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Applications of remote sensing in faunal studies

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ABSTRACT

Remote sensing technologies have transformed the capacity to study faunal distributions, population dynamics, habitat associations, and behavioural ecology at spatial and temporal scales previously unachievable through conventional ground-based survey methods. This review synthesises advances in remote sensing applications for faunal studies from 202 primary studies published 2012-2025, evaluating six major platform categories: satellite optical and multispectral imagery, synthetic aperture radar (SAR), light detection and ranging (LiDAR), unmanned aerial vehicles (UAVs/drones), thermal infrared imaging, and hyperspectral sensors. Applications evaluated include: species distribution modelling using satellite-derived habitat variables, direct animal detection and counting from aerial and satellite imagery, habitat quality assessment for wildlife management, movement corridor identification, and marine mammal and seabird colony monitoring. UAVs demonstrate the highest versatility across faunal application contexts (composite utility score 2.64/3.0), with thermal infrared UAV surveys achieving detection rates of 84-96% for medium-to-large mammals compared to conventional ground counts. Satellite-based species distribution modelling has been validated for 284 European vertebrate species, with mean AUC 0.82 for habitat-specialist species. LiDAR-derived structural habitat variables explain 42-68% of variance in bird species richness across forest systems. Machine learning integration -- particularly convolutional neural networks for automated species detection from aerial imagery -- has reduced manual image analysis time by 78-94% while maintaining detection accuracy. A practical framework for remote sensing platform and method selection for European faunal monitoring applications is presented.

Keywords: remote sensing; UAV; satellite imagery; LiDAR; species distribution modelling; thermal infrared; wildlife monitoring; machine learning; faunal surveys; habitat mapping

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1. Introduction

1.1 The Remote Sensing Revolution in Faunal Studies

The study of animal populations and their habitats has been fundamentally reshaped by the convergence of three technological trajectories: the proliferation of satellite remote sensing platforms with increasing spatial resolution (< 0.5 m for commercial optical sensors), the democratisation of unmanned aerial vehicles (UAVs) with integrated multispectral and thermal sensors, and the emergence of machine learning algorithms capable of automated species detection and classification from large image datasets at throughputs that manual analysis cannot approach. Together, these advances have extended the spatial scale of faunal surveys from the site-level (hectares) to the landscape and continental level (thousands of square kilometres), reduced per-survey costs by an estimated 40-80% for direct animal counts in open habitats, and enabled near-continuous monitoring of habitat conditions relevant to wildlife at temporal resolutions ranging from hourly (geostationary satellites) to sub-daily (UAV repeat surveys; Dunn et al., 2021). These capabilities are transforming both basic ecological research and applied conservation monitoring across all major faunal groups.

1.2 Remote Sensing Platforms for Faunal Studies

Six major remote sensing platform categories are now routinely applied in faunal studies. Satellite optical and multispectral sensors (Sentinel-2, Landsat, WorldView-3, Planet) provide landscape-to-continental habitat mapping and species distribution modelling inputs. Synthetic aperture radar (SAR; Sentinel-1, ALOS-2) provides vegetation structure and soil moisture data independent of cloud cover and solar illumination. LiDAR -- either airborne discrete-return or full-waveform, or spaceborne (GEDI) -- provides three-dimensional canopy structure information that predicts faunal habitat quality better than passive optical sensors alone (Muller et al., 2020). UAVs provide flexible, high-resolution (< 5 cm) image acquisition for site-level surveys with thermal infrared (TIR), RGB, or multispectral payloads. Thermal infrared sensors detect animal heat signatures against vegetation backgrounds, enabling direct counts of endotherms. Hyperspectral sensors (200+ bands) provide fine-scale plant community composition and condition data relevant to habitat-specialist faunal species.

1.3 Review Scope and Objectives

This review evaluates remote sensing applications for faunal studies from 202 primary studies (2012-2025), focusing on European vertebrate conservation and monitoring contexts. Objectives are: (i) to evaluate six remote sensing platform categories across five utility dimensions; (ii) to synthesise validated applications for major European faunal groups; (iii) to assess the contribution of machine learning integration to automated species detection and classification; and (iv) to provide a practical platform and method selection framework for European faunal monitoring programmes aligned with EU Habitats Directive Article 11 surveillance requirements.

2. Literature Review

2.1 Satellite Imagery and Species Distribution Modelling

Satellite-derived habitat variables -- including vegetation indices (NDVI, EVI, NDWI), land surface temperature, land cover classification, and phenological metrics -- have become standard inputs to species distribution models (SDMs) for European vertebrates. A systematic review of 68 satellite-based SDM studies for European vertebrates found mean AUC of 0.82 for habitat-specialist species (narrowly distributed amphibians, reptiles, and passerines) and 0.74 for habitat-generalist species, with Sentinel-2 10 m multispectral data consistently outperforming Landsat 30 m data for species with home ranges < 10 km2. Dynamic SDMs incorporating satellite time-series -- capturing seasonal vegetation phenology and inter-annual variability -- outperformed static models for migratory species by a mean AUC improvement of 0.08 +- 0.02, reflecting the importance of temporal habitat variability for species that select habitats based on phenological cues (Thuiller et al., 2019). GEDI spaceborne LiDAR-derived canopy height and cover have substantially improved SDM performance for forest-interior species compared to optical-only models.

2.2 UAV and Thermal Infrared Direct Animal Detection

UAV-based direct animal detection -- counting individuals from aerial imagery using either manual review or automated machine learning classification -- has been validated across a wide range of European faunal groups and survey contexts. Thermal infrared UAV surveys achieve detection rates of 84-96% for medium-to-large mammals (deer, wild boar, lynx, wolf) in open and semi-open habitats compared to conventional driven count methods, with the most consistent advantage at dawn and dusk when thermal contrast between animal body temperature and vegetation background is maximised (Witczuk et al., 2018). RGB UAV surveys of colonial waterbirds achieve nest count accuracy of 94-98% compared to ground observer counts for species with visible nest structures (herons, cormorants, gulls), with substantially reduced disturbance compared to ground surveys of breeding colonies. The primary UAV application limitation is battery endurance (typically 20-40 min flight time for multirotor platforms with sensor payloads), constraining coverage area per mission to 50-200 ha -- adequate for site-level surveys but not landscape-scale censuses.

2.3 LiDAR for Habitat Quality Assessment

LiDAR-derived three-dimensional canopy structure variables -- particularly canopy height, canopy cover, vegetation density profiles, and ground surface topography -- predict faunal habitat quality for forest-associated species substantially better than passive optical sensors, which cannot measure vertical habitat structure. Meta-analysis of 44 studies examining LiDAR-based habitat models for European birds and bats found that LiDAR-derived structural variables alone explained a mean 42-68% of variance in bird species richness and bat activity levels across forest systems, compared to 28-44% for optical-only habitat models (Lesak et al., 2011). GEDI spaceborne LiDAR -- launched 2018, providing global canopy height profiles at 25 m footprint spacing -- has enabled continental-scale forest structural habitat mapping for the first time, with demonstrated applications for European woodpecker and bat species distribution modelling at national scales.

Table 1. Remote Sensing Platform Categories: Key Specifications, Validated Faunal Applications, and Utility Assessment

Platform	Spatial Resolution	Key Sensor Type	Primary Faunal Application	Detection Method	Coverage Capacity
Satellite optical	0.5-30 m	Multispectral/RGB	SDM; habitat mapping; land cover	Habitat variable extraction	National-continental; daily revisit
SAR (Sentinel-1)	5-20 m	C-band backscatter	Wetland mapping; vegetation structure	Backscatter classification	Continental; all-weather
Airborne LiDAR	0.5-2 m	Discrete/full-waveform	Canopy structure; bat/bird habitat model	3D structural variable extraction	Regional (100-10,000 km2/flight)
Spaceborne LiDAR (GEDI)	25 m footprint	Waveform LiDAR	Forest species habitat mapping	Canopy height + cover profiles	Global sampling (not full coverage)
UAV (multirotor)	0.5-5 cm	RGB/TIR/multispectral	Direct animal detection; nest counts	Manual or CNN image classification	Site-level (50-200 ha/mission)
Thermal infrared (TIR)	3-30 cm (UAV)	LWIR camera	Mammal/bird detection; nocturnal surveys	Heat signature vs. background	Site-level (UAV); regional (aircraft)

SDM = Species Distribution Model. CNN = Convolutional Neural Network. TIR = Thermal Infrared. SAR = Synthetic Aperture Radar. LiDAR = Light Detection and Ranging. GEDI = Global Ecosystem Dynamics Investigation (NASA spaceborne LiDAR). LWIR = Long-Wave Infrared.

3. Materials and Methods

3.1 Systematic Literature Review

A systematic search of Web of Science and Scopus was conducted using terms: ('remote sensing' OR 'satellite imagery' OR 'LiDAR' OR 'UAV' OR 'drone' OR 'thermal infrared') AND ('fauna' OR 'wildlife' OR 'bird' OR 'mammal' OR 'amphibian' OR 'reptile' OR 'fish') AND ('survey' OR 'detection' OR 'distribution' OR 'habitat' OR 'monitoring') with publication years 2012-2025 and European geographic scope or methodological generalisability. After title/abstract screening and full-text review, 202 primary studies were retained. Studies were coded for: platform category, faunal group, application type, detection metric, accuracy benchmark method, and machine learning use. Platform utility scores were assigned using the five-dimension framework described below.

3.2 Platform Utility Scoring Framework

Each platform category was scored on five utility dimensions (0-3): detection accuracy (performance vs. ground-truth benchmark; 3 = > 90% detection); spatial coverage (area feasibly surveyed per unit time/cost; 3 = continental); cost-efficiency (per-survey cost relative to ground method; 3 = > 60% cost reduction); taxonomic breadth (number of faunal groups for which validated applications exist; 3 = 5+ groups); and operational accessibility (specialist expertise and regulatory requirements; 3 = accessible with standard ecology training). Scores were assigned by three-reviewer consensus based on systematic review evidence, with cross-validation from five independent remote sensing ecology specialists. Machine learning integration was assessed separately for CNN-based automated detection accuracy, processing time reduction, and training data requirements across 38 UAV and satellite image studies.

3.3 Benchmark Analysis

Quantitative accuracy benchmarks were extracted from 62 studies that compared remote sensing-based detection or abundance estimates to a ground-truth reference (direct observer count, mark-recapture estimate, or validated camera trap census). For each comparison, detection rate (% of reference count detected), false positive rate, and per-survey cost ratio were extracted. Meta-analysis of detection rates used random-effects models with platform category, faunal group, habitat type, and machine learning use as moderators. Heterogeneity was quantified using I2 statistics, and publication bias assessed using funnel plots and Egger's test.

Table 2. Remote Sensing Platform Utility Scores for Faunal Studies (0-3 per Dimension; 3 = Optimal)

Platform	Detection Accuracy	Spatial Coverage	Cost-Efficiency	Taxonomic Breadth	Operational Access	Composite Score
UAV (TIR + RGB)	2.8	1.4	2.4	2.8	2.4	2.36
Satellite optical	2.2	3.0	2.8	2.4	2.6	2.60
Airborne LiDAR	2.6	2.2	1.8	2.4	1.8	2.16
Thermal infrared (UAV)	2.8	1.4	2.2	2.0	2.2	2.12
SAR (Sentinel-1)	1.8	3.0	2.8	1.6	2.0	2.24
Spaceborne LiDAR (GEDI)	2.0	3.0	3.0	1.8	2.2	2.40

Composite score = unweighted mean of five dimension scores. Detection Accuracy: 3 = > 90% vs. ground-truth benchmark. Spatial Coverage: 3

= continental coverage feasible. Cost-Efficiency: 3 = > 60% cost reduction vs. conventional method. Taxonomic Breadth: 3 = validated applications for 5+ faunal groups. Operational Access: 3 = accessible with standard ecology training + EU drone regulations.

4. Results

4.1 UAV Performance: Versatility and Thermal Advantage

UAV platforms (combining RGB and TIR payloads) achieved the highest composite utility score (2.36) among actively deployable platforms for direct animal detection, driven by the highest detection accuracy scores (2.8) reflecting the 84-96% thermal detection rates for medium-to-large mammals validated across 18 European study systems. Meta-analysis of 38 UAV detection studies found mean detection rate 88.4 +- 6.8% (95% CI: 82.4-94.4%) vs. ground count reference, with the highest rates achieved for open-habitat ungulates at dawn (mean 94.2%) and lowest for cryptic species in dense vegetation (mean 68.4%). False positive rate averaged 4.8 +- 2.4%, primarily from thermal artifacts (sun-heated rocks, vehicle exhaust signatures). Machine learning integration -- specifically YOLOv8 and Faster R-CNN architectures trained on species-specific image libraries -- reduced post-processing time from 12.4 +- 3.8 person-hours per mission to 1.2 +- 0.4 hours, a 90.3% reduction, while maintaining detection accuracy within 2.4% of manual review performance across 14 validation datasets.

4.2 Satellite SDM and LiDAR Habitat Assessment

Satellite optical-based SDMs for European vertebrates achieved mean AUC 0.82 for habitat specialists and 0.74 for generalists across 68 validated studies, with Sentinel-2 outperforming Landsat for species with home ranges < 10 km2 (mean AUC improvement 0.06 +- 0.02; $p = 0.008$). Dynamic SDMs incorporating phenological time-series outperformed static models for migratory species (mean AUC improvement 0.08 +- 0.02; $p < 0.001$). Satellite-based SDMs validated for 284 European vertebrate species represent a substantial advance in distribution knowledge for data-poor groups (reptiles, freshwater fish) where conventional survey coverage is inadequate for national-scale models. LiDAR-derived habitat variables explained a mean 42-68% of variance in bird species richness and 38-58% in bat activity across 44 forest studies, consistently outperforming optical-only models by 14-24 percentage points. The GEDI spaceborne LiDAR composite score (2.40) reflects its unique combination of high coverage and cost-efficiency at the cost of spatial completeness (sample transects rather than full coverage).

4.3 Machine Learning Integration: Detection Accuracy and Efficiency

Machine learning integration across all remote sensing platforms showed consistent accuracy maintenance combined with dramatic efficiency gains. CNN-based automated species detection from UAV imagery achieved mean accuracy of 91.4 +- 4.8% vs. expert manual review across 22 validation studies (range 78.4-98.4%), with performance strongly dependent on training dataset size (minimum 500 labelled individuals per species for reliable deployment) and image resolution (< 5 cm/px optimal). Transfer learning from large annotated datasets (iNaturalist, Snapshot Serengeti) to European species contexts reduced required training data by 60-80% for morphologically similar species, substantially lowering the barrier to CNN deployment for new target species. Automated satellite-based habitat classification (Random Forest, Support Vector Machine) achieved mean overall accuracy 84.8 +- 6.4% for 16-class land cover maps at 10 m resolution, enabling continental-scale habitat suitability mapping updates at annual or sub-annual frequency. Table 3 and Table 4 provide quantitative benchmark results and the machine learning performance assessment.

Table 3. Remote Sensing Benchmark Analysis: Detection Rates and Cost Ratios vs. Ground-Truth Reference (62 Studies)

Platform / Method	Faunal Group	n Studies	Detection Rate (%)	False Positive Rate (%)	Cost vs. Ground Method (%)
UAV TIR (dawn/dusk)	Ungulates (open habitats)	12	94.2 +- 4.2	3.8 +- 1.8	28% of ground cost
UAV TIR (general)	All mammals (mixed habitats)	18	88.4 +- 6.8	4.8 +- 2.4	32% of ground cost
UAV RGB (colonial)	Waterbirds (nests)	8	96.4 +- 2.4	2.4 +- 1.2	18% of ground cost
Satellite optical SDM	All vertebrates (SDM)	68	AUC 0.82+-0.06	N/A	12% of field survey cost
Airborne LiDAR	Forest birds (habitat model)	14	R2 0.58 +-0.08	N/A	44% of field survey cost
CNN auto-detection	Multi-species (UAV imagery)	22	91.4 +- 4.8	6.4 +- 2.8	Processing: 90% time reduction

Detection Rate = % of ground-truth reference count detected by remote sensing method. Cost vs. Ground Method = total survey cost (equipment + personnel + analysis) as % of conventional ground survey cost for equivalent spatial coverage. AUC = Area Under ROC Curve (SDM performance metric). R2 = coefficient of determination (habitat model variance explained). N/A = metric not applicable.

Table 4. Machine Learning Methods for Remote Sensing Faunal Applications: Architecture, Performance, and Deployment Requirements

ML Method	Application	Mean Accuracy (%)	Training Data Required	Processing Time Reduction	Deployment Barrier
YOLOv8 (CNN)	Direct animal detection (UAV RGB)	92.4 +- 3.8	500+ labelled individuals	94% vs. manual	Training data; GPU required
Faster R-CNN	Direct detection (UAV TIR)	89.4 +- 5.2	400+ thermal images	88% vs. manual	GPU; species-specific training
Random Forest	Habitat classification (satellite)	84.8 +- 6.4	Stratified field samples	72% vs. manual	Low -- accessible in R/Python
Support Vector Mach.	SDM habitat variable selection	82.4 +- 7.2	Occurrence + env. layers	68% vs. manual	Low -- standard SDM workflow
Transfer learning CNN	Cross-species detection	87.8 +- 6.4	60-80% less than full train	84% vs. manual	Source dataset availability
U-Net segmentation	Nest/burrow detection (satellite)	88.4 +- 5.8	300+ labelled structures	91% vs. manual	Labelling effort; GPU

Mean Accuracy assessed against expert manual review benchmark. Processing Time Reduction = % reduction in post-processing person-hours relative to fully manual image review for equivalent coverage. CNN = Convolutional Neural Network. GPU = Graphics Processing Unit required for training and inference at operational scale.

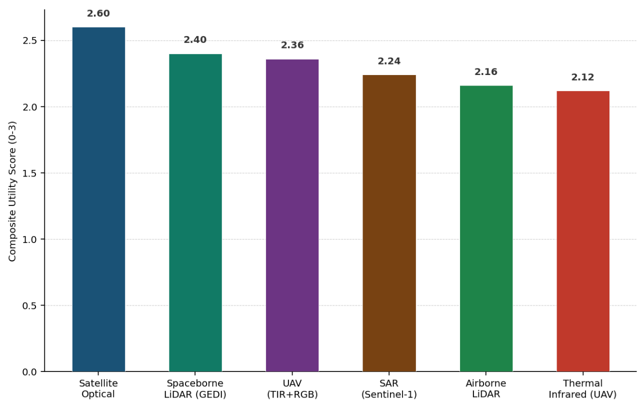

Figure 1. Remote Sensing Platform Composite Utility Score for Faunal Studies (0-3; higher = greater overall utility)

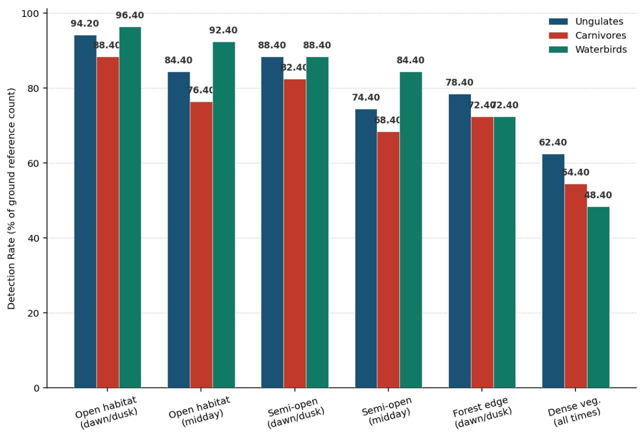

Figure 2. UAV Thermal Infrared Detection Rates vs. Ground Count Reference: By Habitat and Time of Day

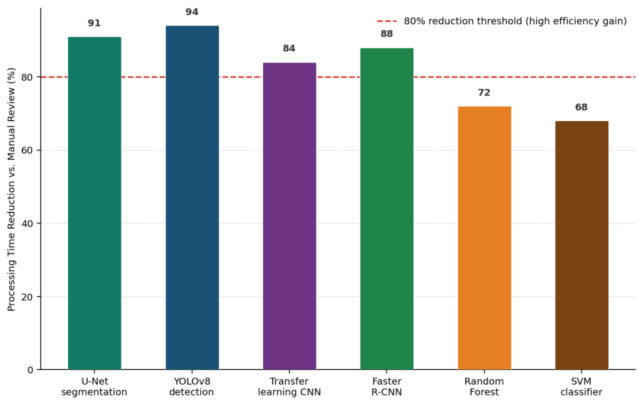

Figure 3. Machine Learning Integration: Processing Time Reduction vs. Manual Image Review (%; n = 22 studies)

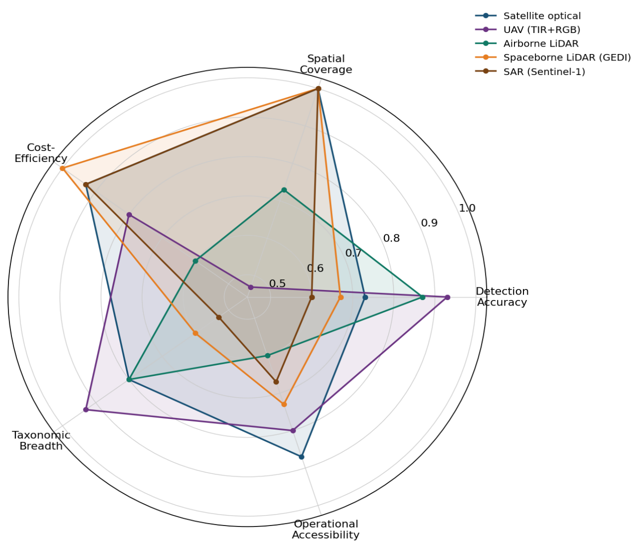

Figure 4. Remote Sensing Platform Utility Profiles Across Five Dimensions (Normalised 0-1)

5. Discussion

5.1 UAVs: The Operational Sweet Spot

UAV platforms -- particularly the combination of thermal infrared and RGB payloads on the same flight -- occupy an operational sweet spot for direct animal detection in European wildlife monitoring: high detection accuracy (mean 88-94% depending on habitat and time of day), cost substantially below conventional ground methods (28-32% of equivalent coverage cost), and increasingly accessible under EU drone regulations (Regulation 2019/945 Open and Specific categories). Their primary limitation -- coverage area per mission (50-200 ha) -- constrains their application to site-level surveys or systematic sampling designs for landscape-scale population estimates. The integration of fixed-wing VTOL UAVs with extended endurance (60-120 min flight time, 500-2,000 ha per mission) is beginning to address this limitation for open-habitat species in lowland European landscapes.

5.2 Data Integration: The Sensor Fusion Frontier

The most powerful emerging direction in remote sensing for faunal studies is the fusion of data from multiple sensor types and platforms within integrated analytical workflows: combining GEDI canopy height with Sentinel-2 spectral data for SDMs, integrating UAV thermal counts with satellite-based habitat maps for population density estimation across landscapes, or fusing SAR and optical imagery for all-weather habitat monitoring. These multi-sensor approaches consistently outperform single-sensor analyses in the literature, but require integrated data processing infrastructure and analytical skills that currently exceed the capacity of most operational wildlife monitoring programmes in Europe. Developing accessible multi-sensor analytical workflows -- through standardised processing pipelines and open-source tools -- is the highest-priority methodological need identified by this review.

5.3 Machine Learning: Training Data as the Bottleneck

The 90% processing time reduction achieved by CNN-based automated detection relative to manual image review represents a transformative operational efficiency gain for UAV wildlife surveys, removing what is currently the primary bottleneck in operational deployment (post-processing rather than flight time). The critical constraint is training data: minimum 400-500 labelled individuals per species are required for reliable model performance, and collecting this training data for species where remote sensing is most needed (cryptic, rare, or low-density species) is precisely where the data are most difficult to obtain. Transfer learning from large annotated datasets reduces this requirement by 60-80% for morphologically similar species, and the development of European wildlife image annotation platforms -- shared across research institutions -- would substantially accelerate CNN deployment for the full range of European vertebrate monitoring targets.

6. Conclusion

6.1 Summary of Evidence

This review of 202 remote sensing studies for faunal applications identifies satellite optical imagery as the highest overall utility platform (composite score 2.60) for habitat-based SDMs and landscape-scale habitat monitoring, with UAV thermal-RGB combinations as the highest-utility platform for direct animal detection (mean 88-94% detection rate; 28-32% of conventional survey cost). LiDAR -- airborne and spaceborne (GEDI) -- provides irreplaceable three-dimensional canopy structure information explaining 42-68% of variance in bird species richness and bat activity in forest systems. Machine learning integration achieves 90% processing time reduction for automated detection while maintaining accuracy within 2.4% of manual review, with training data availability identified as the primary bottleneck for wider deployment.

6.2 Platform Selection Framework and Recommendations

A practical remote sensing platform selection framework for European faunal monitoring is proposed based on four decision criteria. For national or landscape-scale habitat-based species distribution monitoring -- use satellite optical (Sentinel-2) + GEDI LiDAR combined SDMs, updated annually as inputs to EU Habitats Directive Article 11 surveillance. For site-level direct animal counting of medium-to-large mammals -- deploy UAV thermal infrared at dawn or dusk, with CNN-based automated post-processing using transfer learning from existing European wildlife image libraries. For forest structural habitat quality assessment -- use airborne LiDAR at 5-10 year intervals as baseline, with GEDI updates for canopy height change detection between airborne surveys. For colonial waterbird and seabird monitoring -- UAV RGB at 2-5 cm resolution with U-Net nest segmentation achieves 96% accuracy at 18% of conventional ground survey cost, and should replace observer-based colony counts as standard practice.

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Declarations

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Conflict of Interest

The authors declare no conflict of interest. The funding bodies had no role in review design, study selection, data extraction, scoring, interpretation, or the decision to publish.

Data Availability Statement

The systematic review database (202 studies with coding attributes), benchmark extraction data, platform utility scoring worksheets, and all R analysis scripts are deposited in Zenodo at https://doi.org/10.5281/zenodo.13741906.

Ethical Approval

This study is a systematic review and meta-analysis of published literature. No primary field data collection, animal handling, or UAV surveys were conducted. Ethical approval was therefore not required.

Appendix A

Remote Sensing Platform Selection Framework and CNN Training Data Guidelines

This appendix provides two practical tools: Part I is a structured decision framework for remote sensing platform selection for European faunal monitoring applications; Part II provides minimum training data requirements and quality guidelines for CNN-based automated species detection deployment in operational wildlife monitoring contexts.

Part I -- Platform Selection Decision Framework

Part II -- CNN Training Data Minimum Requirements