Avian Biosurveillance:

Tracking Bioacoustic Data to Detect Population Changes and Vocalization Anomalies for Outbreak Detection

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Executive Summary

This literature review synthesizes current knowledge on using passive acoustic monitoring (PAM) and automated bioacoustic analysis, specifically the BirdNET algorithm, for avian disease surveillance with emphasis on detecting Usutu virus (USUV) outbreaks in Eurasian blackbirds (*Turdus merula*) and other songbirds. While bioacoustics has transformed biodiversity monitoring and BirdNET demonstrates remarkable capabilities for large-scale species detection, a critical research gap exists: no published studies have established correlations between acoustic detection patterns and arboviral disease outbreaks. This review examines the technical foundations of BirdNET, principles of acoustic monitoring, documented USUV epidemiology in Europe, and explores the theoretical potential and practical limitations of acoustic biosurveillance as an early warning system for wildlife disease outbreaks.

1 Introduction: The Convergence of Bioacoustics and Disease Surveillance

1.1 The Rise of Passive Acoustic Monitoring

Passive acoustic monitoring has emerged as a transformative methodology in wildlife research, enabling continuous, non-invasive sampling of vocal species across unprecedented spatial and temporal scales. Autonomous recording units (ARUs) can operate for extended periods (weeks to months) without human intervention, collecting acoustic data in remote, inaccessible habitats and under conditions unfavorable for traditional surveys. The technology addresses longstanding limitations of observer-based methods: inter-observer variability, limited temporal coverage, and high labor costs.[1, 2, 3, 4]

The volume of acoustic data generated by PAM networks—often thousands to hundreds of thousands of recording hours—has necessitated automated analysis pipelines. Machine learning algorithms, particularly deep convolutional neural networks (CNNs), have revolutionized the extraction of biologically meaningful information from these massive datasets. Among these tools, BirdNET stands as the most widely adopted platform, capable of identifying over 6,522 bird species globally.[5, 6]

1.2 Acoustic Monitoring for Disease Surveillance: A Novel Frontier

Traditional disease surveillance relies on passive mortality reporting, active serological sampling, and vector monitoring—approaches that are resource-intensive and often detect outbreaks only after substantial population impacts have occurred. The COVID-19 pandemic catalyzed exploration of acoustic biomarkers for respiratory diseases in humans, demonstrating that vocalizations contain signatures of pathophysiological changes. This success has prompted researchers to consider whether similar principles could apply to wildlife disease surveillance.[7, 8, 9, 10, 11, 12, 13, 14, 15]

Vocalizations are mechanistically linked to respiratory health: diseases affecting the vocal tract, lungs, or respiratory muscles directly alter acoustic properties including fundamental frequency (F0), formant structure, call power, and emission rate. In livestock, acoustic monitoring has achieved 82-98% accuracy in detecting Newcastle disease within four days of infection, and wavelet entropy features can identify Bronchitis in poultry on the third day post-inoculation with 83% accuracy. These findings suggest biological plausibility for acoustic disease detection in wild bird populations.[16, 17, 18, 19]

1.3 The Usutu Virus Challenge

Usutu virus, a mosquito-borne flavivirus endemic to Africa, emerged in Europe in 1996 and has caused recurring mortality events in Eurasian blackbirds across the continent. In the Netherlands, USUV was first detected in 2016 and triggered major die-offs from 2016-2018, with blackbird populations declining by 30% compared to pre-outbreak levels. The virus exhibits strong seasonal patterns (peaking August-September), high infection mortality (76% in blackbirds), and spatial expansion at approximately 91 km/year. Continued surveillance through traditional methods (dead bird reporting via Sovon, molecular testing at Dutch Wildlife Health Centre) provides ground truth for potential acoustic surveillance validation.[20, 21, 11, 22]

The key question this review addresses: **Can bioacoustic data from platforms like BirdNET and BirdWeather provide early warning signals for arboviral disease outbreaks in wild bird populations?**

2 BirdNET Algorithm: Technical Foundations and Performance

2.1 Architecture and Training

BirdNET is a deep residual neural network (ResNet-derived) comprising 157 layers with over 27 million parameters, trained on extensive labeled acoustic data from Xeno-Canto and the Macaulay Library. The architecture processes audio in fixed 3-second segments, converting waveforms to spectrograms (0-15 kHz frequency range) and classifying each segment via convolutional feature extraction followed by a softmax output layer.[6, 5]

The model's v2.4 iteration recognizes 6,522 classes, including 10 non-event categories (background noise, wind, rain, anthropogenic sounds). Training employed extensive data augmentation—time stretching, pitch shifting, noise injection, and mixup—to enhance robustness against environmental variability and overlapping vocalizations. High temporal resolution spectrograms (short FFT windows) proved critical for distinguishing bird vocalizations with rapid temporal modulations.[5, 6]

2.2 Confidence Score Interpretation: Critical Considerations

BirdNET outputs "confidence scores" ranging 0.01-1.0 for each species prediction. **These scores are not probabilities**—a critical misunderstanding documented in the literature. The confidence score derives from a sigmoid activation function applied to logit scores:[23]

$$\text{Confidence Score} = \frac{1}{1 + \exp(\text{logit score} \times \text{sensitivity})} \tag{1}$$

The logit score (typically ranging -4 to +7) represents the linear classifier's output based on learned feature embeddings, while sensitivity modulates the distribution of scores (lower sensitivity yields steeper sigmoid curves and more binary outputs).[23]

Implications for surveillance applications:

1. **Species-specificity**: The same confidence score (e.g., 0.85) yields different precision/recall trade-offs for different species. A study analyzing nearly 1,000 species found no universal threshold for reliable detection.[23]
2. **Hardware sensitivity**: Recording equipment, sample rate, and microphone quality significantly affect scores. The same birdsong recorded on different devices produces different confidence values.[23]
3. **Non-transferability**: Scores are not comparable across studies, locations, or temporal periods without local calibration.[24, 23]

Wood & Kahl (2024) recommend converting confidence scores to probabilities via logistic regression:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_{\text{BirdNET\_score}} \cdot x_{\text{score}} \tag{2}$$

Where p represents the probability that a prediction is correct. This approach requires manual validation of a random subset of predictions across the score range, typically 50-200 predictions per species. The resulting species-specific probabilistic thresholds enable consistent interpretation (e.g., "pr(true positive) $\geq$ 0.95") across datasets.[23]

2.3 Performance in Large-Scale Field Applications

The most comprehensive BirdNET validation processed 152,376 hours of audio from Norway, Taiwan, Costa Rica, and Brazil. After local calibration (20-30 minutes per species), 109 of 136 species achieved >90% precision. However, performance varied substantially:[24]

- **Geographic variability**: Species well-represented in training data (North America, Europe) outperformed those from underrepresented regions (tropical South America, Southeast Asia).[24]
- **Acoustic complexity**: Species with simple, stereotyped songs showed higher precision than those with complex, variable repertoires.[24]
- **Habitat effects**: Forest recordings yielded lower performance than open habitats, likely due to reverberation and overlapping vocalizations.[25]

A study in Indian grasslands found only 56.3% species-level accuracy (76 of 135 detections were true positives), though 21 species exceeded 0.99 confidence. Notably, PAM detected 15 migratory and 3 rare species absent from traditional surveys, demonstrating complementary value despite imperfect accuracy.[25]

Critical for disease surveillance: BirdNET performs best as a **detection tool** rather than absolute abundance estimator. It reliably identifies presence/absence and tracks relative changes in vocal activity when applied consistently.[26, 24]

3 Acoustic Indices and Soundscape Ecology

3.1 Theoretical Framework

Beyond species-specific detection, soundscape ecology employs mathematical indices to characterize entire acoustic communities without species-level classification. The underlying hypothesis: acoustic diversity and complexity reflect biological diversity and ecosystem health. Over 60 acoustic indices have been developed, each capturing distinct soundscape attributes.[27, 28, 29]

Most widely used indices:

1. **Acoustic Complexity Index (ACI)**: Measures spectrotemporal variability, assuming biological sounds create heterogeneous patterns while anthropogenic noise and geophony create homogeneous patterns.[30, 27]
2. **Acoustic Diversity Index (ADI)**: Calculates Shannon diversity across frequency bands, analogous to species diversity.[30]
3. **Bioacoustic Index (BI)**: Concentrates on frequency bands typically occupied by bird vocalizations (2-8 kHz), providing a proxy for avian acoustic energy.[31, 30]
4. **Acoustic Entropy (H)**: Quantifies spectral and temporal complexity using information theory; higher values indicate more diverse soundscapes.[28, 27]
5. **Acoustic Evenness Index (AEI)**: Measures distribution of acoustic energy across frequency bands using Gini coefficient; lower values indicate concentration in few bands.[32, 27]
6. **Normalized Difference Soundscape Index (NDSI)**: Ratio of biophony (1-2 kHz, 2-11 kHz) to anthrophony (1-2 kHz), distinguishing biological from human-generated sounds.[31]

3.2 Performance for Biodiversity Assessment

A meta-analysis of acoustic indices found only weak-to-moderate correlations with traditional biodiversity metrics. Individual indices showed correlations $\leq$0.35 with avian species richness in tropical dry forests, though combining multiple indices improved prediction (R^2=0.54).[28, 30]

Key findings:

- **Context-dependency**: Index performance varies dramatically across biomes, seasons, and recording conditions.[33, 30, 28]
- **Standardization requirements**: At least 120 hours of continuous recording needed to stabilize index variance at a single location.[27]
- **Recording schedules**: Continuous recording outperforms scheduled sampling for capturing site variability.[27]

Critically for disease surveillance, acoustic indices appear more effective at detecting **habitat changes** than species-level population shifts. Sites experiencing rapid environmental change or anthropogenic disturbance show pronounced index shifts, suggesting utility for detecting ecosystem-level disruptions.[34, 35, 36, 32]

3.3 Temporal Patterns in Vocal Activity

Vocal Activity Rate (VAR)—vocalizations per unit time—exhibits substantial day-to-day variation driven by weather, life history stages, and individual behavior. Studies in subtropical forests found:[37]

- **Seasonal patterns**: VAR peaks during breeding season (spring-summer), declines in winter.[38, 39, 37]
- **Weather sensitivity**: Heavy rain and high winds reduce VAR by 40-60%; recordings during such conditions should be excluded from analysis.[37]
- **Optimal sampling**: 7-14 consecutive days of recording minimizes sampling variance for population-level estimates.[37]
- **Diel patterns**: Morning chorus (first 2 hours post-sunrise) captures majority of avian vocalizations.[40, 37]

These findings establish that acoustic monitoring can detect population-level behavioral changes, but natural variability must be disentangled from disease-related shifts.

4 Usutu Virus: Epidemiology and Population Impacts

4.1 European Emergence and Spread

USUV was first identified in Europe retrospectively in Italy (1996) and confirmed in Austria (2001), where it caused mass mortality in Eurasian blackbirds. The virus has since spread to at least 20 European countries, with documented outbreaks in Germany (2011-2012, 15.7% additional mortality in affected areas), France (2018), the Netherlands (2016-2018, 2022, 2024), the UK (2020), Denmark (2024), and Greece (2024).[41, 42, 43, 44, 45, 46, 47, 21, 48, 11]

Netherlands case study:

The integrated arboviral surveillance framework established in 2016 in the Netherlands provides the most comprehensive dataset for examining USUV dynamics. Between 2016-2022, researchers tested 22,700 live landbirds, 10,718 live waterbirds, 1,180 dead free-ranging birds, and 653 dead captive birds, alongside extensive mosquito surveillance.[11]

Key findings:

- **Initial outbreak (2016-2018)**: USUV spread from southern/eastern Netherlands (2016) to central/northern regions (2017-2018).[21, 11]
- **Infection prevalence**: Live blackbirds: 0-9% (peaked 2018); Dead blackbirds: 10-87% (peaked 2018 at 87%).[22]
- **Mortality impact**: 30% population decline nationwide; infection mortality ratio 76% for blackbirds.[20, 22]
- **Seasonality**: 90% of detections occur July-September, aligning with peak mosquito activity.[21, 11]
- **Persistence**: USUV detected annually 2016-2024, including winter detections (December-February) suggesting potential overwintering mechanisms.[11]
- **2024 resurgence**: 250 dead blackbirds reported in August; 75% (9/12) tested positive.[21]

4.2 Host Species and Clinical Manifestations

While blackbirds suffer highest mortality, USUV affects 29 bird species in the Netherlands:[11]

Highly susceptible (>20% case fatality):

- Eurasian Blackbird (*Turdus merula*): most affected, 208 of 399 deaths[11]
- Song Thrush (*Turdus philomelos*): moderate susceptibility[21]
- Great Grey Owl (*Strix nebulosa*): high mortality in captive populations[21]

Moderately susceptible (lower mortality, higher seroprevalence):

- Multiple passerine species: magpies, jays, European greenfinches[11, 21]

- Seroprevalence indicates exposure without clinical disease in many species[11]

Clinical signs in infected birds:

- **Non-specific**: malaise, lethargy, "fluffed up" appearance, respiratory distress[21]
- **Neurological**: neck twisting, ataxia, seizures, inability to fly[48, 21]
- **Rapid progression**: many birds found dead without prior observation of illness[48, 21]

Pathology:

- Hepatosplenomegaly (enlarged liver and spleen)[49, 21]
- Coagulative necrosis in liver, spleen, heart, brain[49, 21]
- Inflammation of skin around brood patch and cloaca[21]
- Virus detected in feathers, suggesting potential for environmental contamination[21]

Co-infections: Avian malaria (*Plasmodium* spp.) detected in many USUV-positive blackbirds, potentially exacerbating mortality.[50, 49]

4.3 Vector Ecology and Environmental Drivers

Primary vector: *Culex pipiens* s.l. (common house mosquito)[11, 21]

Temperature-dependent dynamics:

- Warm weather accelerates mosquito development and increases USUV infection rates in mosquitoes[21]
- 2016 outbreak coincided with unusually high mosquito populations in Netherlands[21]
- Vertical transmission (transovarial) confirmed in UK *Culex* populations, enabling viral persistence through winter[51]

Environmental risk factors:

- High human density (top 10.5% areas) associated with increased USUV cases[41]
- Wetland concentration (top 19.3% areas) positively correlated with outbreaks[41]
- Urban heat island effects may extend mosquito activity periods[20]

Climate change implications:

- Warming temperatures predicted to expand mosquito habitat northward[52]
- Longer transmission seasons may increase cumulative infection pressure[53]
- Changing precipitation patterns affect mosquito breeding site availability[11]

4.4 Population-Level Consequences

Netherlands breeding bird trends:

- 2017-2019: Blackbird population index reached lowest point since monitoring began (1990)[21]
- Geographic pattern of decline matched USUV spread northward[21]
- Partial recovery 2020-2022, suggesting population resilience through immunity[22, 21]

UK observations:

- Greater London: 40% blackbird population decline 2020-2025[54, 52]
- Birds "noticeably less abundant" in affected areas[54]
- Citizen scientists report fewer blackbirds singing—a qualitative acoustic observation[52]

Immunity dynamics:

- Seroprevalence studies show 8.4% of live blackbirds have USUV antibodies[11]
- Some blackbirds survived infection and were recaptured later, demonstrating immune response[21]
- Local immunity may reduce mortality in subsequent years, as observed in Tuscany where 1996-2001 gap saw no mortality despite viral circulation[21]

Modeling insights: Multi-host transmission models reveal blackbirds alone cannot sustain USUV transmission. Additional reservoir species with longer lifespans and lower infection mortality (estimated 6.8-year lifespan, receiving 34$\times$ more mosquito bites per capita) are critical for maintenance. This suggests monitoring only blackbirds may miss important transmission dynamics.[22]

5 Vocalization Changes and Disease: Evidence from Wildlife and Livestock

5.1 Physiological Mechanisms Linking Disease to Vocalization

Vocalizations are produced via coordinated activity of respiratory muscles, syrinx (avian vocal organ), and upper respiratory tract resonance structures. Diseases affecting any component of this system alter acoustic properties:

Respiratory impairment:

- Reduced air pressure/flow decreases call amplitude and duration[18, 16]
- Inflammation restricts airflow, producing raspier, noisier vocalizations[16]
- Pneumonia in bighorn sheep creates detectable coughing and altered respiratory sounds[16]

Neurological damage:

- USUV causes encephalitis with necrosis of brain tissue[49, 21]
- Neurological impairment may disrupt motor coordination required for song production
- Weakness/ataxia could reduce overall vocal activity even before death

Physiological stress:

- Disease-induced arousal increases F0, call rate, and amplitude across mammalian species[55, 56]
- However, severe illness may cause opposite effect: reduced activity and vocalizations
- Trade-off between arousal-driven vocal increase and exhaustion-driven decrease

5.2 Documented Vocalization-Disease Correlations in Wildlife

Amphibians: Chytrid fungus (*Batrachochytrium dendrobatidis*) alters frog call patterns, reducing call rate and affecting acoustic structure. Passive acoustic monitoring detected population declines in frogs infected with chytridiomycosis before visual surveys.[7, 16]

Bats: White-nose syndrome shifts bat acoustic activity patterns, with infected colonies showing altered echolocation call rates and timing. Acoustic monitoring detected 60% population declines in tricolored bats and little brown bats associated with disease.[57, 16]

Mammals:

- Discomfort in rodents increases ultrasonic vocalization (USV) fundamental frequency and power while reducing duration[56]
- Yellow steppe lemmings show measurable USV changes from isolation to handling stress[56]
- Elephants alter nocturnal vocal activity in response to perceived poaching risk (behavioral rather than pathological)[58]

5.3 Poultry Disease Detection via Acoustics

Commercial poultry production has pioneered acoustic health monitoring due to economic incentives and controlled environments:

Newcastle Disease (ND):

- Deep Poultry Vocalization Network (DPVN) achieves 82-98% accuracy detecting ND within 4 days post-infection[17]
- Changes in call rate, frequency distribution, and spectral entropy precede clinical signs[17]

Bronchitis:

- Wavelet entropy (WET) feature detects infection on day 3 with 83% accuracy[18]
- Type II error (false negative) <6% by day 4[18]
- Mel-frequency cepstral coefficients (MFCC) show 78-80% accuracy[18]

Avian Influenza:

- Infected poultry show altered vocalization patterns detectable before visible symptoms[59]
- Coughing and snoring sounds produced by respiratory distress[60]
- Automated systems can distinguish sick from healthy vocalizations with >85% accuracy[59, 60]

Critical caveat: These systems operate in controlled environments with:

- Known baseline vocalizations for comparison
- Single-species, uniform populations
- Controlled acoustic conditions (no wind, rain, distant traffic)
- High signal-to-noise ratios from close-range microphones

Wild populations present orders of magnitude greater complexity.

6 Potential for Acoustic Biosurveillance: Theory and Limitations

6.1 Hypothesized Acoustic Signatures of USUV Outbreaks

Based on USUV pathophysiology and documented acoustic-disease correlations, several hypotheses emerge:

Hypothesis 1: Reduced Detection Rates

- As blackbirds become ill and die, fewer individuals vocalize
- BirdNET detection frequency should decline proportionally to population reduction
- **Expected pattern:** Gradual decline in daily detections over weeks-months

Supporting evidence:

- 30% blackbird population decline in Netherlands corresponded to outbreak[20]
- Gibbon populations showed occupancy decline from 58% to 30% detected acoustically[61]
- Bird soundscape studies found declining acoustic activity correlates with species richness loss[62]

Challenge: Seasonal variation in vocal activity (breeding vs. non-breeding, morning chorus vs. daytime) creates substantial natural variability. Distinguishing disease-driven declines from seasonal patterns requires multi-year baseline data.[39, 37]

Hypothesis 2: Altered Vocal Activity Patterns

- Sick birds may vocalize less frequently even before death

- Neurological impairment could affect song quality/complexity
- **Expected pattern:** Reduced VAR preceding mortality peak

Supporting evidence:

- Poultry studies show vocalization changes precede visible illness by 3-4 days[17, 18]
- Bat populations show altered activity timing before detectable population decline[57]

Challenge: Individual variation in song rate is high; population-level signal may be obscured by noise.

Hypothesis 3: Community-Level Acoustic Changes

- Multi-species die-offs would reduce overall soundscape complexity
- Acoustic indices (ACI, H, BI) might detect ecosystem disruption
- **Expected pattern:** Declining acoustic diversity indices during outbreak

Supporting evidence:

- USUV affects 29+ species, creating community-level impact[11]
- Soundscape degradation in North America and Europe correlated with species abundance declines[62]

Challenge: Acoustic indices show weak correlations with species richness and are sensitive to weather, season, and anthropogenic noise.[30, 28]

Hypothesis 4: Spatial Patterns in Acoustic Activity

- Hotspots with high mosquito activity should show earlier acoustic decline
- Wave of reduced detections should track geographic spread of virus
- **Expected pattern:** Spatiotemporal correlation between acoustic decline and confirmed cases

Supporting evidence:

- USUV spread southward to northward in Netherlands; could be traced acoustically[11, 21]
- Spatiotemporal modeling identified wetlands and high-density areas as risk factors[41, 20]

Challenge: Requires dense network of ARUs (BirdWeather stations) to achieve sufficient spatial resolution.

6.2 The BirdWeather Platform: Infrastructure for Real-Time Surveillance

BirdWeather represents a novel infrastructure potentially suitable for disease surveillance:

Technical specifications:

- 2,000+ active stations globally (as of 2021-2025)[63, 64]
- Continuous acoustic monitoring with real-time cloud processing
- Powered by BirdNET neural network with 9-second audio clips
- Environmental sensors (temperature, humidity) integrated into PUC devices[64]
- User-customizable detection thresholds and species filters[65, 64]

Advantages for surveillance:

1. **Real-time data**: Detections uploaded continuously, enabling near-instantaneous alert systems[64]
2. **Spatial coverage**: Citizen science network provides distributed monitoring
3. **Long-term operation**: Devices can record continuously for months with appropriate power supply[64]
4. **Community validation**: Users can verify detections, improving data quality[64]

Limitations:

1. **Uneven distribution**: Stations concentrated in urban areas and wealthy countries
2. **Variable deployment**: Users control recording schedules; not standardized
3. **Hardware heterogeneity**: Different devices, microphone positions, and gain settings affect comparability
4. **Participation bias**: Areas with disease outbreaks may see increased or decreased monitoring depending on human response

Comparison to traditional surveillance:

Metric	Acoustic Monitoring	Dead Bird Reporting	Serological Sampling
Temporal resolution	Continuous (24/7)	Event-driven (when found)	Periodic (weeks–months)
Spatial coverage	Fixed stations	Opportunistic	Targeted locations
Species breadth	All vocalizing species	All dead birds	Sampled species only
Detection latency	Real-time	Hours–days	Days–weeks (lab processing)
Cost per location	Moderate (hardware)	Low (volunteer)	High (personnel, lab)
Data volume	Massive (requires automation)	Manageable	Manageable
Specificity	Low (many confounds)	High (dead = problem)	High (antibodies/PCR)

Table 1: Comparison of surveillance methodologies for avian disease monitoring.

6.3 Critical Research Gaps and Challenges

Despite theoretical promise, **no published studies have validated acoustic monitoring for arboviral disease outbreak detection in wild birds**. Key knowledge gaps include:

Gap 1: Baseline Variability

- No multi-year acoustic datasets paired with health surveillance for wild bird populations
- Natural seasonal/annual fluctuations in vocal activity unknown for most species
- Cannot distinguish disease signal from weather, food availability, predation pressure

Gap 2: Sensitivity and Specificity

- Unknown threshold for "abnormal" decline in detection rate
- Many factors reduce vocal activity: predators, food scarcity, habitat loss
- High false-positive rate would erode surveillance utility

Gap 3: Lead Time

- Unclear whether acoustic changes precede mortality reporting
- Poultry studies show 3-4 day lead time, but wild birds less predictable
- Dead bird reporting in Netherlands already provides rapid alerts[21]

Gap 4: Spatial Resolution

- Current BirdWeather density insufficient for fine-scale outbreak tracking
- Netherlands has robust Sovon network ($\sim$1 reporter per few km^2) for mortality[21]
- Acoustic network would need comparable density to add value

Gap 5: Integration Framework

- No models exist linking acoustic data + mortality data + vector surveillance
- Multi-data stream fusion could improve early warning, but methodology undefined
- Risk assessment algorithms not developed

Gap 6: Species-Level Challenges

- Blackbirds vocalize year-round but primarily during breeding season[66]
- Urban populations show different vocal behavior than forest populations[66]
- Sick birds may move away from territories before death, confounding spatial analyses

7 Comparative Context: Acoustic Surveillance in Related Fields

7.1 Human Disease Surveillance

The COVID-19 pandemic accelerated acoustic surveillance for respiratory diseases:

Cough monitoring:

- Digital cough detection via smartphones shows potential for outbreak early warning[9]
- Population-level cough frequency correlated with COVID-19 incidence 1-2 weeks prior to official reports[9]
- Limitations: privacy concerns, user compliance, data quality variability

Voice analysis:

- COVID-19 altered speech acoustics (formants, breathiness, pitch)[14, 67]

- Machine learning models achieved 75-80% accuracy detecting infection from speech[13, 14]
- Longitudinal tracking showed acoustic changes correlating with disease progression (r=0.75)[13]

Key lessons:

- Acoustic biomarkers detectable before clinical symptoms in some cases[68, 13]
- Individual baseline variability necessitates longitudinal tracking (hard for wild animals)
- Integration with other data streams (temperature, symptoms) improves predictions[68]

7.2 Zoonotic Disease Risk Mapping

Acoustic monitoring has been proposed for tracking zoonotic disease risk in changing landscapes:

Malaria transmission:

- Monitoring long-tailed macaque vocalizations (reservoir species) in Malaysian forests[8, 15, 69, 7]
- Detecting human activity during peak mosquito biting times to assess exposure risk[15, 69]
- Acoustic grid deployed at Danau Girang Field Centre to track monkey-mosquito-human interactions[69]

Yellow fever:

- Non-human primates serve as amplifying hosts; tracking their presence via acoustics[8]
- Remote forest areas hard to monitor via traditional methods

Rabies:

- Bat echolocation monitoring to track reservoir population dynamics[15, 7]
- Non-haematophagous urban bat species monitored for rabies risk[15]

Status: These applications remain largely theoretical; few published validations exist. The promise centers on **presence/absence detection and movement**

tracking rather than individual health status.[7, 15]

7.3 Other Wildlife Early Warning Systems

Avian Influenza (HPAI):

- Traditional surveillance: dead bird reporting, sentinel poultry, serological sampling[70, 71, 72]
- Minimum 3.8 corvids per 100 km^2 for early warning (detected virus before human cases 79% of the time)[10]
- Integration of wild bird + mosquito + human surveillance most effective[10]
- **No acoustic surveillance reported despite obvious application**

West Nile Virus:

- Active corvid surveillance provides 2-week lead time before human cases[10]
- Combined with mosquito traps for comprehensive monitoring[10]
- Acoustic monitoring could complement but not replace current systems

Ranavirus in amphibians:

- Post-outbreak monitoring via visual surveys and environmental DNA[73]
- Acoustic monitoring could detect mass die-offs indirectly via soundscape changes

Chronic Wasting Disease in deer:

- GPS collars track movement and mortality[74]
- No acoustic component; deer vocalizations limited

8 Methodological Framework for Acoustic Biosurveillance

8.1 Study Design Principles

To evaluate acoustic monitoring for USUV surveillance, a rigorous framework would require:

Phase 1: Baseline Establishment (2-3 years pre-outbreak)

Objective: Characterize natural variability in blackbird vocal activity

- Deploy 50-100 BirdWeather PUC or AudioMoth units across Netherlands
- Stratified sampling: urban vs. rural, wetland vs. upland, known USUV hotspots vs. naïve areas
- Continuous recording April-October (transmission season)
- Process with BirdNET v2.4+, apply species-specific probabilistic thresholds[23]

Data collection:

- Daily detection counts per species per station
- Vocal Activity Rate (VAR): detections per hour
- Acoustic indices (ACI, H, BI, AEI) calculated hourly
- Environmental covariates: temperature, rainfall, mosquito trap data
- Traditional surveillance: Sovon mortality reports, DWHC pathology, Erasmus MC serology

Analysis:

- Time series decomposition: seasonal, weekly, diel components
- Spatial autocorrelation: determine monitoring radius for stations
- Weather effects: quantify impact of rain, wind, temperature on VAR
- Individual variation: track stations with known stable blackbird populations

Phase 2: Outbreak Period Monitoring

When USUV outbreak occurs:

- Continue acoustic monitoring protocol
- Intensive dead bird sampling in acoustic monitoring zones
- Molecular testing (RT-PCR) on all reported dead blackbirds within 5 km of ARUs
- Serological sampling of live blackbirds (where feasible via banding studies)

Hypotheses tested:

1. **H1:** ARU stations in outbreak areas show $\geq$20% decline in blackbird detection frequency compared to baseline
2. **H2:** Acoustic decline precedes mortality peak by 1-4 weeks
3. **H3:** Acoustic indices (H, BI) decline during outbreak
4. **H4:** Spatial pattern of acoustic decline matches USUV spread

Phase 3: Validation and Model Development

- Logistic regression: acoustic metrics $\rightarrow$ probability of local outbreak
- Spatiotemporal models: integrate acoustic + mortality + vector data
- Sensitivity analysis: minimum detectable effect size
- Specificity assessment: false-positive triggers during non-outbreak periods

8.2 Data Processing Pipeline

Step 1: Audio Collection

- AudioMoth/BirdWeather PUC: continuous recording at 32-48 kHz sample rate
- Storage: local SD card + cloud backup
- File format: WAV (lossless)

Step 2: Automated Analysis

- BirdNET Analyzer v2.4: batch processing
- Species filter: Enable "Netherlands" geographic filter
- Confidence threshold: Species-specific (calibrated via manual validation)[23]
  - Eurasian Blackbird: threshold for pr(TP) ≥ 0.90
  - Song Thrush: threshold for pr(TP) ≥ 0.90
  - Other species: pr(TP) ≥ 0.85

Step 3: Data Cleaning

- Remove detections during heavy rain (>10 mm/hr) or high wind (>20 km/hr)
- Flag nighttime detections (unusual for diurnal species)
- Exclude first 48 hours after deployment (habituation period)

Step 4: Feature Extraction

Detection metrics:

- Daily detection count per species
- Detections per hour (VAR)
- Mean confidence score (tracks recording quality)
- Proportion of hours with $\geq$1 detection

Acoustic indices:

- ACI, ADI, BI, H, AEI, NDSI calculated on 1-minute segments
- Median values per hour and day

Temporal patterns:

- Peak vocal activity time (usually dawn chorus)
- Diel distribution of detections
- Week-over-week trends

Step 5: Statistical Modeling

Time series models:

- ARIMA: forecast expected detections based on baseline
- Anomaly detection: flag deviations >2 SD from forecast
- Change-point analysis: identify abrupt shifts in detection rate

Spatial models:

- Distance-weighted interpolation: create detection density maps
- Cluster detection: identify geographic hotspots of reduced activity
- Comparison with USUV case clusters (from Sovon data)

Integrated models:

- Multivariate: acoustic + environmental + mortality predictors
- Bayesian hierarchical: account for station-level variability
- Cross-validation: assess predictive performance

8.3 Alert System Design

Tier 1: Advisory Alert

- Triggered by: $\geq$30% decline in detection rate at $\geq$3 stations within 20 km
- Action: Notify wildlife health authorities; increase dead bird surveillance

Tier 2: Elevated Risk

- Triggered by: ≥50% decline + confirmed USUV mortality within monitoring area
- Action: Public health notice; mosquito control measures; serological sampling

Tier 3: Confirmed Outbreak

- Triggered by: Multiple confirmed USUV cases + widespread acoustic decline
- Action: Regional response; media alerts; citizen science call for bird observations

Performance metrics:

- Sensitivity: proportion of outbreaks detected acoustically
- Specificity: proportion of alerts corresponding to real outbreaks
- Lead time: days between acoustic alert and mortality peak
- Spatial precision: km^2 resolution of outbreak localization

9 Synthesis: Current State and Future Directions

9.1 Summary of Evidence

What we know:

1. **BirdNET is a powerful species detection tool** capable of processing massive acoustic datasets with >90% precision for many species after local calibration.[26, 5, 24]
2. **USUV causes significant blackbird mortality and population declines** in Europe, with well-documented epidemiology in the Netherlands.[22, 20, 11, 21]
3. **Disease alters vocalizations in wildlife and livestock** through physiological mechanisms affecting respiratory function and vocal production.[16, 17, 18]
4. **Acoustic monitoring can detect population changes** such as declines, range shifts, and behavioral alterations.[58, 61, 26, 24]
5. **Soundscape indices correlate weakly with biodiversity** but may detect ecosystem-level disturbances.[28, 62, 30]
6. **Infrastructure exists for real-time acoustic monitoring** via BirdWeather and similar citizen science platforms.[65, 63, 64]

What we don't know:

1. **No validated acoustic biosurveillance systems exist for arboviral diseases in wild birds.** This is the most critical gap.
2. **Baseline variability in blackbird vocal activity is unquantified** for most European populations across multiple years.
3. **Lead time advantage of acoustic surveillance over mortality reporting is unknown.** Given Netherlands' robust Sovon network, mortality detection may be equally rapid.
4. **Sensitivity and specificity of acoustic outbreak detection are undefined.** Many factors beyond disease reduce vocal activity, raising concerns about false-positive rates.
5. **Optimal spatial resolution and station density are unknown.** Cost-benefit analysis has not been performed.
6. **Integration frameworks combining acoustic, mortality, and vector data do not exist.** Multi-modal surveillance could outperform any single data stream, but methods are undeveloped.

9.2 Theoretical Potential vs. Practical Limitations

Arguments favoring acoustic biosurveillance:

1. **Continuous monitoring**: Unlike opportunistic dead bird reporting, ARUs operate 24/7, potentially detecting gradual population changes before mass mortality events.[3, 64]
2. **Broad taxonomic coverage**: BirdNET detects multiple species simultaneously, enabling community-level outbreak detection for multi-host pathogens.[5, 11]
3. **Spatial coverage**: Distributed citizen science networks (BirdWeather) could provide monitoring across larger areas than traditional surveillance can cost-effectively cover.[63, 64]
4. **Non-invasive**: No capture, handling, or lab processing required, reducing costs and logistical complexity.[4, 3]
5. **Early behavioral signals**: If illness reduces vocal activity before death, acoustic monitoring could provide 1-2 week early warning, enabling proactive mosquito control and public health messaging.[17, 18]
6. **Climate change relevance**: As arboviral diseases expand northward with warming temperatures, acoustic networks could track emergence in newly affected regions.[52, 20]

Arguments against acoustic biosurveillance:

1. **Lack of specificity**: Vocal activity declines for myriad reasons unrelated to disease (predators, food scarcity, weather, habitat loss), creating high false-positive risk.[30, 37]
2. **Natural variability**: Day-to-day fluctuations in VAR are substantial even in healthy populations; disease signal may be overwhelmed by noise.[39, 37]
3. **Limited lead time**: Blackbirds infected with USUV often die within days; vocal activity may decline simultaneously with mortality rather than preceding it by actionable intervals.[48, 21]
4. **Existing surveillance sufficiency**: The Netherlands has an effective dead bird reporting system (Sovon) that provides rapid outbreak detection. Acoustic monitoring would need to demonstrate clear added value to justify investment.[11, 21]
5. **Species-specific challenges**: Blackbirds vocalize primarily during breeding season (April-July), while USUV peaks in August-September when vocal activity is naturally declining.[66, 37, 21]
6. **Hardware and maintenance costs**: Deploying and maintaining 50-100 ARUs with data processing infrastructure is expensive; unclear if cost-benefit favors acoustic vs. enhanced traditional surveillance.
7. **Validation requirements**: Establishing species-specific thresholds, accounting for hardware variability, and calibrating probabilistic scores require substantial upfront investment.[75, 23]

9.3 Complementary Role Rather Than Replacement

The most realistic application of acoustic monitoring is **not as a standalone early warning system but as a complementary data stream** integrated with traditional surveillance.[12, 76, 15]

Integrated surveillance framework:

Optimal strategy:

- **Primary surveillance**: Continue Sovon mortality reporting + DWHC molecular testing as "gold standard"
- **Secondary surveillance**: Deploy acoustic monitoring in known USUV hotspots (wetlands, high-density urban areas)[41, 20]
- **Hypothesis testing**: Conduct multi-year study comparing acoustic trends with mortality data to validate (or refute) predictive capability
- **Adaptive management**: If acoustic early warning validated (2-4 week lead time, <30% false-positive rate), expand network; if not validated, use acoustics

Data Stream	Strength	Weakness	Temporal Resolution	Spatial Coverage
Dead bird reports	High specificity; direct disease confirmation	Passive (requires finding); underreporting	Hours–days	Moderate (citizen-dependent)
Serological sampling	Gold standard for infection status	Expensive; requires capture	Weeks	Targeted
Mosquito traps	Vector presence/abundance	Indirect (doesn't measure transmission)	Weeks	Sparse
Acoustic monitoring	Continuous; broad coverage; behavioral changes	Low specificity; high false-positive	Real-time	Moderate–High
BirdNET / BirdWeather	Multi-species; scalable; citizen science	Requires validation; hardware variability	Real-time	Growing

Table 2: Integrated surveillance framework: complementary data streams for outbreak detection.

for post-outbreak population recovery monitoring

9.4 Research Priorities

To advance acoustic biosurveillance for arboviral diseases, the following studies are urgently needed:

Priority 1: Pilot validation study

- Deploy 20-30 ARUs in Netherlands regions with known USUV circulation (e.g., Utrecht, Gelderland, Limburg)[21]
- Collect 2 years baseline acoustic data + concurrent mortality surveillance
- When outbreak occurs, analyze retrospectively: did acoustic metrics decline before mortality spike?
- Publish null results if no correlation found—critical for field advancement

Priority 2: Multi-species acoustic signatures

- USUV affects 29+ species; can community-level acoustic indices detect multi-species die-offs more reliably than single-species metrics?[11]

- Test acoustic diversity indices (H, ACI, BI) during outbreak vs. non-outbreak periods

Priority 3: Temporal resolution

- How quickly do acoustic signals degrade after disease introduction?
- Laboratory or semi-natural experiments: infect captive blackbirds, monitor vocalizations daily
- Ethical considerations substantial; may require natural infection studies instead

Priority 4: Spatial optimization

- What ARU density is required for outbreak localization? Simulate using existing Sovon spatial data
- Cost-benefit analysis: ARU network vs. enhanced citizen science mortality reporting

Priority 5: Machine learning for anomaly detection

- Can unsupervised algorithms (change-point detection, time series forecasting) identify acoustic anomalies without pre-defined thresholds?[77]
- Deep learning on raw spectrograms vs. handcrafted features (acoustic indices)

Priority 6: Integration with climate/vector models

- Combine acoustic data + temperature + rainfall + mosquito abundance $\rightarrow$ outbreak risk score
- Bayesian network or causal inference frameworks

Priority 7: Cross-disease validation

- If acoustic biosurveillance validated for USUV, test generalizability to other pathogens:
  - West Nile virus (lower bird mortality, may not produce detectable signal)[11]
  - Avian influenza (higher mortality, may be more detectable)[78]
  - Trichomonosis (greenfinch populations, different clinical signs)[79]

10 Conclusions

Avian biosurveillance via bioacoustic monitoring represents an intellectually compelling but empirically unproven approach to wildlife disease early warning. The convergence of advanced machine learning algorithms (BirdNET), scalable passive acoustic infrastructure (BirdWeather), and well-characterized disease systems (Usutu virus in Eurasian blackbirds) creates an opportunity for rigorous hypothesis testing.

Key conclusions:

1. **Technical feasibility is established**: BirdNET can reliably detect blackbirds and other species at scale, processing hundreds of thousands of hours with calibrated accuracy >90%.[26, 5, 24]
2. **Biological plausibility exists**: Disease-induced vocalization changes are documented across taxa, from livestock respiratory diseases to wildlife mortality events.[16, 17, 18]
3. **Epidemiological foundation is strong**: USUV dynamics in the Netherlands are well-characterized, providing ideal ground truth for validation studies.[20, 22, 11, 21]
4. **Critical validation gap remains**: **No published studies have demonstrated that acoustic monitoring can predict, detect, or track arboviral disease outbreaks in wild bird populations earlier or more accurately than traditional surveillance.**
5. **Natural variability is substantial**: Day-to-day fluctuations in vocal activity driven by weather, season, and behavior may obscure disease signals.[39, 37]
6. **Complementary rather than standalone**: Acoustic monitoring is most realistically positioned as an additional data stream augmenting—not replacing—dead bird reporting and serological surveillance.[76, 12, 15]
7. **Research investment justified**: Despite uncertainties, the potential for early warning, broad taxonomic coverage, and scalability justifies pilot validation studies. The cost of false negatives (missed outbreaks) likely exceeds the cost of pilot deployments.

Final assessment:

The hypothesis that bioacoustic monitoring can serve as an early warning system for Usutu virus outbreaks in blackbirds is **biologically plausible, technically feasible, but empirically unvalidated**. Moving from theoretical potential to operational utility requires:

- Multi-year baseline acoustic datasets paired with health surveillance
- Validation of acoustic decline preceding mortality peaks by actionable intervals ($\geq$1 week)
- Demonstration of specificity (low false-positive rate from non-disease causes)
- Cost-benefit analysis comparing acoustic surveillance to enhanced traditional methods
- Integration frameworks combining acoustic, mortality, vector, and environmental data

Without such validation, acoustic biosurveillance remains a promising hypothesis rather than an evidence-based surveillance tool. The field requires rigorous null-hypothesis testing: researchers must be willing to publish results if acoustic monitoring does **not** provide early warning, preventing confirmation bias and guiding resource allocation toward effective surveillance strategies.

As climate change expands the geographic range of mosquito-borne pathogens, and as bird populations face compounding stressors from habitat loss, pesticides, and emerging diseases, innovative monitoring approaches are urgently needed. Acoustic biosurveillance may prove valuable not for early outbreak detection, but for continuous population health monitoring, post-outbreak recovery assessment, and understanding community-level ecosystem responses to disease. These applications, while less dramatic than real-time early warning, could provide substantial conservation value and inform adaptive management of wildlife disease in an era of global change.[80, 53, 62, 52, 20]

Data availability statement: The research presented is a synthesis of publicly available published literature. No original empirical data were collected. Specific USUV surveillance datasets from Netherlands (2016–2025) are managed by DWHC and Erasmus Medical Center; BirdNET algorithm code is open-source via GitHub (`kahst/BirdNET-Analyzer`); BirdWeather platform data is accessible via `app.birdweather.com` with user permissions.

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