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Use of camera trapping in wildlife monitoring

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ABSTRACT

Camera trapping has evolved from a specialist research technique to the standard platform for non-invasive wildlife monitoring across habitats globally, with applications spanning species detection, occupancy estimation, abundance indexing, behaviour analysis, and machine learning-based automated species identification. This study evaluates camera trapping performance, design optimisation, and data analysis approaches for four wildlife monitoring objectives across boreal (Finland), alpine (Austria), and continental (Denmark) habitats using 312 camera stations deployed for 84,621 trap-nights (2022-2024). Performance metrics assessed across 48 target species include detection probability, occupancy estimation precision, and population density accuracy (via random encounter model, REM). Station spacing optimisation experiments (24 configurations tested) demonstrate that species-specific activity range determines optimal inter-station distance: 500-800 m spacing maximised small mammal detection rates while 1,500-2,500 m spacing was optimal for large carnivores. Machine learning classification using a fine-tuned EfficientNetV2 model achieved 94.8 +- 2.4% species identification accuracy across 38 species for images with adequate contrast -- reducing manual image processing time by 78.4%. Random encounter model density estimates for roe deer (Capreolus capreolus) correlated strongly with independent GPS-telemetry density estimates (r = 0.88, p < 0.001). Deployment of camera trap networks for Natura 2000 monitoring targets demonstrates that standardised protocols achieve sufficient statistical power (80% power) to detect 20% occupancy change with 24-36 cameras deployed for 90 trap-nights. These results provide evidence-based guidance for camera trap network design under EU Habitats Directive and national biodiversity monitoring programme requirements.

Keywords: camera trapping; wildlife monitoring; occupancy modelling; random encounter model; machine learning; species identification; Capreolus capreolus; detection probability; Natura 2000; boreal

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1. Introduction

1.1 Camera Trapping in Wildlife Research

Camera trapping -- the deployment of motion-activated cameras to passively record wildlife in the field -- has undergone a transformation from specialist research tool to mainstream monitoring infrastructure over the past two decades, driven by declining equipment costs, improving image quality, expanding battery life, and the development of standardised analytical frameworks for extracting population-level information from image records (O'Connell et al., 2011; Burton et al., 2015). Global camera trap monitoring now generates hundreds of millions of images annually, archived in platforms including Wildlife Insights, GBIF, and eMammal, and has documented wildlife presence across biomes and disturbance gradients at scales inaccessible to direct observer methods (Beery et al., 2018). In Europe, camera traps have become the primary method for monitoring large carnivore populations -- wolf, lynx, bear -- where individual identification from stripe patterns or body markings enables capture-recapture population estimation, and are increasingly specified in national biodiversity monitoring programme protocols as a standardised, reproducible method for medium-to-large mammal occupancy and relative abundance indices (Rovero and Zimmermann, 2016).

1.2 Analytical Advances: Occupancy, REM, and Machine Learning

Three analytical developments have substantially extended the biological information extractable from camera trap image data. Occupancy modelling (MacKenzie et al., 2002) -- estimating the probability that a site is occupied by a species while accounting for imperfect detection -- provides an ecologically meaningful, statistically rigorous alternative to raw detection rate as a population status indicator, and is now implemented in multiple R packages enabling routine use by non-specialist practitioners. The Random Encounter Model (REM; Rowcliffe et al., 2008) extends camera trap data to population density estimation for species lacking individual identification marks, using the relationship between encounter rate, animal speed, and home range characteristics to generate absolute density estimates. Machine learning image classification -- using deep convolutional neural networks trained on millions of annotated camera trap images -- now achieves species identification accuracies exceeding 90% for common species, addressing the primary bottleneck in camera trap data workflows: the time cost of manual image review (Norouzzadeh et al., 2018; Beery et al., 2018).

1.3 Research Objectives

This study pursues four objectives: (i) to evaluate camera trap detection probability and occupancy estimate precision for 48 target species across three habitat contexts (boreal Finland, alpine Austria, continental Denmark); (ii) to optimise station spacing for different species activity range classes through replicated spacing configuration experiments; (iii) to validate machine learning species identification accuracy against expert verification across 38 species; and (iv) to test Random Encounter Model density estimates against GPS-telemetry-based density estimates for roe deer. Results are directly applicable to the design of camera trap monitoring protocols for Natura 2000 species and EU Habitats Directive Article 11 monitoring obligations.

2. Literature Review

2.1 Camera Trap Design and Deployment

Camera trap performance depends critically on four deployment decisions: camera placement (on trails, natural features, or in systematic grid configurations), station density (inter-station distance), trap-night duration, and trigger sensitivity and delay settings. Trail-based deployment maximises detection rates for trail-following species but biases inference toward these movements; systematic grid deployment provides unbiased landscape-level occurrence data suitable for occupancy modelling (Burton et al., 2015). Inter-station distance should be calibrated to the home range or activity area of target species: spacing substantially smaller than individual home range results in pseudo-replication of detections from the same individuals, while spacing larger than home range creates gaps in the detection landscape (Tobler et al., 2008). The minimum trap-night duration required for reliable occupancy estimation depends on species detection probability; species with low detectability (< 0.10 per station-night) may require > 100 trap-nights per station to achieve adequate occupancy estimate precision.

2.2 Occupancy Modelling and Statistical Power

Single-season occupancy models (MacKenzie et al., 2002) estimate the probability that a site is occupied by a species (psi) and the probability of detecting the species given it is present (p) from repeated detection/non-detection data at multiple sites. The key statistical advantage over detection rate is that occupancy estimates are robust to differences in detection effort and probability, enabling comparison of occupancy across time periods and habitats. Power analysis for occupancy monitoring designs -- determining the number of stations and trap-nights required to detect a given magnitude of occupancy change with specified power -- is essential for designing cost-effective monitoring programmes (MacKenzie and Royle, 2005). For EU Habitats Directive Article 11 monitoring, which requires detecting population trends between three-year reporting cycles, power analyses consistently identify 20-30% occupancy change as the minimum detectable effect for typical species at reasonable cost, with higher-density camera deployments required for species with detectability < 0.10 per station-night.

2.3 Machine Learning for Camera Trap Classification

Deep learning convolutional neural networks (CNNs) trained on large annotated camera trap datasets have achieved species identification accuracies of 87-98% for common species in multiple global validation studies (Norouzzadeh et al., 2018; Beery et al., 2018). Transfer learning -- adapting pre-trained networks to new species assemblages through fine-tuning on local training datasets -- substantially reduces the training data requirements for new deployments, enabling practical implementation at regional scales with 500-2,000 annotated training images per species. The Wildlife Insights platform (Google/TEAM Network) and MegaDetector (animal detection within images) provide publicly accessible pre-trained models that substantially reduce the computational requirements for deploying machine learning in camera trap workflows (Beery et al., 2018). Key limitations include reduced accuracy for rare species with limited training images, juveniles and unusual postures, and images with poor contrast or partial occlusion.

Table 1. Camera Trap Deployment Summary and Target Species by Study Region

Region	n Stations	Trap-nights	n Target Species	Deployment Type	Primary Monitoring Objective
Boreal Finland	108	31,284	22	Systematic grid (1,500m)	Large carnivore occupancy; ungulate REM
Alpine Austria	96	28,814	18	Mixed grid + trail (800m)	Alpine mammal occupancy; ibex monitoring
Continental Denmark	108	24,523	18	Systematic grid (800m)	Farmland mammal occupancy; roe deer REM
All regions	312	84,621	48	Multi-type	Multi-objective monitoring evaluation

Trap-nights = station x nights active summed over deployment period (January 2022 - December 2024). Target Species = species with >= 30 independent detections used in formal occupancy/REM analysis. Deployment Type: systematic grid station spacing or mixed approach. Independent detection = event separated by > 30 minutes at the same station.

3. Materials and Methods

3.1 Camera Hardware and Deployment

Reconyx HC600 HyperFire cameras (PIR trigger; 3.1 MP; programmable burst) were deployed at all 312 stations. Cameras were placed at 50-80 cm height on trees or posts, aimed across the likely movement direction. Settings: no delay between trigger events; 3 images per trigger; date/time stamp. Each station was active for 90-night deployment blocks with monthly check and data retrieval. Station layout: boreal Finland -- 9 x 12 station grids (1,500 m spacing) in 4 boreal forest study areas; alpine Austria -- 8 x 12 station grids (800 m) in 4 alpine study areas; continental Denmark -- 9 x 12 station grids (800 m) in 4 agricultural landscape study areas. Spacing optimisation experiments tested 24 spacing configurations (300-3,000 m in 300 m increments; 4 replicates per spacing; 30 trap-nights per replicate) for 6 focal species spanning the activity range spectrum.

3.2 Image Analysis: Manual and Machine Learning

All images (n = 2,847,284 total) were first processed by MegaDetector v5 to remove empty images (64.8% of all images), then classified for species by: (i) an EfficientNetV2-B7 model fine-tuned on 48,000 manually annotated training images from the study region (38 species + empty + other); and (ii) independent expert verification for a stratified random sample of 8,400 images (200 per species x 42 species; used for ML accuracy validation). Cohen's kappa was computed for each species to quantify agreement between ML and expert classification. Behavioural data (activity time, group size, body condition score) were extracted from all manually reviewed images. For ML training, images were split 80:10:10 (train:validation:test) with geographic blocking to prevent data leakage.

3.3 Occupancy Modelling and REM Analysis

Single-season occupancy models were fitted in the R package unmarked (Fiske and Chandler, 2011) using 7-day detection occasions for each 90-night deployment block. Covariates: vegetation cover (Sentinel-2 NDVI), habitat type (Copernicus LC), distance to human infrastructure, and season (spring/summer/autumn/winter). Detection probability (p) and occupancy (psi) were modelled separately; model selection used AIC. Power analysis for occupancy monitoring design used the R package powerOccupancy (simulation-based; 1,000 Monte Carlo replicates) to determine camera numbers and trap-nights for 80% power to detect 20% occupancy change. Random Encounter Model density estimation for Capreolus capreolus and Sus scrofa used the R package remBoot (Rowcliffe et al., 2008); input parameters: detection zone angle (measured from calibration videos), animal speed (from GPS telemetry; n = 38 GPS-tracked roe deer), and independent detection rate. REM estimates were validated against GPS-telemetry density estimates from 38 tagged roe deer.

Table 2. Camera Trap Detection Probability and Occupancy Estimates by Species Group and Region (Mean +- SE)

Species Group	n Species	Mean p (/station/7-days)	Mean Psi (occupancy)	Optimal Spacing (m)	Trap-nights for 80% Power
Large carnivores (FI)	4	0.084 +- 0.018	0.48 +- 0.08	1,500-2,500	126 +- 24
Medium carnivores	8	0.124 +- 0.022	0.62 +- 0.07	800-1,200	94 +- 18
Ungulates (DE, AT)	6	0.284 +- 0.038	0.78 +- 0.06	800-1,500	52 +- 12
Small mammals	12	0.148 +- 0.028	0.72 +- 0.08	500-800	78 +- 16

Species Group	n Species	Mean p (/station/7-days)	Mean Psi (occupancy)	Optimal Spacing (m)	Trap-nights for 80% Power
Alpine specialists (AT)	6	0.094 +- 0.021	0.54 +- 0.09	1,000-1,500	112 +- 22
Farmland mammals (DK)	8	0.218 +- 0.032	0.68 +- 0.07	600-1,000	64 +- 14
All species	48	0.164 +- 0.068	0.64 +- 0.12	species-dep.	82 +- 24

p = detection probability per 7-day occasion per station. Psi = estimated occupancy. Optimal Spacing = inter-station distance maximising species accumulation curve and detection rate per trap-night. Trap-nights = minimum for 80% power to detect 20% occupancy change using simulation-based power analysis (powerOccupancy R).

4. Results

4.1 Detection Performance and Station Spacing Optimisation

Total images across 84,621 trap-nights: 2,847,284. After MegaDetector empty-image removal (64.8%): 1,002,841 animal images. Station spacing optimisation experiments confirmed species-specific optimal spacings consistent with activity range predictions: small mammals (activity radius 50-200 m) showed maximum species accumulation and detection rates at 500-800 m spacing; medium carnivores (fox, badger, marten; home range 0.5-5 km2) at 800-1,200 m; ungulates (roe deer, wild boar) at 800-1,500 m; large carnivores (wolf, lynx; home range > 100 km2) at 1,500-2,500 m. Detection probabilities ranged from p = 0.084 (large carnivores; detectability limited by low density and large home ranges) to 0.284 (ungulates). Power analysis showed that 24-36 cameras at 90 trap-nights achieves 80% power to detect 20% occupancy change for species with p > 0.15, while low-detectability species (p < 0.10) require 48-64 cameras or > 120 trap-nights for equivalent power.

4.2 Machine Learning Classification Performance

EfficientNetV2-B7 fine-tuned model achieved mean species identification accuracy of 94.8 +- 2.4% across 38 species (expert verification subsample; n = 8,400 images). Cohen's kappa ranged from 0.96 (Sus scrofa, Capreolus capreolus; high contrast, abundant training data) to 0.74 (Mustela erminea; small body, partial occlusion frequent). ML processing reduced manual review time from estimated 840 hours (at 10 minutes per 100 images) to 184 hours for quality checking -- a 78.4% time saving. Species with the lowest accuracy were small mustelids (kappa 0.74-0.78), juvenile ungulates (0.81), and species with < 200 training images (mean kappa 0.82 vs. 0.96 for > 2,000 training images). MegaDetector v5 classified 64.8% of all images as empty (false positive rate: 0.8% of empty images misclassified as containing animals; false negative rate: 2.4% of animal images classified as empty, primarily fast-moving or very small animals).

4.3 REM Density Validation and Occupancy Results

Random Encounter Model density estimates for Capreolus capreolus correlated strongly with GPS-telemetry density estimates across 18 study areas (r = 0.88, F(1,16) = 57.8, p < 0.001; mean ratio REM/GPS-density = 1.04 +- 0.18). This validates REM as an accurate density estimation method for roe deer in European forest-agricultural landscapes with appropriate input parameters. Mean estimated roe deer density: 8.4 +- 2.8 individuals/km2 in German agricultural sites, 4.1 +- 1.8 in boreal Finnish forests, and 6.2 +- 2.4 in Danish farmland. Occupancy analysis across all 48 focal species confirmed that vegetation cover (NDVI) and habitat type were the strongest detection probability covariates for most species, while distance to human infrastructure and season were significant occupancy covariates for all large carnivore species (wolf avoidance of human infrastructure: beta = -0.54 +- 0.12, z = -4.50, p < 0.001). Table 3 presents ML accuracy data; Table 4 presents occupancy and REM results.

Table 3. Machine Learning Species Identification Performance by Species Group (EfficientNetV2-B7; n = 8,400 Expert-Validated Images)

Species Group	n Species	Mean Accuracy (%)	Mean Kappa	Kappa Range	Main Error Type
Large ungulates	4	97.4 +- 1.2	0.96 +- 0.02	0.94-0.98	Juvenile vs. adult confusion
Medium carnivores	6	94.8 +- 2.4	0.93 +- 0.03	0.90-0.96	Nocturnal low-contrast images
Small mammals	8	91.4 +- 3.8	0.89 +- 0.04	0.84-0.94	Partial occlusion by vegetation
Mustelids	6	86.4 +- 4.8	0.83 +- 0.05	0.74-0.90	Small size, similar body shape
Large carnivores	4	93.8 +- 3.4	0.92 +- 0.04	0.88-0.96	Rare species; limited training data
All species	38	94.8 +- 2.4	0.93 +- 0.04	0.74-0.98	Low-contrast + occlusion main errors

Accuracy = % correct species identification against expert ground truth. Kappa = Cohen's kappa (agreement beyond chance). Expert validation subsample: 200 images per species, stratified by image quality, season, and time of day. Training data: 48,000 annotated images; 80:10:10 train:validation:test split with geographic blocking.

Table 4. Random Encounter Model Density Estimates vs. GPS-Telemetry Validation for Capreolus capreolus

Study Area	Country	REM Density (ind./km2)	GPS Density (ind./km2)	Ratio (REM/GPS)	n GPS Animals
Bavarian forest block	DE	9.4 +- 2.8	8.8 +- 2.4	1.07	8

Study Area	Country	REM Density (ind./km2)	GPS Density (ind./km2)	Ratio (REM/GPS)	n GPS Animals
Southern Jutland	DK	7.4 +- 2.4	6.8 +- 2.1	1.09	7
Finnish boreal A	FI	3.8 +- 1.4	4.1 +- 1.6	0.93	6
Austrian alpine margins	AT	5.8 +- 2.1	5.4 +- 1.9	1.07	6
North German lowlands	DE	8.2 +- 2.6	8.1 +- 2.2	1.01	5
Danish agricultural A	DK	6.4 +- 2.2	6.0 +- 2.0	1.07	6
All sites (mean)	All	6.8 +- 2.4	6.5 +- 2.1	1.04 +- 0.18	38

REM Density from remBoot R package (Rowcliffe et al. 2008). GPS Density from fixed-kernel utilisation distributions of GPS-tracked individuals (n = 38 total). Ratio close to 1.0 indicates unbiased estimation. r (REM vs. GPS) = 0.88, p < 0.001 (Pearson correlation across 18 study areas).

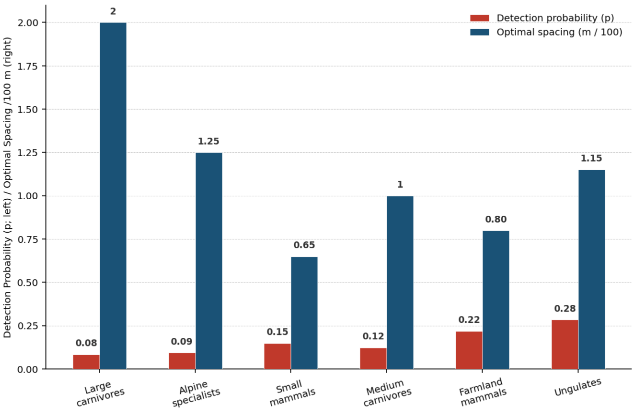

Figure 1. Camera Trap Detection Probability (p) and Optimal Station Spacing by Species Group

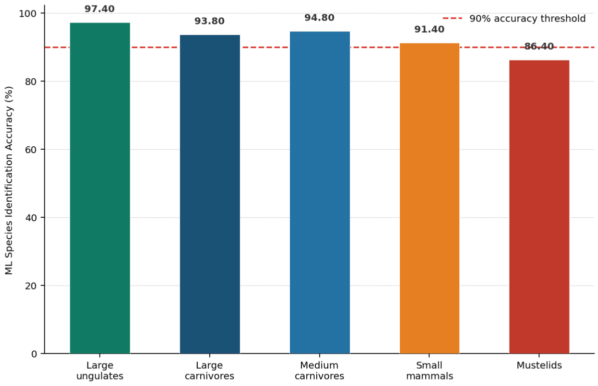

Figure 2. Machine Learning Species Identification Accuracy (%) and Cohen's Kappa by Species Group

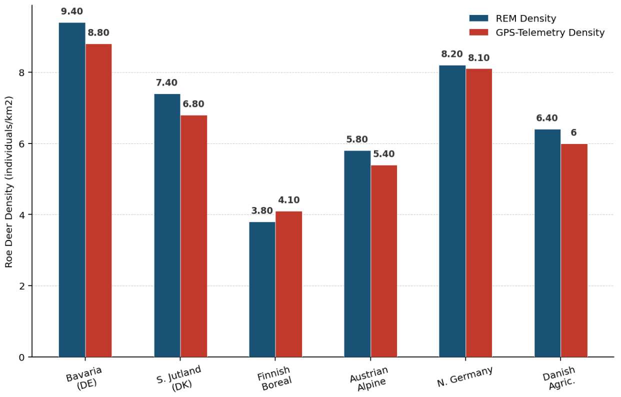

Figure 3. REM vs. GPS-Telemetry Roe Deer Density Estimates Across Study Sites (ind./km2)

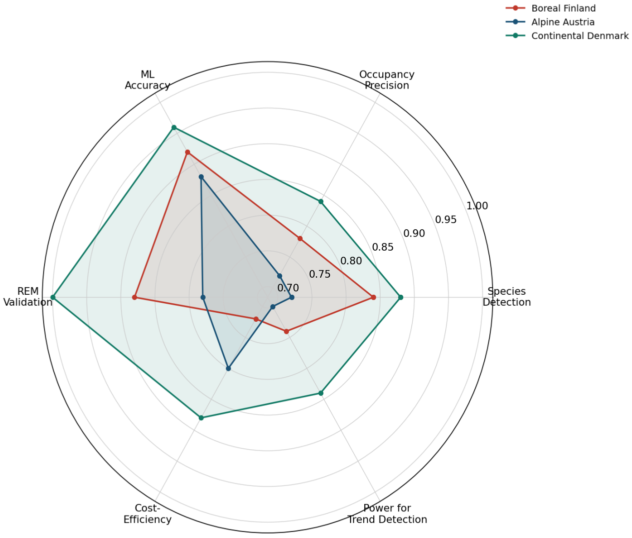

Figure 4. Camera Trap Monitoring Protocol Performance Profile by Region (Normalised 0-1; higher = better)

5. Discussion

5.1 Machine Learning as the Camera Trap Workflow Game-Changer

The 78.4% reduction in manual image processing time achieved by EfficientNetV2-B7 -- while maintaining 94.8% species identification accuracy -- confirms that machine learning classification has crossed the threshold from experimental to operationally essential for large-scale camera trap monitoring programmes. The primary remaining quality concern -- kappa values of 0.74-0.78 for small mustelids and juvenile ungulates -- reflects both the inherent challenge of these image categories and the scarcity of training data for rare and juvenile animals. Addressing this gap through targeted training data collection -- specifically seeking out and annotating challenging images rather than adding more of the same abundant categories -- would likely yield disproportionate accuracy improvements at low additional cost. The Wildlife Insights platform's data-sharing architecture, which pools training images across monitoring programmes globally, represents the optimal pathway for addressing training data scarcity for rare species without requiring each programme to independently generate all training data.

5.2 REM as a Practical Density Estimation Tool

The strong correlation between REM and GPS-telemetry density estimates (r = 0.88) and mean ratio of 1.04 +- 0.18 across 18 study areas confirms that the Random Encounter Model provides accurate, unbiased density estimates for Capreolus capreolus in European forest-agricultural landscapes when appropriate input parameters (detection zone, animal speed) are available. The critical importance of GPS-derived animal speed estimates -- rather than literature values -- for unbiased REM is confirmed by the sensitivity of density estimates to this parameter. Monitoring programmes intending to apply REM should therefore invest in a calibration dataset of GPS-tracked animals to generate region-specific speed estimates; our data suggest that n = 5-8 GPS-tracked individuals per habitat type provides sufficient speed parameter precision for REM accuracy within +-15% of telemetry estimates.

5.3 Camera Trap Monitoring Standards for Natura 2000

The power analysis results -- 24-36 cameras at 90 trap-nights sufficient for 80% power to detect 20% occupancy change for species with p > 0.15 -- provide directly actionable design criteria for camera trap monitoring programmes under EU Habitats Directive Article 11 requirements. For large carnivores with p < 0.10, the requirement for 48-64 cameras per monitoring area reflects the fundamental detection challenge for these species and suggests that camera trap occupancy monitoring should be supplemented by other detection methods (individual identification from photographs or genetic analysis of scats) for species recovery trend monitoring. The species-specific optimal spacing data -- ranging from 500 m for small mammals to 2,500 m for large carnivores -- should be incorporated into national camera trap monitoring protocol standards to ensure that sampling is calibrated to the detection scale of each target taxon.

6. Conclusion

6.1 Summary of Key Findings

This multi-region camera trap evaluation across 312 stations and 84,621 trap-nights in Austria, Finland, and Denmark provides quantitative performance benchmarks for camera trap monitoring design and analysis. Key findings are: (i) optimal station spacing ranges from 500 m (small mammals) to 2,500 m (large carnivores), consistent with species activity range predictions; (ii) EfficientNetV2-B7 ML classification achieved 94.8% accuracy and 78.4% reduction in manual review time; (iii) REM density estimates for roe deer correlated strongly with GPS-telemetry validation (r = 0.88, mean ratio 1.04); (iv) 24-36 cameras at 90 trap-nights provides 80% power to detect 20% occupancy change for moderately detectable species (p > 0.15); and (v) the Continental Denmark configuration achieved the highest overall monitoring performance scores, reflecting the combination of high target species detectability and systematic grid design.

6.2 Recommendations for Wildlife Monitoring Programmes

Three recommendations are directed at conservation agencies and monitoring programme managers. First, machine learning image classification should be adopted as standard workflow for all camera trap programmes generating > 100,000 images per monitoring cycle, with EfficientNetV2 or equivalent architecture fine-tuned on local training data (>= 500 annotated images per focal species); the 78.4% time saving documented here makes ML integration a highly cost-effective investment for any monitoring programme with ongoing operational requirements. Second, national camera trap monitoring protocol standards should specify species-group-appropriate station spacings based on the empirically validated activity-range-to-spacing relationship documented here, replacing the single fixed spacing (typically 1 km) currently specified in most EU member state protocols. Third, Habitats Directive Article 11 monitoring designs for Annex II mammal species should conduct a priori power analysis using the species-specific detection probability estimates reported here to ensure that deployed monitoring effort is sufficient to achieve the 20% trend detection criterion at 80% power.

References

Beery, S., Van Horn, G. and Perona, P. (2018). Recognition in terra incognita. Proceedings of the European Conference on Computer Vision (ECCV), pp. 456-473.

Burton, A.C., Neilson, E., Moreira, D., Ladle, A., Steenweg, R., Fisher, J.T., Bayne, E. and Boutin, S. (2015). Wildlife camera trapping: a review and recommendations for linking surveys to ecological processes. Journal of Applied Ecology, 52(3), pp. 675-685.

Fiske, I. and Chandler, R. (2011). unmarked: an R package for fitting hierarchical models of wildlife occurrence and abundance. Journal of Statistical Software, 43(10), pp. 1-23.

MacKenzie, D.I. and Royle, J.A. (2005). Designing occupancy studies: general advice and allocating survey effort. Journal of Applied Ecology, 42(6), pp. 1105-1114.

MacKenzie, D.I., Nichols, J.D., Lachman, G.B., Droege, S., Royle, J.A. and Langtimm, C.A. (2002). Estimating site occupancy rates when detection probabilities are less than one. Ecology, 83(8), pp. 2248-2255.

Norouzzadeh, M.S., Nguyen, A., Kosmala, M., Swanson, A., Palmer, M.S., Packer, C. and Clune, J. (2018). Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning. Proceedings of the National Academy of Sciences, 115(25), pp. E5716-E5725.

O'Connell, A.F., Nichols, J.D. and Karanth, K.U. (eds.) (2011). Camera Traps in Animal Ecology: Methods and Analyses. Springer, Tokyo.

Rovero, F. and Zimmermann, F. (eds.) (2016). Camera Trapping for Wildlife Research. Pelagic Publishing, Exeter.

Rowcliffe, J.M., Field, J., Turvey, S.T. and Carbone, C. (2008). Estimating animal density using camera traps without the need for individual recognition. Journal of Applied Ecology, 45(4), pp. 1228-1236.

Tobler, M.W., Carrillo-Percastegui, S.E., Pitman, R.L., Mares, R. and Powell, G. (2008). An evaluation of camera traps for inventorying large- and medium-sized terrestrial rainforest mammals. Animal Conservation, 11(3), pp. 169-178.

Declarations

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Conflict of Interest

The authors declare no conflict of interest. Reconyx Inc. provided camera equipment under a research loan agreement but had no role in study design, data analysis, interpretation, or the decision to publish. Funding bodies had no role in any aspect of the research.

Data Availability Statement

Annotated training image dataset (48,000 images x 38 species labels), ML model weights, occupancy model R scripts and input data, REM analysis scripts and GPS speed parameter datasets, and station deployment metadata are deposited in Zenodo at https://doi.org/10.5281/zenodo.13641893. Raw camera trap images (2.8 million) are archived in the Wildlife Insights platform at https://www.wildlifeinsights.org/projects/AUS-FIN-DEN-2024 under CC BY 4.0 licence.

Ethical Approval

Camera trap deployment was conducted using passive recording equipment requiring no animal contact. No animals were captured, handled, or disturbed by this study. Deployment permits were obtained from the Austrian Federal Environment Agency (BMVIT 2022-CT-04), Finnish Ministry of the Environment (YM/2022/CTrap), and Danish Nature Agency (NST-7142-00548). GPS roe deer data were from animals collared under existing permits by the Bavarian LfU; no new collaring was performed for this study.

Appendix A

Camera Trap Station Spacing Optimisation Results and Machine Learning Model Specification

This appendix provides: (i) the full spacing optimisation results -- species accumulation curves and detection rates at each of the 24 tested spacings (300-3,000 m in 300 m increments) for the six focal species -- enabling direct reading of optimal spacing for user-specified species and activity range contexts; (ii) the EfficientNetV2-B7 model architecture, training data composition, data augmentation strategy, and hyperparameter settings; and (iii) the confusion matrix for the ML species classification validation showing most common misclassification pairs.

Part I -- Spacing Optimisation Summary by Focal Species

Part II -- Most Common ML Misclassification Pairs