

# Urbanization alters sandy beach scavenging

## assemblages but not ecosystem function

8 December 2023

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**Key Words:** *anthropogenic disturbance, carrion, spatial subsidies, land-sea connectivity*

**Open Research Statement:** This manuscript uses novel data and code that are publicly accessible in GitHub at the following link, and will be permanently archived in a Zenodo repository upon publication acceptance: [https://github.com/fgerraty/Urban\\_Scavengers](https://github.com/fgerraty/Urban_Scavengers)

## 38 **2. Abstract**

39

40 Urbanization is rapidly transforming coastal landscapes around the world, altering the structure  
41 and function of marine, intertidal, and terrestrial ecosystems. In this study, we explore the impact  
42 of urbanization on the structure of vertebrate scavenging assemblages and the ecosystem  
43 functions they provide in sandy beach ecosystems across 40km of the central California coast,  
44 USA. We surveyed vertebrate scavenging assemblages using baited camera traps on 17 beaches  
45 spanning a gradient of coastal urbanization. We found that urbanization extent within small  
46 spatial scales (i.e., 1km or 3km radii of each site) and the rate of beach visitation by humans or  
47 domestic dogs were the best additive predictors of assemblage structure. We identified  
48 pronounced urbanization-associated shifts in the composition of vertebrate scavenger guilds but  
49 found that that these differences did not lead to subsequent changes in ecosystem functions  
50 performed by shoreline scavengers. Rates of carrion processing did not differ across the  
51 urbanization gradient, with synanthropic and non-native species compensating for the absence of  
52 the predominate native scavengers documented in rural areas. Our results underscore the  
53 pervasive and nuanced effects of urbanization on the dynamics of land-sea connectivity and  
54 demonstrate that urban ecosystems can sometimes sustain critical ecosystem functions in the face  
55 of landscape transformation. Recognizing the intricate interplay between urbanization and  
56 shoreline ecosystem dynamics, we suggest comprehensive consideration of cross-realm impacts  
57 in ongoing conservation and development efforts to ensure the sustainability and resilience of  
58 urban land- and seascapes.

59

## 60 **3. Main Text**

61

### 62 **Introduction**

63

64 Urbanization is one of the fastest and most transformative forms of landscape  
65 modification on the planet (Grimm et al., 2008, Angel et al., 2005). Coastal areas in particular  
66 are associated with large and growing urban centers, leading to pronounced changes in the  
67 structure and function of both terrestrial and adjacent marine ecosystems (Small & Nicholls  
68 2003, Todd et al., 2019). Urbanization often generates complex environmental gradients, from  
69 highly developed urban areas to agricultural or undeveloped landscapes in nearby rural regions  
70 (McDonnell & Pickett 1990). These urbanization gradients provide unique experimental settings  
71 for exploring biotic responses to anthropogenic development and associated shifts in ecosystem  
72 function (Des Roches et al., 2021, Gilby et al., 2022).

73

74 Scavenging is a crucial yet frequently undervalued ecological process that impacts  
75 ecosystem structure, function, and stability (Wilson and Wolkovich 2011). Scavengers play  
76 pivotal roles in maintaining ecosystem health and function by consuming carrion, recycling and  
77 redistributing nutrients within and across ecosystem borders, regulating disease, and stabilizing  
78 food web dynamics (Moleón et al., 2014; Beasley et al., 2015). Scavenging is a particularly  
79 important ecological process in sandy beach ecosystems, which have little *in situ* primary  
80 production and therefore depend on spatial subsidies—often in the form of macroalgal wrack and  
81 marine animal carrion—as an organic matter resource base (Hyndes et al., 2022; Moleón et al.,  
82 2019). Sandy beaches are also attractive for adjacent urban development, such that understanding  
82 how urbanization influences sandy beach scavenging dynamics and carrion processing is central

83 to effective coastal zone management, shoreline habitat conservation and restoration, and urban  
84 planning (Huijbers et al., 2013, Gilby et al., 2022).

85 Anthropogenic development has been associated with changes in sandy beach scavenging  
86 communities and depressed carrion processing rates in other parts of the world (Huijbers et al.,  
87 2013, Huijbers et al., 2015, Gilby et al., 2022). However, such investigations have been  
88 geographically limited to Australian coastlines and have all included sites with red foxes (*Vulpes*  
89 *vulpes*), a widespread and abundant invasive scavenger that substantially changes the rate of  
90 beach-cast marine carrion processing (Brown et al., 2015, Kimber et al., 2020). Examining  
91 urbanization-driven changes to scavenging dynamics in other ecoregions is crucial to assess  
92 whether observed patterns and processes are consistent across diverse ecological contexts. Such  
93 inquiry can provide a more holistic perspective on how urbanization influences sandy beach  
94 ecosystems to better inform place-based management and development strategies.

95 In this study, we investigate the influence of urbanization and human disturbances (i.e.,  
96 human visitation, domestic dog visitation, and agricultural cultivation) on the composition of  
97 vertebrate scavenging assemblages and rates of carrion processing at beaches along 40km of  
98 coastline in central California, USA. The California coast is a biodiversity hotspot with an  
99 extensive footprint of urbanized coastal landscapes, yet the consequences of urbanization for  
100 sandy beach vertebrate scavengers remains unknown in the region (Dobson et al., 1997, Myers  
101 1990). We hypothesized that scavenging assemblages vary systematically across the urbanization  
102 gradient, with scavenging guilds in highly urbanized areas composed of synanthropic species  
103 such as gulls (*Larus spp.*), American crows (*Corvus brachyrhynchos*), and non-native rats  
104 (*Rattus spp.*). In lesser urbanized areas, we hypothesized that scavenging guilds are be composed  
105 of “urban avoider” species such as deer mice (*Peromyscus spp.*) in addition to species considered  
106 highly abundant in nearby coastal grassland ecosystems such as coyotes (*Canis latrans*) and  
107 ravens (*Corvus corax*) (Fischer et al., 2014, Ellington and Gehrt 2019, Kelly et al., 2002). Based  
108 on findings in other regions (e.g., Huijbers et al., 2013, Huijbers et al., 2015, Gilby et al., 2022),  
109 we hypothesized that rates of carrion processing are lower in urban than rural areas, with urban  
110 beaches having insufficient functional redundancy of the vertebrate scavenger guild to  
111 compensate for the absence of scavengers associated with rural beaches. By investigating the  
112 environmental drivers of sandy beach vertebrate scavenger assemblages and the ecosystem  
113 functions these scavengers confer, we intend to inform ongoing shoreline conservation and urban  
114 development initiatives along the California coast.

115

## 116 **Methods**

117

### 118 *Vertebrate Scavenger Surveys*

119

120 We used baited wildlife cameras to assess vertebrate scavenger assemblages on beaches  
121 across a diverse coastal landscape spanning 40km of shoreline in Santa Cruz County, central  
122 California, USA. Our study region contains dozens of sandy beaches and encompasses a  
123 prominent urbanization gradient, providing an excellent opportunity to test the influence of  
124 urbanization on carrion processing in sandy beach ecosystems (Fig. 1). We surveyed 17 sandy  
125 beaches managed by California State Parks and the University of California Younger Lagoon  
126 Reserve distributed across this urbanization gradient from February-May 2023. Within each  
127 beach, survey locations were established above the high tide line at the interface between sandy  
128 beach and foredunes, rocky cliffs, or concrete embankments bordering each beach.

129 To survey coastal vertebrate scavengers and measure carrion consumption rates, at each  
130 site we placed a motion-triggered camera trap (Browning Strike Force HD Pro X) baited with a  
131 single Pacific herring (*Clupea pallasii*) carcass weighing an average of 134g  $\pm$  30g (SE).  
132 Cameras were positioned 1-2m from the fish carrion and programmed to record 20 second HD  
133 videos when triggered, with a 30 second “quiet period” following video capture before another  
134 video could be triggered. We deployed baited cameras within two hours of sunset or sunrise and  
135 replaced bait three times at approximately 12-hour intervals (at sunrise or sunset), resulting in a  
136 48-hour sampling window encompassing two “night” and two “day” surveys (Gilby et al., 2022).  
137 We conducted 2-3 of these 48-hour surveys at each site, resulting in 8 or 12 carcasses deployed  
138 at each site across the four-month study period. At any given time, we surveyed approximately  
139 the same number of high and low urbanization sites (>50% and <50% urbanization extent within  
140 1km radius, respectively; see “Quantifying Land Cover” for further details) to prevent  
141 confounding with weather or season effects. All herring were weighed prior to each 12-hour  
142 deployment, and those that showed evidence of scavenging activity but were not removed by  
143 scavengers were also weighed following deployment. All baited camera trapping protocols were  
144 approved by University of California, Santa Cruz, Institutional Animal Care and Use Committee  
145 (#Raimp\_2207\_a1).

146 While processing the videos, individual scavengers were identified to species or genus (in  
147 the case of rodents) and were classified as scavenging when contact was made between the  
148 scavenger’s mouth and the carcass. We determined the maximum number of individuals of each  
149 vertebrate species observed scavenging the carcass in a single video clip (MaxN)(Gilby et al.,  
150 2017, Bingham et al., 2018). To provide the most conservative relative abundance estimates, we  
151 pooled data across all carcasses deployed at each site and used the largest MaxN value for each  
152 scavenger species for site-level analyses of scavenging assemblages. While processing videos,  
153 we also flagged video clips when the first scavenger arrived at each carcass as well as videos in  
154 which carcasses were removed from the camera field of view (i.e. carcass removal). From these  
155 videos, we were able to determine the time from carcass deployment to the first scavenging event  
156 and to carcass removal—two of four metrics of carrion processing that were used as a proxy for  
157 ecosystem function. We also identified video clips documenting humans or domestic dogs  
158 visiting the carcass or in the video background, and the mean number of videos of humans and/or  
159 dogs per day of camera deployment were used to approximate the rate of beach visitation.

### 160 161 *Quantifying Land Cover* 162

163 We used the U.S. Geological Survey 2019 National Land Cover Database (NLCD) to  
164 quantify the spatial extent of urbanization (i.e., anthropogenic development) and agricultural land  
165 within three buffers of each study site. Buffer radii of 1km, 3km, and 5km were selected to  
166 reflect the approximate home ranges of our focal scavenger species and to identify the spatial  
167 scales at which urbanization and agriculture most strongly influence ecological responses (Riley  
168 et al., 2003, Linz et al., 1992, Neatherlin and Marzluff, 2004). We performed all land cover  
169 quantification and statistical analyses in R Statistical Software (v4.3.1, R Core Team 2023), and  
170 all data and code associated with manuscript is publicly available at  
171 [https://github.com/fgerraty/Urban\\_Scavengers](https://github.com/fgerraty/Urban_Scavengers). To generate metrics of urbanization extent, we  
172 created an urbanized land class that included the following NLCD classes: developed open  
173 space, low-intensity development, medium-intensity development, and high-intensity  
174 development (Kreling et al., 2019). We used the *extract* function from the *raster* package to

175 determine the percentage of land cover (excluding Open Water NLCD class) categorized as  
176 urbanized within the three buffer radii of each site (Hijmans 2023). We used the same procedure  
177 to develop and quantify the spatial extent of an agricultural land class (NLCD classes:  
178 pasture/hay, cultivated crops) within the same buffer radii. These categorical groupings allowed  
179 us to distinguish the relative influence of anthropogenic development, agricultural cultivation,  
180 and undeveloped lands in aggregate.

181

### 182 *Scavenging Assemblage Analyses*

183

184 We utilized two complimentary methods of multivariate community analysis to examine  
185 environmental drivers of scavenging assemblages at each beach: (1) permutational multivariate  
186 analysis of variance (PERMANOVA) and (2) multivariate generalized linear models  
187 (MvGLMs). Eight environmental predictors at each site were considered in assemblage analyses.  
188 These were urbanization extent at 1km, 3km, and 5km scales, agricultural extent at 1km, 3km,  
189 and 5km scales, and the mean daily count of video captures of humans and domestic dogs at each  
190 site. No scavengers were documented interacting with carcasses at one rural beach (Strawberry)  
191 despite observations of common ravens and coyote tracks at the beach during carcass  
192 deployments, so we removed this site from all subsequent analyses.

193 Using the *vegan* and *AICcPermanova* packages, we generated all possible models using  
194 our eight predictor variables and then filtered out models that have a high degree of collinearity  
195 among predictors (maximum VIF>5) (Oksanen et al., 2022, Corcoran 2023). This resulted in  
196 sixty-four combinations of non-collinear predictors (including a null model), which never  
197 included multiple scales of urbanization or agricultural cultivation due to high collinearity. We  
198 used the combinations of non-collinear predictors to fit sixty-four linear models to Bray-Curtis  
199 dissimilarity matrices calculated from scavenger species MaxN values using PERMANOVA  
200 (Table S4). We filtered the fitted models to include only those with delta AICc less than 2,  
201 resulting in seven top models (Table S2). We calculated the adjusted R-squared for each  
202 predictor using AIC and model averaging to further explore the best predictors of scavenging  
203 assemblages (Table S3). Using an information theoretic approach to perform model selection on  
204 a suite of non-collinear models allowed us to account for high levels collinearity among  
205 urbanization and agricultural measures without excluding potentially important predictor  
206 variables.

207 Because violations of mean-variance assumptions may confound dispersion and location  
208 effects when using ordination-based approaches, we supplemented PERMANOVA analyses with  
209 MvGLMs using the *manyglm* function in the *mvabund* package (Warton et al., 2012, Wang et al.,  
210 2022, Jupke and Schäfer, 2020). We fit MvGLM models with negative binomial distributions,  
211 log link functions, and an offset term of sampling effort (number of fish deployed per site) using  
212 the same modeling suite of predictor combinations from PERMANOVA analyses. This resulted  
213 in sixty-four MvGLM models total and, after filtering to only include those with delta AIC less  
214 than 2, four top models (Tables S5, S6). MvGLM also identifies species whose abundance and  
215 prevalence correlate significantly with the multivariate model; following Gilby et al., (2022),  
216 those species that significantly correlated with the best fit model were considered indicator  
217 species in this study. Results of the best-fit MvGLM were visualized using a non-metric  
218 multidimensional scaling ordination, with vectors representing significant predictor terms and  
219 indicator species. Relationships between urbanization and indicator species were visualized

220 using univariate GLMs with the same distributions, link functions, and offsets as the multivariate  
 221 models.

222

### 223 *Carrion Processing Analyses*

224

225 Both community-level multivariate analysis approaches identified urbanization at the  
 226 1km scale as one of the best single-term predictors of scavenging assemblages (see results), so  
 227 we used the 1km scale to explore the impact of urbanization extent on four metrics of carrion  
 228 processing for each carcass: (1) the probability of any vertebrate scavenging activity, (2) the  
 229 probability of complete carcass removal, (3) the time from carcass deployment to the first  
 230 vertebrate scavenging event and (4) the time from carcass deployment to complete carcass  
 231 removal. Our four metrics of carrion processing rates were modelled using generalized linear  
 232 mixed effects models. We used the *glmer* function in the *lme4* package for analyses with  
 233 binomial distribution (1 and 2) and the *glmmTMB* function in the *glmmTMB* package for  
 234 analyses with gamma distribution (3 and 4), and model assumptions were evaluated using the  
 235 *DHARMA* package (Bates et al., 2015, Brooks et al., 2017, Hartig 2022). For each fish carcass  
 236 deployed, the binary probabilities of (1) any vertebrate scavenging activity and (2) complete  
 237 carcass removal were modelled using mixed-effects logistic regression (generalized linear  
 238 mixed-effects models with binomial distribution and a logit link) with site as a random effect.  
 239 The elapsed time (in hours) from carcass deployment to (3) the first scavenging event and (4)  
 240 complete carcass removal were modelled using generalized linear mixed-effects models with  
 241 gamma distributions and log links with site as a random effect.

242

## 243 **Results**

244

245 Across the 189 carcasses deployed at 17 sites, we recorded 1,231 scavenging events by  
 246 12 vertebrate scavenger species. No data were collected from 22 carcass deployments due to  
 247 camera failure or human interference (i.e., carcass removal by humans). The most abundant  
 248 scavenger species we documented were deer mice, common ravens, and American crows. We  
 249 recorded the most unique scavenging events (969 events at 25 carcasses) by deer mice, which  
 250 was largely due to the tendency of deer mice to return repeatedly to carcasses and scavenge  
 251 carrion in place. Common ravens were recorded scavenging the most individual carcasses (42  
 252 carcasses) at the most sites (11 sites) and were also responsible for the most instances of carcass  
 253 removal (40 carcasses) (Figure 3, Table S1). We documented several non-native scavenger  
 254 species—rats, Virginia opossums (*Didelphis virginiana*), domestic cats (*Felis catus*) and  
 255 domestic dogs (*Canis lupus familiaris*)—and several native mammalian mesocarnivore: coyotes,  
 256 gray foxes (*Urocyon cinereoargenteus*), raccoons (*Procyon lotor*) and striped skunks (*Mephitis*  
 257 *mephitis*). While sample size of scavenging events by many of these species was limited, several  
 258 species exhibited distinct temporal patterns of scavenging activity (Fig. 3, Fig. 6).

259

260 Urbanization substantially influenced the structure of vertebrate scavenging assemblages  
 261 on sandy beaches, and beach visitation by humans and domestic dogs were significant additive  
 262 predictors of assemblage structure. Urbanization extent was highly correlated at all scales, but  
 263 both analytical approaches identified urbanization at smaller spatial scales (1km and 3km) as the  
 264 best single-term predictors of scavenging assemblages (Tables S2, S3, S5). The best fitting  
 265 PERMANOVA model identified urbanization at the 3km scale as the best predictor of  
 scavenging assemblages ( $p < 0.001$ ), with next-best fitting models identifying urbanization at the

266 1km scale (PERMANOVA  $p < 0.001$ ,  $\Delta AICc = 0.026$ ), and urbanization at the 5km scale  
267 (PERMANOVA  $p < 0.001$ ,  $\Delta AICc = 0.531$ ) as the best predictors (Table S2). MvGLM modeling  
268 identified urbanization at the 1km scale as the best singular predictor of scavenging assemblages,  
269 with human visitation or domestic dog visitation as significant additive predictors (Table S5).  
270 The best fit MvGLM model included the additive effects of urbanization at the 1km scale  
271 ( $\chi^2 = 43.99$ ,  $p = 0.001$ ) and the rate of beach visitation by humans ( $\chi^2 = 25.32$ ,  $p = 0.022$ ). Testing for  
272 scavenger species with univariate GLMs that correlated significantly with the multivariate model  
273 revealed that the large differences in scavenging assemblages were best explained by variation in  
274 the distribution and abundance of two indicator species: American crows (*Corvus*  
275 *brachyrhynchos*) and deer mice (*Peromyscus spp.*) (Figs. 4, 5).

276 In contrast to urbanization-associated shifts in community structure, urbanization did not  
277 significantly alter any of the four measures of carrion processing rates (Fig. S2). While  
278 individual beaches had somewhat variable rates of carrion processing (i.e., proportion of  
279 carcasses with any scavenging ranged from 0.4-1; proportion of carcasses completely removed  
280 by scavengers ranged from 0.16-1), this variability was not correlated with urbanization extent;  
281 all generalized linear mixed effects models investigating carrion processing rates yielded non-  
282 significant urbanization effects (Fig. S2).

283

## 284 Discussion

285

286 Our findings show that urbanization can lead to pronounced changes in the composition  
287 of shoreline scavenger guilds, but that these differences in scavenging assemblages do not  
288 necessarily lead to subsequent changes in ecosystem functions performed by shoreline  
289 scavengers. Urban environments tended to support synanthropic and non-native scavengers such  
290 as American crows, rats, raccoons, and domestic cats and dogs, while scavenging guilds in rural  
291 areas were dominated by common ravens, deer mice, and coyotes. The retention of function  
292 across urbanization levels suggests that there is some level of functional redundancy in  
293 California's urbanized shorelines, with synanthropic and non-native species compensating for  
294 the loss of the predominate scavengers documented in rural areas. This functional redundancy  
295 underscores the adaptability of urban scavengers to diverse food sources such as beach-cast  
296 carrion, while also providing insight into the often-overlooked ecosystem services provided by  
297 scavengers in urban settings (Inger et al., 2016, Luna et al., 2021).

298 Both scavenging community analysis techniques yielded similar results, enhancing our  
299 confidence in the findings that urbanization at smaller spatial scales (1km and 3km) was more  
300 predictive of scavenging assemblages than larger scales (5km) and that human and domestic dog  
301 visitation rates were important additive predictors. This finding contrasts with that of Gilby et al.,  
302 (2022), which found that urbanization extent at larger scales predicted shoreline scavenging  
303 assemblages better than urbanization extent at smaller scales along the Sunshine Coast,  
304 Australia. Our contrasting results likely reflect ecological differences between regions, such as  
305 variation in the home range size and urbanization response of predominate scavengers, and  
306 highlight the need for comparable investigations in additional locales. Our results suggest that  
307 restoring and conserving small (1-3km radius) patches of undeveloped habitats along urban  
308 shorelines may prove effective in sustaining scavenging assemblages that resemble those in less  
309 urbanized areas along the California coast.

310 If ecosystem function is the target of shoreline management efforts rather than the  
311 presence of the species themselves, then synanthropic species that occupy highly urbanized areas

312 will be able to provide equivalent carrion processing ecosystem functions on sandy beaches in  
313 the absence of conservation or restoration efforts. While several studies have documented  
314 urbanization-associated reductions in scavenger species richness and carrion processing rates  
315 (Sebastián-González et al., 2019, Huijbers et al., 2013, Gilby et al., 2022), in some cases  
316 urbanization may produce spatial refugia (i.e., “human shield”) for generalist mesocarnivore  
317 scavengers and lead to an increased rate of carrion processing relative to adjacent rural areas  
318 (Moll et al., 2018, Patterson et al., 2023). Our findings signal that the consequences of  
319 urbanization for carrion processing can differ across ecosystem types and ecological contexts.  
320 While we found that synanthropic and non-native species associated with urban shorelines can  
321 provide carrion processing rates equivalent to those conferred by scavengers on rural beaches, it  
322 is doubtful that these differences do not lead to other ecological consequences such as altered  
323 pathways of marine-to-terrestrial nutrient redistribution. Incorporating additional measures of  
324 ecosystem function that reflect the impact of beach scavengers on nutrient cycling and terrestrial  
325 food webs could provide a more comprehensive understanding of the true ecological  
326 consequences of modified scavenging assemblages along urban coastlines.

327 While our primary objectives were to examine urbanization-associated shifts in  
328 scavenging community structure and ecosystem function, we noticed several temporal trends of  
329 shoreline vertebrate scavenging activity worthy of further investigation. While the sample size of  
330 scavenging events was low for most species, many species exhibited distinct diel patterns of  
331 scavenging activity (Fig. 3, Fig. 6, Fig. S3). Apart from domestic dogs, mammals were typically  
332 documented scavenging during nighttime hours and birds were most often documented during  
333 daytime and crepuscular hours (Fig. 3, Fig. S3). Among the three species with the most  
334 documented scavenging events—deer mice, common ravens, and American crows—deer mice  
335 were only documented during nighttime hours and exhibited a peak of carcass visitation between  
336 the hours 20:00-22:00, while common ravens and American crows were primarily documented  
337 during daytime hours with notable peaks in scavenging activity between 7:00-9:00 (Fig. 6).  
338 These peaks for avian scavengers likely reflect the first scavenging event after morning carcass  
339 deployment (mean deployment time = 8:03), suggesting that these species rapidly identify and  
340 scavenge shoreline carrion during early daytime hours. For deer mice, the peak in visitation in  
341 the early evening may indicate that the animals engage in opportunistic feeding until satiation,  
342 with scavenging activity tapering off throughout the nighttime hours. Deer mice were also  
343 recorded burying the herring carcasses in sand on several occasions, which may serve to hide the  
344 carrion from diurnal avian scavengers, act as a food cache for future deer mouse exploitation,  
345 and/or retain marine nutrients in sandy beach food webs. Lastly, exploring the interaction  
346 between urbanization and diel patterns of shoreline scavenging activity could elucidate the  
347 ecological consequences of shifts in urban animal behavior associated with human disturbances  
348 (Gallo et al., 2023). We suggest that future research should incorporate temporal processes into  
349 urban scavenging studies to provide additional complexity to our understanding of human-  
350 modified ecosystem dynamics.

351 With more than half of the world’s population now living in cities, contemporary  
352 urbanization is driving extreme and widespread landscape transformation while also presenting  
353 opportunities for sustainability (Grimm et al., 2008). Mitigating negative ecological  
354 consequences of urban development in coastal cities requires understanding the impacts of  
355 urbanization on landscapes and biodiversity, and how these modifications propagate to influence  
356 ecosystem functions in both marine and terrestrial realms (Threlfall et al., 2021). Given the  
357 consequential role of scavengers in human-wildlife interactions and public health initiatives,



358 understanding anthropogenic impacts to scavenging dynamics remains a critical knowledge gap  
359 in urban ecological studies and an important trajectory of future research (Markandya et al.,  
360 2008, Ogada et al., 2012, Luna et al., 2021). Our findings—that urbanization alters vertebrate  
361 scavenging assemblages but not carrion processing rates—highlight the need for a nuanced  
362 approach to coastal urban conservation and management that identifies whether individual  
363 species or the ecosystem functions they perform are the target of ecological interventions.  
364 Incorporating such careful considerations of shoreline scavenging dynamics will be central to  
365 effective cross-ecosystem management and the planning of sustainable and resilient urban land-  
366 and seascapes.

367

#### 368 **4. Acknowledgements**

369

370 We thank S. Williams, M. Laskan, K. Strand, B. Do Carmo Amaral, M. McNelis, R. Mancuso,  
371 and M. Palmada for fieldwork assistance, and extend gratitude to E. Howard, B. Kennedy, and J.  
372 Kerbavaz for assistance with research permitting and approval. We are grateful to P. Raimondi,  
373 C. Wilkinson, J. McDevitt-Irwin, Z. Zilz, C. Braman, G. Gilbert, W. Bragg, M. Douglas, A.  
374 Ellis, and M. McElfish for constructive comments on the manuscript. Animal silhouettes in  
375 Figures 3 and 5 were provided by G Palomo-Munoz, Anthony Caravaggi, and Edwin Price (CC  
376 BY-NC 3.0; CC BY-NC-SA 3.0; CC BY 4.0) through phylopic.org. This research was funded by  
377 a NSF Graduate Research Fellowship and grants from the PADI Foundation, Myers  
378 Oceanographic and Marine Biology Trust, and International Women’s Fishing Association  
379 Scholarship to F.D.G.

380

#### 381 **5. Conflict of Interest Statement**

382

383 All authors declare that they have no conflicts of interests to disclose.

384

#### 385 **6. Ethics Statement**

386

387 All methods were approved by the University of California, Santa Cruz, Institutional Animal  
388 Care and Use Committee (IACUC number Raimp\_2207\_a1). Access to and baited camera  
389 placement on beaches was approved by a CA State Parks district permit and direct approval by  
390 the UCSC Younger Lagoon natural reserve director.

391

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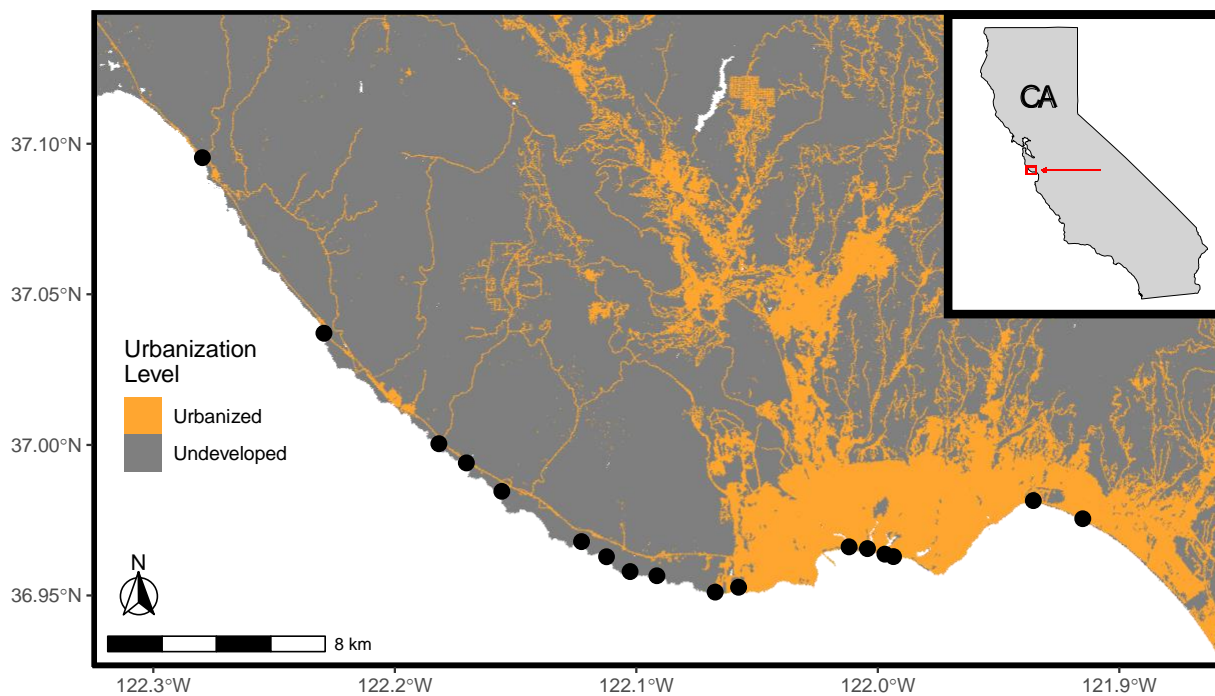
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631 **8. Figures**  
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633 **Figure 1.** Map of urbanized areas and survey sites along the central coast of California (CA).  
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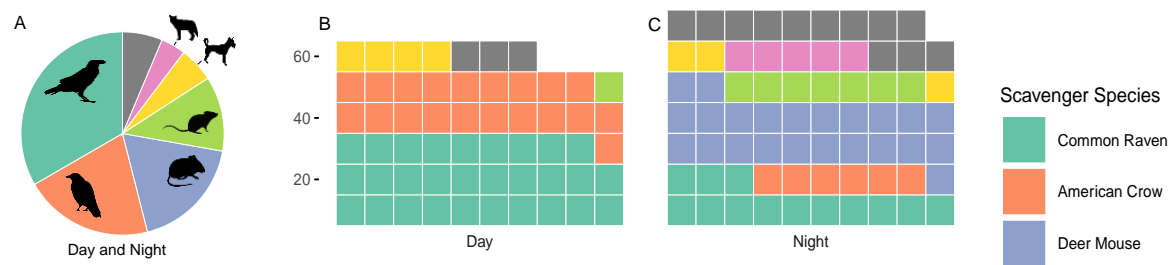


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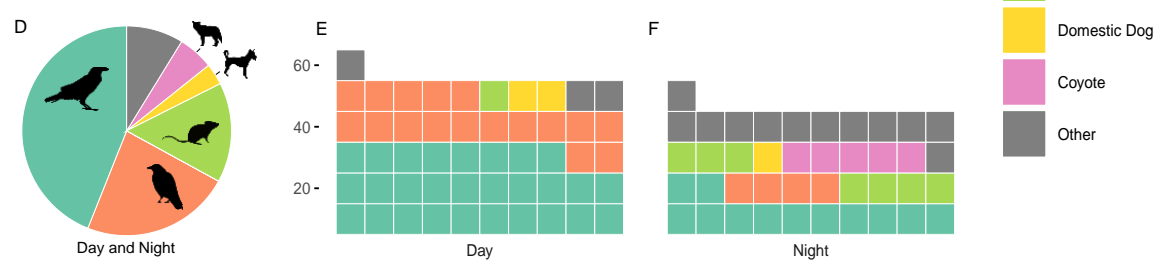
**Figure 2.** Examples of detected scavenger species: (A) coyote (*Canis latrans*), (B) gray fox (*Urocyon cinereoargenteus*), (C) common raven (*Corvus corax*), (D) striped skunk (*Mephitis mephitis*), (E) western gull (*Larus occidentalis*), (F) Virginia opossum (*Didelphis virginiana*)



### Carcass Scavenging

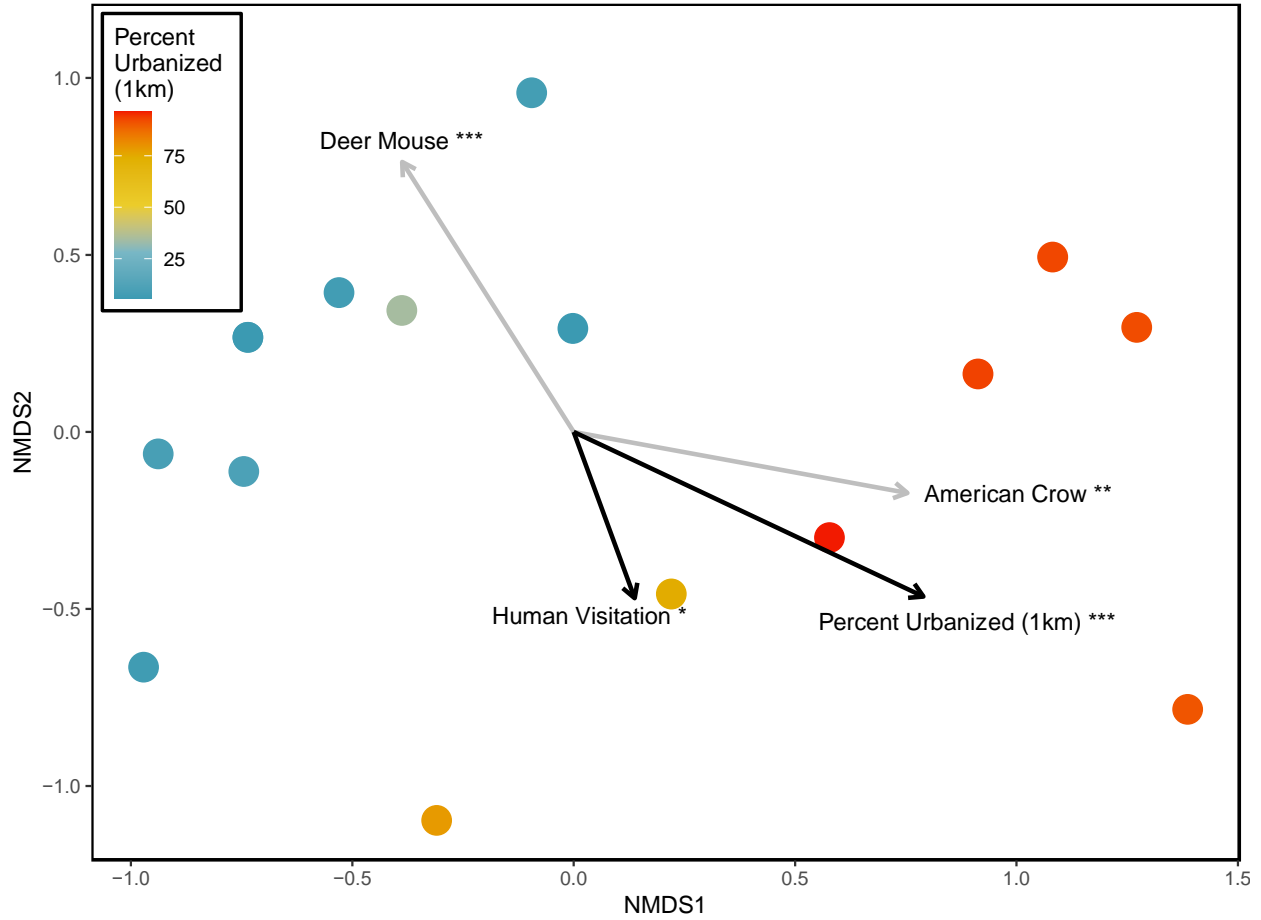


### Carcass Removal



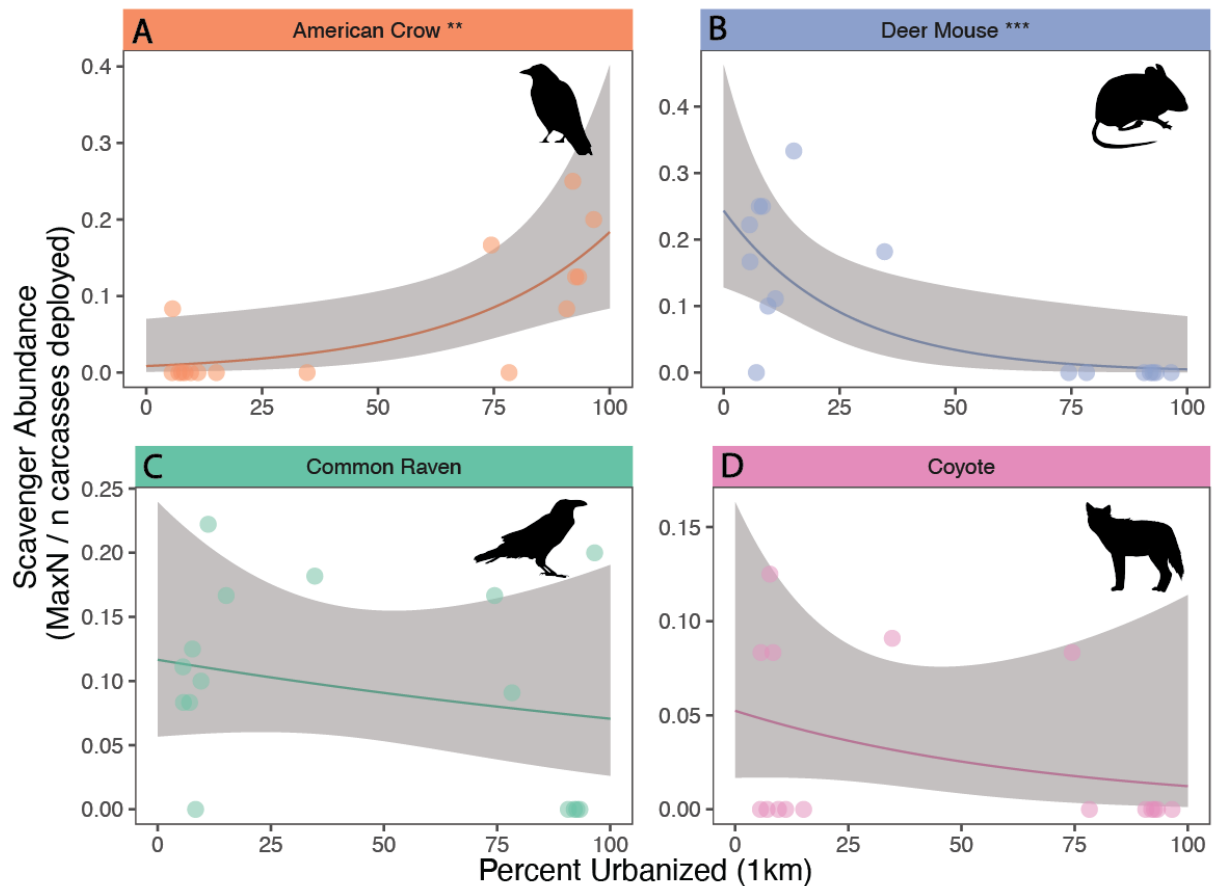
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668 **Figure 3.** Partitioning of scavenging events among primary scavenger species for all scavenging  
669 events (A-C) and events of carcass removal (D-F). Panels show the proportion of scavenging  
670 and carcass removal events attributable to each species (A,D) and the actual number of carcasses  
671 scavenged and removed by each species during diurnal (B,E) and nocturnal (C,F) carrion  
672 deployments.

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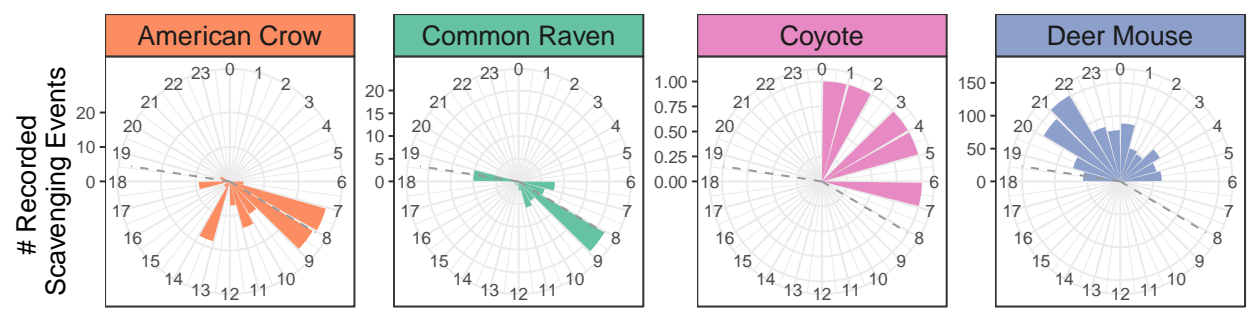
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**Figure 4.** Non-metric multidimensional scaling (NMDS) plot illustrating scavenging assemblages at each site, as well as vectors representing predictor variables and indicator species from the best-fitting MvGLM model. The overall stress of the two-dimensional NMDS is 0.08.

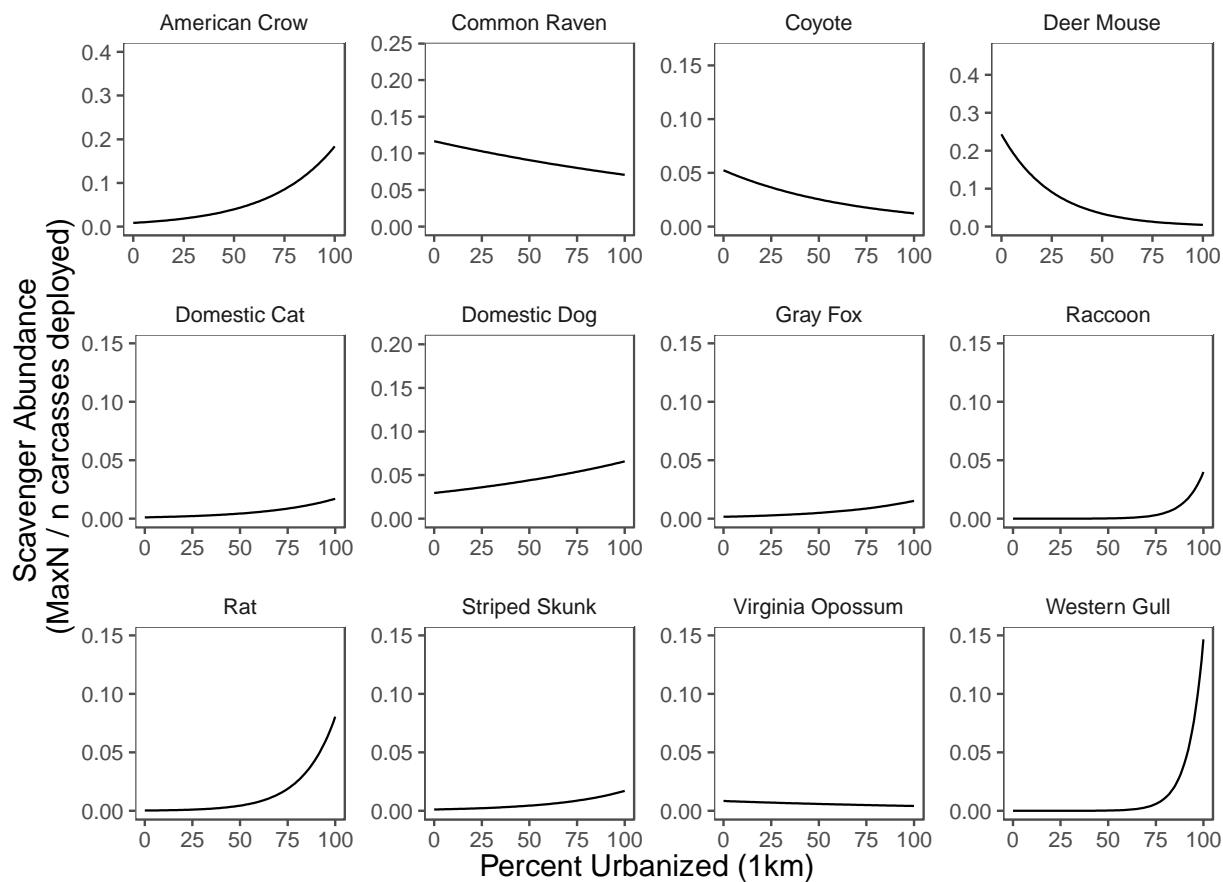


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 718 **Figure 5.** Generalized linear models illustrating relationships between urbanization extent and  
 719 our two indicator species whose abundance and prevalence correlate significantly with the best  
 720 fit MvGLM model—(A) American crows and (B) deer mice—as well as two widely-documented  
 721 scavenger species whose abundance and prevalence are not significantly correlated with the  
 722 multivariate model: (C) common ravens and (D) coyotes. Fitted GLMs have negative binomial  
 723 distributions and log links and are offset by sampling effort (# carcasses deployed per site), with  
 724 shaded regions representing  $\pm$  SE.

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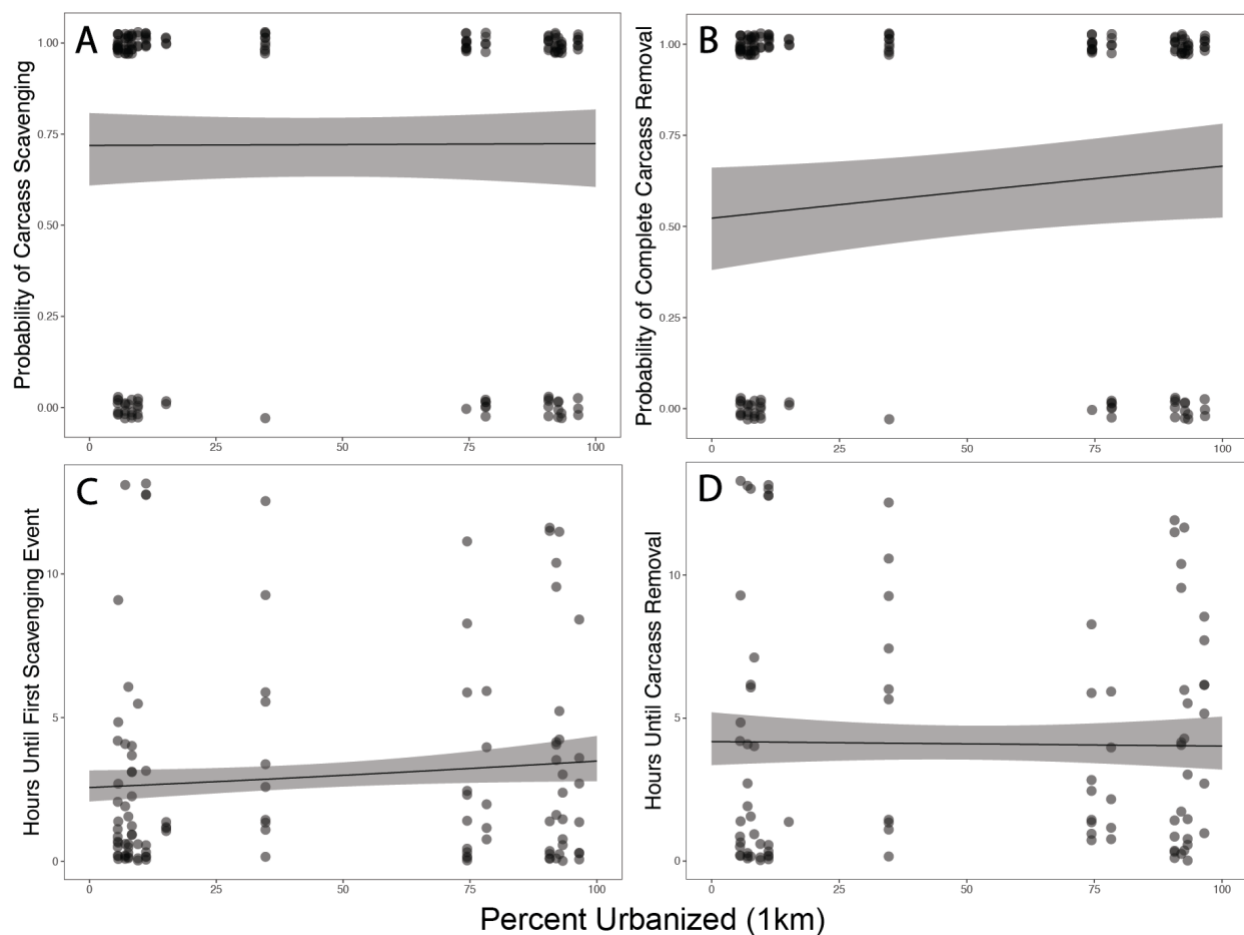


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740 **Figure 6.** Temporal dynamics of scavenging by four widely documented vertebrate scavenging  
741 species. The length of each radiating bar representing the number of documented scavenging  
742 events between each hour marker throughout the 24-hour diel cycle. Dashed lines depict the  
743 average deployment time of morning and evening carcasses throughout our study.  
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775 **9. Supplemental Information**

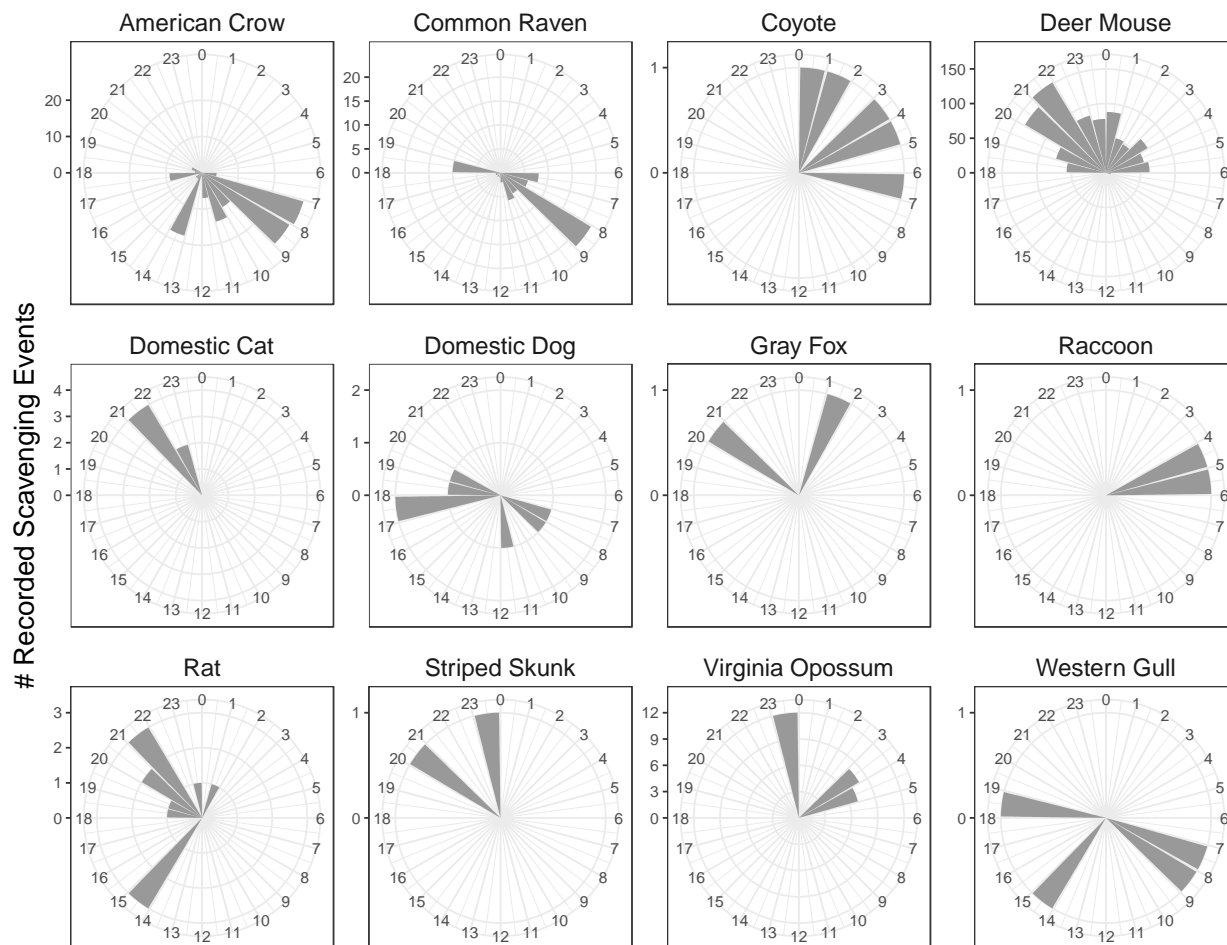
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 777 **Figure S1.** Single-species univariate models illustrating relationships between urbanization  
 778 extent and abundance all scavenger species documented in this study. All fitted univariate  
 779 models have negative binomial distributions and log links and are offset by sampling effort (#  
 780 carcasses deployed per site), with shaded regions representing  $\pm$  SE.

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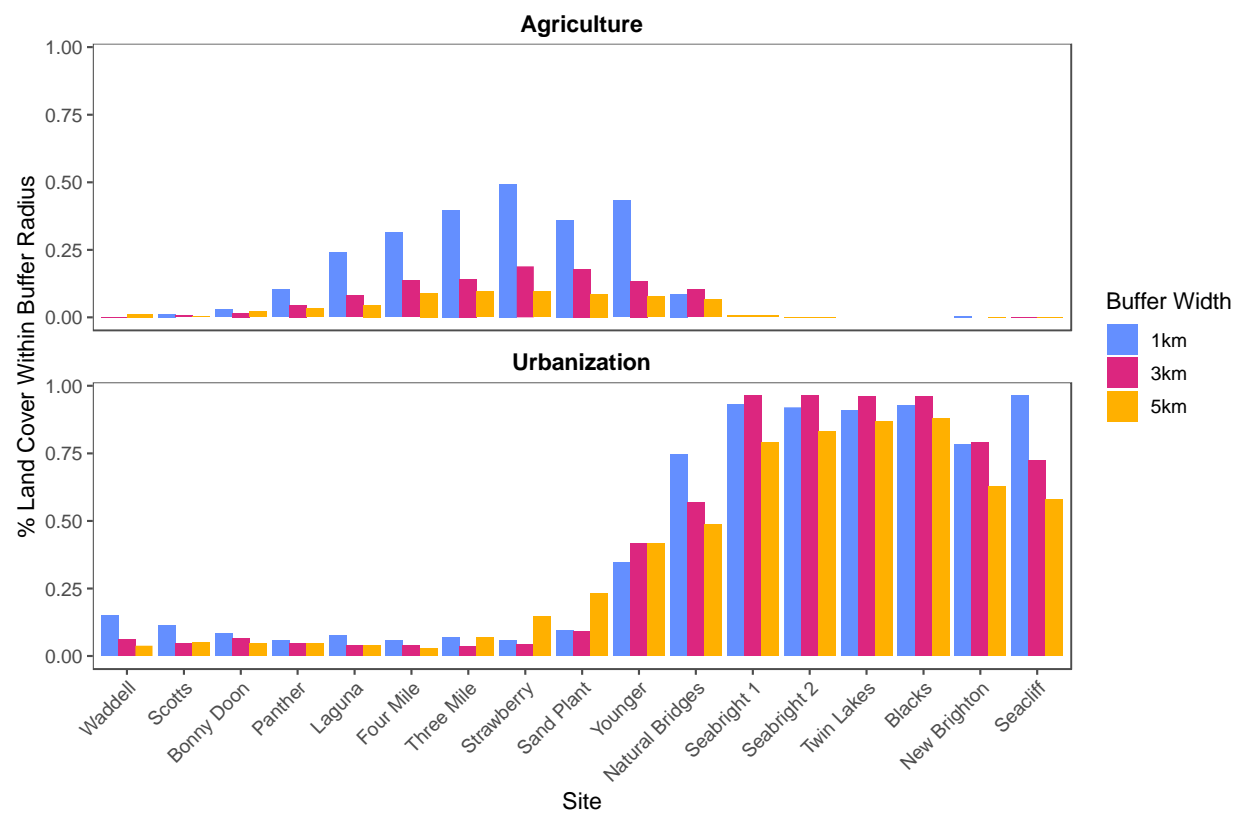
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 798 **Figure S2.** Generalized linear mixed-effects models, with site as a random effect, illustrating the  
 799 relationship between urbanization extent and four metrics of carrion processing: (A) the  
 800 probability of a carcass being scavenged, (B) the probability of a carcass being removed by  
 801 scavengers, (C) the time until the first scavenging event on a carcass, and (D) the time until  
 802 carcass removal by scavengers. Fitted GLMMs have (A,B) binomial distribution and logit links  
 803 or (C,D) gamma distribution and log links, with shaded regions representing  $\pm$  SE. We applied a  
 804 vertical jitter to points in panels A and B to increase readability.

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 820 **Figure S3.** Temporal dynamics of scavenging by all vertebrate scavenging species documented  
 821 in this study. The length of each radiating bar representing the number of documented  
 822 scavenging events between each hour marker throughout the 24-hour diel cycle. Dashed lines  
 823 depict the average deployment time of morning and evening carcasses throughout our study.

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**Figure S4.** Values of agricultural extent and urbanization extent at 1km, 3km, 5km scales for each study site.



864 **Table S1.** Vertebrate scavenger species documented in this study, whether they are considered  
 865 non-native in the region, and several metrics of scavenger abundance.

Common Name	Scientific Name	Considered Invasive in Region?	# Documented Scavenging Events	# Unique Carcasses Scavenged	# Sites Recorded	Sum of MaxN for All Sites
American Crow	<i>Corvus brachyrhynchos</i>		131	27	7	10
Common Raven	<i>Corvus corax</i>		63	43	11	15
Coyote	<i>Canis latrans</i>		5	5	5	5
Deer Mouse	<i>Peromyscus spp.</i>		969	25	8	15
Domestic Cat	<i>Felis catus</i>	Yes	6	1	1	1
Domestic Dog	<i>Canis lupus familiaris</i>	Yes	7	7	6	7
Gray Fox	<i>Urocyon cinereoargenteus</i>		2	2	1	1
Rat	<i>Rattus spp.</i>	Yes	12	8	3	3
Raccoon	<i>Procyon lotor</i>		2	2	1	1
Striped Skunk	<i>Mephitis mephitis</i>		2	2	1	1
Virginia Opossum	<i>Didelphis virginiana</i>	Yes	27	4	1	1
Western Gull	<i>Larus occidentalis</i>		4	4	2	3

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884 **Table S2.** Table of top PERMANOVA models ( $\Delta AICc < 2$ ).

PERMANOVA Top Models Summary ( $\Delta AICc < 2$ )			
Model terms	AICc	$\Delta AICc$	AIC Weight
Urbanization Extent 3km	-26.86358	0.00000000	0.22897755
Urbanization Extent 1km	-26.83722	0.02636014	0.22597941
Urbanization Extent 5km	-26.33244	0.53114315	0.17557256
Urbanization Extent 3km + Domestic Dog Visitation	-25.15868	1.70490332	0.09762878
Urbanization Extent 1km + Domestic Dog Visitation	-25.09082	1.77276216	0.09437186
Urbanization Extent 1km + Human Visitation	-25.02332	1.84026233	0.09123995
Urbanization Extent 3km + Human Visitation	-24.91036	1.95321404	0.08622990

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888 **Table S3.** Table of top PERMANOVA predictors after model averaging.

PERMANOVA Top Predictors Summary		
Predictor	Aikake Adjusted Rsq	Number of Top Models
Urbanization Extent 3km	0.173593196	3
Urbanization Extent 1km	0.173047067	3
Domestic Dog Visitation	0.008550503	2
Human Visitation	0.007023153	2
Urbanization Extent 5km	0.075871554	1

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892 **Table S4.** Table of all fitted PERMANOVA models.

All Fitted PERMANOVA Models			
Model terms	AICc	$\Delta$ AICc	AIC Weight
Urbanization Extent 3km	-26.86358	0.00000000	0.1035336551
Urbanization Extent 1km	-26.83722	0.02636014	0.1021780277
Urbanization Extent 5km	-26.33244	0.53114315	0.0793862480
Urbanization Extent 3km + Domestic Dog Visitation	-25.15868	1.70490332	0.0441434725
Urbanization Extent 1km + Domestic Dog Visitation	-25.09082	1.77276216	0.0426708344
Urbanization Extent 1km + Human Visitation	-25.02332	1.84026233	0.0412547215
Urbanization Extent 3km + Human Visitation	-24.91036	1.95321404	0.0389893959
Urbanization Extent 1km + Agricultural Extent 3km	-24.60041	2.26316538	0.0333919229
Urbanization Extent 5km + Domestic Dog Visitation	-24.54521	2.31836952	0.0324828406
Urbanization Extent 1km + Agricultural Extent 5km	-24.52484	2.33873653	0.0321537300
Urbanization Extent 3km + Agricultural Extent 3km	-24.41956	2.44402234	0.0305048461
Urbanization Extent 3km + Agricultural Extent 5km	-24.34001	2.52356891	0.0293153795
Urbanization Extent 5km + Human Visitation	-24.31543	2.54815191	0.0289572550
Urbanization Extent 1km + Agricultural Extent 1km	-24.18180	2.68177695	0.0270857634
Urbanization Extent 3km + Agricultural Extent 1km	-24.09265	2.77092943	0.0259048967
Urbanization Extent 5km + Agricultural Extent 3km	-24.07902	2.78455434	0.0257290206
Urbanization Extent 5km + Agricultural Extent 1km	-23.86426	2.99931827	0.0231093568
Urbanization Extent 5km + Agricultural Extent 5km	-23.85969	3.00388815	0.0230566137
Urbanization Extent 1km + Human Visitation + Domestic Dog Visitation	-23.03463	3.82894448	0.0152628915
Urbanization Extent 3km + Human Visitation + Domestic Dog Visitation	-22.98090	3.88267380	0.0148583178
Urbanization Extent 1km + Agricultural Extent 3km + Domestic Dog Visitation	-22.37583	4.48775348	0.0109793912
Urbanization Extent 5km + Human Visitation +	-22.30807	4.55550598	0.0106136800

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All Fitted PERMANOVA Models			
Model terms	AICc	$\Delta$ AICc	AIC Weight
Domestic Dog Visitation			
Urbanization Extent 3km + Agricultural Extent 3km + Domestic Dog Visitation	-22.27730	4.58628134	0.0104516103
Urbanization Extent 1km + Agricultural Extent 5km + Domestic Dog Visitation	-22.25013	4.61344940	0.0103105952
Urbanization Extent 3km + Agricultural Extent 5km + Domestic Dog Visitation	-22.13709	4.72649067	0.0097439969
Urbanization Extent 5km + Agricultural Extent 3km + Domestic Dog Visitation	-21.94495	4.91862709	0.0088514668
Urbanization Extent 1km + Agricultural Extent 1km + Domestic Dog Visitation	-21.93704	4.92654315	0.0088165017
Urbanization Extent 3km + Agricultural Extent 1km + Domestic Dog Visitation	-21.92708	4.93650022	0.0087727175
Urbanization Extent 1km + Agricultural Extent 1km + Human Visitation	-21.73190	5.13168215	0.0079570287
Urbanization Extent 1km + Agricultural Extent 3km + Human Visitation	-21.71537	5.14820540	0.0078915615
Urbanization Extent 5km + Agricultural Extent 1km + Domestic Dog Visitation	-21.71198	5.15160224	0.0078781697
Urbanization Extent 1km + Agricultural Extent 5km + Human Visitation	-21.71170	5.15188246	0.0078770660
Urbanization Extent 3km + Agricultural Extent 1km + Human Visitation	-21.66857	5.19501089	0.0077090216
Urbanization Extent 5km + Agricultural Extent 5km + Domestic Dog Visitation	-21.62481	5.23877120	0.0075421790
Urbanization Extent 3km + Agricultural Extent 3km + Human Visitation	-21.53743	5.32614597	0.0072197747
Urbanization Extent 3km + Agricultural Extent 5km + Human Visitation	-21.47718	5.38639555	0.0070055238
Urbanization Extent 5km + Agricultural Extent 1km + Human Visitation	-21.46617	5.39741088	0.0069670458
Urbanization Extent 5km + Agricultural Extent 3km + Human Visitation	-21.26519	5.59839201	0.0063009519

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All Fitted PERMANOVA Models			
Model terms	AICc	$\Delta$ AICc	AIC Weight
Urbanization Extent 5km + Agricultural Extent 5km + Human Visitation	-21.02558	5.83800135	0.0055895347
Agricultural Extent 1km	-20.25336	6.61021998	0.0037991856
Agricultural Extent 5km	-20.04341	6.82016903	0.0034205871
Agricultural Extent 3km	-20.04017	6.82340545	0.0034150564
Null Model	-19.91577	6.94780688	0.0032091089
Domestic Dog Visitation	-19.62992	7.23365816	0.0027817150
Urbanization Extent 3km + Agricultural Extent 1km + Human Visitation + Domestic Dog Visitation	-19.08917	7.77441315	0.0021227027
Urbanization Extent 1km + Agricultural Extent 1km + Human Visitation + Domestic Dog Visitation	-19.04755	7.81602406	0.0020789952
Urbanization Extent 1km + Agricultural Extent 3km + Human Visitation + Domestic Dog Visitation	-19.01852	7.84505894	0.0020490315
Urbanization Extent 1km + Agricultural Extent 5km + Human Visitation + Domestic Dog Visitation	-18.97686	7.88671970	0.0020067909
Urbanization Extent 3km + Agricultural Extent 3km + Human Visitation + Domestic Dog Visitation	-18.96611	7.89747093	0.0019960321
Urbanization Extent 5km + Agricultural Extent 1km + Human Visitation + Domestic Dog Visitation	-18.89473	7.96884884	0.0019260520
Urbanization Extent 3km + Agricultural Extent 5km + Human Visitation + Domestic Dog Visitation	-18.83546	8.02811545	0.0018698141
Urbanization Extent 5km + Agricultural Extent 3km + Human Visitation + Domestic Dog Visitation	-18.73905	8.12452609	0.0017818171
Agricultural Extent 1km + Domestic Dog Visitation	-18.72191	8.14166656	0.0017666118
Human Visitation	-18.58049	8.28308479	0.0016460103
Agricultural Extent 5km + Human Visitation	-18.54671	8.31687087	0.0016184377
Agricultural Extent 3km + Human Visitation	-18.53394	8.32963439	0.0016081421
Agricultural Extent 3km + Domestic Dog Visitation	-18.42946	8.43412024	0.0015262849
Agricultural Extent 1km + Human Visitation	-18.38578	8.47779425	0.0014933167

All Fitted PERMANOVA Models			
Model terms	AICc	$\Delta$ AICc	AIC Weight
Urbanization Extent 5km + Agricultural Extent 5km + Human Visitation + Domestic Dog Visitation	-18.38504	8.47853827	0.0014927613
Agricultural Extent 5km + Domestic Dog Visitation	-18.31188	8.55170314	0.0014391392
Human Visitation + Domestic Dog Visitation	-17.61905	9.24452397	0.0010177912
Agricultural Extent 1km + Human Visitation + Domestic Dog Visitation	-16.28682	10.57675470	0.0005228396
Agricultural Extent 3km + Human Visitation + Domestic Dog Visitation	-16.16088	10.70270249	0.0004909296
Agricultural Extent 5km + Human Visitation + Domestic Dog Visitation	-16.09002	10.77356370	0.0004738402

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907 **Table S5.** Table of top MvGLM models ( $\Delta AIC < 2$ ).

MvGLM Top Models Summary ( $\Delta AIC < 2$ )		
Model terms	df	AIC
Urbanization Extent 1km + Human Visitation	13	260.4491
Urbanization Extent 1km + Domestic Dog Visitation	13	261.1986
Agricultural Extent 5km + Human Visitation	13	262.0895
Urbanization Extent 1km	14	262.1853

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911 **Table S6.** Table of all fitted MvGLM models.

All MvGLM Models		
Model terms	df	AIC
Urbanization Extent 1km + Human Visitation	13	260.4491
Urbanization Extent 1km + Domestic Dog Visitation	13	261.1986
Agricultural Extent 5km + Human Visitation	13	262.0895
Urbanization Extent 1km	14	262.1853
Agricultural Extent 1km + Human Visitation	13	263.7093
Agricultural Extent 3km + Human Visitation	13	264.0475
Urbanization Extent 3km + Human Visitation	13	264.4773
Urbanization Extent 1km + Human Visitation + Domestic Dog Visitation	12	266.9031
Urbanization Extent 5km + Human Visitation	13	266.9189
Urbanization Extent 3km	14	266.9910
Urbanization Extent 1km + Agricultural Extent 5km + Human Visitation	12	267.4801
Urbanization Extent 3km + Domestic Dog Visitation	13	268.3273
Urbanization Extent 5km + Domestic Dog Visitation	13	269.5914
Urbanization Extent 5km	14	269.8151
Urbanization Extent 1km + Agricultural Extent 5km	13	269.9977
Urbanization Extent 1km + Agricultural Extent 3km	13	270.9724
Human Visitation	14	271.5862
Urbanization Extent 3km + Agricultural Extent 5km	13	271.6423
Urbanization Extent 1km + Agricultural Extent 3km + Human Visitation	12	272.2057
Domestic Dog Visitation	14	272.3701
Urbanization Extent 1km + Agricultural Extent 1km + Human Visitation	12	272.8191
Urbanization Extent 3km + Agricultural Extent 3km	13	272.9447
Urbanization Extent 5km + Agricultural Extent 5km	13	272.9639
Agricultural Extent 1km + Domestic Dog Visitation	13	273.7047
Agricultural Extent 1km	14	274.1322

All MvGLM Models		
Model terms	df	AIC
Urbanization Extent 3km + Agricultural Extent 5km + Human Visitation	12	274.4584
Urbanization Extent 3km + Human Visitation + Domestic Dog Visitation	12	274.9716
Human Visitation + Domestic Dog Visitation	13	275.0108
Urbanization Extent 1km + Agricultural Extent 5km + Domestic Dog Visitation	12	275.1098
Urbanization Extent 5km + Agricultural Extent 1km + Human Visitation	12	275.2664
Urbanization Extent 5km + Agricultural Extent 5km + Human Visitation	12	275.2791
Urbanization Extent 1km + Agricultural Extent 1km	13	275.5768
Urbanization Extent 3km + Agricultural Extent 1km + Human Visitation	12	275.7097
Urbanization Extent 5km + Agricultural Extent 3km + Human Visitation	12	276.6337
Urbanization Extent 5km + Agricultural Extent 3km	13	276.7654
Agricultural Extent 5km + Domestic Dog Visitation	13	276.7709
Urbanization Extent 3km + Agricultural Extent 3km + Human Visitation	12	276.8291
Urbanization Extent 5km + Human Visitation + Domestic Dog Visitation	12	276.8751
Urbanization Extent 1km + Agricultural Extent 3km + Domestic Dog Visitation	12	277.6490
Urbanization Extent 1km + Agricultural Extent 1km + Domestic Dog Visitation	12	277.9824
Null Model	15	278.4332
Urbanization Extent 3km + Agricultural Extent 5km + Domestic Dog Visitation	12	278.5873
Agricultural Extent 1km + Human Visitation + Domestic Dog Visitation	12	278.6015
Agricultural Extent 3km + Human Visitation + Domestic Dog Visitation	12	278.6922
Agricultural Extent 3km	14	278.8957
Agricultural Extent 3km + Domestic Dog Visitation	13	278.9896
Agricultural Extent 5km	14	279.0450
Urbanization Extent 5km + Agricultural Extent 5km + Domestic Dog Visitation	12	279.3764
Urbanization Extent 3km + Agricultural Extent 1km	13	279.4531
Agricultural Extent 5km + Human Visitation + Domestic Dog Visitation	12	279.7839

All MvGLM Models		
Model terms	df	AIC
Urbanization Extent 5km + Agricultural Extent 1km	13	280.4272
Urbanization Extent 3km + Agricultural Extent 3km + Domestic Dog Visitation	12	280.6248
Urbanization Extent 5km + Agricultural Extent 1km + Domestic Dog Visitation	12	282.7655
Urbanization Extent 3km + Agricultural Extent 1km + Domestic Dog Visitation	12	282.8540
Urbanization Extent 5km + Agricultural Extent 3km + Domestic Dog Visitation	12	283.3892
Urbanization Extent 1km + Agricultural Extent 3km + Human Visitation + Domestic Dog Visitation	11	286.7540
Urbanization Extent 1km + Agricultural Extent 1km + Human Visitation + Domestic Dog Visitation	11	287.0228
Urbanization Extent 1km + Agricultural Extent 5km + Human Visitation + Domestic Dog Visitation	11	288.2137
Urbanization Extent 5km + Agricultural Extent 1km + Human Visitation + Domestic Dog Visitation	11	291.4385
Urbanization Extent 3km + Agricultural Extent 1km + Human Visitation + Domestic Dog Visitation	11	291.7624
Urbanization Extent 5km + Agricultural Extent 3km + Human Visitation + Domestic Dog Visitation	11	292.2339
Urbanization Extent 3km + Agricultural Extent 3km + Human Visitation + Domestic Dog Visitation	11	292.7097
Urbanization Extent 3km + Agricultural Extent 5km + Human Visitation + Domestic Dog Visitation	11	293.5100
Urbanization Extent 5km + Agricultural Extent 5km + Human Visitation + Domestic Dog Visitation	11	293.6249