human speech in acoustic data and evaluated its performance by carrying out playback experiments in a forest and semi-natural grassland. Here we show results for when the speech was played at a distance of 10m from the recording device. Areas containing speech are denoted with black lines, and the confidence for speech predictions from the model are shown in blue. The model was able to successfully detect regions of speech for man, woman, and child in both types of landscapes.*

We are working on implementing this speech detection algorithm into the Bugg system, so data is automatically anonymised (speech is removed) before it is stored, or any downstream analyses are carried out. This will ensure that data privacy is maintained whilst still allowing us to reap the benefits of fully autonomous large scale ecological data collection.

Whilst anonymisation was the primary purpose of developing a speech detector, it also provides us with a high-resolution measure of human activity. Areas with more speech are likely under greater anthropogenic pressures, and this may have noticeable knock-on effects on species activity and distribution patterns. Whilst measures such as distance from settlements or human population density provide static metrics of human pressure, audio has the potential to provide fine grained temporal metrics that may be more relevant to changing species behaviours. For example, an animal might inhabit an area regularly during quieter weekdays, but when hikers are out in greater numbers it may disappear. Ignoring this temporal component in human animal interactions may lead to misinformed land management or policy decisions, as the true effect of humans on nature is not fully understood.

We are working on validating how both human speech and other anthropogenic sounds (e.g., snow scooters, construction work) can act as a proxy for human pressure, with ground truth human activity data to verify our methods. Initial explorations are providing encouraging results suggesting this is a use of acoustic monitoring that holds great future potential.

3 Recommendations for Norwegian management

Our literature review and the Sound of Norway project have highlighted what is possible using acoustic monitoring technologies as they stand today. Passive acoustic monitoring is a low-cost approach, capable of delivering large scale and long-term data on ecosystems at fine resolutions. After much methodological development, passive acoustic monitoring has come of age and is ready to be applied as an invaluable tool for evidence-based nature management.

The recommendations we have identified focus on integration of acoustic monitoring into active nature management where it can contribute new and complementary information to existing management needs. In addition, acoustics has substantial unrealised potential which can be untapped by further targeted methodological development. Together, these recommendations provide a clear direction for how acoustic monitoring can be most effectively employed in the Norwegian nature management context.

1. Provide complementary temporal data to existing monitoring programs

We recommend integration of passive acoustic monitoring into existing nature monitoring programs to provide complementary continuous monitoring data where currently only static snapshots exist

We have demonstrated that passive acoustic monitoring can allow us to autonomously collect continuous species occurrence data in Norway over long time periods. Many existing nature monitoring programs sample only at one or a few fixed points each year, and therefore lack fine scale data on how their study systems vary in time. Complementing existing monitoring programs with passive acoustic monitoring can provide continuous data on species occurrence and community dynamics, providing data on temporal variabilityOne particularly promising example is the TOVe breeding bird program which conducts highly detailed breeding bird occurrence and abundance surveys at nearly 500 locations throughout Norway at one point in time each year. At each location, ornithologists perform 20 point counts along a line transect. We recommend adding 50-100 recorders across the TOVe monitoring network. From the full set of 500 locations, passive acoustic recording sites should be stratified across a gradient of expected migration timings (e.g., by latitude, or environmental variables).

The addition of passive acoustic monitoring could both aid decision-making on when each site should be sampled (a difficult decision due to weather and climate base variation in the onset of bird song) and contribute phenology data on how bird vocalisations vary throughout the season and between years. After one year of continuous monitoring, it will be possible to assess the accuracy of the automated acoustic species detection models using the manual point counts as ground truth. Furthermore, it will be possible to see whether audio monitoring could have informed improved timing of the breeding bird point counts based on species occurrence variability across the spring season. After two to three years of monitoring, we will begin to understand in fine temporal detail how migration timings vary across Norway, and the potential impacts of human induced climate change on avian phenology.

Another application with a somewhat longer temporal perspective is as a part of environmental change monitoring during environmental impact assessments (EIAs) of proposed developments or monitoring of restoration projects. Here, passive acoustic monitoring can be deployed using a BACI design to monitor continuously prior to, during, and after planned development or restoration works. Acoustic data forms a type of digital time capsule, with identical data types which can be directly compared and reanalysed if questions arise during the later phases of a project (i.e., to determine whether a species that wasn't considered early in the project was in fact present). Other NINA terrestrial monitoring programs that we suggest could benefit from addition of complementary, continuous acoustic data include TOV (program for terrestrial nature monitoring: www.nina.no/Våre-fagområder/Miljøovervåking-på-land/Naturovervåking-TOV), SEAPOP (monitoring and mapping of seabirds: https://seapop.no/) and COAT (monitoring of climate change in the Arctic: https://www.coat.no/en/. Exact details of how passive acoustic monitoring can be deployed in these additional applications should be determined with input from the relevant subject matter experts.

2. Integrate soundscapes into holistic measures of ecosystem health

We recommend a pilot study into how an ecosystem's soundscape fingerprint can be integrated into quantification of ecosystem condition

The soundscape approach gives a higher-level view of an ecosystem's state than individual species occurrence assessments, as it does not disregard any aspects of the acoustic environment. We have shown that soundscapes can quantitatively discriminate between habitat types and temporal changes at sites. Other studies have demonstrated that soundscapes reflect ecosystem health across landscape degradation gradients (Elise et al., 2019; Sethi et al., 2020b). Implementation of soundscape features into ecosystem monitoring programs using traditional methods can provide a new lens through which to monitor ecosystem health, stability, and changes.

One project which could benefit from soundscape derived metrics of ecosystem health is the ANO program for areal representative nature monitoring (https://www.nina.no/%C3%98kosystemer/Arealrepresentativ-naturoverv%C3%A5king-ANO). This is a national monitoring program with a network of 1000 randomly chosen monitoring sites, each of which has 18 sub locations. Two hundred sites are evaluated at one point in time annually, with a rotation over five years. We would recommend placing continuous acoustic monitoring devices at a subset of 50-100 sites from the ANO program stratified representatively across the different nature types. After one year of continuous monitoring, we will be able to see whether different nature types exhibited similar soundscape features and dynamics over the annual cycle. Over a longer timescale of 2-5 years, soundscape features from each of these sites could provide data on ecosystem status and variability between the 5-yearly sampling visits and may act as an indicator of change by tracking shifts in the ecosystem's acoustic fingerprint over time. We may even find that ANO surveys can be dynamically adjusted to focus on sites in areas which are undergoing the fastest change, whereas those with more stable soundscapes can be visited with reduced frequencies.

The question of how to identify reference conditions (i.e., those which should be seen as the gold standard for ecological health) in projects like ANO is currently debated in Norwegian management. One option is to compare ecological conditions to locations which are situated within protected landscapes, whereas the other is to rely on expert evaluations. In either case, as long as control sites can be identified (manually or otherwise) soundscapes can be used to measure the difference in ecological condition between a given site and its reference. Furthermore, even without any concept of a reference condition or reference sites, soundscape data can still be used to provide invaluable data on temporal change of ecosystem condition over time by tracking longitudinal trajectories of acoustic features at any given site.

3. Implement acoustic human disturbance measures into existing monitoring

We recommend integration of audio based human disturbance measures into existing monitoring programs which investigate how nature is affected by anthropogenic pressures

Quantifying human pressures on ecosystems and biodiversity is key to understanding and mitigating the negative effects of anthropogenic change. Types and extent of human disturbance vary over time (e.g., hunting in the autumn and snow mobiles in the winter). The consequences of these different types of disturbance may impact upon distinct ecosystem components uniquely. So, obtaining a nuanced picture of human disturbance over time is important for a full appreciation of ecosystem and biodiversity responses. In this study, we have shown that it is possible to detect and classify human speech from natural ecosystem soundscapes. Detection and classification of other types of human disturbance is common in other fields (e.g., for noise level monitoring in construction sites), and these methods can be straightforwardly translated to ecological applications.

Many existing nature monitoring programs can benefit from measurements of human disturbance over time. These include both biodiversity monitoring such as the Norwegian insect monitoring project, early-detection and warning of new alien species in Norway project, and community monitoring efforts such as TOV and ANO. The TOV monitoring project, for example, surveys seven sites distributed from north to south in Norway. The monitoring program, which has run for over 30 years, aims to document long term trends in nature, detect effects of human disturbance at an early stage and distinguish between human-induced and natural variation. Deploying an acoustic monitoring network across these seven sights could provide fine scale quantification of human disturbance that could provide a new angle to the existing efforts to measure anthropogenic pressures. Additionally, the impact of human traffic on wild reindeer is already being explored as part of the SNO project (Gundersen et al., 2013), so using acoustic measures of human disturbance here would be a valuable addition to an established scientific program.

In addition to helping us understand how the ecology of an area is affected by human disturbance, acoustic based human activity measures can be used for the effective management of visitors. For example, by understanding the most popular hiking routes in a national park, a land manager can ensure paths are maintained to the required conditions and that traffic is managed in a suitable manner. Furthermore, by combining vocalisation detection models with acoustic human disturbance measures, managers can evaluate how the presence of keystone species (e.g., wild reindeer) is affected dynamically by human pressure, and measures such as the temporary closures of certain paths can be taken as and when necessary to restore the balance.

4. Further focussed methodological development for management purposes

We recommend investing in developing better automated vocalisation detection models for key species in Norway

Through our use and evaluation of the BirdNET model we demonstrated how acoustic monitoring could provide large scale and continuous community level monitoring of avian species. Through expert annotations we discovered that the precision of the model varied greatly between species when applied to Norwegian soundscapes. The BirdNET model was developed by the Cornell Lab of Ornithology with data primarily collected in the USA, and therefore it is expected to perform better when applied to American soundscapes.

We recommend investing in developing more accurate vocalisation detection models for species of key interest to Norwegian management authorities (e.g., those endangered, invasive, or providing key ecosystem services). The first step is to create a large library of recordings of the target species’ vocalisations. Collating these libraries can be done by making new field recordings and by mining existing online databases – often both approaches are needed. To collect, clean, and label sufficient data can take between 2-4 months of technician work. Subsequently, training a detection model, iterating the model to work with the nuances of each species, and evaluating the model’s performance can take between 3-4 months of additional researcher work. Once these steps are complete, acoustic data can be used to monitor populations of almost any species with unique vocalisations.

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