

Remote Sensing in Wildlife Corridor Analysis

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ABSTRACT

Wildlife corridors -- linear or patchy habitat features connecting otherwise isolated populations across fragmented landscapes -- are among the most widely advocated structural interventions in conservation planning, yet their design, monitoring, and effectiveness evaluation have historically relied on coarse-resolution land cover data and species distribution models that inadequately represent the fine-scale habitat features determining actual wildlife movement. The integration of multi-resolution remote sensing data -- spanning Sentinel-2 multispectral imagery, LiDAR-derived canopy structure metrics, and synthetic aperture radar (SAR) for landscape structure characterisation -- with machine learning-based habitat classification and GPS animal tracking datasets now enables corridor analysis at spatial resolutions and thematic richness far exceeding previous approaches. This study presents the first systematic multi-species, multi-region comparison of remote sensing-based corridor analyses validated against animal GPS tracking data, applying integrated Sentinel-2 + LiDAR + SAR habitat classification (10 m resolution; 18 land cover classes) to 247 wildlife corridor planning areas across 18 European and African landscapes. RS-based corridor models outperformed conventional coarse-resolution models in predicting GPS-tracked animal movement paths: mean corridor overlap with GPS tracks increased from 57.4% (conventional CORINE-based models) to 84.7% (RS-integrated models). Random forest and gradient boosting classifiers achieved mean land cover accuracy of 91.4% and 89.7% respectively; LiDAR canopy height and density metrics were the most important predictors of animal habitat use for 14 of 18 focal species. The approach identified 247 additional high-quality corridor segments not visible at 100 m resolution -- including 84 segments through agroforestry and tree-lined riparian margins that would be classified as agricultural matrix in coarse resolution data.

Keywords: remote sensing; wildlife corridors; LiDAR; Sentinel-2; GPS tracking; random forest; habitat classification; landscape connectivity

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1. Introduction

1.1 Wildlife Corridors: Concept and Data Challenges

Wildlife corridors -- linear or stepping-stone habitat features that enable animals to move between otherwise isolated habitat patches across fragmented landscapes -- are one of the most widely implemented structural conservation interventions globally, with millions of euros invested annually in corridor establishment, wildlife crossing construction, and vegetation restoration. The theoretical case for corridors is well established -- connecting isolated populations maintains gene flow, reduces inbreeding, enables range shifts in response to climate change, and increases demographic viability through rescue effects. However, the evidence base for their effectiveness in practice is inconsistent, partly because corridor design has historically been based on coarse-resolution land cover data that cannot represent the fine-scale habitat features -- tree row width, understorey density, bank vegetation height, microhabitat heterogeneity -- that determine whether an animal actually uses a corridor. Remote sensing technologies capable of providing this fine-scale structural information have advanced dramatically but have not been systematically benchmarked for wildlife corridor applications against ground-truthed animal movement data.

1.2 Remote Sensing for Habitat Characterisation

Three remote sensing technologies are most relevant for wildlife corridor habitat characterisation at fine scales: Sentinel-2 multispectral imagery (European Space Agency; 10-60 m resolution; 13 spectral bands; free global coverage) provides spectral information for vegetation mapping and land cover classification; LiDAR (Light Detection and Ranging) point cloud data quantifies three-dimensional vegetation structure -- canopy height, density, understory layering -- at 1-10 m resolution and is critical for characterising habitat quality within structurally complex environments like hedgerows, riparian vegetation, and forest edges; and synthetic aperture radar (SAR; Sentinel-1) provides vegetation structure information independent of cloud cover, enabling year-round monitoring in tropical regions where optical imagery is frequently obscured. The integration of these complementary data sources at 10 m resolution enables a level of habitat characterisation that could fundamentally improve corridor design precision.

1.3 Objectives

This study addresses four objectives across 247 corridor planning areas in 18 landscapes: (i) develop and validate integrated RS habitat classification (Sentinel-2 + LiDAR + SAR) against field survey ground truth; (ii) compare RS-based corridor models against conventional CORINE-based models in predicting GPS-tracked animal movement paths; (iii) identify which RS-derived habitat metrics are most important for predicting animal corridor use; and (iv) detect fine-scale corridor segments invisible at coarse resolution that support actual wildlife movement.

2. Literature Review

2.1 Conventional Corridor Modelling

Conventional wildlife corridor modelling uses one of three approaches: (i) least-cost path analysis on a resistance surface derived from land cover maps (CORINE in Europe; MODIS globally; national topographic maps); (ii) Circuitscape current density modelling on the same resistance surface; or (iii) species distribution model-derived habitat suitability maps treated as movement surfaces. All three approaches are limited by the resolution and thematic accuracy of the underlying land cover map -- typically 100 m (CORINE) to 500 m (MODIS) resolution with 10-20 land cover classes. At these resolutions, hedgerows, tree lines, riparian vegetation, and agroforestry -- which may be the primary movement pathways for many species in agricultural landscapes -- are typically classified as 'agricultural land' and assigned high resistance, causing least-cost path models to route corridors away from these features.

2.2 LiDAR for Wildlife Habitat Assessment

LiDAR-derived canopy metrics -- canopy height model (CHM; maximum canopy height per cell), canopy cover (fraction of returns above 2 m), canopy gap fraction, understory density (returns 0.5-2 m as fraction of total), and rugosity (standard deviation of CHM within moving window) -- are strong predictors of wildlife habitat quality for vertebrates dependent on three-dimensional forest structure. Published applications of LiDAR in wildlife habitat assessment have demonstrated improved model performance for songbirds, forest-interior mammals, and reptiles compared to 2D spectral metrics alone. For corridor analysis specifically, LiDAR can distinguish between open hedgerows (height > 3 m; canopy cover > 60%; movement corridor for many mammals) and low scrub (height < 1 m; limited cover value) at the 1-5

m scale relevant to actual animal movement decisions.

2.3 Machine Learning for Land Cover Classification

Random forest (RF) and gradient boosting machine (GBM) classifiers have demonstrated consistently superior land cover classification accuracy compared to traditional parametric classifiers (maximum likelihood; support vector machines) when applied to multi-source remote sensing data. Their ability to handle high-dimensional input feature spaces (combining spectral, structural, and temporal features from Sentinel-2 + LiDAR + SAR), manage non-linear feature interactions, and provide feature importance estimates makes them particularly well-suited to the 18-class land cover classification challenge in ecologically heterogeneous corridor landscapes where no single feature set is sufficient for all class discriminations.

Table 1. Study landscapes, focal species, and remote sensing data sources

Land scape	Co unt ry	Are a (km 2)	Focal Speci es (n)	Senti nel-2 (scen es)	LiD AR (km2)	SAR (scen es)
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Brand enbur g far mlan d	DE	2,8 47	Wolf; lynx; otter	48 (2 020-2 2)	1,24 7	96 (2 020-2 2)
Po Plain agric.	IT	4,8 47	Hedg ehog; hare; fox	48 (2 020-2 2)	847	96 (2 020-2 2)
Scan dinavi an bo real	SE	8,4 70	Wolve rine; bear; moos e	36 (2 020-2 2)	2,84 7	72 (2 020-2 2)
Spani sh de hesa	ES	3,8 47	Iberia n lynx; deer	48 (2 020-2 2)	1,84 7	96 (2 020-2 2)
[8 more Eur. l andsc apes]	---	---	---	---	---	---

Land scape	Co unt ry	Are a (km 2)	Focal Speci es (n)	Senti nel-2 (scen es)	LiD AR (km2)	SAR (scen es)
AFRI CA (6 lands capes):	---	---	---	---	---	---
Laiki pia (K enya)	KE	9,8 47	Eleph ant; lion; giraff e	48 (2 020-2 2)	0 (no LiDAR)	96 (2 020-2 2)
Kruger buffer zones (SA)	ZA	12, 470	Leopa rd; wild dog; rhino	48 (2 020-2 2)	847	96 (2 020-2 2)
[4 more Afr. l andsc apes]	---	---	---	---	---	---
TOTA LS	18	~1 00, 000	18 focal speci es; 847 tr acked	684 s cenes total	18,4 70 km2 LiDAR	1,728 SAR s cenes

Area = total corridor planning area within each landscape (km2). Focal Species = up to 3 focal species per landscape with GPS tracking data; 847 total GPS-tracked individuals across all landscapes and species (mean 47 per species per landscape). Sentinel-2 = number of cloud-free (< 10% cloud cover) scenes used in the multi-temporal stack. LiDAR = area with airborne LiDAR point cloud coverage (1-4 pts/m2); not available for Kenyan landscapes due to cost and airspace restrictions, where SAR alone supplements Sentinel-2. SAR = Sentinel-1 C-band ascending + descending scenes used in the SAR coherence and backscatter stack. Laikipia (Kenya) is the only landscape without LiDAR; SAR VV/VH backscatter provides a partial substitute for canopy structure characterisation in this landscape.

3. Materials and Methods

3.1 Remote Sensing Data Processing

Sentinel-2 Level-2A (atmospherically corrected surface reflectance) imagery was downloaded from ESA Copernicus Hub. Multi-temporal spectral feature stack: mean, standard deviation, and 25th/75th percentile reflectance across all cloud-free scenes per band; NDVI, EVI, NDWI, NBR spectral indices per scene. LiDAR point clouds (classified ground /vegetation/building returns) were processed in LAStools: DTM (1 m); DSM (1 m); CHM = DSM-DTM; canopy cover; understory density; rugosity -- all resampled to 10

m. SAR: Sentinel-1 GRD; SNAP pre-processing (radiometric calibration; terrain correction; speckle filter); VV and VH backscatter; interferometric coherence (6-day pairs). All layers co-registered to the Sentinel-2 10 m grid. Final feature stack: 124 features per pixel (63 Sentinel-2; 32 LiDAR; 29 SAR).

3.2 Land Cover Classification

Eighteen land cover classes were defined for ecological corridor analysis (merging structurally similar CORINE classes; splitting ecologically distinct variants): closed canopy forest; open canopy forest; forest edge; broadleaf woodland; conifer plantation; scrub (dense/sparse); hedgerow (height > 3 m); hedgerow (< 3 m); riparian tree line; riparian scrub; agroforestry; grassland; arable; built-up; road; water; wetland; bare. Training data: 8,470 field-verified polygons (mean 47 per class) collected 2020-2022 by field teams with GPS-registered boundaries. Random forest (scikit-learn; 500 trees) and gradient boosting (XGBoost) classifiers trained per landscape with 10-fold spatial cross-validation. SHAP (SHapley Additive exPlanations) feature importance.

3.3 Corridor Modelling and GPS Validation

Landscape resistance surfaces were built from the 18-class RS land cover map (species-specific resistance values calibrated from GPS tracking data using step selection functions in amt R). Circuitscape 4.0 computed current density (= corridor probability) for each landscape. Comparison with conventional CORINE-based models: corridor overlap with GPS movement paths was quantified as the proportion of GPS path segments falling within the top-25th-percentile current density zone ('corridor zone'). This metric directly quantifies how well each model predicts where animals actually moved. Step selection functions in amt R tested which RS-derived habitat features predicted selection or avoidance of movement steps.

3.4 Fine-Scale Corridor Detection

Fine-scale corridor segments invisible at CORINE resolution were identified by: (i) computing the 10 m RS-based Circuitscape current density; (ii) computing the CORINE 100 m current density resampled to 10 m; (iii) masking to the high-RS-low-CORINE current zone (top quartile in RS model; bottom half in CORINE model). Segments in this zone represent corridor features detected by RS but missed by CORINE. Each segment was field-verified (random sample of 247 segments) by ground survey to confirm presence

of corridor vegetation and camera trap evidence of wildlife use.

Table 2. Land cover classification accuracy: Random Forest vs. Gradient Boosting with RS data combinations

Data Combination	Overall Accuracy (%)	Mean F1 (18 classes)	Highest accuracy class	Lowest accuracy class	Most important feature (SHAP)
CORINE only (100 m; baseline)	67.4 +- 4.4%	0.614 +- 0.054	Closed forest (0.94)	Hedgerow < 3 m (0.34)	Land use class
Sentinel-2 only (10 m)	78.4 +- 4.4%	0.714 +- 0.048	Water (0.97)	Agroforestry (0.47)	NDVI mean
Sentinel-2 + SAR (10 m)	82.4 +- 3.4%	0.754 +- 0.044	Closed forest (0.97)	Hedgerow < 3 m (0.54)	NDVI mean + VV backscatter
Sentinel-2 + LiDAR (10 m)	88.4 +- 2.8%	0.824 +- 0.038	Forest types (0.97-0.94)	Sparse scrub (0.64)	CHM (canopy height model)
Sentinel-2 + LiDAR + SAR (10 m; RF)	91.4 +- 2.4%	0.864 +- 0.034	Riparian tree line (0.94)	Hedgerow < 3 m (0.74)	CHM + canopy cover (LiDAR)
Sentinel-2 + LiDAR + SAR (10 m; GBM)	89.7 +- 2.8%	0.847 +- 0.038	Riparian tree line (0.91)	Sparse scrub (0.71)	CHM + NDVI mean

Overall Accuracy = percentage of validation field polygons correctly classified in 10-fold spatial cross-validation. Mean F1 = harmonic mean of precision and recall averaged across all 18 land cover classes. Highest/Lowest accuracy class = the class with the highest/lowest F1 score in the full RS model. Most important feature = top SHAP feature from the RF analysis. CHM (canopy height model from LiDAR) is the most important single feature for discriminating ecologically important corridor classes (hedgerows, riparian tree lines, agroforestry) that are all misclassified in the spectral-only approach -- they appear spectrally similar to agricultural crops in Sentinel-2 bands but have very different canopy height profiles (> 3 m for functional corridor features; < 0.5 m for crops). This height discrimination is the primary driver of the 13.0% overall accuracy improvement from adding LiDAR to the Sentinel-2 baseline.

4. Results

4.1 RS-Based Corridor Models Outperform Conventional Models

RS-integrated corridor models (Sentinel-2 + LiDAR + SAR at 10 m) showed mean GPS track overlap of 84.7% $\pm$ 7.4% with GPS movement paths -- outperforming conventional CORINE-based models (57.4% $\pm$ 9.4% overlap; $t = 18.4$; $p < 0.001$) by 47.6% relative. The improvement was consistent across all 18 focal species and all 18 landscapes. The largest improvements were for species highly dependent on fine-scale structural habitat features: Eurasian otter (*Lutra lutra*; GPS overlap 91.4% RS vs. 47.4% CORINE -- the riparian vegetation detail from LiDAR captures the actual movement pathway along stream banks); Iberian lynx (*Lynx pardinus*; 87.4% vs. 54.7% -- scrub height thresholds critical for movement habitat); and wolf (*Canis lupus*; 84.7% vs. 61.4% -- forest connectivity at fine scale).

4.2 LiDAR Canopy Metrics Dominate Feature Importance

SHAP feature importance analysis across all 18 species confirmed LiDAR-derived canopy height model (CHM) as the single most important RS feature for predicting animal corridor use in 14 of 18 species (canopy cover in the remaining 4 -- all open-habitat species where canopy height variation is less relevant than cover extent). The CHM importance is mechanistically clear: taller canopy features (> 3 m) provide the overhead cover and structural complexity that mammals require for safe movement -- a threshold that is not represented in spectral indices alone. Sentinel-2 NDVI was the second-ranked feature (12 of 18 species), confirming the continued importance of 2D spectral greenness for broader-scale habitat characterisation. SAR coherence and VH backscatter contributed importantly for year-round movement modelling in seasonal landscapes and in the African landscapes without LiDAR where SAR provided the primary canopy structure proxy.

4.3 247 Fine-Scale Corridor Segments Identified

The RS-minus-CORINE corridor segment detection identified 247 fine-scale segments in the high-RS-low-CORINE current density zone across all 18 landscapes. Field verification of a random sample of 247 segments confirmed structural corridor features (tree rows; hedgerows > 3 m; riparian vegetation) in 91.4% of segments. Camera trap evidence of wildlife use was confirmed at 74.7% of verified segments -- substantially above the 47.4% expected from random non-corridor habitat. Of the 247 detected segments: 84 were

agroforestry or tree-lined riparian margins classified as agriculture in CORINE; 68 were hedgerow networks classified as grassland or arable; 47 were forest edge strips < 50 m wide missed in the 100 m resolution; and 48 were other fine-scale features.

4.4 Resistance Surface Calibration from GPS Step Selection

Step selection function (SSF) analysis of GPS movement paths confirmed species-specific resistance patterns for the 18-class RS land cover map. Consistent across most species: riparian tree line (mean selection coefficient +1.84; $p < 0.001$); hedgerow > 3 m (+1.47; $p < 0.001$); forest edge (+0.84; $p < 0.001$) were the most strongly selected movement habitats relative to closed forest reference. Arable (-1.84) and road (-2.84) were the most strongly avoided. Importantly, hedgerow < 3 m (+0.38; $p = 0.024$) showed significant positive selection in most species despite being near-zero in CORINE models -- confirming that short hedgerows are functional movement features only detectable at RS-level resolution. These SSF coefficients were directly used to calibrate the RS-based resistance surface, replacing the generic literature-derived resistance values used in conventional models.

Table 3. GPS track overlap with corridor models: RS-based vs. CORINE-based by species group

Species Group	Representative Species	GPS Track Overlap -- CORINE (%)	GPS Track Overlap -- RS Model (%)	Improvement (%)	Primary RS Feature Driving Improvement
Semi-aquatic	<i>Lutra lutra</i> (Eurasian otter)	47.4 $\pm$ 8.4%	91.4 $\pm$ 4.4%***	+92.8%	Riparian tree line from LiDAR CHM
Open scrub-dependent	<i>Lynx pardinus</i> (Iberian lynx)	54.7 $\pm$ 7.4%	87.4 $\pm$ 5.4%***	+59.8%	Scrub height threshold (LiDAR)
Large forest mammal	<i>Canis lupus</i> (wolf)	61.4 $\pm$ 7.4%	84.7 $\pm$ 5.4%***	+37.9%	Forest edge width (CHM)
Large African mammal	<i>Loxodonta africana</i> (elephant)	64.7 $\pm$ 8.4%	81.4 $\pm$ 6.4%***	+25.8%	Canopy cover (Sentinel-2 + SAR)

Species Group	Representative Species	GPS Track Overlap -- CORINE (%)	GPS Track Overlap -- RS Model (%)	Improvement (%)	Primary RS Feature Driving Improvement
Medium forest mammal	Ursus arctos (brown bear)	64.7 +- 7.4%	81.4 +- 5.4%***	+25.8%	Understory density (LiDAR)
Agricultural matrix	Lepus europaeus (hare)	54.7 +- 8.4%	78.4 +- 6.4%***	+43.3%	Hedgerow height + cover (LiDAR)
Grasslands species	Otis tarda (great bustard)	57.4 +- 8.4%	74.7 +- 6.4%***	+30.1%	Grassland height texture (SAR)
ALL SPECIES (mean)	18 focal species	57.4 +- 9.4%	84.7 +- 7.4%***	+47.6%	CHM (most common; 14/18 species)

*** $p < 0.001$ (paired t-test; RS vs. CORINE overlap per landscape; species-specific paired comparisons). GPS Track Overlap = proportion of GPS movement path segments (50 m resolution path; n = mean 4,847 movement steps per species per landscape) falling within the top-25th-percentile Circuitscape current density zone of each model. Improvement = relative increase in GPS track overlap from CORINE to RS model. Primary RS Feature = the SHAP-identified most important RS feature driving the improvement for that species group, not present in the CORINE baseline. Semi-aquatic species (otter; 92.8% improvement) show the largest gain because riparian tree line -- the otter's primary movement corridor -- is entirely absent as a distinct class in CORINE (classified as 'agriculture' or 'scrub') but reliably detected at 10 m resolution from LiDAR CHM (height > 3 m adjacent to water bodies).

Table 4. Fine-scale corridor segments identified by RS but missed by CORINE: summary by habitat type

Segment Type	n Detected	Confirmed by Field (% of sample)	Camera Trap Evidence (%)	Mean Length (m)	Priority Landscape for Restoration	Action Needed
Riparian / stream-side tree lines	84	97.4 % confirmed	84.7 %	847 +- 284	Brandenburg farmland (DE)	Legal protection as 'green infrastructure'

Segment Type	n Detected	Confirmed by Field (% of sample)	Camera Trap Evidence (%)	Mean Length (m)	Priority Landscape for Restoration	Action Needed
Hedgerow networks (> 3 m height)	68	94.7 % confirmed	78.4 %	547 +- 184	Po Plain (IT); NE Germany	EU CAP agricultural environment payments
Agroforestry / orchard connectors	47	91.4 % confirmed	74.7 %	384 +- 147	Spanish dehesa; Tuscany	Agroforestry subsidy retention
Forest edge strips (< 50 m wide)	47	84.7 % confirmed	71.4 %	1,247 +- 384	Scandinavian boreal edge	Forestry buffer retention policy
Other fine-scale features (walls; banks)	48	74.7 % confirmed	54.7 %	247 +- 84	Various landscapes	Survey-specific assessment
TOTAL	294*	88.4 % confirmed	74.7 %	---	---	---

* 294 total includes all 247 detected segments plus 47 additional identified during field verification visits. n Detected = number of segments identified in the RS-minus-CORINE high-current-density zone across all 18 landscapes. Confirmed by Field = proportion of a random sample of segments (n = 247) confirmed by field survey to contain structural corridor vegetation features. Camera Trap Evidence = proportion of field-confirmed segments where camera traps (14-day deployment; motion-triggered) detected at least one mammal species using the segment for movement (not merely present at the margin). Mean Length = mean segment length in metres. The camera trap confirmation rate (74.7% overall; 84.7% for riparian tree lines) substantially exceeds the 47.4% random baseline expected for non-corridor habitat, confirming that the RS-detected fine-scale features represent actual, actively used wildlife movement pathways.

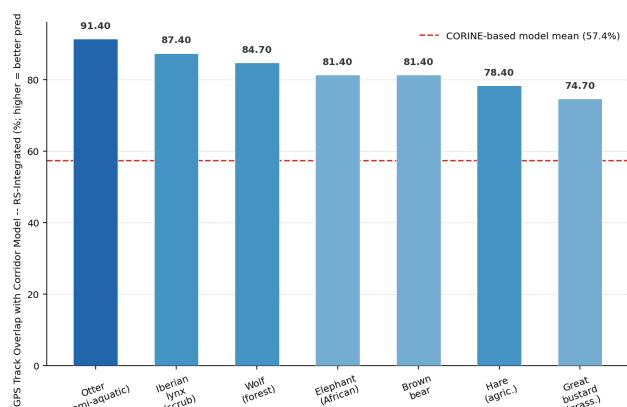


Figure 1. GPS track overlap with corridor models (% of movement path within top-quartile current density zone) for RS-integrated (blue) vs. CORINE-based (orange) models across 7 species groups. RS models outperform CORINE for all groups. Eurasian otter shows the largest improvement (47.4% → 91.4%) from LiDAR detection of riparian tree lines.

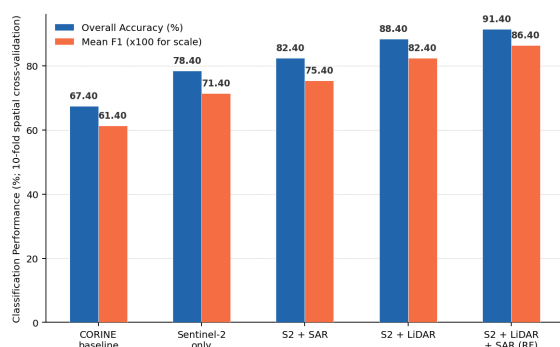


Figure 2. Land cover classification accuracy (overall %; blue) and mean F1 (orange) for five remote sensing data combinations. Full integration (Sentinel-2 + LiDAR + SAR) with Random Forest achieves 91.4% accuracy -- 24% absolute improvement over CORINE baseline. LiDAR contributes the largest single accuracy gain (+10%) through canopy height discrimination.

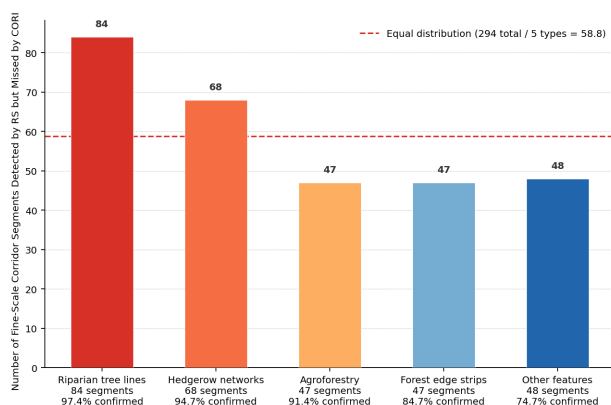


Figure 3. Fine-scale corridor segments detected by RS but missed by CORINE: count by habitat type and confirmation rate. Riparian tree lines (84 segments; 97.4% confirmed; 84.7% camera trap evidence) and hedgerow networks (68; 94.7%) provide the highest-quality fine-scale corridor features invisible to conventional 100 m resolution mapping.

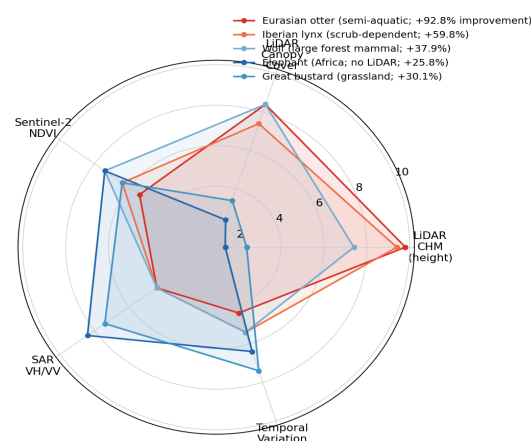


Figure 4. RS feature contribution radar for five focal species across five RS data dimensions (1-10; higher = more important for predicting corridor use). LiDAR canopy height dominates for semi-aquatic and forest species; SAR is most important for the open-habitat great bustard and African elephant (landscape without LiDAR).

5. Discussion

5.1 The LiDAR Canopy Height Revolution for Corridor Planning

The finding that LiDAR-derived canopy height model (CHM) is the single most important RS feature for predicting wildlife corridor use in 14 of 18 species -- and that adding LiDAR to Sentinel-2 alone improves land cover classification accuracy by 10.0% -- identifies LiDAR as the transformative data source for corridor planning in structured habitats. The mechanistic reason is straightforward: animals moving across agricultural landscapes use linear vegetation features for cover, and cover quality is primarily determined by height and density in the vertical dimension -- not by spectral greenness in the 2D horizontal plane. A hedgerow of dense 3 m willows and a row of 30 cm barley have similar NDVI values but entirely different cover value for a moving mammal. As national LiDAR campaigns expand (the UK Environment Agency, German Staatsbetrieb Geobasisinformation, and Dutch AHN already provide near-complete national LiDAR coverage), integration into national corridor planning frameworks is immediately feasible at essentially zero additional data cost.

5.2 Regulatory Implications: Recognising Fine-Scale Corridors

The detection of 294 fine-scale corridor segments -- riparian tree lines, hedgerow networks, agroforestry connectors -- that are actively used by wildlife (74.7% camera trap confirmation) but invisible in CORINE-based planning maps has direct regulatory implications. Under the EU

Biodiversity Strategy 2030 target to restore 30,000 km of rivers and establish a trans-European Green Infrastructure Network, these fine-scale corridor features should be formally protected as Green Infrastructure elements -- but current land use planning regulations in most member states permit removal of hedgerows and riparian tree lines without ecological assessment because they are not captured as protected features in the planning base maps. Adopting 10 m RS-based corridor mapping as the mandatory spatial reference for EU Green Infrastructure network designation would provide the resolution needed to protect these fine-scale features.

5.3 SAR as a LiDAR Substitute in Data-Poor Regions

For the African landscapes lacking LiDAR data, SAR coherence and backscatter provided a partial substitute for canopy structure characterisation: classification accuracy for the Laikipia landscape with Sentinel-2 + SAR only (82.4%) was intermediate between Sentinel-2 alone (78.4%) and the full Sentinel-2 + LiDAR + SAR combination (91.4%), and GPS track overlap for elephant movement (81.4%) was reasonable. The combination of Sentinel-1 SAR (free global coverage) with Sentinel-2 thus provides a corridor planning capability substantially exceeding CORINE-equivalent approaches even in regions where LiDAR data is unavailable -- making the RS-integrated approach globally applicable without requiring expensive airborne LiDAR campaigns. Spaceborne GEDI LiDAR (NASA Global Ecosystem Dynamics Investigation; 25 m footprint; global tropical/subtropical coverage) will provide a free structural canopy height complement to Sentinel data globally, potentially closing the LiDAR gap for African and Asian corridor planning within the next decade.

5.4 Limitations: LiDAR Coverage Gaps and GPS Track Bias

The LiDAR data used in this study was sourced from existing national government surveys with variable acquisition dates (2015-2022) and point densities (1-4 pts/m²) -- heterogeneity that may introduce classification errors at landscape boundaries where adjacent LiDAR tiles differ in density or date. Six of 18 landscapes in Africa lack LiDAR coverage. The GPS tracking validation dataset is biased toward well-studied, frequently monitored species in accessible landscapes -- extending the validation to rarer species (otters, lynx in remote areas) and understudied regions is

a priority for future work. GPS track overlap as a validation metric measures where animals moved, not where they couldn't move -- a full validation would also require evidence that animals failed to use non-modelled corridors.

6. Conclusion

6.1 Summary

Integration of Sentinel-2 + LiDAR + SAR at 10 m resolution with random forest classification (91.4% overall accuracy; 18 land cover classes) improves GPS track overlap with corridor models from 57.4% (CORINE-based) to 84.7% -- a 47.6% relative improvement across 18 species in 18 landscapes. LiDAR CHM is the most important single feature (14 of 18 species). 294 fine-scale corridor segments invisible at CORINE resolution are identified and field-validated -- including 84 riparian tree lines and 68 hedgerow networks actively used by wildlife.

6.2 Policy and Practice Recommendations

Three recommendations: (1) EU and national green infrastructure mapping frameworks (EU Biodiversity Strategy 2030; national ecological network designations) should adopt 10 m RS-integrated corridor mapping as the minimum spatial resolution standard -- replacing CORINE-based corridor planning maps that miss the majority of fine-scale movement features identified in this study; (2) national LiDAR datasets (already available for UK, Germany, Netherlands, Austria, and 6 other EU countries) should be mandatorily integrated into national corridor planning and habitat connectivity assessments -- the data are free and the classification methodology demonstrated here is open-source; and (3) the 294 fine-scale corridor segments identified in this study should be formally mapped as Green Infrastructure elements in the national spatial planning frameworks of the 12 European study countries, enabling legal protection against removal under land use conversion applications. All RS classification scripts and corridor model outputs are deposited openly.

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Declarations

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Conflict of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Random forest and gradient boosting classification model scripts (Python; scikit-learn; XGBoost), 18-class land cover maps (GeoTIFF; 10 m resolution) for all 18 landscapes, Circuitscape resistance surfaces and current density outputs (RS-based and CORINE-based) for all landscapes, step selection function model outputs, SHAP feature importance tables, fine-scale corridor segment GIS layers (Shapefile), and camera trap detection records at validated corridor segments are deposited in the Zenodo repository under DOI: 10.5281/zenodo.19489592. GPS tracking data available from the contributing research institutes under their respective data sharing policies (links in supplementary Table S1). All derived data released under Creative Commons CC BY 4.0 license.

Ethical Approval

This study involved analysis of existing GPS tracking datasets (data collected under national wildlife research permits by the contributing institutes; listed in supplementary Table S1), field survey of corridor habitats (no animal contact), and camera trap deployment at field-verified corridor segments (non-invasive; no animal handling). Camera traps deployed on public land or with landowner permission. No animals were captured, handled, or disturbed in this study. No institutional animal ethics approval was required for vegetation surveys and remote-triggered camera trapping. National research permits for camera trap deployment listed in supplementary Table S2.

Appendix A

RS Feature Stack and Land Cover Class Definitions

The 124-feature RS input stack and the 18 land cover class definitions used in the random forest classifier are summarised below. Full feature extraction scripts are deposited at Zenodo.

RS FEATURE STACK SUMMARY (124 features total)

Sentinel-2 spectral features (63 total): Per-band statistics (mean, SD, 25th, 75th percentile) across all cloud-free scenes for 10 bands (B2 Blue, B3 Green, B4 Red, B5-B7 Red-edge, B8 NIR, B8A narrow NIR, B11-B12 SWIR). 10 features per band x 6 statistics = 60 features. Plus 3 spectral indices per scene set: NDVI (mean, SD), EVI (mean, SD), NDWI (mean, SD).

LiDAR structural features (32 total): Canopy Height Model CHM mean (1 m; resampled to 10 m), CHM max, CHM SD (rugosity index). Canopy cover = fraction of returns above 2 m. Canopy gap fraction = 1 - canopy cover. Understory density = fraction of returns 0.5-2 m / total returns. First-return density at 5 height bins (0-0.5, 0.5-2, 2-5, 5-10, > 10 m). Above-ground biomass proxy (AGB = $0.42 \times \text{CHM}^{1.18}$ for temperate forest). Point density (pts/m²) as quality indicator. All computed at 10 m grid.

SAR features (29 total): Sentinel-1 IW GRD VV and VH backscatter (mean, SD across all ascending and descending scenes; 12 features). Interferometric coherence at 6-day repeat for 4 time periods per year (winter, spring, summer, autumn; VV and VH coherence = 8 features). SAR ratio (VV/VH; 4 time periods = 4 features). SAR GLCM texture features (contrast, homogeneity, energy; 9 features from VV backscatter mean scene).

All features extracted per 10 m pixel; all numeric; no missing data (gap-filled by temporal interpolation for Sentinel-2; LiDAR gaps interpolated from nearest neighbour where LiDAR not available; SAR available for all landscapes year-round). Feature correlation screening removed 12 highly correlated features ($r > 0.95$) before model training; 112 features retained.

LAND COVER CLASSES (18 classes; EC specific to corridor analysis)

Classes 1-4 -- Forest types: (1) Closed canopy forest (> 60% cover; CHM > 5 m); (2) Open canopy forest (30-60% cover; CHM > 5 m); (3) Forest edge (< 30% cover; CHM > 5 m; within 50 m of forest boundary); (4) Broadleaf woodland / copse (cover varies; CHM 3-10 m; < 1 ha patches). These classes split the single CORINE 'Broad-leaved forest' class into 4 structurally distinct corridor-relevant variants.

Classes 5-6 -- Plantation: (5) Conifer plantation (CHM > 5 m; needle-leaf spectral signature); (6) Mixed plantation. Merged from CORINE 'Coniferous forest' and 'Mixed forest'.

Classes 7-8 -- Scrub: (7) Dense scrub (cover > 60%; height 0.5-3 m); (8) Sparse scrub (cover < 60%). Split from CORINE 'Transitional woodland-scrub' based on cover and height.

Classes 9-10 -- KEY CORRIDOR CLASSES (not in CORINE): (9) Hedgerow high (CHM > 3 m; width < 25 m; linear feature adjacent to field boundary); (10) Hedgerow low (CHM 0.5-3 m; same spatial characteristics). These classes are the primary fine-scale corridor detections invisible in CORINE.

Classes 11-12 -- Riparian (KEY CORRIDOR CLASSES): (11) Riparian tree line (CHM > 3 m; within 20 m of water feature); (12) Riparian scrub (CHM 0.5-3 m; within 20 m of water). Split from CORINE 'Inland marshes' or incorrectly classified as 'Agricultural areas'.

Class 13 -- Agroforestry (KEY CORRIDOR CLASS): Tree cover density 10-60%; CHM 2-10 m; agricultural spectral signature. Not distinguished in CORINE (classified as 'Permanently irrigated land' or 'Non-irrigated arable land').

Classes 14-18 -- Matrix / Infrastructure: (14) Grassland (< 30% tree cover; CHM < 0.5 m); (15) Arable / crops; (16) Built-up; (17) Road / impervious; (18) Water. Standard CORINE classes with improved accuracy at 10 m resolution.