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RESEARCH ARTICLE

TABMON: Design and deployment of a transnational passive acoustic monitoring network for European birds

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Abstract

1. Ecological surveys are often fragmented, costly and limited in scale, leading to large and long-standing knowledge gaps which threaten our ability to properly safeguard biodiversity.
2. Passive acoustic monitoring (PAM) has promised to deliver automated biodiversity monitoring, but networks are rarely deployed on scales that can offer truly novel insights due to scalability and standardization challenges around collecting, managing, analysing and sharing data.
3. Here we present the Transnational Acoustic Biodiversity Monitoring Network (TABMON), a standardized deployment of 108 autonomous sensors across Norway, the Netherlands, France and Spain along a continental bird migration route. Audio is recorded continuously, uploaded in near real-time and processed through an automated analysis pipeline designed to support expert validation and the generation of datasets for deriving Essential Biodiversity Variables (EBVs).
4. TABMON provides a methodological blueprint for transnational, networked PAM deployments and highlights both the opportunities and current limitations of near real-time acoustic biodiversity monitoring at continental scales.

KEYWORDS
acoustics, big data, biodiversity monitoring, sensors

1 | INTRODUCTION

Obtaining reliable biodiversity data across large spatial and temporal scales remains a major challenge (Kissling et al., 2026). Despite decades of research documenting substantial biodiversity knowledge gaps (Faith et al., 2013; Santana et al., 2025), these deficiencies persist due to the high financial and logistical demands of traditional field surveys, the need for specialized taxonomic expertise and the fragmented nature of existing monitoring efforts (Wetzel et al., 2018). Across Europe, biodiversity observation continues to suffer from pronounced taxonomic, spatial and temporal biases (Darras et al., 2025; Santana et al., 2025), with many habitats and species groups poorly represented and national programmes operating with limited coordination (Moersberger et al., 2024). Such heterogeneity in methods and coverage impedes the operationalization of Essential Biodiversity Variables (EBVs) and constrains the integration of biodiversity information across borders and biogeographical regions (Lumbierres et al., 2025). Addressing these challenges requires the establishment of scalable and standardized observation frameworks capable of delivering reliable biodiversity data at continental scales (Kissling et al., 2026). Recent advances in digital sensing technologies and autonomous monitoring approaches (Besson et al., 2022) offer a promising path forward by enabling cost-effective, high-frequency and spatially distributed biodiversity data streams that can bridge existing monitoring gaps and strengthen Europe's capacity for coordinated biodiversity assessment.

Among emerging technologies for large-scale biodiversity observations, passive acoustic monitoring (PAM) has become a leading approach owing to its ability to detect multiple taxa simultaneously, its low sensor cost and the growing capabilities of automated processing pipelines (Gibb et al., 2019). Although numerous PAM studies have generated valuable insights at local or short-term scales (Cretois et al., 2024; Darras et al., 2025; Ross et al., 2023; Sugai et al., 2019), applications delivering consistent data across large spatial or temporal extents remain rare. Key barriers include equipment and maintenance costs, data management complexity and slow uptake of standardized protocols (Sugai et al., 2019).

Most PAM deployments rely on recording devices that store data locally, requiring periodic site visits for battery replacement and manual retrieval of storage media (Hill et al., 2019). These constraints often result in fragmented temporal coverage, delayed data access and limited opportunities for timely quality control. In large or remote study areas, logistical constraints can further lead to extended gaps in data collection and reduced continuity of long-term monitoring efforts. In parallel, distributed citizen-science projects have helped cost-effectively expand spatial coverage to scales not achievable by small dedicated field teams (Newson et al., 2015; Roe et al., 2021). However, data quality is impacted by variable sampling effort and observer expertise, and continued coordination of citizen scientists can be complex, time consuming and costly. Networked autonomous recorders powered by off-grid energy sources (e.g. solar) address several of these limitations by enabling continuous operation, automated data transmission and near real-time monitoring of device status and data availability (Sethi et al., 2018, 2024). This approach reduces delays between data collection and analysis, supports early detection of device failure and facilitates standardized workflows across geographically distributed sites. Coupled with automated species identification algorithms, such systems enable rapid, standardized and high-throughput analysis of large acoustic datasets (Bick et al., 2024; Sethi et al., 2020). Although requiring higher initial investment, they support long-term, low-maintenance deployments, near real-time quality control and streamlined data integration. Together, these innovations position PAM as a practical foundation for standardized, continuous and continent-scale biodiversity monitoring.

Here, we describe the design, deployment and operational workflow of TABMON; a Transnational Acoustic Biodiversity MOnitoring Network. Deployed across four European countries along a large latitudinal gradient (108 sites spanning a latitudinal gradient of 3649 km) targeting terrestrial bird species, TABMON aims to: (i) push scalability limits by deploying the first standardized PAM network across multiple European countries and biomes, (ii) deliver tailored machine learning workflows for acoustic identification of European birds at a transnational scale and (iii) fill spatiotemporal and taxonomic gaps in our understanding of the breeding behaviour and migration timing of terrestrial birds across Western Europe (Flack et al., 2022).

2 | SAMPLING DESIGN

The TABMON network spans Norway, the Netherlands, France and Spain, covering a latitudinal gradient of 3649 km (Varanger in Finnmark, Norway to Delta del Ebre in Catalonia, Spain) and a longitudinal gradient of 3539 km (Pasvik in Finnmark, Norway to Mas de Melons in Catalonia, Spain). The network encompasses representative landscapes along major terrestrial bird migration routes in Western Europe and includes habitats of importance to both diurnal and nocturnal species. In total, we selected 108 sites (51 in Norway, 18 in the Netherlands, 21 in France and 18 in Spain; Figure 1), where autonomous acoustic sensors were deployed between January and April 2025 and will remain operational until at least January 2027, covering two complete annual migration cycles. For each deployment, field teams recorded key metadata including GPS coordinates (longitude, latitude), deployment date (YYYY-MM-DD HH:MM-SS format), microphone height (cm) and microphone directionality (cardinal direction or degrees), together with a short field description of the site (e.g. habitat context or connectivity issues). Photographs of the device and surrounding environment (e.g. front, back, left, right) were also collected to support later interpretation of the recordings and troubleshooting of technical issues. The complete deployment metadata are provided in Table S1.1 in Supporting Information S1, and the deployment form used in TABMON to collect site metadata is included in Supporting Information S2.

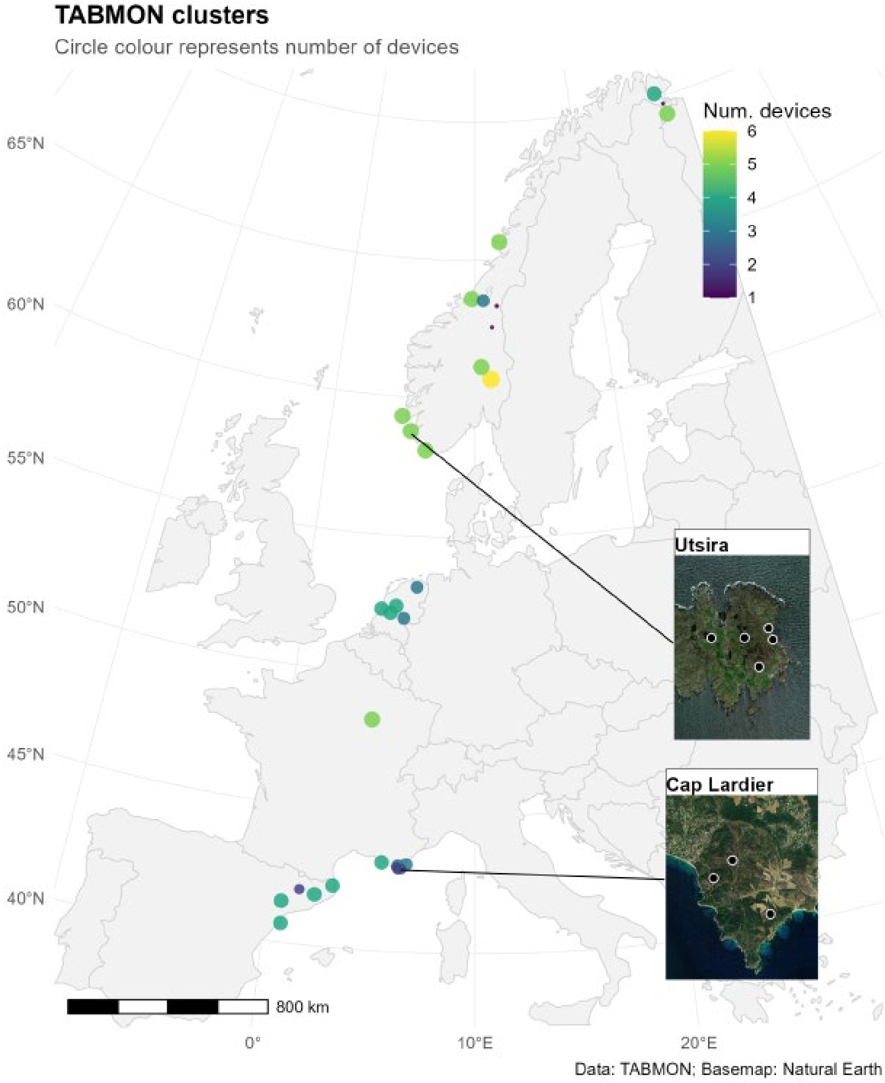

FIGURE 1 Locations of the TABMON clusters spanning Norway, Netherlands, France and Spain with circle colour representing the number of devices within clusters. Small dark blue circles represent single devices. Inset maps represent a detailed view of the Utsira and Cap Lardier clusters.

Site selection followed a combination of ecological relevance and logistical feasibility. Ecologically, sites were prioritized along known or suspected migration flyways and in habitats frequently used as breeding areas, migration corridors or stopover sites. Selection was informed by local ornithological expertise and existing knowledge of bird hotspots. Several deployments were co-located with established monitoring efforts, such as long-term breeding bird surveys, point counts, ringing stations or citizen science observation networks, enabling cross-validation and integration of acoustic detections with conventional monitoring data. In addition, some locations were selected to improve monitoring of nocturnal and cryptic species, which are typically underrepresented in traditional surveys. A complete description of our site selection protocol can be found in Supporting Information S3. Logistical criteria included accessibility (sites reachable within approximately 1 h on foot or skis), cellular network coverage (4G/5G connectivity for data transmission) and proximity to partner institutions or trusted local contacts able to intervene in case of equipment failure (generally within 100 km). The uneven distribution of sites among countries reflects differences in logistical constraints, partner capacity and opportunities for off-grid deployments rather than a stratified sampling design across environmental, anthropogenic and policy gradients (Kissling et al., 2026). Although such geographic imbalance may introduce bias if not considered during analysis, appropriate statistical approaches such as stratified sampling or model-based sampling can mitigate these effects (McEwen et al., 2025).

Sites, defined by the GPS coordinates where individual sensors were deployed, were grouped into clusters of two to six devices. Each cluster represents a geographical unit such as an island, peninsula or protected area containing suitable habitats for migrant passerines or nocturnal birds, as identified by local ornithologists. The cluster design improves logistical efficiency for installation and maintenance while increasing data robustness, as recordings from multiple devices within a cluster can partially compensate for temporary device failures. Within clusters, the median distance between devices is 3.71 km, ranging from 278 meters (Utsira) to 54 km (Trondelag) (Figure S1.1 and Table S1.2 in Supporting Information S1). At local scales, devices are typically separated by >250 m, which reduces the likelihood of the same bird vocalization being recorded by multiple devices (Metcalf et al., 2023). Larger distances within cluster distances mainly occur in extensive protected

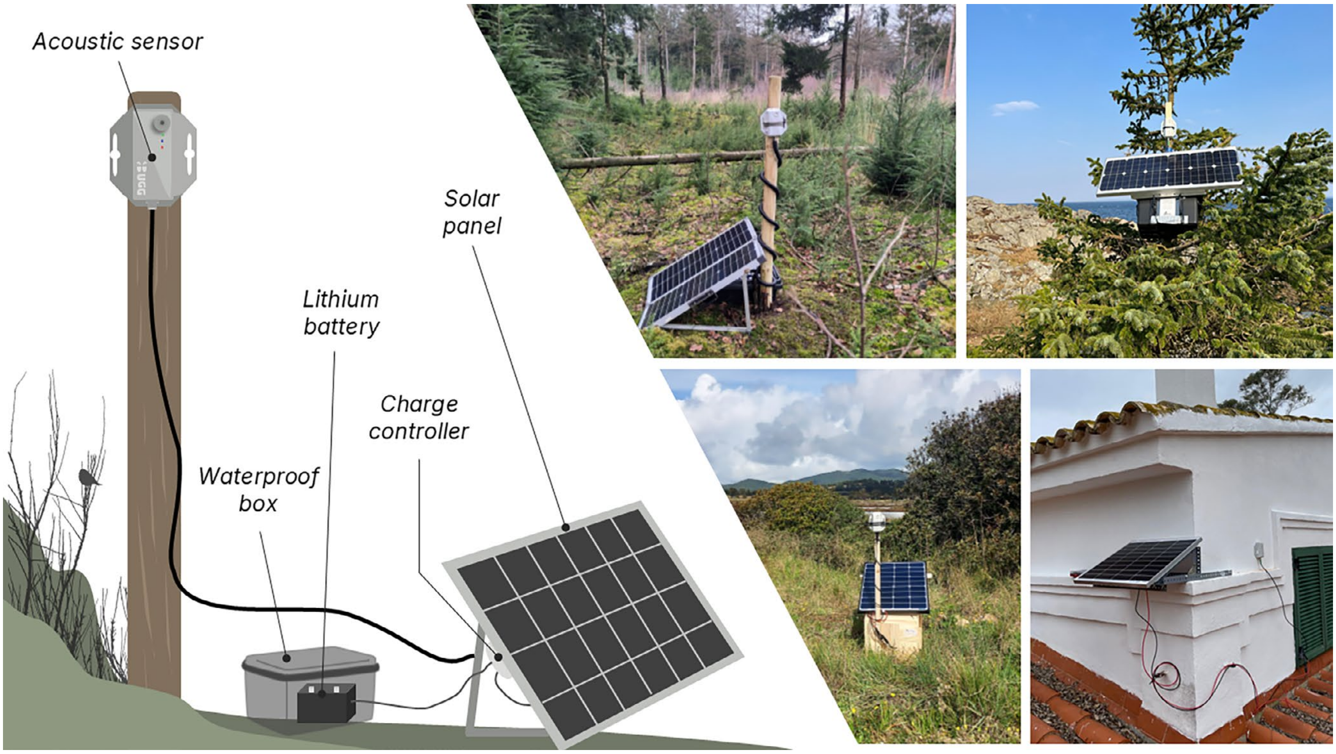

FIGURE 2 Schematic view of the Bugg acoustic sensor deployment set up (left-hand side) and example deployment pictures (right-hand side).

areas or remote landscapes, such as northern Norway, where suitable deployment locations are widely spaced. In more human-dominated landscapes, where suitable habitats are smaller and more fragmented, clusters tend to be more compact, as observed in the Netherlands and France.

3 | SENSORS AND OFF-GRID POWER

At each site, we deployed a Bugg device (Sethi et al., 2018) which transmits near real-time, compressed audio data over a 4G/5G mobile internet connection. Each unit records 5-min monochannel audio files continuously (24h per day) at a sampling rate of 44.1kHz to capture the full range of audible bird vocalizations. MP3 variable bit rate (VBR0) compression is required as most mobile networks do not have sufficient bandwidth to support continuous uncompressed audio transmissions.

Each Bugg is powered by an external lithium battery charged by a solar panel, enabling continuous recording when local conditions allowed (Figure 2). For instance, daylight and temperature limited autonomous operation in Norway to roughly mid-February through mid-October, whilst devices in Spain record year-round. Power-system specifications differed between countries according to site accessibility, resource availability and local equipment availability (Tables S4.1, S4.2, S4.3 and S4.4 in Supporting Information S4).

To limit setup-related bias, consistency in device deployments across all sites is prioritized. Where possible, devices are deployed at a height of between 1 and 2m (using trees or poles) (Metcalf et al., 2023). However, in some cases, devices are placed higher (i.e. up to 4.5m, to limit vandalism and theft risks, damages from grazing animals, snow, flooding or vegetation coverage) or lower (i.e. minimum 0.9m, to limit wind exposure). Bugg devices are primarily oriented with microphones facing towards the habitat of interest. When strong winds could interfere with the recording (e.g. coastal scrublands), the orientation is adjusted to reduce exposure (i.e. opposite to prevailing wind direction). In dense habitats with limited sunlight (e.g. forests), devices are typically installed along south-facing edges or in clearings, directed towards the target habitat. On sloped terrain or where obstacles restricted deployment, the Buggs were positioned towards the most open area. Devices are mounted in an upright position whenever possible, with a slight upward or downward tilt when installed at a non-standard height or when placed on a slope.

4 | DATA INGESTION PIPELINE AND SERVER ARCHITECTURE

4.1 | Infrastructure and servers

Immediately after recording, files are uploaded to Google Cloud, where they are automatically transferred once per day onto a storage bucket hosted by the Norwegian Infrastructure for Research Data (NIRD: NIRD—Sigma2 documentation) to reduce costs of

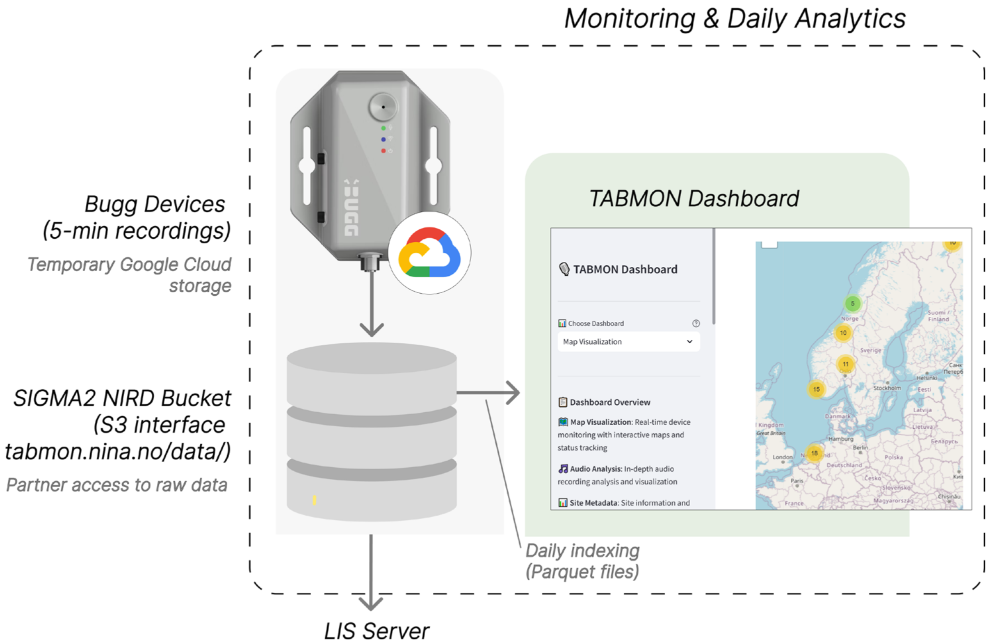

FIGURE 3 TABMON data collection and infrastructure. Audio is uploaded in near real-time from Bugg devices in the field to a Google Cloud Storage bucket. Data is then transferred to a Norwegian Infrastructure for Research Data (NIRD) server, where it can be accessed by partners and visualized through a dashboard. Data is copied to the University of Toulon's LIS server for long-term archival storage and analysis.

data storage (Figure 3). Given its flexibility in access policy, the NIRD bucket serves as the primary entry point for the consortium, providing partners with direct access to the recordings as well as the metadata. The NIRD bucket is mounted as S3-compatible storage, which allows both (i) our TABMON dashboard to visualize network status and data availability, (ii) our TABMON Listening Lab to serve users with BirdNET detection clips for annotation and (iii) partners to directly access raw recordings for quality checks or independent analysis.

For long-term stability and computationally intensive tasks, the entire dataset is copied once per month to a dedicated server at the University of Toulon's Laboratoire d'Informatique et des Systèmes server (LIS server), where access is more restricted than on the NIRD bucket. This LIS server acts as the archival repository for TABMON and hosts most of the large-scale analysis (Figure 4). The LIS server is equipped with 40 NVIDIA GPUs (primarily A100, A40 and RTX 3090) and 250 TB of storage dedicated to the project. Under this configuration, processing a 5-min file takes an average of 8 s. Analyses are performed on a monthly basis, using up to 10 jobs in parallel.

4.2 | Acoustic analysis

Given the very large volume of audio produced by continuous recording (approximatively 25 TB of raw acoustic data in 2025 only), we employ an automated analysis pipeline. The pipeline uses the BirdNET model (Kahl et al., 2021), which is able to identify over 6500 bird species based on their vocalizations and has proven useful for European bird monitoring, for instance for estimating community-level patterns in European soundscapes (Funosas et al., 2024, 2026; Winiarska et al., 2025). We use BirdNET in TABMON as a screening tool for extracting species-level predictions from continuous recordings.

We divide each 5-min recording into non-overlapping 3-s segments and process them with BirdNET. For each segment, the model outputs a predicted species label and an associated confidence score ranging from 0.01 to 1. This score indicates how strongly the model supports a given species identification relative to other possible species in its reference set (Wood & Kahl, 2024).

We use BirdNET (v2.4) via the TABMON data pipeline, built upon the AvesEcho service (Ghani et al., 2024) and optimize the pipeline for parallel execution across multiple GPUs. The AvesEcho filter takes the longitude and latitude of the recorder, the coordinates are converted to a Military Grid Reference System (MGRS) coordinate extracting both time zone and latitudinal band. This rectangle is used to clip the European Breeding Bird Atlas 2 (EBBA2) occurrence map (Keller et al., 2021) (i.e. where species have been reported to breed), which is used to filter BirdNET predictions. Due to the focus on migratory species with differing occurrence and breeding locations, this geographical filtering method was adjusted to include a fixed set of MGRS coordinates (29 W–36 S). This provides complete coverage of TABMON sites and filters the BirdNet classes from 6522 to 480 species.

We store predictions and metadata in a database composed of Parquet files, enabling efficient compression and fast column access. DuckDB enables SQL-based querying of these files, and a FastAPI interface provides access to the data. In addition, we save the 3-second clips for which the detection has been made for validation

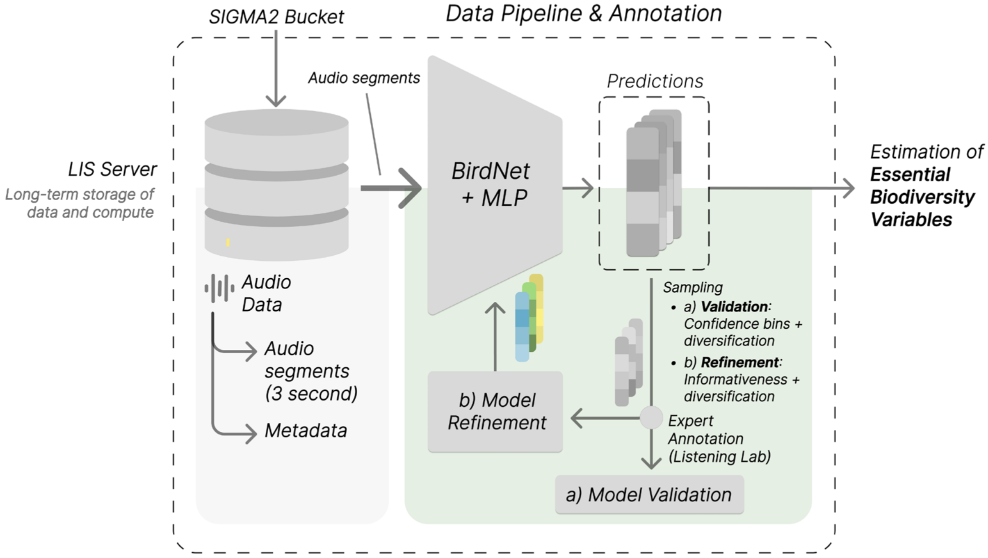

FIGURE 4 The TABMON data ingestion and analysis pipeline. Model predictions are computed on a server which then informs sampling and expert annotation for model performance validation and model training.

purposes. The data pipeline and export interface are open-source and available on GitHub.

4.3 | Data collection for BirdNET validation

Automated predictions alone are often unreliable for ecological interpretation without quantifying model accuracy under network-specific conditions (Tseng et al., 2025). BirdNET performance may vary across species, habitats, seasons, devices and background noise regimes (Citovsky et al., 2021; Gregory & Van Strien, 2010; Lehikoinen et al., 2019; Settles, 2009), and these sources of variation must be assessed before deriving ecological indicators such as species richness.

To validate BirdNET detections we use two complementary annotation platforms. The TABMON Listening Lab for Experts (https://tabmon-listening-lab-expert.nina.no/) is designed for trained ornithologists, with specific datasets being uploaded to this application following a strict protocol. For selected target species and sites, clips are sampled systematically across predefined BirdNET confidence-score intervals (0.1–0.2, 0.2–0.3, etc.), with a fixed number of clips drawn from each bin. This stratified sampling ensures that validation covers the full range of model confidence scores, rather than focusing only on high-confidence predictions (Tseng et al., 2025). Experts log in the application and review the audio segment and the spectrogram where the detection has been made together with the BirdNET predictions and the clip metadata, and then confirm, correct or reject the suggested species labels.

In addition, trained volunteers and citizen scientists are able to review TABMON detections using the public facing TABMON Listening Lab (https://tabmon-listening-lab.nina.no/). The user is able to select a site or species of interest and confirm, correct or reject the BirdNET prediction. While expert annotations provide the basis for formal performance assessment (Figure 4a), citizen-science contributions increase annotation capacity and help broaden taxonomic and geographic coverage.

4.4 | Data collection for BirdNET model refinement

In addition to validation, labelled clips are curated to support future model refinement for European acoustic conditions (Figure 4b). Species predictions in large-scale monitoring follow a long-tailed distribution, with common species dominating outputs and many taxa underrepresented, leading to underwhelming model performance for the infrequent species (Figure S5.1 in Supporting Information S5; Zhang et al., 2024). A naïve sampling approach would therefore provide limited information for improving model performance on rarer or acoustically challenging species. Acoustic recordings collected across countries, habitats and devices are also subject to domain shifts, where background noise, habitat structure, seasonal soundscapes and sensor characteristics differ from the conditions represented in model training data. Recent methodological work carried out as part of TABMON shows that structured sampling strategies accounting for class imbalance and spatiotemporal variation can substantially increase the value of person-time spent on annotation for model adaptation (Bernard et al., 2025; McEwen et al., 2025).

In TABMON, annotation batches intended for model refinement are constructed using stratified sampling rather than simple random selection. Specifically, we construct batches using (i) a BirdNET confidence threshold lower-bound of 0.2 to reduce the false positive rate; combined with (ii) random selection with stratification across predicted species. The batches are sent to a trained ornithologists who confirm or infirm the detection through the TABMON Listening Lab.

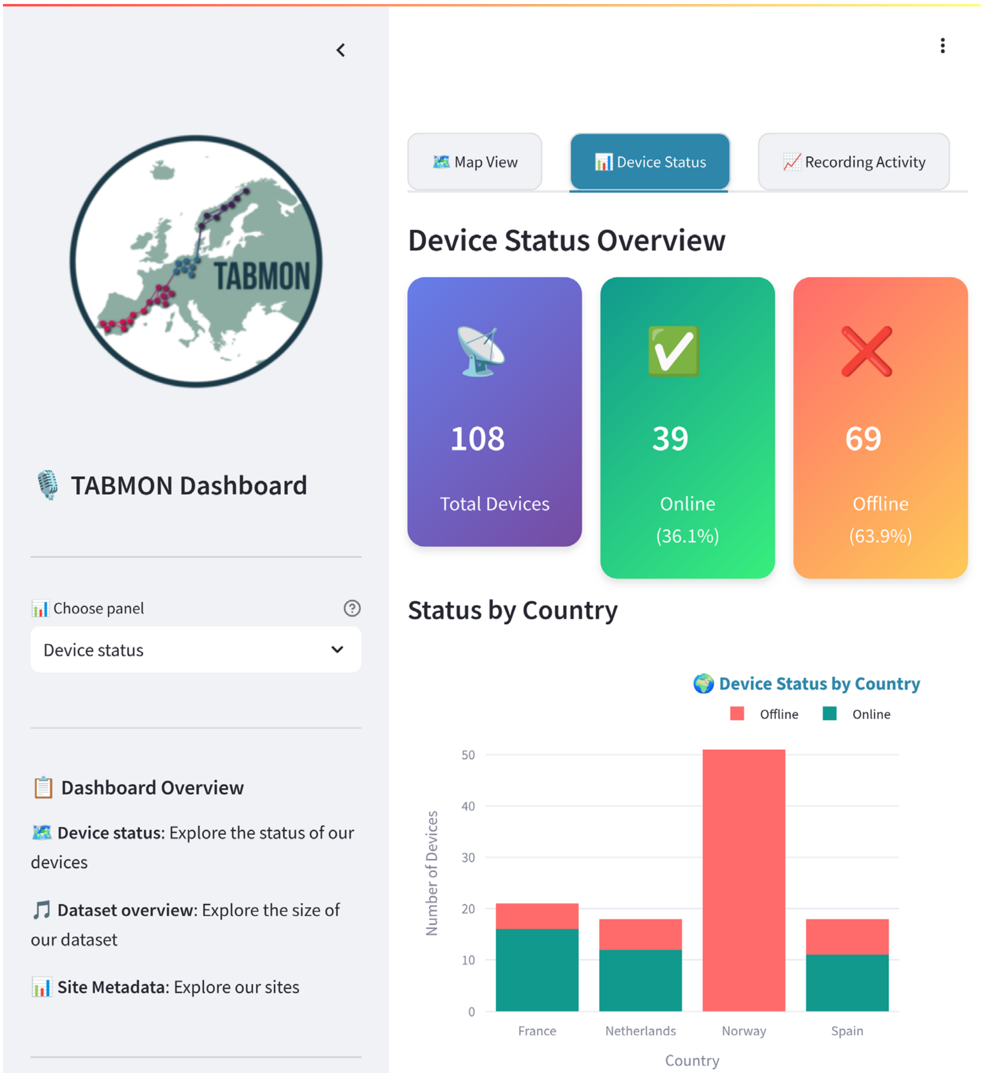

FIGURE 5 Screenshot of the dashboard User Interface. The user can select between three panels: Map Visualization to get a description of site location and online status as well as an overview of the existing dataset, Site Metadata to display the specific site's information including microphone heights and pictures, and Audio Analysis which displays information related to the amount of data collected at a specific site. The screenshot was taken during winter, hence the Norwegian devices are offline.

These annotated samples are finally used to fine-tune BirdNET's classification head (Multi-Layer Perceptron; MLP), that is, to adapt the final part of BirdNET so it becomes better at identifying the bird species we are interested in. This protocol is informed by our previous work on efficient selection of samples (Bernard et al., 2025; McEwen et al., 2025). To date 2000 samples have been annotated using this methodology (Cretois et al., 2025). Future work will investigate complementary strategies, including spatial and temporal stratification, stratification by confidence bins and uncertainty sampling (McEwen et al., 2025).

5 | TABMON DASHBOARD: ACCESSING NETWORK STATUS AND METADATA

The publicly accessible TABMON dashboard (https://tabmon.nina.no) provides a secure and user-friendly interface for exploring the network's deployment, operational status and accumulated data. Built in Streamlit and deployed through Docker containers, the dashboard interfaces directly with the NIRD S3 bucket. To keep the dashboard synchronized with ongoing recordings, all files stored on NIRD are indexed daily. This process extracts file metadata (i.e. device ID, country, site, file size) and writes it to a consolidated parquet file.

The interface is designed to serve both technical partners and the broader research community. An interactive map presents the geographic distribution of the 108 Bugg sensors deployed across the four countries, with device-level indicators showing operational status and cumulative data volumes. For each sampling site, users can access a dedicated panel displaying site metadata, including photographs, deployment details and habitat information, alongside summaries of recording effort and storage volumes (Figure 5).

By consolidating these features, the dashboard provides transparency on network performance and facilitates collaboration among consortium partners. It represents the main entry point to the TABMON infrastructure, allowing the consortium to monitor sensor uptime and track accumulation of audio data.

6 | DATA SHARING AND DOWNSTREAM ECOLOGICAL INSIGHTS

The primary goal of TABMON is to demonstrate how PAM can increase the extent and resolution of monitoring data and enable automated, cost-effective monitoring of terrestrial avian biodiversity. Birds are taxonomically well studied, responsive to environmental change and some species are highly vocal, making them ideal sentinels for biodiversity monitoring (Gregory & Van Strien, 2010). TABMON focuses on terrestrial avian occurrence and phenology, with a particular emphasis on cryptic or night-active species which are vocally active but are difficult to monitor with conventional schemes (e.g. owls, rails) (Duchac et al., 2020), and on vocal migratory species whose behaviour and phenological timing are still relatively poorly understood (Flack et al., 2022). TABMON is designed to support downstream ecological analyses by providing standardized and reliable acoustic observations across diverse sites from several European countries. The data produced in TABMON can thereby contribute to workflows that generate Essential Biodiversity Variables (EBVs) for studying, reporting and managing biodiversity change (Boyd et al., 2023; Kissling et al., 2018; Lumbierres et al., 2025). Specifically, the currently produced TABMON data can be seen as 'EBV-useable data sets' (Kissling et al., 2018) in which raw observations (i.e. sensor detections with AI-inferred species identities and confidence scores) are assembled together with accessible metadata (e.g. timestamp, deployment information, audio filenames, data-sharing licences). This includes having time formats, spatial information and species identities in a standardized way and to openly share these data for subsequent processing (Wiel et al., 2026).

In a second step, TABMON is also working on providing 'EBV-ready datasets' (Kissling et al., 2018). This requires further data quality and cleaning checks, that is, assessing the accuracy of AI detections and identifying errors and wrong identifications. In this context, comprehensive validations of BirdNET confidence scores across species and sites are needed, including assessments of universal and species-specific thresholds (Funosas et al., 2024, 2026; Tseng et al., 2025). TABMON facilitates this by providing online interfaces for validation through expert or citizen scientists (for instance through the TABMON Listening Lab). The validated data can then be used to increase the precision of the acoustic detections generated by automated classifiers (i.e. the percentage of true positives out of all the identified predictions). For example, validated detections can be transformed into calibration curves with a certain threshold of precision (e.g. 0.9 or 0.95) to provide reliable species occurrences that can be summarized into presence or detection frequency within defined spatial (site, cluster, region) and temporal (daily, seasonal, annual) units. Similarly, temporal patterns in vocal activity can then be reliably aggregated to derive phenology-related variables, such as the timing of arrival, peak vocal activity or breeding-related calling periods, and compared to citizen science, for example, from EuroBirdPortal (Border et al., 2024; Bota et al., 2020).

While raw audio recordings cannot be made publicly available due to data privacy considerations and because of logistical constraints (e.g. no online repository accepts such amounts of data at the moment), TABMON is committed to sharing derived products (e.g. EBV-useable and EBV-ready datasets), including metadata, automated predictions and expert annotations. By making these standardized observation-level outputs openly available, TABMON supports reproducibility, independent evaluation and reuse in EBV-oriented analyses and broader biodiversity monitoring initiatives. All bird detections produced as part of the TABMON project (EBV-useable datasets) and the expert annotations can be found on Zenodo and will be updated with the latest analysis (Cretois et al., 2025).

We recognize that the absence of publicly accessible raw audio limits certain forms of reproducibility, independent method benchmarking and re-analysis using alternative detection algorithms. However, we believe that sharing the expert annotations along with the audio clips will contribute to the global effort to better benchmark and refine new methods and models. This represents a trade-off between open data principles, logistical and legal, and ethical constraints associated with continuous environmental audio recording.

7 | KEY COSTS OF THE TABMON SENSOR NETWORK

One of the largest barriers to wider uptake of autonomous monitoring is the significant cost of deploying and maintaining sensor networks (Speaker et al., 2022). Whilst a full economic analysis is beyond the scope of this paper, here we outline a few key considerations and trade-offs (Table 1).

The unique choice to use networked sensors affects TABMON's costs in several ways. Compared to non-networked sensors, connected devices are more expensive (e.g. ~€1000 per Bugg vs. ~€130 per AudioMoth) and require SIM cards with monthly network costs (€1.89–12.52 for 40GB+ monthly). Additionally, each device is connected to its own off-grid solar power system incurring a one-off cost of €300–400. However, the chosen sensor and power delivery systems significantly reduce the operational workload and costs associated with battery replacement, SD card collection and device maintenance visits, an essential consideration for TABMON given the wide geographic distribution of sites and the difficulty of accessing many locations.

Beyond our choice for automated data transfer, there are also the usual costs of collecting, managing and analysing large datasets. The network of 108 sensors can upload over 110GB of audio daily,

TABLE 1 Indicative costs for deployment, operation and analysis in the TABMON project.

Cost category	Item	Unit cost (€)	Frequency	Notes
Hardware (one-off)	Bugg acoustic sensor	~1000	Per device	Networked, autonomous recorder
Hardware (one-off)	Solar power system (panel+battery)	300–400	Per device	Enables off-grid operation
Deployment (one-off)	Installation and setup	Site-dependent	Per site	Travel and labour costs vary by location
Data transmission (recurring)	SIM card & mobile data	1.89–12.52/month	Per device	Depends on national provider and data volume
Data storage (recurring)	Cloud egress (Google → NIRD)	~200/month	Network-wide	Approx. 2 TB transferred per month
Data storage (recurring)	Long-term storage (NIRD)	~100/TB/year	Network-wide	Scales with accumulated data volume
Computation	Analysis infrastructure	Subsidized	Every month	Hosted on national research infrastructure
Annotation	Expert annotation	~1/3-s clip	As required	Depends on availability of skilled annotators

all of which incurs both networking costs (i.e. egress fees, as data is moved between servers or cloud providers) and storage costs. As a reference, we pay ~€200 monthly to transfer 2 TB of data from Google Cloud to our NIRD bucket and €100/TB/year for data storage on NIRD. In total, the average cost of the network is €1350 per Bugg for deployment, plus €150 per Bugg per year for data transfer and storage.

Additionally, computational costs accumulate depending on the complexity of analyses used. Much of our pipeline is hosted in subsidized research infrastructure, but commercial cloud offerings would be more expensive. Finally, when skilled volunteers are not available, ornithologists must be paid to annotate BirdNET predictions to ensure that TABMON delivers reliable biodiversity insights throughout its deployment (approximately 1€ per 3-second annotation).

The sensor network also carries an environmental cost. The production of the sensor and its power supply system is estimated to result in a carbon footprint of 383 kg CO_2e per Bugg, while data transfer, storage and processing contribute an additional 37 kg CO_2e per Bugg per year (See Table S6.1 and Table S6.2 in Supporting Information S6).

8 | DISCUSSION

TABMON demonstrates that transnational acoustic data collection and centralized processing are technically feasible at continental scales. By deploying a harmonized network of 108 autonomous recorders from the Arctic to the Mediterranean, we provide the first working example of a transnational PAM system that continuously generates avian biodiversity data across multiple European biomes. This approach moves acoustic monitoring beyond small-scale or short-term applications, illustrating how digital sensing, automated analysis and shared data infrastructures can together deliver scalable, high-resolution biodiversity observations.

8.1 | Integrating acoustics into continental biodiversity monitoring

TABMON establishes a methodological template for harmonizing autonomous acoustic monitoring across borders. The combination of standardized deployment protocols, centralized data ingestion and open-source analytical pipelines enables reproducible, comparable and rapidly accessible biodiversity information. These characteristics address long-standing issues of fragmentation among national monitoring programmes (Moersberger et al., 2024), help to operationalize EBV workflows at a European scale (Kissling et al., 2026; Lumbierres et al., 2025) and support global biodiversity reporting frameworks based on regional observation systems (Gonzalez et al., 2023). The integration of near real-time data transmission with cloud-based processing further facilitates quality control and adaptive sampling, opening the door to 'digital observatories' for biodiversity.

8.2 | Methodological lessons and challenges at scale

Operating at continental scale exposed substantial logistical and technical challenges, from limited daylight and freezing temperatures constraining solar-powered devices in northern regions to connectivity and equipment interference challenges in more populated southern areas. These contrasts highlight the need for a flexible monitoring architecture that combines networked, solar-powered sensors in remote sites with lower-cost, periodically serviced units where access is easier. While near real-time connectivity reduces maintenance effort, it also increases the cost of power and data transmission (Kissling et al., 2024)—trade-offs that future advances in low-power electronics and edge computing are likely to mitigate. Targeted improvements in the future will come from adaptive schemes for subsampling, reducing and transmitting data.

Considering the analysis stage, the integration of expert informed sampling within TABMON helps to make automated recognition into a scalable strategy despite diverse acoustic and environmental conditions (Bernard et al., 2025; McEwen et al., 2025), providing an adaptable blueprint for future large-scale acoustic or multimodal biodiversity networks. Manual validation will continue to be a crucial factor for the interpretability and usability of AI-derived detections in ecological applications, irrespective of future technical improvements.

8.3 | Towards integrated and multimodal biodiversity observatories

The infrastructure developed through TABMON provides an expandable platform for integrating data from traditional monitoring schemes with sensor-based biodiversity observations (Kissling et al., 2026) Future extensions could couple acoustic sensors with automated camera traps, insect imagers or eDNA samplers to capture multiple trophic levels and ecological processes (Besson et al., 2022; Wägele et al., 2022). Such multimodal networks could support new EBVs on community composition, phenology and ecosystem function (Junker et al., 2023). Equally, linking TABMON outputs to existing European initiatives—such as the EuroBirdPortal, LTER-Europe or the Digital Twin of Nature—would enable dynamic, high-frequency reporting of biodiversity trends, directly informing conservation policy and environmental forecasting.

9 | CONCLUSIONS

By demonstrating a functional, harmonized, acoustic monitoring network across Europe, TABMON bridges the gap between conceptual frameworks for continental biodiversity observation and their technical realization by providing a transparent, harmonized and extensible PAM infrastructure. Its methodological advances—in standardized protocols, automated pipelines and AI validation workflows—provide a foundation that can be readily adopted, scaled and adapted by other research communities. As biodiversity monitoring enters the era of continuous digital observation, TABMON exemplifies a practical blueprint and a scientific foundation for building continental-scale infrastructures to track biodiversity dynamics via in situ sensors.

AUTHOR CONTRIBUTIONS

Benjamin Cretois, Carolyn Rosten, Sarab Sethi, Daniel Kissling, Dan Stowell, Lluìs Brotons, Gerard Bota, Dani Villero, Ricard Marxer and Hervé Glotin contributed to the conceptualization of the project. Julia Wiel, Carolyn Rosten, Benjamin Cretois, Cynthia Barile, Corentin Bernard, Gerard Bota, Lluìs Brotons, Cristian Pérez-Granados and Dani Villero led the field deployment of the monitoring devices. Julia Wiel, Daniel Kissling, Cynthia Barile and Corentin Bernard led the metadata collection and standardization. Benjamin Cretois, Corentin Bernard and Ben McEwen contributed to the design of the analytic pipeline, TABMON dashboard, TABMON's Listening Labs and the TABMON website. Benjamin Cretois led the manuscript writing with input and revisions provided by all coauthors.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interests.

PEER REVIEW

The peer review history for this article is available at https://www.webofscience.com/api/gateway/wos/peer-review/10.1111/2041-210x.70308.

DATA AVAILABILITY STATEMENT

The TABMON dataset containing all the detections made by BirdNET and the expert annotations is available via https://doi.org/10.5281/zenodo.17511367 (Cretois et al., 2025). All software products developed in TABMON are open source, available on GitHub and archived on Zenodo. Data pipeline and export interface available via https://github.com/BenMcEwen1/TABMON-Classification-Pipeline and https://doi.org/10.5281/zenodo.19449747 (McEwen et al., 2026). TABMON Dashboard (https://tabmon.nina.no/) available via https://github.com/NINAnor/tabmon_dashboard and https://doi.org/10.5281/zenodo.19449593 (Cretois & Frassinelli, 2026). TABMON Listening Lab (for citizen scientist: https://tabmon-listening-lab.nina.no; for expert annotators: https://tabmon-listening-lab-expert.nina.no) available via https://github.com/NINAnor/tabmon_species_api and https://doi.org/10.5281/zenodo.19449613 (Cretois, 2026).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Supporting Information S1. TABMON site metadata.

Table S1.1. TABMON site metadata description.

Figure S1.1. Boxplots displaying the pairwise distances between devices within individual clusters for each country.

Table S1.2. Distance between each devices within clusters.

Supporting Information S2. Deployment form.

Supporting Information S3. From continental criteria to country level strategy.

Figure S3.1. TABMON site locations are shown in blue with the number of devices indicated when more than one is present. The red arrows represent the main spring migration flyways of terrestrial birds across Europe between Spain, France, The Netherlands and Norway.

Table S3.1. Description of the information collected in the preliminary species list for WP1 site selection.

Table S3.2. Common migrant terrestrial bird species selected for sharing on public platforms.

Table S3.3. Species of interest for local partners with the countries where they are usually observed (ES for Spain, FR for France, NL for The Netherlands, and NO for Norway).

Figure S3.2. (a) TABMON clusters positions based on knowledge about the main migratory flyways from the VisAviS Biodiversa project. (b) Habitat proportion in each Norwegian cluster based on the EUNIS habitat classification.

Figure S3.3. Total proportion of the different habitats represented in the Norwegian deployments based on the EUNIS habitat classification.

Figure S3.4. Locations of the five study sites (clusters) in the Netherlands. Numbers indicate the number of acoustic sensors deployed within each cluster.

Figure S3.5. Locations of the five study sites in France. Numbers indicate the number of acoustic sensors deployed.

Table S3.4. Description of the clusters in Spain.

Figure S3.6. Locations of the five study sites in Spain. Numbers indicate the number of acoustic sensors deployed.

Supporting Information S4. Off-grid power setups per country.

Table S4.1. Off-grid power setup in Norway.

Table S4.2. Off-grid power setup in France.

Table S4.3. Off-grid power setup in the Netherlands.

Table S4.4. Off-grid power setup in Spain.

Supporting Information S5. BirdNET performance assessment.

Figure S5.1. Evaluation of BirdNET's false positive rate.

Supporting Information S6. Carbon footprint of the material.

Table S6.1. Carbon footprint for one BUGG and its power supply system.

Table S6.2. Yearly footprint of data transfer, storage and processing per BUGG (438 GB/year).

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