Urban Ecosystems (2025) 28:152
https://doi.org/10.1007/s11252-025-01758-8

Environmental contamination predicts mammal diversity and mesocarnivore activity in the Seattle-Tacoma metro area

Yasmine Hentati[1] · Cesar O. Estien[2,3] · Zachary Hawn[4] · Mark J. Jordan[5] · Robert A. Long[6] · Rachael Mueller[7] · Katie R. Remine[6] · Laura R. Prugh[1] · Christopher J. Schell[2]

Accepted: 13 June 2025 / Published online: 27 June 2025

Abstract

Environmental factors influencing the distribution and abundance of wildlife populations in the Anthropocene are increasingly complicated by historical and ongoing industrialization. The legacy of industrialization has enduring impacts on environmental quality, with downstream consequences for wildlife. However, industrial contaminants are not evenly distributed across or within cities, and their effects on free-ranging wildlife at the population and community levels remain poorly understood. We investigated whether environmental contaminant risk from pollutants was associated with mammalian diversity and carnivore activity in the Seattle-Tacoma metropolitan area, Washington, USA. Using camera trap data collected across 74 sites, we modeled environmental contaminant risk, natural land cover, and human population density against several mammal community metrics and against detections of carnivore species. Environmental contaminant risk was measured based on proximity to contaminated industrial and residential sites, using publicly available indices. We found that mammalian diversity and evenness decreased as contaminant risk increased, especially in Seattle. Across the metro area and within Seattle, coyote (*Canis latrans*) activity was negatively associated with contaminant risk, while raccoon (*Procyon lotor*) activity was positively associated with contaminant risk; opossums (*Didelphis virginiana)* showed no response. Within Tacoma, contaminant risk was not significantly associated with mammal community metrics or carnivore activity, but human population density had a negative influence on coyote activity and a positive influence on opossum activity. Our results highlight the potential impacts of industrialization in ecological processes, and the need for species- and city-specific approaches in understanding the role they play in shaping urban wildlife communities. Ecological studies that incorporate these impacts can inform urban planning and conservation strategies that improve environmental quality for urban wildlife populations.

Keywords Urban ecology · Camera traps · Pollution · Environmental contamination · Mesocarnivores · Multi-city

Introduction

Cities are complex landscapes where human and natural systems are intimately coupled, and are characterized by high variation in environmental quality for human and nonhuman life (Collins et al. 2000; Ramalho and Hobbs 2012; McPhearson et al. 2016; Keeler et al. 2019; Des Roches et al. 2021). The quality of wildlife habitat varies both within and across urban areas (Cushing et al. 2015; Estien et al. 2024), and is influenced by factors such as green space availability; point pollution sources such as industrial facilities; non-point pollution sources such as stormwater runoff; and human population density. Environmental quality, or the health of an environment as defined by environmental characteristics that impact living beings, plays a large role in dictating the success of wildlife populations and communities in cities (Collins et al. 2000;

✉ Yasmine Hentati
yhentati@uw.edu

1 University of Washington, Seattle, WA, USA
2 University of California, Berkeley, CA, USA
3 Second Nature Ecology & Design LLC, Berkeley, CA, USA
4 Point Defiance Zoo & Aquarium, Tacoma, WA, USA
5 Seattle University, Seattle, WA, USA
6 Woodland Park Zoo, Seattle, WA, USA
7 Northwest Trek Wildlife Park, Eatonville, WA, USA

Saaristo et al. 2018; Murray et al. 2019; Lev et al. 2020; Fatima et al. 2023). These characteristics reflect the overall condition of the physical environment, often in relation to air, soil, or water quality. However, environmental quality can also refer to specific attributes that vary within a localized region such as access to vegetation, temperature, and noise levels (Cushing et al. 2015; Murray et al. 2022; Estien et al. 2024). In addition to factors such as competition, mating opportunities, and availability of food and shelter, urban wildlife may need to attenuate their responses directly to environmental quality (e.g. heterogeneity in noise pollution, contaminated water sources, green space size and complexity, etc.). For example, predatory birds exposed to pollution exhibited reduced parental care behavior, an adaptive trait that directly affects fitness by influencing offspring survival (Grue et al. 1997).

Environmental quality in cities is heavily impacted by various types of pollution (i.e. environmental contamination, Agyeman et al. 2016), which can result in deleterious health effects or even lethal consequences in both wildlife and humans (Dominoni et al. 2016; Birnie-Gauvin et al. 2016; Sanders and Gaston 2018; Kunc and Schmidt 2019; Kok et al. 2023). Contaminant exposure in wildlife is associated with parasitic disease outbreaks (Murray et al. 2016; Serieys et al. 2015), behavioral differences (Brodin et al. 2013; Flahr et al. 2015; Tüzün et al. 2021), gut dysbiosis (Rosenfeld 2017), reduced fertility (Somers 2011), immune dysregulation (Serieys et al. 2018; Fraser et al. 2018), and endocrine disruption (Guillette 2000). Urban-adapted wildlife species tolerate a wide variety of anthropogenic disturbances and often display high behavioral plasticity that enables them to live in human-dominated spaces (Caspi et al. 2022) – but these adaptations may not protect against the negative impacts of living in contaminated environments (Saaristo et al. 2018). Extensive in situ experimental research exists on the impacts of pollution on mammals, wherein animals are placed in "exposure facilities" and exposed to environmental contamination, acting as sentinels for the impacts of contamination (Somers 2011). For example, one study drew air from a freeway tunnel into a laboratory vivarium to expose rats to air pollution (Patten et al. 2021). Work using this methodology has uncovered evidence of genetic mutations (Yauk et al. 2000), altered behavior (Saaristo et al. 2018), and physiological imbalances (Guo et al. 2020). Recently, studies on wild mammals as sentinels of environmental contamination have allowed researchers to assess population-wide effects (Wainstein et al. 2022). Individual-level impacts on physiology and behavior may further scale up to affect community-level processes, such as competition and predation, by altering the presence and distribution of populations (Saaristo et al. 2018). However, it is difficult to determine population- and community-level effects in an experimental setting. Therefore, knowledge on the consequences of contamination on urban-adapted mammals, and subsequent impact on population and community dynamics, remains limited.

Within urban mammal communities, carnivores are uniquely vulnerable to the health impacts of pollutants due to the biomagnification of toxins at higher trophic levels (Rodríguez-Jorquera et al. 2017). However, due to their large home range requirements, lower population densities, and sensitivity to human activity, large carnivores such as mountain lions (*Puma concolor*) and gray wolves (*Canis lupus*) are less common within urban regions (Foley et al. 2013; van den Bosch et al. 2023). Conversely, mesocarnivores have been highly successful in urban areas due to dietary and behavioral flexibilities that facilitate persistence in novel or disturbed environmental contexts (Bateman and Fleming 2012; Caspi et al. 2022). However, these traits can also expose urban mesocarnivores to unique environmental risks (Murray et al. 2016; Richards et al. 2018; Serieys et al. 2018; Shakouri and Gheytasi 2018). The impact of environmental contamination may be more apparent in synanthropic mesocarnivores such as coyotes (*Canis latrans*) and raccoons (*Procyon lotor*) due to their better ability to exploit and persist in urban environments compared to larger carnivores, which may avoid highly contaminated areas entirely due to their overlap with human activity (Marneweck et al. 2022). Due to their success across urbanization gradients, mesocarnivores may act as sentinels for environmental contamination from various sources, including agricultural pesticides (Kimber and Kollias 2000; Carpenter et al. 2014; Rodríguez-Jorquera et al. 2017), anticoagulant rodenticides (Fraser et al. 2018; Facka et al. 2024; Buckley et al. 2024), and industrial activities (Hernández et al. 2017; Brand et al. 2020; Guo et al. 2020; Aeluro and Kavanagh 2021). However, the importance of environmental contaminants as a predictor of mesocarnivore occurrence patterns within and across urban areas remains poorly understood.

The primary objective of this study was to determine the impacts of environmental contamination on wildlife activity in the Seattle-Tacoma metropolitan region, Washington, USA. In Seattle and its neighboring city Tacoma, dense human populations exist in conjunction with large-scale shipping and industrial activity. Both Seattle and Tacoma are economically significant port cities and are throughways of major interstates. Further, the region (known as the Seattle-Tacoma metropolitan area) hosts an abundance of environmental contaminant sources, such as National Priorities List sites (a.k.a. Superfund sites; sites defined by the U.S. Environmental Protection Agency as containing hazardous substances that pose risks to human health and the environment due to industrial pollution, improper waste disposal, or chemical spills Mariner et al. 1997; Abel and Stephan 2017), historic smelting operations, (Ajax and Meyer 1987), steel plants (Abel and White 2011; Sprague 2015), hazardous waste sites (e.g. asphalt facilities; (Abel and Stephan 2017), and airplane

plants (Abel and White 2011). Pollutants linked to these contaminant sources include PCBs (Vorhees et al. 1999), polycyclic aromatic hydrocarbons (PAH) (Brenner et al. 2002), heavy metals (Mariner et al. 1997), and particulate matter (Abel and White 2011). The legacy of such industrial and waste-producing sites is also long-standing; even in cases where they are removed and rebuilt into residential areas, contaminants still persist in the environment (Abel and Stephan 2017; Bramble et al. 2023). Consequently, wildlife communities in this region are likely experiencing variable contaminated landscapes, with potential consequences for biodiversity. Still, the region hosts a diverse community of native wildlife (Table 2). The Seattle-Tacoma metropolitan area is therefore a fitting case study for exploring the impacts of environmental contaminants on wildlife.

We examined the effects of contaminants on wildlife activity at two taxonomic scales: 1) the mammalian community and 2) individual carnivore species. We compared the importance of environmental contaminant risk relative to natural land cover and human population density, two factors known to affect urban wildlife populations. To address our objectives, we analyzed camera trap data from across our study area. Our overarching hypothesis was that the negative fitness impacts of environmental contaminants would scale up to influence population- and community-level dynamics, resulting in decreased wildlife activity at highly contaminated sites. At the community level, environmental contamination can directly affect sensitive species and indirectly alter competitive or trophic dynamics (Rohr et al. 2006). Species that are less tolerant of contaminated and/or developed environments may either be unable to persist or behaviorally avoid these sites, leaving only disturbance-tolerant species (Kidd et al. 2014; Araújo et al. 2016). Conversely, sites with higher natural land cover may have fewer disturbances and provide more resources to support a heterogenous and diverse community (Gallo et al. 2017; Parsons et al. 2019). We therefore predicted that areas with a higher proportion of natural land cover and lower environmental contaminant risk would have greater relative mammalian diversity, richness, and evenness compared to sites with less natural land cover and those with higher environmental contaminant risk. Further, environmental contaminants may disproportionately affect carnivore populations because they are long-lived, occupy higher trophic levels, and have lower reproductive rates than other mammals (Rodríguez-Jorquera et al. 2017; Suraci et al. 2021). These traits increase their vulnerability to the cumulative impact of biomagnification and bioaccumulation, which are linked with increased physiological stress and reduced reproductive success (Birnie-Gauvin et al. 2016; Parker et al. 2023), thus potentially lowering local population densities. In addition, individuals may behaviorally avoid highly contaminated or highly urbanized areas within their home ranges (Araújo et al. 2016; Saaristo et al. 2018; Parsons et al. 2019). We therefore predicted that higher detection rates of carnivore species would occur in areas with higher proportion of natural land cover and lower contaminant risk.

Methods

We analyzed camera trap data with generalized linear mixed models (GLMMs) and generalized linear models (GLMs) to determine whether three spatial covariates – environmental contaminant risk, human population density, and proportion of natural land cover – were associated with a) mammalian community metrics (diversity, richness, and evenness) and b) detection rates (i.e., activity) of carnivores.

Study area and design

Cameras were deployed as part of the Seattle Urban Carnivore Project (Seattle, Washington), and the Grit City Carnivore Project (Tacoma, Washington) (total $n = 33$ cameras and $n = 41$ cameras, respectively; Fig. 1). These cameras were deployed along urban-exurban gradients following protocols from the Urban Wildlife Information Network (UWIN) camera study design protocol (Magle et al. 2019). In brief, cameras were placed in parks or green spaces along an urbanization gradient, which was defined by impervious surface cover relative to other sites in the study area. In both Seattle and Tacoma, multiple transects originated near the urban core of the city and radiated through surrounding suburban, exurban, and rural regions in different directions (Fig. 1). Along the transects, sites were chosen based on the project team's ability to obtain permissions, with the secondary goal of encapsulating a variety of potential wildlife habitat including but not limited to parks, and golf courses, and cemeteries. Sites were least 1 km apart to ensure site independence. The specific camera location within each site was randomized to the best of our ability, while maximizing the potential to capture wildlife visiting the camera location (e.g. facing an animal trail) and minimizing risk of theft or vandalism (e.g. hidden from passersby). Cameras were mounted to trees or other solid structures at roughly knee-height. Camera transects spanned the cities of Seattle and Tacoma as well as surrounding cities and towns in King and Pierce Counties, including Bothell, Redmond, Tukwila, Renton, Auburn, Puyallup, and Eatonville (Fig. 1).

Cameras were deployed for a minimum of 4 weeks (~ 28 days) in each season: spring (April), summer (July), autumn (October), and winter (January). Cameras were

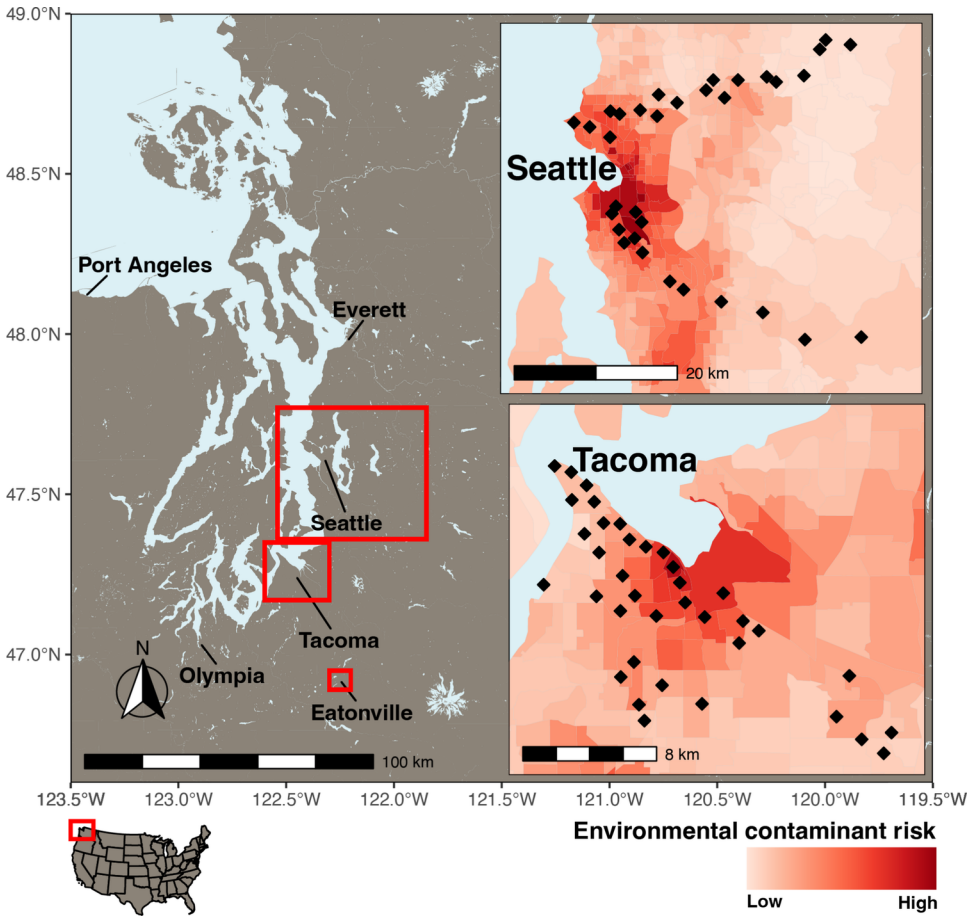

Fig. 1 A map of camera locations in Seattle (top right) and Tacoma (bottom right). In the left panel, dark gray coloring indicates land and light blue coloring indicates water. On the right, census tracts are filled in with a study-area-derived contaminant risk scale (with light pink representing least risk and dark red representing most risk) based on the Washington Environmental Health Disparities Map. Black diamonds indicate camera trap locations. Four sites (located in Eatonville, WA), indicated by the smallest red bounding box on the left side of the map, are not included in the right-hand map but are included in the analysis as part of the Tacoma transect

checked and memory cards swapped after 2 weeks. In cases of theft or vandalism, cameras and memory cards were replaced. Cameras were deployed for a total of 5 seasons (January 2019-January 2020). The UWIN study design protocol during this time period included deployment of fatty acid scent discs paired with each camera trap, which are unlikely to impact mammal detection rates at the temporal and spatial scales of this study (Fidino et al. 2020). Images were identified to the species level by trained staff, students, and volunteers. All images were reviewed by 2 observers; in cases where identification differed between observers, photos were triple reviewed by project staff.

Spatial covariates

All spatial analyses were done in the R statistical software (v4.4.2; R Core Team 2024). For our natural land cover covariate, we calculated proportions for each land cover type using data from the National Land Cover Database (NLCD) in 2019 (Table 1; Dewitz 2021; Haight et al. 2023). For human population density, we used openly available data from the University of Wisconsin (https://silvis.forest.wisc.edu/data/housing-block-change/); this layer was calculated at the census block level using U.S. census data from 2020 (Table 1). Data from census blocks in our study area were then rasterized to a 30 m resolution using the R packages *sf* and *terra*. Values of both natural land cover and human population density were averaged around each camera site in a 1 km buffer using the R package *terra* (Gehrt et al. 2009; Magle et al. 2016).

To quantify environmental contaminant risk, we used data from The Washington Environmental Health Disparities Map, which developed publicly available indices estimating cumulative impacts of environmental pollution burden experienced in Washington state communities (Min et al. 2019, 2021); https://fortress.wa.gov/doh/wtnibl/WTNIBL/). The Washington Health Disparities Map and similar datasets (e.g. CalEnviroScreen in California) are widely used in urban planning, human health, and ecological studies (Cushing et al. 2015; Nardone et al. 2020; Min et al. 2021; Estien et al. 2024). In this map, pollution burden is divided into two cumulative variables: environmental exposures and contaminant risk (contaminant risk is termed "environmental effects" in Min et al. 2019 and Min et al. 2021, but we renamed this variable for clarity). In the Washington Environmental Health Disparities Map, environmental exposures represents cumulative threat based on

Table 1 Descriptions and sources of variables in our analysis, including individual indicators that make up the contaminant risk variable. Descriptions of contaminant risk and indicators are from Min et al. 2019

Variable name	Description	Source
Natural land cover	Total proportion of all non-developed and non-water cover types within the study area: evergreen temperate forest, deciduous temperate forest, forest mix, temperate shrubs, temperate grasses, wetlands	National Land Cover Database 2019 (Dewitz 2021)
Human population density	Number of humans per square kilometer, calculated for each census block	Silvis Lab at University of Wisconsin (data from American Community Survey)
Contaminant risk	Represents cumulative risk based on proximity to sites with adverse environmental quality (i.e., sources of contamination). Values of all contaminant risk indicators (below) scaled within our study sites and averaged	Min et al. 2019 (termed "environmental effects")
Lead risk	Estimated presence of lead in housing within census tract based on total number of houses and year of construction	Min et al. 2019 (data from American Community Survey)
Proximity to hazardous waste generators and facilities	Count of all commercial hazardous waste treatment, storage, and disposal facilities (tracked under the Resource Conservation and Recovery Act) within 5 km of average resident in a block group, divided by distance and calculated as population-weighted average in each census tract	Min et al. 2019 (data from EJSCREEN)
Proximity to Superfund (National Priorities List) sites	Count of sites proposed and listed on the National Priorities List – areas where hazardous waste has been historically spilled or dumped – within 5 km of average resident in a block group, divided by distance and calculated as population-weighted average in each census tract	Min et al. 2019 (data from EJSCREEN)
Proximity to facilities with release of highly toxic substances	Count of facilities with highly toxic substances (tracked through mandated Risk Management Plans with the Environmental Protection Agency), within 5 km of average resident in a block group, divided by distance and calculated as population-weighted average in each census tract	Min et al. 2019 (data from EJSCREEN)

direct measurements of common pollutants (e.g. particulate matter). Contaminant risk represents cumulative threat of adverse environmental qualities that are not direct exposures, but still pose potential health risks (Table 1, Figs. 4, 5, and 6). To re-calculate these cumulative variables for our study area, we used the indicators and methods from Min et al. (2021), which quantified projected pollution burden in human communities. In brief, values of each index were downloaded from the Washington Environmental Health Disparities Map website and converted to spatial data in R using census tract GEOIDs. Each individual indicator was calculated at a 1 km buffer around each camera trap site using the R packages *terra*. Indices were then averaged within their group to create the final "environmental exposure" and "contaminant risk" composite variables for the entire dataset. We excluded one indicator from Min et al. 2021 from our contaminant risk variable – wastewater discharge from treatment plants – because data was missing for over half of our census tracts. We then scaled each composite variable based on indicator values at all study sites, such that a score of 0 represents no burden, and a score of 1 represents the highest burden. This scaling was done separately for the metro-area dataset and each city-specific dataset. Each variable therefore represents the average exposure or risk experienced around the site in relation to other sites in the dataset to be analyzed (Figs. 4, 5, and 6). We found that, at our study sites, environmental exposure and contaminant risk were strongly correlated ($r = 0.83$, Fig. 4). We therefore chose to proceed with only contaminant risk, because it approximates proximity to landscape features (i.e. industrial facilities causing contamination) that have a direct influence on habitat quality

(Table 1). Prior to running models, we assessed variance inflation factors for these and all final variables using the *regclass* package in R, which indicated low multicollinearity (VIF < 2 Petrie 2020).

Data analysis

We used GL(M)Ms to evaluate the effects of our spatial covariates on mammal community diversity (GLMs) and carnivore species activity (GLMMs). Analyses were restricted to sites with 3 or more active seasons and at least 18 active camera-trap nights per season (Magle et al. 2016). Photos within 30 min of each other were removed to ensure temporal independence between detections (Guo et al. 2017). For the mammal community diversity model, we removed all non-mammals as well as rodents smaller than squirrels (*Sciurus* spp.) from the dataset, as consistent capture of small mammals with camera traps is unreliable at distances greater than 1 m (Ortmann and Johnson 2021). We also removed domestic dogs (*Canis familiaris*), cats (*Felis catus*), and humans.

Using our GLM(M) framework, we modeled both mammal community diversity and detection rates of carnivores within and across the two focal cities (Table 2). We modeled the two cities together ("metro-area model") as well as separately to investigate how our selected spatial covariates were affiliated with our response variables both across the metro area and within each focal city transect (Table 2). We used detection rates as a proxy for activity at each site (often referred to as relative abundance) (Lovell et al. 2022; Sievert et al. 2023). We used the glmmTMB package in R to fit our models (Avrin et al. 2021). We included season as a variable due to its potential role in variation of wildlife activity throughout the year (e.g. dispersal, mating seasons). To account for non-independence among seasons sampled at the same station, site was included as a random effect in all models for the carnivore detection models. We scaled all continuous variables with a mean value of 0 and standard deviation of 1 within the model. GLMMs were built for each species of interest, with species detections per site per season as the response variable (Lovell et al. 2022; Sievert et al. 2023). We determined that the negative binomial distribution was the best-fitting discrete distribution for each species using the *car* and *MASS* packages in R (Ripley et al. 2013; Gorjanc et al. 2024). Focal city, contaminant risk, natural land cover, human population density, and season were included as fixed effects in the "metro-area" model. In individual city models, all variables except focal city were included. We used an offset on the log scale to account for variation in the number of sampling occasions at each site (i.e., the number of days the camera was operational during a given season). Model diagnostics were performed using the *dharma* package in R (Hartig and Hartig 2022).

We fit GLMMs for 9 individual carnivore species in our study area (Table 3), but due to data limitations (i.e. not enough detections for models to converge) for 6 of the species, our results focus on 3 common mesocarnivore species in our study area: raccoons, coyotes, and Virginia opossums (*Didelphis virginiana*). Raccoons are highly synanthropic, able to exploit anthropogenic resources amidst urban habitat fragmentation (Graser et al. 2012). Coyotes are successful urban exploiters that have witnessed rapid geographic expansion, establishing populations in a cadre of biomes and ecosystems throughout the North American continent (Grigione et al. 2014; Murray et al. 2016; Sugden et al. 2020). Lastly, while they are taxonomically marsupials, Virginia opossums (hereafter opossums) occupy similar trophic positions to sympatric mesocarnivores, and are persistent across urbanization gradients in North American cities (Wang et al. 2015; Worsley-Tonks et al. 2020; Buckley et al. 2024).

To model mammal community diversity, we calculated Shannon's diversity index, species richness, and Pielou's evenness for the mammal community at each site/season combination using the *vegan* package in R (Oksanen et al. 2013). We then averaged these values across seasons. A GLM was built and fit to a Gaussian distribution for Shannon's diversity and Pielou's evenness, and a Poisson distribution for species richness. No site random effect was included since all community metrics were calculated for 1 data point per site. All other covariates were the same as the individual carnivore species models, and we built metro-area and individual focal city models. Our mammal community included small, medium and large mammal species, ranging from rodents to ungulates to carnivores (17 total species; Table 3).

Results

We collected 5 seasons of data across 74 sites. Deployment periods for each season averaged 35 days (range: 18–51). Aside from small rodents, domestic animals, and humans, 17 mammal species were detected throughout the study period (Table 3). The final dataset included 13,689 camera trap days and 16,226 total independent detections of our focal species (Table 3). We had 1,203 independent detections of coyotes (422 in the Seattle transects, 781 in the Tacoma transects), 2,503 independent detections of raccoons (580 in the Seattle transects, 1,923 in the Tacoma transects), and 911 independent detections of opossums (148 in the Seattle transects, 763 in the Tacoma transects) (Table 3).

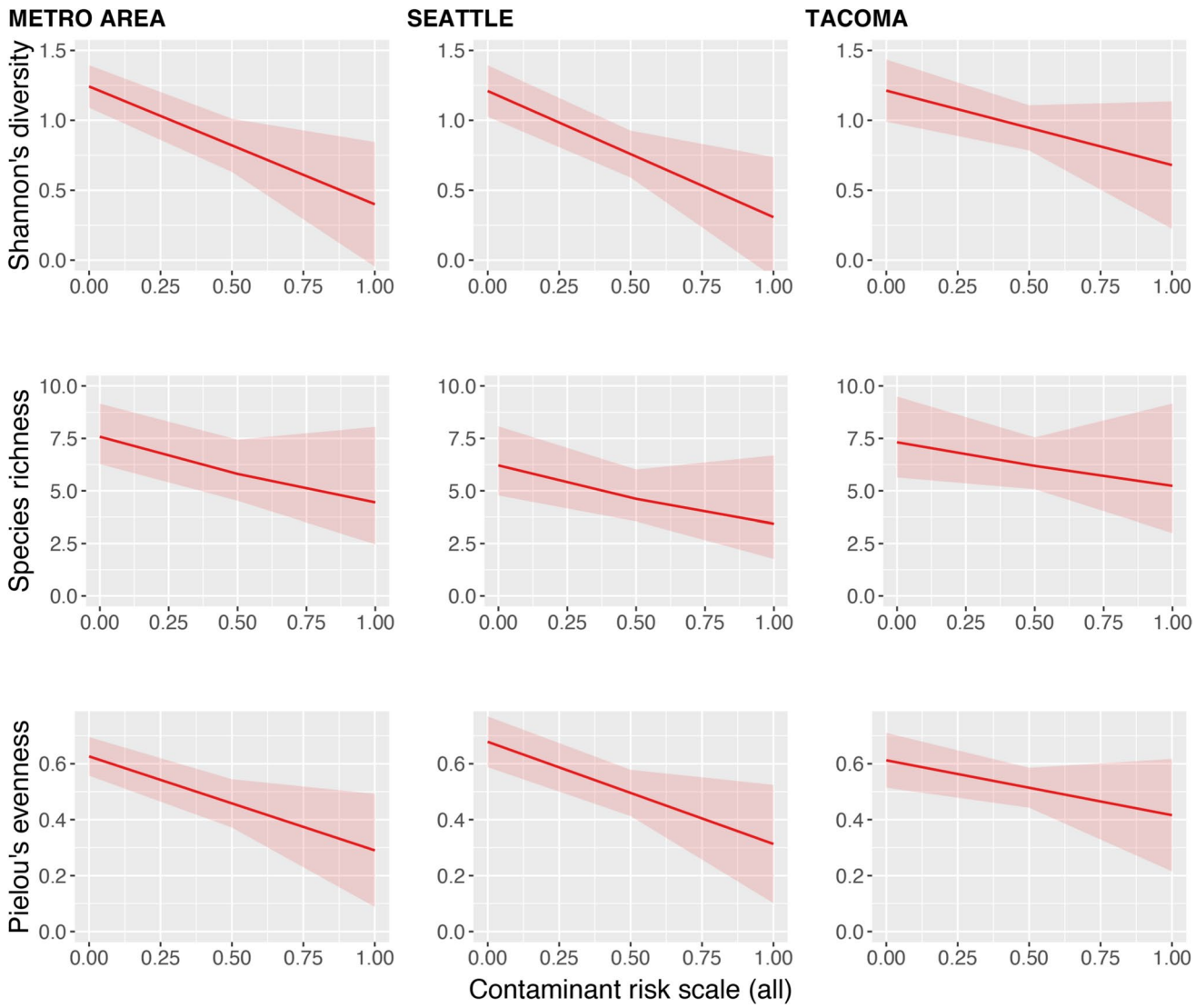

Fig. 2 Marginal effect plots of generalized linear models for Shannon's diversity (first row), species richness (second row), and Pielou's evenness (third row) model results. Plots show contaminant risk on the x-axis and each respective community metric on the y-axis, with results depicted for the metro-area model (left), the Seattle-only model (center), and the Tacoma-only model (right). Light red fill indicates confidence interval

All results are reported as incidence rate ratios on the logarithmic scale (i.e. confidence intervals that cross 1 are insignificant), with an alpha level of 0.05.

Mammal community metric models

Mammal community diversity, as measured by Shannon's diversity index, decreased with contaminant risk in the metro-area model ($\beta = -0.11$; 95% CI = −0.21–0.01; $p = 0.027$; Fig. 2; Table 4); natural land cover and human population density had no significant impact on diversity. In the Seattle model, diversity also decreased with contaminant risk ($\beta = -0.20$; 95% CI = −0.32, −0.07; $p = 0.002$; Fig. 2; Table 4), while in Tacoma, diversity was unaffected by our spatial covariates (Table 4). Species richness was not associated with any of our spatial covariates across all models (Fig. 2), but in our metro-area model, species richness was higher in Tacoma than in Seattle ($\beta = 1.28$, CI = 1.05, 1.07, $p = 0.015$; Table 5). Similarly to Shannon's diversity, Pielou's evenness was negatively associated with contaminant risk in the both-cities model ($\beta = -0.06$, CI = −0.10, −0.01, $p = 0.008$; Table 6) and in the Seattle model ($\beta = -0.08$, CI = −0.14, −0.02, $p = 0.011$; Table 6), but not in the Tacoma model; all other spatial covariates in the evenness models were insignificant (Fig. 2).

Mesocarnivore species activity models

Models for large carnivores (black bear [*Ursus americanus*], mountain lion [*Puma concolor*]) and mustelids (river otters [*Lontra canadensis*], weasels [unknown species]) did not converge due to lack of data. While the metro-area model for bobcats (*Lynx rufus*) converged, we had only 31 total bobcat detections, and neither individual-city model converged (Table 7). For striped skunks (*Mephitis mephitis*), the metro-area and Tacoma models converged, but there was only a single skunk detection in the Seattle dataset, compared to 187 skunk detections in Tacoma (Tables 2 and 7). Hence, we did not include bobcats and striped skunks in further analyses, and moved forward with models for coyotes, raccoons, and opossums.

Overall, the strength and direction of relationships among spatial covariates and mesocarnivore detection rates differed across species in our metro-area model (Fig. 3). In our metro-area model, coyotes were significantly more active in areas with lower contaminant risk ($\beta = 0.47$; 95% CI = 0.28, 0.80; $p = 0.005$). In contrast, raccoons and opossums had no detectable response to contaminant risk (raccoons: $\beta = 1.42$; 95% CI = 0.94, 2.14; $p = 0.093$; opossums $\beta = 0.64$; 95% CI = 0.32, 1.25; $p = 0.190$). Detection rates of mesocarnivores were also not affiliated with human population density or natural land cover in our metro-area model (Table 6). Because the fixed effect for city was a significant predictor for species detections (coyotes: $\beta = 2.65$, 95% CI = 1.10,6.40, $p = 0.030$; raccoons: $\beta = 4.11$, 95% CI = 1.93, 8.72, $p = 0.001$; opossums:$\beta = 6/09$, 95% CI = 1.88, 19.76, $p = 0.003$), we subsequently evaluated detections within each city's transect. In our Seattle models (Table 8), contaminant risk remained a significant negative influence on coyote activity ($\beta = 0.18$; 95% CI = 0.06, 0.47; $p = 0.001$; Fig. 3); raccoon activity increased with both contaminant risk ($\beta =$

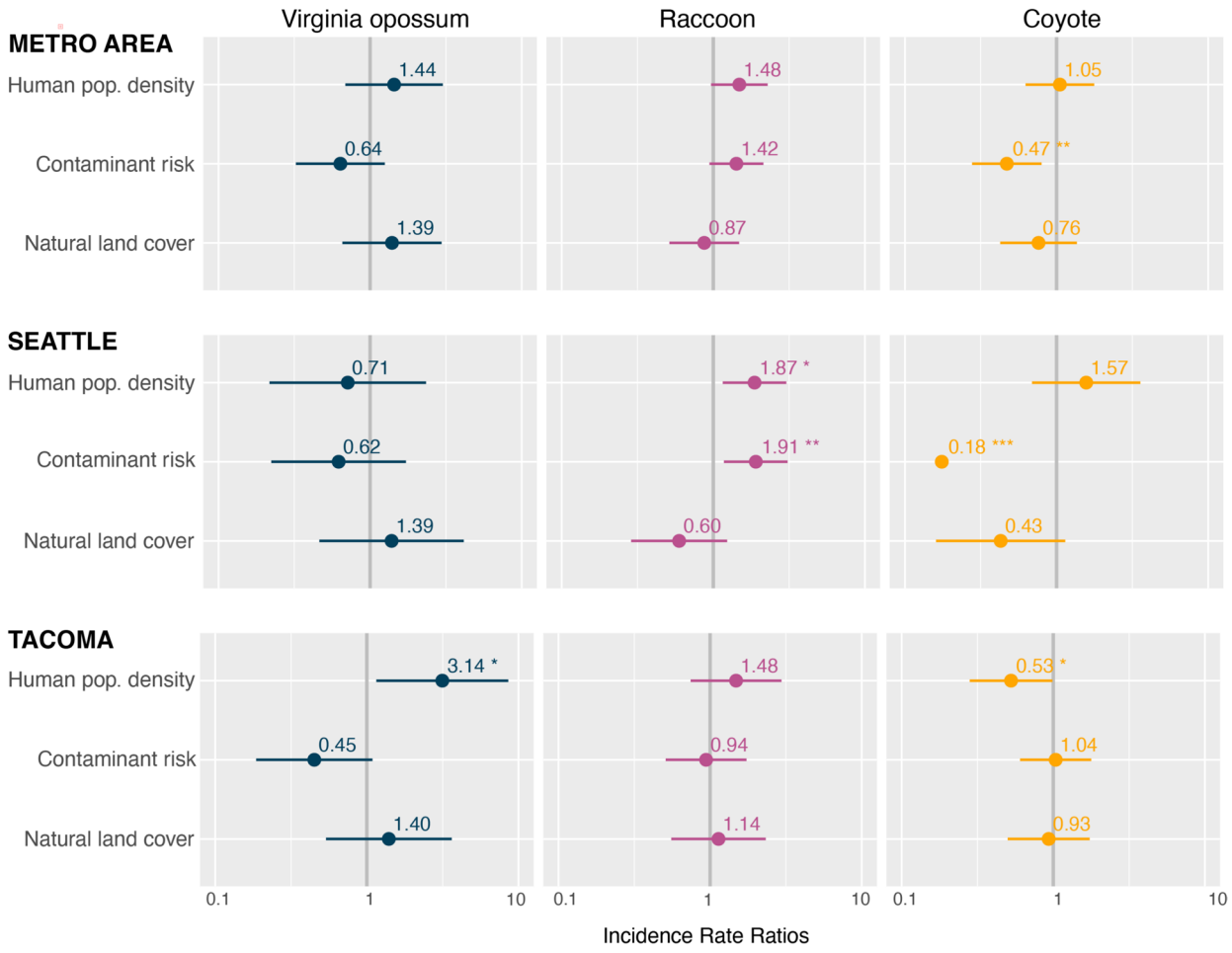

Fig. 3 Forest plot of coefficient estimates for species count generalized linear mixed models in the Seattle-Tacoma metropolitan area, reported as incidence rate ratios on the log scale, with a dark gray vertical line representing the intercept. Panels shown are the metro-area models (top), Seattle models (center), and Tacoma models (rig). Asterisks indicate significant results (* for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$)

1.91; 95% CI = 1.18, 3.09; $p = 0.009$) and human population density ($\beta = 1.87$; 95% CI = 1.15, 3.03; $p = 0.011$); and opossum activity was unaffected by any of our spatial covariates. In our Tacoma models (Table 9), human population density was negatively associated with coyote activity ($\beta = 0.53$; 95% CI = 0.28, 0.99; $p = 0.045$) and positively associated with opossum activity ($\beta = 3.14$; 95% CI = 1.15, 8.56; $p = 0.025$), while none of our spatial covariates predicted raccoon activity.

Discussion

While the impacts of environmental contamination on physiology, behavior, and survival may not be immediately apparent in urban-adapted wildlife populations, these latent factors can indeed influence species distributions and restructure communities (Birnie-Gauvin et al. 2016, Huang et al. 2018, Murray et al. 2019; Schell et al. 2020). In this study, we investigated the influence of environmental contaminants on mammalian diversity and activity of common mesocarnivores in our study area by merging census-level data on human population density, environmental contaminant risk, and natural land cover with camera-trap surveys. Evidence from this study suggests that environmental contamination is an important component of habitat quality for the broader mammal community, with community diversity and community evenness showing negative relationships with contaminant risk. However, the impact of environmental contamination on the mesocarnivore community seems to be species-specific, with coyote activity showing pronounced negative responses to environmental contamination relative to other mesocarnivore species. Indeed, contaminant risk affected coyote activity more strongly than natural land cover or human population density did. Based on their avoidance of highly contaminated regions in our study area, coyotes may serve as sentinels for urban environmental quality.

Contaminant risk detrimentally affected mammal community diversity and evenness, supporting our predictions. Both Shannon's diversity index and Pielou's evenness index decreased as contaminant risk increased in the metro area model and in the Seattle model. Conversely, species richness was not associated with any of our variables. These results suggest that while the number of species remains stable with increasing contaminant risk, the composition and evenness of the mammal community may be an earlier indicator of the effects of contamination. This may be for several reasons. First, habitats with high contaminant risk may present additional challenges such as differences in resource availability and inhibition of dispersal through physical barriers such as large buildings (Gehrt et al. 2009; Magle et al. 2016; Wang and Cao 2017). Second, contaminated habitats may directly disrupt biological processes, such as reproduction (Huang et al. 2018), development (Murray et al. 2019), and immune function (Eccles et al. 2021; Serieys et al. 2018). As suggested by our results among mesocarnivores, species may have different levels of sensitivity towards the cumulative impacts of contamination assessed in our study (Saaristo et al. 2018), leading to variation in how species respond to these indirect and direct pressures, and impacting community composition and diversity (Seebacher and Franklin 2012; Wingfield 2013; Aronson et al. 2017; Hassell et al. 2021).

In our models, contaminant risk emerged as a significant predictor of coyote activity across the metro area and within our Seattle transect. While not a direct measurement of pollutants, contaminant risk is a direct reflection of landscapes experienced by wildlife as well as a proxy for a variety of environmental pollutants (Min et al. 2019, 2021). In our study area, areas with higher environmental contamination generally encompass industrial or previously industrialized zones (Abel and White 2011; Kondo et al. 2022). Along with higher pollution levels, these areas typically have less vegetation, myriad disturbances (e.g. noise and light pollution, truck activity), lower municipal services, industrial waste sites, and abandoned buildings (Silva et al. 2021; Coscia et al. 2024). Our results suggest coyotes may be more sensitive to environmentally contaminated areas than other mesocarnivores. We suggest several reasons for this finding. First, coyotes may be impacted by non-modeled characteristics of environmentally contaminated areas. Areas with greater environmental contamination may be more difficult to navigate, because industrial areas have abundant linear infrastructure (e.g., busy roadways, large buildings; (Wang and Cao 2017; Azhari et al. 2018), which may inhibit individuals from accessing other habitats (Kreling et al. 2024). Further, coyote activity may be driven by other factors that are linked to contamination, but are not included in our models such as noise pollution (Collins et al. 2022) and lower prey diversity as reflected by our community model results. Lastly, coyotes may experience the fitness impacts of contamination more than subordinate mesocarnivores (Rodríguez-Estival and Mateo 2019; Parker et al. 2023). Coyotes play a crucial role in urban ecosystems, often occupying the role of apex predator in the absence of large carnivores (Ellington and Gehrt 2019). Due to their higher trophic level, the effects of biomagnification may reduce coyotes' ability to persist in highly contaminated areas compared to raccoons and opossums (Rodríguez-Estival and Mateo 2019; Parker et al. 2023). Mesocarnivores have broadly been indicated as increasingly important sentinels for pollution, disease, and global change (Aguirre 2009; Marneweck et al. 2022; Parker et al. 2023; Cepeda-Duque

et al. 2023; Clark-Wolf et al. 2024). While additional research is needed to understand the mechanisms by which coyotes avoid highly contaminated areas and the degree to which they are physiologically impacted by contamination, our results suggest that coyotes are a good candidate for a sentinel species in studies investigating the impacts of pollution and overall environmental quality on wildlife.

In contrast to coyotes, raccoon activity was positively associated with contaminant risk and human population density, though only in our metro-area and Seattle models. In Tacoma only, none of our spatial covariates impacted raccoon activity. Raccoons may therefore not be as sensitive to the "negatives" of high-contaminant-risk areas, and may even be attracted to some of the attributes associated with contamination (e.g. shelter in abandoned industrial sites, subsidies from large-scale industrial food waste) (Bateman and Fleming 2012; Hansen et al. 2020). Another potential explanation is that since coyotes avoid highly contaminated areas, raccoons may select them to avoid predation by or competition with coyotes. However, while there is some evidence for temporal avoidance of coyotes by raccoons (Moura et al. 2022; Malhotra et al. 2022), research has shown that raccoons generally exhibit a lack of spatial avoidance (Gehrt and Prange 2007; Chitwood et al. 2020; Avrin et al. 2023). Instead, highly contaminated areas may act as an ecological trap for raccoons, in which individuals preferentially select for degraded habitats due to attractive features such as novel foods, despite negative physiological consequences (Battin 2004; Huang et al. 2018; Parker et al. 2023). Follow-up studies could include assessment of organismal impacts or population dynamics of raccoons in contaminated habitats to determine whether they are indeed "trapped" by these low-quality habitats. While raccoons are often positively associated with human development, as supported by our results in Seattle, this relationship is not consistent across our study area. Raccoons rely heavily on vertical territory that coyotes are not able to access (Smith and Endres 2012; Gámez and Harris 2022), and often exploit anthropogenic subsidies and waste as resources (Schulte-Hostedde et al. 2018). Therefore, perhaps the type of human development matters (Poisson et al. 2024): highly urbanized areas that are primarily residential in nature may not provide adequate refugia or food for raccoons compared to those in industrialized zones, which may present the same amount of natural land cover as dense residential areas (and therefore go unnoticed in studies that do not differentiate between the two) but offer different resources. Opossums are similarly highly synanthropic and share niches with raccoons, including the use of vertical space (Ginger et al. 2003; Voss and Jansa 2021; McTigue et al. 2024). The only significant predictor for opossum activity across our models was human population density in Tacoma, suggesting that unmodeled variables such as prey availability may be driving opossum activity. Future research is needed to understand interactions within the mesocarnivore guild in relation to environmental contamination, but we suggest that raccoons and opossums may simply be selecting for habitats where coyotes are less likely to be due to diverging resource and refugia needs (Hayes Hursh et al. 2023).

The distribution of our variables in both cities across our study sites was similar (Figs. 7 and 8), but responses were different across our models. The differences in significant findings between our metro-area, Seattle, and Tacoma models suggest variability in the impact of contaminant risk across different contexts and scales, and indicate that other factors may be playing a role in mediating wildlife populations and communities between Seattle and Tacoma. Our study did not consider city or neighborhood age or the relative difference in population size between the two cities. Studies across the globe suggest that neighborhood and city age impact biodiversity, but the direction of this trend is not always consistent (Aronson et al. 2014; Norton et al. 2016; Aznarez et al. 2023; Haight et al. 2023). The population size of Seattle is over three times that of Tacoma (although population density at our study sites were similar between the two cities; Fig. 8); however, many cameras in the Seattle transects were in suburban cities and unincorporated regions. Although Seattle and Tacoma are considered part of the same metropolitan area, sharing bus lines, commuters, and an international airport, our results suggest that these cities and their surrounding suburbs are distinct social-ecological systems. Further, our Tacoma study site supports both a richer large carnivore community and a richer overall mammal community than our Seattle study site, potentially influencing dynamics in our metro-area models (Table 1). Lastly, natural landcover and contaminant risk exhibited collinearity at our Tacoma sites (Fig. 4), which may have impacted our results, though VIF was low (Dormann et al. 2013). Future studies using a twin- or multi-city approach should incorporate various proxies for city age, structure, and size to interrogate how varying developmental histories of urban centers within the same biome may result in divergent ecological outcomes (Fidino et al. 2019, 2021).

While the interconnectedness of human societies and urban ecosystems was not always recognized, recently, social-ecological variables have been more commonly incorporated into urban wildlife studies (Magle et al. 2016, 2021; Herrera et al. 2022; Aznarez et al. 2023; Fidino et al. 2024). Much of this literature has focused on the impact of socioeconomic metrics on wildlife, wherein neighborhoods with higher income generally have higher levels of biodiversity and environmental quality (Leong et al. 2018; Chamberlain et al. 2019; Magle et al. 2021). Similarly, variation in urban environmental quality is

often demarcated by societal inequity and structural injustices, such as political power and socioeconomic disparities (Morello-Frosch and Lopez 2006; Cushing et al. 2015; Wright 2021). These injustices and inequities have led to uneven pollution burdens that disproportionately impact humans and our surrounding ecosystems (Jesdale et al. 2013; Yearby 2020; Lane et al. 2022; Swope et al. 2022; Shkembi et al. 2024). Decades of research have shown that ethno-racial minority groups in the United States disproportionately experience effects of environmental hazards such as water pollution, noise pollution, and insufficient sanitation services, with reduced while having access to fewer environmental amenities such as tree canopy and green space (Pastor et al. 2005; Dai 2011; Mascarenhas et al. 2021; Estien et al. 2024). Thus, both humans and wildlife experience differing exposure to pollution as a result of these legacies of injustice (Swope et al. 2022), which has consequences for disease vulnerability, behavior, and long-term mental and physical well-being (Krieger et al. 2020; Levin et al. 2021; Lee et al. 2022). Our paper adds to an accumulating body of evidence that these disproportionately degraded environments have downstream consequences on wildlife and community ecology (Murray et al. 2022; Wood et al. 2024; Estien et al. 2024).

Here, we provide another social-ecological metric that is a more direct representation of habitat quality and may provide additional granularity for urban wildlife biologists seeking to investigate social-ecological phenomena. While this study focused on overall contaminant risk and population-level analyses, future work could isolate specific pollutants that may inform the probability of wildlife presence. Data from our contaminant risk variable were collected at relatively broad spatial and temporal scales, but fine-scale spatial and temporal variances in pollution are known to exist (Caubel et al. 2019). For example, a recent study in Seattle found that epiphytic moss samples from neighborhoods primarily populated by people of color had elevated heavy metals concentrations (Kondo et al. 2022). Future studies could therefore incorporate site-specific data on environmental contaminants via soil samples, air quality monitors, or other fine-scale measurements. However, to fully understand how contamination impacts urban wildlife, it will be essential to further investigate the organismal and fitness consequences of pollution exposure and their projections to population-level processes.

Appendix

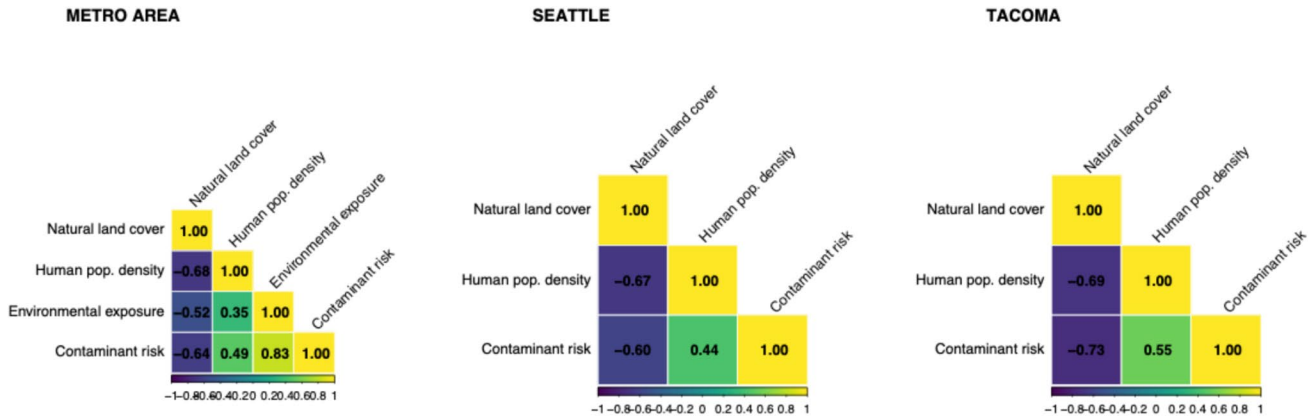

Fig. 4 Correlation plot of variables used in sin this study. Numbers represent Spearman's correlation coefficient for each relationship, with the color gradient ranging from -1 (purple) to 1 (yellow). The leftmost panel shows correlations between all variables in our metro-area model: natural land cover, human population density, and environmental contaminant risk. Correlations are also shown between all variables and the environmental exposure cumulative variable we planned to use in our analysis, which indicates direct measurements of pollutants and was removed from the model due to high correlation with contaminant risk. The center (Seattle) and right (Tacoma) panels show correlations between variables used in our analysis (natural land cover, human population density, and contaminant risk)

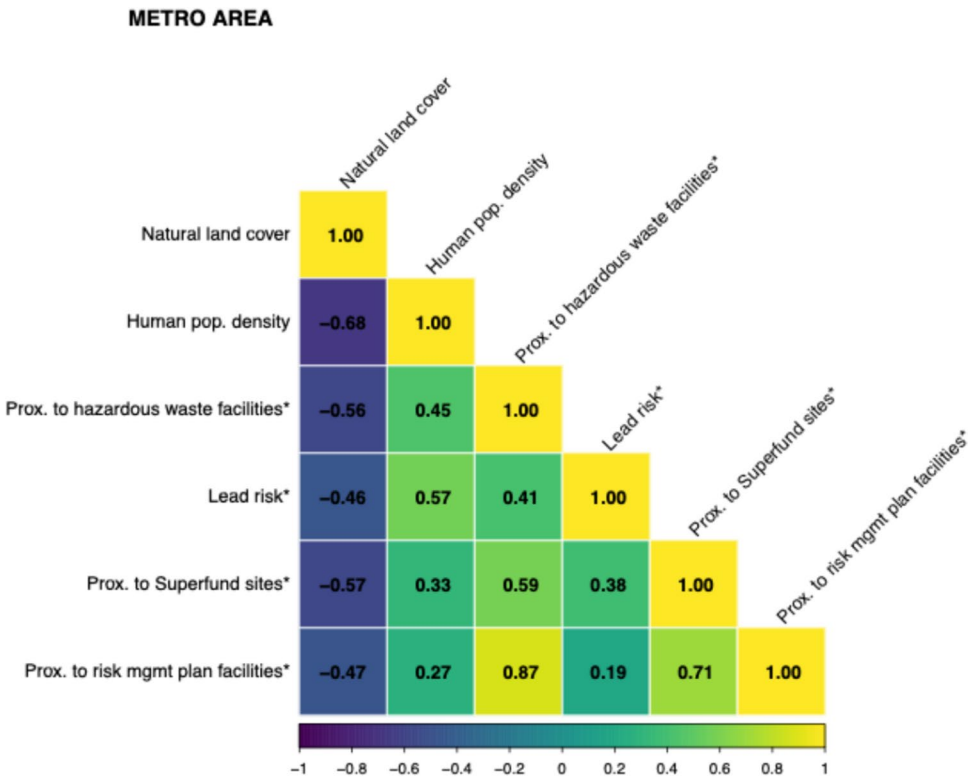

Fig. 5 Correlation plot of variables in the metro area-models, but with individual contamination risk indicators (that together make up the contaminant risk variable). Numbers represent Spearman's correlation coefficient for each relationship, with the color gradient ranging from -1 (purple) to 1 (yellow). Asterisks indicate the indicators that make up the contaminant risk variable: proximity to hazardous waste facilities, lead risk, proximity to Superfund sites, and proximity to risk management plan (toxic release) facilities. Correlations are also shown between each individual indicator making up the contaminant risk variable and the 2 other variables in the study: natural land cover and human population density

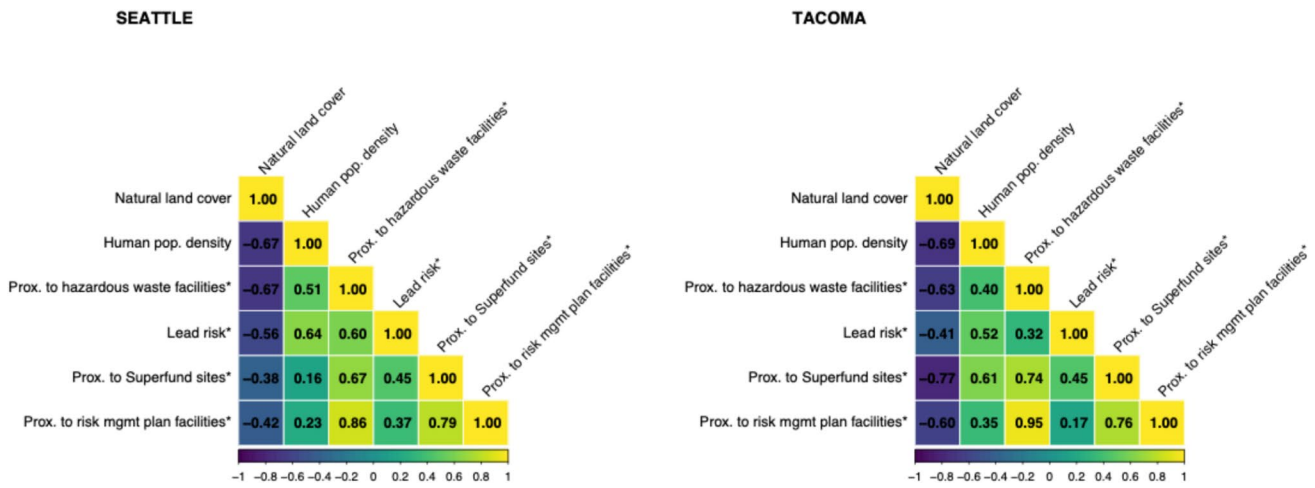

Fig. 6 Correlation plot of variables in the Seattle models (left) and Tacoma models (right), but with individual contamination risk indicators (that together make up the contaminant risk variable). Numbers represent Spearman's correlation coefficient for each relationship, with the color gradient ranging from -1 (purple) to 1 (yellow). Asterisks indicate the indicators that make up the contaminant risk variable: proximity to hazardous waste facilities, lead risk, proximity to Superfund sites, and proximity to risk management plan (toxic release) facilities. Correlations are also shown between each individual indicator making up the contaminant risk variable and the 2 other variables in the study: natural land cover and human population density

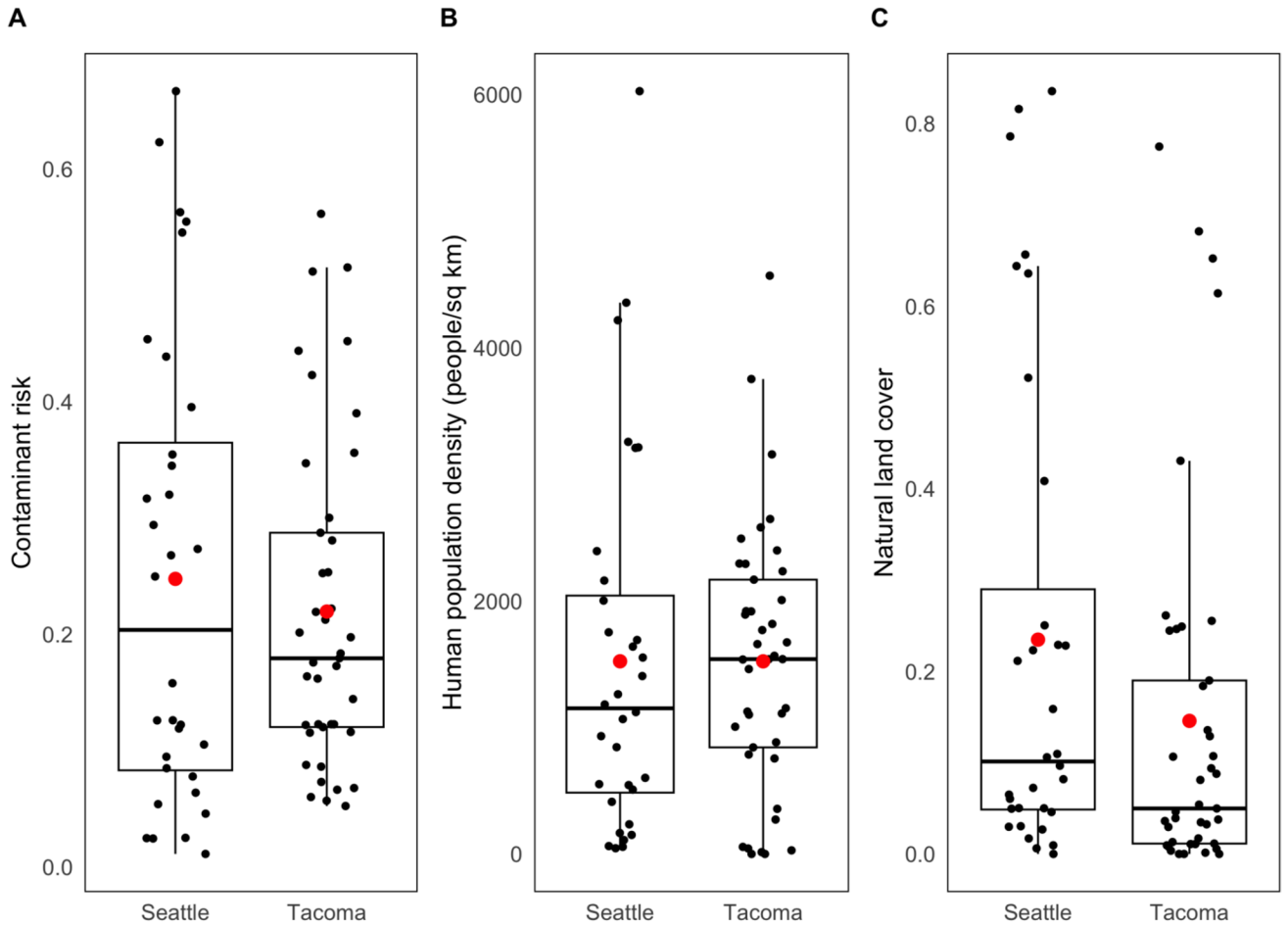

Fig. 7 Boxplots of site values for environmental risk (**A**), population density (**B**), and natural land cover (**C**), plotted by city. Red dots represent means; black dots represent camera trap sites

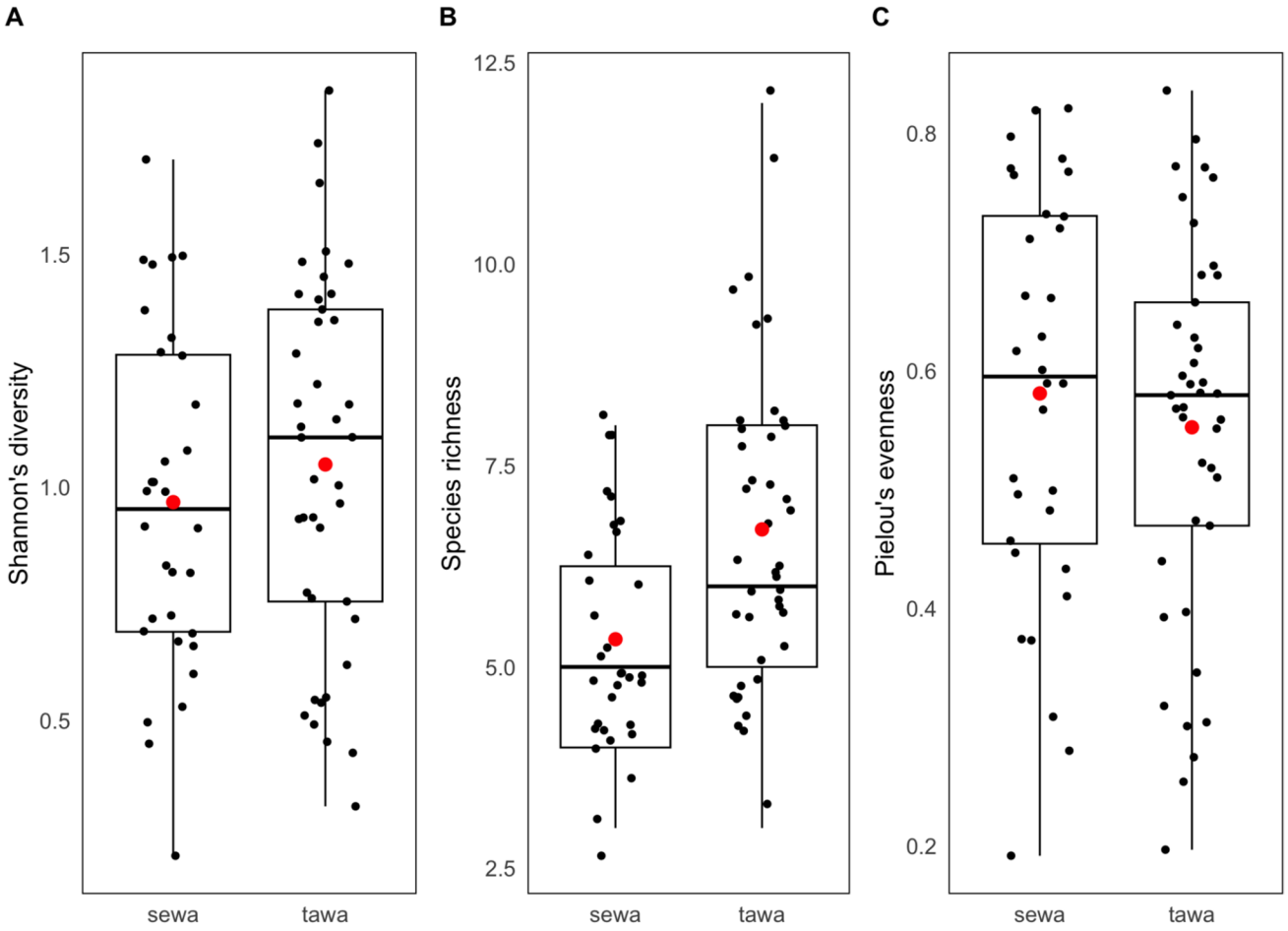

Fig. 8 Boxplots of raw data for Shannon's diversity (**A**), species richness (**B**), and Pielou's evenness(**C**), plotted by city. Red dots represent means; black dots represent sites

Table 2 Structure of GLMMs and GLMs in the manuscript. Each row represents a different model in the analysis. Models are organized by study area – first the structure for the metro-area model (both cities), then the structure for the city-specific models. Each city had its own models with identical structuring. Structures are shown for all mesocarnivore models and all mammal community models. All variables are fixed effects, except for site which is a random effect. Distributions for each model are also shown

Study area	Analysis	Model structure	Distribution
Metro area	Mesocarnivore models	Coyote detections ~ season + city + natural land cover + contaminant risk + human population density + 1|site	Negative binomial
		Raccoon detections ~ season + city + natural land cover + contaminant risk + human population density + 1|site	Negative binomial
		Virginia opossum detections ~ season + city + natural land cover + contaminant risk + human population density + 1|site	Negative binomial
	Mammal community models	Shannon's diversity ~ city + natural land cover + contaminant risk + human population density	Gaussian
		Species richness ~ city + natural land cover + contaminant risk + human population density	Poisson
		Pielou's evenness ~ city + natural land cover + contaminant risk + human population density	Gaussian
Seattle, Tacoma (separate models)	Mesocarnivore models	Coyote detections ~ season + natural land cover + contaminant risk + human population density + 1|site	Negative binomial
		Raccoon detections ~ season + natural land cover + contaminant risk + human population density + 1|site	Negative binomial
		Virginia opossum detections ~ season + natural land cover + contaminant risk + human population density + 1|site	Negative binomial
	Mammal community models	Shannon's diversity ~ natural land cover + contaminant risk + human population density	Gaussian
		Species richness ~ natural land cover + contaminant risk + human population density	Poisson
		Pielou's evenness ~ natural land cover + contaminant risk + human population density	Gaussian

Table 3 Species raw counts, ordered from most to least total independent detections. Totals and minimum/maximum independent detections are then broken down by focal city

Common name (Latin name)	Total Metro-Area Detections	Seattle Total (Min, Max)	Tacoma Total (Min, Max)
Eastern gray squirrel *(Sciurus carolinensis)*	7,646	2,350 (1, 189)	5,296 (1, 297)
Raccoon (*Procyon lotor*)	2,503	580 (1, 55)	1,923 (1, 65)
Black-tailed deer (*Odocoileus hemionus)*	1,638	317 (1, 31)	1,321 (1, 54)
Eastern cottontail rabbit *(Sylvilagus floridanus)*	1,614	473 (1, 76)	1,141 (1, 125)
Coyote *(Canis latrans)*	1,203	422 (1, 165)	781 (1, 81)
Virginia opossum *(Didelphis virgiana)*	911	148 (1, 15)	763 (1, 70)
Douglas squirrel *(Tamiasciurus douglasii)*	293	0 (NA)	293 (1, 52)
Striped skunk *(Mephitis mephitis)*	188	1 (1, 1)	187 (1, 41)
Elk *(Cervus canadensis)*	121	0 (NA)	121 (1, 27)
Townsend's chipmunk *(Tamias townsendii)*	57	0 (NA)	57 (1,21)
Bobcat *(Lynx rufus)*	31	13 (1, 2)	18 (1, 4)
Black bear *(Ursus americanus)*	10	9 (1, 4)	1 (1, 1)
Western gray squirrel *(Sciurus griseus)*	4	0 (NA)	4 (4, 4)
Weasel [cannot ID] *(Mustela* spp.)	3	0 (NA)	3 (1, 1)
Mountain lion *(Puma concolor)*	2	0 (NA)	2 (2, 2)
Fox squirrel *(Sciurus niger)*	1	0 (NA)	1 (1, 1)
River otter *(Lontra canadensis)*	1	1 (1)	0 (NA, NA)

Table 4 Results from generalized linear mixed-effects models evaluating predictors of mammal community Shannon diversity across three datasets: Seattle-Tacoma metro area (left), Seattle (center), and Tacoma (right). Models were fitted using the glmmTMB package in R. Fixed-effect estimates are shown with 95% confidence intervals in parentheses. Predictor variables include fixed effects for city (Tacoma) in the metro area model. All models include fixed effects for natural land cover, contaminant risk (combined and city-specific models), and human population density. Asterisks denote statistical significance (* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$)

Predictors	Estimates (Shannon diversity)	*p*	Estimates (Shannon diversity)	*p*	Estimates (Shannon diversity)	*p*
(Intercept)	0.97 *** (0.85, 1.09)	< 0.001	0.97 *** (0.87, 1.07)	< 0.001	1.05 *** (0.95, 1.15)	< 0.001
City [Tacoma]	0.08 (-0.08, 0.23)	0.354				
Natural land cover	0.05 (-0.06–0.16)	0.377	-0.03 (-0.18, 0.11)	0.656	0.12 (-0.03, 0.27)	0.104
Human pop. density	-0.03 (-0.13, 0.07)	0.538	-0.07 (-0.19, 0.06)	0.299	0.01 (-0.14, 0.16)	0.880
Contaminant risk (Metro-area)	–0.14 ** (-0.23, -0.05)	0.002				
Contaminant risk (Seattle)			-0.20 ** (-0.32, -0.07)	0.002		
Contaminant risk (Tacoma)					-0.11 (-0.25, 0.02)	0.102

Table 5 Results from generalized linear mixed-effects models evaluating predictors of mammal community species richness across three datasets: Seattle-Tacoma metro area (left), Seattle (center), and Tacoma (right). Models were fitted using the glmmTMB package in R. Fixed-effect incidence rate ratios are shown with 95% confidence intervals in parentheses. Predictor variables include fixed effects for city (Tacoma) in the metro area model. All models include fixed effects for natural land cover, contaminant risk (combined and city-specific models), and human population density. Asterisks denote statistical significance (* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$)

Predictors	Estimates (Species richness)	*p*	Estimates (Species richness)	*p*	Estimates (Species richness)	*p*
(Intercept)	5.22 *** (4.47,6.10)	< 0.001	5.30 *** (4.56, 6.17)	< 0.001	6.60 *** (5.86, 7.44)	< 0.001
City [Tacoma]	1.28 * (1.05, 1.57)	0.015				
Natural land cover	1.08 (0.95, 1.23)	0.229	1.00 (0.82, 1.23)	0.998	1.13 (0.97, 1.33)	0.120
Human pop. density	1.00 (0.88, 1.14)	0.976	1.00 (0.83, 1.21)	0.991	1.00 (0.84, 1.20)	0.970
Contaminant risk	0.91 (0.81, 1.03)	0.151				
Contaminant risk (Seattle)			0.88 (0.73, 1.06)	0.179		
Contaminant risk (Tacoma)					0.93 (0.79, 1.10)	0.399

Table 6 Results from generalized linear mixed-effects models evaluating predictors of mammal community Pielou's evenness across three datasets: Seattle-Tacoma metro area (left), Seattle (center), and Tacoma (right). Models were fitted using the glmmTMB package in R. Fixed-effect incidence rate ratios are shown with 95% confidence intervals in parentheses. Predictor variables include fixed effects for city (Tacoma) in the metro area model. All models include fixed effects for natural land cover, contaminant risk (combined and city-specific models), and human population density. Asterisks denote statistical significance (* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$)

Predictors	Estimates (Pielou's evenness)	*p*	Estimates (Pielou's evenness)	*p*	Estimates (Pielou's evenness)	*p*
(Intercept)	0.59 *** (0.53–0.64)	< 0.001	0.58 *** (0.53–0.63)	< 0.001	0.55 *** (0.51–0.60)	< 0.001
City [Tacoma]	-0.04 (-0.11–0.04)	0.314				
Natural land cover	0.00 (-0.05–0.05)	0.934	-0.02 (-0.09–0.05)	0.632	0.02 (-0.05–0.08)	0.577
Contamination risk	-0.06 ** (-0.10 – -0.01)	0.008				
Human population density	-0.02 (-0.06–0.02)	0.379	-0.04 (-0.10–0.02)	0.220	-0.00 (-0.07–0.06)	0.980
Contamination risk (Seattle)			-0.08 * (-0.14 – -0.02)	0.011		
Contamination risk (Tacoma)					-0.04 (-0.10–0.02)	0.173

Table 7 Results from generalized linear mixed-effects models evaluating predictors of mesocarnivore activity in the Seattle-Tacoma metro-area dataset (left to right: coyote *[Canis latrans]*, raccoon *[Procyon lotor]*, Virginia opossum *[Didelphis virginiana]*, striped skunk *[Mephitis mephitis]*, bobcat *[Lynx rufus]*). Models were fitted using the glmmTMB package in R. Fixed-effect incidence rate ratios are shown with 95% confidence intervals in parentheses. All models include fixed effects for city, natural land cover, contaminant risk, and human population density. Asterisks denote statistical significance (* = $p < 0.05$; ** = $p < 0.01$; *** = $p < 0.001$)

Predictors	Coyote	*p*	Raccoon	*p*	Virginia opossum	*p*	Striped skunk	*p*	Bobcat	*p*
(Intercept)	0.01 *** (0.00–0.02)	< 0.001	0.02 *** (0.02–0.05)	< 0.001	0.01 *** (0.00–0.03)	< 0.001	0.00 *** (0.00–0.01)	< 0.001	0.00 *** (0.00–0.01)	< 0.001
City [Tacoma]	2.65 * (1.10–6.40)	0.030	4.11 *** (1.93–8.72)	< 0.001	6.09 ** (1.88–19.76)	0.003	5.91 (0.04–876.23)	0.486	0.42 (0.08–2.05)	0.281
Natural land cover	0.76 (0.43–1.36)	0.357	0.87 (0.51–1.48)	0.611	1.39 (0.68–2.86)	0.387	0.39 (0.01–15.28)	0.614	1.21 (0.44–3.32)	0.714
Contamination risk	0.47 ** (0.28–0.80)	0.005	1.42 (0.94–2.14)	0.093	0.64 (0.32–1.25)	0.193	0.08 (0.08–7.74)	0.831	0.41 (0.17–1.00)	0.053
Human population density	1.05 (0.63–1.77)	0.847	1.48 (0.97–2.28)	0.072	1.44 (0.69–3.02)	0.342	0.81 (0.05–12.42)	0.805	1.08 (0.08–3.84)	0.547
Random effect σ^2	3.68		2.87		4.24		12.00		10.56	

Table 8 Results from generalized linear mixed-effects models evaluating predictors of mesocarnivore activity in the Seattle dataset (left to right: coyote *[Canis latrans]*, raccoon *[Procyon lotor]*, Virginia opossum *[Didelphis virginiana]*). Models were fitted using the glmmTMB package in R. Fixed-effect incidence rate ratios are shown with 95% confidence intervals in parentheses. All models include natural land cover, contaminant risk, and human population density. Asterisks denote statistical significance (* $=p<0.05$; ** $=p<0.01$; *** $=p<0.001$)

Predictors	Coyote	*p*	Raccoon	*p*	Virginia opossum	*p*
(Intercept)	0.01 *** (00–0.02)	< 0.001	0.04 *** (0.02–0.07)	< 0.001	0.01 *** (0.00–0.03)	< 0.001
Natural land cover	0.43 (0.16–1.14)	0.357	0.60 (0.29–1.23)	0.163	1.39 (0.46–4.15)	0.559
Contamination risk	0.18 ** (0.06–0.47)	0.001	1.91 (0.18–3.09)	0.009	0.62 (0.22–1.72)	0.360
Human population density	1.57 (0.69–3.57)	0.847	1.87 (1.15–3.03)	0.011	0.71 (0.22–2.34)	0.577
Random effect σ^2	4.73		3.54		5.15	

Table 9 Results from generalized linear mixed-effects models evaluating predictors of mesocarnivore activity in the Tacoma dataset (left to right: coyote *[Canis latrans]*, raccoon *[Procyon lotor]*, Virginia opossum *[Didelphis virginiana]*, striped skunk *[Mephitis mephitis]*). Models were fitted using the glmmTMB package in R. Fixed-effect incidence rate ratios are shown with 95% confidence intervals in parentheses. All models include natural land cover, contaminant risk, and human population density. Asterisks denote statistical significance (* $=p<0.05$; ** $=p<0.01$; *** $=p<0.001$)

Predictors	Coyote	*p*	Raccoon	*p*	Virginia opossum	*p*	Striped skunk	*p*
(Intercept)	0.03 *** (0.02–0.06)	< 0.001	0.1 *** (0.06–0.17)	< 0.001	0.06 *** (0.03–0.14)	< 0.001	0.00 *** (0.00–0.00)	< 0.001
Natural land cover	0.93 (0.50–1.74)	0.825	1.15 (0.56–2.33)	0.611	1.40 (0.54–3.63)	0.493	0.56 (0.02–20.39)	0.751
Contamination risk	1.04 (0.60–1.78)	0.897	0.94 (0.51–1.74)	0.846	0.45 (0.19–1.09)	0.076	0.29 (0.01–6.78)	0.442
Human population density	0.53 * (0.28–0.99)	0.045	1.48 (0.74–2.96)	0.262	3.14 (1.15–8.56)	0.025	2.10 (0.05–91.22)	0.70
Random effect σ^2	3.22		2.38		3.65		11.19	

Acknowledgements We are grateful to the four anonymous reviewers for their constructive feedback which greatly improved the quality of this manuscript. We would like to acknowledge the authors of the Washington Environmental Health Disparities Map and the stakeholders, agencies, and communities that participated in its inception for providing the framework for our analyses. We thank our colleagues at the Urban Wildlife Information Network, especially Mason Fidino for facilitating data access and providing statistical advice, and Jeff Haight for providing statistical advice. The Seattle Urban Carnivore Project is coordinated by Woodland Park Zoo and Seattle University, with significant contributions of effort from many Woodland Park Zoo community science volunteers and Seattle University students. The Grit City Carnivore Project is a research partnership of Point Defiance Zoo & Aquarium, Northwest Trek Wildlife Park, and the University of Washington, and this partnership is also made possible by a dedicated team of community science volunteers and students that support the data management and field efforts of the project.

Author contribution Y.H. led ideation, data analysis, and writing; C.O.E. contributed to ideation of the manuscript and data analysis. R.A.L., M.J.J., K.R.R., Z.H., and R.M. contributed to project administration and data curation. L.R.P. and C.R.J. led funding acquisition and contributed to ideation of the manuscript. All authors contributed to writing, reviewing and providing feedback on drafts of the manuscript.

Funding This research was funded by NSF grant DEB-2223973 to LRP and CJS. COE was supported by the University of California, Berkeley's Chancellor Fellowship and the National Science Foundation Graduate Research Fellowship under DGE-419–2146752. YH was supported by the National Science Foundation Graduate Research Fellowship under DGE-214–0004 and NSF DEB-2223973.

Data availability Data and analysis scripts for this study can be found at the following GitHub repository: https://github.com/yasminehentati/wa_uwin/

Declarations

Ethics statement All fieldwork was approved by local governing entities.

Conflict of interest The authors declare no competing interests.

References

Abel TD, Stephan M (2017) Streams of toxic and hazardous waste disparities, politics and policy, pp 311–326 In: Holifiel RD, Chakraborty J, Walker G, editors. The Routledge Handbook of Environmental Justice, 1st edn. Routledge

Abel TD, White J (2011) Skewed riskscapes and gentrified inequities: environmental exposure disparities in Seattle, Washington. Am J Public Health 101(Suppl 1):S246–S254

Aeluro S, Kavanagh TJ (2021) Domestic cats as environmental lead sentinels in low-income populations: a one health pilot study sampling the fur of animals presented to a high-volume spay/neuter clinic. Environ Sci Pollut Res Int 28:57925–57938

Aguirre AA (2009) Wild canids as sentinels of ecological health: a conservation medicine perspective. Parasit Vectors 2(Suppl 1):S7

Agyeman J, Schlosberg D, Craven L, Matthews C (2016) Trends and directions in environmental justice: from inequity to everyday life, community, and just sustainabilities. Annu Rev Environ Resour 41:321–340

Ajax R, Meyer J (1987) Policy consideration in the selection of national emission standards for hazardous air pollutants for the Tacoma smelter, pp709–717. Risk Assessment and Management. Springer US, Boston

Araújo CVM, Moreira-Santos M, Ribeiro R (2016) Active and passive spatial avoidance by aquatic organisms from environmental stressors: A complementary perspective and a critical review. Environ Int 92–93:405–415

Aronson MFJ, La Sorte FA, Nilon CH, Katti M, Goddard MA, Lepczyk CA, Warren PS, Williams NSG, Cilliers S, Clarkson B, Dobbs C, Dolan R, Hedblom M, Klotz S, Kooijmans JL, Kühn I, Macgregor-Fors I, McDonnell M, Mörtberg U, Pysek P, Siebert S, Sushinsky J, Werner P, Winter M (2014) A global analysis of the impacts of urbanization on bird and plant diversity reveals key anthropogenic drivers. Proc Biol Sci 281:20133330

Aronson MFJ, Lepczyk CA, Evans KL, Goddard MA, Lerman SB, MacIvor JS, Nilon CH, Vargo T (2017) Biodiversity in the city: key challenges for urban green space management. Front Ecol Environ 15:189–196

Avrin AC, Pekins CE, Sperry JH, Allen ML (2021) Evaluating the efficacy and decay of lures for improving carnivore detections with camera traps. Ecosphere 12(8):e03710

Avrin AC, Pekins CE, Wilmers CC, Sperry JH, Allen ML (2023) Can a mesocarnivore fill the functional role of an apex predator? Ecosphere 14(1):e4383

Azhari A, Latif MT, Mohamed AF (2018) Road traffic as an air pollutant contributor within an industrial park environment. Atmos Pollut Res 9:680–687

Aznarez C, Svenning JC, Pacheco JP, Have Kallesøe F, Baró F, Pascual U (2023) Luxury and legacy effects on urban biodiversity, vegetation cover and ecosystem services. Urban Sustain 3(1):1–11

Bateman PW, Fleming PA (2012) Big city life: carnivores in urban environments. J Zool 287:1–23

Battin J (2004) When good animals love bad habitats: Ecological traps and the conservation of animal populations: ecological traps. Conserv Biol 18:1482–1491

Birnie-Gauvin K, Peiman KS, Gallagher AJ, de Bruijn R, Cooke SJ (2016) Sublethal consequences of urban life for wild vertebrates. Environ Rev 24:416–425

Bramble K, Blanco MN, Doubleday A, Gassett AJ, Hajat A, Marshall JD, Sheppard L (2023) Exposure disparities by income, race and ethnicity, and historic redlining grade in the greater Seattle area for ultrafine particles and other air pollutants. Environ Health Perspect 131:77004

Brand A-F, Hynes J, Walker LA, Glória Pereira M, Lawlor AJ, Williams RJ, Shore RF, Chadwick EA (2020) Biological and anthropogenic predictors of metal concentration in the Eurasian otter, a sentinel of freshwater ecosystems. Environ Pollut 266:115280

Brenner RC, Magar VS, Ickes JA, Abbott JE, Stout SA, Crecelius EA, Bingler LS (2002) Characterization and FATE of PAH-Contaminated Sediments at the Wyckoff/Eagle Harbor Superfund Site. Environ Sci Technol 36:2605–2613

Brodin T, Fick J, Jonsson M, Klaminder J (2013) Dilute concentrations of a psychiatric drug alter behavior of fish from natural populations. Science 339:814–815

Buckley JY, Murray MH, de la Sancha NU, Fidino M, Byers KA, Fyffe R, Magle S (2024) Widespread exposure to anticoagulant rodenticides among common urban mesopredators in Chicago. Sci Total Environ 952:175883

Carpenter SK, Mateus-Pinilla NE, Singh K, Lehner A, Satterthwaite-Phillips D, Bluett RD, Rivera NA, Novakofski JE (2014) River otters as biomonitors for organochlorine pesticides, PCBs, and PBDEs in Illinois. Ecotoxicol Environ Saf 100:99–104

Caspi T, Johnson JR, Lambert MR, Schell CJ, Sih A (2022) Behavioral plasticity can facilitate evolution in urban environments. Trends Ecol Evol 37:1092–1103

Caubel JJ, Cados TE, Preble CV, Kirchstetter TW (2019) A distributed network of 100 black carbon sensors for 100 days of air quality monitoring in West Oakland, California. Environ Sci Technol 53:7564–7573

Cepeda-Duque JC, Andrade-Ponce G, Montes-Rojas A, Rendón-Jaramillo U, López-Velasco V, Arango-Correa E, López-Barrera Á, Mazariegos L, Lizcano DD, Link A, de Oliveira TG (2023) Assessing microhabitat, landscape features and intraguild relationships in the occupancy of the enigmatic and threatened Andean tiger cat (Leopardus tigrinus pardinoides) in the cloud forests of northwestern Colombia. PLoS ONE 18:e0288247

Chamberlain DE, Henry DAW, Reynolds C, Caprio E, Amar A (2019) The relationship between wealth and biodiversity: a test of the Luxury Effect on bird species richness in the developing world. Glob Change Biol 25:3045–3055

Chitwood MC, Lashley MA, Higdon SD, DePerno CS, Moorman CE (2020) Raccoon Vigilance and Activity Patterns When Sympatric with Coyotes. Diversity 12:341

Clark-Wolf TJ, Holt KA, Johansson E, Nisi AC, Rafiq K, West L, Boersma PD, Hazen EL, Moore SE, Abrahms B (2024) The capacity of sentinel species to detect changes in environmental conditions and ecosystem structure. J Appl Ecol 61:1638–1648

Collins JP, Kinzig A, Grimm NB, Fagan WF, Hope D, Wu J, Borer ET (2000) A new urban ecology: modeling human communities as integral parts of ecosystems poses special problems for the development and testing of ecological theory. Am Sci 88:416–425

Collins AC, Vickers TW, Shilling FM (2022) Behavioral responses to anthropogenic noise at highways vary across temporal scales. Front Ecol Evol 10:891595

Coscia C, Lazzari G, Rubino I (2024) Industrial heritage, adaptive reuse and sustainable redevelopment scenarios: Including local communities' multiple values in the decision-making process, pp 347–360 Green Energy and Technology. Springer Nature Switzerland, Cham

Cushing L, Morello-Frosch R, Wander M, Pastor M (2015) The haves, the have-nots, and the health of everyone: the relationship between social inequality and environmental quality. Annu Rev Public Health 36:193–209

Dai D (2011) Racial/ethnic and socioeconomic disparities in urban green space accessibility: where to intervene? Landsc Urban Plan 102:234–244

Des Roches S, Brans KI, Lambert MR, Rivkin LR, Savage AM, Schell CJ, Correa C, De Meester L, Diamond SE, Grimm NB, Harris NC, Govaert L, Hendry AP, Johnson MTJ, Munshi-South

J, Palkovacs EP, Szulkin M, Urban MC, Verrelli BC, Alberti M (2021) Socio-eco-evolutionary dynamics in cities. Evol Appl 14:248–267

Dewitz J (2021) National Land Cover Database (NLCD) 2019 Land Cover Science Product (ver. 2.0, June 2021). U.S. Geological Survey data release, https://doi.org/10.5066/P9KZCM54

Dominoni DM, Borniger JC, Nelson RJ (2016) Light at night, clocks and health: from humans to wild organisms. Biol Let 12:20160015

Dormann CF, Elith J, Bacher S, Buchmann C, Carl G, Carré G, Marquéz JRG, Gruber B, Lafourcade B, Leitão PJ, Münkemüller T, McClean C, Osborne PE, Reineking B, Schröder B, Skidmore AK, Zurell D, Lautenbach S (2013) Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography 36:27–46

Eccles KM, Thomas PJ, Chan HM (2021) Spatial patterns of the exposure-response relationship between mercury and cortisol in the fur of river otter (Lontra canadensis). Chemosphere 263:127992

Ellington EH, Gehrt SD (2019) Behavioral responses by an apex predator to urbanization. Behav Ecol 30:821–829

Estien CO, Wilkinson CE, Morello-Frosch R, Schell CJ (2024) Historical redlining is associated with disparities in environmental quality across California. Environ Sci Technol Lett 11:54–59

Facka A, Frair J, Keller T, Miller E, Murphy L, Ellis JC (2024) Spatial patterns of anticoagulant rodenticides in three species of medium-sized carnivorans in Pennsylvania. Can J Zool 102:443–454

Fatima H, Mahmood T, Hennelly LM, Farooq M, Munawar N, Ali W, Sacks BN (2023) Distributional patterns and habitat association of sympatric carnivores in Margalla Hills National Park, Pakistan, and a comparison of conventional versus molecular identification in carnivore scatology. Anim Biol 73:379–398

Fidino M, Simonis JL, Magle SB (2019) A multistate dynamic occupancy model to estimate local colonization–extinction rates and patterns of co-occurrence between two or more interacting species. Methods Ecol Evol 10:233–244

Fidino M, Barnas GR, Lehrer EW, Murray MH, Magle SB (2020) Effect of lure on detecting mammals with camera traps. Wildl Soc Bull 44:543–552

Fidino M, Gallo T, Lehrer EW, Murray MH, Kay CAM, Sander HA, MacDougall B, Salsbury CM, Ryan TJ, Angstmann JL, Amy Belaire J, Dugelby B, Schell CJ, Stankowich T, Amaya M, Drake D, Hursh SH, Ahlers AA, Williamson J, Hartley LM, Zellmer AJ, Simon K, Magle SB (2021) Landscape-scale differences among cities alter common species' responses to urbanization. Ecol Appl 31:e02253

Fidino M, Sander HA, Lewis JS, Lehrer EW, Rivera K, Murray MH, Adams HC, Kase A, Flores A, Stankowich T, Schell CJ, Salsbury CM, Rohnke AT, Jordan MJ, Green AM, Gramza AR, Zellmer AJ, Williamson J, Surasinghe TD, Storm H, Sparks KL, Ryan TJ, Remine KR, Pendergast ME, Mullen K, Minier DE, Middaugh CR, Mertl AL, McClung MR, Long RA, Larson RN, Kohl MT, Harris LR, Hall CT, Haight JD, Drake D, Davidge AM, Cheek AO, Bloch CP, Biro EG, Anthonysamy WJB, Angstmann JL, Allen ML, Adalsteinsson SA, Short Gianotti AG, LaMontagne JM, Gelmi-Candusso TA, Magle SB (2024) Gentrification drives patterns of alpha and beta diversity in cities. Proc Natl Acad Sci USA 121:e2318596121

Flahr LM, Michel NL, Zahara ARD, Jones PD, Morrissey CA (2015) Developmental exposure to Aroclor 1254 alters migratory behavior in juvenile European starlings (Sturnus vulgaris). Environ Sci Technol 49:6274–6283

Foley JE, Swift P, Fleer KA, Torres S, Girard YA, Johnson CK (2013) Risk factors for exposure to feline pathogens in California mountain lions (Puma concolor). J Wildl Dis 49:279–293

Fraser D, Mouton A, Serieys LEK, Cole S, Carver S, Vandewoude S, Lappin M, Riley SPD, Wayne R (2018) Genome-wide expression reveals multiple systemic effects associated with detection of anticoagulant poisons in bobcats (Lynx rufus). Mol Ecol 27:1170–1187

Gallo T, Fidino M, Lehrer EW, Magle SB (2017) Mammal diversity and metacommunity dynamics in urban green spaces: implications for urban wildlife conservation. Ecol Appl 27:2330–2341

Gámez S, Harris NC (2022) Conceptualizing the 3D niche and vertical space use. Trends Ecol Evol 37:953–962

Gehrt SD, Prange S (2007) Interference competition between coyotes and raccoons: a test of the mesopredator release hypothesis. Behav Ecol 18:204–214

Gehrt SD, Anchor C, White LA (2009) Home range and landscape use of coyotes in a metropolitan landscape: conflict or coexistence? J Mammal 90:1045–1057

Ginger SM, Hellgren EC, Kasparian MA, Levesque LP, Engle DM, Leslie DM Jr (2003) Niche shift by Virginia opossum following reduction of a putative competitor, the raccoon. J Mammal 84:1279–1291

Gorjanc G, Graves S, Heiberger R (2024) Package "car". https://cran.uni-muenster.de/web/packages/car/car.pdf. Accessed 1 Nov 2024

Graser WH, Gehrt SD, Hungerford LL, Anchor C (2012) Variation in demographic patterns and population structure of raccoons across an urban landscape. J Wildl Manag 76:976–986

Grigione MM, Burman P, Clavio S, Harper SJ, Manning DL, Sarno RJ (2014) A comparative study between enteric parasites of Coyotes in a protected and suburban habitat. Urban Ecosyst 17:1–10

Grue CE, Gibert PL, Seeley ME (1997) Neurophysiological and behavioral changes in non-target wildlife exposed to organophosphate and carbamate pesticides: thermoregulation, food consumption, and reproduction. Am Zool 37:369–388

Guillette LJ (2000) Contaminant induced endocrine disruption in wildlife. Growth Horm IGF Res 10:S45–S50

Guo K, Liu H, Bao H, Hu J, Wang S, Zhang W, Zhao Y, Jiang G (2017) Habitat selection and their interspecific interactions for mammal assemblage in the Greater Khingan Mountains, northeastern China. Wildl Biol 2017:1–8

Guo G, Eccles KM, McMillan M, Thomas PJ, Chan HM, Poulain AJ (2020) The gut microbial community structure of the North American river Otter (Lontra canadensis) in the Alberta oil sands region in Canada: relationship with local environmental variables and metal body burden. Environ Toxicol Chem 39:2516–2526

Haight JD, Hall SJ, Fidino M, Adalsteinsson SA, Ahlers AA, Angstmann J, Anthonysamy WJB, Biro E, Collins MK, Dugelby B, Gallo T, Green AM, Hartley L, Jordan MJ, Kay CAM, Lehrer EW, Long RA, MacDougall B, Magle SB, Minier DE, Mowry C, Murray M, Nininger K, Pendergast ME, Remine KR, Ryan T, Salsbury C, Schell CJ, Şekercioğlu ÇH, Shier CJ, Simon KC, St Clair CC, Stankowich T, Stevenson CJ, Wayne L, Will D, Williamson J, Wilson L, Zellmer AJ, Lewis JS (2023) Urbanization, climate and species traits shape mammal communities from local to continental scales. Nat Ecol Evol 7:1654–1666

Hansen CP, Parsons AW, Kays R, Millspaugh JJ (2020) Does use of backyard resources explain the abundance of urban wildlife? Front Ecol Evol 8:570771

Hartig F, Hartig MF (2022) Package "dharma." R Package. Available online: https://CRAN.R-project.org/package=DHARMa. Accessed 5 Sept 2022

Hassell JM, Bettridge JM, Ward MJ, Ogendo A, Imboma T, Muloi D, Fava F, Robinson TP, Begon M, Fèvre EM (2021) Socio-ecological drivers of vertebrate biodiversity and human-animal interfaces across an urban landscape. Glob Change Biol 27:781–792

Hayes Hursh S, Bauder JM, Fidino M, Drake D (2023) An urban cast of characters: landscape use and cover influencing mammal

occupancy in an American midwestern city. Landsc Urban Plan 229:104582
Hernández F, Oldenkamp RE, Webster S, Beasley JC, Farina LL, Wisely SM (2017) Raccoons (Procyon lotor) as sentinels of trace element contamination and physiological effects of exposure to coal fly ash. Arch Environ Contam Toxicol 72:235–246
Herrera DJ, Cove MV, McShea WJ, Decker S, Flockhart DTT, Moore SM, Gallo T (2022) Spatial and temporal overlap of domestic cats (Felis catus) and native urban wildlife. Front Ecol Evol 10
Huang AC, Nelson C, Elliott JE, Guertin DA, Ritland C, Drouillard K, Cheng KM, Schwantje HM (2018) River otters (Lontra canadensis) "trapped" in a coastal environment contaminated with persistent organic pollutants: Demographic and physiological consequences. Environ Pollut 238:306–316
Jesdale BM, Morello-Frosch R, Cushing L (2013) The Racial/Ethnic distribution of heat risk-related land cover in relation to residential segregation. Environ Health Perspect 121:811–817
Keeler BL, Hamel P, McPhearson T, Hamann MH, Donahue ML, Meza Prado KA, Arkema KK, Bratman GN, Brauman KA, Finlay JC, Guerry AD, Hobbie SE, Johnson JA, MacDonald GK, McDonald RI, Neverisky N, Wood SA (2019) Social-ecological and technological factors moderate the value of urban nature. Nat Sustain 2:29–38
Kidd KA, Paterson MJ, Rennie MD, Podemski CL, Findlay DL, Blanchfield PJ, Liber K (2014) Direct and indirect responses of a freshwater food web to a potent synthetic oestrogen. Philos Trans R Soc Lond B Biol Sci 369:20130578
Kimber KR, Kollias GV 2nd (2000) Infectious and parasitic diseases and contaminant-related problems of North American river otters (Lontra canadensis): a review. J Zoo Wildl Med 31:452–472
Kok ACM, Berkhout BW, Carlson NV, Evans NP, Khan N, Potvin DA, Radford AN, Sebire M, Shafiei Sabet S, Shannon G, Wascher CAF (2023) How chronic anthropogenic noise can affect wildlife communities. Front Ecol Evol 11:1130075
Kondo MC, Zuidema C, Moran HA, Jovan S, Derrien M, Brinkley W, De Roos AJ, Tabb LP (2022) Spatial predictors of heavy metal concentrations in epiphytic moss samples in Seattle, WA. Sci Total Environ 825:153801
Kreling SES, Reese EM, Cavalluzzi OM, Bozzi NB, Messinger R, Schell CJ, Long RA, Prugh LR (2024) City divided: Unveiling family ties and genetic structuring of coyotes in Seattle. Mol Ecol 33:e17427
Krieger N, Wright E, Chen JT, Waterman PD, Huntley ER, Arcaya M (2020) Cancer stage at diagnosis, historical redlining, and current neighborhood characteristics: breast, cervical, lung, and colorectal cancers, Massachusetts, 2001–2015. Am J Epidemiol 189:1065–1075
Kunc HP, Schmidt R (2019) The effects of anthropogenic noise on animals: a meta-analysis. Biol Let 15:20190649
Lane HM, Morello-Frosch R, Marshall JD, Apte JS (2022) Historical redlining is associated with present-day air pollution disparities in U.s. cities. Environ Sci Technol Lett 9:345–350
Lee EK, Donley G, Ciesielski TH, Gill I, Yamoah O, Roche A, Martinez R, Freedman DA (2022) Health outcomes in redlined versus non-redlined neighborhoods: a systematic review and meta-analysis. Soc Sci Med 294:114696
Leong M, Dunn RR, Trautwein MD (2018) Biodiversity and socioeconomics in the city: a review of the luxury effect. Biol Let 14:20180082
Lev E, Kahn PH Jr, Chen H, Esperum G (2020) Relatively wild urban parks can promote human resilience and flourishing: a case study of discovery park, Seattle, Washington. Front Sustain Cities 2:497485
Levin R, Zilli Vieira CL, Rosenbaum MH, Bischoff K, Mordarski DC, Brown MJ (2021) The urban lead (Pb) burden in humans, animals and the natural environment. Environ Res 193:110377
Lovell C, Li S, Turner J, Carbone C (2022) The effect of habitat and human disturbance on the spatiotemporal activity of two urban carnivores: the results of an intensive camera trap study. Ecol Evol 12:e8746
Magle SB, Lehrer EW, Fidino M (2016) Urban mesopredator distribution: examining the relative effects of landscape and socioeconomic factors. Anim Conserv 19:163–175
Magle SB, Fidino M, Lehrer EW, Gallo T, Mulligan MP, Ríos MJ, Ahlers AA, Angstmann J, Belaire A, Dugelby B, Gramza A, Hartley L, MacDougall B, Ryan T, Salsbury C, Sander H, Schell C, Simon K, St Onge S, Drake D (2019) Advancing urban wildlife research through a multi-city collaboration. Front Ecol Environ 17:232–239
Magle SB, Fidino M, Sander HA, Rohnke AT, Larson KL, Gallo T, Kay CAM, Lehrer EW, Murray MH, Adalsteinsson SA, Ahlers AA, Anthonysamy WJB, Gramza AR, Green AM, Jordan MJ, Lewis JS, Long RA, MacDougall B, Pendergast ME, Remine K, Simon KC, St Clair CC, Shier CJ, Stankowich T, Stevenson CJ, Zellmer AJ, Schell CJ (2021) Wealth and urbanization shape medium and large terrestrial mammal communities. Glob Change Biol 27:5446–5459
Malhotra R, Lima S, Harris NC (2022) Temporal refuges of a subordinate carnivore vary across rural-urban gradient. Ecol Evol 12:e9310
Mariner PE, Holzmer FJ, Jackson RE, White JE, Wahl AS, Wolf FG (1997) Fingerprinting Arsenic Contamination in the Sediments of the Hylebos Waterway, Commencement Bay Superfund Site, Tacoma, Washington. Environ Eng Geosci 3:359–368
Marneweck CJ, Allen BL, Butler AR, Do Linh San E, Harris SN, Jensen AJ, Saldo EA, Somers MJ, Titus K, Muthersbaugh M, Vanak A, Jachowski DS (2022) Middle-out ecology: small carnivores as sentinels of global change. Mamm Rev 52:471–479
Mascarenhas M, Grattet R, Mege K (2021) Toxic Waste and race in twenty-first century America. Environ Soc 12:108–126
McPhearson T, Pickett STA, Grimm NB, Niemelä J, Alberti M, Elmqvist T, Weber C, Haase D, Breuste J, Qureshi S (2016) Advancing urban ecology toward a science of cities. Bioscience 66:198–212
McTigue LE, Lassiter EV, Shaw M, Johansson E, Wilson K, DeGregorio BA (2024) Does daily activity overlap of seven mesocarnivores vary based on human development? PLoS ONE 19:e0288477
Min E, Gruen D, Banerjee D, Echeverria T, Freelander L, Schmeltz M, Saganić E, Piazza M, Galaviz VE, Yost M, Seto EYW (2019) The Washington state environmental health disparities map: development of a community-responsive cumulative impacts assessment tool. Int J Environ Res Public Health 16:4470
Min E, Piazza M, Galaviz VE, Saganić E, Schmeltz M, Freelander L, Farquhar SA, Karr CJ, Gruen D, Banerjee D, Yost M, Seto EYW (2021) Quantifying the distribution of environmental health threats and hazards in Washington State using a cumulative environmental inequality index. Environ Justice 14:298–314
Morello-Frosch R, Lopez R (2006) The riskscape and the color line: examining the role of segregation in environmental health disparities. Environ Res 102:181–196
Moura CW, Clucas B, Furnas BJ (2022) Humans are more influential than coyotes on mammalian mesopredator spatiotemporal activity across an urban gradient. Front Ecol Evol 10:867188
Murray MH, Hill J, Whyte P, St. Clair CC (2016) Urban compost attracts coyotes, contains toxins, and may promote disease in urban-adapted wildlife. EcoHealth 13:285–292
Murray MH, Sánchez CA, Becker DJ, Byers KA, Worsley-Tonks KEL, Craft ME (2019) City sicker? A meta-analysis of wildlife health and urbanization. Front Ecol Environ 17:575–583
Murray MH, Buckley J, Byers KA, Fake K, Lehrer EW, Magle SB, Stone C, Tuten H, Schell CJ (2022) One health for all: advancing

human and ecosystem health in cities by integrating an environmental justice lens. Annu Rev Ecol Evol Syst 53:403–426
Nardone A, Casey JA, Morello-Frosch R, Mujahid M, Balmes JR, Thakur N (2020) Associations between historical residential redlining and current age-adjusted rates of emergency department visits due to asthma across eight cities in California: an ecological study. Lancet Planet Health 4:e24–e31
Norton BA, Evans KL, Warren PH (2016) Urban biodiversity and landscape ecology: patterns, processes and planning. Curr Landsc Ecol Rep 1:178–192
Oksanen J, Blanchet FG, Kindt R, Legendre P, Minchin PR, O'hara RB, Oksanen M (2013) Package "vegan." Community ecology package, version 2. https://mirror.ibcp.fr/pub/CRAN/web/packages/vegan/vegan.pdf. Accessed 1 Nov 2024
Ortmann CR, Johnson SD (2021) How reliable are motion-triggered camera traps for detecting small mammals and birds in ecological studies? J Zool 313:202–207
Parker KH, Bishop JM, Serieys LEK, Mateo R, Camarero PR, Leighton GRM (2023) A heavy burden: Metal exposure across the land-ocean continuum in an adaptable carnivore. Environ Pollut 327:121–585
Parsons AW, Rota CT, Forrester T, Baker-Whatton MC, McShea WJ, Schuttler SG, Millspaugh JJ, Kays R (2019) Urbanization focuses carnivore activity in remaining natural habitats, increasing species interactions. J Appl Ecol 56:1894–1904
Pastor M, Morello-Frosch R, Sadd JL (2005) The air is always cleaner on the other side: race, space, and ambient air toxics exposures in California. J Urban Aff 27:127–148
Patten KT, Valenzuela AE, Wallis C, Berg EL, Silverman JL, Bein KJ, Wexler AS, Lein PJ (2021) The effects of chronic exposure to ambient traffic-related air pollution on Alzheimer's disease phenotypes in wildtype and genetically predisposed male and female rats. Environ Health Perspect 129(5):e057005
Petrie A (2020) regclass: Tools for an Introductory Class in Regression and Modeling. R package version 1. https://CRAN.R-project.org/package=regclass. Accessed 1 Nov 2024
Poisson MKP, Gebresenbet F, Butler AR, Tate P, Bergeron DH, Moll RJ (2024) The way "urbanization" is defined has strong implications for its effects on mammal abundance. Urban Ecosyst 27:2367–2380
R Core Team (2024) R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/. Accessed 1 Nov 2024
Ramalho CE, Hobbs RJ (2012) Time for a change: dynamic urban ecology. Trends Ecol Evol 27:179–188
Richards NL, Tomy G, Kinney CA, Nwanguma FC, Godwin B, Woollett DA (2018) Using scat detection dogs to monitor environmental contaminants in sentinel species and freshwater ecosystems, pp 193–262 In: Richards NL, editor. Using detection dogs to monitor aquatic ecosystem health and protect aquatic resources. Springer International Publishing, Cham
Ripley B, Venables B, Bates DM, Hornik K, Gebhardt A, Firth D, Ripley MB (2013) Package "mass." http://download.nust.na/pub3/cran/web/packages/MASS/MASS.pdf. Accessed 1 Nov 2024
Rodríguez-Estival J, Mateo R (2019) Exposure to anthropogenic chemicals in wild carnivores: a silent conservation threat demanding long-term surveillance. Curr Opin Environ Sci Health 11:21–25
Rodríguez-Jorquera IA, Vitale N, Garner L, Perez-Venegas DJ, Galbán-Malagón CJ, Duque-Wilckens N, Toor GS (2017) Contamination of the upper class: Occurrence and effects of chemical pollutants in terrestrial top predators. Curr Pollut Rep 3:206–219
Rohr JR, Kerby JL, Sih A (2006) Community ecology as a framework for predicting contaminant effects. Trends Ecol Evol 21:606–613
Rosenfeld CS (2017) Gut Dysbiosis in Animals Due to Environmental Chemical Exposures. Front Cell Infect Microbiol 7:396
Saaristo M, Brodin T, Balshine S, Bertram MG, Brooks BW, Ehlman SM, McCallum ES, Sih A, Sundin J, Wong BBM, Arnold KE (2018) Direct and indirect effects of chemical contaminants on the behaviour, ecology and evolution of wildlife. Proc R Soc B 285:20181297
Sanders D, Gaston KJ (2018) How ecological communities respond to artificial light at night. J Exp Zool A Ecol Integr Physiol 329:394–400
Schell CJ, Dyson K, Fuentes TL, Des Roches S, Harris NC, Miller DS, Woelfle-Erskine CA, Lambert MR (2020) The ecological and evolutionary consequences of systemic racism in urban environments. Science 369:eaay4497
Schulte-Hostedde AI, Mazal Z, Jardine CM, Gagnon J (2018) Enhanced access to anthropogenic food waste is related to hyperglycemia in raccoons (Procyon lotor). Conserv Physiol 6(1):coy026
Seebacher F, Franklin CE (2012) Determining environmental causes of biological effects: the need for a mechanistic physiological dimension in conservation biology. Philos Trans R Soc Lond B Biol Sci 367:1607–1614
Serieys LEK, Lea A, Pollinger JP, Riley SPD, Wayne RK (2015) Disease and freeways drive genetic change in urban bobcat populations. Evol Appl 8:75–92
Serieys LEK, Lea AJ, Epeldegui M, Armenta TC, Moriarty J, VandeWoude S, Carver S, Foley J, Wayne RK, Riley SPD, Uittenbogaart CH (2018) Urbanization and anticoagulant poisons promote immune dysfunction in bobcats. Proc R Soc B Biol Sci 285:20172533
Shakouri A, Gheytasi H (2018) Bioaccumulation of heavy metals in oyster (Saccostrea cucullata) from Chabahar bay coast in Oman Sea: Regional, seasonal and size-dependent variations. Mar Pollut Bull 126:323–329
Shkembi A, Smith LM, Neitzel RL (2024) Linking environmental injustices in Detroit, MI to institutional racial segregation through historical federal redlining. J Eposure Sci Environ Epidemiol 34:389–398
Sievert O, Comley E, Phiri W, Davis RS (2023) Using camera traps to assess carcass use and the intraguild dynamics of understudied African mesocarnivores. Food Webs 36:e00287
Silva LT, Magalhães A, Silva JF, Fonseca F (2021) Impacts of low-frequency noise from industrial sources in residential areas. Appl Acoust 182:108203
Smith WP, Endres KM (2012) Raccoon use of den trees and plant associations in western mesophytic forests: Tree attributes and availability or landscape heterogeneity? Nat Res 03:75–87
Somers CM (2011) Ambient air pollution exposure and damage to male gametes: human studies and in situ "sentinel" animal experiments. Syst Biol Reprod Med 57:63–71
Sprague TS (2015) Products of place: The era of reinforced-concrete skyscrapers in Seattle, 1921–1931. Pac Northwest Q 106:107–119
Sugden S, Sanderson D, Ford K, Stein LY, St Clair CC (2020) An altered microbiome in urban coyotes mediates relationships between anthropogenic diet and poor health. Sci Rep 10:22207
Suraci JP, Gaynor KM, Allen ML, Alexander P, Brashares JS, Cendejas-Zarelli S, Crooks K, Elbroch LM, Forrester T, Green AM, Haight J, Harris NC, Hebblewhite M, Isbell F, Johnston B, Kays R, Lendrum PE, Lewis JS, McInturff A, McShea W, Murphy TW, Palmer MS, Parsons A, Parsons MA, Pendergast ME, Pekins C, Prugh LR, Sager-Fradkin KA, Schuttler S, Şekercioğlu ÇH, Shepherd B, Whipple L, Whittington J, Wittemyer G, Wilmers CC (2021) Disturbance type and species life history predict mammal responses to humans. Glob Change Biol 27:3718–3731
Swope CB, Hernández D, Cushing LJ (2022) The relationship of historical redlining with present-day neighborhood environmental and health outcomes: a scoping review and conceptual model. J Urban Health 99:959–983

Tüzün N, Savaşçı BB, Stoks R (2021) Seasonal time constraints shape life history, physiology and behaviour independently, and decouple a behavioural syndrome in a damselfly. Oikos 130:274–286

van den Bosch M, Kellner KF, Gantchoff MG, Patterson BR, Barber-Meyer SM, Beyer DE, Erb JD, Isaac EJ, MacFarland DM, Moore SA, Norton DC, Petroelje TR, Price Tack JL, Roell BJ, Schrage M, Belant JL (2023) Habitat selection of resident and non-resident gray wolves: implications for habitat connectivity. Sci Rep 13:20415

Vorhees DJ, Cullen AC, Altshul LM (1999) Polychlorinated biphenyls in house dust and yard soil near a Superfund site. Environ Sci Technol 33:2151–2156

Voss RS, Jansa SA (2021) Opossums: An adaptive radiation of new world marsupials. Johns Hopkins University Press, Baltimore

Wainstein M, Harding LB, O'Neill SM, Boyd DT, Koontz F, Miller B, Klütsch CFC, Thomas PJ, Ylitalo GM (2022) Highly contaminated river otters (Lontra canadensis) are effective biomonitors of environmental pollutant exposure. Springer

Wang Y, Allen ML, Wilmers CC (2015) Mesopredator spatial and temporal responses to large predators and human development in the Santa Cruz Mountains of California. Biol Cons 190:23–33

Wang Y, Cao Z (2017) Industrial building environment: Old problem and new challenge. Indoor Built Environ 26:1035–1039

Wingfield JC (2013) Ecological processes and the ecology of stress: the impacts of abiotic environmental factors. Funct Ecol 27:37–44

Wood EM, Esaian S, Benitez C, Ethington PJ, Longcore T, Pomara LY (2024) Historical racial redlining and contemporary patterns of income inequality negatively affect birds, their habitat, and people in Los Angeles, California. Ornithol Appl 126:1–29

Worsley-Tonks KEL, Miller EA, Gehrt SD, McKenzie SC, Travis DA, Johnson TJ, Craft ME (2020) Characterization of antimicrobial resistance genes in Enterobacteriaceae carried by suburban mesocarnivores and locally owned and stray dogs. Zoonoses Public Health 67:460–466

Wright WJ (2021) As above, so below: Anti-black violence as environmental racism. Antipode 53:791–809

Yauk CL, Fox GA, McCarry BE, Quinn JS (2000) Induced minisatellite germline mutations in herring gulls (Larus argentatus) living near steel mills. Mutat Res 452:211–218

Yearby R (2020) Structural racism and health disparities: reconfiguring the social determinants of health framework to include the root cause. J Law Med Ethics 48:518–526