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Traffic density and noise shape wildlife movement in the city: insights from modeling blackbird connectivity in a dense city

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Abstract

Context

Traffic infrastructure fragments wildlife habitats and populations, yet its barrier effects are comparatively understudied in cities where such infrastructure is dense. Connectivity models can quantify these barrier effects and inform restoration but typically rely on land cover and road type information, omitting ecologically relevant factors such as traffic density and noise.

Objectives

We aimed to assess the barrier effects of urban traffic infrastructure on wildlife movement, divided into three components: sealed land cover, traffic density, and noise levels. We aimed to evaluate whether urban connectivity models need updating to better reflect traffic infrastructure effects on wildlife.

Methods

We extended a data-driven framework and used the common blackbird (*Turdus merula*) in Munich as a case study. We compared multiple functions to transform traffic density and noise into landscape resistances, using empirical movement-proxy data to select the resistance set best describing the barrier effect. We subsequently validated the resulting connectivity model against independent movement-proxy data.

Results

Connectivity models incorporating traffic and noise substantially outperformed previous land-cover-only models (R^2 = 0.29 vs. 0.17). High traffic density and noise above 70 dB(A) acted as barriers, with effects extending beyond the linear traffic network into otherwise suitable habitats. Our results indicate that current urban connectivity models underestimate fragmentation caused by traffic density and noise.

Conclusions

Traffic and noise provide underutilized levers for wildlife conservation. Our approach provides a transferable framework, applicable to other cities and species, to better understand the role of traffic for functional connectivity.

Introduction

Traffic infrastructure - encompassing roads in non-urban contexts and streets within cities - is recognized as a primary driver of habitat fragmentation globally, fundamentally altering landscape connectivity and impeding animal movement (Coffin, 2007; Jaeger et al., 2005). The impact of fragmentation varies based on species traits (Patterson et al., 2025) and has been extensively studied outside urban areas, where the field of road ecology originated (Bennett, 2017; Coffin, 2007; Forman et al., 2003). Functional connectivity (hereafter connectivity) - the degree to which the landscape facilitates or impedes movement of a given species - is critical for describing the degree of fragmentation introduced by traffic infrastructure and ultimately the persistence of species in these landscapes (Taylor et al., 1993; Tischendorf and Fahrig, 2000). The fragmentation caused by traffic infrastructure impeding animal movement has multiple components and cannot be explained solely by the absence of vegetation or the change in cover created by the road surface. Empirical studies have shown that the barrier effect of roads also depends on traffic density and traffic noise (Reijnen et al., 1995; Tremblay and St. Clair, 2009). Noise has even been found to be the best indicator for capturing traffic infrastructure's impacts on birds (Reijnen et al., 1995). Traffic infrastructure thus reduces connectivity not only through habitat loss but also through additional behavioral barriers to movement, while the relative importance of surface, noise, and traffic varies across species (Charry and Jones, 2009).

To understand the barrier impact of traffic infrastructure on animal movement, connectivity models are central. They enable landscape-specific assessments of connectivity and identification of key movement corridors, which can then be targeted by restoration measures (Bennett, 2017; de Rivera et al., 2022). Among the different approaches to connectivity modeling, resistance-based models are often the method of choice (Unnithan Kumar and Cushman, 2022). Resistance-based models assign a resistance value to each landscape element representing the cost of traversing it (McRae, 2006; Zeller et al., 2012). This allows

specific barrier impacts to be attributed to different features. Most connectivity models consider environmental variables derived from land cover data, elevation, and climatic features, reducing the landscape to specific components (Zeller et al., 2012). Additional barrier effects that reflect human activity on landscape elements, e.g., noise or traffic density, have generally not been considered (Unnithan Kumar and Cushman, 2022; Habrich and Fahrig, 2025). There is, however, evidence that in highly fragmented and heterogeneous landscapes too, noise and traffic effects should not be ignored, as they have been shown to alter wildlife behavior (Tannier et al., 2016; Tremblay and St. Clair, 2009). Current connectivity models, although helpful for assessing wildlife movement, may thus lack sufficient realism in their depiction of traffic infrastructure.

Considering and understanding the impact of noise and traffic density on animal movements is particularly relevant in urban areas, as urban traffic infrastructure forms dense networks of linear features (Tremblay and St. Clair, 2009). Traffic densities in cities vary strongly depending on the area and location of the street, e.g. residential streets with low traffic densities vs. primary connecting streets with high traffic densities (Clevenger and Wierzchowski, 2006; Forman et al., 2003). Despite this, urban areas host a variety of wildlife species with differences in their occurrence and abundance across different parts of the urban landscape and are therefore affected by traffic infrastructure (Fairbairn et al., 2024). Within their daily movements, urban birds, for instance, must cross traffic infrastructure multiple times daily to access foraging sites, nesting areas, and resources (Martin et al., 2026; Tremblay and St. Clair, 2009). These daily movements within familiar habitats result in different behavior compared to dispersal movements – the latter often being captured by road ecology studies in larger landscapes (see e.g. Zeller et al., 2021). Indeed, animals have been found to be more likely to cross traffic infrastructure in unfamiliar habitats outside their home range (Clark et al., 2001), suggesting that the barrier effect of traffic infrastructure may operate differently for daily movements within established urban home ranges. Empirically, urban traffic infrastructure has been identified as a barrier to urban wildlife movement (Tremblay and St. Clair, 2009), and increases in traffic densities have stronger effects on disrupting connected habitats than additional residential development (Tannier et al., 2016). Yet research on fragmentation by traffic infrastructure has predominantly focused on dispersal-scale connectivity (Balbi et al., 2018). Together, these findings illustrate that both the movement type and landscape context shape how traffic infrastructure functions as a barrier, underscoring the need to study urban fragmentation separately from non-urban landscapes.

Urban connectivity modeling draws on the broader concepts of landscape connectivity research, yet has since matured into an established field in its own right (Lookingbill et al., 2022). Urban connectivity models have already been used to analyze small-scale movement and inform conservation strategies in urban areas (see e.g., Braaker et al., 2014; Grafius et al., 2017). However, existing models simplify barrier effects. Like broader landscape-scale models, urban models usually derive resistance from land-cover maps, focusing on buildings, vegetation types, impervious surfaces, and streets (LaPoint et al., 2015; Pundsack et al., 2025). This means current urban connectivity models assume that animals move from one resource to another and are constrained by features that act as barriers, such as buildings, paved areas, or other non-resource open land, including agriculture and water. As a result, they do not distinguish between traffic infrastructure with different traffic densities or noise levels. Only wider streets are typically treated as stronger barriers than narrow ones, although some models classify streets into broad road types (Adriaensen et al., 2003; Braaker et al., 2014). By not accounting for variables such as noise and traffic density, current models may thus potentially underestimate barrier effects in high-traffic areas and overestimate them in low-traffic areas.

Finally, this simplification is compounded by a broader empirical validation problem: appropriate data for connectivity modeling are generally scarce. As a consequence, resistance values for traffic infrastructure are typically assigned through expert knowledge rather than derived empirically — either based on broad road classifications from land cover maps (e.g. major roads, small roads etc.) or, when traffic density is considered at all, on assumed rather than empirically derived thresholds (Gurrutxaga et al., 2010; Tannier et al., 2016). Some connectivity models use biological data to empirically derive resistance values, potentially enabling the identification of species-specific barrier impacts (Braaker et al., 2014). However, generally resistance values derived for traffic infrastructure are rarely validated against empirical data, making it difficult to assess whether modeled barrier effects reflect actual animal behavior. This is especially problematic in urban landscapes, where traffic infrastructure is particularly dense, while traffic densities and noise are highly variable, imposing non-uniform barriers to urban wildlife movement.

In summary, we lack (1) knowledge on how traffic density and associated noise form barriers to small-scale daily movements within the urban landscape, and (2) approaches to model the impact of traffic infrastructure on urban connectivity in a data-driven way. Addressing these gaps would allow us to better understand the role of traffic infrastructure in urban landscapes and refine

wildlife conservation measures in cities. We hypothesized that traffic density and noise act as barriers at specific, quantifiable levels, and that a data-driven framework can identify these levels and reveal their relative importance for urban small-scale movements.

We address these gaps by developing a connectivity modeling framework that partitions the barrier effects of urban traffic infrastructure into three distinct components: sealed land cover, traffic density, and noise levels. Using AIC-based model selection and independent movement-proxy data for validation, we empirically parametrize resistance surfaces for the common blackbird (Turdus merula) in Munich and empirically quantify their barrier effects. This approach represents a transferable, data-driven framework applicable to urban connectivity modeling studies across cities.

Methods

We used a data-driven urban connectivity modeling framework that models the omnidirectional movement of a priori selected species in urban areas (Merkens et al., 2026), to assess the barrier impact of urban traffic infrastructure on daily wildlife movement. The modeling framework uses species-specific movement-proxy (recorded presence/absence of movement) and occurrence data (recorded presence/absence at locations) to parametrize (1) movement distances, (2) land cover types representing resources, and (3) landscape resistance values, that is, the barrier impacts of individual urban landscape elements. Connectivity models are then constructed using graph theory and least-cost paths (Adriaensen et al., 2003), where resources are represented as nodes (Urban and Keitt, 2001). Whether resources (i.e., nodes) are connected depends on whether intervening landscape elements fall within the species' movement capacity and resistance tolerance.

We summarized our approach into a 4-stage conceptual framework and show how we advanced an existing framework (Merkens et al., 2026) to include and assess the barrier impact of traffic noise and traffic density (Fig. 1).

Stage 1: Data Inputs

Modeled Species, Movement Type, and Study Area

Munich (48°08'15"N 11°34'30"E), as a dense European city covering 310.7 km², comprised our study area. 17% of the city’s land cover is occupied by traffic and other transport infrastructure (Statistisches Amt der Landeshauptstadt München, 2024). Approximately half of Munich's area is covered by vegetation (grass, shrubs, trees), representing potential habitat for urban wildlife (own calculation based on land cover data).

We selected the common blackbird (*Turdus merula*) as our model species, an urban generalist that has successfully expanded from forests into cities using urban areas for nesting and foraging (Evans et al., 2010). Its reliance on vocalizations makes it especially sensitive to traffic noise (Dooling, 2019), making the common blackbird a well-suited species for assessing the barrier impacts of traffic infrastructure on daily movements.

Observational Data

We obtained three presence/absence datasets for the common blackbird in Munich: dataset 1 contains general occurrences at 104 points, dataset 2 contains movement occurrences on 215 transects, and dataset 3 contains movement occurrences on 104 transects recorded along with the occurrences in dataset 1. These datasets are used at separate steps in the modeling framework to ensure that all parameter values are empirically derived and validated, reflecting actual blackbird movement.

Spatial Data

The land cover map of Munich is the foundation of the modeling framework (Fig. 1). The map is used to derive land cover representations of resources (Stage 2.1) and the resistances of the different land covers (Stage 2.3). In addition to land cover data, we obtained traffic density and road noise datasets for Munich (Table 1). Because the land cover data was obtained at a 40 cm spatial resolution, we aggregated it to a 10 m working resolution while preserving sub-pixel compositional information. This

allows us to assess barrier impacts on small-scale daily movement between small resource patches. Detailed processing of the spatial datasets is described in Supplementary Methods.

Table 1
Spatial data used for parametrization as part of the connectivity modeling framework.

Dataset	Description	Processing	Role in Framework	Spatial Resolution	Source
Land cover	Land cover map with 9 distinctive land cover classes (Fig. 2)	Detailed description of production provided in Merkens et al. (2025)	Parametrization of Resources (2.1) Parametrization of Resistances (2.3)	40 cm (aggregated to 10 m)	https://www.ldbv.bayern.de/ https://land.copernicus.eu/en/products/urban-atlas
Traffic density	Vector dataset containing the captured number of motorized vehicles per street transect	Data preprocessing included removing underground street transects (tunnels), which do not represent on-ground barriers to wildlife movement	Parametrization of Resistances (2.3)	10 m	https://www.tomtom.com/
Modeled noise	Road traffic noise is mapped into six different noise level classes in L_{den} [dB(A)][1]	Data was already in raster format and at a spatial resolution of 10 meters with only one indicator, L_{den}, no further processing of the data was required.	Parametrization of Resistances (2.3)	10 m	https://geoservice.dlr.de/web/

[1] L_{den} [dB(A)] is an index that summarizes noise levels modeled at night and during the day, with the latter weighted more heavily (Directive 2002/49/EC).

Stage 2: Parametrization

Graph-based connectivity modeling of species-specific movement requires the parametrization of three aspects: the resources in the landscape (resource nodes), the maximum movement distance between resources (links), and the resistances depicting barriers to movement (resistances on links) (Fig. 1). Each aspect is part of the parametrization of the urban connectivity modeling framework and how it is enacted is described in turn below.

Parametrization of Resources (Stage 2.1)

To create the resource map, we initially considered grass, shrubs, and trees as potential resources for the common blackbird (Schlindwein et al., 2024). To test whether all these potential resources are used by the urban blackbird in Munich and thus required for it to establish a home range, we analyzed the vegetation composition necessary for it to do so. We extracted the amount of shrub, grass, and trees in a radius that matches the home range size of a common blackbird (170 m and smaller radii as part of a sensitivity analysis; see Fig. S1) around our observation points and assessed the composition's importance for blackbird presence (blackbird presence/absence, dataset 1). Because the proportions of the vegetation types (tree, shrub, grass)

were correlated, we applied an uncentered raster Principal Component Analysis (PCA). This ensured that no potential resource type was obscured by more dominant resources and that the contribution of potential resource types to blackbird presence was adequately assessed. To then identify vegetation compositions (PCA Axes) that generally support blackbird presence, we ran Classification and Regression Trees (CARTs) (Pesch et al., 2011). The resulting CART thresholds along these compositional PCA axes revealed which vegetation compositions support blackbird presence. All vegetation types contributing to blackbird presence were consequently designated as resources and thus depicted as resource nodes in our landscape graphs. Running the raster PCA prior to the CARTS ensured that no dominant vegetation type masked the contribution of others.

To ensure the robustness of the identified vegetation compositions, we conducted a sensitivity analysis of home-range radii (or vegetation-extraction radii) and CART hyperparameters, as both can substantially affect the resulting resource classifications. Details are provided in Supplementary Methods (Fig. S1).

Parametrization of Movement Distance (Stage 2.2)

We tested movement distances that represent the distances blackbirds travel between two patches of resource habitat during their daily movements. In the connectivity model's graph, the links between the resource nodes are pruned by the maximum movement distance, meaning links that exceed the distance are removed (see Fig. 1). Based on behavioral literature on the common blackbird, we tested four different maximum movement distances: 30 m, 60 m, 90 m, and 150 m (Cresswell, 1999; Ferry et al., 1981). The parametrization of resistance sets and movement distances occurs simultaneously in the modeling framework (Fig. 1, Stage 3) and is explained in the computation of connectivity models section below.

Parametrization of Resistances (Stage 2.3)

In the next step (Stage 2.3), we created different resistance sets that describe different behavioral responses (barrier impacts) to traffic infrastructure, namely sealed land cover, traffic density, noise, as well as the overall urban landscape.

Land cover-based resistance

We started with a land cover map-based resistance, as is standard in resistance-based connectivity modeling, based on the land cover map of Munich (Fig. 2). The resistance parametrization of land cover included testing varying levels of resistance for buildings depending on their height, while assigning an intermediate resistance value (10) to sealed surfaces such as streets, agriculture, and water bodies (e.g. Isar river), reflecting that these land cover types represent gaps in resource availability that blackbirds can cross but do not prefer. We tested six land cover-based resistance sets with values ranging from no resistance (1) to high resistance (1,000) across nine land cover classes (Merkens et al., 2026). All land cover types identified as resources in the CARTs analyses (Stage 2.1) received a resistance value of 1 (Fig. 3a).

Traffic Density-based Resistance

To test and incorporate the barrier effect of moving vehicles (traffic), we transformed traffic densities into resistance values using exponential and logistic functions (Supplementary Methods). Similar functions have been previously used to transform habitat suitability values into resistances (Keeley et al., 2016; Trainor et al., 2013; Zeller et al., 2012).

In total, we tested five transformation scenarios assigning low resistance (10; equivalent to sealed land) to maximum resistance (1,000) based on normalized, log-transformed traffic densities (Fig. 3b; Supplementary Methods). These functions capture a range of possible behavioral responses to traffic: from logistic increases that gradually level off at high traffic densities (c = 8, Fig. 3b), through approximately linear responses (c = 0.25, Fig. 3b), to threshold-like patterns in the exponential transformations (k = 8, Fig. 3b), where only the highest traffic densities substantially impede movement.

Noise-based Resistance

To test the assumption that higher levels of traffic noise lead to greater resistance to movement, we integrated noise into the framework. We tested five noise resistance sets that assume different hypothetical sensitivity to noise (Fig. 3c): N3 represents the

most graduated stepwise increase across all noise levels, ranging from 1 to 100, as the maximum assigned resistance. N5 treats all noise above 60 dB(A) as a near-absolute barrier, and N1, N2, and N4 assume intermediate threshold-based responses concentrated above 70 dB(A). This range addresses uncertainty about acoustic barrier thresholds, enabling data-driven identification of noise impacts on movement (Fig. 3c). In contrast to traffic density, which only affects the barrier effect of roads, noise emanates into neighboring land covers and affects their barrier function. For example, a grassland next to a road has a higher barrier effect than one without noise.

Creating Resistance Maps

We tested the full set of all possible land cover, traffic, and noise scenarios combinations from **single-factor** (land cover-only, traffic density-only, and noise-only), to **two-factor** and **multi-factor combinations**, generating 251 resistance maps: 16 single-factor, 85 two-factor, and 150 multi-factor combinations (Table S2). The land cover only scenario served as a comparison baseline, aligning with the current level of complexity integration in urban connectivity modeling (Habrich and Fahrig, 2025). When combining the resistance maps from the different factors, for each cell, we assigned the maximum resistance value across all maps. For instance, low-resistance grassland where the noise map indicated high noise because it is close to a noisy street is assigned the highest resistance (1,000 from the noise resistance set), capturing the dominant barrier effect. We also tested an additive combination approach; as the best model was based on the maximum combination, we retained this approach (Table S3). All spatial data processing was done using Python v. 3.13.3.

Computing Connectivity Models

We generated 1,004 graph-based connectivity models by combining the resource map and the 251 resistance maps with four maximum movement distances. In these models, the landscape is represented as a graph in which resource patches are depicted as nodes, connected by links that represent possible movement paths between them (Fig. 1). We used least-cost paths in combination with a cell-based approach, enabling us to identify multiple pathways (links) between single-cell resource patches (nodes) rather than a single path (Merkens et al., 2026), thereby addressing limitations of traditional least-cost methods (Grafius et al., 2017; McRae, 2006).

At our modeling resolution of 10 m, each raster cell covers 100 m^2. To retain sub-pixel information on resource abundance from the very high resolution land cover map, we considered every cell containing at least 20% resources (equivalent to 20 m^2, following Bourgeois et al., 2024) as a resource node. Resource nodes depicted in the resource map were previously restricted to the areas where the vegetation thresholds for blackbird home range establishment from the resource parametrization applied (Stage 2.2). All resources within these areas that were of sufficient size were depicted as resource nodes and graphs were computed using the graph4lg package (Savary et al., 2023) in R v. 4.4.3 which establishes an interface to the Graphab software v. 2.8 (Foltête et al., 2021).

The graphs were then pruned by retaining only links between resource nodes that are within the respective cost-converted distance threshold, i.e., the distance accounting for resistance values of the landscape for movement, to limit the model to ecologically relevant connections. Based on the pruned graphs, we calculated link-based Betweenness Centrality (BC) (Girardet et al., 2015), which quantifies the importance of a link for connectivity by counting how often it is used in possible movements between resources, thereby reflecting small-scale movements. Complete parameter specifications are provided in the Supplementary Methods (Table S1).

Stage 3: Connectivity Model Selection

We then assessed which of the 1004 connectivity model(s) and their corresponding resistance set(s) and movement distance(s) best described the observed blackbird movement. We used Generalized Linear Mixed-Effects Models (GLMMs) to compare the suitability of the computed connectivity models for predicting blackbird movement (presence/absence data from dataset 2).

For this purpose, we extracted, within a 5-meter radius around each observation in dataset 2, the average connectivity values from the computed connectivity maps and log-transformed values to account for their skewed distribution. We repeated this for all 1004 connectivity maps. Given that the data were sampled by different observers, the observer identity was included as a random effect to account for potential differences in observers' ability to detect blackbird movements. We also included the amount of resources within a 5-meter radius and the number of pedestrians observed at the sampled location as fixed effects, as both

variables significantly influenced blackbird movement (see Table S3), and to ensure their variability across observation locations did not confound the effect of connectivity. All variables were standardized before model fitting. Details on model generation and diagnostics are provided in the Supplementary Methods.

Presence/absence of moving blackbird ~ log (connectivity + 1) + resources + pedestrians + (1|observer)

We subsequently compared the connectivity model-based GLMMs using AIC-based model selection, considering models within ΔAIC ≤ 2 equally supported (Sutherland et al., 2023). Because three models fell within ΔAIC ≤ 2, we accounted for model selection uncertainty by computing geometric mean resistance values and the arithmetic mean of the movement distances from these best-supported models (see Merkens et al., 2026). The resulting connectivity model presents our parametrized connectivity model, using resistance sets, that best explain the barrier impact of traffic infrastructure.

Stage 4: Final Connectivity Model Validation

The parametrized connectivity model was validated using an additional movement dataset to adhere to connectivity modeling best practice and ensure validation independence (Creech et al., 2024; Habrich and Fahrig, 2025). We fit a Generalized Linear Model (GLM) to assess the ability of our connectivity model to predict blackbird movement (presence/absence of movement, obtained from Dataset 3). For this purpose, we extracted the averaged connectivity values within a 10 m radius around the observations and log-transformed them to account for their skewed distribution. We used connectivity as a single predictor to assess its causal relationship with blackbird movement. Details on the GLM creation can be found in the Supplementary Methods. Model performance was evaluated using pseudo-R^2 and predictor significance ($p < 0.05$).

Results

Resource Map

The vegetation compositions identified as conducive to blackbird presence by our fitted CART model were predominantly tree-rich habitats, and where tree cover is lower, mixed grass-shrub-tree habitats. In contrast to Merkens et al. (2026), where only shrubs and trees were identified as resources, in our approach, all considered potential resource types, grass, shrubs, and trees, were thus important for blackbird presence. To test whether the inclusion of grass as a resource was justified, we compared our single-factor land cover-based models computed with all three resource types against models using only trees and shrubs, as done in Merkens et al. (2026). Including grass yielded a lower minimum AIC (229 vs. 239) and higher marginal R^2 values (0.26–0.30 vs. 0.19–0.21 in respective ΔAIC models), confirming that its inclusion improves model performance. We therefore consider our approach more ecologically complete; applying a raster PCA prior to CART analysis, as done here, can thus better capture relationships among resource types, particularly when they covary substantially.

The identified vegetation compositions were found broadly across Munich's urban area, including in densely built-up parts of the core city. When not accounting for movement barriers, resources across Munich can thus potentially be utilized by the blackbird, as the surrounding vegetation composition is broadly sufficient to support presence. The resulting resource map was used for all subsequent connectivity model runs. Detailed results of the resource parametrization are provided in Supplementary Results (Fig. S2).

Resistance Set

Three connectivity models best described the barrier impact to blackbird movement (models within ΔAIC). All three models are subsequently referred to as best models, most appropriately describing the barrier impact of the urban landscape, including traffic infrastructure, on blackbird movement (Fig. 4). All best models utilized multi-factor resistance sets, namely land cover-based, noise level-based, and traffic density-based resistance, to describe the barrier impacts of the urban landscape. The average R^2 of these best models was 0.29, explaining a substantial amount of variability in blackbird movement observation, while connectivity is a significant predictor.

Overall, multi-factor models clearly outperformed single-factor models in describing the barrier effect of traffic infrastructure. For each resistance source (i.e., land cover, traffic density, and noise), one or two sets were included in the three best multi-factor resistance sets, indicating that these sets best describe the barrier impact for their aspect.

Regarding land cover, the selected resistance sets assign a resistance value of 100 to low-rise buildings and 1000 to high-rise buildings (Fig. 3, R5, R6). The key difference between the two selected sets lies in their depiction of medium-rise buildings: R6 provides equally high resistance (1000) to both medium- and high-rise buildings, whereas R5 treats the resistance of medium-rise buildings similarly to that of low-rise buildings (100).

For **traffic densities**, all selected multi-factor resistance sets were based on the exponential resistance transformation sets (Fig. 3, exp_k8). This transformation assigned relatively low resistance values across most of the traffic density range, with resistance increasing more noticeably at the highest traffic densities.

Regarding **noise**, the selected connectivity models included two distinct noise-resistance sets that performed equally well (Fig. 3, N3, N5). N3 assumes a gradual increase in resistance with increasing noise levels. N5 represents a sharp binary cutoff at 60 dB(A), above which resistance becomes uniformly high, suggesting strong noise sensitivity in the common blackbird.

Among the first 20 models (ranked by relative AIC), apart from multi-factor resistance sets at a ΔAIC of 3, two-factor sets that include land cover and noise to explain the barrier impact emerge. While these two-factor sets cannot be considered equal to the ones within $\Delta AIC \leq 2$, these resistance sets still represent a better alternative to single-factor model predictions only using land cover. The single-factor model using land-cover-only resistance to describe the barrier impact of the urban matrix has a ΔAIC of 9.4. (Fig. 4, grey point). In this model, connectivity remained a significant predictor of blackbird movement ($\beta = 0.233 \pm 0.076$, $p < 0.05$); however, its effect was less pronounced (see Supplementary Results, Table S2 for complete statistical results), suggesting a lower predictive ability for blackbird movement. A single-factor resistance set consisting solely of noise resistance has a ΔAIC of 10.4 ($\beta = 0.068 \pm 0.023$ SE, $p < 0.05$), and a single-factor resistance set that only accounts for the barrier impact from traffic densities has a ΔAIC of 19 ($\beta = -0.036 \pm 0.023$ SE, $p > 0.1$), clearly performing worse in predicting blackbird movement.

Final Connectivity Model

The final connectivity model, created from the three best models and their respective multi-factor resistance sets, had an average maximum movement distance of 52 meters, which represents the distance blackbirds are assumed to travel between resources. The parametrized resistance map used for the final connectivity model captured impacts of traffic infrastructure that extend beyond the street border into otherwise suitable habitat for urban wildlife (Fig. 5a). The selected inclusion of noise indicates that the impact of traffic infrastructure extends into areas that are otherwise suitable habitat. A detailed description of average resistance values used can be found in Table S4.

This impact from traffic infrastructure is also visible in the final connectivity map (Fig. 5b). Highly connected areas (bright yellow) coincide with large, vegetated areas such as the English Garden, while the urban core and major traffic infrastructure represent non-connected areas (dark blue). Interestingly, linear corridors of connected habitats traverse the city landscape. These are linear assemblies of gardens with low-rise buildings, as well as streets with substantial linear vegetation (Fig. 5b).

Resulting Connectivity Model Validation

The validation of the final connectivity model (Fig. 4b) with an independent movement-proxy dataset revealed that connectivity had a significant positive effect on blackbird movement. Connectivity derived from our parametrized resistance set was significant when considered as a standalone predictor ($\beta = 0.13 \pm 0.038$ SE, $p < 0.001$), explaining about 17% of the movement variance in the independent dataset ($R^2 = 0.174$).

Discussion

In this paper, we assessed the multifactorial impact of traffic infrastructure on urban habitat connectivity for the common blackbird by extending and employing an urban connectivity model. Urban connectivity models have conventionally reduced traffic infrastructure to its physical footprint, treating streets as static landscape elements. Our results challenge this current practice,

demonstrating that other components of traffic infrastructure, traffic density, and noise, in addition to road presence and width, substantially improve the prediction of traffic infrastructure effects on animal movement. Connectivity models incorporating land cover, traffic density, and traffic noise resistances consistently explained blackbird movement better than models that used only land cover data to describe resistances in the urban landscape. Compared to the previous version of the modeling framework, we observed an R^2 increase from 0.17 in Merkens et al. (2026) to 0.29 in our best model. These findings suggest that current urban connectivity models, by omitting traffic density and noise, systematically misrepresent barrier effects: underestimating fragmentation in high-traffic areas and overestimating it in low-traffic ones.

Traffic Density as a Movement Barrier

Our parametrization revealed a threshold-like effect on the barrier effect of traffic density: the steep exponential transformation (exp_k8) was selected as the best model. In this function, low-traffic streets behave like vegetation gaps, with little resistance, while high-traffic streets exhibit near-maximum barriers to movement. This empirically-derived threshold addresses the criticism that resistance values for traffic infrastructure are typically assumed rather than derived from movement data (Zeller et al., 2012) and is consistent with observational studies: decreases in bird movement were only notable at traffic volume increases of 1,000 vehicles or more per day (Tremblay and St. Clair, 2009), indicating the magnitude at which traffic impacts movement. While we cannot compare absolute traffic density values due to constraints in our traffic density data, the magnitude aligns with our overall findings that low traffic densities have only a marginal barrier effect on blackbird movement. Future studies using absolute vehicle counts could build on our findings to empirically derive precise thresholds for various taxa applicable across cities.

The selection of the traffic resistance function that distinguishes high-traffic from low-traffic streets is consistent with previous findings by Merkens et al. (2026) in their land-cover based model. They assigned a single resistance value to all streets in their tested resistance set, failing to account for their heterogeneity in traffic density and noise. Unlike other land covers, the selected resistance sets showed highly variable resistance assignments for streets.

When considering this, and based on our findings, it is crucial to account for differences in traffic when assessing the barrier to movement of streets. We suggest that for some species a binary street classification, as already used in some resistance-based connectivity studies (e.g. Braaker et al., 2014; Pundsack et al., 2025), might be sufficient to capture traffic impacts on movement. The thresholds for whether a street belongs to either of these classes should, however, be empirically derived. Urban connectivity studies that currently treat all street resistance equally do thus not account for variability in barrier characteristics within this group.

Noise as a Movement Barrier

Critically, the modeled noise used in this study revealed barrier effects extending beyond street boundaries (Fig. 4a), capturing spatial impacts not represented by street width alone. Noise became a barrier to blackbird movement at levels of 60–70 dB(A), as indicated by the selection of two distinct resistance sets (N3, N5). N3 assumes that there is a gradual response to noise, with high noise levels still not representing a complete barrier to movement, however, noise above 70 dB(A) being a moderate barrier to movement (Fig. 3c). N5 suggests a sharp binary threshold where noise above 60 dB(A) is a near-absolute barrier. This aligns with Parris and Schneider (2009), who found that noise levels of 60 dB(A) already led to substantially lower bird detections - a relative decrease of 70% compared to areas without traffic noise. Empirical noise thresholds above which anthropogenic noise impacts bird behavior vary considerably between studies, likely reflecting differences in species, habitat context, and noise metrics used (Engel et al., 2024).

The equally good performance of both noise resistance sets (N3, N5) as part of our modeling framework likely reflects heterogeneity in the acoustic environments of our observation locations, including background noise from non-traffic sources (Dooling, 2019), while surrounding habitat composition e.g., a preferred tree species may influence the tolerance to acoustic disturbance (Tremblay and St. Clair, 2009). Disentangling these effects requires controlled experiments that isolate the effects of noise by accounting for local context.

All best models included traffic noise, clearly suggesting that integrating traffic noise into connectivity models of all three resistance sources improves movement predictions. Two-factor models based on noise and land cover-based resistance were also ranked close to our ΔAIC threshold, suggesting noise alone might already be a solid proxy for describing the movement

barrier that traffic imposes (Fig. 3, blue-green dots). This aligns with some previous studies on birds that identified noise as the most important cause for reduced habitat use incl. movement adjacent to roads, hence noise often being used as a proxy to describe traffic (McClure et al., 2013; Reijnen et al., 1995; Tremblay and St. Clair, 2009). Nevertheless, the increased predictive ability when also including traffic densities (multi-factor models) points towards noise not being able to explain all impacts from traffic infrastructures, as also discussed in Summers et al. (2011).

This spatial dispersion has direct conservation implications: habitat degradation from traffic noise that also impacts movement penetrates deeper into adjacent green spaces than physical infrastructure suggests, necessitating buffer zones and noise mitigation in acoustic planning around major transportation corridors. These identified traffic and noise thresholds provide the foundation for more targeted urban planning interventions and demand advances in connectivity modeling practice.

Implications for Urban Connectivity Modeling

Our study thus addresses a critical gap identified in recent reviews of urban connectivity modeling (Habrich and Fahrig, 2025; LaPoint et al., 2015): the exclusion of anthropogenic factors relevant to wildlife movement. Current approaches typically reduce urban complexity to land cover data, treating the matrix as devoid of human activity and thus failing to capture the highly variable traffic densities and noise levels that characterize city street networks and propagate into otherwise suitable habitat. The dense, heterogeneous nature of urban streets produces fragmentation patterns that differ fundamentally from the binary presence-or-absence road distinction typical of rural road ecology - a distinction our findings directly address, given that multifactorial models consistently outperformed land-cover-only approaches.

When factors that shape wildlife movement are not considered, current resistance-based connectivity models may incorrectly identify corridors as permeable when, in reality, movement is impeded by high levels of human disturbance, such as traffic density and noise. This could, for example, be the case for small vegetated private gardens near busy traffic infrastructure. Given that most urban connectivity models are not validated with empirical data (Habrich and Fahrig, 2025), deriving conservation implications from these corridors may lead to suboptimal strategies. The need for empirical testing also extends to the functional form of resistance parametrization itself: the identified nonlinearity of movement resistance with traffic density aligns with concerns about the common practice of linear scaling, e.g., habitat suitability values in resistance-based connectivity modeling (Zeller et al., 2012), suggesting that testing alternative resistance functions should become standard practice, particularly in heterogeneous urban landscapes.

By developing a framework that systematically parameterizes traffic density and noise as movement resistances, we provide a replicable approach for integrating disturbance variables. Unlike previous urban wildlife studies that treated connectivity and disturbances (noise, light) as independent coefficients in regression models (Martin et al., 2026), embedding disturbances directly into resistance surfaces enables us to identify the specific traffic densities and noise levels at which habitat becomes fragmented. Overall, this represents a methodological shift from treating urban streets as static landscape elements toward capturing the human activity that characterizes them.

Finally, the use of open-access modeled noise data enables replication across cities in Europe and beyond, while our finding that binary traffic classification improves predictions suggests even coarse traffic data (e.g., street network classifications from OpenStreetMap, https://www.openstreetmap.de/) can enhance connectivity modeling realism. Our framework also allows for the incorporation and assessment of barrier impacts from additional variables relevant to specific taxa e.g. wind patterns for pollinators, temporal biotic factors (LaPoint et al., 2015).

Implications for Urban Conservation Practice

While non-urban connectivity studies recommend measures such as wildlife crossings to reduce habitat fragmentation (e.g. Mimet et al., 2016), such approaches are not feasible in cities considering the sheer amount and density of streets. By providing a better understanding of the barriers posed by traffic infrastructure and acknowledging their heterogeneity, our results show that some streets still allow for wildlife movement.

Our threshold findings enable targeted interventions: low-traffic streets with moderate noise (< 70 dB(A)) are substantially more permeable than high-traffic and noise infrastructure, representing a barrier comparable to open sealed land. When vegetated, these streets can form linear habitats for animal movement (Fig. 5b). For the blackbird, our results thus indicate that strategic

greening of low-traffic streets with low to moderate noise levels could improve urban permeability for wildlife, expanding conservation beyond traditional park-based approaches. This aligns with previous studies stating that low-traffic streets can function as movement corridors for urban wildlife when habitat patches are provided (Croeser et al., 2022). The potential of streets as linear areas for wildlife is critical in cities, where connectivity can compensate for the lack of large contiguous green spaces (Martin et al., 2026). Given competing space demands in dense urban areas and the lower prioritization of biodiversity-focused interventions (Hansen et al., 2019), integrating wildlife connectivity into urban streetscape design, alongside human-focused benefits, can be an effective entry point for wildlife conservation.

Our findings underline the relationship between transportation planning and biodiversity conservation: reducing speed limits substantially lowers noise levels (Brink et al., 2022), which our models indicate would increase habitat connectivity. Traffic calming measures (30 km/h zones, speed bumps, narrow lanes) thus serve dual functions, enhancing pedestrian safety and wildlife connectivity, a synergy not previously quantified in urban ecological research. This modeling framework thus allows direct quantification of the benefits of traffic-calming measures for urban wildlife.

Limitations

Our study focused on an avian urban generalist; ground-dwelling mammals, reptiles, and amphibians are likely to exhibit greater sensitivity to traffic, requiring an alternate assessment that will likely result in different conservation implications (Rytwinski and Fahrig, 2015).

Second, we quantified only modeled traffic noise, excluding industrial and human activity noise sources that may contribute to additional fragmentation and might alter how additional traffic noise impacts behavior (Engel et al., 2024; Shannon et al., 2016).

Third, our connectivity model used traffic density data aggregated over one month for each street transect in Munich, capturing relative differences between streets rather than absolute densities. Incorporating fluctuations in traffic as well as recorded movement, at different times temporally matched with traffic densities, could instead reveal hourly fluctuations in barrier impacts and connectivity, an extension enabled by our framework but requiring high-resolution data and future research.

While our framework enables empirical barrier estimation from observational movement-proxy data, experimental studies of traffic and noise would be needed to establish a causal mechanism. Similar to Tremblay and St. Clair (2009), the barrier impact of noise should be assessed while controlling for landscape structure and moving vehicles, and the barrier impact of traffic should be assessed while controlling for noise and landscape structure. Local factors may influence the barrier impact, hindering a single noise resistance set from explaining the barrier impact of noise. Future research should thus: (1) test resistance parametrizations across taxa with varying traits, (2) incorporate additional urban noise sources to quantify cumulative acoustic impacts, and (3) extend the framework to other urban variables (artificial light, air quality) that may fragment habitat for specific taxa.

Conclusion

Cities are heterogeneous landscapes whose wildlife habitats are fragmented by dense street networks. We showed that this fragmentation is not determined by land cover alone but by the intensity of human activity within it, a distinction that current connectivity models largely fail to capture. This study thus challenges the prevailing practice in resistance-based connectivity modeling, which focuses on land-cover while overlooking other components that wildlife actually responds to.

The identified threshold effects have direct methodological implications: incorporating empirically derived traffic density and noise resistances substantially improves model performance, while even coarse binary traffic classifications can enhance the realism of connectivity modeling when detailed data are unavailable. Beyond methodology, the findings offer actionable conservation insights: low-traffic streets with moderate noise levels can support wildlife movement, expanding conservation opportunities from parks to streetscapes and making the intensity of disturbances within street networks a central consideration in urban biodiversity planning.

The data-driven, transferable nature of our framework enables replication across European cities, extension to additional disturbance variables, and application to other taxa. Its model-based nature, while capturing urban complexities, makes it a valuable tool for evaluating planning scenarios and generating hypotheses for targeted experimental validation.

Declarations

CRediT author statement

Conceptualization: MP, LM, AM, WW **Methodology**: MP, LM, AM, DG **Software**: MP, DG, LM, AM **Formal Analysis**: MP, DG **Validation**: MP **Visualization**: MP **Writing – original draft**: MP **Writing – review & editing**: MP, DG, LM, AM, WW **Supervision**: AM, WW **Funding Acquisition**: WW

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Data Availability

The blackbird movement data used for model parametrization as well as the land cover map were obtained according to Merkens et al. (2026). The blackbird movement data used for model validation will be deposited in Zenodo upon acceptance and made publicly available at [DOI to be added]. All other data used in this study are described in the Methods and can be acquired from the respective institutions. The code for running the connectivity modeling framework will be made available in a corresponding GitLab repository [link to be added]. The relevant scripts are currently provided as Scripts.zip for review.

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Figures

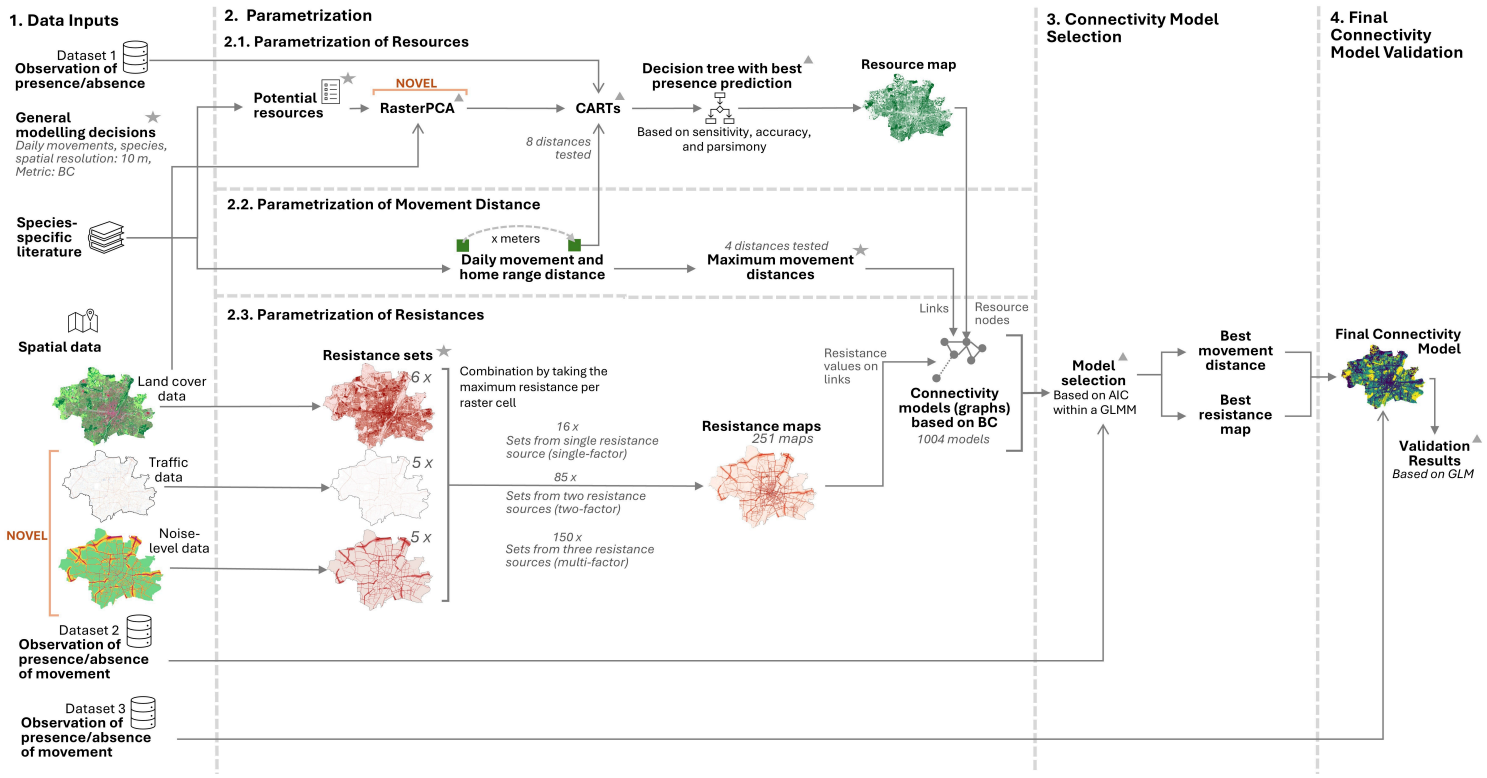


Figure 1

Conceptual workflow of the urban connectivity modeling framework with Munich as case study area. The workflow is based on the general framework presented by Merkens et al. (2026), extended to include noise and traffic density as urban resistance factors and raster Principal Component Analysis (PCA) to compute resource maps. The workflow integrates priori general modeling decisions with various data sources through four sequential stages: (1) **Data inputs** include land cover, traffic density, and noise data alongside species movement parameters and three observation datasets. (2) **Parametrization**involves deriving resource maps from PCA and Classification and Regression Trees (CARTs) model selection, defining movement distances, and generating resistance set combinations. (3) **Connectivity models** were constructed by combining resistance maps with movement distances and calculating Betweenness Centrality (BC). **Connectivity model selection** identifies the optimal movement distance and resistance map using Akaike Information Criterion (AIC) within a Generalized Linear Mixed Model (GLMM) framework. (4) **Final connectivity model validation** tests the performance of the resulting connectivity map through a Generalized Linear Model (GLM). Decision based on ecological literature and theory (*) or statistical evaluation (△). Grey italic text indicates aspects specific to this study.

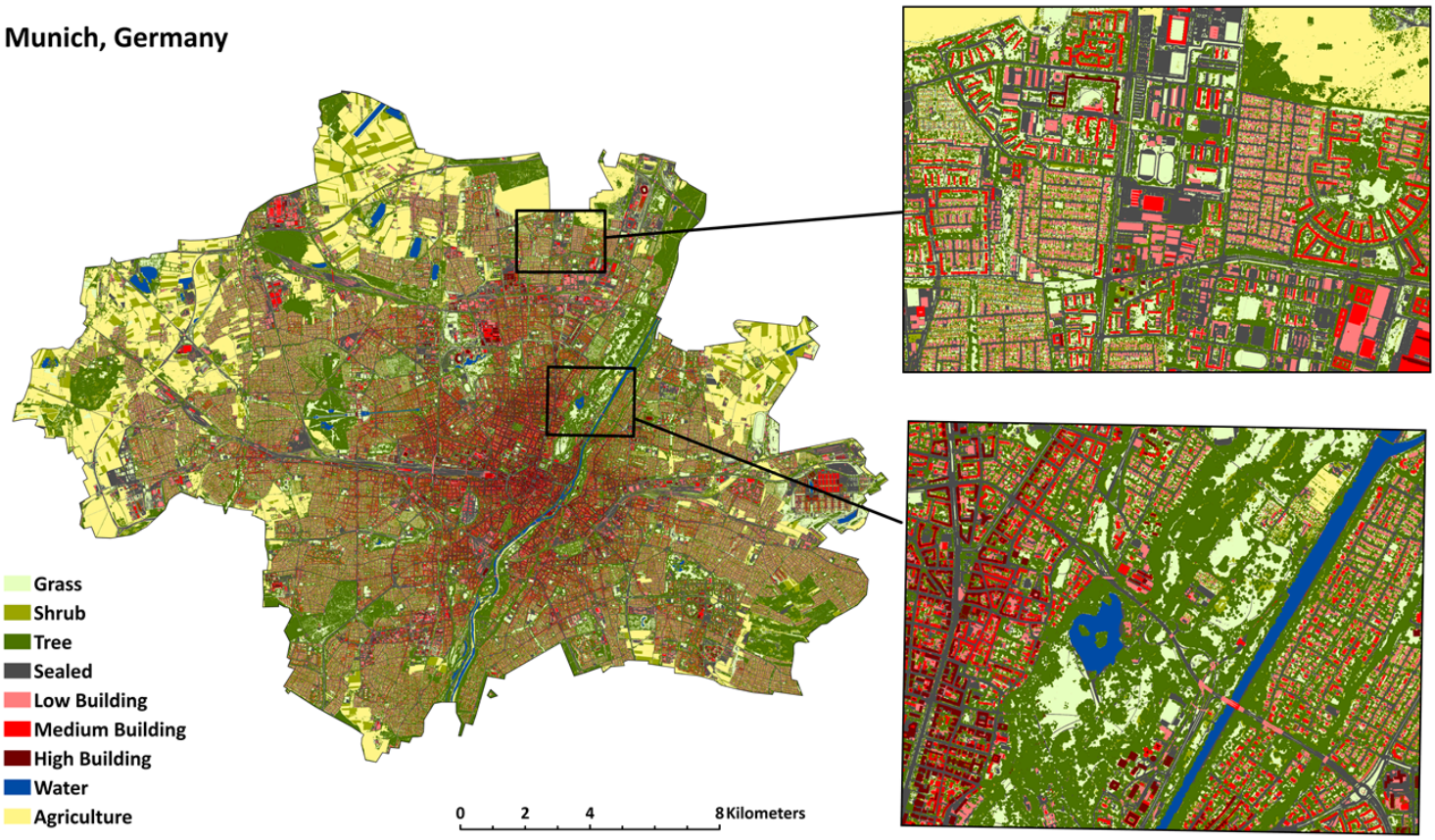


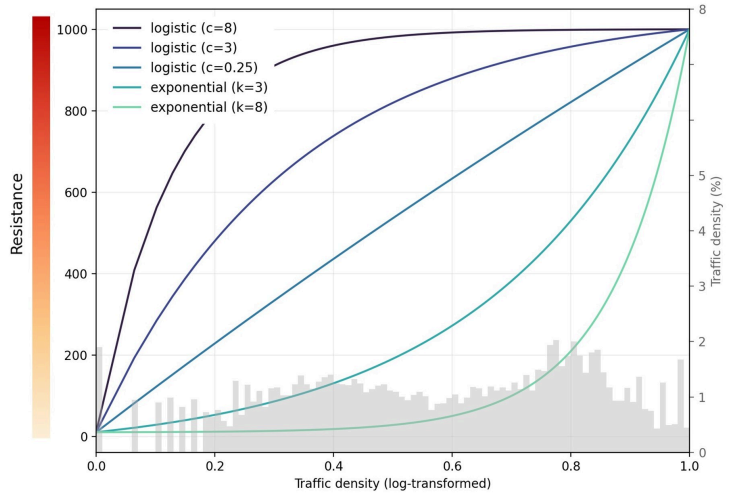
Figure 2

Land Cover map of Munich with nine thematic land cover classes: grass, shrubs, trees, water, agriculture, sealed, and buildings distinguished into three height classes (< 10 m, 10–18 m, > 18 m)

a.

Set	High Buildings	Medium Buildings	Low Buildings	Sealed	Water	Agriculture	Grass	Shrub	Tree
R1	1000	100	10	10	10	10	1	1	1
R2	100	100	10	10	10	10	1	1	1
R3	100	10	10	10	10	10	1	1	1
R4	100	100	100	10	10	10	1	1	1
R5	1000	1000	100	10	10	10	1	1	1
R6	1000	100	100	10	10	10	1	1	1

b.



c .

Set	>= 75 dB(A)	70 – 75 dB(A)	65 – 70 dB(A)	60 – 65 dB(A)	55 – 60 dB(A)	<55 dB(A)
N1	1000	1000	100	10	10	1
N2	1000	100	100	10	10	1
N3	100	100	10	10	10	1
N4	1000	1000	10	10	10	1
N5	1000	1000	1000	1000	10	1

Figure 3

Tested resistance sets for land covers (a), functions to transform traffic densities into resistance values (b), and tested resistance sets for modeled noise levels noise in L_{den} dB(A) (c). Dark red indicates high resistance values, and light-red-to-white indicates low resistance values.

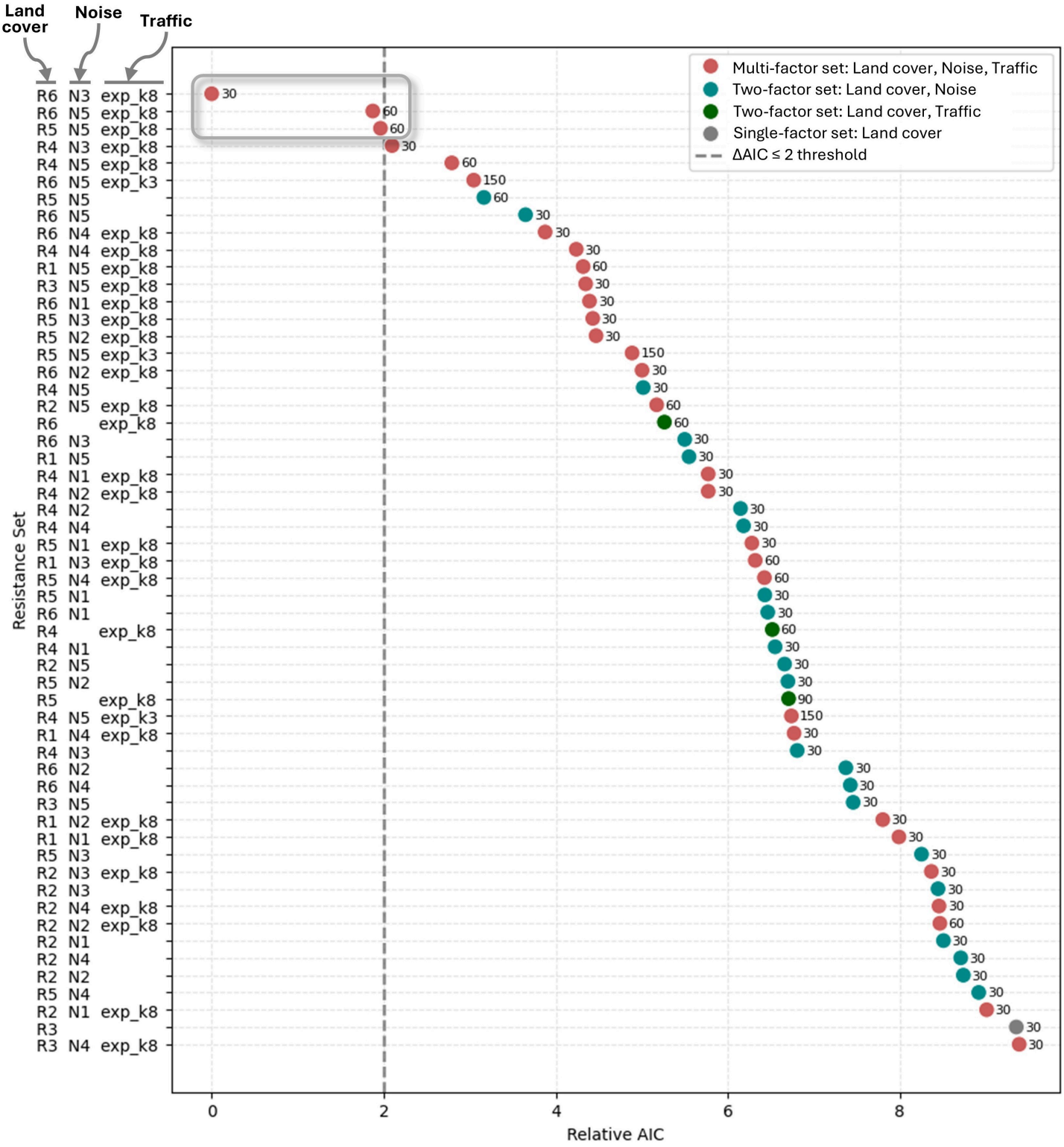


Figure 4

Results of the AIC-based selection of connectivity models with different resistance sets and movement distances for blackbird movement. Colors indicate whether the models were based on multi-factor resistance sets (red dots: land cover, traffic density, and noise), two-factor resistance sets (blue-green dots: land cover and noise; dark green dots: land cover and traffic density), or single-factor (grey dots: land cover). Models within ΔAIC ≤ 2 (grey rectangle) are considered equal and thus selected for final model computation. The number adjacent to each point indicates the daily movement distance of the common blackbird within that model run. Here, for ease of visualization, only models within a relative AIC of 9.4 are displayed (see Table S3 for results on all models).

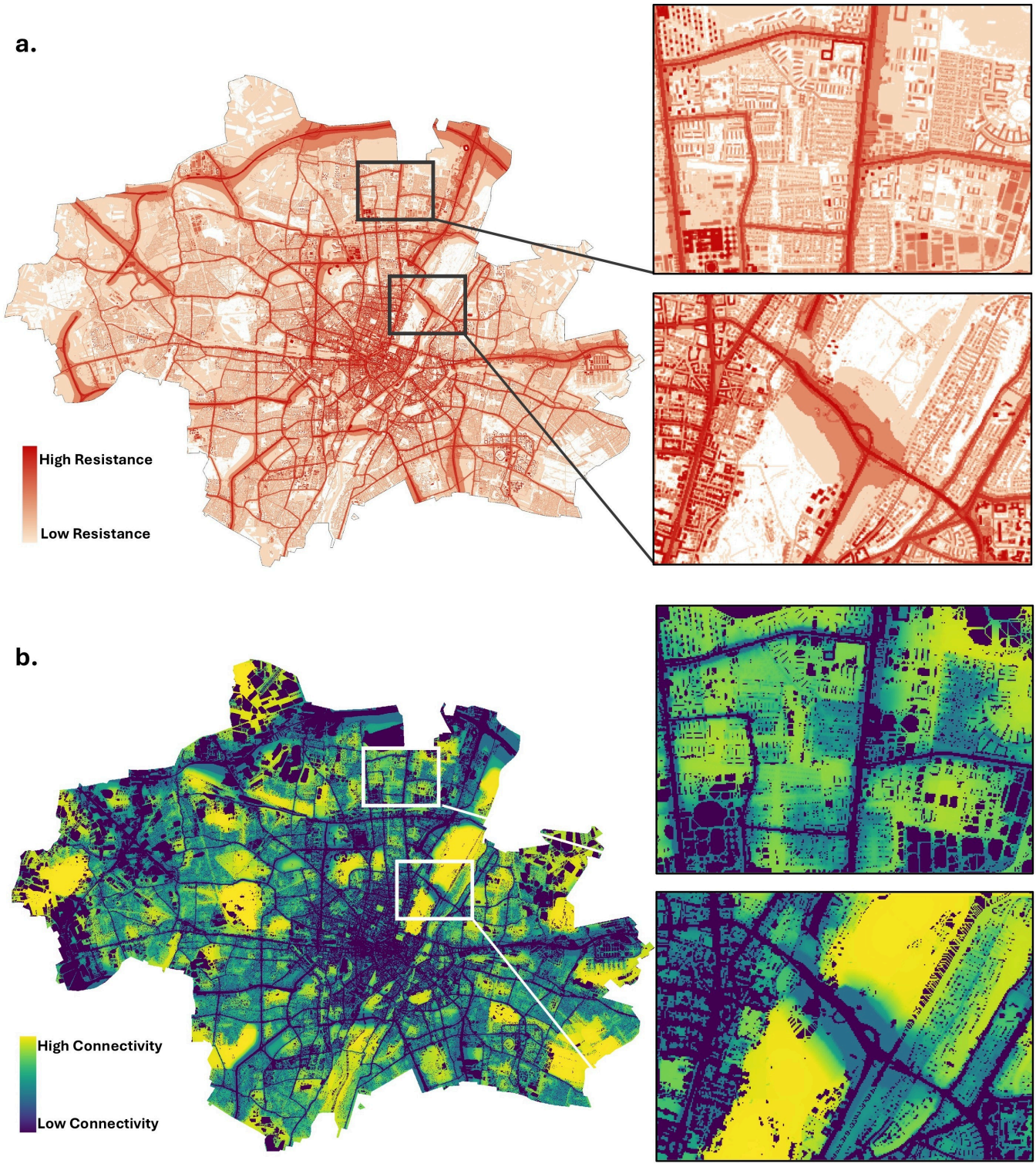


Figure 5

Combined best resistance set (a) and corresponding final connectivity map (b) that best describes the habitat fragmentation for the common blackbird. The multi-factor resistance set includes all three barrier aspects tested: noise, traffic, and land cover.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryInformation.docx
- SupplementaryInformationTableS3.xlsx
- Scripts.zip