Supplementary Materials

S1: Habitat Use and Resistance Modeling Methods for Focal Species

All habitat suitability, use, movement, and landscape genetic analyses were conducted in R [1] across the whole of San Diego County. We created these initial models using relevant environmental variables for habitat use and movement for all focal species (Table S1) using an ecological neighborhood approach. To select the most appropriate scale for each variable, we used the *smoothie* package (v 1.0-1, [2]) to apply a Gaussian smooth to each variable at a variety of biologically-relevant spatial scales for each species based on movement and home range information for each species. We tested scales ranging from 30 m to 180 m for California mouse and woodrat, 30 m to 360 m for wrentit, 30 m to 2,160 m for mule deer, 30 m to 2,000 m for bobcat, and 30 m to 10,000 m for puma.

Ensemble Species Distribution Modeling

For species where only occurrence data were available, we gathered locations from available sources (see Table 1 in the main manuscript) and filtered points by date and spatial accuracy so that only points observed after 1990 with an accuracy of 500 m were retained. To address potential sampling bias, we used two approaches: (1) we spatially filtered out points that were close together based on nearest neighbor distances [3], and (2) we spatially restricted the sampling of background points. For mule deer, we filtered out all points within 1 km of each other. For California mouse, woodrat, and wrentit, we filtered out all points within 500 m of each other. The resulting points for each species were then examined for potential landscape change due to human development by overlaying the points with urban and roads data. We removed all points where landscape change was suspected to have occurred after the observation.

These data cleaning steps resulted in 722 presence points for mule deer, 202 points for woodrat, 216 points for California mouse, and 1,481 points for wrentit. The data for mule deer, California mouse, and woodrat required the selection of pseudo-absence or background points. From a visual inspection of the presence points for these species, it appeared they were heavily biased toward primary and secondary roads in the study area. We confirmed this bias by sampling the presence points on a distance from roads surface. We counted the number of presence points within each 500 m distance from roads bin and randomly sampled the same number of background points in each distance from roads bin, generating a 1:1 ratio with the presence points for each species [4].

We took a different approach for wrentit since the eBIRD database contained actual absence points in the form of observation locations where wrentit were not seen. We randomly selected the same number of background points as presence points from the eBIRD data for wrentit. We assumed background locations to have the same sampling bias as presence locations and therefore did not spatially restrict the wrentit background points like we did for the other species.

Once presence points were cleaned and background points generated and sampled on each of the scaled environmental variable surfaces described in Table S1, we developed multi-scale ensemble species distribution models (SDMs; [5,6]). Using the biomod2 package [7] we combined generalized linear models (GLMs), generalized additive models (GAMs), multivariate adaptive regression splines (MARS), random forest regression (RF), boosted regression trees (BRT), and maximum entropy (MaxEnt) with an AUC-weighted average. These SDMs were used to predict habitat suitability at 30-m resolution for a county-wide extent (11,722 km^2) to avoid artifacts of modeling at a very fine spatial scale. We rescaled habitat suitability from 0 – 1 and converted habitat suitability to landscape resistance using a non-linear inverse transformation [8] for each species (see Eq 1 in main text).

Table S1. Environmental variables used in developing habitat use and resistance surfaces for each focal species.

	Variable	Source/Derivation	Year	Citation
Roads and Development	All Roads	Open Street Map	2014	[9]
	Primary roads	Open Street Map; Motorways	2014	
	Secondary roads	Open Street Map; primary road, secondary road, and trunk road	2014	
	Tertiary roads	Open Street Map; living street, residential, rest area, road, service, tertiary, and unclassified	2014	
	Unpaved roads/trails	Open Street Map; bridleway, cycleway, footway, path, and track,	2014	
	Percent Imperviousness	Derived from a hybrid of the National Land Cover Database percent impervious surface and updated data from the San Diego Association of Governments land use surface	2011 2012	NLCD 2011 [10] [11]
Topography	Elevation	National Elevation Dataset	2009	[12]
	Percent Slope	Derived from National Elevation Dataset		
	Terrain Ruggedness	Total curvature derived from National Elevation Dataset with DEM Surface Tools [13]		
	Topographic Position Index	Derived from National Elevation Dataset		
	Ridges	Derived from Topographic Position Index values >= 8		
	Canyons	Derived from Topographic Position Index values <=- 8		
	Steep Slope	Derived from Topographic Position Index values -8 – 8, slope >=6°		
	Gentle Slope	Derived from Topographic Position Index values -8 – 8, slope <=6°		
Water	Streams	National Hydrography Dataset streams layer	2011	[14]
	Distance to Water	Derived from National Hydrography Dataset calculated as Euclidean distance to blue line streams		
Vegetation Type	Agriculture	Vegetation Data of San Diego County	2014	[15]
	Chaparral	Vegetation Data of San Diego County	2014	[15]
	Coastal Scrub	Vegetation Data of San Diego County	2014	[15]
	Coniferous Forest	Vegetation Data of San Diego County	2014	[15]
	Desert Scrub	Vegetation Data of San Diego County	2014	[15]
	Hardwood Forest	Vegetation Data of San Diego County	2014	[15]
	Herbaceous Grassland	Vegetation Data of San Diego County	2014	[15]
	Riparian	Vegetation Data of San Diego County	2014	[15]
	Sparse/Disturbed	Vegetation Data of San Diego County	2014	[15]
	Water and Wetlands	Vegetation Data of San Diego County	2014	[15]

Point and Path Selection Functions

GPS telemetry data were available for two of our selected focal species, bobcat and puma. For these species, we estimated resource use with a multi-scale point selection function (PSF) analysis, and resource use explicitly during movement events with a multi-scale path selection function (PathSF) conducted at county-wide extent [16,17]. The PSF resulted in a relative probability of habitat use surface, which we used in distributing source points for the connectivity analysis. The PathSF resulted in a relative probability of movement surface which we took the linear inverse of to estimate resistance for puma and bobcat.

Point Selection Function

For bobcat, we subset the data to every three hours so that the data were consistent, and to reduce any autocorrelation that may have been present with hour-long fixes. This resulted in 3,895 of points for 8 individuals (1 female and 7 males) for the point selection function analysis with a per-individual mean of 487 points (range = 7 – 2526). For puma, we subset the data to every 6 hours, which resulted in 24,911 locations from 23 individuals (14 females and 9 males) with a per-individual mean of 811 points (range = 284 – 1,535).

We then estimated the used data as the proportion (for categorical data) or mean (for continuous data) of each predictor variable within a 30 m uniform buffer around each GPS location. We estimated the available data within a larger ecological neighborhood around each used point represented with a Gaussian kernel [18]. Therefore, each used point was paired with an ecologically relevant available area.

We developed our multi-scale models using a two-stage, pseudo-optimized approach [19]. In the *coxme* package [20], we ran univariate models for each predictor variable at each scale in a paired conditional logistic regression model with a random effect for individual [21]. The scale with the lowest corrected Akaike's Information Criteria (AICc) value for each variable was identified as the characteristic scale of selection and was a candidate for incorporation into the multiple regression models.

We tested for collinearity among our predictor variables at their characteristic scales using Spearman's rank correlations. If two variables had $|r_s| > 0.60$ we retained the variable with the highest AIC model weight. The multiple regression models did not converge in the mixed-effects framework; therefore, we ran the multiple regression models without mixed-effects using the coxph function of the *Survival* package [22]. We then fit all possible subsets of our predictor variables with the dredge function in the *MuMIn* package [23]. We used this approach because we had no *a priori* hypotheses to consider any specific combinations of variables and we thought all variables would be influential for bobcat and puma habitat use. We ranked the models using AICc and arrived at our final model by averaging any models within 2 AICc units of the best model. We used the robust standard errors when calculating confidence intervals for the model-averaged coefficients. Finally, we differenced the available from the used for each cell within the study area and applied our model-averaged coefficients to create each predictive surface.

We determined the predictive performance of the PSF models by using the holdout points that were not included in the 3-hour subset of points used for bobcat or 6-hour subset of points used for puma. Using a completely independent set of data for determining predictive ability of our models would have been preferred, but we did not have access to such data. Due to logistical constraints for collecting independent data, hold out data is commonly used for model validation and can still provide a reasonable, though possibly inflated, assessment of model predictive ability [24]. We used the holdout points to calculate the Boyce Index [24,25]. This index compares the values from the predicted probability surfaces with the expected values across the study area and results in a Spearman Correlation value ranging from 0 to 1. Values closer to 1 indicate better predictive ability.

Path Selection Function

For bobcat, we used only the GPS collar data that were collected hourly for each day the collar was on that schedule. We then connected each consecutive point with a straight line, which resulted in 86 daily paths from 8 individuals for use in the analysis (mean for each individual = 12 days, range = 3 - 44). For puma, we used only GPS locations that were collected at a 5 or 15-minute interval. We created paths for each of 39 individuals by connecting consecutive points over a 24-hour time period. This resulted in a total of 1,076 daily paths for the analysis (mean per individual = 30 days, range = 14–106). Movements captured for both species with GPS telemetry included primarily typical home range movements along with several dispersal events, which all fell within the dispersal distances we used for each species in our connectivity modeling (18 km for bobcat, 24 km for puma).

We used Path Selection Functions to estimate the relative probability of movement for bobcats and pumas across the study area [16,17]. We took much the same approach as for the point selection functions above, but our units of inference were the daily paths used by the individual cats. We estimated the used data as the proportion (for categorical data) or mean (for continuous data) of each predictor variable within a 30 m uniform buffer around each daily path. To assess the characteristics of the areas available but not selected in movement paths, we used either the proportion (e.g., for vegetation cover), or the mean (e.g., for elevation) of each predictor variable around each path weighted by the scaled environmental variables described above.

We ran paired logistic regression models and used a two-stage, pseudo-optimized approach for the multi-scale path selection function models via the same process described for the point selection function analysis above. We used the final path selection function model to predict the relative probability of movement across the study area. We calculated the Boyce Index, as described above, using the bobcat and puma GPS points from the PSF analyses. These points were not used in the PathSFs and thus could be employed as holdout data.

Landscape Genetic Analysis

For species with genetic data (puma, bobcat, and mule deer), we performed a multi-scale landscape genetic analysis, which correlates the genetic distance between individuals across the landscape with the resistance distance between individuals across the landscape [26] (landscape genetic approach detailed in [27]). Microsatellite data from prior studies (see data sources in Table 1 in the main manuscript) were used for each of the three species with 22 loci available for 62 bobcats, 15 loci for 223 mule deer, and 44 loci for 146 pumas.

Landscape genetic approaches correlate observed genetic distances among individuals with resistance distances. These resistance distances are often calculated as the least-cost distance among individuals across resistance surfaces defined *a priori*. We explored a number of different resistance hypotheses for each of our environmental variables. We represented each variable using the same scales described above for each species. We then applied seven functions to transform each scaled variable into a resistance value of 1–100 (Figure S1). Positive or negative transformation functions were used to represent increasing or decreasing resistance with increasing values of that variable, respectively. We also used the inverse Ricker transformation to account for variables that might have a low resistance at moderate values.

With the *adegenet* package [28], we calculated pairwise genetic distance using Nei's distance among all individuals for each species. We calculated pairwise geographic distance by calculating the least cost path distance between all sample locations across each *a priori* resistance surface with the *gdistance* package [29]. We then compared all the *a priori* resistance surfaces for a variable by running univariate linear mixed effects models that accounted for the pairwise structure of the distance matrices following the maximum likelihood population-effects (MLPE) method [30,31].

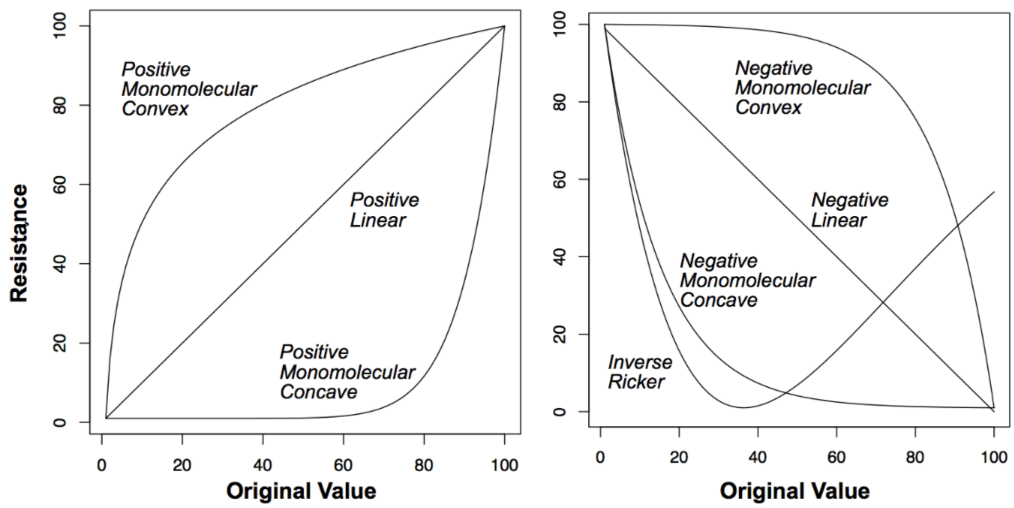

Figure S1. Functions used to transform the environmental variables to resistance, with a range of 1-100, for use in the landscape genetic analysis. Figure adapted from [32].

We used AICc to identify the most appropriate resistance surface for each variable. We assessed correlations among variables and removed variables from correlated pairs with higher AICc values. We then ran multiple regression models with all uncorrelated variables and fit all possible subsets of the variables. We ranked the multiple regression models using AICc and identified our final top model for each species. If models were within 4 delta AICc units of the top model, we averaged these models to derive final averaged beta coefficients. To obtain a final resistance surface from these models, the landscape variables were multiplied by their respective beta coefficient and then summed.

Because this analysis estimates resistance directly, no transformation to resistance was needed. To develop the final resistance surface for species with genetic data, we multiplied the quantile rescaled resistance surface derived from the SDM (deer) or PathSF (bobcat and puma) analyses with that derived from the landscape genetic analysis and rescaled this surface from 1 – 100 (1 = low resistance and 100 = high resistance; [27]. We calculated the Boyce Index, as described above, for these three combined surfaces using the bobcat and puma GPS points from the PSF analyses and a combination of recently collected genetic and telemetry data as well as occurrence data withheld from the SDM for deer.

Data accessibility

Data for each species and final connectivity modeling data are available on FigShare.
Final connectivity files: https://figshare.com/s/8ed5c96e2a193a3859f4
Big-eared woodrat: https://figshare.com/s/173aa1d66fe9757e75e2
Bobcat: https://figshare.com/s/ed8a76009bf32c11ac42
California mouse: https://figshare.com/s/828a436d89138de7cbe5
Mule deer: https://figshare.com/s/9ee8b5c80bc4a5f3220a
Puma: https://figshare.com/s/8b3433f06960da96b3ac
Wrentit: https://figshare.com/s/21f724d2f922e1bd0b8f

S2: Land Facet Analysis Methods

To execute the land facet modeling, we used the Land Facet Corridor Designer [33] toolbox in ArcGIS. We input topographic data from a 30 m digital elevation model to develop unique land facets across our study. We then modeled corridors for each of those land facets, based on the concepts of resistance and least-cost modeling, to identify pathways for movement along those facets.

From the initial digital elevation model, we generated three additional variables that we used to identify land facets in our study region: 1) slope, 2) solar insolation, and 3) a slope position surface categorized into four classes – canyons, gentle slopes, steep slopes, and ridges. Once we identified these original variables, we followed the procedures outlined by [33]. We populated the values for elevation, slope, and insolation at each grid cell for our four slope position classes. We then exported the data for each of these four classes into R to conduct a cluster analysis based on the variables for each slope position class. To identify clusters, we performed a kernel density analysis, identified and excluded values that were outliers, and used fuzzy c-means clustering to classify the pixels into groups using the R functions provided in the Land Facet Corridor Designer Tools [33]. Based on these data outputs, we then selected the number of clusters, or individual facets, for each slope position class that we would use for the remainder of the analysis.

We imported our cluster values back into ArcGIS and used them to generate a land facet raster for each slope position class. Using the Calculate Density Surface tool in the Land Facet Corridor Designer toolbox, we identified the areas of greatest density of each of the new land facet classes. That output was then used to generate termini polygons of the areas of greatest density of each land facet within our wildland blocks of interest. We also used the land facet density surface to create a Mahalanobis distance raster for each class of the land facet raster to be used in our corridor modeling as the equivalent of resistance. To standardize the scale of the Mahalanobis distance raster, we used the Chi Square Raster Transform tool. This creates a "resistance" or "distance" surface (on a 0 to 1 scale) to use in our corridor modeling where cells with a greater distance (closer to 1) from an area of high density of the land facet of interest have a higher resistance value. Finally, because the surfaces created thus far in the process only included topographic variables and did not incorporate any other landscape features that may affect wildlife movement, we clipped this resistance layer using an urban raster mask generated from the SANDAG Current Land Use layer [11] to exclude urban areas from our corridor modeling.

We used Linkage Mapper [34] to generate least cost corridors using the Mahalanobis distance surfaces as our resistance inputs and the termini polygons of high land facet density within blocks of preserved lands as our target core areas to connect. This process generated raster corridor surfaces that can then be truncated to identify corridor extent. We selected cutoff values for each land facet raster that produced a contiguous corridor but was not too wide or expansive. Finally, we converted our raster surfaces to corridor shapefiles which we then cleaned and filled to remove narrow corridor segments and artifacts from the modeling process both manually and using the Fill holes in corridor script in the Corridor Designer toolbox for ArcGIS [35] to fill holes less than 500 m in diameter.

S3: Species-specific Modeling Results

Ensemble Species Distribution Modeling

Based on the results of our univariate models, California mouse selected for environmental variables at either the 90 m or 180 m scale, and only distance from water was better represented at a smaller scale (60 m). After accounting for correlations among variables, the final variable set for the California mouse SDM models included agriculture, canyons, chaparral, coastal scrub, elevation, hardwood forest, herbaceous grassland, primary and secondary roads, riparian areas, percent slope, sparsely vegetated areas, steep slopes, streams, topographic position index (TPI), and water/wetlands (Table S2).

Table S2. Variables and scales included in the final SDM models for California mouse, mule deer, woodrat, and wrentit. Variables without scales indicate it was not included in the final model for that species.

	Variable	Scale included in final SDM model			
		California mouse	*Mule deer*	*Woodrat*	*Wrentit*
Roads and Development	All Roads				
	Primary roads	180 m	1,440 m	90 m	360 m
	Secondary roads	180 m		180 m	180 m
	Tertiary roads				
	Unpaved roads/trails				
	Percent Imperviousness		90 m		60 m
Topography	Elevation	90 m	2,160 m	30 m	360 m
	Percent Slope	90 m		180 m	
	Terrain Ruggedness				
	Topographic Position Index	180 m	90 m	30 m	90 m
	Ridges				
	Canyons	180 m			360 m
	Steep Slope	90 m	360 m	180 m	360 m
	Gentle Slope				
Water	Streams	180 m		90 m	
	Distance to Water		90 m		360 m
Vegetation Type	Agriculture	90 m	1,440 m	180 m	360 m
	Chaparral	180 m	360 m	60 m	360 m
	Coastal Scrub	180 m	720 m	180 m	360 m
	Coniferous Forest		2,160 m		
	Desert Scrub		2,160 m		
	Hardwood Forest	180 m	2,160 m	60 m	360 m
	Herbaceous Grassland	180 m	720 m	60 m	360 m
	Riparian	90 m	720 m	60 m	360 m
	Sparse/Disturbed	180 m		180 m	
	Water and Wetlands	180 m	2,160 m	180 m	360 m

Mule deer selected for environmental variables at a wide range of scales, from 90 m to 2,160 m. After accounting for correlations among variables, the final variable set for the mule deer SDM models included agriculture, chaparral, coastal scrub, coniferous forest, desert scrub, elevation, hardwood forest, herbaceous grassland, riparian, water and wetlands, primary roads, elevation, topographic position index, steep slopes, and distance to water (Table S2).

Big-eared woodrat also selected for variables at a wide range of scales, selecting for TPI, elevation, and canyons at a 30 m scale, chaparral, hardwood forest, and riparian areas at a 60 m scale and the remaining variables at the 90 m or 180 m scales. After accounting for correlations among variables, the final variables for the woodrat SDM models included agriculture, canyons, chaparral, coastal scrub, elevation, hardwood forest, herbaceous grassland, primary and secondary roads, riparian areas, percent slope, sparsely vegetated areas, steep slopes, streams, TPI, and water/wetlands (Table S2).

Wrentit selected for most environmental variables at the 360 m scale. After accounting for correlations among variables, the final variable set for the wrentit SDM models included agriculture, canyons, chaparral, coastal scrub, elevation, hardwood forest, herbaceous grassland, primary and secondary roads, riparian areas, impervious surfaces, steep slopes, distance to water, topographic position index, and water/wetlands (Table S2).

AUC model performance values for each individual SDM model and the final ensemble models are provided in Table S3.

Table S3. SDM model performance for California mouse, mule deer, woodrat, and wrentit. All models with an AUC > 0.75 were included in the final ensemble model. GLM = Generalized Linear Model, GAM= Generalized Additive Model, MARS= Multivariate adaptive regression splines, RF=Random forests, BRT=Boosted regression trees.

	AUC			
Model	**California mouse**	**Mule deer**	**Woodrat**	**Wrentit**
GLM	0.83	0.78	0.80	0.79
GAM	0.80	0.78	0.79	0.80
MARS	0.83	0.78	0.79	0.80
RF	0.88	0.78	0.82	0.82
MAXENT	0.78	0.72	0.72	0.80
BRT	0.87	0.79	0.82	0.82
Ensemble	0.87	0.80	0.82	0.82

Point and Path Selection Functions

Point Selection Functions

For bobcat, the univariate results indicated selection for resources almost exclusively at coarser scales (with the exception of herbaceous grassland and water/wetland). We were unable to fit models with coniferous forest or desert scrub, due to the scarcity of these habitat types in the study area where the bobcats were collared. We were also unable to fit models with agriculture due to complete separation errors.

Bobcats consistently responded negatively to human influences (roads and development), and positively to canyons, water and riparian areas. Bobcats avoided ridges, steep slopes and higher elevations, but preferred higher amounts of topographic roughness (curvature).

After accounting for collinearity among predictor variables we attempted to run a global model with the following variables: all roads, canyons, chaparral, coastal scrub, hardwood forest, grassland, riparian, sparse or disturbed areas, elevation, percent slope, steep slopes, distance to water, streams, and water/wetland. However, the canyons variable was causing a Type S error in the beta coefficient [36], therefore, we removed canyons, and re-ran the global model. Performing dredge on the global model revealed four top models. Model-averaged standardized beta coefficients, robust standard errors, and 95% confidence intervals, are provided in Table S4. The Boyce Index value for the bobcat PSF surface was 0.81.

For puma, the univariate model results indicated a mostly bi-modal response to landscape features. Pumas responded to elevation, percent slope, chaparral, and coastal scrub at fine scales and responded to the other variables at coarse scales. Due to convergence errors, we were unable to fit the models for desert and primary roads.

Table S4. Variable scales, standardized beta estimates, robust standard errors, and 95% robust confidence intervals for the bobcat point selection function model-averaged variables.

	Scale	Beta estimate	Standard Error	95% Confidence Interval
All Roads	1,000 m	-0.287	0.037	-0.309 – -0.265
Chaparral	1,000 m	1.236	0.114	1.167 – 1.305
Coastal Scrub	1,000 m	0.349	0.061	0.312 – 0.386
Distance to Water	1,000 m	-0.257	0.061	-0.294 – -0.220
Elevation	1,000 m	-7.190	0.354	-7.404 – -6.976
Hardwood Forest	1,000 m	0.301	0.051	0.270 – 0.332
Steep Slopes	1,000 m	-0.142	0.048	-0.113 – -0.171
Percent Slope	1,000 m	1.115	0.110	1.049 – 1.181
Sparse Disturbed	1,000 m	-0.176	0.044	-0.203 – -0.149
Streams	519 m	0.138	0.036	-0.160 – -0.116
Riparian	1,000 m	0.006	0.018	-0.005 – 0.017
Water/Wetland	170 m	0.007	0.016	-0.002 – -0.017
Herbaceous Grassland	275 m	-0.007	0.024	-0.022 – -0.008

After removing correlated variables, the global model was identified as the top model. Pumas preferred slightly more rugged terrain, riparian areas and woodland while avoiding high elevation, high slopes, agriculture, barren, chaparral, coastal scrub, grassland, urban, and primary, secondary, and tertiary roads (Table S5). The Boyce Index value for the puma PSF surface was 0.75.

Table S5. Variable scales, standardized beta estimates, robust standard errors, and 95% robust confidence intervals for the puma point selection function variables.

	Scale	Beta estimate	Standard Error	95% Confidence Interval
Elevation	241 m	-21.61	0.60	-21.99 – -21.23
Percent Slope	24 1m	-1.1	0.03	-1.12 – -1.08
Terrain Ruggedness	4,461 m	0.09	0.01	0.08 – 0.09
Agriculture	4,461 m	-0.25	0.02	-0.23 – -0.26
Barren	3,994 m	-0.06	0.02	-0.05 – -0.07
Chaparral	241 m	-0.17	0.06	-0.21 – -0.13
Coastal Scrub	681 m	-0.29	0.03	-0.03 – -0.27
Grassland	4,461 m	-0.38	0.02	-0.40 – -0.37
Riparian	3,497 m	0.38	0.04	0.35 – 0.40
Woodland	4,461 m	0.23	0.02	0.22 – 0.24
Urban	4,461 m	-2.18	0.16	-2.28 – -2.08
All roads	4,461 m	-0.06	0.02	-0.07 – -0.05

Path Selection Functions

For bobcats, we were unable to fit the path selection function models with Coniferous Forest or Desert Scrub vegetation variables due to the lack of representation described above. Bobcats selected more landscape variables at finer scales during movement than during resource use (Table S6). After accounting for collinearity among predictor variables, we attempted to run a global model with the following variables: agriculture, all roads, chaparral, coastal scrub, grassland, riparian, sparsely vegetated areas, elevation, steep slopes, distance to water, and water/wetland. However, agriculture was causing the models to fail due to complete separation errors. Therefore, we removed agriculture, and re-ran the global model. Eighteen top models within 2 AICc units of the top model were identified. Model-averaged standardized beta coefficients, standard errors, and confidence intervals are provided in Table S6. The Boyce Index value for the bobcat PathSF surface was 0.98.

Table S6. Scales, standardized beta estimates, robust standard errors, and 95% robust confidence intervals for the bobcat path selection function model-averaged variables.

	Scale	Beta estimate	Standard Error	95% Confidence Interval
Elevation	519 m	-12.562	3.370	-15.152 – -9.972
All roads	465 m	-2.07	0.712	-2.617 – -1.523
Sparse Distributed	519 m	-0.693	0.821	-1.324 – -0.062
Distance to Water	1,000 m	-0.349	0.534	-0.759 – 0.061
Herbaceous Grassland	170 m	-0.392	0.661	-0.900 – 0.116
Steep Slopes	519 m	-0.241	0.449	-0.586 – 0.104
Riparian	275 m	0.059	0.196	-0.092 – 0.210
Chaparral	519 m	0.010	0.130	-0.090 – 0.110

Pumas selected landscape variables at fine scales during movement behavior (Table S7). After removing correlated variables, four top models were identified and beta coefficients were averaged. Pumas also showed more tolerance for a wider range of landscape variables during movement than during resource-use events. Pumas avoided steep slopes, agricultural areas, urban areas, and roads during movement, but showed a preference for all other landscape variables in the final model, especially riparian and woodland areas (Table S7). The Boyce Index value for the puma PathSF surface was 0.72.

Table S7. Scales, standardized beta estimates, robust standard errors, and 95% robust confidence intervals for the puma path selection function model-averaged variables.

	Scales	Beta estimate	Standard Error	95% Confidence Interval
Elevation	241 m	9.22	1.00	8.51 –9.94
Percent Slope	2,797 m	-1.35	0.21	-1.50 – -1.20
Agriculture	3,819 m	-0.02	0.09	-0.08 – 0.05
Chaparral	3,104 m	1.44	0.30	1.37 – 1.51
Grassland	2,797 m	-0.02	0.28	-0.22 – 0.18
Barren/Open Water	3,104 m	-0.02	0.07	-0.07 – 0.04
Riparian	1,317 m	5.92	1.90	4.56 – 7.27
Woodland	241 m	2.87	0.36	2.61 – 3.13
Urban	241 m	-7.53	2.03	-8.98 – -6.08
All roads	3,819 m	-0.78	0.24	-0.95 – -0.62

Landscape Genetics Analysis

For all species, we identified a single scale and transformation to resistance for each variable out of the suite of *a priori* resistance surfaces tested using the linear mixed effect models. After accounting for correlations, we included the following variables in the multiple regression model for bobcat: agriculture, all roads, chaparral, coastal scrub, hardwood forest, herbaceous grassland, riparian, steep slopes, streams, terrain ruggedness, topographic position index and water and wetland (Table S8). Most of the transformations selected for bobcat indicated the lowest resistance values were at moderate values of that variable. However, resistance for bobcats steadily increased with the amount of roads and water and wetlands and decreased with the amount of chaparral and coastal scrub. AICc values for the top models ranged from -4402 - -4398 while the AICc value for the null isolation by distance (IBD) model was -4367.

For mule deer, we included the following variables in the final model: agriculture, chaparral, coastal scrub, distance to water, elevation, gentle slope, hardwood forest, herbaceous grassland, primary and secondary roads, riparian, sparsely vegetated/urban, steep slopes, streams, topographic position index, and water and wetland (Table S8). Resistance for mule deer increased with increasing values of roads, slope, urban, and coniferous forest. Resistance for mule deer decreased with elevation, topographic position index, distance to water, riparian, agriculture and chaparral.

Resistance was lowest at moderate values of hardwood forest and streams. The AICc values for the top models ranged from -45770 - -45766 while the AICc value for the null IBD model was -45772.

For puma, after accounting for correlations, we included the following variables in the multiple regression model: elevation, percent slope, agriculture, chaparral, coastal scrub, coastal oak woodland, grassland, riparian, urban, and primary roads (Table S8). Variables whose resistance decreased with increasing values were chaparral, percent slope, riparian, coastal scrub, and coastal oak woodland. Resistance for elevation and ruggedness were represented by an inverse Ricker transformation, which decreases until middle values are reached, and then increases for the remaining values, indicating dispersal is facilitated at mid-elevation and mid-ruggedness values. The AICc values for the top models ranged from 10605 – 10609 while the AICc value for the null IBD model was 10616.

Once we combined the resistance surfaces from the SDM for deer and PathSF for bobcat and puma with the final landscape genetic resistance surface for each, we found that the predictive ability was either equal to or better than the original SDM or PathSF surfaces. The Boyce Index values for these combined surfaces were 0.83 for mule deer, 0.98 for bobcat, and 0.98 for puma.

Table S8. Final model variables, scales and transformations to resistance for bobcat, mule deer, and puma. Variables without scales or transformations indicate it was not included in the final model for that species. Plus or minus indicates preference or avoidance of that variable for or movement. A forward slash refers to the inverse Ricker transformation, which indicates the lowest resistance values correspond with values in the middle of the range of values for that variable. The selected resistance transformation for the landscape genetic analysis are indicated by IR = inverse Ricker, NL = negative linear, NMCc = negative monomolecular concave, NMCv = negative monomolecular convex, PL = positive linear, PMCc = positive monomolecular concave, PMCv = positive monomolecular convex.

		Bobcat		**Mule deer**		**Puma**	
	Variable	***Scale***	***Trans-formation/ Sign***	***Scale***	***Trans-formation/ Sign***	***Scale***	***Trans-formation/ Sign***
Roads and Development	All Roads	2,000 m	PL -				
	Primary roads			2,160 m	PMCc -	500 m	PMCv -
	Secondary roads			1,440 m	PMCc -		
	Tertiary roads						
	Unpaved roads/trails						
	Percent Imperviousness						
Topography	Elevation			720 m	NMCc +	6,000 m	IR /
	Percent Slope					8,000 m	NMCc +
	Terrain Ruggedness	465 m	IR /				
	Topographic Position Index	2,000 m	IR /	1,440 m	NMCc +		
	Ridges						
	Canyons						
	Steep Slope	170 m	IR /	720 m	PMCv -		
	Gentle Slope			90 m	PL -		
Water	Streams	465 m	IR /	1,440 m	IR /		
	Distance to Water			720 m	NMCc +		
Vegetation Type	Agriculture	465 m	IR /	720 m	NMCc +	6,000 m	PL -
	Chaparral	1,000 m	NL +	180 m	NMCv +	6,000 m	NMCc +
	Coastal Scrub	2,000 m	NMCv +	1,440 m	PMCv -	500 m	NMCv +
	Coniferous Forest						
	Desert Scrub						
	Hardwood Forest	170 m	IR /	90 m	IR /	2,000 m	NMCv +
	Herbaceous Grassland	2,000 m	IR /	90 m	PL -	500 m	PMCv -
	Riparian	170 m	IR /	2,160 m	NMCc +	500 m	NMCv +
	Sparse/Disturbed			2,160 m	PMCv -	500 m	PMCv -
	Water and Wetlands	2,000 m	PL -	720 m	PL -		

S4: Land Facet Analysis Results

Our analysis of land facets resulted in the identification of 15 total facets, three types for canyons and four each for gentle slopes, steep slopes, and ridges (Table S9). We generated least cost corridor connectivity rasters for each of the 15 facets and truncated them at cost-weighted distance values ranging from 500 to 2,500, based on the relative coverage of each facet across the map to define distinct corridors that remained primarily within each feature type. After cleaning and filling the initial corridor polygons, we compared these land facet corridors to our focal species corridors. We found that there were three areas where land facet corridors were modeled that were not captured by our focal species corridors. Two were near the boundaries of our analysis area and were likely not captured in our focal species corridors due to edge effects during modeling rather than a lack of suitability of the habitat features. As such, we opted not to add those corridors to the linkage network. The third was a region through a large grassland that was captured by the LF2c land facet corridor. The grasslands corridor was located in a region towards the center of our analysis area that was likely not incorporated into our focal species corridors because we had not explicitly chosen a grassland-associate in our suite of focal species. Therefore, we included the LF2c corridor in our final linkage design.

Table S9. Description of the 15 different land facet types identified across the study area. The final selected land facet representing grasslands is identified in bold italics.

Land Facet Category	Topographic Position	Slope	Insolation	Elevation
LF1a	Canyons	gentle	warm	low
LF1b	Canyons	moderate	hot	high
LF1c	Canyons	steep	cool	mid
LF2a	Gentle slopes	gentle	warm	low
LF2b	Gentle slopes	moderate	warm	high
LF2c	***Gentle slopes***	***steep***	***hot***	***mid***
LF2d	Gentle slopes	steep	cool	mid
LF3a	Steep slopes	gentle	hot	high
LF3b	Steep slopes	gentle	warm	low
LF3c	Steep slopes	steep	hot	mid
LF3d	Steep slopes	moderate	cool	mid
LF4a	Ridges	gentle	warm	low
LF4b	Ridges	moderate	hot	high
LF4c	Ridges	steep	hot	mid
LF4d	Ridges	steep	cool	mid

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