

1 **Gut microbiome composition predicts summer core range size in a generalist and specialist**
2 **ungulate**

3

4 J.F. Wolf¹ (<https://orcid.org/0000-0003-0773-4456>), K.D. Kriss², K.M. MacAulay² (<https://orcid.org/0000-0003-1001-6906>), K. Munro^{1,3}, B.R. Patterson^{1,4}, and A.B.A. Shafer^{1,5} (<http://orcid.org/0000-0001-7652-225X>)

7

8 ¹ Trent University, Department of Environmental and Life Sciences, Peterborough, Ontario, K9L 0G2,
9 Canada

10 ² Ministry of Forests, Lands, and Natural Resource Operations, and Rural Development, Smithers, British
11 Columbia V0J 2N0, Canada

12 ³ Ontario Federation of Anglers and Hunters, 4601 Guthrie Drive, Peterborough, Ontario, K9J 8L5

13 ⁴ Ontario Ministry of Natural Resources and Forestry, Wildlife Research and Monitoring Section, Trent
14 University, DNA Building, Peterborough, ON, Canada

15 ⁵ Trent University, Forensic Science Program, Peterborough, Ontario, K9L 0G2, Canada

16

17

18 Corresponding author: jessewolf@trentu.ca

19

20 **Keywords**

21 **Mountain goat, White-tailed deer, Genomics, GPS tracking, Proportional habitat use, Core range**

22 **Abstract**

23 Individuals exhibit differences in their microbial composition that have important implications for both
24 population dynamics and ecological processes. The gut microbiome of animals can vary by age,
25 reproductive status, diet, and habitat quality, and directly influences an individual's health and fitness.
26 Likewise, variation in an individual's home range can lead to differences in reproductive behaviour,
27 feeding strategies, and fitness. Ungulates (hooved mammals) exhibit species-specific microbiomes and
28 habitat use patterns that differ by season, sex, and age-class, leading to variation among individuals
29 occupying a similar geographic area. Here, we combined fecal microbiome and movement data to assess
30 the relationship between space use and the gut microbiome in a specialist and a generalist ungulate. We
31 captured and GPS radiocollared 24 mountain goats (*Oreamnos americanus*) and 34 white-tailed deer
32 (*Odocoileus virginianus*). During captures we collected fresh fecal samples and conducted high-throughput
33 sequencing of the fecal microbiome (i.e. 16S rRNA gene) to quantify gut microbial diversity. We
34 generated Brownian Bridge Movement Models from the GPS location data to estimate core (50%) and
35 home range (95%) sizes and calculated the proportion of use for several important habitat types. An
36 increase in *Firmicutes* to *Bacteroides* ratios corresponded to an increase in core range area in both species.
37 In mountain goats we observed a negative relationship between gut diversity and use of both escape terrain
38 and treed habitat, both critical features for this alpine specialist. There were no relationships between
39 habitat use and the gut microbiome in the more generalist white-tailed deer. We hypothesize that larger
40 *Firmicutes* to *Bacteroides* ratios confer body size or fat advantages that allow for larger home ranges, and
41 that relationships between gut diversity and disproportionate use of particular habitats is stronger in
42 mountain goats due to their restricted niche relative to white-tailed deer. This is the first study to relate core
43 range size to gut diversity in wild ungulates and is an important proof of concept that advances the
44 potential type of information that can be gleaned from non-invasive sampling.

45 **Introduction**

46 The gastrointestinal tract of animals contains trillions of microbes that influence each individual's health.
47 Gut bacteria, hereafter termed the gut microbiome, can modify immune responses (Arnolds & Lozupone,
48 2016), improve and modulate metabolism (De Angelis et al., 2020), and affect behaviour (Shreiner, Kao, &
49 Young, 2015; Zhang, Ju, & Zuo, 2018). While largely stable over time (Coyte, Schluter, & Foster, 2015;
50 Faith et al., 2013), disturbance of gut microbiome can lead to disease (Duvallat, Gibbons, Gurry, Irizarry,
51 & Alm, 2017) and impacts metabolic versatility, meaning the ability to survive equally well when
52 presented with a wide range of dietary compositions and habitat (Esposti & Romero, 2017; Tinker &
53 Ottesen, 2016). Gut microbiome diversity has been shown to impact behaviour; for example, gut
54 microbiome manipulation in mice resulted in higher memory as measured using a passive-avoidance test
55 (Mao et al., 2020). Leitão-Gonçalves et al., (2017) showed that the presence of key gut bacteria species
56 suppressed protein appetite, indicating the ability of the gut microbiome to drive dietary decisions. The
57 mechanistic links are not totally understood, but are thought to follow the microbiota-gut-brain axis where
58 bacteria have the ability to, for example, generate neurotransmitters that influence cognition (Cryan &
59 Dinan, 2012).

60
61 Differences in gut microbiome composition have also been correlated to the landscape; percent urban
62 landcover in ibises is positively correlated with gut microbiome composition (*Pelecaniformes spp*; Murray,
63 et al., 2020) and in multiple bird species, microbial community was significantly correlated to habitat type
64 (San Juan et al., 2019). Individuals in farmland habitats also exhibited higher diversity relative to
65 individuals in natural habitats, reflecting the link between gut microbiome composition and ecosystem
66 alteration (Chang, Huang, Lin, Huang, & Liao, 2016). Levels of daily activity and foraging appear to be
67 influenced by the gut microbiome (Jones et al., 2018; Schretter et al., 2018) and distinct diet types, such as
68 herbivory and carnivory, are associated with unique microbiome profiles (Ley et al., 2008). Herbivores in
69 particular exhibit specific gut bacterial compositions, as certain bacteria allow them to extract energy and
70 nutrients from food and detoxify plant defense compounds (Dearing & Kohl, 2017).

71 Mammalian herbivores are typified by specific gut microbial taxa as they rely on these bacteria to extract
72 energy and nutrients from food, synthesize vitamins, and detoxify plant defense compounds (Dearing &
73 Kohl, 2017). Ungulates, and ruminants in particular, have specialized anatomical and physiological
74 adaptations to accommodate the cellulolytic fermentation of low-nutrition, high-fiber plant materials (De
75 Tarso, Oliviera, & Bastos Alfonso, 2016). A specialized gut microbiome allows ruminants to digest
76 typically indigestible plant biomass (Kruger Ben Shabat et al., 2016) and as a result exploit novel
77 environments. Mountain goats (*Oreamnos americanus*) are large alpine ruminants that are endemic to the
78 mountainous regions of northwestern North America (Festa-Bianchet and Côté 2008). Mountain goats use
79 lower elevation, forested, and warmer aspect habitat during the winter and higher elevation, mountainous
80 terrain in summer (Poole & Heard, 2003; Poole et al., 2009; Taylor et al., 2014; White, 2006). They are
81 considered intermediate browser and eat a variety of forage, with diets generally dominated by grasses
82 (Festa-Bianchet & Côté, 2003; Hofmann, 1989). In contrast, white-tailed deer (*Odocoileus virginianus*)
83 exploit a variety of habitat and food resources and cover a large geographic range that stretches across most
84 of North America and includes part of Central and South America (Hewitt, 2011). White-tailed deer use
85 woody cover habitats year-round, but can also thrive in urban and rural settings (Grund, McAninch, &
86 Wiggers, 2002; Van Deelen, Campa III, Hamady, & Haulfer, 1998); they maintain distinct seasonal ranges
87 in the northern parts of their range and are considered browsing ruminants as well as both habitat and
88 dietary generalists (Berry, Shipley, Long, & Loggers, 2019).

89
90 Our study integrated high-throughput sequencing and GPS telemetry to evaluate the relationship between
91 gut microbiome, home range area, and use of different habitat classes of two ungulates living in contrasting
92 environments. We quantified the relationship between key microbiome diversity metrics on home range
93 size and relative use of different habitat classes inferred from GPS tracking of individuals. From an
94 evolutionary perspective this link between variation in phenotype or behaviour and the gut microbiome
95 assumes selection operates on both the genomes of the constituents (microbiome) and host, otherwise
96 known as the holobiome (Bordenstein & Theis, 2015). We hypothesized that an increase in gut diversity

97 would be linked with an increase in area used, as greater gut diversity would reflect, and possibly drive
98 larger use of space and a more resource-diverse home range, similar to the findings of Ma et al., (2019).
99 High *Firmicutes* to *Bacteroides* ratios correspond to larger body size and fat stores; levels of *Firmicutes*
100 increase and promote more efficient calorie absorption and subsequent weight gain (Duvallet et al., 2017;
101 Koliada et al., 2017; Ley, 2010). As such, we hypothesized that larger *Firmicutes* to *Bacteroides* ratios
102 would be correlated with larger home ranges, as individuals building up fat stores for winter would
103 generally use more space to forage. This relationship may be impacted by resource distribution, as
104 specialists prefer homogenously distributed resources, while generalists prefer heterogeneously distributed
105 resources, which can impact space use (Marrotte et al., 2020) Consequently, we hypothesized that
106 relationships between proportional habitat use and the gut microbiome would be stronger in specialists as
107 they have a more restricted niche with deviations from this having larger consequences, whereas
108 generalists can make use of a variety of habitat areas.

109 **Methods**

110 **Animal captures, sample collection and DNA extraction**

111 We captured and radio-collared male and female mountain goats on three adjacent mountain complexes
112 using aerial net-gun capture northeast of Smithers, British Columbia, Canada (Blunt Mountain, Netalzul
113 Mountain, and Goat Mountain) (Fig. 1). We captured and radio-collared 34 female white-tailed deer
114 (*Odocoileus virginianus*) using baited Clover traps southwest of Ottawa, Ontario, Canada (Fig. 1). For
115 more information on animal captures, see Wolf, Kriss, MacAulay, & Shafer (2020) and Munro (2020).
116 VERTEX Plus and VERTEX Lite Global Positioning System (GPS) collars (VECTRONIC Aerospace,
117 Germany) were used for mountain goats, while store-on-board (G2110D, Advanced Telemetry Solutions,
118 Isanti, MN) or GSM-upload (Wildcell SG, Lotek Wireless Wildlife Monitoring, Newmarket, ON) GPS
119 collars were used for white-tailed deer. Collars recorded locations every four hours for mountain goats and
120 five hours for white-tailed deer. During captures we took fecal pellets from each individual and stored
121 them at -20°C; all captures took place during winter. Lab surfaces were sterilized with 90% EtOH and 10%
122 bleach solution and a small portion of a single fecal sample (~1/4 including exterior and interior portions)
123 was digested overnight at 56°C in 20 ul proteinase K and 180 ul Buffer ATL from the Qiagen DNeasy
124 Blood & Tissue Kit (Qiagen, Valencia, California, USA). DNA was extracted from the digest with the
125 QIAamp PowerFecal DNA Kit (Qiagen, Valencia, California, USA).

126

127 **High-throughput sequencing and bioinformatics**

128 The validated Illumina 16S rRNA Metagenomic Sequencing Library Preparation (#15044223 rev. B)
129 protocol was followed for library preparation using slight modifications (Haworth, White, Côté, & Shafer,
130 2019). The V3 and V4 regions of the 16S ribosomal ribonucleic acid (16S rRNA) hypervariable region
131 were targeted with four variants of 341F and 805R primers designed by Herlemann et al., (2011). A unique
132 combination of Nextera XT indexes, index 1 (i7) and index 2 (i5) adapters were assigned to each sample
133 for multiplexing and pooling. Four replicates of each sample of fecal DNA were amplified in 25 µl PCR
134 using the 341F and 805R primers. The replicated amplicons for each sample were combined into a single

135 reaction of 100 μ l and purified using a QIAquick PCR Purification Kit (Qiagen, 28104) and quantified on
136 the Qubit Fluorometer. Sample indexes were annealed to the amplicons using an 8-cycle PCR reaction to
137 produce fragments approximately 630 bp in length that included ligated adaptors; the target amplicon is
138 approximately 430 bp in length (Illumina 16S rRNA Metagenomic Sequencing Library Preparation;
139 #15044223 rev. B). Samples were purified with the QIAquick PCR Purification Kit and the final purified
140 library was validated on a TapeStation (Agilent, G2991AA) and sequenced in 300 bp pair-end reads on an
141 Illumina MiSeq sequencer at the Genomic Facility at The University of Guelph (Guelph, Ontario).

142

143 The quality of the raw sequences was assessed using FastQC v 0.11.9 (Andrews, 2010) and we determined
144 the low-quality cut-off for forward and reverse reads (see Haworth et al., 2019). Forward and reverse reads
145 were imported into QIIME2 v 2019.4 (Boyle et al., 2019) for quality control, sequence classification, and
146 diversity analysis. Merged, forward, and reverse reads were analyzed independently using the quality
147 control function within QIIME2 and DADA2 to perform denoising and detect and remove chimeras.
148 QIIME2 follows the curated DADA2 R library workflow (<https://benjjneb.github.io/dada2/>) that requires
149 zero mismatches in overlapping reads for successful merging, since reads are denoised and errors are
150 removed before merging occurs. The taxonomy, to the species level, of all sample reads were assigned
151 using Silva 132 reference taxonomy database (<https://docs.qiime2.org/2019.4/data-resources/>). We
152 calculated the relative proportion of *Firmicutes* to *Bacteroidetes* for each of the grouped data. Estimates of
153 diversity included Shannon's Index, observed Operational Taxonomic Units (OTUs) and Pielou's
154 evenness, a measure of diversity that is the ratio of observed diversity to the maximum possible in a sample
155 having the same number of species (Pielou, 1966); these were screened for correlation to one-another and
156 read-depth. Pielou's evenness and the ratio of *Firmicutes* to *Bacteroidetes* were retained for subsequent
157 analyses. We rarefied sample reads to the sample with the least number of reads.

158 **GPS filtering, home range, and proportional habitat use analysis**

159 We used different filtering approaches and seasonal delineations for each species due to the differences in
160 landscapes occupied by mountain goats and white-tailed deer. For the mountain goat data, any N.A. or

161 mortality signals were filtered out as were any GPS points outside of 600 m-2500 m in elevation, as this
162 reflects the maximum and minimum for the study area. Dilution of precision (DOP) values over 10 were
163 plotted against elevation and landscape type, to ensure there was no patterns in distribution, and that
164 filtering would not bias downstream analyses. Movement rates between successive GPS points were also
165 calculated, and any movement rates beyond 15 km/hr were also removed from analyses as these were
166 deemed spurious. Seasons were defined as follows: Summer - May 1st to October 31st and Winter-
167 December 1st to April 30th (Cadsand, 2012; Mountain Goat Management Team, 2010; Poole & Heard,
168 2003; Richard & Côté, 2016). November was excluded from seasonal data as White (2006) noted a large
169 increase in male mountain goat home ranges due to the rut. In white-tailed deer filtering occurred as above,
170 but with no elevation restrictions as the topography of Marlborough Forest is effectively flat. As
171 considerable variation in migration dates was observed, movement trajectories for each individual deer
172 were examined to identify the dates of migration movements to and from Marlborough Forest to
173 differentiate between winter and summer ranges. A migration movement was defined as when a deer
174 moved between non-overlapping seasonal ranges and then occupied one seasonal range until the following
175 migration movement (Munro 2020). As movements to and from Marlborough forest were relative to each
176 individual deer's movement, there was no hard date range. No seasonal GPS data were excluded for white-
177 tailed deer as changes in movement patterns and home range size during the rut are minimal in females
178 (Hölzenbein & Schwede, 1989).

179

180 We used Brownian Bridge Movement Models (BBMMs) to generate individual home ranges using the
181 BBMM package in R (Nielson, Sawyer, & McDonald 2015). A BBMM is a continuous-time stochastic
182 movement model that uses probabilistic and maximum likelihood approaches where observed locations are
183 measured with error to model home ranges (Horne, Garton, Krone, & Lewis, 2007). A minimum of 275
184 GPS points was required to generate a BBMM and individual home ranges were calculated with a
185 maximum lag time between successive locations of two times the expected fix rate. A location error of 20
186 m was used as per Sawyer et al., (2009), with a cell size of 25 m². We generated 50% and 95% isopleths

187 representing the core and home ranges. Isopleths were generated separately for each individual during both
188 summer and winter, as ungulates exhibit sex-specific habitat use patterns, that varies both seasonally and
189 by age-class (Festa-Bianchet & Côté, 2008; Lesage et al., 2000; Mountain Goat Management Team, 2010;
190 Webb, Hewitt, & Hellickson, 2007; White, 2006). We focused on summer isopleths, as deer were baited in
191 winter, which has been shown to bias movement and shift core ranges (Kilpatrick & Stober, 2002). We
192 report only the 50% isopleths, hereafter termed core ranges, to maximize seasonal differences, as they were
193 highly correlated to the 95% isopleths ($t_{46}=9.3$, $r=0.81$, $p<0.0001$) and results were similar between
194 summer 50% and 95% isopleths (Fig. S1). We generated BBMM isopleths using the R package `rgdal`
195 (Bivand et al., 2019) and all analyses were conducted in R v.3.6.1. Shapefiles were imported into ArcGIS
196 Pro 2.5.0 and home range and core areas were calculated in km^2 for further analyses.

197
198 Proportional use of habitats was assessed by calculating the number of GPS points in a given habitat type
199 within an isopleth, relative to the total number of GPS points located in that isopleth. Similar to Johnson's
200 third-order habitat selection, proportional habitat use in this study refers to how specific habitat types are
201 used within a core range (Johnson, 1980). Proportion values in the 50% isopleths were highly correlated to
202 the 95% isopleths ($t_{117}=106$, $r=0.99$, $p<2.2e-16$, Table S1, S2). We selected ecologically relevant features
203 that showed previous evidence for use in both species. Features used in mountain goat models were treed
204 habitat, Heat Load Index (HLI), and escape terrain (landscape where slope is $\geq 40^\circ$; Shafer et al., 2012).
205 These features have shown evidence for disproportionate usage/selection in previous research on mountain
206 goats (Shafer et al., 2012). In the white-tailed deer models, we used forested habitat, treed swamp, and
207 thicket swamp, as each of the three habitat features exhibited $>20\%$ core landcover composition in Munro
208 (2020), and thus, were available for usage in the majority of individuals (Massé & Côté, 2013). For the
209 HLI (McCune & Keon, 2002), the average value of HLI for all GPS points within an isopleth for a given
210 individual was calculated. The Southern Ontario Land Resource Information System (SOLRIS) data set
211 version 2.0 (OMNRF, 2019) was used to determine land cover types for white-tailed deer, while we used

212 the Biogeoclimactic Ecosystem Classification (BEC) dataset (GeoBC, 2019) to determine terrestrial
213 landcover type for mountain goats.

214 **Generalized linear models**

215 We analyzed the associations between core range size, gut microbiome metrics, and age class for both
216 species individually using Generalized Linear Models (GLMs) with the Gaussian family distribution and
217 identity link function. The core range GLMs consisted of core range size as a response variable, a single
218 microbiome metric (*Firmicutes* to *Bacteroidetes* ratio or Pielou's evenness) and age class (adult or
219 subadult) as fixed explanatory effects. The proportional habitat use GLMs consisted of proportion of
220 habitat used as a response variable, a single microbiome metric (*Firmicutes* to *Bacteroidetes* ratio or
221 Pielou's evenness) and age class, as fixed explanatory effects. One exception to this was the HLI GLM, as
222 the response variable was the mean HLI value for GPS points in the isopleth, while the explanatory
223 variables were the same as described above. Individuals 0 - 2 years of age were considered subadults for
224 white-tailed deer, while individuals 0 - 3 years of age were considered subadults for mountain goats
225 (Delgiudice, Fieberg, Riggs, Powell, & Pan, 2006; Festa-Bianchet & Côté, 2008). Effect size and
226 confidence intervals are reported for each model. We conducted five-fold linear model cross validation
227 using the Caret package in R (Kuhn et al., 2020) to test for overfitting of our models and quantify the
228 model's predictive ability. We reported the Scatter Index (SI) and Root Mean Square Error (RMSE): low
229 values in RMSE and SI are indicative of a good model fit and low residual variance.

230 **Results**

231 **Bioinformatic filtering and taxonomic analysis**

232 Twenty-three mountain goat and twenty-five white-tailed deer fecal sample sequences passed QC and a
233 total of ~8.17 million paired-end reads ($n_{MG}=5,488,856$, $n_{WTD}=2,679,668$) were generated (SRA accession
234 number PRJNA638162). FastQC analysis indicated that both forward and reverse reads lost quality > 259
235 bp in length (Phred score <25), so all reads were trimmed to a length of 259 bp. Following DADA2 strict
236 quality filtering, ~1.16 million paired-end reads ($n_{MG}=709,457$, $n_{WTD}=457,541$) were kept for taxonomic
237 and diversity analyses. Losing this many reads to quality filtering is typical (see Haworth et al., 2019), as
238 permitted error rates are extremely low in DADA2, resulting in high certainty among retained reads
239 (Callahan et al., 2016). White-tailed deer had higher averages of both Pielou's evenness (mean 0.95, min
240 0.92, max 0.96, SD 0.012) and *Firmicutes* to *Bacteroidetes* ratio (mean 8.3, min 1.49, max 21.5, SD 6.22)
241 than mountain goats (Pielou's evenness mean 0.92, min 0.84, max 0.95, SD 0.028; *Firmicutes* to
242 *Bacteroidetes* ratio mean 6.90, min 3.51, max 12.10, SD 2.43). Age class and sex averages, in addition to
243 winter data, are shown in Table S3.

244 **Core range and proportional habitat use**

245 Data filtering resulted in 84,932 GPS points for mountain goats (mean per individual 3,679, range 277 -
246 6,704, SD 761), and 63,900 GPS points for white-tailed deer (mean per individual 2,556, range 831 -
247 3,558, SD 906). One individual mountain goat was removed due to a small number of GPS points ($n = 16$).
248 Mountain goats exhibited slightly larger summer core range size of 0.40 km² (min 0.01 km², max 0.72 km²,
249 SD 0.17), compared to 0.36 km² (min 0.13 km², max 0.81 km², SD 0.16) for white-tailed deer. Proportional
250 use of habitat values was variable, ranging from 0.05 to 0.91 (means ranged from 0.41 to 0.63) in mountain
251 goats and from 0.00 to 0.84 (means ranged from 0.13-0.34) in white-tailed deer. The mean proportional
252 habitat use values are reported in Table S4.

253 **Generalized linear models**

254 Sex was not included in the final model as there were no strong differences in core range sizes between
255 sexes in mountain goats ($t_{17,58}=0.374$, $p>0.05$) and all white-tailed deer samples were obtained from

256 females. We compared 50% isopleths from summer and winter; summer core ranges were reported here, as
257 winter core ranges produced qualitatively similar results, albeit with weaker signals (Table S6). In both
258 species, a greater *Firmicutes* to *Bacteroidetes* ratio was associated with larger core ranges with both
259 models explaining an equal amount of variance (Nagelkerkes's $R^2 \sim 0.27$; Table 1; Fig. 2). Mountain goat
260 gut diversity increased with core range size, while a decrease in white-tailed deer was associated with
261 larger core ranges; here the mountain goat model explained a relatively large portion of the variance
262 ($R^2=0.47$; Table 1; Fig. 2). Age-class was a significant predictor in both mountain goat GLMs, but neither
263 of the white-tailed deer models. The use of escape terrain and treed areas were moderately correlated in
264 mountain goats ($t_{20}=2.94$, $p<0.01$, $r=0.55$), and were significant predictors of Pielou's evenness; effect size
265 confidence intervals did not overlap zero in models that measured the relationship between use of escape
266 terrain and treed areas and Pielou's evenness (Table 2). Specifically, a larger Pielou's evenness value was
267 seen in individuals using less treed habitat and less escape terrain (Fig. 3). In HLI GLMs, confidence
268 intervals overlapped zero and exhibited a relative $\sim 2x$ decrease in R^2 value relative to other mountain goat
269 habitat use models ($\beta=0.91$, $R^2=0.12$, Table 2). All GLM estimates in the white-tailed deer models had
270 confidence intervals overlapping zero. Cross validation of linear models supported retaining age class and
271 microbiome metric as a predictor variable of core range size. RMSE values in models with core range size
272 as the response variable ranged from 0.12 to 0.18, and SI values ranged from 0.30 to 0.51, whereas in
273 proportional habitat use models, RMSE values ranged from 0.11 to 0.33 and SI values from 0.033 to 1.14
274 (Table S5); this suggests moderate to high support for the models.

275

276 **Discussion**

277 The link between gut microbiome and host space use and has implications for foraging, activity levels, and
278 ability to use energetically costly habitats. We showed that differences in the gut microbiome between a
279 generalist ungulate and specialist ungulate were linked to patterns of habitat use and home range size.
280 Although the patterns are nuanced, there were some commonalities that collectively suggest the gut
281 microbiota plays a role in determining space use patterns. An increase in *Firmicutes* to *Bacteroidetes* ratios
282 in both species was correlated to an increase in core range sizes (Fig. 2). Increased *Firmicutes* to
283 *Bacteroidetes* ratios are linked to increased Body Mass Index (BMI) and obesity (Duvall et al., 2017).
284 Both *Firmicutes* and *Bacteroidetes* are involved in energy resorption and carbohydrate metabolism;
285 *Firmicutes* can act as a more effective energy source, leading to more efficient calorie absorption and
286 weight gain, while *Bacteroidetes* are involved with energy production and conversion as well as amino
287 acid transport and metabolism (Krajmalnik-Brown, Ilhan, Kang, & DiBaise, 2012; Ottman, Smidt, de Vos,
288 & Belzer, 2012; Turnbaugh et al., 2006). In a comparable study home range size was not correlated with
289 the *Firmicutes* to *Bacteroidetes* ratio in wild rodents (Jameson, Réale, & Kembel, 2020), however,
290 seasonal weight changes are more dynamic in small mammals (Lynch, 1973; Merritt & Zegers, 1991), and
291 we suspect this pattern might be more ubiquitous across temperate ungulates given their specialized gut
292 microbiomes and need to put on fat stores. An individual's gut that is comprised of more *Firmicutes*,
293 bacteria that acts as an effective energy source, may be able to increase body fat more efficiently relative to
294 individuals with lower *Firmicutes* to *Bacteroidetes* ratios, with an increase in *Firmicutes* to *Bacteroidetes*
295 ratios helping individuals to accumulate fat stores to survive the winter by increasing their home range
296 size.

297

298 In large ungulates, increasing levels of body fat is important to survive the winter, when forage is limited
299 relative to the other seasons. In muskoxen (*Ovibos moschatus*), the abundance of *Firmicutes* stayed similar
300 across seasons, while *Bacteroidetes* increased in the summer months, meaning the ratio of *Firmicutes* to
301 *Bacteroidetes* is lower in the summer (Bird et al., 2019). Additionally, an increase in microbial diversity in

302 yak (*Bos grunniens*) was noted in spring (Ma et al., 2020). Increased bacterial diversity in spring relative to
303 summer suggests species are capable of modulating bacterial diversity; but note lower ratios of *Firmicutes*
304 to *Bacteroidetes* does not necessarily correspond to higher diversity. The ability to conserve bacteria
305 necessary for adding fat, namely high levels of *Firmicutes* and low levels of *Bacteroidetes*, while
306 exhibiting increases in gut diversity suggests ungulates can prepare for the winter even though the level of
307 gut bacterial diversity is shifting (see Haworth et al. 2019). This concept is of importance to white-tailed
308 deer, as diet turnover between summer and winter is pronounced in Ontario. Shifting from herbaceous
309 vegetation in the spring to woody browse in the winter may similarly result in increased diversity, while
310 simultaneously conserving bacteria necessary for adding fat.

311

312 Both specialists and generalists tend to shift habitats seasonally, as mountain goats move from alpine
313 summer habitat to subalpine winter areas and white-tailed deer exhibit distinct winter and summer ranges
314 (Grund et al., 2002; Lesage et al., 2000; Poole & Heard, 2003). There was considerably more variation in
315 proportion of habitat used in the generalist white-tailed deer (Table S2), likely a function of their ability to
316 use multiple habitat types and diet sources. Here proportion habitat use-microbiome models had no
317 relationship (Fig. 3, Fig. S1), as all proportion habitat use coefficients in white-tailed deer had confidence
318 intervals overlapping zero (Fig. 3, S1, Table 2). Interestingly, the two habitat variables in mountain goats
319 with clear signals were escape terrain and treed areas (Fig. 3), which are related to the defining habitat
320 characteristics of this species: the use of alpine terrain (i.e. no trees) and steep slopes, (Gross, Kneeland,
321 Reed, & Reich, 2002; Festa-Bianchet & Côté, 2008). Deviations from their specialized and preferred
322 habitat type comes at cost, as ungulates typically exhibit trade-offs with respect to forage quality and
323 predation risk; avoiding predation can lead to decreased forage quality and abundance (Hamel & Côté,
324 2007; Hebblewhite & Merrill, 2009). In mountain goats and bighorn sheep (*Ovis canadensis*), energy
325 expenditures increased when travelling uphill or downhill - termed a vertical cost (Dailey & Hobbs, 1989).
326 A lower *Firmicutes* to *Bacteroidetes* ratio could be linked to the vertical cost associated with spending
327 more time in escape terrain, meaning less-fat or prime conditioned individuals spend more time in escape

328 terrain. Conversely, using more forage-available treed habitat may be correlated with an increase in
329 *Firmicutes* to *Bacteroidetes* ratio, as individuals have increased access to forage, with minimal vertical
330 cost. Collectively, the habitat models had stronger signals in the specialist species compared to the
331 generalist, that we suggest is reflective of their more restricted habitat niche relative to generalists, where
332 microbial deviations generate more prominent shifts in behaviour.

333
334 The potential for the gut microbiome to modulate habitat use patterns is especially important in a specialist,
335 as they have a more restricted niche, where deviations from the usage of important habitat types has larger
336 consequences. While there is potential for modulation of proportion of specific habitat usage, the impact of
337 the gut microbiome on the amount of space used may be more explicit. A lower Pielou's evenness value
338 indicates that a given individual has decreased diversity relative to another individual with the same
339 number of gut microbial species. The relationship between Pielou's evenness and core range size differed
340 in direction between species; greater gut diversity in mountain goats was correlated with a larger core
341 range, while a negative relationship was noted in white-tailed deer (Fig. 2). Increased gut diversity might
342 promote individuals moving through and foraging in larger areas, resulting in a positive relationship
343 between diversity and core range size. This is of added importance in a specialist, as the ability to utilize
344 and forage in a more diverse array of habitat types might allow individuals to access and subsist in areas
345 that other conspecifics cannot, thus increasing their competitive ability (Blake & Karr, 1987; McPeck,
346 1996; Rodewald & Vitz, 2005). Higher relative gut microbiome diversity might allow specialists to forage
347 more like generalists, while lower diversity may limit specialists to their typical niches. The reverse trend
348 in white-tailed deer might reflect the difference in feeding and habitat-use strategies; white-tailed deer are
349 generalists, and thus by definition, all deer can effectively use a variety of habitat and food sources. The
350 negative relationship observed between gut diversity and range size in white-tailed deer might suggest that
351 deer with higher gut microbiome diversity are able to use more diet sources overall and thus can meet their
352 nutritional requirements within a smaller area relative to individuals with less diverse gut microbiomes. As
353 generalists, deer are not as constrained by specific food and habitat types, and thus, their space use may be

354 less heavily influenced by gut microbiome composition. It is possible that winter baiting had an impact on
355 the gut microbiome in white-tailed deer, which could have led to weaker relationships.

356

357 We built our models assuming the microbiome predicts habitat and home range patterns; but this need not
358 be cause and effect, and the relationship is likely one of back-and-forth (Cryan et al., 2019). For example,
359 diet-microbiome covariance has been observed in multiple large-herbivores, and seasonal diet turnover and
360 seasonal microbiome turnover are positively correlated (Kartzinel, Hsing, Musili, Brown, & Pringle, 2019).
361 In this example, our model would assume the gut microbiome impacts diet choice (e.g. Leitão-Gonçalves
362 et al., 2017) and in turn, the correlation between diet turnover and the microbiome drives habitat use of a
363 given species. Assessing this relationship clearly needs experimental testing, and we view our study as a
364 proof-of-concept that provides a testable hypothesis. Still, we demonstrated that quantifying the gut
365 microbiome yields information related to space use and linking these two highly complex components of
366 biology aids in our understanding of selection on the hologenome through the interplay between the
367 individual and its microbial genomes and potential traits under selection (e.g. home range size and
368 proportional habitat use). These findings also demonstrate that using pellet sampling is useful in
369 determining space and habitat use in managed populations, as it is conceivable with a large enough
370 database and validation, one could predict the distribution and behaviour of animals on the landscape from
371 non-invasively sampled pellets. Ultimately, we utilized a specialist and generalist ungulate to explore the
372 link between the gut microbiome and movement to generate quantitative findings surrounding the impact
373 of the gut microbiome on space use in wild populations. Similar analyses of this kind should clarify the
374 extent to which space use is linked to the gut microbiome in other ungulates and in turn, aid in assessing
375 the utility of pellets to predict animal distribution and behaviour.

376 **Acknowledgements**

377 This work was supported by a Natural Sciences and Engineering Research Council Discovery Grant,
378 Canada Foundation for Innovation - John R. Evans Leaders Fund, and Compute Canada awards to ABAS,
379 Habitat Conservation Trust Foundation Enhancement and Restoration Grant to KK (Project # 6-252), the
380 Forest Enhancement Society of British Columbia, the British Columbia Mountain Goat Society, and the
381 Rocky Mountain Goat Alliance grant to JFW. Special thanks to Jeff Bowman, Erin Koen, Kathleen Lo and
382 Kiana Young for their comments on earlier drafts of this manuscript, Spencer Anderson for lab work, and
383 Florent Déry for allowing us to use his digital drawings.

384

385 The authors declare that they have no conflict of interest.

386 **References**

387

388 Andrews, S. (2010). FastQC: A Quality Control Tool for High Throughput Sequence Data [Online].

389 Available online at: <http://www.bioinformatics.babraham.ac.uk/projects/fastqc/>

390 Arnolds, K. L., & Lozupone, C. A. (2016). Striking a balance with help from our little friends – how the

391 gut microbiota contributes to immune homeostasis. *Yale Journal of Biology and Medicine*, 89, 389–

392 395.

393 Berry, S. L., Shipley, L. A., Long, R. A., & Loggers, C. (2019). Differences in dietary niche and foraging

394 behavior of sympatric mule and white-tailed deer. *Ecosphere*, 10(7). <https://doi.org/10.1002/ecs2.2815>

395 Bird, S., Prewer, E., Kutz, S., Leclerc, L. M., Vilaça, S. T., & Kyle, C. J. (2019). Geography, seasonality,

396 and host-associated population structure influence the fecal microbiome of a genetically depauperate

397 Arctic mammal. *Ecology and Evolution*, 9(23), 13202–13217. <https://doi.org/10.1002/ece3.5768>

398 Bivand, R., Keitt, T., Pebesma, E., Sumner, M., Hijmans, R., Rouault, E., ... Rundel, C. (2019). Rgdal:

399 Bindings for the ‘geospatial’ data abstraction library. R package version 1.4-8. [Online] Retrieved

400 from: <https://cran.r-project.org/web/packages/rgdal/index.html>

401 Blake, J. G., & Karr, J. R. (1987). Breeding birds of isolated woodlots: area and habitat relationships.

402 *Ecological Society of America*, 68(6), 1724–1734. <https://doi.org/10.2307/1939864>

403 Bordenstein, S. R., & Theis, K. R. (2015). Host biology in light of the microbiome: ten principles of

404 holobionts and hologenomes. *PLoS Biology*, 13(8), e1002226.

405 <https://doi.org/10.1371/journal.pbio.1002226>

406 Boylen, E., Rideout, J. R., Dillon, M. R., Bokulich, N. A., Abnet, C. C., Al-Ghalith, G. A., ... Caporaso, J.

407 G. (2019). Reproducible, interactive, scalable and extensible microbiome data science using QIIME 2.

408 *Nature Biotechnology*, 37(8), 852-857. doi: 10.1016/j.physbeh.2017.03.040

409 Cadsand, B. (2012). Responses of mountain goats to heliskiing activity: movements and resource selection.

410 (MSc thesis). University of Northern British Columbia, British Columbia, Canada.

411 Callahan, B. J., McMurdie, P. J., Rosen, M. J., Han, A. W., Johnson, A. J. A., & Holmes, S. P. (2016).

412 DADA2: High-resolution sample inference from Illumina amplicon data. *Nature Methods*, 13(7), 581–

413 583. <https://doi.org/https://doi.org/10.1038/nmeth.3869>

414 Chang, C., Huang, B., Lin, S., Huang, C., & Liao, P. (2016). Changes of diet and dominant intestinal

415 microbes in farmland frogs. *BMC Microbiology*, 1–13. <https://doi.org/10.1186/s12866-016-0660-4>

416 Coyte, K. Z., Schluter, J., & Foster, K. (2015). The ecology of the microbiome: Networks, competition,

417 and stability. *Science*, 350(6261), 663–666. <https://doi.org/10.1126/science.aad2602>.

418 Cryan, J. F., & Dinan, T. G. (2012). Mind-altering microorganisms: The impact of the gut microbiota on

419 brain and behaviour. *Nature Reviews Neuroscience*, 13(10), 701–712. doi: 10.1038/nrn3346

420 Cryan, J. F., O’Riordan, K. J., Cowan, C. S. M., Sandhu, K. V., Bastiaanssen, T. F. S., Boehme, M., ...

421 Dinan, T. G. (2019). The microbiota-gut-brain axis. *Physiological Reviews*, 99(4), 1877–2013. doi:

422 10.1152/physrev.00018.2018

423 Dailey, T. V., & Hobbs, N. T. (1989). Travel in alpine terrain: energy expenditures for locomotion by

424 mountain goats and bighorn sheep. *Canadian Journal of Zoology*, 67(10), 2368–2375.

425 <https://doi.org/10.1139/z89-335>

426 De Angelis, M., Ferrocino, I., Calabrese, F. M., De Filippis, F., Cavallo, N., Siragusa, S., ... Cocolin, L.

427 (2020). Diet influences the functions of the human intestinal microbiome. *Scientific Reports*, 10(1),

428 4247. doi: 10.1038/s41598-020-61192-y

429 De Tarso, S., Oliviera, D., & Bastos Alfonso, J. (2016). Ruminants as part of the global food system: how

430 evolutionary adaptations and diversity of the digestive system brought them to the future. *Journal of*

431 *Dairy, Veterinary & Animal Research*, 3(5), 1–7. <https://doi.org/10.15406/jdvar.2016.03.00094>

432 Dearing, M. D., & Kohl, K. D. (2017). Beyond fermentation: Other important services provided to

433 endothermic herbivores by their gut microbiota. *Integrative and Comparative Biology*, 57(4), 723–

434 731. <https://doi.org/10.1093/icb/ix020>

- 435 Delgiudice, G. D., Fieberg, J., Riggs, M. R., Powell, M. C., & Pan, W. (2006). A long-term age-specific
436 survival analysis of female white-tailed deer. *Journal of Wildlife Management*, 70(6), 1556–1568.
437 [https://doi.org/10.2193/0022-541x\(2006\)70\[1556:alasaol\]2.0.co;2](https://doi.org/10.2193/0022-541x(2006)70[1556:alasaol]2.0.co;2)
- 438 Duvallat, C., Gibbons, S. M., Gurry, T., Irizarry, R. A., & Alm, E. J. (2017). Meta-analysis of gut
439 microbiome studies identifies disease-specific and shared responses. *Nature Communications*,
440 8(1874), 1–10. <https://doi.org/10.1038/s41467-017-01973-8>
- 441 Esposti, M. D., & Romero, E. M. (2017). The functional microbiome of arthropods. *PLoS ONE*, 12(5),
442 e0176573. doi: 10.1371/journal.pone.0176573
- 443 Faith, J. J., Guruge, J. L., Charbonneau, M., Subramanian, S., Seedorf, H., Goodman, A. L., ... Gordon, J.
444 I. (2013). The long-term stability of the human gut microbiota. *Science*, 5(341), 1237439.
445 <https://doi.org/10.1126/science.1237439.The>
- 446 Festa-Bianchet, M., & Côté, S. D. (2008). Mountain goats: Ecology, behavior, and conservation of an
447 alpine ungulate. Edmonton, Alberta, Canada: Island Press.
- 448 GeoBC. (2002). Digital Elevation Model of British Columbia CDEC. [Data set] Retrieved from:
449 <https://catalogue.data.gov.bc.ca/dataset/7b4fef7e-7cae-4379-97b8-62b03e9ac83d>
- 450 GeoBC. (2019). Freshwater Atlas Stream Network - Datasets - Data Catalogue [Data set]. Retrieved from:
451 <https://catalogue.data.gov.bc.ca/dataset/freshwater-atlas-stream-network>
- 452 Grieneisen, L. E., Livermore, J., Alberts, S., Tung, J., & Archie, E. A. (2017). Integrative and comparative
453 biology group living and male dispersal predict the core gut microbiome in wild baboons. *Integrative
454 and Comparative Biology*, 57(4), 770–785. <https://doi.org/10.1093/icb/icx046>
- 455 Gross, J. E., Kneeland, M. C., Reed, D. F., & Reich, R. M. (2002). GIS-based habitat models for mountain
456 goats. *Journal of Mammalogy*, 83(1), 218–228. [https://doi.org/10.1644/1545-
457 1542\(2002\)083<0218:gbhmf>2.0.co;2](https://doi.org/10.1644/1545-1542(2002)083<0218:gbhmf>2.0.co;2)
- 458 Grund, M. D., McAninch, J. B., & Wiggers, E. (2002). Seasonal movements and habitat use of female
459 white-tailed deer associated with an urban park. *The Journal of Wildlife Management*, 66(1), 123–130.
460 <https://doi.org/10.2307/3802878>
- 461 Hamel, S., & Côté, S. D. (2007). Habitat use patterns in relation to escape terrain: Are alpine ungulate
462 females trading off better foraging sites for safety? *Canadian Journal of Zoology*, 85(9), 933–943. doi:
463 10.1139/Z07-080
- 464 Haworth, S. E., White, K. S., Côté, S. D., & Shafer, A. B. A. (2019). Space, time, and captivity:
465 Quantifying the factors influencing the fecal microbiome of an alpine ungulate. *FEMS Microbiology
466 Ecology*, 95, 1–12. <https://doi.org/10.1093/femsec/fiz095>
- 467 Hebblewhite, M., & Merrill, E. H. (2009). Trade-offs between predation risk and forage differ between
468 migrant strategies in a migratory ungulate. *Ecology*, 90(12), 3445–3454. doi: 10.1890/08-2090.1
- 469 Herlemann, D. P. R., Labrenz, M., Ju, K., Bertilsson, S., Waniek, J. J., & Andersson, A. F. (2011).
470 Transitions in bacterial communities along the 2000 km salinity gradient of the Baltic Sea.
471 *International Society for Microbial Ecology*, 5, 1571–1579. <https://doi.org/10.1038/ismej.2011.41>
- 472 Hicks, A. L., Lee, K. J., Couto-Rodriguez, M., Patel, J., Sinha, R., Guo, C., ... Williams, B. L. (2018). Gut
473 microbiomes of wild great apes fluctuate seasonally in response to diet. *Nature Communications*,
474 9(1786), 1–18. <https://doi.org/10.1038/s41467-018-04204-w>
- 475 Hofmann, R. R. (1989). Evolutionary steps of ecophysiological adaptation and diversification of
476 ruminants: a comparative view of their digestive system. *Oecologia*, 78(4), 443–457.
477 <https://doi.org/10.1007/BF00378733>
- 478 Hölzenbein, S., & Schwede, G. (1989). Activity and movements of female white-tailed deer during the rut.
479 *The Journal of Wildlife Management*, 53(1), 219–223. <https://doi.org/10.2307/3801337>
- 480 Horne, J. S., Garton, E. O., Krone, S. M., & Lewis, J. S. (2007). Analyzing animal movements using
481 Brownian bridges. *Ecology*, 88(9), 2354–2363. <https://doi.org/10.1890/06-0957.1>
- 482 Jameson, J., Réale, D., & Kembel, S. (2020). Gut microbiome modulates behaviour and life history in two
483 wild rodents. *BioRxiv*, 1–26. <https://doi.org/10.1101/2020.02.09.940981>
- 484 Johnson, D. H. (1980). The comparison of usage and availability measurements for evaluating resource
485 preference. *Ecology*, 61(1), 65–71. <https://doi.org/10.2307/1937156>

- 486 Jones, J. C., Fruciano, C., Marchant, J., Hildebrand, F., Forslund, S., Bork, P., ... Hughes, W. O. H. (2018).
487 The gut microbiome is associated with behavioural task in honey bees. *Insectes Sociaux*, 65(3), 419–
488 429. <https://doi.org/10.1007/s00040-018-0624-9>
- 489 Kartzinel, T. R., Hsing, J. C., Musili, P. M., Brown, B. R. P., & Pringle, R. M. (2019). Covariation of diet
490 and gut microbiome in African megafauna. *Proceedings of the National Academy of Sciences of the*
491 *United States of America*, 116(47), 23588–23593. <https://doi.org/10.1073/pnas.1905666116>
- 492 Kilpatrick, H. J., & Stober, W. A. (2002). Effects of temporary bait sites on movements of suburban white-
493 tailed deer. *Wildlife Society Bulletin*, 30(3), 760–766.
- 494 Koliada, A., Syzenko, G., Moseiko, V., Budovska, L., Puchkov, K., Perederiy, V., ... Vaiserman, A.
495 (2017). Association between body mass index and Firmicutes/Bacteroidetes ratio in an adult Ukrainian
496 population. *BMC Microbiology*, 17(1), 4–9. <https://doi.org/10.1186/s12866-017-1027-1>
- 497 Krajmalnik-Brown, R., Ilhan, Z. E., Kang, D. W., & DiBaise, J. K. (2012). Effects of gut microbes on
498 nutrient absorption and energy regulation. *Nutrition in Clinical Practice*, 27(2), 201–214. doi:
499 10.1177/0884533611436116
- 500 Kruger Ben Shabat, S., Sasson, G., Doron-Faigenboim, A., Durman, T., Yaacoby, S., Berg Miller, M. E.,
501 ... Mizrahi, I. (2016). Specific microbiome-dependent mechanisms underlie the energy harvest
502 efficiency of ruminants. *ISME Journal*, 10(12), 2958–2972. <https://doi.org/10.1038/ismej.2016.62>
- 503 Kuhn, M., Wing, J., Weston, S., Williams, A., Keefer, C., Engelhardt, A., ... Hunt, T. (2020). Caret:
504 Classification and regression training. R package version 6.0-86. [Online]. Retrieved from
505 <https://cran.r-project.org/web/packages/caret/index.html>
- 506 Leitão-Gonçalves, R., Carvalho-Santos, Z., Francisco, A. P., Fioreze, G. T., Anjos, M., Baltazar, C., ...
507 Ribeiro, C. (2017). Commensal bacteria and essential amino acids control food choice behavior and
508 reproduction. *PLoS Biology*, 15(4), 1–29. doi: 10.1371/journal.pbio.2000862
- 509 Lesage, L., Crête, M., Huot, J., Dumont, A., & Ouellet, J. P. (2000). Seasonal home range size and
510 philopatry in two northern white-tailed deer populations. *Canadian Journal of Zoology*, 78(11), 1930–
511 1940. <https://doi.org/10.1139/z00-117>
- 512 Ley, R. E. (2010). Obesity and the human microbiome. *Current Opinion in Gastroenterology*, 26(1), 5–11.
513 <https://doi.org/10.1097/MOG.0b013e328333d751>
- 514 Ley, R. E., Hamady, M., Lozupone, C., Turnbaugh, P. J., Ramey, R. R., Bircher, J. S., ... Gordon, J. I.
515 (2008). Evolution of mammals and their gut microbes. *Science*, 320, 1647–1651.
- 516 Lynch, G. (1973). Seasonal changes in thermogenesis, organ weights, and body composition in the white-
517 footed mouse, *Peromyscus leucopus*. *Oecologia*, 13, 363–376.
- 518 Ma, L., Xu, S., Liu, H., Xu, T., Hu, L., Zhao, N., ... Zhang, X. (2019). Yak rumen microbial diversity at
519 different forage growth stages of an alpine meadow on the Qinghai-Tibet Plateau. *PeerJ*, 7, e7645.
520 doi: 10.7717/peerj.7645
- 521 Mao, J. H., Kim, Y. M., Zhou, Y. X., Hu, D., Zhong, C., Chang, H., ... Snijders, A. M. (2020). Genetic and
522 metabolic links between the murine microbiome and memory. *Microbiome*, 8(1), 1–14. doi:
523 10.1186/s40168-020-00817-w
- 524 Marrotte, R. R., Bowman, J., & Morin, S. J. (2020). Spatial segregation and habitat partitioning of bobcat
525 and Canada lynx. *Facets*, 5, 503–522. doi: 10.1139/facets-2019-0019
- 526 Massé, A., & Côté, S. D. (2013). Spatiotemporal variations in resources affect activity and movement.
527 *Canadian Journal of Zoology*, 91, 252–263. <https://doi.org/10.1139/cjz-2012-0297>
- 528 Mccune, B., & Keon, D. (2002). Equations for potential annual direct incident radiation and heat load.
529 *Journal of Vegetation Science*, 13(4), 603–606. doi: 10.1111/j.1654-1103.2002.tb02087.x
- 530 McPeck, M. (1996). Trade-offs, food web structure, and the coexistence of habitat specialists and
531 generalists. *The American Naturalist*, 148, S124–S138.
- 532 Merritt, J., & Zegers, D. (1991). Seasonal thermogenesis and body-mass dynamics of *Clethrionomys*
533 *gapperi*. *Canadian Journal of Zoology*, 69, 2771–2777.
- 534 Mountain Goat Management Team (2010). Management plan for the mountain goat (*Oreamnos*
535 *americanus*) in British Columbia. [Online]. Retrieved from
536 <http://a100.gov.bc.ca/pub/eirs/finishDownloadDocument.do?subdocumentId=7821>

- 537 Munro, K. (2020). White-tailed fear: The human-created landscape of fear and its effect on white-tailed
538 deer (*Odocoileus virginianus*) behaviour. (PhD thesis). Trent University, Ontario, Canada
- 539 Murray, M.H., Lankau, E. W., Kidd, A. D., Welch, C. N., Ellison, T., H.C, A., ... Hernandez, S. M.
540 (2020). Gut microbiome shifts with urbanization and potentially facilitates a zoonotic pathogen in a
541 wading bird. *PLoS ONE*, 15(3), e0220926. <https://doi.org/10.1371/journal.pone.0220926>
- 542 Nielson, R. M., Sawyer, H., & McDonald, T. L. (2015). BBMM: Brownian Bridge Movement Model. R
543 package version 3.0. [Online]. Retrieved from: [https://cran.r-](https://cran.r-project.org/web/packages/BBMM/index.html)
544 [project.org/web/packages/BBMM/index.html](https://cran.r-project.org/web/packages/BBMM/index.html)
- 545 Ontario Ministry of Natural Resources and Forestry (2019). Southern Ontario Land Resource Information
546 System (SOLRIS) (Version 3.0.) [Data set]. Retrieved from
547 <https://geohub.lio.gov.on.ca/datasets/southern-ontario-land-resource-information-system-solris-3-0>
- 548 Krajmalnik-Brown, R., Ilhan, Z. E., Kang, D. W., & DiBaise, J. K. (2012). Effects of gut microbes on
549 nutrient absorption and energy regulation. *Nutrition in Clinical Practice*, 27(2), 201–214. doi:
550 10.1177/0884533611436116
- 551 Pielou, E. C. (1966). The measurement of diversity in different types of biological collections. *Journal of*
552 *Theoretical Biology*, 13, 131–144. [https://doi.org/10.1016/0022-5193\(66\)90013-0](https://doi.org/10.1016/0022-5193(66)90013-0)
- 553 Poole, K. G., & Heard, D. C. (2003). Seasonal Habitat Use and Movements of Mountain Goats, *Oreamnos*
554 *americanus*, in East-central British Columbia. *Canadian Field-Naturalist*, 117(4), 565–576.
555 <https://doi.org/doi.org/10.22621/cfn.v117i4.825>
- 556 Poole, K. G., Stuart-Smith, K., & Teske, I. E. (2009). Wintering strategies by mountain goats in interior
557 mountains. *Canadian Journal of Zoology*, 87(3), 273–283. <https://doi.org/10.1139/z09-009>
558 <https://doi.org/10.2981/wlb.00572>
- 559 Richard, J. H., & Côté, S. D. (2016). Space use analyses suggest avoidance of a ski area by mountain goats.
560 *Journal of Wildlife Management*, 80(3), 387–395. <https://doi.org/10.1002/jwmg.1028>
- 561 Rodewald, A. D., & Vitz, A. C. (2005). Edge and area-sensitivity of shrubland birds. *Journal of Wildlife*
562 *Management*, 69(2), 681–688.
- 563 San Juan, P., Hendershot, J., Daily, G., & Fukami, T. (2019). Land-use change has host-specific influences
564 on avian gut microbiomes. *The ISME Journal*, 14, 318–321. [https://doi.org/10.1038/s41396-019-0535-](https://doi.org/10.1038/s41396-019-0535-4)
565 [4](https://doi.org/10.1038/s41396-019-0535-4)
- 566 Sawyer, H., Kauffman, M. J., Nielson, R. M., & Horne, J. S. (2009). Identifying and prioritizing ungulate
567 migration routes for landscape-level conservation. *Ecological Applications*, 19(8), 2016–2025.
568 <https://doi.org/10.1890/08-2034.1>
- 569 Schretter, C. E., Vielmetter, J., Bartos, I., Marka, Z., Marka, S., Argade, S., & Mazmanian, S. K. (2018). A
570 gut microbial factor modulates locomotor behaviour in *Drosophila*. *Nature*, 563(7731), 402–406.
571 <https://doi.org/10.1038/s41586-018-0634-9>
- 572 Schweiger, A. K., Schütz, M., Anderwald, P., Schaeppman, M. E., Kneubühler, M., Haller, R., & Risch, A.
573 C. (2015). Foraging ecology of three sympatric ungulate species - behavioural and resource maps
574 indicate differences between chamois, ibex and red deer. *Movement Ecology*, 3(1), 6.
575 <https://doi.org/10.1186/s40462-015-0033-x>
- 576 Shafer, A. B. A., Northrup, J. M., White, K. S., Boyce, M. S., Côté, S. D., & Coltman, D. W. (2012).
577 Habitat selection predicts genetic relatedness in an alpine ungulate. *Ecology*, 93(6), 1317–1329.
578 <https://doi.org/10.1890/11-0815.1>
- 579 Shreiner, A., Kao, J., & Young, V. (2015). The gut microbiome in health and in disease. *Current Opinion*
580 *in Gastroenterology*, 31(1), 69–75. <https://doi.org/10.1097/MOG.0000000000000139.The>
- 581 Taylor, S., Wall, W., & Kulis, Y. (2014). Habitat selection by mountain goats in south coastal British
582 columbia habitat selection by mountain goats in south coastal British Columbia. *Biennial Symposium*
583 *Northern Wild Sheep and Goat Council*, 15, 141–158.
- 584 Tinker, K. A., & Ottesen, E. A. (2016). The core gut microbiome of the American cockroach, *Periplaneta*
585 *americana*, is stable and resilient to dietary shifts. *Applied and Environmental Microbiology*, 82(22),
586 6603–6610. <https://doi.org/10.1128/AEM.01837-16.Editor>

- 587 Turnbaugh, P. J., Ley, R. E., Mahowald, M. A., Magrini, V., Mardis, E. R., & Gordon, J. I.
588 (2006). An obesity-associated gut microbiome with increased capacity for energy harvest.
589 *Nature*, 444(7122), 1027–1031. doi: 10.1038/nature05414
- 590 Van Deelen, T., Campa III, H., Hamady, M., & Haulfer, J. (1998). Migration and seasonal range dynamics
591 of deer using adjacent deeryards in northern Michigan. *The Journal of Wildlife Management*, 62(1),
592 205–213.
- 593 Webb, S. L., Hewitt, D. G., & Hellickson, M. W. (2007). Scale of management for mature male white-
594 tailed deer as influenced by home range and movements. *Journal of Wildlife Management*, 71(5),
595 1507–1512. <https://doi.org/10.2193/2006-300>
- 596 White, K. S. (2006). Seasonal and sex-specific variation in terrain use and movement patterns of mountain
597 goats in Southeastern Alaska. *Biennial Symposium Northern Wild Sheep and Goat Council*, 15, 183–
598 194.
- 599 Wolf, J. F., Kriss, K. D., MacAulay, K. M., & Shafer, A. B. A. (2020). Panmictic population genetic
600 structure of northern British Columbia mountain goats (*Oreamnos americanus*) has implications for
601 harvest management. *Conservation Genetics*, 21, 613–623. [https://doi.org/10.1007/s10592-020-01274-](https://doi.org/10.1007/s10592-020-01274-6)
602 [6](https://doi.org/10.1007/s10592-020-01274-6)
- 603 Zhang, N., Ju, Z., & Zuo, T. (2018). Time for food: The impact of diet on gut microbiota and human
604 health. *Nutrition*, 51–52, 80–85. <https://doi.org/10.1016/j.nut.2017.12.005>

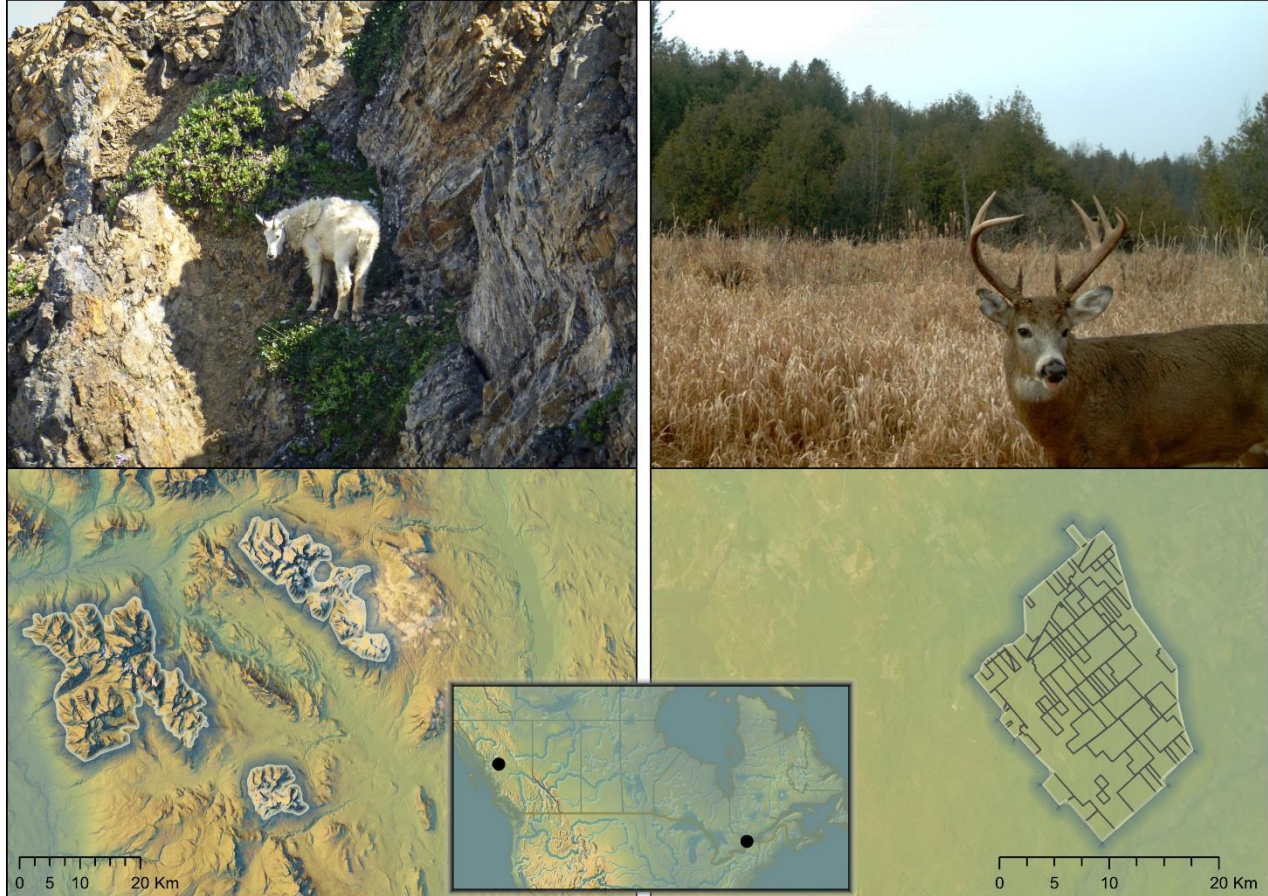
605 **Data Accessibility**

606 **Author Contributions**

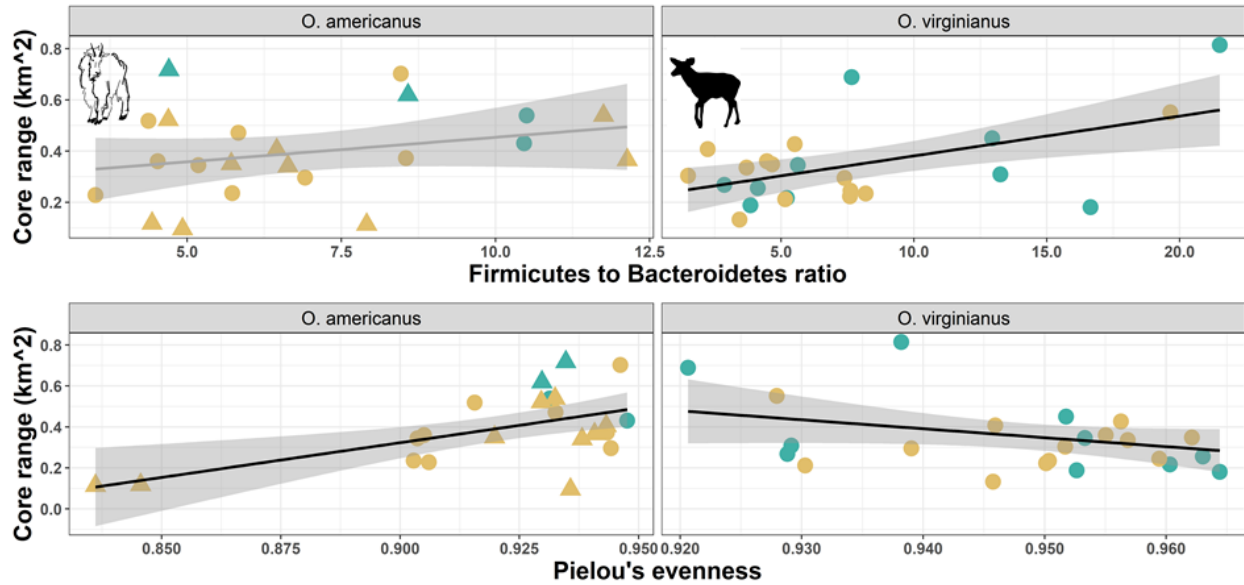
607

608 J.F.W. and A.B.A.S. conceived the ideas; K.D.K., K.M.M., K.M., B.R.P., J.F.W., and A.B.A.S. collected
609 materials and data; J.F.W. analysed the data; and J.F.W. wrote the paper with contributions from all co-
610 authors.

611 **Figures**
612

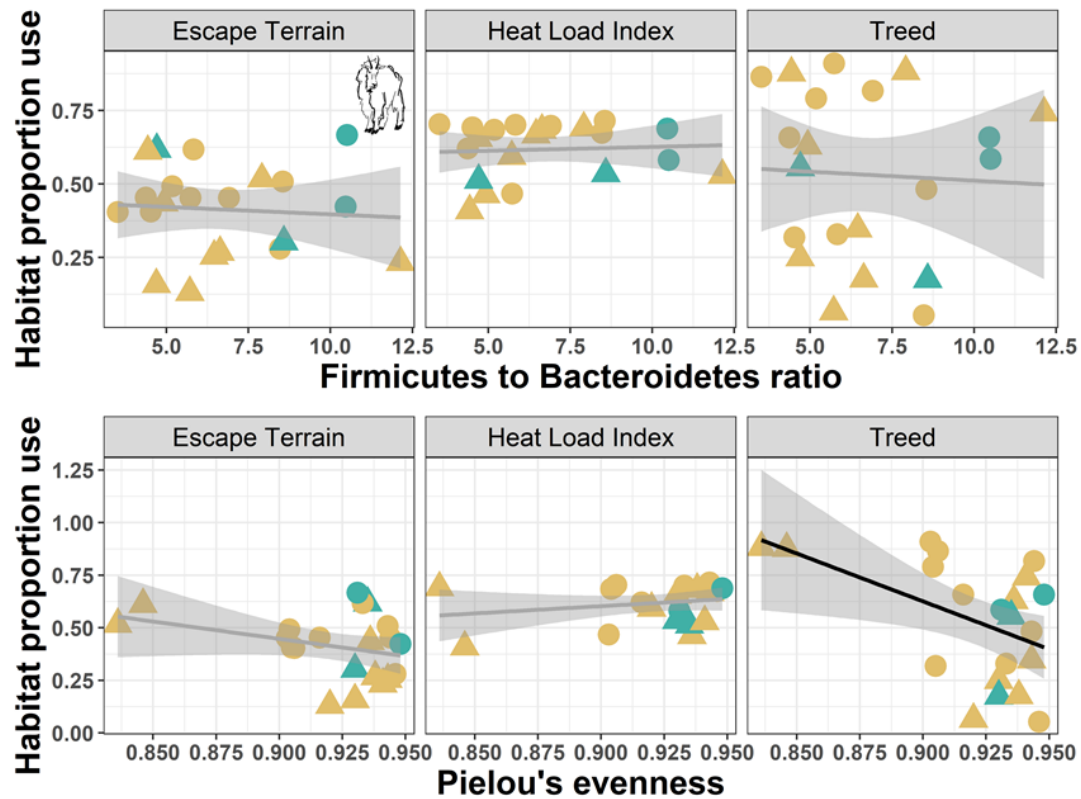


613 **Fig. 1** An example of habitat of both mountain goat (*Oreamnos americanus*) and white-tailed deer
614 (*Odocoileus virginianus*) along with inset sample maps. Colors are reflective of relative elevation and
615 topography. Average elevation of mountain goat habitat was 1614.7m, relative to 113.3m for white-tailed
616 deer.
617
618



619
620
621
622
623
624
625

Fig. 2 Microbiome metrics for mountain goats (*Oreamnos americanus*, n=22) northeast of Smithers, British Columbia, and white-tailed deer (*Odocoileus virginianus*, n=25) Southwest of Ottawa, Ontario, relative to core summer range size. Females are represented by circles and only mountain goats have mixed-sex data. Adults (≥ 3 years of age) are represented in yellow, and subadults in blue. Significant Generalized Linear Models (GLMs) are denoted with a black line.



626
627 **Fig. 3** Microbiome metrics for mountain goats - *Oreamnos americanus* northeast of Smithers, British
628 Columbia, relative to habitat selection coefficients of both Heat Load Index (HLI) and treed habitat (n=21).
629 Females are represented by circles and only mountain goats have mixed-sex data. Adults (≥ 3 years of age)
630 are represented in yellow, and subadults in blue. Significant Generalized Linear Models (GLMs) are
631 denoted with a black line.

632 **Tables**

633

634 Table 1. Generalized linear models for core summer range size of mountain goat - *Oreamnos americanus*
 635 and white-tailed deer - *Odocoileus virginianus* (n_{MG}=22, n_{WTD}=25). The further left column refers to the
 636 model where *Firmicutes* to *Bacteroides* ratios was a predictor, while the right column refers to the model
 637 where Pielou's evenness was a predictor
 638

Mountain goat					
<i>Predictors</i>	<i>Estimates</i>	Core range size		Core range size	
		<i>CI</i>	<i>Estimates</i>	<i>CI</i>	
(Intercept)	0.29	0.10 - 0.49	-2.3	-4.1 - -0.42	
F:B Ratio	0.010	-0.020 - 0.040	-	-	
Pielou's evenness	-	-	2.8	0.85 - 4.8	
Age class (Subadult)	0.20	0.020 - 0.38	0.17	0.020 - 0.32	
R ² Nagelkerke		0.27		0.47	
White-tailed deer					
<i>Predictors</i>	<i>Estimates</i>	Core range size		Core range size	
		<i>CI</i>	<i>Estimates</i>	<i>CI</i>	
(Intercept)	0.22	0.11 - 0.33	5.4	0.62 - 10	
F:B Ratio	0.020	0.00 - 0.03	-	-	
Pielou's evenness	-	-	-5.3	-10 - -0.32	
Age class (Subadult)	0.010	-0.12 - 0.14	0.050	-0.08 - 0.17	
R ² Nagelkerke		0.28		0.21	

639

640 Table 2. Generalized linear models for habitat proportion use for mountain goats (*Oreamnos americanus*)
 641 and white-tailed deer (*Odocoileus virginianus*) (n_{MG}=22, n_{WTD}=25) The further left column refers to the
 642 model where *Firmicutes* to *Bacteroides* ratios was a predictor, while the right column refers to the model
 643 where Pielou's evenness was a predictor
 644

Mountain goat

<i>Predictors</i>	Escape terrain proportion use		Escape terrain proportion use	
	<i>Estimates</i>	<i>CI</i>	<i>Estimates</i>	<i>CI</i>
(Intercept)	0.48	0.28 – 0.69	2.36	0.43 – 4.28
F:B Ratio	-0.01	-0.05 – 0.02	-	-
Age class (Subadult)	0.14	-0.04 – 0.32	0.15	-0.01 – 0.31
Pielou's evenness	-	-	-2.14	-4.24 – -0.05
R ² Nagelkerke	0.127		0.252	

645

<i>Predictors</i>	Treed proportion use		Treed proportion use	
	<i>Estimates</i>	<i>CI</i>	<i>Estimates</i>	<i>CI</i>
(Intercept)	0.56	0.16 – 0.97	4.84	1.23 – 8.45
F:B Ratio	-0.00	-0.06 – 0.06	-	-
Age class (Subadult)	-0.04	-0.40 – 0.32	0.04	-0.25 – 0.34
Pielou's evenness	-	-	-4.69	-8.63 – -0.76
R ² Nagelkerke	0.0050		0.24	

<i>Predictors</i>	Heat Load Index Average		Heat Load Index Average	
	<i>Estimates</i>	<i>CI</i>	<i>Estimates</i>	<i>CI</i>
(Intercept)	0.58	0.41 – 0.76	-0.23	-2.02 – 1.55
F:B Ratio	0.01	-0.02 – 0.04	-	-
Age class (Subadult)	-0.07	-0.23 – 0.08	-0.06	-0.22 – 0.08
Pielou's evenness	-	-	0.91	-0.99 – 2.90
R ² Nagelkerke	0.052		0.074	

646

White-tailed deer

<i>Predictors</i>	Forest proportion use		Forest proportion use	
	<i>Estimates</i>	<i>CI</i>	<i>Estimates</i>	<i>CI</i>

(Intercept)	0.29	0.11 – 0.47	2.86	-4.64 – 10.36
F:B Ratio	0.00	-0.02 – 0.01	-	-
Age class (Subadult)	0.02	-0.18 – 0.22	0.01	-0.19 – 0.20
Pielou's evenness	-	-	-2.74	-10.63 – 5.16
<hr/>				
R ² Nagelkerke	0.025		0.017	
Thicket Swamp proportion use Thicket Swamp proportion use				
<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>Estimates</i>	<i>CI</i>
<hr/>				
(Intercept)	0.19	0.08 – 0.30	-0.85	-5.37 – 3.67
F:B Ratio	-0.00	-0.01 – 0.01	-	-
Age class (Subadult)	-0.10	-0.23 – 0.02	-0.10	-0.22 – 0.02
Pielou's evenness	-	-	1.10	-3.66 – 5.86
<hr/>				
R ² Nagelkerke	0.12		0.13	

647

Treed Swamp proportion use Treed Swamp proportion use				
<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>Estimates</i>	<i>CI</i>
<hr/>				
(Intercept)	0.35	0.17 – 0.53	-3.57	-11.02 – 3.89
F:B Ratio	0.00	-0.02 – 0.02	-	-
Age class (Subadult)	0.05	-0.15 – 0.25	0.06	-0.13 – 0.26
Pielou's evenness	-	-	4.14	-3.71 – 11.99
<hr/>				
R ² Nagelkerke	0.012		0.059	

648